Intelligent Equipment and Special Robots
Q. Zhang (Ed.)

doi:10.3233/ATDE240224

Research on the Improved YOLOv5s Tube Sheet Weld Defect Detection Method

Xiaoqing YU, Hongen WU[1], Yongquan WANG, Jiangbing QIN
School of Mechanical and Electronic Engineering, Shandong University of Science and Technology, Qingdao 266590, Shandong, China

Abstract. In the realm of machine learning-based target detection, there exist several challenges that require attention, namely limited detection range, complex feature extraction, suboptimal detection precision, and significant subjectivity. In this paper, the strengths and weaknesses of existing deep learning target detection algorithms have been investigated in order to address these issues by integrating the actual welding process of heat exchangers. The objective is to improve the model's detection accuracy and speed. To achieve this, we employ the YOLOv5 model to detect and identify weld defects of the heat exchanger tube plate, and propose an enhancement method based on the YOLOv5s model. By implementing several enhancements, such as incorporating the attention mechanism, updating the loss function, and optimizing the feature fusion network, the model's overall performance is enhanced, with a focus on addressing the issues of low detection accuracy, slow convergence, and inadequate real-time performance in detecting small target defects compared to the YOLOv5s model. The improved YOLOv5s_m model improves the detection accuracy by 4.52% and the speed by 4.4 FPS, which solves the problems of low detection accuracy, weak sensitivity of small target defect detection and poor convergence of the bounding box loss function of the YOLOv5s model. These improvements lay the groundwork for enhancing the automation and intelligence of weld quality inspections.

Keywords. Deep learning, defect detection, SVM, YOLOv5, visualization

1. Introduction

Currently, the detection of weld defects in heat exchanger tube plates is primarily conducted manually [1]. This method has several drawbacks, including low levels of automation, potential for fatigue, limited real-time capabilities, and a high likelihood of leakage or incorrect detection. In this paper, the surface defects of pipe plate weld are taken as the research object, and the deep learning algorithm [2] is introduced to achieve the defect recognition of pipe plate weld by comparing with the traditional machine learning method, with the aim of reduce the complexity of the algorithm, and improve the detection speed and accuracy of the model. By repeatedly training and testing on the self-made weld defect dataset presented in this paper, we were able to confirm the efficacy of the proposed algorithm. Related works and methods

The initial dataset is optimised by adopting data augmentation methods such as rotational and translational transformation, image noise enhancement [3], etc. Improving

[1] Corresponding author: Hongen WU, Shandong University of Science and Technology,
e-mail: whenli@sina.com

the model's adaptive capability and detection performance requires increasing the variety and quantity of the dataset.

An improvement method based on YOLOv5s model of weld defects [4] is proposed. Firstly, the CBAM attention mechanism [5] is added to the Backbone part to increase the weights and optimise the learned feature information to improve the overall detection accuracy of the model. The loss function is often used to determine the magnitude of the degree of error between the predicted target frame and the actual frame, and the loss function directly affects the convergence of the model and relates to the detection performance of the model [6]. Replace the default GIoU loss function with the CIoU loss, which speeds up convergence in the training process. Finally, BiFPN [7] network is used for multi-scale feature fusion to change the original path aggregation network Path Aggregation Network (PANet).

2. Improvements to the YOLOv5s model

2.1. Adding CBAM Attention Mechanism

In the feature extraction network of YOLOv5s, attention mechanism modules have been added respectively, with their precise positions marked in Figure 1.

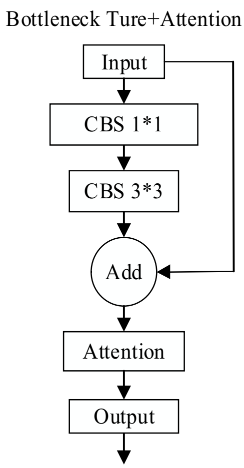


Figure 1. Illustration of the embedded location of the attention mechanism module.

As depicted in the figure above, the attention mechanism is executed for every session of the C3 module, adjusting the attention weights across multiple dimensions and enhancing the precision of small target detection simultaneously.

2.2. Introduction of CIoU losses

The positional loss of the bounding box in YOLOv5s is generally evaluated by the GIoU loss. But GIoU has limitations. As depicted in Figure 2, GIoU degenerates into IoU when the projected bounding box B is completely within the actual bounding box B^{gt}.

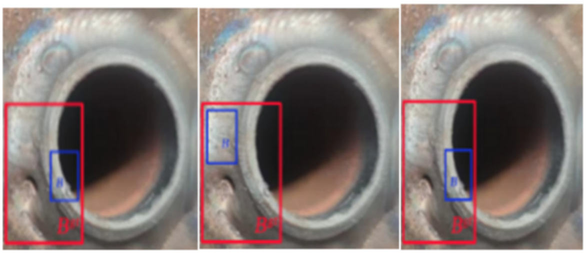


Figure 2. The condition of the prediction box inside the real box.

Given that small target defects like air holes or pits constitute about 1/3 of the samples in this study, the CIoU loss function is better suited for such cases.

3. Experimental dataset production

3.1. Experimental data enhancement

In order to improve the scale of the dataset and the generalization ability of the model, and to avoid problems such as overfitting in subsequent models during training [8]. In this paper, 1276 defect images acquired under different scenes such as strong light, dark light, dust, etc. are expanded by data enhancement methods. Examples of the data enhancement methods are shown in Figure 3.

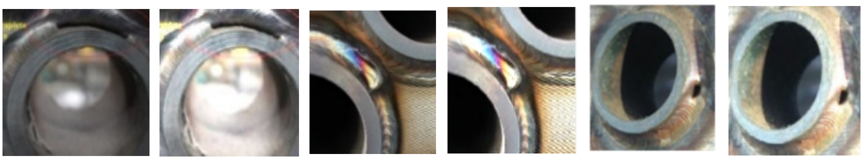


Figure 3. Some data enhancement methods.

The precise number of datasets is presented in Table 1.

Table 1. Statistics on the number of defect data sets of each type

Typology	Normal	Stoma	Arc pit	Not fused	Damaged edges	Crater
Training set	400	611	390	524	451	504
Validation set	50	75	50	68	56	63
Test set	50	78	46	58	57	65
Total	500	764	486	650	564	632

3.2. Sample labelling

In this paper, the labeling types are divided into 6 categories. The normal weld category is 0, label is nm; the edge loss defect category is 1, label is de; the porosity defect category is 2, label is s; the unfused defect category is 3, label is nf; the crater defect category is 4, label is c; and the arc crater defect category is 5, label is ac.

4. Specific training and experimental procedures (Figure 4)

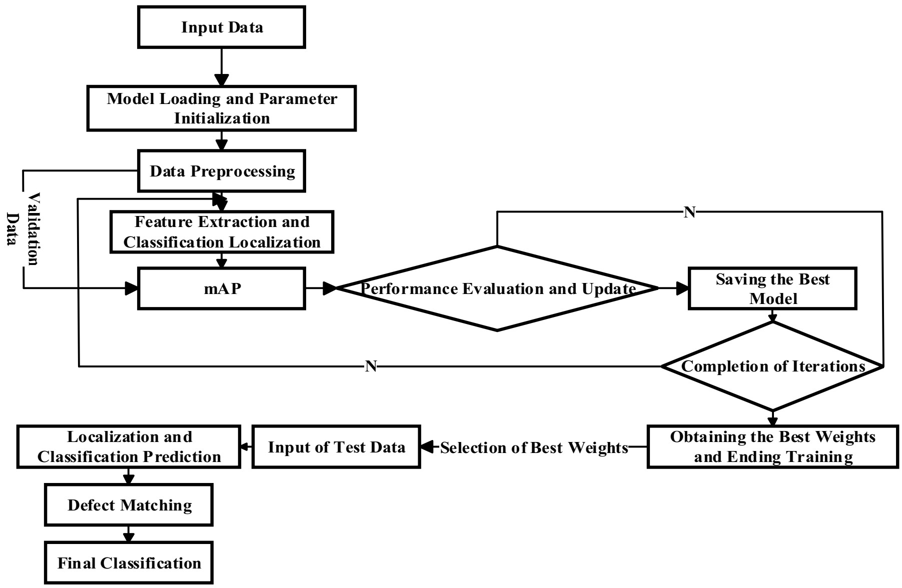


Figure 4. Overall training and experiment flow chart.

5. Experimental results and analysis

5.1. Visualisation of the training process

For ease of differentiation, the improved YOLOv5s model is referred to in this chapter as YOLOv5s_m. Once 300 training epochs were completed, the log files were imported into Origin software to produce the mAP and Precision curves illustrated in Figures 5 and 6, respectively.

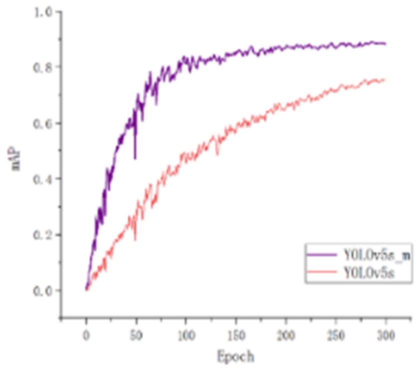


Figure 5. mAP graph.

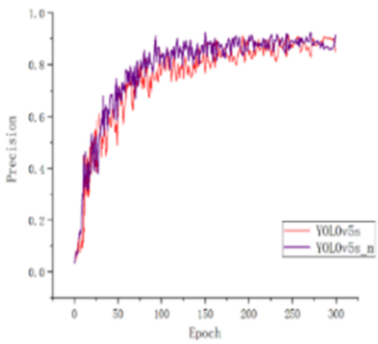


Figure 6. Precision graph.

In this context, AP represents the classification accuracy of a single target category. A higher AP value indicates better predictive performance. The formula for calculating AP is as follows (1):

$$AP = \int_0^1 P(r)dr \tag{1}$$

The mean Average Precision (mAP) refers to the average of AP values across multiple categories. The calculation formula for mAP is as follows (2):

$$mAP = \frac{\sum_{q=1}^{N} AP(q)}{N} \tag{2}$$

The enhanced YOLOv5s_m model exhibits higher detection accuracy in mAP and Precision accuracy compared to the original YOLOv5s model. Once the model reaches saturation, the final detection accuracy remains stable at around 94%, while converging faster and delivering superior performance.

5.2. Improve experimental verification

- Attention mechanism improvement verification

Utilizing the CBAM attention mechanism principle elucidated above, the SENet, the CA, and the CBAM are sequentially positioned at the same locations within the network. Figure 7 illustrates the loss function acquired from the training.

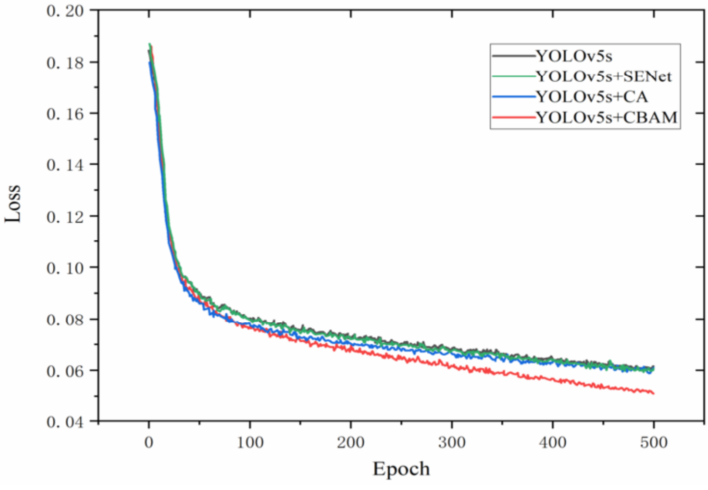
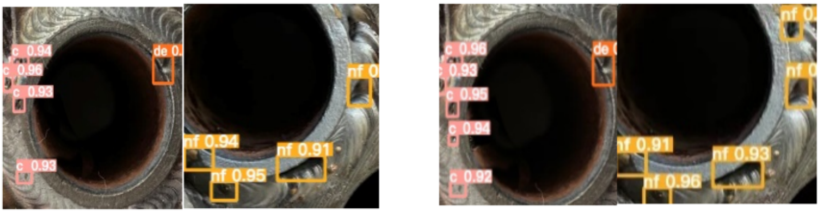


Figure 7. Comparison curves of loss functions for different attention mechanisms.

Upon scrutinizing the three curves, it becomes evident that the YOLOv5s model, which incorporates the CBAM attention mechanism module, displays a more rapid convergence during detection. To further confirm the effective detection impact of different attention mechanism modules on small target defects, the test set is assessed using the weight files generated by the model after integrating the attention mechanism. Several test results are presented in Figure 8.



(a) YOLOv5s Detection

(b) YOLOv5s detection after adding the attention mechanism

Figure 8. Defect testing of small target images.

As can be seen from Figure 8, the model with the introduction of the CBAM attention mechanism can detect some of the pit or air hole type defects more accurately, which verifies that the CBAM attention mechanism enables the model to pay attention to the small targets in a wider range.

- Loss function improvement validation

With respect to improving the loss function, Fig. 9 illustrates the comparison curves of the loss function acquired during the model training before and after the enhancement.

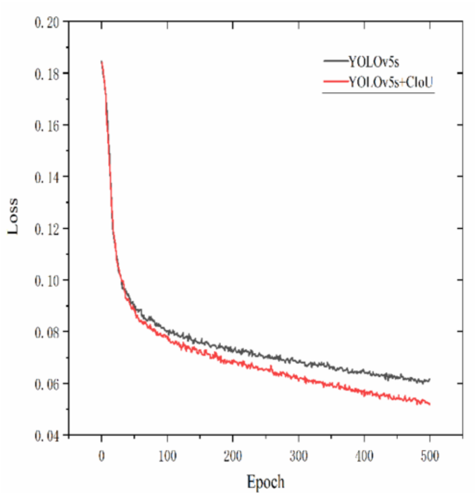


Figure 9. Improved loss function comparison curve.

By utilizing the CIoU loss function, the loss function curve shows a faster convergence rate and a lower final convergence value for the model's loss.

- The comparison results obtained after embedding the BiFPN feature fusion module in YOLOv5s are shown in Table 2.

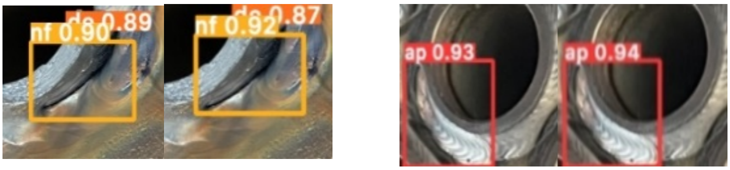
Table 2. Performance comparison after replacing feature fusion networks

Model	AP/%					P/%	mAP/%	Weights /M
	stoma	damaged edges	arc pit	not fused	crater			
YOLOv5s	88.24	92.15	90.63	92.17	87.56	89.78	90.15	16.5
YOLOv5s+BiFPN	90.72	93.43	91.27	92.95	89.11	90.35	91.49	16.7

As can be seen from Table 2, the improved feature fusion method results in a more significant improvement in accuracy for small target defects in the categories of pneumatic holes and pits, resulting in improvement of 2.48% and 1.55%.

5.3. Visualisation of detection results

To further verify the practical impact of the YOLOv5s_m model on detecting weld defects dataset, this section randomly selects several images from the test set for detection, and the visualization results are shown in figure 10 below.



(a) YOLOv5s Detection (b) YOLOv5s_m Detection

Figure 10. Comparison chart of defect detection results.

6. Conclusion

This paper proposes a method to improve the YOLOv5s model, which aims to address the issues of low accuracy in detecting small target defects, slow convergence speed, and inadequate real-time performance in the algorithm as the primary focus. Firstly, the CBAM attention mechanism is introduced to improve the detection accuracy and precision of the model. The next step is to replace the default GIoU loss with the CIOU loss function, which will result in an accelerated convergence of the model and improved robustness. Furthermore, we adopt the concept of the BiFPN network and refine the feature fusion structure. Finally, a comparison experiment is set up. In order to boost the sensitivity and accuracy of detecting small target defects, such as air holes or pits, the feature fusion architecture has been upgraded, incorporating the concept of BiFPN network. To verify the effectiveness of the proposed enhanced approach, a comparative experiment was conducted. The results demonstrate that the improved YOLOv5s_m model significantly outperforms other algorithm models in terms of both detection speed and accuracy.

References

[1] Ryu K, Kim D. Real-time parameter adjustment and fault detection of remote laser welding by using ANN [J]. International journal of precision engineering and manufacturing, 2014, 15: 979-987.

[2] Jiao W, Wang Q, Cheng Y, et al. End-to-end prediction of weld penetration: A deep learning and transfer learning based method [J]. Journal of Manufacturing Processes, 2021, 63: 191-197.

[3] Kalaiselvi V, Aravindhar D J. An Non Destructive Test for the Detection of Weld Defects Using Image Processing [J]. Indonesian Journal of Electrical Engineering and Computer Science, 2018, 9(03): 764-770.

[4] Fang Y, Guo X, Chen K, et al. Accurate and Automated Detection of Surface Knots on Sawn Timbers Using YOLO-V5 Model [J]. BioResources, 2021, 16(3):5390-5406.

[5] Fu H, Song G, Wang Y. Improved YOLOv4 marine target detection combined with CBAM [J]. Symmetry, 2021, 13(4): 623.

[6] Badrinarayanan V, Kendall A, Cipolla R. Segnet: A deep convolutional encoder-decoder architecture for image segmentation [J]. IEEE transactions on pattern analysis and machine intelligence, 2017, 39(12): 2481-2495.

[7] Shina Jia. Small target detection algorithm based on improved YOLOv5 [D]. Nanchang: Nanchang University, 2022.

[8] Jiawei Xie. Research on the detection method of weld surface defects based on machine vision [D]. Urumqi: Xinjiang University, 2021.