

Insulation Detection Algorithm for Gloves Based on Improved YOLOv8n

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ABSTRACT

With the rapid development of China's industry, the safety problems in the process of electrical operation are highly concerned by the electrical industry. In order to reduce the incidence of electrical safety accidents, it is very necessary to wear insulating gloves for electric power construction, which is also of great significance to ensure the safety of electric power production. However, the small target of insulating gloves and the complexity of the electrician operation site, which undoubtedly increases the difficulty of identifying the algorithm model of insulating gloves. For this problem, insulation glove target detection algorithm based on YOLOv8n improvement model. Through many experiments, YOLOv8n was selected as the basic framework of the insulating glove detection algorithm. In order to make the model more accurately locate and identify the targets of interest, the efficient coordinate attention mechanism Coordinate Attention was inserted into backbone to improve the accuracy of the model. The introduction of PConv in neckbricks reduces redundant computation and memory access for a more efficient extraction of spatial features. After the improved YOLOv8n algorithm, the mAP is increased from the initial 96.4% to 98.6%, which provides a good reference value for the subsequent research of the target detection algorithm of insulating gloves.

KEYWORDS

YOLOv8; Coordinate Attention; PConv; mAP; Insulating gloves

1. INTRODUCTION

As the sustained and rapid development of national economy and the people's living standard, power users more and more big, electricity demand for power supply quality requirement is becoming higher and higher, at the same time some of the power sector in the process of large-scale development of power grid construction, lack of power production personnel to wear protective tools and safety supervision, lead to construction personnel have certain safety hidden trouble. At present, some power companies at home and abroad make intelligent detection of whether the power operators wear protective tools, mainly placing the monitoring device in the power production site, and observing whether the operators are wearing protective tools in accordance with the regulations through monitoring. However, due to the complexity of the construction site, the signal of the monitoring device is weak, and the picture transmitted back is not smooth and clear. Similarly, the existence of the monitoring personnel also increases the labor cost virtually. Therefore, it is crucial to implement efficient and accurate detection methods that do not consume excessive human resources.

The YOLO series is widely favored in industrial applications because of its excellent speed and precision balance. The foundation work of this series, YOLOv1 to YOLOv3 [1-3], has innovatively proposed the concept of single-stage detector, and has experienced significant optimization and development. YOLOv4 further innovates by deconstructing the detection architecture into independent components such as backbone, neck, and head, aiming to create a framework that is more

suitable for single GPU training environments. Today, YOLOv7 [4] and the latest YOLOv8[5] are strong candidates for efficient detection models, demonstrating their continued competitiveness and vitality.

Caixia T et al. [6] proposed a research on the wearing state detection of insulated gloves based on an improved YOLOv8s algorithm. Kang R et al. [7] designed a detection method for the wearing status of insulated gloves by substation personnel based on Faster -Yolov8.

However, due to the small target of insulation gloves and the complex and diverse construction scenarios that require algorithm detection, it is necessary to design efficient and accurate insulation gloves detection algorithms with rich application scenarios. According to the above problems, this paper will improve the YOLOv8 algorithm model to make the improved algorithm detection more efficient.

2. METHODOLOGY

2.1. YOLOv8 Algorithm

YOLOv8 Is a new version of the YOLO target detection and image segmentation model. As an advanced (SOTA) model, YOLOv8 introduces new features and improvements to the success of the previous version, to enhance performance, flexibility and efficiency. According to the network width and network depth, it is divided into different versions of YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l and YOLOv8x. The model structure mainly includes: (1) Input (2) Backbone (3) Neck (4) Head.

Input: uses Mosaic data enhancement to synthesize multiple pictures in a certain proportion, so that the model can identify targets in a smaller range, increases the robustness of the model, and improves the performance of small target detection.

Backbone: Referring to the CSPDarkNet structure, C2f is used to replace the C3 module, and the calculation amount is significantly reduced, so that YOLOv8 can obtain richer gradient flow information while ensuring lightweight. The SPPF module introduces a feature pyramid structure, which can extract features at different scales and fuse them to effectively handle objects of different sizes, which can improve the ability of the model to detect small targets.

Neck: PAN-FPN structure is adopted to realize the feature fusion of multiple feature maps with different sizes, which improves the receptive field of the model, and C2f module is also used as the main module of feature extraction in the structure.

Head: First, the Head separates the classification and detection head to alleviate the conflict between the classification and positioning tasks; second, the Anchor-Based is replaced with Anchor-Free, which transforms the feature map into the prediction result of the target box, and can accurately predict the position, category and bounding box information of the target in the image.

2.2. Coordinate Attention Module

The popular SE attention mechanism in mobile networks that employs 2D global pooling to compute channel attention and provides significant performance gains at a fairly low computational cost. However, the SE attention mechanism only considers the encoding of information between channels, and ignores the importance of location information. In this paper, a novel and effective Coordinate Attention [8] mechanism is introduced. By embedding the position information into the channel attention, the mobile network can pay attention to in a large range, so that it can not only capture the information across channels, but also capture the information of direction perception and position perception, while avoiding a lot of computational overhead.

The Coordinate Attention module is used to encode precise location information into neural networks to model channel relationships and long-term dependencies. It consists of information embedding and attention generation. Coordinate Attention module first input features graph into width and height of two directions for the global average pooling, respectively in the width and height of the feature map, then will get the global feeling field width and height of the two directions of the feature graph, then send them into the Shared convolution kernel is $1 * 1$ convolution module , using the ReLU function to channel non-linear characteristics. The feature map is then decomposed into two separate components, horizontal and vertical, along the spatial dimension, increasing the feature dimension using the $1 * 1$ convolution transformation and nonlinear activation using the Sigmoid function. Finally, the two attention channels are multiplied by the original feature graph to realize the attention generation operation.

2.3. PConv Moudle

In order to design fast neural networks, much work focuses on reducing the number of floating point operations (FLOPs), this paper proposes a new partial convolution (Pconv [9]), which can extract spatial features more effectively by simultaneously reducing redundant computing and memory access. PConv only needs to apply regular Conv on a part of the input channels for spatial feature extraction and keep the rest of the channels unchanged. For continuous or regular memory access, the first or last continuous channel is counted as a representative of the entire feature graph. The input and output feature maps are considered to have the same number of channel without loss of generality. Therefore, we will introduce PConv in this paper to more effectively extract spatial features while reducing redundant computation and memory access.

3. EXPERIMENT DESIGN AND RESULT ANALYSIS

3.1. Dataset

Part of the experiment data set from baidu search public "insulation gloves" pictures, part from bilibli video sites, in the video website search "insulation gloves" keywords, and take out the image clear video images, to intercept the picture format conversion, through the image of rotation, translation, zoom expansion to 600 pictures, as the data set of the experiment. Then, 600 pictures were randomly divided into 480 training set pictures and 120 validation set pictures according to the ratio of 8:2. Then, the insulating gloves in the pictures were marked by the labeling annotation tool, with the name "insulating gloves".

3.2. Experimental Setup

Rent the remote server on Autodl and configure the running environment, connect the server on Autodl with the local pycharm, and transfer the local relevant files and code to the remote server. The GPU of the server is A800-80GB (80GB) * 1, PyTorch: 2.0, CUDA version: 11.8. Run after 200 rounds to generate mAP and other data, and the performance of the improved model is judged by data comparison.

3.3. Evaluating Indicator

The index used to evaluate the improvement of the algorithm is the mean mAP expression, as shown in (1):

$$mAP = \sum_{i=1}^{N-1} \frac{AP_i}{N} \quad (1)$$

Where N represents the total number of categories, and mAP refers generally to the mean of the average accuracy (AP) of all categories within all images.

3.4. Comparative Analysis of YOLOv8 Model Experiments

YOLOv8 The pair of time, P, R, and mAP results of the insulated glove data set of each network model are shown in the Table1:

Table 1. YOLOv8 Comparison table of the results of each network model

network model	time/h	P	R	mAP
YOLOv8n	0.105	0.947	0.944	0.964
YOLOv8s	0.134	0.962	0.926	0.969
YOLOv8m	0.22	0.952	0.942	0.971
YOLOv8l	0.301	0.977	0.921	0.979
YOLOv8x	0.414	0.972	0.932	0.979

As shown in Table 1, the training time of the three YOLOv8, YOLOv8m, YOLOv8l and YOLOv8x, is 0.22h,0.301h,0.414h, respectively YOLOv8n and YOLOv8s. Among the various network models of YOLOv8, the YOLOv8n network model has the shortest training time, followed by YOLOv8s. The mAP of YOLOv8n was 0.964, which was only 0.05% lower than the mAP of YOLOv8s, but the detection speed was faster by 0.029h. Comprehensive comparative analysis shows that the detection speed of YOLOv8n in different models of YOLOv8 has obvious advantages, and the detected mAP is very narrow compared with other models. Therefore, YOLOv8n will be chosen as the basic framework for identifying the insulating glove detection algorithm in this paper.

3.5. Results Analysis

YOLOv8n As the basic framework for identifying the detection algorithm of insulating gloves, CoordAtt attention module is inserted into Backbone, PConv is introduced in neck, and the improved algorithm model detection efficiency is improved. Table 2 shows the performance comparison of the original YOLOv8n algorithm model and the improved YOLOv8n algorithm model. Figure 1 shows the structure diagram of the improved YOLOv8n algorithm after the addition of the Coordinate Attention module and PConv.

Table 2. Comparison table of the model performance before and after the improvement

model	R	P	mAP
the original YOLOv8n model	0.944	0.947	0.964
the improved YOLOv8n model	0.942	0.968	0.986

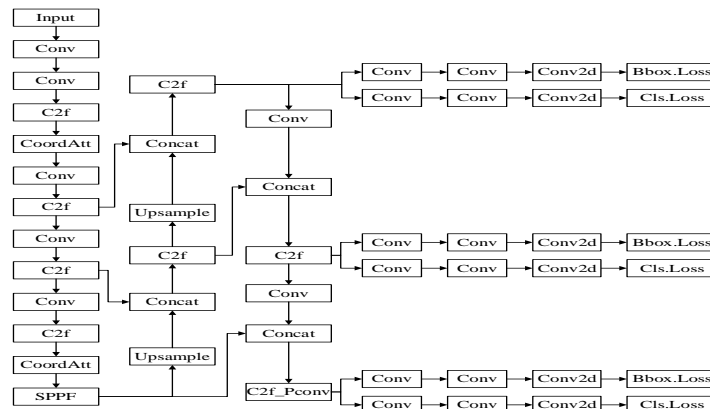


Figure 1. Structure diagram of the improved YOLOv8n algorithm

4. CONCLUSION

In view of the complex and diverse construction scenarios with small target and algorithm detection, YOLOv8n was selected as the basic framework of the YOLOv8 algorithm model through many experiments. On the basis, the attention mechanism CoordAtt module was added, and some convolution PConv was introduced. After the improved YOLOv8n algorithm, mAP increased from the initial 96.4% to 98.6%, and the model identification efficiency was significantly improved, which provided a good reference value for the subsequent research on the target detection algorithm of insulating gloves.

REFERENCES

- [1] Redmon J, Divvala K S, Girshick B R, et al. You Only Look Once: Unified, Real-Time Object Detection [J]. CoRR, 2015, abs/1506.02640.
- [2] Redmon J, Farhadi A. YOLO9000: Better, Faster, Stronger [C]// IEEE Conference on Computer Vision & Pattern Recognition. IEEE, 2017:6517-6525.
- [3] Redmon J, Farhadi A. YOLOv3: An Incremental Improvement [J]. arXiv e-prints, 2018.
- [4] Wang C Y, Bochkovskiy A, Liao H Y M .YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors [C]//arXiv.arXiv, 2022.
- [5] Yan L, Yue M, Ying L. Protocol for assessing neighborhood physical disorder using the YOLOv8 deep learning model [J]. STAR Protocols, 2024, 5 (1):102778.
- [6] Caixia T, Chaoting W, Taiguo L. Detection research of insulating gloves wearing status based on improved YOLOv8s algorithm [J]. Journal of Engineering and Applied Science, 2024, 71(1):
- [7] KangR, HuangX, HuangJ, et al. Insulating Glove Wearing State Detection for Substation Personnel Based on Faster-YOLOv8 [J]. IEEJ Transactions on Electrical and Electronic Engineering, 2024, 19(8):1369-1376.
- [8] Khalid M, Deivasigamani S, V S, et al. An efficient colorectal cancer detection network using atrous convolution with coordinate attention transformer and histopathological images [J]. Scientific reports, 2024, 14(1):19109.
- [9] Zhigang L, Baoshan S, Kaiyu B. Optimization of YOLOv7 Based on PConv, SE Attention and Wise-IoU [J]. International Journal of Computational Intelligence and Applications, 2024, 23(01):