Defect Identification System Using Deep Neural Network for PCB Boards

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Abstract - Automatic Optical Inspection (AOI) systems are critical for boosting PCB production yield, but they frequently create high false alarm rates, necessitating costly manual inspections at Verification and Repair System (VRS) stations. To overcome this issue, we present an Automatic Defect Verification System (Auto-VRS) that uses Deep Neural Networks (DNNs) to accurately classify defects. Auto-VRS classifies PCB images as defective or non-defective and detects particular flaws such as short circuits, open circuits, and other irregularities. The system has a simple Graphical User Interface (GUI) that allows users to upload PCB images, preprocess data, classify problems, and view findings. Real-time flaw identification, defect region highlighting, and feedback on classification accuracy are among the key features.

Key Words: PCB defect detection, deep neural networks, automatic defect verification, image classification, AOI system, machine vision, real-time inspection.

1. INTRODUCTION

The foundation of contemporary electronic gadgets are printed circuit boards (PCBs), which offer a small and effective way to connect electrical components. Depending on complexity and performance needs, PCBs can be single-layer, double-layer, or multi-layer boards, and each is appropriate for a particular application. However, flaws in PCB manufacture are common and can affect dependability and functionality. Short circuits, open circuits, missing parts, solder bridge flaws, and misalignment problems are examples of common PCB errors. Early detection and correction of these flaws is essential for preserving product quality and cutting production costs.

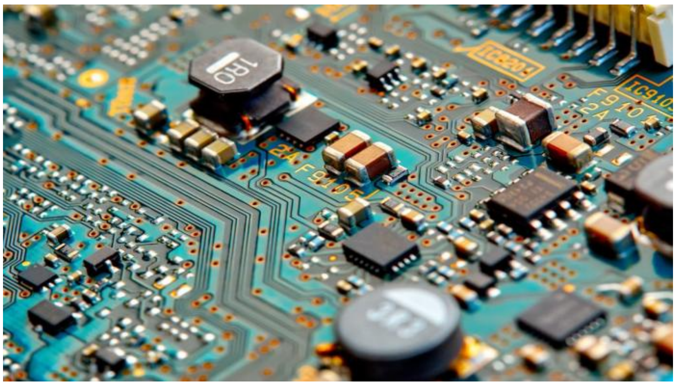

Fig 1. PCB Board

A printed circuit board (PCB) is built up from several distinct levels, each with a unique role in how signals and power move through the board. These levels commonly consist of a foundation material, conductive copper tracks, a protective insulating layer, and printed component labels. To handle intricate circuits, PCBs can include extra internal layers, which help with fast data transfer and reduce unwanted electrical noise. Knowing how these layers are put together is crucial for correctly examining and finding problems.

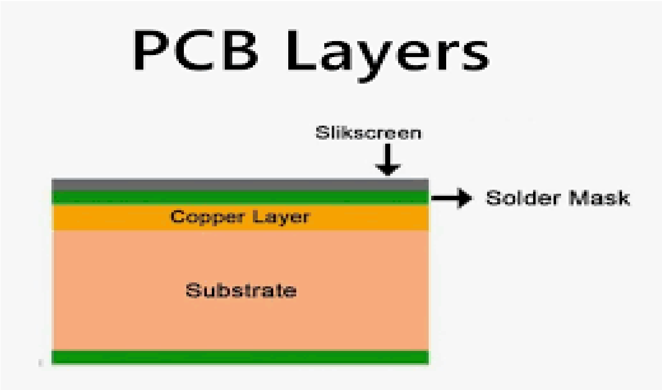

Fig 2. PCB Layers

To develop an accurate defect identification system, we utilized the PCB Defects Dataset from Kaggle. This dataset contains labeled images of defective and non-defective PCBs, covering various defect types. The dataset enables training deep neural networks for automated defect classification, reducing dependency on manual inspection and improving defect detection accuracy.

2. REVIEW OF RELATED STUDIES

Several deep learning models have been developed for PCB defect detection to enhance accuracy and efficiency. One widely used approach is Faster R-CNN (Region-based Convolutional Neural Network), which provides high precision in defect localization by using a two-stage detection process. This model is effective for identifying small and complex PCB defects but is computationally expensive. Another promising model is Vision Transformers (ViTs), which leverage self-attention mechanisms to capture long-range dependencies in PCB images, improving classification robustness. Additionally, Convolutional Neural Networks (CNNs) have been extensively used for PCB inspection, where architectures such as ResNet and EfficientNet provide strong feature extraction capabilities for defect classification.

Even with their effectiveness, current systems have drawbacks. Faster R-CNN, though precise, demands significant computing resources, hindering its use for immediate detection. Vision Transformers (ViTs) need vast amounts of data and powerful hardware, which can be problematic in actual use. Standard Convolutional Neural Networks (CNNs) have trouble adapting when defects differ greatly in size, shape, and lighting. Also, many existing systems depend on large collections of labeled data, which are often scarce, resulting in less-than-ideal performance in real-world scenarios.

Our Automatic Defect Verification System (Auto-VRS) uses YOLOv8, a cutting-edge object detection model that strikes a compromise between speed and accuracy for real-time defect detection, to overcome these difficulties. In contrast to earlier iterations, YOLOv8 incorporates enhanced feature extraction, adaptive learning processes, and sophisticated anchor-free detection, which makes it incredibly effective in detecting PCB flaws of various complexity. For effective model building, we start with dataset gathering and preprocessing, then train YOLOv8 on Google Colab. With the use of the Graphical User Interface (GUI) in the suggested system, users may easily upload, examine, and display defect detection data. Auto-VRS increases problem identification, decreases human inspection labor, and boosts overall PCB production productivity by utilizing YOLOv8's outstanding performance.

3. APPROACH

To identify defects, the process starts by gathering, labeling, and arranging data. The image collection comes from Kaggle's PCB Defect Dataset, which includes images with annotations in XML. These XML annotations are changed to TXT format for use with YOLOv8. Next, the dataset is meticulously marked with six defect types: mouse bite, missing hole, open circuit, short circuit, spur, and spurious copper, guaranteeing accurate defect categorization. The dataset comprises 2,459 images, which are split into 70% for model training, 20% for performance validation, and 10% for final testing. This organized structure ensures the model is thoroughly trained, optimized, and properly assessed on new, unseen data.

To improve model robustness, data augmentation techniques such as normalization, flipping, rotation, and contrast adjustment are applied. These transformations help the model generalize better, making it resilient to variations in defect size, shape, and lighting conditions. Once the dataset is processed, the YOLOv8 model is trained in Google Colab, utilizing pretrained weights to accelerate the learning process. The model is optimized using adaptive learning techniques, ensuring it effectively learns the unique patterns of PCB defects.

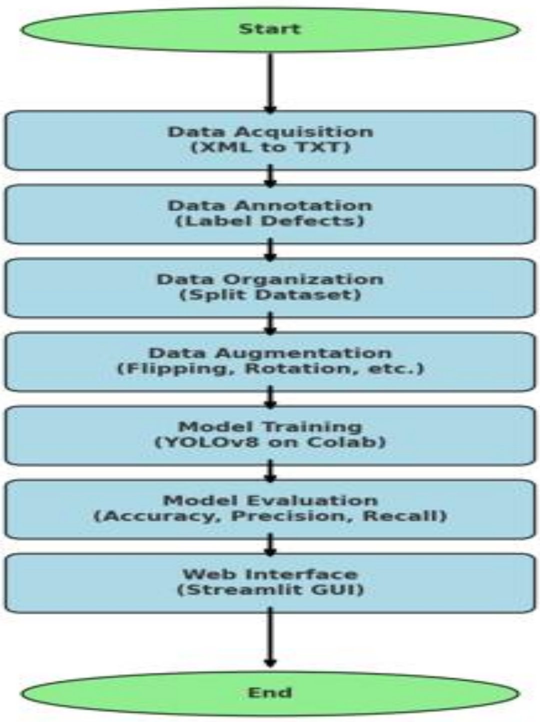

Fig 3. Design Flow

Following training, the model's efficacy is assessed using critical performance indicators like recall, accuracy, and precision. A Streamlit-based online interface is created to improve user accessibility, enabling users to sign up, log in, and contribute PCB images for fault identification. Manufacturers and engineers may easily assess PCB faults with the GUI's real-time forecasts, highlighted defect spots, and presented classification results. In the end, this method reduces human inspection efforts and boosts overall production productivity by guaranteeing an automated, precise, and user-friendly solution for PCB flaw identification.

4. RESULTS

4.1 QUANTITATIVE PERFORMANCE ANALYSIS

This image presents four graphs depicting the training and validation performance of a model, likely for object detection, over 100 epochs. It shows the convergence of loss functions (box, class, and distribution focal loss) during training and validation, alongside the rise in precision, recall, and mean average precision (mAP). Additionally, the learning rate decay is illustrated, indicating a gradual reduction to fine-tune the model's parameters.

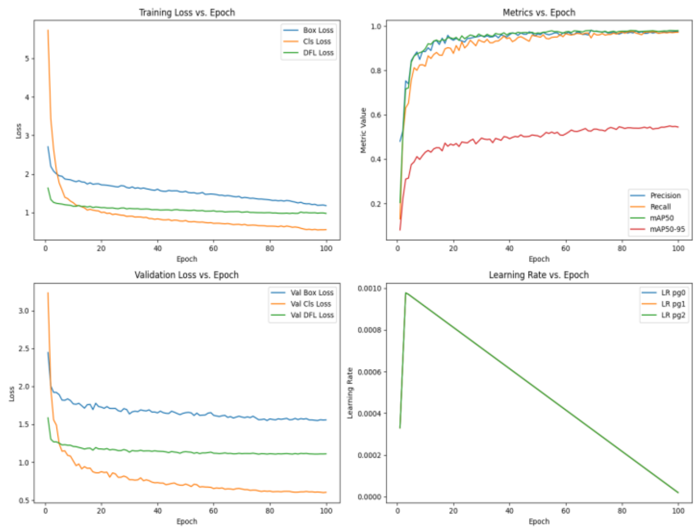

Fig 4.1.1 Model Metric graphs

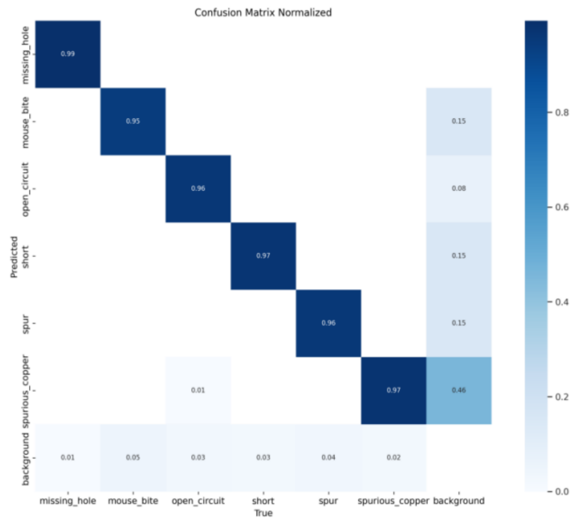

Fig 4.1.2. Confusion Matrix Normalized

This picture displays a normalized confusion matrix that illustrates how well a multi-class classification model performs, most likely for the detection of PCB defects. It compares the model's prediction accuracy to the actual labels for each defect type (missing hole, mouse bite, etc.); higher accuracy is indicated by darker shades.

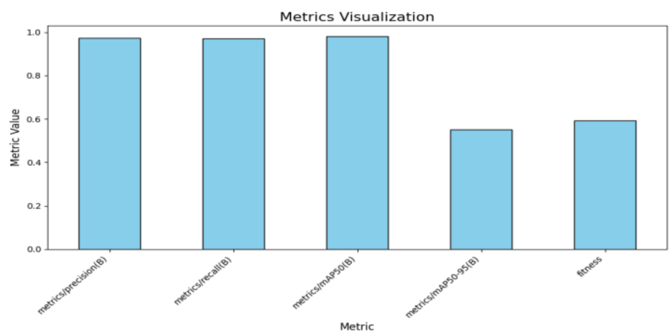

Fig 4.1.3. Metrics Visualization

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

4.2 VISUAL INTERPRETATIONS AND SYSTEM OUTPUTS

The displayed results show live defect detection, marked areas of flaws, and predictions through a graphical user interface, illustrating the system's ability to be used in practical settings. These visuals enable users to quickly understand PCB defects, improving inspection speed and minimizing the need for manual checks.

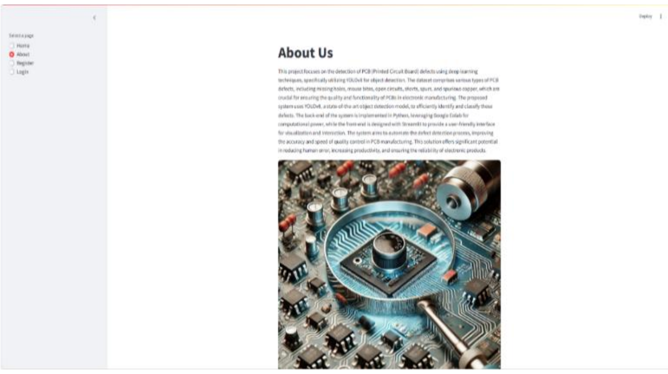

Fig 4.2.1. Home Page

This page streamlines the registration process, ensuring a secure and straightforward way for users to join the platform.

Fig 4.2.2. Register Page

By providing their name, email address, and password, users can safely access the system through this login page. With a form and an eye-catching illustration for visual appeal, it has a straightforward, user-friendly design.

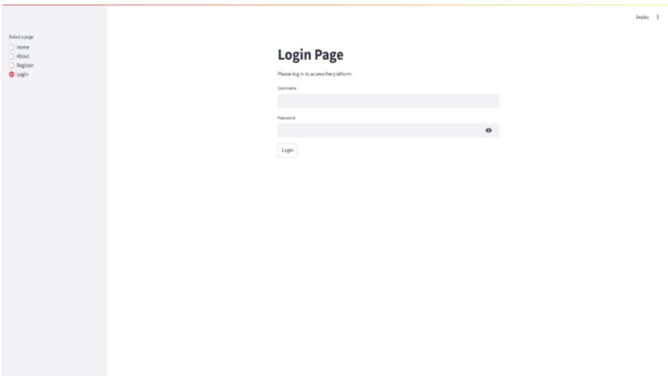

Fig 4.2.3. Login Page

This page consists of PCB Prediction interface, where users can upload images to predict objects on the PCB.

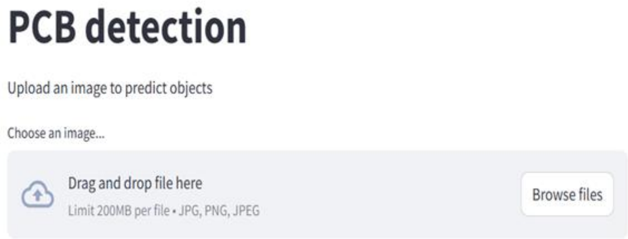

Fig 4.2.4. Prediction Page

The following image presents the identified missing hole errors on a PCB, accompanied by a table of prediction specifics. The defective areas are enclosed in boxes, and the confidence scores represent how sure the model is about its classification. This visual representation proves the YOLOv8 model's capability to correctly locate PCB defects instantly.

Prediction Results:

	x_center	y_center	width	height	confidence	class_id	class_name
0	277.2586	411.4854	34.5417	32.9586	0.8581	0	missing_hole
1	391.3245	218.2231	30.7527	32.7332	0.8324	0	missing_hole

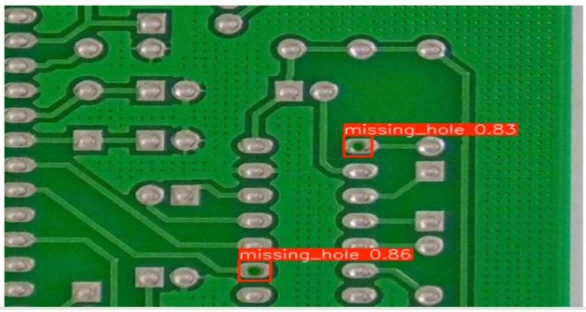

Fig 4.2.5. Prediction Result

5. FUTURE SCOPE

Future advancements and major improvements are possible with the suggested Deep Neural Network-based Defect Identification System for PCB Boards. One significant development is the incorporation of multi-modal defect detection methods, which combine thermal and optical imaging to increase the precision of detecting microscopic or hidden flaws. Furthermore, by gradually adjusting to new defect patterns, self-learning AI models combined with active learning can continuously improve detection capabilities. In order to improve response times and lessen dependency on cloud-based processing, future iterations of the system may use edge computing to enable real-time defect detection directly on PCB manufacturing lines.

Additionally, enhancing the graphical user interface (GUI) to include features for user interaction would enable them to mark defects, offer input, and contribute to training the model with partial supervision.

Another vital improvement involves creating a predictive maintenance component that examines patterns of defects and recommends preventative actions to stop failures before they happen. The system could also be adapted to facilitate automatic defect repair processes, where identified issues are instantly highlighted for robotic correction. Implementing these advancements would transform PCB production by making it more efficient, lessening the need for manual labor, and raising the quality of output.

6. CONCLUSION

This PCB Defect Identification System, utilizing deep neural networks, effectively automates the detection of different flaws in printed circuit boards, thereby improving quality control's efficiency and precision. It can recognize six key defects—mouse bite, missing hole, open circuit, short circuit, spur, and spurious copper—which frequently occur during PCB production. Using the YOLOv8 model, the system achieves high accuracy in locating and categorizing these defects, greatly lessening the need for human inspectors. This refined defect detection method decreases production mistakes, enhances product dependability, and streamlines manufacturing efficiency.

During development, challenges included dataset preprocessing, requiring XML-to-TXT conversion, which was resolved through custom scripts. High computational demands for training were managed using Google Colab's GPU acceleration. Ensuring model robustness across various PCB designs was improved through data augmentation techniques like flipping, rotation, and contrast adjustments. These solutions enhanced model performance and detection accuracy.

Streamlit is used to deploy the system as a web application, providing a user-friendly graphical user interface for defect detection. Using tools like accuracy feedback and defect region highlighting, users can upload PCB images, categorize flaws, and view results instantly. By bridging the gap between automation and usability in PCB manufacturing, this deployment makes AI-driven defect detection feasible and accessible for industrial applications.

ACKNOWLEDGEMENT

We sincerely express my gratitude to Mr. T. Vijaya Kumar, my project guide, for his invaluable guidance, encouragement, and continuous support throughout this research. His expertise and insights have been instrumental in shaping the direction of this work.

We also extend my heartfelt thanks to the Electronics and Communication Engineering (ECE) Department at Vasireddy Venkatadri Institute of Technology (VVIT) for providing the necessary resources and a conducive environment for research.

Finally, we are grateful to our peers, faculty members, and family for their unwavering support and motivation throughout this journey.

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