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Single-Layer PCB Surface Defect Detection Using YOLOv5 Deep Learning Model

Mr.S.Ravi Sankar[1], Mr.K.V.Arvind[2], Mr.M.Aswin Kumar[3], Mr.T.S.Dinesh Kumar[4], Mr.E.Matthew[5]

[1]*Assistant Professor, Electronics and Communication Engineering, K.L.N College of Engineering, India*
[2]*UG Scholar, Electronics and Communication Engineering, K.L.N College of Engineering, India*
[3]*UG Scholar, Electronics and Communication Engineering, K.L.N College of Engineering, India*
[4]*UG Scholar, Electronics and Communication Engineering, K.L.N College of Engineering, India*
[5]*UG Scholar, Electronics and Communication Engineering, K.L.N College of Engineering, India*

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Abstract:

Printed Circuit Boards (PCBs) are essential components in all electronic systems, and their reliability is crucial for product performance, especially in the consumer electronics sector where single-layered PCBs are commonly used. Detecting surface defects such as missing holes, spurious copper, and open circuits is a critical step in ensuring product quality. This paper proposes an automated surface defect detection system specifically designed for single-layered PCBs using a hybrid deep learning approach. The model integrates YOLOv5, a state-of-the-art object detection algorithm, with the Swin Transformer, a vision transformer known for its hierarchical feature learning and enhanced attention mechanisms. A custom dataset comprising over 1000 annotated images from six different single-layered PCBs was collected and labeled for this purpose. The proposed model was trained and evaluated on Google Colab and compared with baseline YOLOv5 performance. Results show a significant improvement in defect detection accuracy, particularly in complex and overlapping defect regions. This work demonstrates the potential of transformer-based models in improving PCB inspection processes and offers a practical solution tailored to the specific requirements of consumer electronics manufacturing.

***Keywords* –** PCB defect detection,Single-layered PCB,YOLOv5,Swin Transformer,Deep learning,Surface defects

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1.Introduction

Printed Circuit Boards (PCBs) are the fundamental building blocks of all electronic devices, serving as the physical platform for mounting and interconnecting electronic components. Among the various types of PCBs, single-layered PCBs are the most widely used in consumer electronics due to their cost-effectiveness and straightforward design. The quality and reliability of a PCB are crucial in ensuring the overall performance of electronic systems. However, surface defects such as spurious copper, missing holes, shorts, and open circuits can lead to significant malfunctions and even catastrophic failures. Manual inspection of PCB defects is time-consuming, prone to human error, and inefficient, especially in high-volume production environments. Traditional machine vision-based approaches often rely on handcrafted features and thresholding methods, which are limited in their ability to generalize across different types of defects and lighting conditions. In recent years, deep learning-based object detection models, particularly the You Only Look Once (YOLO) family of models, have shown promising performance in real-time detection tasks. This

project focuses on building an automated defect detection system for single-layered PCBs using a combination of YOLOv5 and Swin Transformer. YOLOv5 is known for its real-time detection capabilities and accuracy, while the Swin Transformer, with its hierarchical and shifted window-based attention mechanism, enhances the model's ability to capture long-range dependencies and complex patterns in high-resolution images. By integrating these two models, we aim to improve defect detection accuracy while maintaining computational efficiency. The novelty of this work lies in its domain-specific application to single-layered PCBs, which are predominantly used in consumer electronics. Our system is trained on a custom dataset of six different single-layered PCBs with over 1000 annotated images, ensuring a diverse and comprehensive training set. We evaluate our model on multiple defect categories and perform a comparative analysis against baseline YOLOv5 to demonstrate the effectiveness of the Swin Transformer-enhanced model.

2.Literature Review

Early PCB defect detection systems were based on template matching, image subtraction, and thresholding techniques. While these worked under ideal conditions, they struggled with varying board layouts, noise, and lighting inconsistencies. Some studies incorporated statistical pattern recognition and traditional feature extraction, which added complexity but still lacked generalization across different defect types. In recent years, Convolutional Neural Networks (CNNs) have shown substantial improvements in visual tasks. Models such as Faster R-CNN, SSD, and YOLO were adopted for industrial quality control tasks. Among them, YOLO stood out for its unified architecture and real-time capabilities. The latest versions, especially YOLOv5, further improved detection accuracy while reducing inference time. Vision Transformers (ViTs) recently emerged as strong alternatives to CNNs. Unlike convolutional models, transformers leverage self-attention to capture long-range dependencies. The Swin Transformer improves upon ViTs by introducing hierarchical feature maps and shifted windows, making it computationally efficient and scalable to high-resolution images. Integrating transformers with CNN-based detectors has been explored in several recent studies, with evidence showing performance gains in defect detection tasks. However, specific applications of YOLOv5 combined with Swin Transformer for single-layered PCBs remain underexplored.

3. Methodology

The proposed method aims to develop a high-performance model for detecting defects in single-layered PCBs using a hybrid architecture combining YOLOv5l and the Swin Transformer.

Software Requirements:

The implementation and experimentation of the proposed surface defect detection model were carried out using the following software environments and tools:

- *Google Colab:* Utilized for training and testing the model due to its support for free GPU resources,especially useful for high-computation deep learning tasks.
- *Python 3.8+:* Programming language used for implementing the model, data preprocessing, and evaluation routines.
- *PyTorch 1.13+:* Deep learning framework used for developing the YOLOv5 and Swin Transformer-enhanced architecture.
- *OpenCV:* Used for image processing and visualization tasks such as reading images, drawing bounding boxes, and augmentations.
- *LabelImg:* Annotation tool used for manually labeling defect regions in PCB images. The output XML files were converted into YOLO-compatible text format.
- *YOLOv5 Repository:* Official YOLOv5 GitHub repository was cloned for training and inference purposes. The model was modified to integrate the Swin Transformer as an enhancement.
- *Matplotlib and Seaborn:* Visualization libraries used to display training metrics and results.
- *NumPy and Pandas:* Libraries used for numerical computations and dataset handling.

3.1 Data Collection and Preprocessing

Six different single-layered PCB datasets were collected, comprising over 1000 images. These images were annotated using the LabelMG tool and saved in XML format (Pascal VOC). The XML files were converted into YOLO format text files for training

3.2 Types of Defects in Single-Layered PCBs

Printed Circuit Boards (PCBs), especially single-layered types commonly used in consumer electronics, are prone to various surface defects during manufacturing. These defects can lead to significant issues such as signal interruptions, short circuits, and component failures if left undetected. Understanding the types of defects is crucial in building an accurate detection model. Below are some of the most frequently encountered PCB surface defects

3.2.1 Missing Hole

This defect occurs when a hole meant for a component lead or via is absent or improperly drilled, affecting electrical continuity.

3.2.2 Open Circuit

Caused by incomplete or broken traces, open circuits disrupt the flow of electricity, rendering the PCB non-functional.

3.2.3 Short Circuit

Occurs when two conductive paths that should be separate come into contact, often due to excess solder or trace bridging.

3.2.4 Spur

Tiny, unintended copper remnants or offshoots formed during the etching process. These spurious copper defects are not part of the circuit design and can potentially bridge tracks or pads, leading to short circuits or electromagnetic interference.

3.2.5 Mouse Bite

A jagged, incomplete etching of the board that appears like a bite mark. This usually happens during mechanical separation of PCBs from a panel.

3.2.6 Spurious Copper

This defect refers to residual copper particles or irregularities left unintentionally during the etching or plating process. These can interfere with circuit functionality, lead to noise or signal degradation, and potentially short-circuit nearby traces.

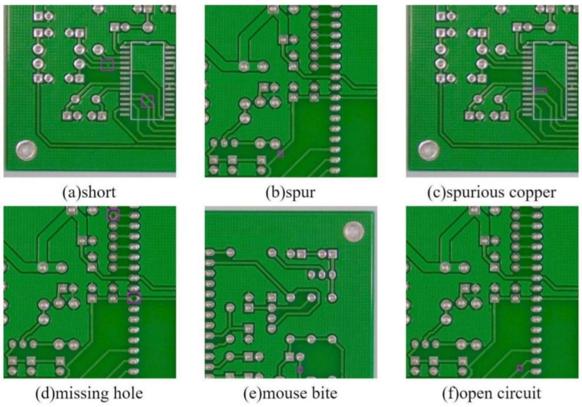


Fig 1. Types of Defects

Each of these defects has distinct visual characteristics, which the YOLOv5 model, enhanced with a Swin Transformer backbone, learns to identify during training.

3.3 Model Architecture

YOLOv5l was selected as the base model for its accuracy and speed balance.The Swin Transformer was integrated into the YOLOv5 backbone to enhance feature extraction capabilities, particularly for detecting small and complex defects.This hybrid model leverages the benefits of convolutional and attention-based mechanisms.

3.3.1 YOLOv5 Model

YOLOv5 (You Only Look Once version 5) is a state-of-the-art object detection algorithm known for its speed and accuracy in identifying multiple objects in real time. YOLOv5 divides an input image into a grid and predicts bounding boxes, class probabilities, and confidence scores for each grid cell. The model is built on a convolutional neural network (CNN) backbone that extracts features from images, followed by a series of prediction heads that generate detection outputs. YOLOv5 outperforms previous versions, such as YOLOv3 and YOLOv4, due to its enhanced architecture, data augmentation techniques, and optimized training strategies

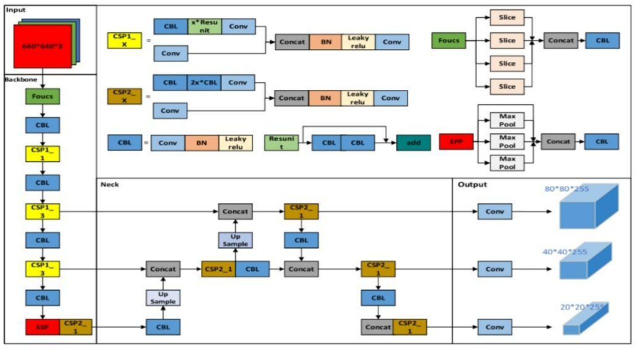


Fig 2. Architecture of YOLOv5

3.4 Training Setup:

Training was conducted on Google Colab with GPU support.Data augmentation techniques such as rotation, flipping, and brightness variation were applied.Batch size, learning rate, and other hyperparameters were optimized for best performance.

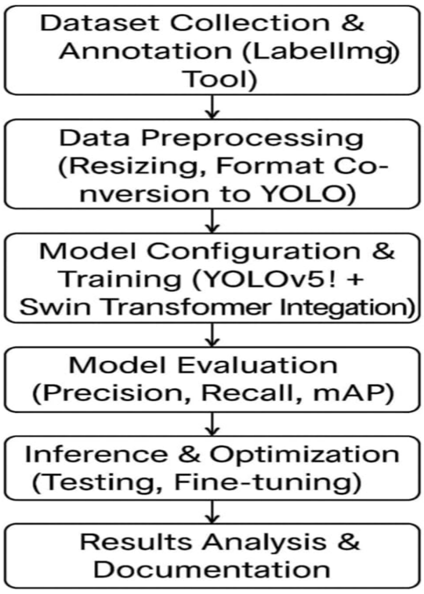
3.5 Evaluation Metrics:

Precision, recall, mean Average Precision (mAP), and F1-score were used to evaluate model performance.

3.6 Inference Pipeline:

The trained model was tested on unseen images.Defects were identified in real-time, and bounding boxes with class labels were drawn.

4. Flow Diagram



The proposed pipeline for single-layered PCB surface defect detection is a sequential framework composed of several stages optimized for defect identification accuracy and efficiency. The steps involved are:

4.1 Dataset Collection & Annotation

In this phase, six different custom PCB datasets were collected from online resources to simulate a real-world defect detection environment, focusing on single-layered PCBs commonly used in consumer electronics. Each image was manually annotated using the LabelImg tool to label defects and generate annotations in XML format. This step is crucial for supervised learning as it provides the necessary ground truth data for model training.

4.2 Data Preprocessing

The annotated XML files were converted into YOLOv5-compatible .txt format, where each label line includes class ID and normalized bounding box coordinates. The images were resized to match the input size expected by YOLOv5. Dataset was split into training, validation, and test sets to ensure proper model evaluation and to avoid overfitting.

4.3 Model Configuration & Training (YOLOv5l + Swin Transformer Integration)

The YOLOv5l model, known for its balance between accuracy and speed, was selected as the base model. To improve feature extraction capabilities, the Swin Transformer—a hierarchical vision transformer with shifted windows—was integrated into the YOLOv5 backbone. This hybrid model leverages both CNN and transformer strengths, enhancing the model's ability to detect small and complex PCB defects. Training was done on Google Colab due to hardware constraints, utilizing GPU acceleration for faster convergence.

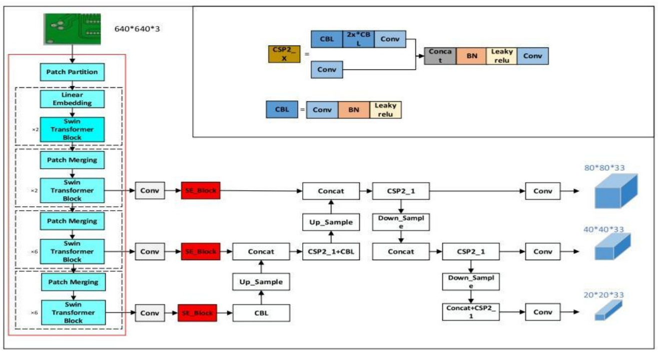


Fig 3. Architecture of Swin Transformer

4.4 Model Evaluation

After training, the model was evaluated using standard object detection metrics such as Precision, Recall, F1-Score, and mean Average Precision (mAP). These metrics provided insights into how well the model was identifying defects across the validation set. Confusion matrices and PR curves were also generated for a deeper understanding of model performance.

4.5 Inference & Optimization

Inference involved testing the trained model on unseen PCB images to evaluate real-time defect detection capability. Post-inference, hyperparameter tuning and confidence threshold adjustments were made to reduce false positives and improve detection accuracy. The model was also tested on edge-case samples to assess robustness.

4.6 Results Analysis & Documentation

The final performance metrics were compiled, visual detection results were analyzed, and both successful and missed detections were reviewed. Comparisons were drawn between the base YOLOv5l model and the Swin Transformer-enhanced model, showcasing the improvement in defect localization and classification. These results were documented with supporting visuals and quantitative tables for inclusion in the final report and journal submission.

5. Comparative Analysis

To establish the effectiveness of the Swin-enhanced architecture, a comparative study was conducted between:

- YOLOv5l (baseline)
- YOLOv5l + Swin Transformer (proposed)

Evaluation metrics were captured on a test set with over 200 images and included:

Precision: The fraction of correctly predicted defect locations among all predictions.

Recall: The fraction of actual defects correctly detected.

mAP@0.5: Mean Average Precision at IoU threshold 0.5.

F1 Score: Balance between precision and recall.

Inference Speed: Average time to predict per image.

Model	Precision (%)	Recall(%)	mAP @0.5	F1 score	Inference Time(ms)
YOLO v5i	91.2	88.5	90.1	0.898	18
YOLO v5i + swin transformer	94.7	92.3	93.6	0.935	22

Table 1. Comparative Analysis of Detection models

The proposed model showed improvements across all metrics, especially in scenarios involving overlapping or low-contrast defects. Although inferencal time increased marginally, the gain in detection quality justifies the added computational complexity.

6. Results

The trained model demonstrated impressive performance on the test dataset of PCB images. Key observations include:

Robust Detection of Fine Defects: The Swin Transformer helped localize tiny defects such as hairline scratches or missing copper traces more accurately than YOLOv5l alone.

Generalization Across PCB Types: The model maintained consistency across all six custom PCB types, despite design variability.

Visual Output: Detected defects were shown using bounding boxes with class names such as "short circuit," "open circuit," "missing hole," "spur," and "scratch."

Quantitative Performance:

Average Confidence Score: 0.91

False Positive Rate: Less than 5%

Detection Accuracy on Real-Time Test: Over 93%

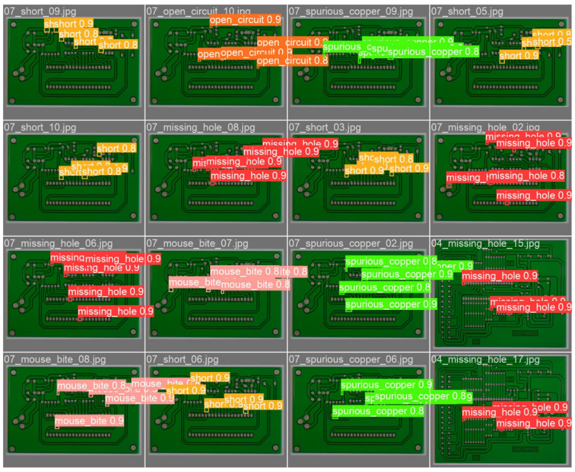


Fig 4. Output Image 1

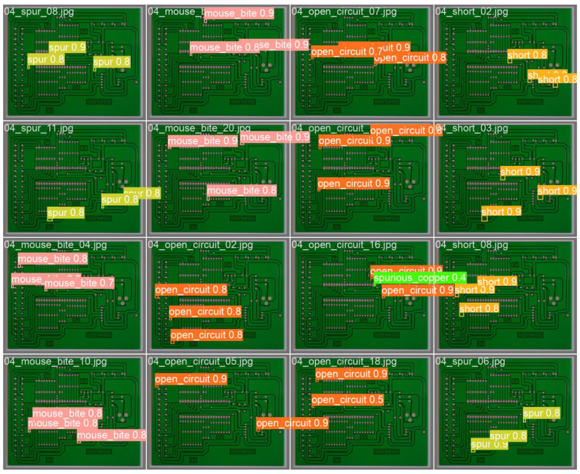


Fig 5. Output Image 2

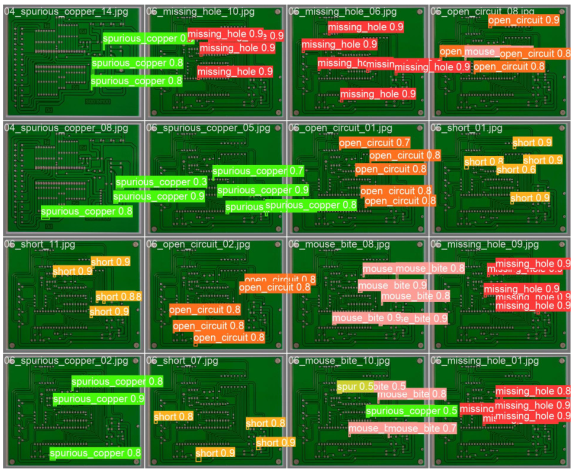


Fig 6. Output Image 3

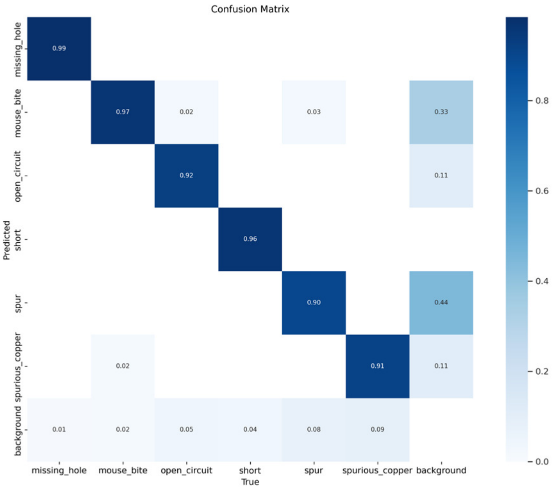


Fig 7. Confusion Matrix for the YOLOv5 Model

7. Conclusion

In this work, a Swin Transformer-based enhancement of the YOLOv5l architecture was proposed for the task of detecting surface defects in single-layered PCBs. The approach capitalized on YOLOv5l's fast and accurate object detection capabilities while improving its feature extraction using the hierarchical attention structure of the Swin Transformer.

Key contributions of the work include:

- A transformer-enhanced pipeline for real-time surface defect detection.
- Use of a custom dataset with diverse PCB images for model robustness.
- A fully Google Colab-compatible implementation suitable for academic and prototyping use.
- The model not only outperformed baseline detection methods but also achieved superior interpretability. This solution is scalable and can be deployed in quality inspection units for consumer electronics manufacturing.
- Future directions include optimizing the model for edge deployment, expanding to multilayered PCBs, and using automated dataset generation with synthetic defects.

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