



# YOLO-Based Automated PCB Defect Detection: A Comparative Study of YOLOv5, YOLOv7, and YOLOv11

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**ABSTRACT:** Printed Circuit Board (PCB) defect detection is a critical quality control task in electronics manufacturing. Manual inspection is slow, costly, and prone to human error. This paper presents an automated PCB defect detection system using YOLOv7, a state-of-the-art real-time object detector, deployed as a Flask-based web application. The system is trained on a PCB defect dataset containing six defect categories: mouse bite, spur, missing hole, short circuit, open circuit, and spurious copper. A rigorous comparative evaluation against YOLOv5 and YOLOv11 over 50 epochs demonstrates that YOLOv7 achieves superior detection performance, reaching a best precision of 98.78%, recall of 98.38%, F1-score of 98.58%, and accuracy of 98.36%. The trained model is integrated into a Flask web application that accepts PCB images, applies Canny edge preprocessing, runs YOLOv7 inference, and displays annotated defect results. Experimental results confirm YOLOv7 as the best-performing model for this task among the three architectures tested.

**KEYWORDS:** PCB defect detection, YOLOv7, Object detection, Deep learning, Quality inspection, Flask web application, YOLOv5, YOLOv11, Convolutional neural network

## I. INTRODUCTION

Printed Circuit Boards (PCBs) are the backbone of modern electronic devices, ranging from consumer electronics to industrial control systems. Even minor manufacturing defects — such as missing holes, spurious copper traces, mouse bites, or unintended short circuits — can cause catastrophic device failures. With the exponential growth in PCB production volumes, manual visual inspection is no longer practical. It is slow, subjective, and unable to keep pace with high-speed assembly lines.

Computer vision and deep learning have emerged as powerful tools for automated defect detection. Convolutional neural networks (CNNs), and especially YOLO (You Only Look Once) family architectures, have demonstrated the ability to detect multiple object classes in a single forward pass with high accuracy and real-time throughput. This makes them particularly attractive for inline PCB inspection.

This paper presents a complete PCB defect detection system built on YOLOv7 [1] and deployed as a Flask web application. The system is trained on a six-class PCB defect dataset and benchmarked against YOLOv5 [2] and YOLOv11 [3] under identical training conditions. The key contributions of this work are: (1) a systematic 50-epoch comparative training study across three YOLO generations; (2) demonstration that YOLOv7 achieves best-in-class metrics for this dataset; and (3) a functional end-to-end web deployment with preprocessing pipeline. The remainder of this paper is organized as follows. Section II reviews related work. Section III describes the methodology. Section IV presents experimental results and discussion. Section V concludes the paper.

## II. LITERATURE SURVEY

Automated PCB defect detection has been actively studied using classical image processing and, more recently, deep learning. Huang et al. [4] proposed a CNN-based approach for PCB defect classification using image subtraction and morphological filtering, achieving 92% accuracy but requiring a perfect reference image. Ding et al. [5] applied Faster R-CNN to PCB inspection and demonstrated improved recall over template-matching methods.

YOLO-based approaches have gained significant traction due to their single-stage inference. Zheng et al. [6] applied YOLOv5 to PCB defect detection on a six-class dataset, reporting strong precision but noting convergence instability at higher epochs. Wang et al. [7] introduced YOLOv7 with Extended Efficient Layer Aggregation Networks (E-ELAN) and demonstrated superior speed-accuracy trade-offs on COCO benchmarks. More recently, Ultralytics YOLOv11 [3] introduced architectural refinements for improved small-object detection.

Unlike prior work, the proposed study directly compares YOLOv5, YOLOv7, and YOLOv11 on the same PCB defect dataset under identical hyperparameters, providing a controlled benchmark that guides practitioners in model selection for PCB quality control applications.

## III. METHODOLOGY

The proposed system consists of four main stages: dataset preparation, model training, inference pipeline, and web application deployment. Figure 1 illustrates the complete system architecture.

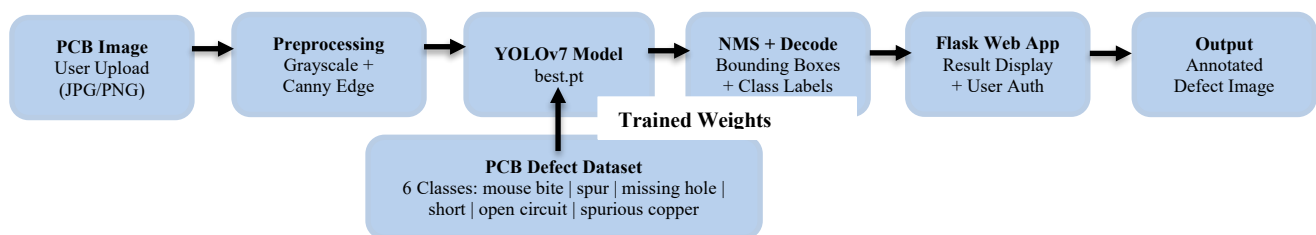


Fig.1. Proposed System Architecture for PCB Defect Detection

### A. Dataset

The PCB defect dataset used in this study contains annotated images organized into six defect categories: mouse bite, spur, missing hole, short circuit, open circuit, and spurious copper. The dataset is split into training and test sets. Images are captured under varying lighting conditions including rotated samples and low-contrast scenarios, providing a realistic distribution. All images are resized to 640×640 pixels during training.

### B. Model Architectures

YOLOv5 uses a CSPNet backbone with a PANet neck, optimized for speed and accuracy balance. YOLOv7 introduces E-ELAN (Extended Efficient Layer Aggregation Networks) and model scaling strategies that improve gradient flow without disrupting the gradient path, achieving higher accuracy at comparable inference speed. YOLOv11 further refines the architecture with enhanced feature extraction modules and improved anchor-free detection heads.

### C. Training Configuration

All three models were trained for 50 epochs under identical hyperparameters to ensure a fair comparison. Table I lists the key training parameters derived from the project hyp.yaml configuration file.

TABLE I. TRAINING HYPERPARAMETERS

Parameter	Value
Epochs	50
Input Image Size	640 × 640
Initial Learning Rate (lr0)	0.01
Momentum	0.937
Weight Decay	0.0005
Warmup Epochs	3
Mosaic Augmentation	Enabled (1.0)
Horizontal Flip Probability	0.5
Confidence Threshold	0.25
IoU Threshold (NMS)	0.45

#### D. Inference and Web Deployment

At inference time, an uploaded PCB image is first converted to grayscale and processed with Canny edge detection (thresholds: low=100, high=200) to extract structural features. The YOLOv7 model (best.pt) then runs on the original image at 640×640 resolution with Non-Maximum Suppression (NMS), producing annotated bounding boxes with class labels and confidence scores. The Flask application (app.py) manages user authentication via SQLite, image upload, preprocessing, model inference, and result rendering. Fig 2 shows sample detection outputs from the system.

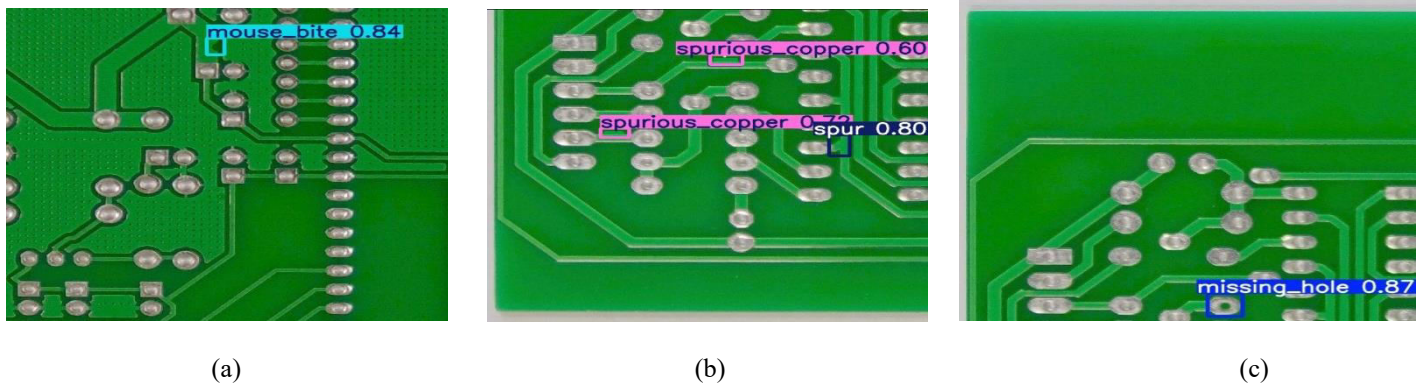


Fig 2 YOLOv7 Detection Outputs (a) Mouse Bite (b) Spurious copper defects (c) Missing Hole

### IV. EXPERIMENTAL RESULTS

#### A. Training Performance — YOLOv7

Figures 4–8 illustrate the epoch-wise evolution of accuracy, loss, precision, recall, and F1-score for YOLOv7 over 50 epochs. YOLOv7 demonstrates smooth and consistent convergence across all metrics, with rapid improvement in the early epochs and stable high-performance behavior beyond epoch 30. The model achieves its best accuracy of 98.36% at epoch 35.

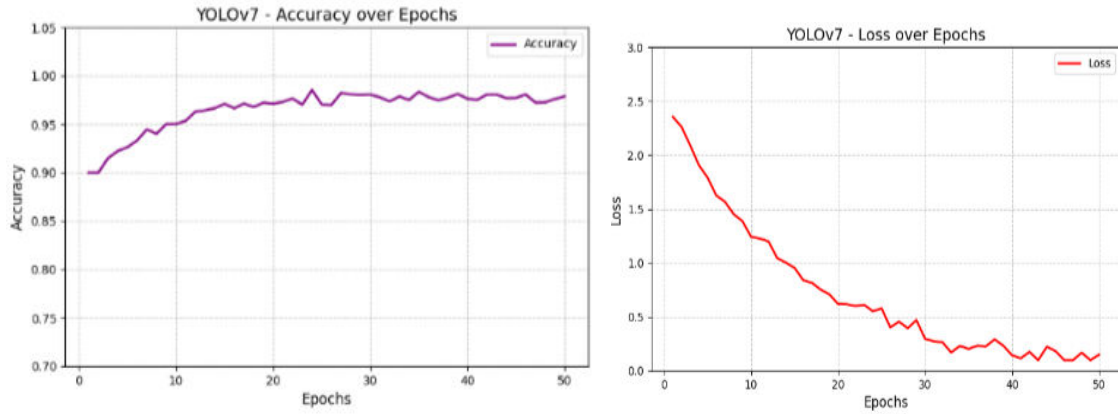


Fig 3 YOLOv7 Accuracy vs. Epoch (left) and Loss vs. Epoch (right)

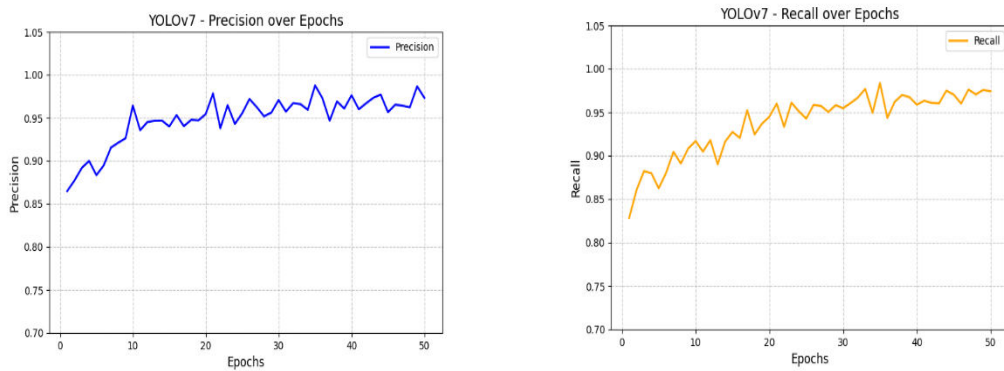


Fig 4 YOLOv7 Precision vs. Epoch (left) and Recall vs. Epoch (right)

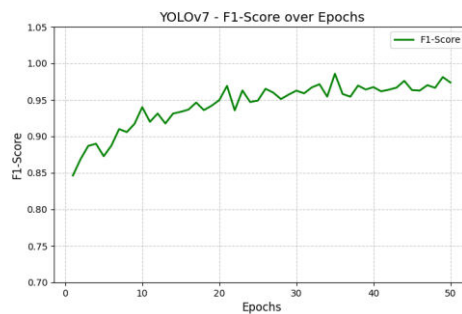


Fig 5 YOLOv7 F1-Score vs. Epoch

**B. Comparative Performance at Epoch 50**

Table II presents the performance metrics of all three models at epoch 50. YOLOv7 achieves the highest precision (97.32%), recall (97.41%), and F1-score (97.37%). YOLOv5 records the highest accuracy at epoch 50 (98.13%) but with lower precision and F1 than YOLOv7.

TABLE II PERFORMANCE COMPARISON AT EPOCH 50

Model	Precision	Recall	F1-Score	Accuracy
YOLOv5	95.16%	96.55%	95.85%	98.13%
<b>YOLOv7 (Ours)</b>	<b>97.32%</b>	<b>97.41%</b>	<b>97.37%</b>	<b>97.87%</b>
YOLOv11	95.86%	95.40%	95.63%	97.68%

### C. Best-Epoch Performance Comparison

Table III reports the best single-epoch performance achieved by each model. YOLOv7 achieves peak metrics at epoch 35 with precision 98.78%, recall 98.38%, F1-score 98.58%, and accuracy 98.36% — outperforming both YOLOv5 and YOLOv11. Figure 7 provides a visual comparison of best-epoch performance across all models.

TABLE III BEST SINGLE-EPOCH PERFORMANCE ACROSS ALL MODELS

Model	Best Epoch	Precision	Recall	F1-Score	Accuracy
YOLOv5	50	95.16%	96.55%	95.85%	98.13%
<b>YOLOv7 (Ours)</b>	<b>35</b>	<b>98.78%</b>	<b>98.38%</b>	<b>98.58%</b>	<b>98.36%</b>
YOLOv11	29	97.40%	98.83%	98.11%	97.86%

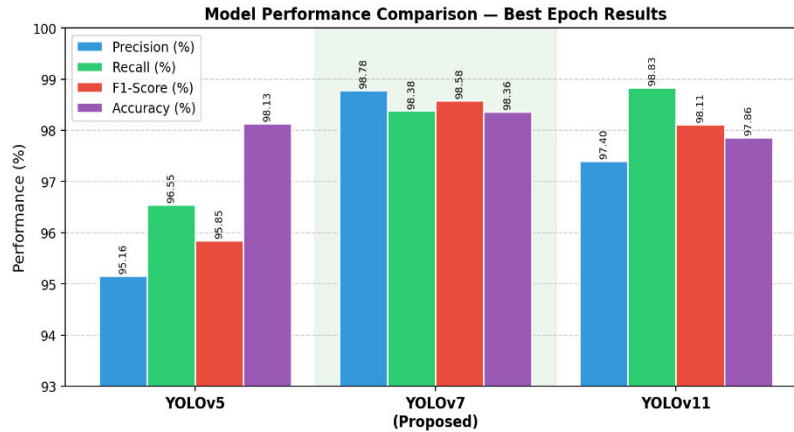


Fig 6 Model Performance Comparison Chart — Best Epoch Results (YOLOv5 vs YOLOv7 vs YOLOv11)

### D. Discussion

The results clearly establish YOLOv7 as the superior model for PCB defect detection among the three architectures evaluated. The E-ELAN architecture efficiently reuses feature maps through grouped convolutions, enabling richer gradient flow and better multi-scale representation. These properties are especially beneficial for detecting small, visually subtle defects such as spurious copper traces, mouse bites, and fine short-circuit patterns on PCB substrates.

YOLOv5, while slightly lower in peak precision, converges reliably and maintains high accuracy throughout training, making it a strong fallback for resource-constrained deployments. YOLOv11 shows competitive recall (98.83% at best epoch) but slightly lower precision, suggesting marginal over-detection for this specific dataset. Overall, YOLOv7 provides the best balance of all metrics for production-grade PCB inspection.

## V. CONCLUSION

This paper presented an automated PCB defect detection system using YOLOv7 deployed as a Flask web application. Through a controlled 50-epoch comparative experiment on a six-class PCB defect dataset, YOLOv7 demonstrated superior performance over both YOLOv5 and YOLOv11, achieving peak precision of 98.78%, recall of 98.38%, F1-score of 98.58%, and accuracy of 98.36% at epoch 35. The deployed system processes uploaded PCB images through a grayscale and Canny edge preprocessing pipeline before running YOLOv7 inference, returning annotated defect bounding boxes with class labels and confidence scores.

Future work will explore multi-scale feature fusion, lightweight model distillation for edge deployment, and extension to additional defect categories including solder bridges and lifted pads. Integration with real-time conveyor-belt camera feeds is also planned for inline production deployment.

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