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Fault Diagnosis of Induction Motors with Imbalanced Data Using Deep Convolutional Generative Adversarial Network

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Abstract: A homemade defective model of an induction motor was created by the laboratory team to acquire the vibration acceleration signals of five operating states of an induction motor under different loads. Two major learning models, namely a deep convolutional generative adversarial network (DCGAN) and a convolutional neural network, were applied for fault diagnosis of the induction motor to the problem of an imbalanced training dataset. Two datasets were studied and analyzed: a sufficient and balanced training dataset and insufficient and imbalanced training data. When the training datasets were adequate and balanced, time–frequency analysis was advantageous for fault diagnosis at different loads, with the diagnostic accuracy achieving 95.06% and 96.38%. For the insufficient and imbalanced training dataset, regardless of the signal preprocessing method, the more imbalanced the training dataset, the lower the diagnostic accuracy was for the testing dataset. Samples generated by DCGAN were found to exhibit 80% similarity with the actual data through comparison. By oversampling the imbalanced dataset, DCGAN achieved a 90% diagnostic accuracy, close to the accuracy achieved using a balanced dataset. Among all oversampling techniques, the pro-balanced method yielded the optimal result. The diagnostic accuracy reached 85% in the cross-load test, indicating that the generated data had successfully learned the different fault features that validate the DCGAN's ability to learn parts of input signals.

Keywords: fault diagnosis; neural networks; unsupervised learn fault diagnosis; frequency-domain analysis

1. Introduction

The intelligent fault diagnosis used on induction motors has increased in recent years. Since induction motors play a significant role in the industry to ensure operational security and avoid faults occurrence, fault detection has become one of the research goals. The related technique can divide into statistical models and machine learning methods. Among them, statistical-based models involve procedures such as the-Wiener process [1], particle filter [2], and Kalman filter [3]. The statistical model requires the knowledge of the professional field to manually extract the characteristics of the signal and perform statistical fault classification, resulting in a higher threshold for establishing a fault diagnosis model. Therefore, there are more machine learning methods widely used in the fault diagnosis of induction motors, including convolutional neural networks (CNN) [4], recurrent neural networks (RNN) [5], Artificial Neural Network (ANN) [6], deep autoencoders [7], etc. The above methods have achieved good accuracy in the fault diagnosis of induction motors. Meanwhile, they significantly reduced manually extracting features' labor and time costs. However, the statistical models and machine learning methods above can only obtain high classification accuracy with sufficient and balanced data. Under general conditions, the induction motors are mainly operating in a normal and healthy state, which caused mostly unbalanced data to be captured.

Therefore, the performance and practicability of the fault diagnosis model are reduced, so the unbalanced training data become one of the unsolved tasks in diagnostic research. At present, the methods used to solve the problem of data imbalance are mostly under-sampling and over-sampling. Among them, under-sampling reduces the number of most datasets to balance the data, while over-sampling [8] is the opposite. To increase the number of minority datasets to expand tradition, among the methods for generating similar data, the Synthetic Minority Over-Sampling Technique (SMOTE) [9] and Adaptive synthesis were standard in the past. The synthetic Over-Sampling Approach (ADASYN) [10] is to synthesize new data through interpolation between actual data and the data of the nearest adjacent edge. Although this method can obtain newly generated data, if there are too little data, there is a problem of overfitting, which makes the generation effect unsuitable, so the method of deep learning is extended. The most representative solution is Generative Adversarial Network (GAN) [11]. In [12–14], the author uses GAN to train noise distribution by learning the actual vibration signal, and then generating realistic data to balance and expand the available dataset. Using the experiment proves that this method provides an effective tool for fault diagnosis in the environment of data imbalance and noise. The authors in [15] proposed an unsupervised learning method for bearing fault diagnosis by combining the Short-Time Fourier Transform (STFT) and the Classification Generative Confrontation Network (CatGAN). In the experimental analysis, the effectiveness of the proposed method is verified, including high diagnostic ability and resistance to load changes. The authors in [16] proposed a fault diagnosis method for rotating electric machines using a GAN with multiple sensing signal fusion technologies (Data-Fusion). Through experiments on two rotating machinery datasets and comparison with other data generation techniques, the superiority of this method in fault diagnosis application is verified. Finally, given the current data imbalance research, most of them are aimed at different improved versions of GAN to improve fault diagnosis accuracy. However, there has not been a comprehensive comparison of different signal processing, load conditions, and data enhancement methods in the study of training data imbalance. This is why our study used the advantages of the convolution operation of the Deep Convolution Generation Network (DCGAN) to generate similar vibration acceleration signals to balance the insufficient training data. Then, we performed the CNN fault diagnosis classification to complete the fault diagnosis of induction motors. By analyzing the experiment case to explore the impact of different signal processing, load conditions, unbalanced training data, and data enhancement techniques on the fault diagnosis of induction motors, we verified the feasibility of generating data with the Deep Convolutional Generation Confrontation Network (DCGAN).

2. Establishment of Induction Motor Defect Model and Fault Diagnosis Technology

This section first introduces the statistics of common fault types and occurrence rates of induction motors used as a reference for the defect models of induction motors by using experimental measurement platform equipment to extract the operating data of induction motors. Meanwhile, we collect the literature and technology of induction motor fault diagnosis worldwide to summarize the pros and cons of fault diagnosis methods and propose the future development direction of this field.

Interventional studies involving animals or humans, and other studies that require ethical approval, must list the authority that provided support and the corresponding moral approval code.

2.1. Establishment of Common Fault Types and Defect Model of Induction Motors

Induction motors play vital roles in the industry; they also are essential equipment in various fields. Ref. [17], the sources of induction motor faults can be divided into internal and external factors, and the types of faults can result from mechanical and electrical causes. Figure 1 shows the statistics of the types of common induction motors faults including bearing faults, stator faults, and rotor faults [18].
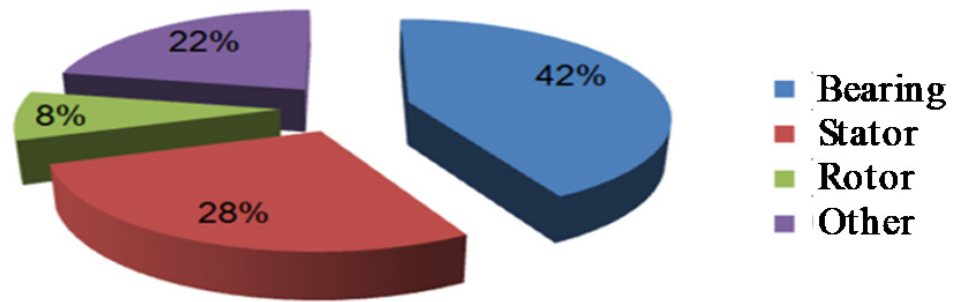
Figure 1. Induction Motor Fault Type Statistics.

In addition, this research has made four induction motor defect models based on the statistics of fault types in Figure 1, including bearing outer ring damage, stator turn short circuit, rotor broken bars, and centering faults, as shown in Figure 2. We captured different operating status data by the laboratory measurement platform under both full loads as well as half load operation.
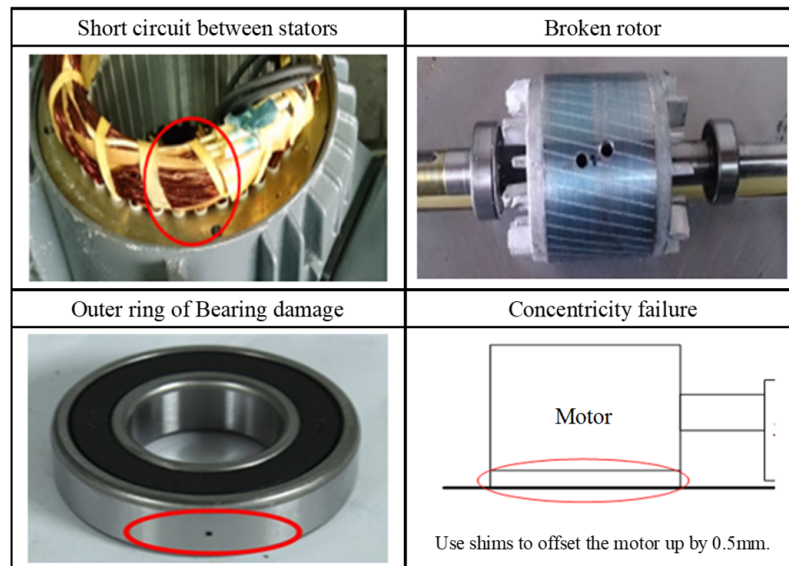

Figure 2. Induction Motor Defect Model. * red circle: the area that caused the blemish.

2.2. Induction Motor Fault Diagnosis Technology

The main tasks of induction motor fault diagnosis are to confirm whether the equipment is normal or not, discover potential equipment failures, and predict equipment failure trends. The authors in [19], statistics on the evolution and classification of fault diagnosis methods can be divided into traditional machine learning, deep learning, and transfer learning methods, as shown in Table 1. First, for formal machine learning, most of them require professional knowledge to extract specific fault characteristics so that the diagnostic model can identify different operating states. The noted methods include SVM, ANN, etc. However, besides the generalization of the diagnostic model being low, the methods require a lot of investment from the workforce, and the professional knowledge used in feature extraction is not conducive to coping with the vast data in the future. Second, the most significant advantage of the deep learning method is that it can automatically identify the characteristics of various operating conditions, which significantly reduces the error of manually extracting features. The noted methods include CNN, RNN, GAN, etc. Although deep learning has made many breakthroughs in fault diagnosis, it needs a large, abundant, and balanced dataset to build a deep learning model. This is not in line with the actual operating conditions of induction motors because most induction motors operate under the normal stage. The fault data are usually hard to obtain resulting in the inability

to obtain practical training for deep learning, and dramatically reduces the accuracy of diagnosis. Therefore, transfer learning has become a new research direction in recent years. It is mainly used to learn diagnostic knowledge from one or more diagnostic tasks and apply it to other different but related tasks. The methods include GAN-based methods. In Ref. [20], the author mentioned the feature of scarce motor fault data, which caused the collected data to be mostly unbalanced, and poor efficiency of the diagnosis. Therefore, this research solves the problem of unbalanced category data and completes the research of induction motor fault diagnosis through the method of Deep Convolution Generative Countermeasure Network (DCGAN).

Table 1. Intelligent Fault Diagnosis Technology Integration.

	Past	Nowadays	Future
Algorithm	**Machine Learning**	**Deep Learning**	**Transfer Learning**
Year	1980~2010	2010~2019	2019~
Methods	Professional system-based method [21], ANN, SVM [22], Other Intelligent method [23]	AE [24], DBN [25], CNN, ResNet [26] method	Feature-based approach [27], GAN [28], Case-based approach [29], Parametric method [30]
Feature	Manually extract fault features Select specific features for training, so that the diagnostic model can automatically recognize the machine's operating status.	Automatically learn the fault features from the original data, and no longer extract features manually	Learn diagnostic knowledge from one or more diagnostic tasks to realize other related but different tasks.
Disadvantage	Feature extraction requires a lot of manpower and expertise. Low generalization reduces diagnostic accuracy.	Collect a large amount of normal operation data but insufficient failure data collection.	Under continuous research, and still not mature enough.

3. Application of Induction Motor Fault Diagnosis to The Problem of Unbalanced Training Data

This section introduces induction motors' signal processing, data imbalance, solution strategy, and fault diagnosis methods. Finally, we summarize the process of the induction motor fault diagnosis system including the Deep Convolutional Adversarial Generative Model (DCGAN) and Convolutional Neural Network (CNN).

3.1. Signal Processing Method

When the induction motor is operating, the signals are in a non-stationary state, making it difficult for the diagnostic model to extract features effectively. Therefore, signal processing is first used to increase the readability of the data. In this study, four signal processing methods will be used to compare the advantages and disadvantages of the case analysis. The following will introduce them one by one.

3.1.1. 2D-Transform (2T)

In this stage, we divided the captured unstable signal into segments and converted each piece into an M × M image matrix. as shown in Figure 3. Then, by storing it in a two-dimensional matrix, we can use the amplitude as information for fault diagnosis.
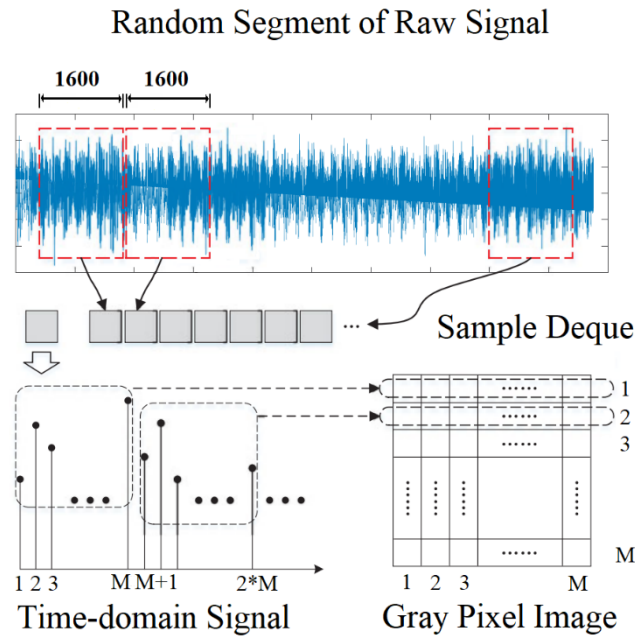
Figure 3. Two-Dimensional Time Domain Matrix.

3.1.2. Fast Fourier Transform Two-Dimensional (FFT)

The Fast Fourier Transform is a linear integral transform that is often used when transforming the signal between the time domain and the frequency domain. The conversion formula is shown in Equation (1), and f represents the frequency. This research used the same processing method as the time domain with two-dimensional matrix to convert the frequency domain signal into an M × M image matrix, which is used as the input for subsequent induction motor fault diagnosis and analysis.

$$X(f) \int\limits_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt \tag{1}$$

3.1.3. Short-Time Fourier Transform (STFT)

Time–frequency analysis can know the instantaneous frequency with amplitude changing at each moment, and Short-Time Fourier Transform being one of the methods. It mainly decomposes the entire time-domain signal into countless pieces of equal length, and then performs the Fourier transform through a fixed-length window. Then, we can obtain the frequency distribution that occurs at a particular time with the Fourier transform. The conversion formula is shown in Equation (2), where t is time and f is the frequency.

$$X(t,f) \int\limits_{-\infty}^{\infty} x(t-\tau)x(\tau)e^{-i2\pi f\tau}d\tau \tag{2}$$

3.1.4. Wavelet Transform (WT)

Another common time frequency that replaces the infinitely long trigonometric function into the attenuating mother wavelet function based on a finite length. By means of scaling and translation of the mother wavelet to match the input signal, we can obtain the relationship between time and frequency. The conversion relationship is shown in

Equation (3) where *a* is the scale and is inversely proportional with frequency. τ is the translation corresponding to time.

$$WT(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) * \varphi(\frac{t - \tau}{a}) dt \tag{3}$$

3.2. Strategies to Solve the Problem of Data Imbalance

In the application of induction motor fault diagnosis, the training set data can be divided into category data balance and data imbalance. At the same time, there are apparent differences in the impact on the diagnosis model. When the training data are balanced, the diagnostic model can effectively distinguish the features of different categories and identify the test samples with high accuracy. However, when the training data are unbalanced, the model tends to be overly inclined to the majority of clusters and causes the diagnostic model to inefficiently generalize the test samples and reduce the classification accuracy. Therefore, data-driven models are usually not easy to distinguish machine failures in this situation, as shown in Figure 4. In Ref. [31], the author mentioned the resolution strategies used in imbalance data including, under-sampling and over-sampling. This research combines data enhancement technology to highlight the method's effectiveness on the problem.
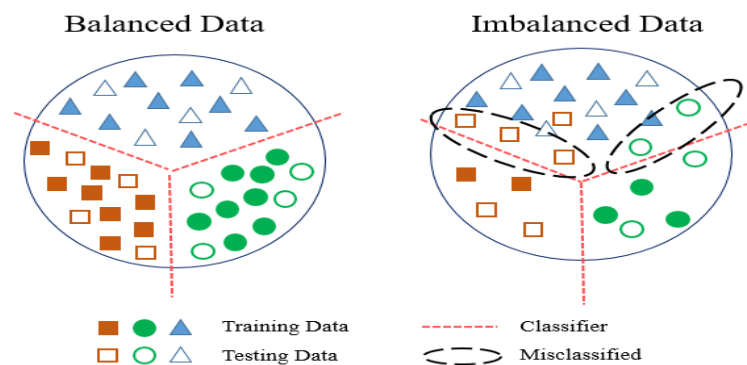

Figure 4. The Impact of Data Imbalance in the Fault Diagnosis Model.

3.3. Fault Diagnosis Method

This section will describe the fault diagnosis methods for data imbalance, including the Deep Convolutional Generative Adversarial Network (DCGAN) used to generate similar data and the Convolutional Neural Network (CNN), which is the critical point of fault diagnosis and classification.

3.3.1. Deep Convolutional Generative Adversarial Network

Generative Adversarial Network (GAN) is a more advanced deep learning method in recent years that is composed of a discriminator (D) and a generator (G). Among them, the discriminator is used to distinguish whether the input is to generate samples or actual data. The generator learns the characteristic distribution of existing data from random noise. After many iterations, the information of the actual data will slowly be fitted until the discriminator cannot determine whether the data are actual data or a fake sample generated by the generator. GAN is widely used in numeral fields, and this research uses an improved version of the Ref. [32] Deep Convolutional Adversarial Generative Network (DCGAN) for subsequent case analysis. Figure 5 is the generative model composed of convolution suitable for image processing and generation.
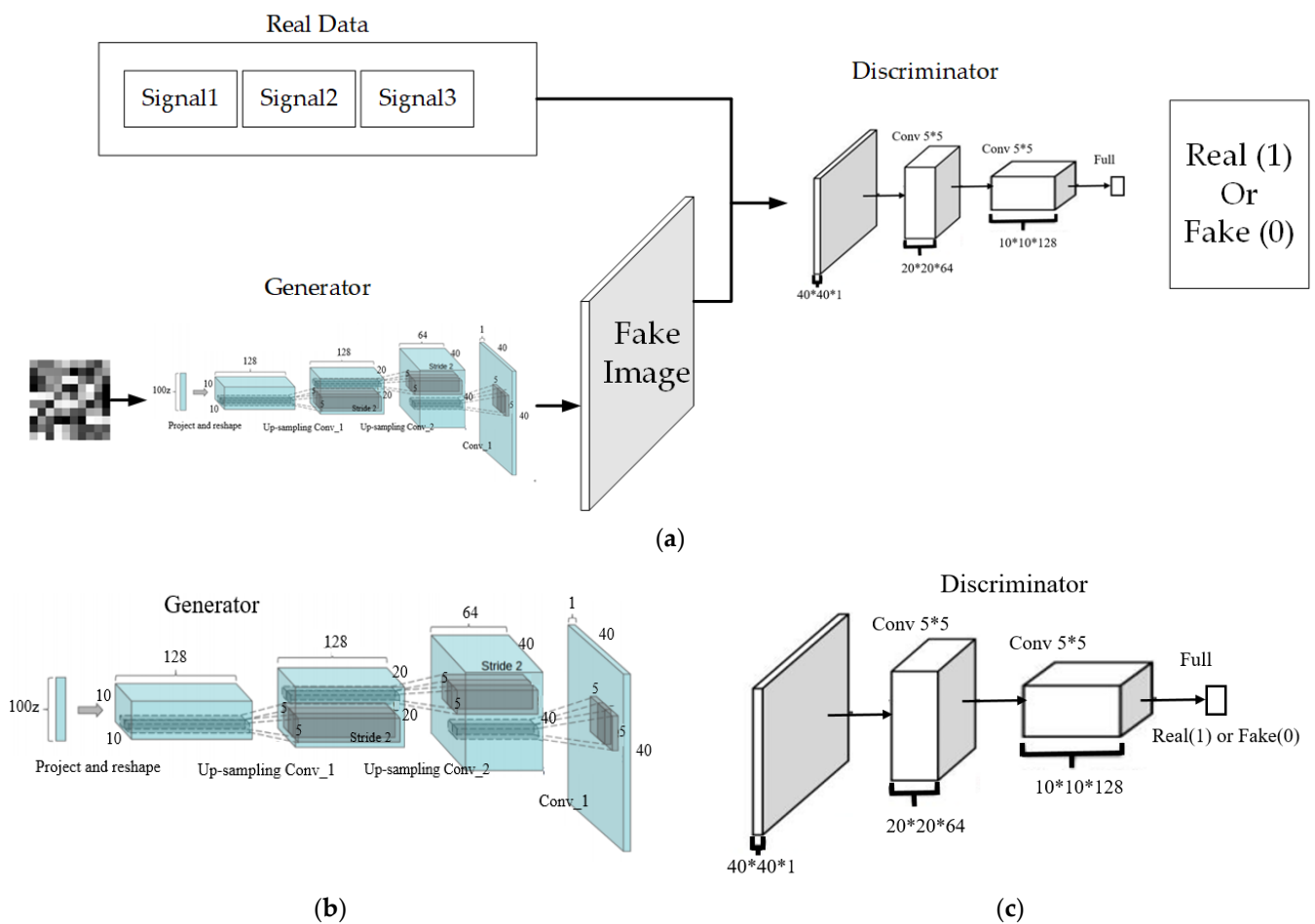
Figure 5. DCGAN: (**a**) DCGAN architecture diagram; (**b**) Generator architecture diagram; (**c**) Discriminator architecture diagram.

3.3.2. Convolutional Neural Network (CNN)

The classifier architecture proposed in this paper consists of three convolutional layers and two dense layers. Figure 6 is the Convolutional Neural Network model architecture. The input layer of the CNN model consists of three channels of RGB images of size 80×80. The first convolutional layer has 80 output filters with a kernel size of 5×5. Two other convolutional layers follow the first convolutional layer with output filter sizes of 8, 16, and 32, and a 3×3 kernel. These all use the kernel. All these convolutional layers use the "same" padding after each convolutional layer, a max-pooling layer of 3×3. The outputs of these three convolutional layers are flattened and connected to two dense layers and their respective dropout layers. The first thick layer has 128 neurons with a dropout factor of 0.25, and the second dense layer has 32 neurons with a dropout value of 0.2. The ReLU activation function was applied to all layers. A softmax activation function was used in the output layer, where the layer size is the same as the number of data classes. In the case of binary types, the sigmoid activation function was applied by convention, with only one hidden unit. The model architecture with the number of parameters is shown in Table 2. All models were generated in Python using the Keras library. The total number of parameters and trainable parameters for this model is 21,149.
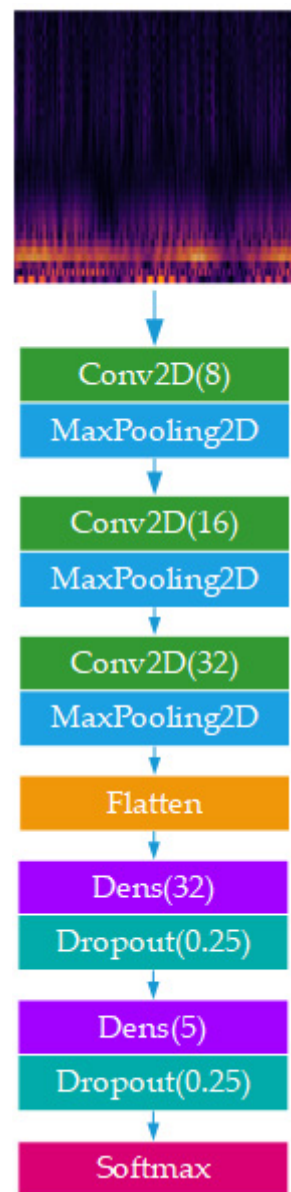
Figure 6. CNN architecture diagram.

Table 2. Parameters of the proposed CNN model.

Layer (Type)	Output Shape	Param
block1_conv2_1 (Conv2D)	(None, 80, 80, 8)	808
block1_MaxPooling	(None, 26, 26, 8)	0
block2_conv2_2	(None, 26, 26, 16)	3216
block2_MaxPooling	(None, 8, 8, 16)	0
block2_conv2_3	(None, 8, 8, 32)	12,832
block3_MaxPooling	(None, 2, 2, 32)	0
dropout	(None, 2, 2, 32)	0
flatten	(None, 128)	0
final_output_2 (Dense)	(None, 32)	4128
dropout_1	(None, 32)	0
class_output (Dense)	(None, 5)	165

3.4. Induction Motor Fault Diagnosis Process

This research aims to simulate the problem of unbalanced training data when dealing with the fault diagnosis of induction motors. The research process includes four stages: data

acquisition, data generation, signal processing, and fault classification, as shown in Figure 7. Among them, the fault characteristics of the vibration signal of the induction motor under different operating conditions are more significant than the electrical signal. This is more helpful for the classification effect of the fault diagnosis. Therefore, this research set the vibration acceleration signal as the analysis object and the imbalance ratio of the training datasets to 0.1 as a criterion for whether the training data are balanced. If the imbalance ratio of the training data is much less than 0.1, it represents the uneven distribution of the training data. The fault diagnosis process in this research is to determine whether the training dataset is sufficient and balanced. The CNN fault diagnosis classification is made directly through signal pre-processing if the dataset is sufficient and balanced. On the contrary, the DCGAN generates new samples to fill in the insufficient training data, adjusts the data imbalance ratio to one, and then performs CNN fault diagnosis classification to explore the feasibility of DCGAN on the imbalance of training data.
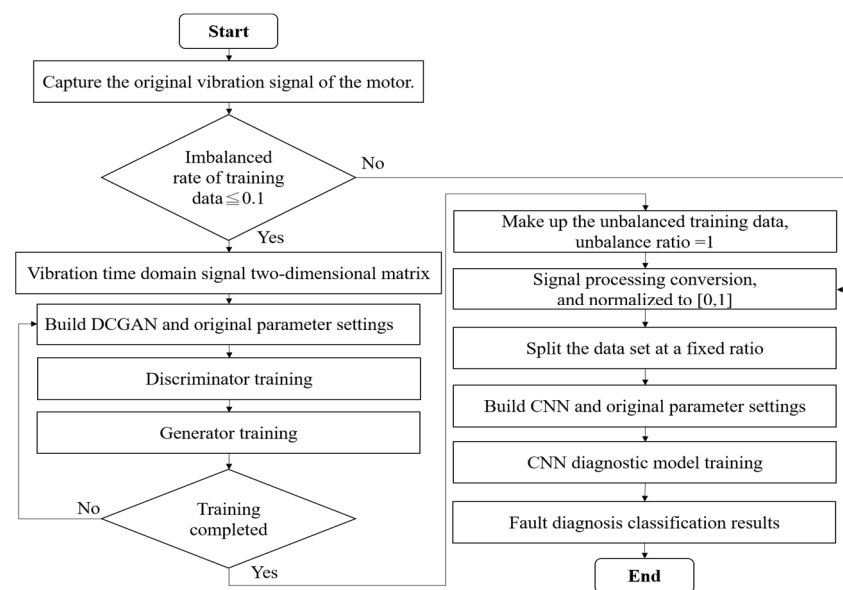

Figure 7. CNN architecture diagram.

4. Experimental Case Analysis and Discussion

This section first describes the data source of the induction motor and the design of the dataset. Then, we analyze the experimental case covering the comparison of different signal processing methods, the problem of data imbalance, and the feasibility of DCGAN.

4.1. Escription of Induction Motor Dataset

The data source of this research is a laboratory-made defect model of a small induction motor, and we obtained the operating status data through a data measurement platform. The sampling frequency was set to 20 kHz, and the sampling time was 5 s.

In addition, there are five active state types in the self-made induction motor defect model of this research, including healthy status (Healthy, H), bearing outer ring damage (Bearing, B), broken rotor bars (Rotor, R), short circuit between stator turns (Stator, S), and centering failure (Misaligned, M). Various operating conditions were operated under full load and half load to facilitate the acquisition of operating data under different loads. Figure 8a,b shows the distribution of vibration acceleration signals in the time domain and frequency spectrum in various operating conditions under other loads.

Half Load

(**a**)

Full Load

(**b**)
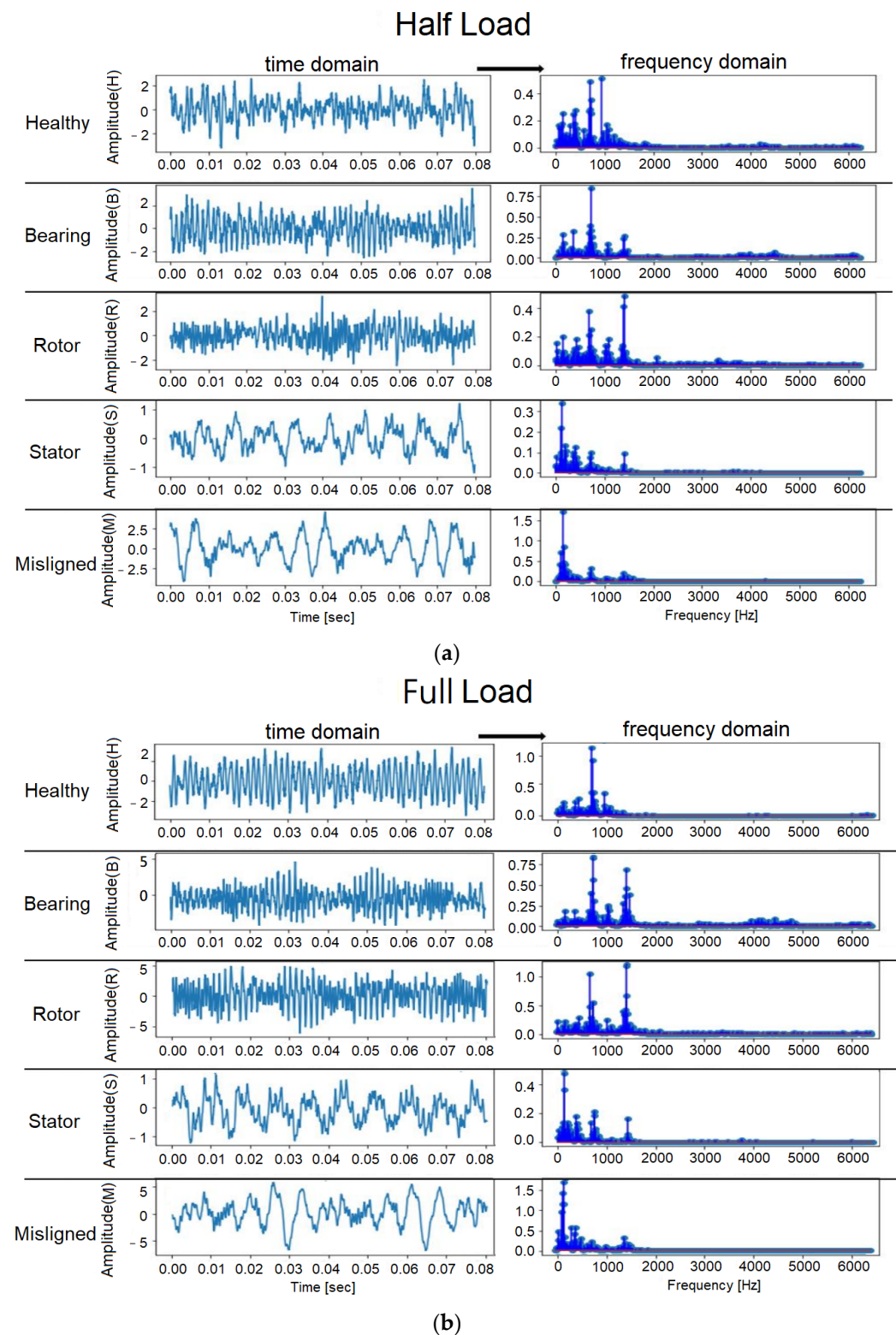
Figure 8. Five operating states in the time domain and frequency domain diagrams: (**a**) Half load; (**b**) Full load.

Finally, in this research, as shown in Table 3, the captured initial vibration acceleration signal was converted through different signal processing and used as the input source of the diagnostic model. As shown in Table 4, we designed the corresponding dataset according to the needs of the case analysis. In terms of actual balanced data, they were mainly used as a control group for data imbalance cases, as shown in Table 5. In terms of

insufficient data, it was assumed that there were only 100,000 points (62 samples) of data for each operating state used as the input of DCGAN to train the generator and amplify the data, as shown in Table 6. Regarding the imbalance of training data, the imbalance rate was used to define the degree of imbalance of the data, as shown in Table 6, to discuss the problem of imbalance of data categories.

Table 3. Signal Pre-Processing.

Sampling Length	Pre-Treatment Method	Resolution	Geometry Processing	Dimension
1600	2T	(460, 460)	Scaling	(80, 80)
1600	FFT	(460, 460)	Scaling	(80, 80)
1600	STFT	(607, 607)	Scaling	(80, 80)
1600	WT	(607, 607)	Scaling	(80, 80)

Table 4. Actual data with sufficient dataset.

Healthy Condition		Health	Bearing	Stator	Rotor	Asymmetry	Load
Label		**0**	**1**	**2**	**3**	**4**	
Dataset (H1)	Training set	1500	1500	1500	1500	1500	50%
Dataset (H1)	Testing set	500	500	500	500	500	50%
Dataset (F2)	Training set	1500	1500	1500	1500	1500	100%
Dataset (F2)	Testing set	500	500	500	500	500	100%
Dataset (M1)	Training set	1500	1500	1500	1500	1500	Mix
Dataset (M2)	Testing set	500	500	500	500	500	Mix

Table 5. Actual data with insufficient dataset.

Points	Sampling Length	Number of Samples	Load Condition
100,000	1600	62	Half-load

Table 6. Actual data with Imbalance dataset.

Healthy Condition	Health	Bearing	Stator	Rotor	Asymmetry	Imbalance Rate
Label	0	1	2	3	4	
Dataset (C1)	500	150	150	150	150	1:0.3
Dataset (C1)	500	50	50	50	50	1:0.1
Dataset (C3)	500	25	25	25	25	1:0.05

4.2. Sufficient Data Balance—Comparison of Different Signal Processing Methods

In order to explore the problem of unbalanced training data, this section uses balanced data and sufficient classification accuracy as a control group for subsequent experimental cases. The input data are shown in Tables 3 and 4. After the input signal is pre-processed by four different signals, the results are shown in Table 6. In the time–frequency analysis, the window length is 64, the Morlet wavelet is used as the STFT-CNN and WT-CNN parameters. It can be observed from Table 7 that under the same load, the four signal pre-processing can obtain high accuracy. When the load is changed, the accuracy of the time domain signal (2T) is significantly reduced if the low-load test is used as the training set. Only about 70% accuracy is left in the time-domain signal and only about 82% accuracy in the spectrum signal, which shows that the single signal processing of the two is not sound in fault diagnosis for changing load. However, in any time–frequency analysis, both methods reach 95.06% and 96.38% accuracy rates, which highlights that time–frequency analysis has more advantages in fault diagnosis and is less affected by load changes. In the same way, it can be verified in the cross-domain load test, which uses the high load test as the training set, and it can be found from Table 7 that we can obtain higher accuracy by

using the low load side as the training set. Finally, the overall average accuracy is more observable. The accuracy of the signal after STFT and WT can reach up to 97%, which is significantly higher than the other two. Time–frequency analysis is effective in fault diagnosis, and frequency-domain signals are better than time-domain signals to handle problems with different load conditions.

Table 7. Comparison of Different Signal Processing Accuracy.

Model	Classification Accuracy of Operating Status							
	* H1	H1→F2	F1	F1→H2	M1	M1→F2	M1→H2	Avg.
2T-CNN	94.45%	71.83%	99.54%	60.75%	99.34%	98.93%	99.13%	89.14%
FFT-CNN	99.99%	82.21%	99.99%	86.17%	99.97%	95.79%	99.97%	94.87%
STFT-CNN	99.97%	95.06%	99.94%	85.37%	99.95%	99.72%	99.81%	97.12%
WT-CNN	99.89%	96.38%	99.97%	86.59%	99.92%	99.63%	99.93%	97.47%

* H1: Train with H1 dataset and test with H1 dataset.

4.3. Generative Adversarial Network—Actual and Generative Graph Comparison

At the beginning of this section, we took advantage of the imbalanced data as found in Table 6 for the input of DCGAN. Then, used it to fit similar generated data and balanced and expanded the insufficient training dataset. This research used the bearing outer ring injury as an example to show the result of generating data. Figure 9 shows the process of DCGAN training, and it can be seen that the discriminator can reach a convergence accuracy of 70% to 80% after training. When the model reaches stable training, it can be observed in Figure 10 that generated data and the actual data are not the same. However, after signal processing, there are similar features. It showed that DCGAN had learned key features on the input signal, which showed the superiority of this method in extracting features. In the same way, the method can be applied to other operating conditions to obtain generative models of various operating conditions.
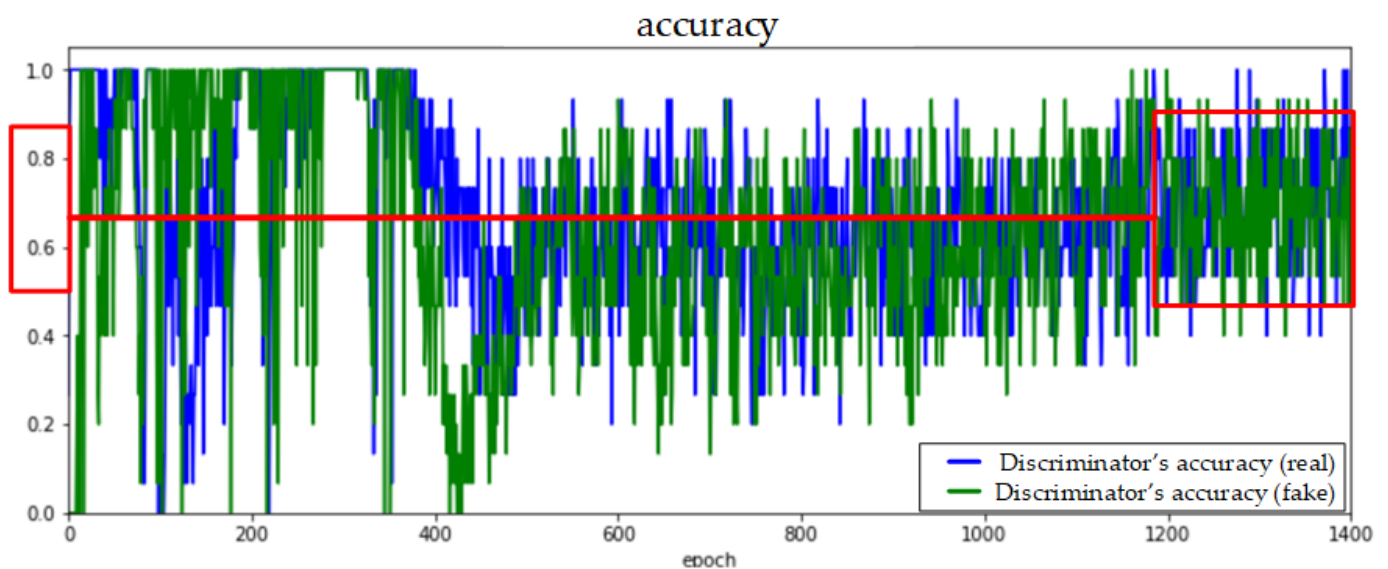

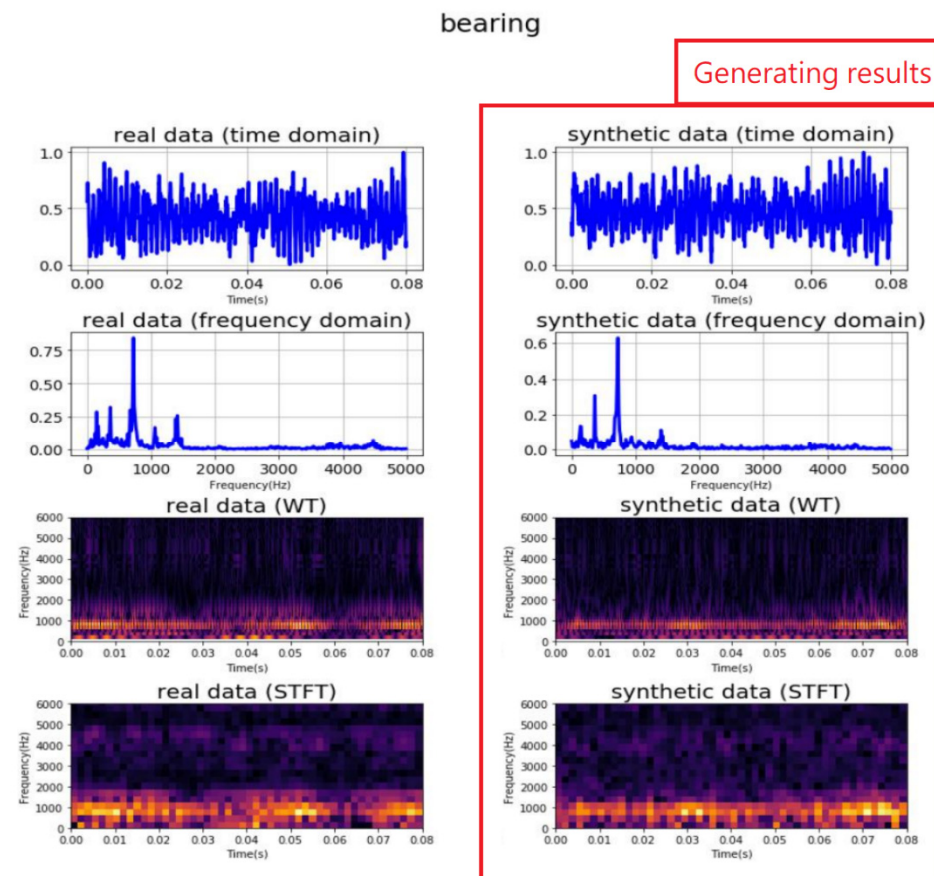**Figure 9.** Training process of bearing outer ring injury.

Figure 10. Comparison of actual and generated data of bearing outer ring damage.

4.4. Imbalance Dataset

Through the generator trained by DCGAN in each operating state, the subsequent data can be generated by the generator and expand the insufficient data. It can be divided into three cases to discuss the effectiveness of the generated data.

4.4.1. The Strategy of Data Imbalance Resolution

In Table 8, when the training data are sufficient and balanced, we can obtain the 99% results of any time–frequency analysis, and the balanced dataset generated by DCGAN can obtain a 75% result after the wavelet transformation. When the training data are unbalanced, it can be seen in Table 9. Under signal processing, the smaller the unbalance ratio, the lower the accuracy rate obtained by the test set. It indicates that the data-driven fault diagnosis method is susceptible to an unbalanced training dataset. In the processing of down-sampling, we can improve the accuracy of the diagnostic model with a balanced dataset even if the data amount is insufficient; in the processing of over-sampling-balance (Pro-Balanced), the accuracy rate is increased to more than 90%, which is a significant improvement, and can even be close to the level of the actual balanced dataset; in the processing of over-sampling-expanding (Pro-Expand), the improved accuracy is very similar to that of over-sampling-balanced (Pro-Balanced). It can be seen that the oversampling method has advantages in the solution strategy, which can be close to the accuracy of the actual balanced dataset with high efficiency of over-sampling-balanced (Pro-Balanced). It shows the validity and superiority of DCGAN in generating a new sample.

Table 8. Comparison of different signal processing.

Signal Processing	Real Data Balanced	DCGAN Generated Data (All-Fake)
WT	99.88%	76.22%
STFT	99.32%	65.71%

Table 9. Comparison of different signal processing and data imbalance.

Signal Processing	Unbalanced Rate	Imbalanced	Under-Sampling	Pro-Balanced	Pro-Expand
WT	C1	90.57%	90.61%	98.6%	99.2%
	C2	31.02%	47.67%	96.07%	98.98%
	C3	20.58%	36.35%	94.39%	91.97%
STFT	C1	96.36%	88.21%	98%	97.51%
	C2	57.77%	61.17%	92.82%	90.57%
	C3	21.86%	44.42%	88.52%	86.71%

Actual balance dataset: All datasets are actual datasets and each type has 500 sheets. Generated balanced dataset: 500 pieces of generated data for each type are used as the training set. Down-sampling: Take the minimum number of samples in each dataset type as the balanced number of each type. Over-sampling-balance: Add a few types of samples to the number of heath conditions. Over-sampling-expansion: Amplify the total amount of data to 7500 sheets by generated data.

4.4.2. Enhancement of Other Dataset

The image processing technology is another standard data enhancement method. However, the time–frequency diagram is composed of vibration acceleration signals in a sequence of numbers; it is not suitable for generating images in a rotating manner. Therefore, this research case chooses vertical (horizontal) translation, scaling, and color enhancement to expand the short dataset. In Table 10, we compare it with the results of DCGAN. It can be found that if all generated data are used as the training set, the test accuracy of DCGAN under the wavelet transformation can be close to 80%, while the image processing technology is about 70%. In Table 11, for data after the over-sampling-balanced (Pro-Balanced) processing, both the two data enhancement technologies can increase the accuracy of the unbalanced training dataset to more than 90%. It is close to the accuracy of the actual balanced dataset, and only a slight difference in accuracy between the two. After processing the over-sampling-expanding (Pro-Balanced) method, there was no noticeable difference in the test accuracy of the two data enhancement techniques. However, the training dataset expanded by DCGAN had higher accuracy than image processing technology under wavelet transformation. If the deep learning method (DCGAN) can be effectively adjusted, its accuracy can be higher than image processing technology.

Table 10. Comparison of DCGAN and image processing techniques.

Signal Processing	DCGAN Generated Data (All-Fake)	Image Processing Generated Data (All-Fake)
WT	76.22%	70.72%
STFT	65.71%	67.77%

Table 11. Comparison of DCGAN and image processing techniques.

Signal Processing	Unbalanced Rate	Imbalanced	DCGAN		Image Processing Technology	
			Pro-Balanced	Pro-Expand	Pro-Balanced	Pro-Expand
WT	C1	90.57%	90.60%	99.20%	98.72%	97.40%
	C2	31.02%	96.07%	98.98%	96.96%	97.08%
	C3	20.58%	94.39%	91.97%	88.45%	95.31%
STFT	C1	96.36%	98.00%	97.51%	96.84%	95.71%
	C2	57.77%	92.82%	90.57%	91.45%	94.43%
	C3	21.86%	88.52%	86.71%	88.17%	91.02%

4.4.3. Different Load Condition

In the case analysis in Table 12, it is mentioned that the accuracy of different signal processing under the actual data is sufficient and balanced. This section discusses the impact of generated data on the cross-load diagnosis. Take time–frequency analysis and low-load measurement as the training set. For example, the unbalanced training data are expanded through the over-sampling-expanding (Pro-Expand) method. The data in the training set can make the accuracy rate comparison under the same number. The result of the comparison is shown in Table 8. We can obtain the time–frequency analysis and 95% accuracy in the cross-load test when the training data are adequately balanced. However, under the imbalance of the training data, the accuracy of the cross-load test with wavelet transformation can still reach close to 85%. We also found that if the imbalance rate is lower, the accuracy rate is lower. When the data are unbalanced, the DCGAN generated data and the amplified training dataset cannot achieve the diagnosis effect of the actual and balanced data. However, it still has an accuracy rate of 80%, and through VGG16 classification, an accuracy rate of up to 94.20% can be obtained. This shows that the generated data have learned distinguishable fault characteristics, and it also shows the ability of DCGAN to learn the characteristics of the input signal.

Table 12. Comparison of accuracy of data augmentation technology.

Condition	Method	Training Set	Testing Set	Accuracy Ratio
Condition1: Balanced data (Actual data)	2T-CNN	H1		71.83%
	FFT-CNN	H1		82.21%
	STFT-CNN	H1		95.06%
	WT-CNN	H1		96.38%
Condition2: Imbalanced data (Add generated data)	STFT-GAN-CNN	C1-expand		84.25%
		C2-expand		77.6%
		C3-expand		73.93%
	WT-GAN-CNN	C1-expand		83.03%
		C2-expand		79.07%
		C3-expand		78.68%
Condition3: Imbalanced data (Different CNN models)	STFT-GAN-CNN (ResNet50)	C1-expand	F2 (Actual data)	85.03
		C2-expand		82.27
		C3-expand		80.63
	STFT-GAN-CNN (VGG16)	C1-expand		93.28%
		C2-expand		91.52%
		C3-expand		82.91%
	WT-GAN-CNN (ResNet50)	C1-expand		85.03
		C2-expand		78.91
		C3-expand		75.83
	WT-GAN-CNN (VGG16)	C1-expand		94.20%
		C2-expand		92.68%
		C3-expand		89.28%

5. Conclusions

In this paper, two learning models of Deep Convolutional Generation Confrontation Network (DCGAN) and Convolutional Neural Network (CNN) are used to complete the fault diagnosis of induction motors for solving the problem of unbalanced training data. First of all, four signal processing methods are compared on the actual and balanced dataset. Time–frequency analysis has the advantage of fault diagnosis under different loads, and the accuracy rate measured by using the low-load side as the training set is higher, which can reach 95.06% and 96.38%. It is significantly better than single signal processing. When the training data are unbalanced, the more unbalanced the training data, and the lower the accuracy of the obtained test set under any signal pre-processing. It shows that the

data-driven fault diagnosis method is susceptible to the impact of the unbalanced training dataset. Therefore, the DCGAN-generated data is about 80% similar to the real examples in addition to the actual samples. After over-sampling the unbalanced data, the classification accuracy can be increased to more than 90%, which is closer to the accuracy of the actual balanced dataset, and the over-sampling-balanced (Pro-Balanced) method is better. In addition, if the parameters of DCGAN can be adjusted effectively, the generated samples can be better than image processing technology, but the training time will be longer. In the cross-load test, we can obtain up to about 85% of the diagnosis results after adding the unbalanced data to the generated data. It shows that the generated data have learned different fault characteristics, and better diagnostic results can be obtained through a deeper CNN model. It also highlights the ability of DCGAN to learn the characteristics of the input signal.

Finally, after the case analysis of this study, it is confirmed that the Deep Convolution Generative Adversarial Network (DCGAN) can improve the impact of the imbalance of training data. However, in the application of actual fault diagnosis, most of them still hope to find the potential fault of the induction motor and repair it as soon as possible. This research can only reach the classification diagnosis after the induction motor fails, so the technology has yet to breakthrough. In addition, unlabeled data still account for the majority of collected data. Therefore, in the future, semi-supervised learning technology can be introduced, and the useful information can be extracted from labeled data and unlabeled data, which will improve the usability of diagnostic models. Transfer Learning, which is still in the development stage, is expected to be applied to cross-domain fault diagnosis in the future and bring breakthroughs to the research of induction motor fault diagnosis.

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