METHOD OF MECHANICAL FAULT DIAGNOSIS UNDER DEEP AUTOMATIC ENCODER UNDER SUPPORT VECTOR MACHINE

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Abstract – The study is employed to reduce mechanical faults and improve the work efficiency of machinery. This paper adopts intelligent detection means and systematically detects the machinery faults. First, a new feature extraction method is used for the sparse automatic encoder that proposed to solve the problem of insufficient feature extraction of the informational fault of the equipment. Second, the binary tree support vector machine (SVM) is used to classify faults. Finally, the electronic circuit of the three-spot resistance welder's fault is detected to verify the reliability of the sparse automatic encoder. The research result shows that the use of sparse automatic encoders can enhance the robustness of non-Gaussian noise. At the same time, the convolutional neural network (CNN) technology is combined to perform edge noise reduction on its encoder. It can improve the feature extraction degree of electronic circuit information. The binary tree SVM can effectively classify mechanical faults and the results of output judgment whether the mechanical equipment is faulty or not. The automatic encoder is used to detect the fault of the three-spot resistance welder, and the fault detection result of the new detection method has higher accuracy and high reliability. The new fault detection method can efficiently detect mechanical faults and promotes the work efficiency of machinery, and ultimately the entire society.

Keywords: Convolutional Neural Network, Support Vector Machine, Automatic Encoder, Intelligent Detection.

1. Introduction

The mechanical fault diagnosis mainly focuses on signal acquisition, feature extraction, and fault diagnosis. Therefore, many experts and scholars have studied these steps around the world. First, in terms of signal acquisition, many scholars have studied it in China. The machinery is monitored through multiple vibration sensors. The scholars have optimized the arrangement of the vibration sensors. Therefore, the efficiency of obtaining the operating state of the machine can be improved. Some scholars have prospected and summarized the future development trend of wireless sensors. They believe that the direction of future sensors is toward the development of low cost and high efficiency [1]. Second, after the completion of the signal acquisition of the machine, the fault signal features of the machine need to be extracted. In China, scholars have studied the fault features of fan gearboxes based on this feature and proposed a method of order tracking to extract signals [2]. Meanwhile, some scholars also proposed sparse extraction methods for the feature signals of rotating machinery. Through an in-depth study of the fault features of planetary gearboxes, a method of iterative generalized synchronous compression transformation was developed [3]. Finally, for the mechanical fault diagnosis method, two methods of intelligent diagnosis of flexible convex hull maximum interval classification and local neural network diagnosis are proposed. Foreign scholars have also conducted in-depth research on the three steps of mechanical fault diagnosis. They proposed to use acoustic emission signals to monitor the health of the machine and obtain signals of the machine's operating conditions. To reduce the influence of harmonics during vibration, American scientists used time-domain synchronization technology for feature extraction. Brazilian scholars used DE trended fluctuation analysis to characterize feature information. Canadian scholars used the step-change method to extract features [4]. When diagnosing faults, British scholars used singular spectrum analysis to perform noise reduction on the feature data, making the data clearer and more comfortable to extract. Also, they used autoregressive models to determine the degree of mechanical fault [5].

In the past, when scholars diagnosed mechanical faults, they needed to analyze and classify a large amount of data, which was time-consuming and laborious.

With the continuous development of the times and the increasing advancement of technology, deep learning has been applied to data analysis by many scholars. In contrast, sparse automatic encoders can adequately express the sparseness of extensive data among many encoders. Also, it has a precise accuracy [6], making the classification of worked data more efficient. Therefore, based on the research of the scholars, this paper combines deep learning technology with the sparse automatic encoder. At the same time, how to effectively reduce the noise of the data is studied, and the previous information extraction methods are improved to enhance the accuracy of the information extraction.

2. Method

For the electronic circuit fault diagnosis method, it can be divided into two types: traditional fault diagnosis and modern fault diagnosis. Both diagnostic methods are shown in Figure 1.

As can be seen from the above figure, traditional fault diagnosis methods include fault dictionary method, verification method and parameter identification method. Modern fault diagnosis methods include expert system, artificial intelligence method and wavelet signal processing method [7].

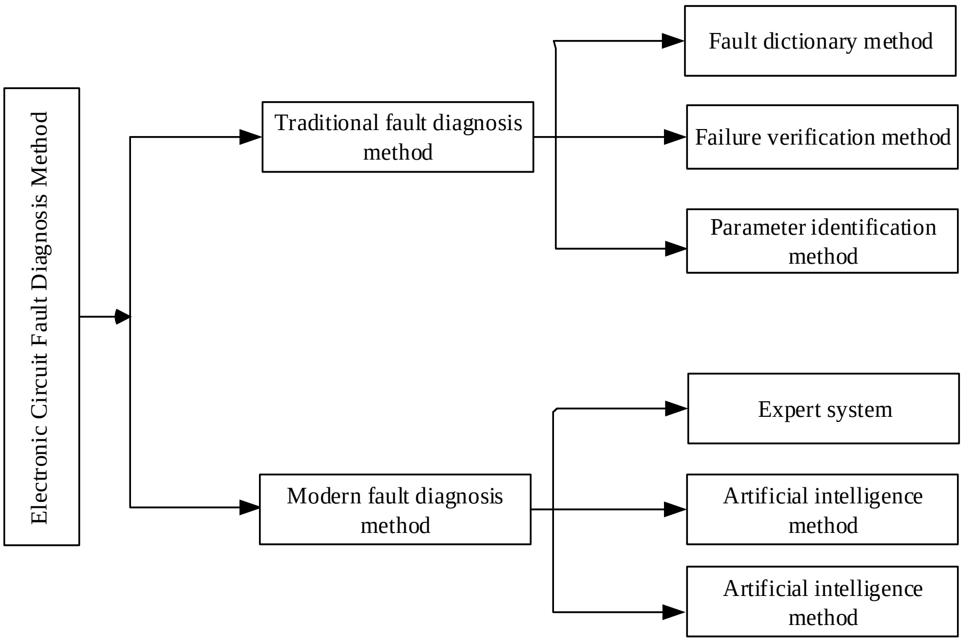

Figure 1. Electronic circuit fault diagnosis method

2.1 Improved sparse marginalized DE noising auto-encoder (ISm DAE)

To enhance the robustness of non-Gaussian noise, this paper is based on the advantages of both sparse automatic encoders and edge automatic noise reduction encoders. It also combines the two to obtain a new ISm DAE. Sparse automatic encoders add sparse restrictions to the automatic encoder to suppress hidden neurons. The edge automatic noise reduction encoder uses marginalization to process the noise immediately added to reduce noise interference. At the same time, the calculation amount of the staff is reduced, and the efficiency of data processing is improved [8]. To achieve this goal, Taylor Expansion is used to approximate the expected loss function of the noise reduction automatic encoder, and finally, it is marginalization is achieved.

Therefore, the ISm DAE adds two improved constraints on the hidden layer of the automatic encoder. One is the sparsity limitation, and the other is the edge noise reduction limitation.

When extracting fault feature information of the electronic circuit by using the ISm DAE, the information of a branch current or a node voltage of the electronic circuit is first collected. Then, it is converted into the processed data range of the ISm DAE.

Finally, it's data samples are trained to achieve the ISm DAE in deep learning to extract fault data information [9]. The process of data extraction is shown in Figure 2 below.

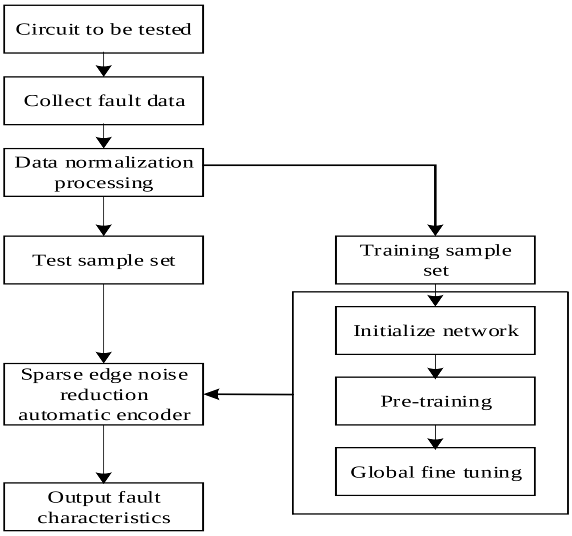

Figure 2. Mechanical fault extraction process of ISm DAE

2.2 Fault classifier of binary tree support vector machine (SVM)

Compared with the artificial neural network, SVM is proposed to make the fault diagnosis classification simpler. It does not need to be trained as much as an artificial neural network, and it has a stronger ability to process small sample data, non-linear data, and high-dimensional data. The machine learning method of SVM is based on the statistical rules of small samples and does not require a large number of samples for training. Although the construction of this SVM is relatively simple, it has more vigorous learning and generalization ability. SVMs use high dimensional feature space to solve the problem of difficult sample classification in low dimensional space. It uses the kernel function to project sample data into a high-dimensional feature space, maximizes the interval sample classification, and reduces the processing of a large number of sample data. Using Lagrangian change, dual form, and optimization solution to improve existing constraints, SVMs flexibly select kernel functions based on the mechanical circuit fault information feature [10]. The structure of the binary tree SVM selected in this paper is shown in Figure 3 below.

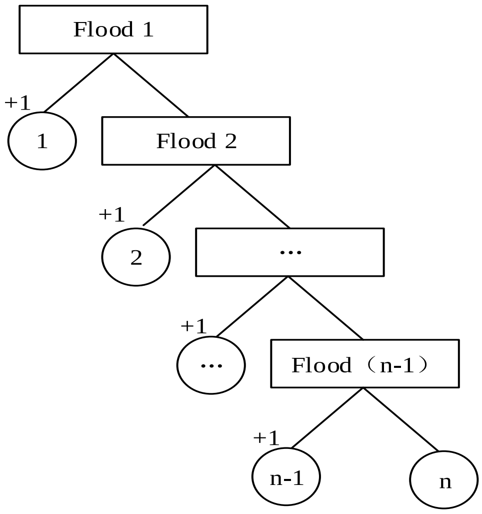

Figure 3. Structure of binary tree SVM

2.3 Feature extraction of electronic circuit fault information of three-spot resistance welder

The three-spot resistance welder is automatic welding equipment. It combines automatic welding machines and welding robots to form an automatic welding machine. Also, it has the advantages of artificial intelligence and an automatic control system, which can save workforce, while ensuring the high quality and efficiency of welding [11].

This method is used to extract fault features of the electronic circuit of the three-spot resistance welder to verify whether the feature extraction method of the edge noise reduction automatic encoder is feasible.

The extraction process of this method is shown in Figure 4 below.

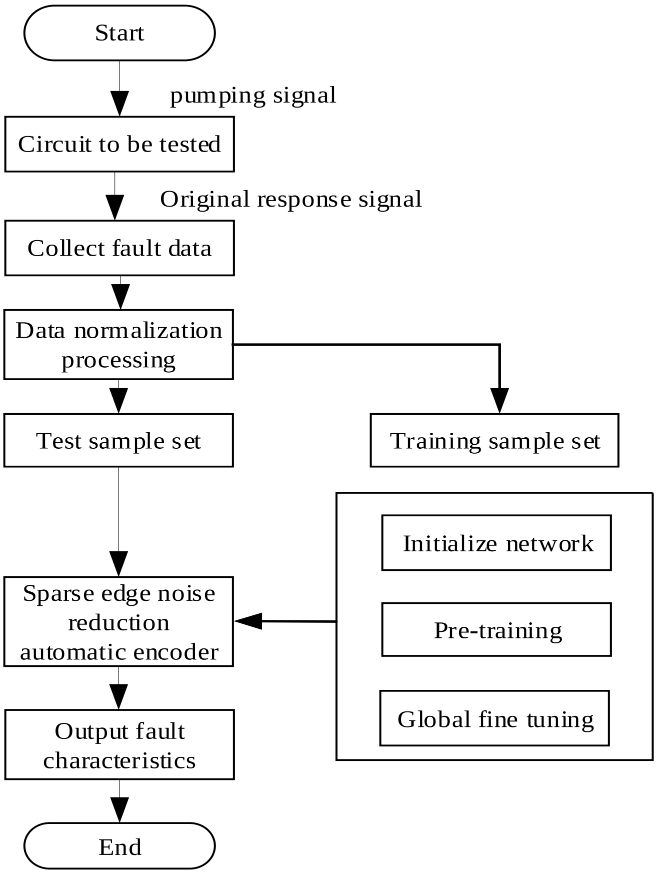

Figure 4: Feature extraction process of electronic circuit fault information of three-spot resistance welder

The first step is to collect fault response data. By applying an excitation signal to the electronic circuit, the fault voltage and current of the output node of the electronic circuit are collected. It is a feature extraction of the electronic circuit fault data of the three-spot welding machine, which contains three welding guns. Therefore, the voltage and current signals of the electronic circuit on each welding gun need to be collected. Then, the values of the voltage and the current signal are collected everywhere [12]. The second step is to normalize and divide the collected data. The data range of fault voltage and current is large. The values that are not in the 0-1 interval are normalized so that they are within this interval. The obtained data samples are divided again, selecting the training sample and the test sample. The third step is to initialize the network. It is necessary to choose the appropriate structure of ISm DAE according to the actual situation. Then, the unit numbers of the input layer, the hidden layer, and the output layer are set [13].

The fourth step is to input the training set samples, adjust the rate and convergence criterion to 0.1 so that the error function meets the convergence conditions, and the training is ended. The fifth step is to fine-tune the fault mode of the electronic circuit by using the decimal system. The number of neurons in the classification layer is determined to be 5. The learning rate and the convergence criterion are both 0.1. The final step is the extraction of fault features. The test sample data is input, and different automatic encoders are used to extract the faults of the electronic circuit to compare the extraction effects of various encoders.

The typical electronic circuit faults of three-spot resistance welders are mainly divided into 5 types [14]. The ISm DAE is used to extract the fault features and the binary tree SVM is used to classify the fault diagnosis. The two are combined to form a new method of fault diagnosis of ISm DAE-SVM electronic circuits. The diagnostic process of this method is shown in Figure 5 below.

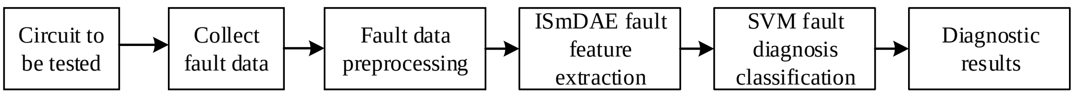

Figure 5: Fault diagnosis process of ISm DAE-SVM electronic circuit

3. Results and Discussion

3.1 Fault information extraction of ISm DAE

Various types of automatic encoders are used to test the fault features of the MNIST dataset, the bg-rand dataset, the CIFAR-10 dataset, and the rot dataset. The comparison of test results are shown in the figure below.

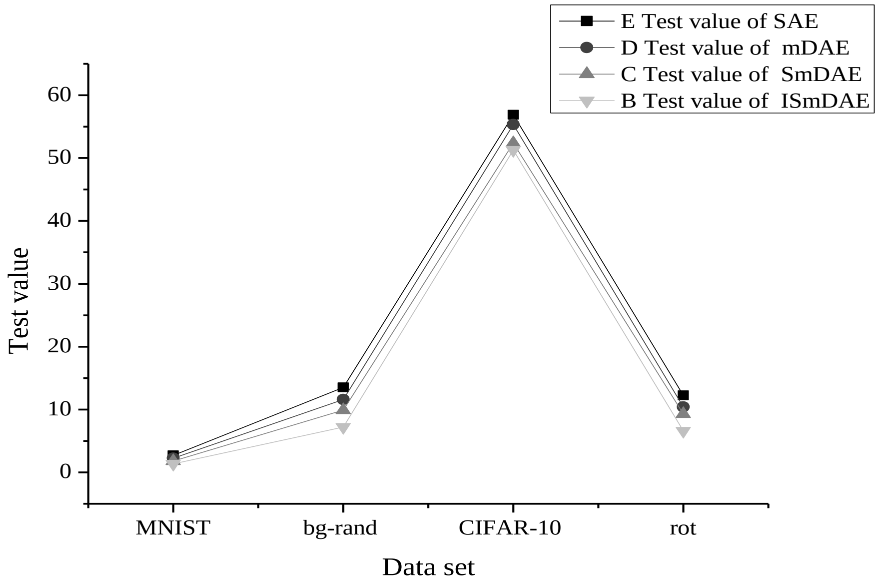

Figure 6: Comparison of test results of various encoders on different datasets

Various types of automatic encoders are used to extract the fault information features of the electronic circuit of the three-spot resistance welder. The extraction results of several encoders are compared, as shown in Figure 7 below.

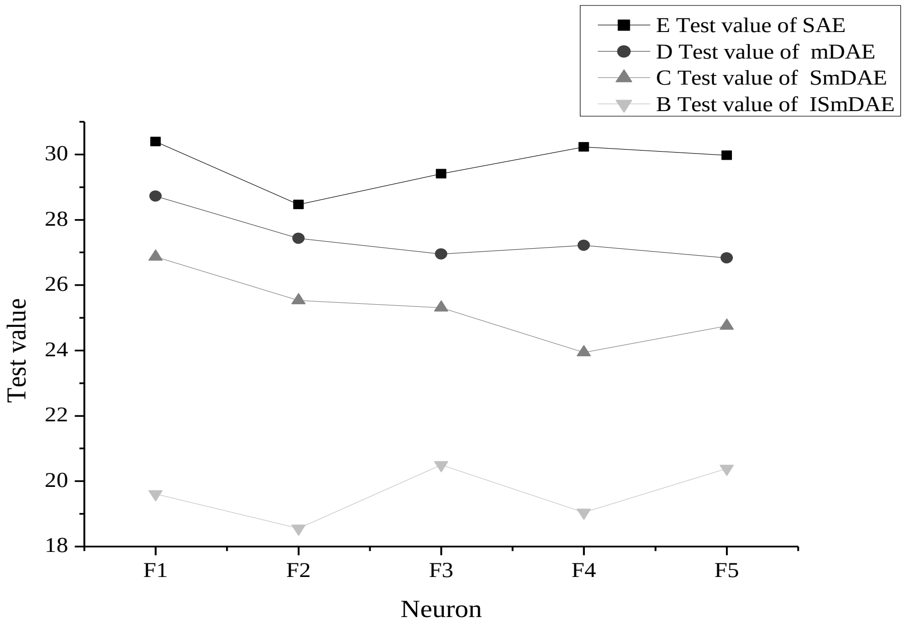

Figure 7: Comparison of test results of various encoders under the electronic circuit fault data of the three-spot resistance welder

From the test results of several encoders in Figure 6 and Figure 7, the extraction error rate of the new ISm DAE has been significantly reduced, improving the accuracy of the electronic circuit diagnosis efficiency.

3.2 Fault information classification by SVM

The SVM can be widely used in electronic circuit fault diagnosis. It is found through research that the method mainly has three advantages: low structural risk, optimal data values, and flexible selection of kernel functions. The structural risk is low because it can reduce the dimension of machine learning. Meanwhile, to ensure that the accuracy of data classification can achieve the expected effect. Therefore, the expected risk of machine learning is minimized. The fault feature classification method of SVM avoids the problem that most machine learning methods easily lead to overfitting. It improves the learning ability of small sample data and balances the learning ability and the promotion ability [15]. Therefore, in the case of small sample data, the accurate diagnosis of mechanical faults can be guaranteed. Solving the classification of SVMs is a programming problem that converts data values into convex quadratic functions. The planning problem is optimally solved for the global to ensure that the solution of SVM is the optimal global solution. The realization of the transformation needs to use the Lagrangian change, dual form, and optimization solution to improve the original constraint conditions. Therefore, when using SVM for fault diagnosis of electronic circuits, the output solution is guaranteed to be the optimal global solution that avoids the situation where the output value is locally optimal. SVM needs to use kernel functions to perform non-linear mapping of input values when inputting feature information.

It can select different kernel functions according to the fault information features of the electronic circuit so that the non-linear problem can be solved. When performing the kernel function mapping, the fault feature information vector can be mapped into a high-dimensional space to solve the problem that some data cannot be divided into a low-dimensional space. Then, the problem that some fault feature information vectors cannot be classified is solved. Then the capability of fault information classification is improved. The feature of the flexible selection of kernel functions can solve the problem of sparse classification due to noise interference and non-linear factors in the fault feature information of electronic circuits [16].

3.3 Analysis of fault diagnosis results of ISm DAE-SVM electronic circuit

This fault diagnosis is used to diagnose the electronic circuit fault information of the three-spot resistance welder. At the same time, it is compared with the fault data of the three-spot resistance welder, as shown in Figure 8 below.

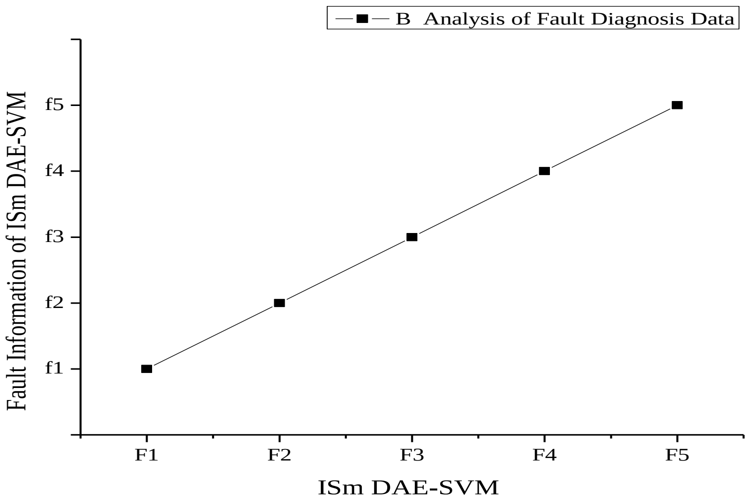

Figure 8: Analysis of fault diagnosis results of ISm DAE-SVM electronic circuit

It can be seen from Figure 8 that the fault diagnosis results of the ISm DAE-SVM electronic circuit overlap with the fault information of the electronic circuit of the three-spot resistance welder. It is turned out that the ISm DAE can enhance the robustness of non-Gaussian noise and effectively extract the fault information of electronic circuits. Moreover, the robustness of binary tree SVMs is also very strong [17]. The combination of the two can effectively extract and classify the fault information of electronic circuits, confirming the feasibility and effectiveness of the method [18-22].

4. Conclusions

Mechanical faults are involved in many fields. Therefore, many scholars have studied and improved the problem of mechanical faults. According to the existing theory and research basis, this study introduced a new method of mechanical fault diagnosis based on a deep automatic encoder under SVM. Taking the electronic circuit fault information of the automatic three-spot resistance welder in mechanical equipment as research direction, the newly proposed diagnostic method is used to pull out the fault information of the electronic circuit to verify the feasibility of this research method.

When extracting fault information of electronic circuits, it is usually disturbed by many factors, which makes it difficult to accurately and efficiently extract information features. In the actual operation process, the fault feature extraction of electronic circuits will be affected by the noise in the environment, and the non-linear problems will also interfere with the extraction of feature information. This study can increase the efficiency of fault information diagnosis by improving the feature extraction method of fault information.

This study makes an understanding and analysis of the fields involved in diagnosing mechanical faults and existing research methods. At the same time, research and discussion are carried out using the currently developing technologies and artificial intelligence methods, which laid the theoretical foundation for this research. Then, because the automatic encoder will be affected by environmental noise, most of the electronic circuit fault information has non-linear features. Therefore, the calculation method of correlation entropy is added to the automatic encoder to enhance the robustness of the sparse automatic encoder to non-Gaussian noise. At the same time, CNN performs edge DE noising on the method to obtain a new ISm DAE. Then, the automatic encoder and several traditional automatic encoders are used to perform fault diagnosis tests on several datasets respectively.

Through experiments on these methods, it is proved that the ISm DAE can obviously reduce the error rate of information feature extraction and classification. Then, this method is used to diagnose the electronic circuit fault of the three-spot resistance welder of the automatic welding equipment. It is found that during this experiment, the ISm DAE still has a strong advantage. The error rate of the fault features extracted by this method has been significantly reduced, which verifies the feasibility of this method in practical life. Finally, a sparse edge noise reduction encoder based on deep learning and a binary tree SVM classifier are combined to form the ISm DAE-SVM electronic circuit fault diagnosis method. It also shows excellent performance in the fault diagnosis experiment of the three-spot resistance welder.

The research results show that the new ISm DAE-SVM electronic circuit fault diagnosis method has a decent performance in practical applications and shows its' superiority. The fault diagnosis experiments on the three-spot resistance welder have also turned out that it can be applied to real-life to resolve the problem of low efficiency of feature extraction of fault information.

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