Open Access Library Journal
2022, Volume 9, e8845
ISSN Online: 2333-9721
ISSN Print: 2333-9705

Bearing Fault Diagnosis Based on Wavelet Transform and Convolutional Neural Network

Chenxue Li, Xiaoqi Yin*, Jiaxue Chen, Hang Yang, Li Hong

Faculty of Electronic Information Engineering, Huaiyin Institute of Technology, Huai'an, China
Email: 471174676@qq.com, *tgzy12345678@163.com, 1908455727@qq.com, 1048221152@qq.com, 1061828044@qq.com

How to cite this paper: Li, C.X., Yin, X.Q., Chen, J.X., Yang, H. and Hong, L. (2022) Bearing Fault Diagnosis Based on Wavelet Transform and Convolutional Neural Network. *Open Access Library Journal*, **9**: e8845.
https://doi.org/10.4236/oalib.1108845

Received: May 5, 2022
Accepted: June 14, 2022
Published: June 17, 2022

Abstract

Rolling bearings are the most prone to failures in mechanical equipment, and the vibration signal is unstable. Therefore, according to this characteristic of the bearing, the time-frequency characteristics of the bearing vibration signal are adaptively extracted. This paper proposes a wavelet transform-based method. And the bearing fault diagnosis method of convolutional neural network realizes intelligent diagnosis. Firstly, the fault signal of the rolling bearing is converted into a wavelet time-frequency map by using wavelet transform, and it is divided into training set samples and test set samples. Secondly, the experimental samples are input into the constructed convolutional neural network model for training, and the training continues updating the network parameters; finally, the training results and accuracy are obtained by testing. The experimental results show that 100% accuracy can be obtained by inputting the wavelet time-frequency map of vibration signal into the convolution neural network model for classification. The results prove the feasibility, stability and convenience of this method in fault diagnosis.

Subject Areas

Automata

Keywords

Roller Bearing, Fault Diagnosis, Continuous Wavelet Transform, Convolution Neural Network

1. Introduction

Rolling bearings are at the core of mechanical equipment. In the modern manufacturing industry, machinery and equipment are developing in the direction of intelligence and automation. Under the influence of various factors, rolling bearings are very easy to damage and fail. The faulty rolling bearing directly affects the operation of the entire machinery and equipment. More seriously in this case, it will also cause damage to the entire machinery and equipment.

If the rolling bearing fails, it is very likely to be the cause of many accidents, that is, when the bearing fails, many accidents may occur. Therefore, the study of bearing failure is of great significance to improve the stability of mechanical equipment operation and the safety of personnel.

At present, more and more scholars have begun to study fault diagnosis. With the development of technology, researchers began to develop in the direction of intelligence on the basis of traditional signal processing and proposed more intelligent diagnosis methods. At present, the research methods of fault diagnosis mostly take extracting the characteristics of fault vibration signal as the main research means for fault data analysis. The methods of extracting characteristics mainly include fast Fourier transform, short-time Fourier transform, time-frequency analysis, etc. The difficulty of this kind of method mainly lies in how to extract more fault features faster and more effectively.

With the development of artificial intelligence technology, the method of fault diagnosis has further developed to the intelligent fault diagnosis method with deep learning as an important means. Zhang Wei *et al.* [1] used the concept of superconvolution kernel and subconvolution kernel to design a new parallel cross-DCNN (PC-DCNN) model to realize bearing fault diagnosis under noisy environment and different workloads; Shao Haidong *et al.* [2] proposed a deep wavelet autoencoder (DWAE) method based on extreme learning machine for the problem of unsupervised feature learning of raw vibration data, which was applied to the analysis of experimental bearing vibration signals; Li Heng [3] aiming at the vibration signal of rolling bearing with strong non-stationarity and easy interference by strong background noise, a fault diagnosis method based on short-time Fourier transform and convolutional neural network was proposed, which realized end-to-end fault pattern recognition; Chen Renxiang *et al.* [4] proposed a fault diagnosis method for rolling bearing faults based on convolutional neural network and discrete wavelet transform for the self-adaptive extraction of time-frequency features and intelligent diagnosis of rolling bearing fault diagnosis; Sun Yan *et al.* [5] based on the accuracy of bearing fault diagnosis, combined with the time-frequency domain characteristics of vibration signals, proposed an improved capsule network diagnosis method in time-frequency domain.

The convolutional neural network has good accuracy in the recognition and classification of one-dimensional data and two-dimensional images. In this paper, a lightweight convolution neural network model is adopted. The bearing fault data are preprocessed by means of wavelet transform and data set enhancement. After being transformed into a time domain diagram, it is used as the training sample of a neural network to achieve high fault diagnosis accuracy.

2. Wavelet Transform

Wavelet transform is often used to analyze the time-scale of signals [6]. It is a commonly used scientific research mathematical tool after Fourier transform in recent years, and has the characteristics of multi-resolution analysis.

The "permissive" condition is an important condition that restricts the reversibility of wavelets. Wavelet transform is only meaningful within a limited window, beyond the limit of the window, the functions are all zero, that is to say, the definition domain of wavelet transform is only partially non-zero [7]. The so-called wavelet transform means that the components it contains have no direct current trend at all, but are in the form of an oscillating wave.

$\psi(t)$ is a wavelet mother function, which needs to satisfy the conditions of tolerance, limited energy and zero mean [8], which are respectively shown by Equations (1.1)-(1.3):

$$\psi(t) \leftrightarrow \psi(\omega) \tag{1.1}$$

$$C_\varphi = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} \mathrm{d}\omega < \infty \tag{1.2}$$

$$\psi(0) = \int_{-\infty}^{\infty} \psi(t)\mathrm{d}t = 0 \tag{1.3}$$

When the above conditions are met, assuming the original signal is $x(t)$, the continuous wavelet transform and inverse transform of the signal $x(t)$ can be defined as:

$$C(\tau,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-\tau}{a}\right)\mathrm{d}t \tag{1.4}$$

$$x(t) = \frac{1}{C_\psi} \iint C(\tau,a)\frac{1}{a^2}\psi\left(\frac{t-\tau}{a}\right)\mathrm{d}\tau\mathrm{d}a \tag{1.5}$$

In Formulas (1.4) and (1.5), the scale factor is represented by a, and the condition of $a > 0$ must be satisfied; in the formula, the displacement is reflected by τ, and there is no positive or negative requirement; because a and τ are both continuous variables, so also known as Continuous Wavelet Transform (CWT) [9].

The continuous wavelet time-frequency diagram can reflect the characteristics of the signal, and the frequency of the signal at different times can be seen in the diagram. Converting the signal into a wavelet time-frequency diagram is more convenient for signal processing and analysis. The wavelet transform is the time-scale analysis of the signal, that is, the transformation of the signal from the time domain to the scale domain. Therefore, it is necessary to obtain the frequency solution corresponding to the signal scale by Equation (1.6) to plot the frequency and wavelength diagram of the signal, namely the wavelet time-frequency diagram.

$$F_a = \frac{F_c f_s}{a} \tag{1.6}$$

In the Formula (1.6), F_c represents half of the wavelet characteristics and is the center frequency of the wavelet. The sampling frequency of the signal is represented by f_s in the formula, and the actual frequency corresponding to a is represented by F_a [10].

3. Convolutional Neural Networks

3.1. Principle of Convolutional Neural Network

Convolutional Neural Networks are a versatile type of neural network. The input layer, convolutional layer, pooling layer, fully connected layer, and output layer make up the convolutional neural network [11]. The local connection conforms to the sparse response of biological neurons and can be used as the connection method of CNN, which reduces the size parameters of the convolutional neural network model to a certain extent, and can also reduce the dependence on training data [12].

Convolution layer: The combination of many convolution kernels finally forms a convolution layer. The convolution operation can denoise the signal and enhance the features of the signal [13].

Convolutional layer gradient calculation:

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * w_{ij}^l + b_i^l\right) \tag{2.1}$$

x_j^l represents the jth feature map of the convolutional layer l, the activation function is represented by f, and M_j represents the set of input features [14].

When the matrix size of the input convolution layer is $w \times w$, the size of the convolution kernel in the convolution layer is $k \times k$, the stride is s, and the padding value is p, then the calculation of the image size is generated after convolution formula:

$$w' = \frac{w + 2p - k}{s} + 1 \tag{2.2}$$

Pooling layer, also known as the downsampling layer, can effectively control overfitting. After the convolutional layer, there will be a downsampling layer, and the purpose is to reduce the parameter amount of the feature map obtained by the convolution. There are two types of pooling layers. When the pooling core moves to an area, the maximum pooling layer (Max Pooling) is to take the maximum value of the area, and the average pooling layer (Mean Pooling) is to take the average value of the area. The pooling kernel is equivalent to a filter in the pooling layer, and the purpose is to make the features more concentrated.

Fully connected layer: The main function of the fully connected layer is classification. The full connection connects all nodes in the $n - 1$ layer with all the nodes in the n layer, that is, integrates the features extracted by the previous convolution, and then uses Softmax logistic regression for classification.

3.2. MobileNet

At present, most neural networks run on servers with strong computing power, but huge networks cannot run on ordinary computers or mobile terminals. Due to the limited computing power of mobile devices, the MobileNet neural network is proposed for this problem.

The main idea of MobileNet-V1 is to use Depthwise Separable Convolution [15] instead of convolutional layers. Depthwise Separable Convolution is a depthwise separable convolution. Depthwise separable convolution is mainly used in model compression. It replaces the original cross-channel 3 × 3 convolution operation with a single-channel 3 × 3 convolution plus 1 × 1 convolution. A comparison of traditional convolutional layers and depthwise separable convolutions is shown in **Figure 1**.

The traditional convolution layer is to convolve the three RGB channels at the same time, and the image with the number of channels M is convolved to obtain a feature map with the number of channels N. The traditional convolution operation uses N different $A \times A \times M$ to traverse the input feature map in the form of a sliding window, and the number of convolution kernel parameters of size $A \times A$ is $A \times A \times M \times N$.

In MobileNet, the convolution is divided into two parts: depthwise convolution and pointwise convolution. Depthwise sets convolution kernels for each channel of the input feature map respectively, and these convolution kernels only work in this channel [16]. Because the multi-channel of convolution is abandoned, the number of parameters of Depthwise is $A \times A \times M$. Pointwise convolution can use 1 × 1 convolution to operate, mainly to increase and decrease dimension or to perform feature fusion, so the parameter quantity is $M \times N \times B \times B$ [17]. Therefore, the ratio of efficiency improvement can be calculated according to the above theory, as shown in Formula (2.3):

$$\frac{AAMBB + MNBB}{AAMNBB} = \frac{1}{N} + \frac{1}{A^2} \tag{2.3}$$

The number of input feature channels in the formula is M, the size of the convolution kernel is A in the formula, the number of 1 × 1 convolution kernels is N, and $B \times B$ represents the size of the output feature map of the convolution layer.

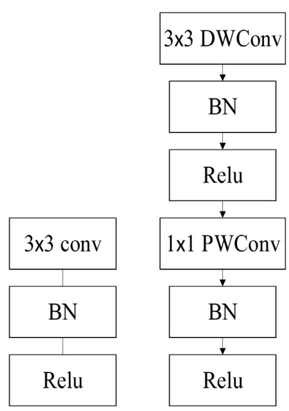

Figure 1. Conventional convolution and deep separable convolution.

From Formula (2.3), assuming that a 3 × 3 convolution is input, the parameter and calculation amount of MobileNet is about 1/8 of that of ordinary convolution.

The activation function adopted by MobileNet-V1 limits the maximum output value to 6, which is the ReLU6 activation function, as shown in Formula (2.4).

$$f(x) = \min(\max(0, x), 6) \tag{2.4}$$

This article adopts the MobileNet-V2 [18] structure. The difference from MobileNet-V1 is that the MobileNet-V2 structure adds a 1 × 1 convolutional layer to the Depthwise convolution, the purpose of which is to "expand" the channel. As the number increases, more features can be obtained. And at the end of the structure, linear structure is used instead of ReLu to prevent it from destroying the characteristics. And learned the structure of the residual network in the network, and finally formed a linear bottlenecks structure, as shown in **Figure 2**.

4. Experimental Tests

4.1. Experimental Dataset

The data used in this experiment is the experimental data of the 6205-2RS JEM SKF bearing in the Western Reserve University rolling bearing experiment. The platform consists of a 1.5 KW electric motor; a torque sensor/decoder; a power test meter and an electronic controller [19]. The bearing damage in the experiment is a single point damage by EDM; the bearing damage is a single point damage by EDM; SKF bearings are used to detect damage with diameters of 0.007, 0.014, and 0.021 inches respectively; when testing the vibration signal of the bearing The acceleration sensor is used, the motor speed is 1796 rpm, the load horsepower of the motor is 0 HP, the sampling frequency is 12 kHz, and the number of rolling elements is 9.

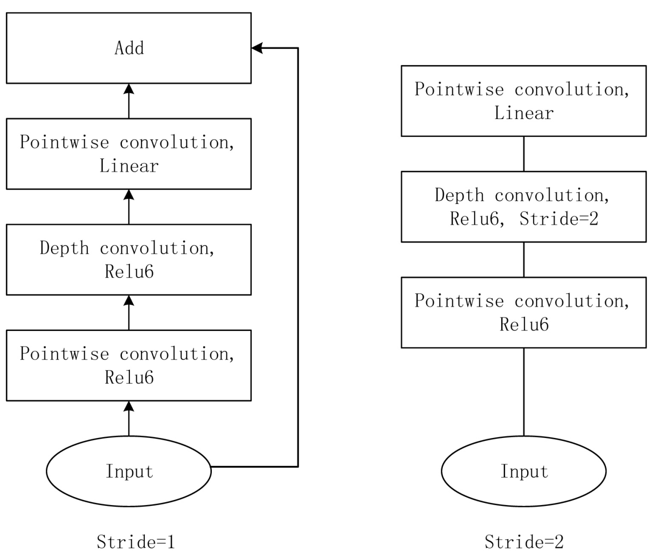

Figure 2. Structure of linear bottlenecks.

In this experiment, the bearing data of Western Reserve University is divided into 10 categories according to different fault sizes and faults in different positions, each category includes 1000 samples, and they are divided into training samples and test samples according to the ratio of 4:1. The experimental data are shown in **Table 1**.

Table 2 shows the structural parameters of the bearing 6205-2RS JEM SKF in the experiment.

The empirical formula for failure frequency is:

Inner ring fault frequency:

$$f_i = 0.6 \times Z \times f_r \tag{3.1}$$

Outer ring fault frequency:

$$f_o = 0.4 \times Z \times f_r \tag{3.2}$$

Cage failure frequency:

$$f_c = 0.381 - 0.4 \times f_r \tag{3.3}$$

Rolling element failure frequency:

$$f_b = 0.23 \times Z \times f_r \left(Z < 10\right);\ f_b = 0.18 \times Z \times f_r \left(Z > 10\right) \tag{3.4}$$

Among them, f_r is the rotation frequency, and Z is the number of rolling elements. The failure frequency of the rolling bearing can be calculated from the above empirical formula, as shown in **Table 3**.

Table 1. Data sheet of 6205 SKF rolling bearing.

	Fault size/mm	file name
Normal Baseline Data	0	97
Outer Race Position Relative to Load Zone (Load Zone Centered at 6:00)	0.1778	130
	0.3556	197
	0.5334	234
Ball	0.1778	118
	0.3556	185
	0.5334	222
Inner Race	0.1778	105
	0.3556	169
	0.5334	209

Table 2. Bearing parameters.

Inside Diameter	Outside Diameter	Thickness	Ball Diameter	Pitch Diameter
25	52	15	7.94	39.04

Table 3. Bearing failure frequency.

Inner race fault frequency/Hz	Outer race fault frequency/Hz	Cage failure frequency/Hz	Rolling element failure frequency/Hz
162.1860	107.3640	11.9293	70.5838

Figure 3 is the signal time-domain diagram of different parts of the bearing in the experiment when faults occur under different conditions. The signal time-domain diagram is the original signal time-domain diagram obtained from the data in the bearing data set after time-domain transformation. From the time domain diagram of the signal in Figure 3, it can be found that it is difficult to accurately determine the fault location of the bearing and the type of the bearing failure only by relying on the time domain diagram of the fault signal.

4.2. Network Model Parameters

The core of mobilenet-v2 adopted in this paper consists of 17 bottlenecks. The network model of mobilenet-v2 is shown in Table 4, where t refers to the dimension extended in the residual block. C is the dimension of the output, which can be used to judge the number of convolution kernels. S is the step size of convolution, and N is that the current line operation is repeatedly applied N times.

4.3. Experimental Process

The software used in this article includes Python3.9.2, MatLab R2017b and Origin 2019b, the operating system is Windows 10, the processor of the experimental environment is AMD Ryzen 7 4800H with Radeon Graphics 2.90 GHz, and the memory is 16 GB.

This experiment adopts the bearing fault diagnosis method of wavelet transform and convolutional neural network. First, the data in the bearing data set of Western Reserve University is converted into a wavelet time-frequency map by using the MatLab software, and then there are 1000 samples for each fault, a total of ten faults, and the total number of samples reaches 10,000. According to the 4:1 ratio The ratio is divided into training test set and verification test set, input the training test set into the built convolutional neural network model, set 0.001 as the learning rate of the training parameters of this experiment, the loss function uses cross entropy, the training period is set to 100, update the network model, input the validation test set into the trained network model, get the accuracy rate, and finally perform image prediction to get the accuracy rate.

Because the experimental data set used in this experiment is large, too many or too few samples will have an impact on the accuracy of the experiment. Therefore, it is necessary to find an appropriate number of batch samples to improve the accuracy of the experiment and the efficiency of the experiment to a great extent [20]. In this paper, the number of four batch samples is set, and the experiments are carried out in turn. The diagnostic results are shown in Table 5.

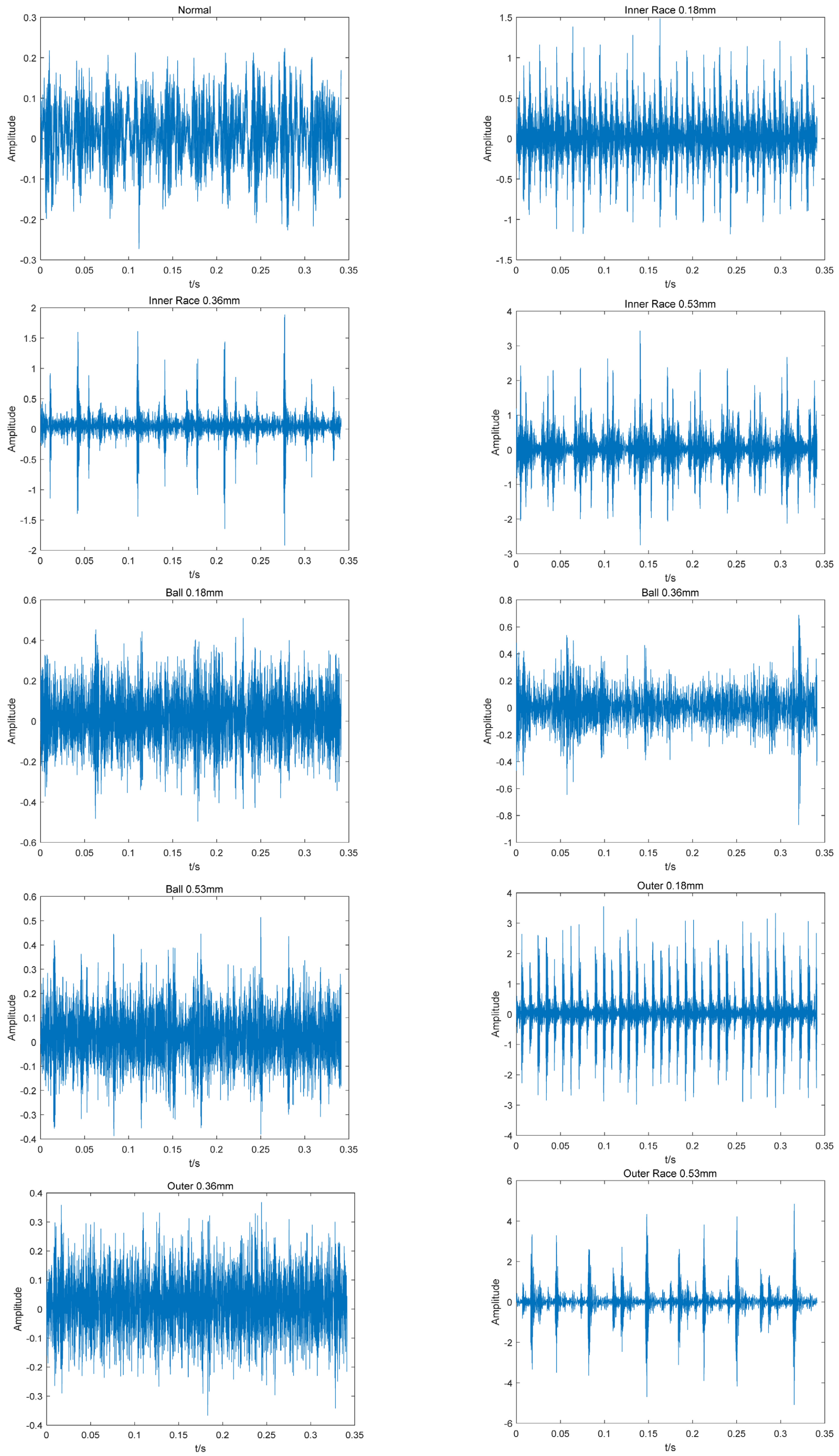

Figure 3. Signal time domain diagram under different fault states.

Table 4. Mobilenet-v2 network model parameters.

Input	Operator	t	c	n	s
2242 × 3	Conv2d	-	32	1	2
1122 × 32	bottleneck	1	16	1	1
1122 × 16	bottleneck	6	24	2	2
562 × 24	bottleneck	6	32	3	2
282 × 32	bottleneck	6	64	4	2
142 × 64	bottleneck	6	96	3	1
142 × 96	bottleneck	6	160	3	2
72 × 160	bottleneck	6	320	1	1
72 × 320	Conv2d 1 × 1	-	1280	1	1
72 × 1280	Avgpool 7 × 7	-	-	1	-
1 × 1 × 1280	Conv2d 1 × 1	-	k	-	

Table 5. The influence of batch sample number on accuracy.

Number of batch samples	Average diagnostic accuracy × 100%	Average training time/s
16	99.63	2.75
32	98.39	1.34
64	98.35	1.13
128	97.39	0.89

It can be seen from the table that when the number of batch samples is 32, the accuracy reaches the highest, and the average training time is close to the best result, so the number of batch samples in this model is 32.

4.4. Experimental Results and Analysis

The experimental model selected GoogLeNet, VGG16 model and MobileNet model for comparison, and input the processed wavelet time-frequency map into the above model for training. The training parameters of the three network models are all set to a learning rate of 0.001, the loss function uses cross entropy, the training period is set to 100, and each batch of training images is 32. During the training process, the loss rate and accuracy rate are recorded every time the model completes one cycle of training. The final training accuracy and loss rate of the three models are shown in **Figure 4** and **Figure 5**.

It can be seen from the above figure that the loss rate of MobileNet is kept below 0.25, the accuracy rate can be kept above 0.97, and the fluctuation of the curve is small. The loss rate of VGG16 starts from about 1.5 and drops to close to 0, and the accuracy rate can also be maintained. Above 0.97, the fluctuation range of the curve is larger than that of MobileNet. The loss rate of GoogleNet starts from about 2.5 and drops below 0.25, and the accuracy rate increases from about 0.8 to more than 0.97, which is the largest fluctuation. In terms of loss

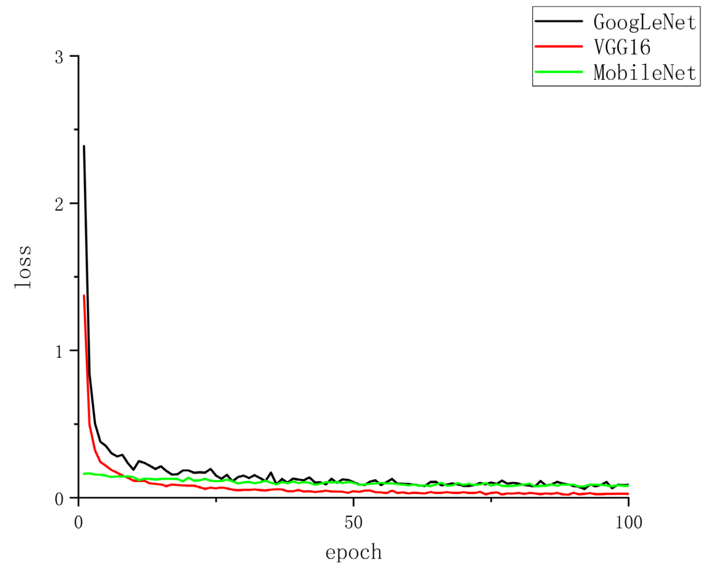

Figure 4. Model training loss rate.

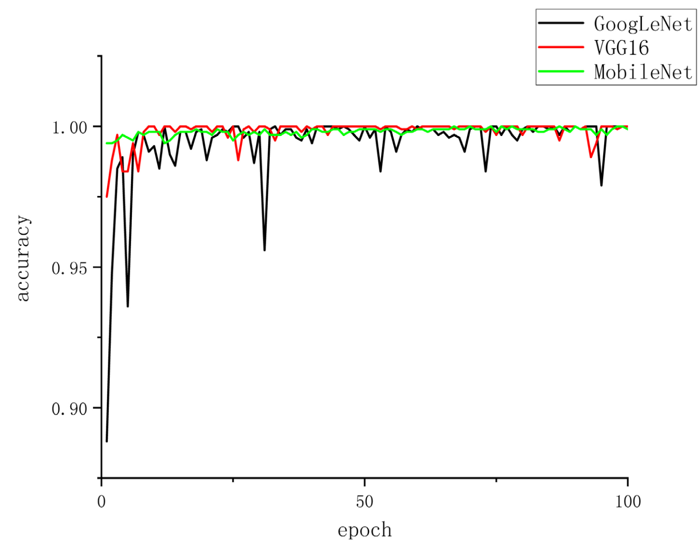

Figure 5. Model test accuracy.

rate, the loss rate of VGG is relatively high at the beginning of training, but after several iterations, the loss rate is close to 0, which is better than that of GoogLeNet and MobileNet; in terms of accuracy, the accuracy rate of MobileNet is not only high, but the basic accuracy rate can reach 1 (Table 6). The accuracy rate is still very stable, significantly better than the VGG16 and GoogLeNet models. Therefore, on the whole, the MobileNet model, as a lightweight network model, is superior to the other two networks in terms of loss rate and accuracy.

Select an inner ring fault data with a speed of 1797 rpm and 0.18 mm from the bearing data set of Western Reserve University, convert it into a wavelet time-frequency map through MatLab, and input it into the built MobileNet model for prediction, as shown in Figure 6. As shown, it can be seen that the prediction accuracy can reach 0.956.

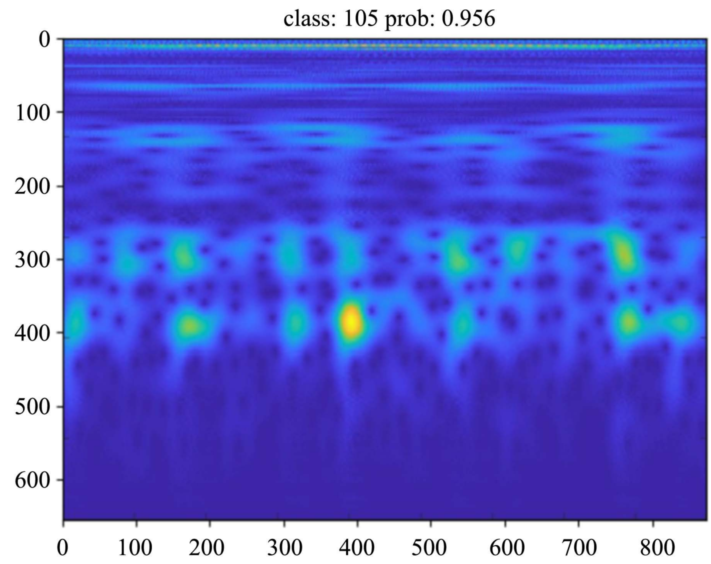

Figure 6. Fault prediction results.

Table 6. Experimental results of different networks.

Networks	accuracy/%
MobileNet	100
GoogLeNet	99.98
VGG16	99.86

5. Conclusion

This paper proposes a bearing fault diagnosis method based on wavelet transform and convolutional neural network. Firstly, the fault signal data of the bearing is converted into a signal time-frequency map by the method of the wavelet transform, and then the convolutional neural network MobileNet network model is used to carry out parameter training and learning to avoid the tedious and complex process of traditional signal processing and relies on the characteristics of personnel experience, which effectively reduces the difficulty in the fault diagnosis process and enhances the intelligence of the diagnosis process. The training results also demonstrate the accuracy and stability of this method. However, there are still many areas for improvement and further research in this method. In the experiment of this paper, the choice of parameters will have a great impact on the experimental results when the algorithm comparison experiment is carried out. In the following experiments, you can try to optimize the parameters with better effect to obtain a better network structure model, and explore the relationship between the experimental results and the changed parameters.

Acknowledgements

Thanks for the support and help from the teachers and the project team in the

process of writing the thesis.

Availability of Data and Materials

Case Western Reserve University Bearing Failure Dataset:

Download a Data File|Case School of Engineering|Case Western Reserve University

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Zhang, W., Li, C.H., Peng, G.L., *et al.* (2018) A Deep Convolutional Neural Network with New Training Methods for Bearing Fault Diagnosis under Noisy Environment and Different Working Load. *Mechanical Systems and Signal Processing*, **100**, 439-453. https://doi.org/10.1016/j.ymssp.2017.06.022

[2] Shao, H.D., Jiang, H.K., Li, X.Q., *et al.* (2018) Intelligent Fault Diagnosis of Rolling Bearing Using Deep Wavelet Auto-Encoder with Extreme Learning Machine. *Knowledge-Based Systems*, **140**, 1-14. https://doi.org/10.1016/j.knosys.2017.10.024

[3] Li, H., Zhang, Q., Qin, X.R. and Sun, Y.T. (2018) Bearing Fault Diagnosis Method Based on Short-Time Fourier Transform and Convolutional Neural Network. *Vibration and Shock*, **37**, 124-131.

[4] Chen, R.X., Huang, X., Yang, L.X., Tang, B.P., Yu, T.W. and Zhou, J. (2018) Fault Diagnosis of Rolling Bearings Based on Convolutional Neural Network and Discrete Wavelet Transform. *Chinese Journal of Vibration Engineering*, **31**, 883-891.

[5] Sun, Y. and Peng, G.L. (2021) Bearing Fault Diagnosis Based on Improved Capsule Network in Time-Frequency Domain. *Combined Machine Tool and Automated Machining Technology*, No. 2, 6-8+13.

[6] Duan, C.D. and Zhang, R. (2019) Fault Diagnosis of Locomotive Bearings Based on Improved Empirical Wavelet Transform. *China Mechanical Engineering*, **30**, 631-637.

[7] Li, Y.H., Wang, G.T., Lu Shuang, L., *et al.* (2016) Vibration Experiment Analysis of Loose Transformer Windings. *Noise and Vibration Control*, **36**, 34-37.

[8] Xu, Y.G., Meng, Z.P. and Zhao, G.L. (2014) Research on Bearing Composite Fault Diagnosis Based on Double Tree Complex Wavelet Transform. *Journal of Instrument and Instrument*, **35**, 447-452.

[9] Wen, B.H., Sun, L.J. and Yu, H.F. (2008) Application of Multi-Scale Wavelet Analysis in Fault Diagnosis of Coal Mine Main Fan. *Journal of Xi'an University of Science and Technology*, **28**, 638-642.

[10] Qian, G.C., Zhao, Z.Y., Zou, D.X., Liu, H.W., Li, C.X. and Yao, C.G. (2017) Detection of Transformer Winding Deformation Fault Types Based on Continuous Wavelet Transform. *High Voltage Technology*, **43**, 2016-2023. https://doi.org/10.1109/ICMA.2016.7558853

[11] Zhou, J.Y. and Zhao, Y.M. (2017) Review of Convolutional Neural Networks in Image Classification and Object Detection. *Computer Engineering and Applications*, **53**, 34-41.

[12] Lou, J.Y., Nan, G.F. and Song, C.C. (2021) Fault Diagnosis of Rolling Bearing Based on Wavelet Packet Decomposition and Convolutional Neural Network. *Journal of Light Industry*, **36**, 79-87.

[13] Li, C.J., Li, F.C. and Liu, J.F. (2019) Recognition of Digital Verification Code Based on Convolutional Neural Network. *Electronic Design Engineering*, **27**, 107-111.

[14] Li, D.J., Guo, H.T., Zhang, B.M., Zhao, C., Lu, J. and Yu, D.X. (2020) Feature Extraction from Remote Sensing Images Combined with Dual Vision Fully Convolutional Networks. *Chinese Journal of Image Graphics*, **25**, 535-545.

[15] Chollet, F. (2017) Xception: Deep Learning with Depthwise Separable Convolutions. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Honolulu, 21-26 July 2017, 1251-1258. https://doi.org/10.1109/CVPR.2017.195

[16] Zhang, Y.Y., Zhang, S., Zhang, Y., Ji, J.M., Duan, Y.F., Huang, Y.T., Peng, J. and Zhang, Y.X. (2020) Autonomous Driving Perception and Computing Based on Multimodal Fusion. *Computer Research and Development*, **57**, 1781-1799.

[17] Zhang, Z.H. and Wang, R. (2020) Improved Face Recognition Method Based on MobileFaceNet Network. *Journal of Beijing University of Aeronautics and Astronautics*, **46**, 1756-1762.

[18] Sandler, M., Howard, A., Zhu, M., *et al.* (2018) Mobilenetv2: Inverted Residuals and Linear Bottlenecks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Salt Lake City, 18-23 June 2018, 4510-4520. https://doi.org/10.1109/CVPR.2018.00474

[19] Chen, C.Z. and Wei, W. (2020) Extraction of Faulty Weak Signals Based on Improved LMD and Wavelet Packet Noise Reduction. *Mechanical Design and Manufacturing*, No. 1, 165-168+172.

[20] Chen, J.X., Yin, X.Q., Li, C.X., Yang, H. and Hong, L. (2020) One-Dimensional Convolutional Neural Network Based Bearing Fault Diagnosis. *Open Access Library Journal*, **9**, 1-11. https://doi.org/10.4236/oalib.1108644