International Core Journal of Engineering
ISSN: 2414-1895
Volume 7 Issue 10, 2021
DOI: 10.6919/ICJE.202110_7(10).0045

Transformer Fault Audio Diagnosis based on GFCC and 1D CNN

Xueming Zhai[1,a], Jia Guo[1,b] and Yujia Zhai[2,c]

[1]School of North China Electric Power University, Baoding 071003, China;

[2]State Grid Shijiazhuang Power Supply Company, Shijiazhuang 050000, China.

[a]2354944374@qq.com, [b]2729270650@qq.com, [c]844306071@qq.com

Abstract

Of the normal operation of transformer sound contains a large amount of state information, in order to solve the problems of the substation environment noise, this paper uses the blind source separation algorithm based on independent component analysis, wavelet packet decomposition after butterworth band-pass filter to filter the two methods was carried out on the voice from the collection of transformer substation noise reduction processing, good reduction when the normal operation of transformer. In order to extract pd fault features of transformer effectively, Gammatone Filter Cepstral Coefficient (GFCC) was used as feature parameter, and one-dimensional Convolutional Neural Networks (CNN) was used as deep learning model, and extracted GFCC parameters were used as training data to train the model. The final results show that the transformer partial discharge fault identification model designed in this paper has a good identification effect, and the accuracy can reach more than 95%, which provides a new idea for power transformer fault detection.

Keywords

Blind Source Separation; Wavelet Packet Decomposition; Gammatone Filter Cepstral Coefficient; Convolutional Neural Networks.

1. Introduction

Power transformer is a very important and key part of the power system, which undertakes the important mission of power transformation, transmission and distribution. To ensure the normal operation of power transformer and improve its safety and stability is of great concern to the power sector [1]. In this context, it is of great significance to carry out transformer condition monitoring and fault diagnosis research to ensure the safe and reliable operation of transformer and power system.

Dissolves Gas Analysis (DGA) and vibration signal Analysis are widely used in transformer fault diagnosis. In terms of DGA diagnosis, Support Vector Machine(SVM) technology is applied to oil-soluble Gas state classification in literature [2]. In literature [3], the relationship between Lyapunov index and zero was used to determine the effectiveness of oil chromatography monitoring device, and the optimal time delay was used to determine the time point of abnormal occurrence. Literature [4] uses weighted comprehensive loss function in DGA fault diagnosis method based on deep learning. In the use of vibration signal diagnosis: Literature [5] proposed a vibration sensor array to avoid vibration misjudgment caused by current fluctuation during single point measurement; In literature [6], LDA projection algorithm was used to process the vibration signal of iron core loosening, and the fault diagnosis of iron core loosening was realized. According to the changes in fundamental frequency, frequency and amplitude of transformer vibration signal when the transformer core and winding are loose, the literature [7] identifies whether there is a transformer fault, and divides the fault types into loose fault and fault fault. However, both of these methods have certain defects. The

ISSN: 2414-1895 DOI: 10.6919/ICJE.202110_7(10).0045

diagnosis method based on DGA takes a long period of time, and has such problems as too absolute limit of characteristic gas ratio, incomplete coding and weak discrimination of fault features, which affect the fault diagnosis effect [8, 9].

The audio signal covers a wide range and does not need to contact the transformer box directly during collection, which is a non-contact measurement. No electromagnetic signal is generated during signal collection and will not interfere with the normal operation of the equipment. The cost of audio acquisition equipment is generally low, the collected data is easy to be unified, and the data analysis space is large after noise reduction, so it has gradually become a hot spot of transformer status monitoring and analysis. Literature [10] proposed a transformer fault diagnosis technology based on vibration signal and sound pattern imaging, and completed the fault diagnosis of 110kV transformer. In reference [11], the auditory feature vector SMVBMDR extracted from the complete human ear centralized parameter model was combined with the improved SVM to achieve transformer fault diagnosis.

In this paper, the transformer audio signal diagnosis method is used to realize transformer fault diagnosis. Firstly, the transformer audio signals are classified according to the types of background noise in the collected transformer audio signals, and then blind source separation and wavelet packet decomposition and filtering are used to reduce the noise. Secondly, the human ear model was considered and the characteristic parameter GFCC with better feature expressiveness and anti-interference was extracted. Thirdly, a one-dimensional CNN model is designed to distinguish the normal and fault states of transformers and verify the effectiveness of the proposed method.

2. Transformer audio signal analysis and acquisition

2.1 Basic characteristics of transformer audio signal

The rated working magnetic density range of the transformer is usually 1.5~1.8T, in which the winding vibration is much smaller than the iron core vibration and can be ignored [12]. In addition, in recent years, advanced iron core stacking technology has been adopted to greatly reduce the vibration between iron core laminates [13], and glass fiber adhesive tape binding technology has been used to greatly reduce the electromagnetic force between silicon steel sheets [14]. Therefore, the vibration and sound of transformer mainly depends on the vibration of iron core. After the transformer is connected to the alternating current, the magnetic field in the iron core is constantly changing due to the influence of the excitation current. The alternating magnetic field causes the magnetic force to act on the silicon steel sheet of the iron core, resulting in the vibration of the iron core due to the magnetostrictive effect [15]. According to the simplified excitation model, magnetostrictive force F_c is:

$$F_c = \frac{1}{2}\nabla(H^2\tau\frac{\partial\mu}{\partial\tau}) = F_{c\,max}\ sin\,2\,\omega t \tag{1}$$

As shown in Formula 1, the magnetostrictive variation period is half of the alternating period of electromagnetic field, so the core vibration frequency caused by magnetostriction is two times of the fundamental frequency of the power supply. China's alternating current frequency is 50Hz, so the iron core produces a vibration of 100Hz, producing a continuous, uniform "buzzing" electromagnetic sound.

2.2 Transformer audio signal acquisition

In order to complete the research, the author went to a 500kV substation in Hebei Province for field data collection and discharge tests in the shielding chamber of the hV hall for many times. Normal working audio was collected in the field, and discharge fault audio was collected in partial discharge fault experiment. The analog discharge experimental circuit is shown in Figure 1.

Before the test, test the voltage resistance and partial discharge level of the whole system to ensure that the discharge power of the system is normal and does not interfere with the normal operation of the system. In this paper, the plate electrode discharge in the insulating oil was simulated in the shielding chamber of the high voltage hall. The model of the discharge experimental transformer was

25 insulating oil, the discharge electrode was plate electrode, and the discharge gap was set as 5mm. In order to ensure the normal operation of the experimental circuit, the test of voltage resistance and partial discharge is carried out first to ensure the normal discharge power. During the test, the voltage of the plate electrode at both ends of the gap was gradually increased, and the voltage was kept stable when the voltage level was 20kV and 25kV, and the partial discharge signals were collected respectively.

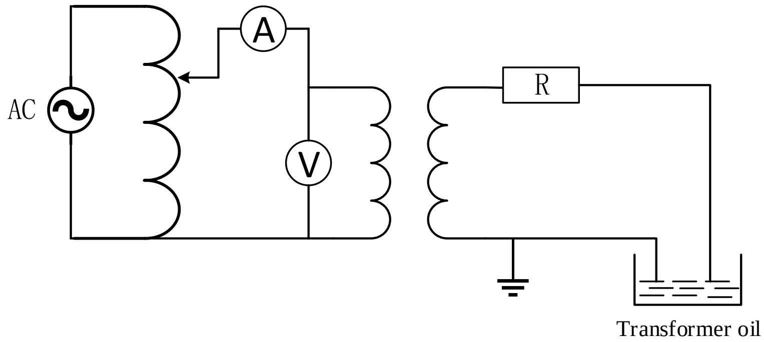

Figure 1. Diagram of fault test circuit

3. Transformer audio signal preprocessing

After collecting and analyzing the audio signals of 500kV substation in the field, this paper classified the different interference noises collected according to their characteristics, as shown in Table 1.

Table 1. Interference noise classification

Interference noise type	Interference noise duration/(s)	Interference noise frequency range/(Hz)
Bird call (unsteady noise)	0.9~2.5	5000~7000
Human speech (unsteady noise)	2~8	200~3500
Sound of rain (short time steady noise)	More than 25	200~3000
Wind (short-time steady noise)	More than 25	20~3000

The interference noise in substation audio collection can be divided into two types, one is unsteady noise and the other is short-time steady noise. Different types of interference noise adopt different denoising methods. The method of blind source separation is used to eliminate the short duration of unsteady noise. For the long duration of steady-state noise, wavelet packet decomposition is used to divide each frequency band of the signal more precisely, and then butterworth bandpass filter is used to filter to achieve the purpose of noise elimination.

3.1 Transformer audio signal noise reduction

For the problem of unsteady noise in this paper, it can be described as a linear instantaneous mixing model, that is, ignoring the time of sound propagation, linear superposition and weighted sum of all source signals can be used to collect audio signals. In this experiment, 4 microphones picked up audio signals at the same time, and each audio signal is the superposition of 2 sound sources, which can be expressed as:

$$\begin{cases} x_1(t) = a_{11}s_1(t) + a_{12}s_2(t) + n_1(t) \\ x_2(t) = a_{21}s_1(t) + a_{22}s_2(t) + n_2(t) \\ x_3(t) = a_{31}s_1(t) + a_{32}s_2(t) + n_4(t) \\ x_4(t) = a_{41}s_1(t) + a_{42}s_2(t) + n_4(t) \end{cases} \tag{2}$$

 Volume 7 Issue 10, 2021
DOI: 10.6919/ICJE.202110_7(10).0045

For the transformer audio collected in this experiment, the noise during recording is the sound source to be separated $S = (s_1, s_2)^T$, so the above equation can be simplified as:

$$X(t) = A \cdot S(t) \tag{3}$$

In this paper, Fast Independent Component Analysis (FastICA) algorithm based on maximum negative entropy is adopted to achieve blind source separation of transformer audio signals, and the probability density function in differential entropy calculation is avoided. Entropy approximation formula is adopted:

$$N_g(Y) = \{E[g(Y)] - E[g(Y_{gauss})]\}^2 \tag{4}$$

After the preprocessing, Z is the matrix of 2,32000, and then FastICA algorithm is used for audio separation of the whitened data Z after the preprocessing. The results of bird song separation are shown in Figure 2 and Figure 3.

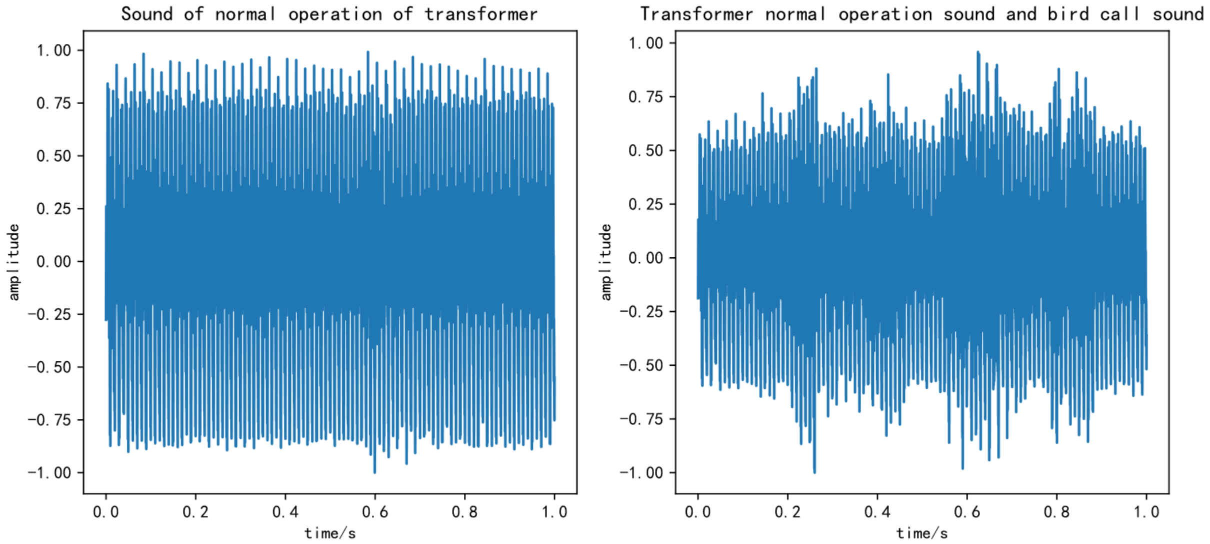

Figure 2. Transformer sound in normal operation and unseparated sound (bird call)

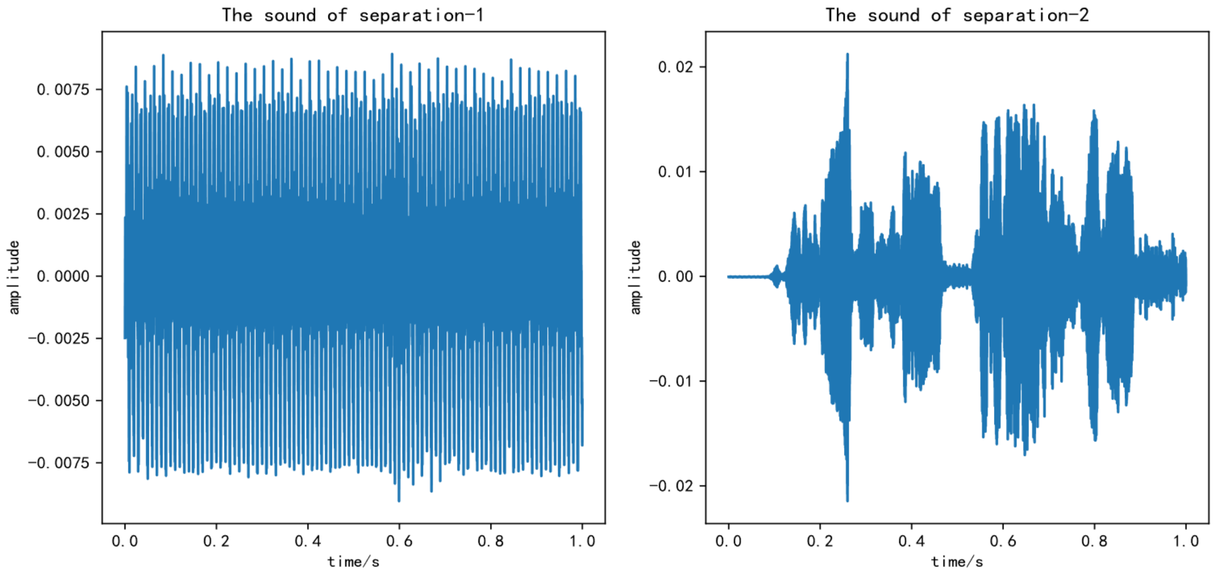

Figure 3. Separated sound 1 and separated sound 2

Due to limited space, the results after the separation of human speech will not be described here. The correlation coefficients before and after separation are compared below.

Volume 7 Issue 10, 2021
DOI: 10.6919/ICJE.202110_7(10).0045

Table 2. Correlation coefficient before and after separation

Interference noise type	Before and after blind source separation	Interference noise frequency range/(Hz)
Bird	Before	0.6101727364729387
	After	0.9467123859103123
Human	Before	0.5273648591237568
	After	0.8123756123859022

It can be seen from the above separation result figure and the correlation coefficient obtained by the experiment that the quality of transformer audio data obtained by using FastICA algorithm is greatly improved compared with that before separation.

In this paper, the db4 wavelet basis function is selected to carry out wavelet packet decomposition for the normal operation sound of transformer including rain and wind collected. The decomposition layer is 2 layers, and the formula is as follows:

$$\Omega_0^0 = \Omega_0^{-1} \oplus \Omega_1^{-1} = \Omega_0^{-2} \oplus \Omega_1^{-2} \oplus \Omega_2^{-2} \oplus \Omega_3^{-2} \tag{5}$$

According to the transformer sound, rain sound, wind frequency difference design 100~400Hz Butterworth bandpass filter. Butterworth filter is selected to ensure that the frequency response curve in the passband is as flat as possible without fluctuation. In order to ensure the filtering effect, the filter is set to order 8 with band-pass attenuation no more than 3dB and band-stop attenuation no less than 20dB

The experiment uses wavelet packet two-layer decomposition, and the four audio samples generated after decomposition are filtered by the 8-order Butterworth bandpass filter designed above. A 30-second fragment is used in this experiment, as shown in Figure 4, Figure 5, Due to limited space, the wavelet packet decomposition results of Fengfeng are no longer displayed.

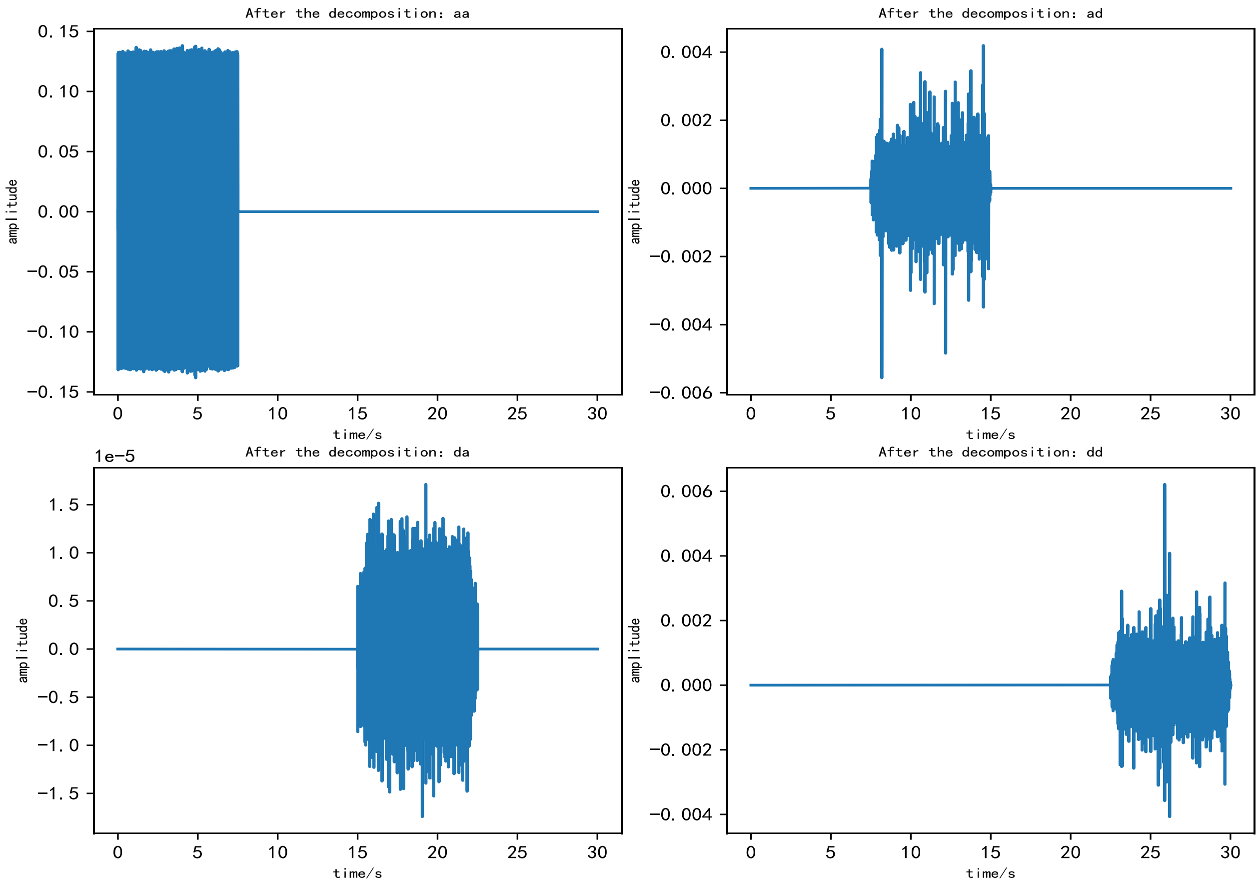

Figure 4. Time-domain waveform of audio filtered by band-pass filter (rain)

Volume 7 Issue 10, 2021
DOI: 10.6919/ICJE.202110_7(10).0045

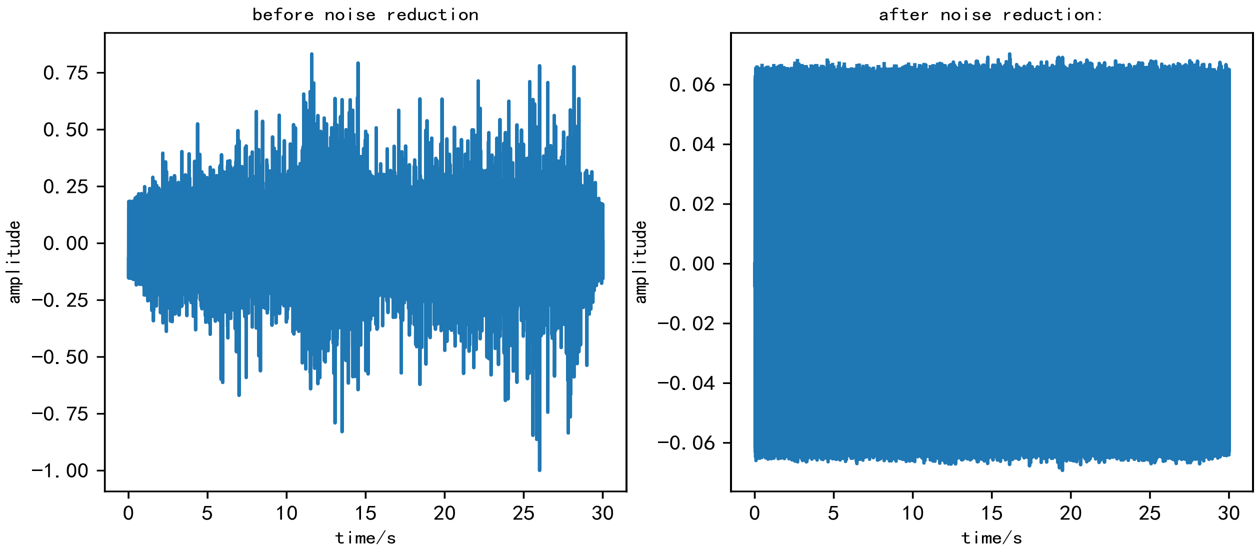

Figure 5. Comparison before and after noise reduction (rain)

The above two parts of the experiment respectively show that the method of blind source separation and wavelet packet decomposition and then filtering can achieve a better noise reduction of the collected transformer audio, and the correlation coefficient between the processing and the normal operation of the sound has been significantly improved.

3.2 Feature extraction of transformer audio signal

There are precedents [17, 18] for integrating characteristic parameters of human ear auditory model into transformer audio signal analysis. Currently, the most widely used characteristic parameters are Mel-frequency Cepstral Coefficients(MFCC), but triangular filters used in MFCC have energy leakage in adjacent Frequency bands. As a result, the simulation effect of frequency division characteristics of human ear basement membrane is poor, and the identification effect of MFCC is poor in places with strong noise interference [19, 20]. Although noise reduction method can greatly reduce noise, it ultimately cannot be solved from the root.

In this paper, Gammatone Filter Cepstral Coefficient(GFCC) is used to extract transformer audio information based on MFCC. Compared with MFCC, the advantages of using GFCC to process transformer audio signals are: (1) Using Gammatone filter instead of MFCC triangular wave filter can better represent the frequency division characteristics of basement membrane and reduce energy leakage. (2) Different from the nonlinear logarithm adopted by MFCC, GFCC performs power normalization first and then uses nonlinear power function, which is more in line with the compression perception of human auditory nerve.

In this paper, the audio after noise reduction is divided into frames. The transformer audio signal belongs to stable signal, so each frame length is set to 500ms and frame shift to 250ms, so the 1s audio is divided into 3 frames. Hamming window is selected to better reflect the frequency characteristics of short-time signal.

4. The experimental results

CNN is composed of convolution layer, pooling layer and full connection layer, which is usually used to process two-dimensional plane data[21]. First by image with different convolution kernels convolution operation to achieve the objective of the local feature extraction, CNN use activation function in the neurons of the input to the output does not change during the process of mapping characteristics of figure size, then pooling layer will merge similar characteristics, reduce the size of the convolution output finally use full connection layer output. The audio data studied in this paper belongs to one-dimensional data, so 1D-CNN, which is similar to 2D-CNN principle, is used for convolution processing.

In this paper, Intel Core I7-9750H CPU: 2.60ghz, memory 16G, GPU as NVIDIA GTX1650, 4G video memory, operating system as 64-bit Windows 10 system, modeling and training using Keras deep learning framework. There are 15,980 audio pieces of training data, and each audio piece lasts 1s, including 8196 normal audio pieces and 7784 faulty audio pieces. The data sources have been explained in Section 1.2 and will not be described here. The training set, verification set and test set were divided according to the ratio of 6:2:2.In this paper, common characteristic parameters in MFCC and improved GFCC audio analysis are selected to identify transformer discharge faults, and the training results are shown in Figure 6.

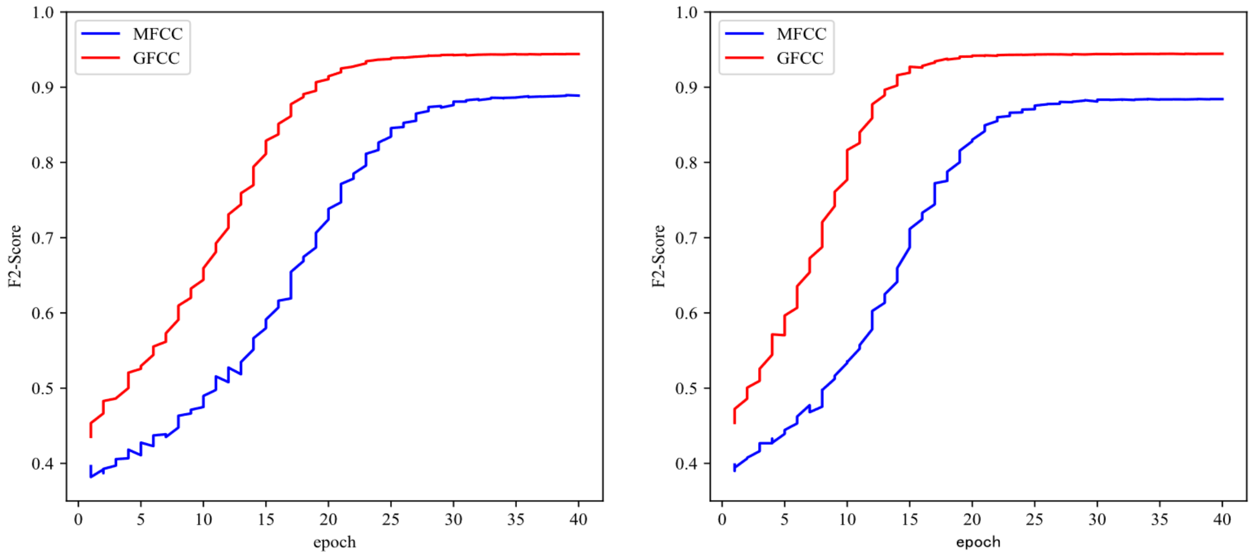

Figure 6. Training results of different characteristic parameters 20kV discharge audio (left) 25kV discharge audio (right)

In order to compare the performance of different classifier models, GFCC was used as the characteristic parameter, BP neural network and convolutional neural network were used as the classifier respectively for experiments. The Batchsize was 32 and the learning rate was 0.01. The experimental results are shown in Figure 7.

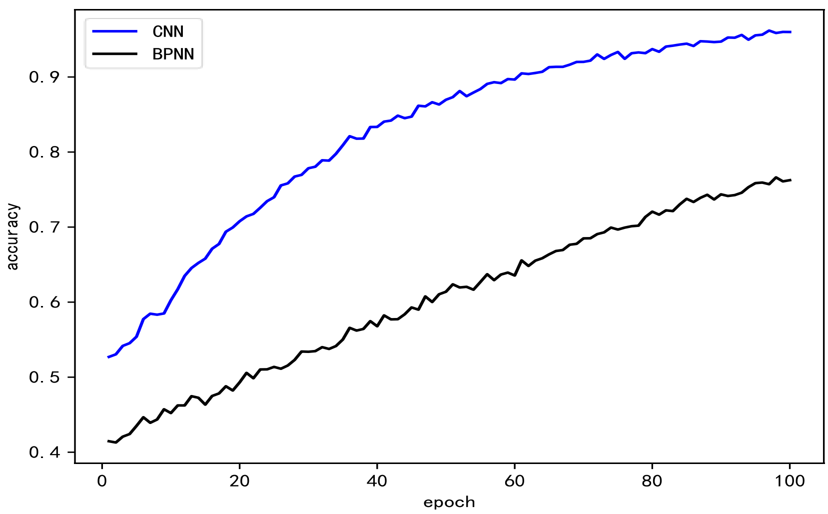

Figure 7. Training results of different recognition models

It can be seen from Figure 7 that when BPNN is used as the classifier, the convergence rate of the algorithm is too slow. Even after 100 iterations, the model recognition rate can only reach 76%. However, CNN model can achieve rapid convergence, and the fault recognition rate after convergence is stable at more than 96.7%, which can be significantly improved compared with BPNN.

5. Conclusion

The sound generated by the normal operation of the transformer contains a lot of state information. Therefore, this paper adopts the GFCC and one-dimensional CNN model to diagnose the partial discharge fault of the transformer and draws the following conclusions:

(1) Using the blind source separation method based on independent component analysis (ICA) can separate the unsteady noise in the collected transformer audio, such as bird song and human voice; The short-time steady noise such as wind and rain can be filtered out by using wavelet packet decomposition and Butterworth band pass filter. After noise reduction, the transformer sound can better highlight the normal working state of the transformer, which is convenient for subsequent deep learning.

(2) In order to solve the problem of energy leakage of MFCC triangular filter, GFCC is adopted as the characteristic parameter in this paper. While retaining its main characteristics, it can more accurately describe whether partial discharge failure occurs in the transformer.

(3) One-dimensional CNN model is used to identify transformer faults. Compared with traditional BPNN, the model in this paper has advantages of faster convergence speed and higher accuracy in partial discharge fault identification of transformer, and the fault identification accuracy can reach more than 95.7%.

References

[1] Wu Shuang, Hu Wei, Zhang Lin, et al. An intelligent key feature selection method of power grid based on artificial intelligence technology [J]. Proceedings of the CSEE, 2019, 39(01): 14-21+316.

[2] Bacha K, Souahlia S, Gossa M. Power transformer fault diagnosis based on dissolved gas analysis by support vector machine [J]. Electric Power Systems Research, 2012,83(1):73-79.

[3] Zhou Zhengqin, Li Xiao, Nie Dexin, et al. Validity evaluation method of DGA monitoring sensor in power transformer based on chaos theory [C]// IEEE Conference on Electrical Insulation and Dielectric Phenomena, Oct 21-24, 2018, Cancun, Mexico: 402-405.

[4] Wang Wei, Tang Qinghua, Liu Liqing, et al. Transformer fault diagnosis method based on weighted comprehensive loss optimization deep learning and DGA [J]. Southern Power System Technology, 2020, 14(03): 29-34.

[5] Shi Yuhang, Lu Weifeng, Zhang Fan, et al. Diagnosis of transformer winding looseness based on vibration sensor array [C]// Condition Monitoring and Diagnosis, Sept 23-26, 2018, Perth, Australia: 1-5.

[6] Zhao Lihua, Zhang Zhendong, Zhang Jiangong, et al. Diagnosis methods for transformer faults based on vibration signal under fluctuating operating conditions [J]. High Voltage Engineering, 2020, 46(11): 3925-3933.

[7] Qian Guochao. Research on spectrum eigenvalues of transformer vibration and its application on diagnosis [C]// IEEE International Conference on Mechatronics and Automation, Aug 7-10, 2016, Harbin, China: 366-370.

[8] Ghoneim S S M. Intelligent prediction of transformer faults and severities based on dissolved gas analysis integrated with thermodynamics theory [J]. IET Science Measurement & Technology, 2018, 12(3): 388-394.

[9] Wang Kang. Research on power transformer fault diagnosis based on dissolved gas analysis in oil [D]. Changchun: Changchun University of Technology, 2020.

[10] Yu Zhangting, Li Dajian, Chen Liangyuan, et al. The research on transformer fault diagnosis method based on vibration and noise voiceprint imaging technology [C]// IEEE Conference on Industrial Electronics and Applications, June 19-21, 2019, Xi'an, China: 216-221.

[11] Shao Yuying, Wang Xiao, Peng Peng, et al. Research on transformer fault diagnosis method based on auditory perception of sound field [J]. China Measurement & Test, 2021, 47(03): 92-97.

[12] Wu Xiaowen, Zhou Nianguang, Peng Jiwen, et al. Noise characteristic and relevant factors analysis of power transformers[J]. Journal of Electric Power Science and Technology, 2018, 33(03): 81-85+146.

[13] Qu Yifeng, Liu Min, Gu Xiaolong. Research of a kind of automatic lamination robot for large trasnsformer core [J]. Journal of Machine Design, 2019, 36(S2): 218-220.

[14] Zhai Haiqing, Chen Minmao. Development of new type iron core binding machine [J]. Transformer, 2013, 50(01): 23-24.

[15] Zhao Lihua, Feng Yao, Xie Rongbin, et al. Analysis of vibration characteristics for oil-immersed transformer core [J]. Proceedings of the CSU-EPSA, 2018, 30(10): 104-110.

[16] Tian Cong. Numerical simulation and experimental study on core vibration of power transformer and shunt reactor [D]. Beijing: North China Electric Power University, 2018.

[17] Zhang Zhongyuan, Luo Shihao, Yue Haotian, et al. Pattern recognition of acoustic signals of transformer core based on Mel-spectrum and CNN [J]. High Voltage Engineering, 2020, 46(02): 413-423.

[18] Liu Yunpeng, Luo Shihao, Wang Bowen, et al. Voiceprint recognition of transformer core clamp looseness fault by Mel-spectrum and convolutional neural network [J]. Journal of North China Electric Power University (Natural Science Edition), 2020, 47(06): 52-60+67.

[19] Baig F, Beg S, Khan M F. Speaker recognition based appliances remote control for severely disabled, low vision and old aged persons [J]. Inae Letters, 2018(3): 1-9.

[20] Shi Xiaoyuan, Yang Haiyan, Zhou Ping. Robust speaker recognition based on improved GFCC [C]// IEEE International Conference on Computer and Communications, Oct 14-17, 2016, Chengdu, China: 1927-1931.

[21] Yanagisawa H, Yamashita T, Watanabe H. A study on object detection method from manga images using CNN [C]// International Workshop on Advanced Image Technology, May 31, 2018, Chiang Mai, Thailand: 1-4.