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Research Article

Inspection Technology of Power Communication Network Based on Machine Vision Graphic Recognition

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With the continuous improvement of maintenance management level and the continuous progress of fault diagnosis technology, equipment condition maintenance has also gradually entered the stage of market use. Especially, in the electric power industry, with the development of the research and production practice of condition maintenance theory, its application areas are becoming more and more extensive. In recent years, with the increasing popularity of computer network technology, the development of communication network monitoring technology has also made great progress. However, the monitoring of communication equipment in China is still in the primary stage, and the complexity of the equipment and the diversity of the equipment make the research on its condition detection a very challenging task. The study introduces the application of computer vision-based graphic recognition technology in power communication networks, which includes two modules: FasterR-CNN and RPN. The model provides real-time monitoring of various performance indicators of power communication network equipment and feedback on its working status, repairs the equipment according to the monitoring results, timely detects potential safety hazards, and makes a maintenance cycle reasonable planning, ensuring the normal operation of the communication network.

1. Introduction

Power communication network is different from general communication network; it is specially designed for power system service, and the services it carries are mainly voice, video, data signal, multimedia conference, remote control, and so on [1]. With the continuous development of power system, people's production and life are increasingly affected by the power system, and higher requirements are put forward for the stability of the power grid. In addition, the development of the power industry and the informationization process of the power industry are increasingly accelerated, and higher requirements are put forward for the emergencies in power generation, transmission, and distribution. Therefore, whether the power communication network equipment can work properly has a nonnegligible role in the reliability of the power grid [2].

Reasonable maintenance time is the key to ensure safe and reliable operation of the power grid. There are various methods of power communication network equipment maintenance, among which are the following:

(1). Regular inspection: this can be done to find faults in time during the inspection process and to ensure the normal operation of the equipment to a certain extent, thus avoiding or delaying the occurrence of faults. On the contrary, because this maintenance method requires an inspection of all the equipment every once in a while, so equipment that does not require maintenance is bound to be repaired, which will not only cause a waste of various resources but also the maintenance method will have a certain impact on the equipment, and even increase the chances of failure of the equipment.

(2). Reliability maintenance: the method is based on the inherent reliability of the equipment to be serviced so that the maintenance interval between various devices is reasonably allocated [3]. However, due to the current level of research on the reliability of communication devices and their own characteristics, it is difficult to find a reasonable reliable calculation method, and it is inevitable that some sudden failures will occur in the process of use.

(3). Condition inspection: condition inspection refers to judging the current working status of communication devices, using advanced condition monitoring technology to discover the harbingers of faults and to determine the composition and severity of faults, so as to decide the maintenance time of each communication device. Offline diagnosis refers to determining whether there is a fault in the equipment by using information such as the operation records, operation time, and maintenance records of the equipment; the online monitoring system can monitor the working status of the equipment in real time and can discover the fault in the shortest possible time and deal with it according to the working conditions of equipment.

From the above analysis, it can be seen that the use of state maintenance method for power communication network devices has the following advantages:

(1). Reasonable arrangement of maintenance cycles and reduction of maintenance costs: using the state maintenance technology, the maintenance time can be reasonably arranged according to the different conditions of the equipment, thus greatly reducing the major failures of the equipment and reducing the various losses caused by equipment failures. There is no need for any maintenance of the equipment, reducing the funds and manpower required for conventional maintenance methods and reducing maintenance costs [4].

(2). Extend the service life of equipment: due to the characteristic and structural features of the communication equipment itself, there is a possibility that, in every maintenance, there will be an impact on its components, and frequent maintenance will shorten the service life of the whole equipment; in addition, the equipment failure caused by the extended maintenance cycle will also have a negative impact on the operation of the whole communication network. The use of condition maintenance mode can effectively prevent the generation of faults and extend the service life of the device.

(3). Ensure the normal operation of the power communication system: the normal operation of the power communication network is closely related to the communication equipment, and sometimes, the failure of one communication device can cause the paralysis of the entire communication system. Therefore, a condition check of communication equipment will enable the timely detection of existing safety hazards and prevent the further spread and emergence of accidents, so as to ensure the normal operation of the communication network.

The monitoring system developed in this study is the most advanced monitoring technology, which provides technical assurance to ensure the safety, stability, and long-time use of equipment [5–8]. With the continuous development of power grid construction, the maintenance of power communication network equipment is also gradually changing from the conventional maintenance mode to condition monitoring. However, China's power communication network equipment operation condition monitoring technology is still immature, so the application prospect of this project is very broad.

2. Introduction to Related Theories

2.1. Neural Network Theory. A neural network is a complex network system consisting of many simple multiple processing units, which simulates the characteristics of the animal nervous system and performs parallel data processing in a distributed manner with high memory and associative ability. Neural network is a system with learning function, which can achieve high level of knowledge to some extent [9]. It has two types of learning methods, one is supervised learning and the other is unsupervised learning. A neural network has a learning function similar to that of the human brain, and it contains a three-layer structure of input, implicit, and output layers, which is capable of fitting an arbitrary nonlinear continuous function accurately, thus providing mathematical guarantees for the application of neural networks in time-series forecasting [10]. With implicit expression of nonlinear relations, better fault tolerance, higher prediction accuracy, and better dynamic adaptability, the neural network forecasting method is suitable for intelligent prediction of complex nonlinear systems.

2.2. Machine Vision Theory. Next, machine vision will become the next development direction of artificial intelligence. Machine vision is to measure and judge objects by mechanical eyes, that is, to obtain external images by mechanical imitation of human eyes. It has a wide range of applications, including transportation, scientific research, meteorology, public security, agriculture, industry, and aerospace [11]. For example, in large-scale industrial production, using manual vision to check the quality of products, its accuracy and efficiency are very low, while using machine vision technology can greatly improve the efficiency and automation level of production, while in the sorting, it is necessary to classify products with the help of machines, which can not only save a lot of manpower and resources but also greatly improve production efficiency and reduce production costs. And in the field of transportation, automatic driving technology is based on machine vision to achieve the detection and identification of people and vehicles, so as to improve road safety. Machine vision will play an important role in all aspects of the national economy.

2.3. Image Processing Theory. There are many contents of image processing, which can be divided into three levels of image preprocessing, image analysis, and image understanding according to its abstraction level, research methods, etc.

2.3.1. Image Preprocessing. The main content of image preprocessing is the change that occurs between different images. It mainly consists of image smoothing, denoising, and edge sharpening to highlight features of interest in the image and the abatement of unnecessary features such as noise points.

2.3.2. Imaging. Image processing techniques are used to detect and measure targets in images, to obtain their objective information, and to describe them [12]. If image preprocessing is the process of conversion from image to image, image analysis is the process of conversion from image to data.

2.3.3. Image Comprehension. The core of image comprehension is to analyze the image, conduct an in-depth study of the properties of each object and their interconnection, then obtain an understanding of its connotation and interpret its original objective situation, and thus provide a basis for decision-making.

The processing of digital images can be divided into two types: spatial domain and transformation domain.

(1) Space Domain Measurement. The null-domain approach treats an image as a collection of pixels in a plane and processes it accordingly. There are two main types of null domain methods: (1) adjacency processing contains gradient operation, Laplace operator operation, smooth operator operation, and convolution operation and (2) point processing contains grayscale processing, area, perimeter, and volume operations.

(2) Transformation Domain Method. The change domain processing technique in digital image processing is to transform the image orthogonally to obtain an array of change area coefficients, then perform a variety of processing [13], and finally inverse transform it to the spatial domain to obtain the corresponding processing effect, for example, filtering and data compression.

3. Application Method Design

The application method design is described as follows.

3.1. Principles of Parameter Selection for the Inspection Index System. To accurately identify the state of the equipment, it is necessary to obtain the state information of the equipment. Therefore, in the inspection, it is necessary to monitor and obtain sufficient state parameters of equipment. The first thing to know about monitoring a special instrument is what parameters indicate its status; the relationship between each parameter and the status of equipment is close [14]. Generally speaking, once the state of the device is changed, regardless of the cause, it will have an impact on the state of the device. The relationship between the change of the state of the device and the state of the device becomes the focus of this paper's research.

The change in the working condition of the device can reflect the working condition of the device, which has a certain correspondence with the working condition of the device [15]: $F = (\alpha 1, \ \alpha 2, \ \ldots)$, where F is the operating condition of the device, $\alpha 1$, $\alpha 2$, ... are the operating parameters of the device. Equipment condition forecasting is to infer the condition of the device based on the changes of the operating parameters $\alpha 1$, $\alpha 2$, ... There are many state parameters that can be used to describe the operating condition of a device, and it would be very complicated and inefficient if all of them were. Therefore, before establishing an efficient and accurate inspection system, the screening of condition parameters must be carried out, which requires clear screening objects and guidelines. A large number of practice have proved that the following principles must be followed when selecting equipment status parameters.

(1) High sensitivity: the selected parameters have a high sensitivity, in the case of very small changes in the state of the equipment, all lead to fluctuations in the state parameters
(2) Scientific: the meaning of the state parameters and evaluation basis should be reasonable and the selected state parameters should reflect the working state of the grid equipment, shall not omit the key parameters, and shall not contain invalid parameters
(3) Realizability: the selected parameters not only are limited to the theory but also can be obtained by certain methods

3.2. Establishment of Inspection Index System. There are many kinds of performance indicators of power communication network equipment, and some of them are listed in the following table. If all the above parameters are used for this system, it will cause the complexity, scale, and inefficiency of the system, thus making the performance of the whole system worse [16–18]. According to the above principles, only the parameters that best reflect the operating conditions of the grid equipment are predicted, and participation in the condition maintenance system not only saves resources and reduces development costs but also improves the efficiency of the system and is more practical.

After selecting the performance parameters, it is necessary to categorize them. The system is graded according to an hierarchical structure, and with the help of references and experts, the devices are divided into three main categories: optical port, electrical port, and device environment. Therefore, according to the components, the parameters are divided into three parameters: optical port parameters, electrical port parameters, and device environment parameters.

In this study, a large amount of information was consulted and the data obtained from the network management system was compared with the data obtained, and finally, the data that needed further processing and participation in maintenance decisions were derived.

3.3. Inspection Process Architecture. After the establishment of the monitoring indicator system, this section details the structure of the monitoring model. The overall flow of the inspection model described in this study is shown in Figure 1. The core idea of the approach is that, first, the performance parameters of equipment involved in the maintenance operation are identified and classified according to their respective interfaces and types. Subsequently, machine vision technology is used to output the inspection images and apply them to the inspection images. By graphical processing of the inspection images, the performance parameter evaluation of the inspection images is finally derived. Then, according to the given weight calculation method, the weighting operation is performed for each parameter [19], and the current score of each device is calculated according to the existing state integral algorithm. Finally, the corresponding monitoring report is generated based on the evaluation results of each parameter.

3.4. Patrol Identification Structure. The inspection identification structure adopts the FasterR-CNN architecture, which is shown in Figure 2. The basic architecture of FasterR-CNN includes (1) RPN (Region Proposal Network) and (2) FastR-CNN. In the detection of electrical equipment, the original image is extracted by using the FasterR-CNN shared network, and then, it is input to RPN and FastR-CNN for processing.

3.4.1. The Image Processing Process of RPN Network in Power Communication Network. RPN network, also known as region suggestion network, mainly uses its own training trials to generate candidate regions and then sends the candidate regions as training samples to FastR-CNN for training and testing.

RPN is a fully convolutional neural network, which consists of a convolutional layer and two fully connected layers [20]; it is a convolutional layer structure, and the latter two fully connected layers have different functions; one is a cls layer, which is used to generate the object location with suggestion.

RPN processes the dataset in the following way:

(1) irst is generating about 20,000 anchors on the original image using a mapping mechanism and then obtaining anchor classification information using IoU (Intersection-over-Union) with artificial tagging (GroundTruth). The following are the main processes:

The feature map is scanned using a 3×3 sliding window, and 9 (k in Figure 2) are generated in one scan ($128{,}256 \times 256{,}512 \times 512$) using 3-scale relationships (1 : 1, 1 : 2, 2 : 1) with the center point of the window as the reference. Based on this, the feature maps generated after shared convolution by FasterR-CNN were scanned, and the 9 recommendation frames corresponding to the centroids were mapped to the original images.

The RPN was trained by backpropagation and stochastic gradient reduction (SGD), in which 256 were randomly selected from 2000 candidate frames, and the number of target objects and the number of backgrounds were equally distributed, but if 128 could not be reached, they were replaced with backgrounds, thus greatly improving the recognition accuracy.

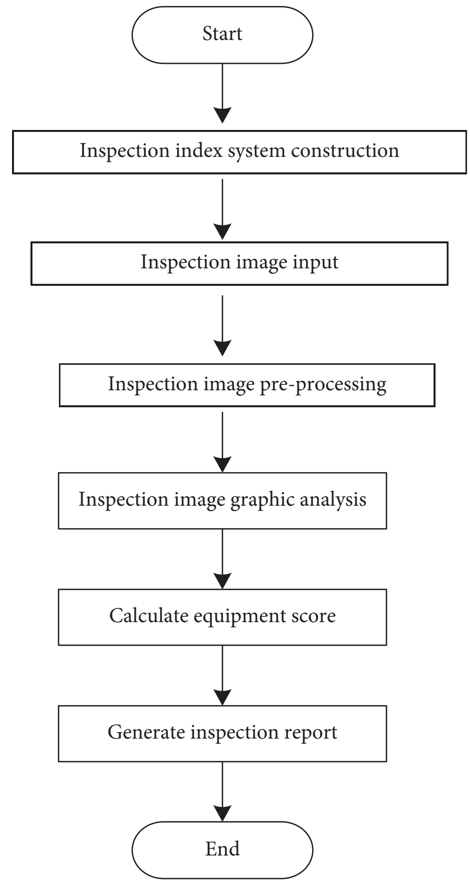

Figure 1: The overall flowchart of power communication network inspection system.

3.4.2. FastR-CNN-Based Image Processing Process for Power Communication Networks. In this thesis, the main function of RPN is to propose regionality for the FasterR-CNN architecture, while FastR-CNN combines the features of the original image with the region suggestions proposed by RPN, based on which classification and boundary regression are performed. The training process of FastR-CNN includes:

(1) A shared convolutional network of FasterR-CNN is used, and a feature curve is obtained by performing a convolutional pooling operation on it.

(2) The candidate region generated by RPN and the feature curve generated by the shared convolutional network of FasterR-CNN are mapped and input to the RoI pooling layer for resizing.

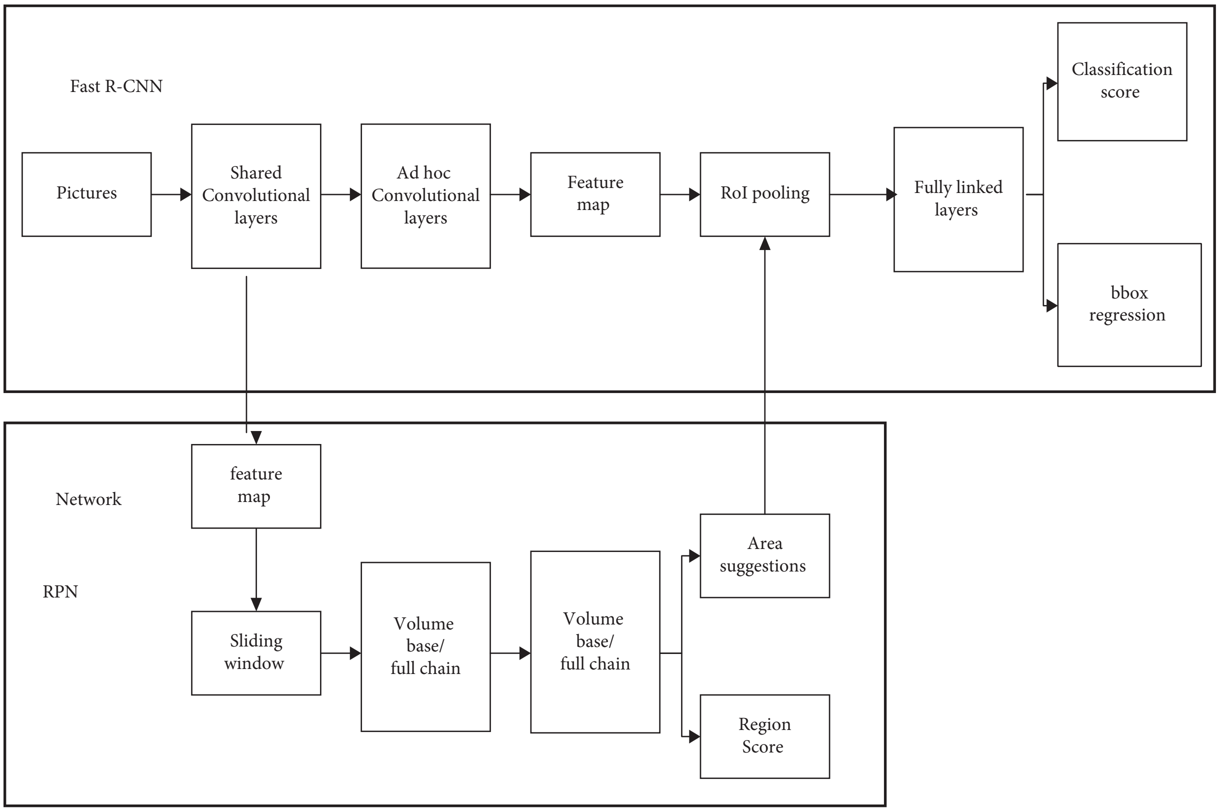

Figure 2: FasterR-CNN structure.

The RoIpooling layer adds a lot of work and a lot of time due in large part to the post fully connected layer of the network (the previous convolutional pooling was not necessary). In FastR-CNN, the RoI pooling layer can replace the full connectivity. Simply put, the RoI pooling layer is a feature map on images of different sizes [21], and a specific dimension is extracted from the feature maps of candidate regions of each size, both to improve the accuracy and to speed up the computation. The extracted fixed feature dimension representation is shown in Figure 3.

(3) The sized feature maps are sent to the fully connected layer for classification scoring and boundary regression.

In terms of algorithm, the whole linkage layer is improved to shorten the training time. Since more than 2000 sensitive regions need to be extracted during target identification and the whole connected layer is time-consuming, the SVD method is used to perform SVD decomposition on the full linked layer, and the results show an improvement of nearly 30% in processing speed.

4. Application Experiment Analysis

4.1. Experimental Setup. In FasterR-CNN, the shared convolutional network is a 5-level convolutional pooling network, which is shared by RPN and FastR-CNN, and the parameter settings of each level are shown in Table 1.

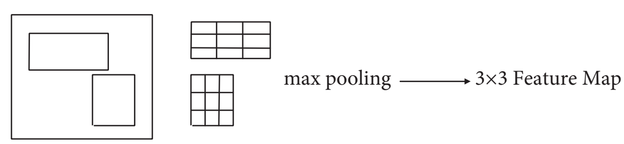

Figure 3: Schematic diagram of RoI extraction of fixed feature dimensions.

Table 1: Shared network parameter settings.

Layer	Size (kernel)	Pad	Stride	Num
CONV1	7*7	3	2	96
POOL1	3*3	1	2	—
CONV2	5*5	2	2	256
POOL2	3*3	1	2	—
CONV3	3*3	1	1	384
CONV4	3*3	1	1	384
CONV5	3*3	1	1	256

The first column in Table 1 shows the names of the convolutional and pooling layers, where the size of the convolutional core (Size) , the edge padding value (Pad), and the feature vector for each layer (num) are indicated.

For the other training parameters, the settings are shown in Table 2.

The stepsize in Table 2 represents the learning rate adjusted every 2000 times, gamma is the learning rate adjustment parameter, both are a parameter in the learning rate adjustment policy (lr_policy), and the final return value is A.

Table 2: Training parameter settings.

Parameter name	Parameter value
Stepsize	2000
Gamma	0.1
Display	20
Average_loss	100
Momentum	0.9
Weight decay	0.0005
Batch size	64

4.2. Applied Model Training. The training method in this thesis is RPN cross-trained with FastR-CNN, which has the advantage that it can make full use of the information in the text to improve its accuracy significantly. Among them, the cross-training procedure consists of four main steps:

(1) First, the pretrained weighted (ImageNet) dataset [22] is used as the initial parameters of RPN. The photos containing electronic products are used to generate positive and negative samples using the RPN network and are adjusted in the process to obtain regional recommendations, which is part of the training, and it can be said that this stage is mainly about adjusting the RPN network to generate regional recommendations.

(2) As in step 1, the parameters generated from the pretrained ImageNet dataset are used as the initial parameters of the FastR-CNN, and then, the FastR-CNN is fine-tuned with the regionally recommended data generated once.

(3) Based on the fine-tuning parameters of FastR-CNN, the RPN network is initialized by fixing the shared convolutional layers together and fine-tuning only the RPN to generate the regional recommendation data.

(4) Fine-tune the FastR-CNN and implement the complete connection to the FastR-CNN based on this.

Combining FastR-CNN with RPN, cross-training, and then fixing the shared convolutional layers together separately, we realize that two networks share one convolutional layer, thus greatly improving the efficiency of use and saving a lot of time.

4.3. Experimental Analysis of Model Comparison. The monitoring structure of conventional CNN and RPN FastR-CNN was compared and analyzed by randomly selecting 200 different types of monitoring images from seven different types of monitoring images. From the experimental results, the structure is much better than the conventional CNN model. The results of the seven types of electrical devices recognition are shown in Table 3, and the mAP comparison before and after data enhancement is shown in Figure 4.

4.4. Experimental Analysis of Model Application. After the model training and comparison is the same, this section will carry out the model application experiment. Power communication network inspection is a key link in the security of power communication network, and it undertakes every operation in the whole monitoring process. First, the performance parameters of each device are obtained through data collection of the power grid and then through graphical recognition and data processing. Then, according to the actual data in the parameter graph, the status of equipment is scored according to the current data and performance index, and the corresponding equipment operation is derived. Its parameter curves are shown in Figure 5. Its actual parameter graph is shown in Figure 5.

Table 3: Seven types of electrical equipment identification results.

Category	Accuracy rate (%)	False detection rate (%)
CNN	76	6
RPN + Fast R-CNN	85.5	1.5

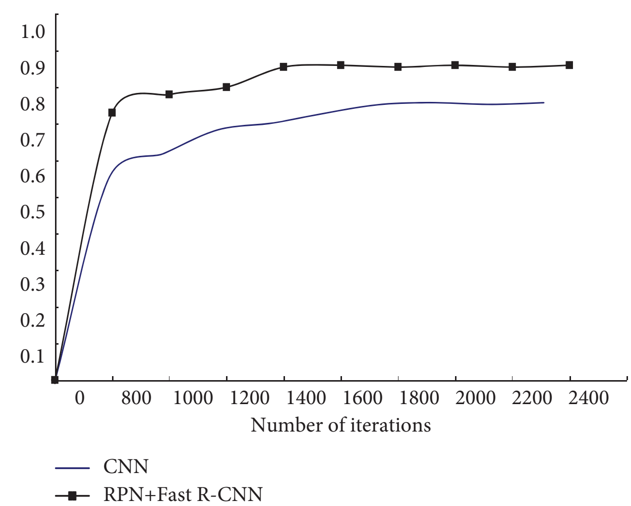

Figure 4: Comparison of mAP before and after data enhancement.

Figure 5: Device parameter map.

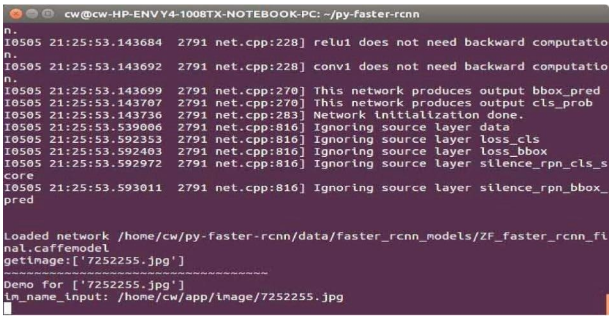

Figure 6: Server-side detection of images.

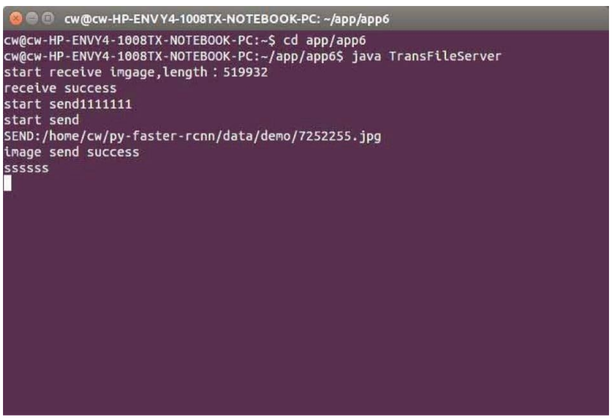

Figure 7: Image sent to the client.

Table 4: Identification results' table.

Equipment number	Equipment name	Equipment status
1	OL4	NO
2	OL1	NO
3	OL64	YES
4	CS	YES
5	CS	YES
6	OL64	YES
7	OA	YES
8	OL4	NO
9	NCP	YES
10	ET1	YES
11	OL16	YES
12	OL64	YES
13	SC	YES
14	SC	YES
15	OL64	YES
16	SFE8	YES
17	OL16	YES
18	OW	YES

After the model network receives the device parameter image, a detected image will appear in the specified folder of the model network. At this time, the terminal responsible for the graphic recognition will directly call the RPN + FasterR-CNN framework, use the trained model in this study for the target recognition task, and then recognize the model according to that model. The detection process is shown in Figure 6.

After recognition by FasterR-CNN, the model network automatically feeds the detected images and sends them to the server. The result is shown in Figure 7.

After the image is detected, the server side sends the image to the client side, which receives it, and then the information of the detected image parameters is identified and fed back, and the identification results are shown in Table 4. From the table, we can see that the device numbers 1, 2, and 6 are the ones with problems, and the rest are normal.

5. Conclusion

In China, the research on grid monitoring technology is relatively lagging behind and is still in the primary stage, but there have been many achievements. In the past ten years or so, domestic equipment condition monitoring and diagnosis technology has been exchanged with international standardization organizations, international equipment condition monitoring and diagnosis technology seminars, equipment condition monitoring, fault diagnosis, artificial intelligence and expert systems, and other advanced technologies, which have rapidly developed China's equipment overhaul technology. At present, China's equipment reliable operation and overhaul system have made great development and are close to or near the international advanced level.

This study proposes a computer vision-based graphic recognition technology for power communication network inspection system, which includes two major parts: (1) RPN (Region Proposal Network) and (2) FastR-CNN. The research contents of the paper include the following. (1) The background of power communication network monitoring technology is introduced. (2) The relevant theories involved in this study are discussed. (3) The indicators, monitoring process, and structure of the monitoring model are introduced in detail. (4) Through comparative tests and application tests of the model, it is concluded that the model is very good and has achieved good results in practical applications.

The inspection model of power communication network developed in this study has reached the basic needs of daily inspection, and to make the model more perfect and the inspection scheme more complete, in-depth research and exploration are needed on.

(1) ot many performance parameters can be obtained at present; if more performance parameters can be obtained, it can better reflect the working state of the whole system

(2) The performance index evaluation table is segmented rather than continuous; if a continuous model can be established, it can better reflect the characteristics of each performance index and thus improve the accuracy of the evaluation

Data Availability

The dataset used in this study can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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