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A GAN-based Method for the Enhancement of Phase-Resolved Partial Discharge Map Data

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Abstract:

Partial discharge (PD) is one of the most important indicators of an impending failure in electrical power system components. The advantages of PD are: first, active maintenance at the very early stage; second, prevent the expensive interruptions in the supply of power; third, reduce the risk of catastrophic failures. The patterns of Phase-resolved partial discharge (PRPD) demonstrate the behaviors of PD. However, the challenges of recognizing the patterns of PRPD remain. Data inadequacy, noise in collected data, as well as differences introduced by different types of detection equipment, could inevitably lead to the deterioration of accuracy. Hence, this paper proposes a GAN (Generative adversarial network)-based method for the PRPD data enhancement. Specifically, we first build our method based on the auxiliary classification adversarial neural network (Auxiliary Classifier GAN, ACGAN) and train the model with four classic PD datasets. Next, we adopt three classic convolutional neural network models LeNet-5, AlexNet, and VGG-16, to validate our method. The results show that our proposed ACGAN-based PD data enhancement method generates a large amount of high-quality data, improving the recognition accuracy effectively. Thus, our method provides an effective solution for this task.

Keywords*: Partial discharge, Deep learning, Pattern recognition Data enhancement, ACGAN.*

I. INTRODUCTION

The interruption of the power transmission system often cuts off industrial production and causes inconvenience to people's daily life, thus resulting in huge economic losses[1-2]. Therefore, maintaining the electrical power system components, monitoring the high-voltage equipment, and detecting the safety of the power grid, are important tasks for electrical engineers [3]. During the past decade, the detection of PD has been widely used in the field of power equipment maintenance and diagnosis [4]. The type of partial discharge defect is closely related to the severity of partial discharge. Therefore, the effective identification of partial discharge defect types can provide important information for partial discharge risk assessment.

The phase-resolved partial discharge (PRPD) pattern is the mainstream feature representation method currently. The feature-evident PRPD pattern can be identified by empirical approaches. With the concept of

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ubiquitous power Internet of Things, different information channels are used to collect PRPD data. However, the PRPD data collected by various information channels is hard to use directly, often consisting of noise and redundancy. Hence, we need to build a model with high recognition precision that can automatically identify and classify the types of partial discharge defects. Hence, we need to build a model to automatically identify and classify the types of partial discharge defects while excluding the negative effects of the sourced data.

Pattern recognition can achieve timely identification and classification of PD types, improving the efficiency of power equipment maintenance. In the past few years, deep learning has achieved significant break-through in many fields. We witness the deep learning technique gradually replace the conventional methods, especially in pattern recognition tasks [5]. Deep neural networks heavily reply on large batches of samples for training [6]. In the past few years, deep learning has achieved significant break-through in many fields [5,7-9]. However, in rea-world, it is difficult to obtain large-scale, high-quality, and relatively uniform labeled datasets. We summarize the main reasons as follows: 1) In practice, different equipment could be used to obtain the data, which inevitably lead to the variations of collected data; 2) High acquisition costs also make the acquisition of datasets very difficult. Aim to solve these issues, we propose to apply data enhancement technique to obtain high-quality data.

The conventional data enhancement approaches mainly depend on affine transformations and image processing technique, such as rotation, scaling, displacement, lighting color transformation, contrast transformation, and noise addition, etc. For example, Bjerrum et al. [10] use affine transformation to generate new samples, however, this method based on geometric transformation and image manipulation did not fundamentally solve the issue of data insufficiency and poor data quality.

Compared with traditional methods, data enhancement algorithms based on deep neural networks can achieve better results [7, 11]. Literature [12] proposes the Faster-RCNN algorithm, which fuses hidden targets threatening the safe operation of power grids with background images, to achieve data enhancement. Reference [13] proposes to use Convolutional neural networks (CNNs) for data enhancement. Literature [14] uses GAN to generate a small number of faulty data, combining with stack noise reduction self-encoding network, to improve the unbalanced fault data in motor bearings. Literature [15-19] are some other neural network-based methods for power grid detection. Although the above-mentioned research has achieved certain improvement, these algorithm models can learn only a single type of data at one time. Nevertheless, PD data sample sets containing multiple types, has to be to learned class by class, generating corresponding classes of enhanced sample sets. Unavoidably, the generation efficiency becomes low.

It is worth noting that research on data enhancement methods in the field of PDPR of power equipment is rare, whether traditional methods or deep neural networks-based data enhancement algorithms. To the best of our knowledge, we are the first to present an ACGAN-based PD data enhancement method.

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Compared with the above-mentioned methods, our approach can obtain the potential distribution of sample data more accurately. More importantly, our model generates multi-category partial discharge data based on the given label, thus realizing the enhancement of the data set more efficiently. Three classic convolutional neural networks, LeNet-5, AlexNet, and VGG-16, are applied to verify our proposed method.

II. PRPD DATA ENHANCEMENT METHOD

2.1 Generative Adversarial Network

GAN (Generative Adversarial Network) is a generative deep network model that learns data distribution through contest. The structure of GAN is shown in Fig 1. It is composed of two parts: the generation network G (Generator) and the discriminant network D (Discriminator). Given an distribution P(z) in a low-dimensional space z, such as the standard normal distribution N (0, 1), the generating network constructs a mapping function G: z→x. The discriminating network is used discriminate whether the input is from the original dataset or is generated by the network. G inputs noise z, and then outputs the generated image data; D can input data that is from either the original dataset, or the constructed data. Finally, the probability is calculated.

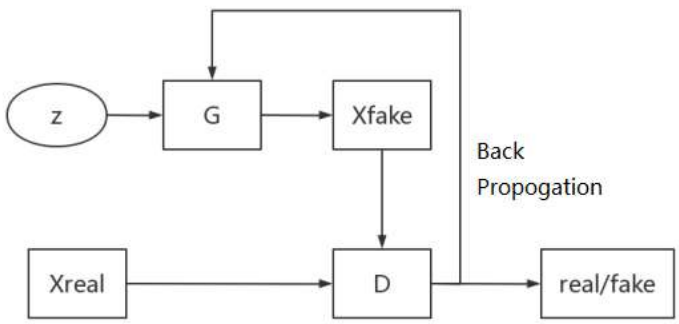

Fig 1: The structure of GAN

The training of G and D is a process of contesting: G attempts to deceive D, while D continuously improves the discrimination ability to prevent being deceived by the data synthesized by G. Theoretically, the final data distribution P_g and the original data distribution P_{data} can be equivalent. In other words, the goal of training is to make the distribution of G(z) and the distribution of the original data P_{data} as close as possible.

Specifically, D aims to achieve a binary classification of input data. If the input is a real sample, the output of D is 1; if the input is a generated sample, the output of D is 0. While G aims to ensure the performance of generated data G(z) on D consistent with the performance of the original data on D. The loss function of G is demonstrated as equation (1):

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$$\min_{G} V_G(D,G) = \min_{G}[E_{z\sim P_z}[\log(1-D(G(z)))]] \tag{1}$$

By continuous learning, the data G(z) generated by D becomes closer and closer to the real sample, thus the discrimination of D to G(z) becomes more and more fuzzy. The loss function of D is illustrated as equation (2).

$$\max_{D} V_D(D,G) = \max_{D}[E_{x\sim P_{data}}[\log D(x)] + E_{z\sim P_z}[\log(1-D(G(z)))]] \tag{2}$$

The overall loss function of the GAN model is demonstrated as equation (3):

$$\min_{G}\max_{D} V(D,G) = \min_{G}\max_{D}[E_{x\sim P_{data}}[\log D(x)] + E_{z\sim P_z}[\log(1-D(G(z)))]] \tag{3}$$

Where x represents the original data; Pdata is the distribution of original data; z is the noise data; Pz is the distribution of the noise data; D(x) is the result from the discriminator; G(z) is the generated data.

2.2 CGAN (Conditional Generative Adversarial Network)

When processing data of multi-category, GAN could lose its direction during training, leading to instability and defects.

On the basis of GAN, CGAN adds category information, i.e., applying constraint y to guide the data generation process. CGAN can improve the stability of the network [11]. The loss function of the CGAN model can be demonstrated as equation (4):

$$\min_{G}\max_{D} V(D,G) = \min_{G}\max_{D}[E_{x\sim P_{data}}[\log D(x \mid y)] + E_{z\sim P_z}[\log(1-D(G(z \mid y)))]] \tag{4}$$

The constraint variable y is used as an additional input layer in generator. Also, y is combined with the generator's noise input P(z) to form a joint hidden layer; while in the discriminator, y and the original data x are also used as input of the discriminant function. After the above-mentioned process, the network combines z and x with y, respectively. The combination is used as the input of both the generator and the discriminator for training. The structure of CGAN is shown in Fig 2, where the condition information y could be any supplementary information, such as class labels, data of other modality, etc.

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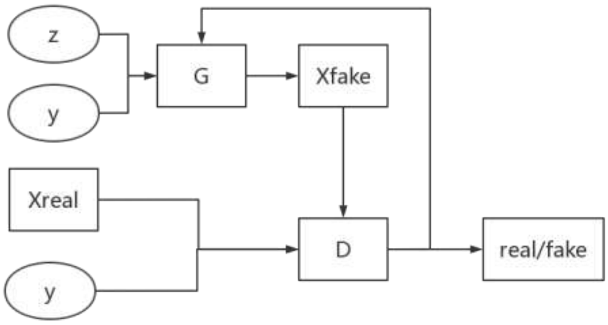

Fig 2: The structure of CGAN

2.3 ACGAN (Auxiliary Classifier GAN)

Auxiliary Classifier GAN (ACGAN) is another variant of GAN, which can apply data labels as part of the input to optimize the performance of the model. In ACGAN, in order to help the generator to generate data according to the label category, the discriminator of ACGAN not only determines whether the input data is the generated, but also uses an auxiliary classifier to identify the type of the data. In other words, the output of the discriminator is divided into two parts, pseudo discrimination and class categorization. Correspondingly, the data input by the generator has to include pictures and tags, hence, specific generated pictures can be obtained by changing the input tags.

The structure of ACGAN is shown in Fig 3. The generation network G contains two inputs, the label classification data c and random noise z. The generated data is Xfake. For the discrimination network D, two types of information are expected. One is to determine whether $P(s|x)$ is the distribution of the original data, the other is to detect the data category $P(s|x)$.

The loss function of ACGAN consists of two parts: the objective loss function LS that detect the source of the data and the loss function LC for data classification, demonstrated as (5) and (6), respectively:

$$L_S = E[\log P(S = real \mid X_{real})] + E[\log P(S = fake \mid X_{fake})] \tag{5}$$

$$L_C = E[\log P(C = c \mid X_{real})] + E[\log P(C = c \mid X_{fake})] \tag{6}$$

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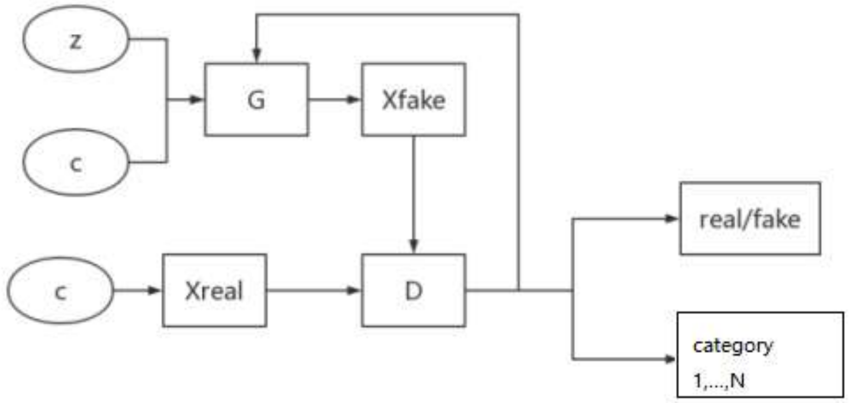

Fig 3: The structure o ACGAN

Hence, the entire optimization process maximizes L_C+L_S for the discriminant network *D* and maximizes L_C-L_S for the generation network *G*.

III. THE TRAINING PROCESS OF OUR DATA AUGMENTATION NETWORK

In this paper, we adopt an alternate optimization method during the training of ACGAN. We discuss the details of the training in this section. The first step is data generation. The generation network and the discriminant network optimize the opposite objective functions to achieve a balance in the constant contest. Specifically, we have to use the partial discharge data to train the AGCAN. The types of partial discharge in the sample consist of corona discharge, insulation discharge, suspension discharge, and free particle discharge. The details of the associated labels are listed as follows: corona discharge is tagged as 0, insulation discharge is tagged as 1, suspension discharge is labeled as 2, and free particle discharge is labeled as 3. We conduct the one-hot encoding on the label c, demonstrated in (7):

$$c = \{[1,0,0,0],[0,1,0,0],[0,0,1,0],[0,0,0,1]\} \tag{7}$$

Next, we use the generating network G to capture the distribution of sample data x. Specifically, we collect m samples with noise from the distribution of sample data x, obtaining random noise from the m samples:

$$z = \{z_1, z_2, \ldots, z_m\} \tag{8}$$

Also, we need to input random noise z and label data c into the generating network G at the same time to generate similar sample data:

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$$X_{fake} = G(z,c) \tag{9}$$

The loss function of the generated network G is shown in equation (10):

$$L_G = \max_G [E_{c\sim P_c}[\log(1 - D(G(z,c)))] - E_{z\sim P_z}[\log(1 - D(G(z,c)))]] \tag{10}$$

We then use the generated sample data, the generated data X_{fake}, and the label information c as inputs for the training of the discriminant network D. The loss function of D is shown in equation (9):

$$L_D = \max_D [E_{x\sim P_{data}, c\sim P_c}[\log(D(x,c))] + E_{c\sim P_c, z\sim P_z}[\log(1 - D(G(z,c)))]] \tag{11}$$

ACGAN not only needs to discriminate the data authenticity but also needs to classify the generated data.

Here, we suppose that after training, the generative network has learned the distribution of the real data. Therefore, in this paper, we would not need to train the generative network anymore. We ensure the generated data and the generated data work together as a data provider to train the classification network. The biggest advantage of the above-mentioned step is that it is not necessary to build a new classification network singularly. And more importantly, the discrimination network is trained directly as a classifier. The detailed process is demonstrated in Algorithm 1.

Algorithm 1 PRPD data enhancement model training algorithm
Parameter setting: Initialization. Generate initial network parameters wG, counter network initialization wD, and iteration number M; For Number in *M*: 1) Obtain the original PRPD sample data x, construct data label c, and obtain random noise z; 2) Calculate the loss function of the generator; $L_G = \max_G [E_{c\sim P_c}[\log(1 - D(G(z,c)))] - E_{z\sim P_z}[\log(1 - D(G(z,c)))]]$ 3) Update the generated network parameters wG via the gradient descent; $w_G \leftarrow w_G + \eta \nabla \overline{V}(w_G)$ 4) Input the original PRPD sample data x to generate Xfake and lable set c; 5) Calculate the loss function of the discriminant network; $L_D = \max_D [E_{x\sim P_{data}, c\sim P_c}[\log(D(x,c))] + E_{c\sim P_c, z\sim P_z}[\log(1 - D(G(z,c)))]]$

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6) Update the adversarial network parameter w_D via the gradient descent;

$$w_D \leftarrow w_D + \eta \nabla \overline{V}(w_D)$$

End For

IV. DATA ENHANCEMENT RESULTS AND ANALYSIS

4.1 PRPD Distribution Spectrum

The PRPD pattern is a widely used partial discharge mode, which is also known as the φ-q-n mode. This model describes the relationship among the power frequency phase φ(0-3600), the discharge amplitude q, and the number of discharges n. Often in a spectrum, the horizontal axis represents the power frequency phase φ, while the vertical axis represents the UHF signal amplitude l. To ensure the diversity and complexity of our data, we conduct our data collecting experiment on various devices under different scenarios, illustrated in Fig 4.

Specifically, four different types of PD are conducted (from the first row to the fourth row in Fig 4), corona discharge, insulation discharge, floating discharge, and free metal particle discharge. The characteristics of each PD behavior are distinct. The phase-resolved pulse sequence (PRPS) of the corona discharge is mainly located at the peak of the applied voltage, and the amplitude is fairly high. The PRPS of the free metal particle discharge is scattered, the number of discharges is small, and the discharge volume is even and spreads over the entire phase. The PRPS of the insulation discharge is mainly located at the rising edge of the positive cycle and the falling edge of the negative cycle. The PRPS of the floating discharge is distributed at the peak of the applied voltage, forming a certain symmetry.

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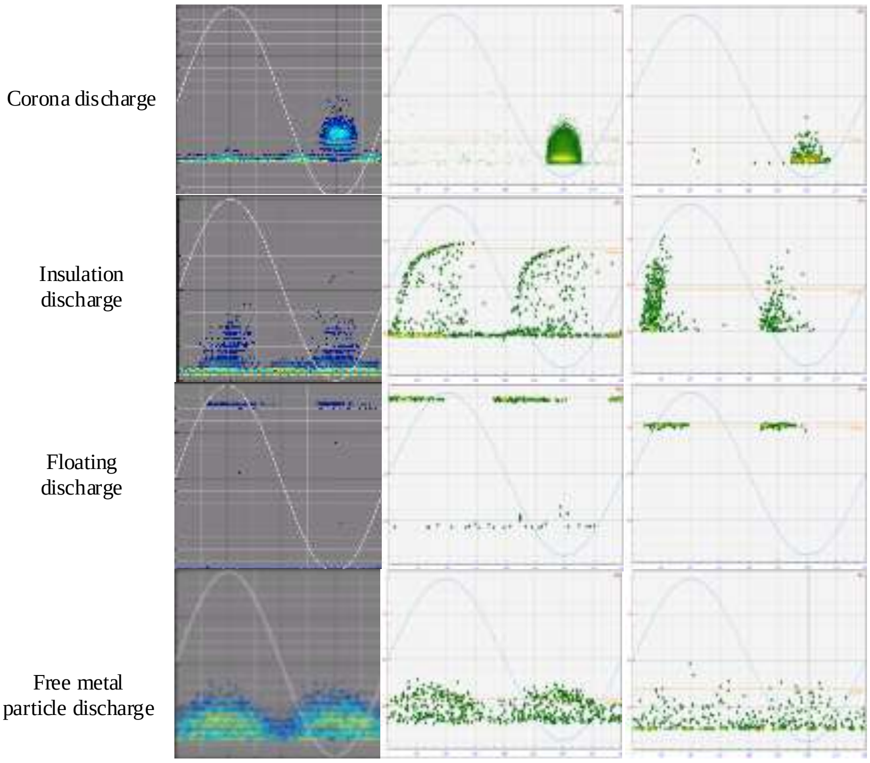

Fig 4: PRPD patterns collected under different devices and different scenarios

4.2 Our ACGAN Model

We train our ACGAN with four different types of PD defects data and their labels. After training, the new set consisting of four types of defects is generated through our ACGAN model. Specifically, in order to reduce the interference of irrelevant information, such as background and grid lines, we need to conduct preprocessing of the sample images before training, as shown in Fig 5.

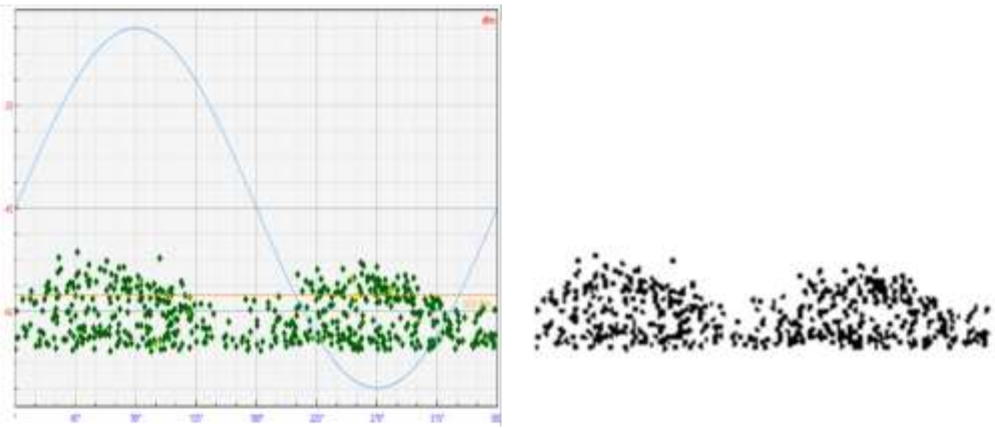

Fig 5: Preprocessing of sample images

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Both the generator G and the discriminator D adopt the CNN (Convolutional Neural Network). The convolution layer of generator G adopts a 5×5 convolution kernel to ensure that the detailed features of the image are fully extracted during the training process. To match the generation capacity of the generator, we again choose a 3×3 convolution kernel as the convolutional layer of our discriminator D. Particularly, in order to make the network more suitable for PRPD map training, we increase the number of convolutional layers and the number of channels on the basis of the original network structure. The detailed structure of our network is shown in Fig 6. At the same time, when building the network, we use batch normalization and ReLU activation functions between the convolutional layers to speed up the convergence while avoiding the gradient disappearance during training. In summary, the above-mentioned steps guarantee the continuous confrontation between the generator G and discriminator D.

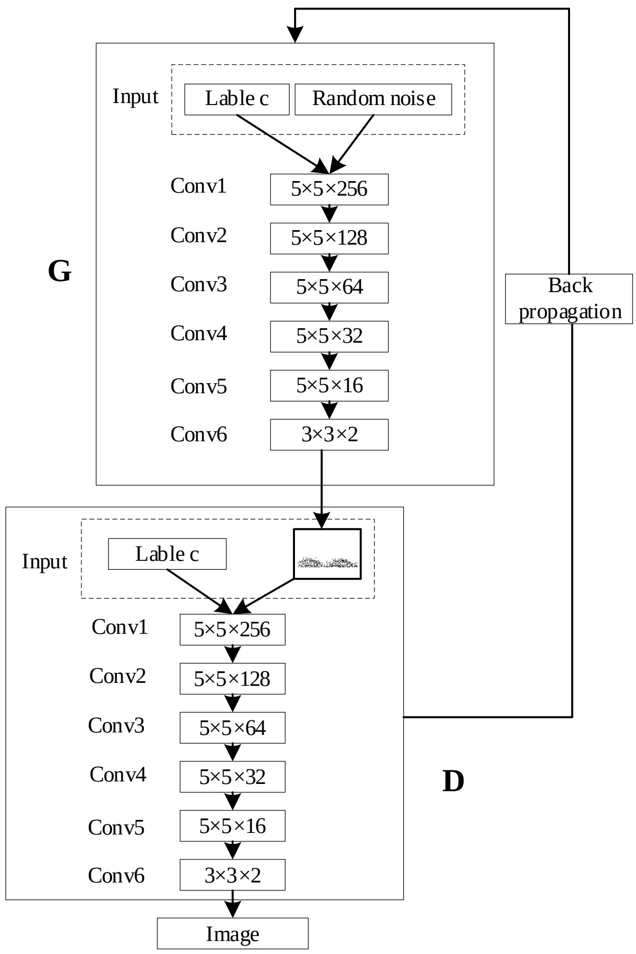

Fig 6: The detailed structure of our ACGAN

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4.3 Experimental Results and Analysis

The dataset applied in the experiment is an open-sourced PRPD pattern detection dataset, as shown in Fig 4. This dataset consists of four types of PRPD patterns with a total of 20,000 images. Especially, 12,000 of these images are for training images while 8,000 are for testing. Fig 7 is the generated data maps of the four PD defect types. We can notice that the images generated by our model is feature-distinctive. Obviously, the distribution characteristics of these maps are distinct.

To verify the effectiveness of data enhancement, we conduct three groups of comparison experiments to validate the classifiers trained on the data generated by different methods. Three different data enhancement implementations are:

(1) Baseline without any data enhancement (C);

(2) The original generative adversarial network (GAN);

(3) Our proposed ACGAN.

Finally, we apply three classic convolutional neural network models, LeNet-5, AlexNet, and VGG-16 to verify the results. We adopt Acc (Accuracy) as our evaluation metric. The experimental results are shown in Tables I, II, and III.

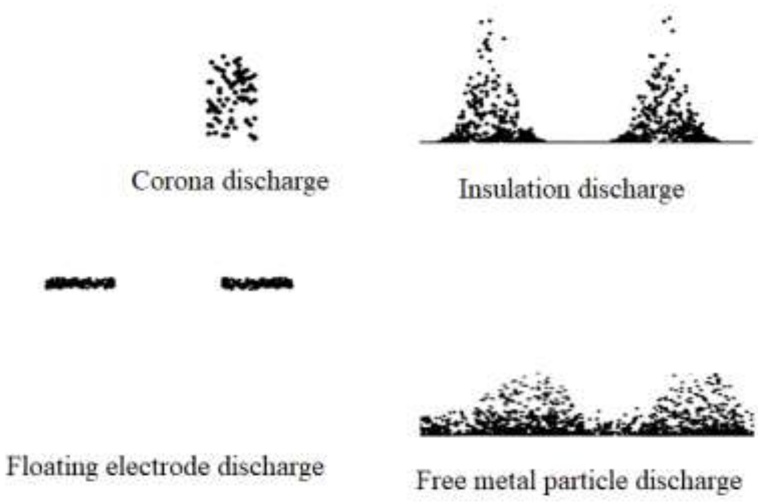

Fig 7: The generated sample of our model

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TABLE I. Accuracy (Acc%) of three data enhancement implementations on LeNet-5 classification task

Data Enhancement Implementation	Accuracy on Training Set (Acc%)	Accuracy on Testing Set (Acc%)
C	84.47	81.52
GAN	90.63	89.13
ACGAN	91.78	90.79

TABLE II. Accuracy (Acc%) of three data enhancement implementations on AlexNet classification task

Data Enhancement Implementation	Accuracy on Training Set (Acc%)	Accuracy on Testing Set (Acc%)
C	85.31	82.87
GAN	92.57	90.30
CGAN	94.91	91.63

TABLE III. Accuracy (Acc%) of three data enhancement implementations on VGG-16 classification task

Data Enhancement Implementation	Accuracy on Training Set (Acc%)	Accuracy on Testing Set (Acc%)
C	87.53	87.25
GAN	92.14	91.77
CGAN	95.73	92.86

From these experimental results, we can observe that our ACGAN easily outperforms the two baselines - C (baseline without data enhancement) and GAN. After data enhancement of our ACGAN, the accuracy of both the training set and the test set is noticeably improved. These comparisons demonstrate that the data enhancement achieved by our ACGAN advances the recognition accuracy when facing known samples. And more importantly, ACGAN also enhances the capability of recognizing unknown samples (a.k.a., samples that have not appeared in training) to a much more significant level.

The main reason could be that our ACGAN improves the generalization ability, thereby alleviating the occurrence of overfitting in training. Consequently, our ACGAN avoids the tough situation of performing excellently on the training set while performing poorly on the test set. This further demonstrates that the images generated by ACGAN share the same implications as the original images while maintaining the diversity of content. Our ACGAN ensures the quality of the generated data, as well as enriches the original data volume. Therefore, our proposed method provides a powerful solution for data enhancement of the

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PRPD map, showing practical significance when solving the recognition task of PRPD patterns.

V. CONCLUSION

PRPD maps are widely used in the field of electrical equipment detection or analysis. However, some disadvantages in the PRPD map data, such as the small size of the existed dataset, the redundancy in the dataset, and the low overall quality of the data, could be obstacles for detection. Moreover, these drawbacks lead to insufficiency of training samples and network overfitting during image classification and recognition. Hence, in this paper, we propose a GAN-based PRPD data enhancement method. The comparison results with other methods show that ACGAN can effectively improve the performance of the classifiers. More importantly, ACGAN ensures that the generated image data share similar implications and content diversity compared with the original data, verifying the feasibility and effectiveness of our proposed method.

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