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Research on radar signal recognition based on automatic machine learning

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Abstract

With the advancement of machine learning and radar technology, machine learning is becoming more and more widely used in the field of radar. Radar scanning, signal acquisition and processing, one-dimensional range image, radar SAR, ISAR image recognition, radar tracking and guidance are all integrated into machine learning technology, but machine learning technology relies heavily on human machine learning experts for radar signal recognition. In order to realize the automation of radar signal recognition by machine learning, this paper proposes an automatic machine learning AUTO-SKLEARN system and applies it to radar radiation source signals. Identification: Firstly, this paper briefly introduces the classification of traditional machine learning algorithms and the types of algorithms specifically included in each type of algorithm. On this basis, the machine learning Bayesian algorithm is introduced. Secondly, the automatic machine learning AUTO based on Bayesian algorithm is proposed. -SKLEARN system, elaborates the process of AUTO-SKLEARN system in solving automatic selection algorithm and hyperparameter optimization, including meta-learning and its program implementation and automatic model integration construction. Finally, this paper introduces the process of automatic machine learning applied to radar emitter signal recognition. Through data simulation and experiment, the effect of traditional machine learning *k*-means algorithm and automatic machine learning AUTO-SKLEARN system in radar signal recognition is compared, which shows that automatic machine learning is feasible for radar signal recognition. The automatic machine learning AUTO-SKLEARN system can significantly improve the accuracy of the radar emitter signal recognition process, and the scheme is more reliable in signal recognition stability.

Keywords Radar signal recognition · Automatic machine learning · AUTO-SKLEARN algorithm · Model integration

1 Introduction

In the modern international war environment, electronic warfare, that is, electronic warfare, has become another important battlefield besides sea, land and air. In the past half century, electronic warfare technology has become increasingly important in local wars that have broken out in various parts of the world. Countries all over the world have gradually realized the critical guiding role of electronic countermeasures technology in the success or failure of future wars. Whoever masters the key technologies of electronic warfare to the greatest extent, and whoever has mastered the right to speak and control the war in the future. Knowing ourselves and knowing each other and winning every battle, electronic reconnaissance technology is bound to become the most important technology in electronic warfare. Only by knowing the various information in a relatively detailed way can we more effectively interfere with the suppression, suppression and cracking of the other party's electronic countermeasure equipment, and then provide a strong guarantee for the correct functioning of electronic devices. The goal of electronic countermeasures is to obtain electromagnetic confrontation and

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information superiority in the battlefield environment, and then win the battle.

In the modern battlefield, there are many kinds of war weapons. Unlike the physical offensive weapons, radar [1], as a key link in electronic confrontation, plays an incomparable role in electronic investigation. The accuracy of radar emitter signal identification directly affects the direction of various decisions in the entire electronic warfare environment and has an incomparable position in electronic warfare. By timely obtaining the signal information of the enemy radar, the obtained radar signal [2] information is processed and analyzed by digital signal processing technology, and then, relevant important information such as radar parameters is analyzed.

Radar emitter [3] identification can usually be divided into radar emitter signal identification, radar threat level evaluation and estimation of radar identification credibility and so on. Radar source signal identification is an important research content of systems such as electronic support measures, electronic intelligence reconnaissance, and radar seek and alarm. It determines the performance of the electronic reconnaissance system, and even the key to the electronic warfare. At the same time, it is also an important basis for the situation assessment of threat assessment and high-level information fusion. To some extent, it represents the advanced level of electronic countermeasures technology. Therefore, research on the identification of radar emitter signals is of great significance.

In the process of identifying the radar source signal, the obtained radar signal is first preprocessed, and the relatively obvious parameter information is extracted, and the basis for subsequent recognition is laid; then, the specific recognition algorithm is adopted. The characteristics of the radar signal are extracted. These features include both the actual parameter information of the radar signal and some important information obtained after the secondary processing. Finally, the feature parameters are obtained and classified to obtain a matching output result.

In general, the identification of radar emitters refers to the type analysis of the signals received by the unknown sources to determine the type of radar, thus creating conditions for further completing the threat determination of the radar and making corresponding countermeasures. The important parameters of the traditional radar emitter signal are: DOA [4–6], PW [7], TOA [8] and PA and RF [9].

There are many traditional identification methods for the identification of radar radiation source signals, but there are shortcomings such as low accuracy and long operation time. With the continuous research of artificial intelligence machine learning [10] and pattern recognition methods, it is realized. After signal feature extraction, the performance of the radiation source signal recognition is further improved by optimizing, merging and designing an excellent classifier.

The machine learning algorithm aims to autonomously find the law from a class of unknown data, and then use this rule to classify the remaining data or predict the next incoming data in advance. Machine learning can also provide guarantees and basis for decision making through the calculation of big data and the mining of hidden data. Machine learning algorithms fall into three categories: supervised learning algorithms, unsupervised learning algorithms and enhanced learning algorithms. There are ten specific methods for supervised learning algorithms and unsupervised learning algorithms: decision tree [11], *k*-means algorithm [12], naive Bayes [13], *K*-NN algorithm, association rule algorithm [14], clustering [15], neural network [16], SVM [17], integrated learning and principal component analysis [18].

As an important method of pattern classification and recognition, machine learning has achieved considerable success in recent years. However, the key to this success depends heavily on the preprocessing of data by human machine learning experts, the selection of appropriate features, the selection of classification models, optimization of model hyperparameters and critical analysis of results. These behaviors of human machine learning experts often go beyond the capabilities of non-application experts, and even for experienced industry experts, it is not easy to accomplish these tasks of data processing, algorithm selection and parameter configuration. So fast-growing machine learning applications promote and create a need for machine learning solutions that are easier to use and require no expert knowledge. This paper proposes a learning solution for machine learning automation—automatic machine learning [19].

Automated machine learning refers to the automatic design of preprocessing and feature recognition processes such as feature selection and feature transformation, and automatically performs hyperparameter tuning. In addition to inputting data, the input can be realized without more manual intervention. Machine learning of data: At present, the research of automatic machine learning mainly focuses on optimizing the model parameters to find the model parameter configuration that can maximize the classification accuracy, especially the model parameters obtained by Bayesian optimization, which has always been ideal or even better than manual adjustment. The classification effect: Automatic machine learning makes the application of machine learning easier. Users do not need to do a lot of relevant knowledge reserves as before, and they can get a well-performing machine learning solution. Radar emitter signal recognition is an application scenario of machine learning. It can also produce some organic combination with automatic machine learning.

In order to solve the algorithm selection and hyperparameter optimization of radar emitter signal recognition, this paper proposes the AUTO-SKLEARN system in the field of automatic machine learning. This method can master and utilize more intelligent algorithms and data processing methods for radar emitter signals. Identification, by testing the effect of AUTO-SKLEARN on the radar signal on the classification and recognition, automatic machine learning of the transformation feature with AUTO-SKLEARN, improving the radar radiation source signal while solving the parameter optimization problem Identify the effect. The specific contributions of this paper are as follows:

(1) Machine learning is more and more widely used in the field of radar signal recognition. However, in the radar signal recognition process, experts in the field are required to select appropriate algorithms and hyperparameter optimization, which will consume a large amount of expert manpower. In this paper, an automatic machine learning AUTO-SKLEARN system with automatic selection algorithm and hyperparameter optimization is proposed.
(2) For the AUTO-SKLEARN system to automatically select the appropriate algorithm and hyperparameter optimization, this paper proposes Bayesian optimization and learning to learn.

2 Proposed method

Radar source signal identification plays a vital role in the battlefield. The traditional way is to identify the conventional eigenvalue azimuth [20], pulse arrival time, pulse width and pulse amplitude [21] of the radar source signal, and to develop it later. The identification of the intra-pulse characteristics of the radar signal is used. The identification methods include template matching method, PRI sorting method, multi-parameter correlation comparison method and multi-parameter sorting method, and extracting signal intra-oral features for sorting algorithms. With the rapid development of radar technology, the electromagnetic environment is increasingly complex. The traditional recognition method does not work well. With the research of artificial intelligence algorithms in recent years, machine learning based on big data is well applied in radar emitter signal recognition. Through the calculation of big data and the mining of hidden data, it can provide guarantee and basis for data prediction and decision making.

Machine learning algorithms can be divided into four categories: traditional machine learning, neural network [16], support vector machine and integrated learning [22]. Among them, traditional machine learning mainly includes Bayesian classifier, nearest neighbor classifier and decision tree classifier; neural network includes BP neural network [23], RBF neural network [22, 24] and its improved algorithm; support vector machine algorithm mainly includes polynomial kernel SVM, RBF kernel SVM and its improved algorithm; integrated learning algorithm mainly includes Bagging algorithm and its improved algorithm. The automatic machine learning algorithm proposed in this paper is based on machine learning Bayesian algorithm optimization design.

2.1 Machine learning—Bayesian algorithm

As a probabilistic statistical method, the Bayesian method has been applied in related work by many meteorological research personnel, and the achievements have been remarkable. The Bayesian classifier with Bayesian idea is a very complex probability classifier. It can directly estimate the parameters based on the training data and does not need to learn, so it has the advantages of high efficiency and good generalization ability. The Bayesian method combines a priori information with sample knowledge and corrects the prior probability. This feature makes the Bayesian learning theory not too small in the field of data mining.

2.1.1 Bayesian formula principle

For any pair of random variables $X, Y : P(X, Y) = P(Y|X)P(X) = P(X|Y)P(Y)$ after adjustment, the following formula, called Bayesian formula, can also be called Bayesian' theorem:

$$P(Y|X) = \frac{P(Y)P(X|Y)}{P(X)} \tag{1}$$

Similarly, we can apply the Bayesian formula to the probability calculation of multidimensional random variables. The calculation formula is as follows:

$$P(Y_i|X_j) = \frac{p(Y_i)P(X_j|Y_i)}{\sum_{k=1}^{m} p(Y_i)P(Y_k|Y_i)} \tag{2}$$

Among them i = 1, 2, 3, …, n, j = 1, 2, …, m.

For formulas (1) and (2), $P(Y)$ and $P(Y_i)$ are called prior probabilities, and $P(Y|X)$ and $P(Y_i|X_j)$ are called the posterior probability. The result calculated by the Bayesian formula is called the Bayesian probability. In summary, the biggest advantage of the Bayesian formula is that it can establish the relationship between the probability problem of a complex event and the probability of several incompatible events. Therefore, we can infer the probability of a complex event by separately observing multiple repeated trial data of several simple events. Compared with the traditional method, the calculation difficulty is greatly reduced and the calculation cycle is shortened.

2.1.2 Bayesian classification

The Bayesian classification method is the most likely classification method based on the existing theoretical knowledge. For example, for any particular one $I = \{x_1, x_2, \ldots, x_l\}$, the result $P\{x_1, x_2, \ldots, x_l\}$ with the highest probability can be determined by the Bayesian classification method as the class label of the event. Among them, $\{x_1, x_2, \ldots, x_l\}$ collectively referred to as the attribute variable (predictor) of the event, the events I in the above example have a total l of attribute variables, C_k will be called class variables, and k is the number of categories. Thus, the probability of a class in an event $I\{x_1, x_2, \ldots, x_l\}$ can be calculated by:

$$P(C_k|x_1, x_2, \ldots, x_l) = \frac{p(x_1, x_2, \ldots, x_l|C_k)P(C_k)}{P(x_1, x_2, \ldots, x_l)} \quad (3)$$

In the above formula, $P(C_k)$ is the prior probability of class C_k, $P(C_k|x_1, x_2, \ldots, x_l)$ is called the posterior probability of class C_k, $P(x_1, x_2, \ldots, x_l|C_k)$ is the conditional probability when attribute variable $\{x_1, x_2, \ldots, x_l\}$ appears in class C_k, and $P\{x_1, x_2, \ldots, x_l\}$ is the probability that attribute variable $\{x_1, x_2, \ldots, x_l\}$ occurs at the same time. Therefore, the calculation result of the posterior probability is related to the selected sample information, and the obtained is often more accurate. The probability of occurrence of the category corrected by the information (3) can be transformed into the following form:

$$P(C_k|x_1, x_2, \ldots, x_l) = \alpha \cdot P(C_k) \cdot \prod_{i=1}^{l} P(x_i|x_1, x_2, \ldots, x_{i-1}, C_k) \quad (4)$$

The α in the formula is called the regularization factor: $\alpha = \frac{1}{P(x_1, x_2, \ldots, x_l)}$.

According to the Bayesian maximum a posteriori criterion, for a given instance $I\{x_1, x_2, \ldots, x_l\}$, the Bayesian classification will actively filter out the class C_k with the largest posterior probability value $P(C_k|x_1, x_2, \ldots, x_l)$ from all categories, and define event I as class C_k.

Therefore, the difference between Bayesian classification and traditional classification is summarized as follows:

1. Different from the traditional taxonomy, the Bayesian classification method determines the class to which an object belongs according to the principle of maximum probability, that is, it calculates the probability that an object may belong to each category and defaults it to the maximum probability.
2. Under normal conditions, all attributes of an event in the Bayesian classification participate in the classification calculation process and have an effect on the classification result.
3. The types of classification objects are variable and can be adapted to a variety of different situations, such as continuous, discrete or mixed with the case object attributes.

2.2 Proposal of automatic machine learning algorithm

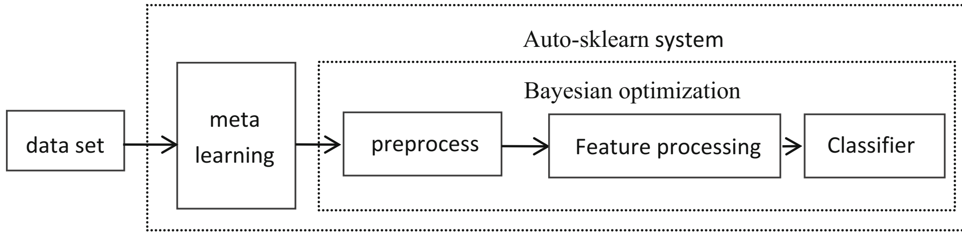
The radar radiation source signal is identified by the machine learning pattern recognition system: Firstly, the radar data are measured; then, the data are preprocessed; then, the signal features are extracted and selected; finally, the classifier and feature classification and identification are designed. How to choose the appropriate preprocessing method, feature extraction and selection method, classification algorithm and hyperparameter configuration of all the above algorithms in the above identification process needs to rely on experienced researchers and consume a large proportion of time. Therefore, in the radar signal recognition, how to develop an algorithm that can automatically configure hyperparameters and select data processing and classification according to data characteristics is presented. In this paper, an automatic machine learning algorithm AUTO-SKLEARN system is proposed based on the combination of algorithm selection and hyperparameter optimization in radar signal recognition.

The framework of the AUTO-SKLEARN system is shown in Fig. 1. For the datasets that need to be trained, firstly, some machine learning framework models whose performance is most likely to be excellent and their hyperparameter configuration are selected through meta-learning, and then in these models and configuration ranges. Bayesian optimization is performed internally, and finally, a model hyperparameter configuration that is most recommended for use is obtained.

AUTO-SKLEARN contains 15 base classifiers: two generalized linear models, two support vector machines, two discriminant analysis methods, one nearest neighbor algorithm, three naive Bayesian methods, one decision tree and four integrated learning methods. In addition to the choice of classifiers, AUTO-SKLEARN also includes a number of different feature preprocessing algorithms that can be selected by Bayesian optimization, and before the above algorithm, the data are preprocessed as follows:

(1) The classification feature is encoded using a unique thermal coding to convert it into a numerical feature.
(2) Replace the default values in the dataset with the mean, median or most frequent values.

Fig. 1 AUTO-SKLEARN system frame structure



(3) Rescale the data, normalize the features to a mean of zero or normalize them to a range of 0–1. Or normalize the dataset to have a unit length, or leave some features unprocessed.

2.2.1 Meta-learning

Meta-learning [25, 26] is also known as learning to learn. In the field of machine learning, it refers to the ability of computers to choose which machine learning method to choose. Meta-learning is actually a typical learning method that guides sample data through big data. It has become another important research branch after reinforcement learning.

Meta-learning infers by evaluating the performance of cross-dataset learning algorithms to mimic this strategy. In this process, by machine learning a large number of datasets, the relationship between certain features of the dataset and the corresponding appropriate learning algorithm is found, so that when a new dataset is encountered, the system can automatically determine Identifying algorithms that are more suitable for such data greatly reduces the search range of algorithm selection and hyperparameter optimization, and significantly improves efficiency.

The specific method is to learn and identify the massive datasets by using the algorithm in the algorithm set, collect their recognition performance data and generate a set of feature transformations for selecting the meta-features of the algorithm, that is, the characteristics of the dataset that can be effectively calculated. Before adopting the Bayesian optimization method for algorithm selection and hyperparameter optimization, the meta-features of the training set are extracted first, and it is judged which algorithms perform well on this dataset, and then, the most suitable algorithm and super is found in these algorithms parameter.

This meta-learning method is complementary to Bayesian optimization for algorithm selection and hyperparameter optimization. Meta-learning can quickly provide a framework for algorithms that can perform well, but it does not provide fine-grained information representation, is it only narrows the scope. In contrast, Bayesian optimization starts slowly, and its degree of slowness is positively correlated with the size of the hyperparameter space corresponding to the entire algorithm space.

2.2.2 Bayesian optimization

The Bayesian optimization method based on tree structure realizes the process of automatic machine learning. Bayesian optimization is used to train a probabilistic model to capture the relationship between hyperparameter setting and classification performance, and then use this model to select the most promising hyperparameter setting, in which a known well-behaved hyperparameter area and an unknown hyperparameter area with good performance potential are evaluated, the configuration of the hyperparameter is evaluated, and the model is updated based on this result and iterated.

2.2.3 Automatic model integration build

AUTO-SKLEARN uses meta-learning methods to quickly target a group of machine learning frameworks with good performance potential, then perform hyperparameter optimization and automatically build model integration to avoid discarding some outstanding models. In order not to discard these models, AUTO-SKLEARN stores them and builds them into an assembly. This automatic integration model avoids simplification of hyperparameter settings and is more robust than point estimation using standard hyperparameter optimization and is less prone to overfitting. In AUTO-SKLEARN, the method of constructing a model combination is a cumulative process starting from an empty set, in which a stepwise iteration adds a model that optimizes the performance of the combination to the combination.

2.3 Application process of automatic machine learning in radar signal recognition

As the key development direction of artificial intelligence technology, automatic machine learning can automatically select the processing and classification methods that conform to the characteristics of data according to the rules learned in the database samples, saving a lot of labor costs for experts in the field of radar signal processing. The flow of radar source signal recognition based on automatic machine learning is shown in Fig. 2.

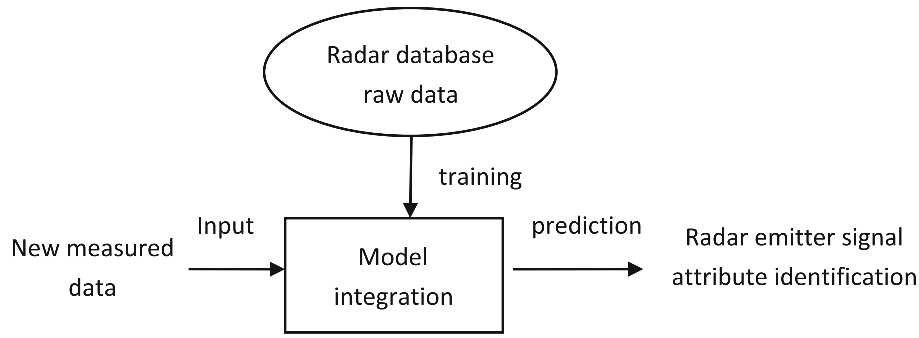


Fig. 2 Automatic machine learning radar radiation source signal identification flow chart

The radar source signal classifier based on automatic machine learning is fundamentally a mapping $c' : X \rightarrow Y$, and the $c'(x)$ function is a rough estimate of the true mapping $c(x)$. The sample form used to train the classifier is $(x, c(x))$, where $x \in X$ is the known sample in the radar database and $c(x)$ is the real category to which the sample belongs. The purpose of automatic machine learning is to automatically create a function c', so that the value of function c' is as close as possible to the real c, in order to improve the accuracy of the attribute information of the radiation source to be identified.

Let $X = \{x_1, x_2, \ldots, x_n\}$ be the set of samples in the radar database, $T = \{t_1, t_2, \ldots, t_k\}$ be the feature vector composed of k feature parameters contained in the sample, and $Y = \{c_1, c_2, \ldots, c_m\}$ is a finite set of class labels with a small base. The known data sample $x_i \in X$ and the corresponding label $C_j \in Y$ are input into the classifier for training, the signal characteristics to be identified are input into the trained classifier, and the corresponding signal category and radiation source information can be obtained.

3 Experiments

Based on the application of automatic machine learning AUTO-SKLEARN system in radar signal recognition, this paper focuses on the effect of radar emitter signal pattern recognition. In order to compare the recognition effect of automatic machine learning, the *k*-means algorithm is used in the experiment. The set of signal recognition, by comparing the accuracy of the two algorithms to the radar emitter signal recognition, based on automatic machine learning, can improve the effect of signal recognition. In this paper, the process of applying the AUTO-SKLEARN system to the radar radiation source signal identification is shown in Fig. 3. In the process of executing the AUTO-SKLEARN system, the calculation efficiency is improved by limiting the evaluation time, and the dataset is converted by the unique heat coding method. After that, the system is optimized to obtain the integration of each recognition model. Each recognition model occupies a corresponding proportion in the model integration. Finally, the set hyperparameters are optimized, and the execution system and algorithm identify the radar signals and statistically identify the effects.

This experiment is to test the effect of AUTO-SKLEARN method, with radar signal CF, PW, PA and four intra-pulse characteristic information dimensions. Wavelet ridge frequency is combined to form feature set 1, and a plurality of hidden layer features is formed on feature set 1 to form feature set 2. In the above figure, the model integration classification of the AUTO-SKLEARN execution process is completed and the *k*-means algorithm is operated and tested 8 times in the two datasets provided by the five radars, respectively, and the results of the signal recognition effect comparison analysis are obtained, as shown in Table 4 of the fourth part. 4 and shown in Figs. 4 and 5.

In order to judge the comparison between the AUTO-SKLEARN system and the *k*-means algorithm for radar emitter signal recognition, SRA is used as the evaluation parameter of radar signal recognition. The formula for correcting the radiation source signal identification is as follows:

$$\mathrm{SRA} = \left(1 - \frac{N_{\mathrm{r}}}{N_{\mathrm{t}}}\right) \times 100\% \tag{5}$$

Among them, N_{r} is the number of error samples identified by the radar emitter signal feature set and N_{t} is the total number of samples of the actual radar emitter signal feature set.

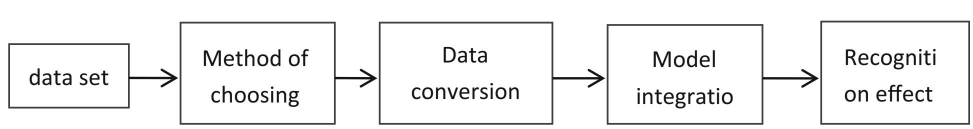


Fig. 3 Flow of the radar source signal identification applied by the AUTO-SKLEARN system

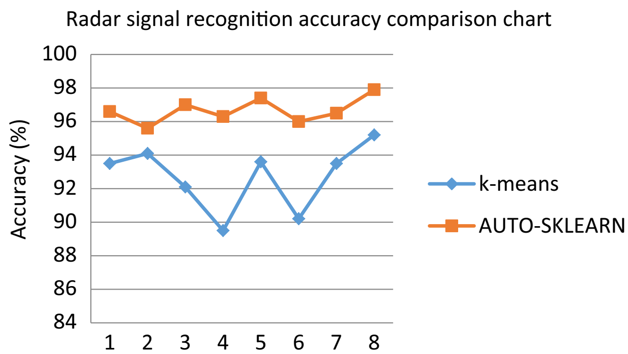


Fig. 4 Comparison of the effect of each experiment on the feature 1 of the two methods

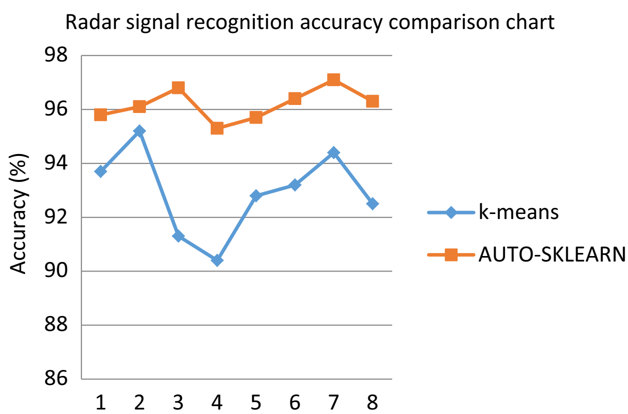


Fig. 5 Comparison of the effect of each experiment on the feature 2 of the two methods

4 Discussion

In order to improve the recognition effect of the radar radiation source signal, this paper uses the automatic machine learning algorithm AUTO-SKLEARN to identify the radar signal and compare the recognition effect of the machine learning *k*-means algorithm. In this experiment, the radiation source signals are extracted from 5 groups of radars. The number of samples of each radar feature set is shown in Tables 1 and 2. On the basis of feature set 1 and feature set 2, the radar signals are identified by two algorithms, respectively. Eight times the results of 8 experiments were obtained. The comparison of the average accuracy of the radar signal recognition of the two algorithms is shown in Tables 3 and 4. The model integration hyperparameter setting is mainly for 4 modules, which are Adaboost module (a multi-classifier algorithm), random deep forest module, feature aggregation module and decision tree module.

From the results of the identification of the five radar emitter signals from Tables 1 and 2, it can be found that the accuracy of the radar source signal recognition using the AUTO-SKLEARN algorithm is above 94%, and the *k*-means algorithm is used under the same conditions. The radar source signal recognition accuracy is at least 90%, which is more than four percentage points lower than the automatic machine learning algorithm; the AUTO-SKLEARN algorithm is more accurate than the *k*-means algorithm in the feature set 1 and feature set 2 for the identification of radar signal samples. The rate is two percentage points higher.

According to the comparison data of Tables 3 and 4, the radar radiation source signal identification contrast line diagrams of different methods as shown in Figs. 4 and 5 are drawn. By identifying the effect of the eight repeated experiments shown in the figure below, it can be intuitively found to adopt. The mode-integrated AUTO-SKLEARN system outperforms the *k*-means algorithm in radar signal recognition, which not only has higher recognition accuracy, but also has a stable accuracy distribution of the identification signal, while the recognition accuracy of the *k*-means algorithm fluctuates. To a great extent, the data comparison shows that the radar signal recognition scheme of the automatic machine learning algorithm is more reliable.

The recognition rate of the radar emitter signal is closely related to the number of signal iterations. The optimal number of iterations of the automatic machine learning AUTO-SKLEARN system and the machine learning *k*-means algorithm is obtained through experiments, and the penalty factors of each algorithm are set on this basis. It maximizes the recognition rate of the radar working mode. By setting the number of iterations of AUTO-SKLEARN system to 20, $C = 160$, the pattern recognition rate reaches 96%; the number of iterations of *k*-means algorithm is 30, $C = 260$, and the pattern recognition rate also reaches the highest value of 88%. The specific results are shown in Table 5.

As shown in Table 6 and Fig. 6, the two algorithms have different average recognition rates for the modulation modes of the radar radiation source signals. The AUTO-SKLEARN system recognition rate is 87.6%, and the *k*-means algorithm recognition rate is 80.9%. The automatic machine learning algorithm is for radar. The recognition rate of the signal modulation method is nearly seven percentage points higher. In the process of identifying eight types of modulation methods, the recognition rate of the fourth type and the fifth type is lower: The fourth type of modulation is [jitter, dwell, slip], and the fifth type of modulation is [fixed, resident, slipping], that is, PW and PRI modulation is the same, and the fourth type of RF modulation is fixed; in the case of noise, it is easy to be confused with the fifth type of modulation, which is divided into one class.

Table 1 Comparison of the recognition effects of the two algorithms on feature set 1 (%)

Radar numbering	*k*-Means algorithm			AUTO-SKLEARN		
	Total number of samples	Identify the number of incorrect samples	Recognition accuracy	Total number of samples	Identify the number of incorrect samples	Recognition accuracy
1	150	5	96.7	150	4	97.3
2	140	14	90.0	140	5	96.4
3	130	6	95.4	130	5	96.2
4	120	10	91.7	120	3	97.5
5	110	7	93.6	110	5	95.5
Average accuracy	93.5			96.6		

Table 2 Comparison of the recognition effects of the two algorithms on feature set 2 (%)

Radar numbering	*k*-Means algorithm			AUTO-SKLEARN		
	Total number of samples	Identify the number of incorrect samples	Recognition accuracy	Total number of samples	Identify the number of incorrect samples	Recognition accuracy
1	165	6	96.4	165	4	97.6
2	155	11	93.5	155	5	96.8
3	145	9	93.8	145	8	94.5
4	135	10	92.6	135	6	95.6
5	125	10	92	125	7	94.4
Average accuracy	93.7			95.8		

Table 3 Comparative analysis of the recognition effects of eight replicate experiments in feature set 1 by different methods

Method	Recognition accuracy (%)							
	1	2	3	4	5	6	7	8
AUTO-SKLEARN	96.6	95.6	97	96.3	97.4	96	96.5	97.9
k-Means algorithm	93.5	94.1	92.1	89.5	93.6	90.2	93.5	95.2

Table 4 Comparative analysis of the recognition effects of eight replicate experiments in feature set 2 by different methods

Method	Recognition accuracy (%)							
	1	2	3	4	5	6	7	8
AUTO-SKLEARN	95.8	96.1	96.8	95.3	95.7	96.4	97.1	96.3
k-Means algorithm	93.7	95.2	91.3	90.4	92.8	93.2	94.4	92.5

Table 5 Working mode recognition rate of two algorithms under optimal parameters (%)

Comparison of algorithm working pattern recognition rate	C	Number of iterations	Recognition rate
AUTO-SKLEARN	160	20	96.32
k-Means algorithm	260	30	88.16

Table 6 Identification rate of modulation schemes of the two algorithms in various categories of radar radiation sources (%)

Comparison of modulation method recognition rate	1	2	3	4	5	6	7	8	Average
AUTO-SKLEARN	100	100	100	61	50	93	97.1	100	87.6
k-Means algorithm	100	45	68	93	55	92	94.4	100	80.9

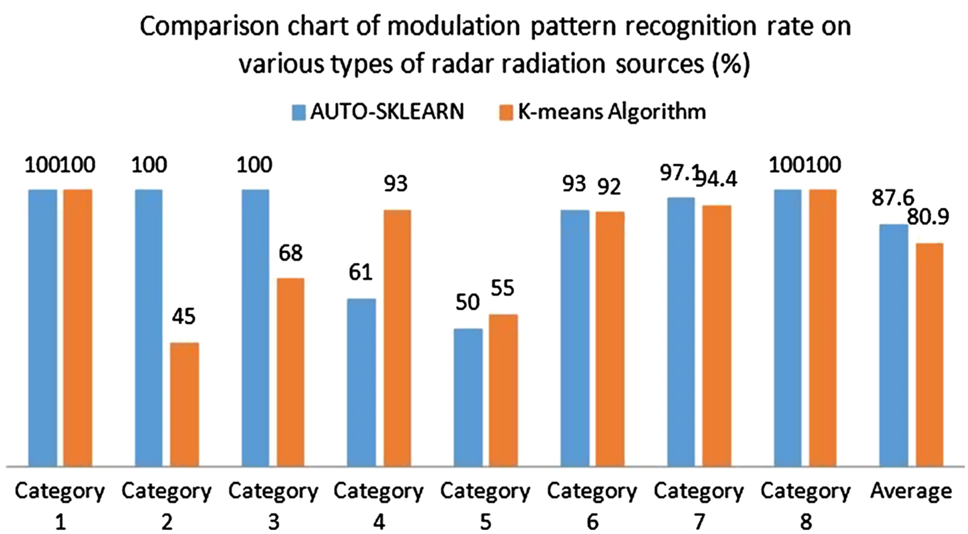


Fig. 6 Comparison chart of modulation recognition rate between the two algorithms on different types of radar radiation sources

After modulating the radar radiation source, the working mode parameters of each radar are clustered, and then, there are two methods to identify the radar working mode. The average value of the accuracy of each working mode of each radar is used as the radar work. The recognition rate of the pattern. According to the dataset identified by the two algorithms, the working mode is recognized, and the recognition rate of the working mode of the radar source is shown in Table 7 and Fig. 7.

5 Conclusions

With the continuous development of computer technology and machine learning, radar technology has also entered a stage of rapid development. How to identify radar signals quickly and effectively has become a hot topic in the military field. Based on machine learning is proposed a kind of automatic machine learning system, and its application in radar emitter signal recognition, by comparing the effect of different methods for the recognition of radar signal found that automatic machine learning AUTO-SKLEARN system can improve the recognition of radar emitter signals is accuracy and stable solutions to identify data, guaranteed reliability, this paper puts forward the automatic recognition of radar signal machine learning system is feasible. After introducing the principle and classification of machine learning Bayesian algorithm, this paper proposes an AUTO-SKLEARN system based on Bayesian optimization and introduces the meta-learning and its implementation scheme and automatic model integration in the system. Finally, the automatic machine is introduced. Learn the process applied to radar emitter signal identification. In the experimental process, the working modes of the two algorithms under optimal parameterization, the radar modulation mode and the recognition rate of the radar radiation source working mode are compared and analyzed. On the basis of selecting two feature sets, the radars of various models are selected. The data provided are executed by the AUTO-SKLEARN system. Through simulation analysis, firstly, the measures to limit the evaluation time can reduce the computation time and improve the efficiency of signal recognition. Secondly, compared with the traditional machine learning

Table 7 Comparison of recognition rates of radar radiation source working modes (%)

Comparison of working pattern recognition rate	1	2	3	4	5	6	7	8	Average
AUTO-SKLEARN	100	100	97	47	73	95	100	98	88.8
k-Means algorithm	100	49	68	86	58	92	96	98	80.9

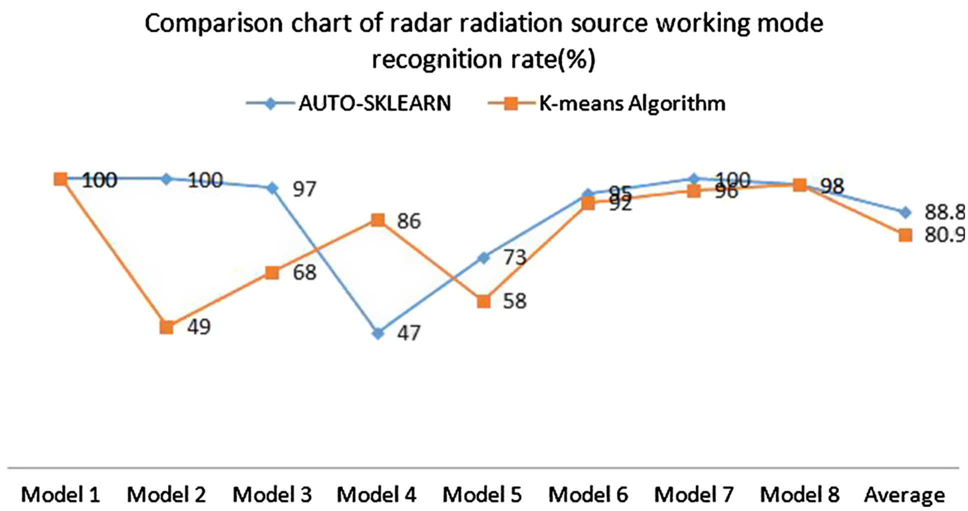


Fig. 7 Comparison chart of radar radiation source working mode recognition rate

k-means algorithm, the automatic machine learning method proposed in this paper has higher signal. The recognition accuracy rate is reflected in the application of automatic machine learning algorithm and radar source signal identification, and the stability of the identification scheme is more reliable.

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Compliance with ethical standards

Conflict of interest There are no conflicts of interests.

References

1. Long T, Zeng T, Hu C, Dong X, Chen L, Liu Q, Xie Y, Ding Z, Li Y, Wang Y, Wang Y (2019) High resolution radar real-time signal and information processing. China Commun 16(02):105–133
2. Jazayeri S, Saghafi A, Esmaeili S, Tsokos CP (2019) Automatic object detection using dynamic time warping on ground penetrating radar signals. Expert Syst Appl 122:102–107
3. Rong H, Cheng J, Li Y (2013) Radar emitter signal analysis with estimation of distribution algorithms. J Netw 8(1):108
4. Zheng Z, Lu J, Wang W-Q, Yang H, Zhang S (2018) An efficient method for angular parameter estimation of incoherently distributed sources via beamspace shift invariance. Digit Signal Process 83:261–270
5. Hermessi H, Mourali O, Zagrouba E (2018) Convolutional neural network-based multimodal image fusion via similarity learning in the shearlet domain. Neural Comput Appl 30:2029. https://doi.org/10.1007/s00521-018-3441-1
6. Cao R, Zhang X (2018) Computationally efficient MUSIC-based algorithm for joint direction of arrival (DOA) and Doppler frequency estimation in monostatic MIMO radar. Trans Nanjing Univ Aeronaut Astronaut 35(06):1053–1063
7. Ter-Avetisyan S, Singh PK, Kakolee KF, Ahmed H, Jeong TW, Scullion C, Hadjisolomou P, Borghesi M, Bychenkov VY (2018) Ultrashort PW laser pulse interaction with target and ion acceleration. Nuclear Inst Methods Phys Res A 909:156–159
8. Bayat B, van der Tol C, Verhoef W (2018) Retrieval of land surface properties from an annual time series of Landsat TOA radiances during a drought episode using coupled radiative transfer models. Remote Sens Environ 47(1):339–349
9. Wen C, Tao M, Peng J, Wu J, Wang T (2018) Clutter suppression for airborne FDA-MIMO radar using multi-waveform adaptive processing and auxiliary channel STAP. Signal Process 154:280–293
10. da Costa KAP, Papa JP, Lisboa CO, Munoz R, de Albuquerque VHC (2019) Internet of things: a survey on machine learning-based intrusion detection approaches. Comput Netw 151:147–157
11. Chen W, Zhang S, Li R, Shahabi H (2018) Performance evaluation of the GIS-based data mining techniques of best-first decision tree, random forest, and naïve Bayes tree for landslide susceptibility modeling. Sci Total Environ 644:1006–1018
12. Gong H (2018) Tibetan character recognition based on machine learning of K-means algorithm. In: Proceedings of 2018 international conference on computer modeling, simulation and algorithm (CMSA2018), vol 3. Advanced Science and Industry Research Center, Science and Engineering Research Center
13. Wu J (2018) A generalized tree augmented naive Bayes link prediction model. J Comput Sci 27:206–217
14. Sarvari PA, Ustundag A, Takci H (2016) Performance evaluation of different customer segmentation approaches based on RFM and demographics analysis. Kybernetes 45(7):1129–1157
15. Elavarasan D, Vincent DR, Sharma V, Zomaya AY, Srinivasan K (2018) Forecasting yield by integrating agrarian factors and machine learning models: a survey. Comput Electron Agric 155:257–282
16. Wan J, Chen B, Xu B, Liu H, Jin L (2019) Convolutional neural networks for radar HRRP target recognition and rejection. EURASIP J Adv Signal Process 2019(1):1–17
17. Panda AK, Rapur JS, Tiwari R (2018) Prediction of flow blockages and impending cavitation in centrifugal pumps using support vector machine (SVM) algorithms based on vibration measurements. Measurement 130:44–56
18. Uddin MN, Islam AKMS, Bala SK, Islam GMT, Adhikary S, Saha D, Haque S, Fahad MGR, Akter R (2019) Mapping of

climate vulnerability of the coastal region of Bangladesh using principal component analysis. Appl Geogr 102:47–57
19. Song Z (2018) Study on automatic identification technology of greenhouse tomato pests and diseases based on machine learning. In: Proceedings of 2018 2nd international conference on systems, computing, and applications (SYSTCA 2018), vol 4. International Information and Engineering Association, Computer Science and Electronic Technology International Society
20. Guan RP, Ristic B, Wang L, Evans R (2018) Monte Carlo localisation of a mobile robot using a Doppler–Azimuth radar. Automatica 97:161–166
21. Curcio A, Dolci V, Lupi S, Petrarca M (2018) Terahertz-based retrieval of the spectral phase and amplitude of ultrashort laser pulses. Opt Lett 43(4):783–786
22. Panigrahi PK, Ghosh S, Parhi DR (2014) A novel intelligent mobile robot navigation technique for avoiding obstacles using RBF neural network. In: Proceedings of the 2014 international conference on control, instrumentation, energy and communication (CIEC). IEEE
23. Kun Q, Tian-zhen W, Tian-hao T, Claramunt C (2014) A novel local BP neural network model and application in parameter identification of power system. In: 33rd Chinese control conference (CCC)
24. Li X (2014) Study on traffic flow base on RBF neural network. In: 2014 sixth international conference on measuring technology and mechatronics automation (ICMTMA)
25. Pimentel BA, de Carvalho ACPLF (2019) A new data characterization for selecting clustering algorithms using meta-learning. Inf Sci 477:203–219
26. Chu X, Cai F, Cui C, Hu M, Li L, Qin Q (2018) Adaptive recommendation model using meta-learning for population-based algorithms. Inf Sci 476:192–210