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Power System Relay Protection Based on Faster R-CNN Algorithm

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ABSTRACT

The technology of relay protection in China's power system has gradually changed from the traditional operation mode to the development direction of informatization, intelligence, and automation. As a result, the role of relay protection in the power system has become more and more important. It brings higher requirements to the reliability of relay protection; effective reliability assessment of the relay protection system and the corresponding condition operation, minimize or avoid accidents, and ensure the safety of power grids. Starting from the operating characteristics of relay protection, it is suitable for practical engineering applications. Aiming at the problems of low work efficiency and low inspection quality in manual inspection of relay protection pressure plate switching state, The Faster R-CNN image processing algorithm will be come up with. This method uses grayscale, binarization and filtering techniques to preprocess the platen photos, and uses RPN.

KEYWORDS

Faster R-CNN Algorithm, Power System, Relay Protection Technology

INTRODUCTION

As the power system evolves, relay protection plays a crucial role in ensuring system stability and safe operation. Among them, the relay protection pressure plate, a key component of the protection device, is of crucial importance in maintaining the power system's stability (Abbassi et al., 2022). However, the growing diversity and quantity of relay protection pressure plates highlights the demand for efficient and accurate identification and verification methods within their operational processes.

Traditional verification methods are often inefficient and present challenges related to quality. Therefore, studying an efficient and accurate method for identifying the status of relay protection pressure plates has become crucial. Status recognition of relay protection pressure plate involves detecting whether the pressure plate is open or closed to determine its operational status. Commonly used state recognition methods include:

- **Direct Observation Method:** This includes observing the appearance of the relay protection pressing plate to determine whether its metal sheets are connected or disconnected.
- **Sound Method:** This involves listening for auditory cues. For instance, the presence of a "da" sound can indicate the status of the spring plate within the relay protection pressure plate. When

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in the input state, the spring plate will be pressed down and will remain silent. When disconnected state, it will make a “da” sound.
- **Manual Method:** This method entails the manual operation of the relay protection pressure plate and observing its state changes after the operation to identify the input status.
- **Positioner Method:** This involves installing a locator on the relay protection pressure plate and reading position information on the locator to determine the plate’s open or closed status.
- **Current Method:** By detecting the current on the relay protection pressing plate, we can determine the input status. When the current reaches a certain value, it indicates an input state, whereas a current reading of zero indicates a disconnected state.

Depending on the verification challenges, the most appropriate state recognition methods can be selected. For example, for large-scale testing of the relay protection pressure plate status, automated equipment can be used for rapid detection. Conversely, for inspecting a smaller number of pressure plates, manual methods may be a more practical solution.

In similar fields, the following are common self-similarity datasets and proof of effectiveness for selecting appropriate machine learning models:

- **Weather Forecast Dataset:** This dataset contains historical weather data and forecast data. The use of time series analysis methods like random forest time series, ARIMA, and LSTM can predict future weather patterns. By comparing the root mean square error (RMSE) values between predicted results and actual data, one can gauge the effectiveness of these models.
- **Natural Language Processing Dataset:** This dataset contains text data and corresponding labels. Deep learning algorithms, including recurrent neural networks (RNN), convolutional neural networks (CNN), and short-term memory networks (LSTM), are used to develop language models for tasks like text classification or sentiment analysis. The effectiveness of these models can be assessed by calculating the accuracy of prediction results and actual data, F1 scores, and other indicators.
- **Image Classification Dataset:** This dataset contains image data and corresponding labels. Deep learning algorithms like CNN can develop classifiers for image classification tasks. The efficacy of these models is assessed by calculating metrics like accuracy, precision, recall, and other indicators. These are then compared against actual data to demonstrate effectiveness.

RELATED WORK

The fundamental objective of the power system is to deliver cost-effective and reliable power to users (Cai et al., 2021). However, the system’s structure and operational mode are becoming more complex and variable, underscoring the threats and challenges faced by the normal operation of the system (Mehrabi-Kooshki et al., 2020). Large-scale and long-term failures will cause significant societal and economic losses (Hou et al., 2021). Therefore, improving the reliability of power supply within the power system is of utmost significance (Lin et al., 2021).

To prevent catastrophic accidents, relay protection is an important part of the power system security system (He, 2020). Ensuring its reliability is vital (Alroobaea et al., 2020). In particular, errors or malfunctions in relay protection will not only exacerbate the failure of the power system but may cause adverse chain reactions, accelerate system collapse, and result in serious consequences (Li & Zhuyuan, 2021).

Therefore, the accurate identification of weaknesses, examination of protective mechanisms, and enhancement of relay protection system reliability have become a focal point for experts in the field of electric power (Lee et al., 2020). In actual operations, it is essential to maintain its condition and safety. These actions are vital to discover and eliminate faults or defects, while adhering to scientific and effective strategies (Shafik et al., 2021).

Thus, within the complex power grid, the study of relay protection reliability serves as an important reference for design and configuration. In addition, it has far-reaching implications for the overall security of the system (Olalekan & Anwar, 2020).

For the grid scale, the quantity of relay protection equipment has increased sharply. This has, in turn, intensified the workload associated with pressure plate verification (Mohan et al., 2021). At present, the verification process relies on manual checks performed by substation operators (Chiu et al., 2022). The manual verification of relay protection plates is labor intensive, resulting in redundant tasks and dependence on personal mental states. This leads to challenges related to efficiency and accuracy (Wei & Li, 2022).

To address these issues and improve the efficiency and quality of relay protection platen verification, this article proposes a method for recognizing the of relay protection plates (Ahmadian et al., 2021). The method uses a handheld terminal to capture an image of a platen protection screen cabinet. It uses grayscale, binarization, and Gaussian filtering techniques to preprocess the image (Jiang & Shi, 2021). Then, the preprocessed image is employed to build the recognition model.

The one is trained on the plate image, and the network model for the recognition of the throwing and retreating state of the platen is obtained (Hensel et al., 2021). Finally, the recognition network model obtained by training is used to test a 110kV substation (Korkmaz et al., 2021). such results show for the correct rate of platen identification will be as high as more than 98%, which can effectively solve the existing problems of manual verification of platens, drops tasks of staff, efficiency and verification (Zu et al., 2021).The algorithm generates a platen detection frame, delimits the search range, and then uses the trained Fast R-CNN algorithm to detect platen features in this range, so as to quickly and accurately identify the target platen's throwing and retreating state. Using the state recognition method of relay protection platen based on platen is carried out in a 110kV substation relay protection panel cabinet of Zhongshan Power Supply Bureau. The state recognition and such effectiveness and correctness, and the recognition effect reaches the level of replacing manual checking, which has great promotion value (Liao et al., 2018).

MATERIALS AND METHODS

Role of Relay Protection

The most common and significant issue is short circuit (Zhang et al., 2022). Short circuits result in several consequences:

1. They can lead to the failure of a faulty factor.
2. Short-circuit currents may pass through non-faulty elements. This can lead to damage of a shortened service life due to excessive heat and stress related to the motor.
3. They can destroy the stability of the user's work or impact the quality of factory products.
4. They can destroy the power system, causing disturbances or system-wide collapse.

For example, an increase in current caused by an electrical load exceeding the equipment's rated capacity can increase temperature levels, accelerating insulation aging and damage, potentially leading to a failure (Cannas et al., 2019). In addition, it may be caused by specific conditions.

States within the power system can cause accidents, resulting in reduced power transmission to users, the deterioration of power quality, and, in some cases, personal injury and damage to electrical equipment. Often, there is a critical need to clear the fault within seconds (Yue & Wang, 2020). It has been proven that only the protection device installed on each electrical component can meet this requirement. These devices not only detect anomalies but send a signal to initiate action like a load reduction or trip (He et al., 2021).

Development and Research Significance of Relay Protection Technology

For decades, relay protection technology has continued to progress, integrating new theories, technologies, and devices in related disciplines. Before the 1950s, electromechanical protection devices were used for relay protection. After nearly 30 years, the technology has undergone major improvements, accumulating rich operating experience. Thus, it remains a reliable source within power systems.

However, this protective device is bulky. The power consumption is large, response times are slow, and complicated maintenance is required. Thus, they cannot meet the demands of modern power systems (Li et al., 2022).

In the 1950s, the development of semiconductor transistors ushered in a new era of transistor-type relay protection devices. The devices were small, low in power consumption, and fast in action. Still, the transistor protection devices were susceptible to malfunctions or damage due to the influence of electromagnetic interference in the power system or from external sources.

In the late 1960s, there were proposals to use minicomputers for relay protection applications. At that time, minicomputers were expensive and difficult to use. Although current microcomputer protection has achieved a rapid development and appear poised to replace the traditional protection, it is essential to acknowledge that the potential intelligent function of computers in microcomputer protection systems need to be further explored. This will allow us to stay aligned with international advancements, promoting the implementation of advanced principles and technologies in power system relay protection.

This article calculates and collects data on relay protection faults, conducts in-depth research on the problem of adaptive relay protection, and achieves satisfactory results.

Research Status of Image Processing Detection Based on Deep CNN

Algorithms are widely used in the detection of defects in various industrial products, including concrete surface cracks, railway track defects, sewage pipe defects, and welding defects. These algorithms often combine deep convolutional neural networks to locate and classify defects, as well as naive Bayesian classification to reduce false positives. However, applying these algorithms directly to the detection of flexible printed circuit (FPC) defects poses challenges due to two disadvantages as compared with the aforementioned defects.

First, some FPC defects are small in size, which makes it challenging for the network to extract features. This impedes the network's learning capabilities and results in poor detection results, creating a "small target problem."

Second, due to the FPC production process, the occurrence of certain types of defects is very small, making it difficult to collect a sufficient number of samples in the production and inspection process. The limited number may lead to overfitting, negatively impacting training and detection measures or the "small sample problem."

Aiming at the above problems, this article adopts the Faster-RCNN algorithm, which offers better detection accuracy and speed. Moreover, the article adds improvement measures to the problems of small targets and small samples. For the small target problem, the article uses a feature fusion module for feature enhancement, a target feature enhancement module, and a multi-receptive field region selection module for extracting target features of different sizes. To address the small sample problem, two feature enrichment strategies are added. The first aims at improving spatial transformer network (STN) parameters. The second involves the use of a binary loss function to reduce inter-class similarity and enhance intra-class dissimilarity.

RESULTS AND DISCUSSION

Origin and Development of Deep Convolutional Neural Networks

Deep learning technology has gradually emerged to enable computers to complete various intelligent tasks required by humans. At its core is the artificial neural network, which draws inspiration from the workings of the human brain. It simulates human brain neurons by connecting hidden layers. Then, networks generally incorporate multiple hidden layers designed to extract features within multiple layers. Through this layer-by-layer feature extraction, the input data can begin to form more abstract and complex features.

In its earliest stages, convolutional neural networks consisted of one or two hidden layers, making them shallow networks. However, in the face of complex and highly abstract challenges, shallow networks exhibited limitations in terms of their weak feature extraction capabilities. Thus, deep networks outperform shallow ones because they can extract more abstract and richer features.

The faster R-CNN algorithm is realized by combining the FastR-CNN and the RPN algorithms. The FasterR-CNN algorithm begins the process by outlining a rough search range through the RPN, identifying the area in which the protective platen is located within the picture.

Then, an extensive dataset of platen images in both the input and exit states is collected to train the Fast R-CNN model. This training improves the Fast R-CNN algorithm's ability to identify the platen throwing and retreating features.

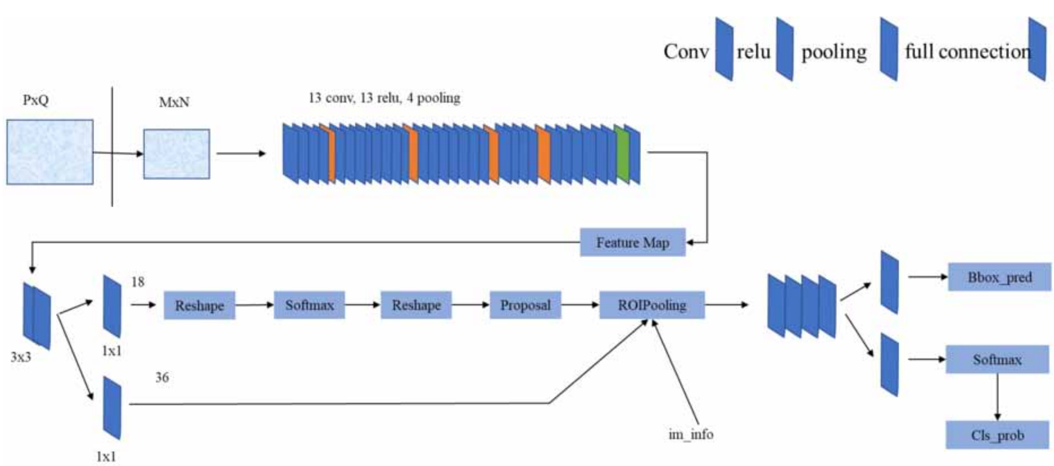
Finally, the trained Fast R-CNN algorithm is used to perform feature retrieval on the search range delimited by the RPN algorithm. This is used to identify the throwing and retreating state of the platen in the search box. The schematic diagram of the Faster R-CNN algorithm is shown in Figure 1.

The RPN layer calculates and corrects the box for accuracy. It shares the feature map with the fully connected layer.

The box, denoted as [x1, yl, x2, y2], corresponds to the M x N scale. Initially, the spatial_scale parameter is used to map it back to the feature map scale of (M/16) x (N/16).

Both the horizontal and the vertical direction are divided into seven parts, and each part is pooled. This process aligns the frame's recommended regions. Within this layer, the feature map of recommended regions is used to calculate the recommended domain category. The bounding box regression is used to obtain the final accurate position of the inspection box. This calculation assigns each recommended region of the frame to its respective category, such as car or person.

Figure 1. Schematic diagram of the FasterRCNN algorithm



Target Detection Algorithm Based on CNN

The main objective of this topic is to distinguish a specific object within an image or video, separating it from unrelated information. This entails determining the presence of a target object and the identification of its category and location.

The traditional target detection method generally selects candidate regions by sliding windows of different scales. Feature information from these candidate regions is then extracted by a hand-designed method. Finally, a classifier is used to identify the feature information. With the capability of deep convolutional neural networks to automatically extract features, many scholars have introduced them into the field of target detection, achieving great success.

Target detection algorithms based on deep convolutional can be broadly categorized into two approaches. The first method separates target localization and classification tasks, often referred to as the two-stage algorithm. The second method, known as the one-stage algorithm, performs target positioning and target classification tasks at the same time.

The two-stage algorithm first extracts the target area from the image and uses the classifier to analyze the target area.

Areas are classified into the realm of object detection, spanning from RCNN to SPP-Net, Fast-RCNN, and Faster-RCNN. These generate significant attention from scholars. The two-stage algorithm divides the target detection process into two parts: the extraction of candidate regions and the classification of candidate regions. However, this approach is slower in terms of processing speed.

Still, there are several algorithms that handle both target localization and target classification tasks simultaneously, achieving rapid detection speeds. This type of algorithm is represented by the YOLO family, including YOLOv1, YOLOv2, and YOLOv3.

The realization is as follows:

$$Confidence = Pr(Object) \times IOU_{pred}^{truth} \tag{1}$$

The detection frame (Bpred) and target real area (Btruth) are shown in equation (2):

$$IOU_{truth}^{pred} = \frac{B_{pred} \cap B_{truth}}{B_{pred} \cup B_{truth}} \tag{2}$$

YOLO performs positioning and classification tasks at the same time and in an efficient manner. There are, however, disadvantages. For example, only one target is detected in each grid although there may be multiple targets within a grid. This can lead to missed detection. Thus, this method is not suitable for small targets because the detection accuracy is not high.

Principle and Two Methods of Neural Network Feature Fusion

The traditional Faster-RCNN algorithm employed the network as the input of the RPN network. While more complex and abstract features could be obtained, it suffered from the drawback of losing low-level features due to the layer-by-layer convolution and pooling. Small targets, due to their smaller scale, were more susceptible to feature loss compared to larger targets. This resulted in a lower detection effect for small targets within the network.

In the deep convolutional neural network, two methods of feature fusion exist, namely cascade and stacking. The "add" method entails concate is (* means convolution):

$$Z_{concate} = \sum_{i=1}^{c} X_i * K_i + \sum_{i=1}^{c} Y_i * K_{i+c} \tag{3}$$

The single output channel of add is:

$$Z_{add} = \sum_{i=1}^{c} \left(X_i + Y_i\right) * K_i \tag{4}$$

$$\sum_{i=1}^{c} X_i * K_i + \sum_{i=1}^{c} Y_i * K_i \tag{5}$$

Ki represents the ith convolution kernel. It can be seen for concate ones.

The target feature enhancement module is the RPN network, zero padding, and feature fusion.

RPN uses functions, which are noted as equation (6):

$$L\left(\left\{p_i\right\},\left\{t_i\right\}\right) = \frac{1}{N_{cls}} \sum_i L_{cls}\left(p_i, y_i\right) + \lambda \frac{1}{N_{reg}} \sum_i y_i L_{reg}\left(t_i, t_i^*\right) \tag{6}$$

This article sets λ = 1. Ncls represents the number of batch input samples, Nreg represents the number of all regions, “i” represents the index of the region, and Lcls represents the classification loss function. This includes two types (target and non-target) of log-likelihood loss functions.

The form of Lcls is as follows:

$$L_{cls}\left(p_i, y_i\right) = -\log p_i^{y_i} \tag{7}$$

The form of Lreg is as follows:

$$L_{reg}\left(t_i, t_i^*\right) = \sum_{s \in \{x,y,w,h\}} L_1\left(t_i^{s^*} - t_i^{s}\right) \tag{8}$$

$$L_1(x) = \begin{cases} 0.5x^2, | x | \leq 1 \\ | x | -0.5, other \end{cases} \tag{9}$$

The candidate region and its coordinate parameters (x, y, w, h) can be obtained through the RPN network. This represents the upper left corner coordinate and width and height of the candidate region, respectively.

In the selection of the network structure, this algorithm introduces the Resnet structure. It uses the pre-trained resnet-50 model to initialize the feature extraction layer, RPN network, and classification network. Thus, this approach introduces transfer learning, which speeds up network training and improves network performance. The STN network can be trained through backpropagation and runs at a high speed without affecting the original running speed:

1. **Locate the Network:** This is the input of the positioning or feature map, the parameter θ used for transformation, in the form of the following formula:

$$\theta = \begin{bmatrix} \theta_{11}, \theta_{12}, \theta_{13} \\ \theta_{21}, \theta_{22}, \theta_{23} \end{bmatrix} \tag{10}$$

2. **Grid Generator:** The grid generator aims to generate a sampling grid and obtain the pixel position of the input feature map corresponding to each grid for subsequent sampling to form the output feature map. See Equation 11:

$$\begin{bmatrix} x_i^s \\ y_i^s \end{bmatrix} = T_\theta \left(G_i\right) = T_\theta \begin{bmatrix} x_i^t \\ y_i^t \\ 1 \end{bmatrix} \tag{11}$$

An STN network branch can only use a single transformation. To enable the network to learn richer features and reduce the impact of the small sample problem, this article sets up three STN network branches. Each branch has its own transformation form, as shown in the following:

$$\theta_1 = \begin{bmatrix} \alpha, 0, 0 \\ 0, \alpha, 0 \end{bmatrix} \tag{12}$$

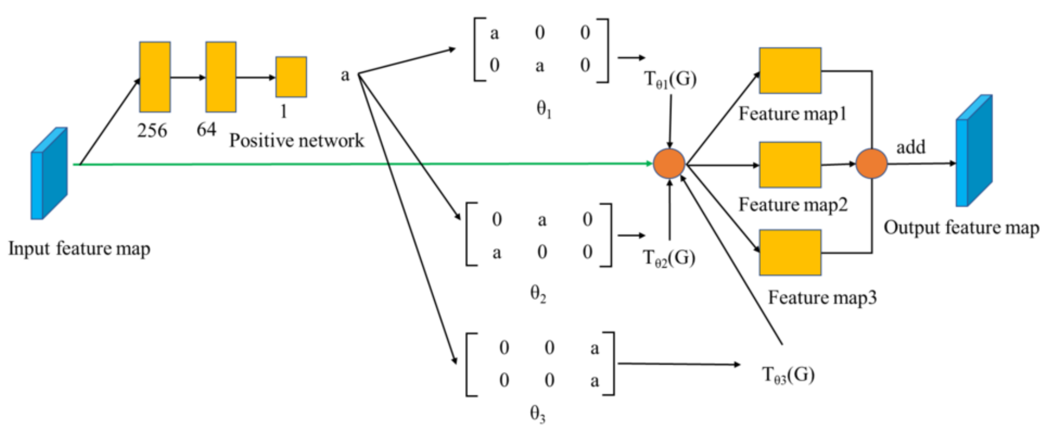
$$\theta 2 = \begin{bmatrix} 0, \alpha, 0 \\ \alpha, 0, 0 \end{bmatrix} \tag{13}$$

$$\theta 3 = \begin{bmatrix} 0, 0, \alpha \\ 0, 0, \alpha \end{bmatrix} \tag{14}$$

where parameter a is obtained from the localization network within STN. The use of these three transformations serves a dual purpose. First, they are completely independent and are not impacted by the value of a. Second, θ1 is a scaling transformation. Thus, it can enlarge the small target, which alleviates the data. For the concentrated small target problem, θ2 is a transformation like θ1, which further enriches this transformation. θ3 is composed of the two remaining parameters related to translation, ensuring that the a variables of θ1, θ2, and θ3 form a random element-wise matrix, resembling the original STN's θ.

The transformation to coordinates within the regular grid of the output feature map is shown in Equation 15. The overall structure of the improved STN based on this strategy is shown in Figure 2.

Figure 2. Structure diagram of limiting the transformation form of STN network parameters



$$\begin{bmatrix} x_i^s \\ y_i^s \end{bmatrix} = \theta \begin{bmatrix} x_i^t \\ y_i^t \\ 1 \end{bmatrix} \tag{15}$$

RESULT ANALYSIS AND DISCUSSION

Experimental Design

The aim was to validate the accuracy of an algorithm designed to identify the “switch-on” and “retreat” status of pressure plates within 46 relay protection panel cabinets in a 110kV substation of the Zhongshan Power Supply Bureau. The process involved collecting sample photos of the platen for the algorithm model. Then, the images to be tested were pre-processed to determine the state of the platen.

The algorithm in this article was exclusively used for training and testing on a personal computer. It was not integrated into any equipment for detecting FPC defects. The hardware consisted of i7-9700K (clocked at 4.9GHz), an RTX2080 Super GPU (with memory of 8GB), the Ubuntu system, and the Keras deep learning backend.

To obtain an enhanced simulation estimation effect, the simulation input range can be determined according to the original input reliability values’ range. In addition, the sample size of the expanded data can be adjusted as needed. In this example, to obtain an expanded data sample with a sample size of 50, a set of 50 random numbers ranging from 0.8 to 1 is arranged into a vector in descending order. The values are then input into the trained BP neural network for simulation, resulting in 50 new random numbers. The generated failure data serves as an augmented sample of the original data. For the expanded data samples, the least squares method is used to estimate the parameters of exponential and Weibull distributions. See Figure 3.

Experimental Results and Analysis

Considering the diversity and nonlinearity of the power system operating state, the network adopts a hidden layer with a learning efficiency coefficient of 0.9. The network is trained using hidden units set at 32, 34, 36, and 38. After several experiments, the final training configuration is selected with a maximum permissible error of 0.002. This corresponds to 32 hidden units. The training error curve, as shown in Figure 4, indicates its feasibility.

In this article, the confidence level of a candidate frame that contains the target is set as I0U. If $IOU \geq 0.5$, the target frame is accurate in positioning the target. It is set as a real example. If the positioning is not sufficiently accurate, it is set as a false positive example. If $I0U = 0$, the detection model interprets the object frame as not containing an object, classifying it as a false negative example. In this section, the area under the curve represents the average precision (AP), in which a higher value indicates better performance.

Figures 5 and 6 show the precision-recall curves of the six algorithms. It is evident that for small-sized short-circuit, open-circuit, and pinhole defects, the maximum recall rates of the six algorithms are consistent. For short-circuit defects, the curves of the six algorithms do not vary. For open circuit defects, however, both the Faster-RCNN and the accuracy with three modules exhibit improvements, showing that for small target defects, all three modules have an impact.

Figure 7 shows the output error using five optimization algorithms. When the iteration increases from 9 to 10, the number of iterations increases by 5. This results in a decrease of 0.036 in the MSE. When the iteration count is increased from 10 to 11, the number of iterations increases by 2, resulting in a decreased of only 0.0121 in the MSE.

Figure 3. Exponential distribution of sample data under the mathematical expectation formula

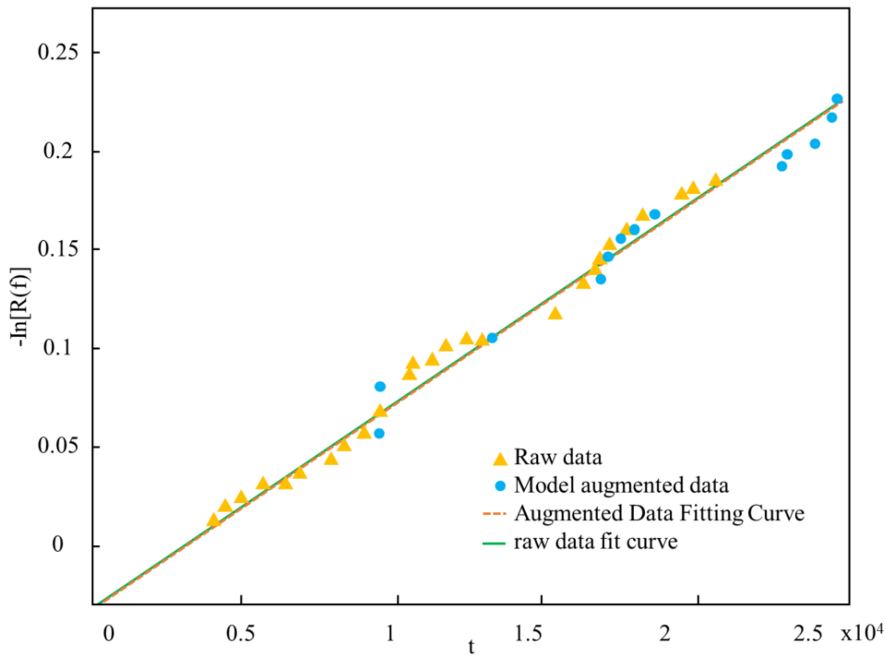
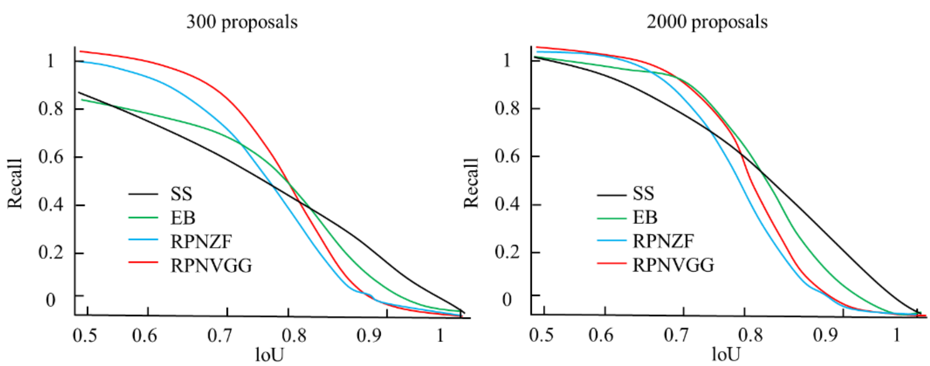


Figure 4. Oscillations identify the subnetwork error curves



At 10 iterations, there is a significant increase in the number of iterations, while the MSE decreases very little. Thus, continuing to increase the iterations has minimal returns, making 10 iterations the best choice. At this time, with 30 iterations, the MSE is 0.0885.

To verify the accuracy of platen recognition, this method was used to identify three groups of platens, and their states were manually verified. The rate for using the Faster R-CNN algorithm yielded recognition rates exceeding 94% for distinguishing between platen throw and retract states. As the number of samples increased, the accuracy of the identification also improved.

In addition, after reviewing pictures of the misclassified platen, it was found that the wrongly identified platen stemmed from incorrect shooting angles and lighting conditions. It is necessary to consider whether the machine learning algorithm can be adapted to similar systems. To generalize

Figure 5. Precision - recall curve - exposed_ copper

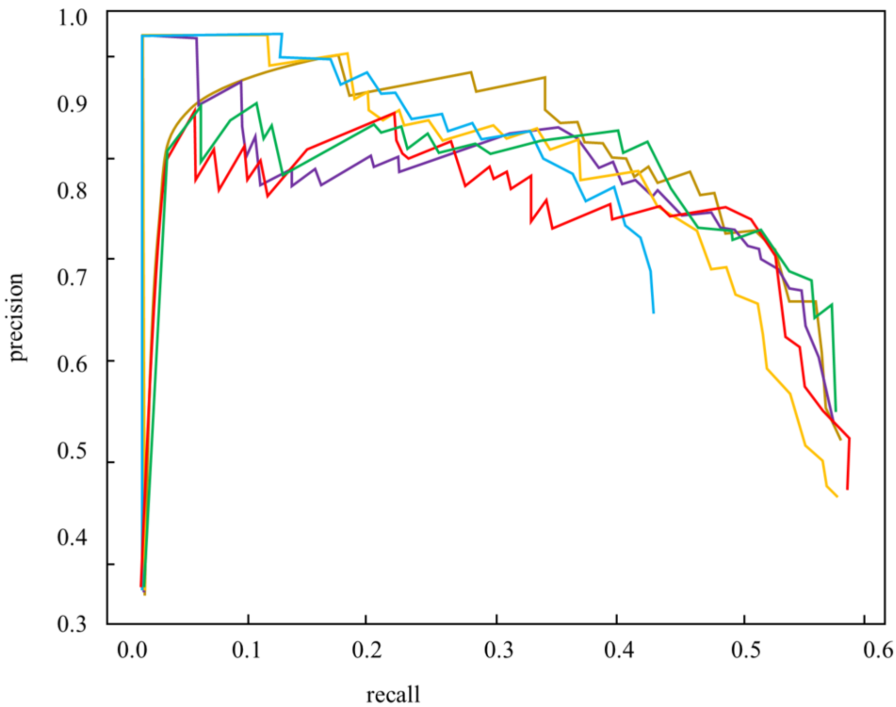


Figure 6. Precision-recall curve-short

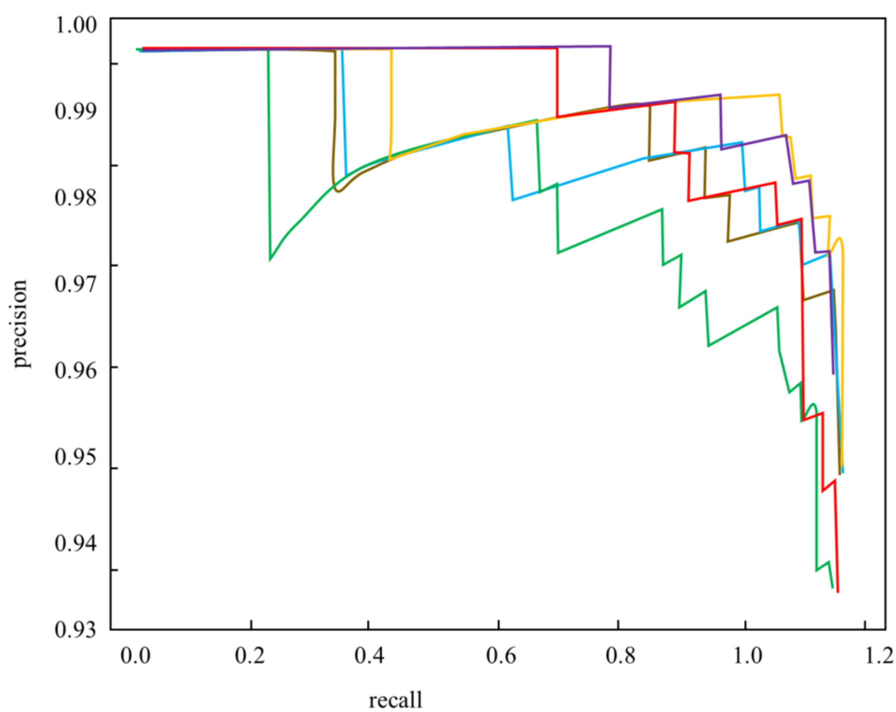
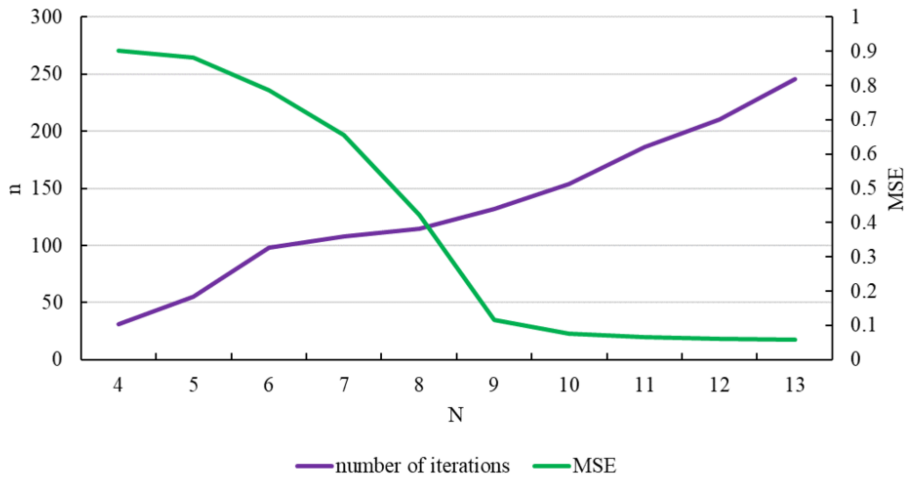


Figure 7. Comparison of optimization results of the faster R-CNN neural network



the results to other systems, more data akin to the system needs to be collected and pre-processed. This includes steps like data cleaning, standardization, and feature selection to ensure data quality and availability.

Using the collected data, we can retrain the fast R-CNN and other machine learning models while finetuning the models. This includes optimizing hyperparameters and adjusting the model structure to achieve peak performance within the new system. After training and tuning, we can compare and study different algorithm models, including factors like accuracy, robustness, real-time performance, and other relevant aspects to identify the most suitable model for the new system.

Finally, we integrate the selected model into the new system and put it into practice. This requires collaboration with system designers and developers to understand the system's architecture and functionality, ensuring seamless integration of the machine learning models with the existing systems for intelligent recognition of the relay protection strap switch status.

CONCLUSION

The development of new technology in power system relay protection relies on the social economy. Nowadays, the emergence of an increasing array of new technologies has promoted the continuous and stable development of the power system. This trajectory will drive the field toward a heightened intelligence and network connectivity, fostering the generation and application of power system technology.

This technological progress is realized by the introduction of Faster R-CNN and its application in recognizing the switching states of relay protection pressure plates, with the experiment carried out in 110kV substation. The method includes several key factors:

1. The Faster R-CNN algorithm is directly used to generate detection frames, distinguishing it from the classical detection method.
2. The approach is used to identify the switching state of the pressure plate, which greatly reduces the workload of substation operators. It also improves the efficiency of inspections, mitigates the occurrence of incorrect or missed switching events, and ensures the secure and stable operation of the power system.

3. The proposed method has strong adaptability and recognition capabilities, attaining recognition accuracy rates exceeding 94%.
4. Its adaptability and the associated enhancements in worker efficiency are pronounced.

DATA AVAILABILITY

The figures used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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