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Research on Bearing Fault Detection Algorithm Based on Convolution Neural Network and SVM[1,2]

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***Abstract*—The traditional bearing fault detection method is using the inner diameter micrometer. This method of manual measurement not only has a large workload and low efficiency, but also has poor reliability and a high rate of leakage, which affects the product quality and makes it difficult to meet the needs of current production. This paper mainly uses the support vector machine (SVM) model and the convolution neural network (CNN) model to solve the shortage of bearing fault manual detection. This paper is based on the Anaconda platform, and uses Python language to program bearing fault detection. To detect bearing fault in SVM model, the main characteristics of bearing signal are extracted by principal component analysis (PCA), and then the main feature parameters are optimized by Particle Swarm Optimization (PSO), which can identify the fault of rolling bearing more quickly and accurately. To achieve the fault diagnosis of CNN model, CNN can use convolution kernel to automatically mine the features that are difficult to extract from the fault signal, and has superior fault diagnosis performance. Therefore, using the SVM model and CNN model to classify and detect bearing faults has the advantages of being fast and efficient, and can well overcome the shortcomings of traditional methods.**

Keywords- Bearing fault diagnosis, Convolution neural network, Support Vector Machine.

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I. INTRODUCTION

Rolling bearing is one of the important mechanical components, which is widely used in aviation, wind power, high-quality machine tools, military equipment and other industries. Because bearings are installed on different mechanical devices, the working environment will be different, which poses a great challenge to the long-term stable operation of bearings. Health diagnosis of rolling bearings is very important, bearing damage can affect the economic interests of the company or endanger the safety of operators. Therefore, it is necessary to diagnose the healthy condition of bearings in time.

Rolling bearing is a common transmission element in mechanical structure. Installed in different working environments, it must bear the unstable load caused by the work. Therefore, the working elements will have pitting, scratching and other faults. If the bearing failure is not detected in time, it will affect other parts of the equipment and eventually lead to serious consequences. For example, in wind power equipment, rolling bearings are installed in non-contactable locations, and the working environment is dry. If the rolling bearings are not lubricated and maintained in time, major failures will occur. Many accidents are caused by rolling bearing failure. In April 2003, a converter ear bearing failure occurred in an iron and steel plant, which closed the plant for nine days and caused direct losses of more than 20 million yuan. In August 2013, a fatigue accident occurred in the rolling bearing of speed-limited elevator in Luohu District of Shenzhen, causing 5 deaths. Therefore, it is necessary to know the health condition of rolling bearings. According to statistics, the failure of rolling bearing accounts for 30% of all mechanical defects, so it is necessary to diagnose the failure of rolling bearing.

Machine learning has become an important research hotspot in the field of computer technology and artificial intelligence, and has been used by many researchers in the actual scientific and technological problems. With the rapid development of artificial intelligence technology, fault diagnosis based on machine learning is also introduced in bearing fault diagnosis field. Researchers usually use signal processing to pre-process the initial information, such as noise reduction and quality reduction. Mathematical functions of time-rate area, frequency area and time-rate frequency area can be obtained from the pre-processed data, and then use machine learning algorithm to train the model to obtain more intelligent and perfect fault diagnosis algorithm. Support Vector Machine (SVM) and Extreme Learning Machine (ELM) are commonly used bearing fault diagnosis methods based on machine learning. Zhao et al. used SVM classification model to classify the fault of rolling bearings after wavelet transformation [1]. Zhao et al. used a particle swarm optimization algorithm to optimize penalty parameter C and kernel parameter G of SVM and achieved good experimental results [2].

A deep learning model consisting of a multilayer neural network has stronger feature extraction ability than a single hidden layer neural network. Traditional machine learning algorithms usually need to extract signal functions, such as the calculation of function parameters in fault diagnosis. However, in-depth learning does not require these steps and allows direct end-to-end fault diagnosis. Lu et al. proposed a depth normalized convolution neural network (DNCNN) for mechanical unbalance fault classification [3]. Yan et al. proposed a dynamic CNN model for rolling bearing fault diagnosis based on intelligent fusion of multilevel wavelet packets. The parallel input of CNN is a two-dimensional matrix that contains time-frequency information of different levels of wavelet packets. Traditional CNN fault diagnosis often needs to convert one-dimensional signal data into two-dimensional signal data and form an image input network, which greatly reduces the diagnostic efficiency. The advent of one-dimensional convolution neural network (1DCNN) solves this problem [4]. Eren et al. successfully applied one-dimensional convolution neural network to bearing fault classification [5]. Deng et al. proposed a bearing fault diagnosis model based on feature channel weights to adjust one-dimensional convolution neural network (SECNN) [6].

Therefore, based on the convolution neural network and SVM bearing fault detection algorithm research, this paper studies the basic structure and characteristics of CNN and SVM algorithm models. By using the CNN and SVM algorithm models, the network extracting feature’s ability is improved, and the fault diagnosis ability of building models is enhanced.

II. RELATED THEORIES

Support Vector Machine (SVM), proposed by Vapnik in 1995, is a supervised machine learning algorithm based on statistical learning theory and the principle of minimizing structural risk [7]. Support Vector Machine (SVM) is a two-class model with many unique advantages in solving small sample and nonlinear classification problems.

A. PCA Dimension Reduction

Principal Component Analysis (PCA) is an important statistical analysis method for dimension reduction of high-dimensional data, which can significantly reduce the dimension of features while minimizing the loss of information [8]. The following are the main steps for data dimension reduction using PCA:

(a) extracting samples of time-domain and Frequency-Domain Characteristic parameters, and extracting K features from n vibration signal samples, which can constitute the group of samples (n × K) order matrix:

$$X=(X_1,X_2,\cdots X_k)^T=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \quad (2.1)$$

(b) The covariance matrix for the above matrix X is calculated as:

$$\Sigma = E[(X - E(X))(X - E(X))^T] \tag{2.2}$$

(c) Calculate the eigenvalues of the covariance matrix, mark it as h, and rank it by size as $\lambda_1 \geq \lambda_2 \geq \lambda_3 \cdots \geq \lambda_k$ If the corresponding unit orthogonal eigenvectors are $e_1, e_2, \ldots, e_k$, the following formula can be obtained:

$$\begin{bmatrix} Y_1 = e_{11}X_1 + e_{12}X_2 + \ldots + e_{1p}X_k \\ Y_2 = e_{21}X_1 + e_{22}X_2 + \ldots + e_{2p}X_k \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ Y_k = e_{k1}X_1 + e_{k2}X_2 + \ldots + e_{kp}X_k \end{bmatrix} \tag{2.3}$$

$Y = [Y_1, Y_2, \ldots, Y_k]$ is the data after dimension reduction, and the j-th principal component of the original feature X_i (i=1, 2,..., k) is Y_J. The corresponding linear transformation coefficient matrix is

$$M = \begin{pmatrix} e_{11} & e_{12} & \cdots & e_{1p} \\ e_{21} & e_{22} & \cdots & e_{2p} \\ \vdots & \vdots & & \vdots \\ e_{11} & e_{12} & \cdots & e_{1p} \end{pmatrix} \tag{2.4}$$

When the contribution ratio of each principal component is calculated from $\lambda_j / \sum_{j=1}^{k} \lambda_j$, the cumulative contribution ratio of the first m principal components $Y_1, Y_2, \ldots, Y_m$ is $\sum_{j=1}^{m} \lambda_j / \sum_{j=1}^{k} \lambda_j$, and the first few principal components can be retained according to the cumulative contribution ratio of demand.

After feature extraction of bearing vibration data, the time domain and frequency domain characteristics obtained have some correlation, and they contain some redundant information. In this paper, the principal component analysis (PCA) is used to reduce the dimension of bearing data. The m-principal component which can reflect the working state of the bearing is obtained, and the main feature which is relatively sensitive to bearing failure is selected, thus reducing the computational complexity.

B. Parameter Optimization

The main parameters of SVM classification are core function parameter G and penalty factor C. Core function parameter G is directly related to the size of function space. Penalty factor C determines the complexity and generalization ability of the model [9]. Too much penalty factor C and core function parameter G result in overfitting of the support vector machine model, which reduces the generalization ability. Therefore, the process of finding the optimal solution of the parameters (C, G) is equivalent to the optimization of the SVM parameters.

Genetic algorithm, ant colony algorithm, grid search and particle swarm optimization are common parameter optimization algorithms. Particle swarm optimization (PSO) algorithm searches for the optimal solution by iterating random solutions. PSO algorithm has the advantages of simple implementation, high accuracy, fast convergence, and has been widely concerned by the academic community. It shows its superiority in solving practical problems. In this paper, the particle swarm optimization algorithm is used to optimize the SVM parameters (C, G).

C. Basic Structure of CNN

LeNet is a CNN model that was proposed earlier, but it is a very successful neural network model [10]. This paper will refer to LeNet neural network model to study bearing fault detection. The purpose of convolution layer is to extract the signal characteristics. The former convolution layer in the neural network structure mainly extracts the details of the signal, and the later convolution layer mainly extracts the global characteristics of the signal. The primary role of the pooling layer is to reduce data dimensions. Softmax typically classifies collections at the output level. During model training, parameters at each level are updated and optimized. The LeNet structure is shown in Figure 2.1:

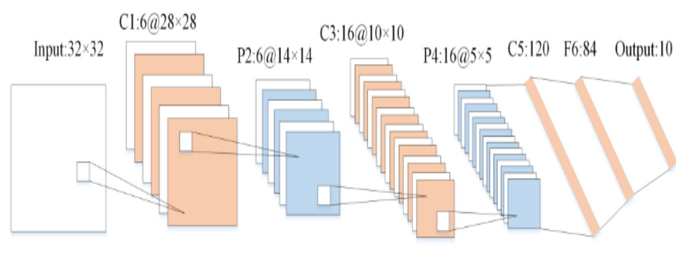

Figure 2.1 LeNet structure diagram

III. BEARING FAULT DIAGNOSIS MODEL DESIGN BASED ON SVM

Obtaining signal data, extracting signal characteristics, selecting signal characteristics, and finally using machine learning model to classify and diagnose faults are the general steps of bearing fault diagnosis based on machine learning. PCA is one of the most common signal function selection methods in signal feature extraction, time and frequency domain signal analysis, waveform training and experience state degradation. In the last part of fault diagnosis, the SVM model is used.

A. Bearing Fault Diagnosis Process Based on SVM

In this paper, the support vector machine model is used for bearing fault diagnosis. Its main work flow is shown in Figure 3.1, with detailed steps as follows:

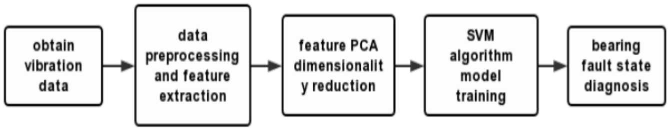

Figure 3.1 SVM workflow

(1) Based on the engine bearing data of Cassey Storage University, it is decomposed into training data and test data, and then the data samples are marked according to each failure type.

(2) Noise reduction and feature extraction of bearing vibration signals, including time-domain and frequency-domain functions, are carried out separately, and standardized calculations are made to form multidimensional feature vectors.

(3) Make principal component analysis of the obtained features to obtain several principal components with a cumulative contribution of 95%.

(4) PSO algorithm is used to optimize the parameters of the main components of PCA after dimension reduction and input them into the SVM model for training. Finally, cross-validate the model.

(5) Determine whether the rolling bearing data is faulty.

B. Bearing Fault Diagnosis Model Based on SVM

In this paper, the fault diagnosis of two-class rolling bearings is studied. In bearing fault diagnosis, the data types of rolling bearings can be divided into normal and failure types. SVM is a supervised learning model for classification and regression analysis. It is also one of the most commonly used classification methods in traditional machine learning methods. This paper applies the machine learning method based on PCA-SVM to the fault diagnosis of rolling bearings.

C. Feature Extraction and Dimension Reduction

Under different fault or normal conditions, the statistical characteristics of bearing vibration signals usually change accordingly, which is usually reflected in time domain, frequency domain and time-frequency domain characteristics [11]. Therefore, many statistical characteristics of vibration signals can be used as the basis for bearing fault diagnosis and monitoring.

Five kinds of fault data and one kind of normal data with bearing signal sampling frequency of 12 kHz and diameter of 0.007 inch and speed range of 1797 r/min are selected in this paper. Training collects 200 samples of each fault signal and 600 samples of normal signal; each sample contains 784 vibration information. The basic feature parameters of bearing fault diagnosis are analyzed with 8 dimensions of data from each group of samples: mean F1, root mean square value F2, root square amplitude F3, variance F4, peak F5, absolute average F6, waveform index F7, peak index F8. Set the vibration data sample set to (i=1, 2, ... N), N is the number of sampling points, in this paper N is 784, and the calculation method of eight formulas is as follows:

$$F_1 = \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \qquad (3.1)$$

$$F_2 = X_{\text{rms}} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \qquad (3.2)$$

$$F_3 = X_r = \left[\frac{1}{N} \sum_{i=1}^{N} \sqrt{|x_i|} \right]^2 \qquad (3.3)$$

$$F_4 = \sigma^2 = \frac{\sum_{i=1}^{N} (xi - \bar{x})^2}{N-1} \qquad (3.4)$$

$$F_5 = X_P = \max\{|x_i|\} \qquad (3.5)$$

$$F_6 = \overline{|x|} = \frac{1}{N} \sum_{i=1}^{N} |x_i| \qquad (3.6)$$

$$F_7 = S = \frac{X_{\text{rms}}}{\overline{|x|}} \qquad (3.7)$$

$$F_8 = C = \frac{X_p}{X_{rms}} \qquad (3.8)$$

The eigenvalues of eight indicators F1, F2, F3, F4, F5, F6, F7 and F8 were calculated, and their respective contribution rates and cumulative contribution rates were calculated in this order. When the sum of multiple Contribution Coefficients exceeds 95%, the corresponding number of eigenvalues is the number of major components.

TABLE 3.1 EIGENVALUES AND VARIANCE CONTRIBUTION

Component	Characteristic value	Variance contribution ratio	Cumulative contribution of variance (%)
PC1	0.00967586	60.539	60.539
PC2	0.00326759	20.444	80.983
PC3	0.00234943	14.700	95.683
PC4	0.00039482	2.4703	98.153
PC5	0.00025927	1.6222	99.776
PC6	0.00002945	0.1843	99.960
PC7	0.00000616	0.0385	99.999
PC8	0.00000019	0.0012	1

From Table 3.1, we can see that the cumulative contribution rate of PC1, PC2 and PC3 is up to 95.683%. Most of the information in the original data is covered, and the redundant information is blocked. Therefore, PC1, PC2, PC3 are selected as the main components of the original data in this paper as the input of subsequent fault diagnosis methods.

The PCA algorithm can increase the sample density (because the dimensionality is reduced) by discarding a part of the information, which can alleviate dimension disasters. The three principal components extracted from five sets of normal data after dimension reduction by PCA are shown in Table 3.2:

TABLE 3.2 POSITIVE DATA AFTER PCA PROCESSING

Sample	PC1	PC2	PC3
1	0.1208	-0.0254	0.0082
2	0.1576	-0.0142	-0.0357
3	-0.0264	0.0034	0.0527
4	0.1024	-0.0283	0.1737
5	0.1773	-0.0126	0.0482

Five fault data are extracted from the inner ring fault, outer ring fault and rolling fault data, and the fault data is reduced by PCA method. The result is shown in Table 3.3:

Comparing normal data of table 3.2 and fault data of table 3.3 for dimension reduction of PCA, the results show that the main component of outer ring fault is negative, while the first main component of inner ring fault is very different from the standard value. The principal components of rollers are similar to those of ordinary data and are prone to confusion. PCA reduces dimensionality by extracting time domain signals and choosing a feature function. When the data is affected by noise, the eigenvectors corresponding to the minimum eigenvalues are often related to noise, so discarding them can reduce the noise to a certain extent.

TABLE 3.3 FAILURE DATA AFTER PCA PROCESSING

Fault Type	Sample	PC1	PC2	PC3
Inner ring failure	1	0.7208	0.1254	-0.0582
	2	0.7576	0.1142	-0.1357
	3	0.8264	0.1834	-0.0527
	4	0.7383	0.1378	-0.0272
	5	0.8243	0.1757	-0.0854
Outer ring failure	1	-0.1424	-0.0383	-0.0537
	2	-0.1473	-0.0478	-0.0472
	3	-0.1476	-0.0542	-0.0457
	4	-0.1386	-0.0467	-0.0627
	5	-0.1375	-0.0501	-0.0523
Rolling body failure	1	0.1464	-0.0219	-0.0194
	2	0.1386	-0.0283	-0.0737
	3	0.1473	0.0178	-0.0672
	4	0.1437	-0.0172	-0.0697
	5	0.1397	-0.0137	-0.0709

IV. DESIGN OF CNN BASED BEARING FAULT DIAGNOSTIC MODEL

Convolutional neural networks are an effective identification technique emerging in recent years. As a novel type of neural network model, CNNs have gradually gained attention, especially in classification. Because it can do not preprocess the data, being able to directly input the initial data into the model. Convolutional neural network models are now being applied in bearing fault detection.

A. Data Preprocessing

On the vibration test bench, when one-dimensional vibration signal of 15052800 signal points is collected, it is then segmented into training and test sets at a certain ratio, and then the training and test sets are segmented into several different signal samples with a fixed width of each segment. In order to guarantee the reliability of the test signal, there should be no repeated signal between the training set and the test set. Data sample length depends on the working conditions during data collection. If the sample length is too long, there will be a problem of inadequate sample size and poor training results. Each sample may contain limited information if the sample data is too short.

The data sample selected for this paper contains 784 data points. A total of 19200 bearing signals were selected and split 5:1 into two groups, obtaining 16000 training signals and 3200 test signals, respectively.

Frequency-domain signals are more regular than time-domain signals, and contain more valid information than the original data. They can quantitatively analyze vibration signals. Therefore, this paper will input the frequency domain data into the CNN model for training. The grouped vibration signal $S_i = \{S_i^1, S_i^2, \ldots, S_i^n\}$ are transformed by FFT and labeled to get the frequency domain signal $T_i = \{t_i^1, t_i^2, \ldots, t_i^n, l_i\}$. In the two modes, I represent the second signal, n represents the dimension of each signal, and Li represents the corresponding label of the signal. Figure 4.1 shows (a) time domain waveform and (b) frequency domain waveform.

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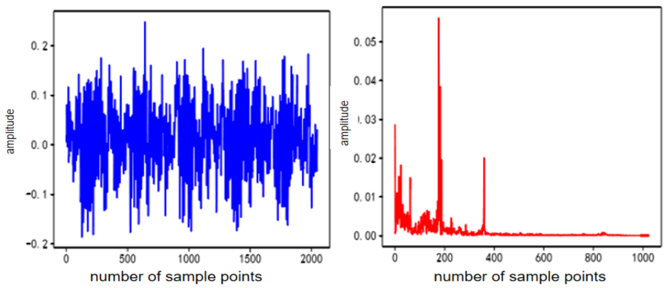

(a)time domain waveform (b)frequency domain waveform

Figure 4.1 Waveform of bearing signal in time and frequency domains

For faster training models, frequency domain data is generally normalized. Normalization process can make each index in the same order of magnitude, facilitate comprehensive comparison, and the process of optimal solution will become gentle, easier to converge correctly. This paper uses MinMaxScaler to normalize the data before entering the model. The MinMaxScaler transformation function is min-max standardization, also known as deviation standardization, which is a linear transformation of the original data. Calculation equation (4.1):

$$X_{\text{scaled}} = \frac{X - X.\min(axis=0)}{X.\max(axis=0) - X.\min(axis=0)} \cdot (\max - \min) + \min \tag{4.1}$$

Where X.min (axis=0) is the row vector of the minimum value in each column, X. Max (axis=0) is the row vector consisting of the maximum value in each column, Max is the maximum value of the interval to map to, default is 1, min is the minimum value of the interval to map to, default is 0.

Once a CNN network is trained, its parameters will be updated, and the data distribution of other layers will change all the time except for the input layer. Because during training, changes in network parameters will cause subsequent changes in the distribution of input data, such as the second layer input, which is derived from the input data and the first layer parameter. The first layer parameter changes with the training, which is bound to cause changes in the second layer input distribution. Batch Normalization (abbreviated as BN) is to solve this problem. In this paper, BN layer is added after convolution layer to normalize the data to the range of mean 0 and variance 1, which improves the generalization ability of the model.

B. Building a Convolution Neural Network Model

In order to detect bearing failure, the vibration signal of bearing failure is identified by the LeNet model. This paper refers to the model of a three-layer convolution neural network. The function of a convolution layer is to extract features from the input data. A convolution layer contains multiple convolution cores. Each element that makes up the convolution core corresponds to a weight factor and a deviation, similar to a neuron of a feed-forward neural network.

To speed up the learning of the network, the BN algorithm is introduced into the convolution layer. A dropout regularization method with a rate of 0.5 is introduced in the convolution layer and the fully connected layer to avoid overfitting the training data. To reduce the phenomenon of over-fitting, the ReLu activation function is introduced into the convolution layer and the fully connected layer. The Adam random gradient descent method is used to iteratively update the network weights based on the data. The specific parameter settings are shown in Table 4.1.

TABLE 4.1 PARAMETER TABLE

Network Structure	Number of convolution cores	step	Output Size	Activation function	Number of parameters
Convolution layer	32	2	392	ReLu	352
Pooled layer	32	2	196	-	0
Convolution layer	32	2	98	ReLu	10272
Pooled layer	32	2	49	-	0
Convolution layer	32	2	25	ReLu	10272
Full Connection Layer	-	-	128	ReLu	102528
output layer	-	-	2	-	258

Using CNN model with the above parameters to diagnose bearing failure, four evaluation indexes of CNN model are obtained: accuracy, recall, accuracy and F-score.

V. ANALYSIS OF EXPERIMENTAL RESULTS

A. CWRU Dataset

The experimental platform of Casey West Storage University (CWRU) consists of an induction motor, an acceleration sensor and a power meter as shown in Figure 5.1. In this paper, a bearing dataset with sampling frequency of 12 kHz, bearing diameter of 0.007 inches and rotation speed of 1797 r/min is selected.

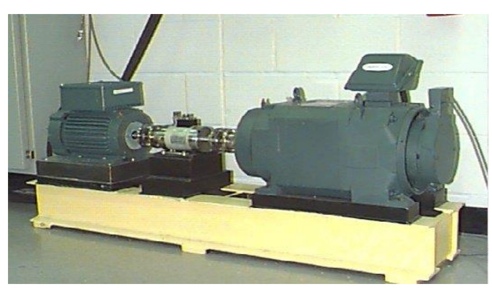

Figure 5.1 Experimental Platform at Casey Western Storage University

B. SVM Result Analysis

First, the data is processed by PCA to reduce the dimension, extract the main feature components of the data, and normalize the data to prevent the difference between the maximum and minimum values of the data from being too large and the phenomenon of over-fitting. In order to clearly show the results of bearing failure identification, the model identification results are displayed using the confusion matrix, which is calculated by comparing the location and classification of each measured cell with the corresponding location and classification in the classification signal. Figure 5.2 is a confusion matrix for SVM diagnostic results.

The predicted and actual values of the data are represented by the rows and columns of the matrix. The values 0 and 1 correspond to the failure and normal condition of the bearing, respectively. The predictive classification model, of course, wants to be as accurate as possible. Then, in the case of confusion matrices, you want the main diagonal to be large. So, when we get the confusion matrix for the model, we need to see how many observations correspond in the second and fourth quadrants, where the larger the number, the better. Conversely, the smaller the observations that occur at the corresponding locations of the first and third quadrants, the better.

Accuracy, recall, accuracy and F-score were used as evaluation indexes to evaluate the diagnostic effect of SVM models. The more effective the model, the larger the F-score. In this paper, the PCA-SVM model is used to classify bearing signals, the accuracy is up to 81%, and the overall classification effect is good.

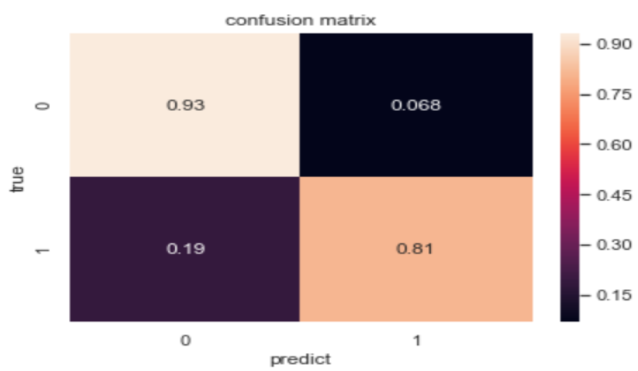

Figure 5.2 Confusion Matrix

C. CNN Result Analysis

In this experiment, a bearing dataset with sampling frequency of 12 kHz, rotation speed of 1797 r/min and bearing diameter of 0.007 inch is selected. 16,000 vibration data were used as training set and 3,200 vibration data were randomly selected as test set.

Firstly, feature extraction and data preprocessing are done by convolution kernel, data is normalized so that data of different dimensions have the same distribution, and data standardization is mapped to the value x in [0,1]. Then the convolution neural network model and training model are built. The training model process is shown in Figure 5.3:

```
Epoch 1/10
400/400 [==============================] - 25s 52ms/step - loss: 0.2679 - accuracy: 0.8750 - val_loss: 1.0418 - val_accurac
Epoch 2/10
400/400 [==============================] - 23s 57ms/step - loss: 0.1252 - accuracy: 0.9436 - val_loss: 0.2043 - val_accurac
Epoch 3/10
400/400 [==============================] - 22s 56ms/step - loss: 0.1109 - accuracy: 0.9517 - val_loss: 0.1035 - val_accurac
Epoch 4/10
400/400 [==============================] - 23s 58ms/step - loss: 0.0996 - accuracy: 0.9559 - val_loss: 0.0970 - val_accurac
Epoch 5/10
400/400 [==============================] - 20s 51ms/step - loss: 0.1002 - accuracy: 0.9567 - val_loss: 0.0903 - val_accurac
Epoch 6/10
400/400 [==============================] - 20s 50ms/step - loss: 0.0939 - accuracy: 0.9609 - val_loss: 0.1142 - val_accurac
Epoch 7/10
400/400 [==============================] - 20s 51ms/step - loss: 0.0965 - accuracy: 0.9597 - val_loss: 0.1793 - val_accurac
Epoch 8/10
400/400 [==============================] - 21s 53ms/step - loss: 0.0925 - accuracy: 0.9619 - val_loss: 0.0953 - val_accurac
Epoch 9/10
400/400 [==============================] - 21s 53ms/step - loss: 0.1032 - accuracy: 0.9590 - val_loss: 0.1091 - val_accurac
Epoch 10/10
400/400 [==============================] - 22s 55ms/step - loss: 0.0905 - accuracy: 0.9628 - val_loss: 0.1022 - val_accurac
```

Figure 5.3 Training Model Process Diagram

If the accuracy of the training set does not differ much from that of the test set, the current iteration number may be considered reasonable and, conversely, it needs to be increased. As shown in Figure 5.4, after 10 iterations, the error rate and accuracy of the model have reached a stable level.

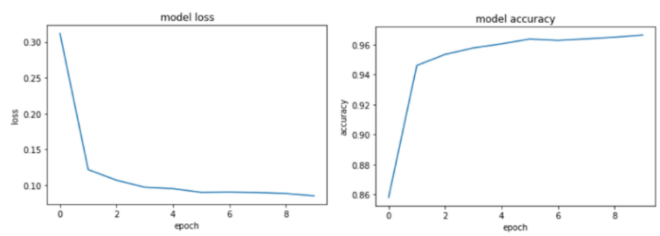

Figure 5.4 Iterative Curve

Confusion matrix is used to compare the classification results with the actual measurement results. Confusion matrix, also known as error matrix, is a standard format for accuracy evaluation and is expressed as a matrix of N rows and N columns. Specific evaluation indicators include overall accuracy, cartographic accuracy, user accuracy, etc. These accuracy indicators reflect the accuracy of signal classification from different aspects. In order to get a clearer result of model identification, a confusion matrix is used. Figure 5.5 is a diagnostic result confusion matrix for CNN. Each column represents the predicted value, and each row represents the actual category.

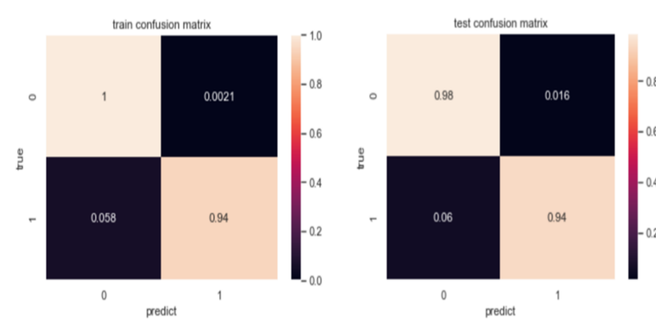

Figure 5.5 Confusion Matrix

Finally, the Accuracy, Recall, Precision and F-score of CNN model classification are obtained.

D. SVM versus CNN

Based on the CWRU (Case Western Storage University) bearing data open dataset, fault detection of bearing dataset is carried out using CNN model and SVM model, and the comparison results are shown in Table 5.1:

TABLE 5.1 COMPARISON OF SVM AND CNN RESULTS

Model	Accuracy	Recall	Precision	F-score
SVM	0.81875	0.81875	0.8199016	0.8185867
CNN	0.954375	0.954375	0.9544006	0.9543744

CNN model can classify bearing faults more accurately than SVM model, the correct rate can reach 95%, and the overall diagnostic effect is better.

From sections 5.2 and 5.3, it can be concluded that bearing fault detection has the following advantages using CNN model:

(1) Compared with the machine learning based SVM classification method, the recognition accuracy is higher. Bearing failure types can be accurately distinguished.

(2) The CNN model has good adaptive ability and high accuracy for fault data identification, which is suitable for engineering practice.

VI. CONCLUSION

With the continuous development of modern industrial system, people pay more and more attention to the safety of mechanical equipment. In recent decades, many scientists at home and abroad have begun to pay attention to bearing fault diagnosis. Due to the continuous development of storage technology and data collection, a bearing fault diagnosis method based on data-driven is developed. First, based on the selection of bearing fault diagnosis parameters, dimensionality reduction and optimization of machine learning algorithm, a PCA-SVM algorithm is proposed. Secondly, based on the problems of over-fitting and accuracy of bearing fault diagnosis model based on deep learning algorithm, a CNN model is presented. The experimental results show that this method can ensure the validity of fault diagnosis, avoid overfitting and improve the diagnostic accuracy. Based on CNN and SVM, this paper completes the construction and implementation of bearing fault detection model. The main work is summarized as follows:

(1) It is difficult to extract features from SVM in machine learning. In this paper, a PCA-SVM model is presented. After processing time domain signal characteristics and PCA dimension reduction, only useful features are retained, and it has strong anti-jamming performance. The accuracy of the experimental model is 0.81875, which proves the superiority of the PCA-SVM model.

(2) It is difficult to select the parameters of CNN model for fault diagnosis, and it is easy to overfit because of the slow training rate and the large amount of data. A reference LeNet model is proposed in this paper. This method has smaller parameters for model training and better model validity. The experimental results show that this method can also improve the validity of fault diagnosis, reduce the possible overfitting phenomenon, and greatly improve the accuracy of judgment.

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