Fault Diagnosis of Shield Machine Based on RFE and ELM

Xuanyu Liu[1], Wenbo Qi[1], Yudong Wang[2], and Qiumei Cong[1]

Abstract—**Shield machine is a complex large-scale tunneling equipment with multiple systems and driving sources. In order to improve the accuracy of fault diagnosis for shield machine, a method based on the combination of reverse feature elimination (RFE) and extreme learning machine (ELM) is proposed. For the characteristics of shield machine operation data with many dimensions and large quantity, the RFE method is introduced to reduce the dimension of the data, eliminate the redundant dimension and remove the correlation between features. To improve the accuracy and efficiency of fault diagnosis, the ELM neural network classifier model is built based on the extremely learning mechanism for fault diagnosis of shield machine. The simulation results based on the field construction data show that this method improves the accuracy of fault diagnosis of shield machine significantly and has good engineering application value.**

Index Terms—**Shield machine, fault diagnosis, extremely learning machine, reverse feature elimination**

I. Introduction

SHIELD machine is a comprehensive large-scale construction machine equipment which integrates machinery, hydraulic, electronic and automatic control, and its structure is shown in Fig. 1. Shield machine is widely used in subway tunnel construction, mining engineering and mountain crossing tunnel construction for its advantages of high quality, high speed and safety. At present, shield machine is developed towards high power and intelligence [1]. However, due to the complexity of the shield machine structure and the relatively closed working environment, it is very easy to have a variety of failures in the working process. The fault diagnosis of shield machine is one of the key technologies to realize its safe and high efficient construction. Therefore, a method is needed to predict the location of the fault the first time or even before the fault occurs, so that work efficiency is improved and economic losses is reduced.

Manuscript received September 17, 2020; revised January 14, 2021. This work is supported by the Scientific Research Funds of Educational Commission of Liaoning Province of China (Grant No. L2019018), and the National Natural Science Foundation of China (Grant No.61803191, 61773190).

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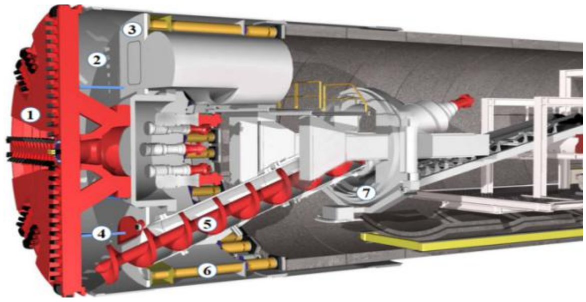

① Cutter head ② Sealed chamber ③Sealed chamber partition ④ Mixing rod ⑤ Screw conveyor ⑥ Hydraulic cylinder for propulsion ⑦ Segment assembling machine

Fig. 1 Structure of shield machine

Many scholars have studied the problem of fault diagnosis of shield machine. In reference [2], an expert system for fault diagnosis of shield machine is proposed. Multi-agent system and fuzzy reasoning mechanism are introduced to diagnose its multiple faults. However, expert system often depends on the experience knowledge of professionals, not the model. In reference [3], the self-learning, self-organizing function and parallel processing mechanism of BP neural network are used for information fusion to classify and diagnose the common faults of shield machine, such as gushing, hob wear and shield shell stuck. In reference [4], differential evolution (DE) and BP neural network (BPNN) are combined to diagnose the hydraulic system of fault in shield machine propulsion. The results inevitably show that BP neural network is time-consuming and requires high data quality. In reference [5], rough set is used to reduce the dimension of data, then BP neural network is used to predict the fault, and the least square method is used to reflect the future operation of shield machine. However, rough set cannot deal with numerical continuous value variables, which limits the applicability of this method.

Compared with traditional support vector machine (SVM), neural network and other methods, extremely learning machine has the advantages of fast learning speed, high accuracy, simple parameter adjustment[6-8], and has obtained good results in the fault diagnosis of large-scale equipment such as aeroengine components, marine diesel engine and so on[9-12].

Therefore, a fault diagnosis method of shield machine is proposed based on RFE and extremely learning machine in this paper. Use the reduced dimension network to eliminate redundant columns as much as possible and gradually reduce the sample of diagnosis data based on RFE. Then the fault is classified by using ELM. Simulation test results show that the model has good data dimensionality reduction ability, short fault diagnosis time and high accuracy.

II. EXTREME LEARNING MACHINE

Extreme learning machine is a new algorithm for single hidden layer feedforward neural network. Compared with the shortcomings of traditional feedforward neural networks, such as slow training speed, easily falling into local minimum and sensitive selection of learning rate, ELM algorithm randomly generates connection weights of input layer and hidden layer and threshold values of hidden layer neurons. In the process of training, there is no need to adjust the weights, only to set the number of hidden layer neurons, and then the unique optimal solution can be obtained. Compared with the traditional training methods, ELM has the advantages of fast learning speed and good generalization performance [13], [14].

For a single hidden layer neural network, suppose there are N arbitrary samples (X_i,t_i), where $X_i=[x_{i1},x_{i2},\ldots,x_{in}]^T \in R^n$ is the input vector and $t_i=[t_{i1},t_{i2},\ldots,t_{im}]^T \in R^m$ is the corresponding expected output vector. The standard ELM network mathematical model with N input neurons, L hidden neurons, M output neurons and activation function can be expressed as follows [15], [16]:

$$H\beta = T \tag{1}$$

where H is the output of the hidden layer node, β is the output weight, and T is the expected output

$$H(W_1,\cdots,W_{\tilde{N}},b_1,\cdots,b_{\tilde{N}},X_1,\cdots X_N) = \begin{bmatrix} g(W_1 \bullet X_1 + b_1) & \cdots & g(W_{\tilde{N}} \bullet X_1 + b_{\tilde{N}}) \\ \vdots & \cdots & \vdots \\ g(W_1 \bullet X_N + b_1) & \cdots & g(W_{\tilde{N}} \bullet X_N + b_{\tilde{N}}) \end{bmatrix}_{N\times\tilde{N}} \tag{2}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}_{\tilde{N}\times m} \quad T = \begin{bmatrix} T_1^T \\ \vdots \\ T_N^T \end{bmatrix}_{N\times m} \tag{3}$$

After the neuron parameters in the hidden layer are randomly generated based on the probability of any continuous sampling distribution, the training samples are given. The output matrix of the hidden layer is actually known and remains unchanged. Eq. (1) is transformed into the least norm least square solution for linear system

$$\dot{\beta} = H^{+}T \tag{4}$$

where H^{+} is the Moore Penrose generalized inverse matrix of the matrix H.

III. FAULT DIAGNOSIS OF SHIELD MACHINE BASED ON RFE AND ELM

A. Idea of RFE

RFE is a dimension reduction method applied to data with a large number of redundant dimensions. First, the original data dimension is calculated to get the accuracy rate of the original data dimension, and then the accuracy rate is calculated by eliminating the first dimension data. If the accuracy becomes higher after the first dimension is eliminated, the first dimension can be considered as redundant dimension, which will be eliminated and the calculation of the second dimension will be started; if the accuracy does not become higher after the first dimension is eliminated, the first dimension will be useful dimension, which will be retained and the second dimension will be calculated. It can iterate through the above until all dimensions are traversed.

B. Fault Diagnosis Based on RFE-ELM

According to the actual construction experience of the shield machine, three main failure types are finally determined: hob wear fault caused by too large torque of the cutter head motor; shield shell stuck caused by too large speed of the jack of propulsion system; pipe blocking failure of the grouting pipeline caused by the grouting fluid flow to be too low. Each main fault is divided into two major secondary fault, and the fault classification diagram is shown in Table Ⅰ.

TABLE Ⅰ
FAULT CLASSIFICATION OF SHIELD MACHINE

Main fault type	Type of secondary fault
Cutter head system hob wear fault	NO.1,5,3,7 cutter head motor torque is too large
	NO.2,6,4,8 cutter head motor torque is too large
Propulsion system shield shell stuck	NO.1,3, jack speed is too large
	NO.2,4, jack speed is too large
Grouting pipe blocking failure of grouting system	Grouting A liquid injection flow is too low
	Grouting B liquid injection flow is too low

Based on the above fault types, the ELM fault classifier of shield machine is constructed by combining the reverse feature elimination method. The process of fault diagnosis is shown in Fig. 2.

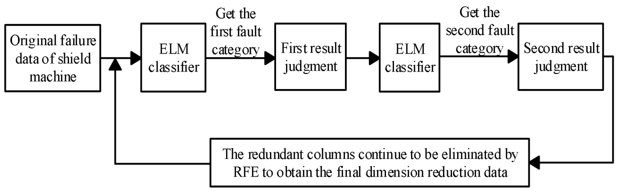

Fig. 2 Schematic diagram of shield machine fault diagnosis process

The dimension of fault data is determined according to the fault types of shield machine, and the sample data are constructed based on the actual monitoring data of shield machine for testing and training. The specific steps of fault diagnosis algorithm of shield machine based on reverse feature elimination are as follows.

Step 1: Select the operation data of shield machine as sample data and generate fault data, and select part of the data as training sample and the other part as test sample.

Step 2: Substitute the original fault data dimension of shield machine into ELM for fault diagnosis, and get the accuracy a of the original fault data dimension of shield machine.

Step 3: Replace the first dimension shield machine fault data with ELM to calculate the accuracy, and get the accuracy b of the first dimension shield machine fault data.

Step 4: Compare a with b. If $a \le b$, the accuracy becomes higher, the first dimension of the shield machine fault data can be considered as redundant dimension, which can be eliminated, and the accuracy calculation of the second dimension of the shield machine fault data can be started. If $a>b$, the accuracy becomes lower, the first dimension of shield machine fault data is the useful dimension, which should be retained and the accuracy calculation for eliminating second dimension of shield machine fault data should be started.

Step 5: Take the accuracy as the judgment standard, and the above rules are used to iterate until traversing all dimensions. Finally, the accuracy of fault diagnosis is obtained which eliminates most redundant dimensions.

Combine with ELM theory to deduce the model.

Firstly, the ith input vector $X_i=[x_{i1},x_{i2},\cdots,x_{ij}]^T \in R^n$, j is the number of samples, and the expected output vector is t_i. t_i is the fault type corresponding to the test data. According to the derivation of Eq. (1)-(4), in the training network, the hidden layer output matrix H is actually known, so the output weight β can be obtained. Input the test samples, so the output vector T_a of the test sample can be obtained according to Eq. (1). Compare test sample output vector T_a with t_i to get the accuracy a in the original data dimension of shield machine fault, and complete Step2.

Then, eliminate the first dimension of all sample data of input vector X_i, and calculate the accuracy rate repeatedly. The output vector T_a of test sample eliminated the first dimension is obtained. Compare T_a with t_i, the accuracy rate b is obtained after eliminating the first dimension fault data, and complete step 3.

Finally, according to step 4, through all dimensions, the accuracy of fault diagnosis for shield machine is obtained by using ELM. In this process, the accuracy rate of fault diagnosis is set as the optimization goal, and the accuracy rate of fault diagnosis is continuously improved during iterative calculation.

In conclusion, the fault diagnosis process of the shield machine based on the elimination of reverse characteristics is shown in Fig. 3.

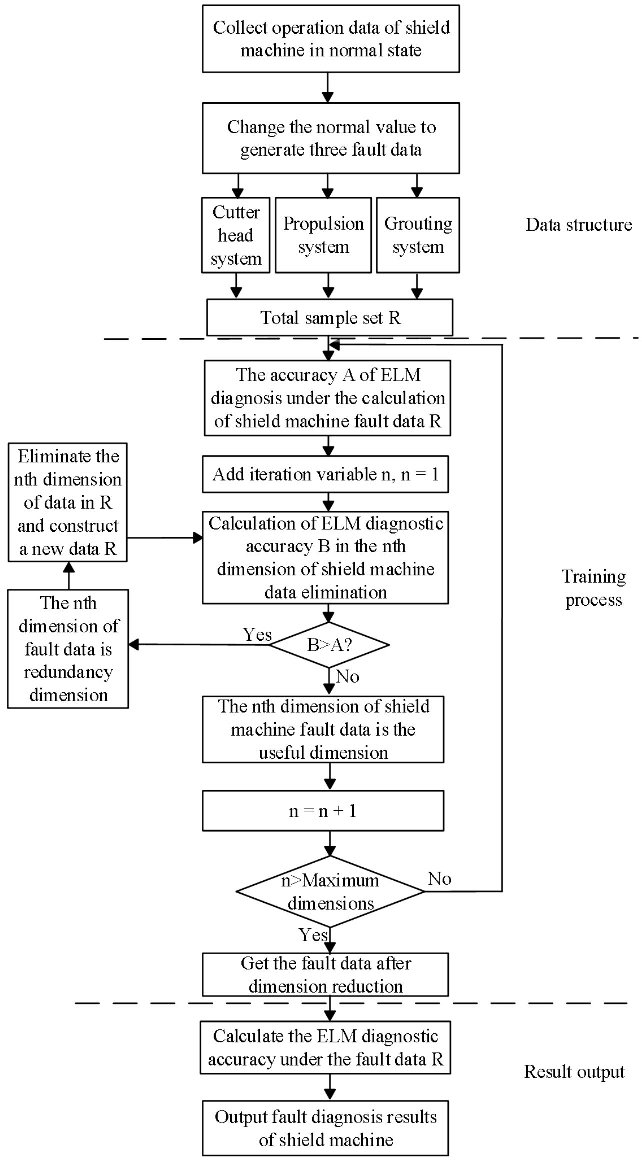

Fig. 3 ELM diagnosis flow chart based on RFE

IV. Experiment And Results Analysis

A. Test Results of Fault Diagnosis of Shield Machine

During the tunneling process, shield machine can usually work properly for most of the time. Therefore, it is very difficult to obtain a large number of actual fault data of shield machine due to less fault components and frequency, the complex tunneling conditions and many factors affecting the driving process. Therefore, using the data of Beijing Metro Line 10, 140 dimensional vector data composed of 140 monitoring parameters under normal conditions are obtained in this paper, and the fault data are generated according to the selected fault type and deviation degree. The three main fault types and their secondary fault types involve 11 dimensions of the 140 total dimensions. A total of 120 groups of data are selected. Each group of data contains 140 dimensional attributes, forming the original matrix of 120 rows and 140 columns, in which 90 rows are selected to form the training data, and the remained 30 rows are formed the test data.

Because of the randomness of neural network operation, each accuracy rate of fault diagnosis is obtained through 100 times of repeated training, and then the average value is added to get a reasonable and stable test accuracy rate, but the calculation time of fault diagnosis is also increased. In the actual application of shield construction, the training times can be appropriately reduced to improve the calculation efficiency.

All the following operation experiments are simulated by MATLAB software on a computer configured with Intel Core i5-7200U, 2.50GHz and 8.00GB memory.

Algorithm parameter setting: the sigmoid functions with the same parameters are selected as activation functions for the ELM algorithm, the same number of hidden layers and nodes. ELM neural network structure consists of input layer, hidden layer and output layer. The input is each group of fault data, and the output is the corresponding fault classification category of this group of fault data. The topology of ELM neural network is shown in Fig. 4.

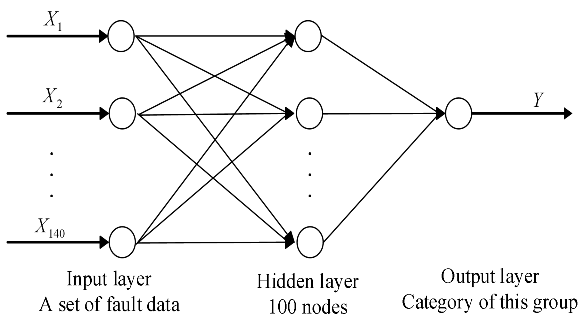

Fig. 4 ELM neural network topology

The validity of RFE-ELM algorithm in this paper is verified, and the results of data dimensionality reduction and fault diagnosis accuracy are shown in Fig. 5.

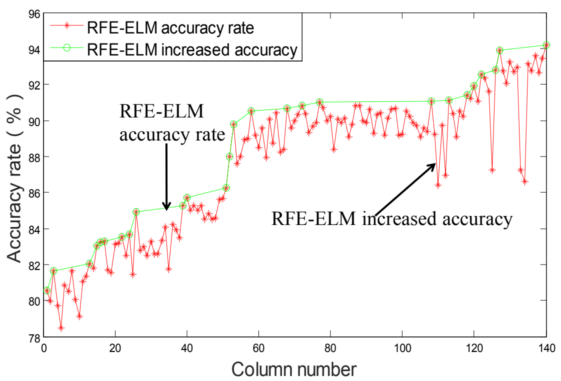

Fig. 5 Accuracy change of ELM fault diagnosis based on RFE for shield machine

In Fig. 5, RFE-ELM accuracy rate refers to that under each dimension eliminated, and the RFE-ELM increased accuracy rate refers to the points where the accuracy rate only keeps rising. As can be seen from Fig. 5, the accuracy of fault diagnosis of shield machine based on RFE-ELM is on the rise. With the continuous elimination of the number of redundant columns, the accuracy rate reached the highest after eliminating 26 redundant columns, and the diagnostic accuracy increased from 80.57% to the highest 94.2%.

The relationship between the number of eliminated columns and the fault diagnosis accuracy is shown in Fig. 6. It can be seen intuitively that the accuracy rate increases with the number increase of elimination columns. At the same time, the ELM diagnostic accuracy is increased, and the accuracy is the highest after eliminating 26 redundant columns.

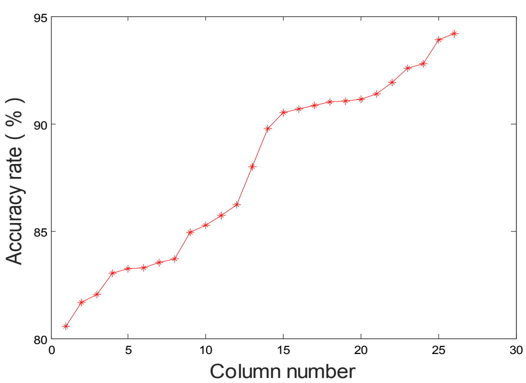

Fig. 6 Relationship between accuracy and the number of eliminated columns

The data after eliminating some redundant dimensions are used for shield machine fault diagnosis classification based on RFE-ELM and compared with the diagnosis results of BP neural network method with reverse feature elimination (RFE-BP). The visual results of diagnosis are shown in Fig. 7. In Fig. 7, the fault classification categories from 1 to 6 are as follows: NO. 1,5,3,7 cutter head motor torque is too large; NO. 2,6,4,8 cutter head motor torque is too large; NO. 2,4 jack speed is too large; NO. 1,3 jack speed is too large; grouting A liquid injection flow is too low; grouting B liquid injection flow is too low. It can be seen from Fig. 7 that the fault diagnosis result of RFE-ELM is basically consistent with the expected output result, while the diagnosis result of RFE-BP is quite different from the expected output. Moreover, the accuracy of RFE-ELM is 93.33%, while the accuracy of RFE-BP is 56.67%. Therefore, it can be concluded that the RFE-ELM method in this paper has high accuracy and better effect in fault diagnosis.

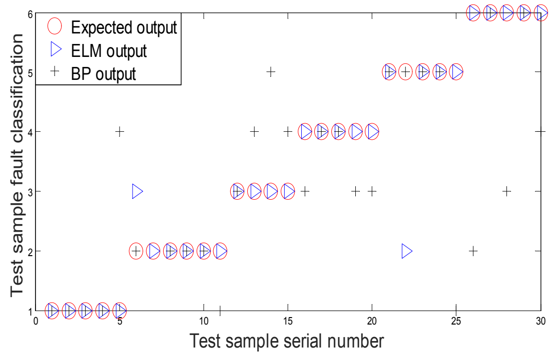

Fig. 7 Fault classification results comparison of RFE-ELM and RFE-BP

B. Comparison and Analysis of The Effectiveness of The Algorithms

In order to verify the effectiveness of this method, the proposed method RFE-ELM is compared with RFE-BP neural network, ELM, BP neural network diagnosis method. Through a lot of experiments, the structure of BP neural network is finally determined to be composed of input layer, two hidden layers and output layer. The input is each group of fault data, and the output is the corresponding classification category of the group of fault data. Each hidden layer has 15 nodes, and its topology is similar to that shown in Fig. 4. The initial parameter learning rate of BP neural network is 0.3, the training target is 0.001, and the training times is 200. The sigmoid functions in all BP neural networks are chosen with the same parameters, the same number of hidden layers and nodes. The simulation results of the four methods are shown in Fig. 8.

It can be seen from Fig. 8 that the accuracy rate of RFE-ELM fault diagnosis in this paper is significantly higher than that of other methods. With the elimination of redundant dimensions, the highest diagnosis accuracy rate reaches 94.2%, which shows that this method has better dimension reduction characteristics and higher fault classification accuracy. However, the accuracy of RFE-BP does not increase after eliminating 100 columns, and it is unstable. The highest diagnostic accuracy is 58%. Because the ELM and BP algorithm do not eliminate the columns and reduce the dimensions, but take the 140 dimensions of the original data as the input for fault diagnosis. So the diagnosis results only present a point in the Fig. 8, which are the ELM accuracy of the original data and the BP accuracy of the original data respectively.

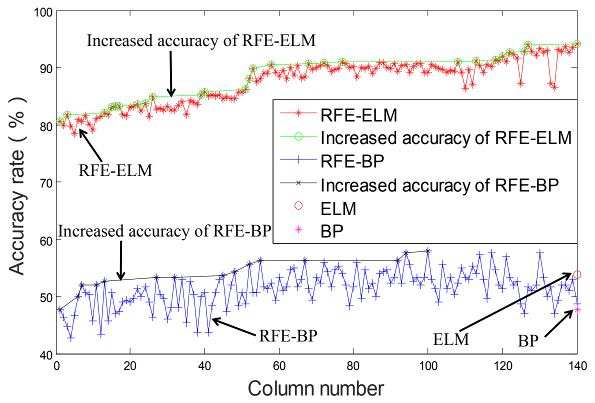

Fig. 8 Comparison of fault diagnosis accuracy of four methods

It is worth noting from the above result that this is not the diagnosis result of column 140, but the diagnosis result of 140 dimensional input. It can be seen that the diagnostic accuracy of ELM algorithm is 53.76%, and that of BP algorithm is 47.67%, which is significantly lower than that of RFE-ELM algorithm in this paper. The RFE-ELM has good fault diagnosis effect for the actual shield construction engineering. The quantitative comparison results of the overall performance of the four methods are shown in Table Ⅱ.

TABLE Ⅱ
COMPARISION RESULTS of THE FOUR DIFFERENT ALGORITHMS

Algorithm	Accuracy rate	Elimination of columns
ELM	53.76%	0
RFE+ELM	94.2%	26
BP	47.67%	0
RFE+BP	58%	15

From Table Ⅱ, it can be seen that the performance of the proposed method is superior to that of the other. When data are trained, different columns will be related to each other, so the columns eliminated by RFE-BP are roughly the same as those eliminated by RFE-ELM, but there are also subtle differences. The number of columns eliminated by RFE-BP is taken as the standard, 15 columns are eliminated in total, while the number of columns eliminated by RFE-ELM is 26, in which 7 columns are the same as RFE-BP, and the similarity is 46.67%. After eliminating redundant columns with strong interference, ELM can get higher accuracy than BP when the next dimension column is eliminated.

In conclusion, the method presented in this paper can effectively eliminate redundant columns and reduce dimensions of shield tunneling machine construction data. Furthermore, the accuracy of fault diagnosis is increased with the elimination of redundant columns. Compared with other methods, this method has higher fault diagnosis accuracy and stability of prediction accuracy, and the overall performance is obviously better than other methods. Therefore, this method can diagnose the component fault of shield machine more effectively during tunneling process. The method can effectively improve the construction efficiency of shield machine.

V. CONCLUSION

In order to solve the problem of accuracy and efficiency of shield machine fault diagnosis, and ensure the underground construction safety, an ELM fault diagnosis method based on RFE is proposed in this paper. Use the RFE to reduce the dimension of data, and the extremely learning machine to improve the efficiency of calculation to realize accurate diagnosis of faults. Based on the field construction data, simulation experiments are carried out to verify the effectiveness of the method, and the following conclusions are obtained:

(1) Compared with RFE-BP, ELM and BP, the accuracy of RFE-ELM is significantly higher than other methods, the highest accuracy is 94.2%. Most of the faults of shield machine can be detected automatically, which is of great significance to shield construction.This is very beneficial to ensure the safety and efficient construction of shield tunneling machine.

(2) Shield machine structure is very complex and contains many subsystems, so it generates massive amounts of data with many dimensions during tunneling. In the future, we can add fault classifications based on the operation data, and the mechanical failures will be detected more accurately and effectively by using the proposed method. This will be very helpful to the safe and efficient construction of shield machine in underground engineering.

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