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Research on Algorithm of Mechanical Fault Detection Based on Convolution Neural Network and GMM[1][2]

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Abstract— *With the development of modern manufacturing industry, various kinds of mechanical equipment are applied more and more widely. However, once such equipment fails, it will not only cause losses to the company, but also may cause casualties even in serious cases. At present, most fault diagnosis of devices relies on feature extraction methods, usually based on information processing technology, to extract fault features manually, to identify device faults according to the differences of fault features, and combined with classifiers. Obviously, this method needs prior knowledge and professional support, and the accuracy of fault diagnosis cannot be guaranteed. This project uses the Gaussian mixture model (GMM) which is widely used in industry and the Convolutional Neural Network (CNN) model which has advantages in image processing to detect the faults of devices. The model is trained using a sound dataset for investigation and inspection of faulty industrial machines that is publicly available on the Web. GMM and tensorflow-keras framework are built using Python language to build convolution neural network model, and the recognition accuracy of the two algorithms is analyzed. The results show that when the training data is small, the recognition accuracy of GMM is 73%, while that of convolution neural network model is 73.2%. When the training data is large, the recognition accuracy of GMM is 75.8%, and that of convolution neural network is 94.2%. When the amount of data is increased, the accuracy improvement of GMM is less than that of convolution neural network.*

Keywords— *Fault detection; Gaussian mixture model; Convolution neural network; Deep Learning*.

I. INTRODUCTION

This In recent years, with the continuous development of modern science and technology, various mechanical devices are more and more widely used in life and industry, and they continue to pursue high speed and intelligence, which leads to a variety of mechanical devices becoming more complex and huger, and these developments have greatly promoted the development of society. However, this kind of equipment will have various failures, which will leave a huge loss to people, and sometimes cause casualties. From 2000 to now, only official reports of serious traffic accidents have reached dozens in China. Overseas, in 2003, the U.S. manned space shuttle Challenger fuel tank exploded, killing seven astronauts and causing enormous economic damage. Four deaths and seven injuries were caused by the leakage of the nuclear power plant in Japan in 2004. In China, in 2002, the bearing rotator of 600 MW steam engine of Harbin Electric Power 3 Limited Company was broken, which caused economic losses as high as hundreds of millions [1]. These important events caused by equipment failure constantly remind people that the safety and reliability of the operation of equipment has become a problem to be solved. How to ensure the safe and faultless operation of equipment and avoid or reduce the occurrence of various serious accidents is a major security problem that needs to be solved urgently at present and in the future.

Mixed Gaussian Model (GMM) is the fastest algorithm in the hybrid model learning algorithm. It has been applied to speaker recognition [2], image processing [3], and other fields. It can cluster features. Cai et al. [4] used GMM to estimate the probability of extracting independent components from WKICA. Liu Jibiao et al. [5] divides the life-span data of sliding bearings by local feature scale, reconstructs all the feature vectors according to time factor, and finally aggregates the feature vectors by GMM, thus smoothly estimates the life-span of sliding bearings. Lucas P et al. [6] developed a hard disk fault detection method based on a non-parametric model. First, feature selection is performed using recursive feature cancellation, and then the extracted feature vectors are trained using GMM. For the given data, different measures are calculated from the model and the fault diagnosis is successfully performed. GMM is still used in industrial applications where sound data is used to detect equipment failures.

At present, the rapid development of computer technology has opened up a new way for equipment fault detection. These technologies, combined with traditional fault feature extraction and detection devices, bring great convenience to automatic detection of device failures [7]. Compared with the artificial feature extraction method, the automatic learning of the neural network will greatly reduce the workload, the error of feature transformation and the possibility of losing important features. On the one hand, CNNs can be used for feature acquisition and fault identification, and on the other hand, they can be used as classifiers for fault detection. In 2019, Grezmak et al. of Case Western University, USA, used vibration signals as time series data, first converted their images into TIME-SPECTRUM images, then divided them by CNN. Dong-Jin Choi et al. [9] developed motor diagnosis

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using two neural models, CNN and cyclic neural network, which proved that the two algorithms have high recognition accuracy in the field of diagnostic application. For the first time, Liu Xingchen et al. [10] of Tongji University systematically proposed a method of mechanical fault diagnosis based on one-dimensional CNN. This method can quickly extract the eigenvalues of various device faults from the sound signals of mechanical vibration, and successfully realized the fault diagnosis of devices.

Therefore, this paper uses CNN and GMM based classification algorithm, this topic uses public datasets on the Internet to experiment, and builds a CNN and GMM based sound classification model. By comparing the two models, the optimal model is obtained. Fault detection of mechanical equipment can improve the accuracy and efficiency of detection to a certain extent.

II. BASIC THEORY

The topic of device fault detection has been paid great attention. This topic first uses MFCC to extract feature values, then inputs the feature values into GMM and CNN models to achieve the detection and classification of device failures, and compares the two algorithms.

In fact, since the development of modern industry, fault diagnosis of equipment has been a problem that people attach great importance to and need to solve. In the early days, people judged whether there were some faults in the device by listening to the vibration sound of the device and relying on previous experience, and put forward maintenance measures. The existing fault diagnosis methods can be analyzed from three perspectives: building mathematical models, real-time detection of data changes, and judging based on professional experience.

Based on the mathematical relationship between the input and output, the corresponding mathematical model is the fault diagnosis method to build the mathematical model. By comparing the relationship between the parameter changes of the device operation and the device failure, the fault can be determined and the location and cause of the failure can be determined. Professional experience judgment relies mainly on the long-term practical experience of experts or researchers in this field. Assuming that the device is operating normally, sound always has a certain regularity. Obviously, this method has a strong dependence on the expertise of experts. The data-driven method mainly uses a series of sensors to monitor various parameters of the device in real-time. In the event of unexpected changes in the data, expert knowledge can be used to judge the failure of the device. It does not require complex mathematical model methods, but requires very sophisticated sensor equipment.

A. *Mel frequency cepstral coefficient*

In the field of sound signal analysis and processing, MFCC plays an important role with good robustness and wide application compared with traditional features. The MFCC feature describes the non-linear response of the human ear to frequency based on the results of a series of human ear auditory experiments. The non-linear frequency band interval of MFCC characteristics is closer to the response of the auditory information system of the human ear to the frequency spectrum, better reflects the characteristics of language, and has a higher discrimination [11]. Because of its excellent performance in speech recognition, MFCC has become the most commonly used feature parameter. This project uses MFCC as the feature extraction of sound to judge whether a device is malfunctioning or not by the sound signal that the device is running.

B. *Gaussian Mixing Model*

The Gaussian Mixed Model (GMM) is a mixture of several Gaussian models defined as Formula 2.1.

$$\mathrm{p}(x|\theta) = \sum_{K=1}^{K} \alpha_k \phi(x|\theta_k) \tag{2.1}$$

Among a_k is the coefficient, $\alpha_k \geq 0$, $\sum_{K=1}^{K} \alpha_k = 1$, $\phi(x|\theta_k)$ is a Gaussian distribution. $\theta_k = (\mu_k, \Sigma_k^2)$

$$\phi(x|\theta_k) = \frac{1}{(2\pi)^{\frac{D}{2}}|\Sigma_k|^{\frac{1}{2}}} \exp\left(-\frac{(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)}{2}\right) \tag{2.2}$$

The core idea of GMM is to assume that all data can be viewed as randomly generated data from K Gaussian models, so under this assumption, each data belongs to a Gaussian model with its mean value μ_K, Variance σ_K and each submodel has one parameter α_K is the parameter to be estimated. In practice, since each GMM has overlapping parts, the GMM solution process is to find the best K Gaussian sub-modes through the corresponding algorithm. Because our goal is to calculate the optimal mean μ、variance σ And weight α, Such problems are usually solved by maximum likelihood estimation, but here, if you use maximum likelihood estimation directly, you get a complex logarithmic function, which is difficult to expand and derive. GMM usually solves this optimization problem with the maximum expectation algorithm (EM algorithm). The basic idea of EM algorithm is:

1. Fix a variable first to make the whole function convex optimization function, and derive the best value.
2. The optimal parameters obtained in Fixed Step 1 are updated by the optimization method for the fixed variables in Step 1.
3. Stop updating if the stop condition is reached; Otherwise, repeat steps 1 and 2.

Using EM algorithm for GMM, the steps are:

1) Initially randomly select the values of each parameter

2) Step E: Calculate x_for each data Probability that J comes from sub-model K

$$\gamma_{jk} = \frac{\alpha_k N(x_j|\mu_k, \Sigma_k)}{\sum_{k=1}^{K} \alpha_k N(x_j|\mu_k, \Sigma_k)}, \mathrm{j} = 1,2,\cdots,\mathrm{N}; \mathrm{k} = 1,2,\cdots,\mathrm{K} \tag{2.3}$$

3) M-step: Optimize the mean of each sub-model based on the probability generated by step E μ variance σ and weight α. among γ_{jk} is an implicit variable with a value of only 1 or 0.

$$\mu_k = \frac{\sum_{j=1}^{N} \gamma_{jk} x_j}{\sum_{j=1}^{N} \gamma_{jk}}, k = 1,2,\cdots,\mathrm{K} \tag{2.4}$$

$$\Sigma_k = \frac{\sum_{j=1}^{N} \gamma_{jk}(x_j-\mu_k)(x_j-\mu_k)^T}{\sum_{j=1}^{N} \gamma_{jk}}, k = 1,2,\cdots,\mathrm{K} \tag{2.5}$$

$$\alpha_k = \frac{\sum_{j=1}^{N} \gamma_{jk}}{N}, k = 1,2,\cdots,\mathrm{K} \tag{2.6}$$

International Journal of Scientific Engineering and Science
Volume 6, Issue 8, pp. 28-33, 2022. ISSN (Online): 2456-7361

4) Repeat steps E and M until convergence occurs. And the convergence condition: $\| \theta_{i+1} - \theta_i \| < \varepsilon$, among ε is a small positive number.

C. *Convolutional Neural Network*

CNN is a kind of feed forward neural network [12] which contains convolution calculation and has depth structure. CNNs can classify input information according to their hierarchical structure with shift invariance, and can conduct supervised and unsupervised learning. The sharing of convolution kernel parameters within the implied layers and sparse interlayer links lead to the possibility that CNNs can be used with smaller statistics, such as picture RGB data and MFCC feature extraction data for sound signals, which are widely used in speech recognition, natural language processing and other fields [13]. And CNN has a good effect on classification problems and edge detection, so this paper mainly uses CNN to identify and classify whether the device is running with faults.

The basic structure of the CNN is shown in Figure 2.1.

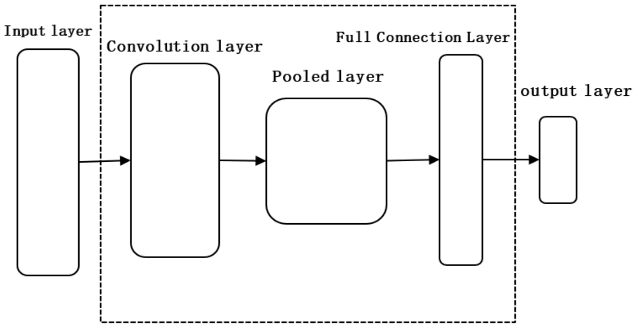

Figure 2.1 CNN Overall Structure

III. Model Design

The design of the model mainly introduces the data preprocessing, GMM building and CNN parameter building, and the selection of related functions. Data preprocessing mainly uses MFCC for feature extraction of sound signals. GMM mainly chooses the number of clusters and covariance type. The CNN parameter and the activation function, the loss function selection is different, so the training results and efficiency will be very different, so the selection of the neural network parameters is the key to the whole prediction process.

A. *Feature Extraction of Sound Signals*

The MFCC feature extraction process is shown in Figure 3-1.

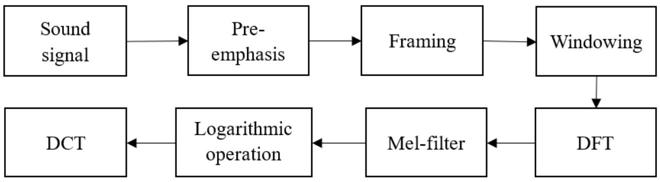

Figure 3.1 MFCC feature extraction process

The conversion formula from frequency to Meyer frequency is as follows:

$$\mathcal{M}(f) = 1125\ln(1 + \frac{f}{700}) \quad (3.1)$$

The implementation of MFCC feature extraction is as follows:

(1) Divide the signal into 25ms frames and add windows, using Hamming window as window function.

(2) Discrete Fourier transformation of each frame signal.

$$S_i(k) = \sum_{n=1}^{N} s_i(n)h(n)e^{-j2\pi kn/N}, 1 \le k \le N \quad (3.2)$$

Where h(n) is a window function of N points (such as the Hamming window), K is the length of the DFT. By Si(k) Estimated power spectrum:

$$P_i(k) = \frac{1}{N}|S_i(k)|^2 \quad (3.3)$$

(3) Mel bandpass filter is used to filter it and calculate the energy of the signal passing through each filter.

(4) Logarithm the energy of each filter bank.

(5) Mel cepstral coefficient is obtained after discrete cosine transformation. In this paper, the dimension of MFCC feature is set to 13.

B. *Gaussian Mixture Model Construction*

This section mainly completes the GMM modeling, then loads the extracted feature parameters into the model to iterate the training model.

Establish GMM and use MIMIMII training data characteristics to achieve GMM training. The probability distribution for K-order Gaussian mixing is:

$$p(x|\theta) = \sum_{K=1}^{K} \alpha_k \phi(x|\theta_k) \quad (3.4)$$

$$\phi(x|\theta_k) = \frac{1}{(2\pi)^{\frac{D}{2}}|\Sigma_k|^{\frac{1}{2}}} \exp\left(-\frac{(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)}{2}\right) \quad (3.5)$$

Among a_k is the coefficient, $\alpha_k \ge 0$, 且 $\sum_{K=1}^{K} \alpha_k = 1$; $\phi(x|\theta_k)$ is the probability density function of the k-th Gaussian model; μ_k is the mean. Σ_k is the covariance matrix.

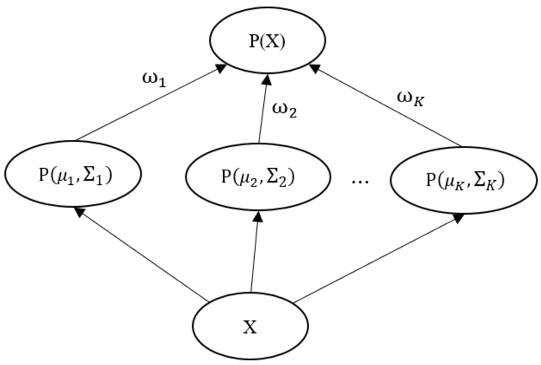

Figure 3.2 Composition structure of Gaussian mixture

GMM Available $\lambda = \{\omega_k, \mu_k, \Sigma_k(k = 1,2,3,\cdots,K)\}$ means that its structure is shown in Figure 3.2. On the GMM training side, mainly after reading the audio data, the MFCC extracts the eigenvalues and inputs them into GMM to realize the function of training model.

C. *Construction Convolution Neural Network Model Construction*

By properly preprocessing the fault sound signal, the MFCC eigenvalue is extracted and input into the CNN model,

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which can accurately and efficiently identify the device failure. CNN parameters are shown in Table 3.1:

TABLE 3.1 CNN Model Parameter Table

Category	parameter
Convolution layer 1	Kernel and its size/step:(32,5x5,1)
Convolution layer 2	Kernel and its size/step:(64,5x5,1)
Pooling layer	Block size/step size:(2x2,2)
Full connection layer	1024
Activation function	ReLU
Softmax layer	Classification is 2
Maximum iteration	100
Batch size	16
Optimizer	Adam
Dropout layer	0.5
Accuracy	Test accuracy/train accuracy:0.9,0.95

D. Implementation Ideas and Processes

This paper uses TensorFlow to implement the CNN classification model. CNN uses gradient descent method to adjust parameters and keep approaching actual values. The input layer accepts the input of data, multiplies and sums the weights of each layer, and finally completes the forward signal transfer process of the system through the conversion of the activation function. Calculate the error between the output value and the true value, update the weight value by gradient descent method, complete one training of the neural network, and make the next output value close to the expected value. When the system reaches the training times or the accuracy of training set is greater than 95% and the accuracy of test set is greater than 95%, the neural network completes the training. Figure 3.3 shows the CNN training process.

E. Selection of Activation Function and Loss Function

Three activation functions are described in above. Finally, the ReLU function is chosen as the activation function and the loss function is the cross-entropy loss function.

The mapping range of the Sigmoid function is [0,1], which is positive, but the gradient disappears in practice. And the gradient calculation is exponential, which is too computational. Compared with the Sigmoid function, Tanh function is more conducive to speed up the training rate, but there is still a problem of gradient disappearance. ReLU alleviates the problem of gradient disappearance. Moreover, since only the input value and the size of zero need to be judged, the calculation speed is very fast, thus the model training process is very fast and the amount of calculation is reduced. The drawback of the ReLU function is that when the input is less than 0, the ReLU function does not work, nor is it a 0-centric function.

The loss function of the neural network is mainly used to measure the difference between the output of the neural network and the expected value, so that the parameters can be easily adjusted. This paper classifies the sound signals of the device as normal and abnormal, so cross-entropy is often the best choice.

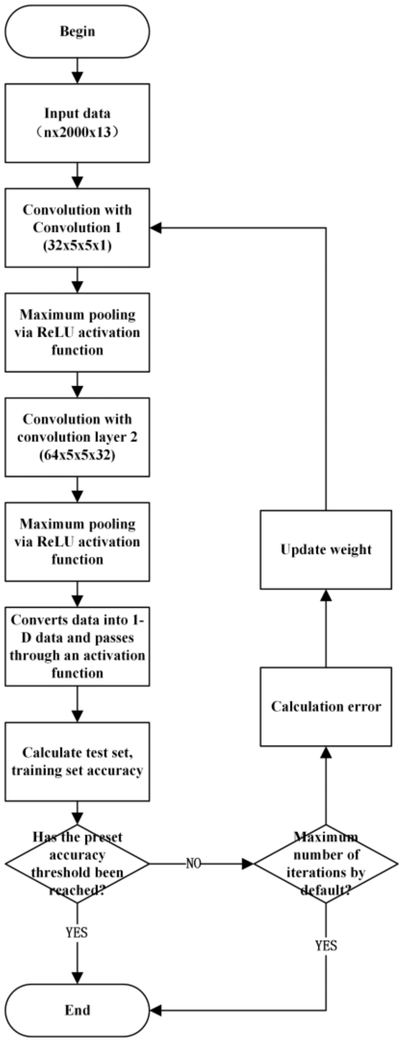

Figure 3.3 CNN training process

F. Selection of learning rate and training steps

The specific learning rate and training steps depend on the model. Different data models, specific learning rate and training steps are different, need to adjust constantly to find the appropriate learning rate and training steps to ensure the final output value of the system is the optimal solution.

G. Selection of Initial Weight Value

Generally, there are two main ways to select the initial weight value. One is by setting all the weight values to 1 or 0; Second, the initial weight value can be set to any random number. However, when all the weight values are set to 0, a very small gradient will be calculated when the inverse propagation occurs, resulting in a poor model update. The learning ability of the neural network cannot be reflected. When the initial weights are randomly chosen, the neural network automatically distinguishes important and unimportant features from the data, thus updating the weights to different sizes. Most of the values of normal distribution are concentrated near 0, which conforms to the learning characteristics of neural networks and is conducive to improving the learning efficiency.

Volume 6, Issue 8, pp. 28-33, 2022.
ISSN (Online): 2456-7361

IV. Experimental Processes and Results

After the model is built, this paper starts training GMM and CNN models with two datasets of different sizes, then uses the training results of two datasets to identify and classify 500 data to be detected, and finally draws a conclusion by comparing the recognition results.

Experimental data: In the scientific community, the emergence of public datasets has led to advances in acoustic detection and fault diagnosis, but most public datasets do not focus on the sound of industrial machines in normal and abnormal operating conditions in real factory environments. Therefore, this experiment uses MIMII dataset (Sound Dataset for Malfunctioning Industrial Machine Investigation and Inspection) (Sound Dataset for Fault Industrial Machine Investigation and Inspection) [14].

A. Train Gaussian Mixed Model

The MFCC feature parameters are as follows: the frame length is 25 ms, the step between consecutive windows is 10 ms, and the dimension D is 13 dimensions.

The first set of data: 600 MIMII dataset training models were randomly selected.

The second group of data: 3648 MIMII dataset training models were randomly selected.

B. Training Convolution Neural Network Model

The MFCC feature parameter value corresponds to the ratio of GMM. Other parameters are set as follows: target accuracy of test set is 0.9, target accuracy of training set is 0.95, initial weight is to randomly generate a phase normal distribution, and the ratio of training set to test set is 7:3.

The first set of data: 600 sets of data identical to the first set of GMM data are used to divide the training set and the test set according to the preset proportion of test set and characteristic value. The final training set contains 420 sets of data and the test set 180 sets of data.

The second group of data: 3648 sets of data identical to the first group of GMM data are used to divide the training set and the test set according to the preset proportion of test set and characteristic value. The final training set contains 2554 sets of data and the test set contains 1094 sets of data.

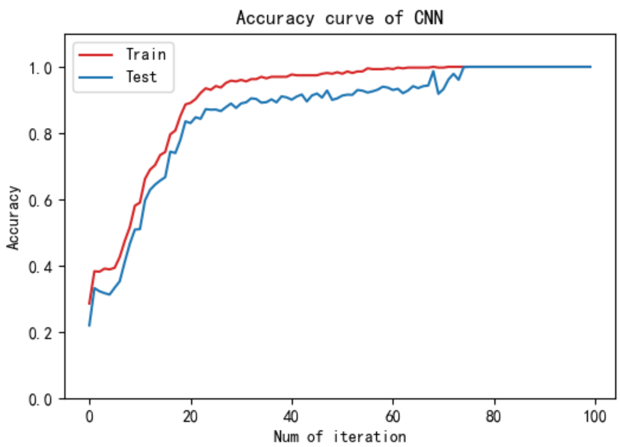

Figure 4.1 500 Line Diagram of Accuracy Change of Data Test Set and Training Set

(1) The training results of the first set of data are shown in Figure 4.1, and the polyline chart of accuracy change of training set and test set is shown in Figure 4.1. The graph of loss change for the loss function is shown in Figure 4.2.

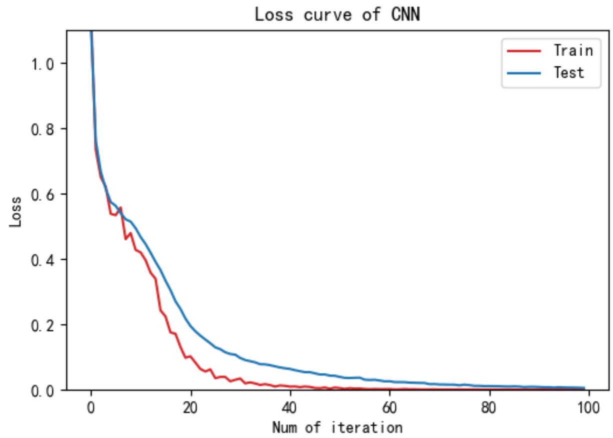

Figure 4.2 500 training loss function change polyline

(2) The polyline chart of accuracy change of the second data training set and test set is shown in Figure 4.3. The graph of loss change for the loss function is shown in Figure 4.4.

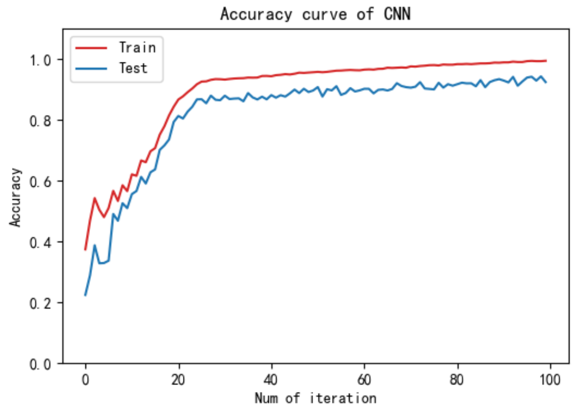

Figure 4.3 Line chart of accuracy change for all data test sets and training sets

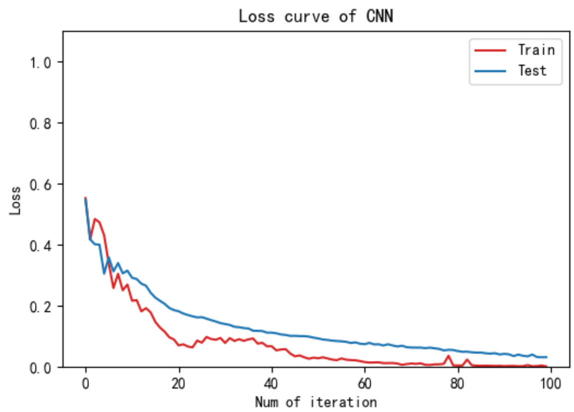

Figure 4.4 Line chart of training loss function changes for all data

C. Test comparison results

The test used 500 sets of randomly selected data to identify and classify. GMM and CNN models identify the same 500 sets of data. The final results are as follows:

TABLE 4.1. Comparison results

Training data volume	GMM	CNN
500	73.0%	75.8%
3648	73.2%	94.2%

By comparing the results, we can see that the CNN model with two groups of data training results are more accurate than GMM. However, the accuracy of both algorithms is about 73%. The difference between the two algorithms is not obvious, but when the dataset is increased from 600 to 3648 sets, the increase of GMM accuracy is not obvious, but the increase of CNN model is significantly better than that of GMM. The recognition accuracy of CNN increased from 73% to about 95%, and the effect was obvious. Therefore, in the device fault detection, CNN recognition accuracy is higher.

V. CONCLUSION

With the development of modern manufacturing industry, various kinds of mechanical devices are applied more and more widely. Fault detection of devices has become a hot topic of research at home and abroad. At present, in-depth learning is widely used in life, and many scholars apply it to device failure detection. This paper establishes GMM and CNN models respectively, and compares the two algorithms to draw conclusions. The research work done in this paper is summarized as follows:

(1) This paper uses the sound dataset of industrial equipment which is open on MIMII network to study. Before starting to use its sound data for model training, this paper uses MFCC to extract the sound feature, and sets the dimension of MFCC feature value to 13.

(2) For model building, GMM is built first, and Gaussian Mixture in sklearn is used to build GMM at the training end, and MFCC eigenvalues are input into GMM for model training. On the recognition side, the data to be detected is input into the model, the EM algorithm is used to estimate the cluster to which it belongs, and finally to judge whether it is normal or not. When building the CNN model, this paper finally uses the tensorflow framework, and finally uses two layers of convolution layer, two layers of maximum pooling layer, and ReLU function. In this paper, the dataset is divided into training set and test set according to 7:3 ratio.

(3) This paper divides the dataset into two groups with different sizes, training GMM and CNN models respectively. By training the same model with different size datasets and identifying the same 500 sets of randomly extracted data, the accuracy of both models is improved, and the accuracy is greater than 60%, which proves that both models are effective for fault detection. Two models are trained with two size datasets, and 500 sets of data are identified with four results. By comparing the accuracy and accuracy growth of different models, it is proved that CNN is better than GMM in fault detection.

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