Research on Automatic Identification and Location Technology of Key Equipment in Distribution Lines Based on Deep Learning

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Abstract

With the global emphasis on sustainable energy systems and low-carbon economies, the intelligent operation and maintenance of distribution networks has become crucial for enhancing energy efficiency and building an environmentally friendly energy system. This study proposes an automatic identification and location technology for key equipment in distribution lines based on deep learning, aiming to improve the intelligent level of distribution networks and reduce the environmental impact during the processes of energy production and consumption. Through deep convolutional neural networks (CNNs) and object detection algorithms, the method presented in this paper can efficiently identify and locate key equipment in distribution lines, helping to monitor the stable supply of energy, reduce operation and maintenance costs, and support the promotion and application of low-carbon energy by improving energy efficiency. Experimental results show that the proposed method has significant advantages in terms of equipment identification rate, location accuracy, and response speed, especially in reducing energy waste

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and optimizing the operation efficiency of distribution networks, and it has high practical application value. The research in this paper provides strong support for the assessment of environmental impacts in energy production and consumption, energy-saving technologies, and the construction of sustainable energy systems, and it has broad environmental and social significance.

Keywords: Distribution circuit, deep learning, object detection, equipment identification, operation and maintenance, low-carbon energy.

1 Introduction

Building objectives like the "Smart Grid" and the "14th Five-Year Plan for the Power Grid Industry" have been proposed one after the other as a result of technological advancements, necessitating a major improvement in the power system's detection and control levels. The development and safe functioning of the power grid may be accomplished by fusing contemporary technology with conventional power systems [1]. The progress of the country greatly depends on the stability of the electricity sector. The foundation for the growth of other sectors is a power supply that is adequate, safe, and dependable [2]. People's everyday lives, education, and employment are becoming more and more reliant on power. People's everyday lives now revolve on a variety of electrical equipment, and the need for the power system to remain stable is only growing. The size of the electricity grid is always growing as cities develop. As the electricity system's terminal component, the number of distribution networks is growing, and so are their more intricate architecture. High-voltage power must be converted into low-voltage before being delivered to homes via the distribution network. A significant malfunction during operation might result in a regional power outage, which would have a negative impact and result in significant financial losses for a number of local enterprises. In extreme situations, it can potentially result in a significant number of casualties. To guarantee the safe and stable functioning of the distribution network, staff members must constantly check the operational state of the equipment in the network in order to identify unusual circumstances quickly and address malfunctions [3, 4]. In regions where the proportion of renewable energy exceeds 40%, the power flow direction of the distribution network changes frequently, posing severe challenges to traditional protection devices and dispatching strategies, and reducing operational efficiency by approximately 15% to 20%. Meanwhile, the increase in the number of distribution network equipment has also raised the difficulty of operation and maintenance. In recent years, the proportion of 10 kV distribution line faults caused by external factors such as tree obstacles and bird damage has reached 35%, while manual inspection can only cover about 60% of the hidden danger points, intensifying the risk of power outages. The distribution wires are mostly above at the moment. Insulators, arresters, switches, transformers, cable connectors, and other equipment are among the many varieties of complicated overhead line equipment. Tree obstructions, bird damage, foreign items, surface pollution, equipment flaws, and the operational environment are some of the elements that hinder a dependable power supply. Manual inspection is now the primary technique used to raise the distribution network's degree of dependable operation. In order to identify the equipment, manual inspection requires the inspectors to carry specialized tools on a regular basis, such as partial discharge detectors and infrared thermal imagers. The primary detection techniques for detecting partial discharges of overhead wires and the equipment that runs along them are ultrasonic and ultra-high frequency techniques. However, the effectiveness and dependability of manual inspection progressively fall short of meeting the safety standards of distribution network inspection due to the contemporary distribution network's increasingly complex structure. Therefore, the development of an artificial intelligence-based distribution network inspection technique is urgently needed [5–7]. The electricity system's automation level has significantly increased as of right now, and communication technology is also continuously evolving. The voltage and current signals are being collected at both ends of the cable without any technical issues. It is possible to measure using the current and voltage transformers that are already in place, which has more practicability, takes less money, and is simple to construct the circuit. The bridge method, a positioning technique based on Wheatston's bridge theorem, is the most popular and traditional approach in impedance method placement [8, 9]. In the literature [10], an equivalent decoupling model was established. The look-up table method was used to locate the fault and establish a relationship table between the fault distance and the amplitude difference of the fundamental frequency currents on both sides of the fault point using the characteristics of the line parameters after decoupling. Literatures [11–13] use parallel capacitor connections to locate faults in low-voltage DC distribution systems, which works well for short-distance transmission lines. However, a short-circuit problem will happen if capacitors are linked in parallel in a 50Hz AC transmission line. A wide-area fault finding approach based on impedance characteristics was presented in the literature [14], however a phasor measuring device must be installed in the system. Measuring the precise site of the fault is challenging since the impedance approach is readily influenced by the power source and line load, particularly at the distribution line's end where there are several load types. (2) Locating faults by signal injection techniques like electromagnetic time reversal and the travelling wave method, among others. In the area of fault location, the travelling wave approach has been used extensively. A novel intelligent placement technique based on the fundamental wave and many harmonics was presented in the literature [15]. The efficacy of this approach was shown by determining that the weighted average of the reciprocals of the main natural frequency and other natural frequency components is the global main natural frequency. In order to increase the wavefront's identification accuracy and get around the drawback of the double-end approach requiring the installation of a synchronous clock, literature [16, 17] improved the travelling wave velocity and used the difference algorithm. The electromagnetic time reversal approach [18–20] may provide more accurate findings than the travelling wave method while requiring a lower sample rate and the exact time of the fault incidence. However, the transient signal may be distorted owing to the capacitive voltage transformer's limited precision in detecting high-frequency transient components, which restricts the method's use. In order to locate the fault, the authors of the literature [21, 22] introduced a low-voltage pulse signal into the distribution line, recorded the pulse emission waveform, and compared the pulse waveforms before and after the fault. However, interference has a significant impact on this detection technique, thus the pulse signal must undergo efficient noise removal processing. Deep learning technology's revolutionary advancements in target identification and picture recognition in recent years have opened up new avenues for the distribution network's intelligent upkeep and operation [23–25]. The target detection algorithm and the deep convolutional neural network (CNN), two key deep learning technologies, provide the benefits of quick real-time reaction, high placement accuracy, and effective identification. Because of these qualities, they are often used in the upkeep and monitoring of distribution network equipment. In addition to significantly increasing the efficiency and accuracy of equipment inspection, the automatic recognition and positioning technology of key equipment in distribution lines suggested in this study can also monitor the equipment status in real time, identify potential faults promptly, minimize the need for human intervention, and improve the safety and stability of the power grid. The distribution network inspection technique based on artificial intelligence will develop into a significant auxiliary technology for raising the intelligent level of the power grid in the future as deep learning algorithms continue to be optimized and distribution network inspection technology matures. By increasing the distribution network's operational efficiency and decreasing energy waste, low-carbon energy may effectively support the achievement of environmental protection and energy conservation objectives, particularly when used on a broad scale. Furthermore, as power grid intelligent technology advances, the extensive use of artificial intelligence will not only boost the distribution network's operational and maintenance effectiveness but also significantly influence the global green energy transition and the advancement of the low-carbon economy.

2 Mechanism of the Model

This chapter briefly introduces the main methods adopted in this paper, including the application of deep learning models in the identification and positioning of distribution line equipment. The important equipment in the distribution network may be effectively identified and located using object identification algorithms and deep convolutional neural networks (CNNs). This research additionally uses data pre-processing and augmentation approaches to guarantee the model's performance.

2.1 Deep Convolutional Neural Network

Instead of using laborious human feature extraction techniques, CNNs can automatically learn features from photos. CNNs extract spatial features from images through multiple convolutional layers and pooling layers, enabling effective equipment identification. In this paper, CNNs are used to process images of power distribution equipment, automatically extracting feature information such as the shape and size of the equipment.

2.2 Object Detection Algorithm

Object detection algorithms (such as YOLO) are used to quickly locate equipment in images. These algorithms not only identify objects in the images but also accurately mark the positions of the objects. In this paper, the YOLO algorithm is adopted, which can locate the key equipment in the distribution lines in real-time, ensuring the accuracy and efficiency of the detection results.

2.3 Model Training

The fault detection model of this study adopts a joint training architecture deeply integrated with device identification and location, and builds an end-to-end framework of CNN and YOLO to achieve three-level optimization: The feature sharing layer extracts common features through the 24-layer CNN backbone and the LeakyReLU/SiLU activation function, and serves device identification and fault detection simultaneously; Collaborative training, with the aid of cross-entropy loss and L2 regularization, jointly optimizes the parameters of the YOLO localization head and the total connected reception fault under GPU acceleration. L2 regularization effectively controls the model complexity through the weight attenuation mechanism, ensuring the stable performance of the model on the test set while preventing overfitting. It forms a complementary advantage with cross-entropy loss and jointly optimizes the balance between model accuracy and generalization ability. Cascaded reasoning follows the process of "location – evaluation – diagnosis". First, the features of the located equipment are extracted, and then the results of the status evaluation are input into the diagnostic network to form an efficient detection architecture of task series.

3 Methodology

3.1 Deep Learning-Based Equipment Recognition Model

In the intelligent operation and maintenance of distribution networks, the automatic identification and positioning of key equipment are crucial for improving energy management efficiency and reducing manual intervention. This study proposes a device recognition model based on deep learning, adopting an improved CNN feature extraction network with a 24-layer convolutional structure, combined with a three-scale detection network based on the YOLOv5s architecture. This model uses the LeakyReLU and SiLU activation functions, and is optimized by adopting the CIoU Loss function and Focal Loss. Through multi-scale feature fusion and residual connection design, it achieves high-precision identification and real-time positioning of various power equipment in the distribution line images. The model can automatically recognize and locate various power equipment in the distribution line images, improving inspection efficiency and reducing maintenance costs.

(1) Convolutional Neural Networks (CNN)

Because CNNs can automatically extract characteristics from pictures, they are often employed in image classification and object identification applications. To analyze input pictures and extract information, CNNs are made up of convolutional, pooling, and fully connected layers.

Convolutional Layer: The convolutional layer applies filters (kernels) to the input image to extract spatial features. The convolution operation is defined as:

$$S(i,j) = (I * K)(i,j) = \sum_{m=1}^{M} \sum_{n=1}^{N} I(i+m-1, j+n-1) \cdot K(m,n) \quad (1)$$

input picture I, convolution kernel K.

Pooling Layer: By reducing the feature maps' spatial dimensions, the pooling layer lessens the computational strain and guards against overfitting. The definition of the max-pooling operation is:

$$P(i,j) = \max(I(i+m, j+n)) \quad (2)$$

(1) Fully Connected Layer: The features are flattened and sent to a fully connected layer for final classification after convolution and pooling.

(2) Object Detection Algorithm (YOLO)

In the localization process, object detection algorithms (such as YOLO) are used to detect and locate multiple objects in images. YOLO (You Only Look Once) turns the object detection task into a regression problem, predicting both the class and position of objects in the image. The output of YOLO is:

$$\hat{y} = \{(x_i, y_i, w_i, h_i, p_i)\}_{i=1}^{k} \quad (3)$$

where the bounding box center's coordinates are (x_i, y_i), the bounding box width and height are w_i, h_i, and the object class probability is denoted by p_i.

(3) Data Preprocessing and Feature Enhancement

The input data goes through a number of preprocessing procedures, such as normalization, denoising, and data augmentation, prior to model training.

Normalization: To guarantee uniform brightness, the picture pixel values are scaled to the interval [0, 1].

Denoising: Filtering techniques are applied to remove noise from the images to ensure that the CNN focuses on extracting relevant features.

Data Augmentation: To improve dataset variety and avoid overfitting, data augmentation methods including rotation, flipping, and scaling are used to the training pictures. Experiments show that the recognition accuracy of the enhanced model has increased from 83.5% to 92.3% under low light conditions, and the fault detection rate has increased from 76.8% to 89.1% in rainy and foggy weather. Meanwhile, data augmentation reduces the overfitting phenomenon of the model by 42% and the cross-scene generalization error by 35%, effectively improving the environmental adaptability and robustness of the model.

3.2 Distribution Network Inspection Integration Model

In the intelligent distribution network, automatic equipment recognition and fault localization are essential for improving inspection efficiency and reducing manual intervention. When combined with the distribution network inspection system, the equipment detection and localization technique presented in this study enables real-time equipment status monitoring, quick defect diagnosis, and alert production. Equipment identification and location, status assessment, defect detection and localization, and alarm production and feedback are the main components of the inspection integration model.

(1) Equipment Recognition and Localization

In the distribution network inspection process, the first step is to capture images and automatically recognize and localize the equipment in the distribution lines using deep learning models. Through the previously mentioned CNN and YOLO models, the system can extract equipment features and precisely locate the equipment in real-time. The key equations for equipment recognition and localization are:

Image Input and Feature Extraction:

$$f_{\text{cnn}}(I) = \text{CNN}(I) \tag{4}$$

where I represents the input distribution line image and $\mathrm{f_{cnn}(I)}$ is the extracted equipment feature from the CNN model.

Equipment Localization and Detection:

$$\hat{y} = \{(x_i, y_i, w_i, h_i, p_i)\}_{i=1}^{k} \tag{5}$$

YOLO allows precise localization of the equipment.

(2) Status Evaluation

Assessing the equipment's operational state in real-time comes after equipment location and identification. Status evaluation typically involves comparing real-time data with historical data, and common methods include threshold-based methods and anomaly detection using machine learning.

The basic principle of status evaluation is to monitor key parameters (such as temperature, current, voltage, etc.) and compare them with historical data. If the device parameters exceed a normal threshold, the device is considered to be in a fault condition. The equation for status evaluation is:

Status Evaluation:

$$S_{\text{state}}(t) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_i(t) - X_{\text{ref},i}}{X_{\text{ref},i}}\right) \tag{6}$$

where $\mathrm{S}_{\text{state}}(\mathrm{t})$ represents the device's status assessment at t, $\mathrm{X}_{\mathrm{i}}(\mathrm{t})$ is the i-th monitoring parameter at t, the historical reference value is $\mathrm{X}_{\mathrm{ref,i}}$, and n parameters are monitored. If the evaluation value exceeds a threshold, the gadget is defective.

(3) Fault Detection and Localization

Fault detection is one of the core functions of the distribution network inspection system, designed to monitor equipment status and quickly localize faults when they occur. Fault detection typically relies on the differences between real-time data and standard equipment parameters. To improve fault detection accuracy, this paper adopts a fault diagnosis model based on neural networks, optimizing network parameters with training data.

Fault Diagnosis Model:

$$y_{\text{fault}} = \mathrm{NN}(f_{\text{cnn}}(I), S_{\text{state}}(t)) \tag{7}$$

where $\mathrm{y}_{\text{fault}}$ is the fault detection result, NN is the neural network model, $\mathrm{f}_{\text{cnn}}(\mathrm{I})$ is the feature extracted by the CNN model, and $\mathrm{S}_{\text{state}}(\mathrm{t})$ is the status evaluation result.

Fault Localization:

$$L_{\text{fault}} = (x_{\text{fault}}, y_{\text{fault}}, w_{\text{fault}}, h_{\text{fault}}) \tag{8}$$

where $\mathrm{L}_{\text{fault}}$ represents the bounding box of the fault equipment's location in the image.

(4) Alarm Generation and Feedback

Once a fault is detected, the system will automatically generate a fault report and notify maintenance personnel through an alarm system. The alarm is typically classified based on the type of fault, severity, and impact on the system.

Alarm Generation Equation:

$$A_{\text{alert}} = f_{\text{alert}}(y_{\text{fault}}, L_{\text{fault}}) \tag{9}$$

where A_{alert} is the alarm information, f_{alert} is the alarm generation function, y_{fault} is the fault detection result, and L_{fault} is the fault equipment's location.

Alarm Feedback:

$$F_{\text{feedback}} = \text{feedback}(A_{\text{alert}}) \tag{10}$$

where F_{feedback} is the feedback information, representing the fault notification and suggestions sent to maintenance personnel.

4 Example Analysis

4.1 Experiment Setup

(1) Dataset

The dataset adopted in this experiment contains 1,000 images from the actual inspection of the distribution network, covering various key power equipment such as transformers, switchgear, utility poles, and distribution boxes. Among them, the normal state images account for 70%, and the fault state images account for 30%. These images were collected from a variety of actual working scenarios, including different lighting conditions (65% normal lighting, 20% low lighting, 15% strong backlighting) and various weather conditions (60% sunny, 20% rainy, 10% foggy, 10% snowy). In particular, it includes 300 images taken under harsh environmental conditions to ensure the robustness verification of the model. The dataset simultaneously covers inspection scenarios in different time periods such as during the day, at night, and at sunrise and sunset, providing a comprehensive and realistic sample basis for model training.

(2) Tools and Technologies

The experiment was conducted in a TensorFlow environment, where CNN was used for equipment recognition, and YOLOv4 was employed for object

Table 1 Fault detection rate

Equipment Type	Total	Correct Recognition	Recognition Accuracy	Localization Accuracy	Fault Detection Rate
Transformer	200	199	99.5%	97.3%	98.5%
Switch	150	148	98.7%	95.5%	96.0%
Pole	150	147	98.0%	96.2%	95.0%
Distribution Box	100	99	99.0%	96.8%	97.3%
Total	600	593	98.6%	96.5%	97.2%

detection. The computation platform used a GPU-accelerated server to ensure efficient training and prediction.

(3) Environmental Impact Assessment Metrics

In addition to evaluating equipment recognition and localization accuracy, this experiment also assessed the environmental impact by analyzing energy efficiency and fault detection efficiency. Key metrics include:

(1) Energy Efficiency: Optimizing the operation and maintenance process by reducing manual intervention and saving electricity.
(2) Carbon Emission Reduction: Reducing carbon emissions by optimizing the inspection process and improving equipment recognition accuracy.

4.2 Equipment Recognition and Localization Results

Through the CNN and YOLO models, we successfully achieved automatic recognition and localization of equipment in the distribution network. The experimental results in terms of equipment recognition and localization are as follows:

(1) Recognition Accuracy: 98.6%
(2) Localization Accuracy: 96.5% (IoU > 0.75)
(3) Fault Detection Rate: 97.2%

4.3 Status Evaluation and Fault Detection

After equipment recognition and localization, real-time monitoring data and historical data were compared to evaluate the equipment's status. The following status evaluation formula was used:

Status Evaluation Formula:

$$S_{\text{state}}(t) = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{X_i(t) - X_{\text{ref},i}}{X_{\text{ref},i}} \right) \tag{11}$$

Through status evaluation, 12 faulty devices were successfully detected, and their locations were localized.

4.4 Environmental Impact Assessment

Intelligent operation and maintenance of distribution networks not only offers advantages in equipment management efficiency but also plays an important role in energy conservation and emission reduction. This section demonstrates the positive environmental impact of this technology by comparing traditional manual inspections with automated inspections in terms of energy consumption and carbon emissions.

(1) Energy Efficiency

Traditional manual inspections consume large amounts of energy due to the need for long hours of human intervention. In contrast, automated inspections reduce energy consumption by minimizing the need for manual intervention.

(2) Carbon Emission Reduction

The quantitative analysis of environmental benefits in this study is based on actual operation and maintenance data and industry standard calculation models. The annual power consumption of 10,000 kilowatt-hours for traditional manual inspection is derived from the measured statistics of the distribution network in typical areas, including the comprehensive energy consumption such as the fuel-electricity conversion of inspection vehicles, the power consumption of detection equipment, and artificial lighting. The 30% energy savings achieved by intelligent systems were measured through comparative experiments and mainly come from three aspects: the reduced vehicle dispatch frequency due to automated inspection, the lower equipment no-load loss due to intelligent diagnosis, and the energy efficiency improvement brought about by optimizing the operation and maintenance path. The reduction in carbon dioxide emissions is calculated based on the regional power grid emission factors announced by the National Development and Reform Commission.

This case study validates the effectiveness of the deep learning-based equipment recognition and fault localization technology in distribution network inspection processes through practical application. It also demonstrates the advantages of this method in improving inspection efficiency, reducing operational costs, and optimizing energy usage. In particular, the proposed equipment recognition model exhibits high robustness and real-time

Table 2 Environmental benefits of intelligent inspection

Project	Traditional Manual Inspection	Intelligent Inspection	Energy Saving & Emission Reduction
Annual Energy Consumption (kWh)	10,000	7,000	30%
Annual Carbon Emissions (tons)	7.2	4.8	30%

performance when dealing with equipment recognition and fault localization under various environmental conditions, according to the experimental results, which demonstrate that it achieves significant accuracy in the automatic recognition and localization of distribution network equipment.

The intelligent inspection technology considerably lowers energy consumption and carbon emissions related to human involvement while simultaneously increasing the efficiency and accuracy of equipment identification as compared to conventional manual inspection techniques. The distribution network's dependability and safety are effectively increased by the high accuracy and fast reaction time of fault detection, which provide maintenance staff rapid equipment status feedback and assist them in identifying and resolving any problems.

The case study also sheds light on the beneficial function that intelligent inspection technology plays in the process of evaluating the influence that humans have on the environment. By optimizing the operation and maintenance processes, energy waste was reduced, energy usage efficiency improved, and carbon emissions were significantly reduced by minimizing the energy consumption required for manual inspections. This outcome not only meets the requirements of green technology but also contributes to the sustainable development of the distribution network.

5 Conclusion

This paper proposes a deep learning-based equipment recognition and localization technology for distribution networks and applies it to the distribution network inspection system. By using deep CNN and object detection algorithms YOLO, automatic recognition and localization of key equipment in distribution lines are achieved, along with real-time monitoring and fault detection of equipment status. According to the experimental findings, the suggested model effectively addresses the complex inspection environments of distribution networks and exhibits notable advantages in equipment recognition accuracy, localization precision, and real-time fault detection, particularly in terms of high robustness under mixed environmental conditions.

The use of intelligent technology in distribution network inspections significantly lowers the expenses and resource consumption related to manual inspections while simultaneously increasing operational efficiency. Compared with traditional manual inspection methods, the deep learning-based intelligent inspection system significantly improves efficiency and accuracy in equipment recognition and localization, while reducing energy consumption and carbon emissions by minimizing human intervention. The distribution network's operating efficiency is maximized and equipment problems are promptly identified and resolved through intelligent inspections, improving the network's safety and dependability.

This study also demonstrates the positive role of intelligent inspection technology in environmental impact assessment. By transforming manual inspections into automated inspections, not only is the consumption of human resources reduced, but energy waste caused by manual inspections is also minimized. Specifically, the deep learning-based inspection system significantly improves energy usage efficiency, and through reducing the energy demand during inspections, it achieves a notable reduction in carbon emissions. Data analysis further shows that the intelligent inspection system can reduce energy consumption by approximately 30% annually, thereby reducing carbon emissions during distribution network operations, contributing to the achievement of low-carbon goals and the promotion of green technology.

In addition, the intelligent inspection system enables real-time monitoring of equipment status while performing intelligent fault diagnosis and alarms. By incorporating equipment status evaluation and fault detection algorithms, the system can monitor key parameters of equipment in real time and determine if the equipment is in an abnormal state based on historical data. If a fault is detected, the system can accurately locate the faulty equipment and generate an alarm to notify maintenance personnel for processing. In addition to improving fault detection efficiency, this intelligent inspection procedure drastically reduces fault reaction time, offering dependable assistance for the distribution network's effective functioning.

We were able to confirm the effectiveness and precision of the intelligent inspection approach that is based on deep learning in terms of equipment recognition, location, and defect detection in distribution networks over the course of this study. The results of the experiments demonstrate that the intelligent inspection system that was proposed is capable of rapidly locating critical equipment in the distribution network, as well as detecting and locating defective equipment in a timely way when faults occur. This provides maintenance staff with fault feedback that is both fast and effective. Additionally, compared to traditional manual inspection methods, the intelligent inspection approach not only improves the accuracy of equipment recognition and localization but also significantly reduces energy waste during manual inspections and lowers carbon emissions, showcasing its potential for green development in distribution networks.

Despite the fact that this study has produced results that are adequate, there is still enough opportunity for development. It is possible for future study to further refine the structure and methods of deep learning models in order to improve the precision of equipment detection and localization, particularly in surroundings that are complex and under conditions that are severe. Moreover, As the variety of equipment used in distribution networks and the difficulty of inspection jobs keep growing, future studies could explore more intelligent inspection systems that integrate additional sensor data, cloud computing, and IoT technologies to further enhance the intelligence level and fault diagnosis capabilities of distribution networks.

Intelligent inspection systems can build a more comprehensive monitoring network by integrating information from various sensors, enhance the stable performance of the system in extreme weather and complex scenarios, and explore more efficient algorithms to reduce reliance on labeled data. With technological advancement, intelligent inspection will be deeply integrated with renewable energy systems, significantly enhancing the utilization rate of clean energy through dynamic optimization of operation strategies. This will provide core support for building a low-carbon distribution network and promote the transformation of the power system towards a sustainable development model of "intelligent detection – efficient operation – green energy".

From an environmental perspective, as intelligent inspection systems become more widespread, the energy usage efficiency of distribution networks will be significantly improved, while energy consumption and carbon emissions will further decrease. Intelligent inspection technology will play a significant role in the future development of distribution networks that are environmentally friendly. This is because many low-carbon energy sources are now being utilized. Future research could focus on how to deeply integrate intelligent inspection systems with renewable energy, energy storage systems, and smart grids, promoting the development of distribution networks towards a greener and more efficient direction.

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