Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 8, No. 3, 2023

Pump Fault Detection Based on MFCC-MLCNN

Chunyin Sun[1], Dexin Song[2], Haorui Liu[2]

[1]Faculty of Information and Control Engineering, Jilin Institute of Chemical Technology, Jilin 132022, China
[2]School of Computer and Information, Dezhou University, Shandong 253023, China

Abstract: Detection of industrial water pumping systems is both a practical and important area of research in industrial production. The accuracy of fault detection is crucial because failure of fault detection can lead to pump damage and reduced productivity. In order to timely and accurately identify the working status of water supply pumps, a pump fault detection method based on Mel Frequency Cepstrum Coefficient with Migration Learning Convolutional Neural Networks (MFCC-MLCNN) is proposed. The sound signals of water pumps under different operating conditions are preprocessed to calculate their MFCC features as static features, and further processed to obtain the first-order difference MFCC features as well as the second-order difference MFCC features as dynamic features. In this study, the audio dataset of water pumps recorded with ambient noise in a real industrial environment is used. Usually, fault detection datasets are unbalanced because the amount of fault data is limited. A practical way to deal with this problem is to use deep migration learning, where high accuracy can be achieved with limited labeled data. In this study, a migration learning convolutional neural network is introduced to establish a pump fault diagnosis model. The experimental results show that the method proposed in this study can effectively recognize the working state of water supply pumps with a small amount of sample data and model parameters.

Keywords: Fault detection, Mel frequency cepstrum factor, Transfer learning, Convolutional neural network.

1. Introduction

Industrial circulating water pump is an important cooling tool, which is widely used in modern industrial production process. Water pumps play an important role in ensuring the normal operation of production and ensuring safe production. Industrial circulating water system in the blast furnace steelmaking and other large-scale industrial production process consists of multiple large water pumps. The performance of the water supply pumping unit directly affects the efficiency of the entire water transfer system. Water pump as a typical rotating mechanism, in the case of long time high-speed operation is prone to bearing damage, pin wear, inhalation of foreign objects, shaft misalignment and other failures, which leads to the circulating water system cooling water supply is insufficient to threaten the safety of industrial production.

Water pump fault detection and prediction is one of the important research areas to ensure the safe and reliable operation of industrial production processes. The fault or abnormality detection of water pumps mainly includes detection methods based on sound signals and detection methods based on vibration signals. Compared with other methods, sound signal acquisition and processing technology has been very mature, sound signal-based detection methods have many advantages [1]: real-time, real-time acquisition and processing of sound signals generated by the pump, real-time monitoring of the pump's operating status; data acquisition is easy, only through the microphone and other simple equipment can be obtained by the pump's sound signals; the detection results are accurate, through the signal processing and fault detection of the sound signal. Accurate detection results, through the sound signal signal processing and fault detection technology to achieve rapid and accurate diagnosis of pump failure; at the same time, as a non-contact detection method, no need to dismantle the pump or change its operating state during the detection, to avoid the inconvenience caused by the traditional detection methods [2].

The mechanical structure of the pump determines that its sound signal is closely related to its mechanical state. Different sounds appearing in the operation of the pump can reflect different abnormal states of the pump, such as bearing damage, pin wear, inhalation of foreign matter, etc. In addition, the long running time of the pump can also lead to changes in the mechanical structure, which can affect the audible sound signal [3]. Water pump fault detection methods based on sound signals can be divided into methods based on manual identification, and methods based on signal feature extraction and classification identification [4]. Artificial identification methods are mainly through manual listening to the sound signal generated by the pump, fault diagnosis and classification based on experience and knowledge, this method has the advantages of intuition, simplicity, etc., but it is highly subjective, and it is difficult to ensure the diagnostic accuracy and efficiency. In contrast, the method based on signal feature extraction and classification and identification, through the acquisition, processing and feature extraction of acoustic signals, extracts the characteristic parameters that can reflect the pump failure, and then classifies and diagnoses the pump failure through the classifier. In terms of acoustic feature extraction, the commonly used feature parameters in the existing sound-based pump fault identification research are Meier frequency cepstrum coefficient (MFCC), linear prediction cepstrum coefficient (LPCC), and Gammatone frequency cepstrum coefficient (GFCC) and so on [5], which have been researched by a large number of scholars and achieved relevant results.

Practice and research have shown that the failure state of the water supply pump during operation is strongly correlated with the sound signal on its drive end. Therefore, collecting the sound signals from the drive end of the water supply pump and analyzing them is an effective means of troubleshooting the water supply pump. Traditional data-driven fault diagnosis methods usually require accurate mathematical models. With the continuous improvement of the pump structure, the fault conditions are becoming more and more complex, and it is more difficult to accurately detect faulty sound signals using traditional sound signal processing methods, and it is difficult to meet the practical needs. In recent years, researchers have introduced deep learning algorithms into fault diagnosis related fields and have made important progress [6-8].

Industrial circulating water system water supply pump is a large-scale equipment, the actual work of more types of faults and relatively low frequency, even if the construction of test platforms to simulate the actual faults need to spend a huge amount of manpower and material resources, so the relative lack of training samples is one of the important constraints that lead to the difficulties of fault diagnosis of industrial circulating water system water supply pumps. Since deep learning-based fault diagnosis methods require a large amount of labeled sample data, it is difficult to achieve satisfactory results in fault identification of water supply pumps based on such methods. While transfer learning (TL) can better solve the problem of small number of samples, this method can migrate the knowledge learned in the source domain to the task in the target domain, save the deep learning model training time, and improve the accuracy of the results [9]. Combining migration learning with convolutional neural networks can be used to solve the problem of insufficient training of deep networks with small sample data [10]. Therefore, the use of migration learning and convolutional neural network methods for fault diagnosis of rotating machinery can not only mine the feature information in the original signal, but also improve the efficiency of fault diagnosis.

Deep learning techniques have shown the advantages of strong generalization ability and high accuracy rate in sound-based fault recognition, while few studies have been carried out in combination with deep learning techniques in water pump fault sound recognition. Therefore, in this paper, we will use the method of signal feature extraction and combine with deep learning technology to realize the water pump fault recognition based on sound signal. Firstly, we extract the MFCC features of the water pump sound signal and calculate its dynamic features, and then we use the Migration Learning Convolutional Neural Network model (MLCNN) as a classifier to realize the sound-based water pump fault and abnormality detection. This method overcomes the inconvenience of constant optimization and adjustment of classifiers in previous methods, and combines the advantages of strong adaptivity and high accuracy of deep learning-based methods.

2. Methods

The flow of the acoustic feature extraction and detection method for water pump based on MFCC and MLCNN is shown in Fig. 1. Firstly, the original sound signal of the pump is preprocessed, and then feature extraction is performed to obtain its MFCC features, and then the first-order and second-order differences of MFCC are calculated as dynamic features. The combined feature data is input into the pre-trained MLCNN model for classification and recognition, and the MLCNN model can judge the working state of the pump according to the input feature information, and finally output the results.

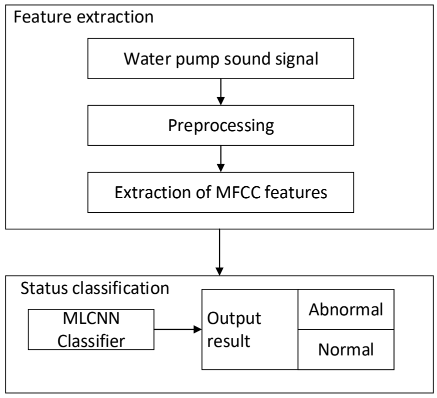


Figure 1. Flow chart of water pump acoustic feature extraction and detection method

2.1. Data set

To design a classifier for the model, it is first necessary to pay attention to the available data. One of the best datasets that can be used for pump audio fault detection is the MIMII dataset.Purohit et al [11] developed this dataset in 2019. This dataset records the healthy state audio of pumps, fans, valves and slides and their fault states under various abnormal conditions such as rotational imbalance, leakage, contamination, etc. These data are categorized into healthy and unhealthy.

A circular microphone array with eight independent microphones was placed at a distance of 500 mm from the pump. The data was recorded in 10-second files as 16-bit audio signals with a sampling frequency of 16 kHz. In addition to the sound of the target machine, background noise was continuously captured in several real factories and eventually combined with the audio of the target machine as a way to simulate the natural environment. The background noise was added to the audio at three different signal-to-noise ratio (SNR) levels: -6 dB, 0 dB, and +6 dB. Due to the summary presented by Purohit et al. in the literature [11] on the difficulty of detecting valve anomalies due to the non-smooth nature of the sound signal, the data used was the data set MIMII in the " Valve" part of the data set MIMII, where the valve is a solenoid valve that repeatedly opens and closes.

The details of the dataset are shown by Table 1.

Table 1. Data set information sheet

Signal-to-Noise Ratio (SNR)/db	Pump Valve Number	Number of normal sounds	Number of abnormal sounds
0	00	991	119
	02	708	120
	04	1000	120
	06	992	120
+6	00	991	119
	02	708	120
	04	1000	120
	06	992	120
-6	00	991	119
	02	708	120
	04	1000	120
	06	992	120
Total number	—	11073	1437

2.2. MFCC feature extraction

The sound signal of water pump working is usually a continuous waveform signal, and this continuous signal needs to be converted into numerical features firstly for the subsequent tasks. In this paper, we will extract the MFCC features of the water pump working sound and compute its dynamic features.MFCC is a kind of feature parameter which is widely used in the fields of signal processing, audio processing, speech recognition, etc. Through the steps of framing, windowing, Fourier transform, Mel filter bank processing and cepstrum analysis of the signals, the feature vectors of the signal with Mel frequency cepstrum coefficients are extracted, which are then used in the subsequent classification and recognition tasks. The feature extraction process is shown in Figure 2.

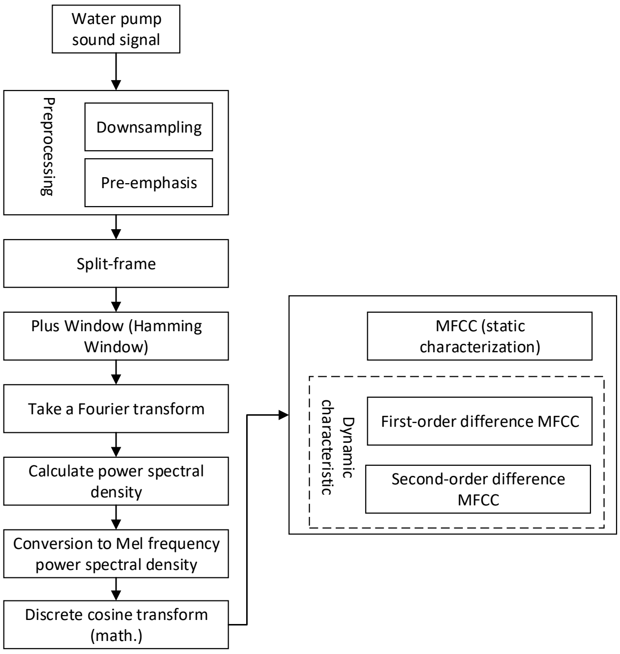


Figure 2. MFCC feature extraction process

① Pump sound data preprocessing

The original audio signal is preprocessed before feature extraction of the pump operating sound signal: including downsampling, pre-emphasis, etc. Let the audio signal of the m-th frame be $x(n)$ obtained after preprocessing.

② Split-frame

The mth frame of the pre-processed audio signal $x(n)$ is sub-framed, and the number of samples per frame, i.e., the length of each frame, is N. A 50% overlap is set between every two frames, and the sampling rate is set to be f_s, so that the time length of each frame is:

$$T = N / f_s \tag{1}$$

③ Plus Window

The signal at each sampling point is windowed using a Hamming window to minimize the spectral leakage effect of the discrete signal. Assuming that the window function of the mth frame is $w(m,n)$, the signal weighted by the window function of the mth frame is:

$$xw(m,n) = x(n) \times w(m,n), 0 \le n < N, 0 \le m < M \tag{2}$$

④ Fourier transform

Perform the Fourier transform of the windowed signal $xw(m,n)$ to find its frequency domain representation as:

$$X(m,k) = FFT[xw(m,n)], 0 \le k < K \tag{3}$$

Eq. (3) by Fourier transform can be the mth frame of the signal sequence $wx(m,n)$ from the time domain to the frequency domain representation, you can get the sequence $X(m,k)$, which contains the signal at different frequencies of the component strength. Where k is the sequence number, each of which corresponds to a frequency in the spectrum; K is the number of points in the Fourier transform.

⑤ Calculate power spectral density

Power Spectral Density (PSD) is a function that describes the power distribution of a signal as a function of frequency. It is the square of the Fourier transform and represents the magnitude of the signal power at different frequencies. The power spectral density $P(m,k)$ is calculated as:

$$P(m,k) = \frac{|X(m,k)|^2}{N} \tag{4}$$

⑥ Calculating the Mel frequency power spectral density

This is usually accomplished with triangular filter banks, each corresponding to a Meier frequency and shaped like a triangle. The triangular filters filter and downsample the signal on the Meier frequency scale to extract audio features that are closer to the frequency response perceived by the human ear. Define a filter bank consisting of I triangular filters, each with center frequency $f(i)$, and its frequency response is:

$$H_i(k) = \begin{cases} 0, \quad k < f(i-1) \\ \dfrac{2[k - f(i-1)]}{[f(i+1) - f(i-1)][f(i) - f(i-1)]}, \quad f(i-1) \le k < f(i) \\ \dfrac{2[f(i+1) - k]}{[f(i+1) - f(i-1)][f(i) - f(i-1)]}, \quad f(i) \le k < f(i+1) \\ 0, \quad k \ge f(i+1) \end{cases} \tag{5}$$

Mapping $P(m,k)$ onto the Mel-frequency scale using a triangular filter bank yields a Mel-frequency power spectral density (MPSD) of :

$$P_M(m,i) = \sum_{K=0}^{I-1} P(m,k) \bullet H_i(k), 0 \le i < I \tag{6}$$

⑦ Discrete cosine transform

The discrete cosine transform (DCT) of the Meier frequency power spectral density yields the MFCC coefficient as:

$$C(m,j) = \sum_{i=0}^{I-1} \ln[N \bullet P_M(m,i)] \cos\frac{\pi j(i+0.5)}{I} \tag{7}$$

Where j denotes the dimension of the MFCC coefficient and I denotes the number of triangular filters.

⑧ Compute the first-order second-order difference of the

MFCC

The MFCC features themselves are static features, which have better time invariance, but lack the information of time series and cannot reflect the dynamic characteristics of the pump sound signal. Dynamic features, on the other hand, are obtained on the basis of static features by differencing or superimposing the features of neighboring time windows. The advantage of dynamic features is that they can reflect the dynamic changes of the pump sound signal, making the model better able to deal with the continuity and timing of the pump sound signal. The combined use of static and dynamic features can improve the accuracy and robustness of the model, making the model more suitable for handling the classification and recognition tasks of water pump sound signals.The first-order difference of the MFCC ($\Delta MFCC$) is calculated as:

$$\Delta C_j(m) = \frac{\sum_{l=1}^{L} l[C_j(m+1) - C_j(m-1)]}{\sqrt{2}\sum_{l=1}^{L} l^2} \tag{8}$$

where L is the range of frames for differential computation, and here L is set to 3. In contrast to normal differential computation using two adjacent frames, here more front and back frames are used to compute the $\Delta MFCC$ to minimize the interference due to noise and perturbation. Further calculation yields the second order difference of MFCC ($\Delta\Delta MFCC$) as:

$$\Delta\Delta C_j(m) = \frac{\sum_{l=1}^{L} [\Delta C_j(m+1) - \Delta C_j(m-1)]}{\sqrt{2}\sum_{l=1}^{L} l^2} \tag{9}$$

The obtained MFCC, $\Delta MFCC$ and $\Delta\Delta MFCC$ will be used as inputs to the MLCNN model to realize the classification and detection of the pump sound signal.

2.3. Migration learning convolutional neural network models

Due to the relatively small amount of water pump fault sample data, based on the idea of transfer learning, ResNet-18 in deep residual network (ResNet) is used as the benchmark model. Firstly, pre-training is performed on the ImageNet dataset, and the generalized features of the model trained on ImageNet are migrated to the MIMII-ResNet model for the pump fault diagnosis task. Using the training data in the MIMII dataset to train again, the generalized features of the MIMII-ResNet model trained on the MIMII dataset are migrated to the MLCNN model for the water pump fault diagnosis task. The MLCNN was trained with the MFCC features of the water pump sound signals, and the trained MLCNN model was used as a classifier and the model was tested with the test data.

He et al [12] proposed Residual Neural Network (ResNet), compared with the convolutional neural network structure of Szegedy et al [13], ResNet can overcome the problems of gradient disappearance and overfitting due to the increase in the number of layers of the model network, and accelerate the training of the neural network. The problem of gradient disappearance and overfitting due to the increase in the number of layers of the model network can be overcome to accelerate the training of the neural network and improve the model accuracy. Therefore, in this paper, we use ResNet-18 network as the benchmark model of MLCNN (Migration Learning Convolutional Neural Network), and the basic structure of ResNet residual learning unit is shown in Fig.3.

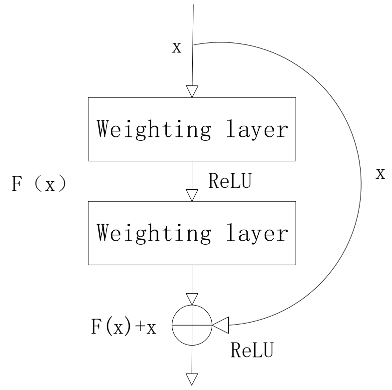


Figure 3. ResNet residual cell structure

The ResNet model unit consists of two basic blocks, the Conv Block and the Identity Block, where the Conv Block changes the network dimension and the Identity Block deepens the network depth, and its basic block structure is shown in Figure 4.

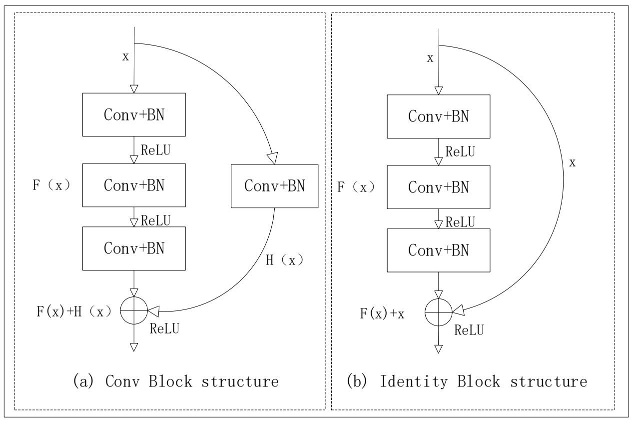


Figure 4. Two basic modules of ResNet

ResNet consists of a stack of multiple residual units, and the mathematical expression for each residual unit can be written as

$$y_i = h(x_i) + F(x_i + W_i) \tag{10}$$

$$x_{i+1} = f(y_i) \tag{11}$$

Where: $F(\cdot)$ is the residual function; $f(\cdot)$ is the activation function; x_i and y_i are the inputs and outputs of the ith residual unit, respectively; W_i is the weight matrix; $h(x_i) = x_i$ is the constant mapping.

ResNet-18 is used as the baseline model for migration learning convolutional neural network for migration training to obtain the MLCNN model, and its training process is shown in Fig.5.

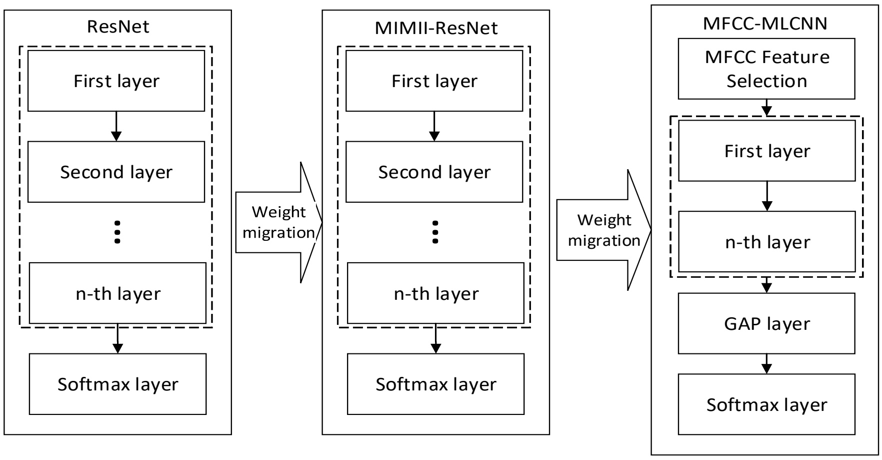


Figure 5. The process of migratory learning

3. Experiments

The training results are obtained after completing the training of the migration learning convolutional neural network model under the training samples. And after that, the data from the test set is used for this model for validation. And the model is compared and analyzed with support vector machine, BP neural network and one-dimensional convolutional neural network. The experimental results show that the MFCC-MLCNN-based pump fault detection model proposed in this study is more effective.

3.1. Training and testing results

The model is trained under the Adam optimizer, and the obtained loss values and accuracy change curves of the training samples are shown in Figures 6 and 7. By observing the change of the loss value of the training samples with Epoch, it can be seen that the loss curve of the samples tends to be smooth after 10 single trainings, which indicates that the model is further learning and will complete convergence, and the accuracy of the training samples finally tends to be close to 100%, and the loss value does not change anymore, and the training of the model is completed.

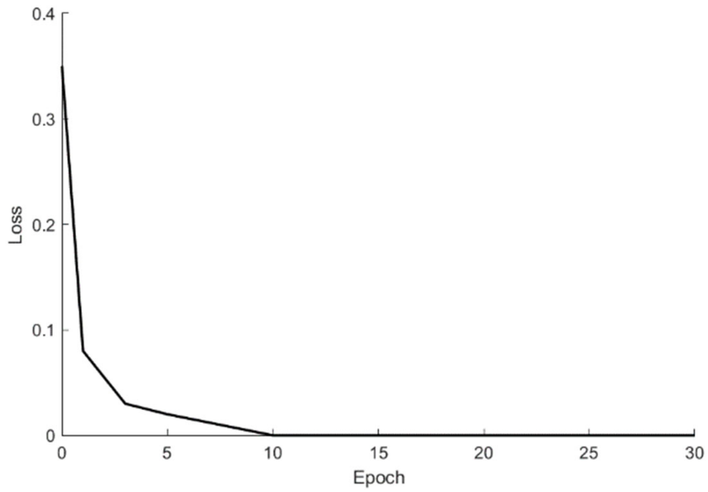


Figure 6. Loss variation of training samples

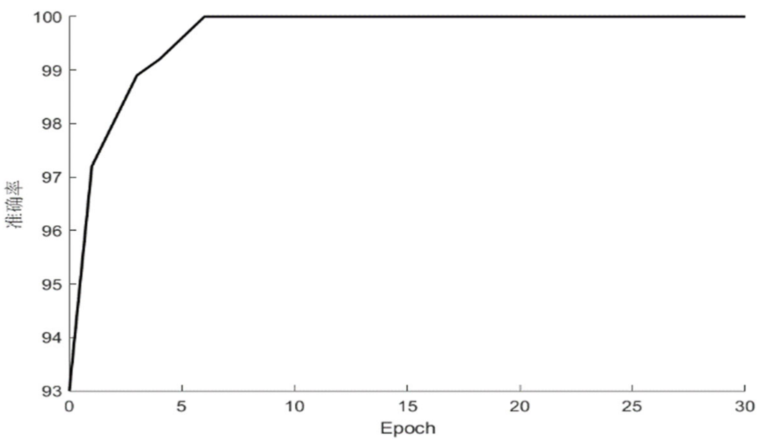
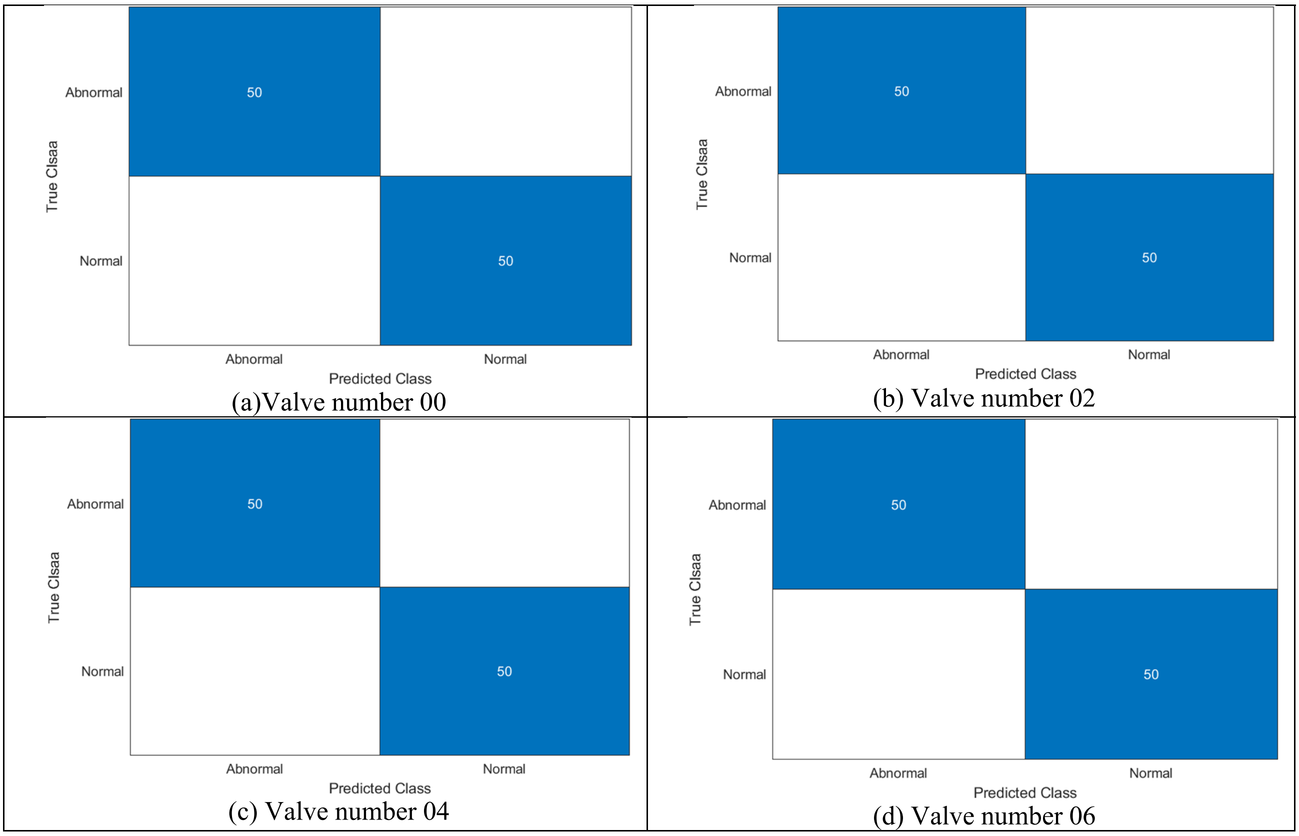


Figure 7. Variation of accuracy of training samples

Fifty training samples are randomly selected from each of the different numbered pump training set samples to diagnose the water supply pump faults based on the MFCC-MLCNN model, and the confusion matrix for the best classification case obtained after several repeated trials is shown in Fig. 8. The rows of the confusion matrix in the figure represent the real labels of each water supply pump operating state, and the columns of the confusion matrix represent the predicted labels of each water supply pump operating state. As can be seen from Fig. 8, the model achieves 100% prediction accuracy on the training set for all cases of pump state detection. From the confusion matrix of the classification results obtained from the fault diagnosis, it can be seen that there is no case in which the fault category is judged to be normal, which shows the good performance of the proposed method. In order to ensure the accuracy of the test and avoid the chance of the results, the average of the results of multiple runs is taken as the final diagnostic accuracy.



(a)Valve number 00 (b) Valve number 02 (c) Valve number 04 (d) Valve number 06

Figure 8. Classification results of training samples

The trained MFCC-MLCNN model is tested for performance with test set data. Table 2 lists the accuracy results of the experiments for normal audio class and abnormal audio class, the results show that the normal audio test set data is judged correctly in the model at more than 95%, the abnormal audio test set data is judged correctly in the model at more than 96%, and the total audio test set data of the total 12510 audio test set data has a total judgment correctness of 96.9% in the model. Where the test set audio files have no intersection with the training set audio files.

Table 2. Test results

Test sample	Number of tests	Number of correct	Accuracy/%
00 (normal)	2973	2861	96.2
00 (abnormal)	357	340	95.2
02 (normal)	2124	2057	96.8
02 (abnormal)	360	344	95.6
04 (normal)	3000	2913	97.1
04 (abnormal)	360	348	96.7
06 (normal)	2976	2923	98.2
06 (abnormal)	360	343	95.3
Total	12510	12129	96.9

3.2. Model evaluation

There are many ways to evaluate binary classification models. In the field of fault detection, assuming that the data of a system is categorized into health and fault classes and a model is trained based on these data, the quality of the model can be evaluated by the following two criteria:

•Diagnose all healthy state data as accurately as possible (do not predict healthy states as faulty states).

•Do your best to keep all identified states as healthy as possible (do not predict faulty states as healthy).

These two statements are fundamentally different. The first reduces maintenance costs because it tries not to predict whether a system is faulty unless it is, but it may detect faulty states as healthy, so it is not suitable for sensitive systems. In contrast, the second criterion is better for sensitive systems. It tries not to misdiagnose faults, but it may detect a healthy state as a faulty state. As a result, it increases maintenance costs.

Thus, it was found that the criteria for determining model assessment are part of any binary classification problem. There are different criteria for this assessment, each of which provides a different view of the problem. These criteria are described below.

F_β score. Understanding this criterion presupposes the definition of two other criteria, namely recall and accuracy. The values of these criteria are calculated as follows:

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

$$Precision = \frac{TP}{TP + FP} \tag{13}$$

Each of these symbols is described below (assuming the data is labeled positive and negative).

•TP (True Positive): number of positive markers and correctly predicted data.

•TN (true negative): number of negatively labeled and correctly predicted data.

•FP (False Positive): the number of data labeled as negative but predicted as positive.

•FN (False Negative): the number of data labeled as positive but predicted to be negative.

The F_β score uses a combination of recall and precision criteria. The score is defined as follows.

$$F_\beta = (1+\beta^2)\frac{precision \cdot recall}{(\beta^2 \cdot precision) + recall} \tag{14}$$

In this equation, as β increases, the effect of accuracy increases. Therefore, different standards can be created by determining the value of β. This number is usually equal to 1 or 2. By placing these numbers in the formula above, two standards, F_1 and F_2, can be obtained.

$$F_1 = \frac{precision \cdot recall}{precision + recall} \tag{15}$$

$$F_2 = 5 * \frac{precision \cdot recall}{4 * precision + recall} \tag{16}$$

Assuming that it is not desirable to predict a healthy state as faulty, the recall criterion is more important, but if it is desirable not to predict a faulty state as healthy, the precision criterion is more important.

AUC score. The area under the curve (AUC) is one of the most widely used metrics for model evaluation. It is commonly used for binary classification problems. AUC measures the entire two-dimensional area below the ROC curve and indicates the degree of separability. The higher the AUC score, the more accurate the model is in making predictions.

In order to verify the performance of the model, three methods commonly used in fault diagnosis are selected for comparison, namely, support vector machine, BP neural network and one-dimensional convolutional neural network, and the comparison results obtained are shown in Table 3.

Table 3. Comparison of performance results

Methods	AUC	F1	F2
Support Vector Machines (SVM)	0.845	0.783	0.726
BP neural network	0.863	0.814	0.785
One-dimensional convolutional neural network	0.936	0.862	0.817
MFCC-MLCNN	0.969	0.914	0.883

In Table 3, when using SVM and BP neural networks for fault diagnosis of signals, it is necessary to manually design the extraction of faulty signal features, and this process is affected by the experience of the researchers, and the final classification accuracy is not high. In the fault diagnosis of signals using one-dimensional convolutional neural network approach, the number and length of signals are limited, resulting in one-dimensional convolutional neural network's sensory field is not large enough, and in the training process, overfitting and other situations may occur, resulting in a decrease in the accuracy rate. While in this paper, the MFCC-MLCNN method is used for fault diagnosis, which is better than the above method and has high portability.

4. Conclusion

Aiming at the problem of water pump fault detection, based on the audio signal of the water pump, using the idea of transfer learning, combining the Mel frequency cepstrum coefficient and the convolutional neural network method, we propose the water pump fault detection method based on MFCC-MLCNN. That is, the MFCC of the water pump sound signal is extracted as a static feature and its first-order second-order difference is calculated as a dynamic feature. A convolutional neural network based on migration learning is used as a classifier to train and detect using the extracted audio features. Experimental comparisons were made between the model used in this study and other commonly used models in the audio domain, and it was finally verified that the model used in this study is significantly better than other models in terms of performance and accuracy. The experimental analysis shows that the method proposed in this paper can effectively identify the normal and abnormal operating states of the pump based on the pump operating sound. Compared with other fault diagnosis methods, the effectiveness of the proposed method in this study is better in pump fault detection.

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