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New Energy Vehicle Tire Defect Detection Algorithm Based on Improved YOLOv8

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ABSTRACT

Aiming at the traditional tire defect detection is difficult to meet the practical application requirements, a defect detection algorithm based on YOLOv8 is constructed. Firstly, the GAM attention mechanism is added to the backbone to improve the feature expression of tire defects and improve the detection efficiency. Secondly, the SPPF is replaced by SimSPPF to effectively capture multi-scale features. Finally, the CIoU loss function is replaced by Wise-IoU to improve the convergence ability of the model. The experimental results show that the constructed improved models P, mAP0.5 and mAP0.5:0.95 reach 86.4%, 88.2% and 46.9%, respectively, which are improved by 2.7%, 2.3% and 0.9% compared with the original YOLOv8n model. The algorithm can better improve the problems faced by traditional new energy vehicle tire defect detection.

KEYWORDS

Tire defect detection; YOLOv8; GAM Attention; SimSPPF; Wise-IoU

1. INTRODUCTION

As an important part of new energy vehicles, the safety performance of tires is an important research direction for automobile factories.

The traditional method of tire defect detection mainly relies on manual inspection, which has problems such as low efficiency, high cost, and strong subjectivity, and is difficult to meet the needs of practical applications. With the development of target detection in the field of deep learning, new energy vehicle tire defects can be better identified through machine detection of new energy vehicle tire X-ray images. For tire defect detection, Zeju Wu et al [1]. constructed a novel pyramid BE-FPN, designed a lightweight sensory field amplification module, and also introduced Meta-ACON, which effectively improves the detection performance of the network. Tang et al [2]. proposed DAGAN, which employs self-encoders for both generator and discriminator to improve the training stability of the model. Mei et al [3]. constructed a Gaussian pyramid-based CDAE architecture to realize the reconstruction of images with different resolutions. Penghui Wang et al [4]. improved the accuracy and speed of detecting tire tread based on the YOLOv5 network model. However, the texture of the tire crown region is complex and most of the defective samples are unbalanced in quality, this paper constructs an improved algorithm based on YOLOv8 to solve the above problems.

2. IMPROVED YOLOV8 DETECTION ALGORITHM

In this paper, for the new energy vehicle tire X-ray image defect problem, firstly, the GAM attention mechanism is added to the backbone; secondly, the SPPF is replaced with SimSPPF; finally, the loss function CIOU is replaced with Wise-IoU. the improved structure is shown in Fig. 1.

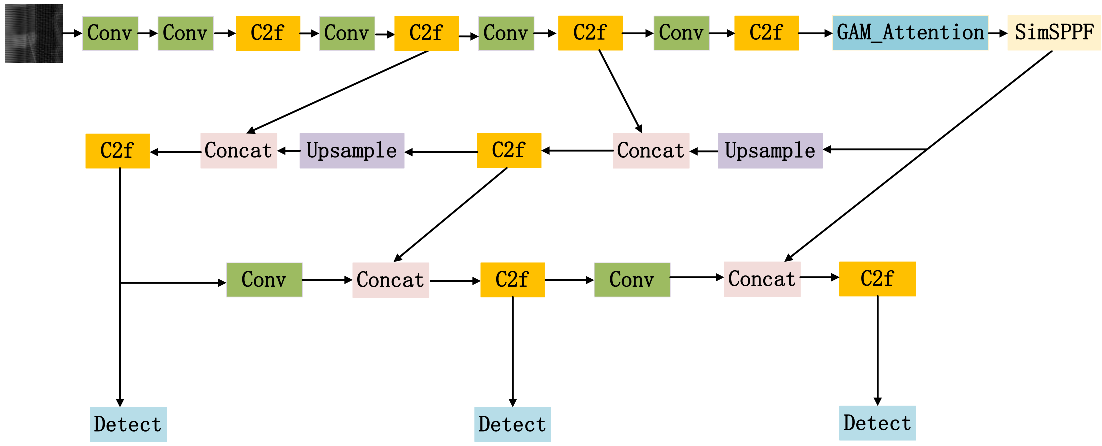

Figure 1. Improved YOLOv8 algorithm network structure diagram

2.1. GAM Attention Mechanism

Tire defects are complex in type and uneven in quality, thus causing great difficulty in detection. In this paper, we introduce a global attention mechanism, GAM [5], to enhance the feature representation of tire defects and improve the detection efficiency. The GAM attention mechanism improves the performance of deep neural networks by amplifying the global interaction representation while reducing the information approximation, and adopts a framework that combines channel attention and spatial attention. The structure is shown in Fig. 2. For channel attention, GAM uses a three-dimensional arrangement to retain information in three dimensions and amplifies cross-dimensional channel-space dependencies through a multilayer perceptron. For spatial attention, GAM uses convolutional layers for spatial information fusion to attend to spatial information. The GAM process is represented by equations (1)(2):

$$F_2 = Mc\mathrm{F}_1 \otimes F_1 \tag{1}$$

$$F_3 = Ms\mathrm{F}_2 \otimes F_2 \tag{2}$$

F1 is the input feature, F2 is the feature after channel attention, F3 is the output feature, Mc and Ms are the channel and spatial attention modules, respectively, and $\otimes$ is the element multiplication operation.

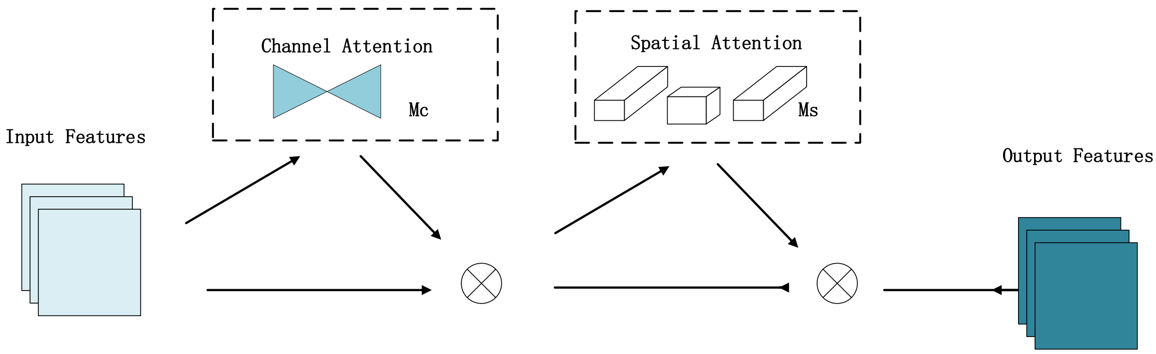

Figure 2. GAM Attention Mechanism Module

2.2. SimSPPF

SimSPPF is a key component introduced in the YOLOv6 architecture to optimize the efficiency of the original SPPF module [6]. The structure is shown in Figure 3. SimSPPF significantly reduces computation and memory consumption by simplifying the original SPPF structure with a fixed-size pooling kernel (typically 5x5), allowing the model to run faster in the inference phase. At the same time, despite using smaller pooling kernels, SimSPPF is still able to efficiently capture multi-scale features because its design allows for the integration of different layers of information in the network, which is important for object detection tasks.

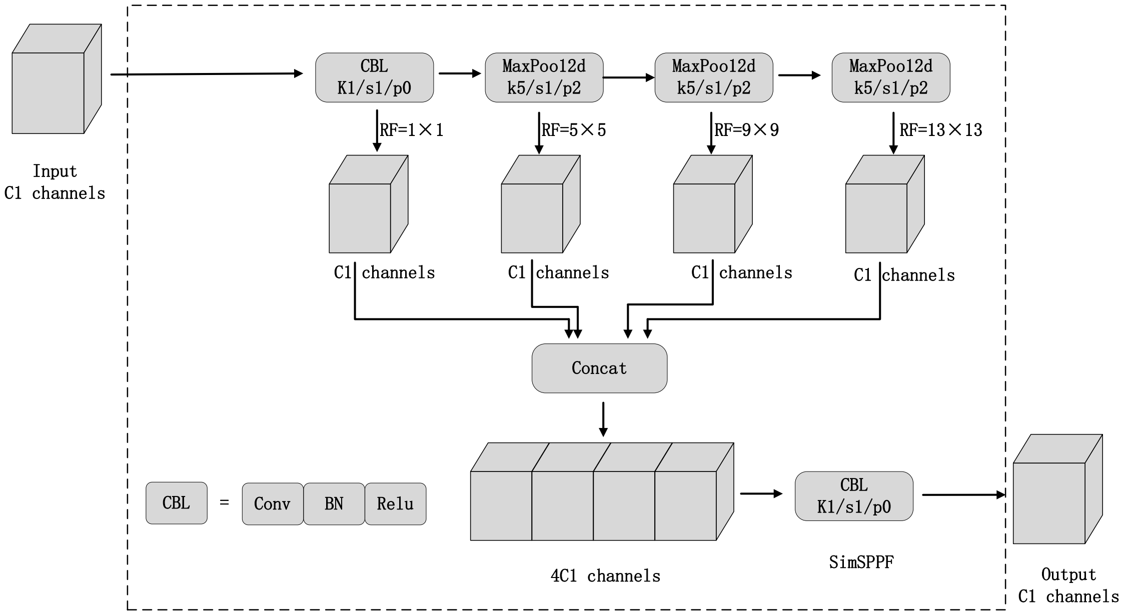

Figure 3. SimSPPF structure

2.3. Wise-IoU

The YOLOv8 model uses CIoU, but CIoU does not take into account the problem of defect sample quality balance, and the defects of the same category of new energy vehicle tires differ greatly, which may lead to slower model convergence and lower prediction accuracy.

To address the problem of unbalanced quality of defect samples in X-ray images of new energy vehicle tires, this paper replaces the CIoU loss function with the Wise-IoU [7] loss function, which enhances the convergence ability of the model to achieve a better bounding-box prediction regression.The Wise-IoU loss function introduces a dynamic non-monotonous focusing factor when calculating the IoU between predicted and real frames, which is dynamically adjusted according to the the quality of the training samples dynamically, as a way to improve the learning effect of the model during the training process. This dynamic non-monotonic focusing mechanism makes the Wise-IoU loss function more flexible and effective in dealing with training samples of different quality.

Wise-IoU losses are defined as:

$$L_{WIoU} = 1 - \frac{\sum_{i=1}^{n} w_i IoU(b_i, g_i)}{\sum_{i=1}^{n} w_i} \tag{3}$$

Where n is the number of object frames; b_i is the coordinates of the ith object frame; gi is the coordinates of the real labeling frame of the ith object; w_i is the weight value; and IOU (b_i,g_i) is the IOU value between the ith object frame and the real labeling frame.

3. DATASET CONSTRUCTION AND EXPERIMENTAL ENVIRONMENT

3.1. Data Set Construction

This experimental dataset is from the open source dataset of the Networked Control Center of Shanghai University, from which 600 defective images are selected as the dataset for the experiments in this paper. Before training the model, the dataset is annotated using labelimg annotation tool to generate XML files. Subsequently, the XML files were transformed into TXT format files that can be recognized by YOLO. The dataset was randomly divided into training set and validation set according to the ratio of 7:3 with 420 and 180 sheets, respectively. The defect types were divided into three categories: open lines in the crown region, thinning of the cord in the sidewall region, and impurities, and an example of the specific categorized dataset is shown in Figure 3.

(a) (b) (c)

Figure 3. Example of classification of defects in tires for new energy vehicles

(a) open line in the crown area; (b) thinning of the cord in the sidewall area; (c) impurities

3.2. Experimental Environment and Configuration

This experiment is built using the Pytorch learning framework, the operating platform is Windows 11, and the experimental environment is shown in Table 1.

Table 1. Experimental environment

Name	Parameters
CPU	Intel (R) Xeon (R) Gold 6226R CPU @ 290GHz 289 GHz
RAM	128GB
GPU	Nvidia GeForce RTX 3080 10 GB (Dual GPU)
Hardware	Pycharm
Environment	Pytorch1.9.1, Anaconda python3.9

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1. Evaluation Indicators

In order to measure the network model's performance in detecting defects in X-ray images of new energy vehicle tires, P and mAP (IoU thresholds are taken as 0.5 and 0.5~0.95) are used as the evaluation indexes for the improvement effect of the algorithm in this paper. The formulas for these indicators are shown below:

$$P = \frac{N_{TP}}{N_{TP} + M_{FP}} \tag{4}$$

$$AP = \frac{TP + TN}{N} \tag{5}$$

$$mAP = \frac{\sum_{i=1}^{N} AP_i}{N} \tag{6}$$

Where N_{TP} denotes the number of positive samples correctly predicted by the model, M_{FP} denotes the number of positive samples where the model predicts actually negative samples, N is the total number of defects detected in new energy vehicle tires (N = TP + TN + FP + FN); and AP_i denotes the actual accuracy of the defects in the ith category.

4.2. Comparison Experiment

In order to further verify the model performance and reflect the generalization and robustness of the improved model, the improved model is compared with the original model of YOLOv8 in the comparison experiment, and the results are shown in Figure 2.

Table 2. Comparison experiment

Model	P (%)	$mAP_{0.5}$ (%)	$mAP_{0.5:0.95}$ (%)
YOLOv8n	83.7	85.9	46.0
Model of this paper	86.4	88.2	46.9

It can be seen that the improved models P, $mAP_{0.5}$ and $mAP_{0.5:0.95}$ constructed in this paper reach 86.4%, 88.2% and 46.9%, respectively, which are 2.7%, 2.3% and 0.9% compared to the original YOLOv8n model. A comparison of the detection results is shown in Figure 4.

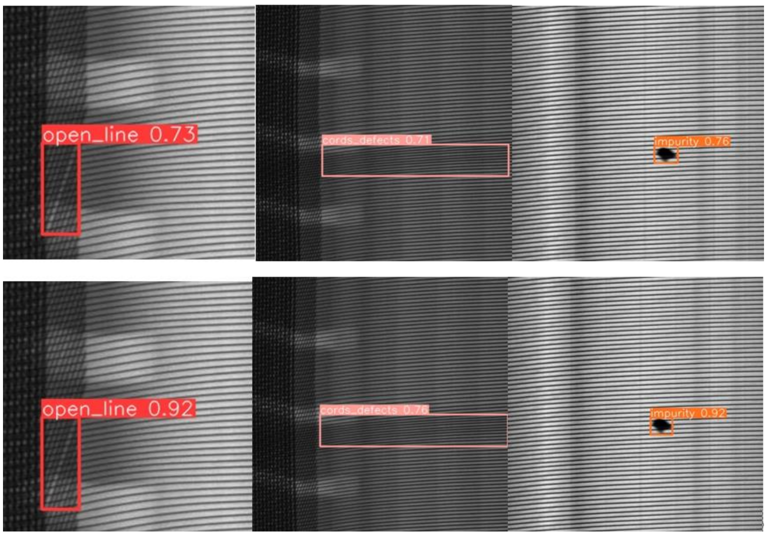

Figure 4. Comparison effect before and after model improvement

5. SUMMARY

In this paper, based on the original YOLOv8 network, firstly, the GAM attention mechanism is added to the backbone to improve the feature expression of tire defects and increase the detection efficiency;

secondly, the SPPF is replaced by SimSPPF to effectively capture the multi-scale features; and lastly, the CIoU loss function is replaced by Wise-IoU to improve the convergence ability of the model. The experimental results show that the constructed improved models P, $mAP_{0.5}$ and $mAP_{0.5:0.95}$ reach 86.4%, 88.2% and 46.9%, respectively, which are improved by 2.7%, 2.3% and 0.9%, respectively, compared with the original YOLOv8n model. The detection effect is improved, providing a certain reference value for defect detection.

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