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Intelligent Monitoring of Protection Devices in Power system with Enhanced Faster R-CNN

Abstract: **-** Relay protection devices are necessary to guard the power system safety and stability. With the significant number of substations and relay protection devices, the maintenance workload has become difficult due to limited manpower, posing hidden dangers to the reliable operation of protection devices. In view of this, this article proposes an enhanced Faster R-CNN algorithm to diagnose the relay protection devices based on image monitoring. The proposed algorithm uses RestNet50 as the main tool to recognize features from input images to generate feature maps. Meanwhile, to improve the image detection accuracy, the Non-Maximum Sup-pression (NMS) algorithm in regional suggestion network (RPN) is optimized from solid thresh-old to soft threshold. By combining the images captured by the surveillance camera, intelligent inspections are conducted on the status of the pressing plate, fiber bending, external object retention, and other items in the relay protection device. A great number of samples are used to train networks for different tasks. The results indicate that the enhanced Faster R-CNN has a higher image recognition rate, and the recognition accuracy of each inspection item for the protection device is higher than 95%.

Keywords: Faster R-CNN, Image Detection, Monitoring, Relay Protection Device

I. INTRODUCTION

Relay protection devices are able to respond to faults in the power network, isolating them from the electrical power system to prevent further damage. The relay protection devices are crucial for the stability of the power network. With the rapid growth in the number of protective devices, their maintenance work is facing enormous pressure. Since utilities need to regularly inspect the protective devices in substations. The large number of devices greatly increases the workload. Besides, manual inspection cannot automatically input inspection data into the statistical analysis system, making it difficult for further data-based analysis. Thus utilities are not unable to detect hidden defects of equipment in a timely or early manner [1,2]. At the same time, negligence in manual detection can lead to accidents. In China for example, several accidents occur due to careless monitoring. The 220kV Xiashan Substation experienced a switch accident during the protection action of the transformer due to the leakage of the protection pressure plate caused by improper operation of the duty personnel. The 220kV Duma II circuit of the 220kV Duyun sub-station in Guizhou Province tripped due to the accidental use of power cabinet pressing plates by personnel. The duty officer of the 220kV Longwan Substation in Qinzhou mistakenly applied the pressing plate, resulting in voltage loss in the entire 110kV Xiaodong and Naqian substations [3,4]. Therefore, it is necessary to research on the intelligent monitoring of protection devices with artificial intelligence, such as image recognition to achieve unmanned inspection of substation protection devices.

Research has been conducted on intelligent inspection and identification of protective devices. Yao Nan et al. [5] studied an algorithm for image classification of protective devices with channel attention and spatial attention. Mou et al. [6] used the grayscale projection method to segment the pressing plate area, labeled the segmented image, and obtained a training sample set. They used it to train a convolutional neural network (CNN), and finally recognized the on/off status of the pressing plate through the trained model. Hongmin Zhu [7] proposed a real-time method to assess the protective devices' state in substations. Their approach processed the video frames with Gaussian blur, binarization of grayscale image, etc. The results demonstrated that the proposed approach has reliable performance. Peng Li et al. [8] proposed a method to remove the saturation light from the pressing plate

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image. Xiaoyong Sun et al. [9] introduced a method to check the relay protection setting based on OCR technology.

Most of the existing literature focuses on a specific object, while there are various issues related with the protective devices, such as the position identification of the protective device's pressing plate, switch handle position identification, terminal strip wiring detachment identification, grounding copper plate detachment identification, and cable damage identification. Traditional CNN methods have difficulty to satisfy the requirements of high recognition rate for all the operation scenarios. In view of this, this article proposes an intelligent inspection technology for protection devices with enhanced Faster R-CNN. Faster R-CNN are widely applied for image recognition, such as metal surface defects [10,11], medical detection [12,13], moving or fixed object recognition [14,15], and power equipment detection [16-18], which proves that Faster R-CNN can meet the intelligent supervision needs in complex scenarios.

II. Intelligent Inspection and Image Recognition Algorithms

A. *Intelligent inspection of protective devices*

Protection device inspection refers to the regular inspection of the operating environment, appearance, indicator lights, pressing plates, switch handles, and other conditions of the device to keep its reliable operation, ensuring that there are no abnormalities in the equipment. In order to perform unmanned inspection, high-definition intelligent cameras need to be installed around the protection device. Daily equipment inspection through image recognition can be achieved. Cameras are installed in the front and back of the cabinet (as shown in Figure 1) to recognize multiple inspection points inside the protective cabinet and determine if there are any abnormalities. The items that can be inspected using image recognition are shown in Table 1. The front screen inspection mainly involves the appearance of device indicator lights and LCD screens, the position of pressing plates, and the position of switch handles. The back screen inspection mainly involves missing cable caps, bent optical fibers, and foreign objects.

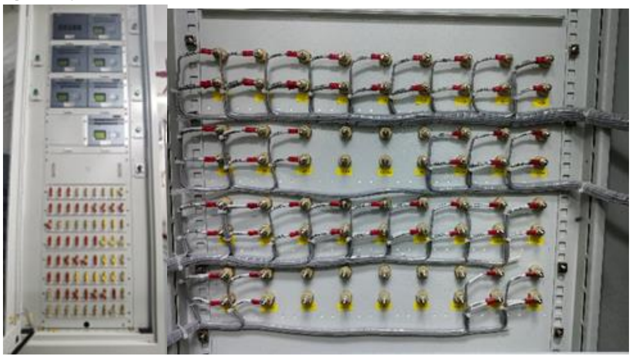

Figure 1: Physical Image of Cabinet

Table 1: Switching Power Status

Position		Inspection items	
Front	the appearance of the device indicator light, LCD screen, etc.	the position of the switch handle set	the position of the pressing plate
Back	terminal strip wiring optical fiber bending foreign object inside the cabinet	falling off of the grounding copper plate dust cap on the spare optical fiber	Cable damage the blocking of cabinet

B. *Faster R-CNN*

The principle structures of Faster R-CNN are Regional Suggestion Network (RPN) and Faster R-CNN, with a typical architecture shown in Figure 2, which mainly includes the following parts [19]:

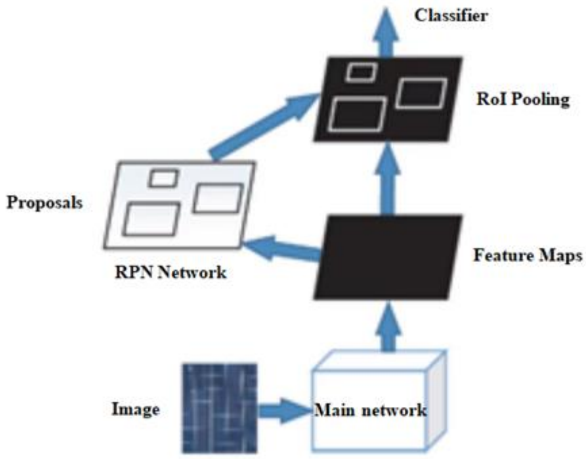

Figure 2: Structure of Faster R-CNN

(1) Main network. The main network is used to recognize features from images to generate features, which are used to feed the subsequent RPN networks. The algorithm adopts VGG16 [20] as the backbone network, which is composed of 13 convolutional layers, with a correction linear unit layer connected after each convolutional layer. In addition, it includes five pooling layers and three connected layers.

(2) RPN. RPN can select the target from the input image. During training, a 3 × 3 window slides along the convolutional feature map produced by the last step. At each position, it simultaneously predicts k anchor frames. The length to width ratios of the anchor frame is varied from 1:1, 1:2, to 2:1. Each ratio is set with three different areas.

(3) RoI pooling. The pooling layer can output suggestion boxes of different sizes as fixed size images. In addition, this layer also collects feature maps and extracts suggested feature maps for subsequent classification and regression.

(4) Classification. The classification section uses the Softmax function via proposed feature mapping to determine the category for each region. The regression section again uses the suggestion box regression to obtain more accurate coordinates for each detection box.

C. Enhanced Faster R-CNN Network

The traditional Faster R-CNN detects objects on a single top-level feature image extracted from the backbone network. Due to the operational characteristics of CNNs, as the network deepens, the image undergoes multiple convolution operations, leading to a decrease in the resolution of the final output feature image. Thus a large amount of detail information is missed, and the features of small targets will be weakened or even omitted. When using top-level feature images for target recognition, the small targets detection accuracy is low and cannot meet the requirements of relay protection device recognition in this paper.

(1) Main Network Improvement

The ResNet50 network draws inspiration from the ideas of ResNEXt network, inception network, and SK Net network. By increasing the interaction between receptive fields of different sizes and cross channels, the accuracy is further improved without significantly increasing the parameter number. The ResNet network (as in Table 2) integrates different feature layers, allowing for the fusion of high semantic information feature maps at lower levels and rough target position feature maps at higher levels, achieving satisfactory results in classification, segmentation, and detection. Due to the appropriate depth and high degree of nonlinearity, the ResNet50 network can extract more detailed features. This article chooses the ResNet50 network to replace the VGG16 network for precise recognition of the protection device.

Table 2: ResNet50 Network Structure

Layer	Size of Output	ResNet50
Conv 1	112×112	7×7,64, stride2
Conv 2	56×56	3×3 max pool, stride2 Block1:×3
Conv 3	28×28	Block2:×4
Conv 4	14×14	Block3:×6
Conv 5	7×7	Block4:×3

As in Figure 3, the implementation of ResNet50 consists of five stages, among which Stage 0 has a simple structure and it is preprocessing of Input. All the other four stages are composed of Bottleneck [21], labeled as BTNK in Figure 3, where BTNK1 and BTNK2 indicated different numbers of input/output. Stage 1 has 3 Bottlenecks. While the remaining 3 stages contain four, six, and three Bottlenecks, respectively.

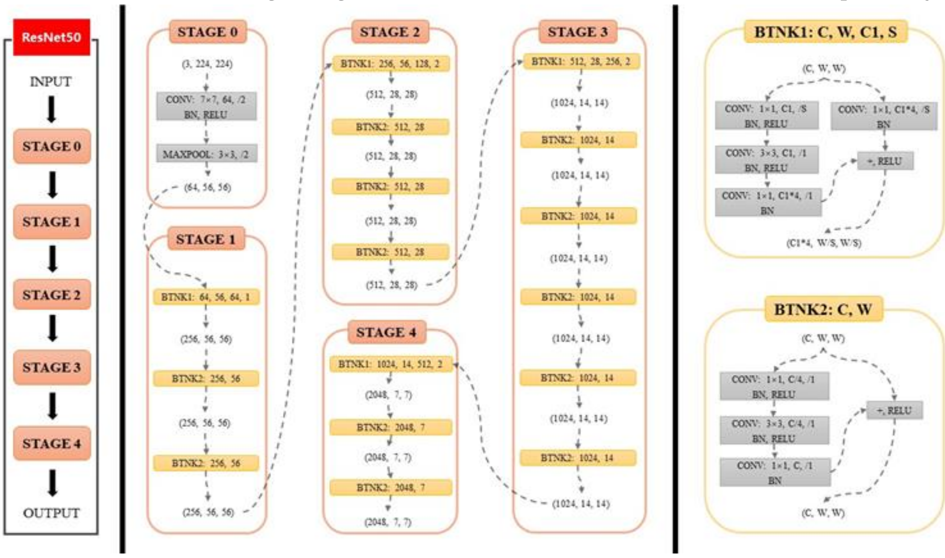

Figure 3: Structure of ResNet50

(2) NMS Algorithm Optimization

Faster R-CNN utilizes RPN directly to obtain the detection frames, which can significantly improve the speed. RPN inputs low dimensional features into two branches: Bounding Box regression (bbox reg) and classification (cls). The convolutional output of reg is to monitor the regression offset of the target, and the predicted target coordinates need to be adjusted using the regression offset. The output of cls is the probability score of the target area being foreground or background. In the subsequent process, the Softmax function is combined with this score for binary classification operation, and then the result is output.

RPN generates multiple recommendation regions, and the number of recommendation windows generated by sliding windows is recorded as k anchor frames. The boundary regression branch requires $4k$ outputs to record regression information, and the classification layer requires $2k$ outputs to record classification information. The loss of the entire network is composed of regression loss and classification loss. The calculation formula for overall loss L of the RPN structure is:

$$L\left(p_i, t_i\right) = \frac{1}{N_{cls}} \sum_i L_{cls}\left(p_i, p_i^*\right) + \frac{\lambda}{N_{reg}} \sum_i p_i^* L_{reg}\left(t_i, t_i^*\right) \qquad i = 1, 2, \ldots, k \tag{1}$$

In the formula: i is anchor index; p_i is probability for anchor point i predicted as the target; p_i^* is probability for the corresponding annotation window; t_i is the predicted border coordinate; t_i^* is true border coordinates; N_{cls} is the minimum batch quantity; N_{reg} is the number of anchor frame positions; λ is the weighted sum parameter which controls the proportion of N_{cls} and N_{reg} in the equation; L_{cls} is the logarithmic loss of t_i and t_i^*; L_{reg} is the regression loss.

To upgrade the monitoring effect of the protection device, the Non-Maximum Suppress (NMS) is adjusted. The NMS directly affects the quality of candidate boxes, thereby affecting recognition accuracy. The traditional NMS algorithm calculates the IOU score based on the intersection to union ratio (IOU). The main idea is to compare the IOU of the target with the size of the set threshold. Generally, the threshold is 0.3~0.5. The target box with IOU exceeding the threshold will be considered redundant and removed. Although this type of algorithm is simple to implement, it may include part of the targets in the removed detection boxes, leading to missed detection of targets and affecting the overall performance of protection device recognition. The traditional NMS algorithm is:

$$s_i = \begin{cases} s_i, & \text{IOU}\left(M, b_i\right) < N_t \\ 0, & \text{IOU}\left(M, b_i\right) \geq N_t \end{cases} \tag{2}$$

where s_i is confidence level; M is the detection with the highest confidence; IOU(M, b_i) is the intersection to union ratio; N_t is the IOU threshold; b_i represents the target box.

To address issues such as missed detections, the NMS algorithm was optimized using a Gaussian weight reduction function. The expression of the improved NMS is:

$$s_i = \begin{cases} s_i, & \mathrm{IOU}\left(M, b_i\right) < N_t \\ s_i f\left(\mathrm{IOU}(M, b_i)\right), & \mathrm{IOU}\left(M, b_i\right) \geq N_t, s_i f\left(\mathrm{IOU}(M, b_i)\right) \geq N_i \\ 0, & \mathrm{IOU}\left(M, b_i\right) \geq N_t, s_i f\left(\mathrm{IOU}(M, b_i)\right) < N_i \end{cases} \tag{3}$$

where N_i is the added threshold; N_t is the IOU threshold set by the traditional NMS algorithm, $N_i < N_t$; f(IOU(M, b_i)) is a Gaussian weight reduction function, expressed as:

$$f\left(\mathrm{IOU}(M, b_i)\right) = e^{\frac{\mathrm{IOU}\left(M, b_i\right)^2}{\sigma}} \tag{4}$$

where σ is the penalty factor. This approach can help to improve the object selection performance.

III. Sample Training and Test Result

A. *Sample Set*

The Faster R-CNN first uses the RPN algorithm to delineate a rough search range, which identifies the area where targets such as protective pressing plates and foreign objects are located in the image. Then, a great number of target images such as pressing plate images and foreign object images are used for training. Thereby the recognition ability of the algorithm is improved for target features such as pressing plate on and off features, foreign object features. Finally, the algorithm is utilized to identify the on/off status of the pressing plate in the search box, the presence status of foreign objects, etc.

For image recognition of different inspection projects, the training and testing sample sets are different. The network and parameters ultimately trained for different projects are also different. A camera collects the required training samples and test samples for different inspection items in front of and behind the cabinet, with a pixel size of 800 × 600. Some typical samples collected are shown in Figures 4 and 5.

Figure 4: Typical Sample of on/off State of Pressing Plate

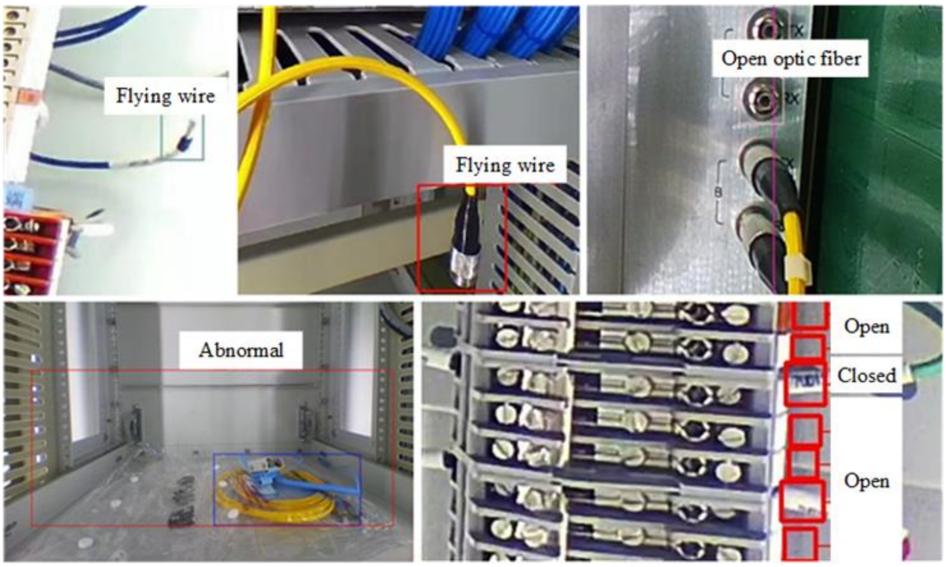

Figure 5: Typical Sample of Flying Wire, Foreign Item and Wire Connection

This article selected a total of 4700 images of the opening and closing states of the pressing plate to train the network, including 1600 closed states, 3100 open states. In addition, 900 test sets were selected to test the trained network. The number of used samples for other projects is listed in Table 3.

Table 3: Sample Number for Different Items

Position	Inspection items	Number for training		Number for testing
		Positive sample	Negative sample	
In front of cabinet	Is the device appearance abnormal?	2500	400	500
	Is the position of the switch handle correct?	2200	450	400
	Is the position of the pressing plate correct	3900	800	900
Behind cabinet	Is the terminal strip wiring standardized?	2100	300	500
	Is the grounding copper plate falling off?	1800	350	450
	Is the cable damaged?	1500	200	300
	Is the optical fiber is broken?	2000	300	400
	Is there no dust cover for the backup optical fiber?	1800	400	300
	Is the blocking of the cabinet normal?	2200	300	450
	Is there any foreign object inside the cabinet?	2500	400	500

B. Sample Training

Firstly, the training sample sets of different projects selected in the previous section are used to train each project network. And then the accuracy of the recognition results is evaluated using the test sample set. When the training time or error rate meets the requirements, the training is stopped. The identification principles of different projects are shown in Figure 6.

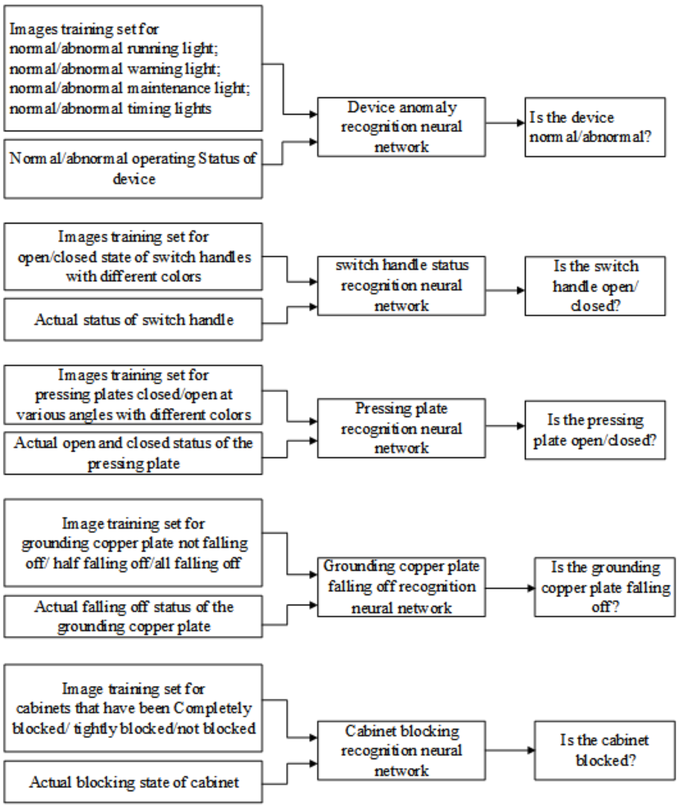

Figure 6: Identification Principles for Different Items

C. Test Results and Analysis

Four detection results exist for object detection algorithms. For positive samples predicted correctly as positive, they are recorded as TP. For negative samples predicted correctly as negative, they are recorded as TN. For negative samples incorrectly predicted, they are recoded as FP. And when positive samples are incorrectly predicted, they are labeled as FN. The rating index for target detection algorithm mainly includes accuracy, recall, average accuracy, and average accuracy. The calculation formulas are as follows.

(1) Accuracy

The accuracy p is commonly used to assess the algorithm:

$$p=\frac{T_p}{T_p+F_p} \tag{5}$$

Where T_P is TP sample number； F_P is FP sample number.

(2) Recall rate

The recall rate r is used to evaluate the model ability to find positive samples, and the calculation formula is:

$$r=\frac{T_p}{T_p+F_N} \tag{6}$$

Where F_N is FN sample number.

(3) Average accuracy

The average precision (AP) is used to indicate the algorithm accuracy:

$$A_p=\int_0^1 p(r)dr \tag{7}$$

(4) Average precision of all categories (m_{AP}). This number is to represent the average accuracy of all categories, which can be calculated:

$$m_{AP}=\frac{\sum_{n=1}^{N} A_p(n)}{N} \tag{8}$$

where n is the category index； N is the categories number.

This study uses the accuracy value as an evaluation indicator for the identification of protective devices. The trained model accuracy is calculated with the test images, as in Table 4. It shows the accuracy using two algorithms to identify targets for different items in front of and behind the cabinet. The Faster R-CNN accuracy to identify different targets of the protection device is between 90% and 93%, while the accuracy with improved Faster R-CNN algorithm to identify different targets of the protection device is above 95%, which has increased by nearly 5%. The improved Faster R-CNN is capable for inspection items of protective devices with high accuracy. It can provide strong technical support for unmanned inspection of protective devices, achieving rapid response to defects in protective devices and precise positioning of hidden dangers.

Table 4: Correct Rate of Different Items

Position	Inspection items	Accuracy	
		Faster R-CNN	Enhanced Faster R-CNN
In front of cabinet	Is the device appearance abnormal?	91.35	96.32
	Is the position of the switch handle correct?	91.87	97.43
	Is the position of the pressing plate correct	92.42	97.15
Behind cabinet	Is the terminal strip wiring standardized?	91.05	95.56
	Is the grounding copper plate falling off?	92.95	97.25
	Is the cable damaged?	90.14	95.13
	Is the optical fiber is broken?	90.86	96.62
	Is there no dust cover for the backup optical fiber?	92.63	97.34
	Is the blocking of the cabinet normal?	91.23	96.28
	Is there any foreign object inside the cabinet?	91.54	97.24

IV. CONCLUSION

In order to achieve intelligent monitoring different items of relay protection device, such as pressing plate position, switch handle position, optical fiber bending, foreign object retention, this paper proposes an enhanced Faster R-CNN algorithm. RestNet50 is used as the main network to recognize features from input images and generate feature maps, and the NMS is optimized. The algorithm is tested using on-site image samples. The recognition accuracy with different inspection items of the protection device is given. The results indicate that the enhanced algorithm improves the recognition performance by 5% compared to the traditional algorithm. And the accuracy of identifying different targets of the protection device is above 95%. The high recognition accuracy lays the foundation for achieving unmanned inspections of protective devices.

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