International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 14, Issue 9 [September 2025] PP: 36-46

Surface Defect Detection on Castings Based on YOLOv5s Algorithm

Chunshan He, Xiaoying Ma, Shixin Dou, , Jingqi Hu
Shool of Mechanical and Vehicle Engineering, Changchun University, Changchun, CHINA
Corresponding Author: Jingqi Hu .

ABSTRACT: *Aiming at the problem of low detection accuracy in the casting surface defect detection method, the improved casting surface defect detection algorithm based on YOLOv5s is proposed. To enhance the casting surface defect dataset, To improve the generalization ability of the model training; Introduction increase (Convolutional Block Attention Module, Fusion module of CBM) replaces the C3 module in the original YOLOv5s, Introduced channel attention and spatial attention to improve the perceptual ability of the model, Enhance the ability of the model to extract features; Replace the Path Aggregation Network (PANet) module in the neck network with the Bidirectional Feature Pyramid Network (BiFPN) network, Introducing a bottom-up and top-down multi-scale feature fusion, Better fusion of shallow feature information; Ininserted behind the Conv layer of the Neck Network (Neck) (Coordinate Attention, CA), To accurately locate and identify the target regions. The experimental results show that the detection effect of the improved model on the surface defect detection data set of the casting is 1.3% higher than the average accuracy value (mAP), and the accuracy (P) is 1.8% higher.*
Keywords: *Deep learning; YOLOv5s; Attention mechanism; Defect detection*

Date of Submission: 25-08-2025 Date of acceptance: 04-09-2025

I. INTRODUCTION

In the casting process, due to the limitations of the manufacturing process, casting defects such as porosity, cracks, shrinkage holes, etc. are inevitably generated. It not only affects the quality of mechanical parts, but also reduces the working performance of machinery, which may cause serious accidents and economic losses[1][2]. Therefore, the detection of the quality of surface defects in castings is of great significance.In the casting process, due to the limitations of the manufacturing process, casting defects such as porosity, cracks, shrinkage holes, etc. are inevitably generated. It not only affects the quality of mechanical parts, but also reduces the working performance of machinery, which may cause serious accidents and economic losses[1][2]. Therefore, the detection of the quality of surface defects in castings is of great significance.

Machine vision-based surface defect detection methods have gradually replaced artificial visual inspection methods in industrial production processes due to their high efficiency and high accuracy[3], however, the implementation of this method relies too much on human feature extraction, resulting in poor generalization ability and robustness, so a deep learning method is proposed. There are two main types of detection methods for surface defects: two-stage and single-stage inspection methods. The two-stage is represented by Fast Region Convolutional Network (Fast R-CNN), Fast Convolutional Neural Network (Faster R-CNN), and Mask Region Convolutional Neural Network (Mask R-CNN) series[4][5][6], which is characterized by the formation of a region box first, and then classification and prediction by the network, which has high detection accuracy, but the model scale is huge and the inference speed is slow. There are the YOLO (You Only Look Once) series[7][8] and the SSD (Single Shot MultiBox Detector) method[9] in the single stage, which increase the detection speed and reduce the detection accuracy.

Among the mainstream target detection methods, the yolov5 model has received wide attention for its high detection accuracy and fast detection speed, and many scholars have conducted relevant experiments and researches on it.Chen et al. proposed an improved model RER-yolo based on yolov5, which was applied to the detection of surface defects on aluminum ingot alloys[10]. Huang et al. proposed a surface defect detection model, TBi-yolov5, which was applied to study the detection of surface defects on crane wire ropes[11]. Li et al. proposed a strip steel surface defect detection method based on You Only Look Once (YOLO) v5s-GC, which is crucial for raising the effectiveness of production and the caliber of the final output.[12]. Lu et al. proposed an improved YOLOv5s model YOLOv5s - FPD in order to solve the problem of difficulty in classifying the fine-grained features of the strip surface image and to improve the defect detection rate, which achieved better detection results[13]. To significantly enhance the single-stage target detection algorithm's ability to identify casting surface flaws, a method to improve YOLOv5s for detecting casting surface defects is proposed, and the innovations of the method mainly include:

Using C3_CM to replace the standard C3 module of the original model enhances the model's perceptual field of view, and fusion with the attention mechanism further amplifies the feature representation, thereby enhancing detection. The CBAM module performs feature attention enhancement operations, which makes the model pay more attention to the information of small and medium-sized targets, so as to improve the detection and positioning accuracy of small and medium-sized targets.

BiFPN network is used to realize top-down and bottom-up bidirectional fusion of deep and shallow feature maps, and better fusion of shallow feature information, in order to achieve the effect of fast and accurate detection of defects.

The CA attention mechanism is introduced in the neck to enhance feature extraction and improve the detection ability of the model.

II. Yolov5 Modeling and Optimization

Yolo is a single-stage target detection method that offers the advantages of fast inference and high-accuracy detection over other methods, and its performance is steadily improving.Since Glenn Jocher proposed the yolov5 method in 2020, many scholars have applied it to various industrial aspects at different scales.Yolov5 has different classifications: YOLOv5s, yolov5m, yolov5l and yolov5x.These four types of models increase in depth and breadth, and in feature representation capability, in that order.Considering that it will be applied to industrial production in the future, the master version of lightweight YOLOv5s is used as a baseline model and the model is improved according to the needs of the research subjects.The network structure of Yolov5-master is shown in Figure 1.

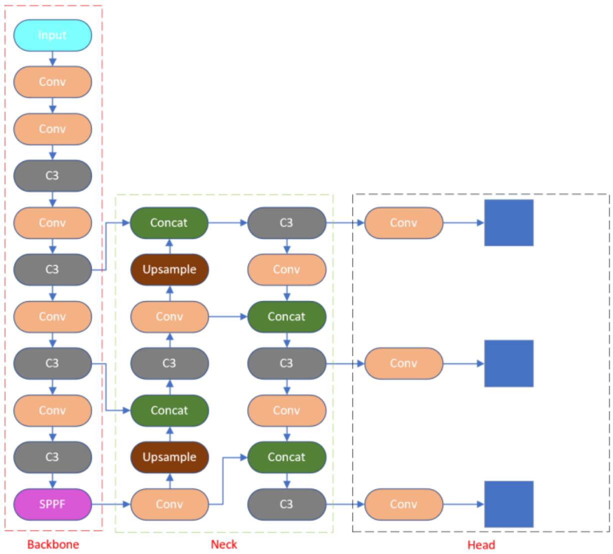


Fig. 1 The network structure of YOLOv5s.

The Yolov5 network architecture consists of three parts: the backbone network, the neck network and the head network.First, in yolov5, the CSPDarknet53 backbone network is used, which is a lightweight network that can minimize computation and memory usage while ensuring high detection accuracy.Next, Neck is utilized to generate feature maps at various resolutions, including FPNs and Path Aggregation Networks (PANet).Where FPN delivers semantic information through a top-down approach, PANet delivers location information in a bottom-up manner, enabling the network to fuse richer feature information.Finally, Head is the prediction network of the model, which computes the three sets of feature vectors, coordinate positions, and confidence scores of the output category prediction frames by convolution for different scales of 80×80, 40×40, and 20×20, respectively.

C3 Module Improvements

The Cross-Level Partial Network (C3) module is a key component in the YOLOv5s network architecture, consisting of multiple convolutional layers and activation functions.Its main purpose is to increase the depth and width relative to the feature map for better extraction of feature information.However, the shallow operation of the convolutional layer in the C3 module makes it difficult to extract more abstract and complex features due to the lack of high-level semantic information within the module. And the C3_CM module after using the fused CBAM attention mechanism has higher feature extraction capability[14], as shown in Fig. 2. Because CBAM has a strong feature representation ability, it can adaptively select and adjust the channel weights and spatial weights of the feature map, so it can better capture and represent the key features in the image. Compared with some other attention modules, the CBAM attention module has a smaller amount of computation and higher computational efficiency. After the C3 module is fused with the CBAM module, the CBAM module performs the feature attention enhancement operation, which makes the model pay more attention to the information of small and medium-sized targets, so as to improve the detection and positioning accuracy of small and medium-sized targets.

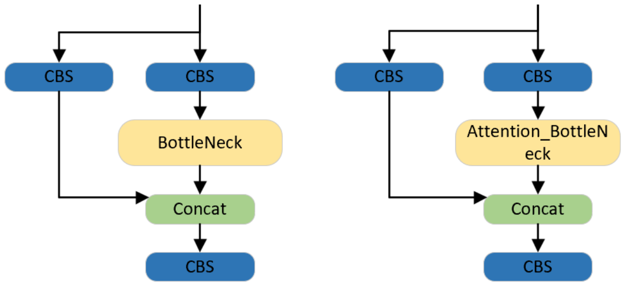


Fig. 2 Structure of C3 module and C3_CM module.

CBAM comprises of two key components: the Channel Attention Module (C-channel) and the Spatial Attention Module (S-channel), which can be embedded into different layers in the CNN to improve the model's perceptual capabilities, thus improving performance without increasing network complexity[15].The specific structure of the CBAM module is exhibited in Fig. 3, Fig. 4 and Fig. 5.

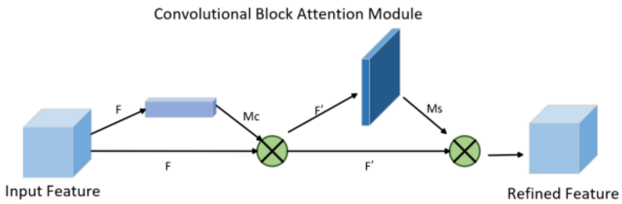


Fig. 3 CBAM Attention Module.

(1)Channel attention module

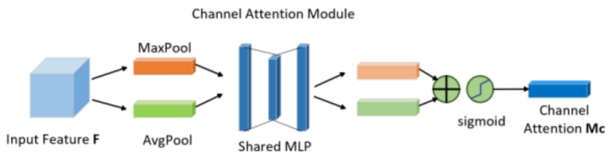


Fig. 4 Channel Attention Module.

The spatial dimension is compressed while the channel dimension remains unchanged. The input feature map is first compressed to x/r (Reduction (Reduction rate) times of the original, then expanded to the original number of channels, and finally passes through the ReLU activation function to obtain the two results after activation. This process changes the feature map from C×H×W to the size of C×1×1. Additionally, the feature map is passed through two parallel MaxPool and AvgPool layers.After adding these two outputs element by element, the output of Channel Attention is obtained using a sigmoid activation function. The output is then multiplied by the original map to return to C×H×W size[16].

$$M_c(F) = \sigma\left(MLP(AvgPool(F)) + MLP(MaxPool(F))\right) = \sigma\left(W_1\left(W_0(F^C_{Avg})\right) + W_1\left(W_0(F^C_{Max})\right)\right) \quad (1)$$

where is the Sigmoid function;$W_0 \in R^{\frac{C}{r}\times C}$,$W_1 \in R^{C\times\frac{C}{r}}$;the weights of the MLP and shared for both inputs.
(2)Spatial attention module

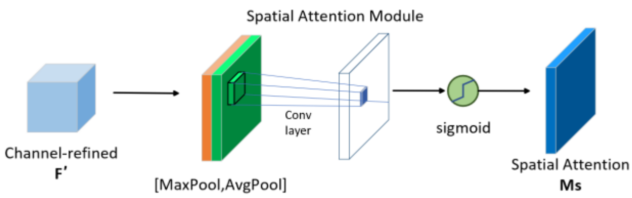


Fig. 5 Spatial Attention Module.

The channel dimension is compressed while the spatial dimension remains unaltered. Maximum pooling and tie pooling are used to obtain the output of Channel Attention, which results in two 1×H×W feature maps. The two feature maps are then split using the Concat operation, which is then transformed into an x-channel feature map by xx convolution. Next, a sigmoid is used to obtain the Spatial Attention feature map, and lastly the output is multiplied by the original map to return it to C×H×W size[16].

$$M_s\left(F'\right) = \sigma\left(f^{7\times7}([AvgPool(F); MaxPool(F)])\right) = \sigma\left(f^{7\times7}(F^S_{Avg}; F^S_{Max})\right) \tag{2}$$

Where σ is the Sigmoid function; $f^{7\times7}$ is the convolution kernel of 7×7

The attention mechanism utilizes the generated weighting coefficients to suppress or enhance the feature map, which can be achieved by focusing on important regional information.

Adoption of The BiFPN Network

As shown in Fig. 6, the traditional FPN (Feature Pyramid Network)[17] uses a top-down approach to aggregate multi-scale feature elements, but this unidirectional information transfer approach loses some of the detail information.As shown in Fig; PAFPN (Pyramid Attention Feature Pyramid Network)[18] used by yolov5 adds bottom-up aggregation to the traditional FPN network, although it improves the limitation of unidirectional information flow of FPNs and can better fuse shallow feature information, the training parameters will be increased accordingly.

Bidirectional Feature Pyramid Network[19] applied top-down and bottom-up bi-directional multi-scale feature fusion to aggregate features of different resolutions, while introducing learnable weights to learn to update the weights of different input features[20], thus achieving improved detection accuracy.

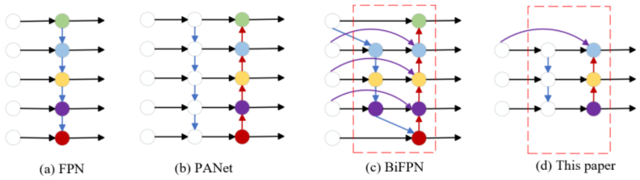


Fig. 6 the traditional FPN (Feature Pyramid Network)

C.Introduction of CA Attention Mechanisms

The CA attention mechanism module embeds location information in the channel attention, allowing the network model to pay attention over a wider area, while reducing the computational overhead[21]. Integration of feature information input along the horizontal and vertical directions into 2 separate directional feature maps effectively integrates spatial coordinate information into the generated attention maps, thus enhancing the performance of the model[22]. The flowchart of the CA attention module algorithm is depicted in Figure 7. (Here, X Avg Pool and Y Avg Pool represent one-dimensional horizontal global pooling and one-dimensional vertical global pooling, respectively). It will be decomposed into a one-dimensional feature encoding operation in the following formula, which is designed to allow the attention block to capture remote interactions using the precise location information of the feature map[23].

$$z_c = \frac{1}{H\times W}\sum_{i=1}^{H}\sum_{j=1}^{W} x_c\,(i,j) \tag{3}$$

where z_c is the output associated with the cth channel.

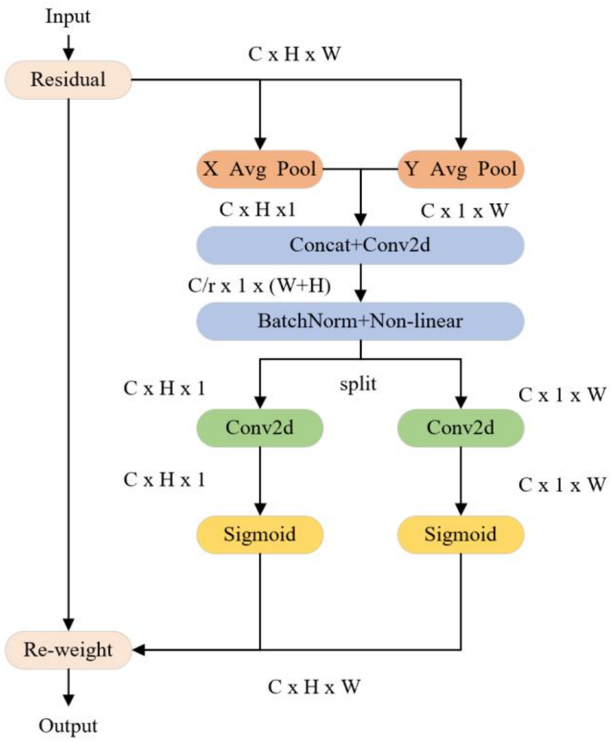


Fig. 7 CA Attention Module Flowchart.

Thus, for a given input X, the CA mechanism allows decoding each channel along the horizontal and vertical coordinate systems, respectively, within the 2 spatial ranges (H, 1) or (1, W) of the pooled kernel.The calculation is expressed by the formula：

$$z_c^h(h) = \frac{1}{W}\sum_{0\le i\le W} x_c\left(h, i\right) \tag{4}$$

Similarly, the output of the cth channel with width w can be expressed as：

$$z_c^w(w) = \frac{1}{H}\sum_{0\le j\le H} x_c\left(j, W\right) \tag{5}$$

The CA mechanism connects two feature maps through the Contact operation to perform the convolutional transformation, which is computed as follows:

$$f = \delta\left(F_1\left(\left[z^h, z^w\right]\right)\right) \tag{6}$$

where δ is the nonlinear activation function,f denotes a spatial information feature map across horizontal and vertical dimensions.F_1Indicates a cascade of merged results.

Improved YOLO Model (BC-YOLOv5s)

In this study, Against YOLOv5s is less effective in detecting small and medium targets, C3_CM is used to replace the C3 module in the original YOLOv5s network structure to enhance the characterization capability of the neural network. BiFPN bidirectional pyramidal feature network is introduced for better feature extraction. At the same time, a CA attention mechanism is added above the first upsampling layer of the neck to enhance the interaction of different layers of features. The structure of the proposed BC-YOLOv5s network is shown in Fig. 8.

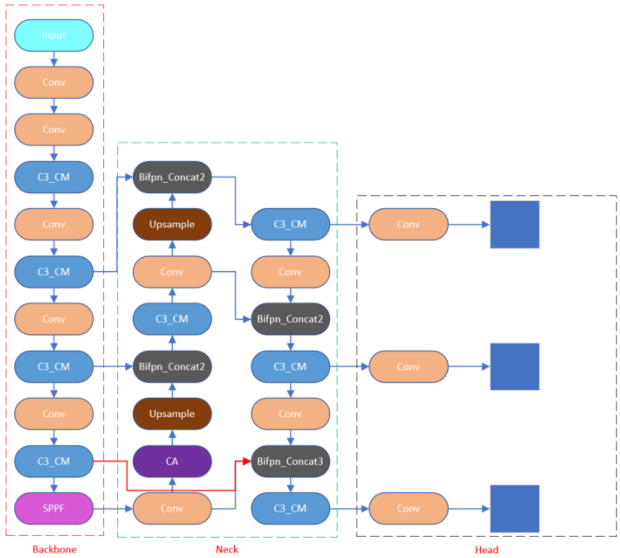


Fig. 8 The improved network structure of YOLOv5s.

III. Results

A. Experimental Datasets and Processing

The experimental dataset of this paper is the submersible pump impeller casting dataset downloaded from Kaggle, using the software Labelimg to classify the defects and manually label a total of 589 images of the dataset, which contains three kinds of defects: shrinkage holes (suo_kong), cracks (lie_wen), and air holes (qi_kong). The size of the defects is mostly small and medium-sized targets, and the number of large targets is small, so the defect detection for the dataset is mainly the detection of small and medium-sized targets on the surface of the casting. as shown in the Fig. 9.

lie_wen qi_kong suo_kong

Fig. 9 Defect type diagram

In deep learning based industrial defect detection techniques, the quality of the dataset determines the generalizability and robustness of the model training.In addition, insufficient samples can lead to overfitting in model training, which directly affects the defect detection results.In order to avoid overfitting phenomenon, the dataset was preprocessed using fuzziness, brightness and noise processing, and the original data was expanded from 589 to 2990 images.The quantities and images of the submersible pump impeller dataset after enhancement are shown in Fig. 10 and Table 1.

a b c d e

Fig. 10 Before and after data enhancement image.

where a is the original image, b is blurriness processing, c is brightness enhancement, d is darkness enhancement, and e is noise processing.

Table1 Number of enhancements for each type of defect

Defect type	Initial number of images	Number of images after amplification
qi_kong	203	1015
lie_wen	197	985
suo_kong	198	990
total	589	2990

B. Experimental Setting and Training Parameters

In this paper, the experimental operating system is Windows 11, the CPU model is 12th- Gen Intel(R) Core(TM) i5-1240P-1.70 GHz, and the deep learning framework of the experimental platform is Pytorch-1.10.0. During the model training process, the division of the training set is 2396, the validation set is 594, and the model is iterated 300 times.

C. Evaluation Indicators

Model evaluation is critical to determine the performance of the model and to judge the compatibility of the improved model with the study population.Regarding the area of target identification, commonly used basic evaluation metrics include precision (P), recall (R), and mean average precision (mAP). P is the probability that how many of all the categories predicted to be positive actually belong to the positive category, reflecting the global accuracy of the model.R is the probability of how many of all samples that are actually in the positive category are predicted to be in the positive category, and reflects the ability of the classifier to find all positive categories. FPS is used to evaluate the processing speed of the model on a given hardware, the number of pictures that can be processed per second. The mAP demonstrates the average recognition ability of all defect categories through modeling. Precision and recall are calculated as follows:

$$\text{Precision (P)} = \frac{\text{Tp}}{\text{Tp+Fp}} \tag{7}$$

$$\text{Racll (R)} = \frac{\text{Tp}}{\text{Tp+Fn}} \tag{8}$$

$$\text{mAP} = \frac{1}{\text{N}}\sum_{\text{i}=1}^{\text{n}} \text{AP} \tag{9}$$

where Tp indicates that the model correctly detects positive samples, Fp indicates that the model incorrectly predicts negative samples as positive samples, Fn indicates that the model incorrectly predicts positive samples as negative samples, and N is the number of sample categories.

D. Experimental Results

Two sets of experiments were designed in this study. The first set of experiments compares the performance of the improved BC-YOLOv5s model with the mainstream target detection model. The second set of experiments performed ablation experiments on the same configuration.

Mainstream Target Detection Performance

To confirm the effectiveness of the improved method BC-YOLOv5s, it was compared with the advanced detection methods SSD, YOLOv3-tiny, YOLOv5s, YOLOv6s, YOLOv8n, YOLOv8s and YOLOv10n on the casting surface defects dataset.The comparison results are shown in Table 2.

Table 2 Comparison of Algorithm Performance

arithmetic	mAP/%	P/%	R/%	FPS
SSD	96.7	68.4	71.1	3.5
Yolov3-tiny	95.2	93.3	89.3	44.2
Yolov5s	95.0	96.3	92.5	16.8
Yolov6s	92.8	93.2	92.5	9.9
Yolov8n	95.4	95.9	89.6	26.4
Yolov8s	95.7	94.3	93.3	29.8
Yolov10n	93.8	95.2	90.0	16.4
BC-YOLOv5s	96.3	98.1	91.7	16.0

Table 2 shows that the algorithm in this paper is not the highest in terms of recall, but compared with other algorithms, the mAP is increased by -0.4%, 1.1%, 1.3%, 3.5%, 0.9%, 0.6%, and 2.5%, respectively, and P is increased by 29.7%, 4.8%, 1.8%, 4.9%, 2.2%, 3.8%, and 2.9%, respectively. The FPS data shows that the improved model can meet the real-time requirements, and the real-time processing capacity is slightly reduced compared with the original model due to the increase of modules in the improved model. In comprehensive evaluation, the performance of the proposed model is significantly better than that of the above seven models.

F. Ablation Experiment

The ablation experiments help to better understand the performance of the target detection method when certain components are added or removed, the dataset and training parameters used for each set of experiments are the same, and the experiments' outcomes are displayed in Table 3.Experiment 1 modeled the original network, and Experiment 2 introduced the C3_CM fusion module on top of the original network.Experiments 3 and 4 used the BiFPN network and CA attention mechanism alone, respectively.Experiment 5 uses BiFPN network when based on experiment 2, which improves the feature extraction accuracy of small targets, mAP by 0.3% and P by 2.1%, demonstrating how the suggested optimization technique raises the original model's low detection accuracy and strengthens its capacity for generalization to produce high-level feature fusion..Experiment 7 is the final improved model of the paper, with a 1.3% increase in mAP and a 1.8% increase in P.

Table 3 Impact of different improvement schemes on model performance

Experiment	C3_CM	BiFPN	CA	mAP	P	R
Experiment1				95.0	96.3	92.5
Experiment2	√			94.7	95.7	92.0
Experiment3		√		95.3	97.0	90.7
Experiment4			√	94.8	96.3	91.6
Experiment5	√	√		95.3	98.4	91.4
Experiment6		√	√	95.5	96.4	92.8
Experiment7	√	√	√	96.3	98.1	91.7

In defect detection, recall and accuracy are equally important, and in the algorithm proposed in this paper, the accuracy and flat accuracy are improved in the case of recall with less loss, so that the overall performance of the model is improved. The results of the verification set are shown in the Fig. 11 and Fig. 12 and Fig. 13, which shows that the improvement of the model is helpful and improved for the detection of surface defects in castings.

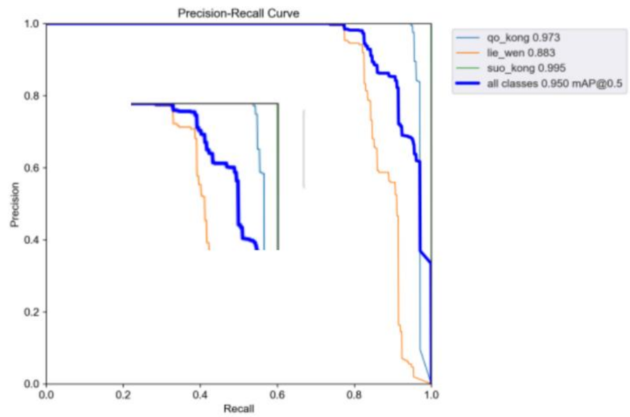


Fig.11. PR plot for YOLOv5s.

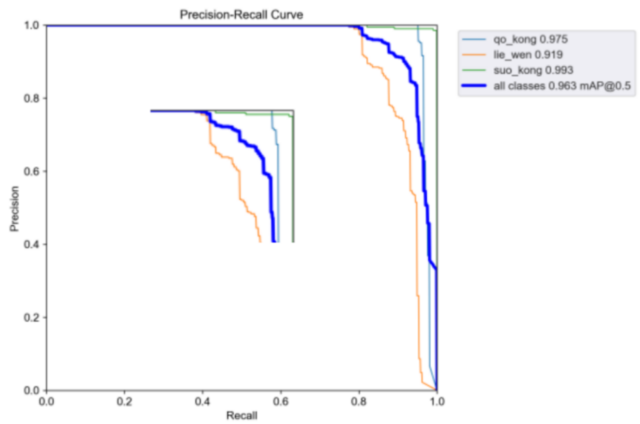


Fig.12. PR curves of improved YOLOv5s.

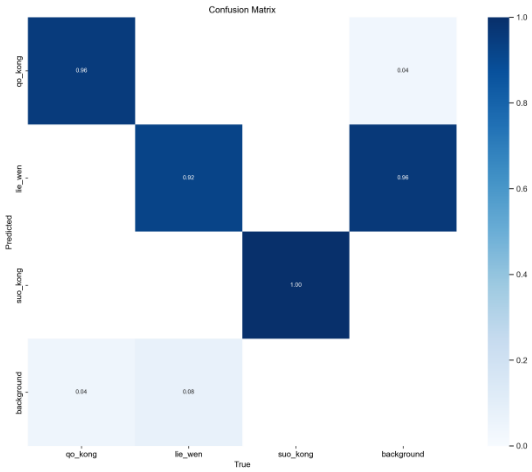
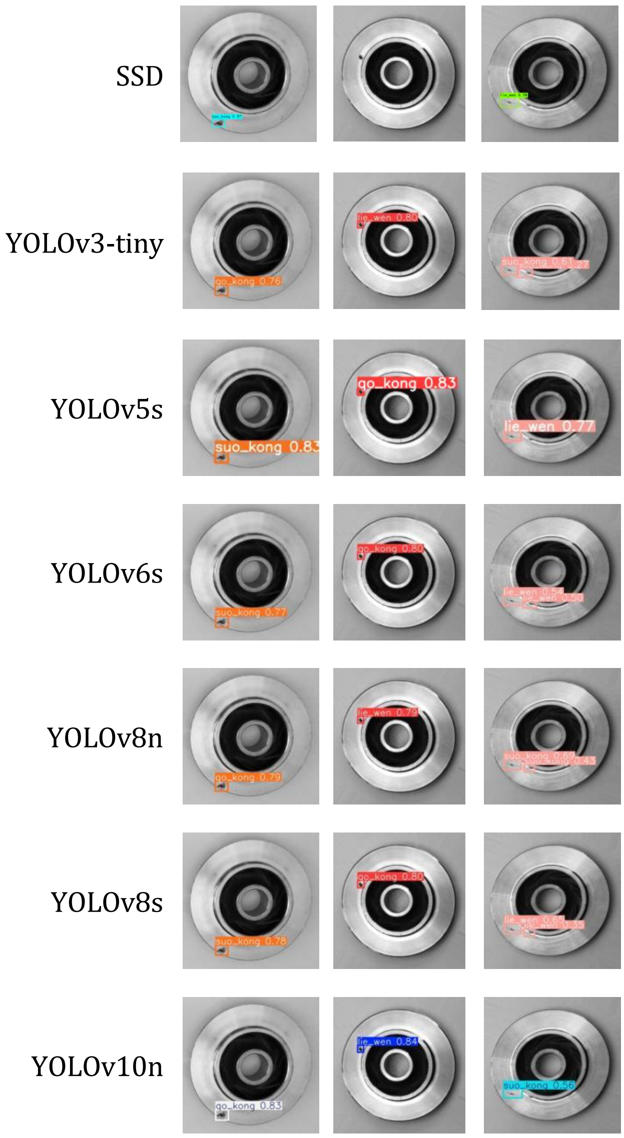
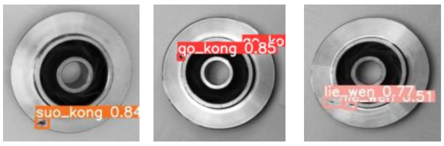


Fig.13. The normalized confusion matrix of BC-YOLOv5s

The visualization results are depicted in Fig. 14. Other models will have the problems of missed detection, false detection and low detection accuracy. Compared with the detection effect of other algorithms, the comprehensive performance of the algorithm proposed in this paper is significantly improved and has practical application value.



This paper



Type suo_kong qo_kong lie_wen

Fig.14. Comparison of detection results between YOLOv5s and the algorithm in this paper.

IV. Conclusion

Aiming at the problem of casting surface defects, this paper proposes an improved algorithm based on YOLOv5s network model.The C3_CM fusion module is introduced in the network backbone to enhance the detection of target defects by strengthening the target features through weighting the feature map channel information and spatial information;At the same time, BiFPN network is introduced to replace the PANet network of the original model, which combines the bottom-level detail information with the high-level semantic information, so that the model can effectively integrate the multi-scale feature information and enhance the model's ability to detect crack defects;The CA attention mechanism is introduced in the network backbone to optimize the algorithm's target localization and recognition accuracy.As shown by the experimental results, the model of the algorithm proposed in this paper achieves a model tie accuracy of 96.3% on the casting surface defect dataset, which significantly improves the detection accuracy of cracks and porosity defects.The network model will be further optimized in the future to improve the detection accuracy. Meanwhile, more data will be collected to expand the dataset and improve the generalization ability of the model.

REFRENCES

[1] Shi, J.; Yang, J.; Zhang, Y. Research on Steel Surface Defect Detection Based on YOLOv5 with Attention Mechanism. Electronics 2022, 11, 3735.

[2] Bo L ,Nanfeng Z ,Xintao L , et al.Surface Defects Detection of Car Door Seals Based on Improved YOLO V3[J].Journal of Physics: Conference Series,2021,1986(1).

[3] Xin L ,Cheng W ,Haijuan J , et al.Surface Defect Detection Model for Aero-Engine Components Based on Improved YOLOv5[J].Applied Sciences,2022,12(14):7235-7235.

[4] Dai X ,Zhao Y ,Zhu C .A study of an improved RCNN network model for surface defect detection algorithm of precision workpiece and its realisation[J].International Journal of Wireless and Mobile Computing,2020,19(1).

[5] Chiraz A ,Juan Z ,Sabra E , et al.Advanced Faster-RCNN Model for Automated Recognition and Detection of Weld Defects on Limited X-Ray Image Dataset[J].Journal of Nondestructive Evaluation,2023,43(1).

[6] Haijiang Z ,Yinchu W ,Jiawei F .IA-Mask R-CNN: Improved Anchor Design Mask R-CNN for Surface Defect Detection of Automotive Engine Parts[J].Applied Sciences,2022,12(13):6633-6633.

[7] Qu Y ,Wang C ,Xiao Y , et al.Optimization Algorithm for Surface Defect Detection of Aircraft Engine Components Based on YOLOv5[J].Applied Sciences,2023,13(20).

[8] Kim Y ,Kim W ,Yoon J , et al.Deep Learning-Based Multiple Droplet Contamination Detector for Vision Systems Using a You Only Look Once Algorithm[J].Information,2024,15(3).

[9] Liu X ,Gan X ,Ping A .Automatic flaw detection of carbon fiber prepreg using a CFP-SSD model during preparation[J].Measurement Science and Technology,2024,35(3).

[10] Chen T ,Cai C ,Zhang J , et al.RER-YOLO: improved method for surface defect detection of aluminum ingot alloy based on YOLOv5.[J].Optics express,2024,32(6):8763-8777.

[11] Huang Y ,Fan J ,Hu Y , et al.TBi-YOLOv5: A surface defect detection model for crane wire with Bottleneck Transformer and small target detection layer[J].Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science,2024,238(6):2425-2438.

[12] LiX ,YangR ,ZhouH .YOLOv5s-GC-Based Surface Defect Detection Method of Strip Steel[J].steel research international,2024,95(4).

[13] Lu J ,Zhu M ,Ma X , et al.Steel Strip Surface Defect Detection Method Based on Improved YOLOv5s[J].Biomimetics,2024,9(1).

[14] Wang, Niannian, et al. "Underground Defects Detection Based on GPR by Fusing Simple Linear Iterative Clustering Phash (SLIC-Phash) and Convolutional Block Attention Module (CBAM)-YOLOv8." IEEE Access (2024).

[15] Tian, Xueyong, et al. "Garbage Classification Algorithm Based on Improved MobileNetV3." IEEE Access (2024).

[16] Woo, Sanghyun, et al. "Cbam: Convolutional block attention module." Proceedings of the European conference on computer vision (ECCV). 2018.

[17] Chang, Yujian, et al. "An Improved Lightweight YOLOv5 Algorithm for Detecting Railway Catenary Hanging String." IEEE Access (2023).

[18] Wang, Shuohe, et al. "EBSE-YOLO: high precision recognition algorithm for small target foreign object detection." IEEE Access (2023).

[19] Tan, Mingxing, Ruoming Pang, and Quoc V. Le. "Efficientdet: Scalable and efficient object detection." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.

[20] Li, Ying, et al. "HRD-YOLOX based insulator identification and defect detection method for transmission lines." IEEE Access (2024).

[21] Hou, Qibin, Daquan Zhou, and Jiashi Feng. "Coordinate attention for efficient mobile network design." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2021.

[22] Lin, Bingyan. "Safety Helmet Detection Based on Improved YOLOv8." IEEE Access (2024).

[23] Raj, G. Deepti, and B. Prabadevi. "Steel Strip Quality Assurance With YOLOV7-CSF: A Coordinate Attention and SIoU Fusion Approach." IEEE Access 11 (2023): 129493-129506.