Partial Discharge Pattern Recognition of Switchgear Based on Residual Convolutional Neural Network

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Abstract. The traditional switchgear partial discharge pattern recognition method lacks a certain generalization performance and the recognition accuracy is low, which is difficult to apply in practical engineering. In view of this, this paper proposes a switchgear partial discharge pattern recognition method based on residual convolutional neural network. By adding a residual module to the network to solve the problem of deterioration after the saturation of the network leads to the saturation of accuracy, and comprehensively utilize the shallow and deep features of switchgear partial discharge data fusion learning to achieve pattern recognition. In this paper, through partial discharge simulation experiments of different insulation defect types of switchgear and on-site detection of distribution stations, a sample database of partial discharge data of switchgear is constructed and analyzed. The experimental results show that the recognition accuracy rate of the proposed method is 96.06%, which is at least 20.22% higher than the traditional recognition methods, and with the increase of the number of samples in the training set, the recognition rate is greatly improved. The comprehensive use of the feature layer fusion module and the residual module significantly improves the generalization performance of the model, and it is more suitable for practical engineering.

1. Introduction
Switchgear is the main equipment in China's distribution network, and its operating status is closely related to the distribution network [1]. Since the power equipment enclosed in the cabinet will inevitably produce insulation defects after long-term operation, it will develop into equipment failure in serious cases, affecting the safe and reliable operation of the distribution network [2]. Partial discharge is an important manifestation of insulation defects in switchgears. The use of partial discharge live test data to identify patterns of equipment insulation defects can understand equipment defects and problems in advance, which is helpful for targeted testing and maintenance of equipment.

The traditional method of pattern recognition based on partial discharge detection data mainly uses expert knowledge, relies heavily on artificial experience, and lacks certain generalization performance [3]. In recent years, with the rapid development of deep learning, models such as Artificial Neural Network (ANN) [4], Support Vector Machine (SVM) [5], Convolutional Neural Network (CNN) [6], have been widely used in the field of partial discharge pattern recognition. The deep learning network is based on data driving, can learn data features autonomously, and has better data mining capabilities. Among them, convolutional neural networks are often used to process two-dimensional matrix data and are widely used in the field of image recognition [7]. The data used for the partial discharge
pattern recognition of the switchgear mainly includes the phase resolved pulse sequence (PRPS) and the phase resolved partial discharge (PRPD), which has a certain similarity with the two-dimensional image format expression.

At the same time, in the detection process, partial discharge of the switchgear will cause certain phase shifts and amplitude fluctuations in the detected data at different times, equipment, and operations. Due to its structural characteristics, the convolutional neural network has displacement and scaling invariance to the input data, which is more suitable for pattern recognition of the above-mentioned atlas data. However, literature [8] pointed out that the performance improvement of the convolutional neural network model mostly depends on the deep network structure, but as the number of network layers continues to increase, the performance declines. At this time, the network causes degradation problems such as information loss and gradient disappearance. In response to this problem, techniques including improving activation functions and using batch regularization have appeared to improve network performance, but they have not been completely resolved.

In sum, this paper proposes a partial discharge pattern recognition method for switchgear based on residual convolutional neural network. The problem of accuracy degradation of deep convolutional network is solved by adding residual module to the network. Firstly, a partial discharge data sample library of switchgear is constructed through partial discharge simulation experiments and live charging detection on the substation. After that, a convolutional neural network model based on residuals is constructed, and the pattern recognition is realized by fusing and learning the shallow and deep features of the PRPS data of the switchgear equipment. Finally, compare the recognition effect of the proposed method with other traditional recognition methods and the influence of the fusion of residual module and feature layer on the performance of the model. Experimental results show that the method proposed in this paper can improve the accuracy of partial discharge pattern recognition of switchgear and has better generalization performance and strong engineering application.

2. Sample database of partial discharge data
Through the partial discharge simulation experiment of the switchgear and the live detection of the partial discharge of the switchgear at the distribution station, the partial discharge data sample database of the switchgear is constructed.

2.1. Partial discharge simulation experiment of switchgear
Aiming at the types of insulation defects of switchgear equipment, this paper uses the switchgear real experimental platform to conduct simulation experiments. In this paper, four types of insulation defects are designed, including tip corona, particle discharge, floating potential and insulation type discharge. Among them, insulation type discharge includes air gap discharge and creeping discharge, a total of five defect models. Figure 1 shows the experimental wiring diagram. A total of 21459 PRPS data have been accumulated, including 4359 tip corona defect samples, 4500 insulation discharge defect samples, 5200 particulate discharge defect samples and 7,400 floating discharge defect samples.

![Figure 1. Switchgear partial discharge wiring diagram](image-url)
2.2. On-site live detection of distribution station
Through the monthly observation of the operation of the switchgear equipment in the substation, a large amount of on-site testing data has been accumulated. For the different interferences existing on the site of the substation, the time-difference localization method is often used to determine whether the detection signal comes from the internal defect of the equipment. Partial discharge data is collected after eliminating interference, and its main type is PRPS data. The data that detected partial discharge signals and confirmed insulation defects through disassembly included 10277 cases.

3. Partial discharge data pattern recognition

3.1. Convolutional Neural Network
The convolutional neural network can reduce the network parameters while improving the network training speed, and has the advantages of displacement invariance to the data. According to this, the convolutional neural network uses the input multi-dimensional data to simplify the process of manually extracting features, and is widely used in the field of pattern recognition [9].

The basic structure of convolutional neural network includes input layer, convolutional layer, pooling layer, fully connected layer and output layer. A common input of a convolutional neural network is an image represented by two-dimensional matrix data, and the hidden layer includes a convolutional layer and a pooling layer. Usually the convolutional layer and the pooling layer appear alternately, then connect several fully connected layers, and finally get the model output according to the classifier. The deeper layers of the convolutional neural network will make the training effect better, but the continuous increase will lead to the deterioration of the accuracy after saturation. Therefore, consider using the residual module to directly transfer the input information to the output ResNet network model. While protecting the integrity of information, it can simplify learning difficulty and goals.

3.2. Pattern recognition process
This paper provides a pattern recognition method for partial discharge data of switchgear based on residual convolutional neural network. The specific steps of pattern recognition for the partial discharge detection data of switchgear are as follows:

- Denoising the PRPS data. After removing the effects of white noise and narrow-band noise, the pre-processed two-dimensional matrix data is used as input data.
- Construct a convolutional neural network model based on residuals, extract low-level and high-level feature maps at the same time, initialize network model parameters, and use the training set for learning and training.
- Select the cross-entropy cost function, use the Adam optimization algorithm to dynamically adjust the parameter learning rate, and update the model parameters. Supervised fine-tuning through back propagation algorithm to optimize the model for pattern recognition.

4. Experimental results and comparative analysis
This paper is based on the convolutional neural network, using TensorFlow and Keras framework, using python to build a network model, and adding a residual module to the network to improve network performance. Based on the partial discharge detection data of the switchgear, that is, the PRPS pattern data, pattern recognition was carried out. Pattern recognition targets are divided into four categories: suspension discharge, tip discharge, insulation discharge and particulate discharge.

4.1. Network structure parameters
Different network structures will affect the recognition performance of the model. For different practical applications, the determination of the network structure needs to combine certain theoretical analysis and specific experimental observations, and finally select the appropriate structure and parameters. For the partial discharge detection data used in this paper, through experimental and
theoretical analysis, the appropriate network model is finally designed and the calculation parameters are determined. The convolutional neural network used in this paper is improved based on the LeNet-5 classic model. There are 13 layers in total, including five convolutional layers and corresponding pooling layers, and the number of fully connected layers is 1. The convolution kernel size of the network is $1 \times 13$, and the pooling kernel size is $1 \times 2$.

For the convolutional neural network model, the lower layer can extract low-level features such as the edge of the input data, and the higher layer can extract more abstract features. PRPS data includes partial discharge data corresponding to 50 power frequency cycles, including both partial discharge characteristics under a single cycle and overall characteristics under multiple cycles. In order to fully learn the local features and overall features of the sample data, this model connects the output of the first convolutional layer and the output of the last convolutional layer to the fully connected layer, and then outputs it to the classifier for final pattern recognition. The convolutional neural network model used in this paper includes three residual modules and one fusion operation. The specific model structure is shown in Figure 2. At the same time, the introduction of dropout for the model, by randomly retaining the weight of the hidden layer nodes according to the proportion during model training, without updating, to prevent the model from overfitting.

![Figure 2. CNN network architecture of pattern recognition](image)

4.2. Analysis of results

The experiment uses five-fold cross-validation method, the training set is 21826 pieces of PRPS pattern data, and the test set is 5455 pieces. Among them, 60% came from partial discharge simulation experiments, and 40% came from on-site testing of distribution stations. The sample data comes from different devices of the same defect type, the same test location of the same device, and different discharge times of the same device.

In order to observe the feature learning of the original samples by the network used in this paper, t-distributed stochastic neighbor embedding (t-SNE) is used to reduce the data to two-dimensional plane for visualization. Figure 3 is the distribution of sample features after dimensionality reduction, where 3 (a) is the original data, 3 (b) is the feature map using the residual convolutional neural network for feature learning, and the output after the third convolution layer. It can be seen from Figure 3 that some insulation defect categories in the original data have a certain degree of coincidence and poor separability. Through model learning and the use of convolutional layers to extract the characteristics of samples, the separability of various types of insulation defects is improved, and different categories are basically clustered together, and the degree of overlap is reduced. By using the t-SNE method to reduce the dimensionality and visualize the data, the distribution of data features can be observed and recognized, and the learning capabilities of further networks can be understood.

Based on the constructed residual convolutional neural network model, the partial discharge detection data is subjected to pattern recognition. The results are shown in Figure 4. Four types of defects were identified in the experiment, including tip corona discharge, metal particle discharge, insulation discharge and floating electrode discharge. The average recognition accuracy of the model used in this paper is 96.06%. Except for cutting-edge corona, the accuracy rates of the other three categories are all over 95%.
4.3. Comparison of classification models
The model proposed in this paper is compared with the traditional classification model to judge the performance of this model. Comparison models include support vector machines (SVM), back propagation neural networks (BPNN), and random forests (RF) based on radial basis functions. The confusion matrix corresponding to the three models is shown in Figure 5. The recognition rate of the support vector machine model is 75.84%, the recognition rate of the back propagation neural network model is 64.45%, and the recognition rate of the random forest model is 75.64%. It can be seen from Figure 5 that the data-driven model based on artificial intelligence is significantly better than SVM, BPNN and RF for pattern recognition of switchgear equipment. In each defect category, the recognition accuracy has been significantly improved, especially the insulation discharge and particle discharge.

The data-driven model is based on data, and the number of samples is an important factor influencing the performance of the model. Therefore, by changing the number of samples in the training set, observe and analyze the dependence and recognition performance of different algorithm models on the data. The number of training sets is gradually reduced according to a step size of 3000. The above four models are used for training respectively, and finally the same test set samples are
used for testing. Compared with the other three network models, the model proposed in this paper has improved the average recognition rate. The specific improvement effect is shown in Figure 6.

![Figure 6](image)

**Figure 6.** Increased accuracy of CNN compared to other models under different train samples

It can be seen that when the number of samples in the training set is 6000 to 18000, the performance of the model used in this paper gradually improves with the increase of the data set. When the sample size is less than 6000, the recognition rate of the model proposed in this article is slightly higher than other models. The larger the number of samples in the training set, the greater the performance gap between the model used in this paper and other comparison models, which shows the important impact of data quality on the performance of the model and the significant recognition effect of the model in this paper. Based on the data-driven technology of artificial intelligence, under the background of massive data accumulation, the model's generalization ability is stronger, and it has better engineering application effect.

### 4.4. Comparison of network structure models

Aiming at the proposed network structure model, it is compared with convolutional neural network without residual module, convolutional neural network without integrated low-level features and abstract features, and the impact of each structure on network performance is analyzed. The comparison network identification effect is shown in Table 1. The effect curves of the three model training sets and test sets with the number of iterations are shown in Figure 7.

**Table 1.** Comparison of performances under different network structures.

| Structure          | Recognition accuracy rate/% |
|--------------------|-----------------------------|
| Model 1: Residual module | 93.07                       |
| Model 2: Feature layer fusion | 90.34                       |
| Model 3: Residual+Fusion    | 96.06                       |

![Figure 7](image)

**Figure 7.** Training and testing results under different models

It can be seen that the model recognition effect used in this paper is superior to the other two models. Using the residual module avoids the loss of information and simplifies the training difficulty.
By synthesizing the feature maps of different convolutional layers, the sample features can be learned more comprehensively, which reduces the misjudgment of the pattern recognition of switchgear equipment and improves the generalization performance of the model as a whole. This article uses the method to comprehensively use the residual module and the feature layer fusion module, which significantly improves the model performance.

5. Conclusion
In this paper, a partial discharge data sample library for switchgear is constructed through partial discharge simulation experiments and live electrification detection of distribution stations, and a method for pattern recognition based on partial discharge data of switchgear is proposed. The method constructs a residual convolutional neural network model and combines the low-level and high-level features of the network to perform pattern recognition on the PRPS data. It integrates the residual module and comprehensively learns the shallow and deep features of the input data, which improves the recognition rate by more than 20%, which is significantly better than traditional recognition methods. With the increase of sample data, the method proposed in this paper has more recognition rate than traditional methods, and is more suitable for engineering applications in the context of big data. The experiment compares and analyzes the influence of the fusion of the residual module and the feature layer on the performance of the model. The results show that the model proposed in this paper can learn the features of the sample comprehensively, improve the generalization performance of the model, and can be effectively used for the partial discharge pattern recognition of switchgear.

Acknowledgments
This work is supported by Science and Technology Project of China Southern Power Grid Company (Research and Application of Key Techniques for Standardization and Efficient Processing of Distribution Equipment Condition Detection Data, No.082100KK52190004).

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