PCB Surface Defect Detection based on YOLOv8n

Rui You, Zhifeng Wang *

Abstract—**In the electronic manufacturing industry, accurate detection of PCB defects is crucial as it directly impacts product quality and reliability. The primary challenges in PCB defect detection include missed detections and false alarms, particularly concerning micro-defects. This study proposes an enhanced PCB defect detection algorithm based on YOLOv8, which incorporates the Global Attention Module (GAM), Partial Convolution Layer (PConv3), and a multi-head detection strategy. The GAM improves the model's sensitivity to micro-defects by capturing and weighting global context information through spatial and channel attention mechanisms applied to the input feature map. The PConv3 optimizes feature extraction, minimizing false alarms due to information loss. The multi-head detection strategy identifies defects at varying scales, preserving detailed information and enhancing the detection of small-sized defects. Experimental results demonstrate that the improved algorithm achieves a 3.6% increase in average precision while meeting real-time detection requirements.**

Index Terms—**Deep Learning, PCB Defect Detection, YOLOv8, Global Attention Module, PConv3, Multi-head Detection**

I. Introduction

In the modern electronics manufacturing field, printed circuit boards (PCBs) are ubiquitous components in electronic devices[1]. As electronic devices evolve towards higher performance, smaller sizes, and more complex designs, the manufacturing quality of PCBs directly impacts the reliability and performance of the entire product[2]. Therefore, ensuring defect-free PCBs during the production process is crucial. However, with the miniaturization of PCBs and the increase in component density, traditional defect detection methods face significant challenges, particularly in detecting micro-defects. In recent years, numerous researchers and engineers have sought to enhance the automation and accuracy of defect detection by introducing advanced computer vision and machine learning techniques[3]. In this research area, various object detection models have been developed and optimized to meet the specific requirements of PCB manufacturing.

Since the introduction of the R-CNN network into the object detection field by Girshick et al. in 2014, convolutional neural networks (CNNs) have been widely applied for their exceptional feature extraction and representation capabilities, enabling high-precision detection through automatic feature extraction. Among these, the evolved version of region-based convolutional neural networks (R-CNN), Faster R-CNN, has been extensively studied for its superior feature extraction capability. Junhao Niu[4] and colleagues proposed an improved PCB defect detection algorithm based on Faster R-CNN, which outperforms current mainstream algorithms in detecting micro-objects by 9.2%, achieving better accuracy for micro-defect detection. Dan Li[5] and colleagues proposed an improved PCB defect detector based on the Feature Pyramid Network (FPN). This detector, which combines Faster R-CNN and FPN as its foundation, achieved higher accuracy and enhanced defect detection and classification performance. Huang C.Y.[6] and colleagues discussed and compared the target detection networks of YOLOv3 and Faster R-CNN, aiming to establish an automatic defect detection system capable of quickly identifying defects on PCBs. These models first identify regions in the image that may contain defects through region proposal networks, and then analyze these regions in-depth to achieve high-precision defect detection. However, despite their excellent performance in accuracy, these models are significantly limited in real-time detection due to the time-consuming processes involved in region proposal and feature extraction.

On the other hand, YOLO series models such as YOLOv3, YOLOv5[7] and YOLOv7[8] have gained attention for their fast detection speed and well-balanced performance. The YOLO model approaches defect detection as a single regression problem, directly predicting the position and category of defects in an image, thereby significantly improving processing speed. Specifically, YOLOv5, while maintaining high speed, further enhances detection accuracy and robustness by incorporating multi-scale training and more complex network structures. However, existing object recognition algorithms still struggle with detecting defects in PCBs with complex circuit layouts.

To address this issue, Stephen Yang[9] and colleagues proposed a novel YOLOv3-DenseNet model for PCB defect detection. They made key improvements to YOLOv3, and comparative results showed that the proposed YOLOv3-DenseNet outperforms other commonly used YOLOv3 models in terms of recognition accuracy, while also having a smaller model size. Li J[10] and colleagues proposed a class-balanced Train/Val (training/validation) segmentation method for YOLOv3, addressing the problem of object detection imbalance in PCB assembly scenes using a feature fusion strategy to balance multi-scale features. Zheng Wang[11] and colleagues proposed an improved YOLOv3 method for PCB solder joint defect detection, combining ordered probability density weighting with attention mechanisms. Testing showed that the improved network's average detection accuracy increased from 84.35% to 96.69%, with better convergence than the original network. Tang J[12] and colleagues proposed an improved PCB surface defect detection algorithm called PCB-YOLO, based on YOLOv5,

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achieving 95.97% mAP at 92.5 FPS—more accurate and faster than many other real-time, high-precision detection algorithms for surface defects in PCBs. WU Junhua[13] and colleagues proposed a fast PCB defect detection method based on an improved YOLOv5, introducing a Parallel Residual Ghostconv Convolutional Block Attention Module (PRG-CBAM). This module eliminates the priority of channel and spatial attention modules, improving the accuracy of object detection.Additionally, by replacing the standard convolution in the PANet module with ghost convolution (Ghostconv), they reduced the number of network parameters and computational costs, thereby improving detection efficiency.

Additionally, Single Shot Multibox Detection (SSD) is also a highly effective model that, by predicting bounding boxes at multiple scales, can better capture defects of various sizes. This characteristic of SSD makes it particularly effective in detecting small-sized or micro-defects. Litian Kang[14] and colleagues proposed a deep learning detection network based on SSD, called multi-layer SSD (mSSD), which includes a small target prediction feature layer module, enhancing the perception of small target features.The improved mSSD network significantly enhanced the detection accuracy of SSD in PCB defect detection.Guangzai Ran[15]and colleagues applied a PCB defect detection and recognition algorithm based on the SSD (Single Shot Detector) deep convolutional network framework to address the low robustness of existing traditional PCB defect detection algorithms.The detection results were optimized by non-maximum suppression (NMS), and experiments showed that the algorithm significantly improved PCB defect detection accuracy.Yusen Wan[16] and colleagues proposed a semi-supervised defect detection method (DE-SSD) with a data augmentation strategy, achieving competitive results for PCB defect detection with fewer labeled samples.

While these models possess distinct advantages, they generally necessitate careful tuning and optimization for specific PCB defect detection scenarios. Consequently, this paper presents a PCB defect detection algorithm based on an enhanced YOLOv8 model, which significantly improves the recognition of micro-defects by integrating the Global Attention Module (GAM), Partial Convolution Layer (PConv3), and a multi-head detection strategy. The Global Attention Module enhances the model's focus on the overall feature map, while the Partial Convolution Layer optimizes information capture, and the multi-head detection strategy enables precise defect detection across varying scales. Through the comprehensive integration of these technologies, our method not only increases detection accuracy but also fulfills real-time requirements, providing an effective solution for automatic defect detection in PCB production lines.

II. RELATED STUDIES

In the field of PCB defect detection, numerous deep learning-based methods have been proposed. These methods primarily rely on convolutional neural networks (CNNs) and object detection models such as SSD, Faster R-CNN, and the YOLO series. YOLOv8, the latest object detection model, has demonstrated significant improvements in both speed and accuracy. The network architecture of YOLOv8 primarily consists of three key components: the backbone, the neck, and the head[17]. This hierarchical design offers an efficient processing framework for object detection, with each component playing a specific role in the entire network. The structured design not only optimizes data flow through the network but also enhances processing speed and detection accuracy[18]. The detailed network architecture is illustrated in Fig 1.

The backbone serves as the core of the network, tasked with extracting fundamental features from images. It comprises modules such as SPPF, C2f, and Conv. The SPPF module stabilizes output size, enhancing the network's adaptability to varying input image dimensions. In the YOLO architecture, SPPF is employed to improve the feature extractor's scale invariance, effectively extracting richer contextual information and bolstering the model's capacity to detect objects at different scales. The C2f module facilitates the connection of features across varying levels, thereby aiding the model in differentiating objects of diverse scales during detection. Conv, a fundamental component in deep learning, processes input feature maps by applying filters to capture local features and generate new feature maps.

The neck, a critical component of the neural network architecture, is responsible for further processing and refining features to enhance the model's ability to recognize complex or small targets. It is designed to optimize the model's feature representation, making it more discriminative and robust for tackling various challenging object detection tasks.

Finally, the head's main task is to convert the processed and enhanced feature maps into final object detection results, such as the categories and positions of the targets.

YOLOv8, the latest version in the YOLO series, has seen significant improvements in multiple aspects. The main improvements include: 1) adopting Darknet-53 as the backbone network to leverage its depth and efficiency for feature extraction; 2) introducing a new Anchor-Free detection head, moving away from traditional anchor-based methods; 3) using VFL Loss as the classification loss and combining DFL Loss with CIOU Loss as the regression loss[19], wwhich enhances training stability and detection accuracy. YOLOv8 offers various models in different sizes, including YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, to meet the needs of different network depths and widths. Considering model size, this paper selects the YOLOv8n network, which is compact and highly accurate, making it more suitable for real-time PCB defect detection[20].

III. IMPROVED YOLOV8N ALGORITHM

Although the YOLOv8n model shows significant advantages in object detection, applying it to PCB surface defect detection presents several challenges. First, PCB images contain complex structures and abundant details, which may cause the model's performance to decline when detecting small-sized or low-contrast defects. Second, PCB surfaces contain a wide variety of defect types, requiring the model to have strong generalization capabilities to effectively detect different kinds of defects. However, the model is limited by the diversity and quantity of training data, which could lead to poor performance on unseen defect samples. Additionally, PCB surface defect detection demands strict requirements for both speed and accuracy, necessitating fast real-time detection while maintaining high precision. Therefore, despite the YOLOv8n model's excellent speed performance,

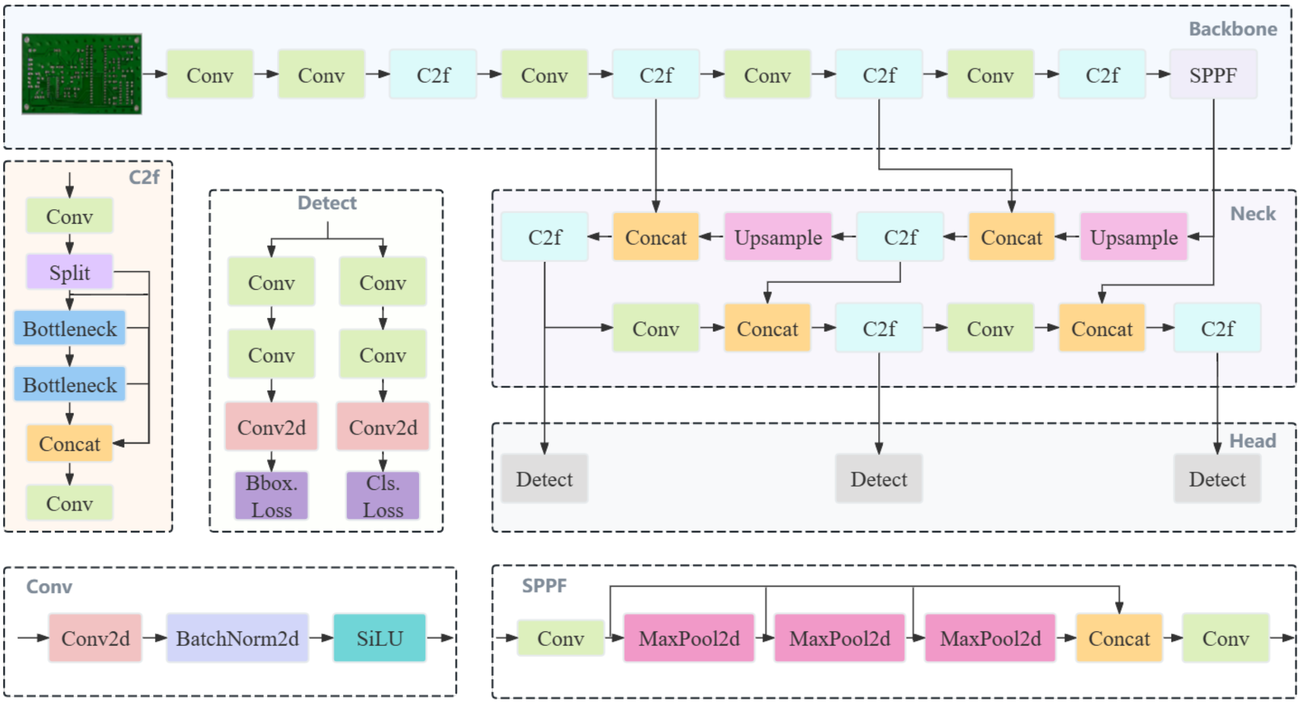


Fig. 1: YOLOv8n Model

further research and improvements are needed to address these challenges in practical applications.

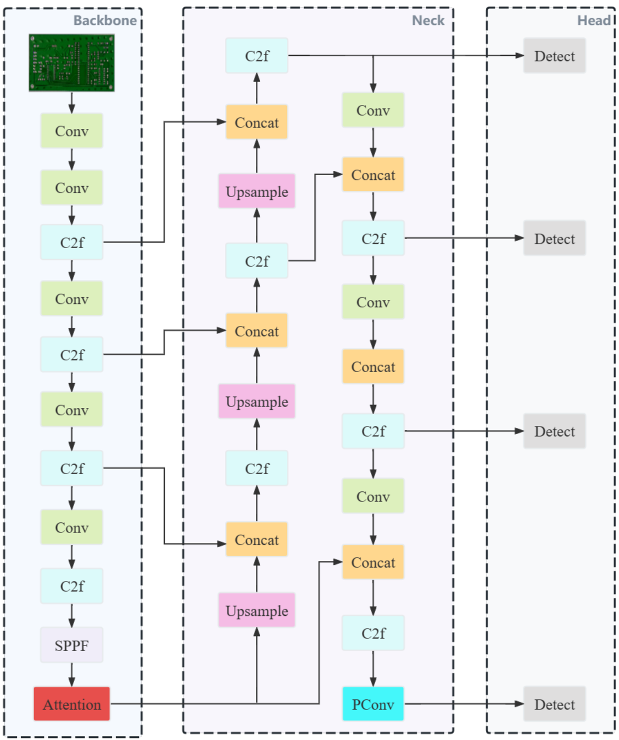


Fig. 2: Enhanced YOLOv8n Model

To address the aforementioned challenges, we propose three key improvements. First, to better handle defects of different sizes, we introduce an additional detection head in the detection component. This enables the model to extract features and detect defects across more scales, enhancing its ability to recognize small defects while ensuring accurate detection of larger ones[21]. Second, we introduce the SPPF (Spatial Pyramid Pooling-Fast) module, a critical component in YOLOv8 that enhances the model's ability to process features at various scales. By introducing the GAM (Global Attention Module) after the SPPF module, the model can effectively focus on crucial areas of the image, particularly those containing small defects, thereby improving detection accuracy and sensitivity[22]. Finally, considering the diverse morphologies of PCB defects, we insert PConv3 partial convolutional layers at the end of the neck network. PConv3 enhances the model's ability to handle irregular defects by providing more flexible convolutional kernel shapes and sizes, particularly for defects with unclear edges or complex morphologies, ensuring high-accuracy defect detection[23]. The specific improvements are illustrated in Fig2.

These customized improvements substantially enhance the performance of the YOLOv8n model in PCB defect detection, increasing its ability to recognize defects of various sizes and shapes while also boosting detection sensitivity and accuracy. Through these technological innovations, YOLOv8n is better equipped to meet the rigorous standards of industrial quality control, providing robust technical support for PCB production.

IV. Improvement Strategy

The method proposed in this paper is based on the YOLOv8 model and integrates the Global Attention Module (GAM) to enhance the model's capacity to learn specific defect features. GAM dynamically adjusts the importance distribution of feature maps, enabling the model to concentrate more on defect regions. The Partial Convolution Layer (PConv3) is specifically designed to address irregular defects in PCB images, effectively managing the details between defect edges and complex backgrounds. Additionally, we employ multiple detection heads to further enhance the accuracy and robustness of defect detection by identifying defects at various scales.

A. GAM Attention Mechanism

The Global Attention Module (GAM) enhances the performance of deep learning models by focusing on global information, particularly excelling in tasks that require emphasizing key feature areas[24]. The entire process is illustrated in Fig3, with Equation 1 and Equation 2 (Woo et al., 2018). Given an input feature map $F1 \in R^{C \times H \times W}$, the intermediate state $F2$and output $F3$ are defined as:

$$F2 = Mc(F1) \otimes F1 \tag{1}$$

$$F3 = Ms(F2) \otimes F2 \tag{2}$$

Here, Mc and Ms are the channel and spatial attention maps, respectively; $\otimes$ denotes element-wise multiplication.

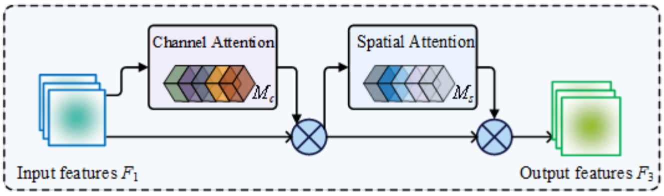


Fig. 3: The overview of GAM

Its basic working principle involves the following steps:

1) Global Context Extraction: Using Global Average Pooling (GAP) to extract global context information from the input feature map F. For each channel, GAP computes the average of values at all spatial positions, generating a global feature descriptor, G. Assuming the size of the input feature map F is CHW (where C is the number of channels, and H and W are the height and width, respectively), the operation of GAP can be represented as:

$$G_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} F_{cij} stateSpaceForm1 \tag{3}$$

Here, G_c is the global context feature of the c-th channel.

2) Attention Weight Generation: Transforming the global feature descriptor G into attention weights A by applying one or more fully connected layers (FC). This process may include activation functions, such as sigmoid, to ensure that the weight values fall between 0 and 1. LetW_g and b_g be the weights and biases of the fully connected layer, respectively; then the calculation of attention weights can be represented as:

$$A = \sigma \left(W_g \cdot G + b_g \right) \tag{4}$$

Here, σ is the sigmoid function, ensuring that the weight A_c of each channel is between 0 and 1.

3) Feature Re-weighting: Finally, the calculated attention weights A are applied to the original feature map F, weighted by element-wise multiplication, to obtain the final weighted feature map F':

$$F'_c = A_c \odot F_c \tag{5}$$

Here, $\odot$ represents the element-wise multiplication operation, and $F'_c$is the weighted feature map.

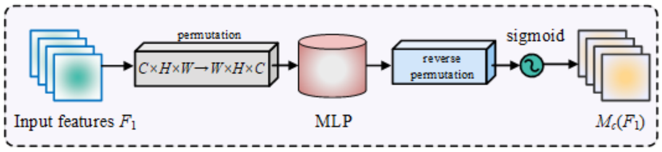


Fig. 4: Channel attention submodule

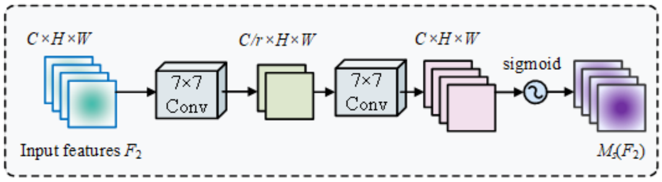


Fig. 5: Spatial attention submodule

In this paper, we enhanced the head network of the YOLOv8n model by integrating the Global Attention Module (GAM) after the SPPF module to improve its ability to detect small targets and establish relationships between these targets and the feature maps. By incorporating the GAM attention mechanism into the YOLOv8n model, we can more effectively capture the critical features of small targets and focus attention on regions essential for their detection and recognition. This approach enables more accurate identification of small targets, thereby improving both detection accuracy and recognition performance.

B. Partial Convolution Module 3 (PConv3)

The PConv3 (third-generation partial convolution module) represents a significant advancement in deep learning for local feature processing. Its core design principle is to utilize local convolution operations instead of traditional global convolutions to enhance the model's ability to capture subtle changes in images [25].

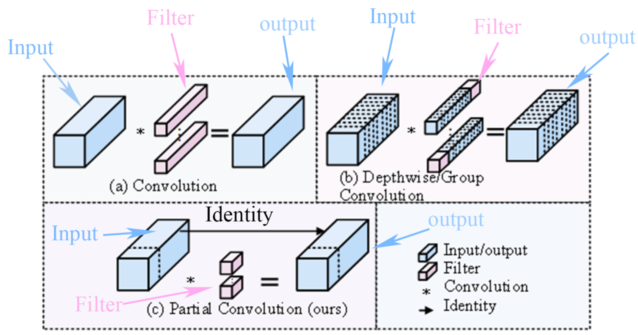


Fig. 6: Comparison of Convolution Techniques

As shown in the Fig6, PConv is fast and efficient, as it applies filters only to a few input channels while keeping the rest unchanged. In implementation, PConv3 customizes operations for each convolutional layer. Specifically, for the input feature map F, PConv3 first analyzes the features of each local region, then dynamically adjusts the convolutional kernel parameters W_{pconv} and bias b_{pconv} based on these features to adapt to the characteristics of that local region. This can be expressed by the following formula:

$$F' = W_{pconv}(F) + b_{pconv} \tag{6}$$

Where F' is the output feature map after processing by PConv3, and W_{pconv} and b_{pconv} are the dynamically adjusted convolutional kernel parameters and bias based on the input features. PConv3 precisely captures local details and features by dynamically adjusting the shape and size of the convolutional kernel according to the local properties of the input feature map, significantly enhancing the model's sensitivity and detection performance for subtle defects.

Additionally, the design of the Partial Convolution Layer (PConv3) emphasizes computational and memory efficiency, optimizing model performance when processing large-scale datasets. PConv3 represents a significant advancement in deep learning for local feature processing, as its local convolution mechanism enhances the model's efficiency and flexibility in capturing subtle variations in images. Particularly in applications such as PCB defect detection, which necessitate highly precise identification, PConv3 markedly improves the detection of subtle defects by dynamically adjusting the convolutional kernel. The implementation of this technology optimizes the model's consumption of computational resources while maintaining high-precision detection, offering an efficient solution for complex visual tasks. Specifically, the local convolution operation of PConv3 can be expressed by the following formula:

$$F' = PConv3(F) \tag{7}$$

Where F is the input feature map, and F' is the feature map after being processed by PConv3. PConv3 dynamically adjusts the parameters of the convolutional kernel based on the local information in F to process each local region in the most suitable way.

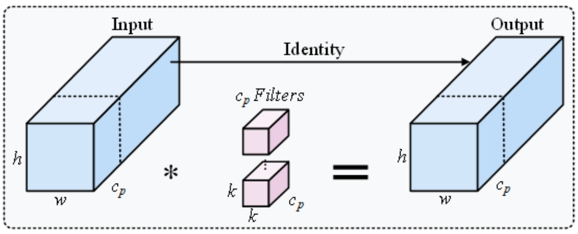


Fig. 7: Partial Convolution(PConv)

In this study, by introducing the PConv3 partial convolution into the neck network of the YOLOv8 model, we achieved efficient local convolution operations on the input feature map. This enhancement enables the model to more flexibly capture local details and features in PCB images, particularly tiny defects. PConv3 provides more sensitive and accurate detection capabilities. By introducing PConv3, the YOLOv8 model exhibits greater flexibility and accuracy in PCB defect detection tasks, particularly in identifying and locating tiny defects in images, significantly enhancing detection performance.

C. Addition of Detection Head

In PCB defect detection, the small-area characteristics of most defects pose a challenge, particularly because the large downsampling factor of YOLOv8 makes it difficult for deep feature maps to capture details of small targets. To address this issue, we innovatively added a high-resolution detection head to YOLOv8, specifically targeting small targets. By refining the downsampling strategy, the generated high-resolution feature map can reveal detailed information about small targets, significantly improving YOLOv8's performance in detecting small defects. Although this increases computational complexity and may affect inference speed, the improvement in detection accuracy confirms the value of this strategy, demonstrating a reasonable trade-off between accuracy and efficiency. Future work will explore algorithm optimization and hardware acceleration methods to enhance computational efficiency and ensure the feasibility of real-time detection.

V. Experimental Results and Analysis

In this chapter, we evaluate the performance of the enhanced YOLOv8n algorithm for PCB surface defect detection. First, we provide a detailed description of the dataset construction process and outline the experimental parameters and environment configurations. Subsequently, we conduct ablation experiments to verify the specific impact of improvements like the small object detection head, GAM attention mechanism, and PConv partial convolution on the algorithm's performance. Additionally, we perform comparative experiments to evaluate our model against several popular models currently available in the market, thereby obtaining comprehensive experimental results and evaluations.

A. Dataset Construction

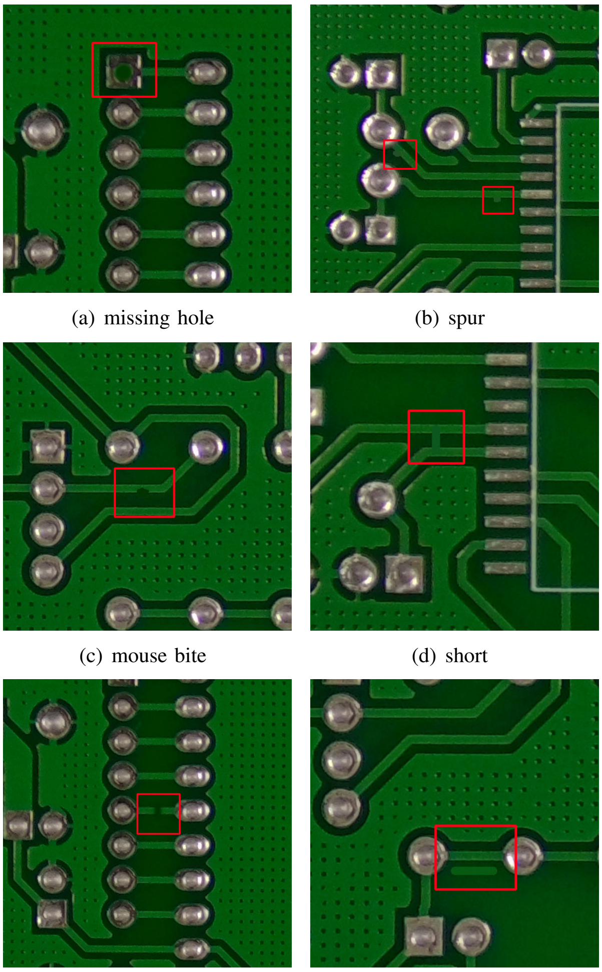
This study utilized the PKU-Market-PCB dataset released by Peking University's Intelligent Robotics Open Laboratory. The dataset comprises 693 high-quality images of printed circuit boards (PCBs) of various sizes, covering six common types of defects encountered in industrial production: missing holes, burrs, mouse bites, short circuits, open circuits, and excess copper. These six defect categories are depicted in the Fig8 below.

These defect categories are evenly distributed across the dataset, with each image containing approximately 1 to 5 defects, providing abundant examples for training deep learning models. Considering the scale of the dataset (only 693 images), directly training on these original images may be limited by insufficient data, which could make it difficult to achieve optimal performance. To address this issue, we employed a series of data augmentation techniques—such as cropping, translation, brightness adjustment, adding noise, rotation, and horizontal flipping—to systematically expand the dataset, enhancing the model's generalization capability and robustness. (Refer to Fig9).

B. Experimental Environment

The experimental environment of this study is shown in Table I.

During training, the dataset was automatically split into training, validation, and testing sets in an 8:2 ratio. The other hyperparameters used during training were set as follows: momentum was set to 0.937, lr0 (initial learning rate) was set to 0.01, lrf was set to 0.015, batch size was set to 16, the



(a) missing hole (b) spur (c) mouse bite (d) short (e) open circuit (f) spurious copper

Fig. 8: Types of PCB Defects

TABLE I:
Experimental Conditions and Environment

System	Windows11
CPU	12th Gen Intel(R) Core(TM) i5-12500H 2.50 GHz
GPU	Nvidia GeForce RTX 3090
Memory	16
Software Conditions	PyCharm
Python version	Python3.8
Deep learning framework	Pytorch

number of epochs was set to 200, and the standard image input size was set to 640×640.

C. Evaluation Metrics

In this study, we use mean Average Precision (mAP), Precision, and Recall as performance evaluation metrics. These metrics collectively provide a comprehensive perspective to quantify the model's performance on PCB surface defect detection tasks.

TP (True Positives): The number of instances correctly predicted as positive (i.e., defects present) by the model.

FP (False Positives): The number of instances incorrectly predicted as positive (actually negative, i.e., defects absent) by the model.

FN (False Negatives): The number of instances incorrectly predicted as negative (actually positive) by the model.

C (Total number of classes): The total number of different defect types in the dataset.

AP (Average Precision): Represents the average precision of the model's prediction results for a single class.

Precision and Recall are key metrics for measuring the model's performance, reflecting the accuracy and completeness of the model in identifying positive samples. Additionally, mAP provides an effective measure of the model's overall performance across all classes, calculated as the average of AP values for all classes. The formulas are as follows:

$$mAP = \frac{\sum_{i=1}^{C} AP_i}{C} \tag{8}$$

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

$$AP = \int_0^1 P(R)dr \tag{11}$$

D. Ablation Experiments

To validate the impact of adding the small target detection head, GAM attention mechanism, and PConv partial convolution on the algorithm, ablation experiments were designed. The data is shown in Table II, where "✓" indicates the corresponding improvement method and its experimental sequence.

In this study, we evaluated the performance of models under different configurations. Initially, we used a baseline model without any enhancements, achieved an accuracy of 93.7%, recall of 92.6%, and mAP of 93.0%. Subsequently, we progressively added different features and observed their impact on performance. When adding the small object detection layer alone, we observed a significant performance improvement, with accuracy increasing to 96.8%, recall to 92.3%, and mAP to 95.2%. Upon introducing the GAM, accuracy slightly decreased to 92.6%, but the recall increased to 94.9%, with an mAP of 94.1%. When PConv was introduced alone, accuracy slightly decreased to 93.7%, but the recall increased significantly to 96.4%, with an mAP of 92.9%. Without PConv, combining the small object detection layer with GAM yielded accuracy, recall, and mAP of 96.2%, 94.3%, and 96.0%, respectively. When both the small object detection layer and PConv were added, the configuration without GAM showed an accuracy of 95.9%, recall of 95.6%, and mAP of 95.4%. The configuration using only GAM and PConv without adding the small object detection layer, was slightly lower than the previous one, with accuracy of 94.6%, recall of 97.3%, and mAP of 95.2%. Finally, with all features added, the model performed optimally, an achieving accuracy of 96.3%, recall of 96.9%, and mAP of 96.6%. These experimental results are presented through clear graphical outputs, a facilitating comparative analysis of the specific impact of various configurations on model performance. (Refer to Fig10).

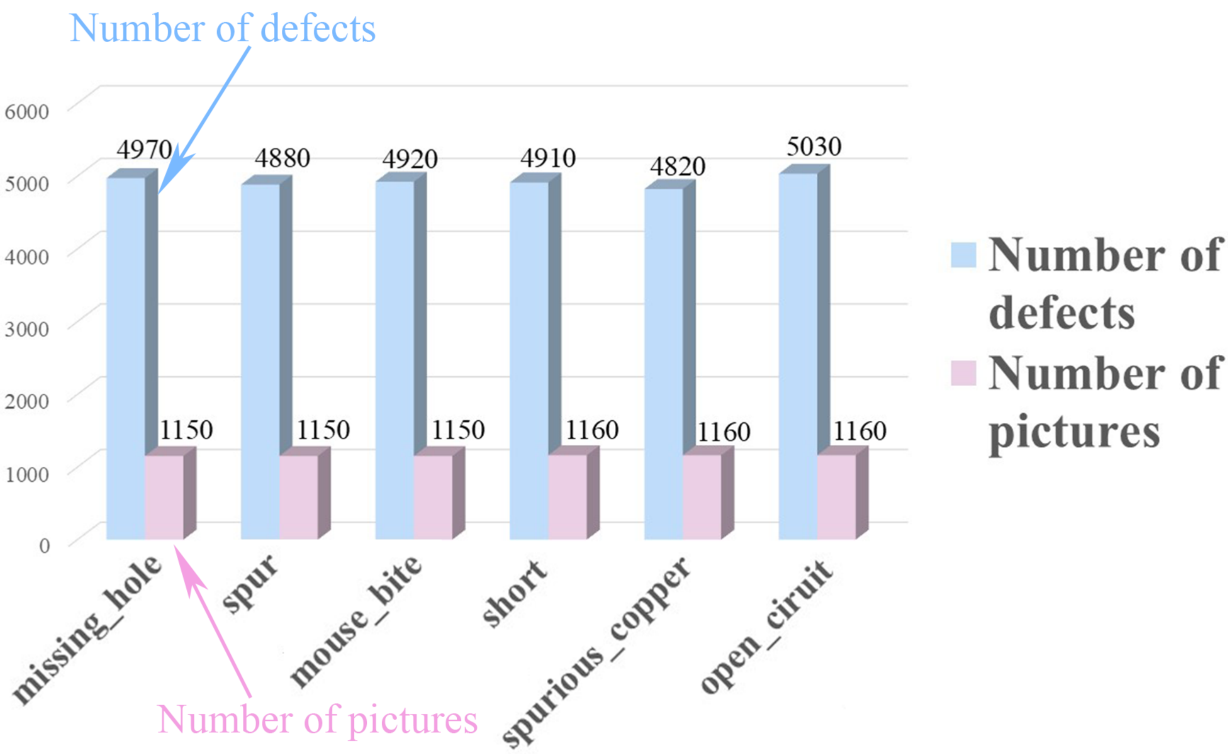


Fig. 9: Distribution of Defect Types in PCB Dataset

TABLE II:
Ablation Experiments

Number	a small goal detection layer	GAM	PConv3	Precision/%	Recall/%	mAP
1	×	×	×	93.7	92.6	93.0
2	✓	×	×	**96.8**	92.3	95.2
3	×	✓	×	92.6	94.9	94.1
4	×	×	✓	93.7	96.4	92.9
5	✓	×	✓	96.2	94.3	96.0
6	✓	✓	×	95.9	95.6	95.4
7	×	✓	✓	94.6	**97.3**	95.2
8	✓	✓	✓	96.3	96.9	**96.6**

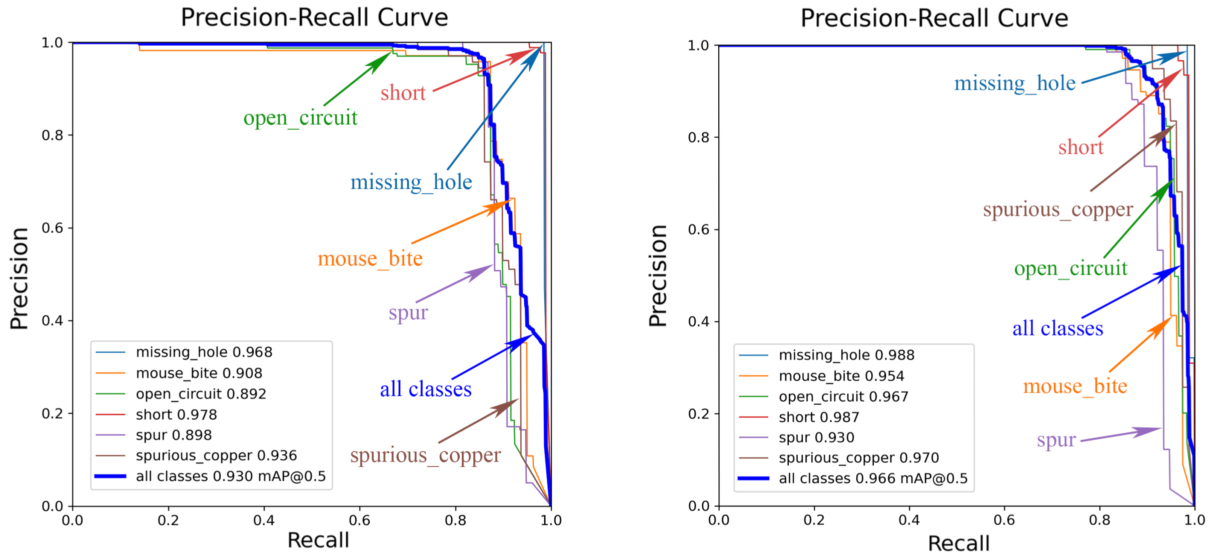
E. Comparative Experiments

In this study, we conducted several experiments comparing our proposed improved algorithm with widely recognized models in the field—YOLOv5, YOLOv7, Faster R-CNN, SSD, and RetinaNet—using a unified dataset and evaluation criteria for PCB surface defect detection tasks. The final results are shown in Table III below.

As seen from the table, the classical YOLOv3, YOLOv5, and Faster R-CNN do not perform well, and their accuracy is reduced, while the performance of other models improves to varying degrees. Our model surpassed other models in terms of the comprehensive performance evaluation metric, MAP, reaching 96.6%. Although our model exhibited slightly lower precision compared to YOLOv7 by 0.6%, and recall lower than RetinaNet by 0.8%, its overall performance remains

TABLE III:
Comparative Experiments

Model	Precision/%	Recall/%	mAP
YOLOv3	92.3	93.4	93.3
YOLOv5	93.5	94.8	94.6
YOLOv7	**96.9**	95.1	95.9
Faster R-CNN	91.5	93.9	93.7
SSD	92.8	95.5	95.4
RetinaNet	95.6	**97.7**	96.3
Ours	96.3	96.9	**96.6**



(a) P-R curve of the YOLOv8n algorithm

(b) P-R curve of the improved YOLOv8n algorithm

Fig. 10: A comparison of the P-R curves between the two models

highly satisfactory.

VI. Conclusion

This study developed an advanced PCB defect detection method based on the YOLOv8 model, effectively enhancing the accuracy and efficiency of the detection system by integrating GAM, PConv3, and multi-detection head strategies. Experiments conducted on the PKU-Market-PCB dataset, combined with extensive training and diverse data augmentation techniques, not only expanded the diversity and scale of the dataset but also significantly improved the model's performance. This method demonstrated outstanding performance in detecting various PCB defects, with precision reaching 96.3%, recall at 96.9%, and average precision (mAP) at 96.6%. These results demonstrate that the method meets the stringent requirements of the PCB manufacturing industry for high-precision and efficient defect detection, showcasing its potential value in industrial applications.

Despite achieving significant results, there are still some limitations in this research. The robustness of the current model under extreme conditions (such as very low contrast or complex backgrounds) needs improvement. Additionally, the model's performance can be further improved when dealing with extremely small or highly overlapping defects. Future research will focus on optimizing algorithms to enhance the model's adaptability and accuracy in various complex environments. Plans include introducing more advanced image processing techniques and deep learning algorithms, such as adaptive image enhancement and deep feature fusion, to further improve detection accuracy. Moreover, considering the significant impact of dataset diversity on model performance, future exploration will also involve augmenting the dataset through synthetic data and simulated defect generation to make training more comprehensive and effective.

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