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Proceedings, Part II

Part 2

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Guan Gui · Ying Li · Yun Lin
Editors

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Preface

Welcome to the International Conference on e-Learning, e-Education, and Online Training in the picturesque city of Yantai! It's a privilege to have such a distinguished gathering of experts and scholars in the field of digital education.

Our conference title, "International Conference on e-Learning, e-Education, and Online Training," reflects the evolving landscape of education in the digital age. As we navigate a world increasingly defined by technology, the exploration of e-learning methodologies, e-education platforms, and online training mechanisms becomes paramount.

The significance of this conference was amplified by the locale. As a coastal city, Yantai's rich history and dynamic spirit offered an inspiring setting to explore groundbreaking ideas that can shape the future of education. Yantai University, one of the nearest universities to the coast, hosted this conference in support of educational development. Through insightful discussions, sharing of research findings, and collaborative networking, we aimed to harness the power of digital tools to democratize education, bridge learning gaps, and foster lifelong learning opportunities for diverse global communities.

Looking ahead, we envision a future where geographical boundaries are no longer barriers to quality education. Personalized learning pathways, augmented-reality classrooms, and AI-driven assessment models are just a glimpse into the possibilities that lie before us.

All participants engaged wholeheartedly in exchanging ideas and seizing this opportunity to contribute to the collective advancement of e-learning and online education. We embarked on this journey of innovation and transformation together.

Thank you for being a part of this inspiring conference. Here's to meaningful conversations, insightful discoveries, and a brighter future for education worldwide.

August 2023 Ying Li

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Contents – Part II

AI Based Educational Modes and Methods

Educational Information Retrieval Method for Innovative Entrepreneurship Training of Accounting Talents Based on Deep Learning

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Abstract. In the education information retrieval of accounting talent innovation and entrepreneurship training, there may be issues such as inconsistent data quality, missing data, and outdated data, leading to a decrease in the performance of education information retrieval. To this end, a deep learning based accounting talent innovation and entrepreneurship training education information retrieval method is designed. Preprocesses such as text cleaning, Chinese word segmentation, vectorization of text, noise filtering, etc. are implemented for all texts. Aiming at the characteristics of high dimensionality and high sparsity of traditional multi classification text representation and classification methods based on bag of words model features, combined with the advantages of deep learning model to effectively extract high-level features, a deep belief convolution neural network model integrating deep belief network is proposed to extract low dimensionality, dense text high-level feature vector representation and implement text classification. Design a short learning model based on Actor Critic algorithm, use TCN to model the user to obtain the user's intention, use two fully connected feedforward neural networks to represent the strategy and value function respectively, implement relevance matching for the query and document classification results, and realize the education information retrieval of accounting talent innovation and entrepreneurship training. The test results show that the design method has higher MAP, lower NDCG and ERR, and has good educational information retrieval performance.

Keywords: DBCNN · Chinese Word Segmentation · Innovation and Entrepreneurship Training of Accounting Talents · Educational Information Retrieval

1 Introduction

China is entering a new stage of digital economy development, the construction of socialism with Chinese characteristics has entered a new era, and the picture of the great rejuvenation of the Chinese nation is slowly unfolding. Accounting education at the new stage of the new era is more important. It not only serves the needs of professional

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talents for the transformation and upgrading of industrial enterprises, but also shoulders the historic task of cultivating qualified builders and successors for the cause of socialism with Chinese characteristics [1, 2]. As an important part of the accounting talent strategy, accounting professional education in colleges and universities is facing unprecedented pressure of change under the impact of complex and changeable business environment, digital technology driven change, organizational management model innovation and other factors. How to change the training of accounting professionals to meet the needs of new accounting talents in the new era is directly related to whether accounting reform and development can obtain effective talent support.

In order to carry out in-depth research on the significance of innovation and entrepreneurship education of accounting talents, it is necessary to search the education information of innovation and entrepreneurship education of accounting talents. In the research of information retrieval, in order to comprehensively improve the comprehensive performance of library integrated information retrieval methods, some scholars proposed a library integrated information retrieval method based on random forest combined with random forest algorithm. Bayesian polynomials are added in the process of building a random forest bottom classifier. Using the data carried in the algorithm, a voting mechanism based on two-dimensional weight distribution is proposed, and library integrated information retrieval is carried out according to the voting results. The simulation results show that the proposed method can effectively improve the retrieval efficiency and accuracy of retrieval results, and obtain satisfactory library integrated information retrieval results. Some scholars have proposed a network information retrieval method based on association rule mining. First, set the URL index parameters of information retrieval, build the retrieval algorithm of rule mining, at the same time, establish the query expansion retrieval model, and use the weighted matrix to achieve network information retrieval. Through testing to verify the applicability of the method, compare the traditional verification retrieval group with the test information retrieval group in the same test environment, and finally get the test results. The results show that the precision of the test information retrieval group is relatively high, that is, the effect of this retrieval method is better and the technology is more mature. The above methods have the problems of low MAP, high NDCG, and high ERR.

Therefore, we design an in-depth learning based educational information retrieval method for innovation and entrepreneurship training of accounting talents. All texts are preprocessed, and the deep belief Convolutional neural network model is used to extract low dimensional, dense high-level feature vectors of texts and implement text classification. Design a sorting learning model based on Actor Critic algorithm, implement correlation matching between query and document classification results, and complete information retrieval for accounting talent innovation and entrepreneurship training education. The design method has a higher MAP and lower NDCG and ERR, which can effectively improve the performance of educational information retrieval.

2 Design of Educational Information Retrieval Method for Innovative Entrepreneurship Training of Accounting Talents

2.1 Text Pre-processing

Preprocesses such as text cleaning, Chinese word segmentation, vectorization of text, noise filtering, etc. are implemented for all texts.

Because the existing text data set contains a large number of invalid characters, such as non text data, long strings of numbers or letters, meaningless text or comments, it will not only cause a lot of waste of resources, but also have a negative impact on the classification effect. Therefore, before using the text set, we must first process the data set through a certain method, that is, remove irrelevant characters in the data cleaning phase. The main methods include: removing invalid characters according to the stop word list, retaining only words containing semantic information, removing punctuation marks and numbers, etc. [3]. Of course, stop words are not immutable, and the list of stop words used in text classification in different contexts should also be changed accordingly. These removed texts are data that have no effect on the text classification results and do not have any emotional color. By removing these data, the space of the text matrix can be reduced, the sparsity can be reduced, and the text can better fit the actual features of the text.

The function of Chinese word segmentation is to cut the cleaned text into word sequences according to certain rules. The Chinese word segmentation model based on fusion features and conditional random fields is used to implement Chinese word segmentation. The model structure is shown in Fig. 1.

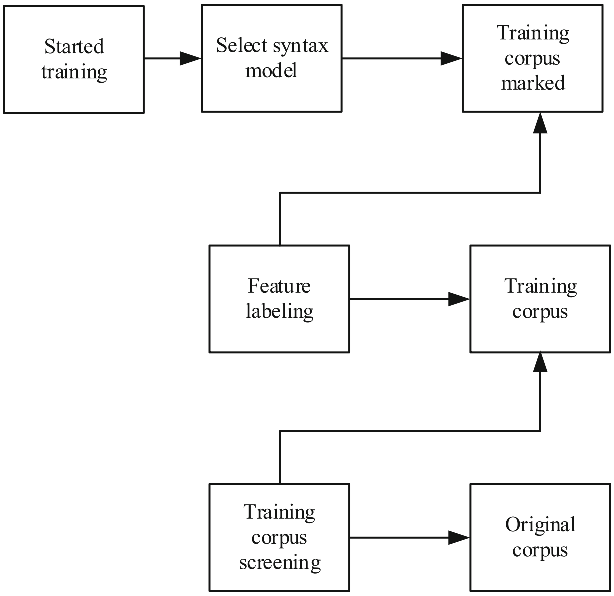

Fig. 1. Model Structure

The training corpus selection is to select the best training corpus for the test corpus. Chinese feature tagging should first determine the features to be used in the field of Chinese word segmentation. After determining the features to be used, the corpus can be preprocessed according to the designed features to complete the tagging of training corpus. The grammar model involves the use of a few yuan grammar model. Intuitively speaking, the general idea is to directly use a sentence as the statistical object, but it is difficult to repeat a sentence in a limited corpus. A large corpus can only list millions of sentences. In order to ensure the effectiveness of training and prevent data sparsity, a combination of one yuan and two yuan grammar is used. For random two words, the probability of occurrence in the corpus is not low, and the problem of data sparsity will not occur. As a model of sequence labeling, conditional random field also needs to pay attention to the problem of training "window", that is, how long the sequence before and after the unary or binary elements and their own positions are trained.

In order to describe the known information of the training corpus, the model needs to capture the statistical characteristics of the known information.The conditional random field uses the feature function information of $\{0,1\}$ real number function to complete the coding of the feature [4]. Set up Y is the Chinese word segmentation window and r metagrammar defines the set of conditions, $\beta \in Y$, O is a training set (annotation set), $o \in O$ then the characteristic function of conditional random field is defined as formula (1):

$$F(\beta, o) = \begin{cases} 1, & \beta = \beta_1 \textit{ and } o = o_1 \\ 0, & \textit{otherwise} \end{cases} \tag{1}$$

In formula (1), β_1 refer to Y other elements in; o_1 means O other elements in.

The essence of Chinese word segmentation of conditional random field is to describe and count the features in the training corpus through the above feature functions, so the selection of features is particularly important. Therefore, this paper proposes fusion features to improve the accuracy of word segmentation. To sum up, the fusion feature needs to focus on four aspects: training corpus selection, feature template, location feature and optimization feature.

For the conditional random field model, in order to achieve the best fitting effect, it is necessary to ensure that the training set and the test set have the same characteristics. In the field of Chinese word segmentation, this feature can be understood as the conditional probability of "character" forming "word". In order to ensure the training effect and reduce the manual workload, this paper will randomly select a small part of the educational corpus and adjust the order as the training corpus.

The fusion feature selects a single 5-word window and a binary 3-word window as the feature template. The characteristics of both are shown in Table 1.

Table 1. Features of Feature Template

S/N	Name	Features
1	Unitary 5- word window	Cn,n = −2, −1, 0, 1, 2
2	Binary 3-word window	Cn Cn + 1, n = −1, 0

Table 2. Common Position Feature Set

S/N	Characteristic set name	Explain	Position feature mark
1	6 Lexemic feature set	The first word (B), the second word (B1), the third word (B2), the middle word (M), the end of the word (E) and the single word (S), where punctuation marks the single word	{B, B1, B2, M, E, S}
2	5 Lexical feature set	The first word (B), the second word (B1), the middle word (M), the end of the word (E), and the single word (S), where punctuation marks the single word	{B, B1, M, E, S}
3	4 Lexical feature set	Initial (B), middle (M), end (E) and separate word (S), where punctuation marks are separate words	{B, M, E, S}
4	3 Lexical features	Word prefix (B), non word prefix (I) and separate word (S), where punctuation marks are separate words	{B, I, S}
5	2 Lexical feature set	Prefixes (B), non prefixes (I), and special words formed separately are also marked as prefixes	{B, I}

According to the characteristics of Chinese grammar and the design of Chinese word segmentation feature set of conditional random field, the first consideration is where the “character” is located in a “word”. Therefore, the fusion feature must first select the location feature as the feature set. As shown in Table 2, according to the position of the word where the character is located, the features of the feature set can be designed into the following types: the feature set of 2 word bits, a Chinese word can be marked in the form of BII……, the feature set of 3 word bits, a Chinese word can be marked in the form of BII……S, the feature set of 4 word bits, a Chinese word can be marked in the form of BMM……E, and the feature set of 5 word bits. A Chinese word can be marked in the form of BB1MM……E, and a Chinese word can be marked in the form of BB1B2MM……E [5] in the feature set of 6 word bits.

After a detailed study of Chinese grammar, the position of "character" in "word", in addition to the relatively simple position of "character" in the beginning and end of "word", there are the following position related elements that can be added to the feature set as optimization features, as shown in Table 3.

Table 3. Optimization feature set

Serial Number	Feature Set Name	Feature tags	Explain
1	The type of character	{CN, EN, NUM, PUN	Chinese (CN), English (EN), Numbers (NUM), Symbols (PUNC)
2	Word length	{1, 2, 3, ……}	One word length (1), two word lengths (2), three word lengths (3)

The grammar of all languages is built on the part of speech, and Chinese is no exception. The process of construction is also the combination and ordering of different types of words according to certain rules. But the part of speech of Chinese is relatively complex, including nouns, verbs, adjectives, numerals, quantifiers, pronouns, adverbs, distinguishing words, and status words. There are nine categories of content words, prepositions, conjunctions, auxiliary words. There are 4 sub categories of modal particles, which are function words, and there are also two special types of words, onomatopoeia and interjection. However, according to this classification, the manual work is too heavy, and the requirements for people's Chinese grammar professionalism are too high, which is not feasible in engineering. In addition, it is easy to appear the phenomenon of over fitting in machine learning. In order to simplify the problem, Chinese can be simply divided into Chinese, English, punctuation marks, and numbers.

Where a "word" is located, the most direct connection is how many "words" a "word" consists of. Therefore, the length of a word can also be considered as a feature. Such features express the probability of a "word" being combined into a long word. According to the length of the word where "word" is located, each "word" can be marked with the length of its own word [6].

To sum up, the fusion feature will add two features: the type of the word and the length of the word where the word is located.

The information structure of Chinese short text is poor, and it is difficult to be directly recognized by computers using natural language. Converting text represented by characters into vector representation with digital significance that can be recognized by computers, namely, text vectorization, is the basis and important step of text classification. A good vectorized representation of text can better represent the spatial mapping of text in space. The vector representation of the text used is word frequency - inverse document frequency.

TF-IDF proposes the concept of inverse text while considering the frequency of words. It considers words that do not carry much information but have a high frequency of occurrence. TF represents the frequency of words, and IDF represents the frequency of inverse documents. For example, formula (2), TF is determined by the frequency of words $z_{i,h}$ the higher, the word ϖ_i the greater the TF value of.However, it is not feasible to simply calculate frequency, because connectives such as “de” and “yes” are very frequent but have little effect on classification. The more words appear in all texts in the text set, the closer the number of documents is to the number of documents containing words, and the closer the IDF value is to 0. Calculate words according to the product of the two ϖ_i TF-IDF value of:

$$TF(\varpi_i) = \frac{z_{i,h}}{\sum_h z_{i,h}} \tag{2}$$

In formula (2), h refers to the number of words.

After word segmentation and representation of Chinese text, the text changes from a continuous string to a series of word strings. But the words appearing in the word string do not mean that the higher the word frequency, the greater the weight, and the stronger the representativeness. Deactivation words are such words, which have a high frequency of occurrence, but have no actual meaning or can not express text features. In Chinese, words such as most letters, prepositions, commonly used adverbs, auxiliary words, quantifiers, commonly used onomatopoeias and commonly used verbs are common stop words. Deactivation words have almost no meaning for the text content. Deactivation words must be filtered in the pre-processing phase. This process is called Deactivation word filtering. Deactivated word filtering will reduce the impact of interference items on the classification results. At the same time, the reduction of vocabulary in the document set will also reduce the computational scale of the algorithm.

However, due to the huge Chinese vocabulary, the stop word dictionary can only cover commonly used stop words. If it is necessary to improve the stop word dictionary as much as possible, it will lead to a large number of stop words in the dictionary and slow query speed. At the same time, the selection of stop words is an expert field, which needs to be accumulated, explored, or analyzed in a certain field. Therefore, in addition to using the stop word dictionary filtering technology, regular expressions are used to perform regular matching on the word segmentation results, because the stop words that need to be removed in a Chinese word often have certain patterns, such as words containing “yes”, “ba”, “no” and other words are almost impossible to be article keywords, and the advantages of regular matching are fully used to filter words with numbers, words with filtered words, words with non Chinese characters, etc.

2.2 Text Classification

Text categorization is a process of text categorization, which predicts unknown texts by feature learning and training models for text datasets of acquired categories. This paper designs a multi - classification text representation and classification method based on DBCNN.

Aiming at the characteristics of high dimensionality and sparseness of traditional multi classification text representation and classification methods based on bag of words model features, combined with the advantages of deep learning model to effectively extract high-level features, a deep belief convolution neural network model integrating deep belief network is proposed to extract low dimensionality, dense text high-level feature vector representation. And then improve the performance of multi classification text representation and classification algorithm.

Considering the training efficiency and training complexity of the model, the model is composed of two two-layer RBM DBN networks, one layer 1D convolution layer, one layer max pooling layer, two layers full connection layer and one layer softmax Te"The Belt and Road" Initiative NN network [7]. Firstly, the dimension of the text input vector is preliminarily reduced based on the DBN model, and the input noise is effectively removed; Then, based on the local features extracted from Te"The Belt and Road" Initiative NN, the dimension of the text feature representation vector extracted from the DBN network is further reduced through the convolution operation and pooling operation of Te"The Belt and Road" Initiative NN to obtain the high-level text feature representation. The deep belief convolution neural network model is shown in Fig. 2.

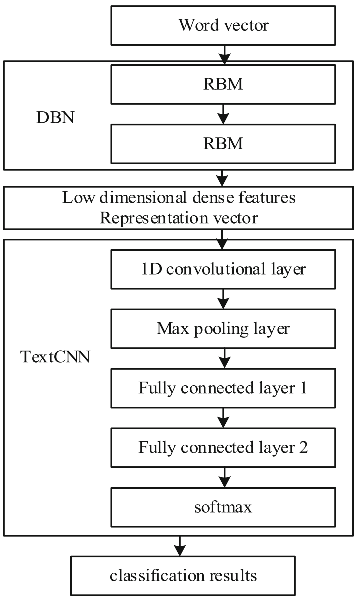

Fig. 2. Deep belief convolution neural network model

DBCNN model training is divided into two stages: 1) DBN pre training;2) Te"The Belt and Road" Initiative NN feature extraction. Firstly, the DBN network is used to preliminarily reduce the dimension of the text input and remove the input noise to extract the low dimensional dense text feature representation vector. Then, based on Te"The Belt and Road" Initiative NN network, the dimension of the text feature representation vector extracted through DBN network is further reduced by using the feature of Te"The

Belt and Road" Initiative NN extracting local features to obtain high-level text feature representation.

(1) DBN pre training

The RBM network structure in the DBN has two layers. The first layer is the visible layer corresponding to visible variables, and the second layer is the hidden layer corresponding to hidden variables. Both visible variables and hidden variables are binary variables, and the state value is $\{0,1\}$. The whole network is a bipartite graph. Only visible cells and hidden cells have edge connections. There is no edge connection between visible cells and hidden cells. In order to improve the computational efficiency in DBN pre training, the contrast hash algorithm [8] suitable for RBM efficient learning is used in DBN pre training.

The steps of DBN pre training are as follows: based on visual variables u get hidden variables in the state of k status of. Through the hidden variable obtained k to reconstruct the visual layer vector u_1, according to u_1 generate a new hidden layer vector k_1. Because there is no connection in the RBM layer, there is a particularity of connection between layers u on the basis of, each hidden cell k_j the activation states of are mutually independent; On the contrary, when a hidden variable is given k on the basis of, the activation status of each visual unit u_j they are also independent of each other.In the contrast hash algorithm, it is considered that the reconstructed visual vector u_1 and hidden vectors k_1 yes $Q(u, k)$ the sample set obtained by multiple sampling is regarded as the $Q(u, k)$ an approximation of. The core formula based on the contrast hash algorithm is shown in Formula (1) and Formula (2). The DBN network trains the entire model by training the RBM structure layer by layer. For a DBN network with a two-layer RBM structure, first train the parameters in the first layer RBM structure, and then use the output of the first layer RBM structure as the input of the second layer RBM structure to train the parameters in the second layer RBM structure [9].

$$Q(u, k) = \prod_j \frac{1}{1 + \exp\left(-\sum_i R_{ij} u_j - b_j\right)} \tag{3}$$

In formula (3), $Q(u, k)$ represent the reconstruction visual variable; R_{ij} represent visual unit i and hidden cells j weight of connected edges between; b_j indicates the offset of the hidden cell.

$$Q(k, u) = \prod_i \frac{1}{1 + \exp\left(-\sum_i R_{ij} k_j - d_j\right)} \tag{4}$$

In formula (4), $Q(k, u)$ indicates a hidden variable; d_j indicates the offset of the viewing unit.

(2) Te"The Belt and Road" Initiative NN feature extraction

The model structure of Te"The Belt and Road" Initiative NN is a variant of convolutional neural network. Set up y_l is the first in the sentence l words g dimension word vector, then the length is m the sentence of can be expressed by formula (3):

$$y_{1\ldots m} = y_1 \oplus y_2 \oplus \ldots \oplus y_m \tag{5}$$

Te"The Belt and Road" Initiative NN's convolution operation is different from CNN's convolution operation. Te"The Belt and Road" Initiative NN's convolution window must contain a complete line in the word vector, and the convolution window slides downward in parallel. Te"The Belt and Road" Initiative NN covers k the sliding window of four words produces eigenvectors.

Further, in the pooling layer, the feature map f is pooled to the maximum to obtain the feature vector $\hat{f} = \max\{f\}$. The maximum pooling operation can not only retain the most important features, but also process sentences of different lengths.

In the Te"The Belt and Road" Initiative NN feature extraction stage of DBCNN model, the first dimension reduction extracted by DBN pre training.

The text feature representation vector s is taken as the input of Te"The Belt and Road" Initiative NN, and then the dimension of s is further reduced through the convolution operation and max pooling operation, the high-level feature representation vector of text is extracted, and then the parameters in the network are updated through the back propagation of Te"The Belt and Road" Initiative NN network. After a certain number of iterations, the training is completed, and the text classification results can be output through the softmax layer.

The process of text classification through DBCNN model is shown in Fig. 3.

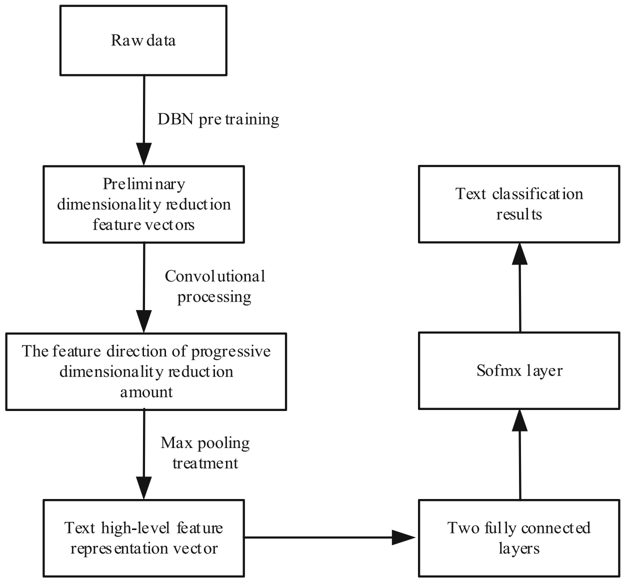

Fig. 3. DBCNN Text Classification Process

This completes the text classification processing.

2.3 Education Information Retrieval

A short learning model based on Actor Critic algorithm is designed to implement relevance matching for the query and document classification results, so as to realize the information retrieval of accounting talents' innovation and entrepreneurship training education.

This model uses TCN to model the user to obtain the user's intention, and uses two fully connected feedforward neural networks to represent the strategy and value function respectively. The two networks are called Actor Network and Critical Network [10] respectively. Calculate TD error in the Critical network to optimize the network's representation of the action value function. TD error will also be returned to the Actor network to construct the loss function of the Actor network, and optimize the sorting strategy after backpropagation. For an interactive sorting scenario, the sorting model based on Actor Critical runs as follows:

(1) Incomplete sampling.Similar to the TD (0) algorithm, only the next action is sampled.
   1. In the status state, sample a document action according to the sorting strategy, and calculate the Dcg at the same time;
   2. Enter the selected document into TCN and enter the next status_state;
   3. In next status_Sample the next document according to the sorting policy in state next_action.
(2) Update of action value function represented by Critical network. In this process, the sampled data is input into the Critical network to calculate TD error.
(3) Update of Actor network. In this process, the loss function is constructed to optimize the sorting strategy.
(4) Set state to next_State to enter the next cycle.

In the whole process, the Critical network represents the action value function more and more accurately with the increase of the number of iterations. The update of the Actor network depends on the $TC - error$ with the update of the Critical network, the sorting strategy of the model is gradually improved, and the final sorting strategy can be obtained after all queries are iterated N times.

In the model, the Actor network outputs the sorting of documents in a given state, and the Critical network evaluates the sorting.

The update of Actor network uses the data returned by Critical network $TC - error$, the loss function of the network is defined as:

$$LOSS_1 = (TC - error) * \lg(G) \tag{6}$$

In formula (6), G refers to the output of the Actor network, representing the score of the document.

The Critical network is responsible for representing the action value function. The state, action, Dcg, and next are transmitted from the Critical network_State and next_The loss function in the action and critical network is defined as:

$$LOSS_2 = (TC - error)^2 \tag{7}$$

Critical processes input data as follows:

1) Pass the state and action to the network to get the current action value Q;
2) Next_State and next_The action is transferred to the network to get the value of the next action Q';

3) Calculate the loss function according to formula (7);
4) Back propagation update parameters;
5) Calculation $TC - error$ and return the value.

$$TC - error = Dcg + \xi * Q' - Q \tag{8}$$

In formula (8), ξ refers to the Critical network parameters.

The processing before the state and action are input into the Actor network and the Critical network is to contact the two vectors directly, and then input the merged vectors into the corresponding network structure.

According to the above process description, the Actor network and the Critical network are interdependent when updating. Because the network is interdependent when updating, the convergence of this model is poor.

3 Retrieval Performance Test

3.1 Experimental Data Set

For the designed in-depth learning based educational information retrieval method for innovative entrepreneurship training of accounting talents, use it to implement educational information retrieval for innovative entrepreneurship training of accounting talents in university database, and test its retrieval performance.

In the test, we simulated the real scene of users using the retrieval model to input keywords for retrieval, assuming that users would not be tired of interest and would give feedback to every document related to keywords.

The simulated retrieval process is that the user inputs keywords, the retrieval model returns a document, and the user gives feedback on the document. The feedback information includes three types, namely, acceptance, partial acceptance, and acceptance. Then the retrieval learns the user's retrieval intention and adjusts its ranking strategy according to the user's feedback, and returns a new document. The whole process continues to cycle until the end of the specified round.

The experimental data set is the data in a university database.

3.2 Evaluation Index of Retrieval Effect

The commonly used evaluation indicators in the field of information retrieval include the average accuracy rate (MAP), the normalized cumulative loss gain (NDCG) and the reciprocal expectation of ranking (ERR). These indicators are used to analyze the sorting performance of the model.

MAP is often used in the ranking learning problem of two-level relevance, that is, for a query, documents are only relevant or not. The calculation formula is:

$$MAP = \left(\frac{1}{N}\right)\sum\left(\frac{1}{k} \times rel(k)\right) \tag{9}$$

In formula (9), N represents the total number of queries, k represents the ranking of the documents retrieved in each query, and $rel(k)$ represents the relevance of the documents in the position of k.

In the lossy cumulative gain DCG, multilevel correlation is considered. The calculation formula is:

$$DCG = rel(k) + \sum \left[\frac{rel(k)}{\log(k+1)} \right] \tag{10}$$

ERR believes that the probability of a document being clicked is affected by other documents before the document, and the two are negatively correlated. The calculation formula is:

$$ERR = \sum \left[\frac{rel(k) - 1}{(k \times P)} \right] \tag{11}$$

In formula (11), P represents the click probability.

3.3 Comparison Method Selection

In the test, the library integrated information retrieval method based on random forest and the network information retrieval method based on association rule mining are used as the comparison methods to jointly test the retrieval performance, and are represented by method 1 and method 2 respectively.

3.4 Test Results

The MAP test results of design method and method 1 and method 2 are shown in Fig. 4.

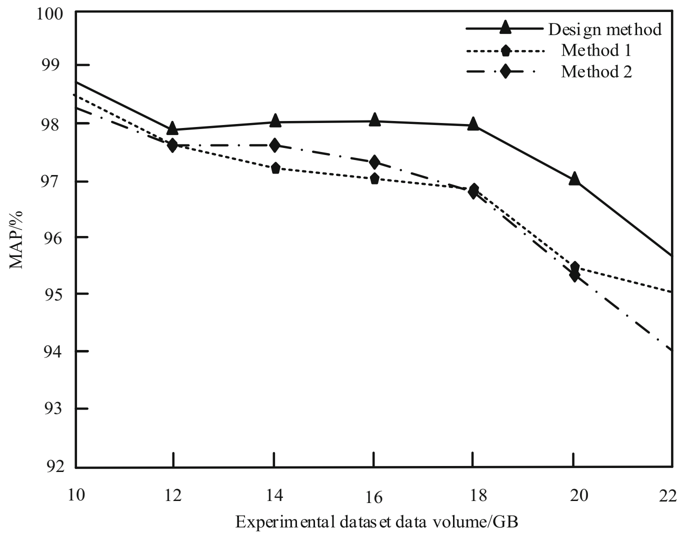

Fig. 4. MAP Test Results

According to the test results in the above figure, the MAP of the design method is generally high, while the MAP of Method 1 and Method 2 is lower than that of the design method.

The NDCG test results of design method and method 1 and method 2 are shown in Fig. 5.

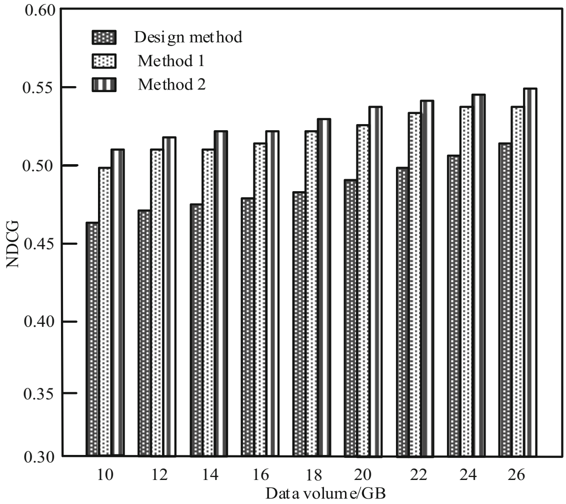

Fig. 5. NDCG Test Results

Figure 5 shows that the NDCG of the design method is lower than the NDCG of Method 1 and Method 2, indicating that it has a stronger sorting ability in retrieval.

The ERR comparison test results of the three methods are shown in Fig. 6.

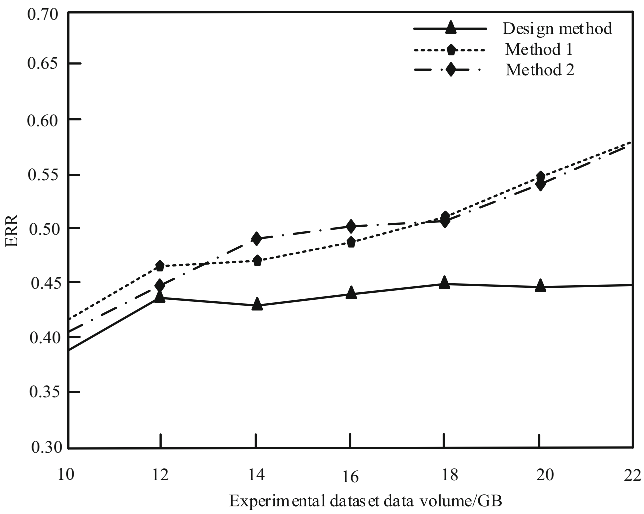

Fig. 6. ERR Comparison Test Results of Three Methods

The above results show that, on the whole, the ERR of the design method is the lowest, and its ERR increase is low, indicating that the retrieval effect of the design method is better than that of method 1 and method 2.

4 Conclusion

Based on deep learning, this paper designs an educational information retrieval method for innovative entrepreneurship training of accounting talents, implement text cleaning, Chinese word segmentation, vectorized representation of text, noise filtering, and other preprocessing for all texts. Design a multi classification text representation and classification method based on DBCNN to complete text classification. A sorting learning model based on Actor Critic algorithm is proposed to implement correlation matching between query and document classification results, achieving information retrieval for accounting talent innovation and entrepreneurship training education. And the method was tested, and the test results showed that the design method has a higher MAP, lower NDCG, and ERR, and has good educational information retrieval performance.

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Evaluation Method of Online Teaching Effect of Chinese Painting Art Appreciation Course in Colleges and Universities Based on Machine Learning Model

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Abstract. In order to promote the benign development of online teaching and improve the quality of online teaching evaluation, this paper proposes an online teaching effect evaluation method of Chinese painting art appreciation course in colleges and universities based on machine learning model. Based on the classroom teaching evaluation model of higher vocational colleges, this paper constructs a teaching evaluation scale, establishes an evaluation index system, and standardizes the evaluation indicators. The Naive Bayesian classification algorithm is applied to train the evaluation index, calculate the weight value of the evaluation index, and automatically give the evaluation result value according to the specific evaluation data. The results show that after the application of the proposed evaluation method, the categories corresponding to the maximum online teaching effect of the Chinese painting art appreciation course in five colleges and universities are general, good, general, poor and very good, which proves the effectiveness of the evaluation method.

Keywords: Machine Learning Model · College Chinese Painting Art Appreciation Course · Weighted Naive Bayesian Algorithm · Online Teaching Effect Evaluation

1 Introduction

Nowadays, quality education is an important part of art education in ordinary colleges and universities. All domestic colleges and universities have widely opened public art courses for all students, providing good conditions and platforms for the aesthetic education of college students. The public art appreciation course has further developed and improved the aesthetic ability and innovative spirit of college students. Under the existing higher education system in China, the value of public art appreciation in ordinary colleges and universities is far from enough. There are some problems in the teaching of Chinese painting in public art appreciation course, such as unclear teaching objectives,

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single teaching content, and excessive reliance on multimedia teaching. In today's society, where western culture, information technology and a large number of new things are constantly pouring in, Chinese painting with traditional cultural characteristics has gradually faded out of students' sight, and national culture is missing. It is understood that many students know little about Chinese painting, let alone appreciate it. The appreciation of painting in ancient China has a long history. With the increasing recognition of the importance of art education in modern times, the appreciation education has also been developing. In today's quality education, the inheritance of national culture needs more understanding of Chinese painting. Chinese painting is the traditional painting of the Chinese nation and the art treasure of our country. It has an important position in the world art field. It is an art form produced by the integration of Chinese traditional culture and national spirit. It has distinctive national cultural characteristics and is an important part of Chinese traditional culture. In today's ever-changing world with new ideas and concepts emerging in endlessly, higher and higher requirements are put forward for college students in terms of ideology, morality, will, ability and emotion. As an important way to train college students to understand and inherit traditional culture and improve the cultural quality of the whole nation, the teaching of Chinese painting appreciation helps to cultivate college students' innovative spirit and strong perseverance, improve their own cultural cultivation, improve their aesthetic ability and moral quality, improve their comprehensive ability, participate in the inheritance of national culture, and further achieve national rejuvenation. It should be the focus of public art appreciation teaching.

Because online teaching avoids crowd gathering and offline contact, it is convenient for teachers and students to complete teaching activities through the network. Therefore, under the general trend of stopping teaching and classes this year, various forms of online teaching are supported by primary and secondary schools, universities and educational training institutions. The distance education APP, represented by Tencent Classroom, Tencent Conference, Rain Classroom, etc., provides online educatees with various forms and rich content of online courses. As a teaching mode with a wide range of systems and a breakthrough in time and space constraints, online live broadcast + video recording teaching is an indispensable link in its learning effect evaluation. Due to the loose structure of online teaching and the openness of distance learning environment, online examination and online evaluation are very difficult [1]. Therefore, it is necessary to establish an accurate and complete evaluation system and model for scientific, reasonable and accurate evaluation of online teaching. With the continuous emergence of new technologies, the teaching evaluation method is no longer a single qualitative assessment, but gradually develops into a combination of qualitative and quantitative assessment, and quantitative assessment of various data often requires the establishment of excellent data models. At present, there is mainstream teaching evaluation method at home and abroad, such as using artificial neural network to model and realize teaching evaluation, introducing the theory of artificial neural network into the teaching quality evaluation of ethnic universities, establishing relevant mathematical models, comprehensively quantifying the indicators, constructing a BP neural network model, and obtaining more reasonable evaluation results; The mathematical model of teaching quality evaluation based on wavelet neural network can better improve the accuracy of teaching quality evaluation indicators. However, in the application process of evaluating the effectiveness of online teaching in courses, the above methods are prone to falling into local extreme points and have strong sample dependency. In order to improve the evaluation level of online teaching effect, this paper proposes an online teaching effect evaluation method of Chinese painting art appreciation course in colleges and universities based on machine learning model. Innovatively apply naive Bayesian classification algorithm to train evaluation indicators, calculate the weight values of evaluation indicators, and automatically provide evaluation result values based on specific evaluation data. Solved the problem of existing neural network algorithms being prone to falling into local extreme points and having sample dependency, and improved the automatic evaluation effect.

2 Research on the Evaluation of Online Teaching Effect Based on Machine Learning

Art appreciation is an activity for students to evaluate, appreciate and comment on art works, thus gradually forming aesthetic interest and improving art appreciation ability. Art appreciation teaching is an important way of aesthetic education for students, which can develop students' potential, enhance their intelligence and promote their all-round development. Therefore, in order to further improve the online teaching results of the Chinese painting art appreciation course in colleges and universities, it is very necessary to conduct online teaching effect evaluation. The effect of online teaching is a key factor of online teaching quality. In order to promote the benign development of online teaching, it is necessary to carry out online teaching evaluation. Establishing an effective effect evaluation method system to effectively monitor and manage the effect of online teaching can ensure the quality of online teaching, regulate the teaching process, guide the teaching direction, and provide a decision-making basis for the development of online teaching [2]. Online teaching evaluation is to make a qualitative or quantitative analysis of all aspects of online teaching, and then make a value judgment under the guidance of the theory of education evaluation, using the evaluation methods and technologies that can be used for reference. Online teaching evaluation should follow certain principles, that is, the evaluation subject must abide by certain codes of conduct in the evaluation process. It is the general principle guiding evaluation activities and the basic requirements for online teaching evaluation.In this kind of evaluation activity, only when the words and deeds of the evaluators are subject to the code of conduct stipulated by the evaluation principles, can different evaluators' value understanding be based on this to achieve consensus, and the evaluation activities of different evaluators can be carried out synchronously on this basis. According to the task and time of assessment, assessment can usually be divided into formative assessment and summative assessment. For online teaching, in order to provide learning objectives, contents and strategies suitable for learners' characteristics, diagnostic assessment of learners is also required. Diagnostic assessment of online teaching measures learners' existing knowledge and ability according to the assessment objectives. The knowledge background, learning conditions, learning requirements, learning attitudes, etc. of learners are understood through questionnaires, and the assessment results are given according to the measured data and questionnaire statistics. In this way, in teaching, students can be grouped according to the evaluation results, different students can be provided with corresponding learning resources, teaching design can be carried out according to the characteristics of different learners, and appropriate teaching progress, strategies and methods can be selected [3]. Online teaching evaluation is a dynamic process. Although the evaluation methods for different evaluation objects are very different, they all go through four stages: preparation, implementation, processing and feedback, as shown in Fig. 1.

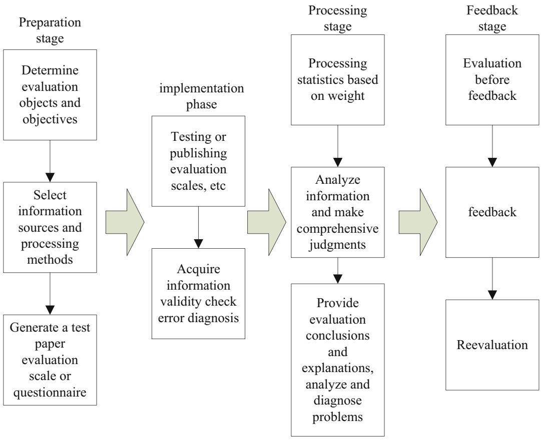

Fig. 1. Online Teaching Effect Evaluation Process

2.1 Evaluation Index System

2.1.1 Composition of Teaching Evaluation Scale

The evaluation scale is one of the indispensable and necessary tools in teaching effect evaluation, and is one of the main tasks in the process of teaching effect evaluation. In the classroom teaching evaluation of higher vocational colleges, the teaching evaluation scale is mainly used to evaluate the teaching quality of college teachers. The teaching evaluation scale is compiled according to the characteristics of classroom teaching and consists of evaluation indicators, evaluation standards and evaluation grades. The evaluation index refers to the goal to be achieved by teaching, and it is the concrete induction of the teaching goal. Teaching evaluation includes teaching attitude, teaching effect, teaching methods, teaching ability and other indicators. Evaluation criteria refer to the criteria and criteria for teachers to make value judgments in terms of the quality and quantity of each evaluation index in classroom teaching, that is, the criteria that the evaluation subject students should follow in evaluating college teachers' classroom teaching. Evaluation criteria are often more specific descriptions and explanations of evaluation indicators. The evaluation grade refers to the degree to which the evaluation index reaches the standard based on the evaluation standard and expressed by a certain grade or score. Classroom teaching evaluation is to use some mathematical modeling methods to interpret data or materials on a quantitative basis, or to conduct empirical evaluation on a quantitative basis to distinguish between high and low grades [4]. Generally speaking, the rating scale is a standardized scale for evaluating classroom teaching behavior. In this paper, numerical scale method is used to design. The advantage of this scale is that it is easy to form and quantify, and it is the most frequently used scale among all evaluation scales. The evaluation scale mainly focuses on the evaluation of teachers' teaching process. Generally, the teaching process is divided into several indicators, and each primary indicator is divided into several secondary indicators, and some even have tertiary indicators. Each level of indicators is described and graded. The users of the evaluation scale of classroom teaching effect evaluation include teachers, students and administrators. In order to improve the reliability and validity of the teaching evaluation scale, two points should be paid attention to when developing and using the scale. First, the evaluation subject students must have direct contact with and long-term understanding of the evaluation object teachers. Second, the evaluation subject should be able to use the evaluation scale and accept the guidance of some professionals when necessary to ensure the objectivity of the evaluation and the consistency of the scoring standards.

2.1.2 Construction of Indicator System

To build a comprehensive and multi-level evaluation index system, we should build a targeted evaluation index table for different evaluation subjects and different objects. One of the basic principles of constructing the evaluation index system is scientificity, and an important aspect of scientificity is its completeness, that is, the evaluation index system must be able to reflect the teaching effect comprehensively and without omission. The evaluation index system of online and offline mixed teaching effect is constructed from the three dimensions of pre teaching, teaching and post teaching. The selection of evaluation indicators is relatively complex. First, a preliminary evaluation indicator system is constructed by means of questionnaires and multiple rounds of expert interviews; On this basis, the Delphi method is used to optimize the primary indicators. First, through literature and social surveys, the preliminary indicators are proposed, and the reasons are listed. The indicators are distributed to many experts in the field in the form of questionnaires. Each expert judges the suitability and importance of the evaluation indicators through independent and anonymous ways, and proposes the missing evaluation indicators based on the indicators. Then conduct a questionnaire survey, discuss the indicators, modify the indicators, until the experts' opinions are consistent, and finally complete the construction of evaluation indicators [5]. The specific process is shown in Fig. 2 below.

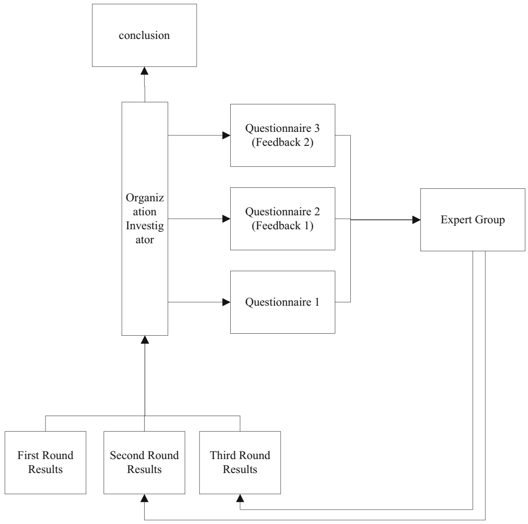

Fig. 2. Indicator optimization process of Delphi method

Through three rounds of Delphi survey, according to the survey content, this research has constructed an online teaching effect evaluation index system, as shown in Table 1 below.

Table 1. Online Teaching Effect Evaluation Index System

Evaluation objectives	Evaluation dimension	evaluating indicator	Evaluation content
Online Teaching Effect of Chinese Painting Art Appreciation Course in Colleges and Universities	Before teaching	Students' commitment to learning	Times of login to online teaching platform
			Number of times to watch teaching videos
			Duration of watching teaching videos
			Whether difficult knowledge points are marked
		Student learning task participation level	Number of posts and replies

(*continued*)

Table 1. (*continued*)

Evaluation objectives	Evaluation dimension	evaluating indicator	Evaluation content
			Teaching task completion
		Student learning ability	Autonomous learning ability
		Student learning guidance evaluation	Knowledge understanding and mastery
			Achievement degree of learning guidance objectives
	During the teaching process	Students' commitment to learning	Time investment
			Behavioral engagement
			Cognitive engagement
		Student learning task participation level	Classroom interaction initiative
			Depth of discussion and exploration
			Learning task completion
		Student learning ability	Autonomous learning ability
			Ability to explore and solve problems
			Ability to communicate and express
			Exhibition effect of works
		Contribution level of the students in the learning team	Number of training activities initiated
			Contribution in team collaboration

(*continued*)

Table 1. (*continued*)

Evaluation objectives	Evaluation dimension	evaluating indicator	Evaluation content
	After teaching	The effect of students' knowledge expansion	Extension of learning project completion
		Real time evaluation	Real-time evaluation of online teaching platform
		Ability improvement	Ability to practice and solve problems

2.1.3 Standardized Processing of Evaluation Index Data

There are two basic variables involved in the multi index comprehensive evaluation: one is the actual value of each evaluation index, and the other is the evaluation value of each index. Due to the different physical meanings represented by each indicator, there are differences in dimensions. This non dimensionality is the main factor affecting the overall evaluation of things. The dimensionless treatment of indicators is the main means to solve this problem. Dimensionless, also known as data standardization and normalization, is a method to eliminate the dimensional impact of original variables through mathematical transformation [6].

(1) For linear indicators, the proportional transformation method is used to standardize the indicators. After the proportion transformation, both positive and negative indicators are transformed into positive indicators.

When the sample characteristics are expected to be large:

$$a_{ij} = \frac{\dot{a}_{ij}}{\max \dot{a}_j} \tag{1}$$

When the sample characteristics are expected to be smaller:

$$a_{ij} = 1 - \frac{\dot{a}_{ij}}{\max \dot{a}_{ij}} \tag{2}$$

where, $\dot{a}_{ij}$ For i No. of samples j Original value of indicators, a_{ij} For i No. of samples j Standardized values of indicators; max $\dot{a}_{ij}$ On behalf of the i No. of samples j Maximum of indicators.

(2) For nonlinear indicators, the specific gravity method (normalization method) is used. After transformation, it objectively reflects the relationship between the original indicators and takes into account the differences between the indicator values.

$$a_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{n} \left(a_{ij}\right)^2}} \tag{3}$$

where, n Represents the number of indicator samples.

2.2 Construction of Online Teaching Effect Evaluation Model

Machine learning is to enable computers to simulate human learning behavior, automatically acquire knowledge and skills through learning, and constantly improve performance. It is a new discipline involving probability theory, statistics, analysis and other disciplines. It mainly uses induction, synthesis and other methods to achieve self-improvement. Machine learning studies how to make machines acquire new knowledge and skills by identifying and utilizing existing knowledge. As an important research field of artificial intelligence, machine learning research mainly focuses on three basic aspects: learning mechanism, learning methods, and task oriented research. Machine learning is an algorithm that can mine hidden rules from a large number of historical data and can be used to predict or classify [7]. The essence of machine learning can be considered as finding a function that maps from training samples to classification results and can learn the essential structure and internal pattern of training samples. The ultimate goal of machine learning is to enable the trained function to be better applied to new samples, not only to have good results on the training samples, but also to select the corresponding training method, use mathematical tools to obtain the feedback of model optimization, so as to constantly adjust the parameters of the classifier, improve the generalization ability of the model, and obtain the classification that can solve general problems. As far as the current evaluation of teaching quality in colleges and universities is concerned, it is mainly the teaching quality evaluation mechanism with expert group as the core, which comprehensively evaluates the teaching quality of a certain teaching process through the scoring of quantitative indicators by experts. We believe that the first-hand data related to teaching quality comes from students and teachers in the forefront of teaching. If we can analyze and extract these data, we can better reflect the essence of teaching quality, and also can better extract the reasons or fixed models that affect teaching quality, so as to ultimately achieve the purpose of effectively guaranteeing teaching quality. The introduction of machine learning into the teaching evaluation system will bring simple and accurate algorithms to solve the above problems. Through the acquired data, machine learning can scientifically and effectively obtain a scientific method that conforms to the evaluation quality of this course. Yu et al. introduced the minimum multiplication in the quantitative evaluation of teaching evaluation, which realized the quantitative evaluation of teaching quality. In his dissertation, Zhu made an in-depth analysis of the teaching quality of colleges and universities, proposed to use fuzzy mathematics to model the teaching quality evaluation system, and gave a preliminary automatic evaluation method [8]. Applications in various fields have shown that using machine learning to quantify the evaluation of teaching quality will be one of the more scientific and effective methods. Machine learning has made new breakthroughs in recent years. Many scholars have studied machine learning itself, semi supervised learning and its combination with other mathematical tools have achieved gratifying results. The rapid development of machine learning will bring new and more extensive applications to its application in the teaching evaluation system. According to the needs of teaching evaluation, classification algorithms can be applied to the process of teaching evaluation. Taking a series of evaluation attribute values as input data, and the comprehensive evaluation grade as class label, learning a classifier through a certain classification algorithm can give the new evaluation attribute value the most likely class label. It is the evaluation result [9]. In order to ensure the credibility of the evaluation results, it is necessary to select a suitable algorithm to construct the classifier. In machine learning, common classification algorithms include naive Bayes, support vector machine, K nearest neighbor, decision tree, neural network, etc. Among them, Naive Bayes (NB) algorithm is a classification method based on Bayesian theorem, which introduces the independent assumption of feature conditions, and the classification model is easy to understand. On the basis of Naive Bayes (NB) algorithm, this paper studies an online teaching effect evaluation model of Chinese painting art appreciation course in colleges and universities based on weighted Naive Bayes.

Bayesian classification is a classification algorithm using Bayesian theorem. The basic principle of classification is to learn a large number of training data to obtain the prior probability of each category, and then calculate an instance accordingly Q The posterior probabilities belong to different categories. Finally, the instance is judged as one of the classes with the maximum posterior probability. Hypothesis P For training data set, $A = \{a_1, a_2, ..., a_n\}$ To evaluate the indicator set, n Is the number of indicators. $G = \{g_1, g_2, ..., g_m\}$ Is the class variable set, m Is the number of categories, then a training sample can be expressed as $\{p_1, p_2, ..., p_n; g_k, k \in m\}$, g_k It indicates that the class label of the training sample is known, while a test sample Q Can be expressed as $\{q_1, q_2, ..., q_n\}$, determine the probability that the test sample belongs to a certain type, and the calculation formula is shown in Formula (4).

$$F(g_k|Q) = \arg\max_{g_k}\left[\frac{F(Q|g_k)F(g_k)}{F(Q)}\right] \tag{4}$$

Among, $F(Q|g_k)$ indicates the prior probability that the test samples Q and g_k belong to the same type, $F(Q)$ indicates the prior probability of the test samples Q, $F(g_k)$ indicates the prior probability of the test samples g_k.

Naive Bayesian classification algorithm is an efficient classification algorithm among Bayesian classification algorithms. The classification model has the advantages of simple and easy interpretation, high computational efficiency, good stability, etc. Its performance is better than that of decision tree, SVM and other classifiers [10–11] in some cases. The naive Bayesian model uses the simplest network structure, as shown in Fig. 3.

Where the root node G Class variable, leaf node $a_1, a_2, ..., a_n$ Is an indicator. The NB classification model is based on the general Bayesian classification model, which removes the restriction of independence between attributes. In practice, the calculation formula of NB algorithm can be expressed as formula (5).

$$F(g_k|Q) \propto \arg\max_{g_k}\left[F(Q|g_k)F(g_k)\right] \tag{5}$$

among $F(g_k)$ can be learned from training data, and the calculation formula is:

$$F(g_k) = \frac{h_k}{h} \tag{6}$$

here h_k Indicates the class in the training sample g_k Number of; h Indicates the total number of training samples.

Naive Bayesian classification algorithm assumes that all indicators are conditionally independent and there is no relationship between indicators, so these indicators are also

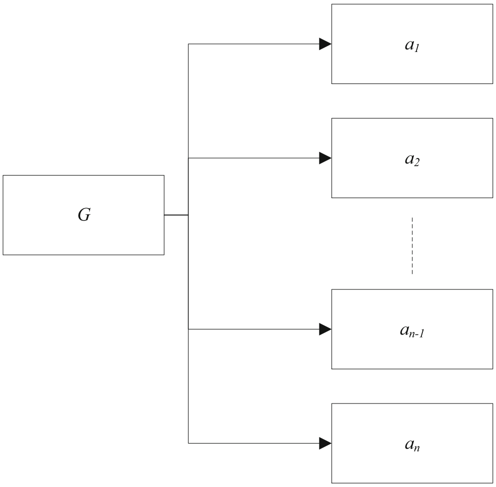

Fig. 3. Naive Bayesian classification model

independent of class attributes g. If there are many indicators in the dataset, $F(Q|g_k)$ The computational cost of is very large, and the introduction of conditional independence assumption can reduce the computational cost, and also lose some computational accuracy. According to the conditional independence assumption, $F(Q|g_k)$ The calculation formula of can be simplified as:

$$F(Q|g_k) = \prod_{i=1}^{n} F(q_i|g_k) \tag{7}$$

Among them, $F(q_1|g_k), F(q_2|g_k), ..., F(q_b|g_k)$ All can be learned from training data. Combined with the above three formulas, the category of test data can be determined.

In order to reduce the computational cost, the naive Bayesian algorithm assumes that the condition attributes are independent from each other, and another implicit assumption is that each indicator has the same importance for decision classification, that is, the weight is set to 1 [12, 13]. In practical application, the importance of each indicator for classification is different, so when the ownership is reset to 1 by default, the accuracy of classification will be reduced.

In this paper, weighted naive Bayesian (WNB) classification algorithm is used to assign a reasonable weight to attributes according to the contribution of indicators to classification, which not only maintains the high speed of the naive Bayesian algorithm, but also reduces the impact of the assumption of indicator independence on the performance of the classifier. The calculation formula is as follows.

$$F(g_k|Q) = \arg\max_{g_k} F(g_k) \prod_{i=1}^{n} F(a_i|g_k)^{s_i} \tag{8}$$

Among them, s_i Indicator a_i The weight value of determines the importance of different indicators in the classification process, s_i The higher the value, the corresponding indicator a_i The more important it is for classification. In practical application, how to determine specific weights for each indicator is the key problem of weighted naive Bayesian model.

According to the correlation between each evaluation index and the comprehensive evaluation value of the teaching evaluation data, the value of each index has different influence on the evaluation results, so this paper proposes a method to determine the weight of each evaluation index by using the correlation probability of class attributes [14, 15]. Each indicator a_i, may have R Different values, using α_r Indicates the specific value, where $r \in R$. Assume a specific example Q, when Q Indicators of a_i The value is α_r For category g_k In terms of, indicators a_i about g_k Correlation probability of $F(a_i|rel)$ And uncorrelated probability $F(a_i|\text{unrelevant})$.

Current indicator a_i The value of is α_r Of g_k The formula for calculating the indicator weight is as follows:

$$s(a_i, \alpha_r, g_k) = \frac{F(a_i|rel)}{F(a_i|\text{unrelevant})} \tag{9}$$

Therefore, the specific calculation formula of weighted naive Bayesian classification algorithm is as follows:

$$F(g_k|Q) = \arg\max_{g_k} F(g_k) \prod_{i=1}^{n} F(a_i|g_k)^{s(a_i, \alpha_r, g_k)} \tag{10}$$

In dataset P If the class tag has m, indicators are n, each indicator has r If there are possible values, the total weight of all attributes is $m \cdot n \cdot r$. If the specific value of the same indicator is different, the weight value is different; When the value of the same indicator is the same, the weight value is different under different categories. Finally, according to the specific value of each indicator, the weight value of the probability related to the current class label is selected for calculation, and the result value of each category is compared. The category corresponding to the maximum value is the evaluation result.

3 Evaluation Test

3.1 Evaluation of Test Objects

The Guiding Plan for Public Art Courses in National Ordinary Colleges and Universities puts forward clear requirements for public art courses for college students. It requires students to establish correct aesthetic concepts through appreciation of art works in teaching practice of public art courses in colleges and universities, improve humanistic quality, and improve their ability to feel, express, appreciate and create beauty. As a public elective course offered by ordinary colleges and universities, art appreciation is an important part of art education for college students. The teaching of art appreciation has gradually deepened from the initial pleasing to the eye to the method of influencing students to observe and understand the world, to cultivate students' basic attitude of loving life and life, and to stimulate students' innovative consciousness. The state regards aesthetic education as an important carrier of strengthening the education of socialist core values, an important form of inheriting and innovating the excellent traditional Chinese culture, an important aspect of implementing the fundamental task of building morality and cultivating people, and an important content of deepening the comprehensive reform in the field of education. Aesthetic education is the education of the soul and an important way to improve the basic quality of individuals and society. Relevant educators should have a deep understanding of the importance and urgency of strengthening aesthetic education in colleges and universities, and accelerate the improvement of aesthetic education with a strong sense of responsibility and mission, more conscious actions and more powerful measures. Taking the online teaching course of Chinese painting art appreciation course carried out by 5 colleges and universities as the object, the teaching effect was compared and evaluated using the evaluation method studied. The experimental conditions are: Windows 10 operating system, Intel i5-9400F processor. Choose the Microsoft SQL Server 200 tool to build a network course teaching database, and save the data in the SQL Server database. The experiment was programmed using a Python program.

3.2 Evaluation Index Standardization Results

According to Table 1, collect and standardize the indicator data of online teaching courses of Chinese painting art appreciation in five universities. Take one university as an example, and the indicator data standardization results are shown in Table 2 below.

Table 2. Example of index data standardization results

Evaluation content	weight
Times of login to online teaching platform	0.6854
Number of times to watch teaching videos	1.4989
Duration of watching teaching videos	0.3178
Whether difficult knowledge points are marked	0.7865
Number of posts and replies	0.4252
Teaching task completion	0.3586
Autonomous learning ability	0.7845
Knowledge understanding and mastery	0.1296
Achievement degree of learning guidance objectives	0.3588
Time investment	2.6888
Behavioral engagement	1.6769
Cognitive engagement	3.6655
Classroom interaction initiative	0.6855

(*continued*)

Table 2. (*continued*)

Evaluation content	weight
Depth of discussion and exploration	0.1875
Learning task completion	3.6895
Autonomous learning ability	2.35458
Ability to explore and solve problems	1.48565
Ability to communicate and express	0.7945
Exhibition effect of works	0.3211
Number of training activities initiated	2.4151
Contribution in team collaboration	1.6847
Extension of learning project completion	0.6924
Real-time evaluation of online teaching platform	1.4687
Ability to practice and solve problems	1.2460

3.3 Evaluation Results

The evaluation model built by weighted naive Bayesian (WNB) classification algorithm is used for evaluation, and the results are shown in Fig. 4 below.

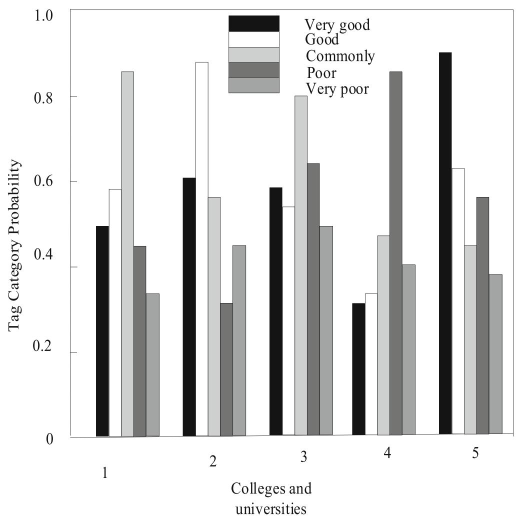

Fig. 4. Evaluation Results

It can be seen from Fig. 4 that under the application of the evaluation method studied, the categories corresponding to the maximum online teaching effect of the Chinese painting art appreciation course in five colleges and universities are general, good, general, poor and very good, which proves the effectiveness of the evaluation method.

4 Conclusion

Art appreciation teaching is an important way of aesthetic education for students, which can develop students' potential, enhance their intelligence and promote their all-round development. In the current prevalence of online teaching mode, art appreciation classes also began to try to use this mode of teaching. Online teaching evaluation is to make a qualitative or quantitative analysis of all aspects of online teaching, and then make a value judgment under the guidance of the theory of education evaluation, using the evaluation methods and technologies that can be used for reference. Therefore, this paper proposes an online teaching effect evaluation method of Chinese painting art appreciation course in colleges and universities based on machine learning model. In this method, the classification algorithm in machine learning is introduced to build a teaching evaluation model, and a classifier based on weighted naive Bayesian algorithm is proposed. Through a large amount of data training, the corresponding weight values are given to each evaluation index, and the evaluation result values are automatically given according to the specific evaluation data. Future follow-up work should also be improved in the following areas: in-depth research is needed in machine learning algorithms. For data in teaching evaluation, in addition to quantitative data value analysis and processing, qualitative evaluation methods should also be combined to provide more reasonable evaluation guidance.

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Evaluation Method of Online Education Quality of E-Commerce Course in Higher Vocational Education Based on Machine Learning Model

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Abstract. In the stage of online education quality evaluation, due to multiple influencing factors and complex indicator parameters, the final evaluation results are prone to significant deviations from the actual situation. In order to improve the accuracy of online education quality evaluation, this article proposes a machine learning model based online education quality evaluation method for vocational e-commerce courses. We designed an education data structure based on BOM and conducted qualitative and quantitative analysis on the factors and parameters that affect the quality of online education. In the construction stage of the evaluation index system, comprehensive indicators are designed from four aspects: school management quality, teacher teaching process, student learning behavior, and academic quality. In the stage of education quality evaluation, the SVM algorithm in machine learning is used to optimize PSO, establish an evaluation optimization model, and train iteratively through parameter optimization to achieve network education quality evaluation. The test results show that the evaluation results of the design method on the quality of online education differ significantly from the actual situation, with a specific error range of 0.02, which improves the accuracy of the evaluation.

Keywords: Machine Learning Model · Vocational E-Commerce Course Online · Education Quality Assessment · Educational Data Structure · Evaluation Index System · PSO-SVM Model

1 Introduction

The purpose of teaching quality monitoring is to objectively evaluate the current situation of teaching and learning, affirm the achievements, find out the problems and find out the causes of the problems [1], formulate effective and feasible improvement measures, help students better find their own strengths and weaknesses [2], and make personality development and individualized teaching become a reality. The evaluation of teaching

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quality can start from two aspects: first, students, who are the most important subject in teaching, can objectively reflect the teaching quality by analyzing students' learning achievements [3]; The main source can also reflect the level of teaching quality through the evaluation of teachers' teaching situation [4]. With the rapid development of Internet technology, China's teaching quality monitoring work is also gradually improving, especially with the arrival of the big data era, the education industry has seen more feasibility, and the huge social value, economic value and scientific research value implied in the big data have attracted all walks of life [5]. The application of big data in the field of education can not only achieve tailored education for students, but also enable parents to learn more detailed education information, and provide more objective and comprehensive teaching feedback for teachers' teaching. Education managers can also obtain information and basis for teaching, better organize education resources, and formulate measures for education reform and development, so as to realize the "student-centered" humanistic education. Education big data brings opportunities to the monitoring and evaluation of teaching quality.

The past evaluation methods also mainly started from these two aspects, but the defect is that the evaluation is either from the perspective of students or teachers, and there is little research on joint evaluation from multiple perspectives. The teaching quality monitoring and evaluation of basic education has achieved remarkable results since it was carried out, basically meeting the standard requirements of quality monitoring, and playing a role in improving the teaching quality of basic education in China [6]. But at the same time, there are still some problems in the monitoring and evaluation of teaching quality.In the past, due to limited technology, in the process of data collection for teaching quality monitoring and evaluation in China, the main method was to collect data manually [7], that is, the school filled in the data with electronic forms, reported the data layer by layer, and finally assigned a special person to collect it. This kind of collection method itself is prone to many subjective errors, one ring of errors, leading to ring of errors. In addition, the data source is single, and the amount of data used for storage, management and analysis is small, so it is difficult to objectively reflect the real teaching quality [8]in a region. Therefore, in the past, the quality evaluation was mainly based on the students' exam scores and rankings. However, in the face of China's vast geographical situation, the development level of various regions is also uneven, and this single evaluation method. It is inevitable to ignore the evaluation of students' overall development ability, limit the scope of teaching quality evaluation [9, 10], and greatly affect the accuracy of evaluation conclusions.

In order to improve the accuracy of teaching quality evaluation, this paper proposes the research on the online education quality evaluation method of higher vocational e-commerce courses based on machine learning model. This article innovatively designs an education data structure based on BOM to quantify the factors and parameters that affect the quality of online education during flight; Design comprehensive indicators from four aspects: school management quality, teacher teaching process, student learning behavior, and academic quality; The PSO-SVM model in machine learning was used to analyze specific indicator system parameters and achieve iterative optimization evaluation of the quality of online education in vocational e-commerce courses. Through comparative testing, the contribution of this design method has been analyzed and verified to improve the accuracy of evaluation of online education quality.

2 Evaluation Method for Online Education Quality of E-Commerce Courses in Higher Vocational Colleges

2.1 Design of Education Data Structure Based on BOM

In the evaluation of teaching quality, due to the diversity of roles, schools and the complexity of evaluation structure, roles and evaluation, the relationship between price indexes is not one to many or many to one, but many to many network structure. Because of this structure, it is difficult to implement in the database, so the repeated sub components are regarded as different components, so the data structure becomes tree structure. As shown in Fig. 1, the structure diagram of the teaching quality evaluation system designed in this paper is shown. The "parent and child items" represent the dependencies between the items that make up the evaluation form. The root node at the top represents the teaching quality evaluation, and the nodes from the second layer to the last layer represent the roles and indicators that make up the teaching quality evaluation. Considering that the structure of the teaching quality evaluation system is similar to the BOM structure, we can use the structure and construction method of BOM for reference to realize the configurability of the teaching quality evaluation system.

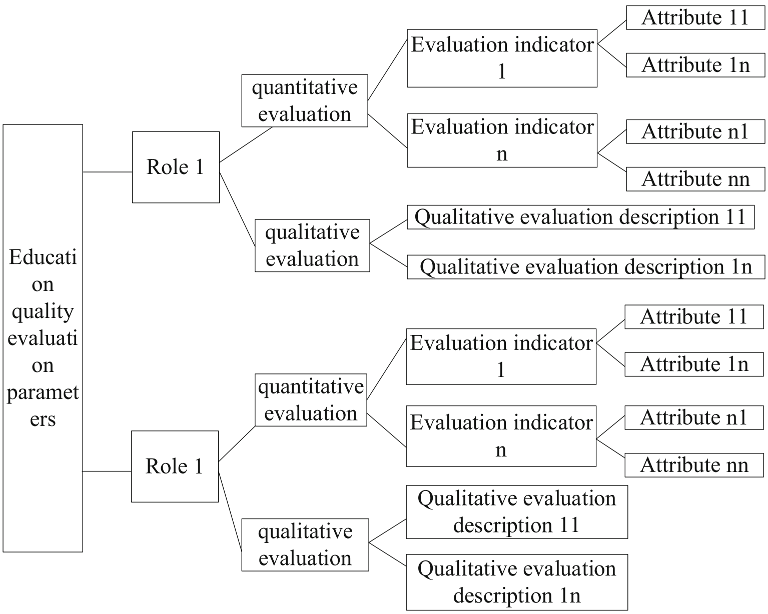

Fig. 1. Teaching quality evaluation system structure

Good BOM data structure is very important for information sharing. In order to improve the operating efficiency of the system and define it clearly, the indicators of the teaching quality evaluation system are dynamically expandable, independent and non overlapping. The structure of the teaching quality evaluation system is a compound BOM structure, and the corresponding table structure is designed, as shown in Table 1. Among them, Sno is the final evaluation indicator number, the parent PSno is the root node of the entire evaluation system, and the parent PSno and child CSno are the evaluation indicators of the entire evaluation system, that is, the association between "parts". The level number indicates the level of parts in the BOM tree.

Table 1. Compound BOM

Record No	Sno No	Parent No	Subcomponent No	Hierarchy No
1	1	1	A	1
2	1	1	B	1
3	1	1	C	1
4	1	A	D	2
5	1	A	E	2

According to the way shown above, realize the design of online education data information structure of e-commerce courses in higher vocational colleges.

2.2 Construction of Evaluation Index System

The construction of monitoring indicator system is the core element of monitoring, an organic whole composed of various monitoring indicators and monitoring standards at all levels, and is conducive to the quantitative and qualitative analysis of teaching quality. The purpose of the most evaluation of teaching quality is to mobilize the enthusiasm of teachers and improve their own teaching level and quality. In the process of evaluating the teaching quality of colleges and universities, the principle of determination should be followed. The evaluation principle plays a key role in ensuring the effectiveness and reliability of the evaluation results, and is the basic requirement for the evaluation work. The teaching quality evaluation index system designed in this paper should follow the following basic principles:

(1) Principle of comprehensiveness

According to the training objectives of college students, and from the fundamental point of view of quality education, this paper constructs the teaching quality evaluation system to follow the principle of comprehensiveness, and examine the comprehensive situation of teaching quality from multiple perspectives and levels. The principles of comprehensiveness include the promotion of the comprehensive development of teachers' teaching level and the promotion of students' quality education. However, comprehensiveness does not include all relevant influencing factors into the teaching quality evaluation system, but scientifically and reasonably screens all evaluation factors to obtain the key influencing factors that affect students' comprehensive quality evaluation, namely the so-called evaluation indicators.

(2) Directional principle

While ensuring the comprehensiveness of the evaluation system of teachers' teaching quality, it should have certain directionality, that is, the principle of pertinence. The evaluation system of teaching quality will train students to become comprehensive talents with strong quality who develop morally, intellectually, physically and aesthetically in an all-round way, meet the needs of society for college graduates, and pay more attention to the targeted cultivation of innovative practical spirit and ability, can promote the development of college students.

(3) Principle of encouragement and improvement

And finally achieve the goal of improving the comprehensive quality of students. Students' differences should also be taken into account in the process of establishing the teaching quality evaluation system.

(4) Objectivity principle

The objectivity of teaching quality evaluation results is the key to teaching quality evaluation. It is necessary to collect evaluation data truthfully and comprehensively, be objective and fair, seek truth from facts, and not mix personal feelings.

Based on the basic principles of constructing the teaching quality evaluation index system mentioned above, this paper establishes a monitoring index system from four aspects: school management quality, teachers' teaching process, students' learning behavior and academic quality.

As for the school management quality indicators, this paper analyzes them from four perspectives: teacher resources, teaching environment, and teaching conditions. The specific indicator construction is shown in Table 2 below.

Table 2. School Management Quality Indicators

Primary indicators	Secondary indicators
Teaching staff	Teachers' teaching level, professional ability and ethics (z11)
	Teachers' teaching ability, teaching research (z12)
	Teacher development and service attitude, ability (z13)
	Teacher Structure (z14)
Teaching environment	Investment and distribution of teaching funds (z21)
	Teaching plan planning and training program design (z22)
	Opening degree of teaching facilities (z23)
	Number of quality courses (z24)
Teaching conditions	Width of social resources (z31)
	Practice Teaching Setup (z32)
	Average reading rate of library (z33)
	Compliance with school discipline and rules (z34)

As for the indicators of teachers' teaching process, this paper analyzes them from four perspectives: teaching content, teaching attitude, teaching skills and teaching effect. The specific indicator construction is shown in Table 3 below.

Table 3. Teaching Process Indicator System

Primary indicators	Secondary indicators
Content of courses	The teaching objectives are clear, meet the requirements of the teaching content, highlight the key points and difficulties, and fully rationalize (u11)
	The professor has clear logic, clear organization, rich and skilled content, reasonable arrangement and appropriate examples (u12)
	Carefully arrange and correct homework, and regularly organize Q&A (u13)
	Integrating theory with practice, focusing on guiding students to think positively (u14)
Teaching attitude	Fully prepared, enthusiastic, conscientious and committed (u21)
	Abide by teaching discipline and start and finish classes on time (u22)
	Teachers are rigorous in learning, strict in teaching, dignified in appearance, harmonious in atmosphere, and respectful of students (u23)
Teaching skills	Mandarin teaching, accurate and vivid language, neat blackboard writing and reasonable layout (u31)
	Flexible and diverse teaching methods, pay attention to training students' ability to analyze, solve problems and solve problems (u32)
	Be able to reasonably use various teaching aids such as network and multimedia (u33)
teaching method	Be able to complete teaching tasks, and students can accept and master the course content (u41)
	Be able to preliminarily use the course content to solve specific problems in the discipline or related disciplines (u42)
	Promote the improvement of students' thinking ability and learning ability (u43)

For the indicators of students' learning behavior, this paper analyzes them from five perspectives: learning objectives, learning performance, style of study, learning effects, and ideology and morality. The specific indicator construction is shown in Table 4 below.

Table 4. Student Learning Behavior Indicator System

Primary indicators	Secondary indicators
Learning objectives	Clear learning purpose and correct learning attitude (v11)
Learning performance	Insist on preview before class, listen carefully in class and review carefully after class (v21)
	Finish the homework on time and correct it in time (v22)
	Speak actively in class and take notes carefully (v23)
	Strong learning ability, good at asking questions, dare to question (v24)
Style of study	Less lateness and early leave (v31)
	Good class discipline and high attendance (v32)
	Actively participate in discussions and maintain a harmonious relationship between teachers and students (v33)
Learning effect	Master the knowledge imparted in class and be able to apply it (v41)
	Ability to understand, think independently, analyze and solve problems (v42)
Ideological morality	Honest and trustworthy, love labor (v51)
	Respect teachers and help others (v52)
	Collective sense of honor (v53)

In addition, based on the academic quality, it is also essential to analyze the online education quality of e-commerce courses in higher vocational colleges. In view of this, taking the subject examination results and test paper answers as the source data, a statistical analysis norm index is constructed to obtain the characteristic data of the examination quality. The construction indicators are as follows:

(1) Average Score

The ratio of the sum of a set of data to the amount of data. It is used to describe the general level of students or the class as a whole.

(2) Standard score

The relative position quantity derived from the original score is used to judge the relative position of the analysis object in a group.

(3) Standard deviation

Describing the discrete difference between scores, it is the value obtained by calculating the arithmetic square root of variance from the sum of squares of the difference between a group of data and its arithmetic mean and the ratio of the data volume. It is used to reflect discrete differences in student or class examinations.

(4) Coefficient of difference

The percentage of the standard deviation of a group of data and its arithmetic mean is also a relative difference. When the mean difference between the two groups of data is large and it is difficult to objectively reflect the difference, the difference coefficient is more true and accurate.

(5) Mode

Represents the value that occurs most times in a set of data. It indicates the maximum number of people in a group at a certain level, reflecting a centralized trend, and the value can be one or more.

(6) Median

The number in the middle of a group of data after being arranged in order. There is one and only one. It can explain the position of a group in the middle level. It reflects the general level of the group and is not vulnerable to extreme values sound.

(7) Skewness

A measure of the direction and degree of skewness of data distribution. When the skewness is close to zero, it indicates that the data is evenly distributed; When the skewness is less than zero, it indicates that the data is skewed, and the overall performance level of the group tends to be better. The farther away from zero, it indicates that the number of people who are biased toward excellence is more than the number of people who are biased; When the skewness is greater than zero, it indicates that the overall performance level of the group tends to be poor. The farther away from zero, it indicates that there are more people who are biased than those who are excellent.

(8) Kurtosis

The larger the kurtosis coefficient is, the steeper the data distribution is compared with the normal distribution, and the more extreme the distribution of this group of data or the more number of data biased towards the mean; On the contrary, it indicates that the data distribution is more gentle than the normal distribution, indicating that the data distribution is more uniform.

(9) Percentage

Represents a percentage of one number relative to another. Through the percentage, it can reflect the progress of students and the learning situation of the class, such as the passing rate, excellent rate, etc. The calculation method is simple and the expression information is intuitive.

(10) Fractional segment

Divide the examinee's original score according to the examinee's score and count the number of scores in each segment. It can analyze the distribution of a test and reflect the real level of the group.

(11) Hierarchical grade

Hierarchical a group of data according to several grades, such as excellent, good, medium and poor. Plan the score segments represented by these grades and make statistics. Compared with the statistics of the score segment, this indicator can more intuitively see the number of statistics at all levels and make a more objective analysis of the class.

(12) Quartile

Quartile, also known as quartile or quartile, refers to the arrangement of all values of a group of data from small to large, and the division into quartiles according to a certain distribution strategy. The values at three dividing points are three quartiles. It can reflect the level gap between classes or grades.

The first quartile (Q1), also known as the “lower quartile”, is equal to the 25th percentile of all data in the sample from small to large.

The second quartile (Q2), also known as the “median”, is equal to the number in the middle of all data in the sample from small to large.

The third quartile (Q3), also known as the “upper quartile”, is equal to the 75% data after all data in the sample are arranged from small to large.

The gap between the third quartile and the first quartile is also called InterQuartile Range (IQR).

(13) Frequency

It refers to the number of times that the variable value represents a characteristic (flag value).

(14) Ranking

The original scores of the examinees are arranged in order from the largest to the smallest. The arrangement position is the position of the examinees under the current group, indicating the position of the examinees’ scores under a group. It is convenient to understand the position of their respective levels in the group, so as to plan their own space for progress.

(15) N score

When evaluating students’ learning at a certain stage, we should pay attention to their previous scores, analyze whether the current stage is progressive or regressive from the perspective of students as a wholeβAdd T score to get.

(16) Ranking frequency

Rank frequency indicates the frequency of each rank in the current group. If you want to count the top 30 students in a grade’s comprehensive score, it is expressed by the ranking frequency.

In accordance with the above ways, the construction of the online education quality evaluation index system of e-commerce courses in higher vocational colleges will be realized, providing a reliable basis for the follow-up evaluation.

2.3 Education Quality Assessment Based on Machine Learning Model

Quantitative is the basis of qualitative, and qualitative is the complement of quantitative. This paper analyzes the online education quality of e-commerce courses in higher vocational colleges from the above two perspectives. In the specific analysis process, the PSO-SVM model in machine learning is used to analyze the parameters of specific index system.

The problem of PSO algorithm is that the slow convergence speed in the later period is easy to cause local optimization. Next, we will proceed from the following two aspects.

Line optimization.

(1) Stochastic parameter optimization

When initializing particle swarm, it is realized through random), which can expand the search range of particle swarm, but to a certain extent, it will cause extreme value oscillation, and the convergence speed will become slower. To solve this problem, a Halton sequence is proposed, which can generate uniform points in the region, defined as

$$X_i = (\varphi_{11}(i), \ldots, \varphi_{mn}(i)) \tag{1}$$

Among them, X_i express i Initial particle swarm optimization of quality evaluation index parameters related to online education of e-commerce courses in higher vocational colleges, $\varphi_{mn}(i)$ express i Parameter information of quality evaluation indicators related to online education of e-commerce courses in higher vocational colleges. Its basic idea is that within the range of [0,1] a Is the denominator, and values are taken repeatedly in the area, with an interval of $1/a$. The calculation method of adding Halton sequence can be expressed as

$$\begin{aligned} k_{id}^{a+1} =& k_{id}^{a} + c_1 hal(k_{id}^{a} - x_{id}^{a}) \\ & + c_2 hal(k_{gd}^{a} - x_{id}^{a}) \end{aligned} \tag{2}$$

Among them, k_{id}^{a+1} express i Sequence iterative updating operator of particle swarm optimization for quality evaluation index parameters related to online education of e-commerce courses in higher vocational colleges, k_{id}^{a} Represents the particle swarm parameters before iteration, c_1 and c_2 Represent iteration coefficient respectively, x_{id}^{a} Represents the education quality evaluation index parameters corresponding to the initialization particles before iteration, k_{gd}^{a} It represents the ideal value of the parameter information of the quality evaluation indicators related to online education of e-commerce courses in higher vocational colleges, hal Represents a Halton sequence function.

(2) Weight optimization

On the basis of the original iterative operator, this paper adds inertia weight and combines the standard PSO model to improve the convergence performance.

The corresponding iterative operator can be expressed as

$$\begin{aligned} k_{id}^{a+1'} =& w k_{id}^{a} + c_1 hal(k_{id}^{a} - x_{id}^{a}) \\ & + c_2 hal(k_{gd}^{a} - x_{id}^{a}) \end{aligned} \tag{3}$$

Among them, $k_{id}^{a+1'}$ After weight optimization i The sequence iterative updating iterative operator of particle swarm optimization of quality evaluation index parameters related to online education of higher vocational e-commerce courses, w Represents a weight parameter. When the weight is large, it can expand the shrinking range to better perform global search; When the weight is small, it can better promote local search. The adjustment of inertia weight includes linear decline, adaptive adjustment, randomization and the introduction of shrinkage weight. Through analysis, it is known that adding shrinkage factor can better perform local search when particles are closer to the target. On this basis, the shrinkage factor is added to improve the convergence performance, and its calculation formula can be expressed as

$$k_{id}^{a+1'} = \chi [w k_{id}^{a} + c_1 hal(k_{id}^{a} - x_{id}^{a})$$

$$+c_2 hal(k_{gd}^a - x_{id}^a)] \tag{4}$$

Among them, χ Represents the shrinkage factor, and its specific calculation method can be expressed as

$$\chi = \frac{2}{\left|2 - \alpha - \sqrt{\alpha^2 - 4\alpha}\right|} \tag{5}$$

Among them, α It is a constant quantity and has

$$\alpha = c_1 + c_2 \tag{6}$$

On this basis, the process of using the improved PSO algorithm to optimize SVM and find the optimal (C, gamma) combination is the process of evaluating the online education quality of e-commerce courses in higher vocational colleges. The specific implementation process is shown in Fig. 2.

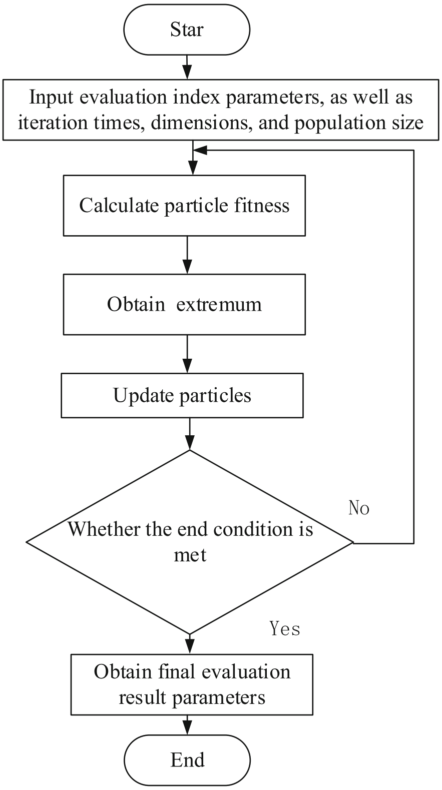

Fig. 2. Education quality assessment process based on machine learning model

Based on the information shown in Fig. 2, the basic steps of online education quality assessment of e-commerce courses in higher vocational education are as follows:

Step 1: parameter initialization, input the online education quality evaluation index parameters of higher vocational e-commerce courses, as well as the number of iterations, dimensions, and population size;
Step 2: To calculate particle fitness, generally the SVM classification accuracy function is used;
Step 3: Obtain the extreme value and global minimum value of individual evaluation index parameters, and update them by comparing with the current value and historical extreme value;
Step 4: Update the particle position and velocity, and use the formula to calculate.
Step 5: Judge whether the end condition is met, and obtain the optimal combination of C and gamma if it is met; Otherwise, increase the number of iterations by 1, return to Step 2 and iterate continuously until the end condition is met, and output the optimal combination of C and gamma. Take the corresponding output value at this time as the evaluation result of online education quality of higher vocational e-commerce courses.

3 Test Experiment Analysis

3.1 Test Data Preparation

In the testing phase, this paper finally determined a total of 1000 groups of data to participate in the experiment, of which 900 groups were used to train the model, so as to get the optimal machine learning model structure, and the remaining 100 groups of data were used for testing. The specific test data information is shown in Table 5.

Table 5. Test Data Information

Test data number	Indicator 1	Indicator 2	…	Indicator 37
1	0.90	0.87	…	0.89
2	0.80	0.54	…	0.81
3	0.76	0.44	…	0.35
6	0.80	0.80	…	0.42
7	0.80	0.90	…	0.36
8	0.78	0.67	…	0.75
…	…	…	…	0.86
95	0.75	0.63	…	0.88
96	0.62	0.74	…	0.62
97	0.69	0.66	…	0.46
98	0.91	0.98	…	0.71
99	0.91	0.98	…	0.74
100	0.74	0.33	…	0.90

Among them, there are 1–37 columns of each group of samples. The data of 37 secondary indicators included in the primary indicators are used as the input values of the model test. The secondary indicator scores are the input data of the machine learning model. The preliminary evaluation results based on the entropy method are the output targets of the model. The first group input samples P = (0.90, 0.87, 0.6, -, 0.94, 0.87), and the output is E = 0.88, and so on. Keep learning. After getting an ideal model, input the score data of the teaching quality evaluation indicators of the 901–1000 groups, and predict and output the teaching quality evaluation results by the machine learning model.

In the specific test process, in order to more intuitively analyze the reliability of design evaluation methods, traditional method 1 and traditional method 2 are set as the control group of the test, and the application effect of design methods is evaluated by comparing the evaluation effect of different methods.

3.2 Test Results and Analysis

In the analysis phase of the test results, the simulation experiment of teaching quality evaluation based on the improved genetic algorithm optimized machine learning model was realized through Matlab2013b, and the teaching quality evaluation results of the 901–1000 groups were predicted, and Figs. 3 and 4 were obtained.

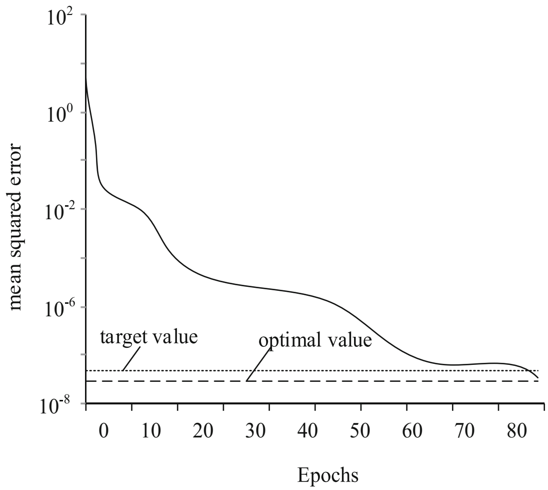

Fig. 3. Mean square error of machine learning model before improvement

Comparing the mean square error curve, it is found that the mean square error of the first 30 iterations of the machine learning model decreases rapidly, and the 31st to 80th iterations are slow. After 87 iterations, the mean square error converges to 8.6066e−08. The iterative speed of the first generation of the machine learning model after adaptive mutation is fast, and the speed of the second to the eighth generation is slow. The convergence occurs in the ninth iteration, and the mean square error converges to 3.3893e−12 (e represents the exponent, representing the power of 10), which improves the convergence speed and convergence accuracy of the machine learning model to a certain extent. The convergence speed is increased by 79.31%, and the convergence accuracy is improved

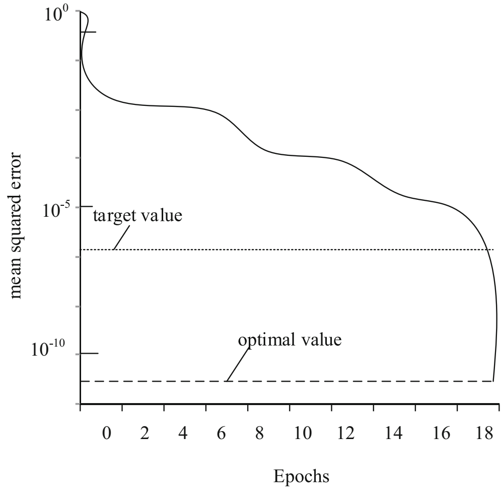

Fig. 4. Mean square error of improved machine learning model

by nearly one to two times, which indicates that the machine learning model designed in this paper can not only accelerate the convergence speed of the network, but also improve the prediction accuracy of the model.

On the basis of the above test environment, the relationship between the evaluation results of different methods and the actual situation is calculated, and the data results are shown in Fig. 5.

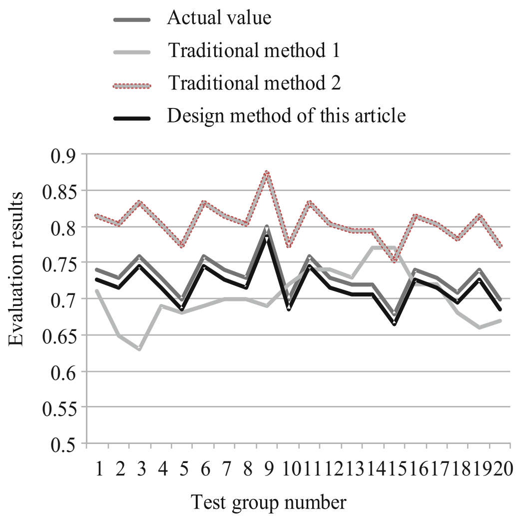

Fig. 5. Comparison of Test Results of Different Methods

Combined with the test results shown in Fig. 5, it can be seen that among the test results of different online education quality assessment methods for different courses, the difference between the assessment results of Yeneng and the actual situation is more obvious. Among them, in the test results of traditional method 1, the degree of difference between the evaluation of online education quality and the actual situation shows obvious instability, and the corresponding maximum error and minimum error are 0.12 and 0.05 respectively. In contrast, in the test results of traditional method 2. The difference between the evaluation of online education quality and the actual situation shows good stability, but the specific error level is relatively high, reaching more than 0.1. In the test results of this design method, the difference between the evaluation of online education quality and the actual situation shows a high stability, and the specific error range is within 0.02.

Based on the above test results, it can be concluded that the online education quality evaluation method of e-commerce courses in higher vocational colleges designed in this paper can achieve objective analysis of education quality, and the corresponding evaluation results have high reliability.

4 Conclusion

The online education quality evaluation method of e-commerce courses in higher vocational colleges based on machine learning model designed in this paper, innovatively designs an education data structure based on BOM, and quantitatively and qualitatively analyzes the factors that flight affects the quality of online education; Design evaluation indicators from four aspects: school management quality, teacher teaching process, student learning behavior, and academic quality; Establish a PSO-SVM model based on machine learning to achieve iterative optimization evaluation of online education quality. The test results verify that the design method improves the accuracy of evaluating the quality of online education. The application of this method can dynamically detect the teaching status of teachers and the learning effectiveness of students, and make it run through the whole teaching process, so that teachers and teaching management teams can improve their work in a timely manner, adjust their working modes and methods, actively correct errors, and coordinate the relationship between all parties. Promote all aspects to play their potential, promote personalized teaching, ensure the all-round development of students and guarantee the quality of talent cultivation, so as to achieve the ideal goal. Therefore, it is very important to have a sound monitoring and evaluation system for teaching quality, which will have a critical impact on the supervision of the daily status of teachers and students, the improvement of teachers' personal teaching ability and other aspects, so that teachers' daily teaching work status, students' learning status and other data can be reflected according to the basic information in the teaching process. The main objective of this paper is to study the collection and analysis methods of evaluation data. In combination with the current popular education big data technology, research a complete set of teaching quality monitoring system to enable it to collect data online, and apply the system to the daily management service of regional schools, which will certainly enhance the comprehensive competitiveness of the school and the entire region in the current education reform, and provide powerful help for walking in the forefront of education innovation. It is of great significance to improve the quality of education and teaching and realize the modernization of education.

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On Line Teaching Data Classification Method for Ramp Control Specialty in Universities Based on Machine Learning Model

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Abstract. In order to improve the accuracy of online teaching data classification results and provide comprehensive technical guidance and help for the standardized implementation of quality education, the machine learning model was introduced to carry out the design and research of online teaching data classification methods, taking the apron control specialty of a university as an example. Collect the basic information of college students majoring in apron control, the information generated in the teaching process, and the phased achievements of professional online teaching, build the online teaching database of college students majoring in apron control, and preprocess the data according to the specifications; The machine learning model is innovatively introduced to visually process the data. The encoding tool is used to transform the data format, so as to achieve the extraction of data characteristics; Calculate the similarity of the online teaching data characteristics of the apron control specialty in colleges and universities, set the classification criteria for the online teaching data of the apron control specialty in colleges and universities, and when the data similarity exceeds the set criteria, divide the data into the same category to complete the design of the classification method. The experimental results show that the designed classification method has a good application effect, and this method can effectively improve the accuracy of the classification results.

Keywords: Machine Learning Model · Classification Method · Online Teaching Data · Apron Control Discipline · Universities

1 Introduction

In 2013, the Civil Aviation Administration of China issued a notice on the transfer of control over aircraft apron operations to airport management agencies, requiring the gradual transfer of control over aircraft apron operations nationwide and improving the comprehensive service capacity of airports. Transferring control of aircraft apron operations to airport management agencies has changed the traditional form of ground control instructions for aircraft aprons, inevitably leading to a secondary distribution of benefits

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and having a significant impact on the adjustment of airport industrial structure. With the advancement of the transfer of control rights for domestic aircraft aprons, standardized control handover areas, handover control processes, and scientific and intelligent apron control and handover control systems have become the key to the successful operation and handover of aircraft aprons. To meet the needs of related work, the number of students enrolled in the apron control major every year is constantly increasing. At present, although the education system for apron control majors is relatively complete, a common problem is that teachers can only teach according to the tasks specified in the teaching syllabus, with little consideration given to students' acceptance level. There are significant differences in the knowledge obtained by students in the classroom. Some students can fully understand what the teacher is saying, while others have more or less missed out on the knowledge points. Therefore, frontline university teachers have been striving to achieve personalized education. With the rapid development of information technology, the in-depth application of educational informatization, and the continuous rise of applications such as online teaching platforms and adaptive learning systems, online learning has become a widely adopted teaching method in many universities [1, 2]. Online teaching of ramp control majors in universities has generated a large amount of data. The existing student database system can effectively achieve functions such as data entry, query, and statistics, but cannot find relationships and rules in the data, and cannot predict future development trends based on existing data. Due to the lack of means to mine knowledge hidden behind data, the phenomenon of "data explosion and knowledge scarcity" has emerged. In order for data to truly provide data for students, we must fully utilize resources to provide services for the school's own business decision-making and strategic development. Otherwise, a large amount of learning resources and online teaching data may become a burden, or even become garbage. In order to fully utilize data resources and provide services for teachers to understand student situations, it is necessary to classify online teaching data [3].

For this purpose, reference [4] collected and integrated learning behavior data from multiple university students on the MOOC online teaching platform, and designed an online teaching data classification algorithm based on data complexity. This algorithm utilizes data complexity to reduce the difficulty of classification between multiple classes, achieving the classification of massive data such as student learning achievements. Reference [5] proposed a data integration classification method to improve the adaptive Random forest algorithm, set the concept drift detector at the Ensemble learning device end, remove the drift detector at each basic tree end, and determine the number of background trees to be trained according to the prediction accuracy of the integrator. Use the improved algorithm to classify more balanced data streams. However, the above methods have not undergone data format conversion and have been applied to the massive online teaching data of ramp control majors in universities, resulting in poor data classification performance.

Machine learning is a multidisciplinary discipline, involving Probability theory, statistics, approximation theory, convex analysis, algorithmic complexity theory and other disciplines. It mainly studies how computers simulate or realize human learning behavior, acquire new knowledge or skills, reorganize existing knowledge structures, and constantly improve their own performance. Machine learning models are the core of artificial intelligence and the fundamental approach to computer intelligence.

In order to improve the effectiveness of online teaching data classification, this article innovatively introduces a machine learning model into this study, visualizing and converting the online teaching data of university apron control majors, and achieving data feature extraction; Calculate the similarity of features in online teaching data, and implement data classification based on the classification standards of online teaching data.

2 Online Teaching Data Acquisition and Pre-processing for Apron Control Specialty in Colleges and Universities

In order to realize the classification and processing of online teaching data of apron control specialty in colleges and universities, professional online teaching data [6] should be collected at online teaching terminals in colleges and universities before relevant research is carried out. In this process, it should be clear that teachers of basic courses will face a large number of students in teaching. They should discuss the factors affecting online teaching according to the students' usual basic learning conditions (such as knowledge base, classroom learning effect, students' interest in the course, homework completion, time spent after class, learning methods used, etc.), take this part of data as online teaching data. According to the data classification requirements, the functional relationship between two or more online teaching data attributes is analyzed, and data collection is conducted from the following three aspects [7].

First, collect the basic information of college students majoring in apron control. The data structure is as follows: student number, name, gender, score, native place, department, major, class, etc. This information can be obtained through the school's student management information system.

Second, the information generated in the teaching process, including students' love for their majors and courses, their mastery of pre-school knowledge, the effect of classroom learning, learning methods, professional knowledge, teaching courseware, PPT, teachers' lesson preparation and teaching records, etc. This information is mainly obtained through surveys and statistical data sources, and some data needs to be filled out by students. In order to solve the problem of data statistics with heavy workload and the fact that the data of manual statistics has a high error rate, relevant data can be collected directly in the online teaching online survey system [8]. In order to avoid data deviation caused by one person filling in multiple forms, student ID and student are required to be used when logging in the online teaching survey system. Since these information are filled in by students, it is inevitable to generate untrue data. In order to avoid such data, the questionnaire also contains students' self-evaluation and opinions on teachers' teaching methods. Based on these information, the credibility of the survey results can be basically determined [9]. Through the analysis and evaluation of the randomly sampled questionnaire data, the mining data is basically true and reliable, thus ensuring the credibility of the further data collection results.

Third, the periodical results of professional online teaching. The results database includes students' usual homework scores and course examination scores. This database is generated by teachers in the teaching process [10, 11].

According to the above method, after completing the collection of online teaching data, the data is preprocessed. The first step of data preprocessing is data integration, which is to merge data from multiple data sources. Use database technology to generate online teaching database for apron control specialty in colleges and universities from multiple database files acquired from data collection, as shown in Fig. 1 below.

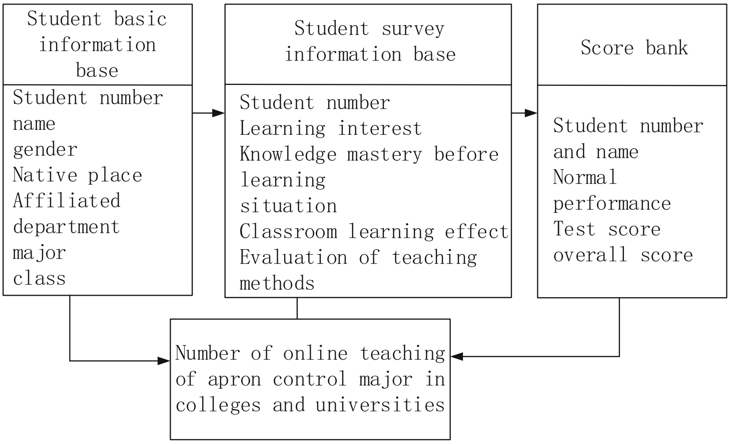

Fig. 1. Construction of online teaching database for apron control specialty in colleges and universities

On the basis of the above contents, the online teaching data of university apron control specialty in the database is cleaned up. The main task of data cleaning is to fill in the missing data values. As can be seen in the database, some key attribute data are missing attribute values. For these gaps, data cleaning technology can be used to fill them. In the filling process, first, you can ignore tuples. This is usually done when the class label is missing or multiple attributes of the tuple are missing values. Second, you can use a global constant to fill in the missing values, and use the same constant for the missing attribute values (such as "*Unknown*") Replace. However, if all the vacant values are used "*Unknown*" Instead, the mining program may mistake the data for a concept. Therefore, although this method is simple, it is not recommended here. Third, use the average value of the attribute to fill in the blank value. Or use the average value of all samples belonging to the same class as the given tuple, and use regression method, Bayesian method or decision tree to determine the vacancy value. This process is shown in the following calculation formula.

$$D = \frac{\ln C}{C} + \alpha \cdot s \tag{1}$$

In formula (1): D Indicates the vacancy value of online teaching data of apron control specialty in colleges and universities; C Represents adjustable parameters; α Represents the ratio coefficient of random sampling; s Represents the original gene expression matrix.

After the above processing is completed, convert the collected data. Data conversion is mainly to normalize data. Since most attributes belong to discrete value attributes, only individual continuous value attributes (such as peacetime score and total score attributes) need to discretize continuous value attributes.

Using concept layering technology, continuous value attributes can be converted to discrete value attributes (i.e. discretization). Histogram analysis is a relatively simple discretization method, which can be divided into two categories: equal width box division and equal depth box division. The equal width box divides the attribute values into equal parts or intervals. In a constant depth sub box, data is divided so that each part includes as many samples as possible. This process is shown in the following calculation formula.

$$\varepsilon(H) = \frac{1 + D(T-1) \cdot K}{T}(h) \tag{2}$$

In formula (2): ε Represents data discretization processing; H Indicates the expected cumulative error after data integration; T Indicates the number of integrated learning; K Represent the correlation between different base classifiers; h Represents the cumulative error expectation of different individual learners. Output the processed data, and complete the online teaching data collection and pre-processing of apron control specialty in colleges and universities.

3 Data Feature Extraction Based on Machine Learning Model

After completing the online teaching data collection and pre-processing of apron control specialty in colleges and universities, machine learning model is introduced to extract data characteristics. In this process, the online teaching data is input into the computer, and the machine learning algorithm in the computer is used to visualize the data. In the process of processing, coding tools are used according to the information obtained in the extraction module *Google Fusion Tables*, perform data format conversion, where *Google Fusion Tables* It is a visual application, mainly responsible for collecting, visualizing and sharing data. There are three steps to realize data visualization by using this program: ① upload the data set to *Fusion Tables* Middle; ② *Fusion Tables* The autonomous detection data is displayed in the table *Map of* $<$ *location column name* $>$ Label; ③ Click the tag to display the corresponding data.

utilize *Karma* Realize the mapping between geographical entities and extracted information, and complete data information calibration. On this basis, the process of feature data extraction is divided into two steps by mapping the implementation data to the entity: ① Configure a semantic type for each column to represent the data type, and judge the association with the semantic type determined in the entity; ② First, define the semantic types that match the teaching data columns obtained from heterogeneous data sources, and then use the association between the specified semantic types to independently associate the attributes of entities. Analyze the data training process of machine learning model, as shown in the following calculation formula.

$$sim(N_1, N_2) = \begin{cases} A_k, A_k < b \\ A_k + (L \cdot \varepsilon(H) \cdot P(1 - A_k)), A_k \geq b \end{cases} \tag{3}$$

In formula (3): *sim* Represents the mapping function; N_1, N_2 Indicates the entity name; A_k Indicates the number of transpositions; b Represents a constant scale factor, the default value is 0.1, and the maximum value is 0.25; L Indicates the length of the common prefix; P Indicates the number of registered characters. After the data mapping is completed, because the entity name itself has a series of problems such as abbreviation and character shift, the similarity calculation method of entity name needs to be fault-tolerant $Jrao - Winkler$ Method is a string calculation method based on the minimum editing distance, which extracts the features of entity data and describes the extraction process, as shown in Fig. 2 below.

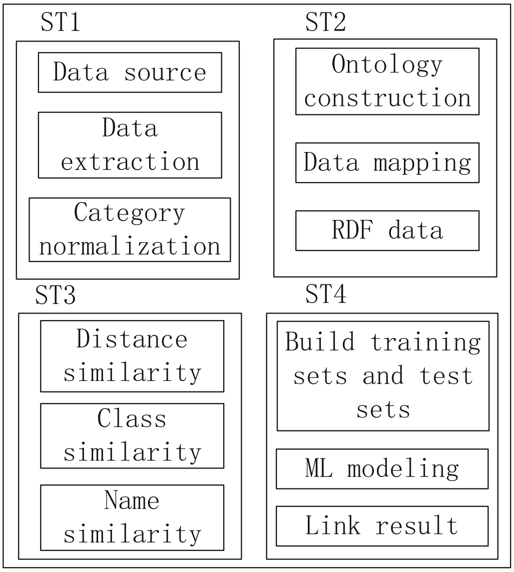

Fig. 2. Data feature extraction process based on machine learning model

In Fig. 2 above, *ML* Modeling is a non negligible step, which is the key to extracting parameters based on machine learning model, *ML* The modeling process is shown in the following calculation formula.

$$J(N_1, N_2) = \left|\frac{N_1 \cap N_2}{N_1 \cup N_2}\right| \cdot sim(N_1, N_2) \tag{4}$$

In formula (4): J express *ML* Modeling process. Substitute the calculation result of formula (4) into Fig. 2, output the link result according to the above process, and use it as the feature parameter of professional online teaching data, so as to realize the research of data feature extraction based on machine learning model.

4 Online Teaching Data Similarity Calculation and Data Classification

After the above research is completed, the similarity calculation of online teaching data characteristics of apron control specialty in colleges and universities is carried out. Before the calculation, cluster analysis of characteristic data in samples is required. Cluster analysis is the process of dividing training samples and test samples into similar sample classes, where clusters are collections of samples. Samples in the same cluster are similar to each other, but different from samples in other clusters. The samples that do not belong to any cluster are regarded as isolated points. The clustering process mainly uses distance to measure the similarity between objects, which is called distance based clustering analysis.

If the sample has n Attribute, you can consider it as n The similarity between two samples is available n The distance between two points in a dimensional space. Therefore, a suitable method to calculate distance is crucial to evaluate the similarity between samples. The Minh distance calculation method is used to calculate the similarity of characteristic data between samples. The calculation formula is as follows:

$$d_{ij}(q) = \left(\sum_{a>1}^{n} \left| x_{ia} - x_{ja} \right|^{q} \right)^{1/q} \tag{5}$$

In formula (5): d_{ij} Represents sample data x_i And sample data x_j Distance; q Represents the calculation coefficient of Minh's function; x_{ia} Represents a sample x_i Phase characteristic attribute; x_{ja} Represents a sample x_j The characteristic properties of. After completing the above calculation, the similarity between online teaching data is calculated according to the distance between sample data. The former is selected for calculation this time, and the calculation formula is:

$$\cos\theta_{ij} = \frac{d}{\sqrt{\sum_{a>1}^{n} x_{ia}^{2} \cdot \sum_{a>1}^{n} x_{ja}^{2}}} \tag{6}$$

In formula (6): $\cos\theta_{ij}$ Represents sample data x_i And sample data x_j Similarity of. Clustering criteria are used to evaluate the quality of clustering results, which are mainly expressed by clustering criteria functions. The selection of clustering criterion function directly affects the quality of clustering results.

After completing the calculation, set a clustering standard for the online teaching data of the apron control specialty in colleges and universities, that is, the classification standard between the data. When the calculation results $\cos\theta_{ij}$ When a certain value is reached or exceeded, it means that the characteristic values between the data are relatively close, that is, the two data can be divided into data of the same category, otherwise, when the calculation results $\cos\theta_{ij}$ When it does not reach or is less than a certain value, it indicates that the characteristic values between the data at this time are quite different, that is, the two data cannot be divided into data of the same category. In this process, the samples are first divided into multiple levels, and then the data samples at different levels are divided. Hierarchical clustering methods can be divided into two types: agglomeration and fragmentation. The aggregation method adopts the bottom-up method, starting with each sample as a separate cluster, and then gradually merging the similar clusters until all clusters are included in a cluster or the termination conditions are met. On the contrary, the splitting method adopts a top-down approach. Start to group all samples into one cluster, and then gradually split each cluster into smaller clusters until each sample ends up in a separate cluster or meets a termination condition. Through this method, we can divide the data of the same category, so as to complete the similarity calculation and data classification of online teaching data, and realize the design of online teaching data classification method for apron control specialty in colleges and universities based on machine learning model.

5 Comparison Experiment

At present, the scale of colleges and universities is constantly expanding, and the strength and level of running a school determine the survival and development of colleges and universities. In the actual school running environment, teaching work has been placed in the first place. How to better carry out teaching and cultivate talents is a particularly important issue in colleges and universities. Among them, the construction of teaching materials is a basic construction work in the teaching work of colleges and universities. It is one of the important signs to measure the level of running a university. It is an important link to further deepen the teaching reform, consolidate the achievements of teaching reform, improve the teaching quality, and cultivate high-quality talents. In the construction of teaching materials, there is no fixed standard for the selection of teaching materials in most colleges and universities at present. Teachers generally choose textbooks freely according to their own teaching plans and contents. The selection of textbooks is very arbitrary, and the use of textbooks is unreasonable, so that the teaching effect may not be ideal, which is not conducive to the development of teaching. Therefore, reasonable and effective evaluation of teaching materials and classification of teaching data are necessary to improve teaching and improve quality education. Online teaching resource classification can provide scientific basis for students to provide appropriate learning resources. In order to implement this work, the research on the design of online teaching data classification method for apron control specialty in colleges and universities based on machine learning model has been completed from three aspects. In order to test the classification effect of this method in practical application, the following tests will be carried out by taking a college as a pilot college, using the method of design comparison experiment.

14 quantitative characteristics of online learning extracted from the online teaching platform, including: the number of times of entering courses, the number of times of asking questions to teachers, the number of times of publishing topics in the course discussion area, etc. These characteristic data are closely related to the online teaching data of the apron control specialty in colleges and universities. After agreeing with colleges and universities that this part is public data that can be used for experiments, according to the specific needs of the experiment, Configure the parameters of the experimental environment, as shown in Table 1 below.

Table 1. Parameter Configuration of Comparison Experiment Environment

S/N	project	parameter
1	Computer Configuration	Dual core processor; 2 GH memory, 320 GB hard disk
2	operating system	Microsoft Windows7
3	Develop software	matlab 8.0; Microsoft fice Access 2017

Among them, Microsoft office Access 2017 is used to manage the data samples used in the experiment, run the program of the new algorithm in the matlab development tool, and connect and process the data samples.

In order to ensure the smooth implementation of the experiment, on the basis of the above contents, the data sample size is selected, and the relevant contents are shown in Table 2 below.

Table 2. Selection of sample size of comparative experimental data

S/N	project	parameter
1	Number of training sample sets	1200
2	Number of test sample sets	1100
3	Number of attributes	8
4	Number of categories	2

In view of the fact that the selection of data sample size is too small, which will increase the number of isolated points, it is easy to make the improved new method close to the classification results of traditional methods, and cannot reflect the advantages of the new method. On the contrary, if the size of data samples is too large, the size of small clusters will become larger and the number will decrease, so that the samples with small similarity will also be divided into the same cluster. Therefore, before the experiment, it is necessary to classify small clusters and isolated points according to the actual situation of the relevant work. On the basis of meeting the experimental requirements, reduce the sample size, save computing overhead, and thus save the overall execution time of the experiment.

According to the above way, after completing the experimental preparation, the online teaching data classification of apron control specialty in colleges and universities is carried out using the method designed in this paper. In the process of classification, we first collected and preprocessed the online teaching data of the apron control specialty in colleges and universities. On this basis, we introduced a machine learning model to extract the characteristics of online teaching data. To ensure that the extracted features can be used to describe professional online teaching data, set the training conditions and parameters of machine learning model data according to Table 3 below.

On the basis of the above design content, the online teaching data similarity is calculated, and the data with high similarity are divided into the same category. In this

Table 3. Machine learning model data training conditions and parameter settings

S/N	project	parameter
1	Learning rate	0.8
2	Number of subtrees	100
3	Random seed	10
4	Exponential decay	0.95

way, the online teaching data of apron control specialty in colleges and universities can be classified.

After the application of the method in this paper in the test environment is completed, the classification methods of teaching data proposed in the reference [5]and reference [6] are regarded as traditional method 1 and traditional method 2.

It is known that there are three types of characteristic data (Characteristic data 1~Characteristic data 3) that can be used as classification targets in the test sample data. Design comparative tests using the proposed method and two traditional methods to classify the sample data. The classification results are presented in the form of scattered data and used as the results of comparative experiments, as shown in Figs. 3 to 4 below.

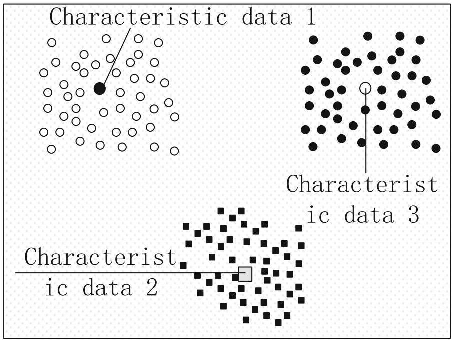

Fig. 3. Classification results of this method

From the results shown in Fig. 3 above, it can be seen that using this method to classify online teaching data of apron control specialty in colleges and universities, discrete data in the space can be clustered to characteristic data, that is, all professional teaching data are classified into corresponding categories according to specifications.

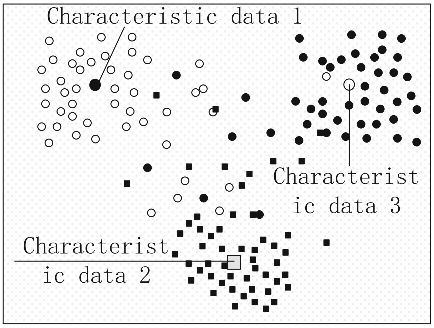

Fig. 4. Classification results of traditional method 1

From the results shown in Fig. 4 above, it can be seen that using the traditional method 1 to classify the online teaching data of the apron control specialty in colleges and universities, the discrete data in the classified space also clusters to the characteristic data, but it is obvious that the edge data in the space has a certain degree of intersection, that is, some data may be incorrectly classified.

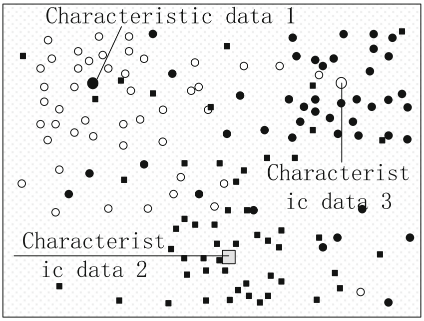

Fig. 5. Classification results of traditional method 2

From the results shown in Fig. 5 above, it can be seen that the traditional method 2 is used to classify the online teaching data of the apron control specialty in colleges and universities. After classification, the discrete data in the space does not cluster significantly to the feature data, not only the edge data in the space has intersection, but also some central data has failed to converge to the feature center, That is, the online teaching data of apron control specialty in colleges and universities failed to be classified according to the specifications.

Based on the above results, it is preliminarily proved that the classification method based on machine learning model designed in this paper can realize the classification of online teaching data of apron control specialty in colleges and universities. On this basis, the accuracy rate of online teaching data classification results of apron control specialty in colleges and universities is taken as the key indicator to test or evaluate the feasibility of this method, and the accuracy rate of classification results is calculated as follows.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} * 100\% \tag{7}$$

In formula (7): ACC Indicates the accuracy rate of online teaching data classification results of apron control specialty in colleges and universities; TP (True Positive) indicates the number of samples correctly classified as positive samples; TN (True Negative) indicates the number of samples that correctly classify negative samples as negative samples; FP (False Positive) indicates the number of samples that wrongly classify negative samples as positive samples; FN (False Negative) indicates the number of samples that wrongly classify positive samples as negative samples. According to the above method, the accuracy rate of the three methods for sample data classification is calculated, and the results are shown in Table 4 below.

Table 4. Accuracy of Three Methods for Sample Data Classification

sample data	Method in this paper (%)	Traditional method 1 (%)	Traditional method 2 (%)
1	99.5	91.2	88.3
2	99.6	92.6	87.1
3	98.7	94.7	85.8
4	99.8	96.2	84.6
5	99.6	95.3	86.9
6	98.6	96.9	86.8
7	99.2	92.6	82.5
8	99.5	93.3	83.3
9	99.3	91.7	85.6
10	98.9	91.2	84.9

According to the experimental results shown in Table 4 above, using this method to classify sample data, the classification accuracy rate is more than 98%; using traditional method 1 to classify sample data, the classification accuracy rate is between 90% and 97%; using traditional method 2 to classify sample data, the classification accuracy rate is less than 90%.

Comparing and testing the data classification efficiency of three methods, the classification time of the three methods for the same data is shown in Table 5:

Table 5. Time of Three Methods for Sample Data Classification

sample data	Method in this paper (ms)	Traditional method 1 (ms)	Traditional method 2 (ms)
1	11.2	23.9	28.2
2	12.6	23.8	27.2
3	14.7	25.3	25.8
4	16.2	22.6	24.6
5	15.3	23.7	26.3
6	16.9	24.9	26.8
7	12.6	26.5	22.5
8	13.3	23.8	23.7
9	11.7	21.4	25.6
10	11.2	22.3	24.5

According to the experimental results in Table 5 above, this method is used to classify sample data and the classification time is less than 17 ms; traditional method 1 and traditional method 2 are used to classify sample data and the classification time is higher than 20 ms. The above data prove that the classification efficiency of this method is relatively high.

Based on the above results, the following experimental conclusions are obtained: compared with the traditional methods, the online teaching data classification method based on machine learning model designed in this paper for the apron control specialty in colleges and universities has a good application effect. Using this method to classify sample data can effectively improve the accuracy of classification results, Provide comprehensive technical guidance and help for the standardized implementation of online teaching work of apron control specialty in colleges and universities.

6 Conclusion

According to the relevant provisions of the Regulations on Safety Control of Civil Aviation Airports and the Regulations on Civil Aviation Transport of China, CAAC proposes that the airport control agency should be responsible for the operation and control of civil aviation airports, and the work related to apron control is becoming more standardized. In order to improve the comprehensive level of apron control, universities have increased their investment in the training of professionals in apron control, Although some achievements have been made in the implementation of related education work, to deepen professional education in a real sense, it is still necessary to divide online teaching data categories based on the existing work and teaching needs. For this reason, this paper uses online teaching data collection and pre-processing, data feature extraction based on machine learning model. The online teaching data similarity calculation and data classification have completed the design of online teaching data classification method for apron control specialty in colleges and universities. The design method has been tested and proved to be effective in improving the accuracy of classification results.

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Evaluation Method of English Online Education Effect Based on Machine Learning Algorithm

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Abstract. Online teaching evaluation requires the use of technical means for data collection and analysis, but current technologies may still have some limitations, such as the inability to accurately capture students' actual performance or evaluate their comprehensive abilities To this end, a method for evaluating the effectiveness of online English teaching based on machine learning algorithms was studied. Firstly, an evaluation index system was constructed through primary selection and principal component analysis. Then collect and process the evaluation information corresponding to the indicators for data reduction, transformation, and anomaly data detection. Utilizing genetic algorithms to optimize the weights of BP neural networks in machine learning algorithms, finding better combinations of weights, and improving the learning ability and prediction accuracy of neural networks. A method for evaluating the effectiveness of online English education based on genetic algorithm optimized BP neural network has been proposed. The research results indicate that it can effectively evaluate the effectiveness of online English teaching.

Keywords: Machine Learning · English Teaching · Evaluation Index System · Genetic Algorithm · BP Neural Network · Online Education Effect Evaluation

1 Introduction

With the rapid development of information technology, network teaching, breaks through the time-space constraints and provides more people with opportunities to receive higher education by virtue of its unique advantages. Network teaching has become another university without walls after correspondence and radio and television universities, and has more advantages than the first two. It is a new, multi-directional and efficient teaching mode. The particularity of e-learning mode determines that e-learning evaluation should pay attention to formative evaluation. The learning system that partially realizes formative assessment adopts the form of electronic files, and does not make full use of computer technology, which greatly increases the workload of teachers and students.In addition, almost all evaluation systems only involve the evaluation of students, and there is no evaluation of teaching resources (including teachers, curriculum materials, etc.) by students.

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The comprehensive evaluation of classroom teaching quality is a problem that many educators are facing. The evaluation mostly adopts the mathematical model of directly establishing the evaluation system, fuzzy comprehensive evaluation, grey system, cluster analysis, etc. [1] These methods can fully consider all kinds of evaluation factors and reflect expert experience and knowledge, but it is difficult to exclude all kinds of randomness and subjectivity in the evaluation process, resulting in the distortion and deviation of the evaluation. Therefore, how to overcome the artificial subjective randomness in the evaluation to make the evaluation more accurate and effective is inevitable. Online teaching evaluation requires the use of technical means for data collection and analysis, but current technologies may still have some limitations, such as the inability to accurately capture students' actual performance or evaluate their comprehensive abilities.

This paper proposes an evaluation method of English online education effect combined with machine learning algorithm. The method for evaluating the effectiveness of online English education based on genetic algorithm optimized BP neural network is innovative. Firstly, an evaluation index system is constructed through primary selection and principal component analysis, and then evaluation information corresponding to the index is collected and processed for data reduction, transformation, and anomaly data detection. Then, genetic algorithm is used to optimize the weights of the BP neural network, find better combinations of weights, and improve the learning ability and prediction accuracy of the neural network. This method can more accurately evaluate the effectiveness of online English education and provide personalized improvement suggestions. This innovative method provides a comprehensive and reliable solution for online teaching evaluation through the comprehensive application of evaluation index system, data processing, and genetic algorithm optimization.

2 Evaluation Model of English Online Education Effect

2.1 Evaluation Index System

2.1.1 Primary Selection of Indicator System

Basic methods for selection and setting of evaluation indicators.When selecting and setting evaluation indicators, the basic method adopted in this paper is the combination of decomposition and synthesis. Generally speaking, the goal of comprehensive evaluation of teaching reform is often a qualitative concept. In order to establish the relationship with quantitative indicators, it is necessary to decompose the comprehensive goal into more specific goals, generally called criteria. These criteria reflect the structural characteristics of the described object system and the requirements of the comprehensive goal from a certain aspect, and further decompose these criteria layer by layer, until it can be described by indicators that are easy to be quantified or qualitative, an indicator system will be formed. This paper defines the concept of indicators that reflect the characteristics of the research object. According to the research object and research purpose, it can determine the characteristic basis that reflects a certain aspect of the research object, including quantitative characteristics and quality characteristics. The indicator system is a whole composed of a series of indicators, which can comprehensively reflect all aspects of the research object according to the research object and research purpose [2].

The key to describing comprehensive goals with an indicator system is to find a set of characteristic indicators that are representative and can fully reflect the requirements of various aspects of the comprehensive goals. These indicators and their combinations can properly express people's quantitative judgments on the comprehensive goals. This basic purpose defines the basic task of our indicator system research: that is, by analyzing the system structure and elements of the described object, establish the corresponding relationship between the comprehensive goal and the system structure and elements, and then study the correlation between quantitative indicators, criteria and comprehensive goals according to relevant theoretical and empirical analysis, so as to determine the selection and setting of indicators [3].

2.1.2 Selection of Evaluation Indicators

For the evaluation indicators of English online education effect selected initially, principal component analysis is used to select them, so as to simplify the indicators. The method was first proposed by K. Pearson, who is known as the "father of statistics", for the calculation of non random variables. Later, it was first proposed by American mathematical statistician Hotelling in 1933. The usual method is to select fewer variables than the original variables, but these selected variables can explain most of the variables in the data. Take such variables as new variables, namely principal components, and interpret the comprehensive indicators of the data through principal component variables. The method can effectively reduce the dimension of variables. It uses the orthogonal transformation of a matrix to simplifies the complex system problem into a mathematical problem that is easy to operate, so as to simplify the problem.

Assume there is n samples, each sample has m variables, which together form a nm matrix of order:

$$G = \begin{pmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{m1} & \cdots & g_{mn} \end{pmatrix} \tag{1}$$

When m when larger m it is troublesome to investigate problems in dimensional space. In order to overcome the difficulties in data dimensionality reduction processing, we need to use dimensionality reduction techniques such as principal component analysis (PCA) to replace the original variable indicators with fewer comprehensive indicators. These comprehensive indicators not only retain as much original information as possible, but are also independent of each other. Through dimensionality reduction processing, we can better understand and analyze the data, improve the interpretability and generalization ability of the model [4].

The definition of principal component analysis is: $\{g_1, g_2, ..., g_m\}$ is the original variable indicator, $\{h_1, h_2, ..., h_s\}$ $(s \leq m)$ is the new variable indicator:

$$\begin{cases} h_1 = v_{11}g_1 + v_{12}g_2 + ... + v_{1m}g_m \\ h_2 = v_{21}g_1 + v_{22}g_2 + ... + v_{2m}g_m \\ ... \\ h_s = v_{s1}g_1 + v_{s2}g_2 + ... + v_{sm}g_m \end{cases} \tag{2}$$

coefficient v_{ij} the determination principle of is:

(1) h_i And $h_j (i \neq j, i = 1, 2, ..., s)$ unrelated;
(2) h_1 yes $\{g_1, g_2, ..., g_m\}$ the largest variance in all linear combinations of; h_2 Yes and h_1 uncorrelated $\{g_1, g_2, ..., g_m\}$ the largest variance in all linear combinations of; h_s yes and $\{h_1, h_2, ..., h_s\}$ are irrelevant $\{g_1, g_2, ..., g_m\}$ the largest variance in all linear combinations of then the new variable indicator $\{h_1, h_2, ..., h_s\}$ they are called original variable indicators respectively $\{g_1, g_2, ..., g_m\}$ first, second,., second s principal component

According to the above analysis, PCA is actually to determine the original variable $g_j (j = 1, 2, ..., m)$ in the principal components $h_i (i = 1, 2, ..., s)$ load on $v_{ij} (i = 1, 2, ..., s; j = 1, 2, ..., m)$.

This paper establish the evaluation model of English online education effect:

Step 1: Collect the raw data required in the indicator system and calculate the correlation coefficient matrix:

$$R = \begin{pmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mm} \end{pmatrix} \tag{3}$$

Standardize, that is $r_{ij} (i, j = 1, 2, ..., m)$ original variable g_i and g_j Correlation coefficient of, $r_{ij} = r_{ji}$, the calculation formula is:

$$r_{ij} = \sqrt[3]{\frac{\sum_{k=1}^{n} \left(g_{gi} - \overline{g}_i\right)\left(g_{gj} - \overline{g}_j\right)}{\sum_{k=1}^{n} \left(g_{gi} - \overline{g}_i\right)^2 \left(g_{gj} - \overline{g}_j\right)^2}} \tag{4}$$

(2) Calculate eigenvalues

The eigenvalue of correlation coefficient matrix R is calculated, including $J_1 \geq J_2 \geq ... \geq J_s \geq 0$, the corresponding eigenvector $I_1, I_2, ..., I_s$, where $I_j = \left(I_{1j}, I_{2j}, ..., I_{sj}\right)^T$, composed of eigenvectors s new indicator variables: $\{Q_1, Q_2, ..., Q_s\}$.

(3) Select $s (s \leq m)$ the principal component contribution rate and cumulative contribution rate are calculated.

The information cumulative contribution rate of J_j

$$a_j = \frac{J_j}{\sum_{k=1}^{s} J_k} (j = 1, 2, ..., s) \tag{5}$$

Main components Q_i the information contribution rate of

$$b_q = \frac{\sum_{k=1}^{q} J_k}{\sum_{k=1}^{s} J_k} \tag{6}$$

Main components $\{Q_1, Q_2, ..., Q_q\}$ cumulative contribution rate of when b_q when it is close to 1 (generally 0.85, 0.9, 0.95), select the front q index variables $\{Q_1, Q_2, ..., Q_q\}$ as q Principal components, replacing the original s index variables, which can be used to q the three principal components were analyzed comprehensively.

After selecting the results of principal component analysis, the evaluation index system is constructed (Table 1).

Table 1. Evaluation Index System

Primary indicators	Secondary indicators
Attitude towards learning	Number of logins
	Total online time
	Time for online course learning
	Score for completing additional assignments
Interaction ability	Number of questions asked in the Q&A module
	Number of Discovered Speeches
	Quality of speech
	Number of times comments have been viewed
	Number of times comments have been replied to
	Number of times to participate in online discussions
	Total time spent participating in discussions
Resource utilization capacity	Number of times to upload resources
	Number of downloads of resources
	The number of times a divination resource has been divined
learning effect	Submit homework or work grades
	Number of online tests
	Results of online quizzes
	Exam results

2.2 Collection and Processing of Evaluation Information

2.2.1 Collection of Evaluation Information

In the network education environment, teachers can not directly and comprehensively understand the learning situation of students. Therefore, it is necessary to find the information collection methods and means suitable for the characteristics of online teaching, and collect the information needed for evaluation comprehensively and objectively according to the established evaluation index system of online learning, and then process it, so as to make a comprehensive, objective and timely evaluation of students' learning on the online teaching platform.In online teaching, learning evaluation information mainly comes from students' online learning activities [5]. On the network teaching platform, there are many ways to collect students' access information. From the location of data collection, it can be divided into server side and client side; From the perspective of the technology used, it includes active methods and non active methods. The non active method generally refers to the direct analysis of the server's log files. The active method needs to embed program code (such as CGI, JSP, JavaScript, etc.) in the system to obtain more detailed and accurate information.Common methods for user identification include: IP address/agent, using cookies, registering, embedding SessionlD, modifying the browser, etc. Among them, it is the easiest to identify users based on IP and agents, but the error is also the largest. The method of writing cookie flag on the client is more accurate, but if the user disables the browser cookie, it cannot be implemented. The registration method can accurately track the access of a user. Therefore, we use the method of student registration and login[6]in the design of the online learning system to facilitate the collection of student learning information.To sum up, according to the specific situation of the online learning platform, the data collection of learning behavior will adopt two ways. On the one hand, students are required to register with their real names, and part of the learning behavior information of students will be recorded into the background database through the embedded program. On the other hand, students' learning behaviors are automatically recorded through the server logs, and then these learning behaviors are analyzed through data mining.

2.2.2 Evaluation Information Processing

(1) Data reduction and transformation

First, data reduction is carried out, attribute subset selection is carried out for the dataset, and irrelevant or redundant attributes are deleted, When processing the original teaching evaluation data, the descriptive language I - "no", "occasionally", "often", "every time", etc. in the evaluation indicators are converted into corresponding values 1, 2, 3, 4.it is necessary to generalize the hundred point system data and map the evaluation value to five grades, namely, unqualified, qualified, medium, good and excellent, The marks are respectively marked by Arabic numerals 1, 2, 3, 4 and 5. The grades are shown in Table 2 below:

Table 2. Description of Evaluation Grade

Category identification	Centennial system	Grading system
1	Below 60 points	unqualified
2	60–70 points	qualified
3	70–80 points	secondary
4	80–90 points	good
5	90–100 points	excellent

(2) Abnormal data detection

In the actual teaching evaluation process, it is inevitable that due to the influence of personal subjective emotions, the evaluation data is not credible.The density based outlier detection method has a better anomaly detection effect [7]for data sets with uneven distribution.Among them, the improved algorithm of outlier detection based on clustering and density proposed by Tao Jing [3] scholars, namely CLOF algorithm, has achieved good experimental results. The core idea of the algorithm is to preprocess the original data and first perform K-means clustering. The specific process is as follows:

Step 1: For the preprocessed dataset, we apply the K-means clustering algorithm to cluster the preprocessed dataset and divide it into several clusters. This algorithm uses the Euclidean distance from the data point to the cluster center as the similarity metric, and iteratively searches for the optimal cluster membership for each data point.
Step 2: Set the threshold of the number of outliers M, count the number of data in each category N_i, if $N_i \leq M$, all such data will be determined as candidate outliers, go to Step 4, if $N_i > M$, go to Step3.
Step 3: Calculate the class center of each cluster by using Eqs. (7) and (8) O_o and class radius T_i.

$$O_o = \frac{\sum\limits_{k \in N_i} o_k}{N_i} \tag{7}$$

$$T_i = \frac{\sum\limits_{k \in N_i} |o_k - O_o|}{N_i} \tag{8}$$

Then calculate each data object through Eq. (9) o_i to the class center of its corresponding class O_o distance d_i calculation formula,

$$d_i = \sqrt{\sum_{j=1}^{M} \left(o_{ij} - O_{oj}\right)^2} \tag{9}$$

if $d_i < T_i$, the data point is judged as normal, if $d_i \geq T_i$, the data point is determined as a candidate outlier.
Step 4: Combine the candidate outliers determined in Step 2 and Step 3, call LOF method for the candidate outlier set to calculate the outlier factor of data points, and sort according to the LOF value.
Step 5: Before outputting the maximum LOF value M points, that is, the final outlier.

2.3 Evaluation Model Based on Machine Learning Algorithm

By analyzing the evaluation of English online education effect in this paper, we can see that the sample is divided into four grades. From the perspective of machine learning, the evaluation process is the classification process [8]. The evaluation of college students' training quality can be realized through the classification model in machine learning.Input the sample data into the evaluation model, and then output the evaluation results [9]. Using machine learning methods to evaluate the effectiveness of online English education needs to select appropriate algorithms and optimize them.

Here we choose the neural network algorithm in machine learning to build an evaluation model. Artificial Neural Networks (ANN) has gradually developed in the field of natural science since the 1940s. It is an information processing system based on imitating the structure and function of biological brain, and has strong self-learning ability and memory, association, and recognition ability. ANN does not need an accurate mathematical model and has the ability of nonlinear mapping [10]. In recent years, artificial neural networks are often used in the evaluation of college classroom teaching. However, although the BP neural network has nonlinear processing ability, because the BP algorithm is based on the essence of gradient descent, there are inevitably some shortcomings such as slow convergence speed in the learning process, easy to fall into local minima, poor robustness and poor network performance. In view of the shortcomings of BP neural network, this paper introduces genetic algorithm (GA) to optimize the weights of BP neural network, and proposes a method for evaluating the effectiveness of English online education based on BP neural network optimized by genetic algorithm.The teacher's teaching quality evaluation system based on neural network is divided into three key steps. In the first step, it is necessary to prepare the data that meets the indicator requirements, and take the qualified data as the input training samples of the network, which has been completed in the first two steps. The second step is to use the BP neural network optimized by genetic algorithm; The third step is to build a BP neural network evaluation model and train the network to obtain a true and effective neural network evaluation model.

2.3.1 BP Neural Network Optimized by Genetic Algorithm

Genetic algorithm is a kind of intelligent optimization algorithm simulating biological evolution, which has obvious advantages and characteristics in solving combinatorial optimization problems. It can effectively use historical information to speculate on the next generation's preferred set with improved expected performance [11]. After continuous evolution and iteration, Obtaining the optimal solution. Implementation steps of BP neural network based on GA optimization:

1) Initialization of parameters: determine the number of neural network inputs and outputs, and determine the number of network layers; Set the population size, randomly generate a certain number of gene individuals (each gene individual is composed of the initial weight and threshold of the neural network), the crossover probability, mutation probability, and evolution algebra of the algorithm.
2) Define fitness function.

$$f(x) = \sum_{i=1}^{U}\sum_{i=1}^{D}\left(Y_i(l) - \tilde{Y}_i(l)\right)^2 \tag{10}$$

where, $Y_i(l)$ and $\tilde{Y}_i(l)$ training data l on page i actual output and expected output of output nodes;

3) Calculate the fitness function value $f(x)$;
4) According to the genetic strategy, The calculation formula of selection probability is as follows:

$$P_i = \frac{f_i}{f_1 + f_2 + ... + f_E} \tag{11}$$

where, P_i on behalf of the i the probability of individual selection; $f_1 + f_2 + ... + f_U$ represents the sum of individual fitness values; f_i on behalf of the i individual fitness value; E represents the group size.
5) Judge whether the group performance meets a certain index. If yes, turn to step 6), otherwise turn to step 3)

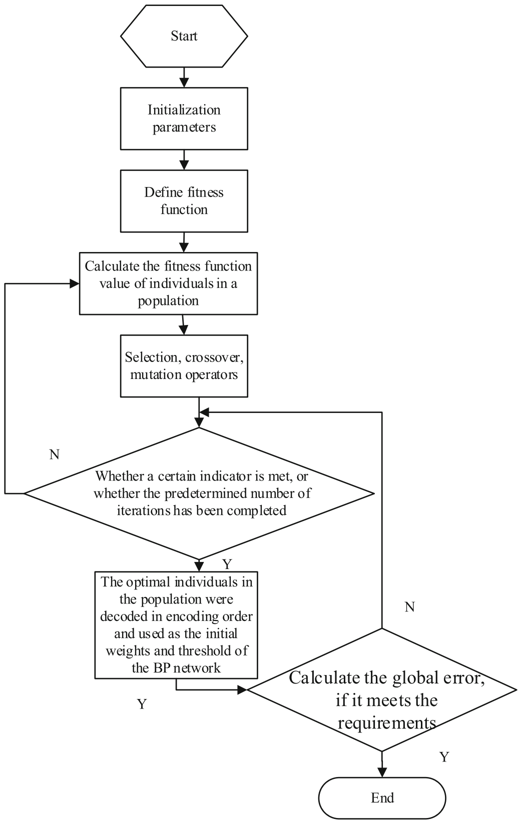

Fig. 1. The genetic algorithm

6) The optimal individuals in the population are decoded in the coding order as the initial weights and thresholds of the BP network.
7) Perform forward propagation calculations to determine whether the error meets the preset requirements. If the requirements are met, the online learning will be completed;

8) If it is less than the number of cycles, back propagation of BP network is carried out, the threshold is modified, and return to step 6); otherwise, network learning is ended.

The optimal initial weight and threshold are given to the neural network, and the optimization of the neural network is completed (Fig. 1).

2.3.2 Improved Neural Network Evaluation Model

There are many learning algorithms for neural networks. BP network is developed on the basis of the back-propagation algorithm proposed by RumeChart et al. in 1985 [12]. It is a multi-level feedback network, which uses the tutor learning algorithm. The evaluation of English online education effect based on the improved neural network is shown in Fig. 2.

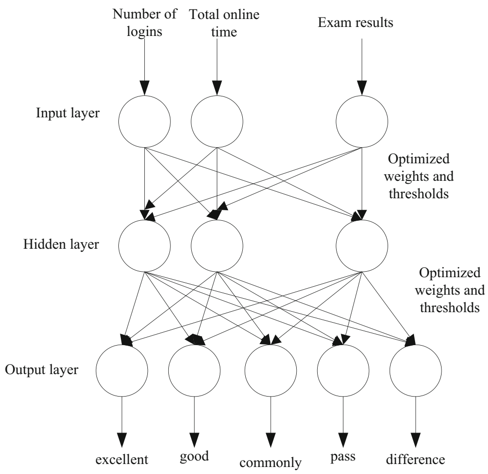

Fig. 2. Improved neural network evaluation model

According to the requirements of the teaching effect evaluation process, a three-layer BP neural network is constructed with 18 two-level evaluation indicators as the input of the neural network. There are 18 nodes in the network input layer, several hidden layer nodes, and five output nodes, respectively corresponding to five evaluation stages of teacher evaluation: excellent, good, medium, pass, and poor, which are quantified as 1000000100000010000001 respectively. The training sample input is composed of the known data corresponding to 18 secondary evaluation indicators, and the five quantitative values of five evaluation levels corresponding to the known input samples are taken as the output for training.The process is shown in Fig. 3 below.

After repeated learning and training, the actual output is close to the expected output. The trained neural network can automatically evaluate similar samples.

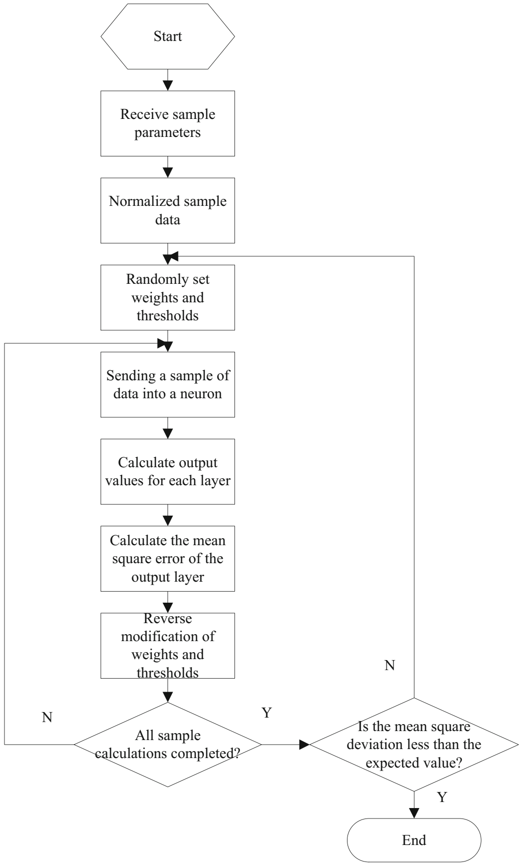

Fig. 3. Improved neural network evaluation model

3 Application Test of Evaluation Method

3.1 Sample Data

The training data is the evaluation data of two grades in the English discipline of a school. A total of 3540 records are used for the experimental test. Each data includes 13 scores. These scores mainly include teacher peer scores, student scores in the teaching class, expert listening scores, etc. 13 scoring options with more data are selected, and these data are divided into 13 groups. The first nine groups are used for neural network training. The last four groups of data were tested to verify the experimental results.

3.2 Establishment of Simulation Evaluation Model

In Matlab tool, an improved neural network evaluation simulation model is established. The process is as follows:

(1) The newff function is extracted from the Matlab tool software, and then the network is constructed from this function. On the basis of the existing samples, the number of neuron cells in the output layer is automatically calculated from this function. Here, the user can provide the relevant training algorithm function and the number of neuron cells in the hidden layer.
(2) Use the Matlab toolbox to call the initialization processing function (init) in the toolbox to initialize the data.
(3) The samples are used to train the neural network strictly.
(4) On the basis of the third step, the neural network is simulated. The trained network can be used to test and evaluate the data.

The initial parameter settings of the improved neural network evaluation simulation model are shown in Table 3 below.

Table 3. Parameter setting of improved neural network evaluation simulation model

parameter	numerical value
Number of input layer neurons	18
Number of hidden layer neurons	24
Number of neurons in the output layer	5
Connection weights for input and hidden layers	0.47
Connection weights of hidden layer and output layer	0.32
Input layer and hidden layer connection threshold	2.85
Connection threshold for hidden layer and output layer	3.0
Target accuracy	0.00001
Learning rate	0.25
Population size	12
The encoding length is	28
Maximum evolutionary algebra	1000
Selection probability	0.33
Cross probability	0.40
Mutation probability	0.65

3.3 Evaluation Results

After using 9 groups of training samples to train 2 improved neural network evaluation models, input 4 groups of test sample data to test and verify the experimental results. The results are shown in Table 4 below.

It can be seen from Table 4 that the effect of online English education evaluated by the four groups of test samples is as follows: the effect of sample 1 is medium; The effect of sample 2 is good; The effect of sample 3 is good; The effect of sample 4 is excellent;

Table 4. Evaluation Results

Test samples	Evaluation level	Evaluation results	Evaluation level
1	excellent	0.3590	secondary
	good	0.6351	
	secondary	0.9253	
	pass	0.4745	
	difference	0.5246	
2	excellent	0.3363	good
	good	0.9368	
	secondary	0.3627	
	pass	0.4965	
	difference	0.2995	
3	excellent	0.5635	good
	good	0.9824	
	secondary	0.4746	
	pass	0.5362	
	difference	0.2414	
4	excellent	0.9552	excellent
	good	0.6324	
	secondary	0.4528	
	pass	0.3634	
	difference	0.2814	

4 Conclusion

This paper constructs a learning evaluation system and a teaching resource evaluation system.Among them, through the analysis of students' online learning behavior and the research of existing online learning evaluation system, the existing learning evaluation index system has been improved, the principal component analysis method has been used to select indicators, and data mining method has been used to collect data on learning behavior. Finally, the online learning behavior is comprehensively evaluated according to the quantified learning behavior data machine learning algorithm. Although I have studied a lot of literature before my research, due to my limited level and the influence of some objective factors, the following problems still need to be solved in the future:

(1) The learning feedback system needs to be improved.Learning evaluation provides data information about students' learning behavior, which can be used to make personalized recommendations to students to improve their learning in the next stage.

(2) Log mining information is not fully utilized. This paper uses the method of letting students score the evaluation indicators of teaching resources to collect the evaluation information of indicators. In the future, we can use log mining technology to collect the information of teachers' behavior and curriculum resources.
(3) How to improve the universality of the evaluation model, make it universally applicable to the evaluation of teaching effects of various types of college courses, and how to extend the model to the evaluation of teaching effects of primary and secondary school courses other than colleges and universities are the problems that we will focus on in the next step.
(4) In future research, further refinement and expansion of the evaluation index system will be carried out, including indicators not limited to academic performance, learning effectiveness, learning attitude, etc. We can consider introducing more dimensions and factors, such as learning motivation, learning strategies, interactive behavior, etc., to comprehensively evaluate the effectiveness of English online teachingss.

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Research on Enterprise Education Information Retrieval Model Based on Machine Learning

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Abstract. With the expansion of enterprise scale and the increase in information volume, traditional manual retrieval methods are no longer able to meet the needs of rapid and accurate retrieval of enterprise education information. To this end, research is conducted to optimize the design of enterprise education information retrieval models based on machine learning technology. Utilize web scraping techniques to gather comprehensive educational data for the company's learning and development initiatives, and complete the pre-processing of the initial enterprise education information through word segmentation, semantic tagging, clustering and other steps. The support vector machine technology in machine learning is used to extract the characteristics of enterprise education information, and the output results of enterprise education information retrieval model are obtained through the steps of feature matching, retrieval expansion, etc. Through the model test experiment, it is concluded that the retrieval accuracy and recall rate of the design model are 99.0% and 99.6% respectively, which shows that the design model has good retrieval performance and running performance.

Keywords: Machine Learning · Enterprise Education · Information Retrieval Model · Support Vector Machine · Grayscale Transformation

1 Introduction

Enterprise education is the dissemination of knowledge, technology or values to employees or customers. Its purpose is to improve the quality of employees, obtain qualified workers, or guide consumption, thus increasing the competitiveness of enterprises. The content includes: the history, current situation, management experience, values, cultural traditions, etc. of the enterprise; Scientific knowledge and work skills that employees should have; Products produced by the enterprise and system knowledge of products; Knowledge and skills in operation and service, etc. Due to the increase of enterprise education information content, it brings greater difficulty to enterprise education. In

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order to maximize the utilization of enterprise information and provide maximum support for enterprise education, an information retrieval model is constructed and applied to enterprise education. Information seeking involves the process of acquiring relevant information resources from a diverse range of information sources to satisfy information needs. These information sources may comprise various information resources available in a collection of information materials [1]. Each information inquirer has different requirements for information and different ways to obtain information, but they have the same retrieval principle, which is the process of representing the information inquirer's demand set and the information resource set with characteristics, then making some specific matching and selection, and then returning to the target object that meets the query requirements.

At present, more advanced models for information retrieval are the ones that involve big data analysis and semantic understanding combined with AI. Reference [2] demonstrates the development of a big data analysis-based information retrieval model. To begin with, professionals analyze relevant digital library information retrieval literature in order to discover the aspects that influence the effectiveness of retrieval efforts. After collecting a large amount of relevant information retrieval data, the big data analysis technology is used to construct a digital library information retrieval model. The efficiency of the newly-built model is then simulated and tested. Reference [3] constructed an intelligent information retrieval model based on semantic understanding and AI, a methodology has been suggested for retrieving information about power equipment, utilizing both semantic comprehension and artificial intelligence. To determine the significance of power equipment information, a weighted method is employed. Based on this, feature information is extracted. The data flow for processing power equipment information based on semantic understanding is designed according to the limiting function between the sentence type and the description object. By utilizing extended query substrings to search for structured and unstructured data, an AI retrieval model founded on semantic comprehension is constructed, thereby quantifying and retrieving power equipment data. However, in the above methods, a relatively complete educational information preprocessing process was not established, resulting in low information retrieval accuracy.

To address the aforementioned issues, a machine learning-based model for enterprise education information retrieval is being investigated. Machine learning is a multidisciplinary field encompassing probability theory, statistics, approximation theory, algorithmic complexity, and theory. Its focus is on teaching computers to mimic or execute human learning behavior [4], which involves learning new skills or knowledge and reorganizing existing structures to enhance performance. Decision tree, support vector machine, random forest, association rule, and artificial neural network algorithms are among the specific machine learning technologies being explored. Machine learning technology specifically includes decision tree algorithm, support vector machine algorithm, random forest algorithm, association rule algorithm and artificial neural network algorithm. Machine learning technology is applied to study the enterprise education information retrieval model to improve the retrieval accuracy and operation performance of enterprise education information. To this end, a machine learning based enterprise education information retrieval model is studied. Establish the basic architecture of an enterprise education information retrieval model, collect enterprise education information and perform segmentation, annotation, clustering, smoothing, and other processing to improve the accuracy of model retrieval. Based on machine learning technology, obtain education information feature extraction results, construct an enterprise education information retrieval engine, and complete enterprise education information retrieval through feature matching, sorting, and expansion.

2 Construction of Enterprise Education Information Retrieval Model

Illustrates the fundamental configuration of the corporate education information retrieval model in Fig. 1.

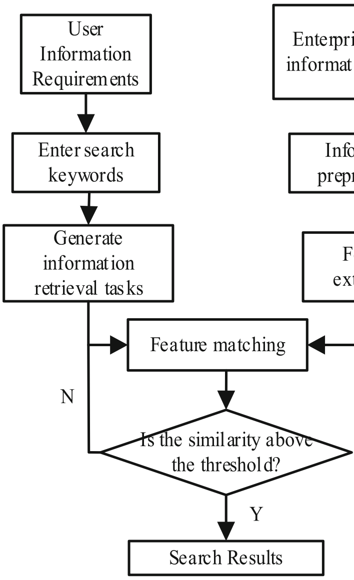

Fig. 1. Enterprise education information retrieval model architecture

Enterprise education information includes text, image and other data, of which image data cannot be retrieved directly. It is necessary to extract logical views [5] from these original data to support information retrieval. The enterprise education information retrieval model designed this time mainly analyzes the text information and image information in enterprise education. With the support of machine learning technology, through feature extraction, matching and other steps, the retrieval result of enterprise education information is obtained, which is the output result of the design model.

2.1 Enterprise Education Information Collection

Use web crawler technology to collect all education information in enterprise education work, and build corresponding information ontology. Web spider technology, also known as web crawler technology, is an automated data capture and information collection technology that simulates the behavior of spiders crawling on the internet, automatically accessing web pages on the internet through programs, and extracting data and information from them. Web spiders have two strategies for traversing Web space: breadth first and depth first. The breadth first strategy is conducive to improving the capture speed of web spiders. In order to correctly extract the links and text information required in HTML documents, the first problem is to parse HTML and transform HTML characters into structured documents composed of HTML tag sequences. According to the Robots protocol, when a web spider enters a website, it should first access a special text file Robots.txt, which is usually placed in the root directory of the website server. The website administrator can use Robots.txt to define which directories cannot be accessed by the web spider, or which directories cannot be accessed by certain web spiders [6]. The website administrator writes the link information into sitemap.htm, then the web spider can use the sitemap.htm file as the portal for website web document crawling, use the web spider to collect the output enterprise education information, follow the five principles and seven steps of ontology construction, and use subject words and keywords to verify, filter and update concepts to build ontology prototypes. Conduct semi-automatic Chinese ontology construction of computer technology. The construction process of enterprise education information ontology is shown in Fig. 2.

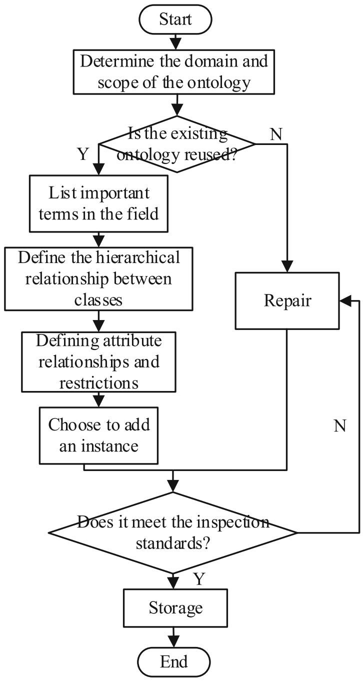

Fig. 2. Flow chart of enterprise education information ontology construction

Ontology aims to capture insights in interconnected areas and foster mutual comprehension within the domain, determine commonly recognized words in this field, and give clear definitions of these words and their relationships from different levels of formal models.

2.2 Enterprise Education Information Pre-processing

According to the form of enterprise education information, preprocess is performed for text information and image information. Text information preprocessing is a process of extracting feature words from enterprise education text information to express the text. Its main task is to segment patent text and remove stop words [7]. Removing stop words means removing symbols and words that have little to do with automatic classification of patent texts. The general approach is to design a stop list, and then remove the words or symbols that appear in the stop list from the text, leaving only the remaining words for further word segmentation. The purpose of processing image information for corporate education is to enhance image quality. As shown in Fig. 3.

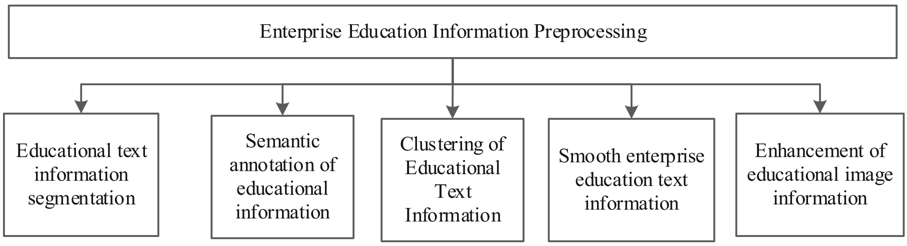

Fig. 3. Enterprise Education Information Preprocessing Architecture

2.2.1 Word Segmentation of Educational Text Information

In educational text information processing, word segmentation is a text preprocessing step that cannot be defaulted. Education text information is mainly Chinese information, and there is no natural separation between Chinese words and English words. In order to extract Chinese words as document features, Chinese documents must be word segmentation. The approach employed in this study to accomplish word segmentation for educational text information is the maximum matching method. The basic idea is that the number of Chinese characters contained in the longest word entry in the automatic word segmentation dictionary is assumed to be i, the first of the current string sequence in the processed text is taken i as a matching field, search the word segmentation dictionary. If there is such a character in the dictionary i word entries are matched successfully, and the matching field is segmented as a word; If no such one is found in the dictionary i for word entries, the matching fails. The last Chinese character is removed from the matching field, and the remaining characters are used as new matching fields before matching. Repeat until the matching is successful.

2.2.2 Semantic Annotation of Educational Information

Semantic annotation is a annotation process. Under the guidance of ontology, it annotates the concept classes, attributes and other metadata of each part of resource content, and also serves as the basis for semantic annotation. The input item of semantic annotation is the document to be annotated and ontology ontology, while the output item is the result of semantic annotation of the document, that is, semantic content. Adding semantic information to the Web enables the Web to develop from a machine readable state to a machine understandable state, and utilize the obtained information to form the basis of the semantic Web implementation. The approach involves extracting and processing the full text content of educational material during its semantic annotation. Word segmentation tools are used to segment the text, followed by part-of-speech tagging. Finally, the segmentation results are analyzed for part-of-speech to establish the foundation of the semantic Web implementation, and extract nouns and verbs. Count the word frequency of extracted nouns and verbs, and set the threshold as J_0 to determine the initial feature words of the document. In order to determine the final feature word of the document, the domain ontology is used to calculate the initial feature word [8] obtained in the previous step. According to the dependency syntax, analyze the syntax of the sentence to which the feature word belongs, and obtain the relationship between the words in the sentence. Extract the semantic triplet relationship of words with dependency, including nouns and verbs, and then obtain the semantic relationship of the document, which is represented by triples, namely:

$$Y = \left(y_{theme}, y_{predicate}, y_{object}\right) \tag{1}$$

In formula (1), y_{theme}, $y_{predicate}$ and y_{object} they respectively represent subject, predicate and object. With the help of ontology's ability to express and describe knowledge, the annotated objects are analyzed and processed according to the above semantic annotation process.

2.2.3 Clustering of Educational Text Information

Use Bayesian method [9] to determine the type of educational text information, and define the attribute value of educational text information as a_i, the attribute value of any educational text information cluster center is c_i, then the clustering process of educational text information can be expressed as:

$$J = \arg\max_{c_i \in C} P(c_i) \prod_{i=1}^{n_e} P_i(a_i | c_i) \tag{2}$$

In formula (2), C it is a collection of clustering centers in educational text information, n_e it represents the amount of educational text information, $P(c_i)$ and $P_i(a_i|c_i)$ it indicates that there are cluster centers c_i and educational text information attributes a_i belongs to the cluster center c_i the probability value of. If the calculation result of formula (2) is higher than the threshold value J_0, it is considered that the current educational text information and the cluster center belong to the same category, and clustering processing can be directly performed, otherwise the text information needs to be measured again until all enterprise educational text information has been clustered.

2.2.4 Enterprise Education Text Information Smoothing

The pseudo document technology is used to estimate the conversion probability between the words in the document and the words in the query, and this information is integrated into the language model method. The formula for smoothing the document model is as follows:

$$P(t_i|\kappa) = \sum P\left(t_i\middle|t_j\right)P\left(t_j|D\right) \tag{3}$$

In formula (3), $P\left(t_i|t_j\right)$ it is a term in enterprise education information t_i reach t_j we can get the conversion probability of, D it is a collection of enterprise education information, κ it represents the smoothing coefficient of enterprise education information. Insert the collected enterprise education text information into formula (3) to complete information smoothing.

2.2.5 Education Image Information Enhancement

The enhancement of educational image information can be divided into filtering and denoising, grayscale transformation and other steps. The filtering and denoising operation is carried out by means of the combination of mean filtering and bilateral filtering. The specific processing process is as follows:

$$\begin{cases} g_m(x,y) = \dfrac{1}{n_{\text{pixel}}} \sum f_{xy}7(x,y) \\ g_b(x,y) = \dfrac{\sum\limits_{x=1}^{n_{\text{pixel}}} \sum\limits_{y=1}^{n_{\text{pixel}}} f_{xy}(x,y) \cdot w(x,y)}{\sum\limits_{x=y=1}^{n_{\text{pixel}}} w(x,y)} \end{cases} \tag{4}$$

In formula (4), $f_{xy}(x,y)$ it is the enterprise education image information initially collected, n_{pixel} is the number of pixels in the image information, $w(x,y)$ is the weight value in the image information, and the final result $g_m(x,y)$ and $g_b(x,y)$ that is, the average filtering and bilateral filtering results of the initial enterprise education image information. In addition, the grayscale transformation process of enterprise education image information is as follows:

$$g_{\text{vary}}(x,y) = a + \frac{\ln[f_{xy}(x,y) + 1]}{b \cdot \ln c} \tag{5}$$

In formula (5), a, b and c are parameters introduced to adjust the position and shape of the image gray curve. On this basis, histogram is used to balance the processed enterprise education image information. This approach is commonly employed to heighten the overall contrast of an image, particularly in situations where the contrast of the informative image data is very similar. By employing this method, luminosity is more evenly distributed across the histogram. It is helpful in increasing local contrast without compromising on the global contrast. The technique of histogram equalization is employed to efficiently broaden the commonly employed luminosity levels [10]. This method is very useful for images whose background and foreground are too bright or too dark, in particular, it can better display the bone structure in the X-ray image and better details in the overexposed or underexposed photos. One of the main advantages of histogram equalization is that it is a fairly intuitive technology and reversible operation. In the event that the equalization algorithm is familiar, the initial frequency distribution chart can be regenerated, and the level of computation required is not substantial. Histogram equalization is a method to obtain a new image with uniform distribution of gray histogram from the original image through some transformation.

2.3 Extracting Educational Information Features Using Machine Learning Technology

The machine learning method of support vector machine is utilized for feature extraction of educational data in the business sector. By mapping the dataset to a high-dimensional, and even infinite-dimensional feature space, the support vector machine technology is able to accomplish this. Usually, this high-dimensional feature space is a Hilbert space. When dealing with complex problems, it usually simplifies the problem and reduces the complexity of computing by reducing dimensions. Following this transformation, the originally non-separable dataset becomes separable in a space with higher dimensions. A hyperplane to optimally separate the dataset with maximum distance is then set up in this new space. This concept is akin to using a nonlinear plane to separate the original data. A visual representation of the core principle of support vector machine is illustrated in Fig. 4.

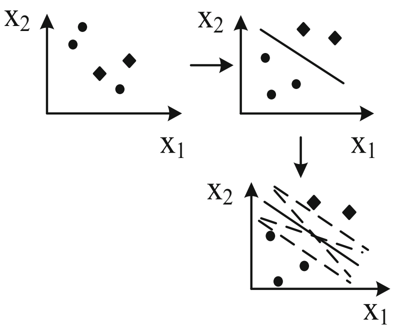

Fig. 4. Basic schematic diagram of support vector machine

As can be seen from Fig. 4, multiple hyperplanes can separate two classes, but only one of them is optimal to maximize the separation interval, that is, the continuous line indicates the section with the most significant distance from the nearest vector separating the two classes. In order to achieve the above purpose, construct support vector machines according to different practical problems, then two key problems must be solved. The first step is to locate a non-linear transformation that can map the input space data set onto the high-dimensional feature space, which enables the data set that cannot be linearly separated in the input space to become linearly separable in the feature space. Once it has been transformed, the next step is to focus on the high-dimensional feature space, the optimal separation hyperplane [11] is obtained according to the support vector machine. For the first problem, we can use the kernel function method to solve it. By selecting a kernel function that meets certain conditions, it is possible to transform the data set that is not linearly divisible in the input area to a high-dimensional feature space that is linearly separable. The all-inclusive equation for the inner product in Hilbert space is:

$$(r_i, R) = H(x, X_i) \tag{6}$$

In formula (6), the image of the vector mapping in the feature space is represented by the letter (r_i, R). For Mercer's condition, an arbitrary symmetric function called $H(x, X_i)$ is used. The choice of kernel function and its parameters determine the complexity and classification of the classifier. In the high-dimensional feature space, a constrained quadratic programming problem is typically solved to find the optimal separation hyperplane using support vector machines. Unlike empirical risk, the objective function of this programming problem is unique to support vector machines. To extract the features from enterprise education information, the samples are input into the support vector machine program and the output provides the feature extraction result. With the support of support vector machine technology, the extraction features of enterprise education text information include: word frequency, word item, weight, etc. The extraction results of word frequency are as follows:

$$\lambda_w = \frac{N(i)}{N_e} \tag{7}$$

In formula (7), $N(i)$ for the occurrence of the i the number of text in paragraphs, N_e it is the total amount of all enterprise education text information. The word frequency feature measures the huge text set by calculating the linear approximate complexity in the training text. The complexity is relatively low, and it is suitable for any text corpus [12]. Its biggest advantage is its fast speed, and the time complexity is linear with the number of texts, so it is suitable for feature selection of very large text datasets. The extraction results of term weight features are as follows:

$$\lambda_\omega = f_{ij} \times f_i \tag{8}$$

In formula (8), f_{ij} and f_i they are item frequency and reverse document frequency. The term "item frequency" denotes the frequency at which a word item manifests in educational materials related to entrepreneurship. The formula used for its computation is as follows:

$$f_i = \lg\left(\frac{N_e}{d_f}\right) \tag{9}$$

In formula (9), d_f is the document frequency.Substitute the calculation result of formula (9) into formula (8) to get the extraction result of term weight feature. In the same way, the extraction results of other feature vectors of enterprise education text information and all features of enterprise education image information can be obtained. Finally, the features are weighted and fused to obtain the extraction results of comprehensive features of enterprise education information.

2.4 Construction of Enterprise Education Information Retrieval Engine

The designed enterprise education information retrieval model uses the retrieval engine as the execution environment, and the structure of the enterprise education information retrieval engine is shown in Fig. 5.

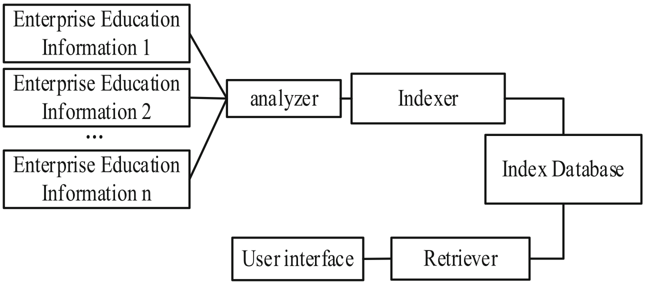

Fig. 5. Structure of enterprise education information retrieval engine

The enterprise education information retrieval engine includes five basic parts: Robot, analyzer, indexer, searcher and user interface. Robot and analyzer use the breadth first strategy to traverse the enterprise education information, and maintain a hyperlink queue in the model, which contains some initial URLs. Starting from these URLs, Robot requests to download the corresponding resource web pages in turn using standard protocols, and extracts new hyperlinks from them and adds them to the queue. The aforementioned procedure will be iterated until the queue has been depleted. The analyzer analyzes the documents downloaded by Robot for indexing. The indexer represents the document as a convenient way to retrieve and stores it in the index database. For example, in the vector spatial index model, each document d is represented as a normalization vector:

$$v(d) = q_i \cdot \varpi_i \tag{10}$$

In formula (10), q_i is an entry, ϖ_i is the weight value of the term in document d. The retriever finds the documents related to the user's query request from the index. First, a method similar to analyzing and indexing documents is used to process user query requests, and then a method is used to calculate the correlation between user queries and each document in the index database. Finally, all documents whose correlation is greater than the threshold value are arranged in descending order of photographic correlation and returned to the user. Of course, the relevance judgment of search engines does not necessarily coincide with the needs of users [13]. It is necessary to provide users with a visual query input and result output interface. In the query input interface, users specify terms to be searched and various simple/advanced search conditions according to the query syntax of the search engine. In the output interface, the search results of the exploration engine are displayed as a linear document list, which contains the title, summary, hyperlink and other information of the document. Users need to browse the search results one by one to find the required documents.

2.5 Implementation of Enterprise Education Information Retrieval

For the text information and image information in enterprise education information, the retrieval results are obtained in the information set by means of feature matching, the information retrieval results are sorted according to the feature matching results, and the complete enterprise education information retrieval results, that is, the final output results of the model, are obtained through search expansion.

2.5.1 Enterprise Education Information Feature Matching

Assume that the comprehensive feature extraction result of enterprise education information output by machine learning technology is τ_{con}, input the search keywords into the model, and obtain the feature vector corresponding to the keywords in the same way, then the feature matching results of enterprise education information are as follows:

$$s = \frac{\tau_{con}(k) \cdot \tau_k}{\|\tau_{con}(k)\| \cdot \|\tau_k\|} \tag{11}$$

In formula (11), $\tau_{con}(k)$ for k feature extraction results of enterprise education information, τ_k it is the feature vector of the input retrieval keywords. When the calculation result from the final calculation formula (11) is higher than the threshold value J_0, Description k the information is one of the search results of enterprise education information, otherwise the search result will be deleted. According to the above method, the retrieval results of enterprise education image information can also be obtained.

2.5.2 Ranking of Enterprise Education Information Retrieval Results

With the support of the enterprise education information retrieval engine, the search results are parsed, and a sort index is established, which is stored in a sort file of intermediate results. The way of writing is to write the intermediate file in the order of feature matching degree from high to low. The stored content includes word ID and triple list. Triple refers to the list of document ID, word frequency and word location, and then empties the index information in memory, but retains the dictionary information to prevent duplicate word IDs. After all the intermediate results are created, they are combined to form a complete sorting file. The method of combination is to scan all the intermediate files. The original sorting file is stored in order according to the ID of the dictionary. When the same dictionary ID is encountered, it is combined to form a complete index, which is written into the sorting file, and then the information of the dictionary is written into the dictionary library file. The contents written include: the content of the word, the dictionary ID, and the starting position of the index. The index start position refers to the byte offset of the sorting index of the word in the sorting file.

2.5.3 Extension of Enterprise Education Information Retrieval

In the process of information retrieval, it often occurs that the search efficiency is too low or even the search fails because the word selected by the user does not match the feature word appearing in the document. Although the features extracted from the text of the two are quite different, they describe the same information content, so they need to be included in the information retrieval results through expansion. The extended process of enterprise education information retrieval is shown in Fig. 6.

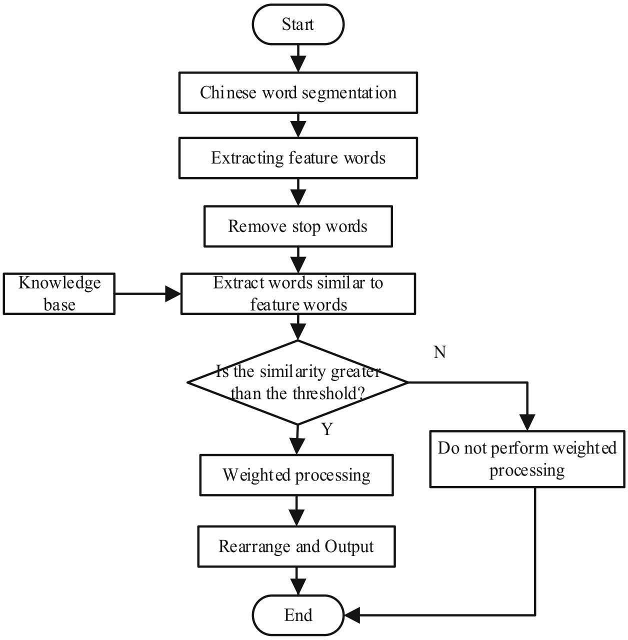

Fig. 6. Flow chart of enterprise education information retrieval expansion

In the above way, the expanded results of information retrieval are added to the output results of the enterprise education information retrieval model, and the output results of the model are reordered.

3 Model Test Experiment Analysis

To test the information retrieval performance of the enterprise education information retrieval model based on machine learning, the model test experiment is designed. This experiment uses a combination of white box testing and comparative testing. White box testing is to judge that the output results of the model are consistent with the expected results when the enterprise education information retrieval goals and results are known, while comparative testing is to compare the retrieval performance and operation performance of the design model with other models. It reflects the advantages of the design model in terms of performance.

3.1 Model Operating Environment

The design of enterprise education information retrieval model based on machine learning uses Java language, and the underlying development uses C++ language. MyEclipse, Visual C++ and MFC are used as development tools. The main environment and tools are: Windows XP, the API provided by lemur-4.8, etc. MyEclipse adopts version 9.0, which is used to develop the Eclipse plug-in collection of Java. It is an extension of the Eclipse IDE, with rich functions and wide support, including complete coding, debugging, testing and publishing functions.

3.2 Prepare a Sample of Enterprise Education Information

This experiment selects the education information released by a logistics enterprise in January 2023 as the experimental data set, and all the information in this data set is the target of enterprise education information retrieval. The selected dataset consists of four parts: induction education, technology/skill education, personnel management education, and transportation safety education. The induction education includes company profile, job description, salary structure, etc. The prepared enterprise education information sample includes two parts: text and image. The total number of documents is 16000, and the total number of images is 56000. The eigenvector dimensions of the sample can reach 45.

3.3 Generate Enterprise Education Information Retrieval Tasks

Select the search keywords of enterprise education information to generate multiple search tasks. The results of some enterprise education information search tasks are shown in Table 1.

Table 1. Enterprise Education Information Retrieval Task Table

Task No	Search keywords	Search Type	Number of information retrieval
1	Induction training	text	209
2	Induction training	image	40
3	Driving safety	text	151
4	Welfare system	text	124
5	Salary structure	text	136

In order to ensure the credibility of the experimental results, 50 groups of retrieval tasks were set up in the experiment, and the expected output results of information retrieval were determined according to the generation of educational information samples, which were used as the comparison criteria to judge the output results of the model.

3.4 Describe the Model Running and Testing Process

Store the prepared enterprise education information in the database in the experimental environment, build the database and connect it with the host computer to ensure real-time data interoperability, input the generated search keywords one by one into the running program of the enterprise education information retrieval model based on machine learning, and output the search results of enterprise education information through the steps of feature extraction, feature matching, search expansion, etc., As shown in Fig. 7.

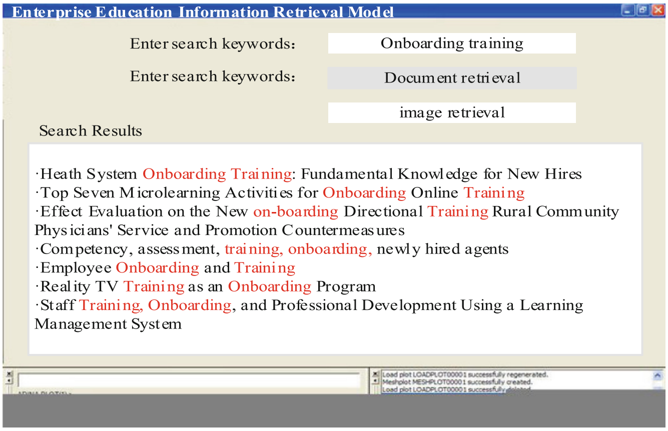

Fig. 7. Output interface of enterprise education information retrieval model

Similarly, the output results of all information retrieval can acquire tasks generated. To showcase the design model's superiority in retrieval and operation performance, the experimental comparison models are the big data analysis-based information retrieval model and the semantic understanding and AI-based information retrieval model, complete the development and operation of the comparison model according to the above way, and obtain the corresponding retrieval output results.

3.5 Setting Model Performance Test Indicators

Establishing the accuracy and recall rates as testing metrics were employed to validate the effectiveness of the model in retrieving information. The numerical results of the above indicators are as follows:

$$\begin{cases} \eta_{accurate} = \dfrac{n_{target}}{n_{out}} \times 100\% \\ \eta_{recall} = \dfrac{n_{out}}{n_{reality}} \times 100\% \end{cases} \tag{12}$$

In formula (12), parameter n_{target}, n_{out} and $n_{reality}$ they respectively represent the exact amount of information in the retrieval output, the amount of retrieval information output, and the expected amount of retrieval information. In addition, the model running delay is set as the test index of the model running performance. The test result of this index is:

$$\Delta t = \left| t_{output} - t_{input} \right| \tag{13}$$

In formula (13), t_{input} and t_{output} the input time of the search keywords and the output time of the search results are respectively indicated. Final calculation accuracy $\eta_{accurate}$ and recall rate η_{recall} the larger the value, the better the retrieval performance of the corresponding model and the running delay Δt the smaller it is, the better the running performance of the corresponding model is.

3.6 Model Test Results and Analysis

The test results reflecting the model information retrieval performance are obtained through the statistics of relevant data, as shown in Table 2.

Table 2. Model retrieval performance test data table

Task No	n_{reality}/bit	Information retrieval model based on big data analysis technology		Information Retrieval Model Based on Semantic Understanding and AI		Enterprise Education Information Retrieval Model Based on Machine Learning	
		n_{target}/bit	n_{out}/bit	n_{target}/bit	n_{out}/bit	n_{target}/bit	n_{out}/bit
1	209	200	201	201	205	208	208
2	40	28	33	33	36	39	40
3	151	140	145	142	147	150	150
4	124	116	120	120	122	122	124
5	136	122	131	131	133	134	135

Substitute the data from Table 2 into Formula 12 and calculate the average accuracy and recall of the three models, as shown in Table 3.

Table 3. Model retrieval performance test data table

Test indicators	Information retrieval model based on big data analysis technology	Information Retrieval Model Based on Semantic Understanding and AI	Enterprise Education Information Retrieval Model Based on Machine Learning
Average retrieval accuracy	94.1%	96.6%	99.0%
Average retrieval recall rate	93.6%	96.3%	99.6%

As shown in Table 3, the average retrieval accuracy of the two comparison models is 94.1% and 96.6% respectively, the average retrieval recall rate is 93.6% and 96.3%

respectively, and the average retrieval accuracy and recall rate of the enterprise education information retrieval model based on machine learning are 99.0% and 99.6% respectively, indicates that the machine learning-based model exhibits excellent retrieval capabilities.

Through the calculation of formula (13), the comparison results of the running performance test of the enterprise education information retrieval model are obtained, as shown in Fig. 8.

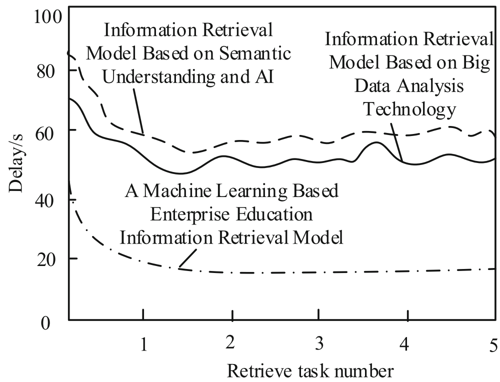

Fig. 8. Comparison curve of information retrieval model operation performance test

It can be seen intuitively from Fig. 8 that the running delay of the enterprise education information retrieval model based on machine learning is significantly lower than that of the two comparison models, this demonstrates that the model proposed in this paper possesses significant benefits in terms of operational efficiency.

4 Conclusion

This research uses machine learning technology to design an enterprise education information retrieval model. Through the model, you can view all the retrieval results of enterprise education information. Experiments show that the enterprise education information retrieval model based on machine learning improves the retrieval accuracy, and at the same time, the operation performance is improved, providing useful reference for enterprises in the decision-making of new technology and new product development. It is of great significance to maximize the use of enterprise education information. In future research, users' historical behavior and preference data can be utilized to achieve personalized enterprise education information recommendation, and targeted educational resources and learning suggestions can be provided by judging users' interests and needs.

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The Detection of English Students' Classroom Learning State in Higher Vocational Colleges Based on Improved SSD Algorithm

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Abstract. The current detection matrix of English students' classroom learning status in higher vocational colleges is mostly a one-way processing form, and the detection range is small, resulting in an increase in the mean difference of unit detection. Therefore, this paper proposes a design and verification study on the detection method of English students' classroom learning status in higher vocational colleges under the improved SSD algorithm. According to the actual detection requirements and the changes in standards, first extract the detection features of English learning status, expand the detection range by using a multi-objective approach, and design MTCNN multi-target detection matrix. Based on this, build a learning status detection model under the improved SSD algorithm, and use multi-level reduction correction to achieve status detection processing. The final test results indicate that the learning status of the selected 6 classes in the English classroom is detected, combined with an improved SSD algorithm. The final unit detection mean difference was well controlled below 1.5, and the detection accuracy for the five types of classroom behaviors remained above 90%, indicating that this learning state detection method has stronger pertinence and reliability, high detection efficiency, controllable errors, and practical application value.

Keywords: Improved SSD Algorithm · Vocational English · Students' Classroom Learning

1 Introduction

In recent years, with the increasingly fierce competition of national cultural soft power, the demand of the society for high-quality composite talents is also growing. In particular, bilingual talents, to a certain extent, can further expand social progress, change people's learning concepts, and English learning has gradually become the orientation trend of the current era [1]. In this context, English learning in higher vocational colleges has become more important, which puts forward more and higher requirements for English learning behavior in higher vocational colleges in the new era. Although students in higher vocational colleges at this stage are well adapted to life, under the information

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technology teaching environment, the use of multimedia, intelligence and other modern educational technologies has promoted the dynamic and vivid English teaching content, which has great appeal to students. Students' performance in the classroom is also relatively good, and a certain teaching effect has been achieved at the initial stage [2].

However, due to the long-term influence of exam oriented education, many students not only failed to explore the rules of English learning in time, but also failed to pay attention to scientific learning methods. Their status in the classroom also became very poor, and there were problems such as wandering off and wandering off. In the process of English learning, some students' English learning efficiency was low, and their learning ability improved slowly. To a certain extent, this will lead to students' lack of concentration in learning, and even lead to emotional loss, lack of learning motivation and other situations, which will affect further learning. Not only that, the current English learning structure in higher vocational colleges is relatively single, with weak pertinence and great pressure on the curriculum, which leads to the poor state of students in the classroom [3]. Combined with the influence of mobile phones, microblogs, WeChat and other applications, students are encouraged to hinder more in the process of learning English, which has a great impact on their life and learning [4].

This paper proposes the design and research of the detection method of the classroom learning state of vocational English students under the improved SSD algorithm. The so-called improved SSD algorithm, whose full name is Single Shot MultiBox Detector, Single shot, mainly refers to a one stage method. Through the improved SSD algorithm, feature maps of different scales are extracted for detection. Large scale feature maps can be used for detection, to obtain the final calculation result [5]. Integrating the improved SSD algorithm with the detection of English students' classroom learning status in higher vocational colleges can, to a certain extent, further expand the scope of actual status detection, improve the accuracy of actual learning status detection, gradually form a more flexible and changeable detection structure, and enhance the processing and analysis effect [6].

In addition, English learning is a long process, so in the process of classroom learning, students need not only to maintain a good learning attitude, a good learning environment, solid basic knowledge, but also to have appropriate English learning strategies, a large amount of learning time. The research spirit of never giving up when encountering difficulties and obtaining profound and advanced professional knowledge through independent and efficient learning, constantly improve their practical ability, cooperation ability, innovation ability and other comprehensive abilities, and realize their self-development and transcendence [7]. In addition, the detection of English phased learning status of vocational college students is also an important part of the phased learning level test. It is directly related to the rationality of students' English learning time allocation, the intensity of learning motivation, the profundity of knowledge understanding and the effectiveness of learning methods at the current stage, and provides reference and theoretical reference for the improvement of English teaching effect in subsequent vocational colleges [8]. By applying the improved SSD algorithm to the detection of classroom learning status for vocational English students, utilizing the advantages of multi-scale feature maps, students' learning status can be more comprehensively captured, and the accuracy and stability of detection can be improved through the improved algorithm. This method has practical application value and can provide effective support and guidance for English education in vocational colleges.

The organizational structure of this article is:

(1) Extract features for English learning state detection: Based on actual needs, extract features for English learning state detection, such as posture, facial expressions, etc. These features will be used for subsequent construction of learning state detection models.
(2) Using a multi-objective approach to expand the detection range: In order to improve the accuracy and coverage of detection, an MTCNN multi-objective detection matrix was designed. This matrix can detect multiple targets simultaneously and can handle targets of different scales and postures.
(3) Construct a learning state detection model under the improved SSD algorithm: Based on the MTCNN multi-objective detection matrix, further construct a learning state detection model under the improved SSD algorithm. This model utilizes a multi-stage reduction correction method to achieve detection and processing of learning states.
(4) Verification and testing: Six classes of English classrooms were selected as test subjects in the experiment, and an improved SSD algorithm was used for learning state detection.

2 Improvement of Classroom Learning State of English Students in Higher Vocational Colleges SSD Measurement and Detection Method

2.1 Extraction of English Learning State Detection Features

Before designing the SSD measurement and detection method for improving the classroom learning status of vocational English students, it is necessary to extract the detection characteristics of English learning status [9] in combination with the actual English teaching needs. In general, one-way face detection is prone to false detection, and in complex background environment, face recognition accuracy is low and applicability is poor [10]. Therefore, this time, we comprehensively improved the SSD algorithm and designed a multi-level, multi-objective structure to detect English students' classroom learning status. This kind of design is to establish a simulated human brain detection learning program and analyze the problem of neural network structure. First, an adaptive fitting nonlinear operation learning state detection model can be designed, which is composed of a large number of neuron nodes connected with each other. Its connection structure needs to be connected and lapped with a set number of recognition detection targets to form a more controllable detection structure, while facilitating the directional capture of learning state features in the later stage. The specific principle structure is shown in Fig. 1 below:

According to Fig. 1, complete the design of the principle of English learning state detection. Its main components are: input detection layer, hidden detection layer and output detection layer. Each part needs to set corresponding detection stage targets to form a multi-level detection form. Then, based on this, the improved SSD algorithm is

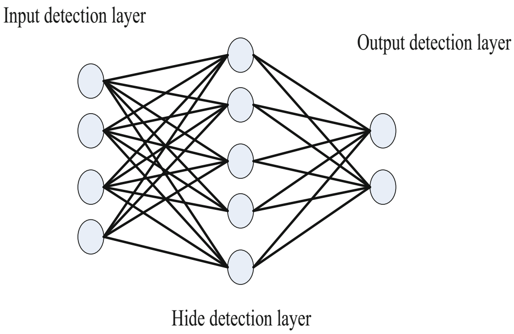

Fig. 1. Schematic diagram of English learning state detection principle

used to calculate the unit detection standard, and the SeetaFace face recognition engine is constructed to achieve the coverage detection of classroom learning state. SeetaFace face recognition engine includes three core modules in total, face detection module, face alignment module and face feature extraction and comparison module. A variety of cascaded structures combining traditional artificial features and MLP (Multilayer Perception) are adopted, and the face alignment module is integrated to construct the face feature point positioning form of the network under the deep self encoder. At the same time, the data and information collected by the node are set to carry out one-way control on the English classroom student learning state recognition module. Form a specific state based detection structure, as shown in Fig. 2 below:

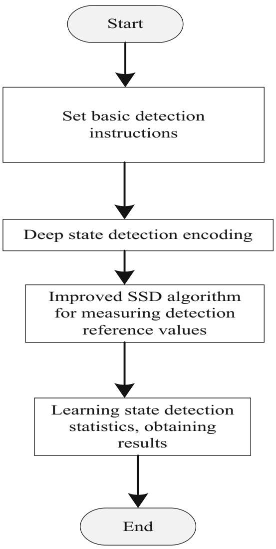

Fig. 2. Diagram of detection framework of learning status recognition module

According to Fig. 2, complete the design and research of the detection framework of the learning state recognition module. Then, according to the data and information of recognition induction, specific detection characteristics are analyzed. Student learning state detection is the first step of directional feature recognition. Only when the face is correctly detected and the face is obtained according to its location information, can the multi-dimensional summary calibration of basic detection features be carried out. First, the sliding window method is used for fixed detection. When the students' faces appear within the detection area, the detection sliding window is set to be 30 × 30 in size and 1280 × 1024 in size. A new type of face detection form with funnel cascade structure is used with improved SSD algorithm. The face detection model architecture is designed from multiple angles and poses, and the detection concept from rough to fine is introduced, specify the specific detection feature perception order to achieve dual assurance.

In addition, the learning state detection classifiers at all levels and the features they use generally become more and more complex. At this time, the face window can be retained and the non-human face candidate window that is increasingly difficult to distinguish from the face can be excluded. In combination with the features such as raising hands, sideways, sleeping, and headland, the secondary screening can be carried out for faces with different poses, such as the left face, the front face. The right face is processed and classified in the next stage, roughly detecting the learning state and specific situation of students at this time, completing further recognition processing of features, and providing reference and theoretical reference for subsequent English learning state detection.

2.2 Design MTCNN Multi-target Detection Matrix

After completing the extraction of English learning state detection features, next, combined with the improved SSD algorithm, MTCNN multi-target detection matrix is designed. Generally, in the learning process of English class, because the classroom environment is more active, many students will become more casual and do many things that have nothing to do with classroom learning, so that the expression of expressions will become more abundant, the behavior will become more diversified, and there will be actions such as lowering the head, leaning sideways, sleeping, etc. These expressions and behaviors that have nothing to do with the classroom will also be easier to detect. Moreover, the change of students' learning state in English classroom can reflect the quality and effect of teachers' teaching.

When the teacher's teaching content is boring, the students will appear listless expression, and their behavior will also appear bowed, sideways and so on; When the teacher's teaching content is more attractive, students will show serious, active and raise their hands to answer questions. Therefore, through the detection of students' English classroom learning status, combined with the improved SDD algorithm, MTCNN multi-target detection matrix is designed. First of all, the unit MTCNN learning state detection program is designed as a special target detection task, position and displacement situation. In face detection, the improved SSD algorithm is widely used to form a basic MTCNN model, and three progressive cascade directional detection and recognition networks are formed by integrating the MTCNN main structure, which can be called P-Net, R-Net, 0-Net.P-Net is to quickly generate rough candidate status detection frame, R-Net filters to obtain high-precision candidate status detection frame, and 0-Net finally generates boundary selection status detection frame and key point coordinates. The specific structure is shown in Fig. 3 below:

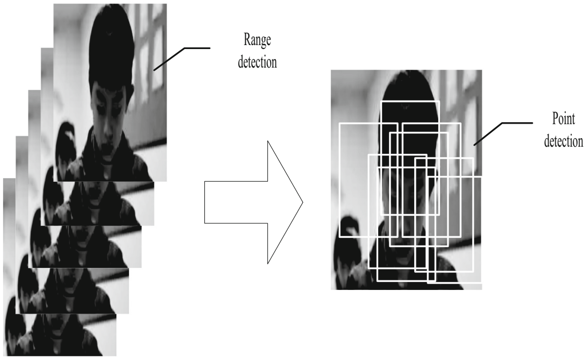

Fig. 3. MTCNN multi-target detection matrix detection structure

According to Fig. 3, complete the design and analysis of the MTCNN multi-target detection matrix detection structure. For the regional association application network of the face area, input the feature image through three convolution layers, use the initial detection matrix to judge the changes of the students' faces in this area, and use the border regression to make a simple prediction of the face area. The output of multiple face regions where faces may exist will be processed subsequently. This part of the matrix structure is overlapped with the initial network program to form a detection window for quickly generating face candidate states. Next, a more complex access state detection network is designed to optimize the selection of students' facial regions obtained from P-Net, so as to achieve high-precision filtering and optimal detection of facial regions.

On this basis, MTCNN multi-target detection structure is designed. Select the face area with a certain degree of confidence. Within the limit range of R-Net matrix, the input will be refined and selected to filter out the wrong input. Finally, the more reliable face area will be output and passed to 0-Net for use and processing. Compared with the features of P-Net's $1 \times 1 \times 32$ using full convolution output, R-Net uses a 128 dimensional full connection layer after the last convolution layer, which retains more directional detection image features of English students' classroom learning status, and its accuracy performance is also better than P-Net. Output Network (O-Net): 0-Net will use more status detection tag information to identify the moving area of students' faces in class, and finally input the location coordinates of facial feature points. A larger full detection connection layer is designed to retain more classroom image detection features. Students' faces are identified and their regional borders are regressed respectively. Finally, the upper left and lower right coordinates of the face area and the five feature point location coordinates of the face area are output, realizing the final design and application adjustment of MTCNN multi-target detection matrix.

2.3 Build a Learning State Detection Model Under the Improved SSD Algorithm

After completing the design of MTCNN multi-target detection matrix, next, combined with the improved SSD algorithm, the design of the detection model of students' learning state in vocational English classroom is constructed. After in-depth research and learning analysis, according to the students' action in the middle, we carry out detection, recognition and orientation classification, associate the classic AlexNet network structure, design a lightweight multi-dimensional detection structure, capture the collected state images, and set the corresponding detection values, as shown in Table 1 below:

Table 1. Setting table of improved SSD algorithm status detection model

Model control indicators	Directional controllable standard	Measured controllable standard
Distinguished size	48 × 36	48 × 48
Maximum pooling ratio	1.35	1.47
Detection range conversion difference	0.3	0.1
Characteristic coefficient	11.03	12.05
Detection resolution/%	89.66	92.16

According to Table 1, complete the setting and adjustment of the state detection model of the improved SSD algorithm. Next, use the improved SSD algorithm to synthesize the designed detection matrix and build a multi-level, multi-target detection program in the initial model. During the preparation of the training data in the early stage, the orientation size of the unified training detection is 48 × 48, and the size of the single channel image input feature map of pixels is 48 × 48 × 2. The first level state detection structure in the model is the convolution layer of the 1 × 1 × 32 convolution kernel, and the detection channel is expanded to 32 channels, which deepens the depth of the student state feature map, but does not change its original size. The second level of state structure is a combination of three operations, namely, 3 × 3 × 64 convolution kernel convolution, 5 × 5 × 64 convolution kernel convolution, and 2 × 2 maximum pooling operation. This module is the convolution guidance target and guidance direction in the model, which is used to extract the specific feature laws of students' state change images. The third level has the same state structure as the second level. The compressed size is used to extract the state detection features in the model. In order to prevent over fitting, the SSD algorithm is comprehensively improved, and the drop out method is used to calculate the detection feature vector at this time, as shown in Formula 1 below:

$$Q = \xi + (1 - \vartheta)^2 \times D \tag{1}$$

In Formula 1: Q Represents the detection feature vector, ξ Represents the number of training tests, ϑ Is the estimated coverage, D Represents the conversion ratio. Combined with the above measurement, the detection feature vector is calculated. Combined with the state detection network structure of students in the whole English learning classroom set in the model, the detection and calibration indicator standards are modified and set, as shown in Table 2 below:

Table 2. Standard Setting Table of Status Detection Network

Indicator Name	input	Conv-1	Conv-2
Nuclear size	64	55	50
fill	1	5	6
Detection step size	1	1	2
Discard ratio	3.5	2.1	2.4
Feature Size	(48, 20)	(48, 20)	(48, 25)
Directional conversion ratio	0.51	0.68	0.69

Complete the setting of the status detection network standard according to Table 2. Next, the improved SSD algorithm is integrated to train and evaluate the student learning state detection model. The prepared 2000 images of students' English classroom learning status were divided into training set, test set and verification set. In order to ensure the sample balance of each category, the method of balanced division was also adopted, with the division ratio of 7:2:1. Then we completed the network training script code, set the training batch of the model to 250, set the batch size to 42, and use the Adam method as the gradient descent method. Combined with the improved SSD algorithm, we calculated the directional detection resolution, which is best controlled between 0.001 and 0.005. After multiple training evaluations and comparison of the model training effect, the final convergence of the trained model is good, indicating that the model has high applicability and adaptability. The training set still maintains uniform detection processing, and the final model can converge well. The TOP1 accuracy rate on the verification set reaches the preset standard, which has practical application value. The basic test results of students' learning status can be obtained.

2.4 Multi Order Reduction Correction to Realize State Detection Processing

After completing the construction of the learning state detection model under the improved SSD algorithm, next, combined with the improved SSD algorithm, a multi-step reduction correction is used to achieve state detection processing. Normally, during the detection of learning state, the current state will be detected and recognized. However, when encountering unrecognized detection behavior, errors often occur. Therefore, it is necessary to combine the form of multi-step reduction correction to expand the actual detection range, strengthen the detection effect and improve the final detection accuracy. On the premise that the training set and the test set are consistent, the integration of AlexNet model, VGG16 model and ResNet50 model is realized in combination with the improved SSD algorithm. The directional training of state detection is carried out respectively, the multi-level reduction correction degree is set, and the built-in program control indicators are set, as shown in Table 3 below:

Table 3. Setting table of detection indicators of multi-stage reduction correction program

name	Model detection level	AUC value	Directional detection conversion ratio
AlexNet	3	0.335	1.13
VGG16	4	0.324	1.25
ResNet50	4	0.152	1.16
This design model	5	0.244	1.25

According to Table 3, set and adjust the detection indicators of the multi-step reduction correction program to form a complete detection structure. However, in this part, it should be noted that since the structure of each model is not identical in the process of detecting the students' state, there is a gap between the design of detection accuracy and the best model. The advantages are simple network structure, less total parameters, and the shortest reasoning time to improve the final state detection accuracy.

In addition, combined with the improved SSD algorithm, the multi-step reduction correction form is used to identify the students' classroom state at multiple levels and squares. In the specific measurement process, it is found that the student face detection model may detect multiple faces. The main reason is that multiple students may enter the camera in the picture, which leads to the problem of multiple detection. Because this problem may lead to multiple results in the subsequent expression classification, which will affect the judgment of the student's learning state, in the process of designing the correction structure, in order to solve this problem, the detection results of the student's face detection model in the first step are screened. Since the main student character objects are in the classroom, the distance from the detection device terminal is relatively advanced. Other students who occasionally appear in the picture will be behind the students in most cases, so in the acquired image and video frame data, the form of multi-step reduction correction is used to separate the students' facial interference targets. When the students' facial detection model detects multiple face targets. By default, only the largest target in the student face detection box is selected as the target face to be cut for recognition of the next learning state, so as to solve the problem of multiple face detection. Also in the process of the experiment, sometimes there may be a small number of students' face false detection, such as the detection of objects similar to face patterns in the screen as target faces, and after cutting, a feature classification is also given in the back state recognition network. Through the analysis of the specific reasons for this situation, the solution of two additional screening points in the whole model was obtained, and the basic multi-step reduction correction processing was completed.

Then, on this basis, the designed model is used to conduct the next stage of student status detection. During the detection process, the confidence value is kept between 0.25 and 0.35. Through the method of increasing the threshold, combined with the improved SSD algorithm and the multi-step reduction correction structure, the threshold value is estimated to be 0.5. When the confidence of the status detection target is less than 0.5, the target detection result will be discarded. The false detection rate of the status detection at this time is calculated through the model, and the largest one is taken as the result of the status detection by default to output, so as to ensure the accuracy and reliability of the probability detection value. In addition, when the state of English classroom learning is relatively loose, the coverage and detection range of multi-level reduction correction can be adjusted, and the corresponding detection work can be carried out in three stages, as shown in Table 4 below:

Table 4. Multi order reduction correction state detection control table

name	Phase 1	Phase 2	Phase 3
Detection unit value	16.35	17.44	19.51
Attitude movement distance/m	3.5	4.6	5.2
Unfolding ratio	2.01	2.11	2.57
Identification frequency/time	12	18	28
Correction error	0.1	0.2	0.2
Directional conversion value	36.34	38.11	41.23
Reduction times/time	3	3	6

According to Table 4, the design and verification research on the control index of the state detection of the multi-step reduction correction is completed. In the form of multi-step reduction correction, the state detection attitude control direction is set, and the multi attitude recognition structure is used for analysis and judgment. A little gap will be a new detection attitude action standard, and the corresponding learning state detection effect will be gradually strengthened to complete the set detection targets and tasks.

3 Method Test

This time is mainly to analyze and verify the practical application effect of the improved SSD algorithm based classroom learning state detection method for vocational English students. Considering the authenticity and reliability of the final test results, the analysis is carried out by comparison, and the English classroom teaching in G vocational colleges is selected as the main target of the test. Use the teaching platform to collect basic data and information, summarize and integrate them for future use. According to the actual testing requirements and changes in standards, the final test results are compared and studied. Next, the initial test environment is built.

3.1 Test Preparation

Combined with the improved SSD algorithm, this paper builds and correlates the detection environment for students' learning status in English classroom teaching in G vocational colleges. First, the specific data information sources are calibrated, and the original data is collected, including the daily English teaching status detection data and information of six classes. The test results and records of the last two times are retrieved for future use. Next, make basic adjustments to the identification and detection devices and equipment. The operating system is Ubuntu 16.04, the processor is InterBCore, the main frequency of the computer is 2.5GHz, the memory is 8G, and the graphics card is GTX1070. The OpenPose detection program is built under the Ubuntu environment. CUDA 8.0 is installed and configured under Ubuntu 16.04. In order to promote the authenticity and reliability of the learning state detection results, the caffe execution framework is built. Selectively enter “make nproc” in the command line to complete the basic installation and build an intelligent detection environment.

Then, based on this, we set the program of image and video capture for English learning state detection, restore the real classroom learning environment, set the shooting device or associated equipment, set the resolution to 1280 × 1024, control the duration of each detection video to 5 min, and take 15 videos in each cycle.2000 images were captured from the captured video, 1600 of which were used for mathematical modeling and analysis of three classroom states: head bowed, sleeping and hands raised, and the remaining 400 were used for testing. See Fig. 4 below for details:

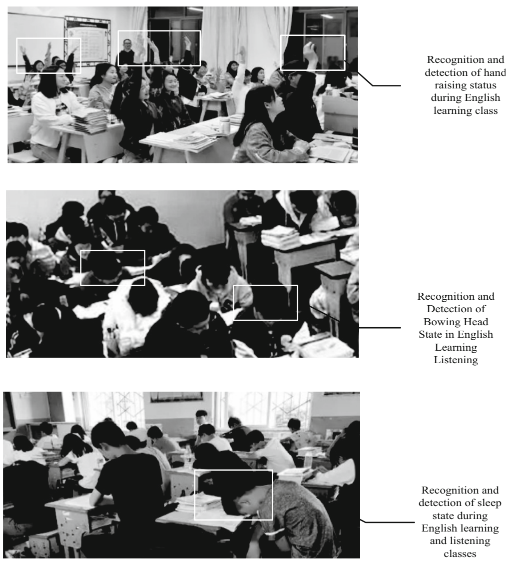

Fig. 4. Standard setting diagram of English classroom learning state detection

According to Fig. 4, complete the setting of testing standards for English classroom learning status. At the same time, raise your hand and head as the basic signs of the state of listening and learning, and side, sleeping, and head lowering are signs of the state of not listening. Then, based on the above analysis, the specific detection time needs to be set. The face is detected in front of the eyes, which means that the student is listening to the class. If the face cannot be detected within a certain period of time, the student is not listening to the class. The human body can’t keep a posture for a long time, and the position of the face will inevitably move in the process of listening to the class. Therefore, on the basis of recording the position of each student's face, the face can be detected within a certain range, which proves that the student is listening to the class. The SSD algorithm can be improved by combining the specific detection duration set first with the improved SSD algorithm, as shown in Formula 2 below:

$$G = (1 - k)^2 + \eta \Im \tag{2}$$

Equation 2: G indicates the test duration, k indicates the controllable detection range, η indicates the directional detection distance, $\Im$ represents the conversion ratio.According to the above settings, the detection duration is calculated and set as the standard detection time standard in the detection model to control the unit detection time. Then, it is also necessary to set the detection program and execution target. The specific implementation method is as follows: record the position and size of the face frames detected during the class roll call, and corresponding to each student's student number, expand these face frames outward, with the center point unchanged, and the length and width of the face frames are twice the original size, as shown in Fig. 5 below:

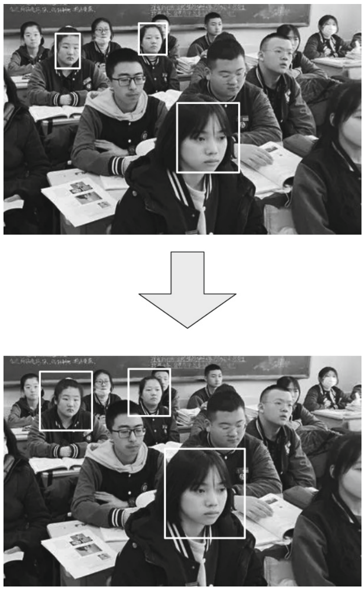

Fig. 5. Extension diagram of learning status detection frame

According to Fig. 5, realize the expansion of the learning state detection box, and use the expanded detection box to collect students' real-time learning characteristics to form detection characteristics. However, it should be noted that English classes are more practical. From the perspective of students' action range, students only move briefly due to reading or taking notes, raising their hands to answer questions, oral communication, etc., so the situation that no face is detected in the previous frame but a face is detected in this frame is recorded as listening, and the listening time is increased by 8 s. Set the total duration of detection video, and take a detection frame every 5 s. After completing the construction of the basic test environment, the next step is to conduct specific test analysis in combination with the improved SSD algorithm.

3.2 Test Process and Result Analysis

According to the actual measurement requirements and standards, combined with the improved SSD algorithm, this paper tests and analyzes the learning status of students in English classes in G vocational colleges. In order to carry out a more detailed analysis of the listening state, this time we will conduct multi-level and multi-objective detection and analysis of the English classroom state. In the actual English classroom videos, the most common states are bowing, sleeping and raising hands. These states are the most authentic and direct reflection of students on the English classroom. They must also reflect the test class and students' English classroom learning state to some extent, and can provide reference for teachers' teaching design. This time, according to the specific situation of the testing class, four detection cycles are set, each cycle is 30 min. During the cycle, the learning image needs to be collected every ten minutes as the detection basis and reference information. Set the basic detection node, and set specific implementation indicators and parameters, as shown in Table 5 below:

Table 5. Basic English Classroom Test Indicators and Parameters

Basic English Classroom Testing Indicators	Directional parameter standards	Measured parameter standards
Unit detection time/s	0.25	0.11
Directional detection difference	0.31	0.21
conversion rate	1.35	2.11
Identification frequency/time	6	9
Input image frames	+54.22	+59.34
Status determination frequency/time	12	18
Forward detection distance/m	12.5	16.5

According to Table 5, complete the setting and adjustment of the basic detection indicators and parameters of the English classroom. Next, combine the actual teaching situation of the English classroom and improve the SSD algorithm, through OpenPose body key point detection, detect the position of the key points of the human body, and use statistical analysis methods to judge the three classroom states of students in the English classroom: head bowed, sleeping and hands raised, so as to realize the function of classroom state analysis in the video. First of all, we can combine the improved SSD algorithm to build a directional detection calculation, and calculate the eigenvalues of the three states according to the data and information collected by the nodes, as shown in Formula 3 below:

$$L = \sum_{y=1} \eta y + (1 - b \times \Re)^2 + \eta \tag{3}$$

In Formula 3: L represents the characteristic values of three states, η indicates the coverage of the detection range, y indicates the number of tests, b indicates the time consumption of orientation, $\Re$ indicates the controllable detection distance. According to the above measurement, the calculation of the characteristic values of the three states is realized. The corresponding differentiation program of feature recognition detection is constructed to form a multi-level, multi-target detection standard structure. Next, check the learning status of students in the class in English class, and use the improved SSD algorithm to finally calculate the mean difference of unit detection, as shown in Formula 4 below:

$$K = \delta^2 - \sum_{r=1} \varphi r + \aleph(\delta + 1) \tag{4}$$

In Formula 4: K indicates the mean difference of unit detection, δ indicates the difference of directional conversion, φ represents the unit detection area, r indicates the number of tests, $\aleph$ represents an identifiable reference value.According to the above determination, complete the analysis of the test results, as shown in Table 6 below:

Table 6. Comparison and Analysis of Test Results

Measure Class	Cycle 1 unit detection mean difference	Cycle 2 unit detection mean difference	Cycle 3 unit detection mean difference	Cycle 4unit detection mean difference,
class 1	1.02	1.26	1.28	1.29
class 2	1.13	1.31	1.35	1.19
class 3	1.14	1.24	1.16	1.05
class 4	1.01	1.16	1.27	1.37
class 5	1.06	1.25	1.21	1.27
class 6	1.13	1.03	1.16	1.46

According to Table 6, complete the analysis of the test results: check the English classroom learning status of the selected six classes, and combine with the improved SSD algorithm. The final mean difference of unit detection is well controlled below 1.5, indicating that this learning state detection method has stronger pertinence and reliability, high detection efficiency, controllable error, and practical application value.

In order to further verify the effectiveness of the proposed learning state detection method under the improved SSD algorithm, different test indicators are selected as the criteria to measure students' learning state. Specifically, five types of classroom behaviors, namely listening, writing, answering, sleeping, and raising hands, were selected as test indicators for students in English classrooms.

In order to compare the detection accuracy of different methods, reference [3] and reference [4] methods in the introduction were selected as the comparison methods. Use different methods to detect these five types of classroom behaviors and record their detection accuracy. The test results are shown in Table 7.

Table 7. Test Results of Different Methods

Algorithm	Detection accuracy/%				
	listen	write	answer	sleep	hand
Proposed algorithm	95	92	95	98	93
Reference [3] Method	82	80	78	85	82
Reference [4] Method	73	84	84	82	84

According to the experimental results in Table 7, it can be seen that the proposed improved SSD algorithm performs well in detecting five classroom behaviors: listening, writing, answering, sleeping, and raising hands. The overall detection accuracy remains above 90%, with high accuracy. In contrast, the methods in reference [3] and [4] in the introduction have relatively low accuracy in detecting these classroom behaviors. By comparing the experimental results, the effectiveness and practical application value of the proposed improved SSD algorithm for learning state detection can be further verified and evaluated.

4 Conclusion

To sum up, the above is the design and verification research on the detection method of classroom learning state of vocational English students under the improved SSD algorithm. Compared with the initial form of learning state detection, this fusion improved SSD algorithm, the designed structure of classroom learning state detection for English students in higher vocational colleges is relatively more flexible, changeable, and more targeted and transformative. After a certain understanding and analysis of the learning state of students in higher vocational colleges, a mathematical detection model of improved SSD algorithm with multiple scores and objectives was established. The students' English classroom learning status is detected in stages. Through intuitive data and information, it helps students to have a clear understanding of their recent English learning status, encourages them to consciously and actively make up for relatively weak links, which has certain guiding significance for students. At the same time, it adopts the structure of multi-directional detection, breaks through the traditional detection method of theoretical English learning status, and combines the improved SSD algorithm to calculate the detection similarity between test samples and training samples, so as to obtain the optimal detection solution, quickly understand students' current English classroom learning status in real time, and make scientific and reasonable teaching adjustments.

However, there are also some shortcomings in this study that require further improvement and research:

1. Number and diversity of data samples: The number of data samples used in this study may be limited, and only the English learning status of vocational college students is considered. Further expanding the data sample size and including more kinds of student groups can improve the universality and reliability of the method.
2. Accuracy and robustness of the algorithm: The improved SSD algorithm has shown good performance in learning state detection, but there are still certain errors and limitations. Further optimization of algorithms to improve detection accuracy and robustness is the future direction for improvement.
3. Personalization of teaching guidance: The current method mainly targets the overall student group for learning state detection and teaching adjustment. Future research can explore how to integrate personalized teaching guidance into students' learning state detection to better meet the needs and characteristics of different students.

In summary, although the proposed improved SSD algorithm for detecting the classroom learning status of vocational English students has certain advantages and practical application value, further improvement and improvement are still needed to improve the accuracy, universality, and personalized teaching guidance ability of the method.

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A Recommended Method for Teaching Information Resources of English Chinese Translation Based on Deep Learning

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Abstract. In the context of mass industry and innovative education, educational institutions and educators need to focus on cultivating students' innovation ability and creativity, and prepare students for their future employment and career development by providing courses and practical opportunities for innovative education. At the same time, enterprises and industries also need to cooperate with educational institutions to jointly promote the development of innovative education and cultivate innovative talents that meet the needs of the mass industry. In order to ensure the effectiveness of English Chinese translation teaching information resource recommendation and improve the accuracy of English Chinese translation teaching information resource recommendation, a deep learning based English Chinese translation teaching information resource recommendation method is proposed. By analyzing students' demand for teaching information resources in English Chinese translation, convolutional neural networks are used to extract the characteristics of teaching information resources in English Chinese translation. By utilizing the self coding neural network in deep learning methods, the correlation between English Chinese translation teaching information resources is excavated, and a recommendation model for English Chinese translation teaching information resources is constructed to achieve English Chinese translation teaching information resource recommendation. The experimental results show that the method proposed in this paper has a good recommendation effect on teaching information resources for English Chinese translation, and can effectively improve the accuracy of teaching information resource recommendation for English Chinese translation.

Keywords: Deep Learning · Convolutional Neural Network · English Chinese Translation Teaching · Information resource recommendation · Self Coding Neural Network

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1 Introduction

In today's era, internet technology, especially mobile internet technology, is rapidly developing, and mobile terminals, especially smartphones, have become popular, which has had a huge impact on people's production and life. College students are willing to accept new things, and mobile internet has become a part of their lives [1, 2]. The rich content and convenient application of internet resources greatly enhance students' access to various academic materials. In this context, teachers should consider how to guide students to use the Internet reasonably and promote teaching and learning. Due to the popularity of Jin Yong's martial arts, discussions and reviews surrounding Jin Yong's books have also emerged, leading to the emergence of "Jinology". In the 1980s, with the development of the internet, Jin Yong's works continued to be disseminated overseas. In 1993, the first overseas research network on metallography, alt.chinese.text (ACT), developed to this day, and a large number of overseas readers have joined the study of metallography and Chinese martial arts culture. It can be seen that martial arts novels have an audience and a market overseas. As the world's largest lingua franca, English translation of martial arts novels is essential for cultural exchange with the world. Therefore, systematizing and standardizing martial arts translation is beneficial for improving translation quality and speed, while also facilitating readers' retrieval, inquiry, and understanding. To achieve good English Chinese translation, one must have a solid foundation in both English and Chinese languages; To have extensive cultural knowledge, especially familiarity with the background knowledge of the translation topic; Be able to flexibly apply various translation methods and techniques; Be familiar with the use of various reference books. Online resources provide a rich material foundation for cultivating the above translation literacy [3]. With the development and application of information technology, the construction and use of teaching resources have become a hot topic in the field of education. In the teaching of English Chinese translation, the traditional teaching model faces many challenges, such as the difficulty for teachers to meet the personalized needs of students in teaching, and the difficulty for students to effectively access and utilize teaching resources in the learning process. Therefore, researching appropriate methods for recommending information resources in English Chinese translation teaching is of great significance for improving the effectiveness of English Chinese translation teaching and promoting the reform of English Chinese translation teaching.

At present, scholars in relevant fields have conducted research on the recommendation of English Chinese translation teaching information resources, and reference [4] proposes a smart recommendation method for learning resources under the information-based teaching mode. With the continuous rise and application of information technology teaching methods, individual differences such as learning habits have led to diverse preferences for resources and activities provided by information technology teaching platforms. It is urgent for the system platform to actively recommend resources and activities that meet students' interests and needs. Through the information-based teaching platform, the collection and acquisition of student user behavior data, data mining and analysis using big data technology, and modeling of student portraits in the information-based teaching platform. Identify students' needs and preferences using methods such as labels and weights. Utilizing matrix decomposition algorithm to update user profiles and achieve intelligent recommendation services for massive educational and teaching resources, providing impetus for promoting personalized education. Reference [5] proposed a research on a recommendation system for ideological and political education resources in courses based on big data. To address the issues of long server response time and low user preference for system recommendation results in practical applications of knowledge graph based recommendation systems, a research on a curriculum ideological and political education resource recommendation system based on big data has been carried out. In the hardware part, design the selection of underlying physical hosts and database servers. In the software section, the reading and searching of ideological and political education resources for courses based on big data were designed. Comparative experiments showed that the designed recommendation system can provide users with higher accuracy and faster recommendation services in practical applications. Reference [6] proposes a teaching information resource management method based on Distributed File System (HDFS) and user interests. This method uses HDFS technology of Hadoop platform to solve the problem of cloud storage of network teaching resources, and analyzes the corresponding HDFS cloud storage architecture. Among them, the teaching resource recommendation function module adopts the LDA user interest topic mining model and introduces a student rating matrix to generate student course attribute preference similarity, improving the quality and accuracy of recommendations. The feasibility of the proposed method was verified by the simulation results of an instance on the Hadoop 2.2.0 platform. In addition, compared to recommendation methods based on standard association rules, the proposed mining recommendation method exhibits higher accuracy. However, the above resource recommendation methods still have problems of poor recommendation effectiveness and low accuracy.

In response to the above issues, a deep learning based recommendation method for English Chinese translation teaching information resources is proposed. The structural description studied in this article is as follows:

Step 1: Based on students' previous browsing content and frequency of English Chinese translation teaching information resources, analyze students' needs for English Chinese translation teaching information resources;
Step 2: Convolutional neural network is used to extract the characteristics of English Chinese translation teaching information resources;
Step 3: Use deep learning methods to explore the correlation between English Chinese translation teaching information resources and construct a recommendation model for English Chinese translation teaching information resources;
Step: 4: Experimental analysis;
Step 5: Conclusion.

2 Design of Recommended Methods for Teaching Information Resources in English Chinese Translation

In order to effectively recommend teaching information resources for English Chinese translation, a deep learning based method for recommending teaching information resources for English Chinese translation is proposed. Analyze students' demand for teaching information resources for English Chinese translation, and extract the characteristics of teaching information resources for English Chinese translation. On this basis, a recommendation model for teaching information resources in English Chinese translation is constructed to achieve the recommendation of teaching information resources in English Chinese translation.

2.1 Analyzing Students' Needs for Teaching Information Resources for English Chinese Translation

This article analyzes the needs of students' English Chinese translation teaching information resources based on their previous browsing content and frequency. The specific operation process is shown in Fig. 1.

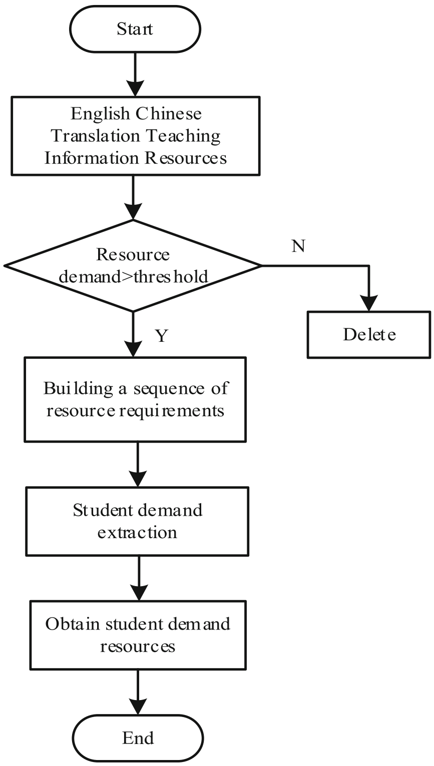

Fig. 1. Analysis process of students' demand for English Chinese translation teaching information resources

In order to independently reflect students' needs for English Chinese translation teaching information resources, based on the content of Fig. 1, a binary function is constructed, which includes:

$$f_q(a_i) = \begin{cases} 1, q = \alpha_1, \alpha_2, \alpha_3 \\ 0, else \end{cases} \tag{1}$$

In formula (1), α_1 represents save, α_2 represents favorite, and α_3 represents download. If $f_q(a_i) = 1$, then it indicates that students have a demand for this type of English Chinese translation teaching information resource; If $f_q(a_i) = 0$, then it indicates that students do not have a demand for this type of English Chinese translation teaching information resource.

Due to the uncertainty in the application process of this function, it needs to be optimized. Considering the content of the English Chinese translation teaching information resources themselves, the time length of the English Chinese translation teaching information resources is set to G_I. The larger this value, the lower the demand for English Chinese translation teaching information resources among students. Assuming N represents the number of times students click on English Chinese translation teaching information resources, this parameter is positively correlated with students' demand for such English Chinese translation teaching information resources. When N is greater, it indicates that students have a higher demand for this type of English Chinese translation teaching information resources. Assuming T_I represents the query time of students' English Chinese translation teaching information resources, there is a positive correlation between students' demand for this type of English Chinese translation teaching information resources, but it is not that the higher the T_I value, the higher the students' demand for it. When evaluating T_I, it is necessary to set $\max T_I$ to constrain it. Based on the above analysis results, the demand of students for a certain English Chinese translation teaching information resource can be calculated using the following formula:

$$f_q = \delta \frac{N}{G_I \max T_I} r^{-|T_I - \max|} \tag{2}$$

In formula (2), δ represents the adjustment factor during the calculation process, and r represents the demand coefficient. Based on the above analysis, students' interest in a specific English Chinese translation teaching information resource can be expressed as:

$$f_q' = \min\{1, f_q(a_i) + f_q\} \tag{3}$$

According to the above formula, when a student's demand for a specific English Chinese translation teaching information resource exceeds f_q, it can be used as a decision-making factor for extracting English Chinese translation teaching information resources.

2.2 Extracting the Characteristics of Teaching Information Resources for English Chinese Translation

After analyzing the needs of students for teaching information resources in English Chinese translation, convolutional neural networks are used to extract the characteristics of teaching information resources in English Chinese translation.

Convolution neural network is a kind of deep neural network widely used in image recognition, speech recognition, natural language processing and other fields. It is a typical method commonly used in deep learning. It uses multiple sets of convolution kernels to extract and abstract features, and ultimately achieves efficient classification of input data [7–9]. Convolutional neural networks mainly focus on convolutional operations, which are a special linear weighting operation that extracts local features from input data through sliding windows, effectively sharing parameters and reducing model complexity. In addition, the convolutional neural network also includes pooling, activation function and other modules. In the process of continuous feature extraction and abstraction, the size of the feature map is constantly reduced and the ability of feature identification is enhanced. Convolutional neural networks have excellent feature extraction and abstraction capabilities, are suitable for processing high-dimensional data, and have a certain degree of translation invariance and the ability to automatically learn features.

Convolutional neural networks are composed of single-layer and double-layer hierarchical structures, including input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The middle three layers are multi-layer structures, and the remaining two layers are single-layer structures. The structure of Convolutional neural network is shown in Fig. 2.

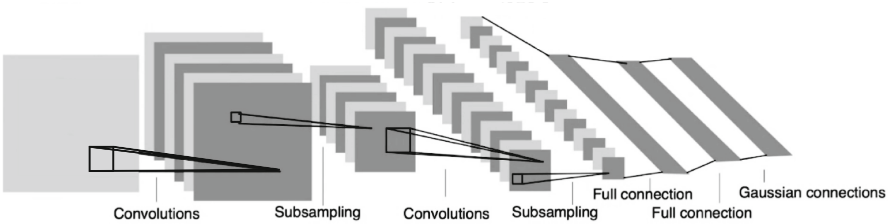

Fig. 2. Structure of Convolutional neural network

If M and C correspond to the height, width, and number of channels respectively, then the English Chinese translation teaching information resource input in the input layer is $M \times M \times C$. After inputting teaching information resources for English Chinese translation, convolution operations are performed on them through convolutional layers. If $N \times N$ represents the size of the convolution kernel and its quantity is K, the convolution calculation can obtain the feature $(M - N + 1) \times (M - N + 1)$ of English Chinese translation teaching information resources. The convolution formula is:

$$X_j^l = f_q'\left(\sum\nolimits_{i \in M_j} X_i^{l-i} W_{ij}^l + b_i^j\right) \tag{4}$$

In formula (4), X_j^l represents the characteristics of English Chinese translation teaching information resources after convolution, and X_i^{l-i}, W_{ij}^l and b_i^j represent vector, offset and activation function respectively.

The pooling layer mainly completes the sampling of X_j^l, and if the determined sampling area of this layer is $a \times a$, the feature $\left(\frac{M-N+1}{a}\right) \times \left(\frac{M-N+1}{a}\right)$ of English Chinese translation teaching information resources after sampling can be obtained, the purpose of sampling is to reduce the dimensionality of X_j^l, thereby reducing the complexity of the model and improving its operational efficiency. The sampling formula for X_j^l is:

$$X_j^l = \left(\sum\nolimits_{i \in M_j} \beta_j^l down\left(X_j^{l-1}\right) + b_i^j\right) \tag{5}$$

In formula (5), $down(\cdot)$ represents the calculation function and β_j^l represents the bias term, which belongs to the feature of outputting teaching information resources for English Chinese translation.

After the above convolution and pooling operations, it is necessary to implement a distributed representation of the characteristics of English Chinese translation teaching information resources. This representation needs to be completed through a fully connected layer and mapped to the sample label space, in order to obtain the categories of English Chinese translation teaching information resources. Namely, X_j^l is transformed into a one-dimensional vector to extract the features of teaching information resources for English Chinese translation. The transformed one-dimensional vector is output by the output layer.

2.3 Constructing a Recommendation Model for Teaching Information Resources of English Chinese Translation

Based on the feature extraction of English Chinese translation teaching information resources mentioned above, deep learning methods are used to explore the correlation between English Chinese translation teaching information resources, and a recommendation model for English Chinese translation teaching information resources is constructed.

Deep learning is a machine learning method that simulates the structure and working mechanism of human brain neural networks. By constructing multi-layer nonlinear neural networks, high-level features are extracted from input data, enabling learning and prediction of multiple complex data types [10–12]. Deep learning can automatically extract features and patterns from data, and has a significant ability to handle high-dimensional and complex data. The self coding neural network in the deep learning technology is a kind of unsupervised learning neural network. Its main purpose is to compress the complex input data into a low dimensional vector through a series of nonlinear transformations, and then re convert the vector into the original input data through the decoder to achieve data reconstruction and feature extraction. Self coding neural networks can represent received data features by capturing data features in low dimensional space, and have strong predictive ability. Therefore, with automatic encoders as the core technology, a recommendation model for teaching information resources in English Chinese translation is constructed. The structure of the self coding neural network is shown in Fig. 3.

In Fig. 2, f, g, and h represent the input gate, output gate, and forgetting gate of the self coding neural network, respectively. Their corresponding teaching information resources for English Chinese translation are represented as R, T, and Y. The input gate and output gate respectively determine the state of the current input sequence and output sequence, while the forgetting gate controls how many units of English Chinese translation teaching information resources will be transmitted to the current state at the final moment.

Through the adaptive encoding and decoding of encoders, the correlation between English Chinese translation teaching information resources is analyzed, and the formula is as follows:

$$y_i = X_j^l f(i)\left[W_i x_i + g(i)h(i)\right] \tag{6}$$

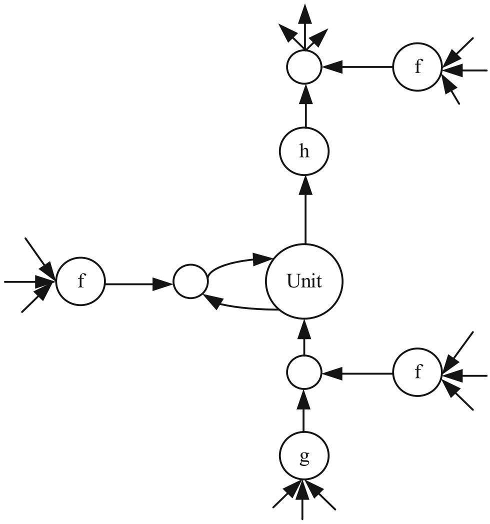

Fig. 3. Self coding neural network structure

In formula (6), y_i represents the correlation between English Chinese translation teaching information resources, W_i represents the weight value of English Chinese translation teaching information resources, and x_i represents the input of English Chinese translation teaching information resources.

The impact factors of recommended English Chinese translation teaching information resources on non recommended English Chinese translation teaching information resources can be expressed as:

$$L_s = y_i \cdot b_i + K_s \tag{7}$$

In formula (7), b_i represents the bias coefficient of teaching information resources for English Chinese translation, and K_s represents the index value of teaching information resources for English Chinese translation.

Assuming that the number of occurrences of a certain English Chinese translation teaching information resource is N_c, N_c contains k keywords of English Chinese translation teaching information resource, and the calculation formula for the probability of k occurrence is:

$$p = \frac{k \times N_c}{L_s \max z} \tag{8}$$

In formula (8), p represents the probability of frequent occurrences of English Chinese translation teaching information resources, and z represents the number of English Chinese translation teaching information resources containing that keyword.

On this basis, calculate the importance level W_{ij} of the keyword j in an English Chinese translation teaching information resource text D_j, which is:

$$W_{ij} = p \times \log \frac{N_c}{n_j} \tag{9}$$

In formula (9), n_j represents the number of important words in the English Chinese translation teaching information resource text.

Using pre similarity to measure students' demand for English Chinese translation teaching information resources, the calculation formula is:

$$S(a_i, v_i) = \frac{W_{ij}}{|a_i||v_i|} \tag{10}$$

In formula (10), S represents the similarity calculation of students' demand for English Chinese translation teaching information resources, a_i represents the feature vector of students' selection of English Chinese translation teaching information resources, and v_i represents the feature vector of English Chinese translation teaching information resources.

By concatenating the feature vectors of teaching information resources for students' English Chinese translation with the feature vectors of teaching information resources for English Chinese translation, the student's rating vector for teaching information resources for English Chinese translation is obtained, which is the recommended model for teaching information resources for English Chinese translation. The expression is:

$$y\prime = \alpha[S(a_i, v_i) \times \vartheta + \psi] \tag{11}$$

In formula (11), $y\prime$ represents the scoring vector of teaching information resources for English Chinese translation, α represents the original features of teaching information resources for English Chinese translation, and ϑ and ψ respectively represent the amount and allocation of teaching information resources for English Chinese translation to be recommended.

Calculate the rating vector of English Chinese translation teaching information resources using the above formula, sort them in descending order based on the results, and use the list of English Chinese translation teaching information resources ranked in the top ξ as the recommended list of English Chinese translation teaching information resources. Thus, achieve deep learning based English Chinese translation teaching information resource recommendation.

3 Experimental Analysis

In order to verify the feasibility of the recommendation method for English Chinese translation teaching information resources based on deep learning, the following experiment is designed.

Table 1. Setting the Experimental Environment

Project	Parameter
System	Windows 7
CPU	Intel Zhiqiang E5–2600
Development tool	Sublime
Deep learning tools	Theano

3.1 Experimental Environment

Set up the experimental environment as shown in Table 1.

The experiment takes information resources from a certain university's English Chinese translation teaching as the research object to test the application effect of the method in this article. The experimental testing process is shown in Fig. 4.

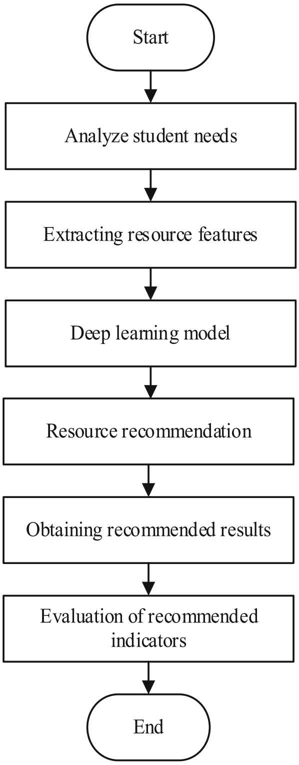

Fig. 4. Experimental Testing Process

The experimental test parameters are shown in Table 2.

Table 2. Experimental Test Parameters Table

Project	Parameter	
Average crawl processing time of web crawler nodes	≤ 2h	
Input data batch size	128 MB	
Training rounds	5 rounds	
Number of different convolutional kernels	70 piece	
Convolutional Kernel Types	3 types	
Hide Layer Size	18 × 2	
Fully connected layer	First level input	128 × L × (18 × 5)
	First layer output	200
	Second layer input	200
	Second layer output	128 × L × (18 × 5)
	Third layer input	200
	Third layer output	200

Note: L represents the feature scale

3.2 Experimental Evaluation Indicators

1) Recall rate:

$$Recall = \frac{R(u)}{T(u)} \times 100\% \tag{12}$$

In formula (12), $R(u)$ is the recommended number of English Chinese translation teaching information resources, and $T(u)$ is the number of all English Chinese translation teaching information resources.

2) Accuracy:

$$Precision = \frac{R(u)}{M(u)} \times 100\% \tag{13}$$

In formula (13), $M(u)$ is the accurate recommended quantity of teaching information resources for English Chinese translation.

3) Normalized cumulative loss gain:

$$NDGG = A_i \sum_{j=1}^{n} \frac{2^{c_j^i} - 1}{\log_2\left(1 + S_j^i\right)} \tag{14}$$

In formula (14), A_i represents the standardization factor, and S_j^i and C_j^i respectively represent the position of student i's j th English Chinese translation teaching information resource recommendation result in the actual English Chinese translation teaching information resource recommendation ranking and the method generated recommendation ranking.

3.3 Experimental Results and Analysis

In order to avoid excessively single experimental results, while maintaining a constant experimental environment, comparative testing was conducted on the methods in this article, the reference [4] method, the reference [5] method, and the reference [6] method. The same English Chinese translation teaching information resources were recommended using these methods, and the recommended comparison results of English Chinese translation teaching information resources for different methods are shown in Table 3.

Table 3. Comparison of Recommended English Chinese Translation Teaching Information Resources by Different Methods

Different methods	Recall rate/%	Accuracy/%	Normalized cumulative loss gain
The proposed method	87.36	97.36	0.3695
The reference [4] method	82.34	90.34	0.3015
The reference [5] method	80.69	91.26	0.3214
The reference [6] method	85.33	89.36	0.3358

By analyzing the results shown in Table 3, it can be seen that compared to the other three methods, the index values of recall, accuracy, and normalized cumulative loss gain of the method proposed in this paper are all relatively large. From this, it can be seen that the recommendation accuracy of this method is relatively high.

On this basis, further comparative testing was conducted on the methods proposed in this paper, the reference [4] method, the reference [5] method, and the reference [6] method. The comparison curves of the hit rates of recommendation results for different methods are shown in Fig. 5.

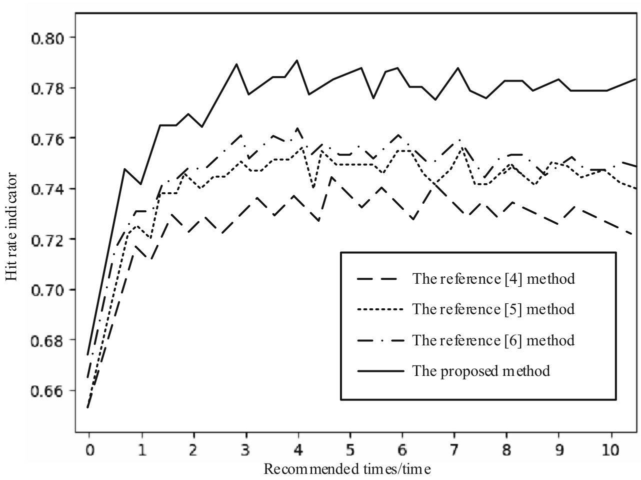

Fig. 5. Comparison Curve of Hit Rate of Recommendation Results for Different Methods

From Fig. 5, it can be seen that compared to the other three methods, the hit rate of the recommended English Chinese translation teaching information resources obtained by applying this method is higher, indicating that this method has a good recommendation effect on English Chinese translation teaching information resources.

4 Conclusion

This article proposes a method for recommending teaching information resources for English Chinese translation based on deep learning. By analyzing students' demand for teaching information resources for English Chinese translation, extract the characteristics of teaching information resources for English Chinese translation. On this basis, deep learning methods are utilized to recommend teaching information resources for English Chinese translation. The method proposed in this article can effectively ensure the recommendation effect of teaching information resources for English Chinese translation, and to some extent improve the accuracy of teaching information resource recommendation for English Chinese translation. However, when new users join the system, due to the lack of personalized historical data, deep learning models may not be able to accurately recommend suitable teaching information resources. Therefore, in the future, it is necessary to address the issue of cold start in order to provide personalized recommendations for new users.

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Attitude Target Tracking of Kabadi Athletes Based on Machine Learning

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Abstract. In order to improve the performance of Kabaddi athlete posture target tracking, a method of Kabaddi athlete posture target tracking based on machine learning is proposed. The threshold change parameter is calculated by using the obtained athletes' posture characteristic parameters, and the golden section is introduced to transform it and smooth the features of athletes' posture are extracted. Constraint loss is added to the local global supervision module of machine learning, and the local features of athlete pose are integrated, and the local parameters of athlete pose are obtained by loss function. Taylor formula was used to calculate the athletes' pose velocity, and Kalman filter was used to evaluate the joint motion data, and Kabaddi athlete pose model was constructed. The frame difference of the background image is calculated by normalizing the athletes' pose image, and the athletes' pose is automatically tracked. The experimental results show that this method can track all nodes of the athletes' posture, and has good performance in the absolute error, detail loss and tracking lag rate of the athletes' posture tracking, so it is helpful to improve the athletes' technical level and improve the training effect.

Keywords: Machine learning · Kabaddi · Athlete posture · Target tracking · Feature extraction · Attitude model

1 Introduction

Kabadi, originated in South Asia, is a sport similar to the Chinese folk game of "eagle catching chicken". Xinjiang Bazhou Special Education School, through the construction and implementation of the Happy Kabadi curriculum, strives to make all students understand the Kabadi sport and its culture through systematic learning and training, and can basically master the relevant skills, tactics, rules, etc., so that physical and mental defects can be compensated to a certain extent, so as to improve physical quality, cultivate hard-working, indomitable will and the spirit of unity and cooperation, to lay a solid foundation for better integration into society in the future. n Kabadi sport, the running route and track of athletes are not a closed loop [1]. Both offensive and defensive sides have rich rhythmic changes to interfere with the opponent, whether it is starting,

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braking, changing direction, turning, or the pursuit and escape of touching the opponent in running, each action is the response of the athletes according to the actual situation. Therefore, we should pay more attention to the foundation of footwork agility in training, and constantly enhance the coordination and quick response of footwork conversion and action connection. A notable feature of Kabadi sports is that the competition is strong in antagonism and fierce in the process of antagonism. If you can ensure the balance of your body in the process of moving in the competition and achieve score or no loss of points, you must have a solid ability to change direction and move. For example, in the return process of attackers, the ability to quickly change direction is required to constantly speed up the break out, the defenders quickly respond, and cut off the return route of attackers.

In domestic research, Li Qi et al. [2]. Compared with the traditional human motion capture system, this system can realize accurate and stable three-dimensional human posture tracking under simple actions, reflect the special nature of the movement process under complex actions, and be used for performance evaluation of sports biomechanics. Zhang Hua et al. [3] proposed a calibration and recognition method of human motion posture feature points based on the nearest specific point in order to improve the accurate detection and recognition ability of human motion posture. Human motion pose image acquisition relies on laser scanning technology to detect the edge contour of the laser image. Combining image segmentation technology, the contour segmentation and feature recognition of human motion pose are carried out. The gray histogram distribution structure model of the laser image is constructed. The human motion pose and action features in the model are extracted by region block matching, The multi-dimensional pixel reconstruction method is used to simulate human motion posture, and the large interval nearest neighbor specific point calibration method is used to calibrate and detect the feature points of human motion posture, so as to achieve the purpose of identifying and optimizing human motion posture. The experimental results show that this method has the characteristics of high accuracy, high recognition accuracy and short recognition time in pose recognition, and improves the ability of human motion pose recognition.

In foreign research, Zhao X et al. [4] proposed a fast recognition algorithm for human motion posture based on multimodal biological information fusion, aiming at the problems of low accuracy of feature extraction, large error of human motion posture recognition and posture recognition, poor recognition effect, and low recognition rate of traditional fast recognition algorithm for human motion posture. Firstly, the wavelet packet decomposition based on sample entropy is used to extract hand features of human motion posture, such as kurtosis, time domain feature skewness, frequency domain feature EMG signal integral value and time domain feature, such as the mean value, standard deviation and interquartile distance of leg motion amplitude. Secondly, after normalizing the two features, the human hand and foot motion feature set is obtained. Finally, the feature set is used to build a fast recognition model of human motion posture based on multimodal biological information fusion, and the feature set is input into the recognition model. The fusion of human motion posture information is completed by improving the canonical correlation analysis method. The fusion result is used as the input of the minimum distance classifier, realize fast recognition of human motion posture. The results show that the algorithm has high accuracy of feature extraction, small deviation of human motion pose recognition, pose recognition error is $-0.21 \sim 0.02$, and the recognition rate is always above 95%. The practical application effect is good.

Based on the above research background, this paper applies machine learning to target tracking of Kabadi athletes' posture, so that the actual posture of athletes is consistent with the standard posture.

2 Design of Athlete Posture Target Tracking Method

2.1 Extract Athletes' Posture Characteristics

In Kabadi sports, the color histogram of the athletes' movement area is distributed $L = \{L_u\}$ Defined as antigen, $u = 1, 2, \cdots, n$ Represent the eigenvalue of the athlete's posture, and based on this, establish the probability density estimation function of the athlete's posture in the movement area, which is expressed as:

$$L_u = \frac{\phi}{f\left[q(x_i) - u\right]} \sum_{i=1}^{n} \omega \left[\left\| \frac{x_i - x_0}{g} \right\|^2 \right] \tag{1}$$

In the above formula, ϕ Is the probability density estimation coefficient, $f[]$ Represents the probability function, ω Represents the pixel weight, $q(x_i)$ Represent the athlete's posture image pixel in the x_i The quantitative eigenvalue of the feature space at is usually used to analyze whether the posture pixel value in the athlete's motion area is in the u Within feature spaces, g Represents the pixel value of the athlete's pose image.

Assume that the shape of the kernel function of the athlete's posture feature extraction is $h(\cdot)$ As the athlete posture image captured by the camera will be interfered by the background environment, compared with the athlete posture image at the edge of the camera lens, the athlete posture image pixels closer to the camera lens center are more stable, $h(\cdot)$ Pixels with larger weight values at the lens edge can be provided to the pixels at the lens center, while pixels at the lens edge can only get a smaller weight value [5].

Color histogram distribution of athletes' posture image in candidate areas $K = \{K_u\}$ It is defined as antibody, Ω It indicates that the athlete's posture is at the center of the current frame u The probability density estimation function of athletes' posture in the candidate area is established, which is expressed as:

$$K_u(\Omega) = \frac{\lambda}{f\left[q(x_i) - u\right]} \sum_{i=1}^{n} \omega \left[\left\| \frac{x_i - \Omega}{g} \right\|^2 \right] \tag{2}$$

Among them, λ The normalization coefficient representing the posture characteristics of athletes needs to meet $\sum_{i=1}^{n} K_u = 1$ Conditions.

In the process of extracting athletes' posture features, the affinity between antigen and antibody can be calculated by formula (3):

$$\chi_t^i = \frac{1}{\sqrt{2\pi}} e^{-\frac{d^2}{2\psi}} \tag{3}$$

Among them, ψ It represents the binding probability of antigen and antibody, d It represents the binding strength between antigen and antibody, and the calculation formula is:

$$d = \sqrt{1 - \zeta} \tag{4}$$

In the above formula, ζ Is the similarity coefficient, between 0 and 1, ζ The higher the value of, the higher the similarity between the athletes' posture characteristics in the movement area and the candidate area's posture characteristics.

When ζ After reaching the maximum value, the athlete's posture in the candidate area will become the athlete's posture feature to be solved in this frame image, and the feature parameter is defined as δ, the calculation formula is:

$$\delta = \sum_{u=1}^{n} \sqrt{L_u K_u} \tag{5}$$

Among them, L_u The characteristic area representing the athlete's posture, K_u It represents the candidate region for athlete posture feature extraction.

Using the characteristic parameters of athletes' posture, the threshold change parameters of athletes' posture are calculated, and the formula is:

$$\sigma_{MDS} = \frac{\varepsilon_1 + \varepsilon_0}{\delta \times Mt} \tag{6}$$

where, ε_1 Indicates the athlete's exercise intensity parameters, M Indicates the number of athletes' postures, ε_0 It represents the movement range parameters of athletes, t Indicates the time of movement.

When tracking athletes' posture, different weights should be given to athletes' motion intensity parameters and motion amplitude parameters. On the basis of introducing the golden section, the threshold change parameters of formula (6) are transformed to obtain:

$$\sigma_{MDS} = \frac{2(0.618\varepsilon_1 + 0.382\varepsilon_0)}{\varepsilon_1 + \varepsilon_0} \tag{7}$$

The threshold change parameter is mapped to (0, 1] In the interval, the mapping formula is:

$$\partial = 1 - \exp(\sigma_{MDS}) \tag{8}$$

If the athlete's continuous exercise time can reach t_e During this period, the athletes' posture characteristics are smoothed, and the threshold value of the athletes' posture characteristics is calculated by eliminating the smoothing error. The formula is:

$$\ell = (\kappa t_e + t_s)(1 + \partial) \tag{9}$$

where, κ Represents the smoothing coefficient, t_s Indicates the total duration of the movement.

If the athlete's posture characteristic parameter is greater than the threshold value ℓ, which indicates that this feature conforms to the real posture of Kabardi athletes, so keep it, or delete it.

By calculating the affinity between the color histogram distribution of athletes' posture and the candidate regions of athletes' posture, the characteristics of athletes' posture are extracted.

2.2 Obtaining Local Parameters of Athletes' Posture

Based on the posture characteristics of athletes, the local parameters of athletes' posture are obtained by using machine learning methods. Machine learning can learn the motion posture characteristics with discrimination ability under the condition of less injected data. In order to constrain the relationship between local and global features of athletes' posture and improve the ability of machine learning to judge athletes' posture features, the relationship between local and global features of athletes' posture is obtained by using the local and global monitoring module of machine learning.

Under the supervision of machine learning training, whether it is the local characteristics of athletes' posture E_g, or No k Weighted features of motion regions E_m^k, you can get athlete posture tags through the activation function and machine learning full connection layer [6]z_i The formula is:

$$p(E) = \text{Softmax}_{z_i}[L(E)] \tag{10}$$

Among them, $L(\cdot)$ Represents the full connection layer of machine learning, Softmax Indicates the activation function.

In the process of athletes' posture image processing, the athletes' posture features are discretized into motion vectors, and the reconstruction results of athletes' posture features are obtained, which are expressed as:

$$G_{a,b} = \begin{pmatrix} g_{(a,b)}(1,1) & g_{(a,b)}(1,2) \\ g_{(a,b)}(2,1) & g_{(a,b)}(2,2) \end{pmatrix} \tag{11}$$

Including:

$$g_{(a,b)}(u,v) = g[2(a-1)+u, 2(b-1)+v] \tag{12}$$

In the above formula, $u \in \{1,2\}$ and $v \in \{1,2\}$ Represent the related factors of the athletes' posture feature points.

In order to distinguish the global and local parameters of athletes' posture, the constraint loss $L_{restrain}$ Added to the local and global monitoring module of machine learning, expressed as:

$$L_{restrain} = \sum \left(\max\left\{0, p\left(E_m^k\right) - p\left(E_g\right)\right\}\right) \tag{13}$$

Machine learning can correctly classify athletes' posture samples into corresponding tags z_i In addition, the posture of athletes is predicted through local and global deep supervision.

Hypothesis X The number of images representing the athlete's posture, Y Represent the parameters of machine learning, and use formula (14) to calculate the loss of athletes' posture:

$$S = -\sum_{n=1}^{X} z_i \log \frac{\exp\left(Y^t \cdot E_g\right)}{\sum_n \exp\left(Y^t \cdot E_g\right)} \tag{14}$$

The local global monitoring module is combined with the local characteristics of the athletes' posture, and the final loss function is used to obtain the local parameters of the athletes' posture, which is expressed as:

$$L = S + \Lambda L_{restrain} \tag{15}$$

where, Λ Represents the balancing factor of machine learning.

Under the supervised training of machine learning, the local parameters of athletes' posture are obtained by using the local characteristics of athletes' posture.

2.3 Building the Posture Model of Kabadi Athletes (2.2 of Human Movements Based on Machine Learning)

In this paper, Kalman filtering method is used to evaluate athletes' joint coordinate information data. Kalman filter is a linear recursive filter [7], which is based on the previous state sequence of the target, and then makes an unbiased optimal evaluation of the subsequent state. In essence, this method is an optimized autoregressive data information processing algorithm, which mainly uses recursive prediction. The specific algorithm formula is:

$$x_k = Cg_{k-1} + Hu_k + Z_k \tag{16}$$

In the above formula, x_k State variables representing athletes' posture, C Represents the transfer matrix, g_{k-1} State vector representing the previous attitude, H Represents the control matrix, u_k Represents control input, Z_k Indicates process noise.

Usually, it is proposed to obey the Gaussian distribution $N(0, Q_k)$, Q_k Represents the process noise covariance matrix, then the measured value of the recursive method is:

$$z_k = Qx_k + S_k \tag{17}$$

where, z_k Is the observed variable, Q Represents the measurement matrix, S_k Represents measurement noise.

The Kalman filter principle is used for calculation.In the prediction stage, the current posture state is generated from the previous posture state of athletes as the prediction value. After entering the analysis stage, the minimum variance estimation method is used to reanalyze the state of the observed data of athletes' posture.With the continuous progress of state prediction and the continuous input of new observation data, the whole process continues to move forward.

However, when using the Kalman filtering method, it is necessary to use an appropriate mathematical model to confirm the system parameters, transfer matrix and measurement matrix in the filtering formula.In this paper, Taylor expansion is used to represent joint movements.For a certain posture of athletes i Indicates that the attitude is X The Taylor expansion of the axis translation speed is:

$$_i(t+1) = x_i(t) + \frac{\Delta T^2}{2} x_i(t) \tag{18}$$

where, x_i Represents the state vector at a certain posture of the athlete, t Represents discrete time points, ΔT Represents the time of sampling.

Similarly, in Y Shaft and Z In the direction of axis position, the local posture speed of athletes can also be expanded in the same way. Because the depth information acquisition efficiency of Kinect sensor is 30 frames/second, when collecting at this speed, the changes in the positions of the athletes' adjacent last two frames are not obvious [8]. Therefore, when establishing the mathematical model, this paper needs to sample the athletes' joint points with the goal of average speed movement. The mathematical model of Kalman filter is established by formula (19) as follows:

$$K(t) = Cx_i(t) + W(t) \tag{19}$$

where, $W(t)$ Represents the covariance matrix.

The measurement matrix mathematical model of behavior and movement of the athletes' posture coordinate data information obtained by Kinect sensor is as follows:

$$Z_i(t+1) = QX_i(t+1) + V(t+1) \tag{20}$$

Measuring noise $V(t+1)$ Measurement noise covariance matrix established in $W(t)$, almost all are diagonal matrices.

After several tests, the final determination $X_i(t+1)$ The diagonal value of is 0.05, the diagonal value is 3, and the initial state vector is determined to be the zero matrix, and the initial error covariance matrix is the identity matrix.Calculated by formula (20)$Z_i(t+1)$ And calculate the athletes' posture points i stay t Position of the.

2.4 Tracking Athletes' Posture

When tracking an athlete's posture, if the camera is stationary, the difference image of the athlete's posture in the front and back frames is defined as $I(k)$, and on $D(k)$ Constantly accumulate in the region, and normalize the athletes' posture images, namely:

$$\Delta^2(k) = \sum_{i \in D(k)} \begin{pmatrix} I(k) \\ \beta \end{pmatrix}^2 \tag{21}$$

In the above formula, β Represents the noise variance of the athlete's posture collection environment.

Assume that the gray level of the original image of the athlete's posture is B, when the gray value of the athlete's posture image is i The number of pixels in the athletes' posture image is n_i, N Represents the total number of pixels, so the segmentation process of athletes' posture image is as follows:

Step 1: By judging the gray level of the athlete's posture image, calculate the normalized histogram of the posture image, which is expressed as $p_i = n_i/N$, then there is:

$$\sum_{i=0}^{B-1} p_i = 1, p_i > 0 \tag{22}$$

Step 2: In the original image of the athlete's posture, calculate the average gray value of all pixels, that is:

$$\mu = \sum_{i=0}^{B-1} ip_i \tag{23}$$

Step 3: Calculate the edge detection threshold of athletes' posture image T:

$$T = \mu \times \frac{5}{3} \tag{24}$$

If the camera shooting area $D(k)$ If the pixels in the camera are fixed, then the normalized difference of the pixels of all athletes' pose images in the camera $I(k)/\beta$ All follow the normal distribution [9], and the probability distribution of athletes' posture image is obtained $p\left(\Delta^2|\Lambda_0\right)$, where Λ_0 The pixels representing the athlete's posture image are still.

According to the normalized processing results of athletes' posture images, the frame difference [10]of athletes' posture background image is calculated, and the formula is:

$$Z = \frac{\sum_{j=1}^{n} H_j}{\sum_{j=1}^{n} g_j} - \frac{\sum_{i=1}^{n} H_i}{\sum_{i=1}^{n} g_i} \tag{25}$$

In the above formula, H_i and H_j Represents the i 、 j Frame the grayscale characteristics of athletes' posture image, g_i and g_j Represents the i 、 j The pixel features of the athlete's posture image.

According to the frame difference of the athletes' posture background image, the automatic tracking algorithm of athletes' posture is designed, which is expressed as:

$$\vartheta = \sum_{j=2}^{n} \left(Z_j, \ldots Z_0\right)^2/n \tag{26}$$

The algorithm of formula (26) is used to realize automatic tracking of athletes' posture, namely:

$$s(x, y) = n\frac{p_{k-1}}{\vartheta(t)} + \overline{\alpha_t} \times \vartheta(t) \tag{27}$$

Among them, $\overline{\alpha_t}$ Represents the switching pixel ratio of the athlete's posture background image.

To sum up, the athletes' attitude tracking algorithm is designed through the segmentation of athletes' attitude images to achieve athletes' attitude tracking.

3 Experimental Analysis

3.1 Experimental Environment and Parameters

In order to verify the performance of the method in this paper in athlete attitude tracking, the experimental parameters are set using Matlab tools, as follows:

Development tool: Unity3D.
Operating system: Windows8.
Graphics card model: GTX1080.
Programming language: C#
Angle resolution of camera: 1°
Camera scanning area: 180°
Athlete posture image pixel: 258 × three hundred and sixty.
Distance resolution of camera: 640 * 480ppi.

3.2 Experimental Data Set

Considering that the collection of athletes' posture data will be affected by many factors, which will lead to more complex data set construction process, this paper combines sensors and cameras to produce CMU Panoptic data set and Human3.6M data set.

The data in the CMU Panoptic dataset is collected jointly by the depth camera and sensors, which can obtain the all-round characteristics of the athletes' posture. According to these multi angle characteristics, the CMU Panoptic dataset is completed.

The data in the Human3.6M dataset is collected by digital cameras, including 5.4 million athlete posture images. The data in the dataset is provided by 2432 subjects, each of whom provides different sports posture.

3.3 Establish Scene Model for Motion Attitude Tracking

Hypothesis $P_i(x_w, y_w, z_w, 1)$ The position point representing the athlete's posture, and the imaging point generated in the camera is $p_i = [u, v, 1]$, expressed as:

$$[u, v, 1]^T = \frac{1}{z_c} KM\left[x_w, y_w, z_w, 1\right]^T \tag{28}$$

Among them, x_w The x-axis coordinate representing the athlete's posture position, y_w Y-axis coordinate representing the athlete's posture position, z_w The z-axis coordinate representing the athlete's posture position, K Represents the parameter matrix during camera imaging, M Represents the transformation matrix between the world coordinate system and the camera coordinate system, expressed as:

$$M = \left[{}_{si}^{C_i}R,{}_{u}^{C}t\right] \tag{29}$$

Among them, ${}_{si}^{C_i}R$ Represents the rotation matrix, ${}_{u}^{C}t$ Represents the translation matrix.

Ignore the turning angle of the camera so that the pitch angle of the camera is θ_i, yaw angle is φ_i, then the rotation matrix is expressed as:

$${}_{w}^{c}R = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta_i & \sin\theta_i \\ 0 & -\sin\theta_i & \cos\theta_i \end{bmatrix} \begin{bmatrix} \cos\varphi_i & 0 & \sin\varphi_i \\ 0 & 1 & 0 \\ -\sin\varphi_i & 0 & \cos\varphi_i \end{bmatrix} \tag{30}$$

According to the construction process of the above scene model, the imaging process of athletes' posture is an irreversible transformation process from three-dimensional space to two-dimensional space. In order to solve this difficulty, this experiment uses the working principle of the laser sensor to transform the construction process of the scene model into the transformation process from two-dimensional space to three-dimensional space.

3.4 Tracking Steps

In the scene model of athlete posture tracking, the steps of athlete posture tracking are designed, namely:

Step 1: Read the first frame of the athlete's motion video, select the tracking target, and determine the central coordinates y_0, calculate its color histogram q;

Step 2: Read the next frame of the athlete's motion video;

Step 3: Calculate the color histogram of the candidate pose target at the center coordinate of the athlete's pose tracking target $p(y_0)$, calculated $p(y_0)$ Babbitt coefficient with formwork $\hat{\rho}(y_0)$;

Step 4: Calculate the position of the candidate attitude target in the new coordinate y_1 Color Histogram at $p(y_1)$, calculate the pasteurization coefficient between the formwork and the formwork $\hat{\rho}(y_1)$;

Step 5: If $\hat{\rho}(y_1) < \hat{\rho}(y_0)$, then $y_1 \leftarrow \frac{y_1+y_0}{2}$, recalculate once $\hat{\rho}(y_1)$, until $\hat{\rho}(y_1) > \hat{\rho}(y_0)$;

Step 6: Get the coordinates of the new position of the athletes' posture through iterative calculation, and track the movement posture.

3.5 Result Analysis

In order to highlight the advantages of the method in this paper in the tracking of athletes' pose targets, the tracking method based on dual Kinect sensors (a), the tracking method based on the nearest neighbor specific point (b) and the tracking method based on multimodal biological information fusion (c) are introduced for comparison. One athlete's pose image is selected in the CMU Panoptic dataset and the Human3.6M dataset respectively, and the tracking results shown in Fig. 1 are obtained.

As can be seen from the results in Fig. 1, when the tracking method based on dual Kinect sensors, the tracking method based on specific nearest neighbor points and the tracking method based on multi-modal biological information fusion are adopted, some attitude nodes cannot be tracked, and the movement posture of athletes under complex movements cannot be accurately and stably identified.By using the method presented in this paper, all nodes of the athlete's posture can be tracked, which has better tracking effect and improves the recognition ability of human movement posture, so that the actual posture of the athlete is consistent with the standard posture, and has better tracking effect.

In the performance test, 1000 groups of athletes' attitude data were selected from the CMU Panoptic dataset and Human3.6M dataset, and the absolute error, detail loss and tracking lag rate of athletes' attitude tracking were tested respectively. The results are as follows.

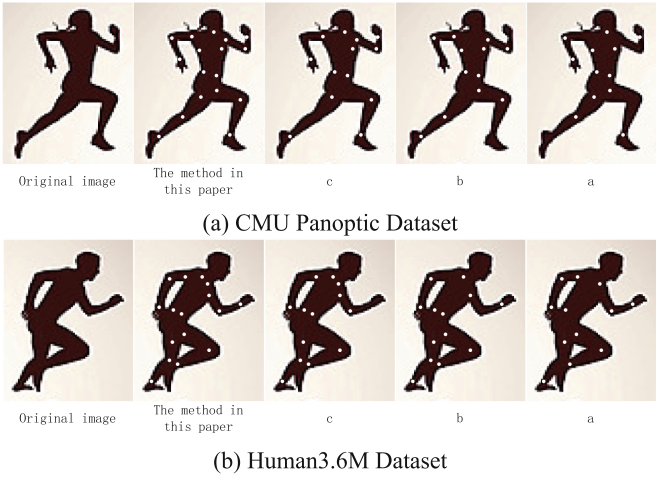

Fig. 1. Athlete Posture Tracking Results

For 1000 groups of athletes' posture data, four methods are used to track the athletes' posture, and the tracking absolute error is obtained. The results are shown in Fig. 2.

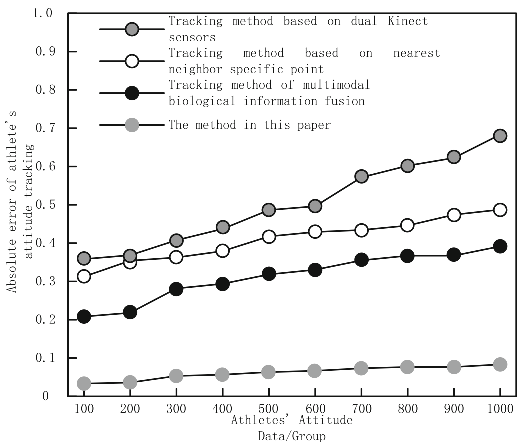

Fig. 2. Absolute error of athletes' posture tracking

In the results of Fig. 2, when the tracking method based on dual Kinect sensors is adopted, the absolute error of the athlete's attitude tracking is the largest, between 0.35 and 0.7, followed by the tracking method based on the nearest neighbor specific point and the tracking method based on multimodal biological information fusion. The absolute error of attitude tracking is between 0.3 and 0.5 and 0.2 to 0.4, respectively. When using the method in this paper, with the increase of athletes' posture data, the absolute error of tracking gradually becomes larger, but always within 0.1. Because the method in this paper uses smoothing processing method to eliminate athletes' posture errors and calculate the threshold value of athletes' posture characteristics, it can greatly reduce the influence of background characters on athletes' posture detection and provide a basis for accurately tracking athletes' posture.

Select a sequence from the athlete's posture image and divide it into 12 frames, 26 frames and 54 frames. Six methods are used to track the image. With the effective area of the athlete's posture contour and the number of image blocks as the measurement criteria, the amount of detail loss of the athlete's posture image is tested. The results are shown in Table 1.

Table 1. Amount of detail loss of 3D human motion pose image

		Method in text	a	b	c
Number of 12 frame sub blocks/piece		42	36	28	22
26 frame sub blocks/piece		36	32	24	18
Number of 54 frame sub blocks/piece		28	26	22	16
Effective area ratio	mean value	0.417	0.729	0.837	0.954
	variance	0.0058	0.0062	0.0068	0.0076

According to the results in Table 1, when tracking the image sequence of athletes' posture using the method in this paper, with the increase of the frame number of athletes' posture image sequence, the number of sub blocks is the smallest and the effective area is the highest. When the other three methods are used, the number of sub blocks and effective area obtained are less than those of the method in the paper, so it can be explained that the method in the paper can reduce the loss of details of athletes' posture, it is verified that the proposed method has strong tracking effect and can capture relatively detailed movement gestures of athletes, indicating that this method can effectively track no matter how small gestures are.

In the process of movement, if the speed of Kabadi athletes is different, the posture tracking of athletes will lag. The results are shown in Fig. 3.

The results in Fig. 3 show that compared with the other three tracking methods, the method in this paper shows great advantages in the lag rate of athletes' posture tracking. With the acceleration of the speed of movement, the lag rate of athletes' posture tracking in the method in this paper is always kept within 10%, greatly improving the efficiency of athletes' posture tracking, in practical applications, it can track the athlete's movement status in real time during the movement process and understand the athlete's training status.

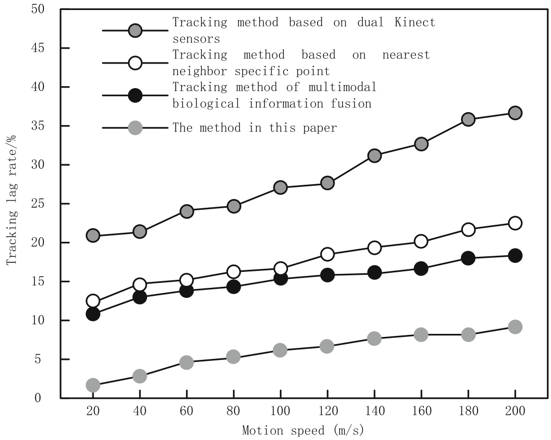

Fig. 3. Posture tracking lag rate of athletes

4 Conclusion

In this paper, a method of Kabaddi athlete attitude target tracking based on machine learning is proposed. The probability density estimation function of the athlete's pose in the moving region and the candidate region is established. Through the similarity between the features in the two regions, the athlete's pose feature parameters are solved, and the threshold change parameters are processed by the golden section to obtain the final athlete features. Activation function and machine learning are used to obtain the probability of the athlete's pose label, and the athlete's pose features are discretized by motion vector, and the local parameters of the athlete's pose are extracted by loss function. The model of Kabaddi athlete's posture is established by sampling the velocity of athlete's node movement. The athletes' pose tracking algorithm is designed through the segmentation of athletes' pose images, and the athletes' pose tracking is realized. The results show that this method has better tracking effect and performance. Although the research in this paper has made some achievements, there are still many shortcomings. In the process of athletes' pose feature extraction, the stability of the camera will affect the accuracy of feature extraction. In future research, it is hoped that the stability of camera calibration can be studied to improve the effect of athletes' pose tracking.

Aknowledgement. 1. A General Research Project about Quality Engineering in Anhui Province (The number has not been given until now)

2. A university - level research program in Sanlian University: A practical research on Kabaddi in Private college under the background of national wide fitness

3. the national-level program of entrepreneurship for undergraduates (a general research program): A practice research on Kabaddi Clubs in private colleges. The item number: 2022109590083

4. A key research project about teaching quality engineering in Sanlian university: A research on the exploration and practice of teaching reform in Kabaddi Clubs in private colleges (22zlgc070)

5. Provincial Social Science Project Vocational Education Reform Project: Sports Intervention of Traditional Ethnic Sports Wing Chun Quan in Special Children's Perception Training (Project No. SSPMC2206)

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Personalized Recommendation of English Chinese Translation Teaching Information Resources Based on Transfer Learning

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Abstract. With the rapid development of information technology, the field of English Chinese translation teaching has accumulated a large amount of information resources. The quantity of these teaching information resources is huge and diverse, and students and teachers face the problem of information overload, making it difficult to find resources that are suitable for their needs. Personalized recommendation technology has emerged to solve the problem of information overload, recommending resources that match users' personal interests and needs from a vast amount of resources. In response to the problem of poor personalized recommendation effectiveness in the existing personalized recommendation methods for English Chinese translation teaching information resources, this article posits a fresh individualized suggestion method for informative resources in regards to teaching the translation of English to Chinese. This paper constructs a state perception model of information resources for E-C edge teaching based on transfer learning. Based on this, obtain student group information, English Chinese translation teaching information resource information, and resource rating information, cluster English Chinese translation teaching information resources, and construct a personalized recommendation model for English Chinese translation teaching information resources. The experimental results show that the information resource clustering effect of this method is good, the diversity of resource recommendations is better, and the F-Measure value is higher.

Keywords: Transfer Learning · Translation between English and Chinese · Teaching Information Resources · Personalized Recommendations

1 Introduction

Personalized recommendation of teaching information resources for English Chinese translation is a method that utilizes personalized recommendation algorithms to provide learners with information materials that are suitable for their learning characteristics, in order to improve their learning effectiveness and teaching quality [1]. In the past few years, with the fast growth of web technology and AI technology, the massive surge in the amount of data has resulted in an increasingly abundant and varied range of educational resources. In this context, the efficient acquisition and selection of material that

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is suitable for a student's learning characteristics and needs have become essential challenges and requirements in advancing the quality and efficacy. Currently, personalized recommendation of teaching information materials for English Chinese translation has become a popular research direction. Some researchers, based on data mining, machine learning and other technologies, have achieved preliminary experiments on personalized recommendation of information materials for students through data such as learners' historical records, interests, and learning behaviors; But there are also some problems and challenges, such as how to protect students' privacy, how to ensure the quality and effectiveness of recommended items, and so on. Therefore, research in this direction still needs to be continuously explored and improved [2].

The advancement of contemporary digital technology has propelled the alteration of learning approaches. Conventional educational techniques are inadequate to cater to the lifelong learning requirements of pupils. As the proliferation of notions such as universal learning and lifelong learning, informal learning has gained more and more attention. The advancement of mobile communication technology has triggered the innovation of unofficial pedagogical techniques, from electronic learning (E-Learning) to mobile learning (M-Learning) [3, 4], and currently pervasive learning (U-Learning). Informal learning methods have also become more flexible, convenient, and personalized. Universal learning refers to the learning process in which anyone uses any device at any time and place to access any learning resources and enjoy ubiquitous learning services for digital libraries and digital learning portals, ubiquitous learning is bound to be the next development trend. Due to the abundance of learning resources in the ubiquitous learning environment, some learning materials that are useless for learning objectives can act as noise and have a certain negative impact on users' learning outcomes. Therefore, meeting the personalized reading needs of users anytime and anywhere is one of the goals pursued by digital libraries in the era of ubiquitous learning.

Reference [5] put forward a suggestion model for web-based educational resources in colleges and universities, founded on online teachings' pragmatic necessities and campus resources' traits. This model obtains teaching requirements from online course systems, collects online teaching resources on campus through internal crawlers, and provides services for teachers, students, and employees through online teaching resource collection driven sub algorithms and fast recommendation sub algorithms. Reference [6] presented a Multi Layer Knowledge Graph Recommendation (MLKR) formula that fuses knowledge graphs. Incorporating knowledge graphs into jobs supported by multi-task characteristic learning; Resulting in an elevated level of communication between latent features and entities through inter-task cross-compression units, ultimately paving the way for a recommendation model. It is accomplished accurate guidance of course assets based on pupils' objectives, passions and proficiency. Reference [7] studied the recommendation system of curriculum ideological and political teaching resources based on Big data. In the hardware part, design the selection of underlying physical hosts and database servers. In the software part, it designs the reading and searching of ideological and political teaching resources based on Big data. Comparative experiments have shown that the designed recommendation system can provide users with higher accuracy and faster recommendation services in practical applications.

Due to the large amount of data support required for personalized recommendation and the sparse nature of students' interest data, it remains a challenge to obtain and process this data reasonably. Therefore, this document suggests an individualized form of guidance for English to Chinese translation tutorial material-based on transfer training. Transfer learning is used to describe the transfer status of teaching information resources, construct the interest matrix of students, and mine the interest of english-chinese translation, so as to ensure the personalized recommendation effect of english-chinese translation teaching information resources. Based on this, the K-means clustering algorithm is used to cluster English Chinese translation teaching information resources, and a personalized recommendation model for English Chinese translation teaching information resources is constructed, resulting in better diversity of personalized recommendations for English Chinese translation teaching information resources and higher F-Measure values.

2 Personalized Recommendation of Resources

2.1 Description of Transfer Status of Teaching Information Resources Based on Transfer Learning

Owing to the substantial volume and intricate varieties of academic informational data, when conducting program development tasks, the edge teaching information resource features perceived by the environment are fuzzy in expression. In this regard, this paper establishes a state perception model of English Chinese edge teaching information resources based on transfer learning [8]. By calculating the state of teaching information resources, it judges the state similarity between different teaching information resources, improves the sensitivity of algorithms to boundaries, and thus enhances the accuracy of resource data perception.

Define the tasks of all teaching information resources in English Chinese translation as dataset $R(x)$, and assume that there are n task teaching information resource data, with the set represented as:

$$R(x) = \{t_1, t_2, t_3, \cdots, t_n\} \tag{1}$$

In the formula, t_n represents the frequency of task execution.

Transfer learning is a machine learning method that takes Task 1 as the initial point of the development model and reuses it in Task 2 development model. Select a task model with high applicability and calculate the changes in relevant parameters of teaching information resources in the transfer task: reduce the search range of the perception model for resource teaching information resources through the transfer frequency and the perception probability of teaching information resource state.

(1) The expression of transfer frequency is:

$$L(x)\{M(n) = t_{i+n} | M(n) = t_i, t_i, t_{i+n} \in R(x)\} \tag{2}$$

Under the specified statistical window, t_i represents the frequency at which the i-th migration task is executed; t_{i+n} represents the frequency of task execution after $n + i$ migrations.

(2) The transfer frequency can be used to determine the transfer probability of tasks within teaching information resources, thereby deriving the transfer probability of the previous teaching information resource in the power Internet of Things. The expression formula is:

$$P(x)\{M(n) = t_{i+n}|M(n) = t_i, t_i, t_{i+n} \in R, n \geq 1\} \tag{3}$$

When $n = 1$ is in the equation, it represents the probability of the next transfer of the current teaching information resources.

Within the specified data statistics window t_n, the probability matrix Q for the next transfer task is defined by the real-time status values of teaching information resources as follows:

$$Q = \begin{Bmatrix} P(x)_{11} & P(x)_{12} & P(x)_{13} & \cdots P(x)_{1n} \\ P(x)_{21} & P(x)_{22} & P(x)_{23} & \cdots P(x)_{2n} \\ P(x)_{31} & P(x)_{32} & P(x)_{33} & \cdots P(x)_{3n} \\ \vdots & \vdots & \vdots & \vdots \quad \vdots \\ P(x)_{n1} & P(x)_{n2} & P(x)_{n3} & \cdots \; P(x)_{nm} \end{Bmatrix} \tag{4}$$

Using the transfer frequency and transfer probability values as the change parameters of the state aware model, when the execution frequency of teaching information resources is $t_i = R_i$, $t_{i+1} = R_j$, O_{ij} is used to express the frequency of each data transfer. At this time, there can be:

$$O_{ij} = O\{M(n) = R_j|M(n) = R_i\} \tag{5}$$

In the formula, R_{ij} denotes the likelihood value of transmitting educational informational data R_i from the origin R_j, expressed as:

$$R_{ij} = P(x)\{M(n) = O_j|M(n) = O_i\} \tag{6}$$

Calculate the time it takes for a data teaching information resource to migrate to another teaching information resource in the Internet of Things, and calculate the average migration frequency of all tasks within that window to obtain the average migration probability R_{ij}^2:

$$R_{ij}^2 = \frac{I_{ij}}{I_i} \tag{7}$$

$$I_i = \sum_{j=0}^{n} I'_{ij} \tag{8}$$

In the formula, I_{ij} represents the frequency at which all teaching information resources are transferred from the same location to another location in English Chinese translation. Usually, a perceived teaching information resource in English Chinese translation can exist in multiple normal states, exhibiting different states at different times or situations. The state sequence of teaching information resource work on the timeline is represented as a state flow. So, through state sequences and state flows, the real-time state of data can be accurately perceived, improving the accuracy of resource recommendations.

2.2 Building a Student Interest Matrix

In this paper, the collaborative filtering method is used to mine the links between students' browsing English websites [9]. Starting from offline data, obtain student group information, English Chinese translation teaching information resource information, and resource rating information, and demonstrate the connection between specific students and specific resources through the student English translation teaching information resource bipartite diagram shown in Fig. 1.

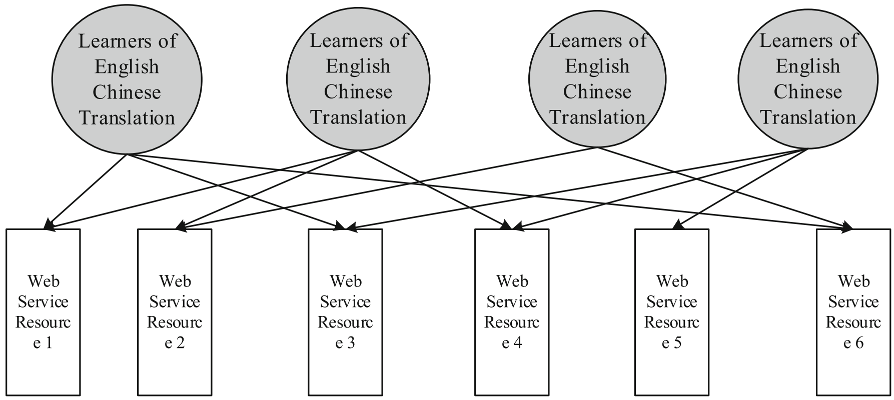

Fig. 1. Two parts of teaching information resources for English Chinese translation

Drawing on the bipartite graph, illuminate the interdependence among pupils and English to Chinese translation tutorial materials, and assign a weight to the scholar's evaluations of the resources. The larger the weight, the more students prefer the service resource. The adjacency matrix is established based on the student project relationship diagram.

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1a} \\ e_{21} & e_{22} & \cdots & e_{2a} \\ \vdots & \vdots & \ddots & \vdots \\ e_{1b} & e_{2b} & \cdots & e_{ab} \end{bmatrix} \tag{9}$$

In the formula, E represents the adjacency matrix of student English Chinese translation teaching information resources, e represents the relevance between resources and students, a denotes the quantity of pupils, and b denotes the overall quantity of service resources.

The evaluation of a certain English Chinese translation teaching information resource by students will be influenced by other students, and the main ways of influence include comments and replies [10]. The calculation formulas for the influence relationship between students' comments and responses are expressed as follows:

$$I_{(i,j)} = \frac{H_{i\to j}}{\sum\limits_{l\in L, l!=i}^{L} H_{i\to l} + 1}, U_{(i,j)} = \frac{\chi_{i\to j}}{\sum\limits_{p\in P, p!=i}^{P} \chi_{i\to l} + 1} \tag{10}$$

The formula consists of the following variables: i, j refer to a pair of learners, I denotes the relative significance of feedback comments, U denotes the weightage of feedback responses, l represents the complete count of resource comments, L denotes the aggregate amount of feedback responses, p refers to the sum total of replies associated with a particular educational resource, P denotes the cumulative amount of feedback responses on a given resource, H represents the number of times student i is affected by student j's comments, and χ represents the number of times student i is affected by student j's replies.

According to the influence values of comments and responses obtained from formula (10), the degree of influence of one student on another student is determined, and then the influence parameters are fused to obtain the student influence relationship matrix:

$$M = \lambda \times I_{(i,j)} + \theta \times U_{(i,j)} \tag{11}$$

In the formula, λ represents the comment influence parameter, θ represents the reply influence parameter, and M represents the student influence relationship matrix. Optimize the initial student interest matrix based on the student influence relationship matrix, reconstruct it into a new student interest matrix, and use it as input for the next step of the maximum entropy resource personalized selection algorithm [11].

2.3 Interest Mining in English Chinese Translation

This study takes the browsing content and frequency of previous English Chinese translation teaching information as the basis, and on this basis, captures and mines students' interest in English Chinese translation. The specific operation process is shown in Fig. 2.

To independently reflect students' interest in English Chinese translation, a binary function is constructed based on the content in Fig. 2, which includes:

$$F(a_i) = [\aleph 1, \aleph 2, \aleph 3] \tag{12}$$

Among them, $\aleph 1$ represents save; $\aleph 2$ represents a collection; $\aleph 3$ represents download. If $F(a_i) = 1$, it indicates that students are interested in this type of English Chinese translation teaching information; $F(a_i) = 0$ indicates that students are not interested in this type of English Chinese translation teaching information. Due to the uncertainty in the application process of this function, it needs to be optimized. Considering the content of the video itself, the duration of the video resource is set to G_I. The higher this value, the lower the interest of students in it. Use N to indicate the number of times students click on teaching information, which is positively correlated with students' interest in

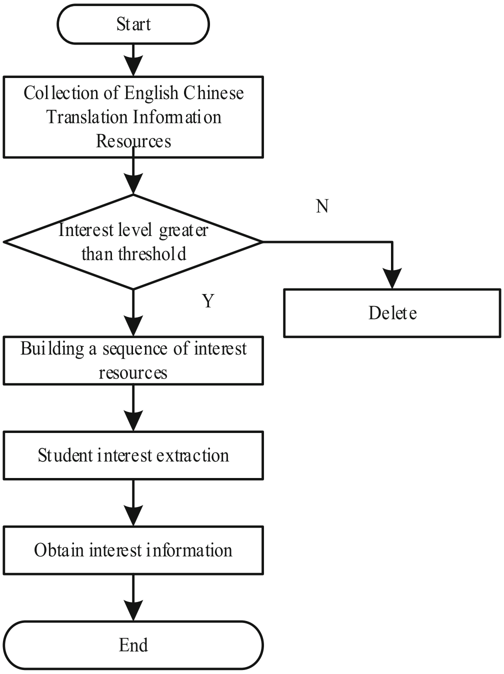

Fig. 2. Process for capturing students' interest in English Chinese translation

such teaching information. The higher the value of N, the higher the students' interest in this type of video [12]. The utilization of T_I symbolizes the duration scholars spend on accessing educational data, and there is a direct link between pupils' enthusiasm regarding educational material categories, but it is not that the higher the T_I value, the more interested students are in it. When evaluating T_I, it is necessary to set a maximum value to constrain it. Predicated on the former analysis outcome, students' interest in a certain teaching information can be calculated using the following formula:

$$f_q = \delta \frac{N}{G_I \max T_I} r^{-|T_I - \max|} \tag{13}$$

Among them, δ represents the adjustment factor during the calculation process; r represents the coefficient of interest. Based on the above analysis, students' interest in a specific type of English Chinese translation teaching information can be expressed as:

$$F_q = \min\{F(a_i), F_q + 1\} \tag{14}$$

According to the above formula, when students' interest in a specific type of English Chinese translation teaching information is greater than F_q, it can be used as a decision-making factor for recommending teaching information.

2.4 Clustering of English Chinese Translation Teaching Information Resources

Cluster processing of English Chinese translation teaching information resources using K-means clustering algorithm. The principle of K-means clustering algorithm is to first obtain k English Chinese translation teaching information resource objects x, and treat them as the clustering center J of the cluster; Solve the distance d between the English Chinese translation teaching information resource object x and the initial k; Move x to the class where J with the smallest d is located; Then calculate the mean of all English Chinese translation teaching information resource samples within the cluster, obtain a new J, denoted as C_{new}; Finally, iterate repeatedly until convergence is achieved, and output the clustering results of English Chinese translation teaching information resources. The clustering criterion function of this algorithm is as follows:

$$U_{\text{Clustering function}} = \sum_{i=1}^{k} \sum_{p \in C_i} \|x - M_i\|^2 \tag{15}$$

Among them, the clustering center of the i-th English Chinese translation teaching information resource object is C_i; The mean of C_i is M_i.

The process of K-means clustering algorithm for processing English Chinese translation teaching information resources is shown in Fig. 3.

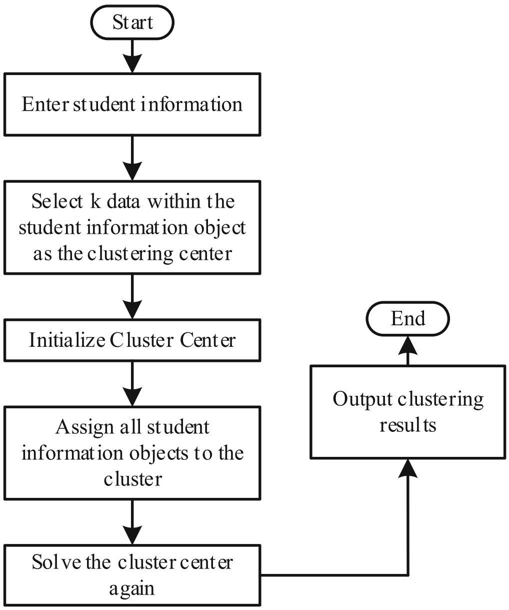

Fig. 3. Clustering Process of Teaching Information Resources for English Chinese Translation

The specific steps for clustering English Chinese translation teaching information resources are as follows:

Step 1: Input the English Chinese translation teaching information resources from the current student database and the previous student database;
Step 2: Based on the teaching information resources of English Chinese translation, determine the clustering number k and utilize it as the initial grouping nucleus;
Step 3: Compute the disparity among the remaining English to Chinese translation tutorial material objects and the solution;
Step 4: Calculate the mean of each English Chinese translation teaching information resource object in each cluster;
Step 5: Repeat steps 3 and 4, with no change in mean as the termination condition;
Step 6: Output the clustering results of English Chinese translation teaching information resources.

The K-means clustering algorithm has the advantages of easy and convenient operation, and can quickly cluster and process English Chinese translation teaching information resources. However, noise points and isolated points have a significant impact on the algorithm, and only spherical clusters can be found, which affects the clustering effect of English Chinese translation teaching information resources. Therefore, a random sampling method is used to improve the algorithm [13].

2.5 Personalized Recommendation of English Chinese Translation Teaching Information Resources Based on Transfer Learning

In order to improve the recommendation accuracy of English Chinese translation teaching information resources under the application of transfer learning, the bipartite graph model is introduced. Suppose that in this model $G(U, I, E)$, U, I and E are composed of the highest-tier group of nodes, the lowest-tier group of nodes, and the set of connections between them, and any nodes contained with in the highest-tier or lowest-tier group are not directly linked. If there are m students in the recommendation system and the goal is to reach n students, generate a weight matrix with $m \times n$ dimensions in the following manner:

$$W = \{w_{pq}\}(1 \leq p \leq m, 1 \leq q \leq n) \tag{16}$$

If student u_p has a rating for label i_q, then w_{pq} in the weight matrix takes a value of 1, otherwise, it takes a value of 0; If student u_p is no label rating available for the specified item i_t, and assign a portion of the available resources to label y. Within the two-partite graph, first send the resources to the students with the connection tag i_t, and then send the resources to all tags through the students. Calculate the resource obtained by any label i_s on label i_t using the following formula:

$$d_{st} = \frac{x}{k(i_t)} \sum_{p=1}^{m} \frac{w_{ps} w_{pt}}{k(u_p)} \tag{17}$$

In the above equation, there are $k(i_t)$ students who assess the rating of the label i_t, and the number of labels rated by student u_p is $k(u_p)$.

Obtain all resource vectors $F = (d_{1t}, d_{2t}, ..., d_{nt})$ for all tags, and express the resource proximity between unrated tags and any tag i_s using the following formula:

$$c_{ts} = \frac{d_{st}}{d_{tt}} \tag{18}$$

The above equation describes the degree of voluntary resource sharing between label V and label i_s, with a numerical span from 0 to 1. The greater the value, the more extensive the level of self-initiated distribution.

Based on the proximity of unrated label i_t to the remaining label resources, calculate the predicted score for student u_p with label i_t, as follows:

$$B_{pt} = \frac{\sum\limits_{R_{ps} \neq \emptyset} c_{ts} \times R_{ps}}{\sum\limits_{R_{ps} \neq \emptyset} c_{ts}} \tag{19}$$

In the above equation, the label i_s possesses a factual score of R_{ps} granted by student u_p.

Once the scoring matrix has been populated initially, the following scoring matrix A with relatively dense architecture:

$$A_{pj} = \begin{cases} R_{pj}, R_{pj} \neq \emptyset \\ B_{pj}, B_{pj} \neq \emptyset \end{cases} \tag{20}$$

Based on the similarity matrix generated by the topic, resource clustering is completed, each category represents a potential subject, and assuming there are two topics x_i and x_k, utilize Euclidean distance to determine the degree of similarity between the two topics, as follows:

$$sim(i, k) = -\|x_i - x_k\|^2 \tag{21}$$

With a collection of topics and their corresponding similarity scores, the attractiveness and membership data between topics are distributed by exploring each category of topics and their representative topics. The iterative stage of two informational metrics is involved in the confidence propagation algorithm's alternative updating process. Attraction $res(i, k)$ refers to the direction from topic x_i to topic x_k, which reflects the accumulated evidence of topic x_k, the topic serves as a proper exemplar and signifies its capacity to represent a category of topics. To determine the designation of a category representative for any given topic x_k, add up the Attraction F and Membership G values for every topic. As a result, topic B is now the certified category representative for topic x_i, as denoted by the following equation:

$$\arg\max_k \{av(i, k) + res(i, k)\} \tag{22}$$

Assuming that the diagonal element $sim(k, k)$ of the matrix of similarity scores is identical numerical value $p = \delta \times sim_{ave}^{(1)}$, initialize the attractiveness and attribution, and obtain:

$$res^{(0)}(i, k) = av^{(0)}(i, k) = 0 \tag{23}$$

Use the following formula to update the information content of attractiveness and belonging:

$$res(i,k) \leftarrow sim(i,k) - \max_{k's.t.k' \neq k}\left\{av\left(i,k'\right) + sim\left(i,k'\right)\right\} \tag{24}$$

When $i \neq k$, there is the following expression:

$$\begin{aligned} &av(i,k) \\ &\leftarrow \min\left\{0, res(k,k) + \sum_{i's.t.i' \in \{i,k\}} \max\left\{0, res\left(i',k\right)\right\}\right\} \end{aligned} \tag{25}$$

$$av(k,k) \leftarrow \sum_{i's.t.i' \neq k} \max\left\{0, res\left(i',k\right)\right\} \tag{26}$$

Retrieve the topic's respective category centers, and if the outcome surpasses the highest value attained in a single iteration, as well as the data variation being lower than a pre-fixed level, and the chosen category centers persist consistently throughout sequential iterations, the algorithm terminates, and the topic category centers are then ranked in a descending order, ultimately producing the final personalized recommendation.

3 Experimental Demonstration Analysis

In this study, a new personalized recommendation method for teaching information resources of English Chinese translation was proposed. To determine the practicality of this method, a trial segment was established to assess the operational efficacy of this methodology. The comparison method is the teaching resource recommendation method based on internal crawler collection proposed in reference [5] and the teaching resource recommendation method based on fusion knowledge graph proposed in reference [6].

The English Chinese translation resources used in this study are the LDC Chinese English parallel corpus, covering 3 types of corpus content, with a total of 5000 teaching information as a video collection. The educational materials utilized in the experiment are presented in Table 1.

Table 1. Experimental Overview

Experimental group	X1	X2	X3
Number of categories	3	3	3
Number of teaching resource corpus information	5000	15000	12000
The maximum number of corpora for various teaching resources	200	1200	1500
Minimum number of corpora for various teaching resources	1000	2000	3000

Use the above data as the video data basis for this experiment, randomly shuffle it and import it into the experimental platform database. Randomly select 10 students as the experimental subjects, and organize the viewing and browsing records of English Chinese translation teaching information of these 10 students within the past month to obtain their favorite teaching information type. In this experiment, five types of teaching information were set as A1, A2, A3, A4, and A5, and students' preferences for teaching information were analyzed based on this classification. A detailed breakdown of the analytical findings can be found in Table 2.

Table 2. Summary of Student Interest Information

Student serial number	Behavior data volume/piece	Number of videos/piece	Interest Type
Student 1	154810	1205	A1, A3
Student 2	215421	1200	A3, A4
Student 3	167881	952	A2, A3
Student 4	89927	3157	A2, A5
Student 5	145266	5152	A1, A5

After analyzing the amount of student behavior data and the number of videos watched, different types of students' interest in English Chinese teaching content were obtained. For the convenience of subsequent experimental analysis, in this study, only the video types that students are most interested in and the second type of interest were summarized, providing a control group for the experimental analysis process.

3.1 Implementation Details and Evaluation Indicators

Collect relevant data on English Chinese translation teaching information resources, including student learning behavior data and attribute data of teaching resources. Transfer learning is used to describe the transfer status of teaching information resources, construct the interest matrix of students, mine the interest of English Chinese translation, cluster the teaching information resources of English Chinese translation by K-means clustering algorithm, and build a personalized recommendation model of English Chinese translation teaching information resources. Using the reference [5] method, the reference [6] method, and the reference [7] method as comparative methods, the recommendation results under different methods are compared. Cluster performance, Intra list similarity (ILS), and F-Measure value indicators are used to evaluate the performance of the method. The experimental results are analyzed in depth to explore the advantages and limitations of the personalized recommendation method studied.

3.2 Clustering Effect Test

The model in this article is used to cluster the teaching information resources of English Chinese translation. The teaching information resources of English Chinese translation consist of three attributes, and the clustering results of the teaching information resources of English Chinese translation are shown in Fig. 4.

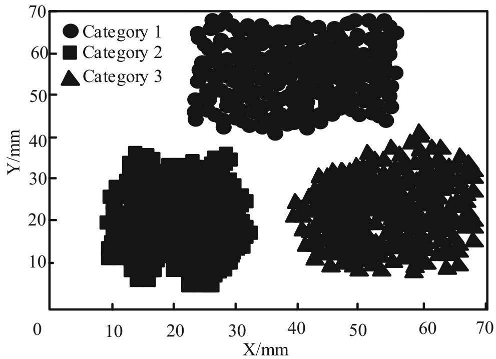

Fig. 4. Clustering Results of English Chinese Translation Teaching Information Resources

According to Fig. 4, the model in this article can effectively cluster English Chinese translation teaching information resources. The clustering results are divided into three categories, which are consistent with the actual number of attributes of English Chinese translation teaching information resources. After clustering, the boundary of English Chinese translation teaching information resources in this model is clear, and there is no confusion. The experiment proves that the model proposed in this paper can accurately cluster teaching information resources for English Chinese translation.

3.3 Diversity Testing

Intra list similarity (ILS) is an evaluation indicator for evaluating the diversity of recommendation lists. Under normal circumstances, the smaller the ILS value, the poorer the diversity of recommendation lists. The diversity evaluation metrics are determined by utilizing the following formula:

$$A = 2/j(j-1)\sum_{x \neq 0} Sim(x_1 \cdot x_2) \tag{27}$$

In the formula, j represents the richness of the recommendation list; x_1 represents similarity measure; x_2 represents student preference characteristics.

To obtain further evidence supporting the diversity-enhanced recommendation capacity of the proposed approach, unique to the aforesaid experiments, the diversity evaluation indicators of four experimental personnel were calculated separately. The diversity rating metrics for various techniques are observed in Table 3.

Table 3. Diversity Evaluation Indicators of Different Methods

Number of experiments	Test method	Diversity evaluation indicators
100	Proposed method	0.97
	Reference [5] Method	0.24
	Reference [6] Method	0.22
	Reference [7] Method	0.65
200	Proposed method	0.95
	Reference [5] Method	0.51
	Reference [6] Method	0.36
	Reference [7] Method	0.66
300	Proposed method	0.96
	Reference [5] Method	0.58
	Reference [6] Method	0.60
	Reference [7] Method	0.65
400	Proposed method	0.98
	Reference [5] Method	0.48
	Reference [6] Method	0.44
	Reference [7] Method	0.69

As shown in Table 3, among the four experimenters, the diversity evaluation index of the proposed method consistently exceeded 0.95, indicating a strong diversity of individual student recommendation lists under the proposed method. The diversity evaluation indicators of both the reference [5] method, the reference [6] method and the reference [7] method are below 0.7, indicating poor diversity of individual student recommendation lists under the reference [5] method, the reference [6] method and the reference [7] method. Through the above comparison, it is further verified that the diversity recommendation performance of the proposed method is superior to traditional methods.

3.4 F-Measure Value Test

Upon thoroughly examining the personalized resource recommendation challenge, it has been ascertained that resolving this matter entails two circumstances: one being recommendation, while the other involves a lack of recommendation. Within the analysis phase associated with recommendation techniques, the issue can be regarded as a classification problem. Therefore, to evaluate the performance of the English-Chinese translation teaching information resource personalized method based on maximum entropy, the F-measure metric was selected as the performance assessment tool, with the following calculation formula:

$$F - Measure = \frac{2 \times P \times R}{P + R} \tag{28}$$

In the equation, P signifies precision and R represents retrieval. The F-Score metric is employed as an assessment criterion, and the greater the computed value, the more appropriate the suggested outcomes are for the requirements of learners.

To precisely exhibit the excellence of the suggested approach in the manuscript, six rounds of recommendation trials were performed by utilizing four different techniques. The number of recommended resources was set to 50, 100, 200, 300, 500, and 1000, respectively. Based on the recommendation results, F-Measure values of different methods were compared as shown in Fig. 5.

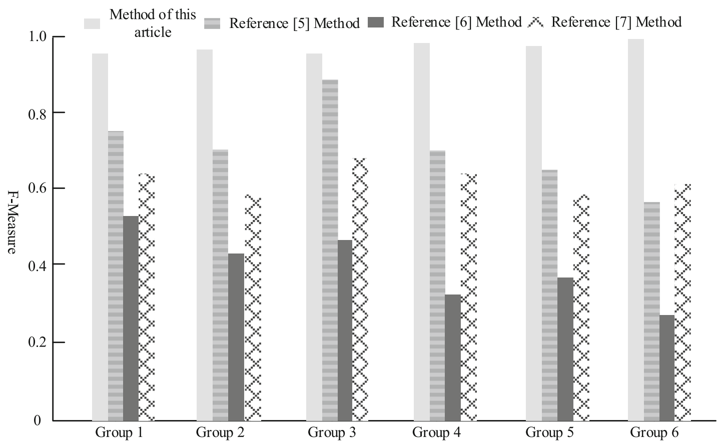

Fig. 5. Comparison of F-Measure values for different recommendation methods

As evidenced by Fig. 5, the mean F-Score outcome of the resource suggestion approach devised in the paper is 0.92, in contrast to the mean F-Score results of 0.51, 0.59 and 0.62 for the other three suggestion methods. From this, it can be seen that compared with the reference [5] method, the reference [6] method, and the reference [7] method, the research method can achieve good application results in personalized recommendation of English Chinese translation teaching information resources.

4 Conclusion

The teaching resources for English Chinese translation are not only abundant in quantity, but also diverse in variety. Therefore, how to classify and filter the vast amount of English Chinese translation teaching resources, and screen out information that matches the personalized needs of learners, is a present issue that necessitates thorough resolution. The current article suggests a personalized suggestion technique for English Chinese translation instructional materials resting on transfer learning. A state perception model of English Chinese edge teaching information resources based on transfer learning is established to calculate the state of teaching information resources, judge the state similarity between different teaching information resources, improve the sensitivity of algorithms to boundaries, and then enhance the accuracy of resource perception. Based on the implicit behavioral characteristics of students, obtain student group information, English Chinese translation teaching information resource information, and resource rating information. On this basis, students' interest in English Chinese translation is captured and mined, and K-means clustering algorithm is introduced to cluster English Chinese translation teaching information resources. An individualized suggestion framework for English Chinese translation instructional resources is established based on the information content of allure and inclusion. As demonstrated by the experimental outcomes, the proposed approach exhibits superior efficacy. However, personalized recommendation relies on a large amount of user behavior data and resource data for model training. However, in the field of education, especially in the field of English Chinese translation teaching resources, there is relatively little available data, resulting in limited model training. Therefore, with the development of educational information technology, more user behavior data and resource data will be collected and organized in the future, providing more and better data to support personalized recommendation model training.

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Research on Evaluation Method of Medical Rehabilitation Teaching Quality Based on Historical Big Data Decision Tree Classification

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Abstract. The current evaluation matrix of medical rehabilitation teaching quality is mostly one-way, and the scope of evaluation is limited, resulting in an increase in the average difference of evaluation. Therefore, the design and research of the evaluation method of medical rehabilitation teaching quality based on historical big data decision tree classification is proposed. According to the actual measurement and analysis, set the basic teaching quality evaluation indicators, use the multi-level form, break the limitation of the evaluation range, develop the multi-level evaluation matrix, design the decision tree classification evaluation structure, build the historical big data decision tree classification evaluation model, and use the top-level improvement analysis to achieve quality evaluation. The final test results show that the analysis of the test results has been completed: after five cycles of measurement, the quality of medical rehabilitation teaching has been evaluated for five items, namely, professional ethics, teaching ability, teaching methods, teaching arrangements, and teaching effects. The final evaluation mean difference has been well controlled below 1.5, indicating that this evaluation method is highly targeted and stable, it has practical application value.

Keywords: Historical big data decision tree · Medical rehabilitation teaching · Teaching quality assessment

1 Introduction

As an important medical applied discipline, medical rehabilitation mainly refers to the use of medical means to diagnose, assess and treat patients from a medical perspective, so as to promote the recovery of physical functions of patients [1]. The application of medical rehabilitation plays an important role in promoting human survival and quality of life to a certain extent. It is of great significance in the whole process of prevention, health care, treatment and rehabilitation throughout the medical work. At present, China's medical rehabilitation is still in its infancy, which is seriously restricted by the

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lack of rehabilitation talents. Therefore, in medical colleges and universities, the evaluation of the quality of medical rehabilitation teaching has gradually become the top priority of the development of professional education [2]. After years of construction and development, medical rehabilitation teaching has made rapid progress. It has made remarkable achievements in curriculum system, curriculum content, teaching methods, textbook compilation and teacher level, and has cultivated a large number of medical talents [3]. However, for a long time, due to the influence of external environment and specific factors, coupled with the background of exam oriented education, some traditional medical rehabilitation quality assessment and assessment methods are not formal and reasonable, which seriously hindered the development of students' personality and the cultivation of innovation ability. For example, the traditional medical rehabilitation examination mostly adopts the form of closed book examination, and the form of assessment presents a more solid form [4]. In addition, some higher vocational medical schools do not attach importance to the evaluation of the quality of medical rehabilitation teaching, and only focus on memorizing key knowledge. The daily teaching situation has not been timely fed back, ignoring the evaluation and analysis of knowledge application and ability cultivation. In addition, there are also great loopholes in the evaluation of the examination [5]. Usually, examinations are also equivalent to a form of targeted teaching quality assessment, but the examination content set by the school is basically a simple repetition of textbooks or notes. Students can easily pass the examination by rote, instead of comprehensively investigating students to obtain the most intuitive teaching quality assessment results. In addition, the evaluation of teaching quality for some abilities that are important in the future society, such as language expression ability, practical operation ability, organizational ability, and the ability to cooperate with others, is often ignored [6]. In particular, medical rehabilitation is a professional subject with strong practical operability. If a relatively complete and closely related teaching evaluation structure is not established, students' ability of linking theory with practice, hands-on ability, and clinical application ability will be poor. It is difficult to make progress in the future. Therefore, aiming at the problem of increasing evaluation difference existing in traditional methods, this paper proposes an evaluation method of medical rehabilitation teaching quality based on historical big data decision tree classification. The so-called historical big data decision tree classification mainly refers to a multi-directional decision classification method that forms a decision tree to obtain the probability that the expected value of the net present value is greater than or equal to zero, evaluate the project risk, and judge its feasibility based on the known probability of occurrence of various situations through the analysis and verification of historical data and information. It is a graphical method [7] that intuitively uses probability analysis. Therefore, this article combines this classification form with the quality evaluation method of medical rehabilitation teaching, further expanding the actual evaluation scope to a certain extent, solving the problem of limited evaluation scope, and achieving the reform of the quality evaluation method of medical rehabilitation teaching. This method first sets basic teaching quality evaluation indicators based on actual measurement analysis, and then adopts a multi-level form to break the limitations of evaluation scope and develop a multi-level evaluation matrix, making the evaluation results more comprehensive and detailed. Finally, design a decision tree classification evaluation structure, construct a historical big data decision tree classification evaluation model, and use top-level improvement analysis to achieve quality evaluation, effectively reducing evaluation differences. This can objectively evaluate the quality of medical rehabilitation teaching and evaluate it based on students' personalized situations, helping medical rehabilitation teachers better meet students' needs. It helps to improve the quality and effectiveness of medical rehabilitation teaching, achieve true evaluation of quality education, promote the cultivation of students' innovative thinking, and improve their comprehensive qualities. The specific Technology roadmap is shown Fig. 1 below.

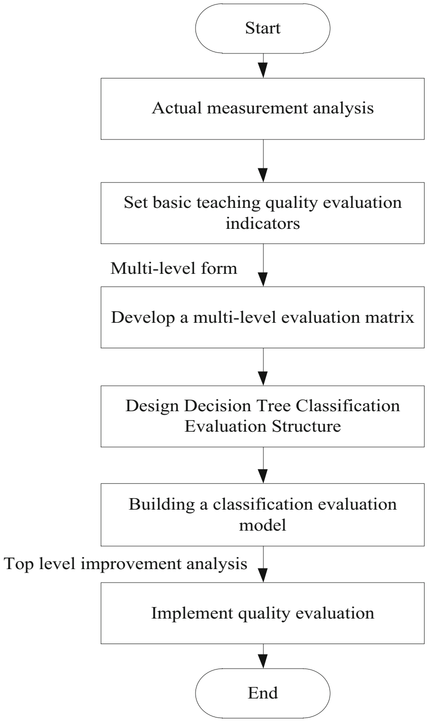

Fig. 1. Schematic Diagram of Technology roadmap

2 Design the Quality Evaluation Method of Medical Rehabilitation Teaching History Big Data Decision Tree Classification

2.1 Setting of Basic Teaching Quality Evaluation Indicators

At present, there are relatively many methods and forms around teaching quality assessment, such as teaching quality assessment, teaching work assessment, classroom teaching quality assessment, subject teaching quality assessment, etc. [9]. The direction and content of the assessment are endless, and the indicators and standards extracted and set are also very different. However, although the directions of measurement are different, they all put forward evaluation objectives with the same value and significance from different angles, gradually forming a more complete and specific multi-level evaluation idea, which effectively promoted the development of teaching quality evaluation research. This time, it is mainly a process of building an evaluation system, setting teaching objectives and teaching requirements, and using a variety of evaluation methods and means to give scientific value judgments on teaching and its effects based on the current teaching quality evaluation basis [10]. First, set and define basic evaluation indicators, as shown in Table 1 below:

Table 1. Basic Teaching Evaluation Index Setting Table

Basic teaching evaluation indicators	define	Teaching quality evaluation stage
Weight value	Proportion of evaluation projects	Basic assessment
Evaluation bias	Differences in the evaluation process	Differences in the evaluation process
Unit measurement value	Standard values for evaluation at the same stage	Basic assessment
Source of rehabilitation teaching data	Daily collection	Practical evaluation
Evaluation standard deviation control ratio	Conversion ratio of evaluation errors	Practical evaluation
Decision Tree Orientation Evaluation Criteria	Evaluation criteria set through historical data	Top level evaluation
Evaluation stage	Basic assessment + practical assessment + top-level assessment	Top level evaluation

According to Table 1, complete the setting and analysis of basic teaching evaluation indicators. The above extracted teaching instruction evaluation indicators are basic measurement indicators, with strong pertinence and wide application scope. Then, the indicators were deepened by integrating the classification principle of historical big data decision tree. In fact, for the teaching evaluation of the medical rehabilitation discipline, the teaching purpose is usually taken as the standard, and the realized teaching purpose is used to grasp the teaching status, design the corresponding evaluation hierarchy and goals, and finally use the inspection and evaluation of the teaching effect to judge the degree of realization of the teaching purpose, so as to obtain the final evaluation results. The setting structure of medical rehabilitation teaching quality evaluation index is divided into two parts, namely teaching process evaluation and teaching achievement evaluation. Teaching process evaluation mainly reflects teaching quality through classroom teaching level, and collects relevant indicators, actual values and information.

The teaching achievement evaluation mainly reflects the teaching quality through the level of students' learning ability. The evaluation indicators designed in the process are more diversified and targeted. Under different background environments, the values will change accordingly, which is more flexible. However, it should be noted that although the perspective and coverage of the two assessments are different, the focus of the assessment is the same, both of which are to assess teachers' teaching quality. Generally, Gaver attaches importance to the evaluation of the teaching process. In this process, teachers are the educational goals set by the root. They formulate and implement teaching plans and guide students to learn, so that students can gradually achieve the expected teaching goals. The evaluation scope is relatively large, and the evaluation is flexible and transformative. They can also conduct appropriate research and observation on students. The feedback information of evaluation is obtained through its real response, and the final evaluation results are analyzed and researched in a timely manner, which lays a solid foundation for the follow-up quality evaluation of teaching indicators.

2.2 Develop Multi-level Evaluation Matrix

After setting the basic teaching quality evaluation indicators, the next step is to develop a multi-level evaluation matrix based on the classification principle of the historical big data decision tree. From the overall point of view, the design of the matrix needs to formulate multi-level and multi-level teaching quality assessment objectives. The basic basis for the matrix design considered in the process is three aspects. One is the basic assessment objectives and guidelines. Including the content of daily teaching quality evaluation, it must be analyzed based on the initially set guidelines, guided by the training objectives, emphasized the general evaluation principles, and formed the basic evaluation guidelines. Calculate the evaluation weight value, as shown in Formula 1 below:

$$H = (1 - m) + \Im n^2 \times \varpi \tag{1}$$

In Formula 1: H Represents the evaluation weight value, and the evaluation weight value represents the directional evaluation conversion ratio, $\Im$ Indicates the deviation of directional evaluation settings, n Represents the number of evaluations, ϖ Indicates the number of overlaps. According to the above determination, the evaluation weight value can be calculated. The evaluation standard is set as the initial evaluation structure to clarify the specific direction of medical rehabilitation education, and the overall goal is to cultivate new qualified medical talents. Second, from the perspective of the evaluation subject of teaching quality, the design of the matrix should be guided by the evaluation guidelines and training objectives, and the comprehensive implementation of the education guidelines and training objectives should be the starting point and foothold of the evaluation work, whether it is daily teaching or directional expansion.

Higher vocational colleges need to conduct their own multi-level and multi-objective positioning, and extract their own characteristics of quality assessment. It is converted into the corresponding matrix to implement the judgment criteria and form a stable evaluation system. The specific training objectives are also the basis for teaching quality evaluation, and the quality standards for training talents must be implemented. This is also a concentrated reflection of the society's requirements for talent specifications. The educational assessment objectives formulated not only restrict the training objectives of colleges and universities, but also provide the overall standards for teaching quality assessment, which provides a more stable social basis for various assessment objectives and assessment standards. That is to say, the overall evaluation goal set by the school needs to be consistent with the social goal, which is not only the fundamental basis for evaluating the level of medical education, but also the basic basis for measuring teaching achievements, forming a correct evaluation value orientation, and obtaining the most authentic evaluation results. The third is the top-level evaluation. After the final teaching of medical rehabilitation, set equivalent analysis standards and build a multi-level and multi-stage evaluation structure, as shown in Fig. 2 below:

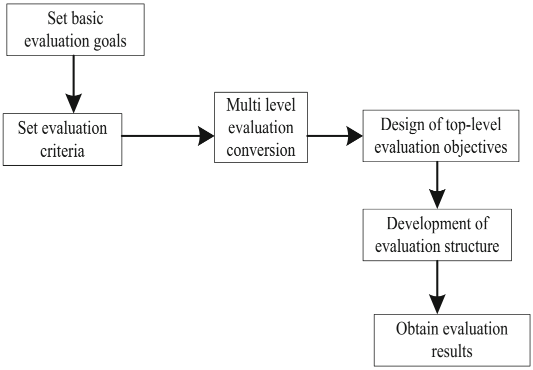

Fig. 2. Top level matrix evaluation structure diagram

According to Fig. 2, the design and validation study of the evaluation structure of the top-level matrix was completed. The top-level design and evaluation processing of the matrix is a relatively comprehensive evaluation form with strong pertinence, which can collect corresponding data and information from multiple directions. Next, based on this, we need to clarify the corresponding evaluation framework in the matrix. The teaching evaluation plan based on the teaching syllabus stipulates the real-time objectives, tasks, requirements and contents of medical rehabilitation teaching evaluation in the form of a syllabus, designs a more influential direct evaluation basis for the matrix, and completes the formulation and application of multi-level evaluation matrix.

2.3 Design Decision Tree Classification Evaluation Structure

After setting the multi-level evaluation matrix, next, design the classification and evaluation structure of the decision tree in combination with the historical big data decision tree classification. In the daily teaching evaluation theory and practice, many different teaching evaluation methods and structures have been formed. These evaluation models can actually make correct and multi-dimensional evaluations of teaching quality from different sides and angles. Through the classification of decision-making, the evaluation structure is divided into the following parts. The first level of the evaluation structure is the quantitative and qualitative evaluation of medical rehabilitation. In fact, unlike other disciplines, medical rehabilitation teaching pays more attention to the training and learning of practical skills. If you want to evaluate the teaching quality, you can first adjust and modify the methods and forms of teaching quality evaluation, and divide the methods of teaching quality evaluation into quantitative evaluation and qualitative evaluation. The so-called quantitative evaluation structure is mainly based on the internal law of teaching, which refines the factors that affect teachers' teaching quality into thousands of aspects, designs a quantitative evaluation index system on this basis, and uses mathematical and statistical methods to make targeted treatment on the teaching evaluation results of medical rehabilitation, so as to form the evaluation results of a certain evaluation content. Quantitative evaluation is a teaching evaluation method formed after the introduction of social science "scientific behaviorism" research method into educational theory. Therefore, the quantitative evaluation method is also called "scientific method" or "standardized method". This is the change of the evaluation demand and standard of medical rehabilitation. The corresponding evaluation data source is collected. The main built-in evaluation methods are examination method, questionnaire method and statistical method. Moreover, in terms of the processing of the evaluation results, the quantitative evaluation methods mainly include scoring method and hierarchical method. In combination with the decision tree, the corresponding evaluation differentiation framework is designed, as shown in Fig. 3 below:

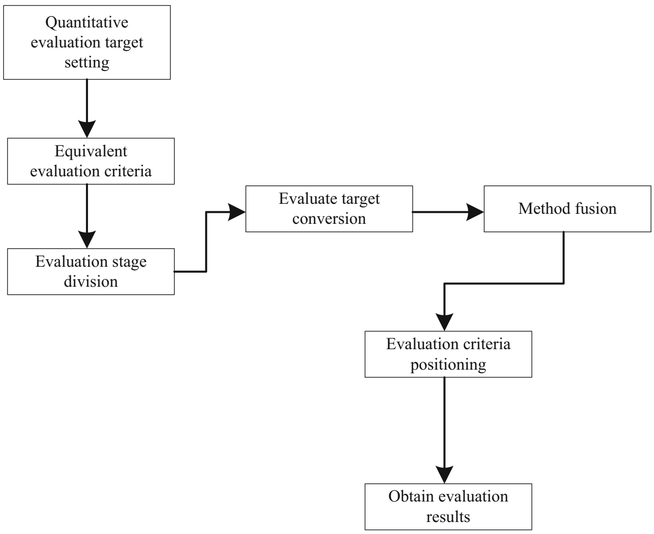

Fig. 3. Structure of evaluation differentiation framework

According to Fig. 3, complete the design and research of the evaluation differentiation framework structure. From the perspective of the evaluation value standard, in the overall structure, quantitative evaluation can also be integrated with relative evaluation method, absolute evaluation method and individual range evaluation method to expand the actual evaluation scope of medical rehabilitation teaching, strengthen the evaluation standard, and obtain more accurate and stable evaluation results. Next, we set the qualitative evaluation structure. This part generally refers to the qualitative analysis of teaching activities and their effects in the evaluation. Although quantitative evaluation has many advantages in the evaluation of medical rehabilitation teaching, as a complex system engineering, there are many factors that cannot be evaluated quantitatively, such as the teaching attitude, ethics and responsibility of medical rehabilitation teachers; In addition, there are some aspects that are not suitable for quantification, such as the teaching and research of medical rehabilitation teachers. For those aspects that cannot be quantified or are not suitable for quantification, we should conduct qualitative evaluation when conducting evaluation. Qualitative evaluation methods mainly include observation, evaluation, interview, etc. At the same time, the qualitative evaluation structure of medical rehabilitation teaching can be divided into internal evaluation and external evaluation. The specific relationship is shown in Fig. 4 below:

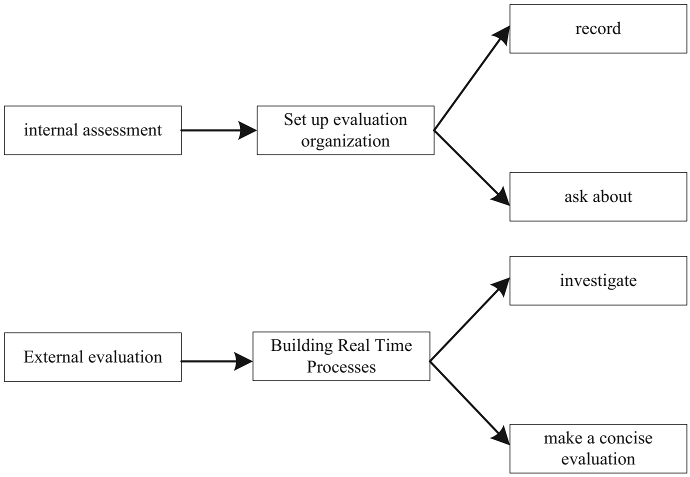

Fig. 4. Structure of the relationship between internal evaluation and external evaluation

According to Fig. 4, complete the design and adjustment of the structure of the relationship between internal evaluation and external evaluation. The so-called internal evaluation of medical rehabilitation teaching mainly refers to the teaching quality evaluation carried out by the internal department of the hospital according to the evaluation system formulated by it. It can be divided into superior evaluation, peer evaluation and subordinate evaluation according to the entity that implements the evaluation. The so-called external evaluation of medical rehabilitation teaching refers to the evaluation of its teaching quality by institutions or units outside the school system, mainly including employers, practice hospitals, and students' work units to evaluate the teaching quality and obtain the final teaching evaluation results by identifying the comprehensive quality of graduates.

At the same time, in the design of the evaluation structure, the organization procedure of the targeted evaluation is designed. The relevant departments of higher vocational colleges uniformly set plans, organize and coordinate. The comprehensive evaluation of the evaluation team is combined with the whole process evaluation of the teaching and research section, teachers' self-evaluation and students' evaluation to form a multi-dimensional comprehensive evaluation system. The organizational teaching quality evaluation system also includes the following steps: preparation before evaluation. For the personnel participating in the evaluation, they should be familiar with the basic contents of the teaching syllabus and teaching materials of medical rehabilitation, and set up a basic evaluation index system so as to know well. Followed by lectures and records. Make records and brief comments against the preset evaluation criteria. The third step is inquiry and investigation. Understanding the teaching evaluation effect of medical rehabilitation professional courses, scoring or rating according to the evaluation index system, and then holding a review meeting by the evaluation team or the teaching and research department is an important method for qualitative analysis of medical rehabilitation classroom teaching. The evaluators discussed the advantages and disadvantages of this class in detail, affirmed the results, pointed out problems and raised hopes. Then, on this basis, combined with the classification of the decision tree of historical big family data, comprehensive assessment needs and changes in standards, multi-level analysis and assessment were carried out. This part mainly focused on the directional performance of medical rehabilitation courses, including qualitative analysis and quantitative analysis, to make a comprehensive assessment of teaching quality, process the assessment results, and feed back to the teachers themselves. Find out the common tendentious problems in the evaluation results of a single teacher, and provide leadership decision-making reference, so as to take targeted improvement measures, strive to improve the teaching quality of medical rehabilitation discipline, and complete the design and application research of the classification evaluation structure of the decision tree.

2.4 Build a Historical Big Data Decision Tree Classification Evaluation Model

After completing the design of the classification and evaluation structure of the decision tree, the next step is to build a teaching quality evaluation model based on the classification principle of the historical big data decision tree. In recent years, with the development of domestic higher medical education, medical rehabilitation teaching is facing great challenges when the enrollment scale of its major vocational colleges continues to expand. In the current economic and social situation, the traditional medical rehabilitation teaching mode has been impacted to a certain extent. Teachers are responsible for three tasks: medical care, teaching and scientific research. It is common to attach importance to medical care, scientific research and teaching. The employment competition brought by the enrollment expansion also makes medical students face various pressures during rehabilitation study or internship, which is not conducive to further development in the future. Therefore, combined with the classification principle of historical big data decision tree, the directional evaluation error is calculated as shown in Formula 2 below:

$$B = \sum_{u=1} \beta u \times \frac{\beta w + a^2}{w(1-l)^2 + \chi} - 1 \tag{2}$$

Equation 2: B Indicates the orientation evaluation error, β Represents the scope of the assessment, u Indicates the evaluation level, w Represents the decision overlap value, l Represents the classified fixed value, a Represents the reference value. According to the above measurement, the calculation of directional evaluation error is realized, and it is set as the basic standard of the historical big data decision tree classification evaluation model, forming a complete evaluation built-in structure. Then, based on this, we set the orientation indicators and parameters of the evaluation model, as shown in Table 2 below:

Table 2. Evaluation Model Orientation Index and Parameter Setting Table

Evaluation Model Orientation Indicators	Reference Value	Controllable edge value
Evaluate balance ratio	1.25	1.64
Intervention value	16.35	18.51
Evaluate Statistical Mean	10.25	10.16
Poor directional evaluation	0.21	0.20
Evaluate coefficient of variation	4.5	6.3
Evaluation classification ratio	1.3	1.5
Poor quantitative evaluation	3.05	2.57

According to Table 2, set the orientation indicators and parameters of the evaluation model. Set the above set evaluation matrix inside the model to form a cyclical evaluation procedure, and calculate the unit evaluation benchmark value, as shown in Formula 3 below:

$$D = \pi^2 \times \sqrt{(1 - s) + \kappa} \tag{3}$$

In Formula 3: D Represents the unit evaluation benchmark value, π Represents the conversion evaluation value, s Represents the value of the basic evaluation unit, κ Indicates the overlapping evaluation range. According to the above settings, the calculation of the benchmark value of the unit evaluation is completed. Adjust the processing structure of the evaluation model by using the classification principle of historical big data decision tree. Next, research is carried out according to quantitative assessment and qualitative assessment to build a relatively complete evaluation system of medical rehabilitation teaching quality, improve and stabilize the teaching quality of rehabilitation medicine, combine the actual teaching needs and standards of higher vocational colleges, cooperate with daily teaching level assessment, and establish and improve a one-way teaching quality assessment model of medical rehabilitation.

However, it should be noted that the construction of the one-way teaching quality assessment model requires careful assessment of the teaching quality of classes, internships, and internships, and later assessment of many specific teaching activities involved in the medical rehabilitation teaching practice, such as ward rounds, case discussions, and various clinical skills, to strengthen the scope and pertinence of the assessment and further develop more detailed more specific evaluation framework, improve the processing capacity of the model through various specific evaluation operation indicators, reduce the occurrence of evaluation errors, and expand the actual evaluation range. On this basis, it is also necessary to combine the historical big data decision tree classification principle, and build an equivalent evaluation standard system for the specific application range and region of the model. Different environments have different evaluation targets, so it is necessary to calculate the allowable limit evaluation value in combination with the implementation stage of medical rehabilitation teaching, as shown in Formula 4 below:

$$F = \int \nu + \theta^2 \tag{4}$$

In Formula 4: F Indicates the allowable limit evaluation value, ν Represents the evaluation standard value of the initial planning, θ Indicates the cosntrollable evaluation range. According to the above determination, the calculation and analysis of the allowable limit evaluation value can be realized, which is set in the initial evaluation model to form a stable evaluation system, obtain the basic evaluation results of medical rehabilitation teaching, and lay a solid foundation for subsequent evaluation and analysis.

2.5 Top Level Improvement Analysis to Achieve Quality Assessment

After completing the construction of the historical big data decision tree classification evaluation model, next, combined with the actual evaluation needs and standards, the top-level improvement analysis method is used to finally achieve the evaluation of the quality of medical rehabilitation teaching. There is a big difference between the top level improvement evaluation processing form and the traditional evaluation form. The traditional evaluation of medical rehabilitation teaching quality is generally one-way. Although the form and structure can achieve the expected evaluation task or goal, it is often affected by the external environment and specific factors, resulting in inaccurate and unreliable evaluation results, affecting the upgrading and transformation of follow-up teaching forms. The top-level improvement just avoids the emergence and expansion of these problems.

Combined with the classification principle of historical big data decision tree, the top-level improvement is set to focus on medical rehabilitation experience and professional knowledge, and the specific mode different from the traditional medical instruction evaluation is designed. The objective and systematic evaluation criteria are used to design the corresponding evaluation criteria, so as to form a stable and cyclical evaluation effect. The specific evaluation system is designed in combination with the actual evaluation needs, as shown in Fig. 5 below:

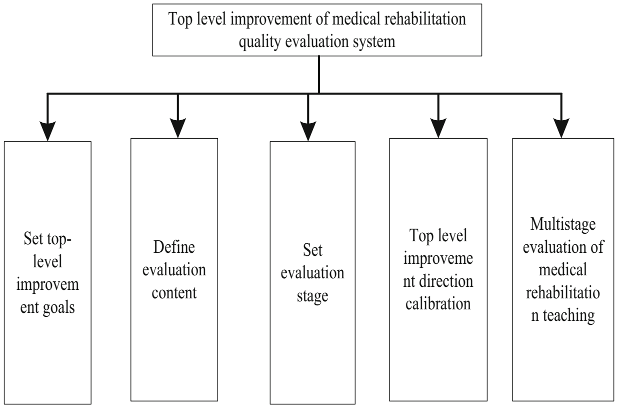

Fig. 5. Top level improved medical rehabilitation quality assessment system

According to Fig. 5, complete the design and research of the top level improved medical rehabilitation quality assessment system. Then, based on this, the top-level improvement processing indicators and parameters will be set. In general, the evaluation of the teaching quality of medical rehabilitation should formulate an improvement plan from the top-level design level, determine the construction plan and guarantee measures of future medical rehabilitation in the form of documents, re-examine the positioning and capability division of each functional department and teaching unit of the college, and further clarify how each work carried out by each department can better serve the teaching evaluation activities. Improve the quality of education and teaching services.

Strictly implement the accountability system of the person in charge of the evaluation department, effectively shift the focus of quality monitoring and guarantee from the establishment of rules and regulations to the implementation and rectification, regularly announce the implementation of evaluation of major issues to the whole school's teachers and students on the campus network or the work group, and urge the evaluation department with slow progress, insufficient strength and poor effect to implement the evaluation and rectify within a time limit. To ensure the progress and effect of quality improvement evaluation and improvement work, and form a more targeted improvement evaluation oriented analysis and discussion structure. At the same time, according to the setting of the actual evaluation range, design the limit range of the top-level improvement evaluation, and calibrate the corresponding conditions before and after the evaluation, as shown in Table 3 below:

Table 3. Evaluation Conditions of Medical Rehabilitation Teaching Quality

Evaluation level of medical rehabilitation teaching quality	Restrictions	Convertible conditions
Evaluate data collection hierarchy	Classification of data and information	Adjustment of evaluation index parameters
Evaluate Target Layer	Setting one-way evaluation goals	Set multi-directional evaluation goals
Transitional class	Evaluate structural adjustments	Establishment of evaluation system
Evaluation analysis layer	Initial Result Analysis	Result deepening research
Top level improvement evaluation layer	Evaluation result judgment	Comparison of evaluation results

According to Table 3, the setting and analysis of completion degree medical rehabilitation teaching quality evaluation conditions, and the evaluation direction and trend of medical rehabilitation teaching quality. Combining the classification principle of historical big data decision tree, adjust the evaluation objectives and constraints of different levels, and strengthen the directional annotation ratio of top level improvement evaluation. Then, based on this, according to the changes of teaching chapters and contents, set the evaluation limits of different levels, and calculate the evaluation range of top floor improvement, as shown in Formula 5 below:

$$M = \vartheta - \sum_{t=1} \Re t + \psi^2 - \zeta \vartheta \tag{5}$$

In Formula 5: M Indicates the scope of the top-level improvement assessment, ϑ Indicates the overlap range, $\Re$ Indicates controllable improvement deviation, t Represents the evaluation limit, ψ Indicates the coincidence range, ζ It represents the general evaluation value. According to the above settings, the calculation of the evaluation scope of top-level improvement is completed. Combined with the constructed evaluation model and the classification principle of the historical big data decision tree, the corresponding coverage of top-level improvement is adjusted, the corresponding evaluation indicators and parameters are defined, the actual evaluation scope is further expanded, the evaluation structure is optimized, and the final evaluation results are obtained from multiple perspectives. However, in this part, it should be noted that the pertinence of the top-level improvement assessment is generally strong, so it is necessary to extract the stage assessment objectives corresponding to the design, form a complete assessment structure, improve the current assessment efficiency and quality, avoid the occurrence of assessment errors, and ensure the stability and reliability of the final results.

3 Method Test

This research is mainly about the design and verification of medical rehabilitation teaching quality evaluation methods based on historical big data decision tree classification. In consideration of the authenticity and reliability of the final test results, the comparison method was selected for analysis, and the medical rehabilitation discipline of School D was selected as the main test target. The intelligent platform was used to collect basic measurement data and information, which were summarized and integrated for future use. According to the actual measurement requirements and standards, the final test results are compared and studied. Next, the test environment is built based on the classification principle of the historical big data decision tree.

3.1 Test Preparation

This time is mainly to measure the actual measurement environment and background of the medical rehabilitation teaching quality assessment method based on the historical big data decision tree classification. In combination with the changes in the assessment needs and standards, the unit setting and processing are carried out. Taking the teaching evaluation of a class of medical rehabilitation students in selected school D as an example, 68 students in the class were collected to evaluate the teaching quality of three medical rehabilitation teachers. Set evaluation items and corresponding evaluation indicators for professional ethics, teaching ability, teaching methods, teaching arrangements, and teaching effects to ensure the comprehensiveness of the final evaluation results. Set the evaluation cycle to 6, 7 days a week, set the corresponding conditions, and adjust the basic evaluation indicators and parameters, as shown in Table 4 below:

Table 4. Basic Evaluation Indicators and Parameter Setting Table

Basic evaluation indicators	Initial parameter standards	Standard for measured edge parameters
Composite weight ratio	1.35	1.21
Hidden layer evaluation unit	10.35	16.35
Iterations/time	12	18
Gradient optimization orientation difference	3.2	2.4
Number of training evaluation rounds	6	8
Evaluation coefficient	2.3	1.6
Eigenvector variation ratio	20.35	27.16

Set the basic evaluation indicators and parameters according to Table 4. Next, according to the actual evaluation needs and changes in the standards, combined with specific evaluation standards and principles, set the corresponding evaluation training levels and clarify the corresponding evaluation settings. Set the training unit, combine the classification principle of historical big data decision tree, and calculate the corresponding evaluation feature vector, as shown in Formula 6 below:

$$L = \lambda^2 + (q - 1) + \rho \tag{6}$$

In Formula 6: L Represents the evaluation feature vector, λ Represents HTER vector, q Indicates two-way action value, ρ Indicates the change value of the evaluation range. According to the above measurement, the evaluation feature vector is calculated. Next, the evaluation structure is designed in combination with the actual evaluation needs and changes in standards, as shown in the following 6:

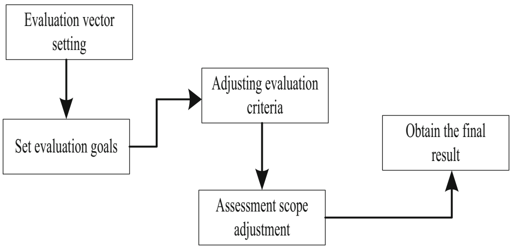

Fig. 6. Structure diagram of multi-level test and evaluation

According to Fig. 6, complete the design and adjustment of the multi-level test and evaluation structure, comprehensively measure the changes in requirements and standards, reasonably modify the evaluation indicators and parameters, and complete the setting of the built-in evaluation structure. So far, we have completed the setting of the test environment and layout. Next, we will carry out specific test analysis in combination with the historical big data decision tree classification.

3.2 Test Process and Result Analysis

Combined with the historical big data decision tree classification, this paper measured and studied the quality evaluation method of medical rehabilitation teaching fingers in School D. First, according to the daily medical rehabilitation teaching progress of the class, set the balanced evaluation chapters and stages, and set the evaluation weight value according to the content set in the evaluation stage, as shown in Table 5 below:

Table 5. Weight Value Setting Table of Multi stage Test and Evaluation

Evaluation indicator stage	First level weight	Secondary weight	Composite Weight
teaching effectiveness	0.3	0.45	0.35
Teaching ability	0.2	0.36	0.31
Teaching coverage	0.6	0.85	0.77
Teaching process positioning	0.6	0.78	0.64

According to Table 5, set and analyze the weight value of multi-stage test evaluation. Next, adjust the specific hierarchical structure of evaluation in combination with the classification principle of historical big data decision tree. At this time, combined with the actual measurement needs and standards, make a targeted evaluation of the five professional ethics, teaching ability, teaching methods, teaching arrangements, and teaching effects set above, and calculate the final evaluation mean difference, as shown in Formula 7 below:

$$H = (o^2 + \phi)^2 \times \rho \tag{7}$$

In Formula 7: H Represents the difference of the average value of the assessment, λ Indicates the controllable range, q Represents the coincidence value, ρ Indicates the directional difference. According to the above measurement, the calculation of the average difference of the evaluation is realized, and the measurement and analysis are carried out in six cycles. In response to the above content, the proposed method and traditional method were used for teaching quality evaluation, and the results obtained by the two methods were compared and studied. The results are shown in Table 6 and Table 7, respectively:

Table 6. Test results of the proposed method

Evaluation indicators	Cycle 1 mean difference	Cycle 2 mean difference	Cycle 3 mean difference	Cycle 4 mean difference	Cycle 5 mean difference
professional ethics	1.35	1.29	1.37	1.35	1.36
Teaching ability	1.24	1.26	1.25	1.26	1.36
teaching method	1.36	1.21	1.23	1.28	1.39
Teaching arrangements	1.38	1.35	1.32	1.38	1.35
teaching effectiveness	1.27	1.27	1.21	1.13	1.25

Table 7. Traditional method test results

Evaluation indicators	Cycle 1 mean difference	Cycle 2 mean difference	Cycle 3 mean difference	Cycle 4 mean difference	Cycle 5 mean difference
professional ethics	2.38	2.81	2.48	2.51	2.46
Teaching ability	2.57	2.74	2.36	2.69	2.37
teaching method	2.41	2.58	2.84	2.47	2.81
Teaching arrangements	2.84	2.47	2.96	2.36	2.76
teaching effectiveness	2.36	2.39	2.44	2.57	2.52

According to Tables 6 and 7, the analysis of test results was completed. After 5 measurement cycles, the quality of medical rehabilitation teaching was evaluated in terms of professional ethics, teaching ability, teaching methods, teaching arrangements, and teaching effectiveness. The final evaluation average deviation of the proposed method was controlled below 1.5, while the final evaluation average deviation of the traditional method was above 2.2. Compared with the two methods, the proposed method can effectively reduce the evaluation mean deviation, indicating that the evaluation method is highly targeted, stable, and has practical application value.

4 Conclusion

In a word, the above is the design and verification research of the medical rehabilitation teaching quality evaluation method based on the historical big data decision tree classification. The evaluation of medical rehabilitation teaching quality is mainly to cultivate medical students with stronger comprehensive ability, better serve clinical rehabilitation, better use systematic and standardized medical thinking, and apply new technology to solve clinical rehabilitation professional problems. Promote the innovative development of medical industry and technology. In combination with the changes in actual teaching evaluation needs and standards, design a problem-based teaching quality evaluation model to further cultivate students' innovative thinking such as active learning and learning to innovate and create, which helps to establish a correct and scientific medical concept, stimulate happy learning, master a scientific way of learning and thinking, and scientifically and effectively solve problems. To develop a multi-level and multi-objective teaching quality evaluation structure, help students learn to actively innovate and create in the process of medical rehabilitation learning, comprehensively improve the comprehensive practical ability and comprehensive quality of medical students, enhance the standardized cultivation level of rehabilitation students' teaching, ensure the establishment and development of high-quality rehabilitation talent system, and promote the better development of rehabilitation clinical specialty. In the future, further attention will be paid to the sources, collection methods, and processing of data to ensure accuracy and completeness, improve the method of selecting indicators, and further improve weight allocation to improve the reliability of the proposed methods, provide more accurate and comprehensive evaluation results, and promote the development and optimization of medical rehabilitation teaching.

Acknowledgements. 1. Research on the Application of Virtual Reality Technology (VR) in Anatomy Experimental Teaching. Changsha Vocational College of Health Project 2020.11 Scientific Research Issue No. 05

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3. Research on Strategies to Promote the Employment Transfer of Rehabilitation Therapy Technology Graduates to Grassroots Medical Institutions under the Background of Healthy Hunan. Project number: 22C1476

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A Method for Identifying Abnormal Behaviors in College English Smart Classroom Teaching Based on Deep Learning

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Abstract. The acquisition of behavior recognition in college English smart classroom teaching helps to achieve real-time monitoring and alerting of student behavior, providing important guarantees for improving the quality and effectiveness of college English smart classroom teaching. To this end, a method for identifying abnormal behavior in college English smart classroom teaching based on deep learning is proposed. On the basis of obtaining a large amount of data on teaching behavior in college English smart classrooms, various abnormal teaching behavior characteristics such as playing with mobile phones, watching screens, whispering, and distraction were extracted and integrated from it. The Convolutional neural network in the deep learning algorithm is used to train and recognize these features, so as to achieve the purpose of identifying abnormal teaching behaviors. The experimental results show that this method can fully utilize deep learning methods to achieve recognition of teaching abnormal behavior, with high recognition accuracy, short time consumption, and high recognition accuracy. It helps teachers discover and solve abnormal situations in teaching in a timely manner, improving teaching effectiveness and students' learning quality.

Keywords: Deep Learning · Smart Classroom · College English · Teaching Behavior · Abnormal Behavior · CNN

1 Introduction

Education is a national strategy, and modernization of education is an important symbol of national development. Currently, the level of informatization among students and teachers is becoming higher and higher, and smart classrooms have become the trend of modern education development. However, in a smart classroom environment, many abnormal behaviors in the classroom, such as dozing off and playing with mobile phones, can cause great interference and impact on teaching order and the effectiveness of teacher and student education, becoming an urgent problem to be solved in the field of education. Based on this, the recognition of abnormal behavior in smart classroom teaching has become a hot research direction in the fields of machine learning [2] and intelligent

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computing. Using computer vision [3], image processing [4], and deep learning techniques, analyze and extract features such as teacher and student postures and actions in the classroom to identify abnormal behavior. Reference [5] combines real-time object detection and tracking to obtain real-time image streams for each student. By utilizing deep spatiotemporal residual CNN to learn the spatiotemporal characteristics of each student's behavior, real-time recognition of classroom behavior targeting multiple student goals in classroom teaching scenarios can be achieved. Reference [6] explores the teaching characteristics and behaviors of online open courses based on image processing. A teaching behavior feature extraction model based on dual stream deep CNN was established using coding scales to achieve teaching behavior recognition.

The recognition of abnormal teaching behaviors is of great significance for intelligent teaching of college English. On the one hand, by monitoring and identifying students' abnormal behaviors in real-time, teachers can timely detect and correct students' non-standard behaviors, and improve teaching effectiveness. On the other hand, for management personnel, abnormal behavior identification can be used to optimize teaching management, timely identify problems, and clear management channels. Especially for college English classrooms where teaching quality and effectiveness are so important, identifying abnormal behaviors is even more important. It helps to improve teaching efficiency and quality, and has a positive promoting effect on students' learning and personal growth. Therefore, the development and popularization of modern educational technology, as well as the construction and improvement of smart classrooms, need to be supported by the recognition of abnormal teaching behaviors to help achieve efficient, intelligent, and personalized education and teaching. The significance of studying the recognition of abnormal behavior in smart classroom teaching lies in: firstly, achieving modernization and informatization of teaching. As a manifestation of educational modernization and informatization, smart classrooms can improve teaching quality, promote teacher-student interaction, and cultivate students' information literacy and innovation ability. In addition, it can also promote teaching improvement and progress. The intelligent classroom teaching abnormal behavior recognition system can timely identify abnormal behaviors that occur in the teaching room. Therefore, this paper proposes a method for identifying abnormal behavior in college English smart classroom teaching based on deep learning.

2 Acquisition of Behavior Recognition in Smart Classroom Teaching of College English

Set up a dataset for intelligent classroom teaching behavior in college English, and describe the dataset:

$$Y = \left(Y_{ji}\right)_{M \times E} \tag{1}$$

In Eq. (1), Y represents the dataset function of college English smart classroom teaching behavior; $\left(Y_{ji}\right)_{M \times E}$ represents M samples of college English smart classroom teaching behavior and E characteristics, so the type parameter of the college English smart classroom teaching behavior sample is:

$$D = \left(d_j\right)_{M \times 1} \tag{2}$$

In Eq. (2), D represents the number of samples of teaching behavior in college English smart classrooms; d_j represents abnormal samples in college English smart classrooms; If the sample dataset of teaching behavior in college English smart classrooms is $(D_1, D_2, ..., D_M)^T$, then the characteristic set of teaching behavior in college English smart classrooms can be represented by $(g_1, g_2, ...g_E)$. The process of using the existing set of teaching behavior features in college English smart classrooms as input until the output of the optimal subset of abnormal teaching behavior features is completed is as follows:

(1) Initialize the subset $H = \emptyset$ of teaching behavior characteristics in college English smart classrooms, and set the candidate feature set as:

$$T = {}^{Y}/_{D}\{g_1, g_2, ..., g_E\} \tag{3}$$

(2) Calculate the information entropy [7] and the mean value of information entropy of each feature, and mark the characteristics of college English intelligent classroom teaching behavior that are greater than the mean value of information entropy into Pearson table.
(3) Calculate the mean Pearson correlation coefficient and Pearson correlation coefficient between each feature, and label the behavioral characteristics of college English smart classroom teaching that are greater than the mean into the Pearson table.
(4) If $H = \emptyset$, add any behavioral characteristics W and $W \in T$ of college English smart classroom teaching.
(5) Select any behavioral feature W in T for college English smart classroom teaching, calculate the classification accuracy of the feature subset, and set it to S_W. Obtain the feature with the highest correlation coefficient among the features in the current subset H of teaching behavior in college English smart classrooms, arbitrarily select feature V from the feature library, calculate the classification accuracy of subset $H/\{V\}$ of teaching behavior in college English smart classrooms to S_V, and set the teaching behavior in college English smart classrooms with the highest values in S_W and S_V as a decision. Then:

$$fS_W > S_V : H \leftarrow H \cup \{W\}, T \leftarrow T/\{W\} \tag{4}$$

(6) Distinguish whether the ending conditions are met, and if they are met, end. Output the subset of behavioral characteristics corresponding to the highest decision value in the list for college English smart classroom teaching. If not, skip to step (4). At this point, we have obtained the $I(x, y)$ of intelligent classroom teaching behavior in college English.

3 Recognition of Abnormal Teaching Behaviors in College English Smart Classrooms Based on Deep Learning

CNN are an efficient deep learning model commonly used in the fields of image and college English smart classroom video processing [8]. In the recognition of abnormal behavior in smart classroom teaching, the use of CNN models can have good feature extraction ability, and can automatically extract useful feature information from complex college English smart classroom video streams. This is very important for the recognition of abnormal behavior. Therefore, after obtaining the teaching behavior of college English smart classroom, the CNN method in deep learning is used to identify abnormal behavior in college English smart classroom teaching.

3.1 Extraction and Fusion of Abnormal Teaching Behavior Characteristics in College English Smart Classroom

Based on the image $I(x, y)$ of teaching abnormal behavior obtained above, FV algorithm is used to extract the characteristics of teaching abnormal behavior, which provides a basis for the recognition of teaching abnormal behavior.

For the image of abnormal teaching behavior, T features are extracted from it, and each feature dimension is d, then $G = \{g_t, t = 1, 2, \cdots, T\}$ can be used to describe the characteristics of abnormal teaching behavior in college English smart classroom. Assuming that T features are independently and identically distributed, then there exists:

$$p(G/\lambda) = \prod_{t=1}^{T} p(g_t/\lambda) \tag{5}$$

In formula (5), p is the probability density function; λ is the parameter. Using a linear combination model with a Gaussian distribution [9] to approximate the distribution of formula (5), the model is represented as:

$$p(g_t/\lambda) = \sum_{i=1}^{K} w_i p_i(g_t/\lambda_i) \tag{6}$$

In Eq. (6), K is the number of linear combinations in the model; w_i is a free variable; p_i is the i-th Gaussian distribution; u_i is the characteristic parameter.

Define the abnormal behavior characteristics of college English smart classroom teaching through formula (7), and its probability is expressed as:

$$\gamma_t(i) = \frac{w_i p_i(g_t/\lambda)}{\sum_{j=1}^{N} w_i p_i(g_t/\lambda)} \tag{7}$$

From formula (7), it can be seen that the teaching abnormal behavior features extracted by the FV algorithm not only contain the original features of the teaching abnormal behavior, but also contain some structural information, which provides a more detailed description of the teaching abnormal behavior features.

3.2 Recognition of Teaching Abnormal Behaviors Based on CNN

The Convolutional neural network in the deep learning algorithm has the advantages of processing large-scale and complex educational data, strong robustness, accurate detection of abnormal behavior in the presence of Confounding, efficient and accurate detection of teaching abnormal behavior, and adaptive adjustment and optimization for different types of data and different abnormal behavior scenarios.

Therefore, matching the extracted features with the image features in the database to classify and identify the types of abnormal teaching behaviors. This paper uses CNN in deep learning algorithms to identify abnormal behavior in teaching. The CNN consists of an input layer, a spatial convolution layer, and an output layer [10], as shown in Fig. 1:

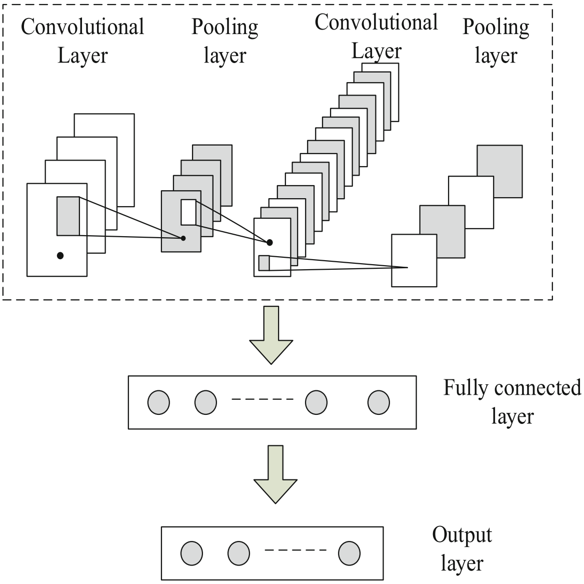


Fig. 1. CNN Structure

In the CNN structure, it is assumed that the objective function for abnormal teaching behavior in college English smart classrooms is:

$$F(x) = \underset{\varpi}{\arg\min} \frac{v}{c} \sum_{i=1}^{c} H_l\left[x_i, \gamma_t(i)\right] \tag{8}$$

where, c represents the number of abnormal teaching behaviors in college English smart classroom, ϖ_l represents the weight matrix, H_l represents the activation function, and v represents the loss function.

After feature extraction is completed, the main purpose of the feature mapping layer is to generate a computational layer, where each feature mapping layer can be viewed as a plane and the weights of neurons on the plane are equal. The sigmoid function is used as the activation function in feature mapping to make it displacement invariant. Using the relationship between the convolutional and computational layers in a CNN, calculate the local average value and perform secondary extraction. This feature extraction structure can effectively reduce the resolution of features.

During this process, each convolutional layer C_1 performs linear filtering on the input plane $z^{l-1}_{1,\cdots,N^{l-1}}$ of layer N^{l-1}, and the calculation method for the value of N^l at

(i, j) in the p^{th} plane is as follows:

$$z_p^l(i,j) = b_p^l + F(x)\sum_q \sum_{s=1}^{K^l} \sum_{t=1}^{K^l} w_{p,q,s,t}^l z_p^{l-1} \tag{9}$$

Train bias b_p^l and filter weight $w_{p,q,s,t}^l$ using backpropagation algorithm. The bit plane of the output layer is $D^{l-1} \times D^{l-1}$, where $D^l = D^{l-1} - K^l + 1$.

Subsampling layer S_l uses smooth filtering on each entry and exit plane:

$$z_p^l(i,j) = b_p + w_p \sum_{s=1}^{K^l} \sum_{t=1}^{K^l} z_p^{l-1}(i - 1 + s, j - 1 + t) \tag{10}$$

Each convolution layer in the CNN will use the nonlinear function $\tanh(\cdot)$ in the operation process, and will use the full connection layer to identify the label vectors. This paper introduces the "softmax" layer to explain these vectors, and its calculation formula is as follows:

$$\tilde{P}_p = \frac{z_p^l(i,j)}{\sum_q \exp(z_p^{l-1})} \tag{11}$$

Each parameter θ in the CNN is optimized by minimizing the likelihood function $L(\theta)$, and its mathematical expression is as follows:

$$L(\theta) = \tilde{P}_p \sum_{n-1}^{N} \lg \tilde{P}_{\theta,y_n}(x_n) \tag{12}$$

After optimization, the random gradient descent algorithm is used to train parameter θ, calculate the gradient of the random sample (x, y), and then update it as follows:

$$\theta - \lambda \frac{\partial L(\theta)}{\partial \theta} \to \theta \tag{13}$$

In order to train θ better and achieve more accurate recognition rate, the likelihood function is further optimized by using time correlation.

Assuming that x_1 and x_2 are two different images from the same university English smart classroom video, their hidden layer features are represented as $z_\theta^l(x_1)$ and $z_\theta^l(x_2)$. Based on their correlation, if the input images x_1 and x_2 are coherent, then $z_\theta^l(x_1)$ and $z_\theta^l(x_2)$ are forced to approach; If x_1 and x_2 are not coherent, then separate $z_\theta^l(x_1)$ and $z_\theta^l(x_2)$. At this point, in order to minimize its losses, the following measures should be taken:

$$L_{coh}(\theta, x_1, x_2) = \begin{cases} \max(0, \delta - \left\| z_\theta^l(x_1) - z_\theta^l(x_2) \right\|_1), x_1 \cap x_2 = \emptyset \\ \left\| z_\theta^l(x_1) - z_\theta^l(x_2) \right\|_1, \ else \end{cases} \tag{14}$$

In Eq. (14), δ represents the edge size.

On this basis, abnormal teaching behaviors in college English smart classrooms are identified, and the results of the identification are:

$$g(a,b) = \frac{1}{c}\sum_{i=1}^{c}(b_i - \ln[H_l(a_i,b_i)] + \eta L_{coh}(\theta, x_1, x_2) \tag{15}$$

At this point, the recognition of abnormal teaching behaviors in college English smart classrooms based on deep learning has been achieved. The algorithm Pseudocode is as follows:

1. Initialize Convolutional neural network parameters.
2. Perform feature extraction:
 - Input data on teaching behavior in college English smart classrooms.
 - Feature mapping of input data.
 - Perform secondary extraction and use linear filtering calculation methods to process the input bitplanes of each convolutional layer.
3. Backpropagation training bias and filter weight:
 - Use the objective function to optimize and minimize the Likelihood function.
 - Train and update parameters using random gradient descent algorithm.
4. Use nonlinear functions for convolution operations:
 - Each convolutional layer uses nonlinear functions to process the bitplane.
5. Use fully connected layers to recognize label vectors:
 - Introducing a ‘softmax’ layer to interpret vectors.
 - Calculate recognition results.
6. Optimize the Likelihood function through time correlation:
 - In order to obtain better training results and accurate recognition rate, time correlation is used to optimize the Likelihood function.
7. Minimize the Loss function:
 - Process the optimized Likelihood function to minimize its loss.
8. Identify abnormal teaching behaviors in college English smart classrooms:
 - Identify input data based on the trained model.
 - Output recognition results.

4 Experiments and Analysis

4.1 Experimental Setup

In order to verify the practical performance of the proposed method for identifying abnormal teaching behaviors in college English smart classrooms based on deep learning, multiple sets of experiments were designed for verification. Deploy the experimental environment before the experiment. Considering that the recognition of abnormal teaching behaviors in the English smart classroom of Dian University relies on the big data environment of instant communication, the deployed experimental environment is shown in Fig. 2.

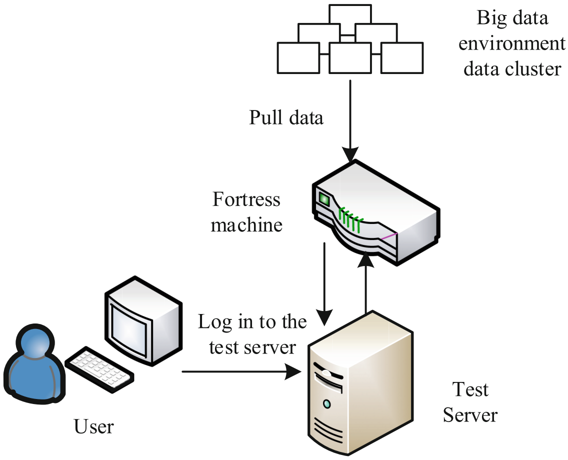


Fig. 2. Schematic diagram of experimental environment composition

In order to test the proposed method, before the experiment, the user obtains root privileges and logs in to the fortress machine as root privileges. The data cluster is accessed through the data access interface to obtain the experimental target data. After obtaining the complete data, the data is saved on the test server.

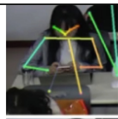
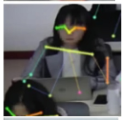
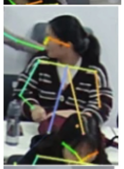
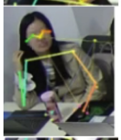
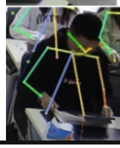
The experiment mainly used monitoring video images of college English smart classrooms to obtain abnormal teaching behaviors. The short-term acquisition and storage recording system was used to achieve the acquisition and storage of experimental images, which was composed of a camera, acquisition card, cable, computer, and acquisition software. The camera parameters are shown in Table 1.

Table 1. Camera Parameters Table

Parameter Name	Numerical value	Unit
Image type	Mono/Color	-
Pixel depth	8/10	bit
Pixel size	5.5 × 5.5	μm
Data output type	Camera Link	-
Maximum frame rate	340	fps
Maximum resolution	2048 × 1088	pixels
Overall dimensions	63.5 × 63.5 × 44.1	mm

In this experiment, the most common abnormal teaching behaviors in college English smart classrooms were mainly collected as image recognition samples, and the sample distribution is shown in Table 2:

Table 2. Sample Images

Smart Classroom Teaching Behavior of College English	Size of feature map	Training samples/piece	Test sample/piece	Image instance
Playing with mobile phones (Image A)	30×30	50	20	
Looking at the screen (Image B)	27×27	50	20	
Interacting with each other (Image C)	20×25	50	20	
Distractibility (Image D)	30×35	50	30	
Reading (Image E)	25×30	50	25	

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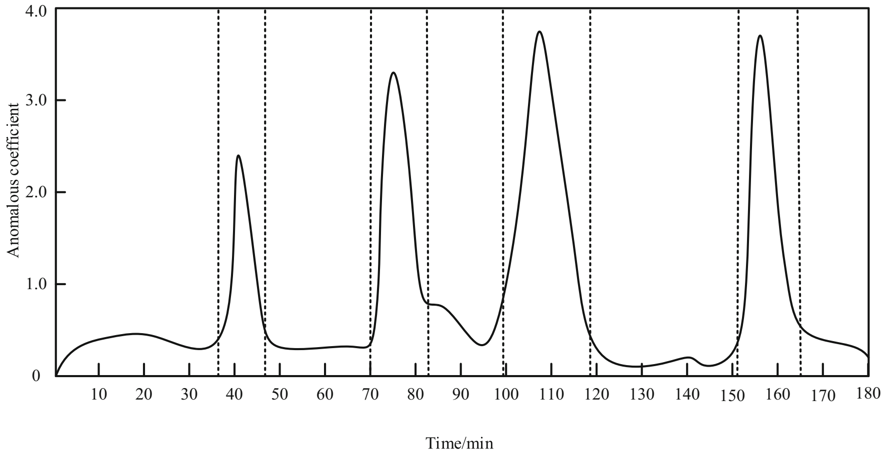


Fig. 3. Injecting abnormal behavior time period

From Fig. 3, it can be seen that there are four peaks representing the injection time periods of four abnormal behaviors, which are 38–47 min, 70–82 min, 99–116 min, 151–164 min, and have durations of 9 min, 12 min, 17 min, and 13 min, respectively.

4.2 Experimental Results

To determine the impact of the number of hidden layer neurons and the number of recurrent neural grids on recognition results, experimental tests were conducted on sample images to obtain reasonable values for both. Firstly, select image samples and train the input data through sparse autoencoders. Based on the trained data, perform convolutional feature extraction on the image sequence. Finally, based on the existing structure and sample images, determine the values of the number of hidden layer neurons and the number of recurrent neural network grids. The effects of changing the number of hidden layer neurons and the number of recurrent neural grids from an increment of 8 to 80 on the accuracy of different feature image recognition are shown in Fig. 4 and Fig. 5, respectively:

From Figs. 4 and 5, it can be seen that when the number of hidden layer neurons and the number of recurrent neural grids is 64, the recognition accuracy reaches its optimal level.

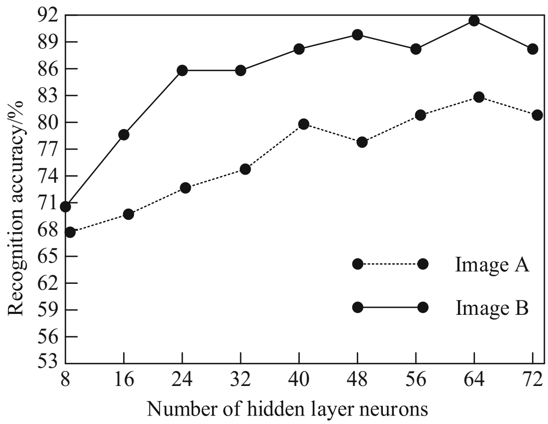


Fig. 4. The impact of hidden neurons on recognition accuracy

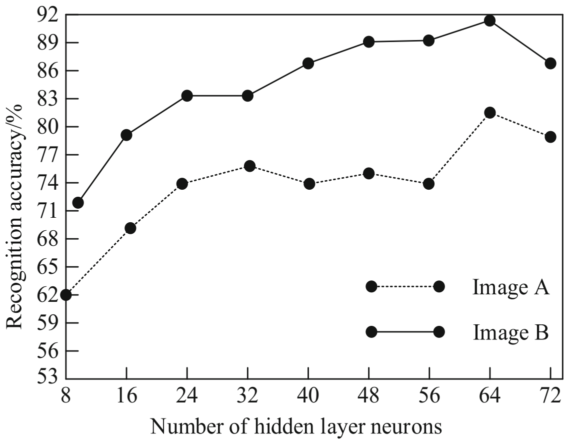


Fig. 5. The impact of the number of recurrent neural networks on accuracy

Input the above experimental data into the method proposed in this paper and calculate the accuracy coefficient for identifying abnormal teaching behaviors, as shown in Table 3.

As shown in Table 3, the average recognition accuracy coefficient of the method in reference [3] is 2.184, while the average recognition accuracy coefficient of the method in reference [3] is 2.254. However, the average recognition accuracy coefficient of the method in this paper is 3.248, effectively improving the recognition effect of teaching abnormal behavior. The reason is that the proposed method extracts and integrates various abnormal teaching behavior characteristics that occur in college English smart classrooms based on the acquisition of teaching behavior in college English smart classrooms. It can identify the characteristics of different abnormal behaviors, improving recognition accuracy.

Table 3. Data Table for Accuracy Coefficient of Teaching Abnormal Behavior Identification

Number of experiments	Image frames	Accuracy coefficient		
		Proposed method	Reference [3] Method	Reference [4] Method
10	100	3.36	2.28	2.58
20	150	3.41	2.03	2.39
30	200	3.02	2.26	2.30
40	250	3.14	2.56	1.97
50	300	3.31	2.14	1.68

Comparing the recognition time of abnormal behaviors in 145 groups of college English smart classroom teaching behavior samples using three methods, the comparative results are shown in Fig. 6:

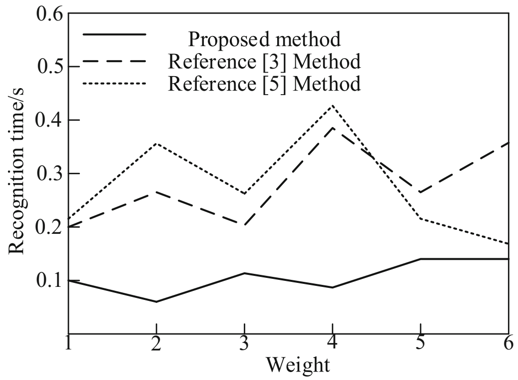
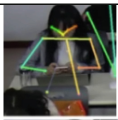
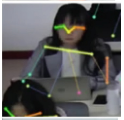
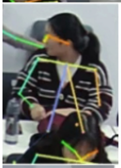
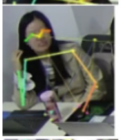
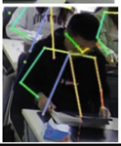


Fig. 6. Time consumption for identifying abnormal teaching behaviors

As shown in Fig. 4, the reference [3] method takes an average of 0.31 s to identify each teaching behavior, the reference [4] method takes an average of 0.28 s to identify each teaching behavior, and the proposed method takes an average of 0.10 s to identify each teaching behavior. It can be seen that the proposed method is fast in identifying abnormal behaviors in college English intelligent classroom teaching, and the recognition accuracy rate is high, which fully indicates that the method in this paper achieves the purpose of identifying abnormal teaching behaviors by using the Convolutional neural network in the deep learning algorithm on the basis of extracting and integrating the characteristics of various abnormal teaching behaviors in college English intelligent classroom teaching, and has good recognition performance.

Identify the sample images in Table 2 using the proposed method, reference [3] method, and reference [4] method, respectively. The recognition performance of the corresponding method was analyzed, and the results are shown in Table 4.

Table 4. Comparison of Recognition Performance

Image instance	Is it abnormal	Proposed method	Reference [3] Method	Reference [4] Method
	Abnormal	Abnormal	Abnormal	Abnormal
	Abnormal	Abnormal	Abnormal	Normal
	Abnormal	Abnormal	Abnormal	Normal
	Abnormal	Abnormal	Normal	Abnormal
	Normal	Normal	Normal	Normal

Analyzing Table 4, it can be seen that the proposed method provides an "abnormal" warning for each abnormal teaching behavior. The methods in reference [3] and reference [4] misidentified each abnormal teaching behavior once and twice, respectively, and considered it as "normal". It can be seen that the proposed method has high accuracy in identifying abnormal behaviors in college English intelligent classroom teaching, which fully indicates that the method in this paper has good recognition performance by using the Convolutional neural network structure.

5 Conclusion and Outlook

The method of identifying abnormal behaviors in college English smart classroom teaching based on deep learning proposed in this paper can effectively identify and monitor abnormal behaviors in the classroom. On the surface of the experimental structure, the proposed method has a good effect on identifying abnormal behaviors in teaching, with an accuracy rate of over 90% for identifying different behaviors. In addition, the implementation of the recognition method for abnormal behavior in college English smart classroom teaching based on deep learning can also help teachers and school management personnel quickly respond to and handle abnormal situations in the classroom, improve teaching order and effectiveness, and promote education modernization and informatization.

Future research directions can be expanded from the following aspects. Firstly, by recording more teaching scenes, the dataset can be enriched, and the generalization ability and recognition accuracy of the model can be improved. Secondly, different abnormal teaching behaviors and corresponding identification methods can be studied based on the teaching characteristics of different disciplines. Finally, data from multiple sensors can be fused, such as sound, human posture, heart rate, etc., to further improve the accuracy and efficiency of recognition. In short, in the future, the recognition of abnormal behavior in smart classroom teaching based on deep learning will be more comprehensive and mature, and will play a greater application value.

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2. 2021 School-level Teaching Reform Research Project, one of the periodical achievements "Research on College English Teaching Practice Based on Curriculum Ideological and Political Concept" (Project No.: JGZD202102).

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Design of Teaching Resources Sharing Method for Economics Major Based on Federal Learning

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Abstract. Under the premise of protecting the privacy of teaching resources, resource sharing is an effective measure to improve the utilization rate of teaching resources. Therefore, this study proposes a sharing method of teaching resources for economics majors based on Federated learning. Firstly, collect teaching resources for economics majors and complete the integration of resources based on their classification results. Then, set the (Transaction Layer Protocol) TLP protocol as the resource sharing protocol, use the Federated learning algorithm to implement encryption processing for text/data, image/video resources, and complete the directional transmission of resources through the selected transmission channel, so as to achieve resource security sharing. The test results show that the average shared resource loss and error rate of this method are 0.27 GB and 1.37%, respectively, and the shared task execution time does not exceed 2 s, indicating that compared with traditional sharing methods, the sharing performance of this method is better.

Keywords: Federal learning · Economics · Teaching resources · Resource sharing · Encryption processing · Directional transmission

1 Introduction

Economics is an undergraduate major of ordinary colleges and universities. It is mainly theoretical economics, has the attribute of applied economics, and has strong applicability and practicality. It aims to cultivate high-quality economics professionals with solid professional basic knowledge and basic theory, as well as international vision and innovation and entrepreneurship ability.

The teaching of economics major needs a large number of teaching resources as support. Teaching resources are all kinds of available conditions such as materials provided for the effective development of teaching, usually including textbooks, cases, films, pictures, courseware, etc., as well as teacher resources, teaching aids, infrastructure, etc., which should also be involved in a broad sense education and other contents [1].

Broadly speaking, teaching resources can refer to teaching process. All the elements used by the learners in the teaching, including the people, money, materials, information, etc. that support teaching and serve teaching. In a narrow sense, teaching resources

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mainly include teaching materials, teaching environment, and teaching backup system. In order to maximize the utilization of teaching resources, teaching resources sharing is an effective measure.

Resource sharing means that the same computer network. The behavior of a computer's computer resources available to other computers on. In other words, it enables a device or some information on the computer to LAN or Intranet Remote access.

The sharing method of teaching resources for economics majors is a sharing method that takes teaching resources for economics majors as the object. At present, more mature resource sharing methods mainly include: resource sharing methods based on cloud computing, resource sharing methods based on agent search, and sharing methods based on virtual reality technology. However, the above traditional methods are mainly aimed at the resource sharing of mainstream courses such as English and mathematics. When they are applied to the teaching resource sharing of economics majors, there are problems such as low resource utilization rate and resource vulnerability.

Federated learning is a distributed machine learning technology. Its core idea is to build a global model based on virtual fusion data by exchanging model parameters or intermediate results without exchanging local individuals or sample data through distributed model training among multiple data sources with local data, so as to achieve the balance between data privacy protection and data sharing computing.

For this reason, in view of the shortcomings of traditional methods, this study applies the Federated learning algorithm to the optimization design of teaching resource sharing methods for economics majors, in order to improve the sharing effect of teaching resource sharing methods for economics majors.

2 Shared Method Design

The sharing method of teaching resources for economics majors is based on physical resources. It provides additional services and functions by virtualizing various actual resources in the physical layer, such as general middleware, scientific research database, teaching database, management database, database administrator, workflow manager, etc. On the physical grid, servers, storage and the actual network are used to provide services for the sharing process, such as the exchange and cooperation of teaching resources, and the mining of the latest information of ideological and political majors. At the same time, all grid resources above the physical resources are modeling services, and ensure that they are not integrated and called by other applications [2].

In the process of sharing teaching resources for economics majors, to establish a central database, it is necessary to integrate all data in the sharing model into the central database, and classify teaching resources according to certain classification standards. The teaching resource sharing framework is shown in Fig. 1.

The sharing framework of teaching resources for economics majors consists of three parts, namely the basic layer, the environment layer and the application layer.

The basic layer is mainly composed of the shared resource library and the system data that provides data for the shared resource library.

The environment layer can execute the operation command after receiving the user's search requirements.

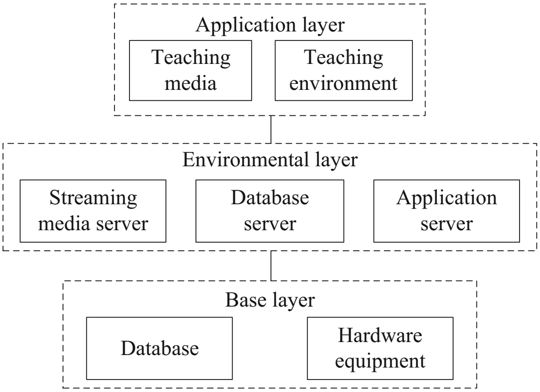

Fig. 1. Resource sharing framework

The application layer is composed of teaching media and teaching environment, which is the interface part to feedback the results to users.

In the case that the complexity and change degree of sharing requirements are not very large, the database mode is used for reuse. The more times of reuse, the greater the reuse cost. In the case of large complexity and change of sharing requirements, reuse knowledge in the way of reuse. No matter how many times of reuse, the reuse cost remains unchanged. In general, the teaching resource sharing model developed through structure can promote the effective use of resources, and make the management of the model simple.

2.1 Collect Teaching Resources of Economics

Collect all teaching resources of economics in the network environment according to the process shown in Fig. 2.

Data collection is a typical general process, which involves collecting raw data and converting it into useful information. The basic process of data collection usually includes four main steps, namely data collection, data sorting, data analysis and report feedback.

The first step is data collection, that is, collecting data from various sources. There are many data collection technologies, such as using sensor devices to collect real-time changing data, using questionnaires to collect quality data, accessing warehouse data, and conducting field observations. At this stage, it is also necessary to check the data received and ensure the accuracy, reliability and privacy of the data.

The second step is to preprocess and clean the collected data in order to sort out the non-standard data into standard data extraction sets. Here, outliers and duplicate values in the data can be effectively detected for subsequent analysis [3].

The third step is data analysis, that is, comprehensive analysis of the collected data for various classifications, and use of various data mining and analysis technologies to better understand the data, so as to find the relevance, potential laws and sensitivity to other factors contained in the data.

The last step is the feedback report. Through the analysis of the conclusions, write a detailed report to guide future decisions, so that the actual management behavior is more accurate and timely.

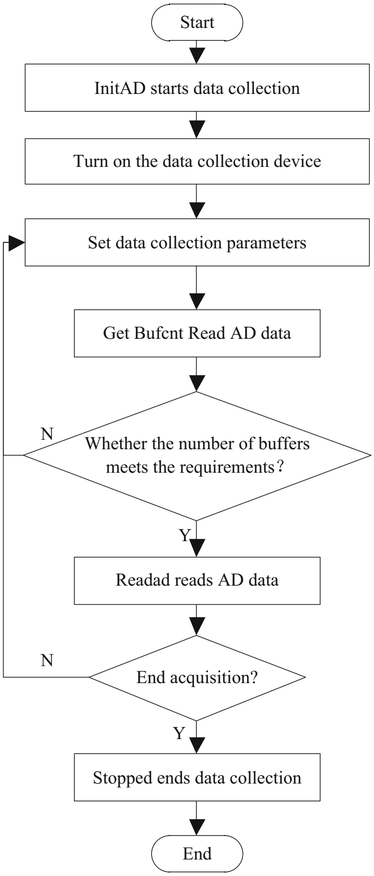

Fig. 2. Flow chart of resource collection

Data collection is a challenging long-term process, which requires scientific design and careful analysis to obtain more accurate data. Effective data collection can provide reliable technical support for actual operation and decision-making, and can also greatly improve the efficiency and accuracy of data analysis. In order to ensure the operability of economics teaching resources, it is necessary to normalize the initially collected economics teaching resources. The processing results are as follows:

$$x' = \frac{X_{\max} - x}{X_{\max} - X_{\min}} \tag{1}$$

where, $X_{\max}$ and $X_{\min}$ They are the maximum and minimum values in the initial collection of teaching resources, x Collect teaching resource data for the initial. Thus, the collection results of the effective value of the economics teaching resources that meet the calculation requirements can be obtained.

2.2 Classification and Integration of Teaching Resources for Economics

Classify the initially collected teaching resources of economics specialty, and integrate all kinds of resources. Assume that the teaching resource data initially collected and processed is X, select randomly from the initial set of teaching resources k Cluster centroids, expressed as C_i, it is necessary to extract the characteristics of clustering centroid points using formula (2):

$$\tau_c = \begin{cases} \dfrac{E\left[(X-\tau_{\text{mean value}}(X))^3\right]}{\left(E\left[(X-\tau_{\text{mean value}}(X))^2\right]\right)^{3/2}} \\ \dfrac{E\left[(X-\tau_{\text{mean value}}(X))^4\right]}{\left(E\left[(X-\tau_{\text{mean value}}(X))^2\right]\right)^{2}} \end{cases} \tag{2}$$

Among them, $\tau_{\text{mean value}}(X)$ Represents the average value of resource collection results, $E[]$ It represents the expected value [4]. On this basis, calculate the cluster to which each resource sample belongs, namely:

$$q^{(i)} = \arg\min_j \left\| x^{(i)} - C_j \right\|^2 \tag{3}$$

Calculate the course content similarity between each course data sample and the centroid point, select the centroid point with a small distance from the course data sample, and divide the samples with the same centroid point distance into the same cluster to complete the initial classification of the course data sample. Recalculate the centroid of each cluster, assuming that economics teaching resources are in the j Cluster, then:

$$d_j = \frac{\sum_{i=1}^{n_{\text{natural resources}}} x^{(i)}}{\sum_{i=1}^{n_{\text{natural resources}}} \left\{q^{(i)} = j\right\}} \tag{4}$$

where, $n_{\text{natural resources}}$ Represents the initial collection quantity of teaching resources, $\sum_{i=1}^{n_{\text{natural resources}}} \left\{q^{(i)} = j\right\}$ express j The number of cluster samples.

Then the average value of sample data of the same category is used as the basis for centroid point update. Repeat the above operation until convergence. Eliminate redundant units from the collected data and convert them into numerical data. For the collected data, normalize the cases with large value differences, and control all values within a reasonable range. According to the classification results of teaching resources for economics majors, integrate teaching resources according to the principles shown in Fig. 3.

As can be seen from Fig. 3, the integration of economics teaching resources in the optimization design method is divided into three dimensions, namely, data level, feature level and decision level. The results of data level resource integration are as follows:

$$X_{data} = \sum_{i=1}^{n\text{natural resources}} x_i \omega_i \tag{5}$$

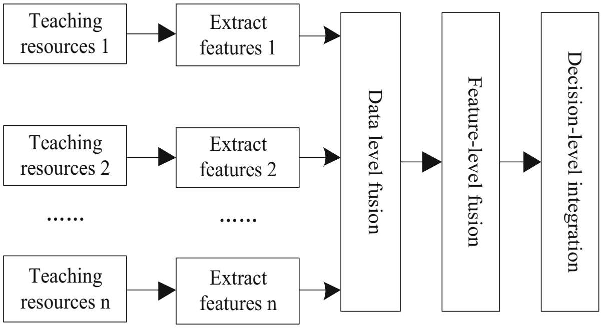

Fig. 3. Principle of resource integration

where, x_i and ω_i Respectively corresponding to the data and weight of teaching resources for economics majors.

Similarly, the integration results of resource data at feature level and decision level can be obtained, thus completing the classification and integration of initial resource data.

2.3 Set up Teaching Resource Sharing Agreement

To ensure the security of resource sharing, the sharing protocol needs to be set as a constraint. The protocol used in this paper is the TLP protocol, which uses reliable TCP connections as the data transmission channel, messages as the data transmission carrier, and requests/responses to achieve two-way data transmission [5]. TLP messages are used to transmit service data. The TLP protocol has two message types with different purposes: request messages and response messages, both of which are composed of message headers, message domains, and message bodies. The specific composition structure of request message and response message is shown in Fig. 4.

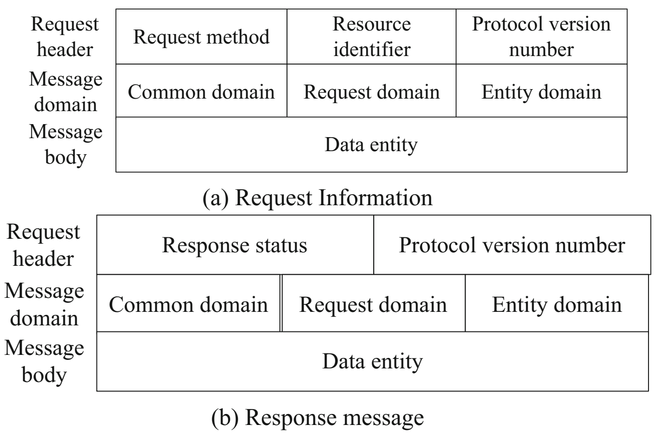

Fig. 4. Structure of request and response messages under sharing protocol

In the request message, the message header indicates the type and purpose of the message. Since the message header already contains the core content of a message, the message receiver can get the main information about the message by parsing the message header for the next operation.

Each TLP message has one and only one header. In the two types of TLP messages, the message header is divided into request header and response header. The message domain is a parameter group used to describe the message itself and its sender information. It is often in the form of key value pairs. It is an optional part of TLP messages. The functional mechanisms in TLP need to be controlled through the message domain. To realize various functions, TLP defines various types of message domains, including common domain, request domain, response domain and entity domain.

In TLP messages, the content of the message domain is flexible and can be extended as needed. At the same time, the message domain is not unique. A message can contain multiple message domains, depending on the actual needs of data transmission. Through the cooperation of multiple message domains, various functional mechanisms in the sharing protocol can be flexibly combined. The message body is used to carry the data entity in the message. These data entities are not necessarily equivalent to service data, but are obtained by compressing, encoding, or encrypting service data before it is encapsulated into the message body. Since the G/S mode is a one-way service mode, the message body generally exists in the response message, but in a few cases, the request message will also have a message body, such as when the system administrator is updating remote data [6].

In TLP, each message can only have one message body at most. Multiple data entities can be linked into one message body or transmitted through multiple response messages. In the sharing process, the protocol constraint generation process is shown in Fig. 5.

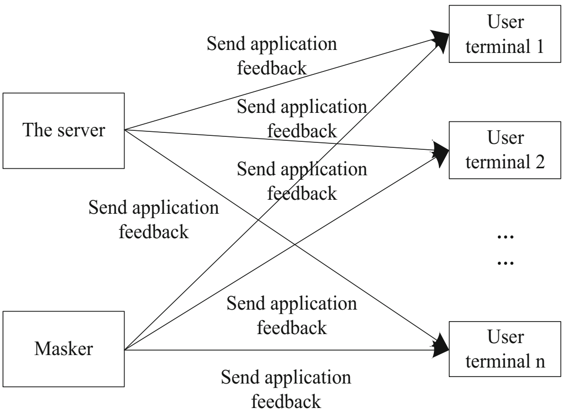

Fig. 5. Flow chart of protocol creation

Complete the sharing application and feedback of economics teaching resources according to the above process, and obtain the creation result of the sharing agreement.

2.4 Encrypt Teaching Resources Using Federated Learning Algorithms

Before the encryption of teaching resources for economics majors, a federated learning algorithm model is constructed, which consists of two parts: local model training and central aggregation. The local model training uses the data stored on the local client, and only sends the local model parameters to the central server to aggregate and obtain the parameters of the central global model.

Figure 6 shows the basic structure of the federated learning algorithm.

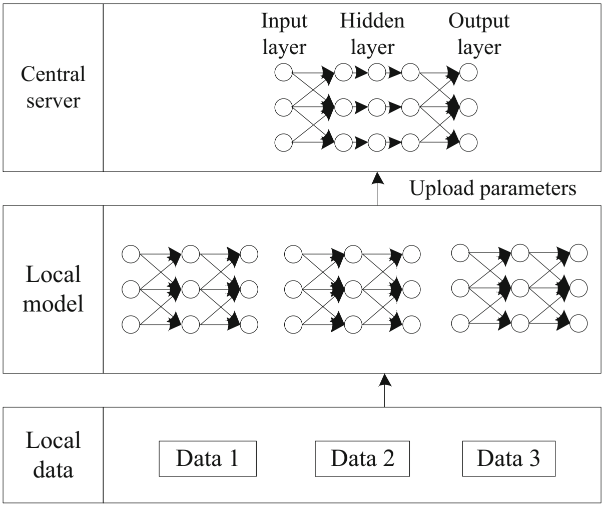

Fig. 6. Structure of federated learning algorithm

The whole process of the federated learning algorithm consists of many communication rounds, in which the client synchronously trains the local model using local data. Assume that the sharing environment of teaching resources for economics majors includes N Users. At the initial stage, each user has its own data set, which can be quantified as:

$$U_i = \{\beta_1, \beta_2, \ldots, \beta_N\} \tag{6}$$

Each user can update the model parameters after their local training $\Delta\delta_{t+1}^N$ Upload to the shared server, $t+1$ Is the number of times the user interacts with the server [7]. Note that it is not necessary to upload all parameters. Each round of uploading is model updating, that is, the difference between the current round and the previous round can be quantified as:

$$\Delta\delta_{t+1}^N = \delta_{t+1}^N - \delta_t^N \tag{7}$$

where, δ_t^N and δ_{t+1}^N Respectively represent the t and $t+1$ The local model parameters of the round. The sharing server performs differential privacy processing on parameter updates sent by each user, that is, adds Gaussian noise to each parameter difference. The processing result is:

$$\delta_{t+1} = \delta_t + \frac{1}{N}\left(\sum_{i=1}^{N} \Delta\delta_{t+1}^{i} + \vartheta\left(0, \sigma^2\right)\right) \tag{8}$$

where, $\vartheta\left(0, \sigma^2\right)$ Represents Gaussian noise, σ Indicates the noise intensity.

The significance of integrated processing is to integrate the parameters of each user, which is more helpful for model optimization. The sharing server will send the parameters of privacy processing back to each user for the next round of training. Repeat the above steps until the privacy budget set in advance is exhausted. Jump out of the cycle. After the training is completed, the model can be published. Through the above process, the privacy of federated learning user data can be protected to a certain extent.

2.4.1 Text/Data Resource Encryption

Teaching resources for economics majors can be divided into text resources, data resources, image resources, video resources and other types. Text/data resources use Advanced Encryption Standard (AES) encryption, and the encryption process is shown in Fig. 7.

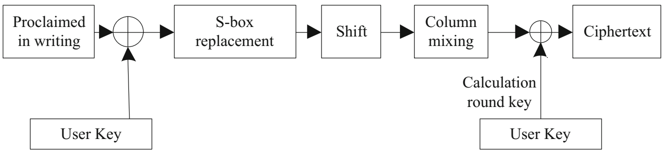

Fig. 7. Text/data resource encryption flow chart

In Fig. 7, the AES encryption process involves four operations: S-box transformation, row shift, column confusion, and round key addition. Each round of key is obtained by expanding the initial key, and 128 bit plaintext in the algorithm uses a 4 × 4 [8]. Box S is a 16 × 16 matrix to complete the mapping from one byte to another. Each byte is mapped to a finite field $G\left(2^8\right)$ The 8 constituent bits are marked as $\gamma_0 - \gamma_6$, and make the following transformation for each:

$$r = \gamma_{(i+4)\ \mathrm{mod}\ d} \oplus \gamma_{(i+5)\ \mathrm{mod}\ 8} \oplus \gamma_{(i+6)\ \mathrm{mod}\ 8} \oplus \gamma_{(i+7)\ \mathrm{mod}\ 8} \oplus \chi \tag{9}$$

Among them, χ Indicates the byte number. Row shifting is to implement a 4 × 4 Displacements between bytes inside the matrix. The moving bytes are determined according to the number of lines. The first line remains unchanged, the second line moves 1 byte to the left, the third line moves 2 bytes, and the fourth line moves 3 bytes. Assume that the matrix is A, the function expression of the matrix is as follows:

$$A[i][j] = A[i][(j+i)\%4] \tag{10}$$

Among them, i and j Is the item in the horizontal and vertical directions of the matrix. Column obfuscation is the use of finite fields $G(2^8)$ The round key addition is a substitution of the above arithmetic feature. In the encryption process, the input of each round is XOR with the round key once to realize the mixing of password and key. The extended key only participates in this transformation, and uses the corresponding extended key to perform bitwise XOR operation according to the number of encryption rounds. The final encryption result of text and digital resources in economics teaching resources is:

$$y = f_{ABS}(X \oplus \kappa) \tag{11}$$

Among them, X and κ They are plaintext and key of economics teaching resources [9]. Finally, the encryption results of text/data resources will be substituted into the federated learning program to further improve the encryption effect of resources, and at the same time, the resource key will be updated.

2.4.2 Image/Video Resource Encryption

The image and video resources in the economics teaching resources are encrypted by hybrid encryption. The encryption of image and video resources is mainly composed of scrambling and replacement. Scrambling is to scramble all pixels in the image. The processing process can be described as:

$$\begin{cases} x_{\text{Disorder}} = (x_i + y_i) \mod F \\ y_{\text{Disorder}} = (x_i + 2y_i) \mod F \end{cases} \tag{12}$$

where, $(x_i.y_i)$ For i Secondary scrambled initial pixel value, F It represents the phase space. In addition, the processing result of image/video resource pixel value replacement is:

$$I_{\text{replace}}(x, y) = I(x, y) \otimes \zeta \tag{13}$$

Among them, ζ Is the generated random pixel value. The encryption result of image/video resources can be obtained by substituting relevant data into formula (13).

2.5 Realize the Sharing of Teaching Resources of Economics

In the process of sharing teaching resources for economics majors, users send sharing requests to the server under the constraints of the transmission protocol, and the sharing server selects the appropriate transmission channel according to the size of the shared resources. Assume that the shared resource size of the application is W, the selection conditions of the shared transmission channel are as follows:

$$\Delta = B - W \tag{14}$$

Among them, B Is the channel capacity. If calculated Δ If the value is negative, it means that the currently selected channel can accommodate the transmission of teaching resources, that is, the channel can be selected as the transmission channel for shared tasks. If Δ If the value is positive, you need to reselect the transmission channel [10] in the current sharing environment. With the support of the federal learning algorithm, the encryption results of the teaching resources of economics specialty are transmitted through the selected channel. After receiving the teaching resources, the target user decrypts them with the key to complete the sharing of the teaching resources of economics specialty.

3 Performance Test Experiment Analysis

In order to test the performance of the economics teaching resource sharing method based on federal learning, the following comparative experiment is designed. The basic principle of this experiment is: store teaching resources in the database, submit resource sharing applications one by one according to the generation of shared tasks, observe whether the target node can obtain the specified resources after the execution of shared tasks, and calculate the amount of resources obtained and the overlap between the actual resources obtained and the resources applied for. Through the comparison of relevant data and indicators, the advantages of optimal design methods in sharing performance are reflected.

3.1 Prepare Samples of Teaching Resources for Economics Majors

Select the economics teaching module under MOOC teaching platform as the sample data source. Before the experiment, extract the background data and database of the economics teaching module under the teaching platform as the teaching resource sample. The teaching resources prepared for this experiment include text, data, courseware, pictures, videos and other types. The total number of samples of teaching resources prepared is 60.5 GB. According to the teaching content of economics, the initial resource samples are divided into several groups of experiments, and the teaching resources are numbered.

3.2 Generating Resource Sharing Tasks

When the sender and receiver are determined, multiple resource sharing tasks are generated. The generation of some shared tasks is shown in Table 1.

Table 1. Educational resource sharing task table

Task No	Resource sender	Resource receiver	Shared resource data volume/GB	Shared resource data type
1	Resource storage server	Terminal 01	13.4	Text, image
2	Resource storage server	Terminal 04	27.2	Image, video
3	Resource storage server	Terminal 05	36.5	number
4	Resource storage server	Terminal 07	29.8	Text, number
5	Resource storage server	Terminal 09	42.1	Image, video
6	Resource storage server	Terminal 10	35.7	Digital, image

A total of 15 groups of shared tasks were prepared for the experiment, and the task contents were marked according to the representation in Table 1.

3.3 Configuring the Shared Method Development Environment

Optimization design method Oracle VM VirtualBox software builds host environment and uses disk array to configure shared storage environment. The running speed between hosts is not affected by IO, and good IO can greatly improve the working efficiency of hosts. For the capacity of the configured storage hard disk, try to consider the size of the hard disk capacity. The hard disk space required by the business is configured in a ratio of 1:2, and this capacity is taken as the minimum space of the magnetic array. In this process, we also need to take into account the manufacturer's error value in the hard disk capacity. The loss is about 7%, and 20% of the space in the RAID magnetic array is consumed. In addition, the disk redundancy, so the space of the magnetic array should be four times that of the hard disk. When configuring services, memory sharing mechanism is strongly discouraged and memory locking mechanism is used. Optical fiber switches are used between hosts and disk arrays to read data, and gigabit Ethernet is used between hosts to exchange data. The optimization design method applies the federated learning algorithm, so it needs to build a client server structure, which has a central aggregation server and several nodes participating in training. In the experiment, each node updates the algorithm 1000 times between every two server aggregation operations.

3.4 Input Running Parameters of Federated Learning Algorithm

In order to ensure the adaptability between the federal learning algorithm and the teaching resource sharing method of optimizing design economics, it is necessary to set the relevant operating parameters of the federal learning algorithm. Figure 8 shows the initial value and change value of the parameter depth in the federated learning algorithm.

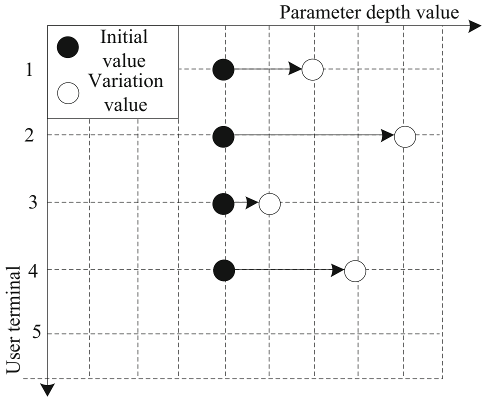

Fig. 8. Depth Values of Federated Learning Algorithm Parameters

Set the size of the image input into the federated learning algorithm to 64×64. The step size and compensation amount are 1 and 0 respectively. Dropout is used between federated learning levels to prevent over fitting.

3.5 Describe the Shared Performance Test Experiment Process

Under the experimental environment of configuration number, the optimized sharing method of economics teaching resources based on federal learning is converted into program code that can be directly recognized and run by the computer, and the running program is started. Input the prepared teaching resources of economics specialty into the storage device of the operating environment, apply one by one according to the generated sharing tasks, and obtain the corresponding sharing results. Figure 9 shows the execution result of shared task No. 1.

The running output results of all shared tasks can be obtained according to the above process. In order to achieve differential privacy protection, Gaussian noise is added to the gradient during the gradient descent of back-propagation of the federated learning algorithm. Before adding noise to the gradient, this paper needs to cut the gradient norm to prevent the influence of gradient on individual data. For the three data sets, the gradient clipping threshold is set to 0.01. In order to reflect the advantages of the optimal design method in sharing performance, the traditional sharing method based on cloud computing and the sharing method based on agent search are set as the comparison method of the experiment, and the development of the two comparison methods is implemented according to the above process, and the corresponding sharing results are output.

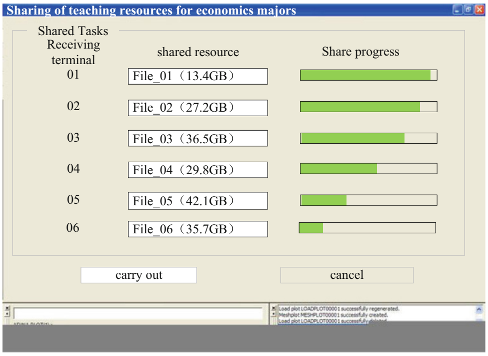

Fig. 9. Resource sharing result interface

3.6 Setting Shared Performance Test Indicators

This experiment tests the sharing risk and sharing efficiency respectively, and sets the loss of shared resources and the receiving error rate as the quantitative test indicators of the sharing risk. The numerical results are as follows:

$$\begin{cases} \psi_{\text{lose}} = W_{\text{share}} - W_{\text{receive}} \\ \psi_{err} = \dfrac{W_{err}}{W_{\text{share}}} \times 100\% \end{cases} \tag{15}$$

Variables in Formula 15 W_{share}, W_{err} and W_{receive} They are the amount of shared data, the amount of shared error data, and the actual amount of data received by the client. The quantitative test indicator of sharing efficiency is the execution time of shared tasks, and the test results can be expressed as:

$$\Delta t = t_{\text{receive}} - t_{\text{apply for}} \tag{16}$$

Among $t_{\text{apply for}}$ and t_{receive} They are the time when the sharing application was submitted and the time when the client received the shared data. Finally, it is calculated that the smaller the loss of shared resources and the receiving error rate, the shorter the execution time of shared tasks, which indicates the better the sharing performance of the corresponding methods.

3.7 Performance Test Results and Analysis

According to the statistics of relevant data, the test results of risk sharing of three methods are obtained, as shown in Table 2.

Table 2. Data Sheet of Teaching Resource Sharing Risk Test

	No.	Amount of data applied for sharing resources/GB	User's actual received resources/GB	Received error data volume/GB
Sharing method based on cloud computing	1	13.4	12.2	1.5
	2	27.2	25.8	1.3
	3	36.5	35.2	0.9
	4	29.8	29.1	1.4
	5	42.1	40.6	1.1
	6	35.7	34.2	1.2
A Sharing Method Based on Agent Search	1	13.4	12.6	0.7
	2	27.2	26.5	0.9
	3	36.5	36.0	0.9
	4	29.8	29.1	0.8
	5	42.1	41.4	0.6
	6	35.7	35.3	0.7
Sharing method based on federated learning	1	13.4	13.1	0.4
	2	27.2	27.0	0.5
	3	36.5	36.3	0.3
	4	29.8	29.4	0.3
	5	42.1	42.0	0.2
	6	35.7	35.3	0.4

By substituting the data in Table 2 into formula (15), it can be calculated that the average values of shared resource loss received by the two traditional methods are 1.27 GB and 0.63 GB, respectively, and the average values of receive error rates are 4.85% and 2.84%, respectively. However, the average shared resource loss received and receive error rates of the method in this paper are 0.27 GB and 1.37%, respectively. From this, it can be seen that the method proposed in this article not only ensures the security of shared resources, but also achieves accurate sharing.

The test comparison results of the sharing efficiency of teaching resources using different methods are shown in Fig. 10.

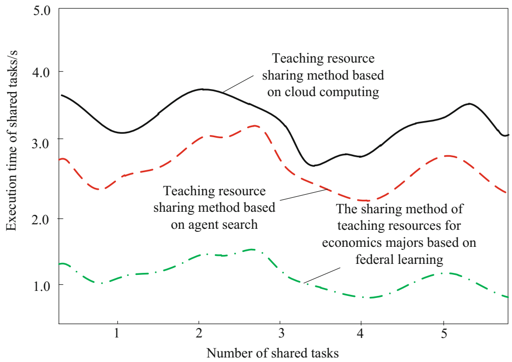

Fig. 10. Analysis of Teaching Resource Sharing Efficiency Test Results

From Fig. 10, it can be intuitively seen that after applying the method proposed in this paper, the execution time of resource sharing tasks has been significantly reduced. Throughout the entire experimental process, the execution time of shared tasks using the method proposed in this paper has never exceeded 2 s, indicating that the method proposed in this paper has significant advantages in sharing efficiency.

4 Conclusion

In the field of public education, it is difficult for schools to share the teaching data resources of economics majors due to competition or privacy protection, which hinders the progress and improvement of economics teaching. Therefore, it is very important to integrate and share data on the premise of protecting the privacy of teaching resources of economics majors. Federal learning can share data while protecting data privacy to optimize the industry alliance model and meet the basic requirements of teaching resource sharing. Therefore, this study utilized this technology to optimize the design of teaching resource sharing methods for economics majors. From the experimental results, it can be seen that the method proposed in this paper can ensure sharing efficiency while improving sharing accuracy, and has high application value in teaching work.

Although the method proposed in this paper has achieved good application results at present, there are still issues with the difficulty of updating and maintaining shared teaching resources in a timely manner. The content and methods of education are constantly evolving, and if shared resources cannot be updated in a timely manner, it may lead to learners being exposed to outdated information and methods. Therefore, in the next stage of research, we will consider combining resource sharing with incremental resource updates.

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A Method of Identifying the Difficulty of College Piano Teaching Music Score Based on SVM Algorithm

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Abstract. In order to improve the accuracy of difficulty recognition in college piano teaching scores, a method based on SVM algorithm for difficulty recognition in college piano teaching scores was designed. Construct a mapping space for the difficulty level features of college piano teaching scores, and extract the difficulty level features of college piano teaching scores. Based on SVM algorithm, a difficulty recognition model for college piano teaching score is constructed, and the difficulty level of college piano teaching score is mapped to the feature space for recognition, eliminating linear errors in difficulty recognition of college piano teaching score and improving the accuracy of difficulty recognition of college piano teaching score. The experimental results show that the proposed method has higher accuracy in identifying the difficulty of college piano teaching scores, and can effectively shorten the time for identifying the difficulty of college piano teaching scores.

Keywords: SVM Algorithm · College Piano Teaching · Music Score Difficulty Recognition Method

1 Introduction

Nowadays, with the rapid development of the Internet, tens of thousands of piano score resources can be purchased from the Internet or even many music websites provide free download services. Judging the difficulty level of piano music score is a relatively complex task [1]. First of all, it is difficult to completely and objectively define the criteria and criteria for judging the difficulty of piano music scores. Now, most of the difficulty levels of music scores still need to be judged subjectively by professionals. However, for the massive digital music scores in the current network, it will be a time-consuming and labor-intensive project to judge the difficulty level one by one, which is unrealistic. Moreover, there are many factors that affect human subjective judgment, especially for multi category problems, it is difficult for human subjective perception to accurately grasp the difference between each difficulty level[2]. Different people may give different levels of difficulty to the same music score, and even for the same music score, the same person will give different levels of difficulty at different times.

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In order to provide difficulty level labels for the massive digital piano scores shared in the network, and at the same time avoid consuming a lot of human work time and avoiding the inconsistency of human subjective judgment of difficulty level, it will be an effective strategy to design an algorithm that can automatically identify the difficulty level of music scores according to the relevant theories of machine learning and pattern recognition.

Piano teaching has always been carried out by means of “one-on-one” oral and heart teaching. Students practice piano independently after class. This learning method has caused problems such as narrow knowledge and insufficient communication between students. Mastering skillful piano playing skills is the most basic part and the most important content for students majoring in piano performance. But in addition to piano playing skills, it is also necessary to broaden students’ artistic vision and knowledge, absorb artistic nutrition, and improve students’ abilities in music aesthetics, understanding of music works, and emotional expression of music. Then improve artistic accomplishment and comprehensive performance ability [3]. However, there are always some hidden dangers in selecting music scores. The music score selected by the teacher for the students may not meet the students’ preferences. Students may increase or decrease their liking for piano learning according to the performance of the music score.

In order to meet the piano learning needs of more students, this paper combines the advantages of SVM algorithm to design a method to identify the difficulty of college piano teaching score. By extracting the difficulty level characteristics of college piano teaching scores and using SVM algorithm, a difficulty recognition model for college piano teaching scores is constructed to identify the difficulty level of college piano teaching scores, eliminate linear errors in difficulty recognition of college piano teaching scores, thereby improving the accuracy of difficulty recognition for college piano teaching scores and shortening the time for difficulty recognition in college piano teaching scores.

2 Design of Difficulty Recognition Method for College Piano Teaching Score Based on SVM Algorithm

2.1 Extraction of Difficulty Level Characteristics of Piano Teaching Scores in Colleges and Universities

Through in-depth study of learners’ cognitive processes and skills development laws, combined with music structure, technical difficulty requirements and other factors of music score, characteristics related to Cognitive load, attention distribution, etc. are extracted, so as to more accurately assess the difficulty of music score. The existing characteristics related to the difficulty of music score mainly involve information such as beat, pitch, time, music score length, note change and hand movement. On the basis of comprehensive analysis of the music score information contained in the existing difficulty characteristics, consult professional music teachers to judge the difficulty of music scores. After referring to the difficulty level classification standards provided by the music website, the characteristics such as interval change, average duration of notes, melody complexity, note density, chord type, and the speed at which notes are pressed, mapping to the difficulty feature space of piano music score [4]. This paper analyzes the seven difficulty characteristics of piano music score, as shown in Table 1 below.

Table 1. Relevant characteristics of score difficulty level

Difficulty characteristics	describe	Extraction method
Chord number	Several notes are pressed at the same time, which is called chord	Count the number of chords, and consider three chord, seven chord and nine chord types respectively, so this feature is three-dimensional
Note density	Number of notes played per second	IR
Interval variation	Interval variation of music score	Feature extraction of pitch value change
Speed change	Changes in music speed	Count the number of changes in music playing speed
Key speed entropy	Statistics the speed information entropy of pressed keys	PVE
Melody complexity	Evaluate melody complexity according to the continuity of voice color and stress, the number of pitch changes, and the self similarity of melody contour lines	According to the expected model, the function of the midtool box toolbox is implemented
Beat change	Measure the change in beat	Note duration

As shown in Table 1, in the process of piano teaching in colleges and universities, this paper adopts a new learning form, which not only brings convenience to learning, but also puts forward new requirements for teachers' teaching and students' learning. In this paper, chord number, note density, interval change, score speed change, key speed entropy, melody complexity, beat change and other features are extracted [5]. Each feature corresponds to its special mapping space and marks the best score difficulty label. The characteristic expression of note density is:

$$IR = \sum |p(i) - p(i+1)| \tag{1}$$

In formula (1), IR Is the feature of note density; $p(i)$ Is the pitch value of the ith note; $p(i+1)$ Is the pitch value of the i + 1 note. Combined with the number of changes in the speed of music playing and the expectations of playing, this paper analyzes the entropy characteristics of piano key speed, and the formula is as follows:

$$PVE = -\sum_{i=1}^{p(i)} p(x_i) \log_2 p(x_i) \tag{2}$$

In formula (2), *PVE* Is the key speed entropy characteristic of piano; $p(x_i)$ Is the key speed x_i Probability of. The piano teaching music score in colleges and universities includes three chords, seven chords and nine chordspitch change, note change rate, minimum rhythm value, pitch value standard deviation, duration standard deviation and other characteristics are divided into different characteristic intervals [6]. Divide triad, velocity change, interval change, hand extension, harmony, and note change rate into a feature space; Seven chords, key speed entropy, average pitch value, different tapping rates, irregular rhythm and the shortest rhythm value are divided into a feature space; Nine chords, melody complexity, average duration of notes, hand exchange rate, hand movement rate, and standard deviation of pitch value are divided into a feature space.

Piano teaching in colleges and universities mostly adopts online and offline hybrid learning. The knowledge and skills learned by students have diversified forms of expression. From the traditional knowledge transmission mode based on textbooks to the diversified knowledge transmission mode, such as video, web page, audio, etc., the presentation of knowledge lacks certain internal relevance and structure. It is mostly presented in a scattered form. The characteristics of the content and content structure of this course require students to have a high ability of knowledge integration in the learning process and be able to form a systematic piano performance. However, during the investigation, it was found that there is fragmentation of knowledge in online learning of students who lack offline teacher guidance, and there is separation between piano playing skills and piano theoretical knowledge. And teachers can better promote students' piano learning effect through teaching guidance and explanation [7]. This paper uses MIDI format music score files containing music score information such as pitch, beat, time, chord, speed, and channel as college piano teaching data. Even if the annotation information such as fingering and expression in music score is lost, the information it contains is enough to identify the difficulty level of digital piano music score. Considering that in many cases of actual piano learning and teaching, scores with four difficulty levels will be used, and a large number of music websites also generally provide four difficulty levels, namely easy, beginner, intermediate, and advanced piano scores, so in order to better evaluate the scalability of the algorithm in this paper, it can be more suitable for the actual piano teaching situation. According to the different difficulty levels of easy, beginner, intermediate and advanced, the piano score is quantified. The quantification process is shown in Fig. 1 below.

As shown in Fig. 1, after the difficulty features of music score are extracted in this paper, the feature corresponding values are larger and mapped to the triad feature space, while the other feature corresponding values are smaller and mapped to the ninth chord feature space[8]. In order to avoid the redundancy of music score difficulty features, this paper uses the normalization algorithm to process the larger eigenvalue and the smaller eigenvalue. The formula is as follows:

$$x_i^* = \frac{x_i - x_{i\,\min}}{x_{i\,\max} - x_{i\,\min}} \tag{3}$$

In formula (3), x_i^* Is the quantified value of difficulty characteristics of music score after normalization; $x_{i\,\min}$ Is the smaller score difficulty eigenvalue; $x_{i\,\max}$ It is the characteristic value of greater difficulty of music score. For the score difficulty feature data set, the data in the feature mapping space of each brother is unbalanced. The data with

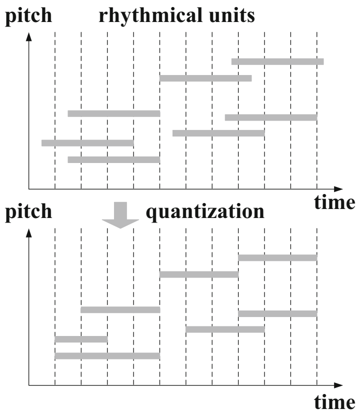

Fig. 1. Flow diagram of note rhythm position quantification

difficulty levels of 5 and 6 are about six times the data with difficulty levels of 2 and 3[9]. In subsequent recognition experiments, if the data of each category in the training data is unbalanced, the recognizer will tend to divide the objects to be recognized into a large number of categories, and the accuracy and credibility of the recognition results will be reduced. Therefore, aiming at the problem of data imbalance, this paper uses SVM algorithm to identify and ensure the overall recognition accuracy of music score difficulty.

2.2 Construction of Piano Score Difficulty Recognition Model Based on SVM Algorithm

Building a piano score difficulty recognition model based on SVM algorithm enables the model to better adapt to piano score difficulty recognition tasks, improving the classification accuracy and generalization ability of the model. In the process of recognizing the difficulty of piano music score, this paper establishes a music score sample dataset according to the music score difficulty mapping space characteristics, and uses the music score feature data of the music score sample dataset to establish training samples for music score difficulty recognition. Considering the distribution of music score features, this paper establishes multiple training SVM models at the same time to conduct evolutionary operations on sample data to generate new candidate music score samples. Then select a sample connection from the candidate score sample set and the score sample data set to construct the sample to be identified. The SVM model is used to identify the Pareto non dominated individuals. The non dominated individuals in the score samples calculate the Pareto non dominated individuals according to the sample crowding distance, and select the non dominated candidate score samples for individual recognition. In order to improve the distribution of Pareto non dominated solution set and the convergence speed of SVM algorithm, and ensure the effectiveness of Pareto dominated recognition method based on SVM in solving music score difficulty problems, this paper designs a new candidate music score sample recognition strategy to improve the convergence speed of the algorithm, maintain the diversity of music score population in the evolution process, and improve the comprehensive performance of SVM algorithm. In this paper, combined with the good generalization ability of SVM algorithm, a recognition method for joint decision-making of multiple candidate score samples is proposed. By training multiple score samples, and combining the distributed distance calculation method, the new candidate score samples are voted to make decisions. The SVM algorithm can more accurately classify and recognize Pareto non dominated individuals of music score samples. The classification and recognition principle of piano music score is shown in Fig. 2 below.

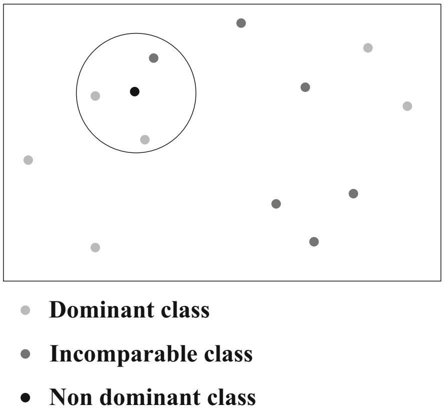

Fig. 2. Schematic diagram of piano score classification principle

As shown in Fig. 2, three kinds of small dots, light gray, dark gray and black, respectively represent Pareto dominant categories in piano music score. In the figure, six light gray dots and six dark gray dots represent two categories respectively, and the category of black dots is judged according to SVM. The three points closest to the black point are shown as solid circles in the figure. If there are two light gray dots and one dark gray dot, the black point belongs to the category of light gray dots [10]. Assuming that the black dot is k, its nearest neighbor music score sample identification, from the calculation of the distance or similarity between the music score sample to be identified and the training sample of the known music score grade sample, find the k nearest neighbors whose distance or similarity is closest to the sample data to be identified, and form the nearest neighbor set N0. The category of most samples in the set N0 is the category of the sample to be identified. The recognition structure of SVM recognition algorithm is shown in Fig. 3 below.

As shown in Fig. 3, combine the score difficulty features extracted in this paper with the existing score features, and use the SVM algorithm in the mapping feature space to train the prior knowledge of the data. The obtained mapping matrix maps the original music score features to a space with higher classification degree. Then SVM algorithm is used to identify the difficulty level of the music score to be determined. The key of SVM algorithm is to find the best mapping matrix, and the expression is as follows:

$$x_i' = Lx_i \tag{4}$$

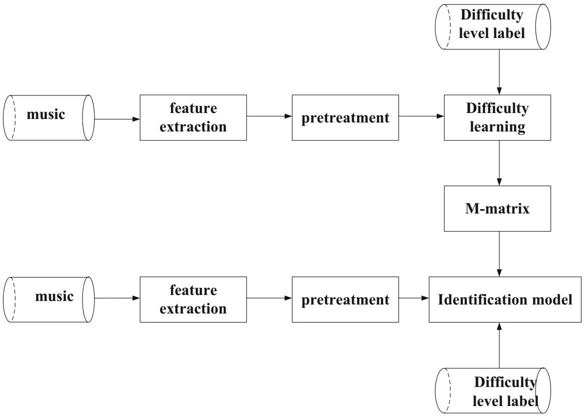

Fig. 3. Identification Structure Diagram

In Eq. (4), x_i' Is the best mapping matrix expression; L Is the characteristic transformation matrix.according to x_i' It can be seen that the new mapping eigenvector x_i' Is the original eigenvector x_i And transformation matrix L A linear combination of elements. It can be seen that the distance measure of mapping space d_L For:

$$d_L(x_i, x_j) = \left\| L(x_i - x_j) \right\|_2 \tag{5}$$

In formula (5), d_L Is the distance measure of the mapping space; x_j Is the eigenvector of piano score difficulty level. To avoid finding the mean square and ensure that the distance is positive, take the square of the distance and express it in matrix form, then the new distance measure is expressed as:

$$D_M = d_L^2 \tag{6}$$

In formula (6), D_M Is a new distance measure in music score samples.Matrix M is expressed as:

$$M = L^T L \tag{7}$$

In Eq. (7), M Is a positive semi definite symmetric matrix; L^T by L The music score difficulty label of the element linear transformation to another feature space. The feature can be mapped to another space through matrix M. It is hoped that the category discrimination in the mapped feature space will be higher, that is, after mapping, the scores with the same difficulty tag will be more similar, and the scores with different difficulty tags will be more differentiated. That is to say, after mapping, scores with the same difficulty tag will be shortened, and the distance between scores with different difficulty tags will increase, at least greater than the distance between data of the same category. Based on the above ideas, the process of solving the mapping matrix M is reduced to solving the following objective functions:

$$Y = \min \sum_{(i,j) \in M} D_M(x_i, x_j) \tag{8}$$

In Eq. (8), Y It is the objective function of music score difficulty recognition. The matrix M when the minimum value is obtained. Where S represents a data pair consisting of two digital scores of the same difficulty level, (x_i, x_j) The difficulty levels are the same. On the basis of the M-matrix, each pair is added with three sets of digital scores of different difficulty levels (x_i And x_j) The difficulty level is the same, x_i It is different from other difficulty levels. The ultimate purpose of recognition is to make the distance between tag data of the same category as small as possible, while the interval between tag data of different categories is at least one unit greater than that of tag data of the same category, that is, the large interval, so as to maximize the discrimination between categories after mapping. In this process, it is very important to identify the difficulty of teaching music score.In this paper, the weight of each feature is determined based on the recognition and mapping features of teaching music score. The formula is as follows:

$$W(A) = D_M - \sum_{i=1}^{p(i)} D_M(x_i, x_j)/L^T L + \frac{p(C)}{1 - p(cl(R))} \tag{9}$$

In Eq. (9), $W(A)$ Is the weight value of the difficulty characteristics of piano music score; $p(C)$ Is a feature C Music label category number of; $cl(R)$ Is a score sample R Class number of; $p(cl(R))$ Is a score sample R The music label of. Combining the mapping features and difficulty weights, this paper constructs a music score difficulty recognition model, which is expressed as follows:

$$K = \begin{cases} \dfrac{R_1[C] - R_2[C]}{\max(C) - \min(C)} \cdot YW(A)/L^T L + \dfrac{p(C)}{1 - p(cl(R))} \\ 0 \\ 1 \end{cases} \tag{10}$$

In Eq. (10), K Is a model expression; $R_1[C]$, $R_2[C]$ Is a sample R In category C Upper difference; $\max(C)$ Is a score category C The maximum score difficulty tag value mapped to the feature space; $\min(C)$ Is a score category C The minimum score difficulty tag value mapped to the feature space. The weight values of features in data sets are generally large, and more feature weights are close to zero, or even negative. This also shows that the more detailed the classification, the more unbalanced the corresponding weights of features. Therefore, after the completion of model recognition, this paper uses SVM to eliminate the linear error of college piano score difficulty recognition, balance the difficulty recognition weight to the greatest extent, and improve the accuracy of score difficulty recognition.

2.3 Eliminate the Linear Error of Difficulty Identification of College Piano Score

On the basis of constructing a piano score difficulty recognition model, eliminate the linear error of difficulty recognition in university piano scores, thereby improving the accuracy of difficulty recognition in university piano teaching scores. In the piano teaching design link, teachers need to do demand analysis, that is, what kind of courses students need, and whether the courses they need are suitable for online teaching. On this basis, determine the required courses. After the establishment of the curriculum, it is necessary to guide the curriculum design by using the relevant theories of curriculum design and development: that is, what is the curriculum goal of the established curriculum, what content needs to be organized to achieve these goals, what are the key and difficult points of the curriculum, which courses can be opened online, and which content must be carried out offline. The characteristics of students' piano learning are the starting point of piano teaching. Based on today's information technology and Internet development, students' piano learning has produced some new piano learning methods and learning characteristics on the basis of the original learning methods. In the process of online online offline hybrid teaching design, teachers need to consider new characteristics and new ways while the basis of the original learning method: first, they need to consider the learners' original piano playing foundation, which is the starting point of piano teaching. Piano teaching must be based on the students' original piano playing level.

No matter what type of piano performance is, music score is indispensable. The closer the difficulty of music score is to the level of performance, the higher the interest of students in learning piano is; On the contrary, it will reduce students' interest in piano learning. After identifying the difficulty of piano music score with the difficulty identification model, this paper uses SVM algorithm based on statistical learning theory to minimize the risk of difficulty identification of music score. According to the complexity of limited music score sample information in the model, the best compromise of music score recognition ability is sought in order to obtain the best recognition ability. SVM algorithm has been widely used in various fields, with perfect theoretical basis, simple mathematical model and extensive practical applications, and has largely overcome the "dimension disaster" and "over learning" problems. Theory and practice have proved that SVM has many unique advantages in solving the problems of small sample size, linear inseparability and high-dimensional pattern recognition. SVM is widely applicable, robust to noise and outliers, and has strong generalization ability, which plays an important role in eliminating the error of recognition model.This paper combines measures d_L, analyze the distance change of adjacent music scores, as shown in Fig. 4 below.

As shown in Fig. 4, for music score data of new difficulty level to be identified, after the same feature extraction and feature preprocessing operations as before, according to the matrix M learned from the data with difficulty level labels, use the distance measurement equation to measure the distance from each music score in the training set. The smaller the value, the more similar it is. Sort by value from small to large, the difficulty level of most scores in the top k scores is the difficulty level of the score to be identified. According to the distance change between the score difficulty labels, this paper divides the score difficulty labels linearly, as shown in Fig. 5 below.

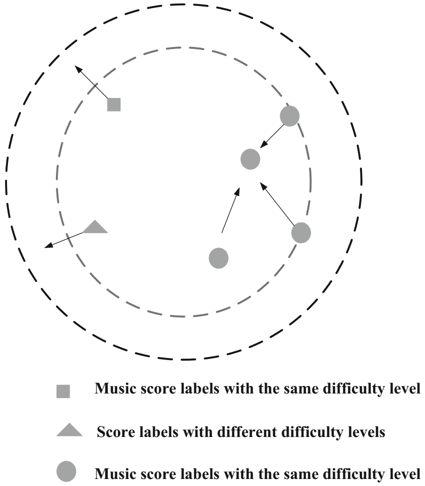

Fig. 4. Schematic diagram of distance change of adjacent music scores

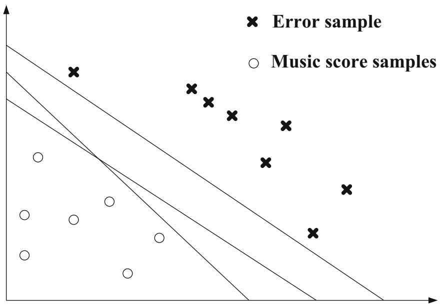

Fig. 5. Linear Classification Diagram

As shown in Fig. 5, the recognition model aims to minimize the training error and only considers the fitting of the classifier to the training samples. By providing sufficient training samples to train the classifier, it attempts to improve the recognition rate on the new test sample set. However, for a limited set of training samples, it is not guaranteed that the classifier that is effective for training samples can also classify test samples effectively. In the case of small sample set, blindly pursuing the classification accuracy of training sample set will lead to over fitting. SVM takes structural risk minimization as the principle to ensure that the training error is as small as possible while the recognition accuracy is as high as possible, which is specifically reflected in the selection of classification models and model parameters. This paper combines the advantages of SVM to find an optimal classification hyperplane that meets the classification requirements, so that the hyperplane can maximize the spacing between the hyperplane and samples while ensuring the classification accuracy. The two types of samples are completely separated by a linear function, and the samples follow the principle of linear separability to eliminate a linear error in the two-dimensional mapping space. This paper uses countless straight lines to completely separate the complete sample from the error sample, and any straight line in the figure can eliminate the error to a certain extent. The classification straight line close to the sample point is vulnerable to noise, and its ability to classify data outside the training sample is weak; The straight line far away from all training samples has strong stability, and has strong recognition ability for samples. In other words, the selection of lines that are far from the label data of music score samples has the ability to eliminate linear errors, which plays an important role in improving the accuracy of music score difficulty recognition.

3 Example Analysis

In order to verify whether the music score difficulty recognition method designed in this paper has practical value, this paper takes X university as an example to conduct an experimental analysis of the above methods. The difficulty recognition method of piano music score based on measure learning support vector machine, the difficulty recognition method of piano music score based on LR algorithm and the difficulty recognition method of piano music score based on SVM algorithm designed in this paper are compared to find the best recognition scheme. The overview and application results of X universities are shown below.

3.1 Overview of Colleges and Universities

X College is an art college, with 8 colleges in total, of which Chamber Music (Double Piano) is a professional course in the music performance professional curriculum system of the Conservatory of Music. The course credits are set as 2 credits. The teaching objectives of Chamber Music (Double Piano) are: to enhance students' ability in playing skills and stage practice through learning the course; The purpose of this syllabus is to further improve the structure of students' professional knowledge by expanding the teaching content. This course is a cooperative performance course as important as the piano performance solo course. It uses one-to-one and one-to-two teaching methods, and the teaching content is the performance training of two piano ensemble modes, namely "double piano" and "four hand playing".

Teachers should adopt corresponding teaching methods according to the conditions and abilities of the teaching objects, scientifically arrange teaching plans and use of teaching materials, so that students can be familiar with piano ensemble works of different periods and styles, and have the corresponding ensemble ability when playing music works with others. According to the analysis of class hours and class hours, the course of Chamber Music (Double Piano) is divided into two semesters, of which the first semester has 18 class hours. The main contents are work arrangement and performance part distribution, single performance guidance, and double ensemble guidance. In the second semester, there are 18 class hours, including 36 class hours of work arrangement and performance assignment, single performance guidance, and double ensemble guidance. In the teaching part of piano ensemble performance skills, the teacher first conducts teaching with "one-to-one" (individual performance training), and then conducts "one-to-two" (two person ensemble training) teaching after the students' individual performance is relatively mature.

Teachers combine theory teaching with classroom practice as a teaching method. In teaching, students' learning enthusiasm will be promoted by means of enlightening explanation, demonstration demonstration, work appreciation, and joint discussion, so that they can master the basic piano ensemble skills. The examination and evaluation time of Chamber Music (Double Piano) is at the end of each semester. The examination results are calculated according to the hundred point system, and all teachers of the Piano Department score according to the requirements of the school, department and this syllabus. Students who miss two thirds of the total class hours due to illness, personal leave or other reasons during the course of learning, or who miss 10 classes in total, cannot take the exam. In the course of course examination, if the students missed the exam or failed in the exam, the College will organize a unified make-up exam for the course. If the make-up exam has not passed the exam, no opportunity will be given to make up the exam. In order to have a clearer understanding of students' learning, this paper uses SVM algorithm to identify the difficulty of piano teaching score in this school. The identification process is shown in Fig. 6 below.

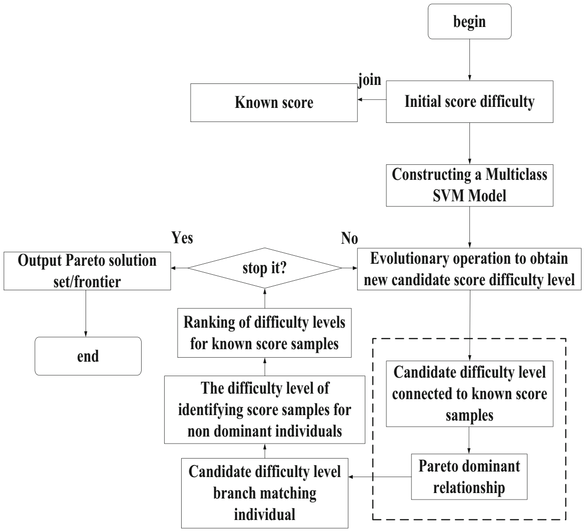

Fig. 6. Flow chart of piano score difficulty identification

As shown in Fig. 6, in the iterative process of score difficulty recognition, this paper selects a small number of new candidate score samples for difficulty level assessment, and puts them into the recognition sample set to provide more score level distribution information for the recognition model and maintain the recognition ability of the model. When selecting the new candidate score samples, multiple SVM models and SVR models are established, and the candidate score sample set is evaluated using the method of multi model joint decision-making. Then, the new candidate score samples are selected by combining the distribution distance and re evaluated accordingly. In order to improve the distribution of Pareto dominated solution set and the convergence speed of the model, and ensure the effective value of Pareto dominance, this paper selects several test functions, so that the recognition model can more accurately identify Pareto non dominated individuals of piano scores, and more accurately evaluate the new candidate score samples. In this process, this paper reduces the number of times to recognize target samples in the process of sample recognition evolution, so as to save recognition resources. This candidate score grade sample can optimize the score recognition decision space to a greater extent, ensuring that the recognition model can drive the candidate scores to rank, and gradually approach the real Pareto optimal surface.

3.2 Application Results

Under the above conditions, this paper randomly selects ZDT1, ZDT3, KUR and other test functions. In the case that other conditions are consistent, the conventional piano score difficulty recognition method based on measure learning support vector machine, the conventional piano score difficulty recognition method based on LR algorithm, and the piano score difficulty recognition method based on SVM algorithm designed in this paper are compared. The final experimental results are dominated by Pareto, and the application results are shown in Table 2 below.

Table 2. Application Results

Test function	Pareto dominance/%			
	Dominant class	Incomparable class	Non dominated	Accurate overall identification
Conventional recognition method of piano score difficulty based on measure learning support vector machine				
ZDT1	76.12	83.10	82.55	80.59
ZDT3	84.36	72.11	80.36	78.94
KUR	70.26	80.45	68.32	73.01
Conventional difficulty recognition method of piano music score based on LR algorithm				
ZDT1	85.46	86.32	85.43	85.74
ZDT3	84.36	88.58	86.67	86.54
KUR	87.28	89.48	90.36	89.04
The difficulty recognition method of piano music score based on SVM algorithm designed in this paper				
ZDT1	95.88	98.67	97.35	97.30
ZDT3	96.78	98.98	97.36	97.71
KUR	99.27	98.26	99.45	98.99

As shown in Table 2, Pareto dominance refers to the recognition accuracy of the difficulty of college piano teaching music score. Dominant, incomparable and non dominated categories are Pareto dominated.ZDT1, ZDT3 and KUR are the test functions of this experiment. Under the condition that the test functions are consistent, the higher Pareto dominance is, the higher the recognition accuracy of piano teaching score difficulty is. After using the conventional piano score difficulty recognition method based on measure learning support vector machine, Pareto's dominant overall recognition accuracy is low, the average value is only 77.5%,, affecting the difficulty recognition effect, and it is unable to carry out piano teaching for college students. After using the conventional recognition method of piano score difficulty based on LR algorithm, Pareto's dominant overall recognition accuracy has increased compared with the measurement learning support vector machine recognition method, and the average value is only 87.1%, but the overall difficulty recognition accuracy is still less than 90%, which leads to the problem of students' great difficulty level leap and decline in learning quality when learning piano. It is in urgent need of improvement. However, after using the difficulty recognition method of piano score based on SVM algorithm designed in this paper, the average accuracy of Pareto dominant overall recognition is as high as 98%, approaching 100% indefinitely. This proves that the method designed in this paper is easier to identify the difficulty of music score, and piano teaching is more targeted, which can ensure the quality of students' learning.

In order to verify the difficulty recognition time of college piano teaching scores using the proposed method, a conventional method for identifying the difficulty of piano score based on measure learning support vector machine and conventional piano score difficulty recognition method based on LR algorithm were used as comparison methods. The comparison results of difficulty recognition time of college piano teaching scores using different methods are shown in Table 3.

Table 3. Comparison of time results for identifying the difficulty of music score in piano teaching in universities using different methods

Music scores for piano teaching in universities/piece	The proposed method/ms	A Conventional Method for Identifying the Difficulty of Piano Score Based on Measure Learning Support Vector Machine/ms	Conventional piano score difficulty recognition method based on LR algorithm/ms
2	1.3	2.8	3.5
4	2.1	4.2	5.9
6	3.9	5.7	7.3
8	4.8	6.6	9.2
10	5.4	7.9	11.2

According to Table 3, as the number of scores for piano teaching in universities increases, the difficulty identification time for different methods of piano teaching scores in universities also increases. When the number of scores in university piano teaching is 10, the difficulty recognition time for a conventional method for identifying the difficulty of piano score based on measure learning support vector machine and conventional piano score difficulty recognition method based on LR algorithm in university piano teaching scores is 7.9ms and 11.2ms, respectively, while the difficulty recognition time for the proposed method in university piano teaching scores is only 5.4ms. From this, it can be seen that the proposed method has a shorter recognition time for the difficulty of score recognition in piano teaching in universities.

4 Conclusion

In recent years, a large number of piano scores have been created every day. How to identify the difficulty level of music scores has become an urgent problem. There have been a large number of piano scores in the history of music. It is a great challenge to find a score that matches the learners' learning level from the huge data of piano scores. One of the main abilities of music teachers is to be able to select piano music scores suitable for students' learning difficulty level. For college students of piano courses, I don't know how to choose a score suitable for their own level from the vast number of piano scores and stop learning. What's more, because of the difficult music score practice at the beginning, the confidence was hit and the enthusiasm for learning was greatly reduced. For piano majors, although there is a set of fixed advanced teaching materials in the learning process, the long time practice of the same music, the learning process is too monotonous and boring, which is also not conducive to developing personalized learning programs for individuals to increase the enthusiasm of learners and improve learning efficiency. Therefore, this paper uses SVM algorithm to design a method to identify the difficulty of college piano teaching music score. Improve the accuracy of music score difficulty recognition from the aspects of difficulty characteristics, recognition models, recognition errors, etc., to provide guarantee for students' effective learning.

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Personalized Recommendation Method of Online Education Resources for Tourism Majors Based on Machine Learning

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Abstract. The online learning platform provides new opportunities for tourism majors to obtain information. However, the diversity and universality of learning resources have led to Exponential growth of data, making it difficult for students to find resources that meet their own needs. To address this issue, this study proposes a personalized recommendation method for tourism professional online education resources based on machine learning. This method combines TF-IDF weight and location information weight on the basis of TextRank algorithm to generate user interest labels and attribute labels for tourism professional online education resources, thereby establishing a user interest model and resource attribute description. By optimizing the K-means clustering algorithm using genetic algorithm, the recommended online education resources for tourism majors are divided into different resource groups. Next, calculate the distance between the user interest model and the center of each resource cluster, and select the resource cluster closest to the user interest model as the recommendation result. Finally, by calculating the similarity between resources, the resources in the resource cluster are sorted to generate a personalized recommendation list. The research results indicate that the recommendation method based on machine learning has a good recommendation effect in personalized recommendation of online education resources for tourism majors. This method effectively utilizes user interest models and resource attribute descriptions to provide personalized learning resource recommendations that meet students' needs, thereby optimizing the learning process and improving learning effectiveness.

Keywords: Machine Learning · Improved K-Means Clustering Algorithm · Online Education Resources for Tourism Majors · Label · Personalized Recommendation Method

1 Introduction

In recent years, with the rapid development of online learning, learners are increasingly demanding personalized and practical learning resources. Whether it is traditional education or online education, the quality of learning resources plays a decisive role in the

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teaching effect, especially in online education. Therefore, online education researchers began to pay attention to the construction of online education resources. The teaching resource database is also an important research topic of "Internet+Education", which has received extensive attention from tourism industry professionals and tourism scholars. However, in general, there are still some problems in the research on the construction of the shared teaching resource database for tourism majors in China. Facing the exponential growth of data caused by the diversity and universality of learning resources, it is very difficult for learners to efficiently obtain learning resources that meet their own interests, cognitive characteristics and learning styles when facing numerous choices. And with the increase of learner behavior logs, the traditional serial recommendation algorithm is limited by hardware configuration, and the storage, computing and processing capacity of resource data has exceeded the capacity of traditional server architecture, unable to achieve fast and real-time recommendation [1]. These problems may bring poor learning experience to learners. Therefore, research on how to achieve real-time and efficient "personalized recommendation" for massive data is in the ascendant. For online learning platform, recommending personalized learning resources to learners can effectively help learners deal with resource overload, knowledge fragmentation and other issues. How to provide personalized learning resources recommendation services for learners has become a challenge for online learning platform. A large amount of historical learning data has been generated in the online learning platform, and there is a large amount of potential information available in online learning resources. Therefore, it is feasible to build personalized online learning resource recommendation methods.

The constant penetration of Internet technology in the field of education has brought the demand for personalized recommendation of online learning platforms to the breaking point. In the 1990s, the Educational Technology Experiment Center of the Netherlands Open University took the recommendation in the field of personalized education as an independent research hotspot for the first time, and it is still improving today. The research on the recommendation of learning resources abroad mainly focuses on the following aspects: content based recommendation is to analyze the content of resources by using information retrieval, information clustering and other technologies, analyze the content of resources, calculate the weight, and then generate a recommendation list to achieve the recommendation of relevant resources. Content based recommendation mainly analyzes the content of resources. In the process of learning resource recommendation, it can map learning resources and learners according to the description of learning resource characteristics and learning records, and then recommend resources that meet their own learning characteristics for learners. This method has high requirements for resource structure, and well structured resources can provide stable preconditions for resource similarity calculation. The association rule based algorithm is based on the data mining technology. It extracts and analyzes the user's historical record data, calculates the associated data, combines these data into a new item set according to the association rules, and stores it in the database. Finally, it matches the data set in the database according to the user's browsing records, and recommends the associated resources to the user. The algorithm is simple and direct in the process of recommendation, and can recommend according to association rules. However, the algorithm is time-consuming in association rule mining, and the personalized degree of learning resource recommendation is not high. The core idea of user based collaborative filtering recommendation algorithm is to recommend resources according to the "similar interest preferences" of users.In the recommendation system, other users with similar interests and preferences to the target user are found according to the user record data, and then the resources of other users' preferences are recommended to the target user. The user based collaborative filtering algorithm recommends resources for target users based on users' similar interest preferences. The algorithm is simple in implementation and flexible in deployment, but there are data sparse and cold start problems.

To sum up, the three personalized recommendation algorithms have their own advantages and disadvantages. Therefore, this research combines machine learning algorithm with content-based collaborative filtering recommendation to study a personalized hybrid recommendation algorithm.

2 Research on Personalized Recommendation of Online Education Resources for Tourism Majors

Aiming at the problems existing in the existing recommendation methods, this paper introduces the current research hotspot - machine learning method, and studies a personalized recommendation method for online education resources of tourism specialty based on machine learning. The research idea is shown in Fig. 1 below.

2.1 User Interest Model Construction and Resource Attribute Description

When adopting content based recommendation, the extraction of resource content features is crucial. After describing resources with feature tags one by one, it is only necessary to judge whether the user has a special preference for a feature tag in his past behavior. If most tags of a resource appear in the user's past behavior records, then the resource is more likely to be a user preference item. When adopting the content-based recommendation algorithm, it is necessary to start from the content characteristics of the resource itself and find out the user's preferred resource type according to the user's browsing history of the resource to generate recommendations [2]. In the data preprocessing stage, it is necessary to more likely include the online education resources of tourism majors that users have browsed into a limited but not sparse type, and summarize users' preferences by "labeling". It can be seen from this that before constructing the user interest model, it is necessary to construct the tags of historical resources that users have contacted according to the historical records of users' browsing online education resources of tourism majors in the past. As one of the commonly used tag generation algorithms, TextRank algorithm considers the potential relationship between words in the iterative calculation process, but only generates tags based on a single document, without considering corpus information. In the TF-IDF algorithm, the importance of words depends on their frequency of appearance in documents and corpora. The weight of TF-IDF increases with the former in direct proportion, and decreases with the latter in inverse proportion. Therefore, adding TF-IDF weight influence factors can eliminate meaningless high-frequency words, add word information in the corpus, and improve

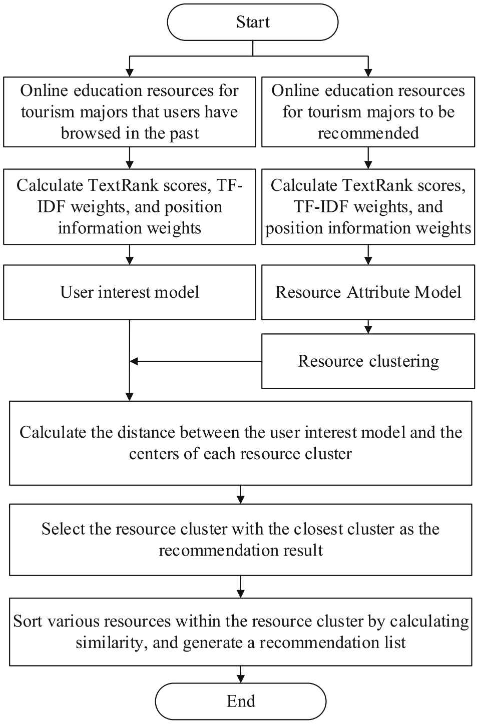

Fig. 1. Research block diagram of personalized recommendation method of online education resources for tourism majors based on machine learning

the quality of tag generation. However, location information also has a certain impact on the weight of words. Generally, the first and last paragraphs of a document and the first and last paragraphs of a paragraph have the function of introduction and summary. Words appearing in these positions should be given a higher weight, and the weight of words in different positions should be different. Therefore, on the basis of TextRank algorithm, this paper fuses location information weight and corpus information to form a multi feature fusion tag generation algorithm [3]. The specific process is as follows:

Step 1: Get the online education resources of tourism majors that users have browsed in the past and record them as resource text A.

Step 2: Check the resource text A Processing of removing stop words, segmentation and part of speech tagging.

Step 3: Use an independent term as a candidate label.

Step 4: Calculate the TextRank score of each vocabulary. TextRank is a graph ranking model. It builds an undirected graph with candidate keywords as nodes, obtains the edge weight value through the co-occurrence relationship between words, and then calculates the score of each word node a_i Score of $B(a_i)$ The calculation formula is as follows:

$$B(a_i) = (1 - b) + b \sum_{a_j \in In(a_i)} \frac{w_{ij}}{\sum_{a_k \in Out(a_j)} w_{jk}} \tag{1}$$

where, a_i Is a node, $In(a_i)$ Is the node set pointing to it; $Out(a_j)$ Is a point a_i Point set pointed to, w_{ij} express a_i and a_j The weight of the side between words is obtained by the number of co occurrences between words; w_{jk} express a_j and a_k Weight of edges between. $\sum_{a_k \in Out(a_j)} w_{jk}$ Means that all points a_i The sum of the weights of the nodes. Perform iterative calculation according to formula (2) until the initial score of TextRank is converged $B(a_i)$. b It is a damping factor, generally 0.85.

Step 5: Calculate the TF-IDF value of each vocabulary.TF-IDF is mainly used to evaluate the importance of a word to a document in the whole corpus. It is a statistical method that measures the importance of words by calculating word frequency and inverse document frequency [4]. That is, the more a word appears in the document, the less it appears in the whole corpus, which indicates that the word has good classification ability and is more likely to be used as a tag. TF-IDF is often used as a weighting factor for information retrieval and text mining. The calculated word weights include corpus information.The calculation formula is as follows:

$$C = TF_{ij} \cdot IDF_i \tag{2}$$

Among them, C Refers to a word i In the online education resource text j The importance of, that is, word weight. TF_{ij} It is word frequency, indicating words i In the online education resource text j The proportion of occurrence times in is calculated as follows:

$$TF_{ij} = d_{ij}/D_j \tag{3}$$

where, d_{ij} Refers to words i In the online education resource text j Number of occurrences in, D_j It refers to the text of online education resources j The total number of occurrences of all words in.

IDF_i Is a word i The inverse document frequency of, reflecting the frequency of words in the overall corpus, is calculated as follows:

$$IDF_i = \log|E|/e_i + 1 \tag{4}$$

Among them, E Is the total number of documents in the corpus, e_i Include words i The denominator plus one is used to prevent the denominator from being zero due to new words not in the corpus. Laplacian smoothing is used to enhance the robustness of the algorithm.

Step 7: Calculate the position information weight.First, segment the document. Assume that the total number of document segments is m, word i The paragraph is F Segment, then F The weight of all words in the section is:

$$V_{F,i} = \begin{cases} \frac{1}{F}, F \le \frac{m}{2} \\ \frac{1}{m - F + 1}, otherwise \end{cases} \tag{5}$$

In the formula, the closer to the beginning and end, the greater the weight of the location information. On the contrary, the smaller the weight of the middle paragraph, and all of them are within the (0,1) interval, the subsequent normalization processing will be carried out to reasonably calculate the location information weight. In a document, the location information in each paragraph is also different, and the first and last sentences serve as a link between the preceding and the following. There may be only one audio and video introduction to educational resources. Therefore, different positions in the paragraph should also be given different weights. The first and last sentences have great weight, while the middle sentences contain small weights of words. Assume that all candidate words in the segment after preprocessing such as word segmentation and de stop words are n, words i At I, the word i In paragraph F The weights within are:

$$\tilde{V}_{F,i} = \begin{cases} \frac{1}{I}, I \le \frac{n}{2} \\ \frac{1}{n - I + 1}, otherwise \end{cases} \tag{6}$$

Then the final position information weight of the word i in the document is:

$$\hat{V}_{F,i} = V_{F,i} \cdot \tilde{V}_{F,i} \tag{7}$$

Weight of position information $\hat{V}_{F,i}$ Carry out normalization processing to obtain the final position information weight $\breve{V}_{F,i}$.

Step 8: Obtained by the above method $B(a_i)$, C, $\breve{V}_{F,i}$ By integrating the potential relationship between words, the influence of corpus on word scores and the influence of document location information on words, the weighted calculation is carried out to obtain the final score of words, which is arranged in descending order according to the score. Top -- K words are selected as labels of online education resources for tourism majors to improve the quality of label generation. Final score $S(a_i)$ The calculation formula is as follows:

$$S(a_i) = \phi_1 B(a_i) + \phi_2 C + \phi_3 \breve{V}_{F,i} \tag{8}$$

where, ϕ_1, ϕ_2, ϕ_3 All greater than 0, yes $B(a_i)$, C, $\breve{V}_{F,i}$ The size of the proportion.

according to K Tags of online education resources for tourism majors Build an interest model for users to browse online education resources for tourism majors [5]. If a user browses online education resources for tourism majors, the tag is represented by 1 when it is included in a dimension of the user interest model. Otherwise, it is 0. take K After all tags are counted in turn, the user interest model can use one K Dimension vector representation.

$$P = \{p_1, p_2, ..., p_K\} \tag{9}$$

where, P Is a collection of user interest tags, $p_1, p_2, ..., p_K$ representative K Tags of interest

Based on the above research, the tourism professional online education resources to be recommended to users are also expressed in the form of tags, as follows:

$$Q_i = \{T_1, T_2, ..., T_K\} \tag{10}$$

where, Q_i Represent the No i Online education resources for tourism majors; $\{T_1, T_2, \ldots, T_\mathrm{k}\}$ Represents a collection of resource attribute tags.

2.2 Generating Personalized Recommendation Based on Machine Learning

In the conventional content-based personalized recommendation process, the next step is to calculate the similarity between the user's interest model and the resource content label model, and recommend the resources most similar to the user's interest model to the target users. This recommendation does not need to worry about the cold start problem and is highly targeted, that is, it is highly personalized, computationally small, easy to implement, and highly explanatory. However, it also has some fatal defects, such as:

(1) Under this recommendation mechanism, only the information that users have browsed, followed or are now following will be recommended by the system using this method. The remaining massive information has no chance to appear in front of users at all. As time goes by, due to the lack of corresponding interest model construction and design, the information obtained by users will be more and more limited to certain types and fields. In the long run, it will inevitably lead to boredom and loss of interest.

(2) It is constantly changing not to adjust everything in the world at the same time with the change of user needs, as is the case with people's hearts. Most people cannot maintain interest in a thing for a long time. With the growth of human age and social experience, their focus on information content will also change. Traditional recommendation methods do not have a keen insight into changes in user interests, and their recommended information often lags behind and lacks timeliness [6].

To solve the above problems, this study uses a machine learning algorithm to replace simple similarity calculation. Machine learning is a multi-disciplinary interdisciplinary, including many disciplines, such as probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory, etc. It specializes in studying how computers simulate or realize human learning behavior to acquire new knowledge or skills, and reorganize the existing knowledge structure to continuously improve its own performance. It is the core of artificial intelligence and the fundamental way to make computers intelligent. If people are taken as examples, machine learning is equivalent to human learning ability and development ability. By comparing human learning with machine learning, we find that machine learning inputs data and learns results called models (similar to function mapping). The process of learning models from data is completed by executing a learning algorithm. In the world of machine learning, the solution to a problem is never unique. There are always several algorithms that can solve a problem. What you need to do is to choose the most appropriate one [1]. Generally speaking, machine learning has three algorithms: supervised learning, including regression model, decision tree, random forest, K neighborhood algorithm, logical regression, etc. Unsupervised learning algorithm, including association rules, K-means clustering algorithm, etc. Reinforcement learning is mainly represented by Markov decision algorithm. K-means clustering algorithm is selected here to generate recommendations.

K-means clustering algorithm is the most common and fastest method among various clustering algorithms. K-means clustering algorithm is a very classic pattern recognition and classification algorithm based on distance calculation, which is widely used because of its fast and simple clustering characteristics. K-means clustering algorithm is a partition clustering method, which divides samples into k clusters and divides them into different types by Euclidean distance [7]. The basic flow of K-means algorithm is shown in Fig. 2 below.

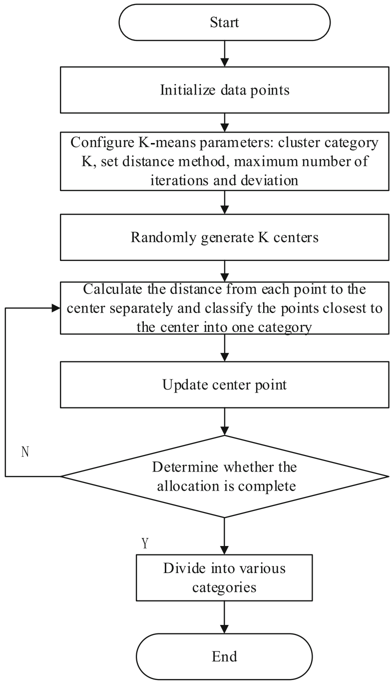

Fig. 2. K Basic flow of mean algorithm

Although the K-means clustering algorithm has the advantages of simplicity, convenience, no need for large test samples, and strong recognition ability, there are also some shortcomings of the K-means clustering algorithm: when the traditional K-means clustering algorithm is used to find the global optimal solution, there will be a local optimal situation, and the K-means clustering algorithm has poor global optimization ability, which will greatly reduce the accuracy of experimental results; The traditional K-means clustering algorithm uses the distance between data points to judge the similarity of the data set. When the data set contains a large value attribute, it will reduce the discrimination and affect the accuracy; The results of traditional K-means clustering algorithm are greatly affected by breakpoints. When there are outliers in experimental training data, these outliers will also reduce the accuracy of experimental results [8]. Therefore, it is necessary to improve the traditional K-means clustering algorithm, overcome the shortcomings of the algorithm itself, and improve the accuracy of the experimental results, which is also a problem that researchers need to break through.

Aiming at the problems of K-means clustering algorithm, genetic algorithm is selected to improve K-means clustering algorithm. A more reasonable initial cluster center is obtained by genetic algorithm, which is closer to the standard cluster center. The standard cluster center is obtained as follows:

Parameter setting: number of samples N, number of clusters U, population size R, crossing probability μ_1, probability of variation μ_2.

Step 1 Initialize the population: select from the samples U The points are used as the cluster center and coded, repeating R The initialization population is generated.

Step 2 Calculate the fitness of individuals in the population.

Step 3 Select the population. First, carry out the elite retention strategy. Step 10 is the direct step for the first 15% of the individuals with fitness, and the rest of the individuals carry out tournament selection.

Step 4 Improve the uniform crossover operation with a certain probability.

Step 5 Perform basic bit mutation operation with a certain probability.

Step 6 Calculate the cluster center based on the classification information contained in the current individual. The distance from all samples to these center points is obtained, and the nearest sample center is determined to be the class of the sample. Modify the corresponding gene locus of the current individual to the category to which the sample belongs, and generate g Mutation operator.

Step 7 The basic bit mutation operator generated by the pair and g The mutation operator is compared when $\frac{G_{\max}-G_{\min}}{\overline{G}-G_{\min}}>2.3$, use g Mutation operator. Otherwise, continue to use the normal mutation operator.

Step 8 Use the substitution strategy to generate a new individual according to the state function, calculate the fitness value and compare it with the threshold value. If it is greater than the threshold value, it will return to the tournament selection; otherwise, it will go to the next step.

Step 9 Whether the individual meets the probability, so as to replace the old individual with the new one; Otherwise, go to the next step.

Step 10 Generate a new generation of population.

Step 11 Judge the end condition, and end the operation output result when the condition reaches the end condition; Otherwise, turn to Step 2.

According to the standard cluster center obtained by the genetic algorithm, run the K-means clustering algorithm to $P = \{p_1, p_2, ..., p_K\}$ Clustering. The specific process is as follows:

Step 1: Assume there are M tourism professional online education resources to be recommended to users, namely $Q = \{Q_1, Q_2, ..., Q_M\}$, each resource is represented as $Q_i = \{T_1, T_2, ..., T_K\}$, $T_1, T_2, ..., T_K$ K attribute labels representing resources.

Step 2: From $Q = \{Q_1, Q_2, ..., Q_M\}$ Random selection in m Objects as the initial cluster center, marked as $O = \{o_1, o_2, ..., o_m\}$, $m<M$.

Step 3: Calculate the remaining individuals in the set to m Distance value of center points.The formula is as follows:

$$d(Q_i, o_j) = \sqrt{\sum_{k=1}^{K} (T_{ik} - T_{jk})^2} \tag{11}$$

where, $d(Q_i, o_j)$ On behalf of the i Resources Q_i And the j Cluster central point resources o_j The distance value of. T_{ik}, T_{jk} On behalf of Q_i, o_j Of k Attribute labels.

Step 4: Use the nearest neighbor principle to divide each resource to the nearest cluster.

Step 5: Recalculate the cluster center points in different classes and update the cluster center.

Step 6: Repeat the steps until each cluster center point of the new generation is no different from the cluster center point of the previous generation, and the clustering result is stable, ending the algorithm operation.

After the above process, M tourism professional online education resources to be recommended to users $Q = \{Q_1, Q_2, ..., Q_M\}$ Resource clusters are divided into several categories. Compute user interest model $P = \{p_1, p_2, ..., p_K\}$ The distance to the center of these resource clusters is calculated as follows:

$$d(P, H_i) = \sum_{k=1}^{K} |p_k - T_k(H_i)| \tag{12}$$

where, $d(P, H_i)$ Represent user interest model P And the i Distance between resource cluster centers of each category; p_k On behalf of the k Interest tags; $T_k(H_i)$ On behalf of the i No. of resource cluster centers of categories k Attribute labels.

Compute user interest model P The distance from the cluster center of all types of resources is arranged from small to large, and the smallest is selected $d(P, H_i)$ A corresponding cluster, which is the tourism professional online education resource cluster to be recommended to users. Finally, calculate each educational resource and user interest model in the cluster P Similarity.

$$sim\left(P, h_j\right) = \frac{\sum_{k=1}^{K} p_k h_{jk}}{\sqrt{\sum_{k=1}^{K} p_k^2} \cdot \sqrt{\sum_{k=1}^{K} h_{jk}^2}} \tag{13}$$

where, $sim\left(P, h_j\right)$ Represent user interest model P In the resource cluster j Similarity of resources; h_j Represent the No j Resources; h_{jk} Represent the No j Of resources k Attribute labels.

take $sim\left(P, h_j\right)$ Rank from the largest to the smallest, and select the top $\Im$ As the final personalized recommendation resources of online education resources for tourism majors, these resources generate a recommendation list [9].

3 Recommended Test Method

3.1 Resource Sample Set

The data set used in this experiment is from the historical data of undergraduates who have undergone desensitization and other security processing in the business system of a university from 2012 to 2016. These data include 17534 pieces of students' professional background information, 688078 pieces of history exam scores, and 1684307 pieces of book borrowing records. The background information of each major includes the following attributes: student number, gender, major, college and grade; Each examination result includes: student number, course name, course nature, examination results and credits; The information of each book borrowing letter includes: student number, book name, classification number, borrowing date and return date.

Before executing the recommended algorithm, preprocess the data set so that the data can be accepted and run by the algorithm:

(1) This paper uses the tag system to describe the recommended project model. For the curriculum outline in the dataset, we use the word segmentation technology to extract the keywords in the outline to build the curriculum relationship model. Therefore, for the curriculum outline, we need the curriculum description information, teaching objectives and designated teaching materials, and also need to store the key phrases describing the curriculum.
(2) This experiment uses the cross validation method to divide the experimental data into non repeated subsets. Set the training set (and test set (The proportion is. To ensure the accuracy of the experiment, repeat the experiment five times. Select a pair of training data sets and test data sets each time, use the records in the training data set as the basic user, and conduct recommended tests on the target users in the test data set. The data sets for each test are different. After cross validation, calculate the mean of the errors as the error results of the experimental algorithm.

3.2 Evaluation Index

(1) Novelty

Novelty mainly refers to the novelty of resources relative to users. The higher the novelty of resources that users have not seen or touched, the higher the novelty of many systems with high accuracy. Because of the over fitting phenomenon caused by the persistent pursuit of high accuracy, a user has been recommended resources that he has already browsed, and the novelty is just opposite to this problem. It can recommend some new resources to the user, and the feeling brought to the user is measured by the surprise, which can reflect the user's liking and satisfaction with this recommendation.

$$LO = \frac{\sum d(w)}{m \cdot Ls} \tag{14}$$

In the formula, LO Represents novelty; m Is the number of users; Ls Is the length of the recommended list; $d(w)$ As a favorite resource w Number of users for.

(2) Recommended precision

The effectiveness of recommendation results can often be analyzed through accuracy and recall. Accuracy P_r It can be expressed as the ratio of the number of resources related to students in the recommended resource set to the recommended list. Its calculation formula is shown in (15); recall R_e It indicates the ratio between the recommended list and the resources actually selected by the students. The calculation formula is shown in (16). Our final recommendation is F_1 The average of recommendation accuracy and recall rate of all students in the test set is an indicator commonly used to measure the accuracy of the model. The calculation formula is shown in (17).

$$P_r = \frac{\sum_{i \in \kappa} |\sigma_i \cap \vartheta_i|}{\sum_{i \in \kappa} |\sigma_i|} \tag{15}$$

$$R_e = \frac{\sum_{i \in \kappa} |\sigma_i \cap \vartheta_i|}{\sum_{i \in \kappa} |\vartheta_i|} \tag{16}$$

$$F_1 = 2\frac{P_r \cdot R_e}{P_r + R_e} \tag{17}$$

where, ϑ_i On behalf of users in the test set i Actual favourite resources; σ_i Is the recommended result set; κ Is a user set.

3.3 Recommended Performance Analysis

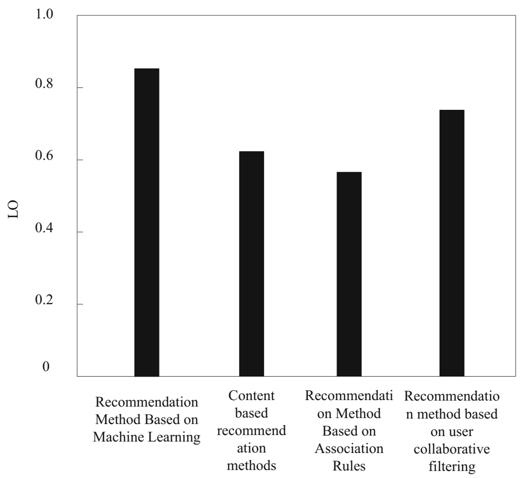

Fig. 3. Novelty *LO* Comparison Chart

Table 1. Recommended Precision

Method	P_r	R_e	F_1
Recommendation Method Based on Machine Learning	0.921	0.882	0.914
Content based recommendation methods	0.874	0.756	0.827
Recommendation Method Based on Association Rules	0.844	0.784	0.809
Recommendation method based on user collaborative filtering	0.901	0.821	0. 857

It can be seen from Figure 3 and Table 1 that under the application of the recommended method studied, the novelty and recommended precision F_1 They are larger than content-based recommendation methods, association rule based recommendation methods, and user collaborative filtering recommendation methods, which shows that machine learning based recommendation methods have better recommendation effects.

The following table shows the statistical results of recommendation time of different resource recommendation algorithms.

As can be seen from the data in Table 2, compared with the other two algorithms, using machine learning based teaching resource recommendation algorithms takes less

Table 2. Teaching resource recommendation algorithm recommendation time-consuming statistics/ms

Group	Recommendation Method Based on Machine Learning	Content based recommendation methods	Recommendation Method Based on Association Rules	Recommendation method based on user collaborative filtering
1	187.4	320.9	307.8	228
2	176.9	336.4	313.2	235.8
3	178.7	341.2	316.7	267.94
4	180.3	355.5	324.6	248.6
5	183.1	360.8	340.1	279.1

time. The average time of this algorithm is 181.28 ms, the average time of Content based recommendation methods is 342.96 ms, the average time of Recommendation Method Based on Association Rules is 320.48 ms, and the average time of Recommendation Method Based on user collaborative filtering is 251.89 ms. This indicates that machine learning based teaching resource recommendation algorithms can achieve resource recommendation more efficiently and have high application value.

4 Conclusion

The personalized recommendation method for tourism professional online education resources based on machine learning combines TextRank algorithm, TF-IDF weight, and location information weight, and establishes a user interest model and resource attribute description by generating user interest labels and attribute labels. At the same time, genetic algorithm is used to optimize the K-means clustering algorithm, and the recommended online education resources for tourism majors are divided into different resource groups. Based on the distance between the user interest model and the center of each resource cluster, the nearest resource cluster is selected as the recommendation result, and the resources in the resource cluster are sorted by calculating similarity to generate a personalized recommendation list.

With the development of information technology, learning resource recommendation has become increasingly important in online learning. Addressing issues such as learning loss and inappropriate resource recommendations is crucial for improving learning efficiency. This study applies machine learning to a learning resource recommendation system, providing the possibility of personalized learning. This system provides learners with learning resources that meet their actual needs, optimizes the learning process, and improves the efficiency and quality of online learning.

However, there is still room for improvement in this study. Firstly, although good results have been achieved on the movie dataset, further research is needed on how to apply the method to other datasets and improve the generalization ability of the model. In addition, when evaluating the recommendation effectiveness of personalized recommendation systems, multiple evaluation criteria need to be integrated to evaluate the performance of recommendation models, including user satisfaction, coverage, and so on. Therefore, future research can evaluate and improve this recommendation method from more perspectives.

In summary, the personalized recommendation method for online education resources in tourism based on machine learning provides learners with personalized learning resource recommendations, optimizes the learning process, and improves learning effectiveness. However, there is still room for further improvement and evaluation to further improve the performance and user satisfaction of the recommendation system.

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3. Excellent Young Talents Project of Anhui Provincial Education Department, Research on the Influence Mechanism of Rural Tourists' Behavior in the Context of Normalization of Epidemic (gxyq2022037).

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Automatic Classification and Sharing of Teaching Resources in English Online Teaching System Based on SVM

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Abstract. In order to improve the classification and sharing performance of teaching resources, an automatic classification and sharing method of teaching resources in online English teaching system based on SVM is proposed. According to learners' demands for teaching resources, the tasks and objectives of online English teaching are determined, and the content performance characteristics of teaching resources are given through the digital integration of teaching resources in the online English teaching system. Based on learners' internal psychological activity process and cognitive rules, a feature extraction model of teaching resources is constructed to extract the features of English teaching resources. According to the optimal classification plane of support vector machine, the nonlinear classification problem of teaching resource features is transformed into a quadratic optimization problem, and the Gaussian kernel function is selected as the kernel function of support vector machine to classify the features of English teaching resources. By calculating the weighted vector of English teaching resources, English teaching resources are cleaned, and the continuous sliding window distance of English teaching resources attribute compression is given by using attribute compression. Combined with the spatial trajectory function of quantitative coding, the characteristics of English teaching resources are quantified and coded. Combined with the design of teaching resource sharing algorithm, the automatic classification and sharing of teaching resources in online English teaching system is realized. The experimental results show that the proposed method can improve the utilization rate of teaching resources, reduce the sharing delay and improve the classification and sharing performance of teaching resources, no matter with or without manual intervention. Therefore, it shows that this method can improve the classification and sharing effectiveness of English teaching resources.

Keywords: Support vector machine · Online teaching system · Teaching resources · Classification sharing · Feature extraction · Utilization ratio

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1 Introduction

The research background of automatic classification and sharing of teaching resources in online English teaching system is that it is a challenging task to classify and share a large number of teaching resources accurately in the current online English teaching system. Many systems still rely on manual classification and management, which is not only time-consuming, but also subjective and inconsistent. Therefore, it is of great significance to study how to realize automatic classification sharing method.

The automatic classification sharing method can improve the efficiency of resource management and make the sorting and searching of resources more efficient and convenient by quickly and accurately classifying resources [1]. Secondly, this method supports personalized learning. According to the needs and interests of learners, the system can automatically recommend suitable teaching resources, provide personalized learning experience, and improve learning results. In addition, the automatic classification sharing method promotes the sharing and cooperation of teaching resources, and different educational institutions and teachers can learn from each other and improve the teaching quality and effect by sharing classified resources. Finally, this method is helpful to improve teaching quality and innovation ability. Through in-depth analysis and evaluation of teaching resources, advantages and disadvantages can be found and teaching contents and methods can be improved.

To sum up, the research on the automatic classification and sharing method of teaching resources in online English teaching system is of great significance for improving resource management efficiency, personalized learning support, promoting resource sharing and cooperation, and improving teaching quality and innovation. This will have a positive impact on the development and application of online English teaching system.

In the domestic research, Tang Xiaojuan et al. [2] the platform is composed of four levels: preprocessing, feature extraction, classification and sharing of teaching resources for collaborative work. In the preprocessing phase, redundant information is deleted to reduce the system storage space; The feature extraction module uses the semantic adjacency matrix to calculate the feature value of the vocabulary in the resource and select the vocabulary with larger feature value; In the classification module, the hierarchical relationship is used to build a classification framework, calculate the relationship strength between each word pair, and achieve classification according to the different strength; The resource numbers that complete the classification are stored separately, and teachers can directly find and complete resource sharing. The experimental results show that the classification accuracy of the teaching resource sharing platform is 98.6%, and the average resource sharing time is 1.15 s, which indicates that the accuracy and efficiency of the teaching resource sharing platform are high. Xiao Qun [3] proposed the design scheme of ideological and political teaching resource sharing model based on machine learning in view of the problems such as slow update of resource database, untimely promotion of high-quality teaching resources, and serious lag in the development of teaching resource sharing. The clustering algorithm in machine learning is used to classify and sort out all kinds of resources. At the same time, the teaching resource sharing model is constructed with three modules, namely, the base layer, the environment layer and the application layer, to form a data set that is easy to find. After receiving the user's retrieval requirements, execute the graphical user interface program, and feedback the results to the user through the user interface, and realize the management, sharing and publishing of teaching resources with functional modules. By investigating the actual application effect of the application sharing model, the results show that the proposed model has a positive role in promoting the sharing of ideological and political teaching resources.

Liang X et al. [4]proposed a balanced recommendation algorithm of sports network teaching resources based on trust relationship, aiming at the problems of poor balance of recommended resources and low trust of recommended sports network teaching resources in traditional sports network teaching resources recommendation. Classify the teaching resources of sports network through SVM algorithm, delete the invalid data of the teaching resources of sports network, take the remaining teaching resources of sports network as the extraction object, and complete the extraction of teaching resources of sports network. Through Kalman filtering method, the data of sports network teaching resources with noise are reduced, and then the data with high similarity are fused to complete the preprocessing of sports network teaching resources data. By building a trust relationship model, the relationship attributes between the recommended sports network teaching resource data are determined. The experimental results show that the highest resource balance degree recommended by this method is about 96, and the recommended resource trust degree is high.

With the continuous development of network technology, the rapid flow of information resources and the continuous growth of complex and diverse data. In order to better serve student users, professional scholars have studied the classification and sharing methods of teaching resources in English online teaching system from different perspectives. The use of resource integration and sharing technology is conducive to improving the ability of teaching resource processing. The complex and diverse teaching resources make the traditional classification and sharing methods face many shortcomings, such as: the specific classification and sharing system has limited functions, cannot meet the needs of student users in all aspects, the system has low operating efficiency, high energy consumption, and the sharing and utilization of teaching resources after sharing is low. In the current context, there is an urgent need for a classified sharing scheme of teaching resources that meets the above requirements.

Based on the above research background, SVM is applied to the automatic classification and sharing of teaching resources in online English teaching system, and the feature extraction model of teaching resources is constructed to extract the features of English teaching resources. According to the optimal classification plane of support vector machine, the nonlinear classification problem of teaching resource features is transformed into a quadratic optimization problem to classify English teaching resource features. Based on the spatial trajectory function of quantization coding, the characteristics of English teaching resources are quantized and coded. Combined with the teaching resource sharing algorithm, the classification and sharing of English teaching resources in school are completed.

2 Automatic Classification and Sharing of English Teaching Resources

2.1 Extract Features of English Teaching Resources

In order to achieve automated classification and sharing of teaching resources in English online teaching systems, it is necessary to extract the characteristics of teaching resources. Firstly, obtain the learners' needs for teaching resources L_δ, and determine the goals of online English teaching tasks, namely:

$$\theta(e) = \frac{L_\delta \times p_c}{\varpi_b} \times \eta^\tau(w) \tag{1}$$

In the above equation, p_c represents the content of English online teaching, $\eta^\tau(w)$ represents the task activity requirements of the English online teaching system, and ϖ_b represents the teaching knowledge field provided by the English online teaching system.

Through the digital integration of teaching resources in English online teaching system[5], the content performance characteristics of teaching resources are given, namely:

$$\psi(\kappa) = \frac{g_U \times \mu_W}{v_o} \times \mu_j \times \varpi_b \tag{2}$$

Among them, g_U represents the design process of course content in the English online teaching system, μ_W represents the teaching activities of learners, v_o represents the content performance characteristics of linear learning by learners in the English online teaching system, and μ_j represents the content performance characteristics of jumping learning by design learners in the English online teaching system.

Decompose and reorganize the knowledge content ξ_c presented in the English online teaching system [6], and provide a teaching resource extraction structure suitable for learners' remote learning according to their organizational form, namely:

$$\chi(y) = \frac{v_o \times \mu_j}{\xi_c} \times \frac{k_\rho \times z_i}{\ell_a/\partial_n} \tag{3}$$

In the equation, k_ρ represents the learner's learning motivation, z_i represents the learner's performance in the English online teaching system, ℓ_a and ∂_n represent the learner's internal psychological activity processes and cognitive patterns, which are represented as:

$$\ell_a = \frac{\zeta_c \times \gamma_l}{v_o} \iota_\vartheta \tag{4}$$

$$\partial_n = \frac{\iota_\vartheta \times \mu_j}{L_\delta} \tag{5}$$

In the above equation, ι_ϑ represents the learning status of learners in the English online teaching system, and γ_l represents the optimization and selection process of teaching resource content by teachers.

Based on the learners' internal mental activity process and cognitive laws, a feature extraction model of teaching resources is constructed to extract the features of teaching resources in English online teaching system, namely:

$$m(g) = \frac{\iota_{\vartheta}}{B_i} \times \varsigma_{\Omega} \times \alpha_d \tag{6}$$

Among them, B_i represents the learner's autonomous learning strategy provided in the feature extraction of teaching resources, ς_{Ω} represents the learners' attention to the teaching resources of the English online teaching system, and α_d represents the satisfaction of the teaching content with the learning needs of different types of learners.

According to the learners' demand for teaching resources, the goal of English online teaching tasks is determined. Through the digital integration of teaching resources in the English online teaching system, the content performance characteristics of teaching resources are given. Based on the learners' internal psychological activity process and cognitive laws, the feature extraction model of teaching resources is constructed to extract the features of English teaching resources.

2.2 Characteristics of Classified English Teaching Resources

Based on the feature extraction results of teaching resources in English online teaching system, support vector machine is used to classify the features of teaching resources. Support vector is a statistical learning method [7] based on the principle of structural risk minimization. Support vector machine classification is to find an optimal hyperplane, try to make the plane meet the constraints of classification, separate all points in the data set to be classified, and make the points as far away from the hyperplane as possible. The classification diagram is shown in Fig. 1.

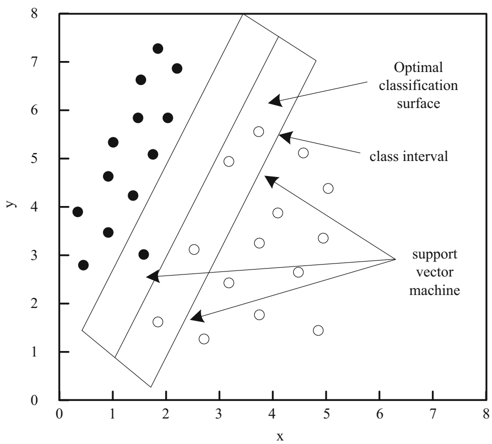

Fig. 1. Optimal classification plan of support vector machine

For the classification problem of teaching resource features in English online teaching systems, given a dataset (x_i, y_i), $x_i \in R^n$, $y_i \in \{-1, 1\}$, $i = 1, 2, \ldots, n$, x_i represents the attributes of teaching resource feature classification. When the dataset belongs to a positive class set, output $y_i = 1$, otherwise $y_i = -1$. The objective of support vector machine is to minimize the risk, so the optimal hyperplane can be expressed as:

$$y = \omega^T \varphi(x) + b \tag{7}$$

where, ω represents the normal vector of the hyperplane, and b represents the offset vector of the hyperplane.

For the linear inseparability problem of teaching resource features in the English online teaching system, in order to make the shortest distance between any feature point vector and the hyperplane in the training set of teaching resources as the maximum optimal hyperplane, the nonlinear classification problem of teaching resource features needs to be transformed into a quadratic optimization problem [8], namely:

$$\min J(w, \xi) = \frac{1}{2}\|w\|^2 + \phi \sum_{i=1}^{n} \xi_i \tag{8}$$

Among them, ϕ represents the penalty parameter that controls the degree of punishment for misclassified feature samples, and ξ represents any feature point vector in the teaching resource training set.

The constraints of the optimization problem are:

$$y_i(w \times \varphi(x_i) + b) \cdot 1 - \xi_i \tag{9}$$

$$\xi > 0, i = 1, 2 \cdots, n \tag{10}$$

For the classification problem of large samples, the learning speed of support vector machine is quite slow, so the classification problem of support vector machine is transformed into its dual problem by introducing Lagrange multipliers, and this hyperplane optimization problem is solved by the dual problem, so as to speed up the classification speed of teaching resource features, so that the following hyperplane classification functions can be obtained:

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{l} \alpha_i y_i (\varphi(x) \cdot \varphi(x_i)) + b\right) \tag{11}$$

Among them, sign(.) represents the signed function, and α_i represents the Lagrange multiplier.

The kernel function $K(x_i, x)$ replaces the dot product $(\varphi(x) \cdot \varphi(x_i))$, so the classification function of the support vector machine becomes as follows:

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{l} \alpha_i y_i k(x_i \cdot x) + b\right) \tag{12}$$

The classification performance of support vector machine is closely related to its kernel function and parameters. The Gaussian kernel function is selected as the kernel function of support vector machine to classify the features of English teaching resources.

2.3 Quantitative Coding of Teaching Resource Characteristics

Quantifying the coding of teaching resource features is of great significance. Firstly, by quantifying and encoding the features of teaching resources, it can facilitate resource management and organization, and improve resource utilization efficiency. Secondly, quantitative coding can support personalized learning and recommendation systems, accurately recommending suitable teaching resources based on learners' needs and interests, and improving learning effectiveness. In addition, quantitative coding is also helpful for teaching evaluation and quality monitoring. By analyzing and comparing the characteristics of resources, the teaching effectiveness and quality of different resources can be evaluated, providing reference for teachers and educational institutions to improve teaching. Finally, quantitative coding promotes the sharing and exchange of teaching resources, achieves resource standardization and sharing, and improves the overall quality and accessibility of educational resources. In summary, quantifying the characteristics of teaching resources is of great significance for improving educational quality, promoting educational innovation, and improving learning experience.

According to the classification of the characteristics of English teaching resources, the characteristics of English teaching resources are weighted, and the associated weighted vector of the characteristics of English teaching resources is obtained:

$$E(t) = \frac{1}{\chi^0}(e_0(t), \cdots, e_{k-1}(t)) \tag{13}$$

Among them, χ^0 represents the feature vector of English teaching resources, $e_0(t)$ represents the weighted vector value, and $e_{k-1}(t)$ is the $k-1$ th feature weighted vector of English teaching resources.

The weighted feature vector of English teaching resources is used to link the directional weight vector with the data cleaning criteria [9] to process the characteristics of English teaching resources. The formula is:

$$Q = \frac{1}{E(t)} \times \log_2 \sqrt{Z(v_i)} \tag{14}$$

Among them, $Z(v_i)$ represents the characteristics of the processed English teaching resources.

The interactive information attribute compression method in one-dimensional space was used to compress n time windows of the English online teaching system, and the continuous sliding window spacing of the feature attributes of English teaching resources was obtained through the following formula:

$$L_j = \frac{1}{e_i(t)} \sum_{i=0}^{\gamma-1} w_{ij}(t) \tag{15}$$

Among them, $w_{ij}(t)$ represents the weighting coefficient of the characteristics of English teaching resources, and i represents the number of interactive information attributes of English teaching resources.

Assuming that $\dot{M}$ represents the energy density of English teaching resource features, at the minimum window distance, the sampling Λ_j of English teaching resource interaction features is obtained, and the spatial trajectory function of English teaching resource interaction features is given using formula (16):

$$f(x) = \frac{\Lambda_j}{L_j} \times \min_{0 \le j \le N-1} \{\dot{M}\} \tag{16}$$

Using the spatial trajectory function obtained above, the interactive features of English teaching resources are transmitted to the terminal of English online teaching system, and the terminal decompresses and draws the features of English teaching resources, namely:

$$J = \frac{1}{\partial}\left[\frac{SGF(\xi, \vartheta)}{\delta}\right] \tag{17}$$

Among them, ξ and ϑ represent the scaling coefficients of English teaching resource features, δ represents the English teaching resource database, and ∂ represents the scaling function of quantitative encoding.

The interaction subset directed by entity features of English teaching resources is divided into a 3×3 topology, and a specific window function $f^j(k)$ is selected and quantized:

$$f_M(x, y) = \frac{p^j(k)}{f^j(k) \cdot f(x)} \sum_j^M \varsigma_j(k) \tag{18}$$

Among them, $\varsigma_j(k)$ represents the quantitative coding set of English teaching resource features, and $p^j(k)$ represents the density function of English teaching resource interaction features.

By calculating the weight vector of English teaching resources, the English teaching resources are cleaned. Using attribute compression, the continuous sliding window distance of English teaching resources attribute compression is given. Combining the spatial trajectory function of quantitative coding, the quantitative coding of English teaching resources characteristics is completed.

2.4 Automatic Sharing of English Teaching Resources

For each teaching resource data point x_i in the English online teaching system's shared teaching resource set $X = \{x_i | x_i \in R^d, i = 1, 2, \cdots, N\}$, two important parameters need to be calculated, namely the local density p_i and the distance δ_i between the high local density points, namely:

$$p_i = \sum_j \chi(V(k) - d_c) \tag{19}$$

$$\delta_i = \min_{j:p_j > p_i} V(k) \tag{20}$$

Among them, d_c represents the truncation distance, p_j represents high-density points, and p_i represents low-density points.

For the teaching resource data point with the highest density, we can get:

$$\delta_i = \max_j V(k) \tag{21}$$

In order to better select the initial cluster center and determine the number of clusters, the expected cluster center is given below:

$$EC_i = (\delta_i) \geq 2\sigma(\delta_i) \tag{22}$$

In the formula, EC_i represents the expected clustering center, and $\sigma(\delta_i)$ represents the standard deviation of all distances.

Due to the significant distance between the cluster center and other educational centers [10], the distance between other points in the teaching resource dataset will be less than $2\sigma(\delta_i)$. However, for outliers, there are some larger values δ, and the local density, p is relatively small. By using the above formula, outliers cannot be separated from the expected cluster.

In order to accurately separate the outliers in teaching resources, the following formula is adopted:

$$LC_i = EC_i \geq \mu(p_i) \tag{23}$$

In the formula, LC_i is the local clustering center after excluding outliers; $\mu(p_i)$ is the mean of local density p_i.

By combining formula (22) and formula (23), it is found that the local density p and δ values are higher than those of neighboring points. By merging the local density cluster centers, assuming that the minimum distance between each local cluster center is less than the truncation distance d_c, they are merged into one cluster center. After the local clustering centers are merged, the global education resource clustering centers are obtained, and the number of teaching resource clusters is determined:

$$C(l) = \sum_{i=1} \sum_{k=1} (\|\mu(P_i) * EC_i\|)^2 \tag{24}$$

After determining the number of teaching resource clusters, expand the feature vector of teaching resources and design the sharing algorithm of teaching resources, which is expressed as:

$$\hat{W} = \overline{U} \wedge \overline{U}^r = \begin{bmatrix} U \\ B^T U \wedge^{-1} \end{bmatrix} \wedge W \tag{25}$$

Among them, U represents the shared teaching resources, W represents the clustering matrix of teaching resources, and $\overline{U}$ represents the approximate feature vector of W.

To sum up, the cluster center of teaching resources is adaptively generated according to the clustering rules, the number of teaching resources is determined, and the clustering algorithm is used to share the clustered teaching resources. The automatic classification and sharing process of English online teaching resources based on SVM is shown in Fig. 2.

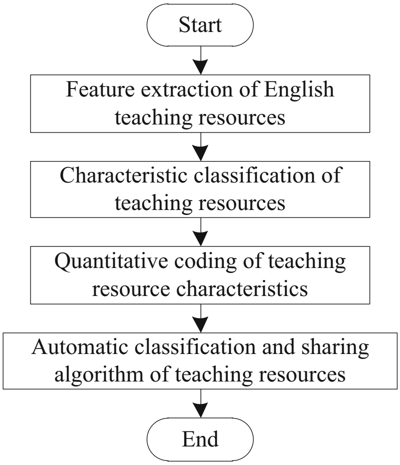

Fig. 2. Process of automatic classification and sharing of teaching resources

3 Experimental Analysis

3.1 Building an Experimental Platform

In order to verify the performance of the method in this paper in the automatic classification and sharing of teaching resources in the English online teaching system, an experiment was conducted. The experimental environment parameters are:

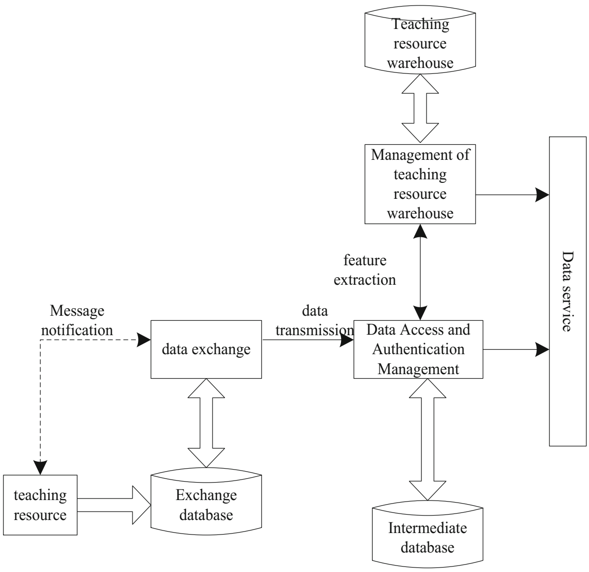

Fig. 3. Structure of Experimental Platform

Operating system: Windows 10 Professional Edition (64 bit).
Processor: AMD Ryzen 52400G with Radeon Vega Graphics 3.60 GHz.
Memory: 32 GB.
Browser: v4.0.9.112 Cent Browser.
Language development environment: v8.11.1 node.
Solidity compilation environment: v0.4.24 version of Solc.

Under the above experimental environment parameters, an experimental platform for classified sharing of English teaching resources has been built, and its structure is shown in Fig. 3.

3.2 Setting the Dissimilarity Threshold

In the online English teaching system, the dissimilarity threshold of automatic classification and sharing of teaching resources can avoid the impact of manual intervention in the classification and sharing of teaching resources. During the experiment, the dissimilarity threshold was set, as shown in Fig. 4.

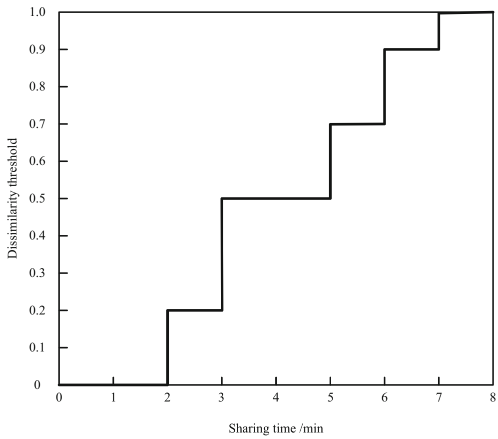

Fig. 4. Setting of dissimilarity threshold

In Fig. 4, when the sharing time is within 2 min, the dissimilarity threshold is 0, indicating that the sharing time of teaching resources will not be subject to manual intervention within 2 min. When the sharing time is between 2 min and 8 min, the dissimilarity threshold is 0.2, 0.5, 0.7, 0.9 and 1.0, respectively, indicating that teaching resources will be subject to manual intervention if the sharing time exceeds 2 min.

3.3 Setting Evaluation Indicators

During the experiment, the utilization rate of teaching resources and sharing delay index are used to measure the performance of automatic classification and sharing of teaching resources in English online teaching system. The calculation formula is:

$$\eta = \frac{N_d}{N_{all}} \times 100\% \tag{26}$$

$$T = T^* - T_0 \tag{27}$$

Among them, η represents the utilization index of teaching resources, N_d represents the successfully shared English teaching resources, N_{all} represents the total amount of English teaching resources, T represents the delay of English teaching resource sharing, T^* represents the time when English teaching resource sharing ends, and T_0 represents the time when English teaching resource sharing begins.

3.4 Result Analysis

In order to highlight the advantages of the proposed method in English teaching resource sharing, the sharing method based on VEM framework, machine learning and trust relationship are introduced to compare and test the performance of teaching resource sharing without human intervention and with human intervention.

The sharing performance test indexes are teaching resource utilization rate and teaching resource sharing delay. The performance of various methods with or without manual intervention is tested to verify the effectiveness of the proposed method.

3.4.1 Results Without Manual Intervention

Without manual intervention, the test results of teaching resource utilization and sharing delay are as follows.

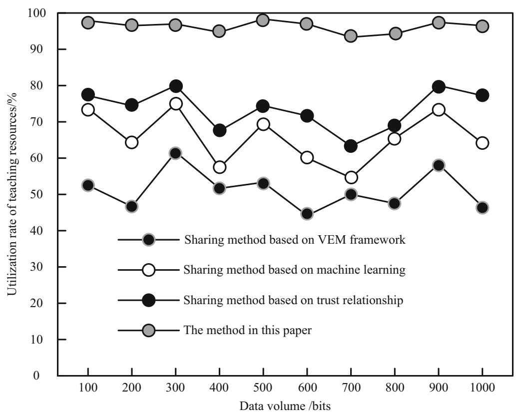

Fig. 5. Test results of teaching resource utilization without manual intervention

According to the results in Fig. 5, the utilization rate of English teaching resources is between 40% and 65% when using the sharing method based on the VEM framework without manual intervention, which indicates that English teaching resources under the VEM framework are vulnerable to the impact of redundant components when sharing, reducing the utilization rate of teaching resources. When the sharing method based on machine learning is adopted, the utilization rate of English teaching resources is between 50% and 75%. When the sharing method based on trust relationship is adopted, the utilization rate of English teaching resources is between 60% and 80%.When using the method in this paper, the utilization rate of English teaching resources is more than 90%, which shows that support vector machine can avoid the influence of redundant information in the classification and sharing of English teaching resources, and greatly improve the utilization rate of English teaching resources.

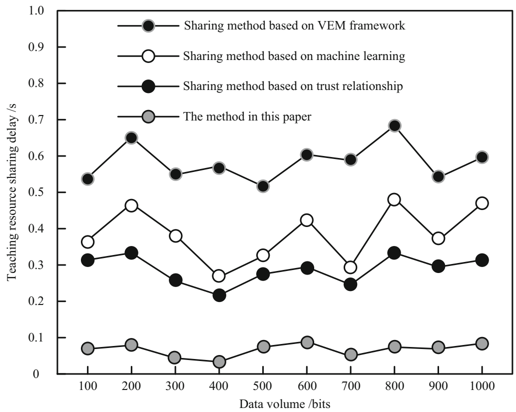

Fig. 6. Delay test results of teaching resource sharing without manual intervention

It can be seen from the results in Fig. 6 that the delay of teaching resource sharing exceeds 0.5 s when using the sharing method based on the VEM framework without manual intervention. When machine learning based sharing method and trust based sharing method are adopted, the delay of teaching resource sharing is 0.25 s ~ 0.5 s and 0.2 s ~ 0.35 s respectively. When using the method in this paper, the delay of English teaching resource sharing is within 0.1s, which shows that the performance of support vector machine for English teaching resource sharing is higher than that of VEM framework, machine learning and trust relationship model, and the efficiency of English teaching resource sharing is improved.

3.4.2 Results with Manual Intervention

With manual intervention, the test results of teaching resource utilization and sharing delay are as follows.

According to the results in Fig. 7, when using the sharing method based on the VEM framework with manual intervention, the utilization rate of English teaching resources is the lowest, between 30% and 60%. The reason is that the VEM framework has insufficient processing of redundant information of English teaching resources, which reduces the utilization rate of teaching resources. When machine learning based sharing method

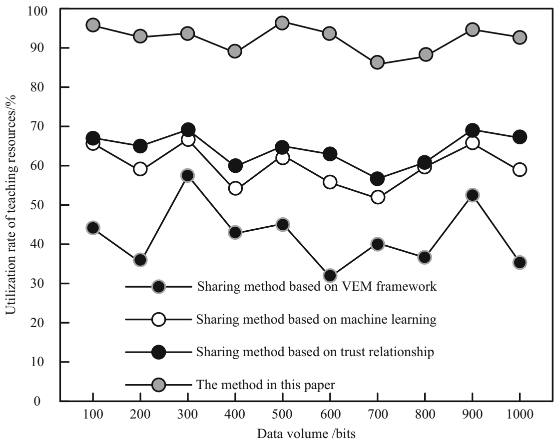

Fig. 7. Test Results of Teaching Resource Utilization with Manual Intervention

and trust relationship based sharing method are adopted, the utilization rate of English teaching resources is relatively close, between 50% ~ 70% and 55% ~ 70% respectively. The reason is that the clustering algorithm in machine learning has low accuracy in classifying teaching resources, and the trust relationship model cannot guarantee the security of teaching resources sharing, which leads to noise in teaching resources sharing, It reduces the utilization rate of teaching resources. When using the method in this paper, the utilization rate of English teaching resources is the highest, more than 85%, which shows that support vector machine can improve the classification accuracy of English teaching resources and improve the utilization rate of teaching resources. Although the utilization rate of teaching resources with manual intervention is lower than that without manual intervention, it can still ensure the full utilization of English teaching resources.

It can be seen from the results in Fig. 8 that, in the case of manual intervention, compared with the sharing method based on the VEM framework, the sharing method based on machine learning and the sharing method based on trust relationship, the method in this paper has the shortest delay in the process of teaching resource classification and sharing. When the amount of teaching resource data increases from 100 bits to 1000 bits, the teaching resource sharing delay is always within 0.2 s. Although the sharing delay is longer than that without human intervention, it can still ensure the efficiency of automatic classification and sharing of teaching resources in English online teaching system.

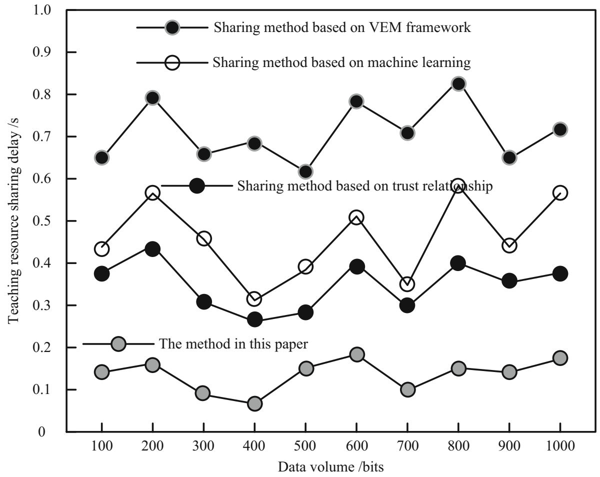

Fig. 8. Delay test results of teaching resource sharing with manual intervention

4 Conclusion

In this paper, an automatic classification and sharing method of teaching resources in online English teaching system based on SVM is proposed. Experimental tests show that the method is less affected by manual intervention in the automatic classification and sharing of English teaching resources, and can effectively improve the performance of automatic classification and sharing of teaching resources in online English teaching system. Although this research has made some achievements, there are still many shortcomings. In future research, it is hoped that particle swarm optimization algorithm and support vector machine can be combined to find an optimal path of teaching resource sharing, so as to further improve the efficiency of automatic classification and sharing of teaching resources in online English teaching system.

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Data Association Mining Method of Vocational College Students' Employment Education Based on Machine Learning Model

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Abstract. In the process of data association mining using traditional methods, data mining is affected by incomplete data mining, resulting in large errors in data mining. A data association mining method based on machine learning model for vocational college students' employment education is proposed. Analyze the internal and external factors affecting students' employment, calculate the difference series formed by two data under a certain time series, and determine the spatial correlation of the series. The confidence is compared with the expected confidence, and the interest is obtained. According to the association rules, the machine learning model of educational data association rules is constructed. Build a data gain evaluation function, calculate the frequency of word segmentation feature set in education data, and calculate the similarity between any two education data. Through the similarity calculation results of association oriented data, the implicit low rank characteristics of the data are obtained, and the association education data clustering is realized. Preprocess the associated data, and design the process of clustering data association mining under the machine learning model. The experimental results show that the mining data type of this method is consistent with the experimental data type, and the minimum mining error is 0.05, which shows that this method can obtain good mining results.

Keywords: Machine Learning Model · Vocational College Students · Employment Education · Data Association Mining

1 Introduction

In today's increasingly severe employment situation, the employment situation of vocational college graduates is the key to the development of vocational education. Many vocational colleges have invested a lot of manpower and material resources in student employment research and management. However, facing the expansion of enrollment scale and the increase of the number of students on campus, the employment management of college students is becoming increasingly onerous and complex. In the employment management of college students, a large number of data need to be processed. These information are inextricably linked with each other, but also contain some important

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information. In general, there is a structural contradiction between supply and demand. From the perspective of "supply", the comprehensive quality and ability of graduates cannot meet the needs of all sectors of society for high-quality personnel at all levels; From the perspective of "demand", there are still structural difficulties in graduates' employment to a certain extent due to problems in the employment mechanism, demand structure, talent concept and other aspects of talent demand units. Massive information not only brings convenience to people, but also brings problems. Information is too much to digest; Inconsistent form, difficult to handle uniformly; The technical conditions are limited, and the safety is difficult to guarantee; The data is not standardized, and the true and false are difficult to identify.

Applying data mining technology to the field of college students' employment research and management, extracting these important information from the database can provide valuable information for enrollment, educational administration and other departments, and provide strong information support and work guidance for college students' employment research and management personnel. Literature [1] proposed a mining method based on RBF neural network, which selected 400 groups of evenly distributed sample measurement points to form environmental data, thereby establishing a large-scale environmental database, and building an environmental prediction model based on radial basis function neural network. The setting parameters of the student employment environment are taken as the input parameters of the neural network, and the employment speed of the inspection point is taken as the only output to train the RBF network, and the network parameters are optimized through the clustering algorithm. After the model training is completed, the unknown employment environment is predicted and analyzed; Literature [2] proposed a data mining algorithm based on deep integrated learning. This algorithm first mines employment environment data, extracts employment environment data features based on data mining results, and then uses the extracted data features to build a deep integrated learning model. Through this model, abnormal data can be predicted, so as to obtain employment environment abnormal data, and realize employment environment abnormal data mining; Literature [3] proposed a data mining algorithm based on association rules and similarity. By reading in data at one time and constructing a matrix, it uses the characteristics of association rule support measurement to increase judgment attributes to speed up the end of the iteration process, thus improving the problem of Apriori algorithm scanning the database frequently. Then, the similarity algorithm is used to remove redundant association rules. Finally, combining confidence, support and user target matching, the mining results are sorted and output, so as to get the association rules that users are interested in and obtain the mining results.

In the employment environment of vocational college students, the above methods can no longer meet the requirements of rapid data association and data mining, and there are also large deficiencies. Therefore, this paper proposes a data association mining method based on machine learning model for vocational college students' employment education. Unlike the above methods, this article innovatively analyzes the internal and external factors that affect student employment, calculates the difference sequence formed by two data in a certain time series, and determines the spatial correlation of the sequence. By calculating the similarity of associated data, low rank features hidden in the data were obtained, achieving fast clustering of associated education data. Preprocessing the association data before association analysis improves the convenience of subsequent association clustering and improves mining speed.

2 Data Correlation Judgment of Internal and External Factors Affecting Student Employment

The internal and external factors that affect students' employment mainly include external factors and internal factors.

(1) External factors.

The economic factor is the first factor affecting the employment of college students. The employment of college students is restricted by many factors such as the economic scale, economic structure and labor supply in a certain period. Economic factors are the most direct and important factors affecting graduates' employment. Economic scale determines the employment scale, while economic structure determines the structure and level of talent demand [4]. Relevant research shows that under the extensive economic development model in the past, every one percentage point of GDP growth can boost the employment of more than 2 million people.

The employment contradiction in the whole society is very prominent, and the overall characteristics of the labor market are that supply exceeds demand. At present, the employment situation is still grim, and the newly growing labor force has entered a peak period, especially college graduates, with many increases and great pressure, while the overall situation of the job demand in the entire employment market is relatively tight. At the same time, with the advancement of the national industrialization process, some recessive unemployment left over from the planned economy period is gradually turning into explicit unemployment, which is highlighted by the increasing number of urban laid-off workers [5]. Moreover, with the acceleration of China's urbanization process, more and more rural surplus labor has been transferred to cities. From the overall trend of the country, the situation of the total supply of labor force exceeding the demand will exist for a long time. The financial crisis that broke out in recent years has increased the difficulty of college students' employment.

Market defects and system reform lag behind. First, the market is not fully developed and perfected, and the degree of marketization is low; There are many employment markets around universities, regions and industries, but a relatively unified large market has not been formed, resulting in high search costs for graduates and employers; The market rules are not unified, and some markets are even in disorder, which leads to incomplete competition, incomplete information and high costs in the employment market, affecting employment. Secondly, due to the current urban-rural dual structure in China, regional development is extremely unbalanced, and wages and benefits differ significantly in different regions and industries [6, 7]. Thirdly, the current college students' employment market is not perfect and standardized, the graduate employment information system is still relatively backward, the employment service system is not perfect, and the national unified college students' employment information system has not yet been formed.

Other factors, such as the mistaken ideas of employers, such as the requirement of high education, restrictions on the source of students, gender discrimination, etc. [8].

(2) Internal factors

The higher education system does not meet the needs of the market economy. At present, the export of talents trained by colleges and universities has become market-oriented, but the enrollment entrance and training process of higher education are planned. The planned economy of the higher education system is very strong. Some universities have great blindness in specialty and curriculum setting, and the phenomenon of specialty convergence is very serious, resulting in a serious oversupply of demand. The specialty division of universities is becoming more and more detailed, but always lags behind the pace of market changes. This practice inevitably leads to the cultivation of students who are too "specialized", have a single knowledge structure, low comprehensive quality, and poor flexibility [9].

The quality of college students does not meet the market demand. Some schools still follow the traditional teaching method of exam oriented education, and some students are trained with high scores but low abilities [10]. In higher education, the training mode of emphasizing knowledge infusion rather than ability cultivation is still very prominent, and college graduates themselves also have many problems. For example, when choosing employment areas, college graduates are excessively concentrated in economically developed areas such as Beijing, Shanghai, Guangzhou, etc.; At the same time, college students' employment psychology of "high success, low success" has more serious impact on job selection and employment.

From the perspective of internal and external factors affecting students' employment, the spatial correlation of education data is usually: the perception data between adjacent data is the same at a certain time, or may be similar. When fitting data, the error rate is lower than the specified threshold. Using historical perception data to mine the relationship between two nodes can determine the spatial association of data. This method does not need to transmit the sensing data, but only needs to send the relevant mode to the cluster node, so that the sensed data can be recovered to the cluster without node sensing data.

To ensure that the difference series formed by two data Δx_i can be calculated under a certain time series, the formula is:

$$\Delta x_i = a_i(x) - b_i(x) \tag{1}$$

In formula (1), $a_i(x), b_i(x)$ respectively i cluster head nodes in high-dimensional spatiotemporal data association And intra cluster nodes; x represents educational data.

Calculate the difference series of two nodes and analyze the fitting error of the two series. The formula is:

$$\varepsilon = \sqrt{\frac{\sum_{i=1}^{n} (\Delta x_i - y_i)^2}{n}} \tag{2}$$

In formula (2), n represents the number of calculations; y_i represents the original sequence of cluster nodes. If the fitting error is less than the given error threshold, it can be determined that the two node data are spatially related. Otherwise, it has no relevance.

3 Association Mining of Educational Data Based on Machine Learning Model

3.1 Construction of Machine Learning Model for Educational Data Association Rules

Combined with machine learning method, the basic learner is used to generate problem data, and the meta learner's learning program is used to process metadata. The constructed machine learning model of educational data association rules is shown in Fig. 1.

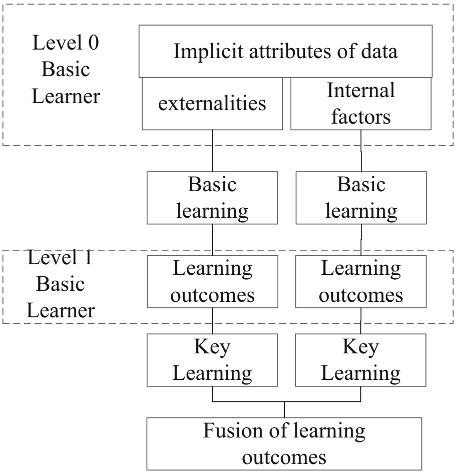


Fig. 1. Machine learning model of educational data association rules

It can be seen from Fig. 1 that layer 0 represents the basic learner of level 0, and layer 1 represents the meta learner of level 1. Meta learner is a kind of learning behavior based on machine learning model. In the whole process of machine learning, the combination rules are defined, and the learning results are fused after model training. In general, machine learning is a simple learning process, which can effectively avoid over fitting.

When mining association rules of educational data through the machine learning model built, we need to use data mining algorithms to query and analyze data according to the characteristics of the data. Usually using item sets A, B To indicate that the two item sets are independent of each other and do not have duplicate attributes. The two sets are useful and the personalized rules between sets are universal and interesting. Each information has a symbol, which is called φ, A, B are itemsets, glyph φ include A, B, if and only if $A, B \in \varphi$. Personalized association rules have $A \Rightarrow B$ Implication, where $A \subset 1$, $\mathrm{B} \supset 1$, and $A \cap \mathrm{B} = \emptyset$.

Collect the target related objects and reference sets into the database. The association rules in the database $A \Rightarrow B$, the percentage of all things, called $A \Rightarrow B$ The expected confidence of. The confidence is compared with the expected confidence, and the interest is obtained as follows:

$$\eta = \frac{U}{U'} \tag{3}$$

In formula (3), U, U' represent confidence level and expectation confidence level respectively.

According to the above association rules, when predicate calculation is performed at a rough level, the target is set as the smallest bounding rectangle, the extraction distance falls within a predetermined threshold as an object, the predicate of object relations is stored in the database, and the attribute value is set as a single value or a group of values. Different predicates have different supports, namely:

$$f_{AB} = \eta \cdot f_A \cdot f_B \tag{4}$$

In formula (4), f_A, f_B Represent association rules respectively $A \Rightarrow B$ Support. Exclude the threshold with low support to form a common database. Perform accurate spatial calculation in common databases, use MBR technology to check the relationship between predicates, eliminate the predicate relationship that does not conform to the actual situation, and then form a topology data table, so as to calculate the support of predicates, exclude items with less support, and then form the optimal database. Generalize the topological relationship to form a new topological relationship data table, and then complete the machine learning of the association rules of education data.

3.2 Association Oriented Data Similarity Calculation

The selection of association oriented data is regarded as an optimization problem. It directly filters the key data from the database to form the oriented data, so that the oriented data has query relevance. By identifying the guidance data on the machine learning model, the data similar to the input data can be obtained according to the threshold screening results, so that the implicit key data can form a vector form with semantic description ability.

Implicit key data vector model construction, as shown in Fig. 2.

It can be seen from Fig. 2 that a method based on association oriented data vector is proposed, that is, to extract basic concepts and features that can express their subject content from the database. When building the data vector of the database, the processed data must be preprocessed first; Secondly, the concept data in the database is extracted; Finally, using the knowledge based on ontology rough set, extract the relevant features from the instance, and then construct a data vector containing conceptual data and attribute description.

In order to facilitate the extraction of key data, the data is divided into small strings with punctuation as the boundary, and the key data extraction methods of the largest public string and traditional data segmentation are used to make the key data as complete as possible, filter out the unqualified key data, and obtain the key data attributes. A

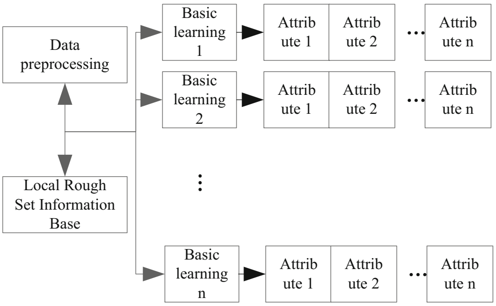


Fig. 2. Implicit key data vector model

common key data extraction method, data gain method, is used. Data gain refers to the difference of data entropy of a feature in the data, that is, the feature provides basic data for key data extraction. The data gain evaluation function is defined as:

$$F = \sum_{i=1}^{m} m(b_i|c_i) \log m(b_i|c_i) \tag{5}$$

In formula (5), b_i, c_i represent the characteristic data of different classes respectively; $m(b_i, c_i)$ represents the number of occurrences of characteristic data of different classes. Since the query contains key data, it can be determined that the guidance data is composed of different sentences. The length of oriented data and query correlation are taken as the key parameters of the adaptation function, and the query correlation is measured by analyzing the average similarity between oriented data and query data.

For the calculation of average similarity of educational data, the vector space in the form of eigenvectors should be analyzed first, and then the cosine value between different eigenvalues should be calculated to obtain the similarity of educational data. In order to obtain the query document education data set, you can first determine the input APP user privacy protection text and query text. After preprocessing the protection text and query text, you can directly determine the query document education data set W Collection of Heci Features Q. Education data can be converted into vector form, and the formula for calculating the frequency of word feature set in education data can be expressed as:

$$l = l_Q \cdot Q + l_W \cdot W \tag{6}$$

In formula (6), l_Q is the frequency of expression features;l_W is the frequency of inverted educational data representing word features.

Any two education data W_i and W_j is the similarity calculation formula between can be expressed as:

$$sim\left(W_i, W_j\right) = \frac{\omega_{i1} \cdot \omega_{j1} + \ldots + \omega_{in} \cdot \omega_{jn}}{|W_i| \cdot \left|W_j\right|} \tag{7}$$

In formula (7),ω_{in}, ω_{jn} respectively represent the Weight of i, j. Assuming that there is some oriented data in the database, you can determine the relevance of the oriented data query.

3.3 Clustering of Related Educational Data

Through the similarity calculation results of association oriented data, the implicit low rank characteristics of data are obtained. However, data in reality usually contains noise, so a robust low rank constraint model is adopted, which can extract pure low rank and suppress noise. Its model is as follows:

$$T = \min_{\varsigma} \|\iota\| + \gamma\mu \tag{8}$$

In formula (8), ι Represents the representation coefficient of the noise impact model; γ Represents the noise regularization term; ς Represents the noise item; μ Represents the balance parameter.

For nonlinear data, it is proposed to use the kernel function method to map the original nonlinear data to the high-dimensional kernel Hilbert space, so as to expand the low rank constraint model of the original space to the kernel space, thus obtaining the denoising low rank constraint model. Among them, the introduced balance parameter can effectively separate the outliers, thus enhancing the robustness of the machine learning model. On this basis, a weight based algorithm is proposed, which can not only avoid the selection of kernel functions and parameters, but also effectively fuse the complementary information between multiple candidate cores, generate the best consensus core, and improve the performance of the algorithm. On this basis, the clustering function of related education data constructed can be expressed as:

$$L = T + \sum_{i=1}^{k} \left\| o_i - o_i' \right\|^2 \tag{9}$$

In formula (9), o_i Express consensus core; o_i' express i Candidate cores; k Indicates the number of cores. By constructing a clustering function of related educational data, the feature weighting strategy of educational data gives full play to the representation ability of each core.

By constructing a clustering function of related education data, it is necessary to first determine the European distance between different types of data when clustering data. The formula is:

$$d_{b_i c_i} = \sqrt{\left|\left(d_{b_1} - d_{c_1}\right)\right|^2 + \left|\left(d_{b_2} - d_{c_2}\right)\right|^2 + \cdots + \left|\left(d_{b_i} - d_{c_i}\right)\right|^2} \tag{10}$$

In formula (10), d_{b_i}, d_{c_i} Respectively b_i, c_i Class cluster distance corresponding to data. According to the calculation results, arrange the distances from small to large. After obtaining the corresponding marking results, for two clusters in each distance, one cluster does not belong to the weighted subspace cluster cluster, then merge the cluster into one cluster until the total cluster value is 1. To ensure that all clusters are fused into one cluster, it is necessary to determine the optimal number of clusters to facilitate the clustering of educational data. On the premise of determining the optimal number of clusters, obtain the topology of the node with the lowest similarity between the two clusters. Once the node topology no longer appears packet forwarding, it indicates that all spatial education data are completely clustered.

3.4 Clustering Data Association Mining Based on Machine Learning Model

In the process of data association mining for vocational college students' employment education, frequent item sets are generated through the relationship between time and space, and frequent item sets are generated through the minimum set cycle. On this basis, the efficiency of data mining is improved through machine learning model. The combination of machine learning model greatly improves the speed of data association mining. The detailed steps are as follows:

Step 1: Cluster data preprocessing.

In the data pre-processing process, the data is filtered, and redundant and useless data is proposed. According to different communication requirements, the data is pre-processed to help the system extract useful data from massive data.

Data pre-processing is to convert the Internet of Things environment with irregular distribution test into regular test mode through interpolation, which is convenient for computer operation. In the Internet of Things environment, big data is generally incomplete and cannot be directly mined. Therefore, data must be preprocessed first. The data preprocessing steps are shown in Fig. 3.

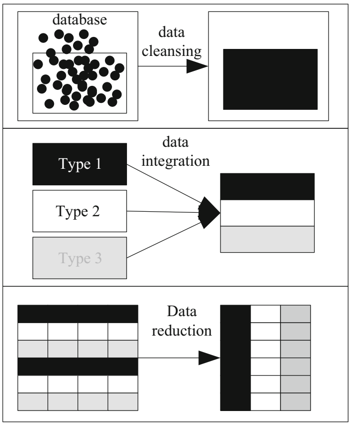


Fig. 3. Data pre-processing steps

(1) Data cleaning: This process is to clean dirty data, including filling in missing values, clearing noise data and correcting inconsistent data.
(2) Data integration: integrate multiple database data and merge data sources into the same data store. Since the same field exists in different databases, redundant data will appear. Therefore, when preparing data, you should clean it again after data integration.
(3) Data reduction: improve the system communication speed by aggregating and deleting redundant data. Under normal circumstances, data reduction mainly has two ways, namely dimensional reduction and numerical reduction. For dimension reduction, data coding scheme is used to obtain compressed data packets and data

attributes; The logarithmic linear model is used for numerical reduction, and the smaller representation is used to take algebra to form reduction data.

(4) Data transformation: Data is transformed into a form suitable for data mining through smooth aggregation.

Through data pre-processing, in the original resource database, the average value is usually used to fill in incomplete data. This process needs to be implemented by the moving average method. Moving average method is a key method to take the average value of resource data in a certain stage as the forecast value in a certain period in the future, and use this data as the later mining data.

The moving average is calculated as follows:

$$z = \sum_{i=1}^{m} \left(\frac{l_i'}{m} \right) \tag{11}$$

In formula (11): z Is the excavation value; l_i' Indicates the moving length.

In order to facilitate that all data in the resource database have the same attribute, its transformation rules need to be defined and the format should be unified before mining. Because noise data is illogical deviation data, which often affects the accuracy of resource mining, data smoothing technology is used to eliminate noise data. Through data pre-processing, we can automatically mine the employment education data of vocational college students.

Step 2: Scan all data sets and record the number of data occurrences each time. Determine whether the time and spatial data are in the same dimension according to the requirement definition, and record them in the header table if they exist;

Step 3: Recycle the dataset, delete the data not in the item header table, and arrange the data according to the increasing order of the item header table. Cycle the data set again to generate a frequent pattern tree. In the frequent pattern tree, all nodes represent high-dimensional spatial and temporal data, and numerical values represent the number of times high-dimensional spatio-temporal data occurs;

Step 4: In the circular item header table, search the entries in the regular pattern tree and the leaf nodes of the entries in descending order, and eliminate the duplicate node data to obtain a separate tree structure dataset. At this time, the dataset is a collection with relevance.

Step 5: Output the tree structure data set of all single paths to form the final result set.

Step 6: The system designs the data association extraction process according to the determined result set. When entering query conditions in the system, the system will start the Map program according to the entered conditions, and extract qualified data from the text set according to the query relevance of the guided data.

4 Experiment

In order to verify the effectiveness of the data association mining method of higher vocational students' employment education based on machine learning model, the experiment is carried out on Matlab platform through Unix operating system.

4.1 Experiment Overview

The employment of vocational college graduates is affected by many factors. From the perspective of students' individual characteristics, this paper discusses the correlation between students' employment and students' individual characteristics. Therefore, according to the survey data of five universities in China, a data warehouse for student employment is established. Using the powerful analysis function of MS SQL Server 2005 software, the correlation between the employment destination of students and their individual characteristics is analyzed. The simulation experimental environment is: operating system Win10, Intel i5-9400F processor. The experiment used Python programming language to train and test machine learning models on the Tensorflow deep learning framework.

Relying on the national education science planning project, the research team carried out a survey on the employment of students from March to October 2020. By means of random sampling, the research team collected the basic information and employment information of 14410 graduates of 2018, 2019 and 2020 from five universities. Based on the collected information, a database named STUDENT was established.

Design data table: student basic information table, student course selection table, curriculum table, student comprehensive quality scoring table, student employment information table, etc. The field information of each table is as follows: the student basic information table includes student number, gender, major, political outlook, student origin, scholarship, and competition award; The information table of student course selection includes student number, course number and course score; The course information table includes course number, course name, course nature, class hours and credits; The student comprehensive quality score sheet includes student number, political quality, professional achievements, physical and mental quality, ideological and moral quality, humanistic quality, and innovative practical ability; The student employment information table includes student number, employment status, employment region, unit nature, industry, position and annual income.

Table question relationship interface is shown in Fig. 4.

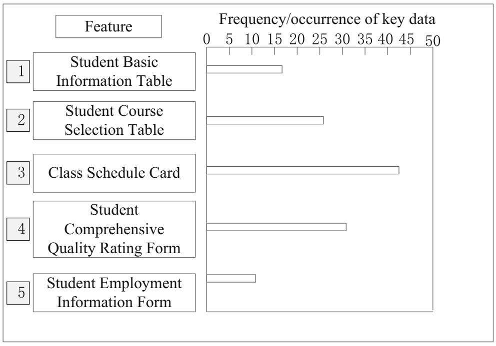


Fig. 4. Table question relation interface

It can be seen from Fig. 4 that the bubble chart on the left is the result of marking data topics. The bubble radius depends on the number of topics contained. The right column displays the key data selected on the left and its occurrence frequency.

4.2 Determination of Experimental Indicators

(1) Excavation integrity rate

The calculation formula of data association mining integrity rate is as follows:

$$P = \frac{N}{M} \times 100\% \tag{12}$$

In formula (12),N Represents the amount of data mined;M Represents the total amount of data. The larger the value of the calculation result, the more complete the data association mining result is.

(2) Mining error

The calculation formula of data association mining error is as follows:

$$e = \frac{|x_1 - a_1| + |x_2 - a_2| + \cdots |x_n - a_n|}{\alpha} \tag{13}$$

In formula (13), α Represents the number of excavations; a_n Indicates information whose data has not been searched. The larger the value of the calculation result, the more accurate the data association mining result is.

4.3 Analysis of Experimental Data

In order to make the experiment result obvious, take five kinds of data, namely, student basic information table, student course selection table, curriculum table, student comprehensive quality scoring table, and student employment information table, as examples, and expand each kind of data to obtain the experimental data set shown in Fig. 5.

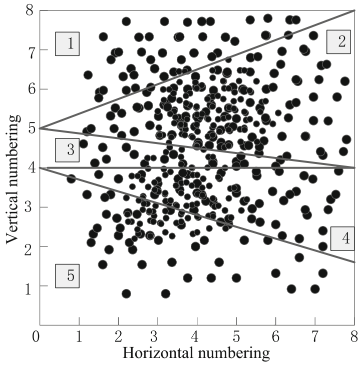


Fig. 5. Experimental data set

In the dataset, the similarity retrieval is carried out for the dataset in Fig. 5 in order to provide data support for the experiment.

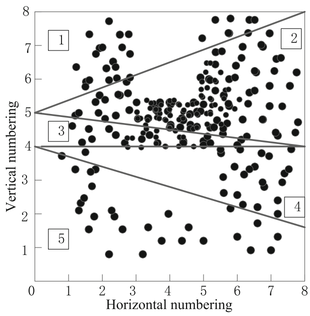
4.4 Experimental Results and Analysis

The mining method based on RBF neural network, the data mining algorithm based on deep integration learning, the data mining algorithm based on association rules and similarity, and the association mining method based on machine learning model are respectively used to compare and analyze the mining integrity of different methods, as shown in Fig. 6.

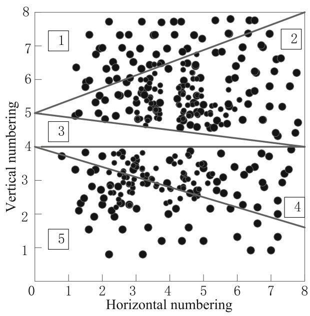
As shown in Fig. 6, the integrity rate of five types of data mining methods based on RBF neural network is low; The data mining algorithm based on deep integration learning has a low data mining integrity rate, and does not mine the third type of data at all; Data mining algorithm based on association rules and similarity data mining algorithm data mining integrity rate is low, and the first and fifth types of data mining integrity rate is relatively low; Using the association mining method based on machine learning model, the mining data type is consistent with the experimental data type, indicating that the mining results using this method are complete.

The comparison results of mining errors using the four methods are shown in Table 1.

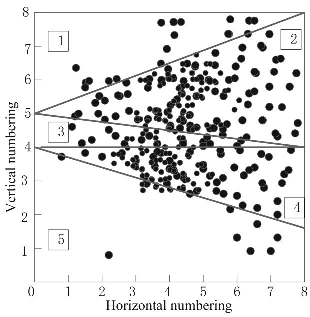
Table 1 shows that the minimum mining error is 0.50, 0.32 and 0.21 respectively when using the RBF neural network based mining method, the data mining algorithm based on deep integration learning, and the data mining algorithm based on association rules and similarity. The minimum mining error is 0.05 when using the association mining method based on machine learning model. The above data prove that the method designed in this paper has a small error and a high mining accuracy. This is because this paper fully analyzes the internal and external factors affecting students' employment and determines the spatial correlation of this factor sequence. Using association rules, a machine learning model of educational data association rules is established, calculating the similarity between the frequency of word feature set in educational data, and improves the mining accuracy is improved.



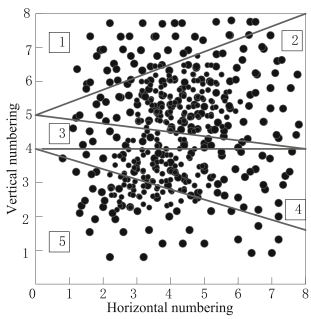
(a) Mining Method Based on RBF Neural Network



(b) Data Mining Algorithm Based on Deep Integration Learning



(c) Data Mining Algorithm Based on Association Rules and Similarity



(d) Association Mining Method Based on Machine Learning Model

Fig. 6. Comparison and Analysis of Mining Integrity Rate by Different Methods

Table 1. Comparison and Analysis of Mining Errors of Four Methods

Excavation times/time	RBF neural network(Literature [1])	Depth Integrate study(Literature [2])	Association rules and similarity(Literature [3])	Machine learning model
20	0.53	0.39	0.23	0.04
40	0.51	0.35	0.27	0.06
60	0.50	0.32	0.23	0.06
80	0.52	0.36	0.25	0.08
100	0.53	0.39	0.26	0.04
120	0.56	0.34	0.21	0.04
140	0.52	0.38	0.24	0.06
160	0.57	0.35	0.26	0.06
180	0.56	0.36	0.23	0.06
200	0.58	0.35	0.28	0.05

5 Conclusion

There are many factors affecting the employment of college students. From the current situation of the development of higher education in China, the difficulty of college students' employment is more a structural relative surplus. Due to the changes in the social and economic structure (including industrial structure, product structure, regional structure, etc.) of college students during the study period, the majors, knowledge, skills, regional distribution, etc. of graduates do not meet the requirements of the changes in the economic structure, and they can not adapt to the needs of the employment market when they graduate, resulting in the failure of smooth employment. From the comprehensive analysis of the survey data, the following conclusions can be drawn:

This paper proposes a data association mining method for higher vocational students' employment education based on machine learning model, which determines the support degree between data by calculating the implication degree, and combines machine learning model to mine the association of education data. This method effectively solves the problems existing in the current traditional methods, and verifies the rationality of this method through experiments. Since the problem studied is still in the aspect of single level association, in order to expand the application field of this method, we should focus on the research of multi-level association in the later stage to further improve the efficiency of data association mining.

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A Personalized Course Content Pushing Method Based on Machine Learning for Online Teaching of English Translation

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Abstract. A personalized course content delivery method based on machine learning for online teaching of English translation is studied. The difficulties and challenges faced in English education are introduced, pointing out that there are differences and diversity in levels, interests and learning styles, etc.; machine learning algorithms are used to deeply analyze data in students' personal files, including their learning history records, course grades and personal information, etc., to discover students' learning levels, learning interests and learning characteristics, etc. Given a training sample of course standards, an interest model, solving the similarity among users using the similarity of clouds, acquiring the nearest neighbors of target users, and generating the pushed course contents and learning materials. The experimental results show that the results of personalized course content pushing for online teaching of English translation meet the real needs and have good application effects.

Keywords: Online Teaching · English Translation Courses · Personalized Content

1 Introduction

With the development of globalization and the popularity of information technology, English learning has become an integral part of modern society. However, due to the differences and diversity of students, traditional English education methods often fail to meet the individual needs of each student. Therefore, how to introduce personalized teaching methods in English education to meet the learning needs of different students and improve the efficiency and quality of learning has become one of the key points and hot spots of current research.

With the continuous acceleration of globalization, English has become the universal language for international communication and business cooperation. In this context, more and more people are starting to learn English and gradually making it a necessary skill. In English learning, besides the training of basic skills such as reading, listening, speaking, and writing, the learning of English translation is also an important part. For

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those who want to engage in translation work, learning English translation skills is crucial.

The traditional English translation teaching model usually involves teachers teaching students basic knowledge and skills, and mastering and consolidating them through group discussions, assignments, and exams. However, there are some problems with traditional teaching methods, such as overly rigid teaching processes, low student interest in learning, and insufficient targeting, which seriously affect students' learning efficiency and interest. Therefore, in English translation teaching, how to design personalized courses to meet the needs of each student has become an important task that needs to be explored.

With the development of machine learning, online education platforms are gradually applying this technology to teaching and learning, so as to realize personalized teaching. As a language subject, English translation is the focus of many students' learning, and it has become a major problem in English education to realize personalized teaching by tailoring teaching contents for students. In order to solve this problem, the traditional teaching methods are often class-based, with uniform assignments and unified listening, reading, writing and listening training. However, since each student has different backgrounds, interests, learning styles and learning progress, such uniform teaching is difficult to meet students' individual needs, and may even make some students feel boring and lead to a decline in interest and learning motivation. Therefore, it is an important task to explore how to provide students with personalized course content pushing through machine learning technology in English translation teaching.

In this paper, we analyze students' personalized English translation learning based on machine learning technology with the help of artificial intelligence algorithms, and provide each student with personalized learning content pushing that meets his or her individual needs by establishing a student model, a course model and an assessment model, and combining a series of factors such as knowledge mastery, learning duration and learning intensity. This personalized learning method based on machine learning can not only improve students' learning effect and interest degree, but also help teachers discover students' learning problems in time, analyze students' learning level, learning interests and learning characteristics by mining data in students' personal files, and push suitable learning contents and materials for students [1, 2] for targeted teaching and guidance, so as to optimize The purpose of teaching effect. It is of great practical value and promotion significance to effectively improve students' learning efficiency and interest in learning. In this paper, we will discuss this issue, analyze the concrete implementation and application effects of the personalized course content pushing method for online teaching English translation based on machine learning, and conduct relevant discussions and summaries.

The structure of this article is as follows: Firstly, it introduces the relevant knowledge, teaching models, and problems of English translation, as well as the background, application scope, and principles of machine learning. Secondly, a detailed description is given of the personalized course content push method for English translation online teaching based on machine learning, and experimental results and analysis are provided. Finally, a summary and outlook of the methods proposed in this article are presented, pointing out the directions and issues that need further research in the future.

2 Pre-processing of Personalized Courses for Online Teaching of English Translation

With the continuous development of machine learning technology, more and more online education platforms are applying it to teaching, achieving personalized teaching. Based on this background, this article will explore a personalized course content push method for English translation online teaching based on machine learning. By constructing student models, course models, and evaluation models, based on a comprehensive analysis of students' language background, learning progress, learning interests, and learning styles, we provide personalized learning content push for each student. This personalized learning method based on machine learning will greatly improve students' learning effectiveness and interest, and better meet their personalized needs.

The characteristics of personalized courses for online teaching of English translation are as follows:

(1) Difference and diversity of students: there are differences and diversity in different students' levels, interests and learning styles in English learning, etc., and traditional English education methods are often difficult to meet the individual needs of different students.
(2) Lack of teaching resources: At present, there is a lack of online teaching resources for English translation in the market, and a lack of scientific teaching resources with certain authority and effectiveness, which brings great trouble to students' learning.
(3) Uneven teaching quality: Due to the high mobility and uneven quality of the English translation online teaching market, some institutions, websites and platforms have poor teaching quality and lecture level, which leads to poor learning effect of students and affects their confidence and motivation [3, 4].
(4) Single form and lack of interactivity: at present, most English translation online teaching platforms still take recorded videos as the main form, lacking interactive communication with students, leading to discounted learning effects.

In summary, the current dilemma faced by online teaching of English translation is obvious, and it needs to be optimized and adjusted through new technologies and methods [5] in order to better meet students' learning needs and improve the effectiveness and quality level.

2.1 Initial Classification of Courses

Based on the usability and maintainability of course knowledge, the following guidelines for constructing course ontology have been determined:

(1) There is no ambiguity between any two knowledge points in the course ontology, that is, the definition and description of knowledge points should be unique. The definition of knowledge points in the course ontology should be as detailed and complete as possible to maintain the integrity of the course ontology.
(2) The knowledge in the course ontology should be dynamically updated and deleted, maintaining the latest state of the course ontology and maintaining it in real-time.

(3) The granularity of course knowledge should be appropriate. The smaller the granularity of knowledge, the higher the degree of reuse, but it will lead to the complexity of knowledge recombination.

So for the granularity division of course knowledge, first ensure the local integrity of the knowledge, and then correspond the representation of the knowledge to the corresponding teaching steps. Assuming that given the course standard training sample $\left\{x^{(1)}, x^{(2)}, \cdots, x^{(n)}\right\}$, each $x^{(i)} \in R^n$ and j are clustered.

Randomly select K cluster centroid points and represent them as $u_1, u_2, \cdots, u_n \in R^n$.

Loop through the following steps until convergence:

Calculate the class to which each sample i belongs:

$$c^{(i)} = \arg\min_j \left\| x^{(i)} - u_j \right\|^2 \tag{1}$$

According to the top-down approach of the skeleton method, the course ontology is determined. The design process is as follows: Requirements analysis. The main users of the course ontology in this article are teachers and students, which can effectively represent knowledge, share and reuse knowledge, maintain knowledge, and guide students in autonomous learning. Determine the concept set of ontology based on the structure of knowledge, arrange upper and lower level concepts reasonably, and cover all concepts of knowledge. When establishing the hierarchical structure of concepts, it is important to ensure that the definitions between concepts are unambiguous and that concepts at the same level cannot intersect. Calculate the similarity of course content between each course data sample and the centroid point [6], select the centroid point with a small distance from the course data sample, and divide the samples with the same centroid distance into the same cluster to complete the initial classification of the course data sample. The traditional curriculum structure is based on a hierarchical structure of chapters, while ontology based curriculum is based on a conceptual node structure. Curriculum ontology often needs to modify relationships between general ontology concepts such as "parent class subclass", but instead requires the addition of new concepts such as precursor relationships and successor relationships. The establishment of a conceptual attribute hierarchical structure only represents the skeleton of the ontology, and it is necessary to add conceptual attributes to the hierarchical structure to expand the properties and features of the concept. In the course ontology, there are two types of attributes of concepts: static and dynamic. The formalization of ontology is described through ontology description language, which facilitates the expression and expansion of ontology.

2.2 Machine Learning Based Interest Feature Sample Set

Existing user vector space usually exists in the form of n-dimensional vector. At this time, we can establish a feature sample set, such as:

$$(K, M) = \{(k_1, m_1), \cdots, (k_n, m_m)\} \tag{2}$$

In the formula, (K, M) represents the weight of the feature vectors in the user model;(k_n, m_m) is its manifestation in n-dimensional space. When the interest model in the scenario tuple can be represented by a feature set, it can be obtained that:

$$H_m = \{(f_1, p_1, n_1, d_1), \cdots, (f_n, p_n, n_n, d_n)\} \tag{3}$$

In the formula, H_m represents the set of interest features of the user subject [7–9]; f_n represents the feature vector of n-dimensional interest topics; p_n represents the topic weight in n-dimensional vector space; n_n represents scenario elements in n-dimensional space; d_n represents the actual feature items in the theme document. At this point, the standard value of topic weight can be obtained through initialization:

$$g_i = \sum_{i=1}^{n} I(page_i) \tag{4}$$

In the formula, g_i represents the standard value of topic weight; $I(page_i)$ represents the user's interest in the topic document, which is generally represented by *page* [10–12]. While estimating multidimensional user models, user models can also be established:

$$Q(h, m, n) = \frac{f_{user}}{\sum\limits_{i=1}^{n} f_{context_i}} \tag{5}$$

In the formula, $Q(h, m, n)$ represents the information rating of the user model under the same cultural level, time, and location factors; f_{user} represents the user's interest level; $f_{context_i}$ represents the interest standard value that the topic document can bring. At this point, an expression for user profile interest can be established:

$$Q_{context} = \frac{\prod\limits_{i=1}^{n} (context_h \times context_m \times context_n)}{Q(h, m, n)} \tag{6}$$

In the formula, $Q_{context}$ represents the rating of the user interest matrix; $context_h$, $context_m$, and $context_n$ represent the scoring criteria for cultural level, time, and location, respectively. At this time, we can get the interest estimation of English translation online teaching personalized curriculum resources of user profiles, and establish the information collection of English translation online teaching personalized curriculum resources at the user's place based on the user information. The advantage lies in the automatic acquisition of information by the system. By constructing a domain ontology, knowledge within that domain can be easily integrated. The system quickly Pushs knowledge to users based on the ontological structure of resources, thereby ensuring the real-time performance of the system. The accuracy of resource Pushation is high.

Due to the fact that ontology based Pushation is studied from a semantic perspective, analyzing user demand information and contextual information of learning content, the system can quickly find relevant knowledge and Push it to users. Resources have sharing and reusability. By constructing domain ontology, relevant domain resources can be shared and reused to avoid repetitive work.

Ontology based Pushation can not only Push relevant knowledge points to users, but also Push the matching connections (learning paths) of current knowledge points to users based on the "predecessor successor" relationship of knowledge. The learning path is a learning sequence composed of a series of knowledge points, which can improve the service quality of Pushations, transform Pushations from "points" to "surfaces", and greatly improve learning efficiency.

3 Resource Similarity Analysis and Push

Using cloud models to predict the similarity of personalized course resources for English translation online teaching, the specific steps are as follows:

Step 1: According to the effective personalized course resource X retrieved in Sect. 2.2, count $A(a_1, a_2, a_3, a_4)$ of each English translation online teaching personalized course resource, and use reverse cloud algorithm to solve $W_i = (Ex_i, En_i, He_i)$ of each English translation online teaching personalized course resource. The English translation online teaching personalized course resource numbers are i, $1 \leq i \leq m$; The i-th personalized course resource preference feature vector for English translation online teaching is W_i; The expectation, entropy, and stability of the i-th personalized course resource for English translation online teaching are Ex_i, En_i, and He_i;

Step 2: Calculate the similarity s between the personalized course resources p of unrated English translation online teaching and the other personalized course resources s of English translation online teaching based on the similarity of the cloud. The formula is as follows:

$$s(p, i) = \cos\left(x_p, x_i\right)\lambda = \lambda \frac{x_p \cdot x_i}{\left\|x_p\right\| \|x_i\|} \tag{7}$$

Among them, the personalized course resource vectors formed by the digital features of the cloud are x_p and x_i; The constant is λ.

Step 3: The neighbor English translation online teaching personalized course resource set with the maximum number of items s as p, is to search for the English translation online teaching personalized course resource set $X_P = \{X_1, X_2, \cdots, X_P\}$ within the entire X, and the number of searched English translation online teaching personalized course resource sets is P, making $p \notin X_P$. At the same time, the similarity between English translation online teaching personalized course resources X_1 and P is $s(p, X_1)$, followed by X_2 and $s(p, X_2)$ of p, and so on;

Step 4: After obtaining X_P, predict the user α The formula for scoring p is as follows:

$$V_{\alpha,p} = \lambda \frac{\sum_{y \in X_P} s_{p,y} \times F_{\alpha,y}}{\sum_{y \in X_P} \left|s_{p,y}\right|} \tag{8}$$

where the similarity between p and English translation online teaching personalized course resource y is $s_{p,y}$; the rating of α on y is $F_{\alpha,y}$; and a random similar English translation online teaching personalized course resource is y.

The purpose of the personalized course resource Pushation system is to provide a convenient and fast course resource interface for all students in the school. Compared to the number of users targeted by enterprise level course Pushation systems, the number of users in this system is limited. However, in order to facilitate the later expansion needs of the system, higher requirements for system performance should also be put forward in the system design and development process. Therefore, this article will analyze performance requirements from the following aspects:

(1) Usability requirements refer to whether the operation of system functions is simple, easy to learn, and user-friendly. After the implementation of personalized course resource Pushation system, it is mainly aimed at non-technical personnel, which puts forward requirements for the system such as simple and convenient operation, easy learning and understanding, and beautiful and elegant interface.
(2) The ultimate goal of designing and developing a personalized course resource Pushation system for compatibility requirements is to provide users with personalized Pushation services for course resources. Therefore, the system should be able to work stably under different operating systems and adapt to various database systems without unexpected program termination issues. Therefore, during the development of this system, we chose to use the Bootstrap framework and SSM framework, which are compatible with both mobile and PC devices.
(3) The stability requirement is a requirement proposed for systems that may exceed system load in certain extreme situations. Therefore, a good application system should be able to ensure the stable operation of the system. When there are abnormalities in the system, the system can also recover data in a timely manner to avoid unnecessary losses.
(4) The maintainability requirement of a system indicates the ease with which a software product can be modified, and the easier the product is to be modified, the stronger its maintainability. Therefore, an excellent system should be easy to maintain and still maintain its integrity during system maintenance.
(5) The scalability requirement of a system refers to its ability to adapt to changes. As user demand increases, the system's performance requirements will also become higher. Therefore, throughout the entire lifecycle of system development, it is important to consider the possibility of continuous improvement and iteration of system functions.

After obtaining the ratings of the unrated English translation online teaching personalized course resources, the similarity between users is solved using the similarity of clouds to obtain the nearest neighbors of the target users and generate the pushed personalized course resources, as follows:

Step 1: According to the user rating table with the valid personalized course resources X retrieved, solve the user personalized course resource matrix $X_{\beta \times m}$ with the behavior user, the number of users is β, listed as English translation online teaching personalized course resources, the number of documents is m. Let the rating of user α for English translation online teaching personalized course resource y be $F_{\alpha,y}$ and α for unrated English translation online teaching personalized course resource p is $V_{\alpha,p}$, then for random English translation online teaching personalized course resource $p \in A_{\alpha y}$, the rating frequency vector of the αth user's yth English translation online teaching personalized course resource is $A_{\alpha y}$, and if α has rated English translation online teaching personalized course resource p, then α's rating of p is $F_{\alpha,p}$, and if α has not rated English translation online teaching personalized course resource p, then α's rating is $V_{\alpha,p}$;

Step 2: According to $X_{\beta \times m}$, count the rating frequency vector A of each user, solve the rating feature vector $Q_\alpha = (Ex_\alpha, En_\alpha, He_\alpha)$ of the αth user using the inverse cloud algorithm, and the stability of the expectation, entropy and entropy of the αth user is $Ex_\alpha, En_\alpha, He_\alpha$;

Step 3: solving the similarity $s(\alpha, \eta)$ of users α and η using Eq. (1) to build the user similarity matrix;

Step 4: the set of personalized course resources for online teaching English translation with a number of items with the highest s as the neighbors of the target user L is to find the set of nearest neighbors $\theta_L = \{\theta_1, \theta_2, \cdots, \theta_\sigma\}$ of L in the space of all users, and the number of nearest neighbors is σ; let $L \notin \theta_L$, while the similarity $s(L, \theta_1)$ of user θ_1 and L is the highest, followed by the similarity $s(L, \theta_2)$ of user θ_2 and L, and so on;

Step 5: Based on the weighted average of each user's rating of personalized course resources for English translation online teaching within θ_L, the personalized course resources of interest to L are pushed.

Collection of relevant information. Collect user information based on their registration information and relevant historical browsing information when logging into the system. According to the design criteria of the ontology, design the course ontology reasonably, and then import the information of the course ontology into the database for storage.

(1) Related calculations. Calculate the semantic similarity of the course concepts that the user is learning, find a set of concepts similar to the current concept in the course ontology information structure, and select an appropriate number of concepts as Pushed candidate sets. By updating the user interest model, calculating the interest level of concepts and the weights of their corresponding relationships, real-time user interest is obtained. Based on the level of concept interest, appropriate user interested concept sets are selected as Pushed candidate sets. Finally, by calculating the similarity of users, similar user groups are obtained, and then collaborative Pushations are made using similar user groups to discover new interests of users. The concept set with high ratings that users have not visited is placed in the candidate Pushation set.
(2) Generate an initialization Pushation set. Collect the Pushation results calculated above and put them into the initialization Pushation set.
(3) Push optimization measures. Optimize Pushations by adjusting the number of Pushed concepts, the difficulty of concepts, whether Pushed resources can be rated, and selecting the presentation method of Pushed resources, among other interactive factors, to make the Pushation results more personalized. The main function of Pushation optimization is to further Push learning content that is suitable for the user's own situation based on their abilities, knowledge mastery, learning plans, etc. At the same time, users can also rate resources (interactivity) to provide corresponding feedback on the Pushed results.
(4) Push enhancements. By adding additional content to Pushed knowledge, users can enhance their mastery of learning knowledge, which enhances the effectiveness of Pushations. For example, users may need some learning examples to enhance their understanding of concepts, and through practice and testing to check their level of

knowledge mastery, in order to provide feedback on Pushed content and update the effectiveness of Pushations accordingly.

(5) Generation of learning paths. The learning path is generally represented by a sequence of learned knowledge, which is composed of the current knowledge, its predecessor knowledge, and subsequent knowledge in a shallow to deep manner according to the difficulty of the knowledge.

By generating a suitable learning path through a learning path generation algorithm, the pre and post knowledge of the Pushed knowledge is transformed from a “point” to a “surface”, thus distinguishing it from general learning Pushations that only have knowledge points. The generation of learning paths can help users to “look ahead and consider the future”. While learning the later knowledge, they can also review the previous knowledge, reducing the time for reviewing the previous knowledge and greatly increasing learning efficiency.

4 Experiments

In this paper, we selected personalized course data for online English translation teaching on mobile teaching platforms as the data source, which includes videos of 207 single online knowledge points and learning logs of 1198 learners. These datasets contain field attributes such as learner ID, video knowledge point ID, learning frequency, pause and drag frequency, cumulative learning duration, and teacher evaluation performance information. However, after processing the text data information of learners, recommendation algorithms cannot directly generate corresponding knowledge point recommendation lists for target learners based on these text data information. Therefore, it is necessary to process the text data information appropriately to adapt to the recommendation process of subsequent algorithms. We replace learner ID and video knowledge ID with numbers, and carry out corresponding pre-processing, so that the original dataset can be used for algorithm recommendation.

In order to evaluate the performance of the proposed recommendation algorithm, we conducted performance tests to verify the algorithm’s performance from different perspectives. We use accuracy, recovery rate, and F1 value as evaluation indicators to measure the performance of the proposed algorithm, in order to comprehensively evaluate the advantages and disadvantages of the teaching resource recommendation algorithm. The accuracy indicator measures the degree to which the recommendation results of the recommendation algorithm match the actual needs, the recovery rate indicator measures the proportion of the recommendation algorithm that can cover the actual needs, and the F1 value combines accuracy and recovery rate. By evaluating these indicators, we can gain a more comprehensive understanding of the performance and effectiveness of personalized course content push methods for online English translation teaching based on machine learning.

Taking a learning behavior database as an example, the selected dataset includes 500 samples, and each sample contains feature information such as student ID, selected course, course status, and recent usage time, where student ID is the unique identifier. The parameters used in the experiment include:

(1) Student personal information: including gender, age, education, and college attended, etc.
(2) Learning records: including courses taken, learning progress, course evaluation, assignment submission, etc.
(3) Learning performance: including test results, attendance, etc.

The data set is divided into training set and test set, and 70% of the data is usually used for training algorithms and 30% for testing algorithms in the experiments.

The experimental steps are as follows:

(1) Data collection: collect data such as students' learning records, course grades and personal information to establish students' personal files.
(2) Data mining and analysis: Apply machine learning algorithms to deeply analyze the data in students' personal profiles to discover students' learning levels, learning interests and learning characteristics, etc.
(3) Personalized course content pushing: Based on the data in the student's personal profile, push the course content and learning materials suitable for that student. For example, for students with better academic performance, more in-depth learning materials can be pushed, while for students with lower academic performance, more basic learning materials can be pushed.

The accuracy rate, recall rate and F1 value under different push numbers are analyzed, and the analysis results are shown in Fig. 1.

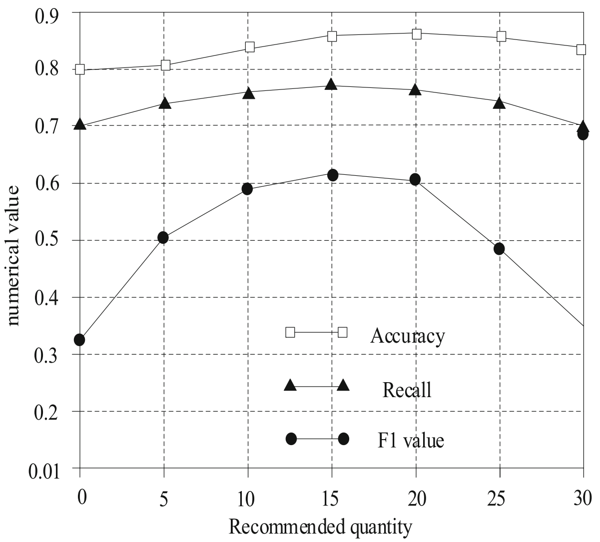

Fig. 1. The impact of different personalized course resource push quantities on push accuracy

From the data in Fig. 1, it can be seen that as the number of push increases, the accuracy of the three types of push shows a trend of first increasing and then decreasing, and the accuracy and recall rates have always been high. As the optimal option for personalized course resource library resource combination push, under this parameter, different resource push results can be obtained as shown in Fig. 2.

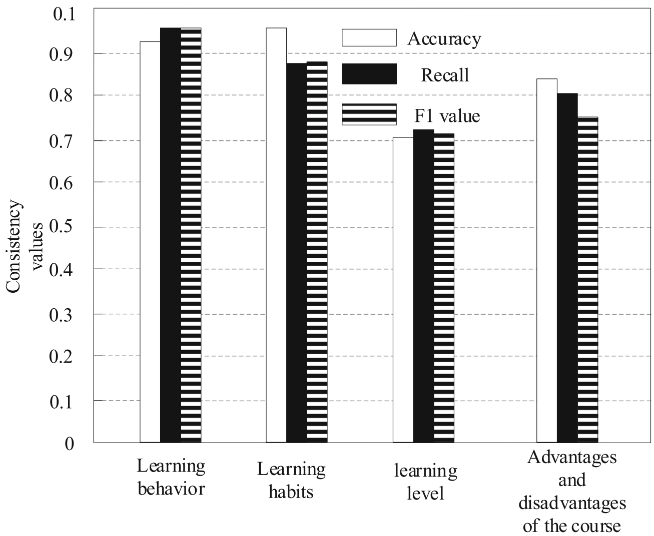

Fig. 2. Pushing Results of Different Resources

As shown in Fig. 2, the accuracy, recall, and F1 values of different resource push results have consistently exceeded 0.7; The matching effect between interest points and courses is good.

The personalized course content push method for online English translation teaching based on machine learning has achieved very good results, with high accuracy, recovery rate, and F1 value.

Firstly, for accuracy indicators, high accuracy means that recommendation algorithms can accurately push course content suitable for learners' learning needs. This indicates that the recommendation algorithm can accurately match and push relevant English translation courses based on learners' interests, abilities, and learning objectives. Learners can obtain the knowledge and skills they need from the recommended courses, improving learning outcomes and outcomes.

Secondly, a high recovery rate means that recommendation algorithms can cover a higher proportion of learners' actual needs. This indicates that recommendation algorithms can widely meet the diverse needs of learners, and the course content pushed can cover different fields and knowledge points of interest to learners. Learners can explore and learn various English translation related topics and techniques in the recommended courses, enriching their knowledge and skills.

Finally, a high F1 value indicates that the recommendation algorithm achieves a good balance between accuracy and recovery rate. This means that recommendation algorithms can cover the actual needs of learners as much as possible while maintaining high accuracy. Learners can obtain accurate and extensive learning resources from recommended courses, improving their English translation ability and application level.

In summary, this method can provide learners with accurate, extensive, and personalized course recommendations. Learners can choose and learn English translation knowledge and skills that are suitable for themselves based on their interests and needs. This will help improve learners' learning outcomes and outcomes, and meet their personalized learning needs.

5 Conclusion

Apply a personalized course content push method based on machine learning to establish a student profile, collect and organize data such as student learning history, course grades, and personal information. Then, machine learning algorithms are used to conduct in-depth analysis of these data to discover students' learning levels, interests, and characteristics. Find the corresponding concepts in the course ontology through the learning content related to the user's interest model, and then calculate other concepts with high semantic similarity to that concept. Based on the calculated similarity, sort the other concepts corresponding to the target concept, and then select appropriate similar concepts to place in the candidate set. Users can learn from concepts with high similarity, which plays a good guiding role for users who have not studied this course. However, if the user has already learned relevant knowledge, they need to push the learning content to the user based on other methods. At this point, they can be pushed with the latest knowledge concepts they are interested in based on their current interests. Based on the analysis results, push suitable course content and learning materials for the student, and provide timely feedback on learning progress and results. It can effectively improve students' learning efficiency and interest, meet their learning needs, and improve the quality and effectiveness of the curriculum.

However, there are still some areas worth further exploration and improvement in this study. Firstly, machine learning algorithms and models can be further improved to improve the accuracy and effectiveness of personalized recommendations. Secondly, it is possible to consider introducing more learning data and features to better understand students' learning needs and interests. In addition, we can also explore how to combine other Assistive technology, such as Natural language processing and emotion analysis, to provide more comprehensive and in-depth learning support.

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A Method for Detecting False Pronunciation in Japanese Online Teaching

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Abstract. In order to accurately distinguish the wrong language signals and word signals in the process of online Japanese teaching, and realize the accurate detection of oral pronunciation errors, this paper studies the detection methods of oral pronunciation errors in the process of online Japanese teaching. According to the phoneme characteristics, the key audio features are extracted, and then the quality of Japanese pronunciation is evaluated by solving the linear prediction coefficient. On this basis, the corpus and pronunciation test set are constructed, and the oral signals are combined to determine the value range of detection interpolation, and the design of oral error pronunciation detection method in the process of online Japanese teaching is completed. The experimental results show that the accuracy of error language signal and word signal is more than 90% under the above method, which is in line with the practical application requirements of accurate detection of incorrect pronunciation in spoken Japanese.

Keywords: Japanese online teaching · Mispronunciation · Audio characteristics · Linear prediction coefficient

1 Introduction

Online learning is a way of online teaching and learning with teachers in a network virtual classroom through the computer Internet or mobile wireless network. The online learning platform can intelligently connect a cloud question bank with the platform to complete your learning goals according to your learning needs. For example, students can learn the course system synchronized with their own learning online and then answer questions synchronously. After the answer is completed, the system intelligence will show you the problem solving process to help you improve your academic performance. With the development of the Internet, the education industry has promoted distance education ten years ago, and realized remote video teaching and electronic document sharing through the Internet virtual classroom, so that teachers and students can form an interaction of teaching and learning on the network; The advent of the 4G era makes it more convenient to learn not only through heavy computers, but also through a mobile phone with large traffic. Through the fast 4G network, students can directly learn online through

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mobile phones and other handheld tools, while the wireless network makes people's daily interactions more effective [1]. E-Learning is online learning. It refers to the learning conducted in the electronic environment composed of communication technology, microcomputer technology, computer technology, artificial intelligence, network technology and multimedia technology. It is technology-based learning. With the advent of the knowledge economy, learning models have been impacted unprecedentedly, and various new learning models have emerged like a tide. Among all learning models, the most powerful one is web-based learning, also known as online learning, which is a new way for students to use the network for online learning by establishing an online education platform. This online learning mode is a new learning environment composed of multimedia online learning resources, online learning community and network technology platform. Compared with other learning modes, it has incomparable advantages.

Japanese pronunciation is an important manifestation of Japanese ability. The accuracy of pronunciation determines the smoothness of communication. Incorrect oral pronunciation is very easy to cause misunderstanding and unnecessary misunderstanding. The best way to teach oral pronunciation is to teach students pronunciation and correct students' pronunciation errors. However, the economic development in different regions of the country is different. Due to the lack of teacher resources in many regions, the focus of Japanese teaching is all on words and grammar. It is impossible to have both oral pronunciation and correct students' wrong pronunciation one by one. Some Japanese teachers' oral English is also substandard, which is easy to cause teaching errors in oral pronunciation. Professional Japanese training is expensive, which makes many learners flinch [2]. Now we have entered the information age, and the level of science and technology has made remarkable progress. Computers have entered people's lives, which has led to the upsurge of online language teaching. However, most online teaching only provides correct oral pronunciation videos, and does not check students' pronunciation errors, pointing out students' pronunciation errors. At present, automatic pronunciation error detection and correction mostly rely on language signals for judgment, ignoring the role of word signals in pronunciation error detection and correction. In fact, many Japanese phonemes have different language features, especially vowels, which can almost be distinguished by the degree of lip roundness and tightness in appearance. Therefore, it is of great significance to realize end-to-end multimodal pronunciation error detection by integrating speech signals and word signals. In response to the above development background, a method for detecting oral errors in Japanese online teaching is proposed. This method extracts key audio features and evaluates the quality of Japanese pronunciation through linear prediction. Construct a corpus and pronunciation test set, and combine the oral signals within them to determine the range of detection interpolation values to complete the detection of oral errors in Japanese online teaching process.

2 Japanese Pronunciation Quality Assessment

For the evaluation of Japanese pronunciation quality, it is necessary to implement audio feature extraction according to phoneme characteristics, and then improve the specific evaluation scheme according to the actual numerical level of linear prediction coefficient.

2.1 Phoneme Characteristics

During Japanese pronunciation, the lips remain open, and the organs in the mouth do not contact directly, and will not interfere with the airflow through the pronunciation. For Japanese phonemes, the appearance can be distinguished by the condition of the lips, the position of the tongue and the tightness of the lips. In the frequency domain, the formant can be used to distinguish. The formant is the frequency band where the sound energy gathers. In fact, the formant has a lot to do with the position of the tongue. Each vowel has three formants (P1, P2, P3). Generally, P1 and P2 can be used to distinguish wrong spoken phonemes. The corresponding relationship between Japanese spoken phonemes and formants is shown in Fig. 1, where the horizontal line represents P2, the vertical line represents P1, and the black dots distributed between the horizontal and vertical lines represent Japanese phonemes.

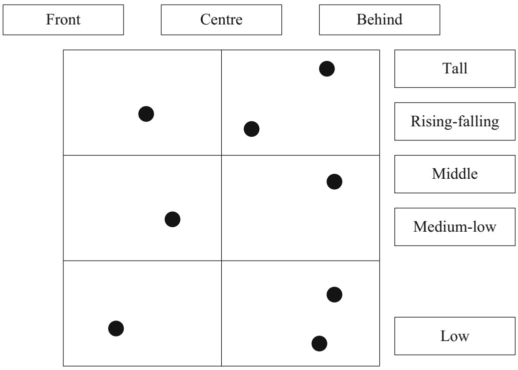

Fig. 1. Wrong formant relationship of Japanese phonemes

In the field of acoustics, P1 relates to the height of tongue position, and P2 relates to the front and back of tongue position. The pronunciation error detection and diagnosis model task is essentially a special phoneme recognition task. The system first receives the learner's input audio, then recognizes the input audio, compares the recognized user's real pronunciation phoneme sequence with the standard phoneme sequence corresponding to the text, to find the errors in the learner's pronunciation, and diagnose the location and type of errors [3]. Therefore, the phoneme recognition accuracy of the pronunciation error detection and diagnosis system is very important, which directly affects the performance of the entire system.

Speech error detection and diagnosis can be regarded as a special speech recognition task. The difference between speech recognition and speech recognition is that the task of speech recognition is to recognize the input audio as characters, while the task of speech error detection and diagnosis is essentially to recognize the phoneme sequence of the user's voice, Because the task has known in advance that the standard text corresponding to the input audio needs to compare the recognized phoneme sequence with the standard text phoneme sequence, detect and diagnose the difference between the two, and feed back the error information to the user.

The process of pronunciation error detection and diagnosis is that the system gives the text, the user reads according to the text, and the system detects whether there are pronunciation errors and diagnoses the wrong position and type of pronunciation. This task usually identifies the phoneme sequence of the user's actual pronunciation and compares it with the standard phoneme sequence of the given text to find out the differences between the two sequences and feed them back to the user.

Assuming β represents the parameter for distinguishing Japanese pronunciation errors, w represents the encoding coefficient of spoken phonemes, $Q_{\max}$ represents the maximum value of spoken resonance vector, $Q_{\min}$ represents the minimum value of spoken resonance vector, ΔT represents the unit pronunciation period, and ΔQ represents the unit accumulation of spoken resonance phonemes. Combined with the above physical quantities, the definition formula for the characteristics of Japanese spoken phonemes with errors can be expressed as:

$$q_\alpha = \frac{\sqrt{\frac{1}{\beta}\sum_{w=1}^{+\infty} |Q_{\max} - Q_{\min}|^2}}{(\Delta T) \cdot (\Delta Q)} \tag{1}$$

To sum up, whether the pronunciation error diagnosis task can be correctly performed depends on the accuracy of the pronunciation error detection task. When performing the pronunciation error detection task, the system judges whether there is an error in the user's pronunciation by comparing the recognized real pronunciation phoneme sequence with the standard phoneme sequence of the given text.

2.2 Audio Feature Extraction

By extracting audio features, we can obtain audio features that are smaller in dimension and conducive to speech classification. It has been studied that many automatic speech recognition systems attach importance to the characteristics of human auditory system when selecting audio features. Facts have also proved that audio features based on human auditory system model have excellent performance in automatic speech recognition systems.

Audio feature extraction is an important step to improve the detection accuracy in oral pronunciation detection and correction. The audio feature obtained is more suitable for online teaching mode than the original audio. The common feature extraction methods in the field of speech detection include pre emphasis and FFT.

Preemphasis: Sound propagation is essentially energy propagation. High frequency sound energy loss is more serious than low frequency sound. Preemphasis compensates the loss of high frequency components of sound, improves the high frequency components, makes the signal more stable in the frequency domain, and can obtain the spectrum through the same signal to noise ratio in the full frequency band. Another point is to remove the reaction between the vocal cords and lips during phonation to highlight the high-frequency resonance peak. Pre emphasis is calculated using Eq. (2), where e_α

represents the sound sampling point.

$$E = \frac{|e_\alpha \cdot q_\alpha|^2}{\chi \times \left(\left|\delta^2 - 1\right| \cdot \dot{W}^{\frac{1}{\varepsilon^2}} \right)} \tag{2}$$

In the equation, χ represents the pre emphasis parameter of Japanese incorrect spoken phonemes, δ represents the high-frequency resonance vector, $\dot{W}$ represents the vibration characteristics of incorrect spoken phonemes, and ε represents the time-frequency vibration coefficient.

Fast Fourier Transform: Compared to the time domain, it better reflects the characteristics of sound signals in the frequency domain. Therefore, transforming sound signals into energy distribution in the frequency domain can be more intuitive for analysis, and the difference in energy distribution reflects the differences in sound characteristics. Therefore, energy distribution on the spectrum can be obtained through windowing and fast Fourier transform. The energy spectrum of the signal can be calculated by finding the square of the spectrum modulus and then averaging it [4]. As shown in formula (3), where ϕ represents the energy spectrum parameter of Japanese incorrect spoken phonemes, and $\tilde{r}$ represents the mean spectral vector. To achieve accurate detection of Japanese incorrect pronunciation, it is required that the inequality value condition of $\phi \neq 0$ remains true.

$$R = \phi\tilde{r} - \sqrt{\left|\frac{r_\alpha}{q_\alpha}\right|^2 - 1}\,\Bigg|_{\phi \neq 0} \tag{3}$$

In fact, all kinds of spoken Japanese phonemes are partially repeated in the filtering frequency band, so the energy value obtained has certain relevance. Fast Fourier transform can reduce the dimension of data compression and abstract processing. After processing, the feature parameters have no imaginary part, and it is more convenient in calculation. Because sound is a continuous signal in the time domain, continuous signal is a dynamic process, but a single frame only reflects the characteristics of a single moment, and cannot reflect the continuity of the signal. Therefore, the feature dimension is increased, and the dimensions of the front and back frames are added, that is, the common first-order difference and second-order difference.

Simultaneous formula (2) and formula (3) can define the audio feature extraction expression of Japanese wrong spoken language as:

$$Y = \begin{cases} E \cdot R \cdot |\vec{\varphi}|^2, \vec{\varphi} > 0 \\ 1 - \left(\dfrac{ER}{\vec{\varphi}}\right)^2, \vec{\varphi} < 0 \end{cases} \tag{4}$$

Among them, $\vec{\varphi}$ represents the transmission vector of spoken phonemes within the sound spectrum.

Due to the diversity and variability of pronunciation errors, it is difficult for error detection methods based on phonetics knowledge and distinguishing features to capture all possible forms of the same error type, and even more difficult to generalize to the pronunciation error detection of all phonemes [5]. If the pronunciation error is not within the scope of the rule definition, it is difficult to detect it. Therefore, this method can only detect the pronunciation errors of certain phonemes in some specific application scenarios. In the current Japanese online teaching process, all kinds of wrong pronunciation are detected by combining phoneme characteristics and audio features.

2.3 Linear Prediction Coefficient

The design idea of linear prediction is to represent the speech signal at the current time through the linear combination of the speech signals sampled at the previous time, and then approach the actual speech sampling from the perspective of the minimum mean square error, so as to calculate the linear prediction coefficient. In linguistic acoustics, human voice is affected by the change of vocal tract, and the formant of human voice will also change accordingly. The voice recognition and vowel recognition of different speakers depend on the formant differentiation of their voices.

Linear predictive analysis refers to characterizing signals in the form of models, that is, taking signals as the output of the model, and expressing the characteristics of signals through the internal structure and parameters of the model. In the idea of error detection based on the calculation of a posteriori probability of phonemes, the local speaker's standard pronunciation data is usually used to train the acoustic model, so the practicality of the posteriori probability of phonemes can be expressed as the difference between the phoneme corresponding speech segment and the standard pronunciation [1]. Obviously, the greater the posterior probability is, the more standard the pronunciation is, and vice versa. This method does not need additional language learning data, and adjusts the system gate value to adapt to different application scenarios. The method based on posterior probability calculation is simple to implement and has strong language expansion, so it is often used in actual language teaching systems for automatic scoring and error detection of spoken English.

There is a positive correlation between the accuracy of phoneme posterior probability calculation and the discrimination of standard pronunciation models. Therefore, various discrimination training methods in speech recognition, such as maximum mutual information estimation, minimum classification error, minimum phoneme error, and minimum word error, have also been introduced into practical applications.

Let y_1 and y_2 represent two randomly selected linear prediction samples of spoken phonemes, whose values always satisfy the expression conditions shown in formula (5).

$$\begin{cases} y_1, y_2 \in [1, +\infty) \\ y_1 \neq 0, y_2 \neq 0 \\ y_1 \neq y_2 \end{cases} \tag{5}$$

The simultaneous formulas (4) and (5) can be used to calculate the linear prediction coefficient of oral errors in Japanese online teaching as follows:

$$U = \frac{\dot{I}^2 / u_1 + u_2}{\gamma - 1} \times \left| \frac{Y}{y_1 \cdot y_2} \right|^2 \tag{6}$$

In the equation, u_1 represents the prediction vector that matches the parameter y_1, u_2 represents the prediction vector that matches the parameter y_2, $\dot{I}$ represents the data sample matching feature based on linear conditions, and γ represents the linear discriminant parameter.

The linear prediction coefficient uses a model suitable for lip processing to extract features, and the information contained in the lip is expressed in geometric form. The selected geometric features are not affected by lighting conditions or lip shape transformation in general, such as lip movement, rotation, mouth deformation, etc., this method is more robust. The extracted geometric features include the height, width and other information of the lips, but the focus is completely on the lips, and does not include the information inside the lips, such as the information of the tongue in the lips, the information of the exposed teeth and other information that few linear parameters only contain. Therefore, in general, the information extracted by this method is much less than that of pixel feature extraction, but it is also difficult for common spoken phonemes to capture the transformation in the lips. Therefore, compared with the previous method, this method has smaller feature dimensions and more applications.

3 Detection of Wrong Pronunciation in Spoken English During Online Teaching

Based on the evaluation conditions of Japanese pronunciation quality, a corpus structure is constructed, and then the pronunciation test set is combined to solve the detection interpolation index, so as to realize the design and application of oral error pronunciation detection method in Japanese online teaching.

3.1 Corpus Construction

In order to achieve a good recognition effect, the detection model of Japanese spoken error pronunciation must select an appropriate audio data set. The quality of the audio data set plays a decisive role in the recognition accuracy. Common audio data sets include AVLetters data set based on alphabetic words, BANCA data set based on numerical sequences, GRID data set based on phrases, OuIuVS data set based on daily statements, etc. [6]. Audio corpora are more scarce than single-mode acoustic corpora, and most audio corpora are not open to the outside world. GRID corpora are sentence level audio corpora that are rarely open at present, and are widely used in lip recognition.

The overall framework design of the corpus consists of five parts. The first part establishes an audio corpus database, obtains audio files and annotation files suitable for oral pronunciation detection, and records oral pronunciation test sets. The second part preprocesses audio information and voice information respectively. The third part extracts the features of audio information and voice information respectively, the fourth part establishes a pronunciation detection model based on audio feature level fusion, and the fifth part realizes pronunciation detection and error correction. The specific framework is shown in Fig. 2.

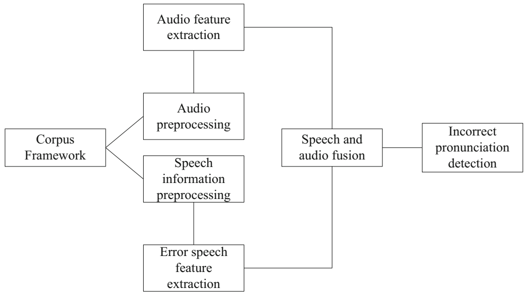

Fig. 2. Overall Framework of Corpus

There are usually two ways to obtain corpus. The first is to manually click to download on the web page, which is time-consuming and laborious. The second method is to use Python crawlers, which can more conveniently and quickly download the corpus files required for classification and storage. The web page of the corpus website is relatively simple, and the target tag information can be obtained by using the Xpath technology. Xpath is a language that can query information in html files. To import the request and etree packages, the first step is to find all the links, use request to request the web page, get the source code of the web page, and use etree. HTML, function to build objects that can be parsed by Xpath, use the Xpath technology to filter tags, eliminate file names that do not need to be downloaded, and finally get the audio and video file names that need to be downloaded and save them in the document.

The second step is to make the wget command to complete the path of the file name saved in the first step to ensure that the completed path can be downloaded normally. Use cat last.list parallel in the Ubuntu based system shell to download in parallel. Create an. sh file in Ubuntu to decompress and save all the files. Pay attention to file renaming during the decompression process, or the file will be overwritten. The key point of the sh file is to use mkdir to create folders for saving data, and use circular statements in combination with tar xf-c to decompress, and use my statements to move to the folder to be saved.

3.2 Pronunciation Test Set

There are two kinds of modal information in Japanese online teaching, audio modal and video modal, and their preprocessing methods are different. In order to facilitate the subsequent feature extraction, it is necessary to preprocess the two modal data respectively.

(1) Audio preprocessing

Some of the audio in the audio data set is not clear due to recording or storage problems, so it is necessary to manually remove unqualified audio one by one to avoid adverse effects on the test results. The audio data set format is unified into wav files, the sampling rate is set to 50 kHz, and the sound channel is dual. The most important step in the preprocessing stage is to highlight the characteristics of the audio signal and remove the miscellaneous parts, so as to facilitate the subsequent audio feature extraction. Therefore, operations such as pre emphasis, framing and windowing are indispensable. The end to end model is used to detect spoken Japanese mispronunciations. Compared with the traditional acoustic model, the complex forced alignment process can be abandoned in the preprocessing phase.

(2) Speech preprocessing

For speech information pre-processing, first of all, the speech segment should be converted into a frame object set according to the set segmentation form. In order to remove the impact of noise on the recognition results on the speech frame, first of all, the signal denoising should be carried out on the segmented object frame to obtain the detection frame set containing spoken information. Then the next step is to process the detection frame collection.

The detection data framing processing is divided into two parts. The first part is to determine the interval of voice segment segmentation, and the second part is to perform information segmentation. The number and order of speech segmentation frames are very important in pronunciation prediction, because the speech frames in the set are arranged in time sequence, and the number or order error will affect their performance of dynamic information. After segmentation, each frame of voice has a digital number, and the obtained voice frame data set number must be arranged in the order from small to large, without wrong or less order, or it will affect the corresponding relationship of audio information in time sequence [7].

The specific process of establishing pronunciation test set is shown in Fig. 3.

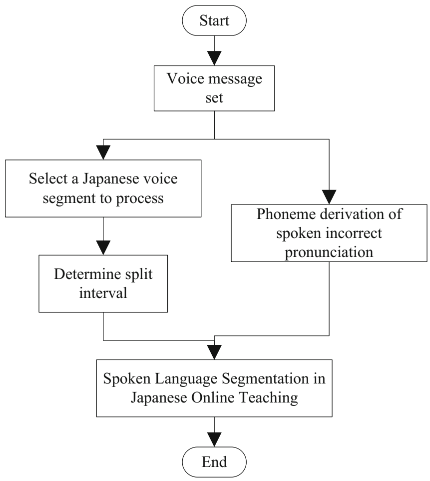

Fig. 3. Setting process of pronunciation test set

In pronunciation error detection and diagnosis, the posterior probability scoring algorithm relies on the acoustic model from speech recognition. However, the training data used for this algorithm only includes voice data labeled with text, which is unsuitable for an end-to-end structured pronunciation error detection and diagnosis model. Moreover, Japanese online teaching usually requires a significant amount of accurately annotated data for sufficient model training and satisfactory results.

Let p represent a randomly selected oral error pronunciation test parameter in the online Japanese education process, and the value condition of $p \neq 0$ remains true. $\hat{f}$ represents the audio preprocessing vector, $\hat{S}$ represents the speech preprocessing vector, a_1 and a_2 represent two unrelated error speech parameters, λ_1 represents the recognition parameter related to a_1, λ_2 represents the recognition parameter related to a_2, and ΔA represents the unit cumulative amount of phonemes to be recognized.

$$\Phi = \left\{ p|p = \frac{1}{U} \cdot \frac{\frac{1}{\hat{f}}\left|\lambda_1(a_1)^2 + \lambda_2(a_2)^2\right|}{\hat{S}^2 \cdot |\Delta A|} \right\} \tag{7}$$

In the online teaching process of basic Japanese, the model used is usually transferred from the acoustic model in the speech recognition task. Therefore, this method is usually used for speech recognition training, which only marks the data of the words corresponding to the voice for training, and does not need to accurately mark the data set with information such as the location and type of pronunciation errors for training.

3.3 Detection Interpolation

In the new era, different students have different needs for oral Japanese learning. In order to better meet the needs and characteristics of students, it is necessary to actively analyze the detection and interpolation of online learning in the process of oral English teaching. Only by analyzing the detection and interpolation of online learning can we effectively understand online learning. For the advantages of students' oral Japanese learning and teachers' oral English teaching, so as to comprehensively promote the improvement of oral teaching quality and maximize the students' subjective initiative and enthusiasm in learning [8]. In the process of studying Japanese oral mispronunciation, the analysis of detection and interpolation is mainly shown in the following aspects.

First, asynchrony. In the past oral classroom teaching process, teachers were usually the main body, teaching students a lot of knowledge, and students' learning methods were basically synchronized with teachers' teaching methods. In the process of applying online learning methods, it was conducive to maximizing students' learning autonomy, and students could learn knowledge effectively through online learning, In this way, the time for students to learn oral English will be extended. Through online or online learning, students can learn oral knowledge and content all the time. At the same time, online learning also extends the time for interaction and communication between teachers and students. Teachers can also carry out effective interaction and communication with students after class through the network platform and online learning platform to solve the problems and shortcomings of students' learning in class, thus effectively playing the role of online learning in cultivating students' good learning ability.

Second, repetition. During the traditional oral teaching, students will repeatedly train and memorize relevant knowledge by taking notes or combining learning methods of textbook knowledge. Although this method can promote students to memorize relevant knowledge in a short time, it is also difficult to achieve the goal of consolidating students' learning effects and achievements in the long run [9]. Through online learning, teachers can combine sounds, words, videos and pictures organically by combining teaching resources to make course teaching courseware, guide students to learn in the process of online learning, combine relevant media resources and teaching courseware to make students' learning more intuitive, and this learning method can also be repeated, so as to continuously improve the learning efficiency and effectiveness of students.

The third aspect is cooperation. Online learning enables students to engage in cooperative learning during oral language acquisition. Students can access learning resources through the internet, share and interact with online resources alongside their peers. By communicating and interacting with other students, they can discuss problems and share experiences encountered during the learning process. This fosters the enhancement of students' learning efficiency and helps them establish positive emotional connections and harmonious relationships with their fellow learners.

The solution to the interpolation of oral mispronunciation detection in Japanese online teaching meets the following expression:

$$k = \frac{\vec{h}}{M'} \times \left| \vartheta \frac{(l_1 + l_2)^2}{\dot{j}} \right| \tag{8}$$

Among them, l_1 and l_2 represent two non zero speech samples in the pronunciation test set Φ, $\dot{j}$ represents the popularization parameter of Japanese online teaching, ϑ represents the real-time detection coefficient, M' represents the interpolation definition result of the speech information to be tested, and $\vec{h}$ represents the real-time detection vector.

So far, the calculation and processing of relevant parameters and indicators have been completed. Without considering other interference conditions, the design and application of the detection method for oral mispronunciation in the online Japanese teaching process have been realized.

4 Example Analysis

In order to highlight the practical value of the detection methods of oral mispronunciation, sensor network based detection methods, and multimodal end-to-end detection methods in Japanese online teaching, the following comparative experiments are designed.

4.1 Experimental Environment

In the process of Japanese online teaching, the recognition ability of the terminal teaching host for wrong language signals and wrong word signals can be used to describe the detection accuracy of the host components for spoken error pronunciation. Generally speaking, the higher the detection accuracy of the terminal teaching host for wrong language signals and wrong word signals, the stronger the host components' accurate detection ability for spoken error pronunciation.

The following table shows the specific models of the selected equipment components in this experiment (Table 1).

Table 1. Selection of Experimental Equipment

Item	Device Name	Component model
1	Terminal teaching host	W-2223
2	Data processor	RTX3060TI
3	Data register	N5095
4	Voice information recording equipment	13700KF
5	Identify the host	iGameM380
6	Speech signal resolution element	GTX1650
7	Voice database	XQuery
8	Speech recognition chip	JRF930
9	Voice Player	JQ8900-16P

4.2 Test Steps

The specific execution process of this experiment is as follows:

Firstly, the method of detecting incorrect pronunciation in Japanese online teaching is applied to identify incorrect pronunciation, and the accuracy of the terminal teaching host's detection of incorrect language signals and incorrect word signals under the action of this method is recorded. The results obtained are the experimental group variables.

Then, the sensor network based detection method and multimodal end-to-end detection method were applied to identify oral incorrect pronunciation, and the accuracy of the terminal teaching host's detection of incorrect language signals and incorrect word signals under the influence of this method was recorded. The results obtained were variables in the A control group and B control group.

Finally, based on the experimental results obtained, summarize the experimental rules.

4.3 Data Analysis

The following figure reflects the detection capability of the terminal teaching host for the wrong language signal and wrong word signal.

Through the analysis of the results in Fig. 4, it can be observed that the experimental group has a relatively high average level of error language signal detection accuracy, and the global maximum reaches 97.1%. In contrast, the average accuracy of false language signal detection in control group A and control group B was significantly lower than that in the experimental group, with the maximum value of 73.0% in control group A and 56.4% in control group B.

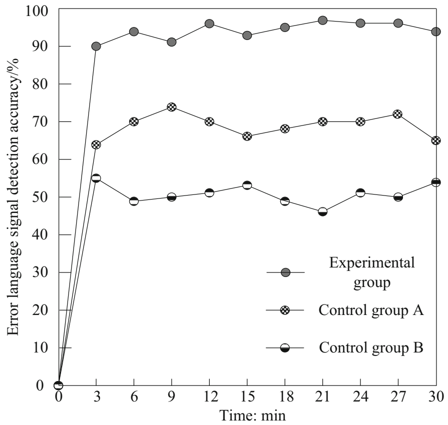

Fig. 4. Error Language Signal Detection Accuracy

The significant differences in these results indicate that the method adopted by the experimental group shows higher accuracy and effectiveness in the detection of false language signals. The experimental group may have used more advanced algorithms, techniques, or models to identify and detect false speech signals, thus achieving higher accuracy. In contrast, control group A and control group B may have used more traditional or simple methods, resulting in lower accuracy.

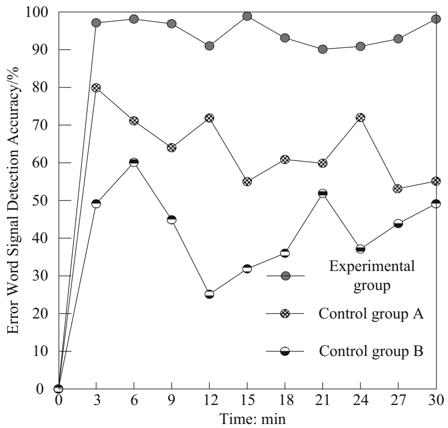

Fig. 5. Detection accuracy of wrong word signal

Through the analysis of Fig. 5, it can be observed that the experimental group has achieved remarkable results in the accuracy rate of false word signal detection. The experimental group achieved A maximum accuracy of 99.2%, while control group A and control group B achieved a maximum accuracy of 79.9% and 60.1%, respectively. Compared with the control group, the maximum accuracy of the experimental group increased by 19.3% and 39.1%, respectively.

These results show that the method adopted by the experimental group has higher accuracy and effectiveness in detecting the wrong word signal. The experimental group may have applied more advanced algorithms, models, or techniques to identify and detect false word signals, thus achieving higher accuracy. In contrast, control group A and control group B may have used more traditional or simple methods, resulting in lower accuracy.

5 Conclusion

Oral Japanese pronunciation error detection and diagnosis is an important part of online teaching and learning system. An excellent pronunciation error detection and diagnosis model should be able to accurately detect learners' pronunciation errors and give good diagnostic feedback, so that learners can clearly obtain their own pronunciation error information and achieve the purpose of improving learners' oral pronunciation level. Therefore, a new method for detecting mispronunciation in online Japanese teaching is proposed. Taking advantage of the fact that text is known information in pronunciation error detection and diagnosis tasks, a multi-feature model based on linear prediction parameters is constructed. Compared with traditional methods, the model does not require acoustic model to force alignment, nor does it require manual rules to extend the decoding network. The model only needs the original audio and phoneme sequences as input to detect and diagnose pronunciation errors. The experimental results show that the proposed method can accurately detect the wrong word signal and improve the detection performance of the wrong pronunciation.

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A Key Frame Extraction Algorithm for Physical Education Teaching Video Based on Compressed Domain

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Abstract. In order to solve the problem of low accuracy and detection rate of video keyframe extraction in existing methods, a compressed domain based keyframe extraction algorithm for sports teaching videos is proposed. Based on the logical structure of physical education teaching videos, convolutional autoencoders are used to extract video features; Introduce HSV space and use non-uniform quantization of HSV space to achieve shot segmentation in sports teaching videos, and restore lost key frames; On the basis of video preprocessing, key frame extraction of physical education teaching videos is achieved through compressed domain. The experimental results show that the accuracy of keyframe extraction and detection rate of this algorithm are high, indicating that this algorithm has high application value.

Keywords: Compressed Domain · Teaching Videos · Keyframe Extraction · CAE Network · DCE Algorithm

1 Introduction

With the continuous progress of science and technology and the rapid development of computer technology, physical education has gradually ushered in the era of intelligent education. Among them, the extraction of key frames in physical education teaching videos is an important research direction [1, 2]. Key frame refers to the static frame images that can represent the important information in the physical education video. By extracting key frame, information source can be provided efficiently, and convenient learning and teaching methods can be provided for students and teachers. The research and application of key frame extraction in sports teaching video is of great significance for improving the quality of physical education, developing intelligent education and promoting the development of sports industry [3, 4].

Reference [5] proposed a semantic based video key frame extraction algorithm, which first uses hierarchical clustering algorithm to preliminarily extract video key frames; Then, combining semantic related algorithms, histogram comparison is performed on the preliminarily extracted keyframes to remove redundant frames and determine the keyframes of the video; Finally, compared with other algorithms, the results

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show that the redundancy of the keyframes extracted by this algorithm is relatively small, but there is a problem of low detection rate. Reference [6] proposes a keyframe extraction algorithm based on moving object features, which emphasizes moving object features while weakening background features, thereby preventing missed detection and redundancy caused by moving objects being too small and the background occupying the main content of the video image. According to the entropy value of the video frame, frames with significant color changes are selected as partial keyframes. For frames without color changes, the feature points of the moving object within the frame are obtained through the scale invariant feature transformation (SIFT) of the moving object. Finally, video keyframes are extracted based on the frame entropy value and the distribution of SIFT points of the moving object. Experimental results show that the key frame omission rate of this algorithm is low, but the accuracy is low. Literature [7] proposes a key frame extraction algorithm of reinforcement learning that integrates multi-channel features and attention mechanism. Firstly, the algorithm extracts human skeleton points from video sequences through human posture recognition algorithm. Then, S-GCN and ResNet50 networks were used to extract motion features and static features from the video sequences, and weighted fusion was performed between them. Finally, the attention mechanism is used to calculate the importance of video frames, and reinforcement learning is used to extract and optimize key frames. Experimental results show that this algorithm performs well and has strong stability when detecting video frames containing key actions, but it also has the problem of low detection rate.

In order to solve the problem of low detection rate and accuracy of video key frames in existing methods, a key frame extraction algorithm based on compression domain is proposed. The main innovation points of this algorithm are as follows:

(1) Before performing video keyframe extraction processing, it is necessary to first clarify the logical structure of the video, which is conducive to more reasonable and effective hierarchical processing of the video.
(2) After extracting and quantifying compressed domain features, the DCE algorithm is used to evolve the feature distribution curve. The DCE algorithm performs mutation and crossover operations on the feature distribution curve, allowing the curve to gradually approach the target distribution, thereby better reflecting the characteristics of the video and improving the extraction effect of key frames in sports teaching videos.

2 Physical Education Teaching Video Preprocessing

2.1 Logical Structure of Sports Teaching Videos

Before performing video keyframe extraction processing, it is necessary to first clarify the logical structure of the video. Only after a clear understanding of the logical structure of the video can the video be reasonably and effectively layered until the goal of keyframe extraction is achieved. A video sequence refers to a segment of video that is connected in time or space, used to express a story composed of events and plots or convey specific visual content. Because video sequences have advanced semantic characteristics, and the extraction of advanced semantics often depends on specific application background, lacking a unified processing mode, it is difficult to extract Semantic information from the visual features [8]. Therefore, it is necessary to further divide the video sequence into logical layers and extract features from its underlying layers.

In order to better access video sequences, the structure of video sequences can usually be divided into four levels from high to low, namely, video sequence layer, scene layer, shot layer and image frame layer, as shown in Fig. 1.

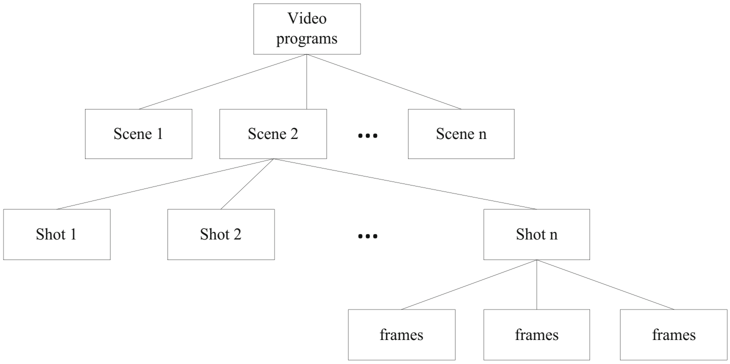

Fig. 1. Video sequence hierarchy diagram

A video sequence can be divided into several scenes, which are a set of semantically related and time-adjacent shots. Each scene describes a complete event, and the scene contains one or more shots. Lens is all the content obtained by the camera continuously at one time, which is used to represent the continuous action in time and space in a scene. It is the basic unit of video logical structure, and lens is composed of the smallest unit of video logical structure, image frame. Image frames are static images that can be processed using image feature extraction techniques to extract static features such as color, texture, shape, or dynamic features of spatial motion. Among them, image frames and shots are syntactic structures, scenes are semantic structures, and any video is connected by shots. Therefore, shots are the basic units of video logical structure. Only by extracting video features and segmenting each shot in the video sequence can the next step of video processing and analysis be possible.

2.2 Feature Extraction of Sports Teaching Videos

The traditional K-means clustering video key frame extraction method is to calculate the Euclidean distance of each frame image in pixel space to measure the difference between the images, so as to complete the image clustering. This traditional method uses pixel-level features of the image, but a single pixel cannot carry enough semantic information of the image, it is easy to be affected by noise, and will cause a large amount of computation due to the large size of the image. Therefore, the paper considers the calculation of Euclidean distance in the feature space to measure the differences between the images, namely, the Convolutional Auto-Encoders (CAE) are used to realize the video feature extraction. Automatic encoders are mainly used in image reconstruction, image compression and feature extraction. Input data is compressed into a potential representation space by the encoder, and then the data in the potential space is reconstructed by the decoder, so as to obtain output data similar to the input [9, 10]. The CAE network structure is shown in Fig. 2.

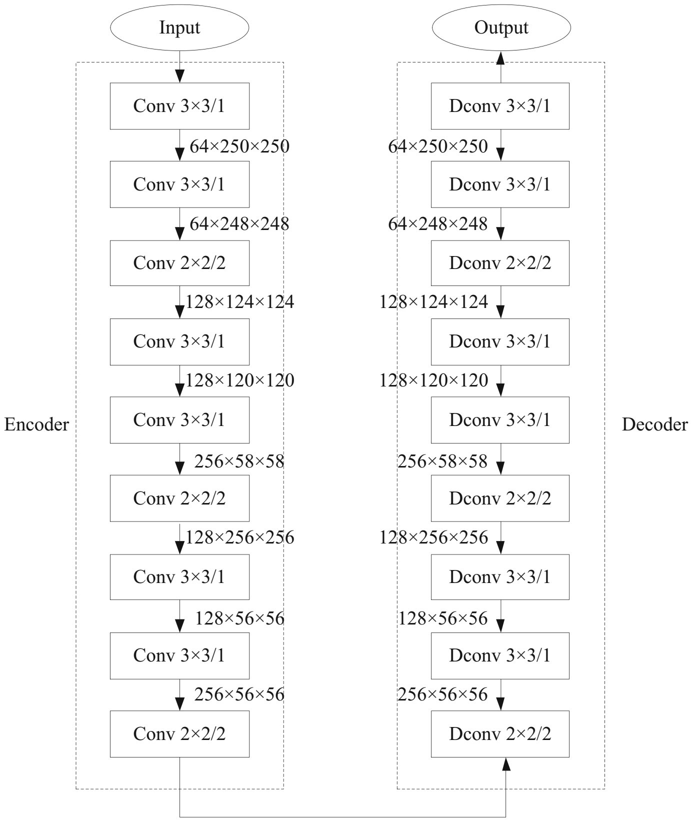

Fig. 2. Schematic diagram of CAE network structure

Using convolutional layers instead of fully connected layers in simple autoencoders, utilizing convolutional and pooling operations of convolutional neural networks, downsampling the input image to provide smaller dimensional latent representations and achieve unsupervised feature extraction. The training set of CAE is randomly captured video frames from color videos in the SLR dataset. Considering the convenience of experimental operations, all training data is unified as 252 × The 252 grayscale image is normalized and used as a training set for unsupervised training. After network training, the size of 1080 × 720 video frames undergo the same data preprocessing, and after input into the encoder in the network, 56 can be obtained × A two-dimensional feature vector representing 56 important feature attributes of the frame is used to obtain the feature extraction results of sports teaching videos.

2.3 Footage Segmentation of Sports Teaching Videos

Shot segmentation is the basis of video structural system. It is to accurately detect different type transitions between continuous shots and distinguish in-shot motion so as to eliminate its interference to video shot detection. According to different editing characteristics of shot switching, the transformation mode between shots can be divided into shear and gradient. The existing lens shear detection methods are relatively mature, but gradient detection is very difficult.

Colors can be represented by three color components in RGB space, but there is a great correlation between RGB3 primary colors, and RGB color representation is very different from human subjective vision. Therefore, in order to make the color distance in the proposed algorithm better adapt to human visual features, HSV space is introduced. Compared with RGB space, HSV space can better represent the position information of image. In the processing of this paper, each pixel of RGB color space should first be converted into HSV color space.

This article adopts the method of non-uniform quantization of HSV space, dividing the hue space H into 8 parts, and dividing the saturation space S and brightness space V into 3 parts each. It introduces one-dimensional feature vectors to simplify color features, and finally forms a 72bin one-dimensional histogram. There are many ways to apply histograms, and this article adopts an improved approach - histogram intersection. Due to the fact that color histograms do not consider the position information of known pixels, completely different images may also have similar histograms. Therefore, this article improves the histogram based method through non-uniform blocking and weighted preprocessing to highlight the contribution of the central part to inter frame differences, while greatly reducing the impact of small range motion within the lens on shot detection. Compared with traditional global histogram methods, the results obtained are closer to human visual cognition.

The similarity of the H-component between adjacent frames is defined as follows:

$$S_h(t, t-1) = \sum_{i=1}^{N} \frac{\min(f_t(i), f_{t-1}(i))}{\max(f_t(i), f_{t-1}(i))} \tag{1}$$

where, $f_t(i)$ and $f_{t-1}(i)$ represent the histogram of H component of frame t and $t-1$ respectively; N stands for image gray level or color quantization level. Similarly, the histogram similarity of S and V components is $S_s(t, t-1)$ and $S_v(t, t-1)$, respectively.

In the HSV space, the histogram similarity of frames t and $t-1$ is:

$$S(t, t-1) = \frac{u_h \times S_h(t, t-1)}{3} + \frac{u_s \times S_s(t, t-1)}{3} + \frac{u_v \times S_v(t, t-1)}{3} \tag{2}$$

The human eye has the most sensitive visual characteristics to the H component. Based on the weighted ratio of H, S, and V components, the coefficient ratio of H, S, and V components can be obtained after obtaining the quantified values of H, S, and V. In this article, the coefficient ratio is set to 9:3:1. In order to better reflect the contribution of S and V components to histogram similarity, the weighted coefficient ratio of u_h, u_s, and u_v 3 components is set to 0.9:0.3:0.1.

In order to further improve the detection rate and accuracy of shot detection, after using the improved histogram method to detect shots, the frame difference method is used to filter the obtained results, forming a comprehensive method for shot detection that combines histogram method and frame difference method. It effectively reduces the potential missed and false detections caused by histogram based methods.

2.4 Restoring Lost Key Frames

During video transmission, it is easy to be affected by environmental factors and external factors, so that the phenomenon of key frame loss is easy to occur in the video and the comprehensiveness of the video key frame extraction is affected. Therefore, the lost key frame is restored on the basis of video segmentation.

Let G be a lens of the video, the frame image corresponding to the lens is w, and let n frame image exist in the lens, then:

$$G = \{w_1, w_2, w_3, \ldots, w_n\} \tag{3}$$

Using the frame number as the horizontal axis and the similarity between each frame of the video as the vertical axis, the feature comprehensive similarity curve between each frame of the video is drawn to obtain the feature comprehensive similarity curve. After obtaining the comprehensive similarity curve of features, search for high curvature points on the curve to further determine the missing video keyframes. The specific steps are as follows:

Firstly, the sliding window is constructed. On the feature comprehensive similarity curve line, point Q to be processed is taken as the construction center, and a sliding window with maximum value $e_{\max}$ and minimum value $e_{\min}$ is constructed. During the construction of the sliding window, points X and O on both sides of point Q to be processed are found, among which points X and O meet the following constraints:

$$\begin{cases} e_{\min} \leq |Q_\alpha - Q_\beta| e_{\max} \\ e_{\min} \leq |Q_\alpha - Q_\gamma| e_{\max} \end{cases} \tag{4}$$

Among them, Q_α represents the maximum left sliding value of point Q to be processed; Q_β represents the maximum sliding value on the right side of point Q to be processed; Q_γ represents the maximum sliding value on the upper side of point Q to be processed.

Next, calculate the inscribed angle and construct a triangle with the point Q to be processed as the vertex. The other two vertices are X and O points, respectively. Define the inscribed angle θ of the triangle:

If the distance between point O and point Q to be processed is d_{OQ}, the distance between point X and point Q to be processed is d_{XQ}, and the distance between point O and point X is d_{OX}, then the inscribed angle θ is angle OQX. Use the following equation to calculate the inscribed angle θ:

$$\theta = \frac{d_{OQ} + d_{XQ} + d_{OX}}{2 d_{OQ} d_{XQ}} \tag{5}$$

It is also necessary to determine the admissible triangle and define the maximum admissible Angle $\theta_{\max}$, where the inner Angle θ must satisfy: $\theta \leq \theta_{\max}$.

Through the above constraint conditions, the flat inner Angle can be excluded and the allowable triangle can be constructed. When the feature synthetical similarity curve cannot form an admissible triangle for a certain point, it is necessary to assign the default value of the inner Angle. At the point Q to be treated, since there are many admissible triangles, it is necessary to define the least admissible Angle among all the admissible triangles:

$$\theta(Q) = \min(\theta \leq \angle Q) \tag{6}$$

Finally, determine the high curvature points, select the candidate curvature distance range, and determine the high curvature points within this range. There is a point in the neighboring left and right vertices of point Q that satisfies the following constraint conditions $T : |Q_\alpha - T| \leq e_{\max}$.

When the inscribed angle between point T and point Q satisfies $\theta(T) \leq \theta(Q)$, it can be determined that point Q is the high curvature point being sought. After determining the high curvature point on the feature synthesis similarity curve, the video intermediate frame corresponding to the adjacent high curvature point is the lost video keyframe.

3 Key Frame Extraction of PE Teaching Video

Given the important role and practical application value of keyframes in video structuring, this section proposes a compressed domain based keyframe extraction method for sports teaching videos based on the preprocessing of sports teaching videos. Traditional compression domain methods require decoding and re encoding of compressed videos, which increases processing complexity and time consumption. In response to this issue, this article improves the traditional compression domain method to enhance the effectiveness of video keyframe extraction. Specifically, video features are described through compressed domains. After extracting and quantifying compressed domain features, the DCE algorithm is then used to evolve the feature distribution curve. The DCE algorithm can adaptively evolve according to different video feature distributions. It performs mutation and crossover operations on the feature distribution curve, allowing the curve to gradually approach the target distribution, thereby better reflecting the characteristics of the video and improving the extraction effect of key frames in sports teaching videos.

3.1 Video Feature Description in the Compression Domain

The video key frame extraction in the compression domain can be divided into two categories according to the different feature information used: one is to compare the DcT coefficient of the frame; The other kind compares the motion compensation information of frame macro block. The former mainly uses the I-frame information in the video stream, which is about one I frame in every 13 frames according to the international video coding standard MPEG. Therefore, this kind of method consumes less resources and has high time efficiency. In contrast, the latter needs to compare the macro block information of all frames, which has low time efficiency and large amount of calculation. Considering the processing efficiency, the former method is used in this section to extract and quantify the feature data.

In video compression coding, the MPEG standard uses image group GOP as the encoding unit, and its structure is shown in Fig. 3. GOP is mainly composed of three types of frames, namely I frame, B frame, and P frame, arranged in a certain order. There is a motion reference relationship between these three types of frames, where B frame and P frame both use I frame as the reference and adopt motion compensation mechanism for inter frame encoding. B frame also references the motion information of P frame, while I frame does not need to refer to other frames and directly performs intra frame encoding. Through these analyses, the DCT coefficients of the I frame can be directly obtained in the video stream through entropy decoding and inverse quantization methods, which facilitates and quickly extracts the video information carried, while the other two frames cannot directly extract the DCT coefficients.

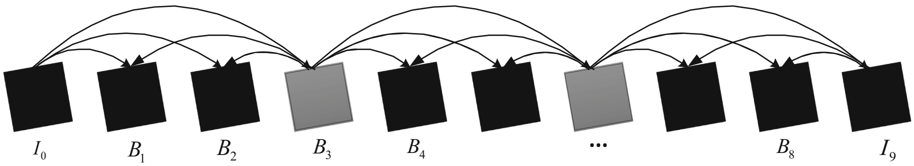

Fig. 3. GOP Structure Diagram

The most natural solution for extracting video features in the MPEG compressed domain is to use the DC coefficient related to the pixel domain image's base color tone and the AC coefficient related to the texture. That is, the DC component of the discrete cosine transform in the MPEG data stream is used to extract the base color tone information of the video frame, and the AC component is used to extract the texture information of the frame. Two formulas (7) and (8) are defined below to quantify the feature information and its difference of the I frame, respectively:

$$R_n = A\sum_{i,j=1}^{N} DR_n(i,j) + B\sum_{i,j=1}^{N} ER_n(i,j) \tag{7}$$

$$S(R_n, R_{n+1}) = (R_{n+1} - R_n) \tag{8}$$

where, R_n and $S(R_n, R_{n+1})$ represent the characteristic quantity and its difference of frame n respectively; $DR_n(i,j)$ and $ER_n(i,j)$ represent the primary color and texture information of the (i,j) sub-block of frame n respectively. A and B are the influence factors of primary color and texture information on frame characteristics, and meet the requirements of $A + B > 1, A > B$ and $A, B \in [0, 1]$. The values of A and B in this paper are 0.75 and 0.25, respectively.

3.2 Physical Education Video Key Frame Extraction Implementation

After extracting and quantifying compressed domain features, the DCE algorithm is then used to evolve the feature distribution curve, and based on the evolution results, key frame extraction of physical education teaching videos is achieved. The current keyframe extraction techniques in the compressed domain are divided into three types based on their mechanisms:

(1) The method of sampling at equal time intervals. It is the most direct and simple method for extracting keyframes, which extracts video frames at fixed time intervals and uses them as keyframes for video sequences. The advantages of this method are obvious, the algorithm is simple and the computational complexity is low, and it can extract keyframes in real-time and sequentially. However, this method is only based on time downsampling and does not consider the content of video frames. Therefore, it has the following drawbacks: (a) for video segments with short time and rich meanings, it is easy to miss key frames, while for video segments with long time, basic stillness, and few meanings, it will extract multiple key frames, causing redundancy; (b) The keyframes extracted using this method cannot guarantee that they are not exactly transitional frames or frames with intense motion during the lens transition period, which is not conducive to subsequent processing.
(2) The method based on interframe content change. This method is a method to extract key frames according to the content variation degree of each video frame. It can express the video content more completely, and the extracted key frame set has less redundancy. The current research mainly focuses on how to extract the features representing the content of video frames in the compression domain, how to calculate the degree of content change between two frames, and how to judge whether a video frame can be used as a key frame according to the content change value between frames.
(3) Clustering based method. The principle is to regard each frame in the video sequence as a point in the feature space, cluster these points, filter the noise, and select the corresponding frame of the point closest to the clustering center in each cluster as the key frame. Current research on this method mainly focuses on how to convert video frames from image space to feature space. The clustering method is the most commonly used method in key frame extraction because of its small number of key frames, strong representativeness and no manual intervention. Although this method can extract a more compact set of key frames, it is not suitable for real-time application and cannot preserve the time order relationship of key frames.

The key frame extraction algorithms discussed above are all applied to the underlying features of video frame images, and the purpose of key frame extraction is to maximize the representation of video content with a small frame set as much as possible. However, due to the semantic gap between low-level features and high-level semantics, these keyframe extraction methods are not suitable for certain specific applications. For example, searching for a specific person in a video and extracting a large number of keyframes without facial information will add unnecessary burden to subsequent processing. To solve this problem, a key frame extraction method that combines low-level features and high-level semantic features is a new research approach. This article analyzes the logical structure of sports teaching videos in the previous text, and obtains the semantic features of sports teaching videos. Based on this, DCT coefficients are used to process the stratigraphic features of sports teaching videos. The specific steps are as follows:

Input: a video stream of physical education
Output: Lens and keyframe
Step 1: Extract the DCT coefficient of frame I from the video stream, and calculate the frame feature quantity and feature difference represented by the primary color and texture information respectively according to formula (7) and (8).
Step 2: Perform Gaussian filtering to remove noise from the video frame feature difference extracted in step 1, and then calculate the valley value and peak point of the filtered data curve.
Step 3: Generate a new data curve according to the valley value and peak point, and apply DCE algorithm to process it, and then get a curve that meets the key point NOKP.
Step 4: Lens segmentation and key frame extraction are realized according to the destination curve generated in Step 3. Peak points in the curve indicate that the content of the shot has changed greatly, while valley points indicate that the content between frames has changed little and is relatively stable with strong similarity, which can be used as the key frame representing the content of the shot.

Figure 4 shows the flow chart of key frame extraction in the compression domain.

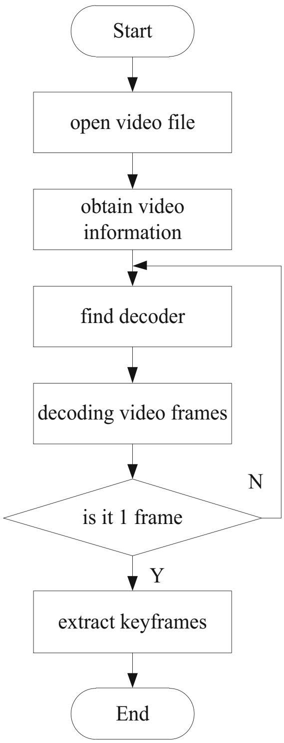

Fig. 4. Flow chart of key frame extraction in sports teaching video

4 Experiment and Result Analysis

In order to verify the application effect of the proposed compressed domain based keyframe extraction algorithm for sports teaching videos, experimental verification was conducted.

4.1 Experimental Setup

The experimental environment is Intel i5-3230M processor, 12 GB memory and MatlabR2016a programming. The data set used in the experiment included 30 physical education videos, the length of which ranged from 0.5 min to 2 min, the frame rate was 25frame/s, and the frame size was 768 pixel × 576 pixel.

4.2 Experimental Indexes

The detection rate and accuracy are used to measure the video keyframe extraction performance of the proposed algorithm, literature [5] algorithm, and literature [6] algorithm. The expression for detection rate and accuracy is as follows:

$$R_d = M_a/(M_a + M_k) \times 100\% \tag{9}$$

$$P_d = M_a/(M_a + M_z) \times 100\% \tag{10}$$

where, M_a, M_k and M_z are the correct detection number, missed detection number and false detection number of video key frames respectively.

4.3 Experimental Results

In order to quantitatively evaluate the video keyframe extraction performance of the proposed algorithm, literature [5] algorithm, and literature [6] algorithm, the detection rate and accuracy of the above algorithms were tested. The experimental results are shown in Table 1 and Table 2.

It can be seen from the data in Table 1 and Table 2 that the detection rate and extraction accuracy of key frames of physical education video obtained by the proposed algorithm are higher than the two traditional algorithms. Among them, the highest detection rate of key frames of physical education video of the proposed algorithm is 96.3%, and the highest extraction accuracy of key frames of physical education video of the proposed algorithm is 98.3%. The highest accuracy values of the algorithms in reference [5] and [6] were 92.6% and 93.0%, respectively, while the highest detection rates of the algorithms in reference [5] and [6] were 86.4% and 87.5%, respectively. From this, it can be seen that the proposed algorithm can extract key frames of sports teaching videos more comprehensively and accurately, which is beneficial for improving the effectiveness of sports teaching. This is because the proposed algorithm utilizes the DCE algorithm to evolve the feature distribution curve. The DCE algorithm can better reflect the characteristics of the video, which is beneficial for improving the extraction effect of key frames in sports teaching videos.

Table 1. Comparison results of detection rates

Video number	Detection rate/%		
	Proposed algorithm	Reference [5] Algorithm	Reference [6] Algorithm
1	96.3	85.2	78.6
2	95.1	84.3	74.2
3	94.8	86.4	79.3
4	92.0	81.5	72.6
5	93.6	81.9	80.1
6	94.3	80.7	82.6
7	90.9	80.2	87.5
8	91.7	77.6	76.9

Table 2. Accuracy Comparison Results

Video number	Accuracy rate/%		
	Proposed algorithm	Reference [5] Algorithm	Reference [6] Algorithm
1	98.3	89.7	90.6
2	87.6	90.2	91.5
3	96.3	92.6	93.0
4	95.0	92.6	89.9
5	97.5	91.6	87.5
6	97.0	90.7	88.3
7	96.3	88.9	85.2
8	97.9	89.4	89.3

In order to further evaluate the keyframe extraction performance of the proposed algorithm, various typical video streams with different features were selected in the article. These video streams include shot transitions such as abrupt transitions to shots, gradients to fade in/out, melting, scanning, flipping, panning, and feature film editing with added special effects and complex movements. The length of the video sequence varies from 2000 to 6000 frames. The results are shown in Table 3.

From the experimental results in Table 3, it can be seen that the proposed algorithm can accurately and comprehensively represent the video content, and has good performance in judging key frames of cuts, gradients, and complex motion in the video sequence, with only one omission, further verifying the effectiveness of the proposed algorithm.

Table 3. Test results of video keyframe extraction effect

Parameter	Actual frame count	The number of frames extracted by the proposed algorithm
Number of shear keyframes	25	24
Number of gradient keyframes	9	9
Number of key frames for complex motion	31	31

5 Conclusion

This paper proposes a key frame extraction algorithm based on compressed domain for sports teaching video. According to the logical structure of sports teaching video, this algorithm uses convolutional Autoencoder to extract video features; Introduce HSV space and use non-uniform quantization of HSV space to achieve shot segmentation in sports teaching videos, and restore lost key frames; On the basis of video preprocessing, key frame features of sports teaching videos are extracted through compressed domain, and the feature distribution curve is mutated and crossed using DCE algorithm to achieve video key frame extraction. The experimental results show that the method has the following advantages: (1) the video key frame detection rate is high; (2) Effectively improve the accuracy of video key frame extraction. It shows that the application of this algorithm is of great significance to improve the quality of physical education, develop intelligent education and promote the development of sports industry.

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Interactive Design Method of Multi Person VR Distance Education for New Media Art Teaching

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Abstract. In order to solve the problem of limited number of online people in the teaching of new media art majors, this research focuses on the Interaction design method of multi person VR distance education, and is committed to creating a more authentic multi person VR interactive education environment. Firstly, by improving the "dominant subject" teaching structure of new media, we aim to enhance teaching effectiveness and participation. By selecting key application technologies, determine the real-time connection status of the teaching project editor, and then define the connection conditions of the education editor for teaching new media art majors. Secondly, a multi person teaching scenario was designed, and with the help of VR remote education editor components, response objects at all levels of terminals were retrieved to construct an interactive scenario model. This design can achieve a multi person VR remote education interaction method for teaching new media art majors, providing students with a more realistic and immersive teaching experience. Finally, the effectiveness of the above method was demonstrated through experiments. The experimental results show that the application of the above methods can significantly increase the number of remote online people in the teaching task of the new media art specialty, and meet the practical application needs of creating a real multi person VR interactive education environment.

Keywords: New Media Art · Professional Teaching · Multi Person VR · Distance Education · Application Technology · Project Editor · Teaching Situation · Interactive Scene Model

1 Introduction

With the rapid development of information technology, it also accelerates the innovation of education and teaching to a certain extent. Under the influence of the information age, teaching is changing from a single mechanical model to a personalized teaching model supported by information technology. The development and utilization of network information resources also provide numerous teaching resources for the education field, and certainly bring a broader prospect for art teaching. The use of the latest technology to assist teaching is an inevitable trend of the future development of education, so the new media technology with the network as the media will also be more widely used

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in education and play an irreplaceable role [1]. New media teaching is a new form of combining network information technology with education. This new situation will inject fresh vitality into education and teaching. In addition, with the gradual scale promotion of 5G networks, the coverage of wireless networks will be expanded, providing more convenient conditions for smart phones and other devices to access the Internet. At present, mobile phones are recognized as the "fifth media" after the "fourth media" of the Internet, and new media will continue to emerge with social progress. At the same time, with the wide application of WeChat, QQ and other applications, it also promotes the arrival of the "micro era", which is promoting the informatization of education and teaching, art teaching. New media educators in the information age should conform to the trend of the times, actively learn new ideas, explore new techniques, master new media technology and carry out teaching, so as to nurture new vitality in the classroom.

In the teaching of new media art specialty, with the increasing complexity of teaching tasks, how to improve the number of remote online people, so as to create a more authentic multi person VR interactive education environment, has become an urgent problem to be solved. The interactive teaching method based on the intelligent education network judges the number of client terminals participating in the teaching task according to the response state of the core scheduling host, and then realizes the on-demand transmission of the remote education task through unified forwarding. The interactive teaching method based on the learning model, with the cooperation of the terminal host, schedules the response objects of the lower level receptors, and then transmits the stored teaching resources to the application devices at all levels through the interactive channel organization. However, the above two methods have limited application ability in solving the problem of limited number of remote online students in the teaching of new media art specialty, which does not meet the practical application needs of creating a real multi person VR interactive education environment.

VR interactive education has developed a set of virtual reality content production system using Unity 3D, UE4, OPENGL, VRML and other types of software mechanisms. This system is a virtual reality content production tool integrating content editing and playing functions. Designers can independently complete the production of various virtual reality content without complex programming, In addition, the modification and portability rate of the generated executable files have been greatly improved, which greatly saves the production cost of virtual reality content, enables the production of virtual reality content from simple to complex, reduces the production cost, and improves the production efficiency [2]. Aiming at the problem that the application ability of intelligent education network teaching methods and learning model teaching methods is limited, a multi person VR distance education interaction method for new media art teaching is designed.

2 Innovation Points and Contributions

In order to optimize the interactive effect of multi person VR remote education in the teaching of new media art majors, this article proposes a new interactive method. The specific innovation points and contributions are as follows:

(1) Improving the teaching structure of "leading subject" in new media art: In the teaching of new media art majors, by introducing new media technology, a "leading subject" teaching structure is designed, that is, through the design of editors, teachers become the leaders and students become the main participants. This structure can better stimulate students' creativity and initiative, and improve learning outcomes.
(2) Application technology selection: In the Interaction design of multi person VR distance education, the selection of application technology is an important innovation. Through comprehensive consideration of teaching needs and technical feasibility, select appropriate technologies to support distance education interaction. This can provide a better teaching experience and increase interaction and cooperation among students.
(3) Interaction scenario and model construction: When designing VR remote education interaction scenarios, it is necessary to pay attention to the realism of the scene and the precision of the model. Through the design of the editor, a variety of interactive scenarios and model options can be provided to meet different teaching needs. This can enhance students' sense of participation and learning interest, and improve teaching effectiveness.

3 Definition of Teaching Editor for New Media Art Specialty

Optimizing the education structure is the premise of improving the VR distance education method of new media art teaching. Under the support of the "leading subject" teaching structure, necessary application technologies should be selected to define the connection form of the teaching project editor. This chapter will conduct in-depth research on the above contents.

3.1 New Media "Leading Subject" Teaching Structure Improvement

In the teaching of new media art, the "teacher centered" approach still dominates. Although the slogan of "return the classroom to the students" has been put forward for many years in the theoretical circle, due to people's insufficient understanding of the background and basic content of "student-centered", "student-centered" has not really been implemented in teachers' education and teaching actions. Another reason is that the number of students is too large and the number of teachers is too small to effectively monitor teaching activities and students' learning effects. Teachers are often in a state of surplus but insufficient strength, which is determined by China's national conditions and development status [3]. The main reason is that the art discipline has a strong logic, systematicness and structure, and many mathematics teachers lack the ability to grasp the whole discipline and new educational concepts, so they can not continue to "student-centered".

To sum up, the teaching structure of the new media art specialty should be dominated by the "leading subject" teaching structure at present, and the "leading subject" teaching structure can also be called the teaching structure with equal emphasis on learning and teaching. The complete new media "leading subject" teaching structure is shown in Fig. 1.

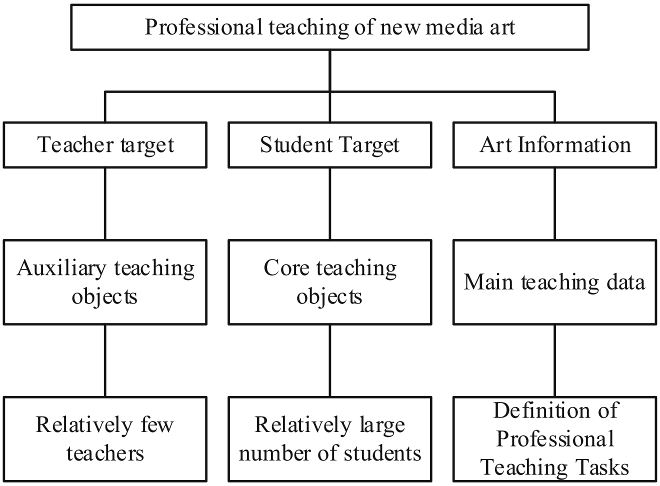

Fig. 1. New media “leading subject” teaching structure

The “leading subject” teaching structure of new media is based on the constructivism theory, which can not only reflect the dominant position of teachers in the classroom, but also can not ignore the dominant position of students in the classroom. For the study of art disciplines, in addition to the mastery of basic art knowledge and concepts, it is also necessary to cultivate students’ artistic thinking ability, because students’ artistic thinking ability is formed and developed in teaching activities. Especially in the new media environment, with the help of the convenience of information technology and the prevalence of teaching tools, information technology is used as a teaching aid and emotional incentive tool, and is also a cognitive tool for students to understand art knowledge. Using the new media environment, teachers can easily design a large number of mathematical activities. In this process, teachers actually “activate” the content of art books, visualize abstract content, and restore the vividness, image, and creativity of their original knowledge.

set up $\dot{q}$ It represents the response characteristics of the teaching information of the new media art major, α It indicates the parameters for improving the teaching structure, δ It represents the vector of “leading subject” teaching structure definition, β Represent the representational parameters of new media thinking in art teaching projects, $\hat{W}$ It represents the emotional incentive coefficient of art major teaching. Combining the above physical quantities, the definition formula of the “leading subject” teaching structure of new media art major can be expressed as:

$$Q = \frac{1}{\sqrt{\alpha \cdot \dot{q}}} \sum_{\delta=1}^{+\infty} \beta \times \left| \hat{W} \right|^2 \tag{1}$$

New media plays a media role in transmitting and feedback information in the process of art teaching. It plays the following roles in teaching: 1. The role of teaching tools: providing innovative hardware equipment for the traditional classroom, creating situations through new media can make the classroom atmosphere more active; 2. The role of helping teachers: preparing lessons for students, classroom demonstrations, educational activities, and after class discussions, so that the classroom is no longer a single "full house"; 3. The role of tutoring students: to stimulate students' thirst for knowledge, and to be their friends and helpers in learning, so that students can get immediate learning reminders, improve, enhance and give feedback on learning activities.

3.2 Selection of Application Technology

To improve the education structure for the teaching of new media art majors, three technical means, UE4, Unity 3D and VRML, need to be applied at the same time. The conditions for selecting each technical means are shown in Table 1.

Table 1. Application Technology Selection of New Media Art Teaching

Classify	UE4 Technology	Unity 3D technology	VRML technology
Underlying code	C++	JavaScript, C#, Boo language	JAVA, JAVA Script programming languages
Script Format	Blueprint - Visualization Script	Transform application components	VRML Script Script Language
Educational Information Definition Format	Virtual reality content	Boolean type global variable	Java program text
Teaching platform	Steam VR Platform	NGUI plugin	3D virtual space platform
Do you want to download teaching software	Correct	Deny	Correct

UE4 engine and Steam VR platform are combined to develop VR with the help of external device "HTC VIVE". The first thing to do is to correctly install and connect the "HTC VIVE" hardware device to the PC. Instantiation is a very important tool for Unity 3D to dynamically control VR elements in the teaching of new media awareness. Instantiation module array for storing VR elements is opened in Unity 3D, and VR elements are dynamically generated and updated through scripts [4]. There are many sensor nodes in VRML. Sensor nodes are used to realize the most basic interaction functions, such as touch sensors, collision sensors, proximity sensors, time sensors, etc. Each sensor has its own functional characteristics. Through sensor nodes, users' actions can be sensed, and then users can conduct remote VR operations according to events and routes.

Regulations w_1 Represents the UE4 engine application vector, w_2 Represents the application vector of Unity 3D technology, w_3 Representing the application vector of VRML script, the simultaneous formula (1) can define the application technology selection expression for new media art teaching as:

$$E = Q \times \left[\left(\frac{w_1}{\chi_1} \cdot \frac{w_2}{\chi_2} \cdot \frac{w_3}{\chi_3} \right)^2 - 1 \right] \tag{2}$$

Among them, χ_1 Indicates the remote start parameters of the UE4 engine, χ_2 Represents the remote startup parameters of Unity 3D technology, χ_3 Represents the remote startup parameters of the VRML script.

The new media art professional teaching courseware made by three technical means of UE4, Unity 3D and VRML is interactive and participatory. The UE4 engine can build a virtual three-dimensional space in which the attributes of objects can be added. In addition, according to the characteristics of Unity 3D technology, the virtual teaching courseware can be directly published on the Internet. Since the entire execution process is coordinated by VRML scripts, even in the case of distance education. The running stability of teaching courseware will not change significantly.

3.3 Teaching Project Editor

The role of the new media art oriented teaching project editor is to set and edit the associated scene attribute parameters, which mainly includes three parts: outgoing items, internal links, and functions.

(1) Scene attribute parameters

In the interactive environment of multi person VR distance education, scene attributes are mainly divided into layer scene attributes, group scene attributes, object scene attributes and teaching information scene attributes. These attributes also contain the same or different sub attributes. According to the actual programming needs, the common parts of the attributes need to be promoted for the inheritance of advanced attributes in the way of base classes. For example, the space transformation attribute can be used for multiple scene attributes. At this time, the common part is the space transformation attribute. Therefore, the space transformation attribute is written into a separate class. Other objects or scenes that need this attribute can create a new class based on this class or define this class as a member of the class for calling.

The solution to the attribute parameters of the teaching scene of the new media art specialty is as follows:

$$e = \frac{\int_{-\infty}^{+\infty} \tilde{R} \cdot u^{1-\left(\frac{1}{\varepsilon^2}\right)}}{E \times |\Delta T|} \tag{3}$$

where, $\tilde{R}$ It represents the space transformation parameters of the teaching project of the new media art specialty, u Represents the common transformation coefficient, ε Represents the writing parameters of a separate class, ΔT Represents the writing cycle of teaching project scenarios.

(2) Outgoing items and internal connections

From the creation of the teaching project scene to the objects that can be used, the problem is simplified by using the class inheritance method. The creation of classes is the basis, just the definition of attributes, without visualization and corresponding response operations and logical operations. Therefore, the next step is to carry out the front-end UI and operation response control design and the back-end lua script logic design [5] for the teaching of new media art. Lead out items and internal links are the basis for UI interface design and operation response control function design. The Qt Designer designer provided by Qt is used to design the visual interface. According to the set UI, add and modify the style of controls to make the UI as simple and usable as possible.

By using formula (2), we can express the definition conditions of leading out items and internal connections in the teaching of new media art as follows:

$$t = \frac{\left|1 - \sqrt{\gamma E}\right|^{-1}}{\sqrt{\dot{y}\varphi^2 - |\Delta Y|^2}} \tag{4}$$

γ Indicates the running parameters of lua script, φ It represents the leading vector of the teaching project of the new media art specialty, $\dot{y}$ It represents the internal attribute characteristics of the teaching project of the new media art specialty, ΔY It refers to the unit cumulative quantity of the content of the art teaching project.

(3) Function Connection Conditions of Teaching Item Editor

The outgoing item and internal connection can take the parameters of one attribute as the dependent variables of the parameters of another attribute. This operation can be between scene objects or between the attributes of this object. The connection of the teaching item editor must distinguish between out and in. Out is the dependent variable, which is the reason leading to the change of another attribute. The ratio is 1 [6]. Because the operation of internal connection is divided into internal connection input and internal connection output, in the connection editor, it is necessary to distinguish whether the selected object attribute is the source attribute or the target attribute. Only when the source attribute and target attribute are both valid, the editor connection button can be enabled. It is considered that the connection will be triggered and written into the output list at the same time.

Formulas (3) and (4) derive the function connection conditions for the new media art teaching project editor as follows:

$$U = \hat{I}\sqrt{\frac{1}{\phi}} + \sum_{o \in (0, +\infty)} o(e \times t)^2 \tag{5}$$

Among them, $\hat{I}$ Represents the dependent variable parameters of the new media art teaching project, ϕ Indicates the operation permission of the teaching item editor, o It represents the target attribute parameters of new media art teaching.

The teaching item editor correctly fills in the function form and sets an attribute connected to the target attribute list. According to the definition of the function form, the target attribute of the target object is associated with the inner connection, leading out item or animation in the formula, that is, the response function of the target attribute is set, and the change of a functional relationship is presented to the correlation signal. This process is similar to the association process of the inner connection. The algorithm that the function needs to implement can be used to set the function object as an external lua call to implement the logic operation of various specific algorithms or formulas, and return the results to the attribute value object, so as to achieve the corresponding associated response.

4 Design of Multi Person VR Distance Education Interaction Method

Combined with the teaching editor of the new media art specialty to define conditions, the design of the interaction method of multi person VR distance education for the teaching of the new media art specialty was completed according to the processing flow of multi person teaching situation setting, VR distance education editor connection, and interactive scene modeling.

4.1 Multi Person Teaching Situation Setting

The teaching situation setting of multi person VR distance education interaction method is based on the definition of learning style. The learning style is operational learning. Learners can learn the conceptual knowledge of magnet and magnetic field knowledge through hands-on operation in a virtual environment, and obtain behavior results and environmental feedback through experimental operation, so as to better master the correct experimental operation behavior and experimental knowledge.

The design of learning activities and learning tasks is the secondary content of multi person teaching situation setting. Learning activities and learning tasks mainly include two categories, namely experimental operation and knowledge learning. VR experiment operation mainly provides learners with interactive operation. Learners can operate interactively in the scene according to the question prompts, and think about problems by operating with the objects in the scene. Just like VR experiment in the real classroom, students can think and solve problems by hand [7]. The second is knowledge learning. Learners learn basic conceptual knowledge through text and 3D object display. And the knowledge feedback that can be carried out after the VR experiment enables students to better understand the knowledge, thus enhancing the learning effect.

The following expression is satisfied for the solution of teaching situation setting conditions of multi person VR distance education interaction method.

$$P = \frac{\sqrt{\left(k'\overline{L}\right)^2 - \tilde{l}(U+1)^2}}{\lambda^2} \tag{6}$$

where, $\overline{L}$ Represents the unit cumulative amount of VR experimental data, k' Represents the remote operation coefficient of the education scenario, $\tilde{l}$ Indicates the teaching effect evaluation parameters of distance education, λ Represents the interactive operation vector of VR experiment.

Because the teaching of the new media art specialty includes a variety of immersion, it is necessary to meet the teaching and learning needs and use situations of teachers and students when designing and developing applications. This application is mainly used as a tool for teachers and students to teach and learn in the classroom, so it should have two major characteristics. One is to facilitate use and interaction in the classroom. It is convenient for teachers and students to use in class. The second is to ensure that teachers and students, students and students can communicate and cooperate when using the application. Therefore, students' use of desktop semi immersive VR is selected when designing the VR educational application.

4.2 VR Distance Education Editor

The UI image framework used for the development of VR editor system is Qt. The design principle of the framework itself is based on the MVC three-tier software design pattern. Qt contains a set of classes using the model/view structure, which can be used to manage data and present it to users. The separation introduced by this architecture makes developers more flexible in customizing projects, and provides a standard model interface to allow a wide range of data sources to be used in existing views. This kind of development mode makes the development division more clear, makes the UI design synchronized with the logical operation design, and further speeds up the software development process [8]. In the design of the whole and sub structure parts of the software, the MVC design pattern is followed to make the design between the whole and part of the software, part and detail more clear, achieving a good decoupling effect, and at the same time, laying a foundation for later upgrade and maintenance.

The complete VR distance education editor connection model is shown in Fig. 2.

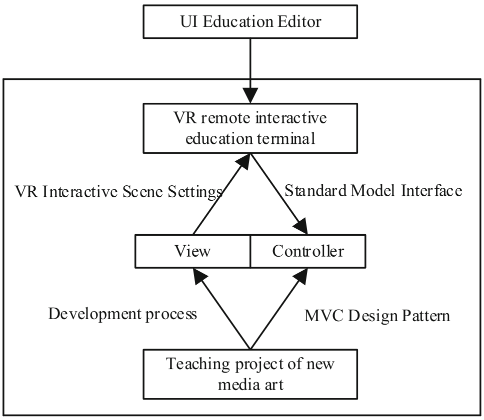

Fig. 2. VR Distance Education Editor Connection Model

Set up s, a Indicates two randomly selected educational resource access parameters, and $s \neq a$ The inequality value condition of is always true, h_s Indicates parameter based s VR distance education resource boundary parameters, h_a Indicates parameter based a VR distance education resource boundary parameters, κ Indicates the response permission of MVC software protocol in the editor host, f Represent the VR distance education project definition vector, the simultaneous formula (6), and the derived VR distance education editor response expression is shown in formula (7).

$$J = P \sum_{\substack{s=1 \\ a=1}} \left| \frac{f}{\kappa} \right|^2 \cdot |h_s + h_a|^2 \tag{7}$$

Before the introduction of MVC into the VR distance education editor, the user interface design often combines these objects. The decoupling of MVC brings flexibility and reusability. If views and controller objects are combined, the result is a model/view structure, which still separates the teaching data of new media art from the way it is presented to users, but provides a simple framework based on the same principle. This separation enables it to display the same data in several different views, and to implement new types of views without changing the underlying data structure.

4.3 Interactive Scene and Model Construction

The interaction design of multi person VR distance education is to trigger various VR combination teaching based on the amount of events, and add interactive operations on each object or group. The purpose is to add interactive switches to the given object, such as adding interactive trigger operations to object objects, selecting object objects, right clicking to select new interactive operations, popping up the interactive operation setting panel, and selectingSet appropriate parameters [9]. The design process of this interactive triggering operation is simple, fast, and efficient. In addition, there is a script editing box on the interactive settings panel, which can be used to write scripts for interactive design according to your own requirements.

g It refers to the interactive trigger parameter of multi person VR distance education, and its definition formula is as follows:

$$g = \sqrt{\frac{\dot{d}}{\mu - 1}} \cdot \overline{Z} \left(\frac{\varpi}{\vartheta} \right)^2 \tag{8}$$

$\dot{d}$ It represents the script running characteristics for new media art teaching, μ Represents the sampling parameters of VR distance education information, $\overline{Z}$ Represents the unit cumulative amount of VR distance education information, ϖ Indicates the educational information editing parameters, ϑ Represents logical interaction parameters.

In VR distance education, teachers should teach according to students, focus on students, create a comfortable and intelligent teaching environment for students, use diversified evaluation methods, promote students' personalized learning, let students connect their knowledge with real life, and promote the development of students' academic literacy. VR education is a combination of social development and information technology to change the traditional monotonous classroom teaching. At the same time, with the help of information technology, it can help teachers reduce the workload, have more energy to develop new intelligent teaching forms, achieve intelligent learning environment, stimulate their learning interest and motivation, and improve learning efficiency [10].

The definition of VR distance education interaction capability meets the following expression:

$$x = \sum_{\theta=1} C^{\nu+1} \frac{\sqrt{(V_{\max} - V_{\min})}}{\overline{X}^2} \tag{9}$$

θ Represents VR distance education information accumulation parameters, C It represents the practical efficiency of VR distance education, ν Is the burden coefficient of education project, $V_{\max}$ Represents the maximum value of VR distance education evaluation parameters, $V_{\min}$ Represents the minimum value of VR distance education evaluation parameters, $\overline{X}$ It represents the average value of the evaluation vector of the education project.

The simultaneous formula (7), formula (8) and formula (9) can express the definition formula of multi person VR distance education interaction scene model for new media art teaching as follows:

$$M = \frac{\left[gx - \frac{m(b_1+b_2+\cdots+b_n)^2}{\dot{B}}\right]}{\eta \times J} \tag{10}$$

Among them, η Represent the interactive transmission efficiency of multi person VR distance education information, m It refers to the adaptability evaluation parameters between new media art teaching and multi person VR distance education, $b_1, b_2, \cdots, b_n$ express n Unequal interactive education project definition characteristics, B Represents the diversity evaluation weight of interactive teaching projects.

With the support of interactive teaching services, multi person VR distance education can promote interactive activities in the teaching of new media art majors, and can reflect the leading role of teacher-student interaction in the teaching process. Specifically, teachers and students, their interactive activities mainly include: questions and answers, launching questions, timely feedback, tutoring and answering questions, assigning homework and organizing discussions. Questions and answers require teachers to create a reasonable situation and set questions in advance to stimulate students' interest in learning. When students' answers are inaccurate or wrong, the teacher questions the students' answers, guides them to think deeply and find answers. In the process of teaching, it is not guaranteed that all students can achieve their learning goals and provide guidance and answer questions for their questions. In inquiry activities or group activities, teachers organize students to discuss. Assignments should be targeted, focusing on consolidation and practice.

5 Example Analysis

In the teaching of new media art, the limited number of remote online students is the main reason for the poor authenticity of the interactive VR education environment. This experiment selects three groups of methods, namely, the interactive design method of multi person VR distance education, the interactive teaching method based on the learning model, and the interactive teaching method based on the intelligent education network, for the teaching of new media art majors, to analyze the numerical changes of the number of remote online teaching people of new media art majors under different methods.

5.1 Improvement of Experimental Process

The specific implementation process of this experiment is as follows:

Connect the server equipment to the teaching terminal client terminal system to provide a stable network transmission environment for the teaching information of the new media art specialty.

Record the experimental value of the number of remote online people under the effect of multi person VR distance education interaction design method, and the results are experimental group variables.

Record the experimental value of the number of remote online people under the effect of the interactive teaching method based on the learning model, and the results are compared with (1) group of variables.

Record the experimental value of remote online number of people under the effect of interactive teaching method based on intelligent education network, and the results are compared with (2) groups of variables.

Collect the data samples and summarize the experimental rules.

5.2 Teaching Environment

Distribute the same type of VR experience device to students, and start the experiment after students finish wearing it. See Fig. 3 for classroom details.

Fig. 3. VR classroom for new media art teaching

The specific models of the selected equipment elements in this experiment are shown in Table 2.

First, play a short teaching video, complete the commissioning of the VR device, ensure that the video picture is completely stable, and then play the complete teaching

Table 2. Distance education equipment

Item	Equipment components	Name and model
1	Modeling equipment	3D scanner
2	3D visual display equipment	Headworn Stereo Display
3	Sound equipment	3D stereo speakers
4	Interactive devices	3D input device
5	Projection system	VR-Platform CAVE
6	Input device	3D Mouse

video of the new media art specialty; Then, students choose the time to access the remote education terminal according to their personal learning of the teaching content; Secondly, record the number of remote online students every 20 min. During this experiment, 6 groups of experimental values need to be recorded; Finally, analyze the specific number of students in the experimental group and the control group.

5.3 Integrity Analysis

The integrity data of interactive data is shown in Fig. 4.

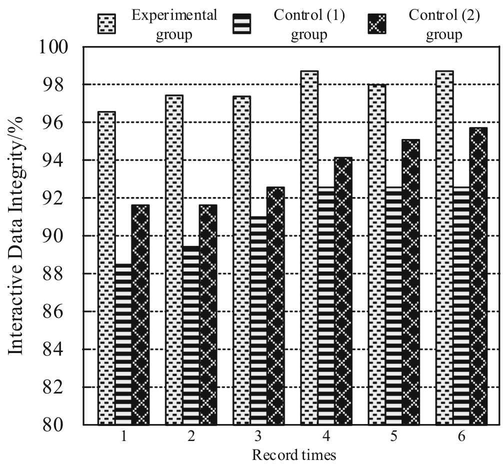

Fig. 4. Interactive Data Integrity Data Graph

Compared to the comparison method, the proposed method achieved a maximum integrity value of 96% for interactive data, indicating better data exchange and secure transmission performance.

5.4 Online Population Analysis

The following figure reflects the specific experimental value of the number of VR distance learning online students during the experiment (Fig. 5).

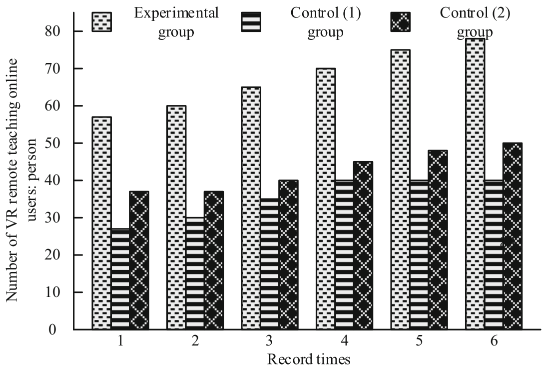

Fig. 5. Online Number of VR Distance Learning

Experimental group: During the whole experiment, the number of VR distance learning online students in the experimental group kept increasing, and by the end of the experiment, the maximum number reached 77.

Control (1) group: During the first 80 min of the experiment, the number of online VR distance learning people in the control (1) group has been increasing. During the 80–120 min of the experiment, the number of online VR distance learning people in the control (1) group has always remained stable. During the entire experiment, the maximum number of online VR distance learning people in the control (1) group can only reach 40, which is less than the numerical level of the experimental group.

Control (2) group: During the first 40 min of the experiment, the number of online VR distance learning people in control (2) group remained stable. During the first 40 to 120 min of the experiment, the number of online VR distance learning people kept increasing. By the end of the experiment, the maximum number reached 50, which was also less than the numerical level of the experimental group.

To sum up, the conclusion of this experiment is:

(1) The application ability of interactive teaching method based on learning model in improving the online number of VR distance learning is weak, and it is unable to create a multi person VR interactive education environment that meets the real needs.
(2) The interactive teaching method based on the intelligent education network has a slightly stronger application ability in improving the online number of VR distance learning than the interactive teaching method based on the learning model, but it still cannot meet the actual application needs.
(3) The application of interactive design method of multi person VR distance education effectively solves the problem of limited number of online people in the teaching of new media art specialty, and has prominent value in creating a real multi person VR interactive education environment.

6 Conclusion

The teaching project for the new media art major is a professional VR content education task that integrates content editing, production and broadcasting. In terms of production, it is mainly aimed at teachers and students to complete the production of various VR courseware content without complex programming. The interactive education method was explored, and the education editor was designed and produced using KRISMA VR editor, showing the real access situation of multi person VR. Through VR, students can truly understand the truth of the teaching of new media art, learn to explore the connotation of distance education independently, and improve their ability to analyze and understand problems in learning. The experimental results show that this method is helpful to improve the teaching effect and quality of new media art specialty, and provide a reference for the optimization of Interaction design of multi person VR distance education.

Due to the limitation of time and ability, this study still has some shortcomings and needs further improvement. Based on the analysis of relevant important literature and typical examples, this paper proposes a new media art professional teaching project to guide VR support. Due to the lack of research on relevant cases and insufficient mature experience, the design principles and development models proposed by the research need further improvement and perfection.

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