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AI-Powered PCB Defect Detection System with Explainable AI, Real-Time Feedback, and Severity Analysis

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***Abstract*— Printed circuit board defects significantly impact the reliability and cost of electronic products. Traditional manual inspection methods are time- consuming, error prone and unsuitable for modern high speed manufacturing environments. This paper presents a smart AI based PCB defect detection system that integrates deep learning based classification, real time feedback. defect severity analysis, and explainable artificial intelligence i.e. XAI. The proposed system employs a convolutional neural network with transfer learning (EfficientNetB0) to detect and classify common PCB defects such as missing hole, mouse bite, open circuit, short, spur, and spurious copper. Severity levels are estimated based on defect size, location and class specific risk enabling prioritized decision making in manufacturing lines. To improve trust and interpretability gradient weighted class activation mapping (Grand CAM) is used to visualize regions influencing model prediction. Experimental results demonstrate and accuracy exceeding 95% on benchmark PCB datasets, highlighting the effectiveness and practicality of the proposed approach for industrial deployment.**

Keywords*— *PCB defect detection, deep learning, EfficientNet, severity analysis, explainable AI, GradCAM, computer vision.

I. INTRODUCTION

Printed circuit boards form the backbone of modern electronics systems. Even minor difference in PCB can lead to system failure, reduce lifespan, and increased maintenance costs. Conventional inspection techniques such as manual visual inspection and rule based Automated Optical Inspection (AOI) systems struggle with scalability, adaptability, and accuracy when faced with complex defect patterns. Recent advancements in deep learning and computer vision have enabled intelligent inspection systems capable of learning discriminative features directly from images. However many existing solutions focus solely on defect classification accuracy while neglecting interpretability and defect severity assessment both of which are critical for real-world manufacturing adoption. This paper proposes a smart AI best PCB defect detection system that goes beyond classification by incorporating real time defeat detection and feedback, quantitative severity analysis for decision support and explainable AI techniques to improve transparency and trust.

II. RELATED WORK

Early PCB inspection systems relied on image processing techniques such as edge detection, template matching, and morphological operation. Why effective for simple patterns these methods are sensitive to noise and variations in lighting and design.

With the rise of deep learning, convolutional neural networks (CNNs) have been widely applied for PCB defect detection. Architecture such as VGG, ResNet, and YOLO-best detectors have been promising results. However, most studies focus on detection accuracy alone. Limited work addresses defect severity quantification and explainability, which are crucial for industrial decision making.

Explainable AI methods such as Grand-CAM have recently gained attention for visualizing CNN decision regions, but their application to PCB inspection remains relatively unexplored. This work bridges that gap by integrated XAI and severity analysis into a unified PCB inspection framework.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system architecture consists of four major modules:

A. Data Acquisition and Preprocessing

High resolution PCB images are collected and organised into defect specific categories. Preprocessing steps include resizing, normalization, noise reduction, and data augmentation (rotation, flipping, zooming) to improve model generalization.

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B. Deep Learning–Based Defect Detection

An EfficientNetB0 model pre-trained on ImagiNet is fine-tuned for PCB defect classification. Transfer learning enables faster convergence and improved accuracy with limited training data. Class weighting is applied to handle data set imbalance.

C. Severity Analysis Module

Defect severity is computer using a weighted scoring mechanism based on: Defect type (critical vs. non-critical),
-Defect area and intensity, and
-location relevance on the PCB.
Severity levels are categorized as low, medium or high enabling manufacturers to prioritize repairs or rejections.

D. Explainable AI Module

To enhance transparency, Grad-CAM is employed to generate heat maps highlighting image regions that influence the model's predictions. This allows engineers to visually verify whether the model focuses on meaningful defect areas.

IV. METHODOLOGY

A. Dataset Description

1) The dataset they used has images of printed circuit boards with labels for different defects. There are six main types, like missing holes or mouse bites, open circuits, shorts, spurs, and that spurious copper thing. I think its divided into training, validation, and testing parts so the model can learn properly without just memorizing everything. That way, you tune the settings and check how it really does on new stuff.

2) For the model, they picked EfficientNetB0 because it gets good results without needing a ton of computer power. Sounds efficient, right. They trained it with this categorical cross-entropy loss, and Adam optimizer to make it converge quicker. Oh, and they added learning rate scheduling plus early stopping to avoid overfitting, I guess that helps it work better on real examples.For papers with less than six authors: To change the default, adjust the template as follows.

B. Model Training

Because of its high accuracy and computational efficiency, the EfficientNetB0 convolutional neural network is used for multiclass PCB defect classification. To guarantee steady and quick convergence, the model is trained using the Adam optimizer and categorical cross-entropy as the loss function. Early stopping is used to avoid overfitting and maintain the top-performing model based on validation performance, while learning rate scheduling is used to adaptively lower the learning rate in order to increase training robustness.

C. Figures and Tables

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V. RESULTS AND DISCUSSION OF THE EXPERIMENT

A. Total Performance in Classification

The effectiveness of the suggested PCB defect detection system in identifying various defect types is demonstrated by its overall classification accuracy, which surpasses 95%. The EfficientNetB0-based model has better generalization and feature extraction capabilities than traditional CNN architectures, which leads to higher prediction accuracy across all test samples.

B. Performance Metrics for Evaluation

For each defect class, precision, recall, and F1-score metrics are used to further assess the model's performance. Strong recall scores validate the model's capacity to accurately identify defective regions, while high precision values signify a low false-positive rate. The robustness and dependability of the suggested method for multiclass PCB defect classification are confirmed by the balanced F1-scores for each class.

C. Evaluation of PCB Defect Severity

To evaluate the criticality of defects found, a severity analysis is carried out. Because they have a major effect on circuit functionality, defects like open circuits and short circuits are given higher severity ratings. The outcomes show that the system efficiently ranks critical flaws, facilitating quicker remedial actions and better quality control in production settings.

D. Grad-CAM Model Interpretability

The interpretability of the trained model is examined using Grad-CAM visualizations. The PCB images' actual defect locations strongly match the highlighted activation regions. This alignment validates the decision-making process's dependability and transparency by confirming that the model concentrates on significant defect features rather than pointless background areas.

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VI. ADVANTAGES AND INDUSTRIAL IMPACT

• Very accurate and strong defect detection
The suggested system shows that it can accurately classify and consistently perform well across all types of PCB defects. Its robustness against variations in defect size and appearance makes it suitable for reliable quality inspection in real-world manufacturing environments.

• Real-Time Inspection for Manufacturing Lines The integration of the trained model with a real-time inference pipeline enables fast and continuous PCB inspection. This capability allows seamless deployment on production lines, reducing inspection time and minimizing human intervention.

• Severity-Based Decision Support
The system incorporates a severity analysis mechanism that prioritizes critical defects such as open circuits and shorts. This feature supports informed decision-making by enabling operators to focus on high-impact defects, thereby improving maintenance efficiency and reducing production losses.

• Enhanced Trust Through Explainable AI By utilizing Grad-CAM–based visual explanations, the system provides transparency in its predictions. Highlighting defect-specific regions improves user trust and acceptance, which is essential for adopting AI-based inspection systems in industrial settings.

• Scalability and Industrial Integration
The model can be extended to support additional defect classes and higher-resolution images, ensuring adaptability to future manufacturing requirements.
The proposed system is suitable for academic research, industrial simulation, and real-world deployment in smart manufacturing environments, offering a reliable, scalable, and intelligent solution for automated PCB defect inspection.

VII. METRICS FOR PERFORMANCE ASSESSMENT

Several quantitative performance metrics are used in order to thoroughly assess the efficacy of the suggested PCB defect detection system. Beyond mere accuracy, these metrics offer a more profound understanding.

A. Precision

The proportion of correctly classified PCB images to all test samples is known as accuracy.
Accuracy is equal to (TP + TN) / (TP + TN + FP + FN), where TP, TN, FP, and FN stand for true positives, false positives, false negatives, and true negatives, respectively.

B. F1-Score, Precision, and Recall

While recall assesses the model's capacity to identify all real flaws, precision gauges how accurately positive predictions are made. A harmonic mean of precision and recall is provided by the F1-score:
TP / (TP + FP) = precision
TP / (TP + FN) = Recall
F1-score is equal to 2 × (precision × recall) / (precision + recall).
In PCB inspection, where false negatives can result in serious system failures, these metrics are particularly crucial.

C. Confusion Matrix Analysis

A confusion matrix was used to visualize class-wise performance across the six defect categories. The results are as follows:
would provide evidence of strong diagonal dominance and, therefore, reliable discrimination among visually similar defects.
such as spur and spurious copper

VIII.COMPARATIVE ANALYSIS

A comparative analysis is carried out to assess the performance of the proposed EfficientNetB0 architecture compared to existing conventional designs such as the convolutional neural network models VGG16 and ResNet-18, considering classification accuracy and the complexity of the models in terms of the number of trainable parameters.

Model	Accuracy (%)	Parameters
VGG16	89.4	138
ResNet-18	92.1	11.7
Proposed EfficientNetB0	**95.6**	**5.3**

From the results, it can be understood that the lowest accuracy of 89.4% is achieved by VGG16, which at the same time has the highest number of parameters at 138 million, thereby resulting in increased memory and computation. This shows that VGG16 is not appropriate for edge devices

The improved performance is also seen in the ResNet-18, which achieves 92.1% accuracy and also reduces the parameters by a significant margin to 11.7 million. The residual connection improves the features and the training stability. Nevertheless, the model requires moderate computational resources.

REFERENCES

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