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A New Application of Optimized Random Forest Algorithms in Intelligent Fault Location of Rudders

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ABSTRACT During the movements of aircraft, missiles, and ships, the rudder plays an important role in their direction control. In order to test the parameters of the rudders, we have to manually measure each item one by one in traditional production and manufacturing of rudders, which waste a great quantity of manpower and time. In this paper, we present a new application in rudder fault test by using machine learning technology and recommend a new intelligent method for fault location. The main subject revolves around prediction-oriented problems of multi-dimensional performance parameters data mining and the modeling of classification, including the analysis and processing of data features and the solution of fault location based on classification model. In addition, to improve the accuracy of the classification model, we optimized the random forest (RF) algorithm with the shuffled frog leaping algorithm (SFLA), which we call shuffled frog leaping algorithm-based random forest (SFLA-RF). It effectively solves the problem of voting competition among each tree, which makes the decision of the model more efficient and accurate. In a word, by means of automatic test and intelligent analysis, this new method breaks through the technical bottleneck of low efficiency of parameters test and the shortcomings of traditional rudder fault location.

INDEX TERMS Rudder test, fault location, machine learning, SFLA-RF, data mining.

I. INTRODUCTION

In 1980s, the United States took the lead in proposing standardization, serialization and modularization of weapon equipment testing system, forming a series of automatic test equipment, such as integrated testing equipment for the Army (Integrated Family of Test Equipment, IFTE), a joint automatic support system for the Navy (Consolidated Automated Support System, CASS) [1], a joint military electronic combat system testing equipment for the Air Force (Joint Services Electronic Combat System Tester, JSECST) and a third echelon testing system for the Marine Corps (Third Echelon Test Set, TETS) [2]. In recent years, with the development of computer technology and bus technology, some powerful and automated test equipment have been designed. The stability and reliability of both military and civilian test equipment have been higher. However, most of the fault detection devices are used in health management during the operation of the equipment [3].

Rudder has been widely used in aerospace field. As a position servo driver, it is often used in situations such as pitch, yaw and roll motion of missile attitude change that require constant change of angle and can be maintained. As we know, the rudders must be tested before use to ensure that all parameters are in normal condition. The parameters that need to be tested can be roughly divided into state parameters, static characteristics and dynamic characteristics. The test equipment of rudders has been developed for a long time: The testing methods of the state parameters and static characteristics have not changed greatly, whereas the test methods of dynamic parameters have undergone several stages of changes. In the past few years, a set of data needs repeated measurements to be obtained, and then frequency characteristic curves are drawn based on multiple sets of experimental data. Then, with the popularity of computers and the emergence of common interfaces, a simple frequency testing system has emerged, and automatic testing has been

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preliminarily realized. In the latest generation of automated test system, the computers take part in the generation of excitation signal and analysis of measurement characteristics, replaces the hardware functions of the test instrument with powerful soft wares, and integrates the computer with the measurement instrument. The test equipment like this has got a faster calculation and a higher measurement accuracy with the optimized structure and the new measurement method [4]. However, no matter which method is used, the large number of final test results still need manual analysis and judgment, which is far away from intelligent test and wastes a lot of manpower and time.

In recent years, the rapid development of machine learning technology has provided new ideas for the progress of manufacturing industry so that intelligent manufacturing has entered a new stage [5]. Thus, a more intelligent method of fault location is important and necessary in the field of rudder testing so as to test rudders in a large quantities and quickly in this way. Machine learning algorithms are very suitable for processing and analyzing various types of data and are used in various fields currently. In agriculture, the random forest algorithm has a good performance in predicting the background above-ground biomass of corn [6]. In the medical field, machine learning technology provides predictive capabilities for early intervention in patients with sepsis [7]. On environmental matters, the urban environment can be scored by machine learning technology as well [8]. Machine learning is seldom used in rudder test, but it is more widely used in the field of fault diagnosis and prediction, which is relatively close to rudder test. By using random forest algorithm, Chunzhi Wu et al. realized intelligent fault diagnosis of gearbox [9], in addition, Cerrada Mariela and Xi Chen respectively completed the fault diagnosis tests for spur gears [10] and transformers [11]. Fault location of rudder is based on multi-dimensional test parameters for data mining and machine learning. On the problem of data-based machine learning, a great quantity of data which is from helicopter health and usage management systems is used to test faults of them [12], besides, Gao et al. use failure data from the core components of the aircraft fuel system for fault detection as well [13]. At present, fault diagnosis technology based on machine learning has been involved in many fields, and has achieved good results. Here, we apply machine learning to rudder testing, mainly using random forest algorithm to study on it, and we propose a new method suitable for rudder data to improve the efficiency of rudder testing and more convenient to achieve fault location. Tree model has a good performance in fault diagnosis. Decision Tree (DT) model [14] is the basis of various complex tree models among which Random Forest (RF) [15] is the most commonly and widely used intelligent algorithm. In this paper, we try to optimize random forest to train the test data, and we finally realized fault location of rudder with a good performance by optimized random forest algorithm: Shuffled Frog Leaping Algorithm-based Random Forest (SFLA-RF).

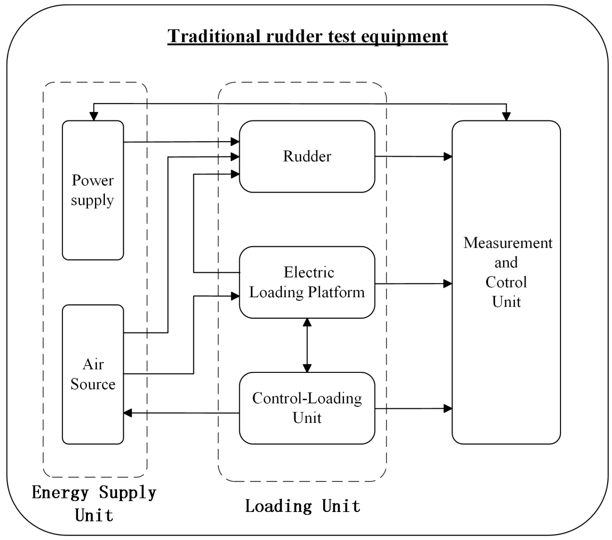

FIGURE 1. Structure of traditional rudder test system.

II. TRADITIONAL RUDDER TEST EQUIPMENT

Traditional rudder test equipment consists of energy supply unit, loading unit and measurement and control unit. The test system is shown in Fig. 1.

As shown in Fig. 1, the energy supply unit is mainly composed of two parts: power supply and air source. The power supply of the system consists of an adjustable voltage module and several DC/DC conversion modules. In order to supply power to all sub-circuits and components in the system, we choose 24V DC voltage as the output of the power module and convert it into 5V DC voltage through the DC/DC module. Besides, the air source refers to an air supply device that provides compressed air with a certain pressure and flow rate for pneumatic rudders.

The loading unit consists of an electric loading platform (with four independent loading channels and one mounting table for the installation and fixing of rudder) and a control loading unit (which is composed of motor drivers and pneumatic control valves). The loading channel can realize the independent loading of torques, lateral forces and inertial loads of the rudders. Equipped with torque sensors and photoelectric, it can collect the torque and angle signals of the rudder.

After receiving all kinds of signals from the loading unit, the measurement and control unit transmits them to the conditioning chip and the acquisition chip, and finally to the industrial control computer which is the most important part in the measurement and control unit. With the test software and the special oscilloscope software, the whole system is controlled and measured by industrial computer.

After testing by the traditional equipment, we can get the parameters of the tested rudder, including the rising time and its overshoot at no-load, the falling time and its overshoot at no-load, the zero input response, the hysteresis characteristics, and the settling time, overshoot and steady-state error at a positive loading and a negative loading, etc. We use a large number of multi-dimensional parameters of the rudders for machine learning, which makes the judgment of the rudder test equipment more rapid and intelligent.

III. METHODS FOR MACHINE LEARNING ALGORITHM

The traditional rudder testing method can only observe and analyze a large number of test data manually, and the addition of machine learning algorithm can greatly save manpower. Here, we introduce the random forest algorithm and its optimization algorithm. 20435 historical test data were used in this experiment. Before it, we should divide the data set into train set and test set. Train set is used to train the model and accounts for about 80% of the total data, whereas the test set is used to evaluate the effect of the model and accounts for about 20% of the total data.

However, If the data set is divided randomly, the train set and test set will be different from the original each time the program is running. Assuming that training continues on the original model, there is no guarantee that some data in the test set has not been trained by the model.

Therefore, we use identifiers (using index values as identifiers) to divide the data set. The specific method is: using the index of each sample as the identification, the hash function is calculated. Then we take the last byte ($0 \sim 255$) of the hash function. If the value is less than 51.2 (i.e. 20% * 256), we put it into test set, otherwise, we put it into train set.

A. ESTABLISHMENT OF RANDOM FOREST

Random Forest (RF) is an integrated algorithm based on decision tree, which trains multiple models by using statistical sampling principle. When a new sample needs to be predicted, these models are used to predict the new sample separately, and then the class of the new sample is determined by the principle of minority subordinating to the majority [15]. Single models are often sensitive to noise of data, resulting in high variance. RF is a Bagging algorithm, which is based on bootstrap sampling method. It can reduce the sensitivity to data noise and improve the accuracy and stability of the model. This method does not require additional input, and can be implemented simply by training multiple models for the same data set. RF algorithm is not trained by all features, but by selecting a subset of features randomly. It has two key parameters: one is the number of decision trees, the other is the number of features used to construct a single decision tree. The construction steps of random forest are as follow (for the data set with m samples and n features):

Step 1: After m times sampling with replacement from the original data set, a new data set with m samples (there may be duplicate samples) can be obtained. Also, using the rule of sampling without replacement, f features are taken from the n features as input features.

Step 2: For the new sample-set D (with m samples and f features), if the subset of the samples belonging to class c_k is C_k, then the Gini impurity is:

$$Gini(D) = 1 - \sum_{k=1}^{K} (\frac{|C_k|}{|D|})^2 \tag{1}$$

For each feature A and its possible value a, calculate $Gini(D, A)$ according to (2):

$$\begin{aligned} Gini(D, A) &= \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2) \\ D_1 &= \{(\overrightarrow{x}, y) \in D | \overrightarrow{x}^{(A)} = a\} \\ D_2 &= \{(\overrightarrow{x}, y) \in D | \overrightarrow{x}^{(A)} \neq a\} = D - D_1 \end{aligned} \tag{2}$$

Step 3: Selection of optimal feature and optimal segmentation point: The A and a, which minimize Gini impurity, are the optimal feature and optimal segmentation point. According to them, the training set is divided into two sub-nodes.

Step 4: Recursively call the *step 2* and *step 3* for these two sub-nodes. And finally, a decision tree is constructed with the new data set (with m samples and f features).

Step 5: Repeat *step1* to *step 4* t times to construct t decision trees to form a RF model.

Once the RF model is established, for each new test sample, the prediction result depends on the joint decision of all decision trees in the random forest. RF only select a subset of features to construct decision tees in order to have a good performance on the problem of "tendency" of features, i.e., if all features are selected to construct a decision tree, as long as an input feature and the result are strongly correlated, this feature will be reflected in all the decision trees, which causes all them make decisions according to this feature as much as possible, while ignores the contribution of other features to the result. In addition, the problem of overfitting is well solved by randomly selecting subsets of features to construct decision tees in random forest.

However, every tree in RF has the same voting rights, whether it makes the right or wrong decisions, and it also increases the possibility of a wrong result.

B. SHUFFLED FROG LEAPING ALGORITHM-BASED RANDOM FOREST

In order to improve the accuracy of the model in fault location, we propose a new combination algorithm, namely: Shuffled Frog Leaping Algorithm-based Random Forest (SFLA-RF), whose principle is to use the SFLA to assign a weight to each decision tree in the RF, so that the sub-tree with high accuracy has a higher weight, and the weight is depended on the performance of the sub-tree.

SFLA is a new heuristic population evolution algorithm with high computational efficiency and excellent global search ability. As a bionic optimization algorithm, Eusuff first proposed and applied it to the optimization of water distribution network design in 2003 [16]. It combines the advantages of particle swarm optimization algorithm and memetic algorithm, which is mainly used to solve multi-objective optimization problems [17].

The main idea of SFLA-RF is to assign a weigh value to each tree in RF, and the values are searched for the optimal solution by SFLA. Its establishment steps are as follows:

The Step 1 to Step 5 are the same as the steps in Section 3.1, so that a RF model with t trees is established.

Step 6: Initialize SFLA parameters. Frog population number is N in which includes m memeplexes, and there are n frogs in each memeplex (i.e. $N = m \times n$). Dimension of search space is S. Moreover, $D_{\max}$, $L_{\max}$, $G_{\max}$ and $r_{\max}$ represent respectively the maximum distance a frog can move, the maximum number of local searches, number of global mixed iterations and maximum local search radius.

Step 7: Generate a frog population. Generate the original frog population with N frogs randomly, the population $P = \{X_1(t), \cdots, X_k(t), \cdots, X_N(t)\}, k = 1, 2, \cdots, N$, and iterative counting initial value $t = 0$. Each frog $X_k(t)$ represents a set of solutions (i.e. the weight of each tree in the random forest), and then calculate fitness function values for each solution, $F_k(t) = F(X_k(t))$ (the fitness function here refers to the accuracy). Next, rank frogs in order of fitness function from high to low and store them in the form of $U_k(t) = \{X_k(t), F_k(t)\}$, and the best frog is $X_g(t) = U_1(t)$.

Step 8: Divide frogs into memeplexes. Divide U into m memeplexes, and there are n frogs in each memeplex: $M^1(t), \cdots, M^j(t), \cdots, M^m(t), j = 1, 2, \cdots, m$. Record the best frog $X_b^j(t)$ and the worst frog $X_w^j(t)$ in the memeplex according to (3): let M^k denote the set of frogs in the kth memeplex

$$M^k = \{X_{k+m(l-1)} \in P | 1 \le l \le n\}, \quad 1 \le k \le m \tag{3}$$

Step 9: Memetic evolution. Local search for the worst frog $X_w^j(t)$ in the memeplex $M^j(t)$, i.e. calculating step length and position updating of frog jump according to (4) and (5):

$$D = r \times (X_b - X_w) \tag{4}$$

$$X_w^{'} = X_w + D, \quad \|D\| \le D_{\max} \tag{5}$$

Calculate the fitness function of the updated frog. if it is better than the original one ($F(X_w^{'}) > F(X_w^j)$), the new updated frog $X_w^{'}$ will replace the original one X_w^j. Otherwise the global optimal solution $X_g(t)$ will replace the local optimal solution $X_b^j(t)$, and perform local search again according to (2) and (3). If there is still no improvement, a new frog is randomly generated to replace the worst one $X_w^j(t)$, and then the local search is continued for a total of $L_{\max}$ times, finally the evolved memeplex $M^1(t)', M^2(t)', \cdots, M^m(t)'$ is obtained.

Step 10: Shuffle memeplexes. Shuffle frogs in the new updated memeplexes $M^1(t)', M^2(t)', \cdots, M^m(t)'$, record as: $U(t+1) = \{M^1(t)', M^2(t)', \cdots, M^m(t)'\}$. Rank the new frogs in order of fitness function from high to low, and update the best frog in the population: $X_g(t+1) = U_1(t+1)$.

Step 11: If the number of global searches is less than its maximum: $t + 1 < G_{\max}$, then jump to the *step 8*. Or, output the best frog as the best solution (the best combination of weights). The best frog $X_g = (w_{g1}, w_{g2}, \cdots, w_{gt})$.

The structure of SFLAL-RF is shown in Fig. 2.

SFLA-RF is an ensemble learner composed of t base-learners: $tree_1, tree_2, \cdots, tree_t$, and the final decision result is:

$$SFLA - RF(\overrightarrow{x}) = X_g \cdot RF = \sum_{i=1}^{t} tree_i(\overrightarrow{x}) w_i \tag{6}$$

SFLA algorithm combines the advantages of two population intelligence optimization algorithms, namely, meme evolution based memetic algorithm and swarm behavior based Particle Swarm Optimization (PSO) algorithm. Some traditional bionic algorithms such as genetic algorithm and PSO have poor global convergence [18], whereas SFLA is a global convergence algorithm. In theory, as long as the number of iterations meets the requirements, SFLA will find the global optimal solution [19].

IV. EXPERIMENTAL RESULTS

A. ALGORITHMS COMPARISON

Fault location of rudders is a common multi-classification problem in machine learning. In this experiment, aiming at the problem of fault location, we compare two most commonly used classification algorithms in machine learning (SVM and RF) and an optimized RF model (SFLA-RF) to analyze the result. The data set consists of 20435 samples, each sample has 12 features (rudder parameters) and 1 label (rudder state), and the data set is divided into training set (about 80% of data set: 16201 samples) and test set (about 20% of data set: 4234 samples). In this multi-classification problem, there are 14 types of fault location states, including twelve single-fault state, one multi-fault state and one qualified state. We use Python as the modeling platform and the performance of each algorithm are shown in Table 1.

From Table 1, we see that the performance of SVM (Support Vector Machine) is not as good as the other tree-models. In train set, the accuracy of SVM is 99.092%, however, by comparing the results of cross-validation, we can see that it has a certain degree of over-fitting. Besides, the optimized algorithm SFLA-RF has a better and more stable performance than RF. In the experiment, the parameters of each algorithm on Python platform are shown in Table 2 (parameters not mentioned in the table use default values).

B. PARAMETER TUNING AND RESULT ANALYSIS

After determining the model as SFLA-RF, we need to optimize the parameter of the model. Specifically, we need to find the number of the trees and features can be used by each tree that can optimize the result. Fig. 3 shows the relationship between the accuracy and the above two parameters in the test set.

Respectively, (a) and (b) in Fig. 3 show the accuracy and recall of the SFLA-RF model in different situations. Because of the dual randomness of SFLA-RF model (i.e., the randomness of sampling and the randomness of feature selection), but in general, with the increase of the number of trees and the number of features used by each tree, the accuracy and recall of SFLA-RF model will also increase. However, too many

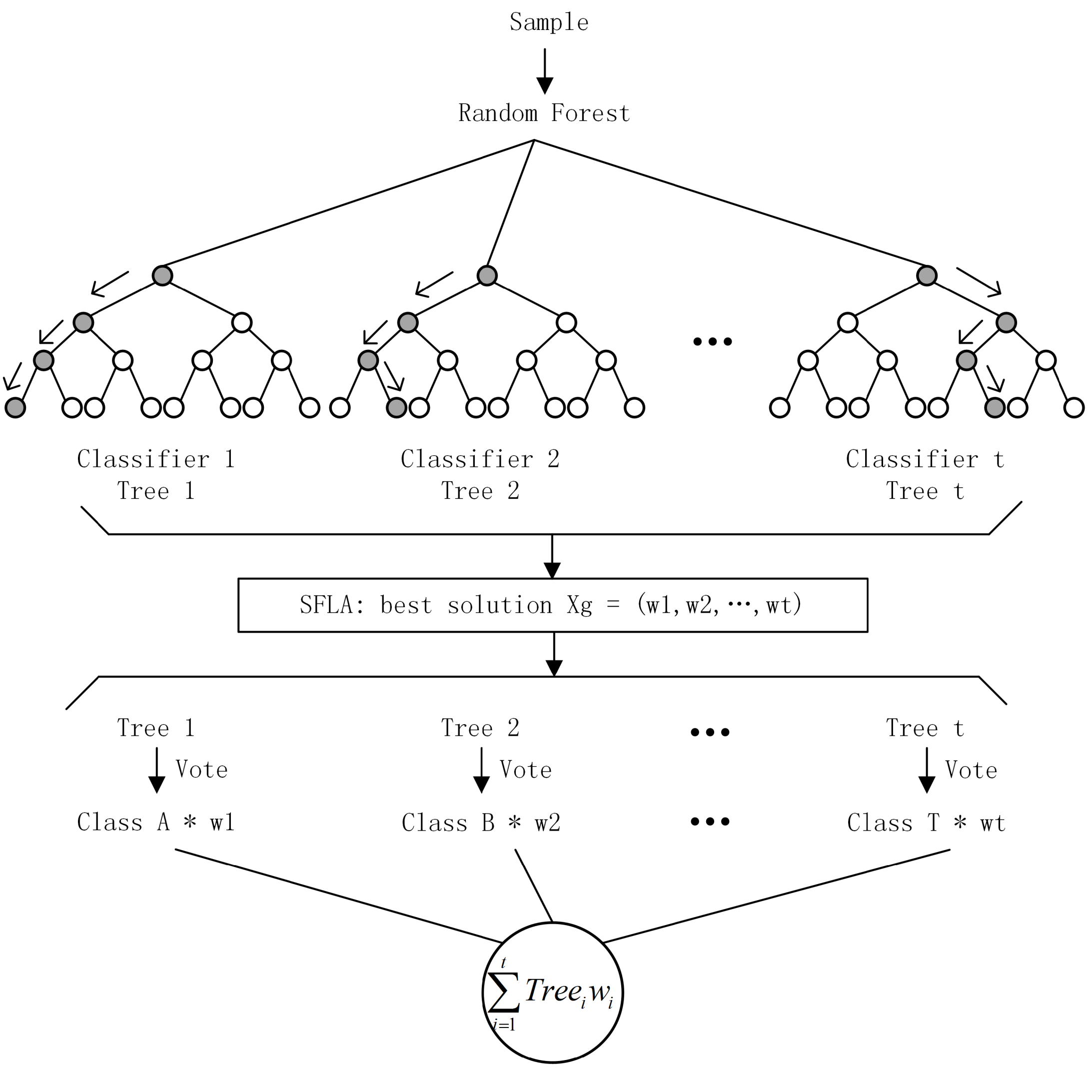

FIGURE 2. Structure of SFLA-RF model.

TABLE 1. Accuracy and cross validation of three models.

Classification Algorithm	Train set			Test set
	Accuracy	Result in cross-validation		Accuracy
		Mean	Standard deviation	
SVM	99.092%	76.798%	0.00168	76.216%
Random Forest	99.975%	99.753%	0.00138	99.669%
SFLA-RF	99.987%	99.899%	0.0009	99.787%

trees will affect the running speed of the model, as well, that too many features are used by each tree can also lead to the tendency of model results to the "strong correlated" feature. To sum up, we finally decided to construct 20 trees to form a random forest, and each tree used 8 features. In this case, the accuracy of the SFLA-RF model is 99.787% and the recall is 99.266%.

Table 3 shows the detailed prediction of the experiment by confusion matrix. The element x_{ij} in the confusion matrix represents the number of samples that actually belong to class i and are predicted to class j.

Class FA to FL in Table 3 mean the single fault (fault A to fault L), and class MF means "multiple faults", while the class Q means the rudder state is qualified.

TABLE 2. **Parameters of algorithms.**

Algorithms	Parameters	description	Value
SVM	C	Penalty factor	1
	kernel	Kernel function	'rbf'
	gamma	Kernel function parameter	'auto'
	decision_function_shape	Classification rule	'ovo'
Random Forest	max_features	Features can be used by each tree	8
	n_estimators	The number of trees	20
SFLA-RF	max_features	Features can be used by each tree	8
	n_estimators	The number of trees	20
	N	The number of frogs	100
	M	The number of memeplexes	10
	L	The maximum number of local searches	10
	G	Number of global mixed iterations	10

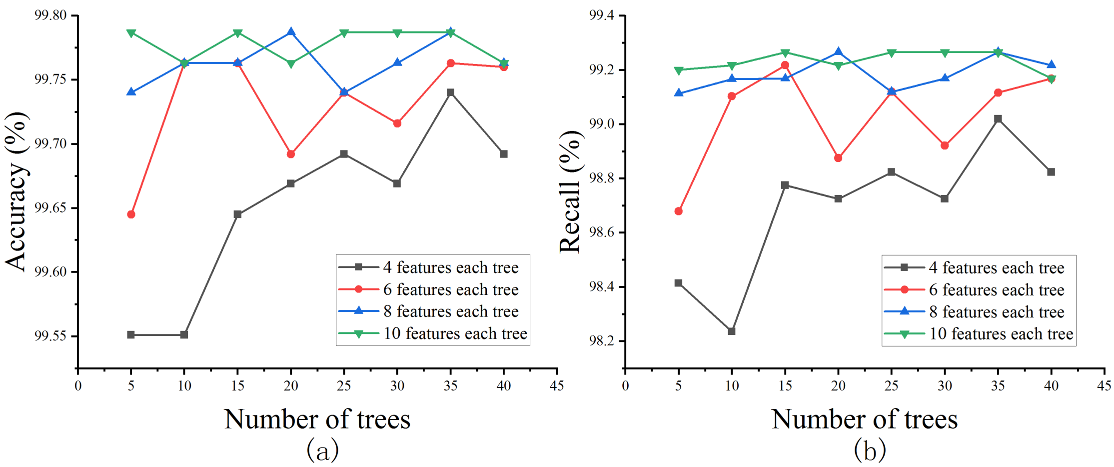

FIGURE 3. **Accuracy and recall of rudder fault location in test set.**

TABLE 3. **Confusion matrix of the model.**

		Prediction results													
		FA	FB	FC	FD	FE	FF	FG	FH	FI	FJ	FK	FL	MF	Q
Actual results	FA	153	1												
	FB	2	68			1		1		1					
	FC			45											
	FD				47										
	FE					148									
	FF						64								
	FG		1					71							1
	FH								71						
	FI									55					
	FJ										45				
	FK											107			
	FL												72		
	MF													53	
	Q			1											3226

In addition to observing the accuracy and recall of the model, we also need to examine the consistency between the model results and the actual results by *Kappa* coefficient according to (7).

$$Kappa = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \tag{7}$$

The *Kappa* coefficient of the final SFLA-RF model is 99.486%.

Comparing with the state-of-art algorithms, SFLA algorithm has a better performance. The most commonly used optimization algorithms such as particle swarm optimization (PSO) and genetic algorithms have poor global convergence, while SFLA is a global convergence algorithm.

In theory, as long as the number of iterations meets the requirements, SFLA will find the global optimal solution.

V. CONCLUSIONS

In this paper, the data processing method of machine learning is added to the traditional rudder test equipment, which changes the current situation of manual observation and judgment, can further save the testing time of rudders and improve the testing efficiency.

Furthermore, our study proposes a more intelligent fault location method for rudders: using machine learning algorithm to analyze the test data of rudders, solving the prediction-oriented problems of multi-dimensional performance parameters data mining and the modeling of classification. SFLA-RF model assigns different weights to each tree in RF by finding the optimal solution, which makes the trees have different votes during voting. This also gives better trees greater rights and restrains those trees that do not perform well. The experiment results show that the SFLA-RF model has a good performance for the fault location of rudders, and basically meets the requirements of the rudder test. In the experiment, we decided to build 20trees to form a random forest and each tree randomly selected 8 features to construct. These 20 trees have different voting rights, and the final results is decided with majority rule. Each tree does not use all the features in its construction, avoiding the feature that is strongly associated with the predicted result appearing in each tree, thus avoiding the tendency of the final result to this feature. SFLA-RF not only has the advantage of random forest, but also pays attention to the effect of each tree on the results, which has a stable and accurate performance in rudder test.

To sum up, it is a new application to apply machine learning technology to the field of rudder test. The new method effectively simplifies the manual work and uses computer instead of human brain for data analysis and decision-making.

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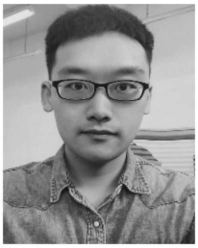

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