

# Research On Bird Nest Detection Method of Transmission Line Based on Yolov8

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## ABSTRACT

In this study, we propose a YOLOv8-based method for detecting bird nests on transmission lines, aiming to solve the safety hazards caused by transmission lines being affected by nesting birds. First, we collect a large-scale image dataset containing transmission lines and label the bird nests in it. Then, we used YOLOv8 as a target detection model to enable accurate detection of bird nests in transmission lines by end-to-end training on the dataset. During the training process, we adopt Bounding Box Loss, Vision Feature Loss, and Classification Loss loss functions to help the model learn more accurate and meaningful feature representations and improve the detection performance. The experimental results show that our proposed method achieves high accuracy and recall on the bird nest detection task, which can effectively help the transmission line maintenance personnel to detect and deal with bird nests in time, and ensure the safe and stable operation of transmission lines.

## KEYWORDS

YOLOv8; Deep learning; Nest

## 1. INTRODUCTION

With the enhancement of the awareness of nature protection, the frequent activities of birds and their wide distribution range have led to many birds nesting on transmission lines, which may damage the insulation performance of the towers and become the main cause of tripping accidents in the power system, posing a threat to the stability of the power grid and the safe operation of the power grid [2]. The traditional manual inspection method is not only labor-intensive and costly, but also has certain safety risks. Therefore, the use of drones equipped with bird's nest inspection software for automatic inspection has become a mainstream trend. The advantage of drones is that they can cover a wide range of transmission lines in a relatively short period of time, and they can carry out inspections in areas that are difficult to reach [7]. By integrating the bird's nest detection software into the UAV system, it can realize the rapid inspection of a wide range of transmission lines, making the safety management of the whole transmission line more efficient and timelier. It can cover a large range of transmission lines in a relatively short time, and can inspect in areas that are difficult to reach, such as mountainous areas and forested areas [11]. In addition, the drone equipped with bird's nest inspection software can also effectively reduce the risk and labor intensity of the staff, avoiding the risk of traditional line inspection methods that require personnel to climb transmission towers or use helicopters for inspection [5]. This approach not only reduces costs, but also improves work efficiency and, to a certain extent, protects the safety of staff. With the continuous development of technology and algorithms, the application potential of YOLOv8 based on YOLOv8 in the field of transmission line bird's nest detection will be broader.

## 2. YOLOV8 ALGORITHM

### 2.1. YOLOv8 Network Architecture

The basic network architecture of YOLOv8 is composed of the Backbone network, Neck, Head and Output layers. The structure is shown in Figure 1.

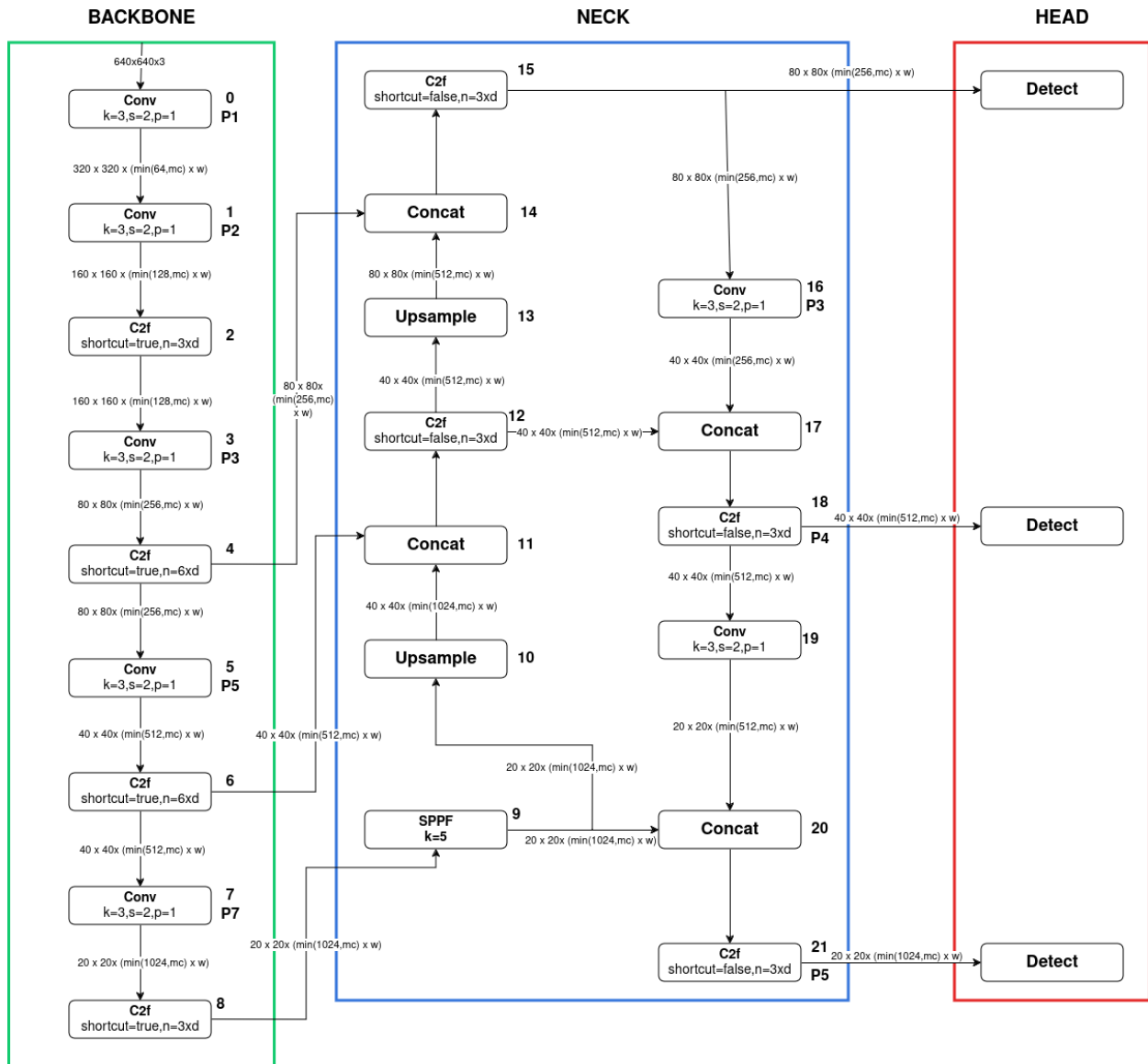
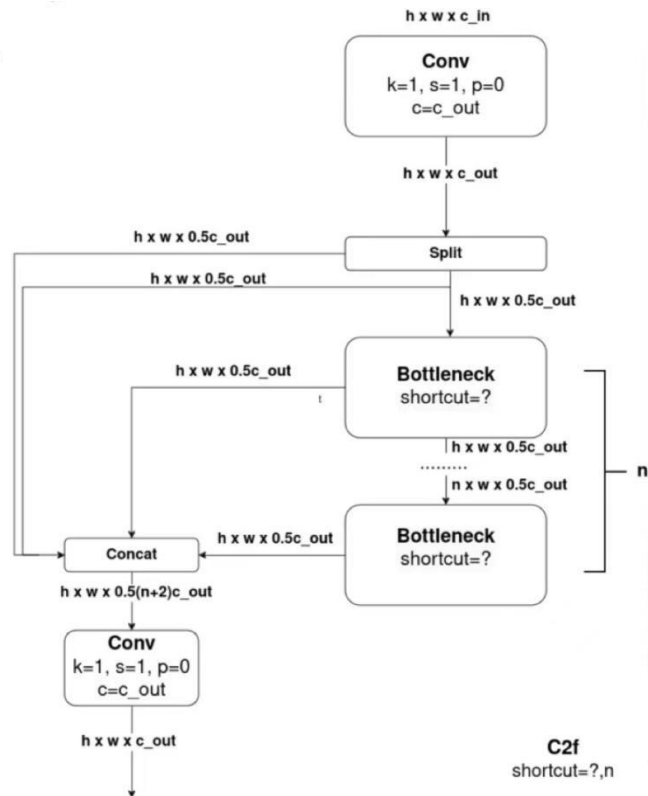


Figure 1. YOLOv8 model network structure

### 2.2. Backbone

The Backbone part is responsible for feature extraction and employs a series of convolutional and anti-convolutional layers  $Q$ . Residual connections and bottleneck structures are also used to reduce the size of the network and improve performance. This part utilizes the C2f module as the basic building block, which has a smaller number of parameters and better feature extraction capabilities than the C3 module of YOLOv5<sup>[4]</sup>. Specifically, the C2f module reduces redundant parameters and improves computational efficiency through a more efficient structural design. In addition, the Backbone section includes some common improvement techniques such as Depthwise Separable Convolution and Dilated Convolution<sup>[1]</sup>. The structure of the C2f module is shown in Figure 2.



**Figure 2.** C2f module structure diagram

### 2.3. Neck.

The Neck part of YOLOv8 adopts PAN-FAN structure for feature fusion and enhancement to achieve feature aggregation and feature attention one enhancement. The Neck structure diagram is shown below in Figure 3.

PAN is a feature pyramid network structure used in target detection models, aiming to enhance the detection performance of the model through the aggregation of multi-layer features[6]. Its main feature is that it adopts both top-down and bottom-up feature fusion paths, which can broadcast high-level features to low-level and propagate low-level features to high-level. Moreover, through the multi-scale fusion of feature maps, PAN can effectively enhance the feature representation of targets at different scales[4], thus improving the detection capability of the model.

FAN is mainly used for attentional enhancement of feature maps to emphasize important features and suppress irrelevant features. Its main feature is that it adopts an attention mechanism, which weights the input feature maps to enhance key features through channel attention and spatial attention mechanisms[5]. And through the attention mechanism, FAN can enhance the model's attention to the target region and improve the detection accuracy.

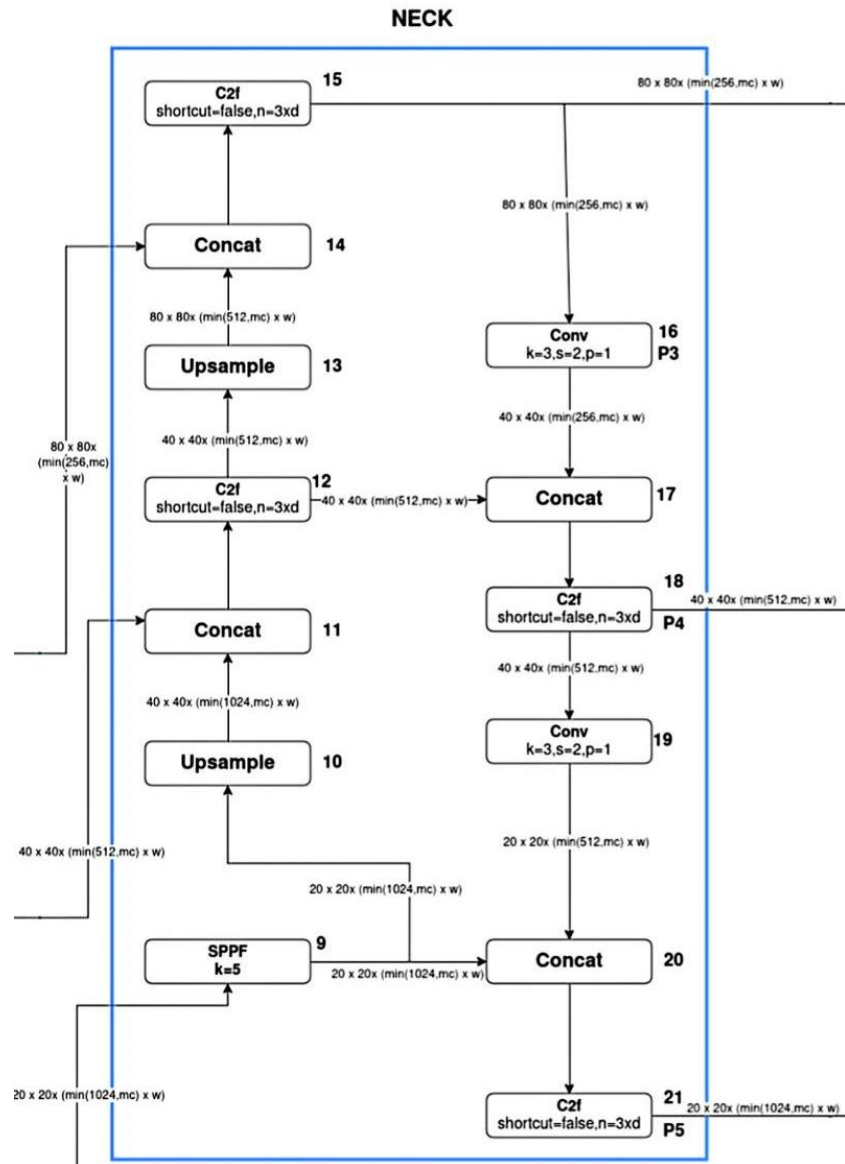


Figure 3. Neck Structure Diagram

## 2.4. Head

In YOLOv8, the Head part is responsible for further processing the features output from the Neck part to generate the final detection results. The main function of the Head part is to convert the feature maps into the specific information needed for target detection, including the category, position and confidence[9]. It is mainly composed of three parts: convolutional layer and activation function, prediction layer and Non-Maximum suppression. The Head structure diagram is shown below in Figure 4.

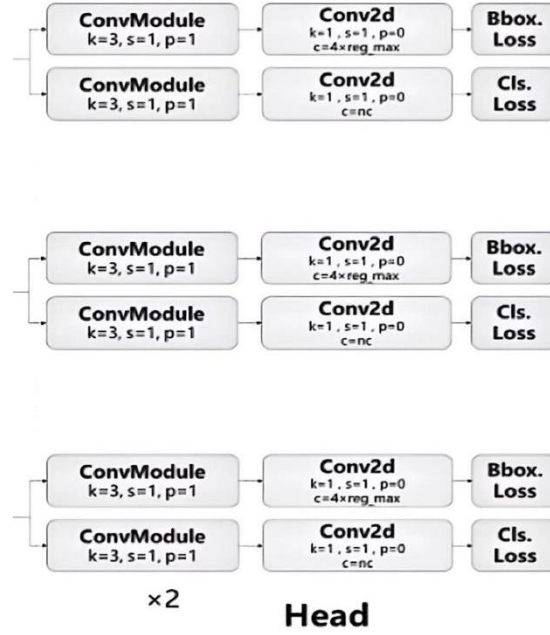


Figure 4. Head Structure Diagram

## 2.5. Loss Function

### 2.5.1. Bounding Box Loss

CIoU Loss, a variant of IoU (Intersection over Union), is used in bounding box loss to measure the degree of overlap between two bounding boxes. Compared with the traditional IoU, CIoU takes more factors into account, including the offset of the center point, the deviation of the aspect ratio, etc., and therefore measures the similarity between two bounding boxes more accurately. CIoU not only takes into account the position and scale information of the box, but also takes into account the shape information, and therefore the CIoU Loss is chosen. The formulas are as in Eqs. (1) (2) (3).

$$\text{CIoU} = \text{IoU} - \frac{D_2^2}{D_C^2} - \alpha v \quad (1)$$

$$\alpha = \frac{v}{(1-\text{IoU})+V} \quad (2)$$

$$V = \frac{4}{\pi^2} \left( \arctan \frac{w^{\text{gt}}}{h^{\text{gt}}} - \arctan \frac{w}{h} \right)^2 \quad (3)$$

### 2.5.2. Classification Loss

The use of the cross-entropy loss function in category loss measures the difference between the probability distribution of the categories predicted by the model and the true category labels. When the model's predictions are in perfect agreement with the true labels, the cross-entropy loss function reaches a minimum value of 0. And when the model's predictions differ significantly from the true labels, the cross-entropy loss function takes on a larger value. The cross-entropy loss function formula is shown in Equation 4.

$$H(p, q) = -\sum p(x) \log(q(x)) \quad (4)$$

Where  $p(x)$  is the distribution of the real data and  $q(x)$  is the model's predictive distribution.

### 2.5.3. Vision Feature Loss

The VFL (Vision Feature Loss) loss function is a novel loss function that combines ideas from the image generation field, such as adversarial training and image reconstruction, to help improve the performance of a target detection model. The design of the VFL loss function is inspired by the understanding of the learned feature representation of the model as well as the understanding of the relationship between the features of different layers in the model. Exploration. Its formulation is shown in Equation 5.

$$\text{VFL}(p, q) = \begin{cases} -q(q(\log(p) + (1 - q) \log(1 - p))) & q > 0 \\ -\alpha p \log(1 - p) & q = 0 \end{cases} \quad (5)$$

$q$  is the IoU of  $\text{bbox}$  and  $\text{gt}$ , IoU being the intersection of the predicted box and the true box divided by the concatenation of the two boxes, and then  $p$  is the score, i.e., probability.

## 3. EXPERIMENTS AND THE RESULTS OF THE EXPERIMENTS

### 3.1. Experimental Setting

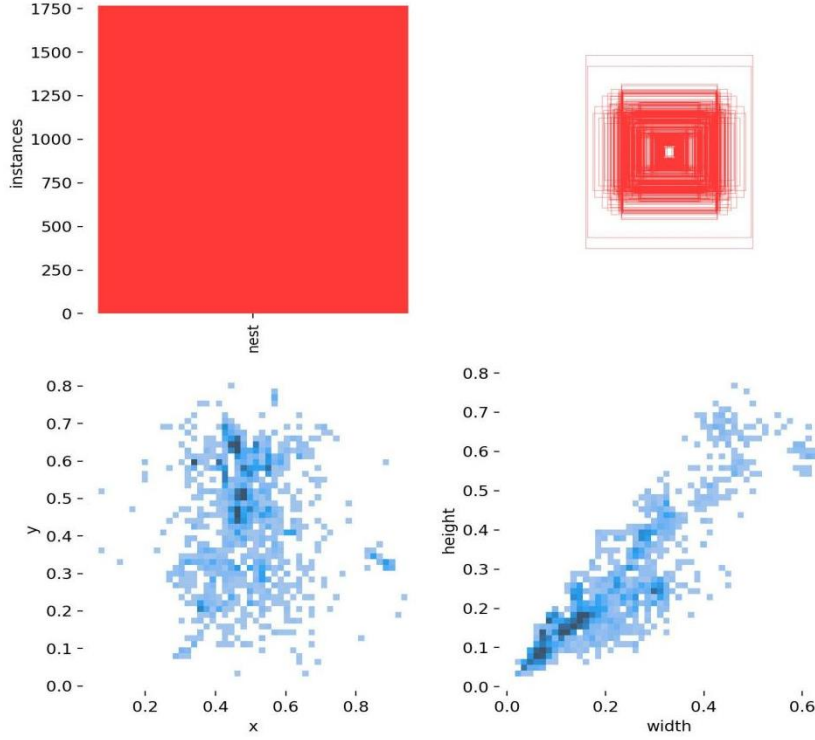
The experimental setup of this paper is as shown in the following Table 1.

**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 is a dataset consisting of taken photos and images of transmission line insulators searched on the Internet, take to rotate the dataset, alignment, and a total of 2297 contained, then we divided the image dataset, in which the training set contains 2067 images and the validation set contains 230 images. And the bird's nests in the dataset were labeled in YOLO format using the labeling software LabelImg. For each image, a txt file with the same name was created, and each line in the txt file represents a label instance, and each label includes the category label, the x-coordinate of the center point, the y-coordinate of the center point, and the width and height of the bounding box from left to right. The dataset labeling diagram is shown in Figure 5.



**Figure 5.** Dataset Labeling Chart

### 3.3. Evaluation Indicators

The evaluation metrics for the YOLOv8-based transmission line bird nest detection method study include Precision, Recall, mAP50, and mAP50-95. These metrics together give the overall performance of YOLOv8 on the target detection task.

The correct detection of a bird's nest is recorded as TP (True (True Negatives)); the wrong judgment of the target to be detected as a bird's nest is recorded as FP (False Positives); and the wrong judgment of the target as not being a bird. Detection accuracy is expressed as Precision and Recall using Precision and Recall. Precision and Recall formulas are shown in (6) (7). 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.

$$\text{Precision} = \frac{TP}{(TP + FP)} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (7)$$

Where mAP50-95 is the average accuracy over a range of different IoU thresholds. A typical way to calculate mAP50-95 is to calculate the average accuracy over a range of IoU thresholds from 50% to 95%. This process involves using different IoU thresholds to calculate the APs for each category and then averaging them as mAP50-95, for the calculation of APs  $P_i$  denotes the accuracy at the  $i$ th recall, and  $\Delta R_i$  denotes the difference between the  $i$ th and  $i+1$ th recall, with the formulas shown in (8) (9).

$$AP = \sum(P_i * \Delta R_i) \quad (8)$$

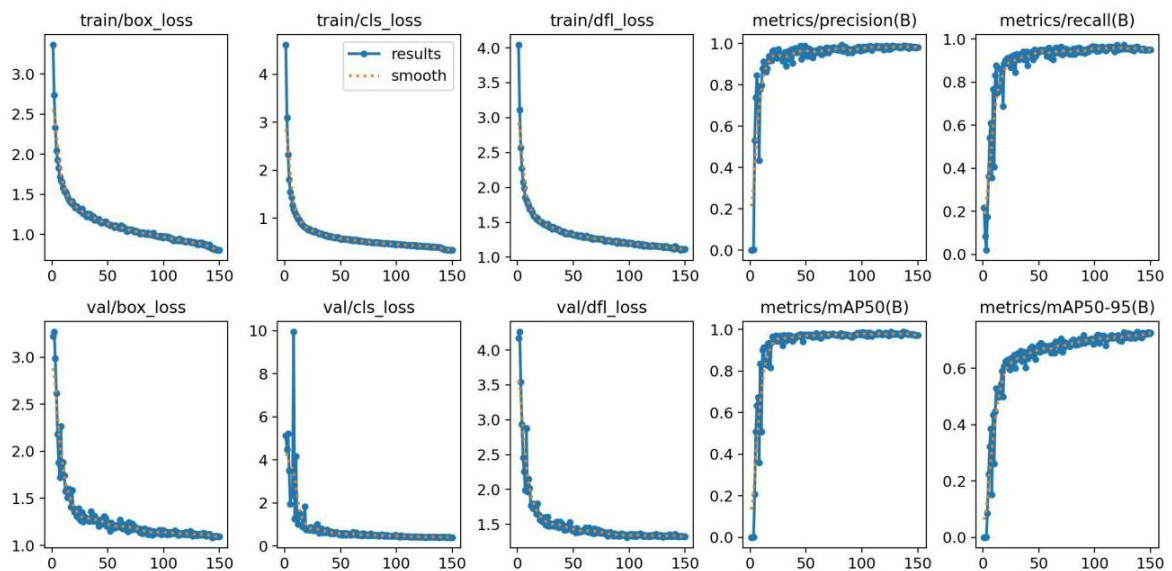
$$mAP = \sum \frac{(AP_i)}{N} \quad (9)$$

### 3.4. Experimental Results

We tested with YOLOv8 on the dataset and recorded Precision, Recall, mAP50, and mAP50-95 metrics as shown in Table 2 and 6, 7.

**Table 2.** Experimental Results Data

Class	Images	Box (precision)	Recall	mAP50	mAP50-95
Nest	230	0.991	0.965	0.986	0.728



**Figure 6.** Result curve



**Figure 7.** Test Result Chart

## 4. SUMMARY

In this paper, a research method for detecting bird nests on transmission lines based on YOLOv8 is proposed. The YOLOv8 model performs well in detecting bird nests. A high average precision and recall are demonstrated, which means that the model is able to accurately localize and identify most of the targets in the image. In terms of real-time performance, the model is able to run at 25 frames per second, The experimental results show that the YOLOv8 model performs well in terms of accuracy, speed, and model size, and is a powerful tool for performing complex target detection tasks that can be used in real-world scenarios.

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