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A Fault Diagnosis Model Based on Convolution Neural Network for Wind Turbine Rolling Bearing

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Abstract. The rolling bearing has become the component with high failure rate in the wind turbine due to its poor operating environment. This paper proposes a fault diagnosis model based on convolutional neural network for the rolling bearing. The input of model is the short-time Fourier transformed spectrum of the vibration data of the rolling bearing, and the output is the codes of various fault types. The proposed model is verified by the bearing test data of Case Western Reserve University. In addition, the samples with various noise levels and those after wavelet de-noising are input into the fault diagnosis model respectively, and the anti-noise performance of the proposed model is discussed. The result shows that the proposed model can automatically find fault features and identify various rolling bearings fault, avoiding the expert experience and feature engineering. This makes it more practical and generalizable in the fault diagnosis of rolling bearing of wind turbine.

1. Introduction

Wind power as a kind of renewable and clean energy has been developing rapidly in the world. As one of the basic components of wind turbine, rolling bearing has the advantages of high efficiency, small friction resistance, simple assembly and easy lubrication, which is widely used in the transmission chain system of wind turbine [1]. However, due to the fluctuation of wind speed, power load, air temperature, and air pressure, the failure rate of rolling bearing is high, which seriously affects the safe and stable operation of the unit [2].

A large number of studies have been carried out on the fault diagnosis of wind turbine in the literature. Vibration data are often collected for signal analysis, such as spectrum analysis, envelope analysis and wavelet analysis, to diagnose faults in the transmission chain of wind turbines. Yang et al. eliminated noise and other interference in wind turbine vibration signals based on wavelet transform, and adopted the combination of time and frequency domain for fault recognition [3]. Zhao et al. proposed to combine MCKD with EMD and use MCKD algorithm to filter the noise so as to reduce the impact on EMD [4]. In the case of very low signal-to-noise ratio, Chacon et al. proposed a de-noising method combined with wavelet transform, using Hilbert transform and autocorrelation function to extract the envelope line to find the pattern in the signal for bearing fault localization [5]. Z Feng et al. proposed a time frequency analysis method based on Kalman filter for non-stationary faults of the planetary gearbox in wind



turbines [6]. Modal analysis is the fault diagnosis by measuring the change of operating parameters relative to their normal values. Wang et al. proposed a condition monitoring method based on deep belief network to monitor the working condition of the main bearing in real time, and established a DBN-based temperature prediction model for the main bearing by selecting appropriate modeling variables [7]; H Niemann et al. proposed a model-free fault diagnosis and condition monitoring method for the rotor system of wind turbines based on the detection of asymmetry caused by faults in the rotor system [8].

Although the above methods have good fault diagnosis effect, some of them rely too much on feature engineering methods and expert experience. Under the complex working conditions of wind turbines, it leads to poor versatility and scalability. This paper presents an intelligent diagnosis method of wind turbine rolling bearing based on convolution neural network, which can identify the condition of wind turbine rolling bearing better and more flexibly.

2. Convolutional neural network

In recent years, typical deep learning algorithms represented by convolutional neural network have achieved great success in speech recognition, image recognition and many other fields [9]. Convolutional neural network (CNN) is a kind of artificial neural network with multiple processing layers. Its weight sharing reduces the complexity of the network model and the number of weights, which is more obvious when the network input is multi-dimensional image. The basic structure of CNN generally includes input layer, hidden layer and output layer, and hidden layer generally includes convolution layer (C layer), down-sampling layer (S layer) and full connection layer, as show in Fig. 1.

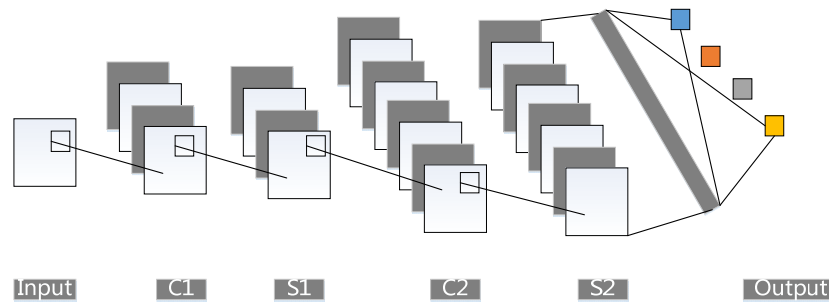


Figure 1. Convolutional neural network.

Input layer: the energy of vibration signal distributed in time-frequency domain is used in this paper. This energy distribution obtained by short-time Fourier transform can describe the variation of the frequency-spectrum component of the signal with time, which represents the joint distribution information of time domain and frequency domain. The formula of short-time Fourier transform is shown in equation (1):

$$STFT(\zeta, \tau) = \int_R f(t)g(t - \tau)e^{-j\zeta\tau} dt \quad (1)$$

In the above formula, the source signal $f(t)$ is multiplied by the time window function $g(t - \tau)$ to realize the addition and translation of window near τ , then Fourier transform is performed.

Convolution layer: fault feature extraction is carried out in the convolution layer, and different grades of abstract features are extracted in different layers. The formula of convolution operation is shown in equation (2):

$$x_j^l = f\left(\sum_{i=N_j} x_i^{l-1} * \alpha_{ij}^l + b_j^l\right) \quad (2)$$

x_j^l represents the j feature in the convolution layer l ; $f(x)$ represents the activation function of ReLU; α_{ij}^l represents the weight of the j characteristic graph and the i input data in the convolution layer l ; N_j

represents the set of input data; *stands for convolution; b_j^l represents the offset of the j characteristic of the convolution layer of layer l.

Pooling layer: it is usually necessary to add a Pooling operation after the convolution layer to retain the most important features. After the pooled operation with the size of $n \times n$, the edge length of the output characteristic graph was changed to $1/n$, and the number of characteristic graphs remained conservation. Pooling layer can significantly reduce the number of feature mapping neurons, thus greatly reduce the dimension of features, and avoid network overfitting. The formula of pooling layer is shown in equation (3):

$$x_j^l = f(\beta_j^l \text{down}(x_j^{l-1}) + b_j^l) \quad (3)$$

$\text{Down}(x)$ represents the lower sampling function; β_j^l is the weight l of layer neuron j; $f(x)$ represents the activation function of ReLU.

Full connection layer: the role of the full connection layer is to further carry out the nonlinear transformation of fault features, combined with Softmax activation function as the output of the network. The formula of the full connection layer is shown in equation (4):

$$x_j^l = f\left(\sum_{i=1}^n x_j^{l-1} \bullet \overline{w}_{ji}^l + b_j^l\right) \quad (4)$$

L represents the current number of layers; n is the number of neurons in the previous layer; \overline{w}_{ji}^l represents the connection weight l of layer neuron j and the upper layer neuron i.

3. Fault diagnosis of rolling bearings

3.1. Spectrum diagrams of vibration signals

To simulate wind turbines bearing vibration data under different working condition, the vibration data of bearing damage test published by wetern Reserve University is adopted in this paper. Due to the variable speed and load characteristics of wind turbines, data samples are marked only by fault types, regardless of bearing speed and load.

The SKF6205-2RS deep groove ball bearing is used in the bearing damage test, and the single point damage simulation bearing failure is processed by electrical spark. The severity of the fault was simulated by the size of the damage diameter. The simulated bearing faults include inner race faults, rolling element faults and outer race faults. The location of outer race faults is at 3 o'clock, 6 o'clock and 12 o'clock. The time domain diagrams of vibration signals of different faults are shown in figure 2.

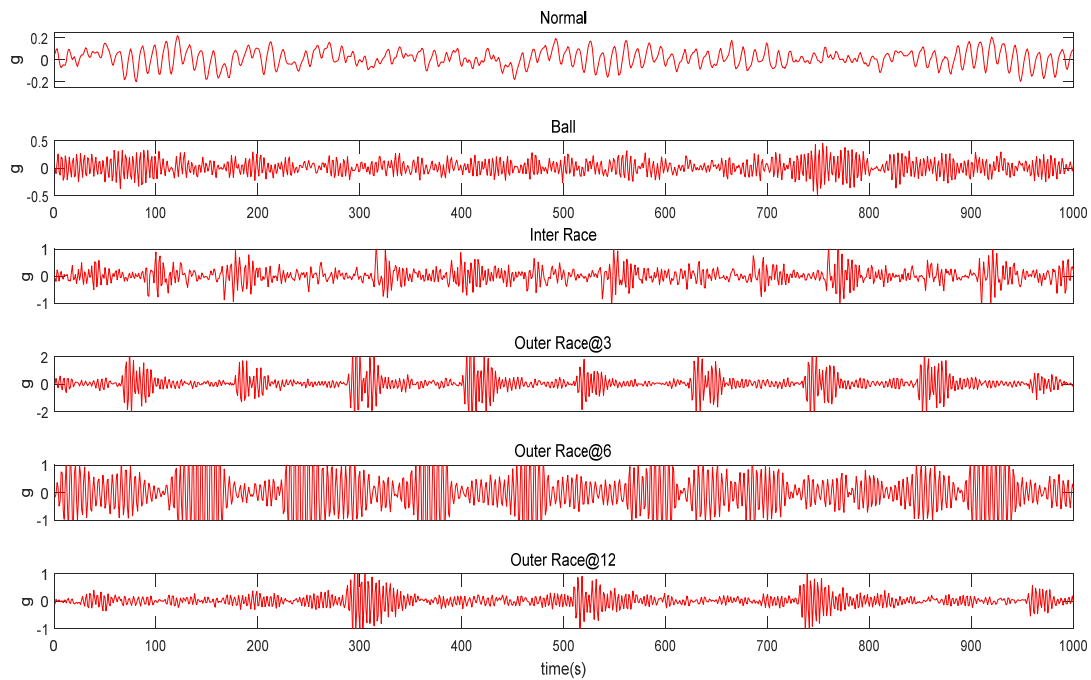


Figure 2. Convolutional neural network.

The short-time Fourier transform is performed on the data sample of different conditions to obtain the time-frequency spectrum of each sample. In this paper, the short-time Fourier transform is applied by calling the specgram function in the Scipy library in Python. Using hamming window, the short-time Fourier transform length is 100 points, the number of overlapping samples per segment is 64, and the sampling frequency is 1200HZ. Figure 3 shows the amplitude spectrum of various samples after short-time Fourier transform. With abscissa in the time domain and ordinate in the frequency domain, the spectral dimension of each sample is 51×26 .

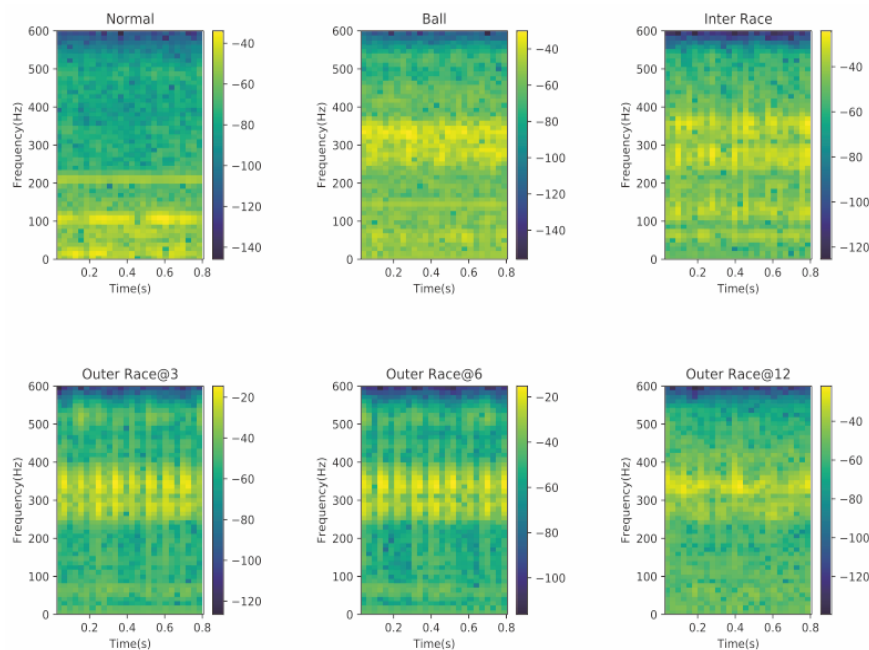


Figure 3. Spectra of a sample of a rolling bearing.

3.2. Convolution neural network diagnosis model

The CNN structure adopted in this paper is a three-layer network structure. The first layer is the input layer with 51×26 pixels; in the convolution layer, the input image is convoluted with $16 \times 2 \times 2$ convolution kernels and bias terms; ReLU is used as the excitation layer function to perform nonlinear transformation; the pool layer is 2×2 , with the maximum pooling of one step and the Dropout layer avoiding overfitting. The output of the upper layer is the input of the next layer and the output of the last layer combines features with the full connection layer. The six kinds of sample data are classified by the Softmax activation function.

The verification steps are as follows:

(1) Short-time Fourier transform is performed on different kinds of data samples. The transform length is 100, the number of overlapping samples is 50, and the sampling rate is $F_s=1200$ Hz. The spectrum of each sample is obtained and normalized;

(2) The train_test_split function in Python divides data samples into 75% training sets and 25% test sets;

(3) The training data set is input into CNN in batches, in which each batch of training data is 256, and the number of training rounds is 200. The trained model is saved for fault identification tests;

(4) The test data set is input into the trained identification model for fault classification test, and the test accuracy is 98.24%. The results are shown in Table 1 and table 2.

Table 1. Confusion Matrix of Identification Result.

		Diagnostic Results					
		Normal	Ball	Inter Race	Outer Race@3	Outer Race@6	Outer Race@12
Actual Faults	Normal	506	0	0	0	0	0
	Ball	1	814	0	3	3	0
	Inter Race	0	0	852	1	0	0
	Outer Race@3	0	7	0	551	0	1
	Outer Race@6	0	17	1	0	536	0
	Outer Race@12	0	6	5	18	1	315

Table 1 shows the confusion matrix of actual faults and their diagnostic results by our model. For example, there were 506 normal samples in the test, which were all identified correctly by the CNN model. Among the 821 sample of ball fault, 814 were identified correctly, although 6 were wrongly recognized as the outer race fault and 1 was wrongly treated as normal sample. As mentioned before, there are three types of outer race fault which locate at 3 o'clock, 6 o'clock and 12 o'clock of the outer race and are described as outer race@3, outer race@6 and outer race@12.

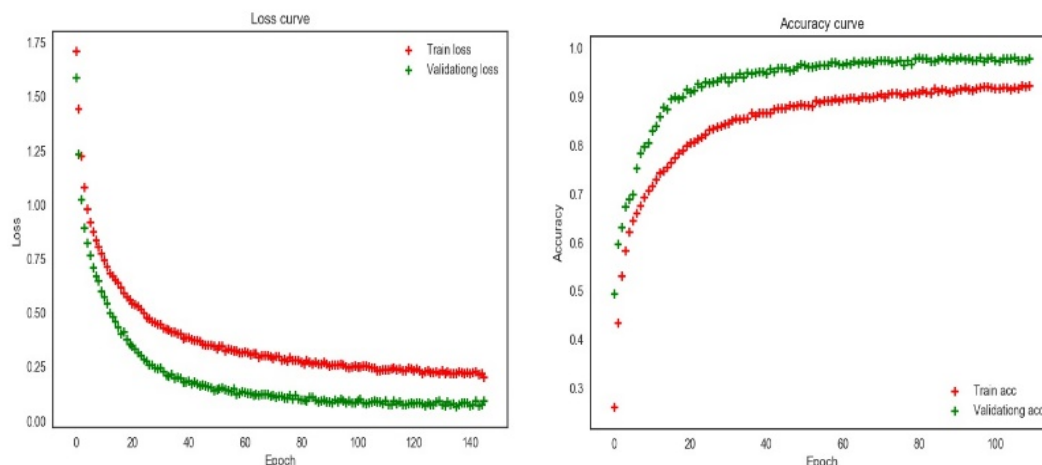


Figure 4. Loss function and change of accuracy rate.

Figure 4 shows the change of Loss curve and Accuracy curve in the training process with the increase of the number of iterations. It can be seen from the figure that the algorithm has good convergence. The algorithm gradually starts to converge after 60 iterations in the training set, and the loss function does not fluctuate much.

4. Anti-noise Performance of CNN

4.1. Influence of signal-to-noise ratio on model accuracy

In the process of collecting vibration signals of rolling bearings of wind turbines, it is unavoidable to be affected by environmental noise, working conditions, instrument error and other factors, therefore the signals are often mixed with the interference signals and noise components generated by other vibration sources. By using the AWGN function of MATLAB to simulate the wind farm data by adding Gaussian white noise to the vibration data of bearing failure test, the influence of different signal-to-noise ratios (SNR) on the performance of the CNN diagnosis model is verified. Figure 5 shows the original time domain signal and the time-domain signal superimposed by Gauss white noise.

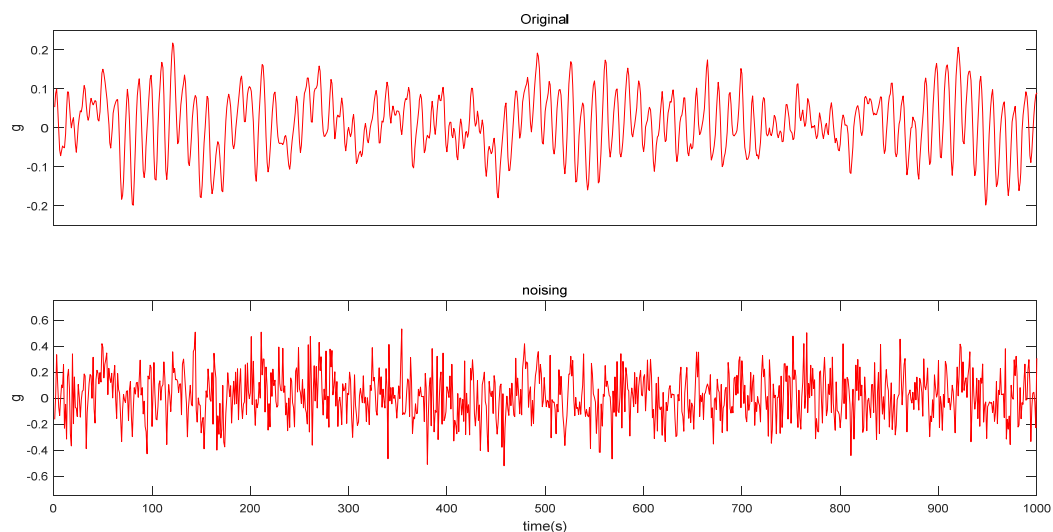


Figure 5. Original signal and signal with Gauss white noise.

The original vibration samples are superimposed with Gaussian white noise to form signals with different SNR, which are input into the deep CNN model. The recognition accuracy of the CNN model is observed, and the anti-noise characteristics of the CNN diagnosis model are studied. The curve shown in Figure 6 fits the diagnostic accuracy of the recommended CNN model for input of bearing fault signal samples with different SNR levels. Fig. 6 can clearly observe the increasing trend of diagnostic accuracy with noise reduction mode, and when the SNR is greater than 30 or less than 5, the diagnostic accuracy of the model has little effect.

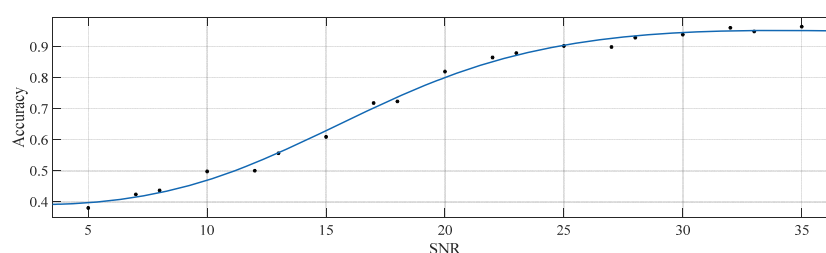
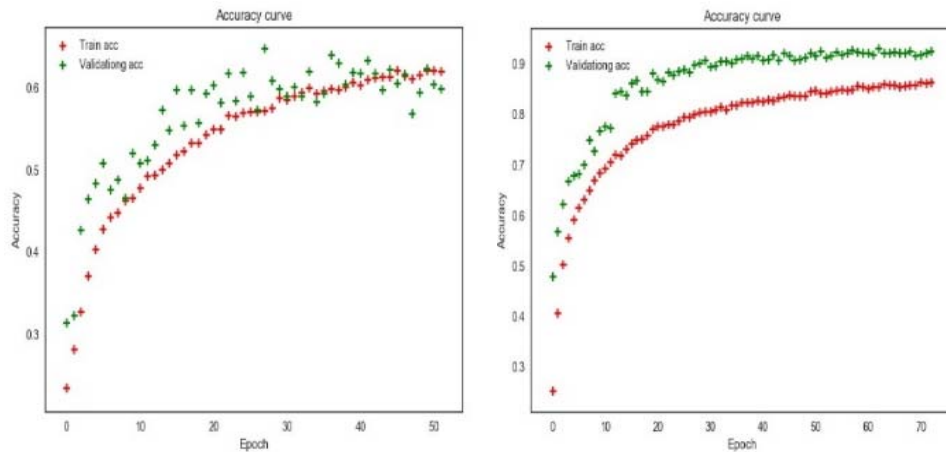


Figure 6. Diagnostic accuracy of CNN for signals with different SNR.

Fig. 7a and Fig. 7b show the variation of the accuracy of the training set and verification set with the increase of the number of iterations of the SNR 15 and SNR 30, respectively. This verifies that the greater the SNR, the better the stability of the CNN model.



a. Diagnostic accuracy for signal with SNR 15 b. Diagnostic accuracy for signal with SNR 30

Figure 7. Variation of the diagnostic accuracy of CNN.

4.2. Effect of noise reduction on diagnostic accuracy

The main purpose of signal de-noising is to improve the signal to noise ratio of sensors. Because wavelet de-noising has good time-frequency localization property, this paper uses wavelet de-noising method, calling the DWT function of MATLAB to de-noise the data samples which have been overlapped with noise. Figure 8 shows the time domain signal after noise reduction for noise signal with SNR 15.

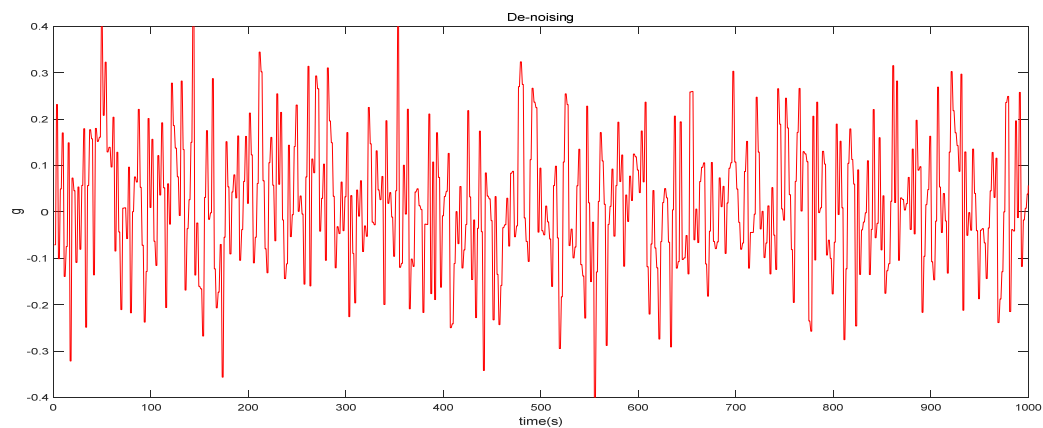


Figure 8. Time domain signal after noise reduction.

The above noise signals with different SNR are processed by wavelet denoising processing, and then input into the convolution neural network model to test its diagnostic accuracy. The influence of de-noising algorithm on the diagnostic accuracy of the model is discussed.

When the SNR exceeds 30, the influence on the diagnostic accuracy of the model is not great, so the signal whose SNR is lower than 30 is de-noised based on wavelet transform, and the de-noised signal is input into the convolution neural network model.

When the SNR exceeds 30, it has little influence on the diagnostic accuracy of the model, therefore the signal whose SNR is lower than 30 is processed based on wavelet transform, and the de-noised signal is input into the CNN model. Fitting curves of diagnostic accuracy for different SNR signals are shown in Fig. 9. The accuracy of CNN after noise reduction is about 90%, which shows that the proposed

CNN model has a good recognition effect in fault diagnosis of rolling bearing of wind turbine after wavelet noise reduction.

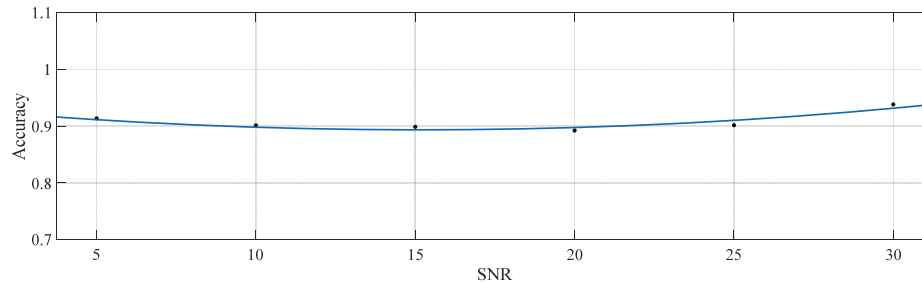
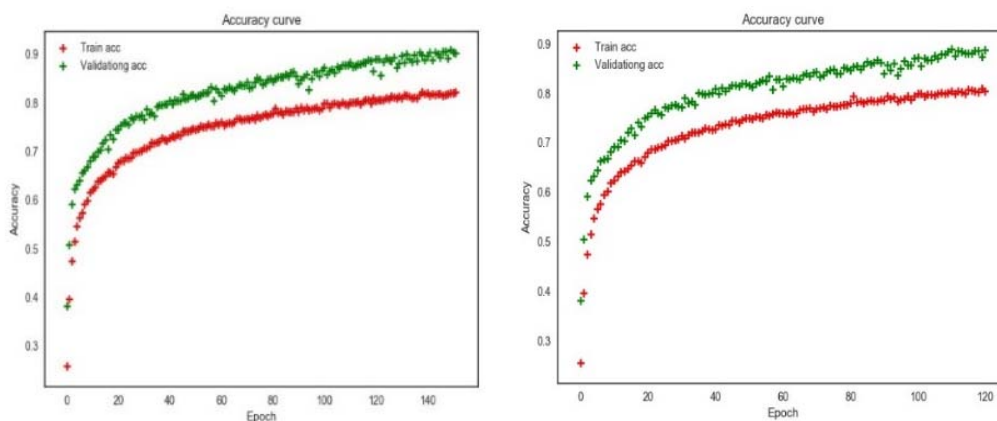


Figure 9. Test accuracy after noise reduction under different signal to noise ratio.

Fig. 10a and Fig. 10b are the diagnostic training process after wavelet de-noising for the data samples of SNR 15 and SNR 30, respectively. It can be seen from the graph that the accuracy of training set and verification set increases gradually with the number of iterations, and the convergence is stable.



a. Accuracy of de-noised signal with SNR 15 b. Accuracy of de-noised signal with SNR 30

Figure 10. Variation of the diagnostic accuracy of de-noised signal.

5. Conclusion

CNN is a new information processing technology that has developed in recent years and has been widely and effectively applied in many fields. In this paper, the effect of CNN in the fault diagnosis field of rolling bearings of wind turbines can be concluded as follows:

- (1) This CNN model has ideal performance in fault diagnosis of rolling bearing of wind turbine.
- (2) The rolling bearing signals with different signal-to-noise ratios are input into CNN fault diagnosis model after noise reduction, which verifies the anti-noise performance of the proposed model.
- (3) Compared with the traditional diagnosis method, it not only has good diagnostic performance, but also avoids feature engineering, and has stronger generality.

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