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Resistance Spot Welding Defect Detection Based On Improved YOLOv8

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Abstract— **This paper proposes an improved YOLOv8 model named A-YOLOv8s, which aims to improve the efficiency and accuracy of resistance spot welding (RSW) defect detection. The model is improved on the basis of YOLOv8s in the following ways: the Adown module is used to replace the original downsampling convolution in the Backbone part to enhance the multi-scale feature extraction capability; the C2f-GhostDynamicConv module is introduced in the Backbone and Neck parts to improve the efficiency of feature fusion; and the EfficientHead is used in the Head part to optimize the detection head structure and reduce the amount of calculation. Experimental results show that A-YOLOv8s outperforms YOLOv8n and YOLOv8s in terms of mAP50, and achieves a good balance in terms of parameter quantity and GFLOPs, which shows that the model can effectively improve the detection performance while maintaining lightweight. The improved model of this study provides an efficient and automated solution for RSW defect detection, and has the potential to be widely used in industrial automated detection.**

Index Terms—**Resistance spot welding defect detection, YOLOv8, Deep Learning, target detection.**

I. INTRODUCTION

Resistance spot welding (RSW) is an economical and efficient joining technology widely used in the automotive manufacturing industry. It generates resistance heat between two metal workpieces and achieves local melting and joining of the workpieces by combining electrode pressure. This welding method has the advantages of high production efficiency, low energy consumption, and easy automation control, making it a key process in automobile body manufacturing [1]. However, resistance spot welding is affected by many process factors, including welding current, electrode pressure, welding time, electrode material, workpiece material properties, and plate alignment. Fluctuations in these factors may lead to inconsistent welding quality. Traditional quality inspection methods for resistance spot welding have some disadvantages, such as low efficiency and destructiveness of manual offline inspection, high dependence on coupling agent and high operator skill requirements for ultrasonic inspection, and easy environmental interference and difficulty in determining defect type and location. In contrast, deep learning-based resistance spot welding inspection technology provides an efficient and automated solution that can significantly improve inspection accuracy and reduce labor costs. It also has good adaptability and scalability, and can realize real-time online inspection of welding quality, thereby improving production efficiency and product quality.

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II. RELATED WORKS

In this section, we discuss some quality inspection techniques for resistance spot welding.

A. Manual offline inspection

At present, most companies still use manual offline inspection for RSW, such as full destructive inspection or manual sampling inspection. These will lead to low inspection efficiency, high inspection cost, and cannot guarantee the inspection of each weld. In addition, the traditional sampling inspection process is easily affected by randomness and cannot fully guarantee the welding quality. Therefore, it is extremely important to dynamically ensure the quality of RSW, and it is urgent to study more effective and convenient methods to achieve the upper limit of inspection [2, 3].

B. Ultrasonic testing

Ultrasonic testing is the most commonly used nondestructive spot welding inspection method in the automotive industry. Athi et al. [4] proposed a real-time ultrasonic nondestructive testing system to monitor the quality of RSW by installing transducers on the upper and lower electrode arms of the welding gun. Liu et al. [5] used ultrasonic signals to inspect four types of stainless steel RSW specimens and analyzed the characteristic signals of 14 different types of spot welds in the time and frequency domains. The tensile strength and fatigue life of the spot welded joints of three-layer thin plates were studied.

C. Thermal imaging

Thermal imaging is another method that provides fast, non-contact, and reliable spot weld testing. Due to the rapid development of infrared imaging technology, infrared imaging technology has been widely used in non-destructive testing. Chen et al. [6] developed a non-destructive testing system based on an infrared camera to detect the quality of spot welds on the underbody of an automobile. The system can be used as both a real-time detection system and a post-weld detection system with an induction heating device. The results show that the measurement accuracy of the spot size and thickness is good. Lee et al. [7] used three different techniques such as optical infrared thermal imaging, ultrasonic infrared thermal imaging, and lock-in method to obtain information to evaluate the reliability of the weld. Schlichting et al. [8] used flash thermal imaging technology for spot weld inspection and studied the main feasibility of thermal imaging technology for galvanized samples.

D. Deep Learning

In recent years, RSW defect detection based on deep learning has attracted attention. Dai et al. [9] improved YOLOV3 and established a lightweight deep convolutional neural network for online defect detection of RSW. Xiao et al. [10] proposed a fine coordinate attention (FCA) module that can be embedded in any CNN model to improve performance with only an increase in computation. The RSW-d dataset was also made public.

III. Method

A. YOLOv8

YOLOv8[11] is widely used in the industry, especially in defect detection on automated production lines, cargo identification and classification in warehouse management, and visual navigation of industrial robots. The network structure of YOLOv8 is divided into three parts: Backbone network, Neck network, and Detect Head. Backbone is used to extract features, Neck further fuses the extracted features, and Head makes the final prediction based on the features of different scales after Neck fusion. YOLOv8's Backbone adopts the CSPDarnet-53 structure, which consists of a series of Conv blocks and C2f modules. The Conv block consists of standard convolution, Batch Normalization, and SiLU activation functions, which are used to extract image features. The C2f module consists of two Conv blocks and several Bottleneck structures, including jump-join and split operations to reduce memory and computational costs. C2f combines high-level features with contextual information to improve detection accuracy. At the top layer of Backbone, YOLOv8 uses the SPPF structure to map features of different scales to fixed-size feature maps for pooling to speed up the network's calculation speed. Neck mainly includes some C2f modules and Conv blocks. It fuses feature information between different feature layers through upsampling and connection operations and outputs them to the Detect Head for result prediction. Neck outputs three feature maps of different sizes to the Detect Head, which are used to predict large, medium, and small targets respectively. Figure 1 shows the architecture of YOLOv8.

YOLOv8 provides five models of different sizes - Nano (YOLOv8n), Small (YOLOv8s), Medium (YOLOv8m), Large (YOLOv8l) and Extra Large (YOLOv8x) to adapt to different application scenarios from resource-constrained environments to those requiring high-precision detection.

B. A-YOLOv8

In order to strike a balance between accuracy and speed, this study selected YOLOv8n as the benchmark model and proposed a new algorithm model A-YOLOv8, aiming to improve the efficiency and accuracy of resistance spot welding (RSW) defect detection while maintaining the lightweight and fast reasoning ability of the model. In order to strike a balance between accuracy and speed, this study selected YOLOv8n as the benchmark model and proposed a new algorithm model A-YOLOv8, aiming to improve the efficiency and accuracy of resistance spot welding (RSW)

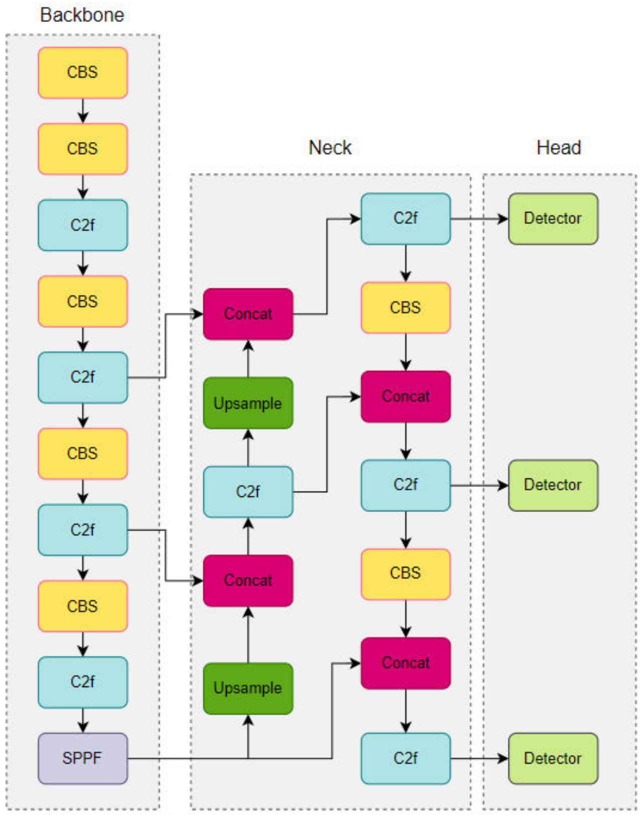

Fig. 1. YOLOv8 network structure

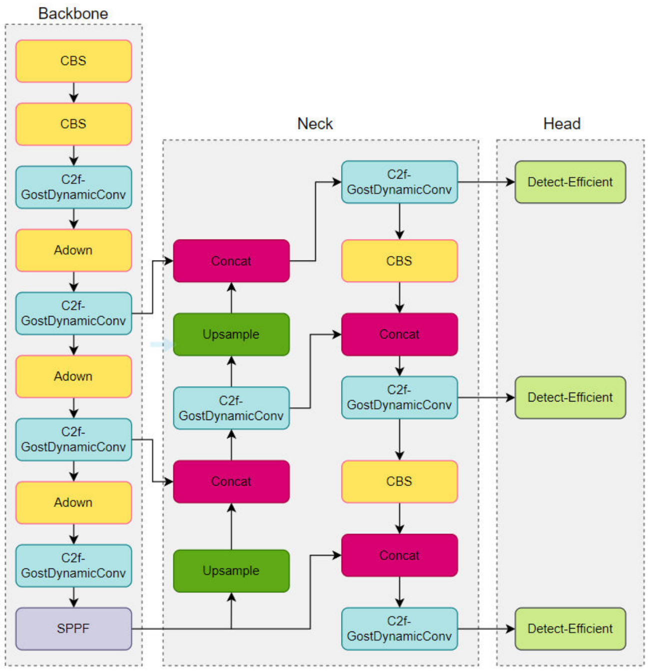

Fig. 2. A-YOLOv8 network structure

defect detection while maintaining the lightweight and fast reasoning ability of the model. Its network architecture is shown in Figure 2. In the backbone part, Adown is used to replace the original downsampling convolution, in the backbone and neck parts, C2f-GhostDynamicConv modules are used to replace the original C2f modules, and in the head part, EfficientHead is used to replace the original detection head.

1) Adown

The Adown[12] module downsamples the input feature map through average pooling and maximum pooling, and adjusts the number of channels through convolution operations. This module can extract multi-scale feature information to enhance the performance of the model. It can be embedded in a more complex network structure as part of downsampling and feature fusion. Figure 3 shows the structure of the ADown module.

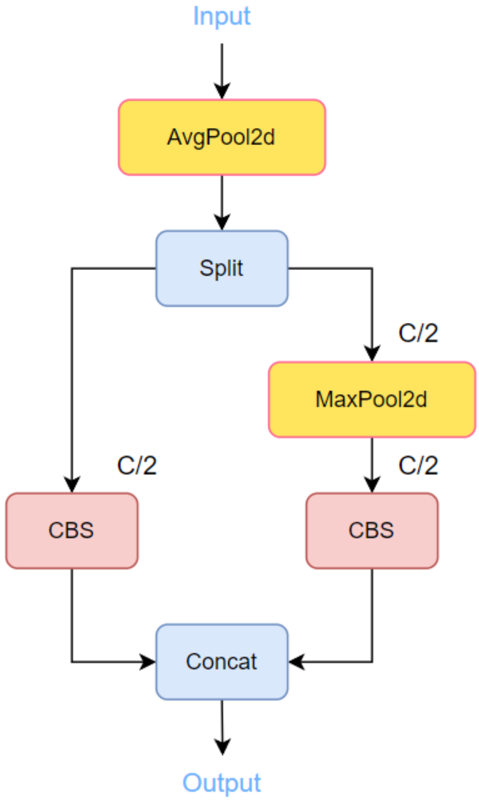

Fig. 3. Adown module

2) GhostModule

Dynamic convolution is an innovative convolution technique that significantly increases the number of model parameters with almost no increase in computational cost (FLOPs) by introducing dynamically generated coefficients and multiple convolution weight tensors (dynamic experts). This design allows the model to dynamically adjust its behavior based on the characteristics of the input samples, thereby improving its flexibility and adaptability. The implementation of dynamic convolution involves a coefficient generation module, dynamic weight fusion, and a convolution process, which work together to generate an output feature map. In ParameterNet[13], dynamic convolution is used to build models with more parameters but similar FLOPs, allowing low-FLOPs networks to benefit from large-scale visual pre-training and overcome the low-FLOPs trap. Experimental results show that dynamic convolution can significantly improve the accuracy and performance of the model while maintaining low computational cost.

3) EfficientHead

Detect_Efficient improves the efficiency and accuracy of target detection by integrating multiple convolution structures and dynamic convolution techniques. The module contains the stem part for feature processing, the cv2 convolution layer for predicting bounding boxes, and the cv3 convolution layer for predicting class probabilities. In addition, it also uses the DFL (Deformable Feature Learning) layer to enhance feature representation, thereby improving the accuracy of bounding box prediction. The design of the Detect_Efficient module takes computational efficiency into consideration, and optimizes model performance through grouped convolution and dynamically adjusting anchor points, making it suitable for deployment in resource-constrained environments.

IV. EXPERIMENT

A. Dataset

The dataset used in this experiment is RWS-D, which was created by Xiao et al. based on the images of body-in-white welds. It contains a total of 7 types of defects. Each image contains multiple welds. There are 4134 images in RSW-D, which are divided into training set and test set in a ratio of 9:1.

B. Experimental Environment Configuration

In this paper, model improvement and code experiments are carried out on the local computer, and model training and verification are carried out on the remote server. The software and hardware configuration parameters are shown in Table 1.

Table 1
Detailed configuration information

Environment Configuration	Configuration Information
Operating System	Windows10
GPUs	RTX 4090
Random Access Memory	24G
Toolkits	Anaconda
Development Language	Python3.7
Development Framework	Pytorch

C. Evaluation Indicators

In this experiment, we used mean average precision (mAP), parameter count (Params), and floating point operations per second (FLOPs) as evaluation indicators to comprehensively evaluate the performance of the target detection model. Among them, mAP50 is the most commonly used evaluation indicator in the field of target detection. The higher its value, the better the detection performance of the model. The parameter count reflects the complexity of the model, while FLOPs measures the computational efficiency of the model.

D. Comparison of Experimental Models

In order to verify the effectiveness of the model improvement, based on YOLOv8s, this paper uses Adown to replace the original downsampling convolution in the backbone part, uses C2f-GhostDynamicConv modules to replace the original C2f modules in the backbone and neck parts, and uses EfficientHead to replace the original detection head in the head part. The improved model is named A-YOLOv8s and compared with YOLOv8n and YOLOv8s. Through experimental comparison, it is found that A-YOLOv8s performs better than YOLOv8n and YOLOv8s in mAP50, and the number of parameters and GFLOP are lower than the baseline model YOLOv8s, and slightly higher than YOLOv8n. This shows that our model A-YOLOv8s has achieved better performance while being lightweight, which not only improves the detection accuracy, but also effectively controls the number of parameters and computational complexity of the model, so that it can run efficiently on resource-constrained devices. This is of great significance for application scenarios that require the deployment of efficient target detection models on resource-constrained devices. The specific comparison is shown in Table 2.

Table 2
Results of evaluation indicators for each model

Model	mAP50(%)	Params(M)	FLOPs(G)
YOLOv8n	96.0	3.2	8.7
YOLOv8s	97.5	11.2	28.6
A-YOLOv8s	97.9	4.4	9.7

V. Conclusion

Aiming at the limitations of traditional methods in resistance spot welding (RSW) defect detection, this paper proposes an A-YOLOv8s model based on improved YOLOv8. By introducing the Adown module in the Backbone part to replace the original downsampling convolution, the multi-scale capability of feature extraction is effectively improved; the C2f-GhostDynamicConv module is used in the Backbone and Neck parts to enhance the efficiency and accuracy of feature fusion; and in the Head part, the use of EfficientHead further optimizes the detection head structure and reduces the amount of calculation and the number of parameters. These improvements enable A-YOLOv8s to significantly improve the detection accuracy while keeping the model lightweight. The A-YOLOv8s model provides an efficient and accurate solution for resistance spot welding defect detection and is expected to be widely used in industrial automation detection.

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