Application research on fault diagnosis of food machinery equipment based on neural network

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Abstract: Aiming at the problems of poor generalization ability and low fault recognition rate in fault diagnosis of food machinery and equipment, in order to improve the effect of fault diagnosis of machinery and equipment, this paper aims to study the application of fault diagnosis of food machinery and equipment based on neural network. Firstly, a method of fault signal recognition of food machinery and equipment based on external correction is proposed. The function of external intervention is set, and the fault features of mechanical equipment are periodically corrected, so that the frequency curve of equipment fault feature vibration shows the periodic dynamic features, and the signal features of equipment fault are extracted. Then, an equipment fault diagnosis method based on enhanced migration convolutional neural network is proposed. A convolutional neural network and two data classifiers are established to train the fault data in the network source domain, detect the target domain data samples at the decision boundary, establish the data classification loss function and classifier discriminant function, and minimize the difference in feature distribution between the source domain and target domain, Complete the application research of fault diagnosis of food machinery equipment based on neural network. And through experiments, it is proved that the method proposed in this paper has strong generalization ability, can effectively improve the effect of mechanical equipment fault diagnosis, and improve the safety of equipment operation.
Keywords: Convolution neural network; Food machinery and equipment; Fault diagnosis; Enhanced migration;

1. Introduction

With the gradual promotion of economic development, a large number of different machinery and equipment have been put into use. However, various accidents caused by mechanical equipment failures have occurred frequently, causing serious negative impacts on production efficiency and personal safety of staff. Mechanical equipment is the main force of national production and construction. The development level of mechanical equipment directly represents a country's scientific research capacity and comprehensive national strength. In terms of ensuring the reliability of food machinery and equipment, reducing the probability of accidents and economic losses, the fault diagnosis technology of food machinery and equipment has important practical value [1].

With the gradual development of technology, the functional requirements for food machinery and equipment are gradually increasing. The more integrated functions of equipment, the more complex the equipment structure is. The corresponding failure modes of equipment are also complex and diverse. It is very difficult to diagnose mechanical equipment only by manpower. Because the traditional fault diagnosis of mechanical equipment is mainly based on the experience and knowledge of relevant experts and maintenance personnel, At the same time, regular inspection and maintenance of mechanical equipment are required, which consumes a lot of manpower and time with low efficiency and cannot meet the requirements of the current mechanical equipment fault diagnosis market. With the gradual development of information technology and neural network algorithm, the main research contents of fault diagnosis methods for food machinery equipment at home and abroad [2]. The traditional food machinery fault diagnosis has the problems of poor generalization ability and poor recognition rate of fault diagnosis.

The innovations of this paper are as follows:(1) Firstly, a method of fault signal recognition of food machinery and equipment based on external correction is proposed. The function of external intervention is set, and the fault features of mechanical equipment are periodically corrected, so that the frequency curve of equipment fault feature vibration shows the periodic dynamic features, and the signal features of equipment fault are extracted. Then, the equipment fault diagnosis method based on enhanced migration convolution neural network is proposed, and the application research of fault diagnosis of food machinery equipment based on neural network is completed. (2) Compared with other fault diagnosis methods of food machinery equipment, the method proposed in this paper can effectively improve the equipment fault identification rate, but also effectively improve the reliability of mechanical equipment operation.

2. Related work

At present, the fault diagnosis of food machinery mainly depends on the data of each component when the machinery is running. With the rapid development of information technology, sensors have been widely used. Li Yuji et al. studied the fault diagnosis model of food machinery equipment based on machine learning, so as to improve the anti-interference ability of equipment fault diagnosis and effectively ensure the safe and stable operation of food machinery equipment. Firstly, the feature extraction algorithm with global resource description function and identification of projection equipment is adopted to extract the time-domain features and the optimal projection matrix vector to measure the failure of food machinery and equipment. The learning algorithm of ART neural network is optimized and improved through Mexican straw hat function, effectively weakening the power function, so as to improve the convergence effect and clustering effect of the algorithm, The column vector of the optimal projection matrix is used as the input of the improved ART neural network. After stage learning and training, the fault diagnosis of food machinery and equipment can be effectively realized. The simulation experiment shows that the proposed method can effectively improve the efficiency of fault diagnosis and the accuracy of fault diagnosis is high, but the method does not improve the reliability of mechanical equipment operation [3].Fang xuechong et al. proposed a fault diagnosis method for food machinery equipment based on continuous variation mode decomposition and supervised local linear embedding, aiming at a series of problems such as the difficulty of fault identification for food machinery equipment and the fact that the collected signal is easily interfered by background noise. The continuous variation mode decomposition is used to analyze the collected equipment signals, so as to obtain specific expected mode components, and obtain the label information of component classes. The class label information can be used to expand and scale the distance between different categories of components. The supervised local linear embedding is used to reduce the dimension of the processed mechanical equipment sample data, and accurately identify the fault type of food mechanical equipment. The equipment vibration signals collected by the pattern experiment platform are analyzed in detail, and the accuracy of clustering identification is high, but this method does not improve the accuracy of equipment fault diagnosis, resulting in low feasibility of this method [4].Li Zhixing et al., in the real working environment, most of the useful signals in food machinery and equipment are weak and easily submerged by noise, which makes it difficult to extract the features of mechanical equipment faults. Aiming at this phenomenon, a fault diagnosis method of stochastic resonance mechanical equipment based on time delay constraint is proposed. First, build a stochastic resonance model with time delay, describe the structure and functional characteristics of the model function in detail, theoretically deduce the mathematical expression of signal to noise ratio, study and analyze the influence of the relationship between system parameters, time delay length and noise intensity, and then realize the matching of stochastic resonance through the parameter optimization performance of the ant colony algorithm itself. The proposed fault diagnosis method is applied to the simulated food machinery and equipment for fault diagnosis. The analysis results show that this method is less interfered by noise, and the effect of food machinery and equipment fault diagnosis is more obvious, which can effectively improve the ability of food machinery and equipment fault diagnosis. However, this method has the problem of poor stability of equipment operation [5].Guo Liang et al., for the fault diagnosis method of food machinery equipment, a large number of labeled data is an important condition for effective model training, but this condition is difficult to meet in some application scenarios. In order to solve this problem, a fault diagnosis method for food machinery equipment based on feature knowledge transfer is proposed. First, a one-dimensional depth convolution neural network is established to realize the depth mapping from the original vibration signal to the fault of food machinery and equipment. In the neural network of depth convolution, domain adaptive regular constraints are added to realize the deep transfer of feature knowledge between monitoring data of different food machinery equipment. Finally, the fully connected neural network is used to identify the health status of food machinery and equipment. In order to verify the effectiveness of the proposed method, simulation experiments are carried out. The experimental results show that the proposed method can effectively realize the adaptation of data feature knowledge migration of different food machinery and equipment. Compared with other traditional fault diagnosis methods for food machinery and equipment, the proposed method can effectively improve the accuracy of fault diagnosis, but this method has the problem of poor efficiency of fault diagnosis [6].

3. Fault Signal Recognition of Food Machinery Based on External Correction

Model

3.1 Optimization correction of external excitation equation

The early failure of food machinery is that the vibration signal can not be effectively described, and there are defects in the purification process. Therefore, this paper adds the external excitation equation to the traditional description algorithm. Represented by:

(1) P_z represents the average static elastic deformation force of mechanical equipment after bearing the force;

(2) $l(t)g(t)$ represents the elasticity caused by the error of food machinery and equipment;

(3) P_t represents the active excitation force of the active exciter [7-8].

The above contents are the key analysis contents in external excitation, which can be incorporated into the equation of active excitation force, showing the modulation phenomenon of stochastic resonance. When this phenomenon occurs, the mechanical equipment system is analyzed. If the signal meets $x(0) = x_0$ and $\dot{x}(0) = \dot{x}_0$, it has:

$$\begin{cases} S(x) + dx + l(t)x = \hat{P} \\ x(0) = x_0, \dot{x}(0) = \dot{x}_0 \end{cases} \quad (1)$$

Let $x_1 = x$ and $x_2 = \dot{x}_1 = \dot{x}$ have:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = -\frac{l}{S}x_1 - \frac{d}{S}x_2 + \frac{P}{S} \end{cases} \quad (2)$$

The formula (2) is transformed into a matrix and expressed as:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{l}{S} & -\frac{d}{S} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{S} \end{bmatrix} P \quad (3)$$

The vector expression of the corrected state equation of the food machinery equipment system fault is obtained from Formula (3). Where, x_1 represents the state variable of displacement and x_2 represents the state variable of velocity. It mainly describes the dynamic characteristics of the food machinery equipment system, which can effectively enhance the equipment signal characteristics, and is conducive to the purification operation during fault diagnosis [9-10].

The equation of failure regulation state of food machinery and equipment is expressed as:

$$\dot{X} = EP + F\hat{P} \quad (4)$$

3.2 Fault feature recognition of mechanical equipment

Based on the nonlinear time series analysis method, the phase space of the fault signal sequence of food machinery equipment is reconstructed, and the one-dimensional time series is displayed in the multi-dimensional space during the reconstruction of phase control. In this paper, the average mutual information method is used to calculate the scalar time series, and the false nearest neighbor method is used to calculate the embedded dimension of phase space reconstruction [11-12]. According to the above method and Takens' embedded definition, it can be concluded that the vibration signal system of food machinery and equipment fault after reconstruction is:

$$x_i = \left(x_i, x_{i+\tau}, \cdots, x_{i+(m-1)\tau}\right) i = 1,2,\cdots, N-(-1)\tau \quad (5)$$

Where, $\{x_n\}_{n=1}^{N}$ represents the time series of vibration signals under the fault state of mechanical equipment detected by signals, assuming that the length is N . In the m dimensional phase space reconstructed by the above method, the points where the distance between phase points x_j and x_i is less than x_j are:

$$Q = \sum_{j \neq 1} H(r - \|x_i - x_j\|) \quad (6)$$

In formula (6), $H(\cdot)$ represents the Heavside function.

The concept of correlation function is set here, which is defined as the correlation function for the proportion of all points whose distance r is smaller than the given distance in the total points. It can be expressed as:

$$C_N(r) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} H(r - \|x_i - x_j\|) \quad (7)$$

In Formula (7), the numerator is 2, which is mainly used to exclude repeated calculations. Norms are used to represent the distance between two image points. It can be concluded that the distance between two phase points is the maximum difference of two vectors, expressed as:

$$\|x_i - x_j\| = \max_{1 \le k \le m} \|x_{i-(k-1)\tau} - x_{j-(k-1)\tau}\| \quad (8)$$

The vector with no greater than r relative to the distance is called the correlation vector. Suppose that the data of one-dimensional food machinery and equipment vibration sequence is n, then the number of vector points in phase space reconstruction is $N = n-(m-1)\tau$. Calculate the phase point logarithm with correlation in the phase point, and the $N(N-1)/2$ matching proportions with all possibilities are correlation integral, which can be expressed as:

$$C_m(r)=\frac{2}{N(N-1)}\sum_{i=1}^{N}\sum_{j=i+1}^{N}H(r-\|x_i-x_j\|) \quad (9)$$

Because the length of mechanical equipment vibration signal detected in practical applications usually does not reach $N\to\infty$, the length of data time is infinite, or $r\to 0$ and other conditions. Therefore, in view of the actual situation of fault vibration of food machinery equipment, the system proposes an improvement method, starting from the correlation function. When the time series is $N\to\infty$, the length r of the correlation distance is relatively small. If the correlation dimension integral $C_m(r)$ follows the law of index, it is:

$$\lim_{r\to 0} C_m(r)\infty r^D \quad (10)$$

Therefore, the approximate value of the correlation dimension can be equal to:

$$D=\frac{\ln C_m(r)}{\ln r} \quad (11)$$

4. Fault Diagnosis of Food Machinery Based on Convolutional Neural Network with Enhanced Migration

4.1 Description of neural network structure

Figure 1 shows the diagnosis scheme of food machinery equipment fault based on enhanced migration convolutional neural network [13-14].

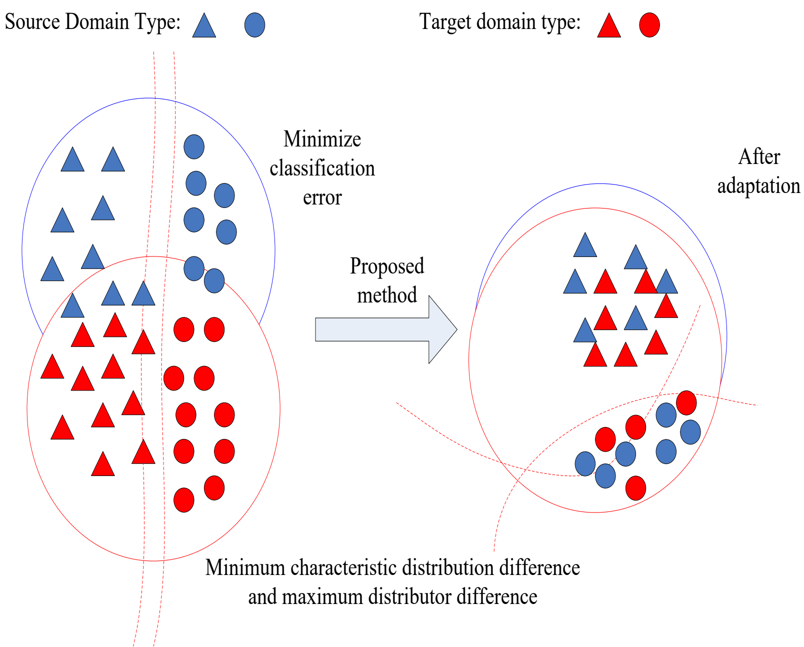

Fig. 1 Fault diagnosis scheme of food machinery equipment based on enhanced migration convolutional neural network

The fault diagnosis framework of food machinery equipment based on enhanced migration convolutional neural network is shown in Figure 2. The network structure is mainly composed of feature extractor G_f and two independent classifiers C.

Mechanical equipment fault feature extractor G_f is composed of multiple one-dimensional convolution layers, normalization layer and maximum pooling layer, which can expand one-dimensional original equipment input signals. The classifier is composed of full connection layer and Softmax layer, which is specifically responsible for processing the fault characteristics of high-rise mechanical equipment and learning the decision boundary of input data classification.

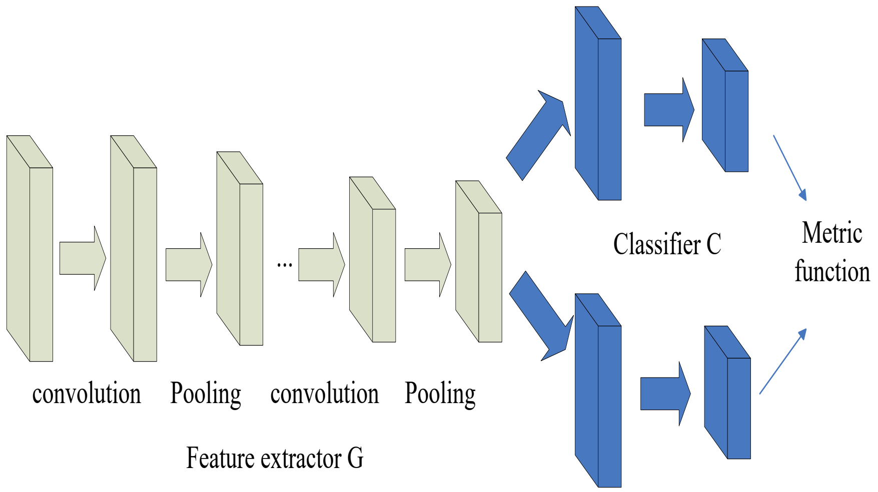

Fig. 2 Fault diagnosis framework of food machinery equipment based on enhanced migration convolutional neural network

The parameters of the convolutional neural network structure are shown in Figure 3. The input data of the neural network is a one-dimensional vibration signal. The first layer uses a relatively large convolution kernel to carry out sliding window and convolution operations, so as to enhance the feature learning and anti noise performance of the neural network. Other convolution layers mainly improve the ability of neural network to learn detailed features [15-16]. In addition, in each convolution layer, normalization layer and maximum pooling layer, the size of pooling is 2 * 1, which can reduce the size of output characteristic graph between pooling, thus reducing the complexity of neural network. The Softmax function is used to perform the final classified mechanical equipment output task.

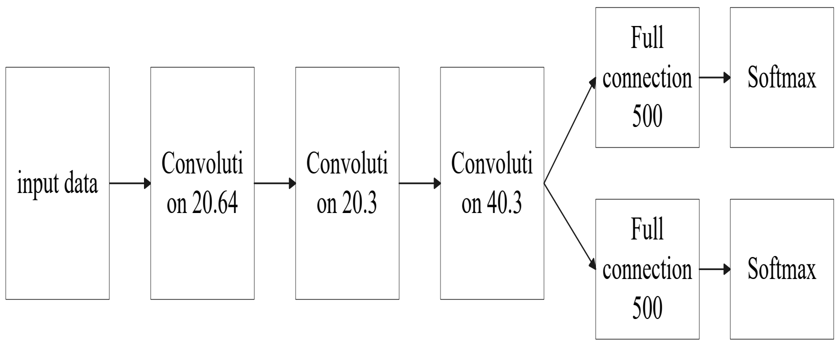

Fig. 3 Parameters of convolutional neural network structure

4.2 Fault diagnosis method of food machinery

The proposed convolutional neural network fault diagnosis method for food machinery and equipment based on enhanced migration comprehensively considers the influence of the discriminant boundary of the source domain on the fault samples in the target domain. Two relatively independent classifiers can be used as discriminators to align the features of machinery and equipment between different domains. The detailed learning process is as follows:

(1) Supervised training feature extractor G_f and feature classifier C. The data set $\{X_s, Y_s\}$ of the source field is composed of the original food machinery equipment data X_s and the corresponding label Y_s, while the food machinery equipment fault target field data $\{X_t\}$ is composed of the data X_t without any labels [17-18].Input the source domain data X_s into the mechanical equipment feature extractor G_f, and obtain that the mechanical equipment data has high-dimensional features, and input it into two data classifiers C_1 and C_2. The two data classifiers divide the source domain data into K classes, and the classifier mainly uses Softmax function as the output to obtain the distribution of class probability. The loss function of the classification is expressed as:

$$L_{cls}(X_s, Y_s) = -E_{(x_s, y_s)\sim(X_s, Y_s)} \sum_{k=1}^{K} 1_{[k=y_s]} \lg p(y|x_s) \quad (12)$$

In formula (12), $p(y|x_s)$ corresponds to the output of the classifier for the sample probability of the source domain. The traditional supervised learning method is used to optimize the parameters of the feature extractor and data classifier of the neural network by training the feature extractor G_f with the minimum cross entropy loss and the corresponding mechanical equipment two data classifiers C_1 and C_2:

$$\min_{G_f \cdot C_1 \cdot C_2} L_{cls}(X_s, Y_s) \quad (13)$$

(2)The discriminant loss function of data classifier for food machinery and equipment is established. Because the initialization parameters of data classifier C_1 and C_2 are different, when the source domain data is used to train the network, two mechanical equipment data classifiers with different discrimination characteristics can be obtained. Because two data classifiers can learn different decision boundaries, and two data classifiers can obtain different data classification results, the neural network introduces the discriminant loss function of data classification, namely:

$$L_{dis}(X_t) = E_{x_t \sim X_t}\left[d(p_1(y|x_t), p_1(y|x_t))\right] \quad (14)$$

In formula (14), $p_1(y|x_t)$ represents the probability output of data classifier C_1, and $p_2(y|x_t)$ represents the probability output of data classifier C_2 [19-20].

The absolute value of the difference between the probability outputs of two data classifiers is used as a measurement function to measure the difference between the outputs of two classifiers, which is expressed as:

$$d(p_1, p_2) = \frac{1}{K}\sum_{k=1}^{K}|p_{1k} - p_{2k}| \quad (15)$$

In formula (15), d represents the measurement function, which is calculated by L_1 distance, p_{1k} represents classifier C_1 probability output for class K, and p_{2k} represents classifier C_2 probability output for class K.

(3) The negative number of the discriminant function of the classifier is introduced. The neural network uses the minimum classification loss function and the loss function of the classifier to update the parameters of the food machinery and equipment data classifier as follows:

$$\min_{C_1 \cdot C_2} L_{cls}(X_s, Y_s) - L_{cls}(X_t) \quad (16)$$

The above optimized data classifier can detect target domain samples outside different decision boundaries, but cannot reduce the difference in data distribution between source domain and target domain. Therefore, fix the parameters of the two classifiers, reduce some differences between target domain samples and source domain samples, and achieve data distribution between source domain and target domain. The neural network optimization function is calculated as:

$$\min_{G_f} L_{dis}(X_t) \quad (17)$$

Repeat the training process from (1) to (3) until the optimized food machinery equipment diagnosis network is obtained and applied to mechanical equipment fault diagnosis. The above process completes the application of fault diagnosis of food machinery equipment based on enhanced migration convolutional neural network. Figure 4 shows the detailed flow of food machinery fault diagnosis based on enhanced migration convolutional neural network.

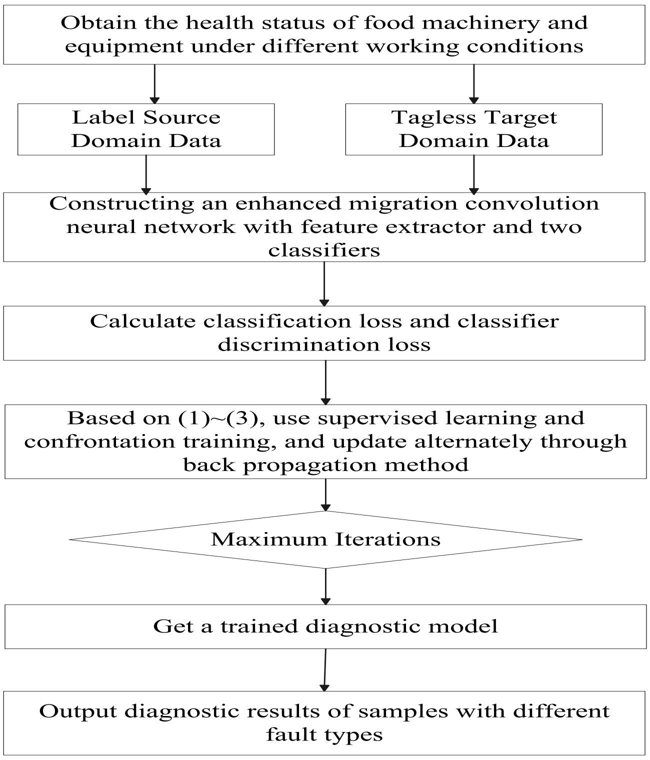

Fig. 4 Detailed flow of food machinery fault diagnosis based on enhanced migration convolutional neural network

5. Experimental result

5.1 Experimental data

In order to verify the effectiveness of the application research on fault diagnosis of food machinery equipment based on neural network proposed in this paper, simulation experiments are carried out in the Matlab simulation environment. Table 1 represents the parameters of the experimental platform, and Table 2 describes the experimental sample data.

Table 1 Parameter Setting of Relevant Experimental Platform

parameter	Set value
SetPoint DCT gear set model	DQ381
Number of gears for electric control equipment	10
Spindle revolutions of the experimental platform	1 000 r/min
Maximum sampling frequency of the system	10 000 Hz
Theoretical characteristic frequency range	500 Hz ～ 1 500 Hz
Maximum contact angle of pulley	120°

Table 2 Data Description of Experimental Samples

Fault Diameter (in.)	Motor load (horsepower)	Number of experimental samples (group)	Training set (group)	Test Set (Group)	Bearing status (label)
0 0.007	0 0	59 types for each state,	250 groups according to	104 groups according to	1 2~6

		354 groups in total	the ratio of 7:3	the ratio of 7:3	

5.2 Comparative analysis of experiments

(1) Comparison of generalization ability

The comparison between the generalization performance of equipment fault diagnosis using the method proposed in this paper and the method proposed in [3] and [4] is shown in Figure 5.

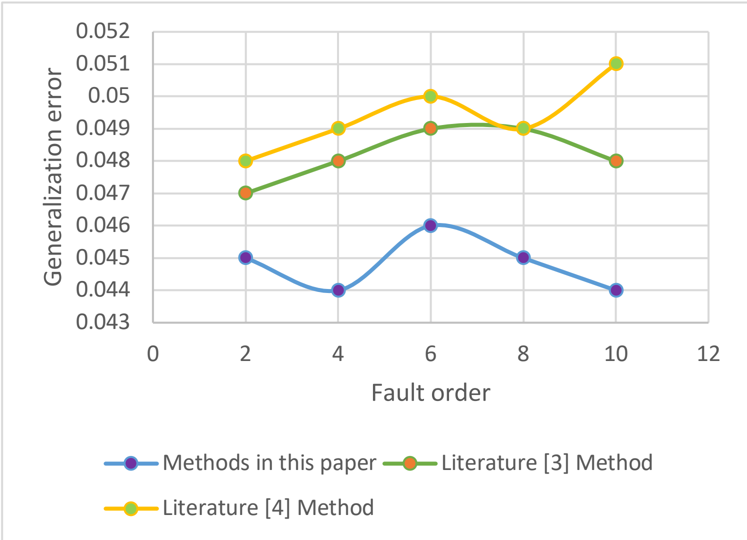

Fig. 5 Comparison of equipment fault diagnosis generalization capabilities of different methods

It can be seen from the analysis of Figure 5 that with the improvement of food machinery and equipment failures, the generalization errors of different methods of machinery and equipment fault diagnosis also change. The maximum generalization error of the method proposed in literature [3] can reach 0.049%, the maximum generalization error of the method proposed in literature [4] can reach 0.051%, and the maximum generalization error of the method proposed in this paper is 0.046%, The generalization errors of the two literature methods are higher than those of the method proposed in this paper, which shows that there are relatively few generalization errors in the process of using this method to diagnose the faults of food machinery and equipment.

(2) Fault identification comparison

Randomly select 25 failures of food machinery and equipment for data analysis, and compare the identification ability of food machinery and equipment failures using the methods proposed in this paper with those in literature [5] and literature [6]. The analysis results are shown in Table 3.

Table 3 Comparison of fault identification capabilities of food machinery equipment by different methods

Number of failures/different methods	Methods in this paper	Literature [5] Method	Literature [6] Method
5	98%	94%	88%

10	93%	86%	79%
15	90%	79%	76%
20	89%	71%	69%
25	87%	69%	61%

It can be seen from Table 3 that with the gradual increase of the number of equipment failures, the capability of equipment failure identification of the three methods is also gradually reduced. The capability of equipment failure identification of the method proposed in literature [6] has been kept at the lowest level, and the identification rate of equipment failures with the increase of the number of equipment failures is rapidly declining. The identification rate of equipment failures of the method proposed in literature [5] is always higher than that of the method proposed in literature [6], but compared with the method proposed in this paper, it is still lower, The method proposed in this paper has a small decline in the fault identification rate, which shows that the method proposed in this paper has a good effect on equipment fault identification.

(3) Comparison of fault diagnosis results

Compare the fault diagnosis degree of food machinery and equipment under different signal-to-noise ratios between the method proposed in this paper and the method proposed in literature [4], and the analysis results are shown in Figure 6 and Figure 7.

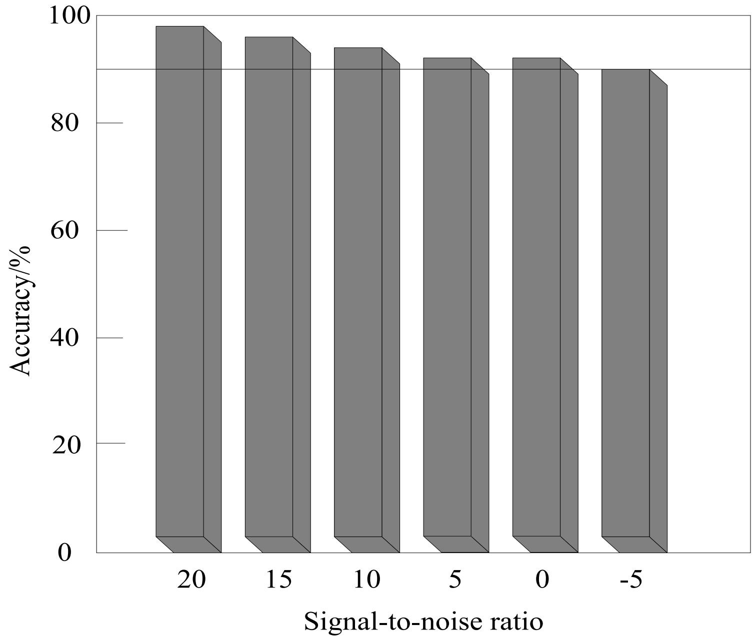

Fig. 6 Mechanical equipment fault diagnosis results of the method proposed in this paper

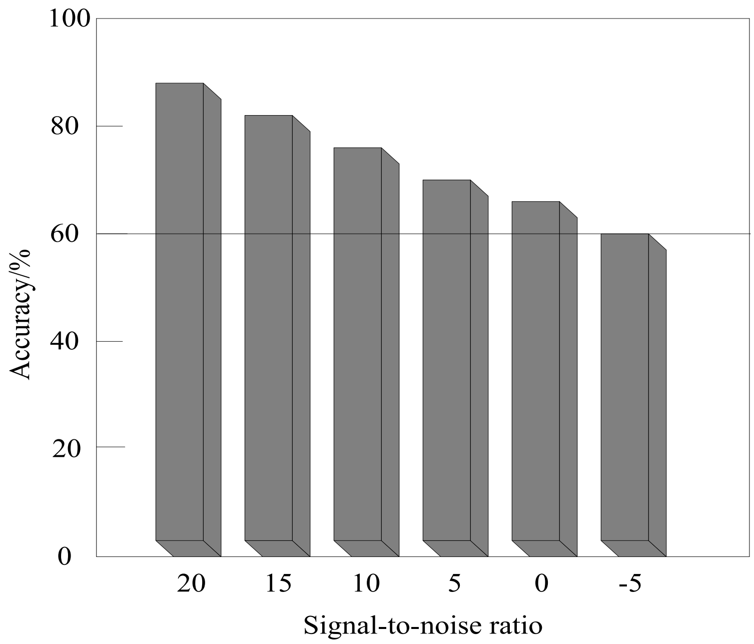

Fig. 7 Mechanical equipment fault diagnosis results of the method proposed in literature [4]

It can be seen from the analysis of Figure 6 and Figure 7 that the accuracy rate of fault diagnosis of food machinery and equipment by different methods also decreases due to the reduction of the signal to noise ratio. The accuracy rate of fault diagnosis by the method proposed in literature [4] is 88% when the signal to noise ratio is 20dB, but the accuracy rate of fault diagnosis is 60% when the signal to noise ratio is - 5dB, while the accuracy rate of fault diagnosis by the method proposed in this paper is 20dB, The accuracy rate of fault diagnosis is 98%, but when the signal-to-noise ratio is - 5dB, the accuracy rate of fault diagnosis is 90%. The method proposed in this paper is always higher than the method proposed in literature [4], which shows that the accuracy rate of mechanical equipment fault diagnosis proposed in this paper is relatively high.

6.Conclusions

In modern production, the failures in the production process will not only have a direct impact on product quality and output, but also lead to serious equipment and personal safety accidents. The long-term production practice has made the public realize that in order to make the machinery and equipment operate safely and reliably and bring its benefits into play, it is necessary to conduct in-depth research on the fault diagnosis technology of food machinery and equipment. Therefore, this paper uses neural network method to study the application of fault diagnosis of food machinery equipment. Firstly, the fault signal of mechanical equipment is identified, and then the enhanced migration convolutional neural network is used to diagnose the fault of food mechanical equipment. The simulation experiment shows that the method proposed in this paper has strong generalization ability and can effectively improve the effect of fault diagnosis.

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