An Efficient YOLO Model for PCB Defect Detection

Based on Multi Scale Attention

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Outline

- Introduction
- Method
- Implementation & Result
- Summary

Introduction

PCB Dataset & Defect

HRIPCB Dataset

Data

Contains 1,386 images. Each image has 3 to 5 randomly distributed defects of the same type.

Defection

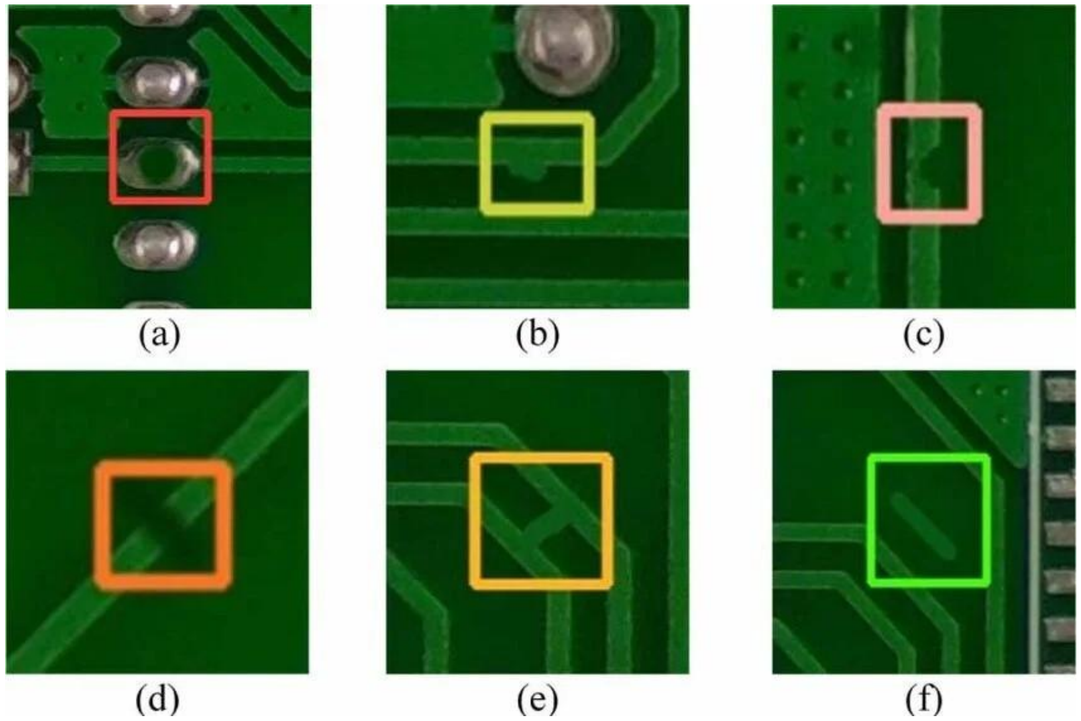
Identifies the 6 most common PCB defects:

1. Missing hole
2. Mouse bite
3. Open circuit
4. Short circuit
5. Spur
6. Spurious copper

PCB Defect

Introduction

PCB Dataset & Defect



(a) Missing hole. (b) Spur. (c) Mouse bite. (d) Open circuit. (e) Short. (f) Spurious copper.

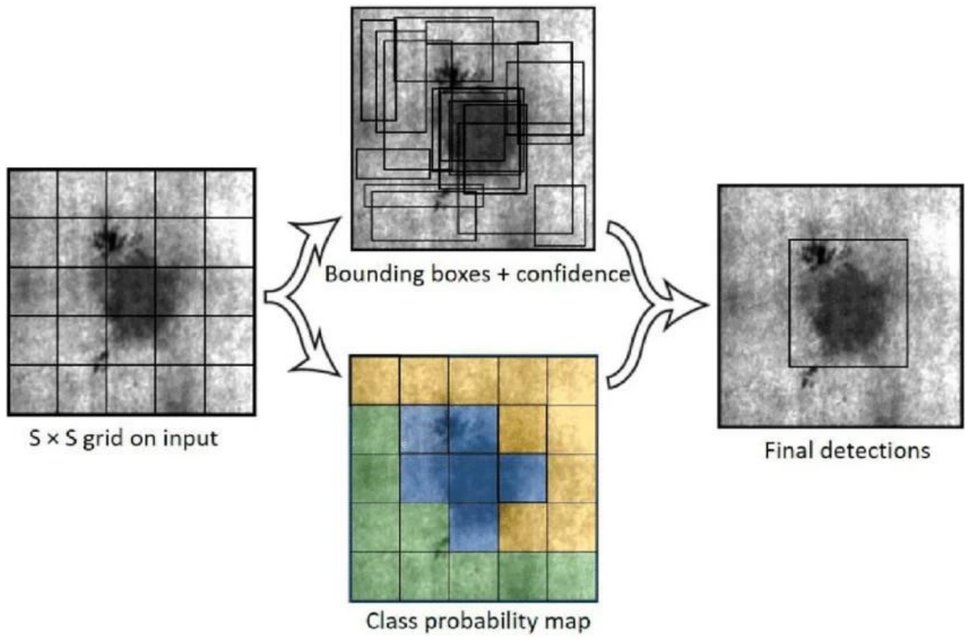
You Only Look Once (YOLO)

Introduction

YOLO Model Structure

Image Detection

YOLO divides the image into a grid and predicts bboxes and class probabilities.



YOLO Model Structure

Backbone (Feature Extraction)

1. Downsampling and convolution to increase semantic information.
2. Outputs multi-scale features for small, medium, and large objects.

Neck (Feature Fusion)

1. Upsampling and fuses information from different scales.
2. Combines high-level semantics with low-level details to strengthen multi-scale detection.

Head (Multi-task Output)

Detection: Bounding box locations and scores.
Segmentation: Pixel-level masks.
Classification: Category prediction.

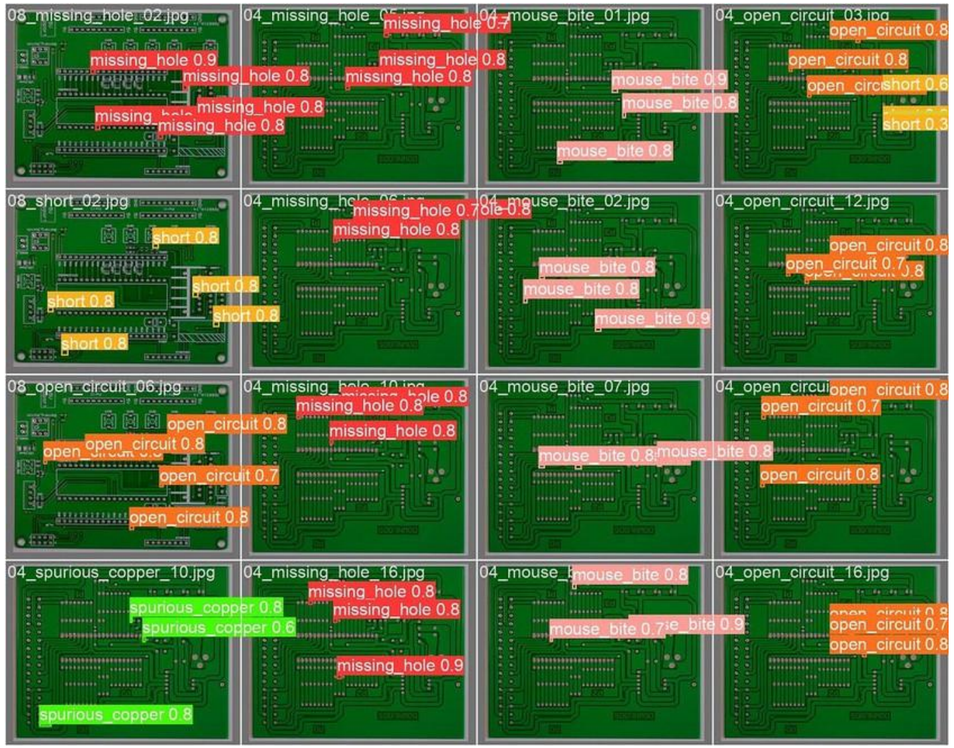
Introduction

YOLO Model Structure

Visualization

Introduction

YOLO Model Structure



Information

- Multi-class Detection

Challenge

Loss of Tiny Objects during Sampling

Defects like "mouse bites" or "spurs" often consist of only a few pixels, causing convolutional features to disappear during sampling.

Fixed Receptive Field

Standard convolutions calculate normal pixel signals equally, leading to weak defect signals being submerged.

Speed

Traditional attention mechanisms involve time-consuming pixel-by-pixel comparisons, which reduces the rapid detection speed required for industrial production lines.

YOLO with Multi-scale Attention

Method

Attention Mechanism

Multi-scale Attention

Adaptive receptive field to fuse multi-scale features.

Multi-head Self-attention

Self-attention mechanism to find correlation while maintaining efficiency.

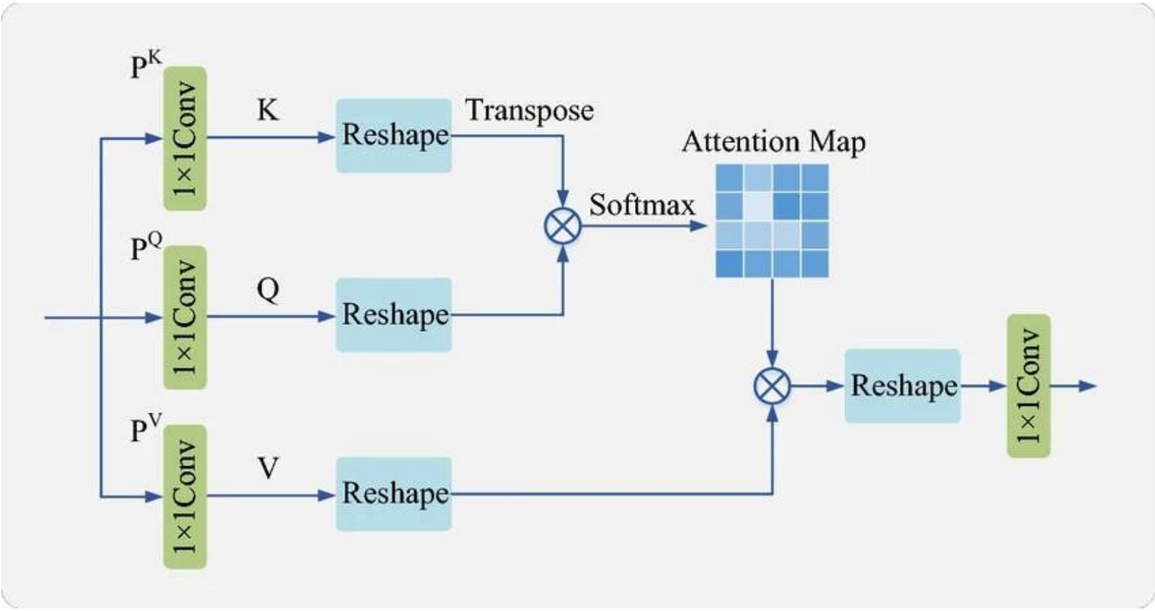
Multi-channel Attention

Concatenate avg pooling, max pooling, and conv pooling to keep features.

Multi-head Self-attention

Method

MHSA Mechanism



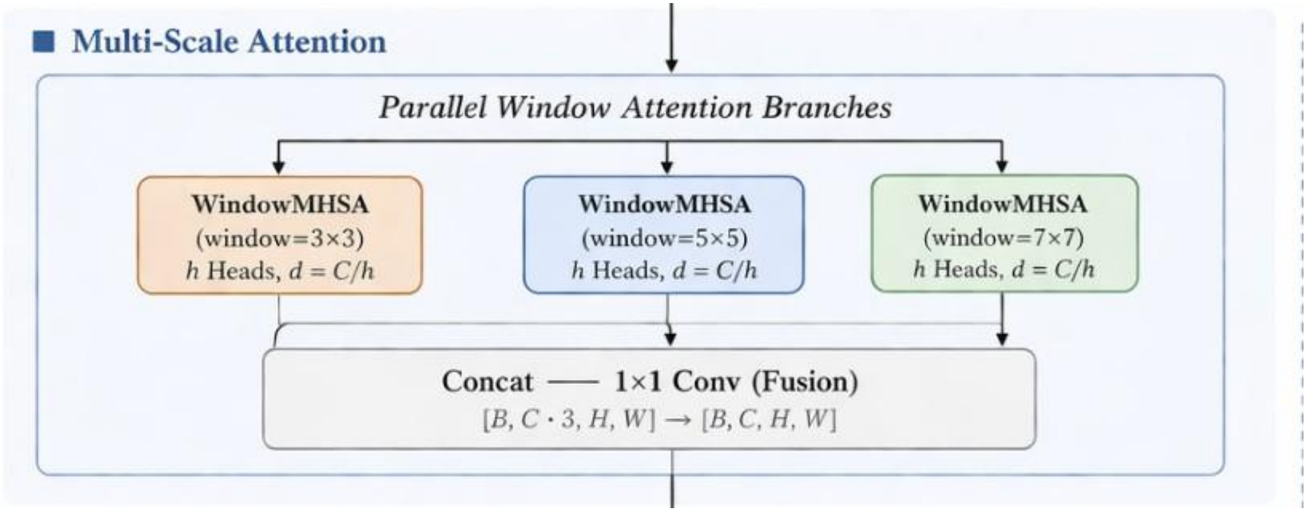
Key features

- Divides the image into multiple windows based on downsampling size.
- Performs Self-Attention within each window.
- Different windows operate independently, significantly reducing the amount of computation.

Multi-scale Attention

Method

MSA Mechanism



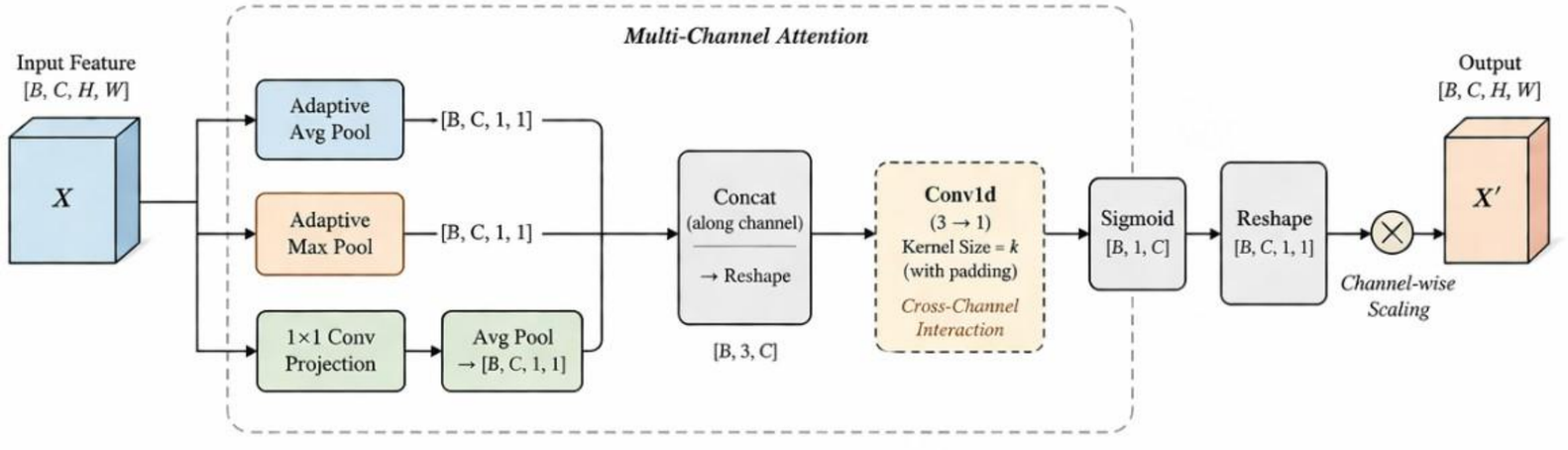
Key features

- 3 types of convolutions (3x3, 5x5, 7x7) to detect defect features of different sizes before fusing them.
- Mitigates the loss of shallow features caused by downsampling and convolution.

Multi-channel Attention

Method

MCA Mechanism



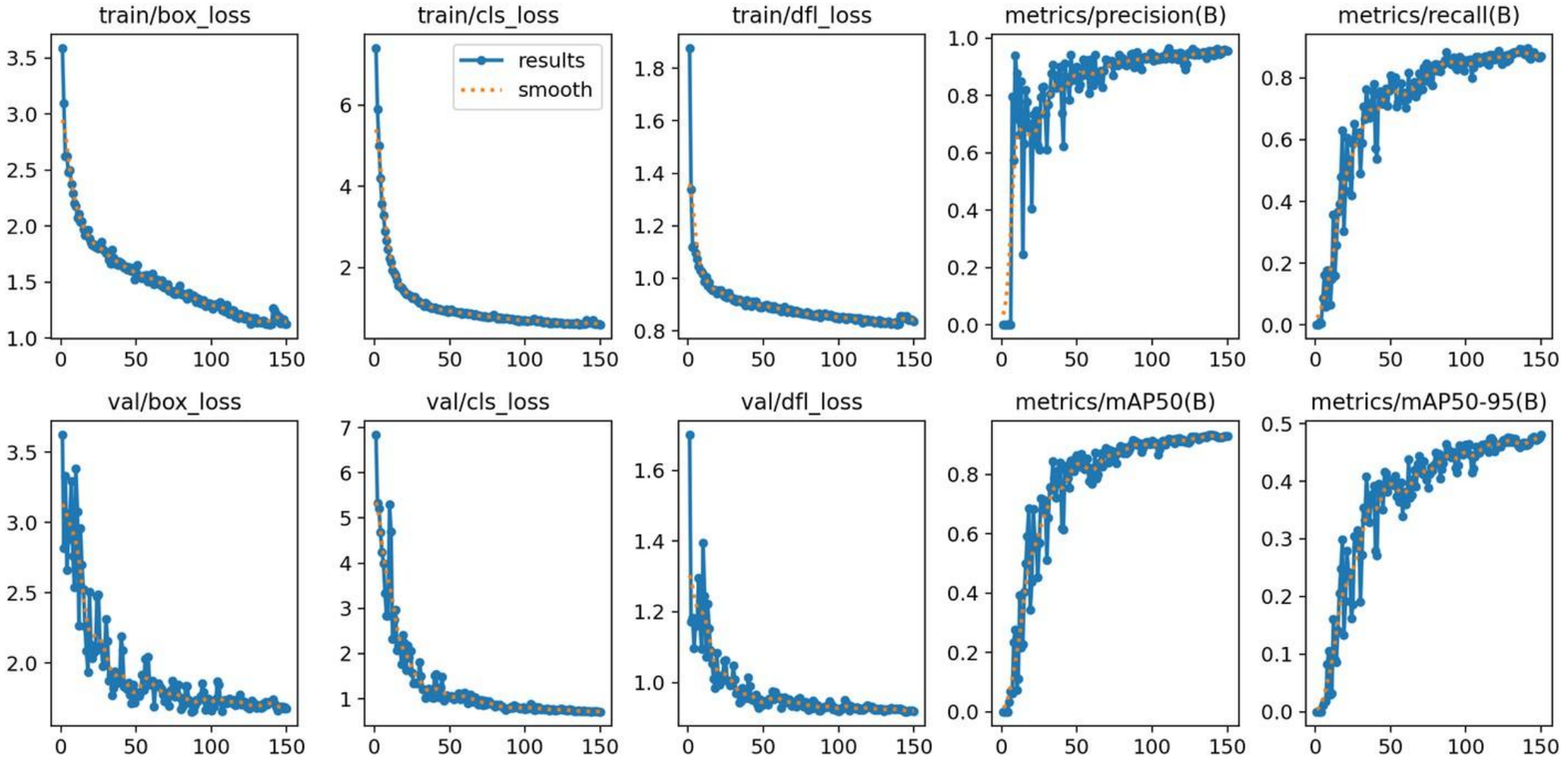
Key features

- Feature Extraction: Average, Maximum, and Convolutional Projection.
- Concatenate features to calculate final attention weights.
- Prevent feature degradation during upsampling process.

Overall Results

Result

Trained Model



mAP@0.5: 0.926

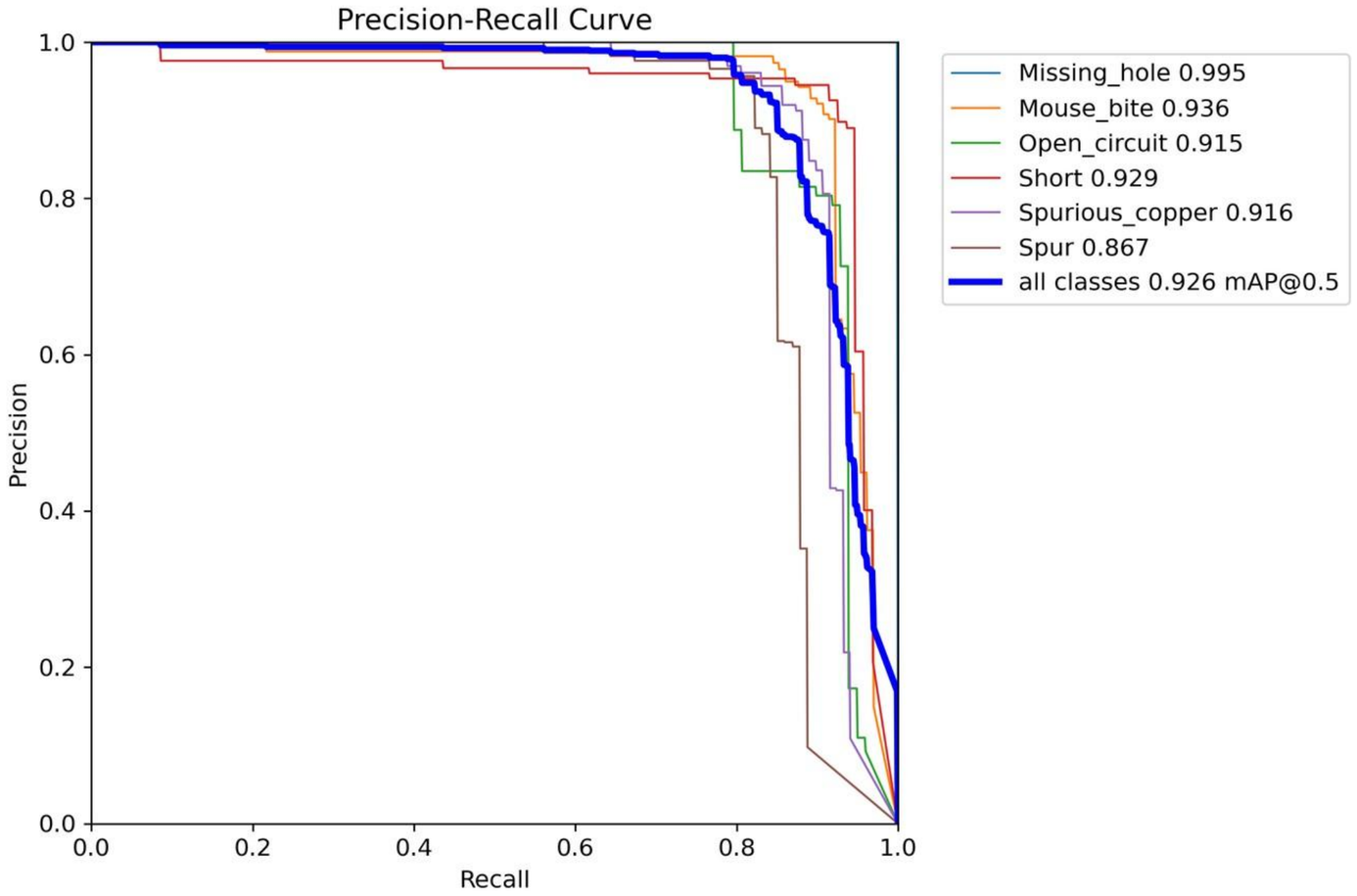
Precision: 0.937

Recall: 0.896

Significant Metrics

Result

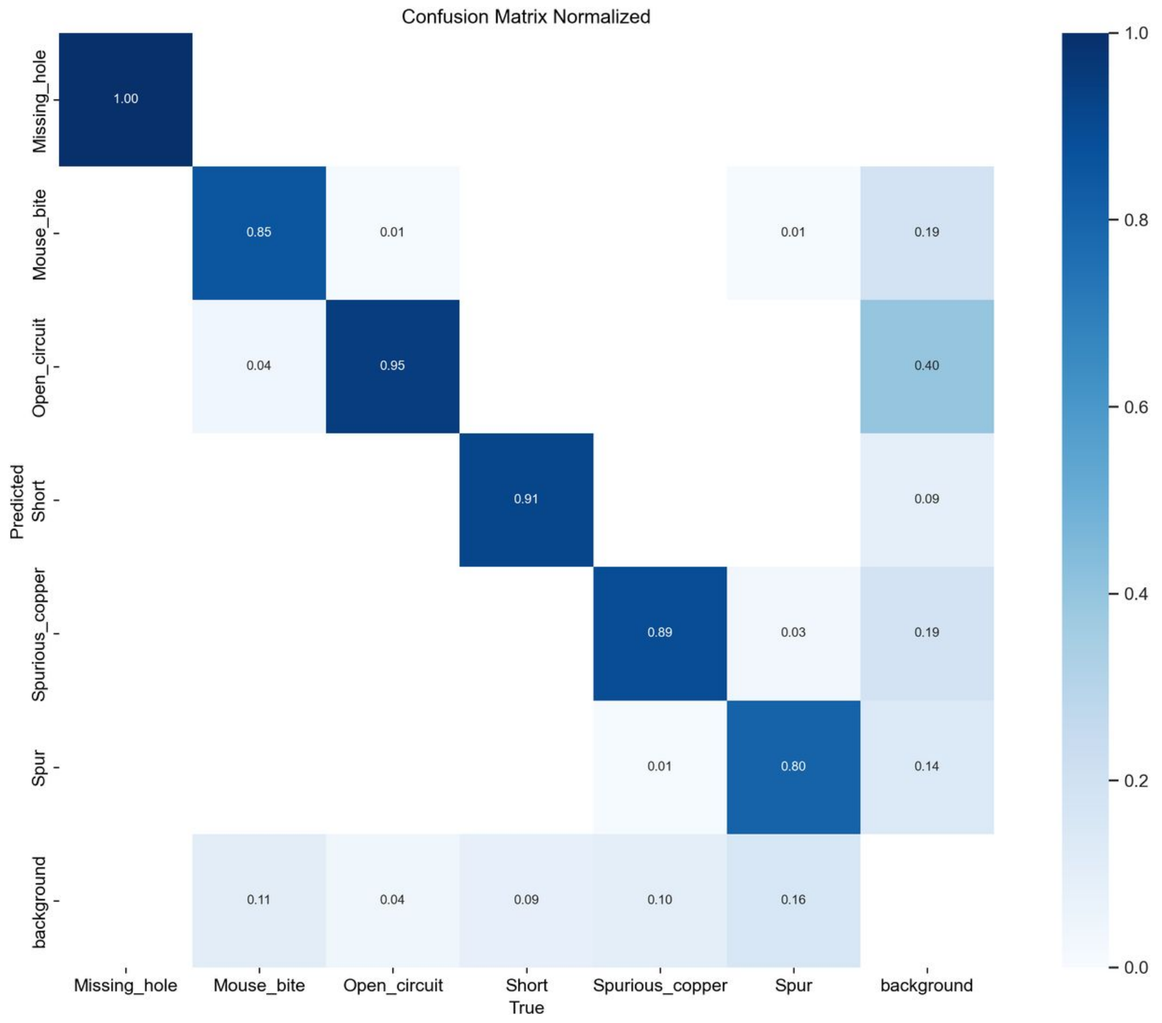
Trained Model



Significant Metrics

Result

Trained Model



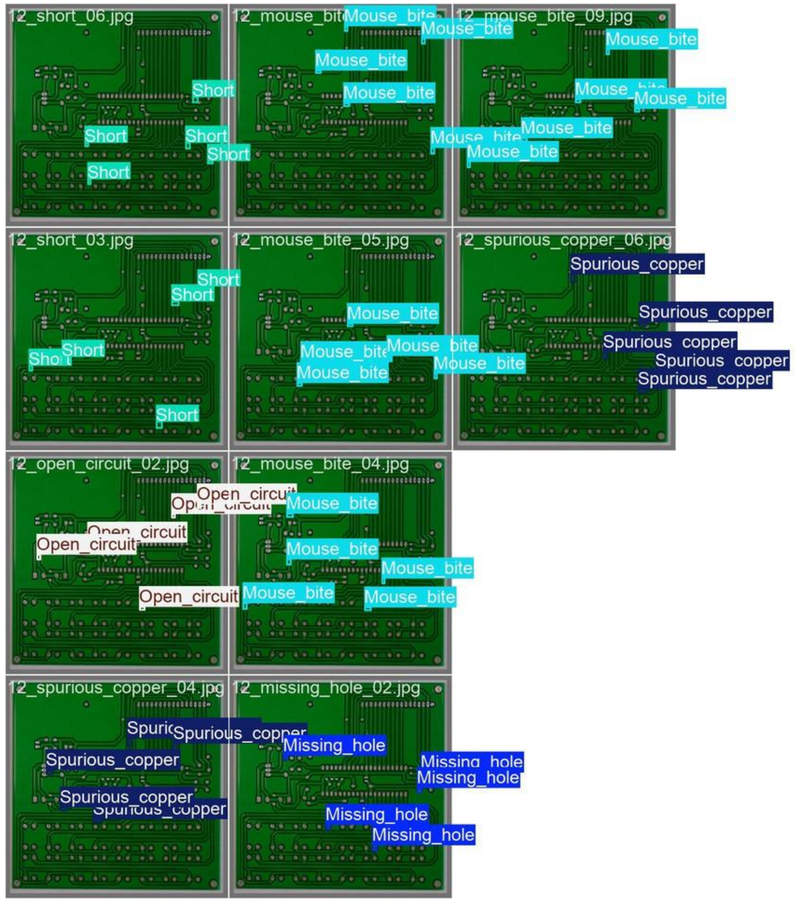
Row: Ground Truth
Col: Prediction

Visualization

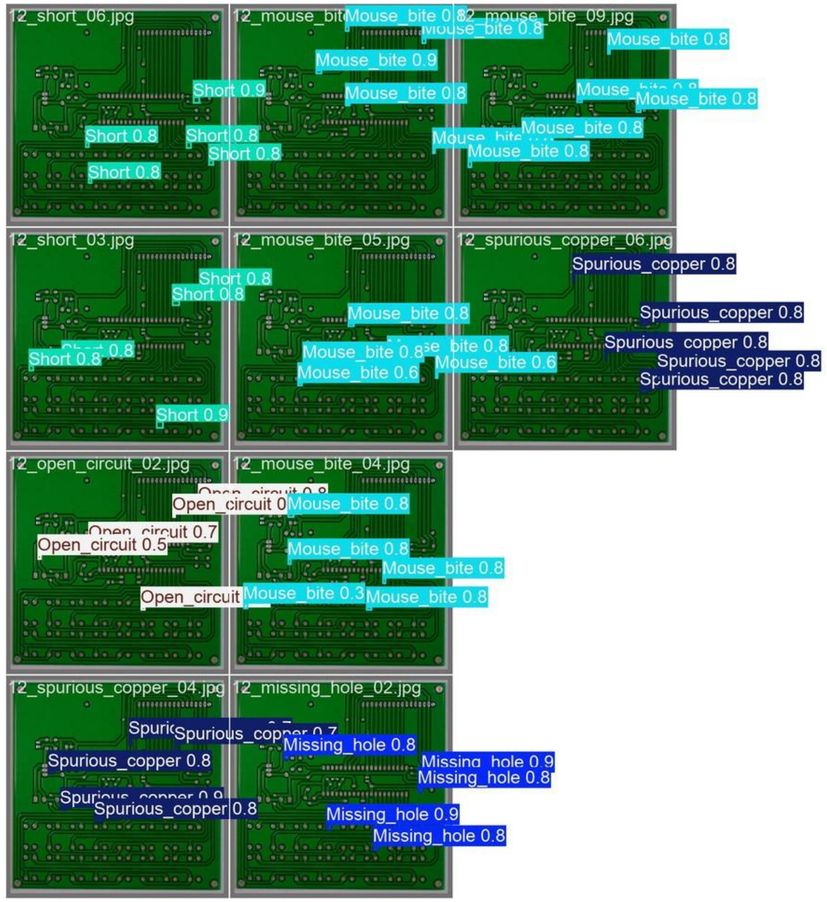
Implementation

Visualization

Ground Truth



Prediction



Summary

In the Final Exam

Summary

Method

- Multi-scale Attention
- Multi-head Self-attention
- Multi-channel Attention

Steps

- Multi-scale Attention for feature fusion.
- Multi-head Self-attention captures dependencies.
- Multi-channel Attention prevents feature loss.

Result

Defect detection model with high accuracy.