ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the application of infrared image anomaly recognition algorithm for substation main equipment in smart grid environment

Yihui Zheng[1], *Fang Luo*[1,*], *Shaoping Wang*[1], *Maoxin Xu*[1], *Jian Pang*[1] *and Zhilin Xie*[1]

[1] Guangdong Power Grid Co., Ltd. Guangzhou Power Supply Bureau, Guangzhou, Guangdong, 510000, China

SUMMARY: *This paper is based on the YOLO series of object detection models. By increasing the depth of the network and integrating a dense network structure, the training performance of the model is improved. Additionally, improvements are made to the NMS algorithm by using a decreasing function to adjust the probability scores of adjacent detection boxes, effectively retaining valid detection results with weaker confidence. An adaptive weighted averaging method is introduced for preprocessing infrared images of main equipment in substations, and experiments on anomaly detection of infrared images of main equipment in substations are conducted on this dataset. The proposed algorithm effectively extracts infrared image features of different substation equipment using convolutional layers. The model converges within 40 iterations for coordinate loss, confidence loss, and classification loss. The Soft-NMS algorithm used in the model achieves good redundancy removal, with infrared image anomaly detection accuracy, recall rate, mAP 0.5, and F1 score values of 94.53%, 96.38%, 94.01%, and 95.45%, respectively. The average fault detection rate and early warning accuracy of the improved method are 93.65% and 90.56%, respectively, significantly higher than those of the comparison method. In the identification of ground faults and two-pole short-circuit faults, the anomaly detection accuracy error of this method is within 3%. The experimental results fully demonstrate the practical value of the method proposed in this paper.*

KEYWORDS: *YOLO; Dense Network Structure; NMS Algorithm; Anomaly Detection; Substation*

1 Introduction

With the sustained growth of China's economy and the rapid development of society, the demand for electricity continues to rise, making the safe and stable operation of the power system an urgent priority [1, 2]. As a core component of the power system, the normal operation of substation equipment directly impacts the safety, reliability, and economic efficiency of the entire power system [3, 4]. However, the rapid development of the power system has led to a significant increase in the volume of operational data generated by substation equipment, along with a rise in abnormal operational conditions, resulting in increasingly prominent issues related to data anomalies [5-7]. To ensure the accuracy of automatic detection methods for abnormal operation of main substation equipment, it is necessary to identify a reliable detection method to recognize real-time abnormal signals generated by equipment operational anomalies. The substation main equipment abnormal operation early warning method based on infrared image recognition, as a non-contact detection approach, holds significant application potential [8-11].

*tempmail0808@163.com
https://doi.org/10.65102/is2026662
Published: 30 April, 2026

Infrared image recognition algorithms are a non-destructive testing method based on the principle of infrared radiation. They capture infrared radiation signals from the surface of equipment, analyze their temperature distribution characteristics, and determine the operational status of the equipment [12-14]. Infrared image recognition algorithms do not require contact with electrical equipment, thereby reducing risks during the detection process and ensuring personnel safety [15, 16]. Additionally, this non-contact nature allows detection to be conducted while the equipment is operational, without disrupting normal power supply [17, 18]. The anomaly detection method based on infrared image recognition can monitor the operational status of electrical equipment in real time, promptly identify potential fault hazards, and enhance the safety and reliability of power systems [19-21]. Furthermore, infrared image recognition algorithms are highly sensitive to temperature changes, capable of detecting minute temperature differences, thereby reflecting abnormal conditions within electrical equipment [22-24]. In power systems, infrared image recognition algorithms are primarily applied to thermal diagnosis of main equipment in substations, enabling real-time monitoring of temperature changes during equipment operation and providing a basis for warning of equipment abnormalities. Their application in substation equipment anomaly warning systems offers significant advantages, as real-time monitoring, early warning, and timely handling can effectively prevent equipment failures and ensure the safe and stable operation of power systems [25-28].

Literature [29] emphasizes the negative impacts caused by thermal defects in substation equipment, the importance of temperature in thermal defect detection in infrared images, and the limitations of traditional detection methods. It proposes a thermal defect detection method based on infrared images using convolutional neural networks, revealing that this method is superior to traditional methods. Literature [30] highlights the importance of power plant equipment and designs a support vector machine (SVM) infrared image classifier to identify various common power equipment faults, verifying the feasibility and effectiveness of the classifier. Literature [31] uses a convolutional neural network for substation equipment identification, combines infrared images for image registration, and then employs a deep belief network to determine equipment abnormal states, demonstrating the high accuracy of the aforementioned methods. Reference [32] addresses various issues encountered in the diagnosis of abnormal heating faults in power equipment by proposing a target detection method based on YOLOv4, combined with infrared image data and power equipment. The study validated that YOLOv4 achieves high accuracy and can be effectively applied to infrared detection of substation equipment. Literature [33] proposes a comprehensive method covering preprocessing, target recognition, and thermal fault diagnosis for infrared images of complex electrical equipment, providing a reference for the automation of electrical equipment inspections. Literature [34] addresses the issues of low accuracy and slow speed in the thermal state diagnosis of substation equipment, proposing an improved diagnostic strategy that enhances the fault tolerance of equipment thermal state diagnosis and improves the operational stability of substations. Literature [35] discusses how infrared image diagnosis technology for substation equipment is hindered by complex background interference, making fault diagnosis challenging. Based on this, an improved CenterNet algorithm is proposed, and its effectiveness is validated, providing support for fault detection in substation equipment. Literature [36] constructs an infrared image recognition model for substation equipment using an improved YOLOv3 algorithm, achieving automatic real-time localization of infrared image targets, and proposes a comprehensive fault diagnosis solution. Reference [37] proposes a method based on deep learning algorithms to automatically process a large number of infrared fault images and compares several unsupervised pre-training methods that consider the importance of the pre-training process. Experiments show that the proposed algorithm has good performance. Reference [38] emphasizes the importance of long-term stable operation of substation equipment and proposes a defect detection method based on infrared detection. By using an improved temperature difference recognition method to detect defects, it not only achieves automatic diagnosis but also enhances the intelligence level of substations. Reference [39] proposes an improved YOLOv4 algorithm, which, when applied to the identification of abnormal regions in infrared images, reveals that the algorithm can detect thermal phenomena in electrical equipment. Reference [40] introduces the important role of infrared thermal imaging technology in the monitoring and inspection of power equipment, which contributes to the stability of power systems, and proposes a novel intelligent fault diagnosis method for power equipment, verifying its effectiveness.

The study introduces the object detection algorithms used in the task of identifying anomalies in infrared images of main equipment in substations under a smart grid environment, and improves the algorithm based on the YOLOv3 model. The concept of dense connections is introduced to achieve better connection effects through feature reuse. The probability scores of adjacent detection boxes are adjusted using a decreasing function, and the confidence scores of candidate boxes are adjusted using a weakened decay method to improve the accuracy of infrared image anomaly identification. To reduce noise in each unit of the infrared system, an adaptive weighted averaging method is introduced to filter and improve infrared images, resulting in a custom-made infrared image anomaly detection dataset. The study concludes with simulation experiments to validate the effectiveness of the proposed method.

2 YOLO series object detection models

YOLO is a one-stage detection algorithm that uses a single CNN network to directly predict the categories and locations of different objects, providing end-to-end real-time prediction capabilities [41].

The Yolov1 network is a pioneering work in one-stage object detection and holds significant research value in the field of object detection. Yolov1 models the object detection task as a regression problem, dividing the image into a fixed number of grid cells and predicting bounding boxes and object category probabilities within each cell. This design enables Yolov1 to simultaneously complete object detection and classification tasks in a single forward pass, resulting in fast inference speeds.

YOLOv2 introduces numerous modifications over YOLOv1 to achieve better performance. First, YOLOv2 adopts a deeper and more complex network architecture, incorporating the Darknet-19 network with residual structures as its backbone network, thereby enhancing the network's feature extraction capabilities. Second, YOLOv2 omits dropout processing in its design and applies batch normalization (BN) processing after all convolutional layers. By normalizing the input through batch normalization layers and normalizing the data for each batch, the input distribution of each layer remains stable, accelerating gradient propagation and enabling the network to more easily learn effective feature representations. This accelerates convergence while also stabilizing gradients to suppress gradient vanishing or exploding issues.

The improvements to the Yolov3 network primarily focus on the following aspects: introducing multi-scale prediction, which enables better handling of targets of different scales and sizes by performing object detection on feature maps at different levels. Adopting a new deeper and larger backbone network, Darknet-53. Outputting three different-scale bounding boxes for detecting small, medium, and large-scale targets. These designs better cover targets of different scales, improving detection accuracy and stability [42]. This paper is based on the

Yolov3 version and has undergone a series of modifications and optimizations to form the new network model presented in this paper.

The Yolov4 network focuses on introducing data augmentation strategies such as Mosaic, which greatly improves the model's generalization ability. It also adopts the FPN structure, which can perform object detection on feature maps of different scales, improving the detection ability of objects of different scales.

YOLOv5 is another milestone version in the YOLO series, primarily enhanced for engineering applications. Compared to previous versions, YOLOv5 has a larger and deeper network architecture, enabling more effective extraction and representation of image features, thereby improving detection accuracy. YOLOv5 introduces automatic data augmentation technology, optimizing the dataset through adaptive data augmentation strategies to enhance the model's generalization ability and robustness.

Versions after Yolov6 do not have a strict inheritance relationship; they are all products of integration and improvement based on the latest detection technology and the Yolo architecture. Among them, Yolov6 introduces the RepVGG parameter reconstruction idea, using a large number of parameters during training and reconstructing them into a network with a small number of parameters during inference, thereby reducing network complexity and achieving the dual effects of improving inference speed and network accuracy. Additionally, YOLOv6 employs a hybrid channel strategy to construct a more efficient decoupled head.

Yolo7 optimizes and improves upon these by using ELAN as the feature extraction unit, employing max pooling and convolutions with a stride of 2 for downsampling, and utilizing a decoupled head for the detection component. Yolo8 employs a C2f structure with richer network gradient flow, a decoupled head structure, a loss function changed to the TaskAlignedAssigner positive sample allocation strategy, and introduces DistributionFocalLoss, significantly improving model performance.

3 Infrared image anomaly detection algorithm based on optimized YOLOv3 model

This paper presents a method for identifying anomalies in infrared images of main equipment in substations in a smart grid environment based on the YOLOv3 object detection model. By optimizing the connection structure of the feature extraction network and introducing the concept of dense connections, the method enhances feature reuse and enhancement in feature extraction. An improved non-maximum suppression algorithm is used during the selection of bounding boxes to avoid the removal of overlapping bounding boxes in dense scenes.

(1) Dense Connection Approach

To improve accuracy, the network depth can be increased to expand the receptive field and increase model complexity. Additionally, to reduce training difficulty, skip connections can be applied using highly interconnected layers. The residual module components in the YOLOv3 model draw inspiration from the design philosophy of residual networks, directly connecting the bypass branch inputs to subsequent layers. This allows subsequent layers to directly learn residuals, with gradients flowing through the identity function to reach earlier layers, enabling deeper network depth. The residual function expression is as follows:

$$x_l = H_l(x_{l-1}) + x_{l-1} \tag{1}$$

In the equation, x_l represents the output of layer l, and H_l represents a nonlinear transformation. The output of layer $l-1$ undergoes a nonlinear transformation and is then added to the output of layer $l-1$ to obtain the output of layer l of the residual module. This method of adding the output of the identity mapping and the nonlinear transformation is not conducive to the flow of information between network layers.

In the dense network structure (DenseNet), each layer's feature map can be learned by all subsequent layers, allowing features to be reused throughout the network [43]. Feature reuse can achieve better results with fewer parameters, making the network structure more compact. The dense connection function is expressed as follows:

$$x_l = H_l([x_0, x_1, \cdots, x_{l-1}]) \tag{2}$$

In the equation, $[x_0, x_1, \ldots, x_{l-1}]$ denotes the concatenation of the output feature maps from layers 0 to $l-1$. The dense module consists of multiple convolutional layers, where each layer H_i is composed of batch normalization, ReLU, and subsequent convolutions. The input to H_l includes not only the output of the previous layer but also the outputs of all previous layers and the original input, i.e., $x_0, x_1, ..., x_{l-1}$ respectively.

Compared to residual connections, dense connections enhance feature reuse and amplification through additional bypass connections, which helps improve network training and has a regularization effect, effectively mitigating model degradation and gradient vanishing phenomena. The dense network structure is shown in Figure 1.

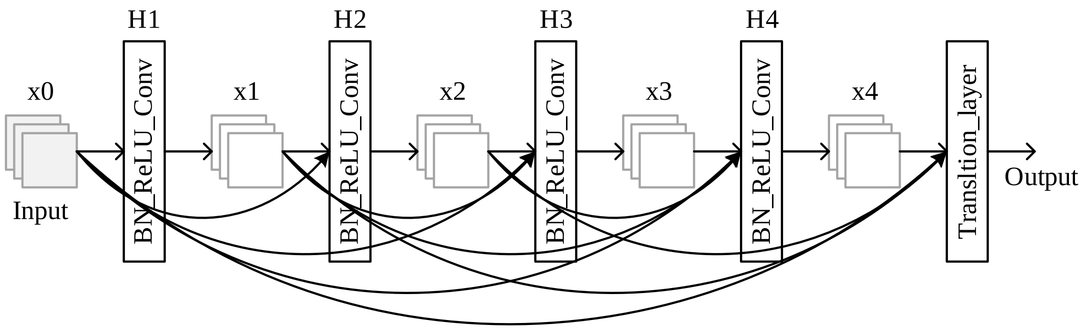

Figure 1: DenseNet network structure

(2) Improving the NMS algorithm

The NMS (Non-Maximum Suppression) algorithm addresses the issue of multiple detections in the same image. Its basic idea is as follows: use the candidate box with the highest confidence as the suppression box, calculate the IOU between the other candidate boxes and the suppression box, and if it exceeds a threshold, it is considered that the other candidate boxes mark the same object as the candidate box, and the other candidate boxes are discarded [44].

The process of using the NMS algorithm to filter object detection boxes is as follows:

Step 1: Sort all candidate boxes in ascending order to obtain the candidate box sequence bbox_list.

Step 2: Check the length of the candidate box sequence. If it is 0, it is considered that no objects were detected. If it is not 0, take the candidate box with the highest confidence as the suppression box.

Step 3: Iterate through all candidate boxes and calculate the intersection-over-union (IOU) between the candidate box and the suppression box.

Step 4: Evaluate the IOU. If it exceeds a threshold, discard the candidate box with low confidence; otherwise, retain the candidate box in the prediction result sequence real_bbox, which represents the predicted bounding box.

Finally, output all predicted bounding boxes and display the prediction information in the image.

The NMS algorithm process is shown in Figure 2.

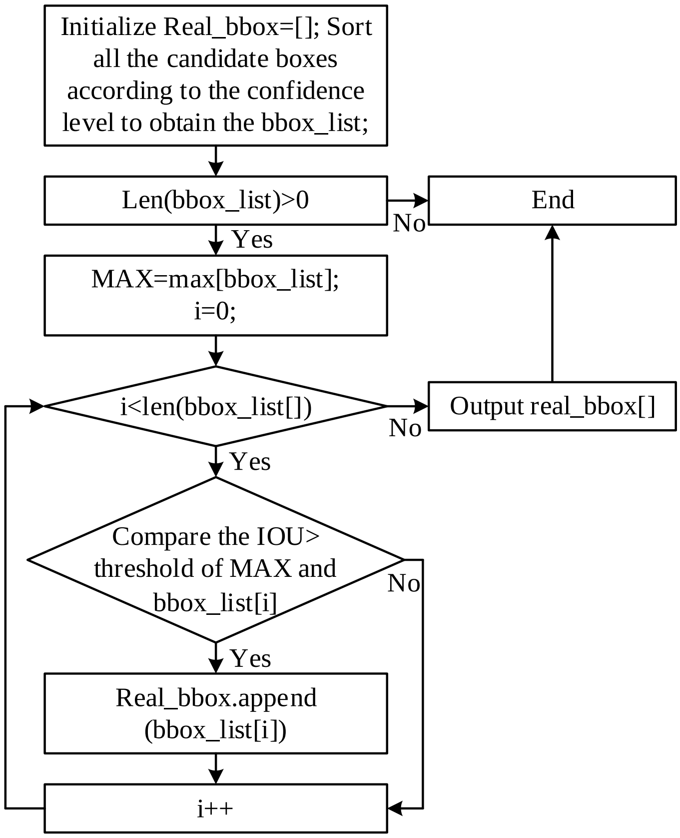

Figure 2: Flowchart of the NMS algorithm

The score reset function of the NMS algorithm is as follows:

$$s_i = \begin{cases} s_i & iou(M, b_i) \le N \\ 0 & iou(M, b_i) > N \end{cases} \tag{3}$$

The NMS algorithm has significant drawbacks: when the intersection-over-union ratio exceeds the set threshold, it discards candidate boxes with lower confidence, potentially causing one of the adjacent targets to be overlooked. Additionally, small-sized targets may appear within the detection boxes of adjacent targets, which is detrimental to the detection of small targets and reduces the average detection accuracy. When capturing infrared images of power equipment, due to factors such as the shooting angle of the infrared thermal imager, the image may contain densely packed equipment. In such cases, effective detection boxes with less distinct shapes may be filtered out, leading to missed detections. Additionally, high-confidence error candidate boxes may be retained, resulting in false positives and reducing target detection accuracy.

The Soft-NMS algorithm improves upon the NMS algorithm, enhancing detection accuracy in dense scenes. Unlike the NMS algorithm, which directly ignores detection boxes with overlapping regions when confidence levels differ, the Soft-NMS algorithm avoids false negatives and false positives in dense target scenes, thereby improving detection accuracy. The basic idea of the Soft-NMS algorithm is to use a decreasing function to adjust the probability scores of adjacent detection boxes. Unlike the traditional NMS algorithm, which directly eliminates candidate boxes by adjusting their confidence scores, the Soft-NMS algorithm uses a weakening decay method to adjust the confidence scores of candidate boxes. This effectively retains valid detection boxes with weaker confidence scores, improving detection accuracy in dense scenes. The score reset function is as follows:

$$s_i = \begin{cases} s_i & iou(M, b_i) \le N_i \\ s_i(1 - iou(M, b_i)) & iou(M, b_i) > N_i \end{cases} \tag{4}$$

As can be seen from the Soft-NMS algorithm score reset function, when there are adjacent detection boxes that overlap with the suppression box, their confidence scores are regularly attenuated. The larger the overlapping area between the adjacent detection boxes and the suppression box, the more likely false positives are to occur, and the corresponding probability attenuation is increased accordingly.

4 Preprocessing of infrared images of main equipment in substations

Infrared thermal imaging cameras create images by detecting infrared radiation from targets and their backgrounds. After undergoing a series of processing steps, including atmospheric transmission, optical imaging, photoconversion, and electronic processing, the infrared imaging system can be treated as a linear spatial invariant system.

Since each unit in the infrared system introduces noise, the form of noise is diverse. First, due to material and process limitations, there are parameter differences between detector pixels in the system, leading to variations. Second, the signals generated by each pixel must be injected into the readout circuit for output, resulting in signal coupling between the detector pixels and readout circuit, as well as differences in charge transfer efficiency of the readout circuit. Third, noise caused by unstable external inputs.

Traditional selective masking algorithms use arithmetic averaging to average pixels when assigning values to central pixels, without considering the influence of different pixels on the central point. This paper introduces an adaptive weighted averaging method to improve this approach.

Assuming that the median gray value in the template window is Med, and the gray value of a point in the window is $f(x, y)$, the weight of that point can be expressed as:

$$r(x, y) = \frac{\dfrac{1}{1 + abs(f(x, y) - Med)}}{\sum_{k=1}^{N} \dfrac{1}{1 + abs(f(x, y) - Med)}} \tag{5}$$

As can be seen from the formula, the closer the gray value of a pixel within the window is to the median value within the window, the greater its weight. If the gray values of the pixels within the window are not significantly different, it approaches mean filtering. If the gray values within the window are significantly different, it approaches median filtering.

Finally, the gray value of the center point is expressed as:

$$g(i, j) = \sum_{k=1}^{N} r(x, y) \times f(x, y) \tag{6}$$

where N is the number of pixels in the window, $r(x, y)$ represents the weight at pixel (x, y), and $g(i, j)$ represents the weighted grayscale value when the center point is at (i, j).

The input parameter of the algorithm is the device infrared image img, and the output result is the filtered grayscale matrix img_filtered. The algorithm steps are described as follows:

Step 1: Obtain the grayscale matrix $G_{p\times q}$ of the image, along with the number of rows p and columns q of the matrix. Create a $p\times q$ matrix img_filtered to store the filtered grayscale data of the image. Create a 1×9 weighted average matrix means and variance matrix bunsan to store the weighted average and variance of the grayscale values corresponding to the 9 window templates.

Step 2: Obtain the pixel grayscale values in the grayscale matrix $G_{p\times q}$. Since a 5×5 window template is used, the range of values for the row index when obtaining pixel grayscale values is 3 to (p-2), and the range of values for the column index is 3 to (q-2).

Step 3: Use the 9 window templates to calculate the weighted average and variance of the grayscale values within each template, and store them in means and bunsan, respectively.

Step 4: Obtain the index m_index corresponding to the minimum variance value from the variance matrix bunsan.

Step 5: Use the weighted average value corresponding to m_index as the grayscale value for the corresponding position in the output image.

Step 6: Repeat steps 2 to 5 until all values in the grayscale matrix have been processed, and return the filtered grayscale matrix img_filtered.

This paper uses Matlab R2015a as the programming tool and selects a 340×240 infrared image of a 500k V inductor terminal as the experimental object. An adaptive weighted selective mask algorithm is used to filter the image. A total of 4,858 images were obtained, including 875 voltage transformers, 1,849 surge arresters, and 2,134 insulators. All images were labeled using the labelImg software. The dataset was expanded using techniques such as flipping and rotation to serve as the data foundation for subsequent research.

5 Simulation results of infrared image anomaly detection for substation equipment under a smart grid

The experimental hardware configuration for the study is as follows: Windows operating system, 16 GB of memory, and a 64-bit operating system. Programming language: Python. Under this environment, a simulation experiment was conducted for infrared image anomaly detection of substation equipment in a smart grid.

5.1 Visualization and performance analysis of infrared image features

To validate the performance of the improved YOLOv3 algorithm proposed in this paper for detecting anomalies in infrared images of substation equipment, infrared image anomaly detection was conducted on three types of substation equipment: voltage transformers, surge arresters, and insulators.

During the training process, the visualization diagram of the features extracted by the improved YOLOv3 network is shown in Figure 3. As can be seen from the figure, the feature maps extracted by the model's convolutional layers for different types of substation equipment contain features that are almost entirely different, each with its own focus—some emphasize edges, while others emphasize the overall structure. The shallow features obtained after the first and second GhostConv layers are mostly complete, containing more positional and detailed information. The deep features obtained after the third GhostConv are already difficult to distinguish the specific equipment contours. As the network deepens, the deep features of the image can be converted into abstract semantic information readable by computers, thereby better describing the overall information of the image. Overall, the method proposed in this paper performs well in improving target recognition accuracy, meeting the dual requirements of accuracy and real-time performance in substation scenarios.

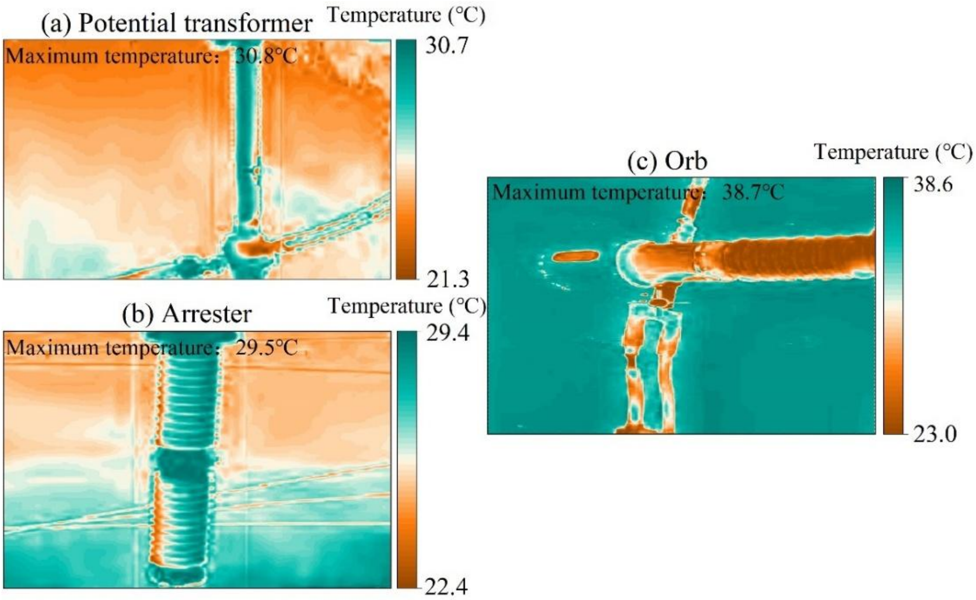

Figure 3: The improved YOLOv3 network extracts the feature visualization diagram

The loss function curve reflects the learning quality of a deep learning model. Analyzing the convergence of the loss curve can help better evaluate model performance. This paper trained the model on the infrared substation equipment dataset using the network parameter configuration shown in Table 1, and the changes in the loss function during training are shown in Figure 4. The loss function consists of three parts: coordinate loss (box_loss), confidence loss (obj_loss), and classification loss (cls_loss). To improve the detection accuracy of the model, this paper modifies the coordinate loss function of the improved YOLOv3 algorithm to SIoU Loss to accelerate function convergence and improve anchor box localization accuracy, thereby addressing issues such as false detection, multiple detection, and missed detection to a certain extent.

Figure (a) shows the changes in the loss function during the training process, and Figure (b) shows the changes in box_loss before and after the improvement. As shown in Figure (a), the network did not exhibit overfitting or underfitting during training and converged before the end of the iteration. As shown in Figure (b), the improved loss function converges faster than the original function, with smaller loss values, and eventually stabilizes around 0.041. The improved algorithm demonstrates significantly enhanced convergence performance compared to the original algorithm.

Table 1: Network parameter settings

Parameters	Value
Epoch	200
Size of batch	32
Learning rate	0.0001
Weight decay	0.001
Image size	340×240
Momentum	0.8

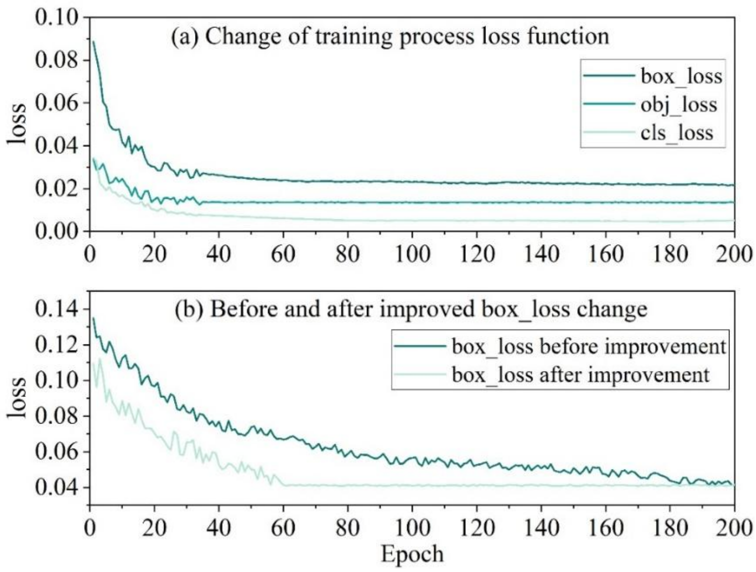

Figure 4: Variation of loss function curves

The performance of the algorithm in anomaly detection is evaluated using precision, recall, mAP 0.5, and F1 scores. Table 2 lists the recognition results of various types of substation equipment targets using the algorithm in this paper on the infrared substation equipment dataset. The data in the table shows that the algorithm in this paper performs excellently in the recognition of various types of equipment targets, even achieving high precision on voltage transformers with fewer samples.

Table 2: Recognition results of various targets

Equipment type	Precision (%)	Recall (%)	mAP 0.5 (%)	F1 (%)
Potential transformer	98.73	91.25	90.24	94.84
Arrester	95.41	94.63	96.47	95.02
Orb	97.65	93.89	95.28	95.73
All types	96.84	92.96	94.63	94.86

In addition, to address the large number of redundant prediction boxes generated by massive learning data samples during model training, different schemes were used to screen prediction boxes, and four different NMS post-processing schemes were selected for experimental comparison. The performance comparison of models processed by different NMS schemes is shown in Figure 5. The experiment used different schemes, including: original NMS, Cluster-NMS, Cluster-NMS with SPM constraints, and Soft-NMS proposed in this paper. The experimental results indicate that Cluster-NMS performs better than the traditional NMS method, showing improvements across all four objective metrics. By adding SPM constraints and center point distance constraint terms, the performance metrics of the model can be further enhanced. The method proposed in this paper achieves the best measurement results across the four objective evaluation metrics, with precision, recall, mAP 0.5, and F1 scores of 94.53%, 96.38%, 94.01%, and 95.45%, respectively. This indicates that the proposed method is most effective at removing redundant data in the task of detecting anomalies in infrared images of main equipment in substations, thereby retaining the optimal detection results.

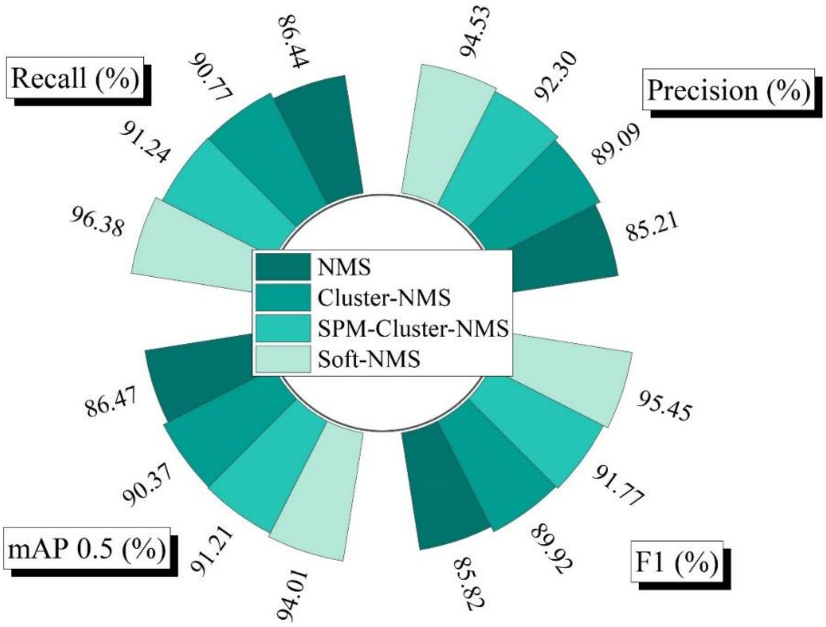

Figure 5: Model performance comparison after different NMS processing

5.2 Substation equipment anomaly identification and early warning effectiveness

To validate the effectiveness and accuracy of the abnormal operation early warning method for main equipment in substations based on infrared image recognition described in this paper, experiments were conducted. The experiments were conducted at a certain substation, with the main equipment including a FLIR T1020 infrared thermal imager (1024×768 pixel resolution, thermal sensitivity <0.02°C), a DELL PowerEdge R740 server (equipped with two Intel Xeon Gold 6130 processors, 384GB RAM, and six 1TB SSD drives), and a self-developed anomaly detection software platform.

An infrared image dataset collected during the actual operation of the aforementioned substation was selected, including infrared images of voltage transformers, surge arresters, and insulators. The FLIR T1020 infrared thermal imager was deployed at the substation site to periodically capture images of the equipment's operational status. The DELL PowerEdge R740 server was used for data processing and model training. The experimental environment temperature was controlled at 26°C, and humidity was maintained at 50% RH.

The model's infrared image anomaly recognition performance was evaluated using fault detection rate and early warning accuracy. The experiment compared SIFT, LSTM, and the pre-optimized YOLOv3 model, with the fault detection rate and early warning accuracy for main equipment infrared image anomaly recognition shown in Figures 6 and 7, respectively. It can be seen that the optimized YOLOv3 infrared image recognition method in this paper outperforms the three comparison methods in terms of fault detection rate and early warning accuracy. The average fault detection rate of the infrared image recognition method is 93.65%, while the comparison methods range from 78.22% to 84.07%. The higher fault detection rate indicates that infrared image recognition technology can more effectively capture abnormal conditions of the equipment, reducing the false negative rate. Additionally, the early warning accuracy of the infrared image recognition method in this paper is 90.56%, higher than the 81.54% of the unoptimized YOLOv3 algorithm, further validating the advantages of infrared image recognition technology in detecting abnormal conditions in substation equipment.

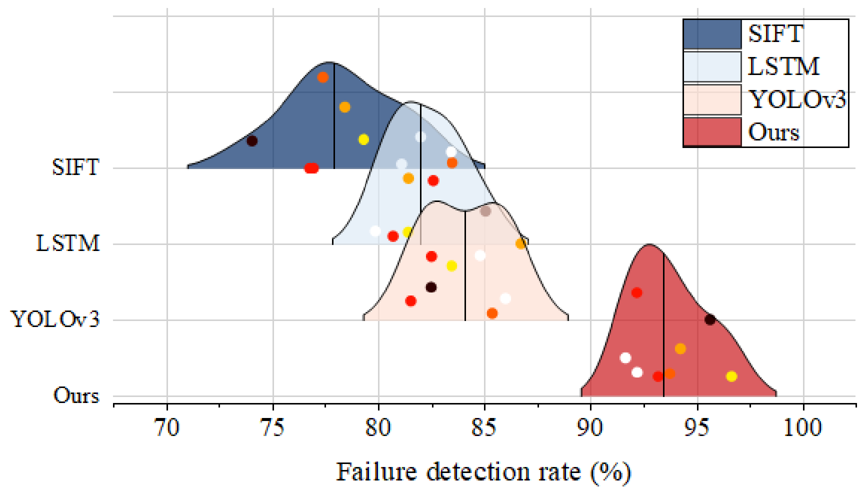

Figure 6: Fault detection rate of infrared image anomaly identification

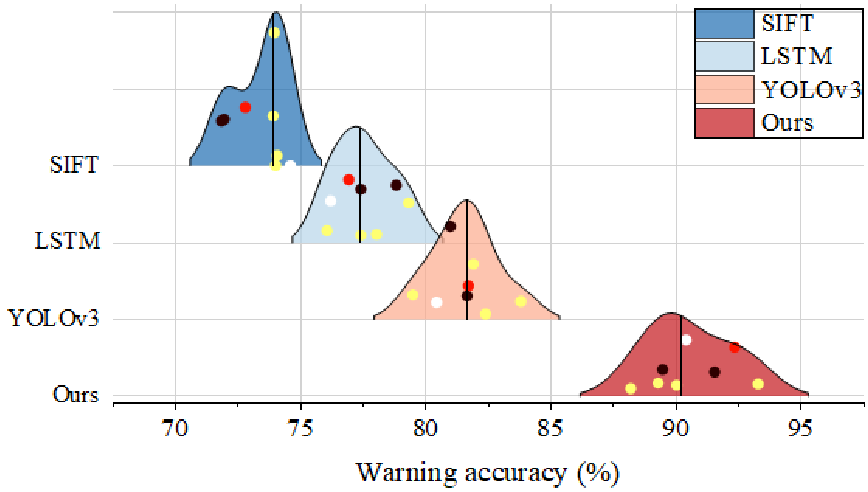

Figure 7: Warning accuracy of infrared image anomaly recognition

5.3 Evaluation of the accuracy of equipment fault anomaly detection results

To validate the effectiveness of the method proposed in this paper for identifying abnormal operation of main equipment in substations, ground faults and two-pole short-circuit faults were simulated at 0.5 km and 10 km from the beginning of the transmission line. The algorithm proposed in this paper was used to identify abnormal conditions in the substation, and the identification accuracy error was calculated.

The simulation results for identifying ground faults and two-pole short-circuit faults are shown in Tables 3 and 4, respectively. As shown in the tables, the method proposed in this paper can accurately calculate the location of equipment faults based on correlation algorithms. In the 0.5 km ground fault scenario, the method calculated fault distances of 0.5017, 0.5052, and 0.5074 km under overcurrent resistances of 0, 10, and 50 Ω, respectively, with errors within 2%. In the case of a 10 km ground fault, the anomaly detection distances were 10.283, 10.146, and 10.098 km, respectively. While the anomaly identification distance error may have improved slightly, the accuracy error remained below 3%. The proposed method achieved an anomaly detection accuracy error of less than 2% in two-phase short-circuit faults. The experimental results validate the effectiveness of the proposed algorithm.

Table 3: Experimental results of the ground circuit fault in different locations

Position	Type	Resistance (Ω)	Left port energy (kJ)	Right port energy (kJ)	Fault distance (km)	Error (%)
0.5	Positive pole	0	1.0562	0.0016	0.5017	0.34
	Negative pole	10	1.1099	0.0024	0.5052	1.04
	Positive pole	50	1.2085	0.0026	0.5074	1.48
10	Negative pole	0	0.0043	0.0022	10.283	2.83
	Positive pole	10	0.0051	0.0024	10.146	1.46
	Negative pole	50	0.6075	0.0028	10.098	0.98

Table 4: Experimental results of the polar circuit fault in different locations

Position	Type	Resistance (Ω)	Left port energy (kJ)	Right port energy (kJ)	Fault distance (km)	Error (%)
0.5	Positive pole	0	3.1279	0.1628	0.5030	0.60
	Negative pole	10	3.2041	0.1495	0.5055	1.1
	Positive pole	50	3.0157	0.1586	0.5087	1.74
10	Negative pole	0	1.4627	0.5719	10.197	1.97
	Positive pole	10	1.4619	0.5944	10.131	1.31
	Negative pole	50	1.4597	0.5832	10.084	0.84

6 Conclusion

The paper improves the YOLOv3 algorithm by introducing the concept of dense connections to optimize the feature extraction network structure. An improved non-maximum suppression algorithm is adopted during the selection of bounding boxes to enhance the model's anomaly detection accuracy in dense scenes. Additionally, an adaptive weighted selective masking algorithm is applied to filter infrared images of main equipment in substations, reducing noise interference from infrared system units. Abnormal recognition simulation experiments were conducted on the processed infrared image data, yielding the following results: The improved YOLOv3 algorithm can clearly distinguish the infrared features of main equipment in substations. In terms of coordinate loss, the optimized algorithm's loss value is smaller than that of the unoptimized algorithm, stabilizing around 0.041. Under the Soft-NMS algorithm, the precision rate, recall rate, mAP 0.5, and F1 score for infrared image anomaly detection all exceed 90%. The method demonstrates significant advantages in anomaly detection for substation equipment, with average fault detection rates and early warning accuracy rates of 93.65% and 90.56%, respectively. The proposed method achieves high detection accuracy for substation equipment anomalies, with detection errors within 2% under ground fault conditions. The experimental results validate the superior performance of this method in the anomaly detection of infrared images of main equipment in substations.

About the Authors

Yihui Zheng, male, 2005-2009, Zhejiang University, majoring in Electrical Engineering and Automation, Bachelor's degree. He focused on neural networks and power grid load forecasting. 2013-2016, South China University of Technology, majoring in electrical engineering, Master’s degree. His primary research focused on the application of online monitoring systems in the substation field. As a senior engineer, he is the senior manager of substation operations. With 16 years of specialization in technical management of substation operations, he is engaging in research on the intelligent operations and maintenance technologies for substations. As the first author, he has published 3 core power engineering journals, and participated in development and construction of China Southern Power Grid’s pioneering Substation Operational Support System. He has been honored with several awards from Guangzhou Power Supply Bureau, including the First Prize in Management Innovation (2023), the First Prize in the Substation Operation Competition (2012), and specific recognition for Employee Innovation & Achievement Promotion. He has awarded the Third Prize in Employee Innovation from China Southern Power Grid as well.

Fang Luo, female, 2015-2018, South China University of Technology, majoring in Electric Machines and Electric Apparatus, Master’s degree. She is an Engineer and a technician at China Southern Power Grid Co., As a pioneering contributor to the first wave of digital grid transformation, she spearheaded the advancement of remote intelligent operation and maintenance (O&M) for substations, conducting critical research on substation cybersecurity protection, equipment defect identification, and infrared-based device diagnostics.

Shaoping Wang, male, a senior engineer of China Southern Power Grid, he prolonged engagement in substation operation management and digital transformation for power supply enterprises, specializing in hands-on and managerial experience in substation operations. He spearheaded the formulation of comprehensive management standards and full-process digital production protocols for substation operations, and organized the development of SPG’s first Operational Support System for substations, enabling panoramic equipment-state perception and intelligent risk pre-warning, who made pivotal contributions to advancing remote, intelligent, and standardized substation maintenance.

Maoxin Xu, male, 2014 - 2017, South China University of Technology, majoring in Electrical Engineering, Master's Degree. He focused on research of artificial intelligence algorithms in reactive power optimization of power systems during the master's program. 2010 - 2014, Southwest Jiaotong University, majoring in Power System and Automation, Bachelor's Degree. He graduated with outstanding academic performance and received multiple university-level scholarships. He is working at Guangzhou Power Supply Bureau as a senior engineer, participated in multiple engineering projects including the construction and commissioning of the Central Guangdong Converter Station, with a focus on substation operation and maintenance. He participated in a project on the application of a digital twin-based intelligent operation and maintenance system in converter stations, and won the Third Prize for Scientific and Technological Progress at Guangzhou Power Supply Bureau.

Jian Pang, male, 2018 - 2021, North China Electric Power University, majoring in Electronic Science and Technology, Master’s degree. His direction during the Master’s degree program was the advanced transmission and substation technology. 2014 - 2018, North China Electric Power University, majoring in Smart Grid Information Engineering, Bachelor’s degree. Since 2021, employed by Guangzhou Power Supply Bureau, he is working in substation operation and participating in the construction of digital substation production systems. He has published 1 paper in a Chinese core journal, 1 paper in an EI-indexed conference and obtained 1 national authorized invention patent during university.

Zhilin Xie, male, 2012 - 2014, Sichuan University, majoring in Electrical Engineering and Automation, Bachelor's Degree. 2013 - 2018, as a dedicated emergency management specialist, he served in the safety management department, responsible for on-site safety supervision and control, as well as organizational emergency management. He has participated in multiple on-site emergency response operations, significantly enhanced safety management and emergency response capabilities. He now works in the production technology department and responsible for production monitoring.He has received several honors.Second prize, (2015) China Southern Power Grid Technology Improvement Contribution Award. First Prize, (2017) Guangzhou Power Supply Bureau Technology Improvement Contribution Award (Research and Application of Comprehensive Management Strategy for Substation Geological Hazard Prevention).First Prize, (2021) Guangzhou Power Supply Bureau Technology Foundation Management Improvement Award (Visualized Dynamic Perception and Multi-dimensional Coordinated Management for Project Life-cycle).

References

[1] Meegahapola, L., Sguarezi, A., Bryant, J. S., Gu, M., Conde D, E. R., & Cunha, R. B. (2020). Power system stability with power-electronic converter interfaced renewable power generation: Present issues and future trends. Energies, 13(13), 3441.

[2] Javaid, S., Kaneko, M., & Tan, Y. (2021). Safe operation conditions of electrical power system considering power balanceability among power generators, loads, and storage devices. Energies, 14(15), 4460.

[3] Li, G., Sun, Y., Pan, L., Luo, C., Deng, Q., Xie, D., ... & Wu, Y. (2024, April). The analysis and research of the programming operation based on substation equipment status. In 2024 7th International Conference on Energy, Electrical and Power Engineering (CEEPE) (pp. 454-458). IEEE.

[4] Wang, Y. (2022). Condition Monitoring of Substation Equipment Based on Machine Vision. Frontiers in Energy Research, 10, 908999.

[5] Banihashemi, S., & Zhang, J. (2023). Soft sensing image analysis and processing method of substation equipment defects. International Journal for Applied Information Management, 3(4), 154-161.

[6] Pal, D., Meyur, R., Menon, S., Reddy, M. J. B., & Mohanta, D. K. (2018). Real-time condition monitoring of substation equipment using thermal cameras. IET Generation, Transmission & Distribution, 12(4), 895-902.

[7] Liu, Y., Lv, H., He, Z., Shi, Q., & Chen, W. (2023, April). An Environment Adaptive Detection Algorithm for Substation Equipment Inspection. In 2023 Panda Forum on Power and Energy (PandaFPE) (pp. 2152-2156). IEEE.

[8] Luo, L., Ma, R., Li, Y., Yang, F., & Qiu, Z. (2021). Image recognition technology with its application in defect detection and diagnosis analysis of substation equipment. Scientific Programming, 2021(1), 2021344.

[9] Yang, Y., Wang, S., Ren, J., & Zhang, Y. (2023, July). Abnormal scene image recognition method for intelligent operation and maintenance of electrical equipment in substations.

In 2023 3rd International Conference on Energy Engineering and Power Systems (EEPS) (pp. 298-305). IEEE.

[10] Changfu, X., Bin, B., & Fengbo, T. (2017, May). Research of substation equipment abnormity identification based on image processing. In 2017 International Conference on Smart Grid and Electrical Automation (ICSGEA) (pp. 411-415). IEEE.

[11] Ullah, I., Yang, F., Khan, R., Liu, L., Yang, H., Gao, B., & Sun, K. (2017). Predictive maintenance of power substation equipment by infrared thermography using a machine-learning approach. Energies, 10(12), 1987.

[12] Hou, F., Zhang, Y., Zhou, Y., Zhang, M., Lv, B., & Wu, J. (2022). Review on infrared imaging technology. Sustainability, 14(18), 11161.

[13] FANG, L. (2023). Fault Diagnosis of Electrical Equipment Based on Infrared Thermal Imaging. Nonlinear Optics, Quantum Optics: Concepts in Modern Optics, 57.

[14] Yue, K., Wang, Z., Yuan, P., Gao, F., Jia, Y., Xu, Z., & Li, S. (2024, May). A Novel Infrared Image Segmentation Algorithm for Substation Equipment. In 2024 Second International Conference on Cyber-Energy Systems and Intelligent Energy (ICCSIE) (pp. 1-6). IEEE.

[15] Li, B., Wang, T., Hu, Z., Yuan, C., & Zhai, Y. (2022). Two-level model for detecting substation defects from infrared images. Sensors, 22(18), 6861.

[16] Lu, M., Liu, H., & Yuan, X. (2021). Thermal Fault Diagnosis of Electrical Equipment in Substations Based on Image Fusion. Traitement du Signal, 38(4).

[17] Shi, W., & Ren, X. (2022). Electrical fault detection equipment based on infrared image fusion. Procedia Computer Science, 208, 509-515.

[18] Wu, G., Yu, M., Shi, W., Li, S., & Bao, J. (2020). Image recognition in online monitoring of power equipment. International Journal of Advanced Robotic Systems, 17(1), 1729881419900836.

[19] Zhang, Y., Li, D., Liu, J., Liang, Y., & Chen, Y. (2024, November). Development and Research of Image Recognition System for Substation Equipment based on Convolutional Neural Network. In Proceedings of the 2024 International Symposium on Integrated Circuit Design and Integrated Systems (pp. 166-171).

[20] Feng, B., Jin, Y., Yin, Z., Liu, Y., Wang, X., & Zhao, Y. (2023, October). Infrared image recognition and classification of typical electrical equipment in substation based on YOLOv5. In 2023 2nd Asian Conference on Frontiers of Power and Energy (ACFPE) (pp. 140-144). IEEE.

[21] Han, S., Yang, F., Yang, G., Gao, B., Zhang, N., & Wang, D. (2020). Electrical equipment identification in infrared images based on ROI-selected CNN method. Electric Power Systems Research, 188, 106534.

[22] Han, S., Yang, F., Jiang, H., Yang, G., Wang, D., & Zhang, N. (2022). Statistical analysis of infrared thermogram for CNN-based electrical equipment identification methods.

Applied Artificial Intelligence, 36(1), 2004348.

[23] Zhao, Z., Feng, S., Zhai, Y., Zhao, W., & Li, G. (2023). Infrared thermal image instance segmentation method for power substation equipment based on visual feature reasoning. IEEE Transactions on Instrumentation and Measurement, 72, 1-13.

[24] Zhang, C., Yuan, P., Song, C., & Yang, Z. (2020, June). A text recognition method for infrared images of electrical equipment in substations. In 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 1116-1121). IEEE.

[25] Wang, X., La, Y., & Wang, Z. (2025, July). Application of multispectral infrared thermal imager in infrared imaging accurate recognition of substation equipment under complex conditions. In International Conference on Optoelectronic Information and Communication Technology (OICT 2025) (Vol. 13684, pp. 59-65). SPIE.

[26] Liu, J., Xu, C., Ye, Q., Cao, L., Dai, X., & Li, Q. (2024). Thermal imaging-based abnormal heating detection for high-voltage power equipment. Energies, 17(16), 4035.

[27] FENG, J., DUAN, Y., KANG, W., LI, Z., & LIU, X. (2022). Research on the Application of Image Recognition Technology in Transformer Equipment Fault Monitoring. Nonlinear Optics, Quantum Optics: Concepts in Modern Optics, 56.

[28] Tao, H., Paul, A., & Wu, Z. (2024). Infrared Image Detection and Recognition of Substation Electrical Equipment Based on Improved YOLOv8. Applied Sciences, 15(1), 328.

[29] Wang, K., Zhang, J., Ni, H., & Ren, F. (2021). Thermal defect detection for substation equipment based on infrared image using convolutional neural network. Electronics, 10(16), 1986.

[30] Shi, Z., Zhao, Y., Liu, Z., Zhang, Y., & Ma, L. (2021). Diagnosis and classification decision analysis of overheating defects of substation equipment based on infrared detection technology. Scientific Programming, 2021(1), 3356044.

[31] Yilin, J., & Jian, S. (2020, October). Substation equipment fault identification based on infrared image analysis. In Journal of Physics: Conference Series (Vol. 1659, No. 1, p. 012004). IOP Publishing.

[32] Liu, T., Li, G., & Gao, Y. (2022). Fault diagnosis method of substation equipment based on You Only Look Once algorithm and infrared imaging. Energy Reports, 8, 171-180.

[33] Tang, Z., & Jian, X. (2024). Thermal fault diagnosis of complex electrical equipment based on infrared image recognition. Scientific Reports, 14(1), 5547.

[34] Wang, Y., Yin, Y., & Ren, J. (2019). Research on thermal state diagnosis of substation equipment based on infrared image. Advances in Mechanical engineering, 11(4), 1687814019828551.

[35] Zheng, H., Cui, Y., Yang, W., Li, J., Ji, L., Ping, Y., ... & Chen, X. (2022). An infrared image detection method of substation equipment combining Iresgroup structure and

CenterNet. IEEE Transactions on Power Delivery, 37(6), 4757-4765.

[36] Zhang, X., Lv, Z., Sun, Y., Huang, B., Niu, Z., Liu, G., & Mu, K. (2021, December). Intelligent detection technology of infrared image of substation equipment based on deep learning algorithm. In 2021 IEEE Sustainable Power and Energy Conference (iSPEC) (pp. 3855-3860). IEEE.

[37] Lin, Y., Sun, J., Li, C., Ma, Y., Geng, Y., & Chen, Y. (2016). Deep learning for intelligent substation device infrared fault image analysis. In MATEC Web of Conferences (Vol. 55, p. 03007). EDP Sciences.

[38] Jin, M., Jiang, X., Qiu, Z., Jiao, Y., Su, Y., & Cui, Y. (2025, March). Defect Detection Method for Substation Equipment Based on Infrared Detection. In 2025 2nd International Conference on Smart Grid and Artificial Intelligence (SGAI) (pp. 1228-1231). IEEE.

[39] Wang, L., Ou, J., Wang, J., Hu, C., Fan, Y., & Xie, F. (2023). Thermal Anomaly Area Intelligent Recognition Method Based on Infrared Inspection Image of Electrical Equipment. Authorea Preprints.

[40] Hui, Z., & Fuzhen, H. (2015, July). An intelligent fault diagnosis method for electrical equipment using infrared images. In 2015 34th Chinese Control Conference (CCC) (pp. 6372-6376). IEEE.

[41] Haonan Tian. (2025). A comprehensive review of YOLO object detection algorithms. Electronics Science Technology and Application,12(2),

[42] Bai Jie,Sun Jing,Cheng XiaoGuang,Liu Fan,Liu Hua & Wang Xu. (2023). Construction and Application of Rib Fracture Diagnosis Model Based on YOLOv3 Algorithm.. Fa yi xue za zhi,39(4),343-349.

[43] Akshaj Singh Bisht,Karthik R,Armaano Ajay & Abhay Karan Singh. (2025). Virus-FusionNet: an explainable deep learning-based approach for virus classification from TEM images using DenseNet and lightweight hierarchical semi-local feature extraction network. Engineering Research Express,7(3),035242-035242.

[44] Jiachun Wu,Jinlai Zhang,Jihong Zhu,Fengkun Wang,Binqiang Si,Yi Huang... & Yanmei Meng. (2025). Lightweight peach detection using partial convolution and improved Non-maximum suppression. Journal of Visual Communication and Image Representation, 111, 104495-104495.