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Imbalanced Learning for Fault Diagnosis Problem of Rotating Machinery Based on Generative Adversarial Networks

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Abstract: Learning from imbalanced datasets has become a significant and challenging problem and gained much attention in machine learning and many aspects. Accumulated historical data collected from the working process of industrial machines are often imbalanced, which means the number of recorded observations in some classes are significantly scarcer than other classes. There are already various different methods addressing this problem, among which most strategies focus on generating similar data for the minority classes. Synthetic minority oversampling technique (SMOTE) is an important and valid algorithm, which generates synthetic samples along the line segment, and a great many of variations have been proposed and proved effective. Generative adversarial networks (GANs) were originally invented to generate images from an adversarial training process. While SMOTE approaches are based on local information, GAN methods learn from the overall class distribution. In this paper, we proposed a deep convolutional GAN (DCGAN) model to simulate the original distribution from minority classes and generate new data to solve the imbalance problem. To verify the effectiveness of proposed DCGAN model, we compare the performance against multiple different resampling algorithms. The results show that the quality of generated data using DCGAN is significantly better than other oversampling method and therefore the classification accuracy is superior for fault diagnosis.

Key Words: Imbalanced dataset, fault diagnosis, generative adversarial networks

1 Introduction

Vibration signals of rolling-element bearings are commonly used in the process of condition monitoring and fault diagnosis of rotating machinery in modern industry. Research in fault diagnosis has received great deal of attentions and made great achievements during recent years. Vibration signals are acquired by sensors attached to the rotating machine.

Fault diagnosis methods focus on distinguishing signals under different conditions. Accumulated historical data collected from the working process of industrial machines are usually imbalanced, which means the number of recorded observations in some conditions are significantly scarcer than others. In many supervised learning applications, there is a significant difference between the prior probabilities of different classes, which is known as the class imbalance problem. There are already various different methods addressing this problem in many referenced articles. [1][2] It is common in many real problems from telecommunications fraud [3], credit card fraud [4], ecology, biology, cancer detection [5] and many other aspects [6] including fault diagnosis problem.

To deal with imbalance problem, several strategies have been tried out. A common approach to deal with the imbalanced data is sample handling. The key idea is to preprocess the training set to minimize the differences between classes. In other words, sampling methods alter the priors distribution of minority and majority class in the training set to obtain a more balanced number of instances in each class. [7] These approaches are often relatively easy to implement. Under Sampling is a non-heuristic method that removes instances of the majority class in order to balance the distribution of classes. The over-sampling is an approach that increases the proportion of minority class by duplicating observations of this class. An advanced method of over-sampling called SMOTE is introduced in [8]. The main idea of SMOTE is generating synthetic samples along the line segment, and a great many of variations have been proposed and proved effective as in [9][10]. Other approaches focus on the classification algorithm. The use of ensemble learning methods was popular for a long time to boost classifier performance on a data set, such as bagging [11], boosting [12], adative boosting (Adaboost) [13] and random forests [14]. Also in other methods, changing the cost in learning sequences has proven be a practical and effective solution to the unbalanced data issue. [15]

Generative adversarial networks (GANs) are a class of generative models that learn through a competitive process composed of two networks: The discriminator (D) that learns to discriminate between real and fake data, and the generator (G) that learns to generate fake data that can fool the discriminator. [16] Since its invention, GAN has become a well used method in different machine learning applications, especially in computer vision and image processing [17-19].

In this paper, we propose a novel approach for fault diagnosis with imbalanced dataset. A new DCGAN model is proposed and applied on raw and imbalanced vibration signals. A support vector machine (SVM) [20] classifier is trained on the original dataset and the complemented dataset to verify the effectiveness of the generative model.

This paper is organized as follows. Section 2 describes some resampling algorithm and GAN. A brief explanation of the proposed method is also given in section 2. In section 3, experiments are carried out under different situations. Some details of the structure and parameter are also discussed in this part. In section 4 we make a conclusion about the proposed approach and possible modifications.

2 Methodology

2.1 Resampling Algorithms

Resampling methods are used to rebalance the sample space for an imbalanced dataset in order to alleviate the effect of the skewed class distribution in the learning process. Resampling techniques consist of three classes: under-sampling, over-sampling and hybrid methods.

There are two types of under-sampling. Random under-sampling (RUS) exclude randomly observations from majority class and focused under-sampling (FUS) exclude the majority class observations present on the borders between the two classes. Also, other than random over-sampling (ROS) which randomly duplicate observations and focused over-sampling (FOS) which duplicate observations on the borders between the majority and minority class, SMOTE is a more advanced method.

The disadvantage of under-sampling and over-sampling is obvious. The exclusion of data may lead to loss of information contained in the original dataset, and the simple duplication of original data may not enrich the effectiveness of the minority classes. In SMOTE method, the minority class is over-sampled by taking each minority class sample and introducing synthetic examples along the line segments joining all of the selected *k* minority class nearest neighbors. Depending upon the amount of over-sampling required, neighbors from the *k* nearest neighbors are randomly chosen.

The process of SMOTE can be described as below and shown in Fig. 1. Firstly, for each observation *x* of the minority class, identify its *k*-nearest neighbor, as the red arrows in the figure. Then randomly select *k* neighbors (the number depends on the rate of over-sampling). At last, new data are generated along the line joining the original observation *x* to its nearest neighbor.

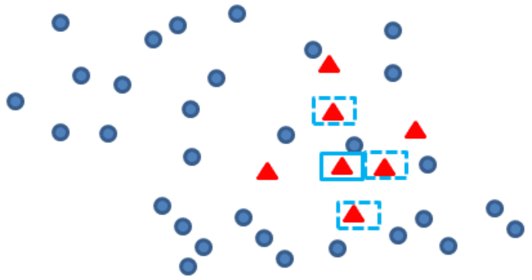


Fig. 1: The SMOTE process

2.2 Generative Adversarial Networks

GANs generate images from an adversarial training, the generator attempts to produce a realistic image to fool the discriminator, which tries to distinguish whether its input image is from the training set or the generated set.

The framework of adversarial process is rather straightforward to apply. To learn the generator's distribution p_g over data x , we define a prior on input noise variables $p_z(z)$, then represent a mapping to data space as $G(z;\theta_g)$, where G is a differentiable function represented by a multilayer perceptron with parameters θ_g . We also define a second multilayer perceptron $D(x;\theta_d)$ that outputs a single scalar. $D(x)$ represents the probability that x came from the data rather than p_g . We train D to maximize the probability of assigning the correct label to both training examples and samples from G . We simultaneously train G to minimize $\log(1-D(G(z)))$. In a word, a value function $V(G,D)$ is presented as below:

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

The training process of GAN is simultaneously updating the discriminative distribution so that it discriminates between samples from the data generating distribution p_x from those of the generative distribution $p_g(G)$. In each iteration, sample minibatch of m noise samples $\{z^{(1)},\ldots,z^{(m)}\}$ from noise prior $p_g(z)$, and then sample minibatch of m examples $\{x^{(1)},\ldots,x^{(m)}\}$ from data generating distribution $p_{data}(x)$. As we can calculate from fomula (1), the discriminator can be updated by ascending its stochastic gradient as below:

$$\nabla_{\theta_d} \frac{1}{m}\sum_{i=1}^{m}[\log D(x^{(i)}) + \log(1-D(G(z^{(i)})))] \quad (2)$$

After updating the discriminator, the generator can be updated by descending its stochastic gradient as:

$$\nabla_{\theta_g} \frac{1}{m}\sum_{i=1}^{m}\log(1-D(G(z^{(i)}))) \quad (3)$$

If G and D have enough capacity, the discriminator is allowed to reach its optimum

$$D^*(x) = \frac{p_{data}(x)}{p_{data}(x)+p_g(x)} \quad (4)$$

given G , and p_g is updated so as to improve the criterion, p_g can converge to p_{data} .

The traing process is shown in Fig. 2. Figure (a) shows the original situation where p_g (solid line) and p_{data} (dotted line) are different, the discriminator (dashed line) is not very accurate. In (b), the discriminator is updated and converged, the original data and generated data can be separated perfectly. In (c), the generator is updated and p_g gets much closer to original distribution p_{data} . After several iterations, we get $p_g = p_{data}$, and the discriminator can no longer distinguish two distributions.

2.3 Deep Convolutional Generative Adversarial Networks

DCGAN attempts to scale up GANs using convolutional neural networks (CNNs) to better model images. Several improvements are made including replacing pooling layers

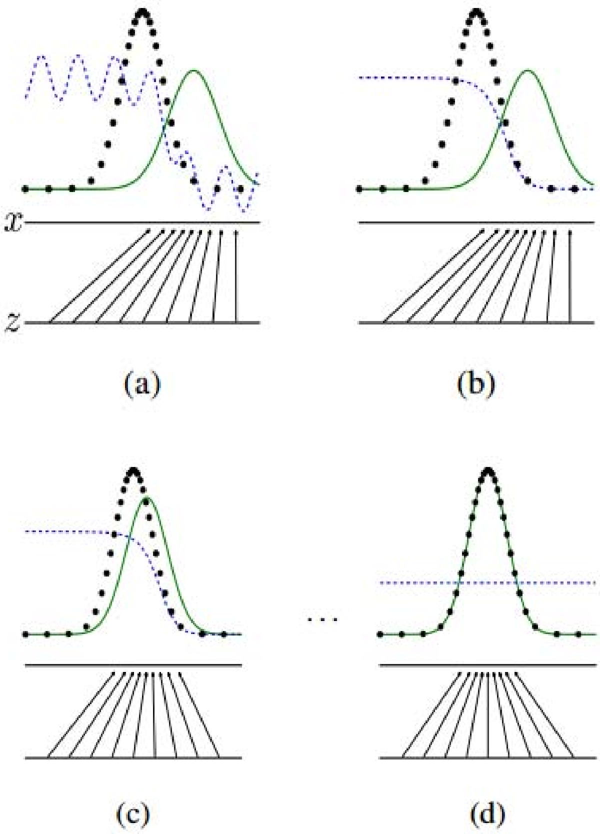


Fig. 2: GAN training process

with convolutional layers, using batchnorm in generator and discriminator, removing fully connected hidden layers and using ReLU activation function in generator and discriminator.

Details of adversarial training and other problem concerning DCGAN will not be talked about in this paper.

2.4 Structure of the Fault Diagnosis Approach

The basic structure of our fault diagnosis approach dealing with imbalanced dataset is shown in Fig. 3. In the data generate process, after original training data are selected, DCGANs are applied on minority classes. The original data and generated data are joined together as the new training dataset.

In the fault diagnosis part, a SVM classifier is trained after feature extraction of the training data. The testing dataset are directly selected from the vibration signals and verified in the trained model.

3 Experiment and Result

3.1 Experimental Setup and Data Selection

As shown in figure 4, the test platform consists of a two horse power motor, a torque transducer, and a dynamometer. Vibration data was collected using accelerometers, which were attached to the housing with magnetic bases.

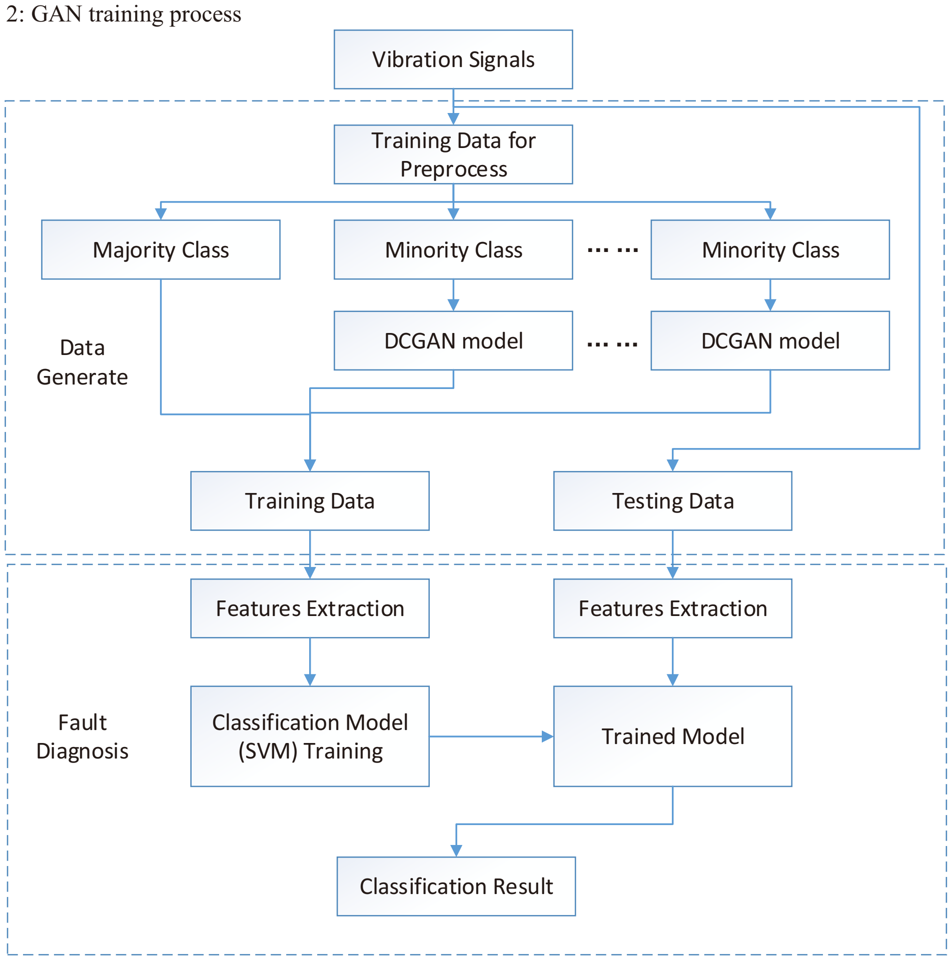


Fig. 3: Representation of proposed fault diagnosis structure

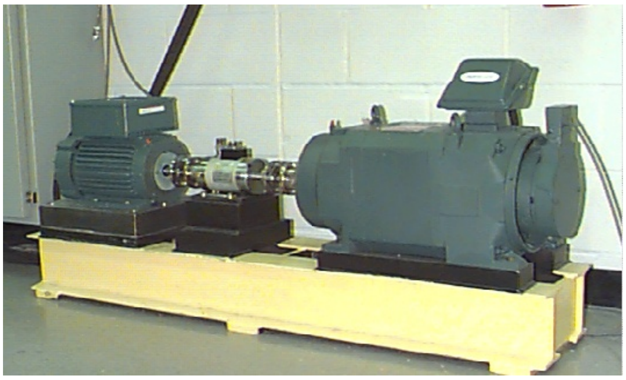


Fig. 4: Experiment apparatus for vibration signal acquiring

Three bearing components, the inner race (IR), the outer race (OR) and the ball of rolling bearing (BA), are studied in in the database of CWRU. Vibration signals under different motor loads and fault diameters are collected for analysis. The sampling frequency of the platform is 12 kHz.

The bearing data used in this paper are arranged in table 1.

Table 1: Bearing Fault Data Arrangement

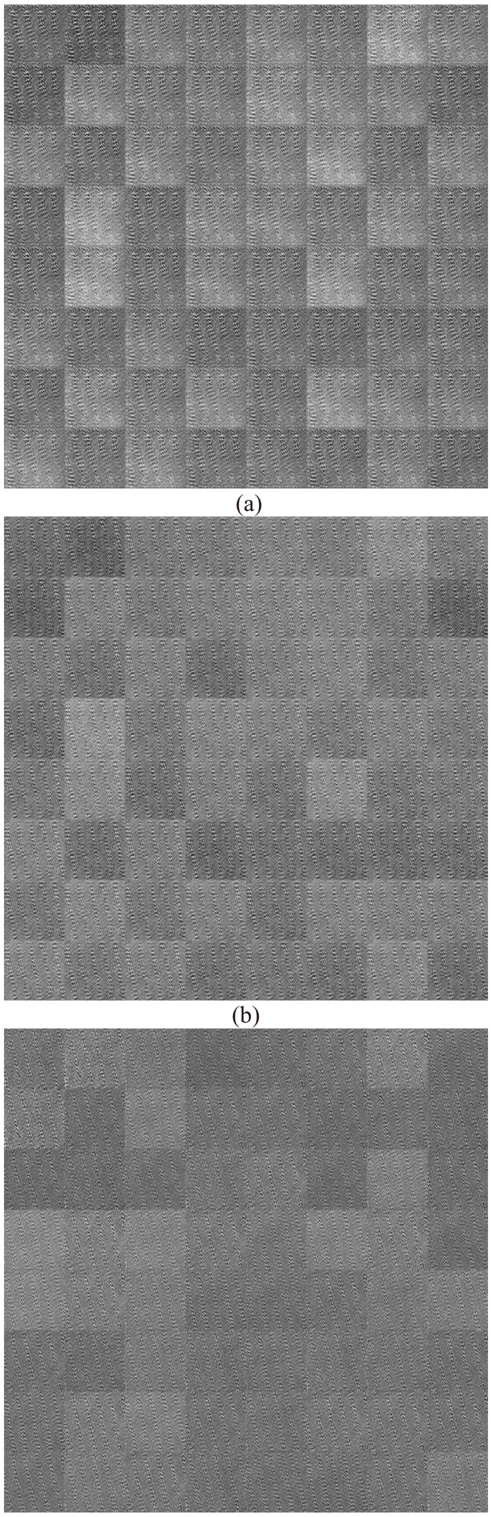
ID	Fault Position	Motor Load /horse power	Training Samples	Test Samples
1	Null	0	1094	100
2	Null	1	2294	100
3	Null	2	2300	100
4	Null	3	2303	100
5	IR	0	481	100
6	IR	1	484	100
7	IR	2	485	100
8	IR	3	489	100
9	OR(@6:00)	0	484	100
10	OR(@6:00)	1	487	100
11	OR(@6:00)	2	482	100
12	OR(@6:00)	3	487	100

As shown in table 1, 12 categories of vibration signals are chosen from CWRU database. Each sample contains 4900 points. Samples in normal conditions are more than in faulty conditions as in practice machines work in normal conditions much more than other situations. In working condition 5-12, there are only around 500 samples available and the ratio between normal condition and faulty condition is 5:1. For each condition, 100 test samples are selected.

3.2 GAN Training Process in Experiment

As shown in last section, the ratio between condition 2 and condition 5 is nearly 5:1, even normal condition 1 does not have enough samples comparing to other normal conditions, which may lead to an inaccurate classification result. In this paper, we train different DCGAN models for vibration data generation of the minority classes.

Each sample contains 4900 points and is reshaped into a 70×70 matrix. The DCGAN model is designed to take in the matrix and a total of 4 convolutional layer are designed for the discriminator and generator individually. The training iteration is set to 25 and a mini-batch number of 64 is selected in this experiment. Take condition 5 as an example, the number of training samples is 481. In each epoch, the dataset is divided into 8 mini-batches and is trained successively.



(a)

(b)

(c)

Fig. 5: Results in the DCGAN training process

Results in the training process is shown in figure 5. Each picture contains 64 samples as a mini-batch. Picture in (a) is the result in the first epoch, while (b)(c) are after 5 and 20 epochs. As we can see, the result in (a) shows a lot of jitter, contains much noise while after 20 training epochs the result is much more stable, and shows a clear pattern that fits the original distribution of the vibration data.

Fig. 6 shows a comparison of the original signal and the newly generated data. The difference is precious little as we can see from the figure.

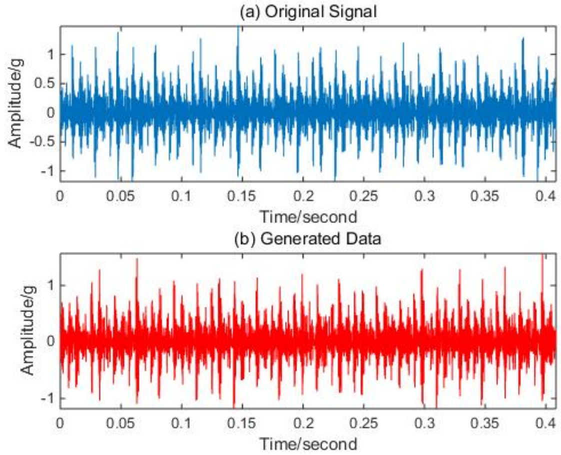


Fig. 6: Comparison between original signal and generated data

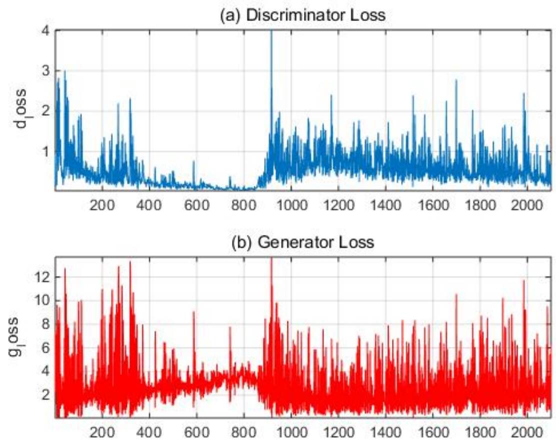


Fig. 7: The discriminator loss and generator loss in training process

The discriminator loss and generator loss in the training process in shown in figure 7. The discriminator loss can be relatively small while the generator loss is still unstable after 25 iterations.

After data generation of all the minority classes, the new training dataset is shown in table 2. In the final training dataset, the number of each class is almost even.

Table 2: Training Dataset after Data Generation

ID	Fault Position	Newly Generated Samples	Final Samples
1	Null	1216	2310
2	Null	0	2294
3	Null	0	2300
4	Null	0	2303
5	IR	1856	2337
6	IR	1856	2340
7	IR	1856	2341
8	IR	1856	2345
9	OR(@6:00)	1856	2340
10	OR(@6:00)	1856	2343
11	OR(@6:00)	1856	2338
12	OR(@6:00)	1856	2343

3.3 Data Process and Feature Extraction

For fault diagnosis of rotating machinery, feature extraction is very important. There many features can be used in fault diagnosis such as mean value, standard derivation and skewness. In this experiment, 13 commonly used time-domain and frequency-domain features are selected as table 3. [21][22]

Table 3: Fault Diagnosis Features Selection

Feature	Domain	Formula
Mean Value	Time	$\bar{x} = \frac{1}{N}\sum x_i$
Standard Derivation	Time	$\sigma = \sqrt{\frac{1}{N}\sum (x_i - \bar{x})^2}$
Skewness	Time	$\frac{1}{N}\sum \frac{(x_i - \bar{x})^3}{\sigma^3}$
Kurtosis	Time	$\frac{1}{N}\sum \frac{(x_i - \bar{x})^4}{\sigma^4}$
Root Mean Square (RMS)	Time	$\sqrt{\frac{1}{N}\sum x_i^2}$
Maximum	Time	$\max \lvert x_i \rvert$
Minimum	Time	$\min \lvert x_i \rvert$
Crest Factor	Time	$\frac{\max \lvert x_i \rvert}{\sigma}$
Logarithmic Average	Time	$\frac{\sum \log(x_i + 1)}{\log(\sigma)}$
Mean Value	Frequency	$\bar{f} = \frac{1}{N}\sum f_i$
Standard Derivation	Frequency	$\sigma_f = \sqrt{\frac{1}{N}\sum (f_i - \bar{f})^2}$
Maximum	Frequency	$\max \lvert f_i \rvert$
Minimum	Frequency	$\min \lvert f_i \rvert$

3.4 Experiment Result and Analysis

After data process and feature extraction, a SVM classification model is trained for fault diagnosis. For comparision, we train several models on dataset modified using random over-sample, random under-sample and SMOTE.

The classification result is shown in table 4. As we can see, the training accuracy and test accuracy of our proposed DCGAN structure show better performance than other approaches.

Table 4: The Fault Diagnosis Classification Results

Method	Training Samples	Training Accuracy	Test Accuracy
None	11870	90.9857% (10800/11870)	82.4167% (989/1200)
ROS	28480	95.2107% (27116/28480)	82.5% (990/1200)
RUS	5879	92.5838% (5443/5879)	77.6667% (932/1200)
SMOTE	28480	95.3722% (27162/28480)	83.75% (1005/1200)
DCGAN based Generation	27934	**95.654% (26720/27934)**	**86.3333% (1036/1200)**

4 Conclusion

In this paper, a novel approach for fault diagnosis with imbalanced dataset is proposed. A new DCGAN model is designed and applied on raw and imbalanced vibration signals. A SVM classifier is trained on the original dataset and the complemented dataset and the results verify the effectiveness of our generative model.

While regular ROS or RUS can not enrich or even eliminate the information for classification, SMOTE approaches are based on local information and DCGAN methods are able to learn from the overall class distribution. Our proposed approach is demonstrated to achieve a better performance than other methods and can be applied for imbalanced fault diagnosis problems.

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