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Original scientific paper

A Complex Device State Feature Selection Method based on Improved Hybrid Algorithm

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Abstract: In this study, the authors aim to analyze how to improve equipment health state prediction by reducing the dimensionality of complex equipment condition monitoring features. In this paper, a hybrid algorithm that improves Filter and Wrapper based on mutual information is used, and simulated annealing and immunization algorithms are added to the search strategy for implementation. Experimental results show that the hybrid algorithm has advantages over the Filter and Wrapper algorithms alone, which not only improves the efficiency of feature selection while solving the feature redundancy problem well, but also improves the accuracy of state prediction greatly. This study is an effective means of fault prediction and health management intelligence, which can solve the problems of low accuracy and long delay of complex equipment health state prediction, and has a reference role in cost reduction and efficiency improvement for maintenance management departments.

Keywords: feature selection; health state prediction; hybrid algorithms; maintenance management; redundant features

1 INTRODUCTION

For a long time, the timeliness and accuracy of equipment health state prediction has been an important problem plaguing industrial, military, aviation and other fields [1]. The damage of any part may lead to abnormal operation or even downtime of the equipment, and even cause casualties. For this reason, equipment management departments have tried every method to improve the effectiveness of equipment condition prediction. At present, the most adopted method is to carry out equipment health state prediction work by monitoring the parameters of equipment working state [2]. For example, the U.S. military in the aerospace, defense and military fields used in the failure prediction and health management (Prognostic and Health Management, PHM) technology, that is, through the use of sensor technology, the collection of a variety of operational data during the work of the equipment, while the integration of the working environment and the future mission and other information, the use of intelligent algorithms to complete the key components of the equipment, feature extraction, health assessment and health status of the equipment. By using intelligent algorithms, the key components of the equipment can be feature extracted, health status evaluated and remaining life predicted, thus providing scientific decision support for rational optimization of maintenance activities and intelligent maintenance management [3-4].

However, with the increasing complexity of equipment composition and structure, and the increasingly harsh working environment, more and more feature information is required to be monitored to reflect the working state of the equipment, which not only leads to too many feature dimensions, but also results in the redundancy problem between the features, which brings great challenges to the work of predicting the health state of the equipment based on the state features [5]. How to scientifically and reasonably select the state features of complex equipment without reducing the accuracy of subsequent state assessment due to low dimensionality, and without causing computational inefficiency and inability to quickly predict the health state of equipment due to "dimensionality disaster" [6], has become an important problem in the field of equipment failure maintenance that needs to be solved problems.

The process of feature selection [7] is to search multiple key features in the initial feature set that can accurately describe the state of the equipment, so as to combine these key features into a new feature set according to some standard or criterion, and ultimately realize the reduction of computational complexity by lowering the dimensionality of the initial feature set on the basis of ensuring that the accuracy of the fault assessment is not reduced. Currently, the research on feature selection mainly focuses on two types of methods, Filter and Wrapper [8].

Among them, Filter methods evaluate and select features based on their statistical properties without considering the learner used, i.e., feature selection algorithms based on feature subset evaluation strategies. Commonly used filtering methods include variance-based feature selection and relevance-based feature selection. Mangai (2012) used Ward's minimum variance measure for feature selection, to minimize resource utilization during classification [9]. Zhang (2021), by calculating the correlation and redundancy terms of class-independent features based on symmetric uncertainty coefficients, and by calculating the relevance and redundancy terms of class-independent features based on independent categorical information criterion to calculate the correlation and redundancy terms of class-related features, and then complete the feature selection by combining the selection criteria of the above two features [10].

With the continuous improvement of computer performance and the wide application of artificial intelligence algorithms, the research hotspot of feature selection methods has been shifted to the Wrapper method [11]. Wrapper considers a specific learning algorithm, and evaluates and selects a subset of features by the effect on that algorithm. This method directly uses the performance of the model as a criterion for feature selection, so it is often referred to as a feature selection algorithm based on a search strategy [12]. Zhang (2016), Betty (2019), and others on the particle swarm algorithm, genetic algorithm, respectively, to perform a search and solve for feature selection [13-14]. Algin et al. (2020), respectively, used a number of algorithms, including Migratory Bird Optimization (MBO), Simulated Annealing (SA), Differential Evolution (DE) and Particle Swarm Optimization (PSO) as search algorithms for feature selection problem were compared and tested using three classifiers, k-nearest neighbor, plain Bayes and decision tree [15]. Li (2022) improved the Ant Colony algorithm used in the year, and achieved better results [16]. Javier (2022) comprehensively combed the use of Warpper for feature selection in the field of intrusion detection in cybersecurity, expanding the application areas of the Wrapper method [17]. Jain (2023) integrated Artificial Intelligence (AI) with existing wrapper algorithms, using AI to develop performance prediction models and allowing the wrapper algorithms to evaluate the model without constructing the model performance of a subset of features in a model without constructing the model [18].

Although the Filter method is computationally efficient, simple, versatile, and does not rely on classifiers, it is slightly insufficient in terms of redundant feature processing and classification accuracy, while the Wrapper method, although it obtains results with high accuracy, has a relatively high computational cost because it also needs to be combined with machine learning algorithms, and it is not suitable for high-dimensional datasets [19-21]. Therefore, many scholars have used the Filter and Wrapper methods in combination, utilizing the advantages of each for feature selection, with the aim of obtaining better state prediction. Divo (2020) used the Filter-Wrapper method for robust wavelength selection, which produces better model accuracy while improving model interpretability [22]. Mochammad (2021) used a hybrid feature selection method in compressor fault diagnosis to enhance the robustness and accuracy of fault targeting [23].

In summary, the hybrid Filter-Wrapper algorithm has advantages over using either method alone. However, the Filter algorithm has a very important drawback, which is its weak problem solving ability for redundant features. And as more and more features are used to monitor the health status of complex equipment, redundancy will inevitably occur between features, so how to, in Filter, perform redundancy processing of features is one of the problems to be solved in improving the effectiveness of hybrid algorithm feature selection. Meanwhile, the search strategy can be divided into global optimal search strategy and random search strategy. In Wrapper, although both strategies can complete the selection of features, the global search strategy is only valuable in low dimensions and has lower efficiency and higher computational cost; while the random search strategy is applicable to all kinds of scenarios, but the accuracy will be reduced when the feature data is complex [24]. Therefore, how to strengthen the advantages of the two strategies in Wrapper and make up for their respective deficiencies is another one of the problems to be solved in improving the feature selection effect of hybrid algorithms.

This study is an attempt to improve the efficiency and effectiveness of feature selection and ultimately improve the accuracy of equipment state prediction in complex equipment feature selection by improving the hybrid method, solving the redundancy problem of the traditional Filter method for feature selection, and adjusting the search strategy of Wrapper, which not only can expand the theory of maintenance management to a certain extent theoretically, but also can improve the accuracy of equipment state prediction in practice by improving the effect of predicting the health state of complex equipment, providing reliable support for the equipment maintenance management department to carry out advance maintenance, which is an effective way to improve the maintenance efficiency and reduce the maintenance cost. The rest of this paper is organized as follows: in the next section, the main research methods used in this study will be introduced, then the results obtained from the experiments based on the methods of this study will be presented, and the data results will be analyzed, and finally, this study will be summarized.

2 RESEARCH METHODOLOGY

In this study, the Filter-Wrapper hybrid method is adopted to achieve the effect of improving the equipment state prediction while ensuring the efficiency of feature selection by utilizing the efficient computational capability of Filter for preliminary feature selection and then utilizing the powerful global search capability of Wrapper. In order to solve the problem of weak ability to deal with redundant features in the traditional Filter method, the Laplace score in the traditional Filter method is improved by adopting the principle of mutual information based; in order to prevent from falling into the local optimum when adopting the Wrapper's global search method, the simulated annealing algorithm is added; and in order to improve the convergence speed and algorithmic accuracy of the Wrapper, the immunization algorithm is added.

2.1 Feature Selection based on Traditional Filter Algorithm

In order to better manage complex devices, more state information needs to be collected on its key components when the device is working [25], so that the health state management of the device can be carried out more accurately. Filter can evaluate the merit of each feature in the data set by relying only on the internal characteristics of the data, and its efficient computational ability is just suitable for dealing with such data sets of complex devices with a relatively large scale of feature state information.

The idea and steps of the solution based on the Laplace score are as follows:

(1) Suppose the feature set $X = \{x_1, x_2, ..., x_m\}$ in a dataset with sample number *m*. According to the graph theory, a proximity graph *G* can be constructed with the sample points x_i. Obviously, x_i and x_j can be connected only if the sample points x_i and x_j are the closest points and are said to constitute the proximity neighbors whose connections are the edges of the graph *G*.

(2) For the nearest neighbors x_i and x_j, each element of the weighting matrix *S* of the graph *G* is:

$$s_{ij} = e^{-\frac{\left\|x_i - x_j\right\|^2}{t}} \tag{1}$$

where, *i*, *j* are connected sample node numbers; *t* is a constant, which can take the value of 1 for simplicity in the calculation; $\|\bullet\|$ is the Euclidean distance.

Also, for non-nearest neighbors x_i and x_k, let $s_{ij} = 0$.

The weighting matrix *S* thus constructed can also be used as a similarity matrix for the selected samples.

(3) For any feature z in the feature set, there is $f_z = \left(f_{z1}, f_{z2}, ..., f_{zm}\right)^T$. If D is defined as the diagonal matrix of S, it is $D = diag(SI)$, where I is the unit vector.

The Laplacian matrix $L = D - S$ for graph G.

(4) Doing averaging on f_z so that $\overline{f}_z = f_z - \frac{f_z^T DI}{I^T DI} I$, the z th eigen-Laplace score L_z is:

$$L_z = \frac{\overline{f}_z^T L \overline{f}_z}{\overline{f}_z^T D \overline{f}_z} \tag{2}$$

(5) Feature Selection. According to the above method, the weight of each feature can be measured. Among them, the smaller L_r is, the more similar the two neighboring ones are in the r th dimension feature, which means that the feature is more important and its weight should be larger.

2.2 LS Improvement Algorithm based on Mutual Information Principle

As mentioned earlier, the traditional Filter algorithm is weak in solving the redundant feature problem. And with the increasing number of complex device health state features, redundancy between features is inevitable. Therefore, it is necessary to perform redundancy processing on the selected features on the basis of feature selection based on LS. In information theory, Mutual Information (MI), as an information metric, can be used to calculate the amount of information that any random variable contains about another random variable. Obviously, MI can measure the redundancy of each feature in the feature set very effectively. Therefore, adding the computation of mutual information in the Laplace score algorithm can realize the treatment of redundant features [26]. If there is a sample dataset D, the improved LS process based on MI is shown in Fig. 1.

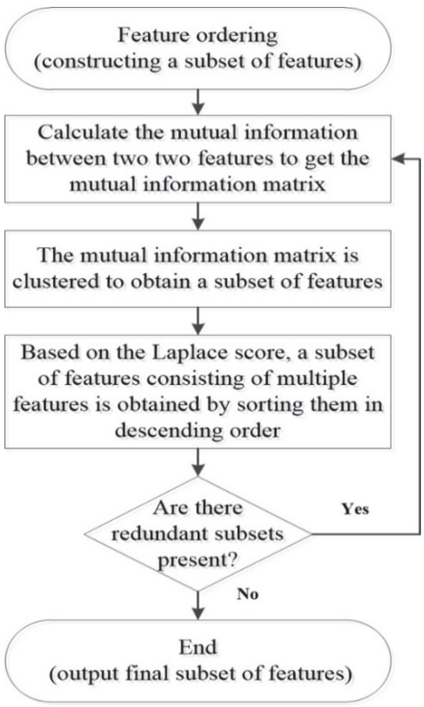

Figure 1 Improved LS process based on MI

The main steps include:

(1) Calculate the Laplace score L_z for all features according to 2.1.

(2) Calculate the mutual information (I_{ij}) of each feature in the data set D.

$$I\left(X;\, Y\right) = \sum_{x \in X} \sum_{y \in Y} p\left(x, y\right) \log \frac{p\left(x, y\right)}{p\left(x\right) p\left(y\right)} \tag{3}$$

where $p\left(x, y\right)$, $p\left(x\right)$ and $p\left(y\right)$ are the joint and marginal distributions of the characteristic variable $\left(x, y\right)$, respectively.

(3) According to the above mutual information formula, calculate the mutual information between each feature in the feature set in turn, and construct the mutual information matrix.

$$MIF = \begin{bmatrix} 0 & I_{12} & I_{13} & \cdots & I_{1n} \\ 0 & 0 & I_{23} & \cdots & I_{2n} \\ 0 & 0 & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & 0 & I_{m-1n} \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \tag{4}$$

where I_{mn} is the mutual information of the m th and n th features.

(4) Clustering is performed according to I_{mn} to obtain a subset of k features, and then a few largest features according to the reverse order of L_z are selected from the subset. The feature subset D_k consisting of multiple features can be obtained.

It can be seen that the improvement of LS based on mutual information not only retains the computational efficiency of the Filter algorithm, but also solves the problem of redundancy that is highly prone to occur due to the large number of features.

2.3 Wrapper-based Feature Selection Optimization

Wrapper's search method needs to be used in conjunction with a later classifier algorithm. In this way, the judgement of the performance of the classifier in the machine learning algorithm can be used as the judgement of the feature weights, thus enabling the optimization of the features.

1. Classifier selectiony.

In the existing literature, the health state of equipment is often categorized into five states: healthy, subhealthy, general deterioration and severe deterioration and failure [27, 28]. Obviously, complex equipment health state prediction belongs to a multi-classification problem. In machine learning, the available classifiers are KNN, decision tree, plain Bayes and support vector machine. Among them, Support Vector Machine (SVM) is widely used in several fields due to the advantages of having strict mathematical theoretical support and being able to handle nonlinear classification tasks [29]. Therefore, SVM is chosen as a classifier for feature optimization.

Many of the problems encountered in the real world are nonlinear, and SVM introduces penalty coefficients and slack variables in order to adapt to nonlinear problems.

And they control the balance of plane deviation and data deviation, and the degree of error allowed for deviation, respectively. In the nonlinear case, the kernel function needs to be utilized instead of the dot product. The optimal hyperplane model and constraints are as follows:

$$f(x)=\sum_{i=1}^{n}\alpha_i y_i K(x_i, x)+b \tag{5}$$

$$\max_{\alpha}\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i, x_j)$$
$$s.t.\quad \sum_{i=1}^{n}\alpha_i y_i=0,\ 0\le\alpha_i\le C,\ i=1, 2, ..., n \tag{6}$$

where n is the number of samples; x_i is the i th feature vector; y_i is the class labeling; $K(x_i, y_i)$ is the kernel function; α is the Lagrange multiplier vector; b is the optimal parameters; and C is the penalty function.

2. Search algorithm of Wrapper strategy.

Wrapper method often uses heuristic search strategies such as genetic algorithm, particle swarm optimization (PSO), etc. Compared with genetic algorithm, particle swarm algorithm has the advantages of high computational efficiency and low memory consumption [30]. Therefore, particle swarm algorithm is used as the search algorithm for Wrapper in this study.

In the PSO algorithm, individuals (particles) in the swarm change their search speed and flight direction by learning from their own experience and the experience of all other particles, and keep approaching to a more optimal search area. The particle position and velocity update computational equation is shown below:

$$V_i(t+1)=w\times V_i(t)+c_1\times r_1\times(pBest_i-X_i(t))+$$
$$+c_2\times r_2\times(gBest-X_i(t)) \tag{7}$$

$$X_i(t+1)=V_i(t+1)+X_i(t) \tag{8}$$

X_i is the position of the i th particle; V_i is the velocity of the i th particle; *pBest* is the individual best position, i.e., the position that produces the best fitness value of the particle; *gBest* is the global best position of the whole particle swarm; w is the inertia weight used to balance the global and local searching ability; c_1, c_2 are acceleration constants indicating the weight of the random acceleration term that pulls each particle towards the positions of *pBest* and *gBest*; r_1, r_2 are two random numbers in the range of [0,1].

3. Improvement of PSO algorithm.

When the data dimension is high, the PSO algorithm not only becomes slower in convergence speed, but also the situation of generating local optimal solutions or even failing to converge in the late iteration is very easy to happen. Therefore, in order to avoid the above problems, the PSO algorithm can be improved by using simulated annealing algorithm and immunization algorithm. Its detailed flow is shown in Fig. 2.

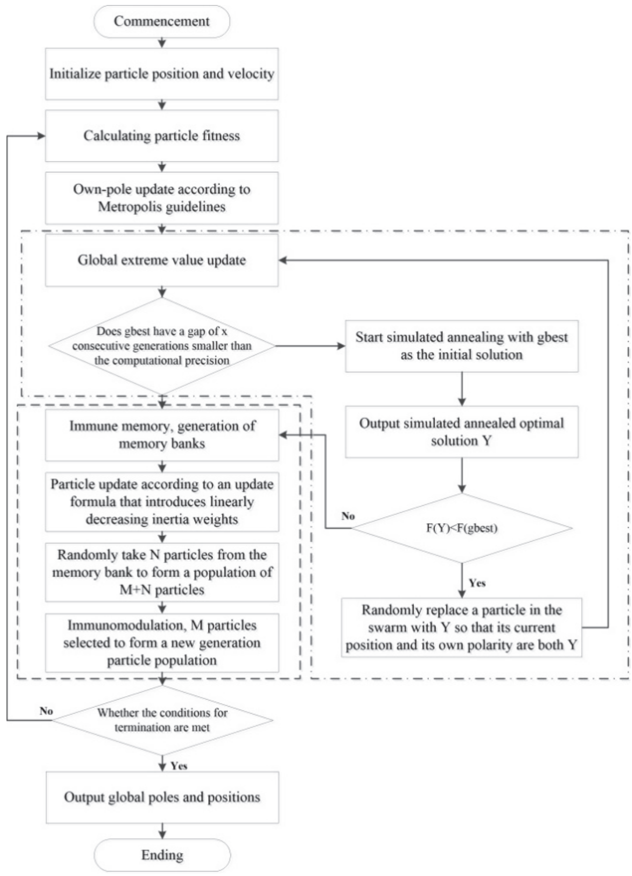

Figure 2 PSO improvement process based on simulated annealing algorithm and immunization algorithm

In Fig. 2, there are two main parts.

In the first part, the simulated annealing algorithm [31] is added to avoid falling into the local optimum, so that the locally optimal particles can jump away with some probability through the perturbation mechanism it generates, thus realizing the global search function of PSO. According to the Metropolis criterion of the simulated annealing algorithm, the probability of a particle jumping away during the cooling process is:

$$p=e^{-(E_j-E_i)/(k\times T)} \tag{9}$$

where E_i and E_j are the internal energies during the cooling process and k is the Boltzmann constant, and the probability of jumping away changes as the temperature decreases.

At the same time, in order to improve the convergence speed of the PSO algorithm and enhance the accuracy of the algorithm, the immunization algorithm [32, 33] is added to immunize the particles after a specified number of iterations or the value does not change much through the immunization mechanism, i.e., the part of the concentration that is high is suppressed. If we let $\varphi(x_i)$ be the concentration of the i th particle, the concentration selection mechanism is:

$$p(x_i)=\frac{1/\varphi(x_i)}{\sum_{i=1}^{n}\frac{1}{\varphi(x_i)}},\ i=1, 2, ..., n \tag{10}$$

The higher the concentration $\varphi(x_i)$, the lower its probability of being selected; and vice versa, the higher its probability of being selected. Accordingly, the search speed of the particle swarm is enhanced by immunizing some of the particles.

2.4 FeatureSelection Process based on Filter-Wrapper Hybrid Algorithm

The above feature selection stages are synthesized to design a hybrid algorithm based feature selection process as shown in Fig. 3.

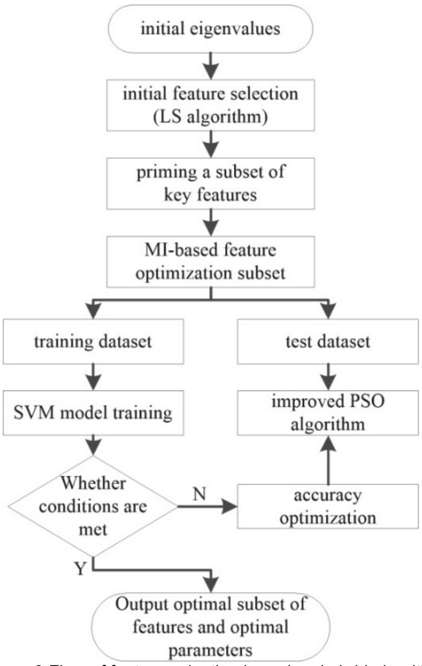

Figure 3 Flow of feature selection based on hybrid algorithm

As can be seen from Fig. 3, theoretically, the feature selection based on the hybrid algorithm not only selects the optimal feature set out in the final output result, but also completes the optimization calculation of the classifier parameters at the same time. The classifier model can be directly provided to the equipment maintenance management system for health state prediction. The feature selection based on hybrid algorithm is more in line with the requirements of intelligence and efficiency of equipment maintenance management.

3 RESULTS OF THE STUDY

3.1 Environment and Data Selection

Programming experiments were conducted using scikit-learn, a machine learning tool based on the Python language, under a Windows 10 operating system configured with a CPU of AMD Ryzen 7 5800H@3.20 GHz and 16 Gigabytes of RAM.

The laboratory has a mechanical vibration test bed that can acquire monitoring signals for more than 40 features. In this experiment, the data were collected from the rolling bearings in the test bench, 120 sample data and 40 feature values in a certain time period were randomly selected. In order to realize the state prediction, the sample data are divided into five states, namely, "healthy, sub-healthy, general deterioration, severe deterioration and failure", which occupy 10%, 50%, 20%, 10% and 10% of the total sample number, respectively.

At the beginning of the experiment, the SVM takes the same parameters and initial values of the kernel function, and takes the average value after 10 experiments.

3.2 Results of the Experiment

1. Accuracy of different prediction algorithms.

In order to verify the improvement in state prediction accuracy of the method proposed in this study, the following five algorithms were selected for the calculation.

SVM: Support Vector Machine algorithm using machine learning species alone.

LS-SVM: Filter-machine learning algorithm without improvement.

LS-SVM (PSO): traditional Filter-Wrapper hybrid method.

LS-SVM (IPSO): hybrid Filter-improved Wrapper method. That is, an annealing algorithm and an immunization algorithm are added to perform the particle swarm global search.

LS-MI-SVM (IPSO): a hybrid Filter-improved Wrapper method. That is, the annealing algorithm and the immunization algorithm are added in performing the particle swarm global search while the Laplace score is improved by using mutual information.

The number of feature selections and final health state prediction accuracy of the different methods are shown in Tab. 1.

Table 1 Number of feature selections and final fault prediction accuracy for different methods

Methodologies	Number of feature dimensions / one	Completion time / s	Fault prediction accuracy
SVM	40	180.4	89.83%
LS-SVM	16	23.23	90.25%
LS-SVM(PSO)	13	12.58	91.32%
LS-SVM(IPSO)	13	8.66	93.30%
LS-MI-SVM(IPSO)	9	6.38	96.26%

The variation of optimal individual fitness for three different methods, LS-SVM(PSO), LS-SVM(IPSO) and LS-MI-SVM(IPSO), is shown in Fig. 4.

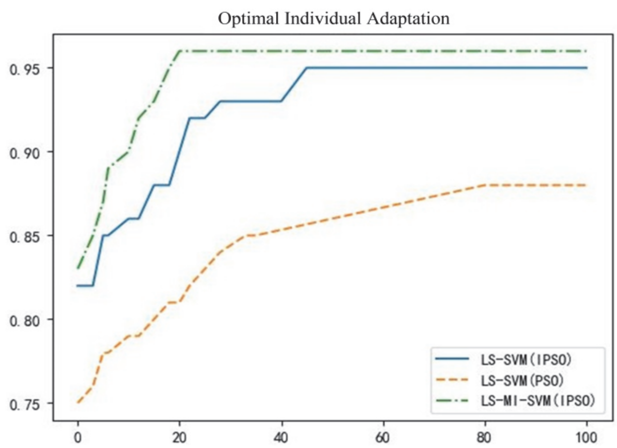

Figure 4 Variation of fitness function for different methods

2. AUC and G-mean of different prediction algorithms

For complex equipment such as airplanes, rolling stock, power generation equipment, etc., the accuracy of state prediction is important, but the seemingly small number of anomaly samples that are not identified in the training of prediction models are the information that equipment managers are really concerned about and that have important research value for the field of equipment maintenance. Errors in classification prediction can have unpredictable consequences for complex equipment.

For this reason, AUC and G-mean metrics also need to be examined [34]. The results of this study on the AUC and G-mean values of the four methods mentioned above are shown in Tab. 2.

Table 2 AUC, G-mean values of different algorithms

Norm	SVM	LS-SVM (PSO)	LS-SVM (IPSO)	LS-MI-SVM (IPSO)
AUC	0.725	0.816	0.866	0.912
G-mean	0.712	0.800	0.858	0.908

4 DISCUSSIONS

4.1 Analysis of Results

As can be seen from Tab. 1:

① The traditional Filter-Wrapper hybrid method can not only effectively reduce the dimensionality of the state features, but also better improve the accuracy and efficiency of the prediction than the single use of Filter method.

② The LS algorithm, which has been improved based on mutual information, can not only effectively reduce the dimensions of the initial state features, but also solve the problem of feature redundancy that cannot be handled by using the LS algorithm alone. In this experiment, four redundant features were removed. On this basis, mixed with the improved Wrapper algorithm, the efficiency and effectiveness of state prediction can be improved again. It is the best method in this experiment.

From Tab. 2, we can see:

① By using the prediction algorithm in machine learning alone (SVM in this experiment), although all the collected feature data are used, its AUC is < 0.8, which indicates that it is not effective in predicting complex devices, i.e., many fault states are not recognized;

② By the hybrid algorithm, despite the reduction in the number of features, it is clear that by the prediction of the retained feature data, the AUCs are all greater than 0.8, which is a large improvement over the prediction effect of both without the hybrid algorithm;

It can be seen from Fig. 4: Improving Wrapper's hybrid method, by adding annealing simulation algorithm and immunization algorithm to the PSO algorithm, can significantly improve the convergence efficiency of the search.

Therefore, the state prediction method based on hybrid algorithm proposed in this study, by improving LS and PSO, makes the prediction effect further improved again, which is the best value in this experiment.

4.2 Practical Significance

It can be seen that this research is a supplement to the existing feature selection methods, and in the case of complex equipment that can be monitored by more and more state parameters, it can quickly select the features to carry out equipment state prediction, thus greatly improving the efficiency and effectiveness of equipment state prediction, and reducing the risk of equipment failure due to incorrect equipment state prediction or long prediction time.

4.3 Future Research Directions

In this study, although the effectiveness of the hybrid algorithm in equipment state prediction is verified through experiments, the sample data from the laboratory is used for this experiment. The state information data collected in the laboratory is more stable and has better data imbalance compared to the state information data when the equipment operates in different environments, which may cause limitations in this study. Therefore, it is necessary to add the analysis of the effect of unbalanced data in future studies.

5 CONCLUSION

Drawing on mutual information theory, annealing algorithm and immunization algorithm, this study explores an improved Filter-Wrapper based hybrid feature selection method. The results of the study show that the method utilizes the improvement of Laplace scores by mutual information to solve the redundant feature problem when applying Filter for the initial selection of features, and the annealing algorithm and the immune algorithm to improve the particle swarm searching ability, which leads to a higher accuracy in the prediction of the health status of the complex equipments and better AUC indexes evaluated by the algorithms, while improving the efficiency and effectiveness of the feature selection. This study can provide a reliable basis for the equipment management department to accurately predict the equipment state and implement effective preventive maintenance.

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