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Research Article

Panoramic Assessment Method of Substation Equipment Health Status Based on Multisource Monitoring and Deep Convolution Neural Network under Edge Computing Architecture

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In view of the low efficiency of the traditional manual evaluation method of substation equipment status under the background of complex environment, a panoramic evaluation method of substation equipment health status based on multisource monitoring and deep convolution neural network under edge computing architecture is proposed. Firstly, a panoramic sensing system for substation equipment is built based on edge computing, and an edge computing server is deployed in the substation to process the massive data obtained from multisource monitoring nearby. Then, the improved YOLOv4 network is used to detect the equipment state in the substation, in which the Squeeze-and-Excitation attention module and deep separable convolution are used to optimize the YOLOv4 network. Finally, based on the status image of substation equipment, the health status of equipment is evaluated on the panoramic platform of substation combined with the characteristics of multisource data, and four states are divided according to the evaluation criteria. Based on the selected dataset, the experimental analysis of the proposed method is carried out. The results show that the index values of accuracy, recall, and mean precision are 91.53%, 93.07%, and 92.28%, respectively. The overall performance is better than other methods and has certain application value.

1. Introduction

In recent years, intelligent substation has developed rapidly. Various complex instruments such as transformer, switch, bus, control, and metering transformer in substation realize mutual operation and information sharing in substation through high-speed network communication [1]. How to ensure the safe and stable operation of various instruments in the substation has become the top priority of the realization of intelligent substation [2, 3]. With the development of unattended substation, video analysis technology, and image recognition technology, image intelligent analysis system has been used in the state recognition and linkage protection of substation equipment at home and abroad. By combining visualization with infrared image acquisition and ancintegrating on-site online monitoring data, a comprehensive health status assessment of substation equipment is carried out, so as to further realize the remote and unattended intelligent substation system and ensure the safe and stable operation of substation equipment [4].

Due to the variety of equipment contained in the substation, the safety, stability, and reliability of its operation directly depend on the operation of various instruments in the substation. With the development of image processing, pattern recognition, and deep learning technology, it is a feasible scheme to use computer vision to assist the monitoring and analysis of substation equipment. Equipment identification is the premise of automatic inspection and monitoring. The image analysis method after equipment identification has wide application value in UAV line inspection, intelligent robot monitoring, small substation inspection, and so on [5]. Combined with the research of domestic and foreign scholars on multisource information fusion in recent years, its research results provide a good reference significance for the comprehensive condition monitoring of power equipment [6]. However, there are still some limitations in the evaluation and research on the health status of power equipment, mainly reflected in the complexity of substation equipment and the uncertainty of operating environment, the limited learning ability of analysis methods, and the neglect of multivariate data fusion [7, 8]. Therefore, the comprehensive evaluation and analysis of substation equipment still needs to be deeply studied in order to improve the reliability of safe and stable operation of equipment.

At present, there is little research on the comprehensive state evaluation of substation equipment, which is mainly reflected in the analysis and detection of some single data sources and some image recognition and analysis. According to the types of monitoring and analysis data, the following studies have been carried out. Sultanov et al. [9] analyzed the loss and insulation deterioration rate of distribution network transformers and completed the evaluation of substation equipment status on the basis of considering the impact of voltage and current harmonic components on the reliability of electrical equipment in power plants and substations. However, only relying on the harmonic components of current and voltage, the reliability of the evaluation results is not high. Sultanov et al. [10] introduced the evaluation method of the technical condition of the existing power generation system equipment and considered the advantages of the maintenance and repair system in the actual situation. Morita et al. [11] designed detection equipment for evaluating the lightning protection performance of the grounding system of railway substation, which can effectively measure the grounding resistance, high-frequency grounding impedance, and voltage difference of the grounding system. However, it is only applicable to lightning protection devices, with poor universality. Yoo et al. [12] analyzed long-term solar radiation data for a given location of photovoltaic power station and introduced a series of evaluation methods to calculate the optimal capacity of grid-connected substation and energy storage of photovoltaic power station. However, due to the limitation of monitoring information from a single data source, the evaluation results cannot completely reflect the operation status and health degree of substation equipment.

According to the different analysis and evaluation methods of substation equipment operation and equipment health status, the existing research mainly includes traditional analysis methods and analysis methods based on machine learning [13]. Eltyshev and Kostygov [14] proposed a method of equipment condition evaluation based on nondestructive testing technology. Through comprehensive analysis, the irregular condition evaluation of substation equipment is carried out, which is conducive to improving economy and time efficiency. However, nondestructive testing technology is only applicable to specific faults of some equipment and is not comprehensive. Liu et al. [15] took the acquisition card of electronic current transformer as an example, analyzed the influence of electromagnetic interference source on the reliability of acquisition card, and creatively put forward a quantitative evaluation method of output waveform disturbance to realize the evaluation of equipment performance. Tang and Chen [16] proposed an improved three-frame difference algorithm for substation equipment identification and condition monitoring, which can more accurately identify the moving targets, so as to better complete the intelligent monitoring of substation. Ding [17] proposed an image recognition and condition monitoring algorithm of substation equipment based on deep learning algorithm. Using the monitored infrared and visual images, the substation equipment was deeply analyzed and identified, which effectively improved the efficiency of equipment condition evaluation.

Aiming at the problems of low evaluation accuracy and low efficiency of most existing methods, a panoramic evaluation method of substation equipment health status based on multisource monitoring and deep convolution neural network under edge computing architecture is proposed. Compared with traditional methods, the innovation of the proposed method is as follows:

(1) In order to improve the data processing efficiency in the substation, the edge computing architecture is integrated, all kinds of data in the station are processed, and the system delay is reduced.

(2) Due to the high amount of parameters of YOLOv4 model, the proposed method uses deep separable convolution in PANet feature enhancement network, integrates SE module to improve CSPNet structure, and uses K-means + + algorithm to improve clustering effect, so as to improve the operation efficiency and evaluation performance of the proposed method.

This paper is organized as follows. Section 1 is the introduction, which summarizes the shortcomings of the existing methods and the innovation of the proposed methods. Section 2 introduces the panoramic information perception system of substation equipment, including data acquisition and preprocessing and image preprocessing. Section 3 introduces the equipment state detection method based on deep convolution neural network and realizes the equipment state classification by improving the YOLOv4 network. Section 4 introduces the proposed panoramic assessment method of substation equipment health status. Section 5 is the experimental part, which demonstrates the effectiveness of the proposed method. Section 6 gives the conclusion and outlook.

2. Panoramic Information Perception System for Substation Equipment

In the substation panoramic information sensing system, the image and data information of the equipment in the substation is collected in an all-round way by means of inspection robots and sensors and preprocessed such as denoising. At the same time, the power production management system (PMS) is adopted to obtain equipment ledger and real-time status information, achieving crisis management. Due to the large number of substations and complex equipment in the station, in order to shorten the information perception time, the edge computing stage is deployed in each substation to alleviate the operation pressure of the dispatching master station [18]. The architecture of substation equipment panoramic perception system based on edge computing is shown in Figure 1.

Among them, the edge computing node collects the monitoring information of all equipment in the station, completes preliminary operations such as data and image preprocessing, and then uploads it to the cloud center of the dispatching master station for in-depth analysis, such as equipment status evaluation and fault identification. Through the substation panoramic information perception system, the asset information, operation and maintenance information, and operation data information of substation equipment can be obtained in real time, and the operation state of power equipment can be visualized.

2.1. Multisource Monitoring Information Collection. The equipment data information of substation is mostly provided by various devices, such as relay protection equipment, safety and stability equipment, fault recording equipment, detection and control system, watt-hour meter, primary equipment online monitoring system, video monitoring system, and DC screen. These devices collect the data of integrated automatic protection system, fire prevention system, production management system, online monitoring system, patrol inspection system, video surveillance, and other kinds of system to support the intelligent operation of substation [19, 20]. The image information of substation equipment is captured by the inspection robot, and cameras are set up around the important equipment in the station for real-time monitoring to obtain the corresponding image and video information.

Among them, the panoramic data of substation mainly include three categories:

(1) Data of substation transmission conditions: three-phase current and voltage, total active power and total reactive power, split phase active power, and split phase reactive power of the line; current and voltage at high, medium, and low voltage sides of transformer, total active power and total reactive power, split phase active power, and split phase reactive power; three-phase current of bus tie circuit breaker; bus voltage and frequency of the system; position information of each circuit breaker, disconnector, and grounding knife switch.

(2) Data of equipment status: The primary equipment in the substation includes main transformer, conductor, bus, circuit breaker, transformer, cable, and gas insulated switchgear (GIS). The status data of these kinds of equipment can reflect the operating conditions of the equipment. The secondary equipment in the substation includes relay protection device, measurement and control device, switch, metering device, and fault recorder. The status data of the secondary equipment can reflect the performance of the single equipment and the communication status of the secondary system.

(3) Data of substation control and measurement: The fault recorder in the substation is responsible for relay protection, measurement, and control. Therefore, the data reflecting substation control and measurement in the panoramic data of the substation are the data that need to obtain the operation status, measurement, and control feedback of the above equipment. For example, the control and measurement data of relay protection include relay protection tripping events, equipment parameter setting, soft pressing plate, control word, and protection function setting. Control and measurement data of measurement and control: remote signaling, telemetry, remote control, and remote adjustment.

2.2. Data Preprocessing. The monitoring data of power equipment are not only large but also have structured and semistructured data, which lead to certain difficulties in data mining and analysis. Therefore, it is necessary to carry out data preprocessing, including data cleaning, data analysis, and especially normalization, so as to eliminate the adverse effects caused by strange sample data.

The standardization method of data normalization processing is to carry out a series of linear transformations on the original substation equipment data. Assuming that $\Omega_{\min}$ and $\Omega_{\max}$ are the minimum and maximum values of attribute Ω, respectively, an original value a of Ω is mapped into a value in the interval [0, 1] through standardization. The mathematical expression of normalization is as follows:

$$a^* = \frac{a - \Omega_{\min}}{\Omega_{\max} - \Omega_{\min}}. \tag{1}$$

2.3. Image Preprocessing

2.3.1. Image Correction. In image acquisition, the quality of the acquired image is affected by the problem of shooting angle or lens, and the scene deviation will also produce certain deformation. Due to the deformation of the image, the original information of the image may be lost to a certain extent. During image matching, the matching may be inaccurate due to insufficient information [21]. As a result, the image detection effect is not good, so it is necessary to correct the image and restore the original information of the image.

Firstly, the coordinate transformation of distorted image shall be established and the image coordinate transformation shall be carried out. Set the corrected image coordinate system as (X, Y) and the original distorted image coordinate system as (x, y). First, calculate the distance d from any point (x, y) in the correction image to the image center, that is, the reference image height. Then, the shape parameter φ of the pixel (X, Y) is calculated according to d:

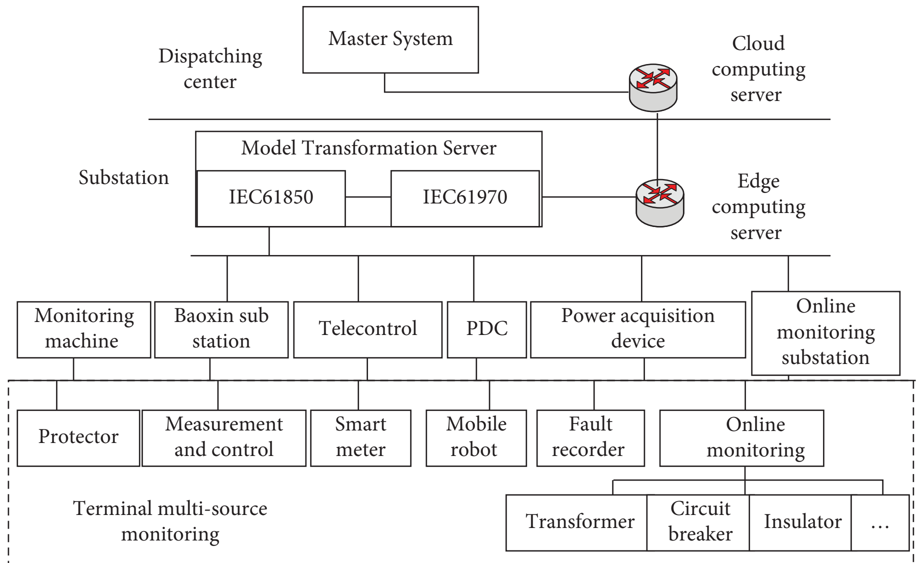

Figure 1: Architecture of substation equipment panoramic perception system based on edge computing.

$$\varphi = \arctan\left(\frac{d \tan \varphi_{\max}}{d_{\max}}\right), \tag{2}$$

where $d_{\max}$ is the maximum value of d and $\varphi_{\max}$ is determined according to the actual correction effect, taking 94.

Next, the distortion rate ζ is calculated from the shape parameter φ value:

$$\zeta = \frac{(\varphi - \tan \varphi)}{\tan \varphi}. \tag{3}$$

Finally, the original point coordinates are calculated from the ζ value:

$$\begin{cases} x = (1 + \zeta)X, \\ y = (1 + \zeta)Y. \end{cases} \tag{4}$$

2.3.2. Image Denoising. Due to the influence of illumination, angle, and noise of the image, the illumination and color of the image have certain differences. Therefore, these factors are eliminated by filtering to make the original information of the image clearer and avoid the influence of the difference of external conditions on the later image stitching, resulting in the unsatisfactory effect of image stitching.

Gaussian filter is used for image denoising. It is a filter based on Gaussian function, which weights and averages the pixels. When the weight value is different, the filter is also different, and the selection of filter is related to the weight. The Gaussian filter output is

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right), \tag{5}$$

where σ is the standard deviation.

3. Equipment State Detection Method Based on Deep Convolution Neural Network

3.1. Model Construction. The overall flowchart of substation equipment state detection model based on improved YOLOv4 network is shown in Figure 2.

Firstly, the input image is preprocessed and the image size is adjusted to 416×416, and then input it into the improved YOLOv4 model. Combined with the nine a priori frame sizes obtained by K-means++ clustering, the prediction diagrams under three different scales are output, and the state detection results of substation equipment are obtained through confidence screening.

3.2. YOLOv4 Network Structure. YOLOv4 is improved mainly in three aspects: (1) using cross stage partial network (CSPNet) to modify Darknet53 to CSPDarknet53, which further promotes the fusion of underlying information and realizes stronger feature extraction ability; (2) using spatial pyramid pooling (SPP), four different max-pooling operations are added at the final output to further extract and fuse features; the convolution kernel sizes are (1×1), (5×5), (9×9), and (13×13), respectively; (3) the structure of feature pyramid network (FPN) is modified to path aggregation network (PANet). The structure of YOLOv4 is shown in Figure 3.

YOLOv4 uses CSPDarknet53 as the backbone feature extraction network to obtain the effective feature layer and then uses the spatial pyramid pool structure to maximize the pool of features after three times of convolution. It uses PANet to complete operations such as upsampling, downsampling, convolution, and feature layer fusion, Finally, Yolo Head decodes and predicts the three feature layers obtained [22, 23]. The loss function of YOLOv4 consists of complete intersection over union (CIOU) error as regression box prediction error, which is composed of regression box prediction error L_{loc}, confidence error L_{conf}, and classification error L_{cls}.

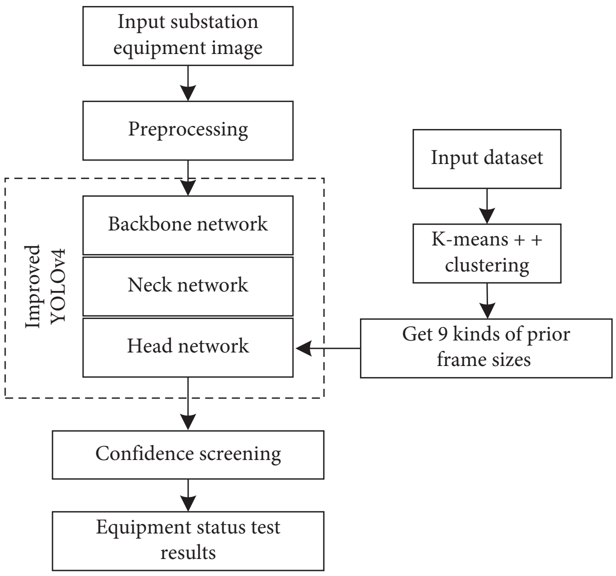

Figure 2: Overall flow of substation equipment state detection model based on improved YOLOv4 network.

Regression box prediction error L_{loc} is

$$L_{loc} = 1 - I_{ou}(A,B) + \frac{\lambda^2(A_0,B_0)}{l^2} + \alpha v,$$
$$\alpha = \frac{v}{[1 - I_{ou}(A,B)] + v}, \quad (6)$$
$$v = \frac{4}{\pi^2}\left(\arctan\frac{w_A}{h_A} - \arctan\frac{w_B}{h_B}\right)^2,$$

where $I_{ou}(A,B)$ is the intersection and union ratio of prediction frame A and real frame B; $\alpha^2(A_0,B_0)$ is the Euclidean distance between the center points of A and B, where A_0 and B_0 represent the center points of A and B, respectively; l is the diagonal distance of the minimum closed area containing both A and B; and w and h are the width and height of the frame, respectively.

Confidence error L_{conf} is

$$L_{\text{conf}}\&9; = \sum_{i=0}^{S^2}\sum_{j=0}^{M} I_{ij}\left[\overline{C}_i^j \log\left(C_i^j\right) + \left(1 - \overline{C}_i^j\right)\log\left(1 - C_i^j\right)\right]$$
$$\&9; \quad +\lambda \sum_{i=0}^{S^2}\sum_{j=0}^{M} I'_{ij}\left[\overline{C}_i^j \log\left(C_i^j\right) + \left(1 - \overline{C}_i^j\right)\log\left(1 - C_i^j\right)\right], \quad (7)$$

where I_{ij} indicates that the predicted bounding box contains the target; I'_{ij} indicates that the predicted bounding box does not contain targets; $\overline{C}_i^j$ is prediction confidence; C_i^j is the actual confidence; λ is the parameter value set; and S, M represent the number of prediction frames.

Classification error L_{cls} is

$$L_{\text{cls}} = \sum_{i=0}^{S^2} I_{ij}\sum_{c}\left\{\widehat{p}_i^j(c)\log\left[p_i^j(c)\right] + \left[1 - \widehat{p}_i^j(c)\right]\log\left[1 - p_i^j(c)\right]\right\}, \quad (8)$$

where c is the type of detection target; $p_i^j(c)$ refers to the actual probability of belonging to category c; and $\widehat{p}_i^j(c)$ is the prediction probability.

3.3. Improved YOLOv4 Network Structure.

3.3. Improved YOLOv4 Network Structure. The parameter quantity of YOLOv4 model is high, and its application in substation equipment status evaluation has problems such as long loading time [24]. Therefore, the deep separable convolution is used in the PANet feature enhancement network, the Squeeze-and-Excitation (SE) module is integrated to improve the CSPNet structure, and the K-means++ algorithm is used to improve the clustering effect, so as to improve the operation efficiency of YOLOv4.

3.3.1. Improvement of CSPNet Structure Integrating SE Module. The main principle of SE attention module is to obtain the importance of each feature channel through learning, strengthen more useful feature channels in convolution operation according to the degree of importance, and suppress relatively unimportant feature channels. The integration of SE module between the residual blocks of CSPNet structure can increase the correlation between various channels and obtain richer feature information in substation. On the other hand, because the whole SE module uses the full connection layer, the problem of many parameters and large amount of calculation of ordinary convolution layer is avoided, and the detection efficiency is improved [25]. The SE module consists of two parts, as shown in Figure 4.

The first part of the SE module is the Squeeze part. The feature map with size $W \times H \times C$ after convolution is processed by using the global average pooling operation to obtain a channel evaluation vector with size $1 \times 1 \times C$, in which each channel vector will obtain a score. The second part is the Excitation part, including two FC (full connection) layers and a ReLU function. Firstly, the dimension of the channel scoring vector is reduced to the input $1/r$ through the first FC layer and then activated by the ReLU function. Finally, the normalized weight between 0 and 1 is transformed into a sigmoid function to obtain the output corresponding to the weight value of each channel and the characteristic diagram input by the SE module.

3.3.2. PANet Features Enhance Network Optimization. PANet is the feature enhancement network of YOLOv4 detection model, which accurately saves spatial information and correctly locates pixels by using path enhancement and other methods. However, the amount of parameters of ordinary convolution is large. Therefore, the deep separable convolution is used, which reduces the amount of network parameters and calculation while affecting the accuracy less and improves the operation efficiency [26]. This method decomposes the ordinary convolution operation into two processes. Firstly, a convolution core is divided into two independent cores, and then different convolution cores are adopted for different input channels. This method takes into account the changes of channel and region at the same time

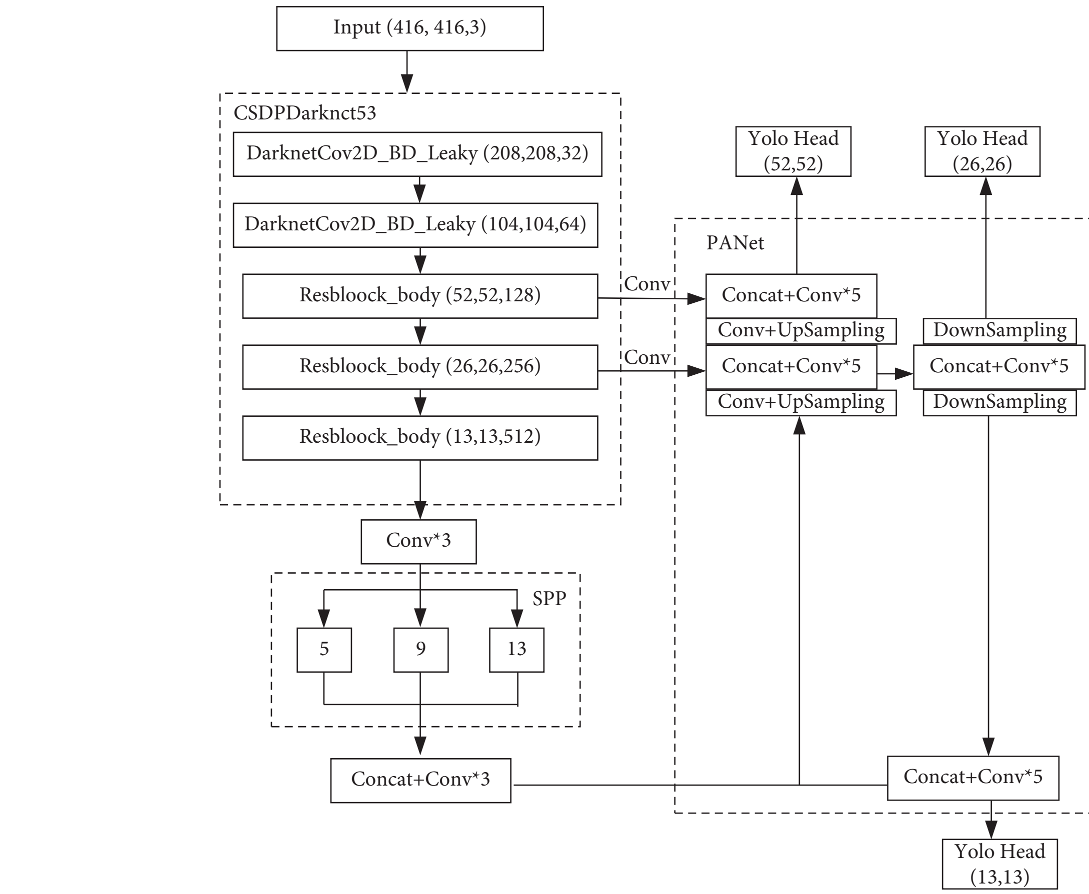

Figure 3: Structure of YOLOv4 network.

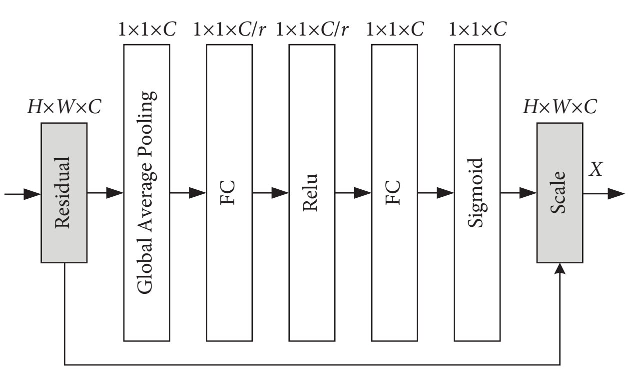

Figure 4: Structure of SE module.

and realizes the separation of channel and region. The working mode of depth convolution is shown in Figure 5.

For the ordinary convolution method, assuming that there is an input with size $N \times H \times W \times C$ and k convolution kernels of 3×3, the output is $N \times H \times W \times k^{\circ}$ For deep separable convolution, Depthwise is used to extract the spatial features of each channel, and Pointwise is used to collect the features of each point. The parameter quantity of ordinary convolution is $N \times 3 \times 3 \times k$, and the calculation quantity is $C \times W \times H \times 3 \times 3 \times k$. The parameter quantity of depth separable convolution is $N \times 3 \times 3 + N \times 1 \times 1 \times k$, and the amount of calculation is $H \times W \times C \times 3 \times 3 \times H \times W \times C \times k$.

The cost of calculation and parameter quantity is

$$\begin{cases} \dfrac{\text{Dwise}}{\text{Conv}} = \dfrac{H \times W \times C \times 3 \times 3 + H \times W \times C \times k}{H \times W \times C \times 3 \times 3 \times k} \\ = \dfrac{1}{k} + \dfrac{1}{3+3}, \\ \dfrac{\text{Dwise}}{\text{Conv}} = \dfrac{N \times 3 \times 3 + N \times 1 \times 1 \times k}{N \times 3 \times 3 \times k} \\ = \dfrac{1}{k} + \dfrac{1}{3+3}. \end{cases} \tag{9}$$

3.3.3. A Priori Box of K-Means++ Algorithm. The image information of the substation is complex and special, so the K-means++ algorithm with better clustering effect is used to optimize the method of randomly initializing the centroid of the K-means algorithm. The clustering process of K-means++ algorithm is as follows.

Step 1. The random a priori frame is selected set as the initial clustering center, and the distance $D(x)$ between the current clustering center and other a priori frames is calculated. The original Euclidean distance is easy to cause large error and is

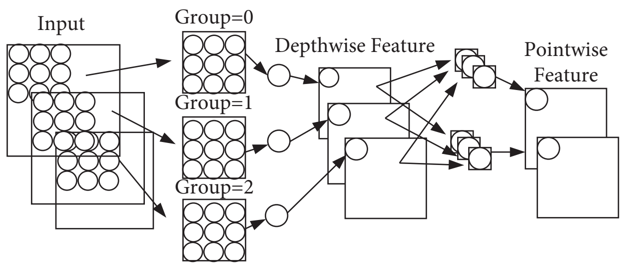

Figure 5: Principle of deep separable convolution.

not suitable for the calculation of a priori frame in the proposed method. Therefore, it is improved to IOU distance calculation:

$$D(x) = 1 - \mathrm{IoU}. \tag{10}$$

Step 2. Calculate the probability $P(x)$ that the a priori box of each substation equipment is selected as the next cluster center:

$$P(x) = \frac{D(x)^2}{\sum_{x\in X} D(x)^2}. \tag{11}$$

Step 3. Keep cycling until k cluster centers are found, then assign each sample in the dataset to the nearest cluster center, and update the cluster center of each category c until the a priori box size tends to be stable and does not change, as follows:

$$c_i = \frac{1}{|c_i|} \sum_{x\in c_i} x. \tag{12}$$

The 9 prior frame sizes obtained after clustering are [(94, 40), (34, 95), (62, 80)], [(136, 51), (123, 35), (166, 61)], [(54, 14), (40, 9), (51, 20)].

4. The Proposed Panoramic Assessment Method of Substation Equipment Health Status

After obtaining the status of substation equipment based on the improved YOLOv4 network, the health status of the equipment is evaluated in combination with the data provided by each acquisition device in the substation. The overall framework is shown in Figure 6.

In the proposed evaluation framework, it is mainly divided into two branches, corresponding to two types of input. The input equipment data information is processed through normalization and other operations. For the input substation equipment image, the improved YOLOv4 network is used to extract the characteristics of the equipment area and complete the target detection. Finally, the two parts of information are fused, and the equipment health status is classified through the full connection layer, including healthy, slightly abnormal, moderately abnormal, and severely abnormal.

Taking some current heating equipment as an example, the health status of the equipment is evaluated in combination with temperature characteristics and equipment image characteristics, in which the relative temperature discrimination method is adopted, and the calculation is as follows:

$$\eta = \frac{\tau_1 - \tau_2}{\tau_1} \times 100\% = \frac{T_1 - T_2}{T_1 - T_0} \times 100\%, \tag{13}$$

where τ_1, τ_2 represent the temperature change value of hot spot and normal point, respectively; T_1, T_2 represent the temperature of hot spot and normal point, respectively; and T_0 is the temperature of the environmental reference body.

The health state criteria of some current heating equipment are shown in Table 1.

5. Experiment and Analysis

In the experiment, the computer is equipped with Intel's ninth generation core i7-9700 processor, 64 GB RAM server, and 1080Ti graphics card. The embedded device required in the test adopts the edge computing device Jetson TX2 launched by NVIDIA, in addition to the high-performance NVIDIA Pascal™. The graphics card is also equipped with 16 GB ARM and 59.7 GB/s video memory bandwidth. In addition, the software environment includes Ubuntu 18.04 operating system, PyTorch 1.12.0 deep learning framework, and OpenCV software package. For the parameter setting of the improved YOLOv4 network: the batch size is 64, the number of training rounds is 160, the intersection and combination ratio is 0.5, and the learning rate is 0.001.

The image set used in the experiment includes the substation maintenance records and images actually taken in the substation and crawled by Python program. After image acquisition, it was first cleaned and sorted out, and a total of 1583 equipment fault images were obtained. By analyzing the internal elements, the substation equipment was divided into 5 categories (transformer, switchgear, lightning protection equipment, power cable, and distribution equipment), 24 components (relay, bus, lightning rod, insulator, respirator, etc.), 19 fault types (crack damage, silica gel discoloration, falling, falling off, screw loosening, oil leakage, dirt, paint peeling, rust, strand breaking, burning, abnormal indication, etc.), and corresponding measures and suggestions. Then, the collected image data are manually screened to remove the repeated, blurred, and inconsistent images. After screening, 932 high-quality images are selected as the initial image set, and the size of these images is uniformly processed to 416×416 pixels.

Through the image enhancement method, the number of images in the image set is expanded to 4879, of which 3903 images are used as the training set and 976 images are used as the test set. Among them, simulate the complex scenes in the substation, such as cloudy day, rainstorm, and white fog, and these weather factors will change the equipment image according to the intensity of light, which will cause great interference to the equipment state evaluation.

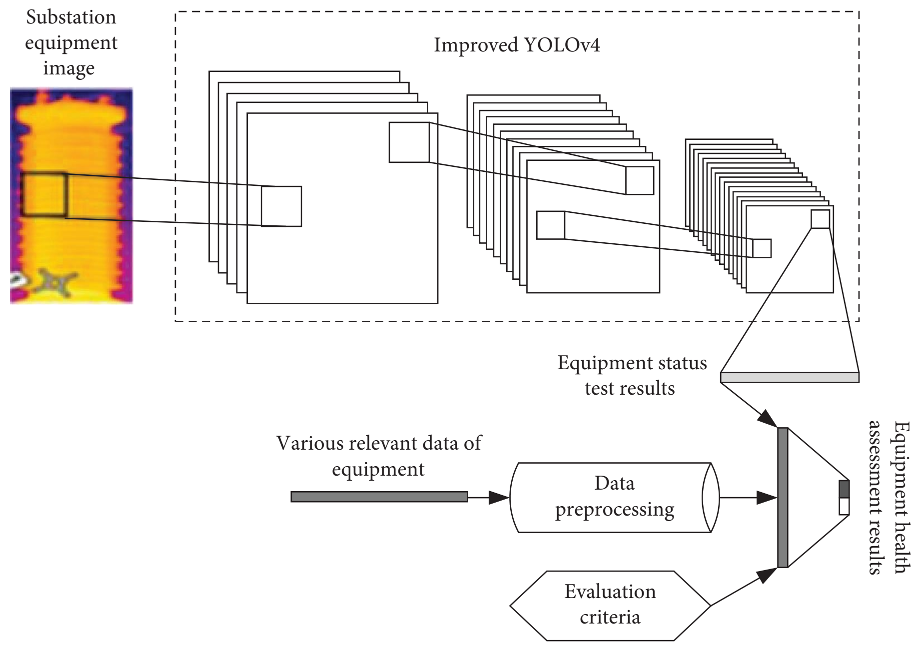

Figure 6: Panoramic assessment process of substation equipment health status.

Table 1: Health state criteria of electrothermal equipment.

Device types	Relative temperature difference (%)			
	Healthy	Slightly abnormal	Moderately abnormal	Severely abnormal
Circuit breaker	<20	≥20	≥80	≥95
Disconnector	<35	≥35	≥80	≥95
Oil filled bushing	<20	≥20	≥80	≥95
Other diversion device	<35	≥35	≥80	≥95

5.1. Evaluation Index. The evaluation criteria are accuracy rate P, detection speed FPS, recall rate R, and mean precision $\overline{P}$, which are calculated as follows:

$$P = \frac{T_P}{T_P + F_P},$$
$$R = \frac{T_P}{T_P + F_N}, \tag{14}$$
$$\overline{P} = \frac{\sum \int_0^1 \mathrm{PdR}}{N_{(\mathrm{class})}},$$

where T_P is the number of positive classes divided into positive classes; F_P is the number of false positives of negative classes; F_N is the number of false positives to negatives; $\overline{P}$ is the average accuracy, which is the performance index of each sample classifier; and $N_{(\mathrm{class})}$ represents the total number of samples.

5.2. Loss Value of Different Methods. There are 3903 images in the image set as the training set for model training. The loss function curve of the proposed method and the methods in [16, 17] is shown in Figure 7.

As shown in Figure 7, the total training loss of the proposed method is significantly lower, and the convergence is realized when the training round is 80. The proposed method adds SE module and deep separable convolution in YOLOv4 network to shorten the training time of network model. Combined with panoramic technology and multi-source monitoring, the effect of equipment condition evaluation is further guaranteed. Therefore, the loss value is close to 0.7. Reference [16] uses the improved three-frame difference method for equipment detection and analysis. This method does not consider the complex scene and small equipment of substation equipment, so the loss value is large, exceeding 1.3. Reference [17] completes the detection and state evaluation of substation equipment based on the deep learning algorithm. Compared with Reference [16], the overall performance is improved, but the consideration of type information is lacking. Therefore, the loss value is about 0.85, and the convergence speed of the model is slow.

5.3. Substation Equipment Identification and Detection Effect. Taking the insulator image in the substation as an example, the detection and recognition results of the proposed method and the methods in [16, 17] are shown in Figure 8.

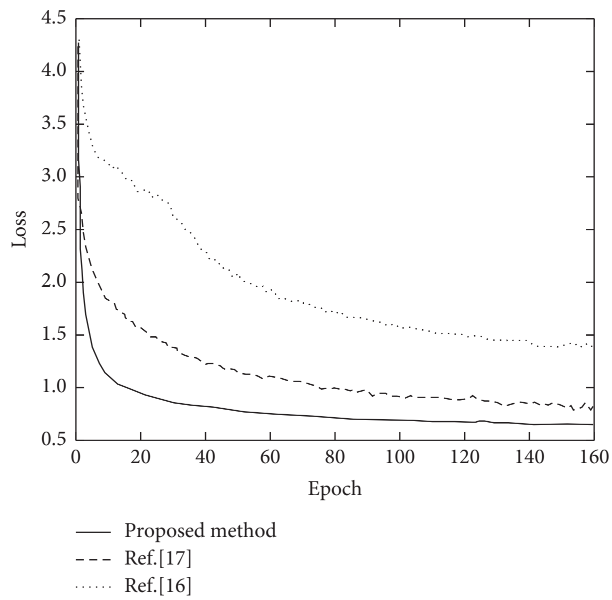

FIGURE 7: Loss curve of different methods in training stage.

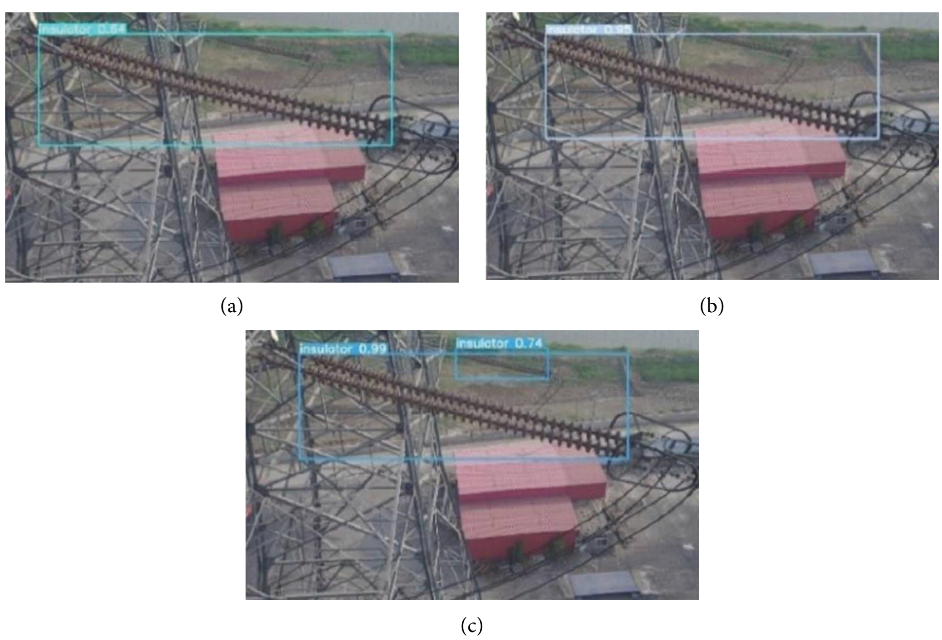

FIGURE 8: Insulator detection results of different test methods. (a) Reference [16]. (b) Reference [17]. (c) Proposed method.

As can be seen from Figure 8, References [16, 17] have different degrees of missed detection and low detection accuracy. In particular, Reference [16] not only has missed detection but also has low detection accuracy. It is suitable for simple scenes, but the detection effect is not ideal for complex substation equipment images. The proposed method uses the improved YOLOv4 network for equipment detection, and the detection result is better than other comparison methods. It can detect all targets and ensure the ideal detection accuracy. Therefore, the proposed method has better detection performance, can identify the power equipment under complex background, and then provide image support for equipment condition evaluation.

In addition, some detection results of the proposed method in substation equipment are shown in Figure 9. Combined with the information obtained by a variety of devices and using the improved YOLOv4 network for image detection, it can accurately detect the target and clarify the anomaly type, and the detection effect is ideal.

5.4. Performance Comparison of Different Methods. The health assessment results of substation equipment status by different methods are shown in Figure 10, in which the mean precision $\overline{P}$ is used to measure the assessment results of four equipment health statuses.

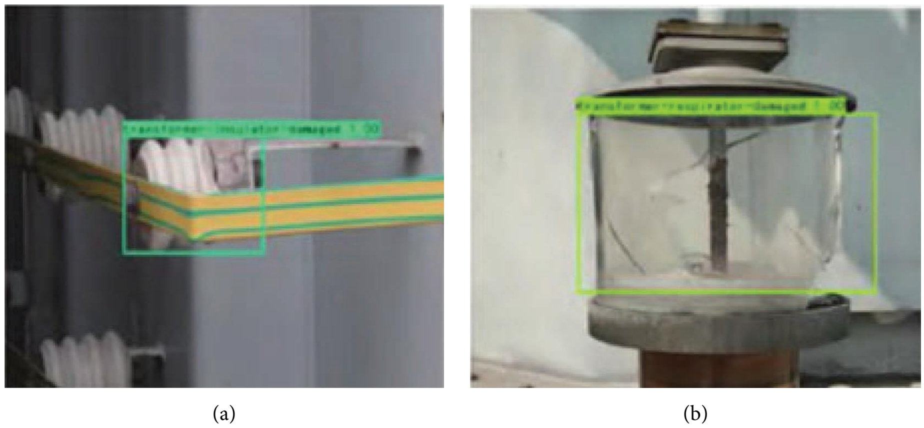

Figure 9: Partial test results of substation equipment. (a) Insulator damage. (b) Respirator damage.

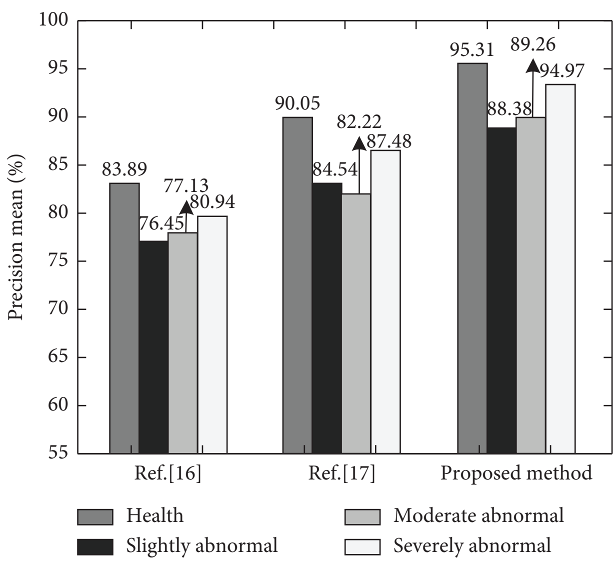

Figure 10: Evaluation results of different methods for each state.

As can be seen from Figure 10, the proposed method has the highest mean precision for the evaluation of the four states of the equipment, especially in the healthy state, and the mean precision reaches 95.31%. The proposed method integrates multisource monitoring data and detects the equipment state based on the improved YOLOv4 network. Even the mild and moderate abnormal states of the equipment that are easy to be confused show a good evaluation effect, and the mean precision is more than 88%. The evaluation method in Reference [16] is relatively simple, and the evaluation precision for four health states is not ideal. The evaluation mean precision for equipment in mild abnormal states is only 76.45%. Reference [17] adopts deep learning algorithm to realize evaluation, but it lacks comprehensive analysis of multisource data, and the evaluation precision needs to be further improved.

In addition, the evaluation accuracy, recall, mean precision, and detection time of different methods are shown in Table 2.

Table 2: Evaluation results of different methods.

Method	Reference [16]	Reference [17]	Proposed method
P (%)	79.36	87.18	91.53
R (%)	80.17	88.62	93.07
$\overline{P}$ (%)	79.94	87.65	92.28
Detection time (s)	0.392	0.481	0.452

As shown in Table 2, the proposed method has obvious advantages in the index values of accuracy, recall, and mean precision, which are 91.53%, 93.07%, and 92.28%, respectively. It further shows that the proposed method has efficient feature extraction ability for substation equipment and can meet the requirements of power equipment condition evaluation. However, due to the large amount of calculation of the improved YOLOv4 network, the evaluation time is increased by 0.452 s compared with Reference [16]. The method in Reference [16] is simple, easy to implement, and takes less time, but the evaluation accuracy is not high, and the overall accuracy is less than 80%. The deep learning algorithm in Reference [17] has complex parameters and takes a long time for equipment evaluation, which is 0.481 s, and the evaluation accuracy is not ideal.

6. Conclusion

Based on the rapid development of image processing and monitoring technology, a panoramic assessment method of substation equipment health status based on multisource monitoring and deep convolution neural network under edge computing architecture is proposed. In the panoramic perception system of substation equipment based on edge computing, the improved YOLOv4 network is used to detect the state of equipment in the substation, and the health state of equipment is evaluated combined with the data obtained by multisource monitoring equipment. Experimental results show the following:

(1) Using SE module can simplify the network parameters and ensure the performance. The image detected by the proposed method is complete and accurate, and the detection time is 0.452 s, which meets the actual requirements.

(2) The proposed method integrates a variety of substation equipment data and image information and carries out in-depth analysis and processing. The index values of accuracy, recall, and mean precision are 91.53%, 93.07%, and 92.28%, respectively. The overall evaluation performance is ideal.

Due to the complex data in the system, the evaluation efficiency of the proposed method needs to be improved. In the next step, we will try to introduce the transformer attention mechanism supporting parallel computing and conduct quantitative perception training on the model to further improve the efficiency of the target evaluation model on the embedded platform.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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