

Article

Rolling Bearing Fault Diagnosis Based on CEEMDAN and CNN-SVM

Lei Shi *, Wenchao Liu, Dazhang You and Sheng Yang

School of Mechanical Engineering, Hubei University of Technology, Wuhan 430068, China;
wenchao.liuhg@163.com (W.L.); yodazhag@163.com (D.Y.); 20211068@hbut.edu.cn (S.Y.)

* Correspondence: 102110065@hbut.edu.cn

Abstract: The vibration signals collected by acceleration sensors are interspersed with noise interference, which increases the difficulty of fault diagnosis for rolling bearings. For this reason, a rolling bearing fault diagnosis method based on complete ensemble empirical model decomposition with adaptive noise (CEEMDAN) and improved convolutional neural network (CNN) is proposed. Firstly, the original vibration signal is decomposed into a series of intrinsic modal function (IMF) components using the CEEMDAN algorithm, the components are filtered according to the correlation coefficients and the signals are reconstructed. Secondly, the reconstructed signals are converted into a two-dimensional grey-scale map and input into a convolutional neural network to extract the features. Lastly, the features are inputted into a support vector machine (SVM) with the optimised parameters of the grey wolf optimiser (GWO) to perform the identification and classification. The experimental results show that the rolling bearing fault diagnosis method based on CEEMDAN and CNN-SVM proposed in this paper can significantly reduce the noise interference, and its average fault diagnosis accuracy is as high as 99.25%. Therefore, it is feasible to apply it in the field of rolling bearing fault diagnosis.

Keywords: rolling bearing; complete ensemble empirical model decomposition with adaptive noise; convolutional neural network; support vector machine; fault diagnosis



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1. Introduction

With the development of modern science and technology, all kinds of mechanical equipment tend to be large-scale and complicated, thus increasing the uncertainty of the safety of mechanical equipment [1]. In the field of industrial production, rotating machinery and equipment is a kind of extremely important machinery and equipment, playing the role of supporting and reducing the friction of the unit [2,3]. Rolling bearings are the core components of rotating machinery and equipment, and due to long-term high-speed rotation, easily produce all kinds of damages. These damages may cause excessive energy consumption and mechanical fatigue of the equipment, or cause major safety accidents [4,5]. Therefore, effective fault diagnosis of rolling bearings is essential to ensure the safe operation of production equipment and the safety of people's lives and property.

At present, the rolling bearing fault diagnosis method based on vibration signal is the mainstream method [6]. However, due to the complex working environment of rolling bearings, the collected vibration signals are interfered by external noise, which makes it difficult to extract fault characteristics. Therefore, the vibration signal is usually preprocessed first. Commonly used methods include Fourier transform, wavelet transform, empirical mode decomposition (EMD), etc. Huang et al. proposed the EMD algorithm, which is completed by decomposing the original signals step-by-step and generating some intrinsic mode functions (IMF) [7]; however, the EMD has very serious mode aliasing and endpoint effects [8]. Wu and others proposed the ensemble empirical mode decomposition (EEMD) [9], which

adds white noise to the original signal, then decomposes the noise-added signal using the EMD algorithm and finally averages the results of multiple decompositions, which effectively suppresses the phenomenon of modal aliasing. However, the EEMD decomposition method has noise residuals, which leads to reconstruction errors [10]. Torres et al. improved the EEMD algorithm and proposed a new signal-processing algorithm of complete ensemble empirical model decomposition with adaptive noise (CEEMDAN) [11,12]. The CEEMDAN algorithm effectively solves the deficiencies of EMD and EEMD, and is a very effective decomposition algorithm [13].

When traditional machine learning algorithms are applied to the field of fault diagnosis, expert knowledge and experience are required, and the extracted features are affected by human factors [14]. With the development of deep learning, convolutional neural networks have shown significant advantages in the field of fault diagnosis by virtue of their powerful feature extraction capability. CNNs are able to automatically extract and identify key features related to faults by learning the features in the data by themselves, which has led to a significant improvement in the accuracy and efficiency of fault diagnosis [15,16].

Dongliang Zhang et al. proposed a bearing fault diagnosis technique based on parameter-optimised variational pattern extraction and an improved one-dimensional convolutional neural network [17]. Baosu Guo et al. proposed an attention-based ConvNeXt with parallel multiscale dilated convolution for the fault diagnosis of rotating machinery [18]. Guan Yang et al. proposed a rolling bearing fault diagnosis method based on vibration image coding and a multi-scale neural network [19]. However, traditional CNN for fault diagnosis usually uses the Softmax classifier to achieve fault classification, but the SVM classifier has higher accuracy than the Softmax classifier in multi-classification.

Aiming at the problem that the bearing vibration signal is affected by noise which leads to the difficulty of fault feature extraction, a fault diagnosis method based on CEEMDAN and CNN-SVM is proposed in this paper, which is completed as follows: Firstly, the original vibration signal is decomposed using the CEEMDAN algorithm to obtain a series of IMF components. Secondly, the correlation coefficient of each IMF component is calculated, the components are filtered and the signal is reconstructed. Thirdly, the reconstructed signal is converted into a 2D grey-scale map and input into the CNN for feature extraction. Finally, the feature vectors extracted by CNN are input into a GWO-SVM classifier for fault classification. The experimental results show that the method proposed in this paper can effectively reduce noise interference, and the average fault diagnosis accuracy is as high as 99.25%, which is higher than the traditional method.

2. Basic Principles

2.1. CEEMDAN Decomposition Algorithm

The CEEMDAN algorithm is a decomposition algorithm proposed for the shortcomings of EMD and EEMD, which decomposes the original signal into multiple intrinsic mode functions by adding adaptive white noise and iterative decomposition of residual signals, and better solves the problems of mode aliasing and white noise residuals. The specific steps are as follows:

1. Add i ($i = 1, 2, \dots, m$) times of Gaussian white noise $n^i(t)$, obeying the standard normal distribution of the original signal $y(t)$, and obtain the new signal $y^i(t)$.

$$y^i(t) = y(t) + n^i(t) \quad (1)$$

2. The EMD decomposition of $y^i(t)$ is performed, the first modal component is retained and a mean-taking calculation is performed to obtain the I_{IMF1} :

$$I_{IMF1} = \frac{1}{m} \sum_{i=1}^m I_{IMF1,i} \quad (2)$$

The residual component at this point is $R_1(t)$:

$$R_1(t) = y(t) - I_{IMF1} \quad (3)$$

3. Adding i ($i = m$) times Gaussian white noise $n^i(t)$, obeying standard normal distribution, to the residual component $R_1(t)$ yields $R_1^i(t)$:

$$R_1^i(t) = R_1(t) + n^i(t) \quad (4)$$

and EMD decomposition is performed to retain the first modal component, and the expression I_{IMF2} , after taking the mean value, is obtained:

$$I_{IMF2} = \frac{1}{m} \sum_{i=1}^m I_{IMF_{2,i}} \quad (5)$$

4. Repeat the above steps j ($j = n$) times until the residual component cannot be decomposed. $I_{IMF1}, I_{IMF2}, \dots, I_{IMFn}$ and residual components are obtained sequentially. The original signal can be expressed as:

$$y(t) = \sum_{j=1}^n I_{IMFj} - R_n(t) \quad (6)$$

2.2. Convolutional Neural Network

Convolutional neural network is one of the core algorithms of deep learning and has achieved great success in the field of computer vision, including tasks such as image classification, target detection and image segmentation. In recent years, CNNs have also been applied in areas such as natural language processing and fault diagnosis. CNNs are deep feed-forward neural networks consisting of convolutional layers, pooling layers and fully connected layers.

2.2.1. Convolutional Layer

The convolutional layer performs convolutional operations on local regions of the input image by means of convolutional kernels to generate new feature maps. The mathematical expression for the convolution operation is shown below:

$$x_j^l = f(\sum_{i \in m_j} x_i^{l-1} * k_{ij}^l + b_j^l) \quad (7)$$

where: l is the convolutional layer of layer l , x_i^l is the output of layer l , x_i^{l-1} is the input of layer l , k_{ij}^l is the weight matrix, b_j^l is the bias and f is the activation function.

2.2.2. Pooling Layer

The pooling layer is located after the convolutional layer and its main roles include feature selection, dimensionality reduction and removal of redundant information. Among them, the most common pooling operations include maximum pooling and average pooling. The maximum pooling expression is:

$$X = f[\alpha S(x) + b] \quad (8)$$

where: X is the output, f is the activation function, α is the multiplicative bias, $S(x)$ is the sampling function and b is the bias.

2.2.3. Fully Connected Layers

The fully connected layer flattens the high-dimensional features and expands them into one-dimensional vectors. Finally, the classification task is usually implemented using the

Softmax function, which converts the output of the fully connected layer into a probability distribution such that the output values for each category are in the interval (0, 1). For k categories, the Softmax function output expression is:

$$\text{Soft max} = \frac{e^{x_k}}{\sum_k e^{x_k}} \quad (9)$$

2.3. Support Vector Machines

The basic principle of an SVM is to achieve the correct classification of samples by finding the optimal hyperplane and using support vectors to determine the location of this hyperplane [20]. When the training samples are not linearly separable in the original space, the introduction of a kernel function can make an otherwise complex, nonlinearly separable problem linearly separable [21,22].

For the binary classification problem, let the input feature vector be x_i ($i = 1, 2, \dots, n$) and the classification label, $y \in \{-1, +1\}$. The SVM can determine an optimal classification hyperplane from the input feature vector. The expression is given by:

$$f(x) = \omega^T + b = 0 \quad (10)$$

where: ω is the hyperplane normal vector, which determines the direction of the hyperplane, and b is the intercept, which determines the distance between the hyperplane and the origin.

2.4. Grey Wolf Optimiser

GWO was proposed by Australian researchers Mirjalili et al. [23]. It has a simple algorithmic structure with few parameters, which can quickly converge and find the optimal solution when solving complex optimisation problems [24,25].

GWO imitates the way wolves hunt in nature to construct its unique social hierarchy level model [26]. As shown in Figure 1, wolves are divided into four social classes α , β , δ and ω , according to the fitness values of individuals in the wolf pack. Among them, α wolf is the leader in the wolf pack; β wolf is in the sub-leader position in the wolf pack and is responsible for assisting α wolf; δ wolf is responsible for observing the surrounding environment and detecting the location of the prey in the wolf pack; and ω wolf is an ordinary member of the wolf pack, following the guidance of the leader wolf for hunting [27,28].

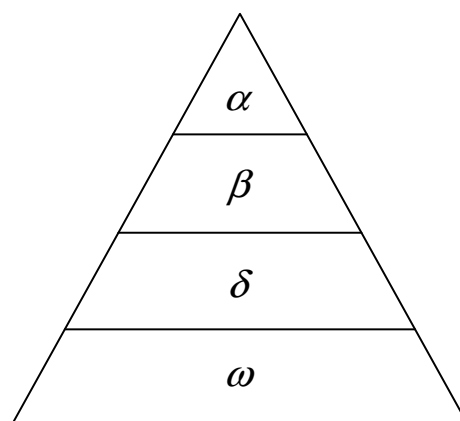


Figure 1. Hierarchical model of the grey wolf.

The algorithm is modelled as follows:

$$\begin{aligned} D &= |C \cdot X_p(t) - X(t)| \\ X(t+1) &= X_p(t) - A \cdot D \end{aligned} \quad (11)$$

where: D is the distance between the grey wolf and the prey, X_p is the position of the prey, X is the position of the wolf pack, A and C are the coefficient vectors and the formula is as follows:

$$\begin{aligned} A &= 2a \cdot r_1 - a \\ C &= 2r_2 \end{aligned} \quad (12)$$

where: a is the convergence factor and r_1, r_2 are random numbers in the range of $[0, 1]$.

The formula for updating the position and direction of the wolf pack is as follows:

$$\begin{aligned} D_\alpha &= |C_1 \cdot X_\alpha - X| \\ D_\beta &= |C_2 \cdot X_\beta - X| \\ D_\delta &= |C_3 \cdot X_\delta - X| \end{aligned} \quad (13)$$

$$\begin{aligned} X_1 &= X_\alpha - A_1 \cdot D_\alpha \\ X_2 &= X_\beta - A_2 \cdot D_\beta \\ X_3 &= X_\delta - A_3 \cdot D_\delta \end{aligned} \quad (14)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (15)$$

3. CEEMDAN and CNN-SVM Fault Diagnosis Models

3.1. CNN Network Structure Design

In order to take advantage of the powerful feature extraction capability of CNN, a CNN structure is designed in this paper as shown in Figure 2. The convolutional layer is used to extract image features from the input image; the pooling layer serves to downscale and compress the features, remove redundant information and reduce the computational effort; the fully connected layer spreads the feature vectors into one-dimensional vectors; the dropout layer prevents overfitting by discarding the neurons; and finally, fault classification is achieved by the GWO-SVM classifier.

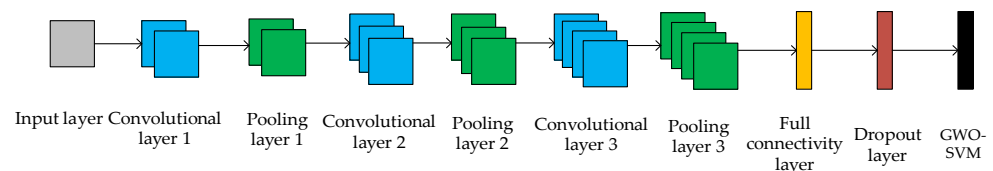


Figure 2. CNN structure diagram.

The specific parameters of the CNN are shown in Table 1.

Table 1. Model parameters.

Network Layer	Parameter Setting	Pacemaker	Network Layer Output
Convolutional layer 1	8@3 × 3	1	8@32 × 32
Pooling layer 1	2 × 2	2	8@16 × 16
Convolutional layer 2	16@3 × 3	1	16@16 × 16
Pooling layer 2	2 × 2	2	16@8 × 8
Convolutional layer 3	32@3 × 3	1	32@8 × 8
Pooling layer 3	2 × 2	2	32@4 × 4

The model hyperparameters were set as follows: the initial learning rate was set to 0.001; the ReLU function was used as the activation function of the network; the cross-entropy function was used as the loss function; the batch size in the training was set to 64; the number of iterations was set to 150; the deactivation rate of dropout was set to 0.2; and the Adam optimiser was used to update the network parameters.

3.2. GWO-SVM Classifier

For nonlinear classification problems, SVMs use kernel functions to map the data from the original space to a higher dimensional feature space, thus making the data linearly differentiable in the higher dimensional space. Among them, the radial basis kernel function has few parameters and a simple model and is most widely used. Therefore, in this paper, the radial basis function is chosen as the kernel function, and its expression is:

$$K(x_i, y_i) = \exp\left(-\frac{\|x_i - y_i\|^2}{2\sigma^2}\right) \quad (16)$$

where: $k(x_i, y_i)$ is the kernel function of the SVM, and σ is the kernel function parameter.

The kernel function can effectively solve the problems of dimensional catastrophe and nonlinear separability, but the classification performance is easily affected by the penalty factor C and kernel parameter σ . Therefore, in this paper, we used the optimisation-seeking ability of GWO to find the optimal parameter penalty factor C and kernel function parameter σ of SVM in order to improve the classification performance of SVM. The specific steps are as follows:

1. Initialise the number of wolves M and the number of iterations N , set the penalty factor C and the range of values of the kernel function parameter σ , initialise the location of the wolves and calculate the value of the individual initial fitness.
2. Using the error rate as the objective function, the parameter penalty factor C and the kernel function parameter σ are used as the prey for the optimisation search.
3. When the objective function value is smaller than the individual fitness value of the grey wolf, update the individual fitness value to the current optimal objective function value.
4. When the maximum number of iterations is reached, the optimal penalty factor C and kernel function parameter σ are obtained, and the optimal parametric SVM classifier is built.

3.3. Fault Diagnosis Process

The flowchart of the rolling bearing fault diagnosis method proposed in this paper is shown in Figure 3, and its specific steps are as follows:

1. Signal decomposition using CEEMDAN algorithm. The original vibration signal is decomposed into multiple IMF components using the CEEMDAN algorithm, each with different frequency characteristics.
2. Filter and reconstruct the signal. By calculating the correlation coefficient of each IMF component, screen the IMF components and reconstruct the signal to remove noise interference.
3. Signal transformation and division of the data set. The reconstructed one-dimensional vibration signal is converted into a two-dimensional grey-scale map, and the training set, validation set and test set are divided according to the ratio of 3:1:1.
4. Feature extraction using CNN. CNN extracts feature vectors from the 2D grey-scale map which will be used for subsequent fault classification.
5. Training of GWO-SVM classifier. Optimise the parameters of SVM using GWO to retrieve the SVM classifier with optimal parameters.
6. Perform fault classification and output results. Input the feature vectors of the test set into the SVM classifier with optimal parameters, perform classification and output the fault classification results.

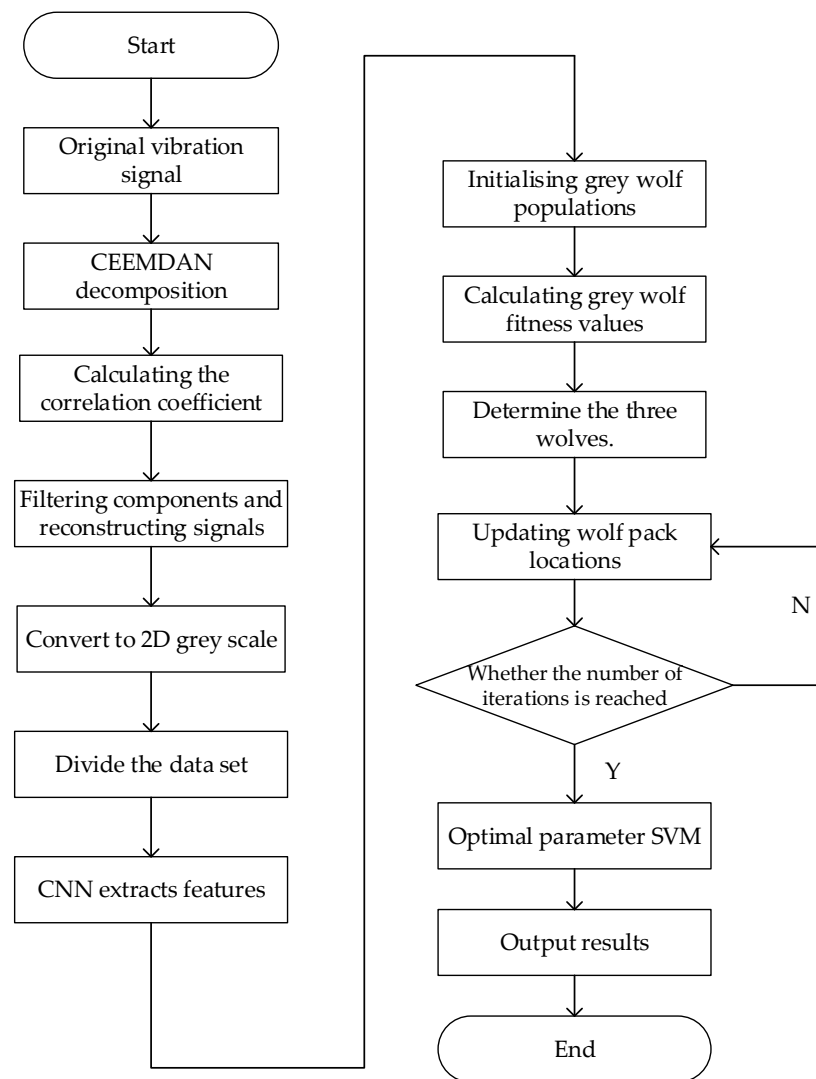


Figure 3. Fault diagnosis flowchart.

4. Experimental Validation

4.1. Experimental Data Sources

This experimental data acquisition platform is shown in Figure 4, which is mainly composed of a high-speed variable frequency motor, a load balancing disc, a radial loader and an acceleration sensor. Among them, the high-speed variable frequency motor drives the whole system to rotate according to the set rotational speed. The load balancing disc is used to maintain the dynamic balance of the system during rotation to reduce vibration and noise. The radial loader is used to simulate the radial pressure that the bearings may be subjected to in the actual working environment. The acceleration sensor, model 356A15, is used to collect bearing vibration signals.

The rolling bearing model chosen for this experiment is NSK6205, which has four different states: normal state, outer ring failure, inner ring failure and rolling element failure. Among them, each failure state has two failure diameters of 0.2 mm and 0.5 mm. The conditions of this experiment are a radial pressure of 600 N, motor speed of 1800 r/min, sampling frequency of 10.24 kHz and acquisition time of 60 s. A total of seven types of rolling bearing vibration signals were collected for the normal condition, outer ring failure, inner ring failure and rolling element failure states.



High-speed inverter motor Torque Speed Sensor Load balancing disk Radial loader

Figure 4. Data acquisition platform.

4.2. Data Processing

Firstly, 400 sample data of each of the seven states were selected, respectively, to obtain a total of 2800 samples, and the sample of experimental data is shown in Table 2.

Table 2. Experimental data.

Bearing Condition	Fault Diameter (mm)	Sample Length	Sample Size	Label
Normal state	0	1024	400	1
Rolling body failure	0.2	1024	400	2
	0.5	1024	400	3
Inner ring failure	0.2	1024	400	4
	0.5	1024	400	5
Outer ring failure	0.2	1024	400	6
	0.5	1024	400	7

Secondly, the CEEMDAN algorithm is used to decompose the seven labelled samples into the corresponding IMF components, and the decomposition results are shown in Figure 5, taking one sample with label 4 as an example.

The correlation coefficient indicates the magnitude of correlation between the component and the original signal; using the correlation coefficient to filter the component and reconstruct the signal can effectively reduce noise interference. The formula of the correlation coefficient is as follows:

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (17)$$

where: X_i is the original signal, Y_i is the IMF component, $\bar{X}$ and $\bar{Y}$ are the average values of the corresponding signals.

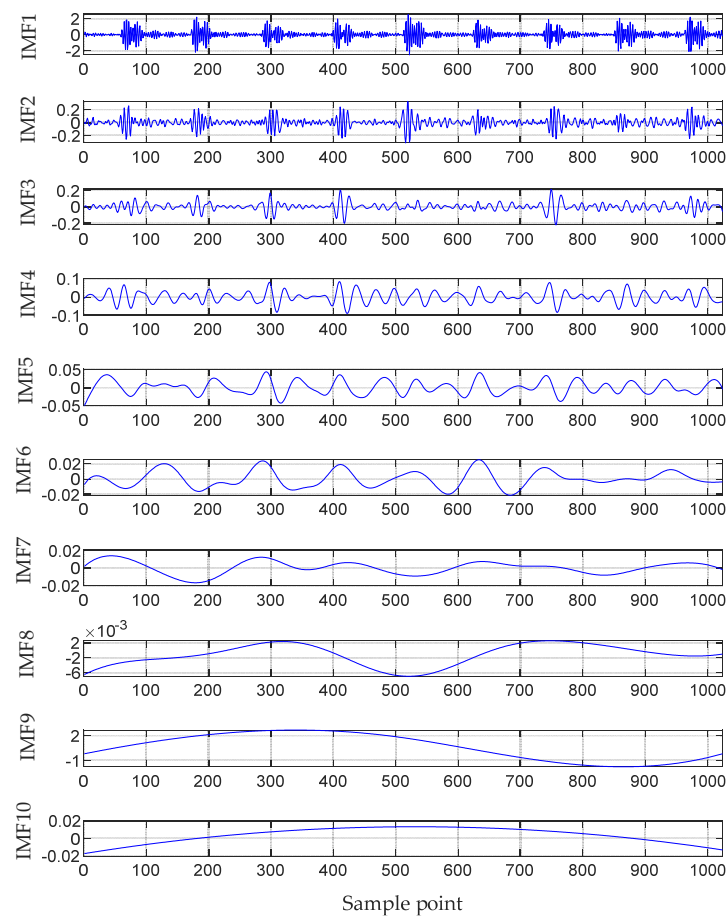


Figure 5. CEEMDAN decomposition diagram.

The correlation coefficient plots of each IMF component for the seven labels are shown in Figure 6. From the figure, it can be learnt that the correlation coefficient value decreases with the increase in the number of layers of decomposition and the first five IMF components have high correlation coefficient values. Therefore, the first five IMF components are selected for signal reconstruction to obtain the signal after noise reduction.

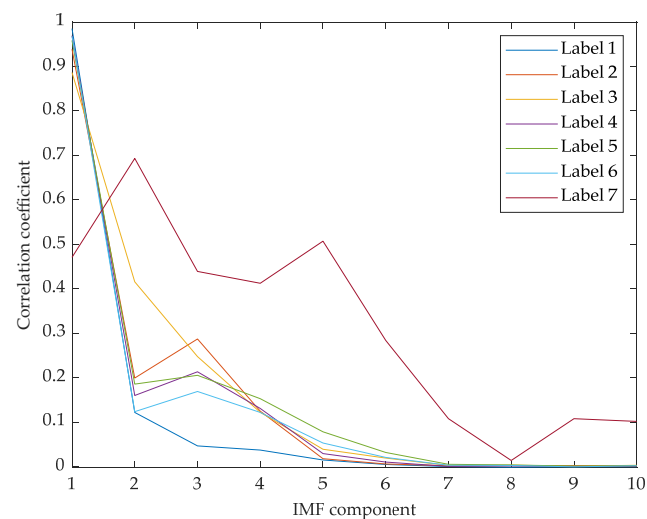


Figure 6. Plot of correlation coefficients.

After obtaining the reconstructed vibration signal, it needs to be converted into a 2D grey-scale map. The grey-scale map is an effective visualisation tool for displaying and analysing the time domain characteristics of the signal. The specific steps of grey-scale map conversion are as follows: Firstly, the signal is normalised, and the normalised signal values are mapped to $[0, 255]$. Secondly, the normalised signal is reconstructed into a two-dimensional matrix. Finally, the values in the 2D matrix are converted to their corresponding grey values and a grey-scale map is generated. In this paper, this method is used to convert a one-dimensional signal with a length of 1024 into a 32×32 two-dimensional matrix and then visualise it as a grey-scale map.

4.3. Visualisation of Feature Extraction

The one-dimensional signal with a length of 1024 after noise reduction is converted into a 32×32 two-dimensional grey-scale map for feature extraction by inputting it into CNN. In order to have a deeper understanding of how CNN extracts and distinguishes fault features, this paper uses the t-SNE algorithm to visualise the feature extraction results of CNN.

The t-SNE is a stream-learning algorithm for the visualisation of high-dimensional data. It preserves the local structure in the original data by converting the similarity between data points into a probability distribution and finding a similar probability distribution in the low-dimensional space. The t-SNE algorithm projects the high-dimensional feature space into a two- or three-dimensional space for intuitive analysis and visualisation. Figure 7 shows the CNN input layer data visualisation results and Figure 8 shows the CNN output layer data visualisation results.

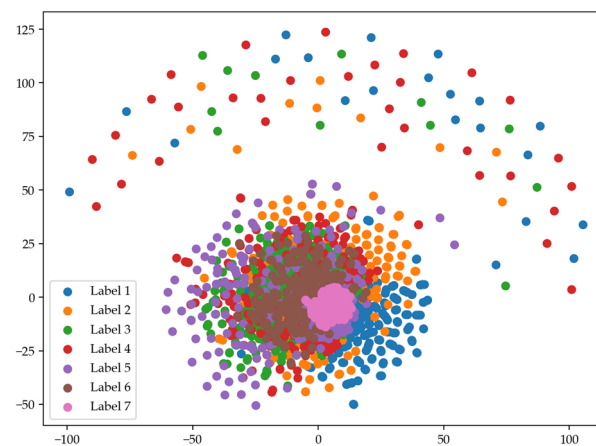


Figure 7. Input layer visualisation.

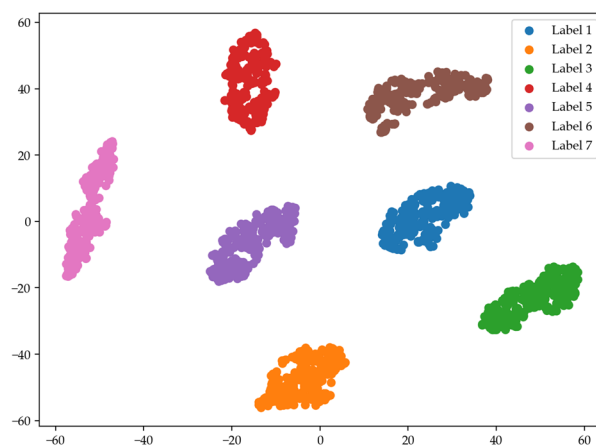


Figure 8. Output layer visualisation.

It can be seen from Figures 7 and 8 that in the input layer, the original data distribution is very scattered and mixed with each other; in the output layer, the data points of different categories are tightly clustered together to form an obvious cluster structure, and the boundaries between different categories become very obvious. It can be learnt that the CNN successfully transforms the original data into feature representations that are easy to classify, thus achieving the basic classification effect.

4.4. Experimental Results and Analyses

The change curves of the accuracy and loss function of the CNN-SVM model are shown in Figures 9 and 10, respectively. It can be seen from the figures that when the number of iterations reaches 20 times, the accuracy curves of the training and validation sets begin to converge and gradually tend to be stable. It can be concluded that the CNN-SVM model has a high degree of accuracy and stability on the fault diagnosis task, reflecting the powerful ability of CNN in feature extraction and the accuracy of SVM on the classification task.

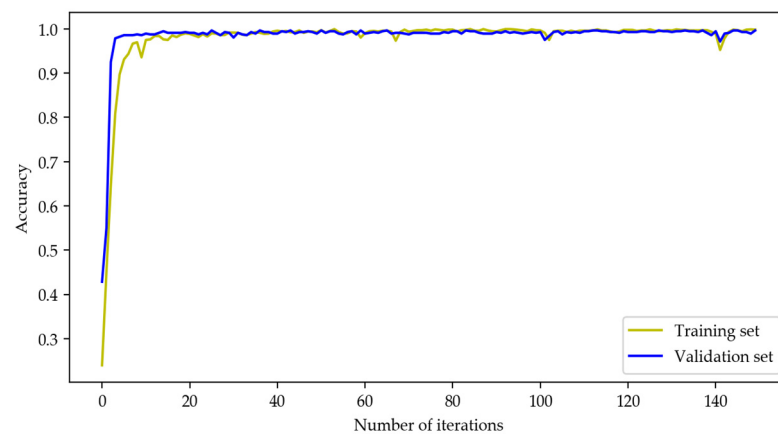


Figure 9. Accuracy of CNN-SVM model.

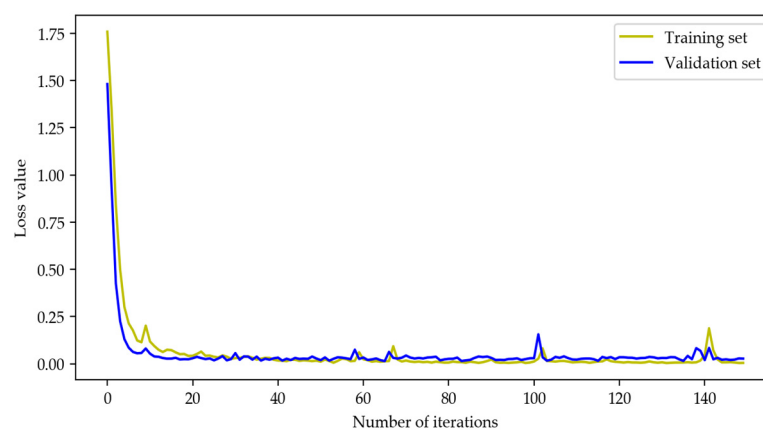


Figure 10. Loss function of CNN-SVM model.

The CNN-SVM model test set fault diagnosis results are shown in Figure 11. From Figure 11, it can be concluded that six samples with true label 6 in the confusion matrix are incorrectly classified as label 5 and the final fault classification accuracy of 98.93% is obtained after calculation.

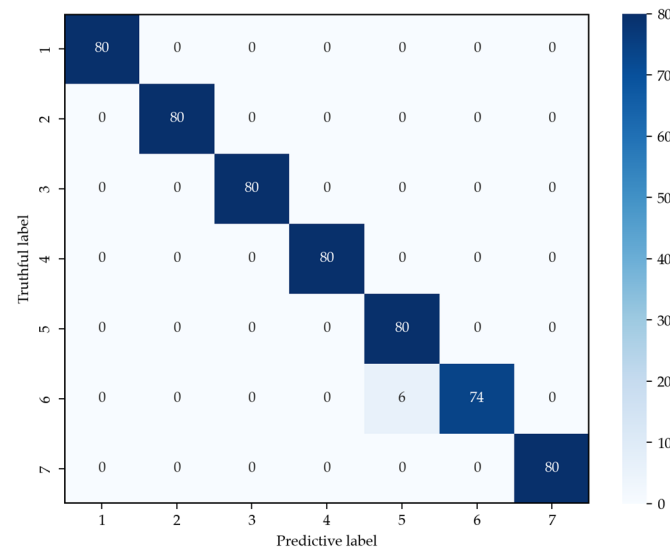


Figure 11. CNN-SVM model confusion matrix.

In order to reduce the error and enhance the credibility of the experimental results, the average of 10 experiments is taken as the final result in this paper. The fault diagnosis results of different models are shown in Table 3.

Table 3. Fault diagnosis accuracy of different models.

Model	Accuracy (%)		
	Maximum Value	Minimum Value	Average Value
SVM	86.25	81.61	82.71
CNN	90.54	88.93	89.73
EMD+CNN	96.25	94.64	95.11
EEMD+CNN	98.04	96.43	96.87
CEEMDAN+CNN-Softmax	98.59	97.86	98.52
CEEMDAN+CNN-SVM	100	98.39	99.25

From the data in the table, it can be learnt that the proposed method CEEMDAN+CNN-SVM has the best classification effect, with an average accuracy of 99.25%. Compared with single SVM and CNN, the average accuracy is 16.54% and 9.52% higher; compared with EMD+CNN and EEMD+CNN models, the fault diagnosis accuracy is improved by 4.14% and 2.38%, respectively; compared with CEEMDAN+CNN-Softmax model, the fault diagnosis accuracy is improved by 0.73%. It can be learnt that the method proposed in this paper can effectively reduce the noise of the original signal and has a high fault classification accuracy.

5. Conclusions

Aiming at the problem that the rolling bearing vibration signal collected by an acceleration sensor is mixed with noise interference, which leads to the difficulty of fault feature extraction, a rolling bearing fault diagnosis method based on CEEMDAN and CNN-SVM is proposed in this paper. The experimental results show the feasibility of the method proposed in this paper, which effectively solves the problem of low fault diagnosis accuracy of traditional methods in the noise background and achieves an average fault diagnosis accuracy of 99.25%. The following conclusions can be drawn from the experimental results: Using the CEEMDAN algorithm to decompose the vibration signal, filter the components and reconstruct the signal can effectively reduce the noise of the original signal. The SVM with the optimal parameter penalty factor C and kernel function parameter σ , obtained

by GWO optimisation search, has a better classification performance than the Softmax classifier, and the average accuracy is improved by 0.73%.

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