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Analysis of children's sub-health treatment effect based on multi-scale feature fusion network from the perspective of medical informatization

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Abstract

Sub-health state is a state of health and low quality between disease and health. The theoretical basis of children's sub-health is to start from the whole. The common clinical sub-health conditions cannot be explained by modern detection methods, and it can be screened and analyzed with the help of big data in medical informatization. The combination of "Internet + " and the health care model is an innovation in the construction of medical informatization. It can provide many considerate services to the masses in time and alleviate the anxiety of illness. Therefore, it is very necessary to carry out the efficacy evaluation of children's sub-health from the perspective of medical information. Therefore, this paper completes the following work with the help of AI neural network: (1) This paper proposes an improved AlexNet network evaluation method based on attention mechanism. In this study, attention mechanism is added to the original AlexNet model to weight each channel of the feature layer. At the same time, we improve the large convolution kernel of the previous layers of the original AlexNet network and use batch normalization instead of the local response normalization (LRN) layer in the original model. (2) This paper proposes an evaluation method based on improved residual network, which improves the original residual block of the residual model and widens the residual block. The residual block can effectively reduce the amount of network parameters and improve the efficiency of network training. (3) This paper proposes an evaluation method of multi-scale feature fusion (MSFF). The features extracted from the improved AlexNet and residual network are fused and then evaluated. At this time, the training time is greatly shortened, and the accuracy is higher than that of single model.

Keywords Children's sub-health · Medical informatization · Efficacy evaluation · AI neural network

1 Introduction

In addition to the health status and disease status, the human body also has a non-disease and non-health status, including mild symptoms or no clinical symptoms, but the body already contains some potential pathological information. This third state is defined as "sub-health state" [1, 2]. Based on years of research on sub-health problems, scholars have proposed that the body of people in sub-health status has undergone some functional changes without organic diseases, and their main complaints are not fixed and their symptoms are varied, which is also known as "indefinite statement syndrome" [3, 4]. Many countries in the world have a large number of sub-health conditions, which is a common phenomenon in economically developed and competitive countries. Traditional Chinese medicine (TCM) is a medical theoretical system characterized by syndrome differentiation and holistic concept. TCM attaches great importance to the laws of human functional activities and physiological characteristics, so it has unique advantages over modern medicine in terms of

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classification, diagnosis and treatment of sub-health status [5]. Prevention of disease is one of the basic contents of TCM, including the following two aspects: prevention before disease and prevention of existing disease. Prevention before disease is the preventive measure for disease before it occurs. Prevention of existing disease is to prevent the development of diseases like diseases in a timely manner when symptoms appear. Measures should be taken in a timely manner to block the development and transmission of diseases [6]. The performance of children's sub-health varies according to their age. In early childhood, they are anorexia and lack of trace elements. Preschool children mainly have bad breath, restless sleep at night, inconvenience, crying and irritability, yellow urine, yellow face, hot hands and feet, and fatigue. School-age children can see inattention, poor memory, hyperactivity, etc. [7]. The performance of each stage is closely related to many factors, such as social and psychological factors, besides improper diet, some acute and chronic diseases, external feelings and physical factors. According to TCM, children's sub-health is caused by poor diet, improper feeding, chronic diseases, and damage to the spleen and stomach [8]. The treatment of sub-health with TCM has been reported in China for a long time. According to different treatment schemes, sub-health status is classified according to clinical manifestations of sub-health status. For example, according to the syndrome differentiation and treatment of spleen deficiency and dampness, heart and spleen deficiency, liver stagnation and qi stagnation, and liver and kidney deficiency, there are corresponding prescriptions [9]. If the spleen and yang fail to move and cause internal dampness, the treatment is based on strengthening the spleen and replenishing qi, and it can be used to seep moisture and water. You can choose raw lotus leaves, raw wisdom seeds, white lentils and other boiled soup to eat. If the symptoms are obvious, add Shenbo Baizhu powder and Huo Puxia Quan soup [10]. Traditional Chinese patent medicines and simple preparations are used to treat sub-health. It is reported that the clinical efficacy of BFS capsule in treating sub-health is observed. The clinical observation efficiency of oral BFS capsule for patients with sub-health of various syndromes is more than 90%. The clinical efficacy of Qinggong Changchun Capsule in the treatment of sub-healthy liver and kidney deficiency type was observed by randomized double-blind control method. The results showed that the total effective rate of the treatment group was more than 85%. The total effective rate of the control group is more than 75%. The researchers believe that Qinggong Changchun Capsule can significantly improve the symptoms of sub-healthy liver and kidney deficiency, and it is superior to Jinjing Shenqi Pill in some diseases. It is one of the effective drugs for treating sub-healthy state [11, 12]. Therefore, in future, we should strengthen the discussion of the law of diagnosis and treatment in order to provide scientific theoretical basis and experimental basis for improving clinical efficacy. In clinical application, the method should be flexibly applied according to the actual situation, and the indications, contraindications and dosage should be strictly controlled. The disease should be eliminated immediately, and the drug should not be used excessively. Otherwise, it is easy to damage the positive qi, resulting in water loss, electrolyte disorder, and even aggravation of the disease [13, 14]. Therefore, it is very important to analyze the curative effect of different TCM on children's sub-health. With the gradual application of AI technology in the medical field, AI neural network can also be used to evaluate the medical effect. This can not only avoid the inaccuracy of human evaluation, but also reduce repetitive work [15]. Therefore, this paper proposes a MSFF evaluation model. In this paper, two improved CNNs are used to extract different features, and the transfer learning and feature fusion methods are used for evaluation, so as to improve the model feature expression ability and the model generalization ability. The contributions of this paper are as follows:

- First, this paper proposes an improved AlexNet network evaluation method based on attention mechanism.
- Secondly, this paper proposes an evaluation method based on improved residual network, which improves the original residual block of the residual model and widens the residual block.
- Thirdly, this paper proposes an evaluation method of MSFF. The features extracted from the improved AlexNet and residual network are fused and then evaluated.

The work arrangement of the whole article is as follows: The first chapter introduces the research background and significance of this article; the second chapter mainly introduces the current research situation of the treatment of children's sub-health with TCM; the third chapter proposes the MSFF model; the fourth chapter mainly carries on the experimental analysis to the proposed method; and the fifth chapter comprehensively summarizes the main research work of this paper and briefly introduces the future improvement scheme.

2 Related work

At present, there is no effective treatment method for children's sub-health in western medicine, while TCM has unique advantages in diagnosis and treatment of sub-health from the perspective of prevention of disease and has made great progress. Now, the research progress of TCM in recent years is summarized as follows. There is no special description of "child sub-health" in TCM, but it is classified into "deficiency syndrome," "body deficiency cold," "anorexia," "sweat syndrome" and other categories according to physical factors, disease inducements and syndromes. TCM believes that its pathogenesis is mainly due to the weakness of the three organs of the lung, spleen and kidney, and the weakness of the outside of the body [16]. Reference [17] believes that the causes of sub-health in children mainly include the following aspects: first, disharmony between the spleen and stomach, and poor gastrointestinal function. The second is in the "sick period." The third is the repeated use of multiple antibiotic drugs. The fourth is the physical reasons. Reference [18] believes that children's sub-health status is related to children's physiological and pathological characteristics. Scholars believe that children's delicate viscera, spleen is often insufficient, diet is not proper, and cold and temperature cannot regulate themselves are the main reasons for children's sub-health status. Reference [19] summarized the main influencing factors of children's sub-health as follows: diet, living, premature exposure to inappropriate knowledge and information, drug abuse, stress, etc. Most scholars believe that the spleen is responsible for children's sub-health. If the function of spleen is normal, and the digestion and absorption function of the body is sound, it can provide enough nutrients to transform and produce essence, qi, blood and body fluid. This makes the viscera and tissues of the whole body fully nourished to maintain normal viscera functions. On the contrary, if the spleen fails to function properly, the digestive and absorption functions of the body will be abnormal, resulting in abdominal distension, loose stools, loss of appetite, fatigue, wasting and other pathological changes [20]. Reference [21] believes that children's sub-health is closely related to the disharmony between the spleen and stomach in children and points out that some acute and chronic infectious diseases can lead to disharmony between the spleen and stomach and endogenous damp heat due to late treatment failure or long-term repeated use of antibiotics, insufficient innate endowment, improper diet, etc. This makes the ascending and descending functions of the spleen and stomach dysfunctional, and the treatment should be based on regulating the spleen and stomach. Reference [22] proposes that children's sub-health should be based on the spleen. Scholars believe that the normal growth and development of children need the subtle qi generated by the acquired spleen and stomach to replenish. The recovery of the disease depends on the health and biochemistry of the spleen and stomach. Children with congenital deficiency need to be adjusted and replenished day after day. In the course of disease treatment, doctors should be careful to use the products of severe cold and severe attack to avoid damaging the spleen and stomach. Sub-health science divides sub-health syndrome into 8 types, including liver-qi stagnation, liver-qi stagnation, liver-qi stagnation and spleen-qi deficiency, liver-kidney yin deficiency, heart-spleen deficiency, lung-spleen qi deficiency, spleen-deficiency and dampness resistance, and phlegm-heat internal disturbance syndrome [23, 24]. Reference [25] divides children's physical condition into three states: health, sub-health and disease and summarizes the common physical conditions of children, including the peaceful quality of healthy children, and eight physical types of children's "sub-health." It believed that the focus of children's physique identification is to identify the physique of "sub-healthy children" and completely distinguish it from the "syndrome" of the disease state, so that children in sub-healthy state can recover to the healthy state through "correction."

Reference [26] believes that the formation of children's physique is related to children's congenital endowment, feeding and living, regional environment, disease and treatment. The author summarized five types of children's constitution and their clinical characteristics from the rise and fall of yin and yang qi and blood combined with the five viscera endowment. Reference [27] treated sub-healthy children with nutritional deficiency due to deficiency of spleen due to deficiency of spleen with empirical Yunpi Formula and observed various indicators before and after the intervention. The results showed that after the intervention of Yunpi Formula for 12 weeks, the subjects not only had a significant increase in food intake and body mass, but also had a good effect. Reference [28] believes that children with asthma in remission are mostly in sub-health state. There are many inducing factors inside and outside the body. The patient uses Yupingfeng oral liquid and ginseng and schisandra decoction to treat the lung and spleen deficiency syndrome in the remission stage of bronchial asthma, which can not only significantly relieve the clinical symptoms, improve the lung function, but also help to improve the immune function of the body and achieve good results. Medical quality is a standard used to evaluate and measure the level of doctors and nurses, the comprehensive strength of hospitals and the treatment effect of departments on specific conditions. Generally, it is necessary to measure the medical staff's professional proficiency, the final treatment effect and the quality of work in the process of serving patients. Reference [29] is based on the evidential reasoning theory and uses the AHP method to give weight to the evaluation index, which has a more objective description of the quality evaluation in the network on the basis of preserving the objectivity of the original information. Reference [30] builds an indicator system based on DRGs, uses Delphi-RS to determine the weight of each indicator, uses fuzzy membership method to determine the scoring result as the result of medical quality evaluation, and verifies the effectiveness of DRGs to build an indicator system. Reference [31] focuses on the performance of CAF model in the evaluation of public service quality, so as to encourage the government to adopt this model to improve public service quality.

3 Multi-scale feature fusion network

3.1 Improved residual network

3.1.1 Residual network

It is a problem to overcome gradient dispersion and gradient explosion, while the number of layers of neural network is deepened. So the researchers designed the residual network. This is because it is not easy to have a gradient of 0 or a large gradient in the back propagation of the shallow neural network, so a backoff mechanism can be added to the deep network. When the deep neural network degenerates, the shallow characteristics of the network are transmitted to the high level, and the performance of the neural network can reach the shallow effect. The residual network adds multiple residual blocks between input and output. The structure of the residual blocks is shown in Fig. 1. Input a first passes through two convolution layers to obtain output $R(a)$ and then adds with input a. Here, we need to consider whether the shape between $R(a)$ and a can be directly operated; otherwise, we need to perform corresponding operations on a, so that $R(a)$ and a can be directly operated. The final output $R(a)$ is obtained:

$$P(a) = a + R(a) \tag{1}$$

where $P(a)$ is called the residual module. Since a is the observed value and $P(a)$ is the predicted value, the $R(a)$ that needs to calculate is the residual, so it is called the residual network.

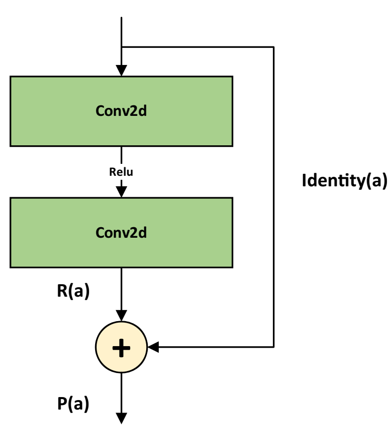


Fig. 1 Residual module

3.1.2 Construction of improved residual network model

This section makes the following improvements to the original Resnet18 network model.

(1) For the convolution layer with the convolution core size of 1×3 in the model, group convolution is used. This group fusion operation not only reduces the number of training parameters, but also enables the network model to learn more features. The grouping convolution is to group the characteristic graph and perform the convolution operation for each group. Packet convolution is to group each channel of the feature graph, so the depth of the corresponding convolution core should also be grouped with the input packet. After the convolution of the input of the packet and the convolution core of the packet, the features are combined, so that the final number of channels is the original C.

(2) In order to prevent over-fitting, this paper also uses L2 regularization at each layer and adds a dropout layer after each layer's full connection layer to prevent over-fitting. There are two main solutions to over-fitting. On the one hand, reduce the complexity of the model, that is, reduce the number of parameters. The second is to limit the size of the weight to a small range. Researchers can use regularization to keep the weight smaller, which is conducive to making the model smoother. Regularization is to add some restrictions to the loss function of the neural network, so as to improve the generalization ability of the model and prevent the occurrence of over-fitting of the network.

(3) This paper also improves the original residual block and widens the original residual block. In this paper, a network model with four residual blocks is designed. Compared with the original residual block, the convolution Kernel of the widened one-dimensional residual block is one-dimensional, and an additional residual channel is added. This paper replaces the original 3×3 convolution kernel with the 1×3 convolution kernel in the residual block, and the parameters can be reduced to one-third of the original. Then, the parameter amount of a complete widened one-dimensional residual block is only two-thirds of that of an original residual block. Therefore, the residual block can effectively reduce the amount of network parameters and improve the efficiency of network training. In addition, the widened network structure can enable each layer of network to obtain richer features. The improved residual network model is shown in Fig. 2.

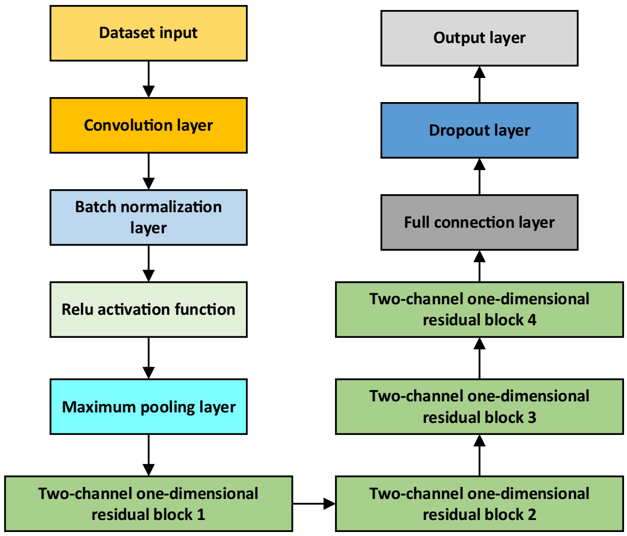


Fig. 2 Block diagram of improved residual network model

The residual block of the traditional residual network has only one residual connection channel to input the characteristics of the low-level network into the high-level network. When the error is back-propagated, the residual block does not have enough weight to learn features, and most of the residual blocks can only share a small amount of information, which results in the reduction of reusable features. The widened residual block model designed in this chapter reduces the number of layers and parameter usage of the model, speeds up the training time, and correspondingly reduces the number of convolution cores in each layer. At the same time, L2 regularization and dropout are added to prevent over-fitting. Figure 3 shows the network structure of the widened residual block. The original one-way residual block is widened to a symmetrical two-way residual block, and the original 3×3 convolution kernel is replaced by a one-dimensional 1×3 structure.

3.2 SE-net network structure

This paper uses SENet, a typical application model of soft attention mechanism. The focus method essentially consists of learning a weight and then applying that weight to each feature map individually using the neural network's feature map. The SE-Net network paradigm is a cross-channel attentional processing framework. By analyzing the association between channels, the SE-Net network model instantly assigns a weight to each channel of the input feature map, thereby determining the relative significance of the features. The characteristics associated with high-weight channels are then prioritized for improvement, while those associated with low-weight channels are downgraded. The SE-Net network is relatively simple to implement, and it is easy to apply to various

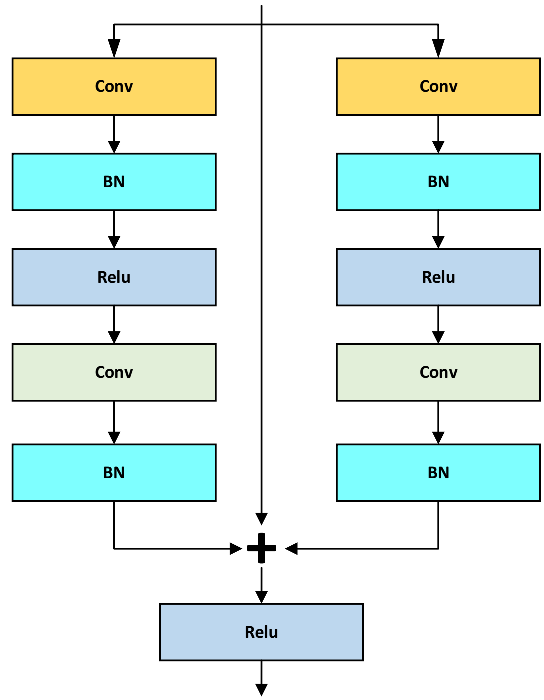


Fig. 3 Structure of improved residual block

CNN frameworks. Figure 4 is the network structure of the channel attention mechanism SE-Net.

By learning the weight of each channel, the SE-Net network assigns a value to each channel based on its traits and then uses a one-dimensional vector with the same number of dimensions to rate each channel's performance. If there is a strong connection between the characteristics of this channel and the job, and the weight acquired is high, then the characteristics of this channel will be powerful.

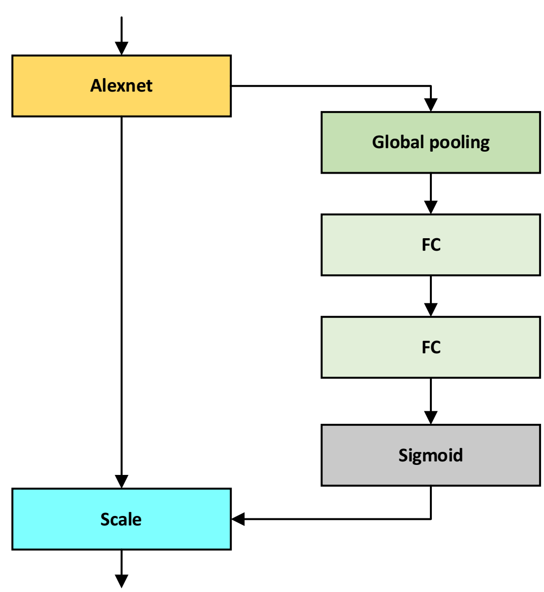


Fig. 4 SE-Net network structure

The lesser the features of this channel, and thus the lower the weight acquired, the less of a link there will be between those characteristics and the job.

3.3 Integration of attention mechanism Senet and AlexNet network model

3.3.1 AlexNet network model analysis

AlexNet deepens the network structure on the basis of LeNet5. Its good local area awareness, weight sharing and other characteristics make it more robust than BPNN and LeNet5 and more effective for local feature deformation of data. Each neuron of AlexNet only affects a part of the neurons in the adjacent layer and has strong local feature capture ability. AlexNet is a 14-layer network structure, in which the first two layers of convolution and the fifth layer of convolution follow the maximum pooling layer, and the LRN layer follows the maximum pooling layer. The AlexNet network uses the LRN layer to relatively increase the neurons with larger feedback, inhibit the neurons with smaller response, and improve the generalization ability of image classification and recognition. At the same time, LRN on the feature map can improve the performance of classification and recognition. The LRN calculation formula is:

$$N_{x,y}^{a} = \frac{e_{x,y}^{a}}{\left(r + \beta \sum_{b=\max(0,a-m/2)}^{\min(M-1,a+m/2)} \left(e_{x,y}^{b}\right)^{2}\right)^{\delta}} \tag{2}$$

where $N_{x,y}^{a}$ represents the neuron obtained from the LRN processing. $e_{x,y}^{a}$ represents the convolution of the a th convolution kernel at position (x, y) to obtain the elements in the feature graph. m represents the number of adjacent convolutions. M represents the total number of convolution cores in a certain layer. r, β, δ are super parameters.

AlexNet employs random regularization (Dropout) between completely linked layers to prevent over-fitting during training. The network's buried layer neurons are removed at random during forward transmission with a chance of p = 0.5. Next, remove neurons at random, run backpropagation, change the parameters, and restore the ones you just erased. If you want to maintain the same amount of input and output neurons while decreasing inter-neuronal contact, repeat the steps above. The calculation process of dropout is shown below.

$$V_{s}^{(h)} \sim Bernoulli(p) \tag{3}$$

$$\widetilde{y} = V^{(h)} \times y^{(h)} \tag{4}$$

$$Q_{a}^{(h+1)} = d_{a}^{(h+1)} \widetilde{y}^{h} + N_{a}^{(h+1)} \tag{5}$$

$$y_{a}^{(h+1)} = f(Q_{a}^{(h+1)}) \tag{6}$$

where h represents the number of hidden layers, $Bernoulli(p)$ generates the probability vector V, s represents the intermediate result after some neurons stop working with probability V, Q represents the vector input into layer h, d and N represent the weight and deviation of layer h.

AlexNet uses the random gradient descent method to train the model. The momentum is set to 0.85, and the weight attenuation is set to 0.001. Small weight attenuation can effectively avoid the over-fitting problem of the model and reduce the training error of the model. The weight update rule of AlexNet is:

$$k_{a+1} = 0.85 \cdot k_{a} - 0.001 \cdot \theta \cdot d_{a} - \theta \cdot \left\langle \frac{\partial L}{\partial d} \mid d_{a} \right\rangle_{T_a} \tag{7}$$

$$d_{a+1} = d_{a} + k_{a+1} \tag{8}$$

where d is the weight, a is the current number of iterations, k is the momentum, θ is the learning rate, and T_a is the average value of the derivative T_a of the objective function of the ith batch with respect to d.

3.3.2 Improved AlexNet network model

This section uses AlexNet as the basic network structure and then improves and optimizes the original AlexNet network structure. Compared with the original AlexNet model, this section mainly has the following improvements.

(1) The low level of the original AlexNet model uses 11 × 11 large convolution kernel, which increases the number of parameters of the model and takes a long time to train, and cannot meet the requirements of real-time detection. In order to capture small features, we improve it to a small convolution kernel of 3 × 3.

(2) The LRN layer in the original model is replaced by BN. BN algorithm is proposed to deal with the increasingly DNN. The training of neural network is to take the training results of the previous layer as the output of the next layer, and so on, and stack them layer by layer. The change of the weights and offsets of the previous layer directly leads to the change of the distribution of the input of the next layer, which gradually maps to the nonlinear function and approaches the limit saturation zone of the value interval. As a result, it is difficult to train the neural network, so we have to choose a smaller learning rate to adapt to more appropriate parameter changes. This phenomenon is called internal covariate shift. In order to solve this problem, the author proposes a scheme: normalize the inter-layer input values.

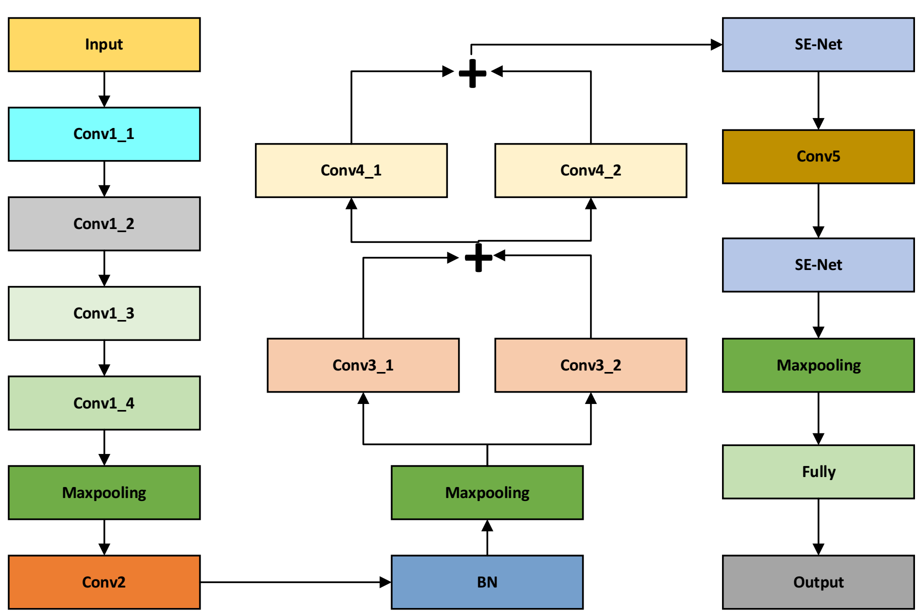
Convert the probability distribution of the output results of the previous layer into standard normal distribution. After the standard normal transformation, the data before the input activation function will fall into the sensitive area of the activation function, so that the problem of gradient disappearance can be avoided during the back propagation. Batch is because the normalization operation is carried out on the small batch of training data. The method of BN has greatly improved the effect of training, and it allows the initialization parameters to be less cautious. It carries out BN for the output data of hidden layer at all levels during the training process. Through BN analysis and processing, the change of data distribution of hidden layer in the network during the training can be reduced, thus reducing the impact on the parameters in the neural network, improving the convergence speed of the neural network, and enhancing the stability of the network. The operation of batch normalization needs to be solved after the volume layer and before activating the function.

(3) In order to pay attention to the relationship between each channel in the feature map, the attention mechanism is introduced here. SE-Net mainly studies the correlation between each channel in the feature map and filters out the attention for each channel. Figure 5 shows the improved AlexNet network structure diagram. This chapter mainly adds the attention model SE-Net module to the high-level feature map to focus on the evaluation of sub-health effects of each channel in the feature map and Chinese medicine. MSFF technology is used on the mid-level feature map, and features of different scales are obtained by using convolution kernels of different sizes for feature fusion.

3.4 Multi-scale feature fusion evaluation model

In this chapter, the AlexNet model based on attention mechanism is used to extract high-level features of the dataset and the features of different scales extracted based on the widened residual network are fused. According to many experiments, multi-model fusion algorithm can get better evaluation results than single model algorithm. There are two common methods of MSFF, namely series multi-scale fusion and parallel multi-scale fusion. Cascade feature fusion is a way to extract different features based on concatenation for fusion. The serial multi-scale feature structure, represented by FCN and U-Net, is to fuse the features of non-adjacent feature layers. Parallel feature fusion is a way to extract different features based on parallel mode for fusion. Operate the input data with several convolution kernels of different sizes, and then fuse the obtained characteristic graph. This parallel fusion method is used in the Inception network structure. In this chapter, the residual network model and AlexNet model are integrated into the attention mechanism SE-Net network. Figure 6 shows the overall block diagram of the improved residual model and the SE-Net network and AlexNet fusion model in this chapter. First, the improved AlexNet model is used to change the large convolution cores of 11×11 and 5×5 at the lower level into small convolution cores of 3×3. This greatly reduces the parameters used in the training model, saves training time and increases the speed of the algorithm. Secondly, we add the attention

Fig. 5 Improve the network structure of AlexNet



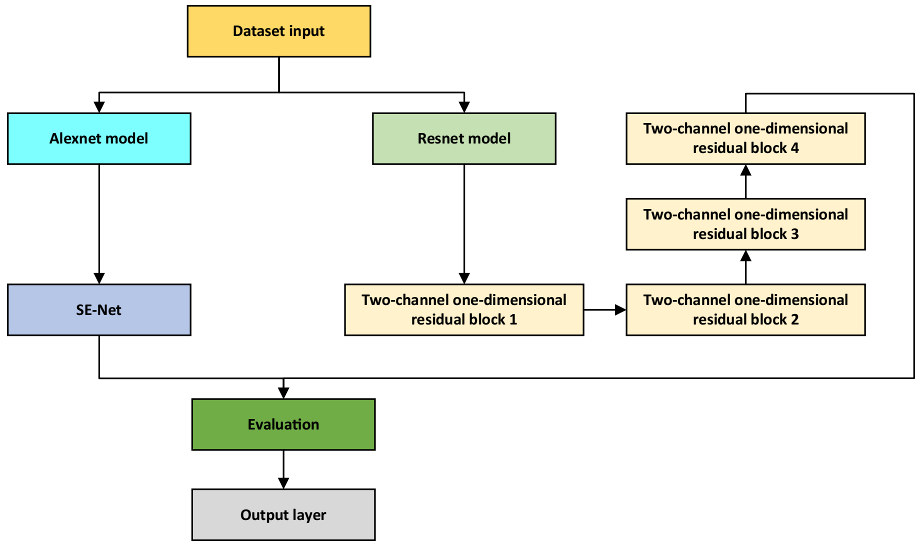


Fig. 6 Block diagram of multi-scale feature fusion system

mechanism SE-Net model to the high-level semantic feature map, so that the high-level semantic features pay more attention to the current features, rather than other irrelevant features. Then, we use the improved residual model to extract the features of the dataset. The improved residual network includes four residual blocks. In this model, we mainly improve the structure of the residual block, change the original residual block into a dual-channel one-dimensional symmetric residual block, and replace the original 3×3 convolution kernel in the residual block with a dual-channel 1×3 convolution kernel. This not only widens the residual model, but also reduces the training parameters and saves the running time of the algorithm. Finally, the multi-scale features learned from the two networks are fused. The specific multi-scale feature fusion system block diagram is shown in Fig. 6.

3.5 Evaluation index system of curative effect of TCM for children's sub-health

This study combines sub-health with self-rated health and conforms to the change of health measurement from one-dimensional to multidimensional, from group to individual. This paper refers to the commonly used scales of psychology, sociology and other aspects at home and abroad, combines the cultural background, social structure and values of our country, and fully considers the individual's cognition and expectation of their own health status. This study screened indicators from three aspects of physical, psychological and social health, and established an evaluation index system for the efficacy of TCM for children's sub-health, which overcame the shortcomings in the previous sub-health measurement and evaluation, and tried to reflect the connotation of TCM treatment for children's sub-health more comprehensively and accurately, so as to accelerate the research pace of children's sub-health treatment in China. In this study, the operation of sub-health is defined as: Sub-health state refers to a kind of healthy low-quality state and experience in terms of physical, psychological and social adaptation when individuals are clearly diagnosed without physical, psychological and other diseases. This state is mainly manifested in physical symptoms, organ function and body movement function weakening, energy decline, etc. Psychologically, it is manifested as a low-quality state in terms of psychological symptoms, cognition and emotion. In terms of social function, it shows the decrease or decline of social communication and social support. Through consulting experts and consulting a large number of data, this paper has carried out the final screening of the evaluation index system of the efficacy of TCM for children's sub-health, as shown in Table 1.

Table 1 Evaluation index system of curative effect of TCM for children's sub-health

Index	Label	Index	Label
Appetite	T1	Auditory system	T12
Sleep quality	T2	Skin abnormality	T13
Hair growth	T3	Asthenia of limbs	T14
Exhaustive sweating	T4	The faculty of memory	T15
Inexplicable pain	T5	Learning ability	T16
Sore throat	T6	Concentration	T17
Bitter or dry mouth	T7	Mental strain	T18
Gastrointestinal function	T8	Be down in spirits	T19
Stool condition	T9	Family relations	T20
Urination condition	T10	Collective activities	T21
Sense of pressure	T11	Sense of fear	T22

4 Analysis

4.1 Data source

This paper collects data on the treatment of children's sub-health by TCM through big data technology and forms two data sets CHSD1 and CHSD2 according to different characteristics of the data. CHSD1 and CHSD2 contain 580 and 1075 groups of data, of which 75% are used for training and 25% for testing. The data of the two data sets are expanded in two dimensions to adapt to the CNN model proposed in this paper.

4.2 Experimental results and analysis

This study collected several other models to compare with the MSFF model proposed in this paper and tested them with the two data sets constructed in this paper. The results are shown in Table 2.

It can be seen that the recall rate of MSFF model in data set CHSD1 can reach 97.6%, which is 3.3% higher than AlexNet, 2.5% higher than Resnet, and more than 5% higher than other models. MSFF model also has a recall rate of 97.3% in the dataset CHSD2. At the same time, the accuracy of MSFF model is also better than other models. The result also shows that using two independent channels can obtain more abundant features than single channel. Combining the features obtained from the two models, the experiment shows that the evaluation accuracy and recall rate of this method are superior to the above single-channel model. Therefore, the two modules are analyzed by experiments.

The improved residual network model can effectively reduce the amount of network parameters and improve the efficiency of network training. In addition, the widened network structure can enable each layer of network to obtain richer features. Next, the influence of the improved residual network module on the evaluation results of MSFF model is verified by experiments. Therefore, this paper will use two improved AlexNet networks to form a two-channel input model and then compare it with the MSFF model with the improved residual network module. The experimental results are shown in Fig. 7.

It can be seen from the figure that the two-channel model composed of two improved AlexNet networks is also more accurate than the single-input channel model, but it is not as accurate as the above MSFF model. On CHSD1, the accuracy rate of MSFF model combined with the improved residual network module reached 98.1%, and the recall rate reached 97.6%, which was 3% and 1.8% higher than that of the two improved AlexNet network dual-channel models, respectively. It can be seen that the residual network module can effectively improve the accuracy and recall rate of MSFF model. The same conclusion can be reached on CHSD2.

This paper proposes an improved Resnet18 network model with widened residual blocks for multi-feature fusion. In this experiment, the initial learning rate is set to 0.01, and Adam is used as the optimizer to randomly sort all the data in the training set in CHSD1, and each batch trains 20 epochs. Figure 8 shows the accuracy and recall curves of the training set using the original Resnet18 model and the widened residual model.

It can be seen from Fig. 8 that the initial accuracy rate of the residual model using the improved residual block has reached 74% and finally reached 97.3% in the training set. The initial recall rate of the residual model using the improved residual block has reached 75%, and the final accuracy rate in the training set has reached 98.5%. It can be judged that the performance of the improved residual model is significantly improved.

The improved AlexNet model can improve the accuracy of the model. Next, the influence of the improved AlexNet module on the evaluation results of MSFF model is verified by experiments. Therefore, this paper will use two improved residual network models to form a two-channel input model and then compare it with the MSFF model with the improved AlexNet module. The experimental results are shown in Fig. 9.

It can be seen from the figure that the two-channel model composed of two improved Resnet networks is also more accurate than the single-input channel model, but it is not as accurate as the MSFF model. On CHSD1, the accuracy rate of the MSFF model integrated with the improved AlexNet module reached 98.1%, and the recall rate reached 97.6%, which was 3.5% and 2.2% higher than the two improved AlexNet network dual-channel models, respectively. It can be seen that the improved AlexNet module can also effectively improve the accuracy and recall rate of MSFF model. The same conclusion can be reached on CHSD2.

Table 2 Experimental comparison of different models on the test set

Model	CHSD1		CHSD2	
	Recall (%)	ACC (%)	Recall (%)	ACC (%)
BP	83.3	83.5	83.7	84.2
SVM	85.6	86.3	86.2	86.5
DBN	89.2	88.4	88.7	87.9
CNN	92.8	92.2	91.5	91.8
Improved Resnet	95.2	95.0	95.5	95.3
Improved AlexNet	94.5	93.3	94.4	93.5
MSFF model	97.6	98.1	97.3	97.2

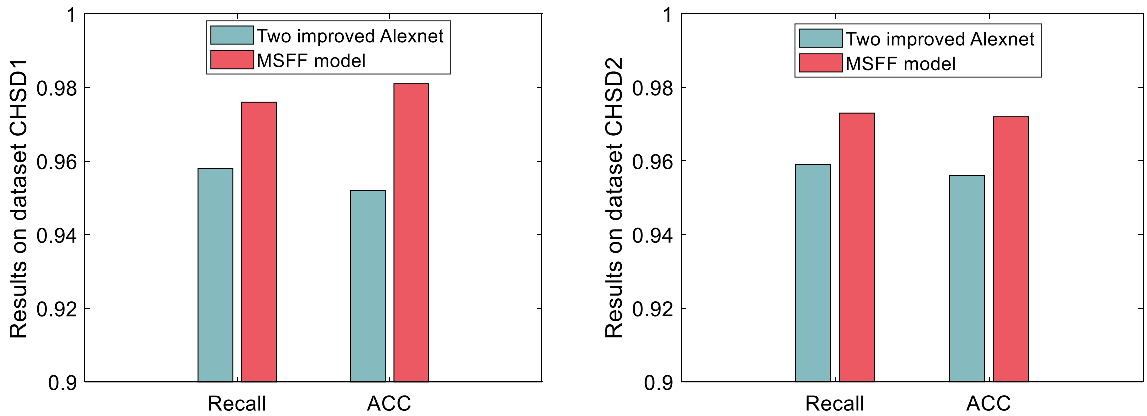


Fig. 7 Effect of improved Resnet on the recall and accuracy of MSFF model

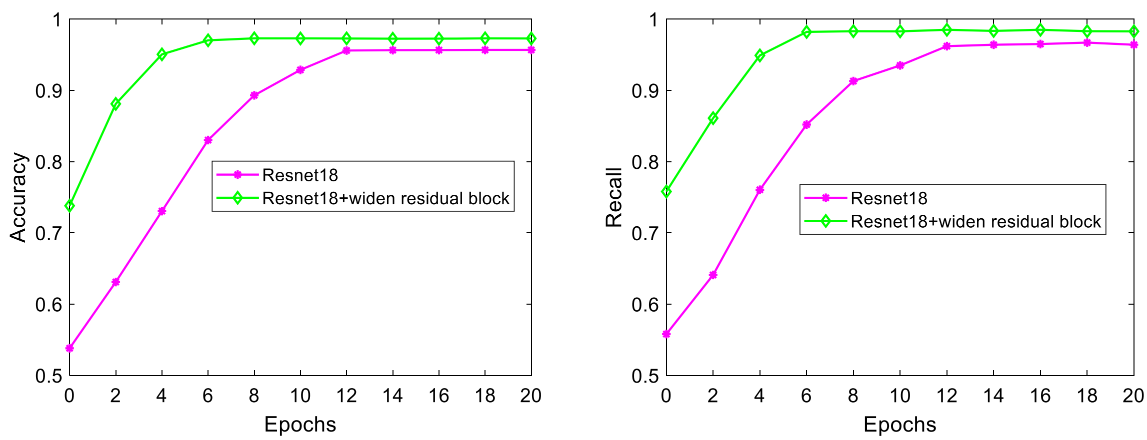


Fig. 8 Resnet18 model and improved model training accuracy and recall curve

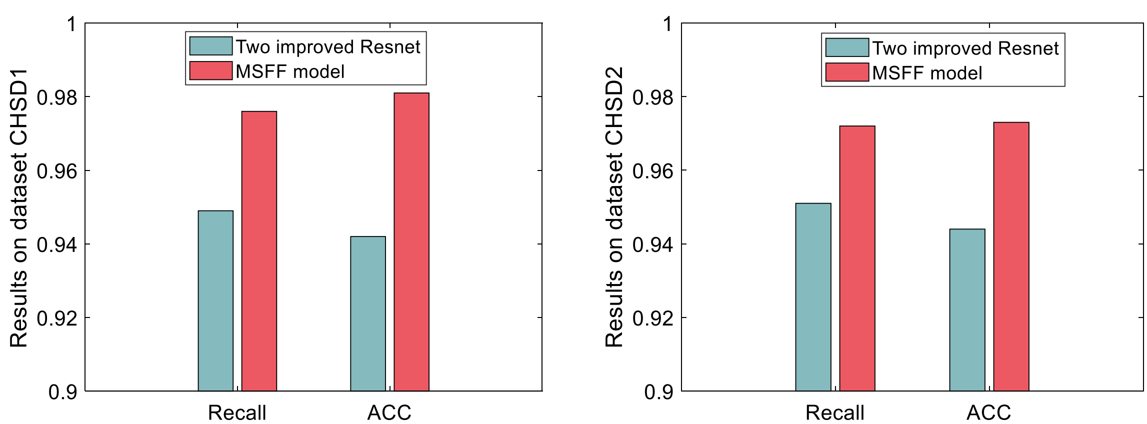


Fig. 9 Effect of improved AlexNet on the recall and accuracy of MSFF model

This paper proposes an AlexNet network model with SE-Net attention mechanism to fuse multiple features. In this experiment, the initial learning rate is set to 0.01, and Adam is used as the optimizer to randomly sort all the data in the training set in CHSD1, and each batch trains 20 epochs. Figure 10 shows the accuracy and recall curves of the training set using the original AlexNet model and the AlexNet network model using the increased SE-Net attention mechanism.

It can be seen from Fig. 10 that the initial accuracy of the AlexNet network model with SE-Net attention mechanism has reached 78% and finally reached 97.2% in the training set. The initial recall rate of the AlexNet network model using the increased SE-Net attention mechanism has

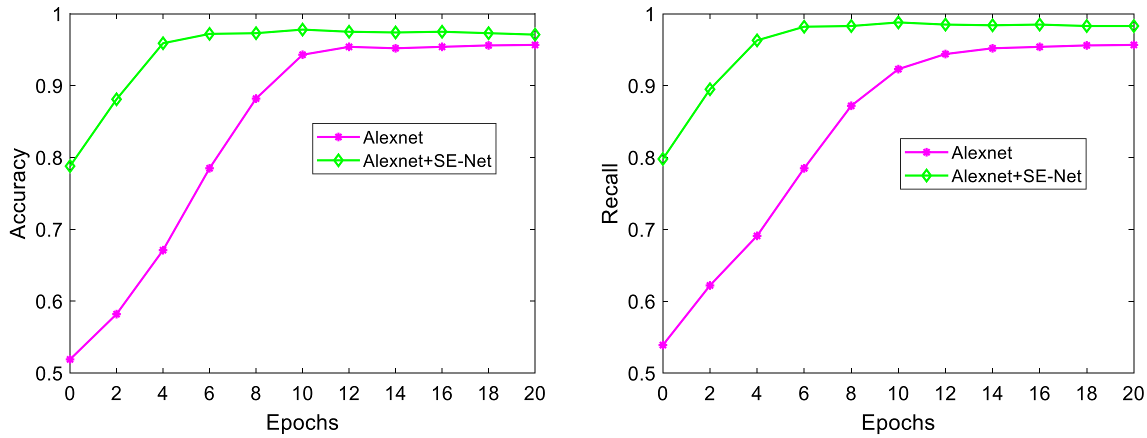


Fig. 10 AlexNet model and improved AlexNet model training accuracy and recall curve

reached 79%, and the final accuracy rate in the training set has reached 98.3%. It can be judged that the performance of the improved AlexNet model is significantly improved.

5 Conclusion

The sub-health status of children is still not up to the standard of health, which is characterized by no weight gain within a certain period of time, and other aspects are characterized by decreased functional adaptability, but it does not meet the clinical and subclinical diagnostic criteria for diseases related to modern medicine. The theoretical basis of children's sub-health is to start from the whole. The common sub-health conditions in clinic cannot be explained by modern detection methods. The etiology and pathogenesis of children's sub-health can be explained by the thought of disease prevention and the method of syndrome differentiation in TCM. Therefore, it is very necessary to carry out research on the treatment of children's sub-health with TCM. This paper proposes to use AI technology and neural network to evaluate the treatment of children's sub-health with TCM, so as to scientifically demonstrate its role in this regard. This paper completes the following work: (1) This paper proposes an improved AlexNet network evaluation method based on attention mechanism. In this study, attention mechanism is added to the original AlexNet model to weight each channel of the feature layer. At the same time, we improve the large convolution kernel of the previous layers of the original AlexNet network and use batch normalization instead of the local response normalization layer in the original model. (2) This paper proposes an evaluation method based on improved residual network, which improves the original residual block of the residual model and widens the residual block. The residual block can effectively reduce the amount of network parameters and improve the efficiency of network training. (3) This paper proposes an evaluation method of multi-scale feature fusion. The features extracted from the improved AlexNet and residual network are fused and then evaluated. At this time, the training time is greatly shortened, and the accuracy is higher than that of single model. This research is not perfect, and subsequent research can use multimodal model to increase the generalization ability of the model.

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Data availability The datasets used during the current study are available from the corresponding author upon reasonable request.

Declaration

Conflict of interest The authors declare no conflict of interest exists.

References

1. Wang C, Yu C, Guo W et al (2022) Identification of typical sub-health state of traction battery based on a data-driven approach. Batteries 8(7):65
2. Feng S, Liu W, Zuo S et al (2016) Impaired function of the intestinal barrier in a novel sub-health rat model. Mol Med Rep 13(4):3459–3465
3. Chen SL (2003) Psychological nursing of patients with unidentified clinical syndrome. Mod J Integr Tradit Chin West Med 12(17):1909–1910
4. Liu JH, Wang XG (2003) 20 cases of unidentified clinical syndrome treated by acupuncture at renying point. Shandong J Tradit Chin Med 22(10):612–612
5. Chan RYP, Chien WT (2013) Concepts of body constitution, health and sub-health from traditional Chinese medicine perspective. World J Transl Med 2(3):56–66
6. Liang Z, Yin D (2010) Preventive treatment of traditional Chinese medicine as antistress and antiaging strategy. Rejuvenation Res 13(2–3):248–252
7. Zhang Y, Tian S, Zou D et al (2022) Screen time and health issues in Chinese school-aged children and adolescents: a

systematic review and meta-analysis. BMC Public Health 22(1):1–12
8. Yao Y, Wang L, Chen Y et al (2015) Correlation analysis of anxiety status and sub-health status among students of 13–26 years old. Int J Clin Exp Med 8(6):9810
9. Sang X, Wang Z, Liu S et al (2018) Relationship between traditional Chinese medicine (TCM) constitution and TCM syndrome in the diagnosis and treatment of chronic diseases. Chin Med Sci J 33(2):114–119
10. Wang X, Zhang A, Sun H et al (2012) Systems biology technologies enable personalized traditional Chinese medicine: a systematic review. Am J Chin Med 40(06):1109–1122
11. Qian H (2005) Discussing and analyzing prevention and cure strategy of traditional Chinese medicine according to characteristic of sub-health condition. China J Tradit Chin Med Pharm
12. Zhao J, Liao X, Zhao H et al (2016) Methodological quality evaluation of randomized controlled trials for traditional Chinese medicines for treatment of sub-health. China J Chin Materia Med 41(21):4041–4050
13. Ma D, Wang S, Shi Y et al (2021) The development of traditional Chinese medicine. J Tradit Chin Med Sci 8:S1–S9
14. Fang R, Yang Y, Ren J, et al. (2018) Discussion on comparison and fusion of preventive treatment of Chinese medicine and health management in the perspective of "equal importance on Chinese medicine and western medicine. World Sci Technol Mod Tradit Chin Med 1929–1935
15. Patel JL, Goyal RK (2007) Applications of artificial neural networks in medical science. Curr Clin Pharmacol 2(3):217–226
16. Wang J, Li Y, Wang Q (2019) Identification of Chinese medicine constitution in public health services. Chin J Integr Med 25(7):550–553
17. Jiang QY, Li J, Zheng L et al (2018) Constitution of traditional Chinese medicine and related factors in women of childbearing age. J Chin Med Assoc 81(4):358–365
18. Xu X, Zeng Q, Ding H et al (2014) Correlation between women's sub-health and reproductive diseases with pregnancies and labors. J Tradit Chin Med 34(4):465–469
19. He QH, Zeng S (2008) Children's sub-health is based on spleen. Chin Med Mod Distance Educ China 6(9):991–992
20. Hou JH (2002) Spleen-stomach disharmony and children's sub-health. J Tradit Chin Med 43(9):716–717
21. Qiu ZF (2021) Clinical effect analysis of three-character meridian massage for children with sub-health state of spleen deficiency. Cap Med 28(6):173–174
22. Zheng B, Zhang X, Zhang W (2019) The effect of press needle on children with spleen deficiency Tye sub-health based on the theory of preventive treatment. Chin Med Mod Distance Educ China 17(6):79–81
23. Zhou R, Chen Z, Liu LP (2022) Treating 69 cases of sub-health insomnia by Suanzaoren Tang and Guipi Pills from synopsis of golden chamber. Western J Tradit Chin Med 35(10):90–93
24. Zhang H, Dong F, Huang BM et al (2021) Treatment of sub-health in children with acupoint application based on the solar terms. Henan Tradit Chin Med 41(8):1159–1162
25. Song YY, Zhang H, Chu CZ (2020) Investigation and research on sub-health constitution of 3 to 6-year-old Children in Southern Anhui province-a case study in Jinghu district of Wuhu City. Mod Chin Med 40(1):108–112
26. Pei J, Zhong K, Li J, Yu Z (2022) PAC: partial area clustering for re-adjusting the layout of traffic stations in city's public transport. IEEE Trans Intell Transp Syst 24:1251–1260
27. Jin L, Sun YL, Jiang LR et al (2013) Effect of yunpi prescription early intervention on food consumption and subcutaneous fat thickness of sub-health children with nutritional deficiency. Chin J Inf Tradit Chin Med 20(1):75–76
28. Li X (2008) Observation on the therapeutic effect of Tianmeng oral liquid on patients with sub-healthy insomnia. China Med 3(z1):19–20
29. Yucesan M, Gul M (2020) Hospital service quality evaluation: an integrated model based on Pythagorean fuzzy AHP and fuzzy TOPSIS. Soft Comput 24(5):3237–3255
30. Barouni M, Ahmadian L, Anari HS et al (2021) Investigation of the impact of DRG based reimbursement mechanisms on quality of care, capacity utilization, and efficiency-a systematic review. Int J Healthc Manag 14(4):1463–1474
31. Kalfa M, Yetim AA (2020) Organizational self-assessment based on common assessment framework to improve the organizational quality in public administration. Total Qual Manag Bus Excell 31(11–12):1307–1324