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Research On Transmission Line Insulator Defect Detection Method Based on Yolov8

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ABSTRACT

Transmission line insulators are an important part of the power system, and their defects can seriously affect the safety and reliability of the power system. The traditional insulator defect detection method mainly relies on manual inspection, which is inefficient, costly, and easily affected by subjective factors. In order to improve the efficiency and accuracy of insulator defect detection, this paper proposes a YOLOv8-based insulator defect detection method for transmission lines. The method makes use of the powerful target detection capability of the YOLOv8 model to identify and locate transmission line insulator images and classify defect types. The experimental results show that the method achieves good results in insulator defect detection, can effectively identify and locate different types of insulator defects, and provides a reliable technical guarantee for the safe operation of transmission lines.

KEYWORDS

Transmission line; Insulator; Defect detection; YOLOv8; Deep Learning

1. INTRODUCTION

1.1. Research Significance

Insulators and dampers, as essential power components in transmission lines, play an critical part of supporting the line, blocking the current, and preventing damage to the transmission line [1]. In HIGH-VOLTAGE transmission lines, insulators are widely used electrical devices primarily for wire support and ground insulation, playing a crucial role in the safe and stable operation of the power grid [2]. Power companies face a major challenge in inspecting and diagnosing power lines [3]. Currently, identification of transmission line equipment relies predominantly on manual inspections that are susceptible to the influence of natural surroundings, resulting in sluggishness and a high rate of false detections. Foot patrolling is slow, inaccurate, and only capable of doing surface-level checks, thereby ignoring important problems [4]. Manual inspection means that power inspection personnel arrive near the overhead transmission line on foot, vehicle, etc., and use it under the line or on the tower by climbing a tower [5]. Currently, drone inspections are gradually replacing traditional manual inspections due to their efficiency and convenience [6].

1.2. Related Research

Nowadays, in order to meet the requirements of the continuous development of the smart grid, artificial intelligence technology has been continuously introduced into various fields of the power system, and image recognition and object detection through computers can be more efficiently replaced by manual recognition. In recent years, object detection has witnessed significant advancements in model architectures [7]. With the development of deep learning techniques in the past few years, the use of deep learning techniques for monitoring and detecting insulator defects as well as other power equipment detection algorithms has become increasingly popular [8]. However, transmission line insulator defects are small in size, and traditional target detection algorithms are usually difficult to recognize the defect targets, with a high rate of misdetection and missed detection.

Many researchers have begun to identify and locate defects in drone aerial images to further improve the quality of transmission line detection [9]. Xueli sheng et al. proposed a target detection algorithm based on YOLOv8n for the problem of low accuracy of small target detection in drone aerial photography detection task, which is based on YOLOv8n Compared with other classical algorithms, the SFE-YOLO algorithm has a lower number of parameters and a higher detection accuracy, and has a wide range of potential applications and practical value. However, the proportion of insulators in the inspection pictures taken by UAV is very small, and the defective part accounts for a small part of insulators, the defect detection effect of the inspection pictures is often unsatisfactory. HuMiao used a two-phase approach to accomplish the task of detecting insulator self-destructive defects, focusing on the detection of self-destructive defects of the insulators, while there are also insulator defects such as corrosion, soiling, and cracking. li WeiXing et al. In order to detect insulator defects in transmission line images, SSD convolutional neural network method is used to detect image targets. However, the experiments found that the defective insulator misdetection rate is high and many of the misdetected parts are not on the insulators. Yifu Chen, Hongye Liu et al. proposed an improved insulator defect recognition algorithm Insu-YOLO based on the latest YOLOv8 network in order to maintain the balance between the accuracy and speed of insulator defects detection by UAVs in the process of electric power inspections [10], but it needs to further improve the accuracy of tiny defect detection while optimizing the detection speed.

2. MODEL INTRODUCTION

2.1. Model Structure

YOLOv8 is an efficient and accurate target detection algorithm with the advantages of fast detection speed, high detection accuracy, and applicability to a variety of target detection scenarios, such as image classification, target detection, instance segmentation, etc [11].The model structure of YOLOv8 mainly consists of the following components:

(1) Input Layer: Receives input images and performs preprocessing, such as resizing and normalization.

(2) Backbone: Extracts deep features from images, such as CSPDarknet53, EfficientNet, etc.

(3) Neck: Fuses feature information of different scales to enhance the model's ability to detect objects of various sizes, such as PAN, BiFPN, etc.

(4) Head: Predicts the category and position information of targets, such as Decoupled Head, IoU-aware Head, etc.

(5) Output Layer: Outputs target bounding boxes, class labels, and confidence scores.

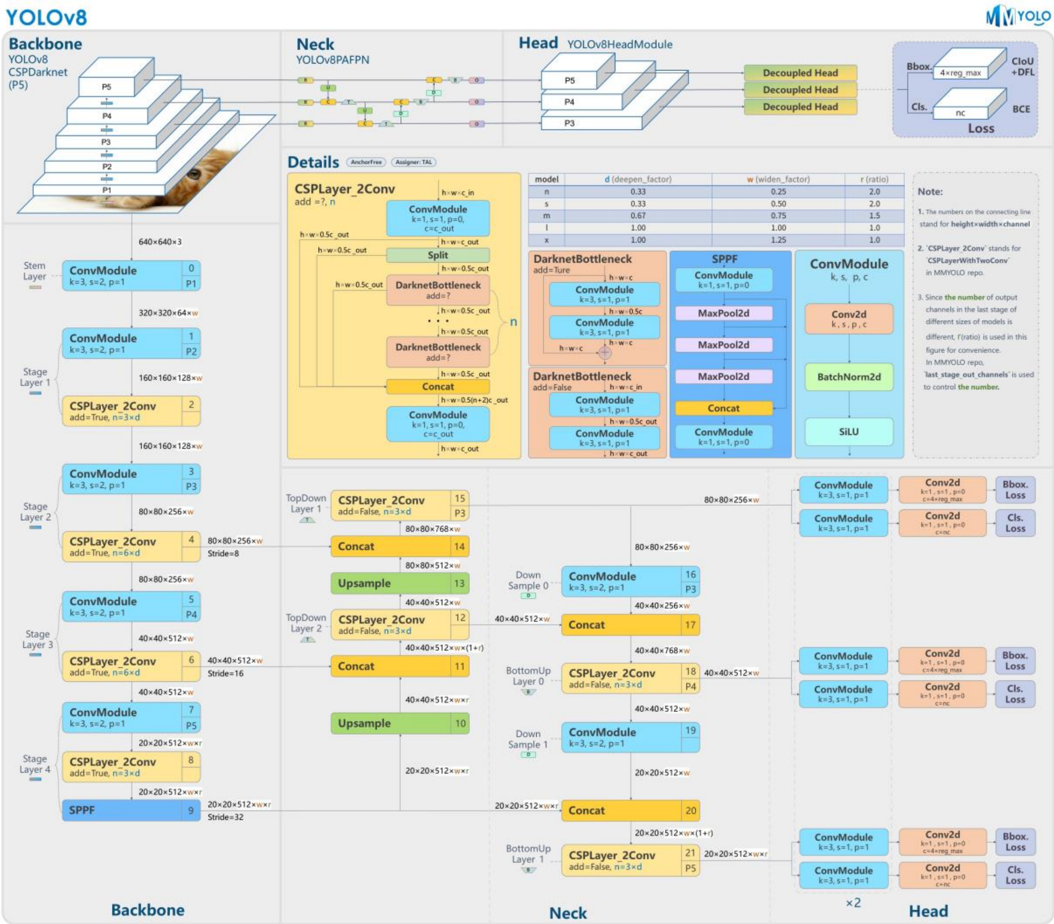

Figure 1. YOLOv8 model network structure diagram

2.2. Network Infrastructure

2.2.1. Backbone.

YOLOv8 by default employs CSPDarknet53 as its Backbone network. CSPDarknet53 is an enhanced version of the Darknet53 network, which introduces the Cross-Stage Partial Connections (CSP) structure. It replaces the C3 module in Yolov5 with the C2f module, achieving further lightweighting. Additionally, it retains the SPPF module from Yolov5 and meticulously fine-tunes models of different scales. This effectively reduces redundant gradient information transmission in the network, thereby enhancing both training efficiency and accuracy.

EfficientNet is also supported as a Backbone network in YOLOv8. EfficientNet is an efficient convolutional neural network that combines model scaling, resolution scaling, and network structure scaling. It reduces computational and parameter overhead while maintaining high accuracy.

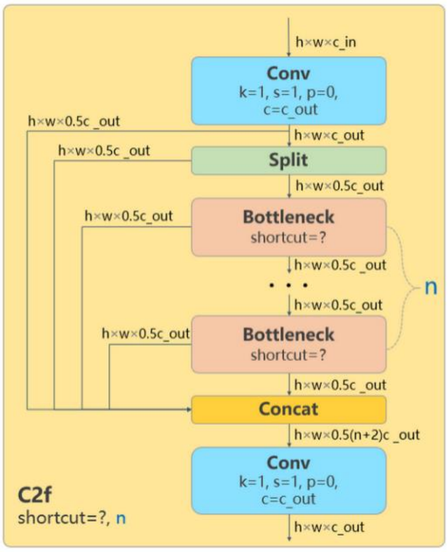

Figure 2. C2f Module Diagram

C2f module first splits the input tensor (n, c, h, w) through a Conv1 layer into two parts: (n, 0.5c, h, w). One part directly undergoes n Bottleneck operations, while the other part undergoes a Shortcut operation after each layer, maintaining the size of (n, 0.5c, h, w). Finally, the outputs are convolved through a Conv2 layer. This corresponds to n+2 Shortcuts (including the first branch tensor from Conv1 and the split tensor).

In C2f, the number of channels for each input tensor in the Bottleneck is only half of the previous level, significantly reducing computational complexity. Additionally, the increase in gradient flow can significantly enhance convergence speed and effectiveness.

2.2.2. Neck.

PAN (Path Aggregation Network) is a feature fusion structure that aggregates feature information of different scales through both top-down and bottom-up paths, enhancing the model's ability to detect objects of different scales.

BiFPN (Bi-directional Feature Pyramid Network) is a bidirectional feature pyramid network that effectively fuses feature information of different scales through bidirectional connections, further enhancing the model's performance.

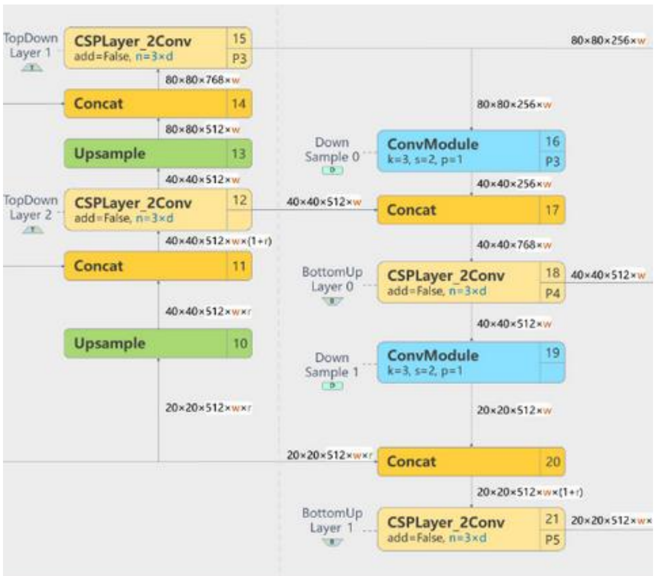

Figure 3. Neck Structure Diagram

2.2.3. Head.

Decoupled Head separates the prediction of object categories and object positions, utilizing independent networks for each prediction task. It decouples the regression branch and the prediction branch, employing the integral form proposed in the Distribution Focal Loss strategy specifically for the regression branch. This enhances both the accuracy and efficiency of the model.

IoU-aware Head considers the Intersection over Union (IoU) of the predicted object position when making predictions. This improves the accuracy of the model's predictions regarding object positions.

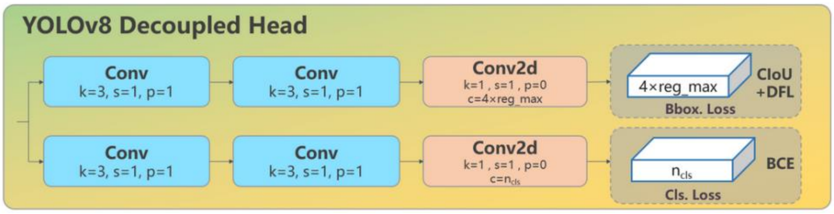

Figure 4. Head Structure Diagram

2.3. Loss Function

YOLOv8's loss function consists of three main components: Bounding Box Loss, Classification Loss, and Depth Feature Loss. Each component utilizes specific loss functions to measure the difference between the model's predictions and the ground truth labels, guiding the model to continually optimize during training.

2.3.1. Bounding Box Loss.

YOLOv8 employs CIOU Loss as the bounding box loss function. CIOU Loss is an improved version of IoU Loss, as it considers not only the overlap area of bounding boxes but also factors in the distance between bounding box centers and their aspect ratios, providing a more comprehensive assessment of bounding box prediction accuracy.

CIOU Loss builds upon IoU Loss by incorporating penalties for the distance between bounding box centers and aspect ratios. The formula is as follows:

$$\mathrm{CIOU}_{\mathrm{Loss}} = \mathrm{IoU} - \frac{\rho^2}{c^2} - \alpha v \tag{1}$$

Where:

ρ: the distance between the center point of the predicted bounding box and the center point of the real bounding box.

c: diagonal length of the smallest outer rectangle of the predicted bounding box and the real bounding box.

α: a weighting factor to control the penalty strength of the center point distance and aspect ratio.

v: a measure of the consistency of the aspect ratio between the predicted bounding box and the true bounding box, calculated as

$$v = \frac{4}{\pi^2} * \left(\arctan\frac{w\_gt}{h\_gt} - \arctan\frac{w\_pred}{h\_pred}\right)^2 \tag{2}$$

Where, w_gt and h_gt represent the width and height of the real bounding box, and w_pred and h_pred represent the width and height of the predicted bounding box, respectively.

2.3.2. Classification Loss.

YOLOv8 uses Cross-Entropy Loss as the category loss function. Cross-Entropy Loss can effectively measure the difference between two probability distributions. The formula for Cross-Entropy Loss is as follows:

$$CE_{Loss} = -\Sigma\, y\_i * \log(p\_i) \quad (3)$$

Among them:

y_i: true category label, taking the value of 0 or 1, indicating whether the category is the target category.

p_i: predicted category probability, taking values from 0 to 1, indicating the probability that the model predicts the category to be the target category.

2.3.3. Depth Feature Loss.

YOLOv8 uses L1 Loss as the deep feature loss function. L1 Loss can effectively measure the difference between two feature vectors. The L1 Loss formula is as follows:

$$L1_{Loss} = \Sigma\, |x\_i - y\_i| \quad (4)$$

Where:

x_i: the i-th element in the depth feature vector predicted by the model.

y_i: the i-th element in the real depth feature vector.

3. EXPERIMENTS AND THE RESULTS OF THE EXPERIMENTS

3.1. Experimental Setting

The experimental setup of this paper is as shown in the following Table 1.

Table 1. Experimental Configuration Table

Item	Configuration
OS	Linux
GPU	3080
CPU	Inter (R) Xeon (R) Platinum 8255C
Framework	PyTorch2.0
Data annotation	LabelImg

3.2. Dataset

The dataset consists of 1,209 maps of transmission line insulators, including photographs and images of transmission line insulators obtained from the Internet as well as from aerial photography. The dataset was then randomly divided into a training set containing 1,088 images and a validation set containing 121 images. The dataset was annotated using LabelImg software in YOLO format to label the insulators. After annotation, each image corresponds to .txt file with the same name as the image. Each line in the .txt file represents an instance of annotation, including the category label, centroid x-coordinate, centroid y-coordinate, width and height.

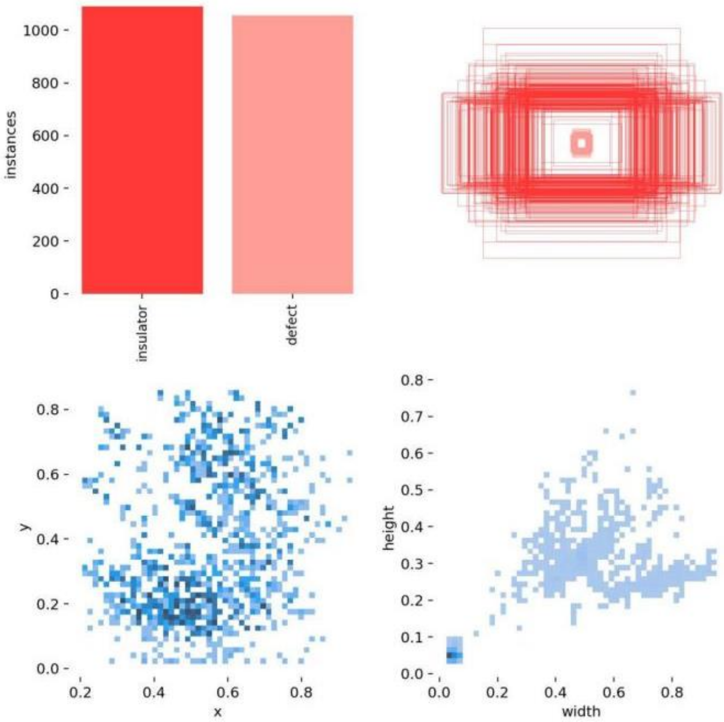

Figure 5. Dataset Labeling Chart

3.3. Evaluation Indicators

In the study of defect detection methods for transmission line insulators based on YOLOv8, commonly used evaluation metrics include precision, recall, mAP50, and mAP50-95. These metrics are closely related and collectively reflect the detection performance of the model.

3.3.1. Precision.

The precision of bounding boxes increases as the number of training iterations rises, indicating that the proportion of correctly predicted target bounding boxes is becoming higher. The formula for precision is as follows:

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{5}$$

Here, TP represents the number of samples correctly predicted as positive by the model, and FP represents the number of samples incorrectly predicted as positive by the model.

3.3.2. Recall.

The recall of bounding boxes increases as the number of training iterations rises, indicating that the model is detecting an increasing number of targets. The formula for recall is as follows:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

Among these, FN represents the number of samples that the model incorrectly predicted as negative.

3.3.3. MAP50.

The mean Average Precision (mAP) metric increases as the number of training iterations rises, indicating that the overall performance of the model is improving when the IoU threshold is set to 0.5. The formula for mAP is as follows:

$$mAP = \Sigma \frac{(AP\_i)}{N} \quad (7)$$

3.3.4. MAP50-95.

The mean Accuracy Precision (mAP) metrics, when the IoU threshold is between 0.5 and 0.95, the mAP metrics gradually increase with the number of training iterations, indicating that the model achieves better detection results for targets of different sizes.

3.4. Experimental Results

From the experimental results, it can be observed that the YOLOv8 model exhibits a positive trend in various metrics during the training process, indicating that the model's training effectiveness is excellent and its performance is continuously improving. The model has achieved favorable outcomes on both the training and validation sets, and has also attained commendable results in evaluation metrics, demonstrating that the model possesses strong generalization capabilities.

Table 2. Experimental Results Data

Class	Images	Instances	Box (precision)	Recall	mAP50	mAP50-95
all	121	239	0.992	0.996	0.992	0.843
insulator	121	122	0.992	0.992	0.995	0.931
defect	121	117	0.992	0.999	0.99	0.756

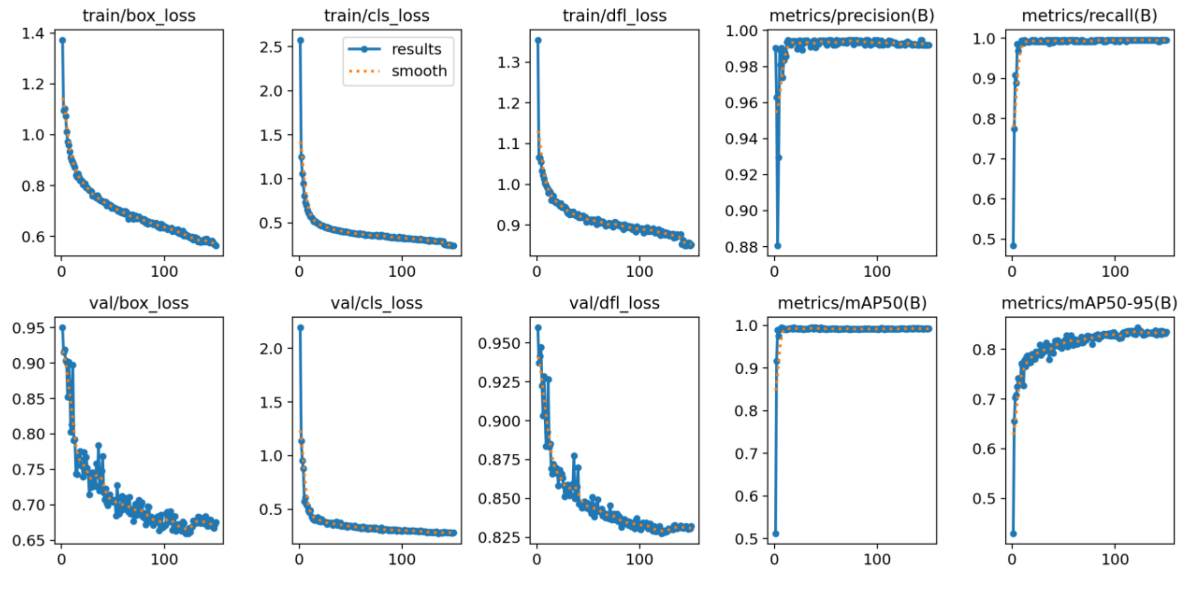

Figure 6. Result

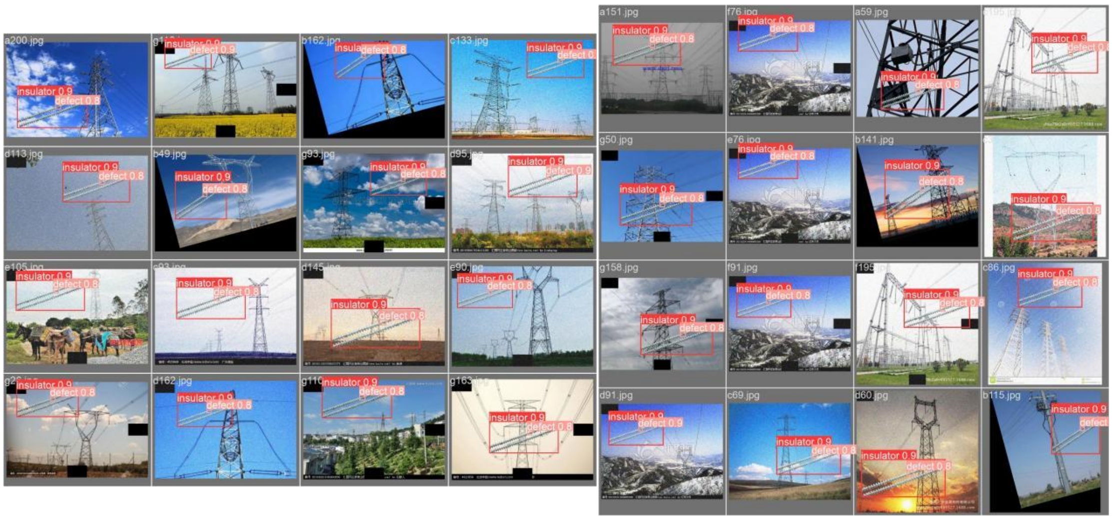

Figure 7. Chart Of Predicted results

4. SUMMARY

In this paper, a YOLOv8-based defect detection method for transmission line insulators is proposed. The method utilizes the powerful object detection function of the YOLOv8 model to identify and localize transmission line insulator images and classify defect types. Experimental results show that the model performs well during training and achieves commendable results on both the training and validation sets. This indicates that the model has strong generalization ability and can be effectively applied to real-world scenarios.

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