Insulator and Burst Fault Detection Using an Improved Yolov3 Algorithm

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Insulators play an important role in the operation of outdoor high-voltage transmission lines. However, insulators are installed in outdoor environments for long periods and thus failures are inevitable. It is necessary to conduct timely insulator inspection and maintenance. In this paper, an improved Yolov3 target detection network (Yolov3-CK) is proposed in order to achieve higher detection accuracy and speed. First, Yolov3-CK uses the CIOU loss function instead of the mean square error loss function from Yolov3. Second, the Yolov3-CK model uses cluster analysis of the priori box via the $k$-means++ algorithm to obtain a priori box size that is more suitable for the detection of insulators and their burst faults. Finally, we use a dataset obtained by performing data enhancement on the China power line insulator dataset to train and test the data-enhanced Yolov3-CK model. The mean precision of Yolov3-CK reaches 91.67% with 47.9 frames processed per second. Yolov3-CK provides better detection accuracy and a higher processing rate than Faster RCNN, SSD, and Yolov3. Therefore, the Yolov3-CK model is more suitable for the detection of insulators and their burst faults.

1. Introduction

With the increasing demand for electrical energy, especially in the context of smart grids, high-voltage transmission is becoming increasingly important. Insulators provide electrical protection in power transmission and transportation applications, but long-term exposure makes bursting failures inevitable [1]. Insulator burst failures endanger the safety and steady performance of the entire electrical transmission line and can even impose huge economic losses on the power grid [2]. Therefore, it is important to conduct regular inspections of transmission and distribution line insulators in order to ensure normal operation of the high-voltage transmission system and electric grid. It is also important to repair and replace failed insulators in a timely manner.

At present, there are three main types of insulators. They typically use one of three types of fault detection: traditional image detection, machine learning detection, and deep learning target detection.

The first class of methods is based on traditional image detection algorithms. Traditional image detection insulator methods mainly use the threshold segmentation, edge detection, and texture feature extraction methods. For example, Huang and Zhang [3] proposed segmentation of insulators based on their features and setting appropriate thresholds. The researchers then detected failures by matching algorithms. Yao et al. [4] determined whether the insulator had experienced a burst fault by segmenting the insulator region, extracting regional features, and comparing the regions for similarity. Zhenbing et al. [5]...
proposed a method of performing edge extraction from aerial insulator images based on a non-downsampling contour wave transform. The extracted images were then detected. Li et al. [6] used the MPEG-7 margin histogram method to extract and identify insulator texture features. They optimized and improved the original MPEG-7 edge histogram based on this method in order to improve the accuracy with which insulators could be identified to some extent. Luo and Tian [7] proposed combining several image processing techniques. They also proposed an improved Canny operator based on the detection of insulators and other metallic equipment in images.

The second category of fault-detection methods uses machine learning algorithms for insulator detection. Integration algorithms and support vector machines (SVMs) [8] are the machine learning detection algorithms most commonly used for insulator detection. Jiang et al. [9] proposed a combination of SVM and fuzzy set theory that addresses problems with uncertain linear division to classify faults in metallic equipment such as insulators. Zhao et al. [10] proposed the use of deep convolution to detect insulators in infrared images and used SVM to achieve insulator classification. Reddy et al. [11] transformed the original image to the Lab color space, performed $k$-means clustering of color features within this color space, and then used SVM to detect the image regions where the insulators were located in order to detect insulator targets. To detect insulator targets, Zhai et al. [12] proposed a structural insulator model and threshold segmentation as an optimal entropy method. They mainly used mathematical morphological algorithms to segment insulators from images. They then used the Ada-Boost integration algorithm to perform insulator detection in complex images. These commonly used machine learning methods sometimes provide better reliability than traditional target detection methods, but their recognition time and accuracy still need improvement.

In recent years, deep learning based on novel machine learning strategies has become widely used in target detection [13, 14]. Deep learning is more able to process targets with complex backgrounds than traditional image processing methods that rely on commonly used machine learning algorithms. At present, there are two types of deep learning-based target detection models. A two-stage target detection network divides target detection into feature extraction and feature classification. Typical double-stage target detection networks include Fast RCNN [15] and Faster RCNN [16]. Chen et al. [17] proposed the use of an improved Faster R-CNN approach for insulator detection. It achieved a detection precision of 90.5% but processed only 11 frames per second. Typical single-stage detection networks include Yolov3 [18] and SSD [19]. Lai et al. [20] used a Yolov2 detection network to perform online identification of insulators. The average precision was 90% and the throughput was 30 frames per second. Dong [21] used the Yolov3 model for critical power component detection. The insulator detection precision was 90.2% and the throughput was 57 frames per second. Miao et al. [22] proposed the use of an improved SSD model for insulator detection, achieving a precision of 90.42% and a throughput of 16 frames per second. Although the single-stage detection network is inferior to the two-stage detection network in terms of average detection precision, the single-stage detection network is faster than the two-stage detection network in terms of detection rate.

The detection rate of the Yolov3 model is much higher than those of the other models, but the detection accuracy is not as good as those provided when the SSD and Faster RCNN models are applied to insulator images. Therefore,

![Figure 1: The Yolov3 network structure.](image-url)
this paper improves the detection precision of the Yolov3 model while ensuring its real-time performance.

The remainder of this paper is organized as follows. Section 1 describes existing work on insulators and burst fault identification; Section 2 explains the Yolov3 detection model and the improved Yolov3-CK model; and Section 3 presents and analyzes the experimental results. Finally, Section 4 concludes the paper.

2. Materials and Methods

Yolov3 is a deep neural network algorithm-based object recognition and localization algorithm that evolved from Yolo and Yolov2 [23]. The single-stage detection network provides better detection rates and accuracies than the double-stage detection network because it does not require the generation of a large number of candidate boxes. The overall structure of Yolov3 is shown in Figure 1. The Yolov3 model resized the input image to 608×608, obtained the corresponding priori boxes via clustering analysis of the priori boxes from the coco dataset [24], and then used the Darknet53 network for feature extraction. The extracted feature layers were fused for feature fusion in order to support prediction. The prediction section was divided into three main parts (Detection 1–3).

Yolov3 used Darknet53 as its backbone network. The Darknet53 network had two main features. The first was a residual network structure (Residual_block) that was characterized by its ease of optimization and its ability to improve precision by adding considerable depth. Second, each convolution of the Darknet53 network was followed by the use of BatchNormalization normalization via the LeakyReLU function (formula (1)).

\[
y_j = \begin{cases} 
  x_i & x_i \geq 0 \\
  \frac{x_i}{a_i} & x_i < 0 
\end{cases}
\]  

Unlike the ordinary ReLU function that outputs all negative input eigenvalues \( x_i \) as zero, the LeakyReLU function gives each negative input eigenvalue \( x_i \) a corresponding non-zero slope. This helps to avoid the problem of gradient disappearance [25].

During feature extraction, Yolov3 uses the extraction of three feature layers for target detection. The feature layers are located at different positions on the Darknet53 backbone [26]. After obtaining the three effective feature layers, we used them to construct a feature pyramid network (FPN) in order to enhance feature extraction (Figure 2). After
feature fusion was used to achieve full extraction of information from the three effective feature layers, 76×76, 38×38, and 19×19 image feature maps were developed. Finally, prediction was performed to determine the results for each category, confidence level, and prediction box parameter set in the image.

2.1. Improving the Priori Box. The priori box idea is used in the Yolov3 network structure. The obtained priori boxes were generally analyzed by clustering the coco dataset priori boxes and then putting the resulting mine priori boxes into the model for training. However, the k-means clustering algorithm imposed some randomness with regard to the selection of the center of the initial trial cluster. This tended to cause large errors. In addition, there were relatively large differences between the priori box sizes of the insulators and their burst faults. To improve efficiency, the Yolov3-CK model used the k-means++ clustering algorithm to cluster the priori box from the Chinese power line insulator dataset (CPLID). K-means++ gets rid of the dependence
on initializing cluster centers. The average IOU (intersection over
union) is plotted versus the number of clustering cen-
ters after clustering the priori box using the k-means++ algo-
rithm in Figure 3. The picture analysis shows that the change in the value of the average IOU tended to level off as the number of set cluster centers increased. When nine priori boxes were set, the average IOU was 89.01%. When k was greater than 9, the change in the value of the average IOU tended to level off. Therefore, nine clustering centers were used for the insulator and burst fault priori box data. The final priori boxes were (14, 18), (19, 36), (35, 33), (36, 75), (76, 55), (144, 45), (359, 263), (407, 106), and (407, 164).

2.2. Improving the Loss Function. The intersection over union (IOU) is one of the evaluation criteria used with deep neural networks. It is represented by the rate of overlap between the prediction box and the priori box. However, when the prediction box and the priori box do not overlap, the IOU does not reflect the real distance between the relevant boxes. Under these circumstances, the loss function is not derivable and the IOU loss function cannot be used to optimize the case of non-intersection between the prediction and priori boxes. In contrast, the complete intersection over union (CIoU) resolves the inability of the general IOU to optimize the part of the prediction box that does not overlap directly with the priori box [27]. Therefore, the Yolov3-CK model used the CIoU loss function instead of IOU loss function. The loss function used in the Yolov3-CK model is defined in formula (2). It consists of three main components: the CIoU loss function \( \text{loss}_{\text{ciou}} \), confidence loss function \( \text{loss}_{\text{conf}} \), and classification loss function \( \text{loss}_{\text{cls}} \). These are formulas (3), (4), (5), (6), and (7).

\[
\text{loss} = \text{loss}_{\text{ciou}} + \text{loss}_{\text{conf}} + \text{loss}_{\text{cls}},
\]

\[
\text{loss}_{\text{ciou}} = 1 - \text{IoU} + \frac{\rho^2}{m^2} + \alpha \cdot v,
\]

\[
\alpha = \frac{v}{1 - \text{IoU} + v},
\]

\[
v = \frac{4}{\pi^2} \left( \arctan \frac{w}{h} - \arctan \frac{\bar{w}}{\bar{h}} \right),
\]

\[
\text{loss}_{\text{conf}} = \sum_{i=0}^{s^2} \sum_{j=0}^{B} I_{ij} \left[ C_{ij} \cdot \log \left( \hat{C}_{ij} \right) + \left( 1 - C_{ij} \right) \cdot \log \left( 1 - \hat{C}_{ij} \right) \right] + \lambda_{\text{noobj}} \sum_{i=0}^{s^2} \sum_{j=0}^{B} I_{ij} \left[ C_{ij} \cdot \log \left( \hat{C}_{ij} \right) + \left( 1 - C_{ij} \right) \cdot \log \left( 1 - \hat{C}_{ij} \right) \right],
\]

\[
\text{loss}_{\text{cls}} = \sum_{i=0}^{s^2} \sum_{j=0}^{B} \sum_{c=\text{class}} I_{ij} \left[ P_{ij}(c) \cdot \log \left( \hat{P}_{ij}(c) \right) + \left( 1 - P_{ij}(c) \right) \cdot \log \left( 1 - \hat{P}_{ij} \right) \right].
\]

In formulas (3), (4), (5), (6), and (7), \( \text{IOU} \) represents the intersection and union ratio of priori and prediction boxes; \( \rho^2 \) represents the distance between the priori and prediction boxes; \( m \) represents the distance between the diagonal of the smallest closed region that can contain the prediction and priori boxes; and \( \bar{w} \) and \( \bar{h} \) represent the width and height of the prediction box, respectively. The formula \( s^2 \) is the number of grids on the output feature layer; \( B \) is the number of a priori boxes produced by each grid; \( I_{ij} \) represents whether an object falls into the \( j \)-th predicted box of grid \( i \); \( \lambda_{\text{noobj}} \) represents the confidence error weights; \( C \) and \( \hat{C} \) are the confidence levels of the prediction box and the priori box, respectively; and \( P \) and \( \hat{P} \) are the categorization probabilities of the prediction and priori boxes, respectively.

3. Experimental Results and Discussion

In this section, we describe the data preprocessing and evaluation metrics in detail. Experimental details and results analysis are provided. To analyze the performance of our proposed model, we compare it to other models.

3.1. Data Processing. The CPLID was used in this experiment but the number of insulator burst fault samples obtained was not sufficient for training. Therefore, in order to train a robust model, we created simulated insulator burst fault samples using Photoshop software. The software was used to remove the normal insulator string and background pixels were used to fill the space. Various insulator burst failure images produced using Photoshop are shown in Figure 4.
The final 750 images were obtained using the above method. To ensure better generality of the trained model, more insulator images were generated by rotating some images to various angles and adjusting the exposure and hue during training. Some of the adjusted insulator images are shown in Figure 5. Finally, 1900 images were obtained via adjustment and the dataset was divided according to a 4:1 ratio; 1520 images were chosen randomly as the training set and 380 were used as the test set.

3.2. Model Evaluation Metrics. We used the number of frames per second (FPS) processed to evaluate the real-time performance of the model and the mean precision (mAP) to measure model accuracy. These quantities are defined in formulas (8) and (9).

\[
\text{mAP} = \int_0^1 P(R) dR, \tag{8}
\]

\[
\text{FPS} = \frac{1}{t_{\text{avg}}}, \tag{9}
\]

\[
P = \frac{TP}{TP + FP}, \tag{10}
\]

\[
R = \frac{TP}{TP + FN}, \tag{11}
\]

\[
F = 1 - P, \tag{12}
\]

where \( P \) is the accuracy rate and \( R \) is the recall rate. It is obvious that in formula ((8)), mAP is equal to the area under the accuracy-recall rate (P-R) curve, which is between 0 and 1. In formula ((9)), \( t_{\text{avg}} \) is the time required to recognize an insulator image and FPS is the number of images that can be recognized in one second. Missed and false detections have large impacts on transmission line inspection, so the recall rate (R) and false alarm rate (F) can also be used to verify model reliability. In this experiment, the quantities of true positives (TP), false positives (FP), and false negatives (FN) are used to compute the accuracy, recall, and false alarm rate values. The formulas are shown in (10-12).

3.3. Experimental Details. Our experiments were performed using the Pytorch framework, which ran on a Ubuntu Linux 20.04 system with an Intel (R)-i9 processor, a GeForce GTX 3080 graphics card, and 64 GB of RAM. Details of the relevant hardware and software are presented in Table 1. We trained 140 epochs. This article uses Step LR to adjust the learning rate. The first 70 epochs were trained by freezing to speed up the training; the learning rate was set to \( 1 \times 10^{-4} \); the batch size was 8; and the number of iterations in an epoch was 195. The second 70 epochs were trained using a full network with a learning rate of \( 1 \times 10^{-3} \), batch size of 4, and 390 iterations in an epoch. The results are shown in Table 1.

3.4. Results and Analysis. To verify the reliability of our proposed model, we obtained the best two-stage network Faster RCNN and single-stage network SSD, Yolov3, Yolov4, and Centerent models. Meanwhile, the improved Faster RCNN model in document 17 is reproduced and compared with the improved Yolov3 model in document 18. The above models are trained and tested in the same environment and dataset. It can be seen from the table that the two-stage fast RCNN network has high detection accuracy for insulators, but its detection speed is far lower than other detection models. The detection accuracy of Yolov3 model is slightly lower than that of Faster RCNN model, but it is better than other detection models, and its detection speed is also better than other models. Based on Yolov3 model, Yolov3 CK model is obtained. Yolov3 CK model is better than the improved model in literature 17 and 18, and Yolov3 CK model is better than other models in detection accuracy and detection speed. The results are shown in Table 2.
adjusting exposures, and adjusting hues. Second, to enhance model performance, we improved the priori box and loss function of the Yolov3 model. Finally, the resulting Yolov3-CK model was trained, tested, and compared to other models experimentally. The Yolov3-CK model exhibited strong advantages over other models because of its detection accuracy and real-time nature. The final mAP value of 91.67% and FPS of 47.9 showed that the model can detect insulators and their burst faults in complex backgrounds. In summary, the Yolov3-CK model can achieve real-time detection. In future studies, we will simplify the size of our model and research ways to improve the model detection rate without losing accuracy.

Data Availability
All data, models, and code generated or used during the study appear in the submitted article.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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