An Efficient Method Based on Conditional Generative Adversarial Networks for Imbalanced Fault Diagnosis of Rolling Bearing

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***Abstract*—Fault diagnosis of rolling bearing has always been a vital component in industrial field, and effective fault diagnostic methods can guarantee normal progress of manufacturing production. However, the scarcity of fault samples in practical scenarios is still a vexed question, which will seriously affect the accuracy of data-driven diagnostic methods. For the settlement of above problem, this paper introduces a supervised generation model CGAN (Conditional Generative Adversarial Network) to generate multitudinal fault data, and replaces the real fault data with the generated one to constitute a new dataset to train the classifiers adequately. In order to verify the effectiveness of the proposed method, the experiments are carried out on both artificial dataset and real one. The results show that the generated data of CGAN not only has a high degree of similarity with the real data, but also effectively improves the fault diagnosis accuracy of rolling bearing.**

Keywords-fault diagnosis; rolling bearing; CGAN

I. INTRODUCTION

With the development of science and technology, more and more high-precision equipment has been developed gradually. On the one hand, it has improved productivity and reduced production costs, but at the same time, it has also imposed stricter requirements on equipment maintenance and reliability operation. In real scenarios, minor failures will affect the stability and security of the entire system, and even catastrophic consequences for people and property. Therefore, the fault diagnosis of equipment has gained more and more attention, in which the fault identification of rolling bearing is a crucial part. Rolling bearings are critical rotating parts in mechanical equipment and also one of the most important fault sources. According to incomplete statistics, about one-third of faults in rotating machinery are caused by the malfunction of rolling bearings. Prompt fault detection of rolling bearings and taking effective measures can reduce losses to a large extent. Thus, rolling bearing fault diagnosis is of paramount importance to the entire machinery industry.

A. Related Work

Fault diagnosis of rolling bearing is a process of comprehensive evaluation of its working state, fault type and severity by comprehensively analyzing the vibration signal, noise, temperature and working parameters of rolling bearings under various working conditions [1]. Its essence is a problem of pattern recognition. Because of the significance of rolling bearing in industrial applications, it has been a very popular research. Many fault diagnosis methods have been developed in this field, which can be roughly divided into traditional methods and machine learning based ones.

The traditional methods basically judge whether there is a fault through physical characteristics of equipment, mainly including vibration, sound, heat and oil [2]. Among them, vibration diagnosis technology is one of the most widely used methods [3]. Vibration-based fault diagnosis of rolling bearing chiefly monitors and diagnoses fatigue cracking, deformation, indentation and local corrosion of rolling bearings in rotating machinery by collecting and processing vibration signals of bearings during operation [4]. Its core lies in the effective extraction of features representing faults, which are often characterized by amplitude, characteristic frequency, autoregressive parameters, fractal dimension and cyclostationarity in practical applications [5]. The commonly selected methods of feature extraction include FFT (Fast Fourier Transform) [6], DWT (Discrete Wavelet Transform) [7], and EMD (Empirical Mode Decomposition) [8].

The research of traditional methods has been carried out earlier, and its basic theories and practices are relatively mature. Therefore, the classic approaches have widespread application in many real-world scenes, but it also has some defects. For example, traditional methods in the analysis and processing of vibration signals tend to ignore some important features and deep correlations among data, resulting in unsatisfactory performance of fault diagnosis. In contrast, the methods ground on machine learning are more superior.

Machine learning methods have been applied to various fields because of their standout ability in covering complex distribution of data. With the progress of machine learning, intelligent methods become a hotspot in the field of fault diagnosis [9]. SVM (Support Vector Machine) is a traditional machine learning method frequently adopted in the fault diagnostic of rolling bearing [10, 11]. Combining SVM with PSO (Particle Swarm Optimization) algorithm to construct an optimal classifier in order to diagnose faults in rolling bearings

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is a common practice [12, 13]. Unlike the above, Li et al. view the multi-layer SVM as a tool of feature extraction to deal with fault identification of rolling bearings [14]. In this model, the diagnostic results are the output of the last layer. In addition, the integration of deep learning and traditional machine learning algorithms is also a valid means. Gong et al. [15] take the representative features extracted by CNN (Convolutional Neural Network) as the input of SVM to train an efficient classifier for fault recognition in vibration signals of rolling bearings. Wang et al. [16] also treat CNN as feature extractor, but the difference is that the fault classifier is HMM (Hidden Markov Model). In order to improve the fault diagnostic accuracy of rolling bearing, the stacked LSTM which experts at extracting inherent features of temporal signals is proposed by Yu et al [17].

Although the intelligent diagnosis methods mentioned above can efficiently handle the problem of fault diagnostic for rolling bearing data with complex distribution, these algorithms require a large amount of balanced data for training. However, normal data are much more than fault samples in actual application, especially in the fault diagnosis of rolling bearings. And the imbalance of training set will seriously affect the performance of classifiers. Therefore, an efficient method based on CGAN which can generate high-quality samples is adopted in this paper to deal with imbalanced fault diagnosis of rolling bearings. The main contributions of this paper are as follows: 1. The imbalanced dataset after preprocessing is used to train CGAN and generate sufficient fault data; 2. Analyze the quality of data generated by CGAN from multiple perspectives; 3. Replace real fault data with ample generated samples to train classifiers adequately. Experiments show that the generated data of CGAN not only have high similarity with real data, but also effectively improve the accuracy of fault diagnosis.

The remainder of this paper is organized as follows. The second section gives a brief review of GAN, and introduces the process of fault diagnosis based on CGAN. The third section chiefly describes the datasets and experiment results. The fourth section summarizes this paper and put forward the focus direction of future work.

II. Proposed Method

This section concisely overviews GAN and CGAN, and succinctly describes the fault diagnosis process in this paper. Finally, some criteria for evaluating the quality of generated data are listed.

A. Overview of GAN

Goodfellow et al. [18] proposed GAN model in 2014, including the generative model D and the discriminant model G, whose structure is shown in the Fig. 1. The generator can learn the distribution of original data, and then output fake data similar to the training ones. The discriminator is capable of determining whether the input is from the generated dataset or the real dataset. And the objective function of GAN is as follows:

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))] \quad (1)$$

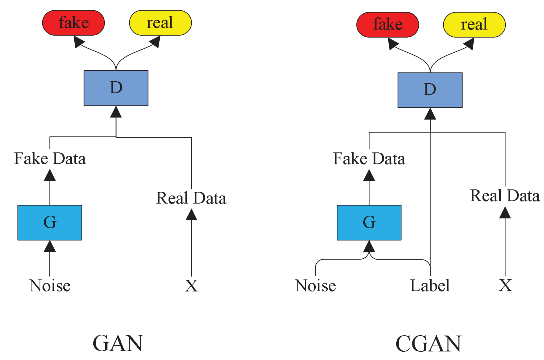


Figure 1. The structure of GAN and CGAN

During the training process, the generator continuously learns the distribution of the real data to generate fake ones that the discriminator cannot discriminate, and the discriminator constantly enhances its ability to distinguish between real data and generated ones. By means of uninterruptedly gaming, the error of both the generator and the discriminator will gradually decrease, which will reduce the loss of the entire model.

B. Conditional Generative Adversial Network

Mirza M et al. [19] proposed CGAN (Conditional Generative Adversarial Nets) based on GAN, as shown in the Fig. 1. CGAN enhances the performance of the generator and discriminator by adding auxiliary information to the input of generator and discriminator. This conditional information can be tags or other modal data. Its objective function is as follows:

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x\mid y)] + E_{z\sim p_z(z)}[\log(1-D(G(z\mid y)))] \quad (2)$$

CGAN is a supervised generation model, which differs from GAN. The use of conditional information allows CGAN's generator to produce desired and differentiated data, rather than generating data with no purpose like GAN. Therefore, CGAN is more suitable for data with complex modalities, which also makes it applicable to the generation of diverse types of fault data.

C. Imbalanced Fault Diagnosis Based on CGAN

The ultimate goal of this paper is to generate high-quality bearing fault data, so as to fully train the classifiers and make more effective decisions. The detailed process of the method in this paper is as follows: 1. Train CGAN with real imbalanced labeled data which contain normal and fault instance for a certain number of times; 2. Generate substantive fault samples by taking noise and labels as the input of CGAN and verify their validity; 3. Replace fault data in real dataset with corresponding generated one to form new dataset; 4. Train classifier with new dataset and use well-trained classifier to discern various faults in test set. See the Fig. 2 for specific process, and the meanings of each annotation in Fig.2 refer to Table □.

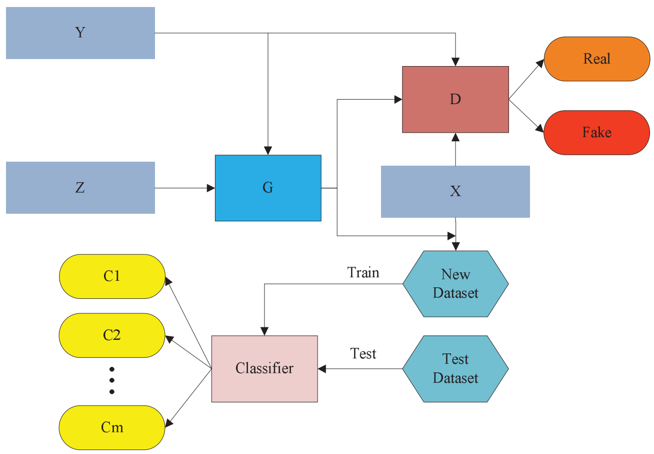


Figure 2. Flow chart of the proposed method

TABLE I. THE MEANINGS OF ANNOTATIONS

Parameters	Meanings
z	Random noise obeying normal distribution
Y	The encoded labels of samples
D	The Discriminator of GAN
G	The Generator of GAN
X	Real dataset
C	The real labels of samples

D. *Evaluation Criterion*

Generally speaking, the data generated by GAN or other GAN-based models are multi-dimensional, and it is difficult to make intuitive judgment like the data on two-dimensional plane. Therefore, some measures are adopted to evaluate the generated data, such as Euclidean distance, cosine distance and PCC (Pearson Correlation Coefficient). Euclidean Distance refers to the real distance between two points in m-dimensional space. It can be used to measure individual position difference in Euclidean space. The formula is as follows.

$$Euclidean(\mathbf{x},\mathbf{y}) = \sqrt{\sum_{i=1}^{m}(x_i - y_i)^2} \tag{3}$$

where both $\mathbf{x}$ and $\mathbf{y}$ are vectors. However, data following the same distribution in high-dimensional space may also have a large Euclidean distance, so only using Euclidean distance to measure the similarity between data is not sufficient. Therefore, this paper also introduces Pearson correlation coefficient, which is widely used to measure the correlation between two vectors, and the value of PCC is between -1 and 1. The formula is as follows:

$$r_{\mathbf{xy}} = \frac{\sum x_i y_i - n\bar{x} * \bar{y}}{(n-1)s_x s_y} \tag{4}$$

where $\bar{x}$ and s_x represent the mean and standard deviation of the vector $\mathbf{x}$ respectively. The closer $r_{\mathbf{xy}}$ approaches 1 or -1, the more linearly dependent $\mathbf{x}$ and $\mathbf{y}$ are. In addition, cosine distance is also used in this paper to weigh the difference in direction between vectors, and its formula is as follows:

$$cos\_dist(\mathbf{x},\mathbf{y}) = 1 - \frac{\sum x_i y_i}{\sqrt{\sum x_i^2}\sqrt{\sum y_i^2}} \tag{5}$$

And the closer the cosine distance close to 0, the smaller the divergence between vectors in direction.

III. EXPERIMENTS

This part mainly presents the datasets used in this paper and the results of various comparative experiments.

A. *Datasets*

In the experiment, two kinds of dataset are adopted to verify the proposed methods, which are artificial dataset and real dataset.

The artificial dataset is all two-dimensional data, and the samples of each dimension follow normal distribution. In addition, there are five types of data in the dataset, each with 1000 samples, and some categories have different shape. The purpose for the construction of the artificial dataset is to compare the capability of GAN and CGAN in covering the distribution of data. Fig. 3 shows the artificial dataset.

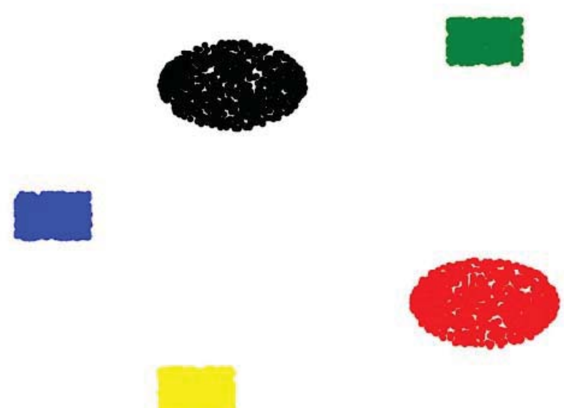


Figure 3. The artificial dataset

The real dataset is CWRU, from the Case Western Reserve University Bearing Data Center, which contains normal data and bearing fault data with different damage diameters. The types of faults in the dataset include ball fault, inner race fault and outer race fault, which are collected at different locations. The test stand used for the acquisition of CWRU dataset is shown is Fig. 4.

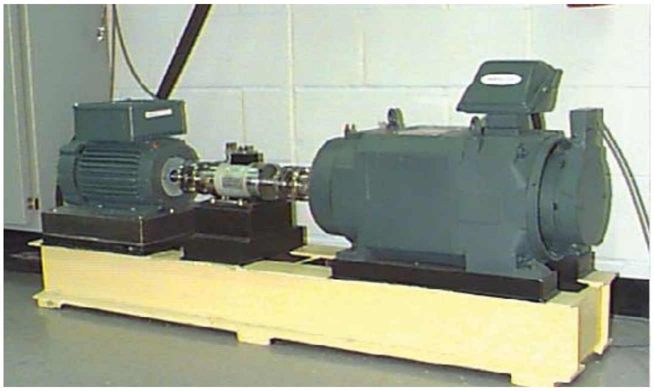


Figure 4. The test stand for data acquisition.

The experiments in this paper use normal and three faults with a damage diameter of 0.007 inches in the CWRU dataset. Because the raw data are only one dimension, which needs to be processed preliminary. The preprocessing process in this paper is as follows: 1. Slice raw data into samples of length 2048; 2. Perform discrete Fourier transform on the sliced data; 3. Normalize the data processed in the second step. Part of the data obtained through the above process are shown in Fig. 5. The normalized formula is as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{6}$$

where x_{max} and x_{min} are the maximum and minimum values of each dimension of data, respectively. The number and label of each type of data in the experiment are shown in Table Ⅱ.

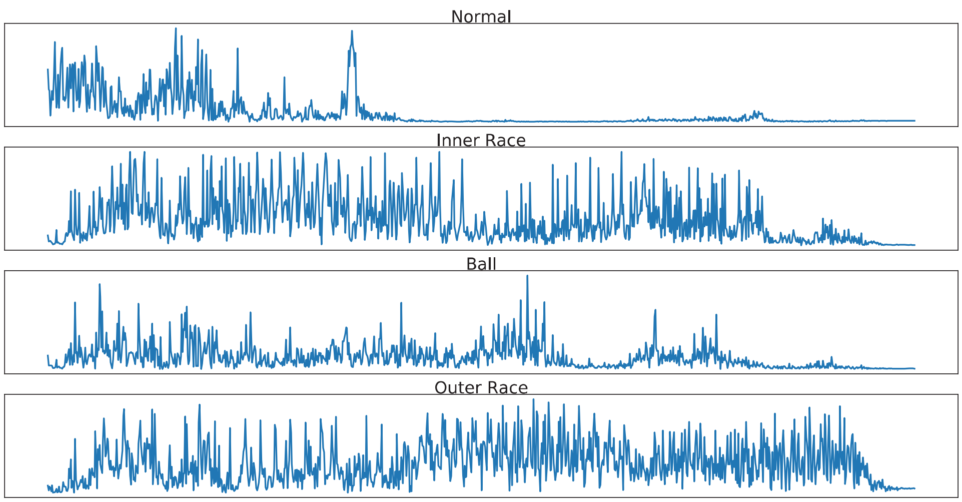


Figure 5. The preprocessed data. From top to bottom are the data of normal, inner race, ball and outer race.

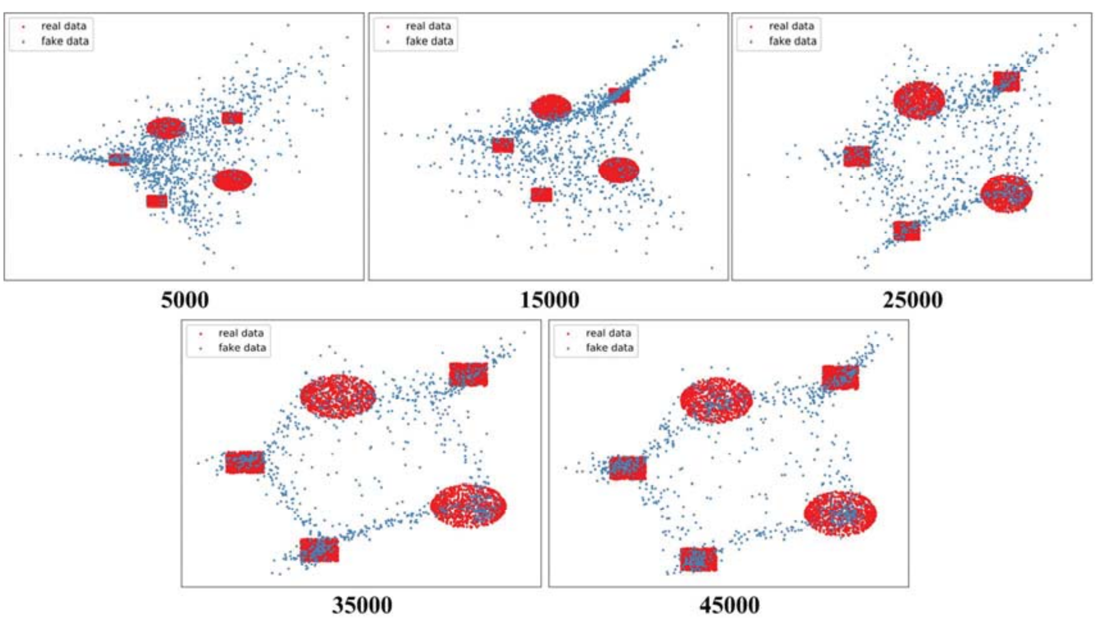


Figure 6. The data generated by GAN.

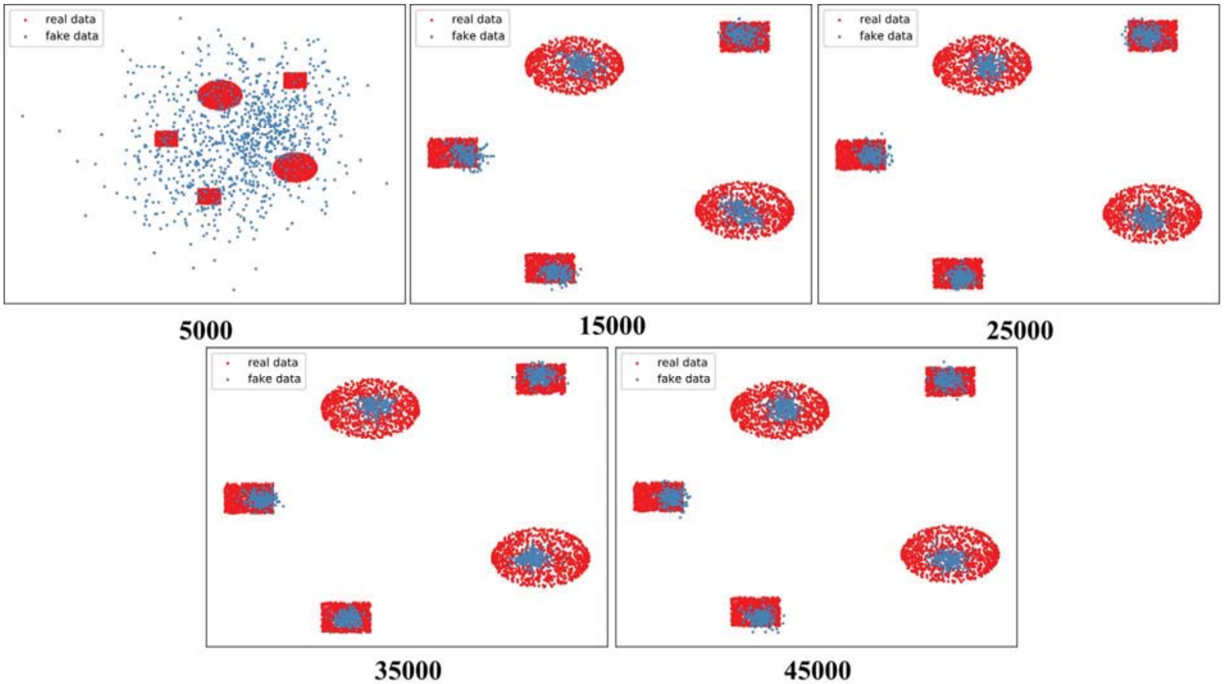


Figure 7. The data generated by CGAN.

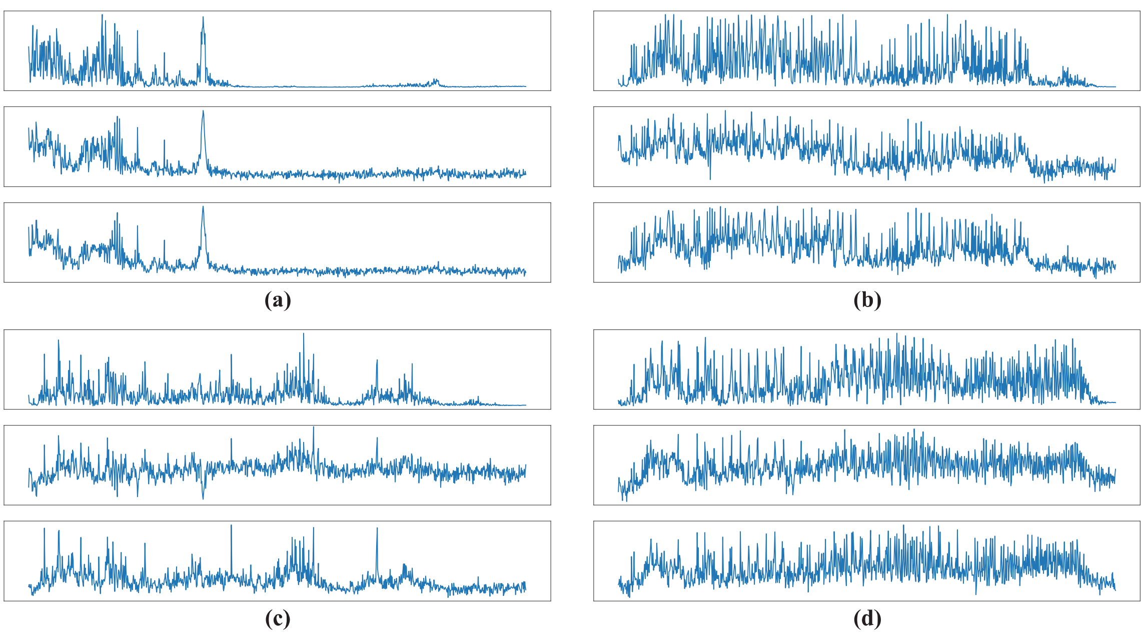


Figure 8. The comparison of generated data on CWRU dataset. (a) ~ (d) represent the comparison on normal data, inner race data, ball data and outer race data respectively. From up to down are real data, the data generated by GAN and the data generated by CGAN in each sub graph.

TABLE II. THE PROPORTION AND LABEL OF DATA IN THE EXPERIMENT

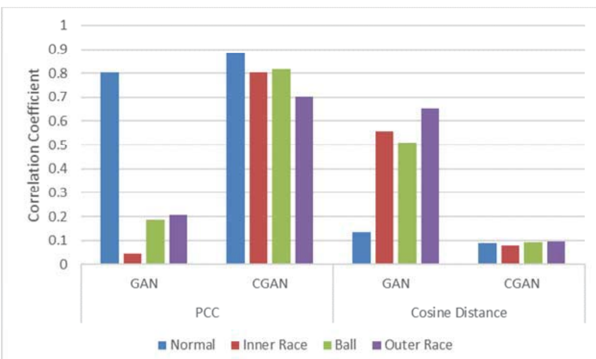
Fault Type	Length of Instance	Training Samples	Valid Samples	Test Samples	Label
Normal	2048	800	100	100	0
Inner Race	2048	50	100	100	1
Ball	2048	50	100	100	2
Outer Race	2048	50	100	100	3

B. *The Quality Comparison of Generated Data*

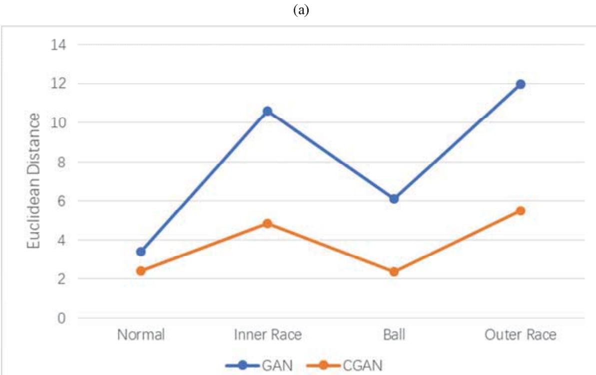
In order to verify the ability of CGAN in learning data distribution, the experiments are carried out on artificial dataset and CWRU dataset respectively, and the generated results are compared with GAN.

The artificial data are shown in Fig. 3, which are divided into five categories. The input of GAN is unlabeled data, while the input of CGAN contains labels. Both the generator and the discriminator of model use a three-layer MLP (Multi-Layer Perception) and the same learning rate, where the number of neurons in the hidden layer is 512. During training, each model is trained 50,000 epochs, and the generated data are recorded every 10,000 times to observe its quality. Fig. 6 and Fig. 7 show, in contrast, the data generated by the GAN and the CGAN, where red dots represent real data and generated data are marked in blue.

As can be seen from Fig. 6, GAN can gradually learn the distribution of the data with the progress of training and, at the end, generate differentiated data. However, there is still a lot of noise between two categories. Compared with GAN, the data generated by CGAN have higher quality and there is no noise data in two categories, as shown in Fig. 7. Moreover, CGAN learns faster. When training less than 10,000 times, CGAN can generate data that are basically consistent with the original distribution, while GAN requires 50,000 times or more of training.



(a)



(b)

Figure 9. Comparison of data generated by GAN and CGAN in various evaluation criteria. (a) includes the comparison of PCC and Cosine distance, while (b) is the comparison of Euclidean distance.

It can also be explained from the comparison of Fig. 6 and Fig. 7 that the addition of conditional information can accelerate the model's learning of data with simple distribution. To further verify the effectiveness of CGAN in rolling bearing fault data with complex distribution, this paper uses the CWRU dataset to train GAN and CGAN respectively. The data generated by the two models is shown in Fig. 8.

From the experiments of CWRU dataset, the data generated by GAN is only similar to the normal one. The main reason for the above problems is that there are 800 normal data in training set, and only 50 samples in each type of fault. But under the same training set and parameters, each class in the data generated by CGAN bear much resemblance to the corresponding category in the real dataset. So as to confirm the above statement, the Pearson correlation coefficient, cosine distance and Euclidean distance between the real data and the corresponding generated data are calculated respectively. Since there are a lot of data for each class, the final value obtained in the experiment is the mean of the above evaluation indicators. The detailed comparison is shown in Fig. 9.

According to PCC, only the normal data resemble the real normal one in the generated dataset of GAN, and the similarity between the other three types of fault is low, which is consistent with the conclusion obtained in Fig. 8. Unlike GAN, CGAN is superior in this respect. When combined with cosine distance and Euclidean distance, the overall distance from CGAN's generated data to the real one is smaller than that of GAN. Therefore, CGAN gains advantage over the GAN in generating rolling bearing fault data, both in terms of visual illustration and numerical comparison.

C. Comparison of Diagnostic Accuracy after Samples Replacement

No matter what model is used to generate data, our eventual goal is to solve the problem of insufficient fault samples in fault diagnosis of rolling bearing. In the previous part of the experiment, we compare the similarity between the real data of the generated one of CGAN and CGAN from different aspects, but whether the data with high similarity will improve the accuracy of fault diagnosis is still unknown. To illustrate this point, we conduct this part of experiment.

Firstly, we replace the fault data in the real dataset with the fault one generated by each model to form new training sets, and then use the new training set to train various classifiers. Finally, the same validation set and test set are used to obtain the diagnostic accuracy of the classifiers trained by each new dataset. The validation set and the test one are both real data after preprocessing. The specific comparison results are shown in Fig. 10, and the construction process of new training sets is shown in Fig. 11.

By comparing the results, it can be found that the classifiers trained with the 'gan-m' (m=50, 100, 150, 200) dataset generally has lower diagnostic accuracy on the same test set than the classifiers trained with the real data set. This also indicates that the bearing fault data generated by the GAN cannot improve the final diagnostic accuracy. On the contrary, the data generated by CGAN can effectively improve the fault diagnosis accuracy of rolling bearing. From the above results, it can be explained that even if the real fault data are not used, the fault data generated by CGAN can help the classifiers achieve higher diagnostic accuracy.

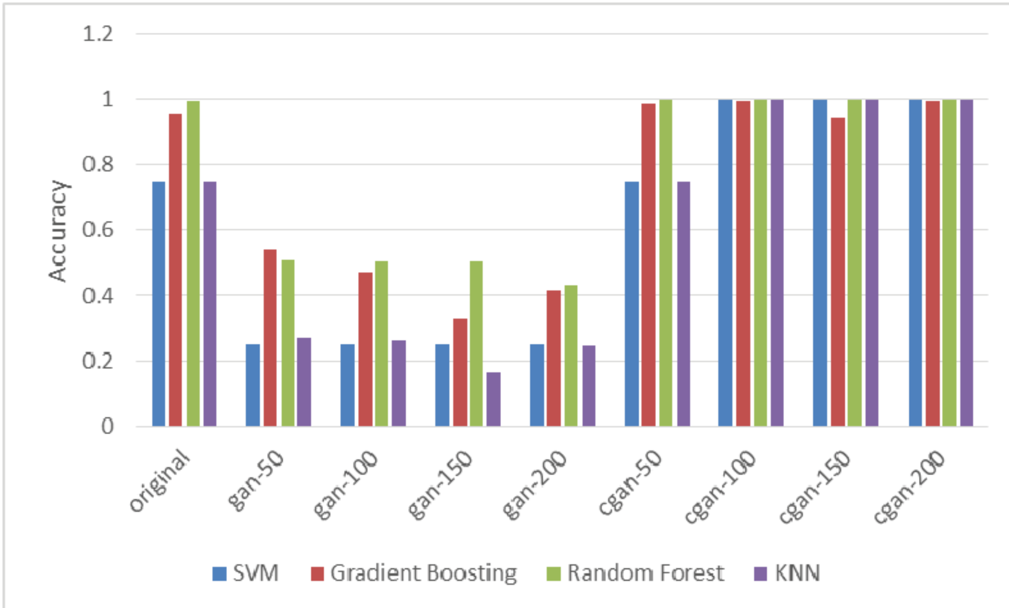


Figure 10. Comparison of diagnostic accuracy after fault samples replacement. 'original' represents the source dataset. While 'cgan-50' represents the new dataset formed by replacing the fault data in the original dataset with the ones generated by CGAN, and there are 50 replacement samples in each class. The other datasets in the above figure are analogous.

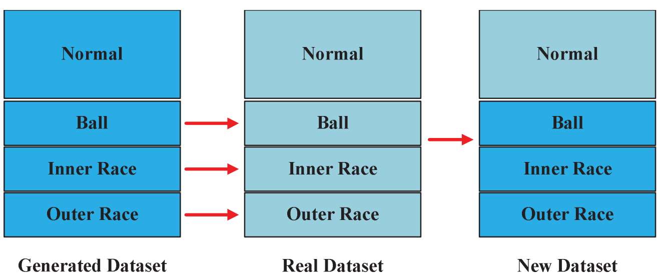


Figure 11. The process of combining generated data with real data to form a new training set.

IV. CONCLUSIONS

In this paper, the generation model CGAN is introduced to generate fault data to settle the scarcity of fault samples in rolling bearing fault diagnosis. In specific experiments, real bearing data with four categories and serious imbalance are applied to train the generative model, and plentiful failure samples are obtained. Finally, the quality of the data generated by CGAN is analyzed though various evaluation criteria, and the effectiveness of the generated data in improving the accuracy of bearing malfunction diagnosis is verified on multifarious classifiers. The above experimental results show that CGAN can effectively learn the distribution of real bearing data and is applicable to the problem of rolling bearing fault diagnosis under unbalanced scenario.

However, the current generation model cannot directly use the original data for training, and most of the model inputs need to be preprocessed. Therefore, how to generate high quality fault data with only original data as train set is still a worthy work.

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