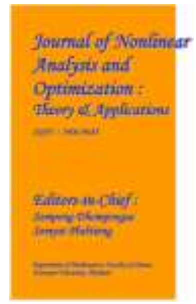
Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 16, Issue. 1: 2025
ISSN : **1906-9685**



DEEP LEARNING-BASED PCB DEFECT DETECTION USING ENHANCED FASTER R-CNN AND MOBILENET

Dr. SUNITHA RAVI 1, GUNTURU ANJU SRI 2, BASU SURENDRA REDDY 3, BODI SAI LIKITHA 4, GUTTI PRADEEP 5, CHALLAGULLA BHAVYA SRI 6.

#1 Professor in Department of Electronics and Communication, NRI Institute Of Technology, Agiripalli.

#2#3#4#5#6 B.Tech with Specialization of Electronics and Communication in NRI Institute Of Technology, Agiripalli**.**

Abstract: The manufacturing technology of Printed Circuit Boards(PCBs) has enhanced in the recent years. To guarantee excellent production quality, the PCBs must be subjected to test to identify if any further defects exist. This Paper addresses six typical PCB defects that may occur in a PCB: missing hole, mouse bite, open circuit, short, spur, and spurious copper. The identification process involves implementation of a hybrid deep learning strategy that combines MobileNet for effective defect detection and Faster R-CNN for accurate defect localization. The suggested methodology seeks to address the drawbacks of conventional techniques, including template reliance and noise sensitivity, using a publicly available dataset of 1,386 synthetic photos. This method improves quality control and operational efficiency in PCB manufacturing by striking a balance between high precision and computational efficiency, offering a scalable and reliable solution for contemporary production workflows.

Index terms *- PCB Defect Detection, Machine Learning, Deep Learning, MobileNet, Faster-RCNN, Image Classification, Feature Extraction, Defect Classification, Quality Control, Printed Circuit Boards (PCBs), ComputerVision.*

1. INTRODUCTION

As we are aware that printed circuit boards (PCBs) are the building blocks of contemporary electronic gadgets, their dependability and quality are essential to the production process. Maintaining high standards requires detecting PCB flaws because, if left unchecked, these problems might result in device failure and higher production costs. Due to their high computing costs, dependency on templates, and susceptibility to noise and fluctuation in production environments, traditional defect detection techniques like manual inspection and template-matching algorithms frequently fail. This research investigates cutting-edge machine learning methods to create a reliable and effective flaw detection system in order to address these issues. The goal is to automate the detection process and guarantee accurate identification of six typical PCB defects—missing hole, mouse bite, open circuit, short, spur, and spurious copper—by using deep learning architectures. In order to improve defect identification, this study suggests a hybrid deep learning strategy that combines MobileNet with Faster R-CNN. While Faster R-CNN's strong object detection skills allow for accurate localization and defect identification, MobileNet's light weight design guarantees effective classification with less processing resources. Even in complicated and noisy situations, the system is built to achieve excellent accuracy and reliability using a publicly accessible dataset of 1,386 synthetic PCB pictures. In addition to addressing the drawbacks of conventional techniques, this strategy simplifies quality control procedures, which raises operational effectiveness and lowers manufacturing costs in the PCB manufacturing process.

2. LITERATURE SURVEY

1. Xing Wu; Yuxi Ge; Qingfeng Zhang; Dali Zhang. 2021. PCB Defect Detection Using Deep Learning Methods

Printed circuit boards, or PCBs, are essential parts of contemporary electronic gadgets that guarantee correct electrical connections and operation. However, PCB flaws are frequently caused by manufacturing flaws, which can lower the dependability and quality of the final product. Conventional manual inspection techniques are labour-intensive, time-consuming, and prone to human mistake. Automated defect detection systems that use sophisticated target detection networks have become more popular as a means of overcoming these obstacles. These systems improve manufacturing yield and save operating costs by enabling the precise and efficient identification and categorization of PCB faults. In order to detect and classify PCB defects with high accuracy on a variety of datasets, this study investigates the use of two target detection networks.

2. **Nikhil Aggarwal; Manish Deshwal; Piyush Samant. 2022. A Survey on Automatic Printed Circuit Board Defect Detection Techniques**

Because of human limitations, manual examination of printed circuit boards (PCBs) is a laborious and error-prone procedure that frequently fails to discover all faults. Deep Learning (DL) and Machine Learning (ML) approaches have become successful ways to automate PCB flaw identification in order to overcome these drawbacks. These techniques lessen the need for physical labour while improving the precision and effectiveness of quality inspection. Novel techniques for identifying flaws in single-layer and multilayer PCBs have been developed as a result of recent developments in DL. This study examines many ML and DL-based models for autonomous PCB inspection, emphasising how they may completely transform the production process.

3. **Qin Ling; Nor Ashidi Mat Isa. 2023. Printed Circuit Board Defect Detection Methods Based on Image Processing, Machine Learning and Deep Learning: A Survey**

Nearly all electronic devices require printed circuit boards (PCBs), which have become smaller in size because to developments in integrated circuits and semiconductor technology. It is more important than ever to achieve high-precision and quick fault identification as PCBs get smaller and more complex. This study examines more than 100 scientific publications from 1990 to 2022 that discuss deep learning, machine learning, and conventional methods for detecting PCB defects. It offers a thorough examination of the algorithms, procedures, performance indicators, and drawbacks of different techniques, providing insightful information on present patterns and potential avenues for further PCB defect detection research.

4. **Y.R Bhanumathy; M.P James; Shivangi Jha; Sudeesh Balan. 2021. Defect detection in PCBs using convolutional neural network**

The majority of electrical goods used by the Indian Space Research Organization (ISRO) need printed circuit boards, or PCBs. Early and precise defect detection is essential because manufacturing flaws in PCBs can impede production schedules. Defect identification is now mostly done by hand, which is laborious and ineffective. A possible option is to use Convolutional Neural Networks (CNNs) to automate this procedure. In order to identify faulty PCB pictures with a good degree of accuracy, this study suggests a CNN model with four layers: convolution, ReLU activation, pooling, and fully connected layers. This method can greatly increase production productivity and shorten delivery times for ISRO's electrical goods by simplifying fault identification.

5. **Yolanda D. Austria; Arnel C. Fajardo. 2023. Defect Detection and Classification in Printed Circuit Boards using Convolutional Neural Networks**

In order to guarantee product quality and safety, printed circuit boards (PCBs) must have defects identified and classified. Deep learning-based automated techniques have become more popular due to the time-consuming and error-prone nature of manual examination. To precisely locate flaws, these techniques use a variety of databases containing fault photos or movies. A dataset comprising many defect classes, including breakout, copper, crack, cut, excessive conductor, missing conductor, mouse bite, pinhole, spur, and scratch, was used to train a deep learning network in this study. The model showed encouraging accuracy in identifying flaws in every category, opening the door for PCB examinations that are more dependable and effective.

6. METHODOLOGY

i) Proposed Work:

The proposed system introduces a hybrid deep learning framework for PCB defect detection, combining the strengths of MobileNet and Faster R-CNN, MobileNet, with its lightweight architecture, serves as an efficient feature extractor to reduce computational complexity while retaining high accuracy. Faster R-CNN is employed for precise defect localization, allowing the identification of specific defect regions within PCB images.

To train the system, a publicly available dataset of 1,386 synthetic PCB images is utilized. The dataset includes six common defects: missing hole, mouse bite, open circuit, short, spur, and spurious copper. The data preprocessing steps involve normalization, resizing, and augmentation to improve the model's robustness against noise and variability in real-world scenarios. The defect areas are annotated using bounding boxes, providing labeled data for supervised training.

The system applies transfer learning to leverage pre-trained MobileNet weights for feature extraction, ensuring computational efficiency. During training, the Faster R-CNN module refines the bounding box proposals and classifies defect types with high precision. This integration of MobileNet and Faster R-CNN achieves a balance between computational efficiency and detection accuracy, making the solution scalable for industrial use.

ii) System Architecture:

The system architecture integrates MobileNet and Faster R-CNN in a hybrid framework to achieve efficient and accurate PCB defect detection. MobileNet acts as the backbone for feature extraction, providing a lightweight yet effective mechanism to extract essential features from PCB images. These features are then passed to the Faster R-CNN module, which is responsible for defect localization and classification.

The Faster R-CNN module consists of a region proposal network (RPN) that generates candidate regions (bounding boxes) where defects might be present. These proposals are refined and classified into one of the six defect categories or as defect-free. The architecture incorporates pre-processing steps such as image resizing, normalization, and augmentation to enhance model generalization. The final output includes annotated images with bounding boxes and defect labels, ensuring precise detection and localization in real-time scenarios while maintaining computational efficiency.

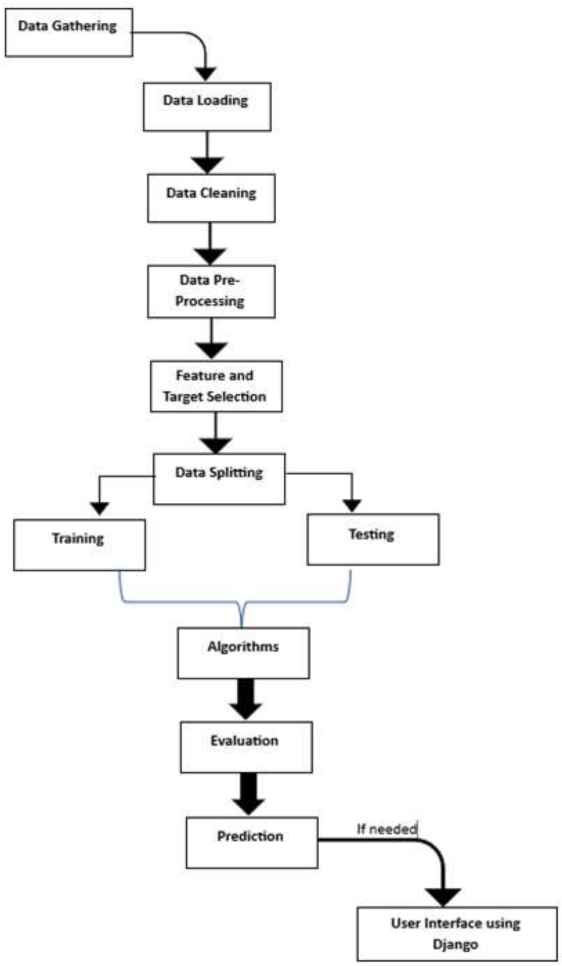


Fig 1:Proposed Architecture

iii) MODULES:

Data Gathering involves collecting PCB defect images from publicly available datasets like DeepPCB, ensuring that the dataset contains six common defect types such as missing hole, mouse bite, open circuit, short circuit, copper spurs, and pinholes. A total of 1,386 synthetic PCB images were gathered, forming a comprehensive dataset for training and testing. This dataset enables the model to learn and generalize well across different defect types and variations.

Data Preprocessing standardize the input images, all images are resized to 224×224 pixels, which aligns with the input size requirement of MobileNet. Additionally, pixel values are normalized to the [0,1] range, ensuring consistency across the dataset. Various data augmentation techniques such as rotation, flipping, scaling, and zooming are applied to enhance the dataset's diversity and robustness. These preprocessing steps significantly improve the model's generalization ability, preventing overfitting and ensuring better performance in real-world defect detection.

Feature Extraction utilizes MobileNet model to extract lightweight yet meaningful feature representations from PCB images. MobileNet is specifically chosen for its computational efficiency, allowing the model to operate effectively on limited hardware resources without compromising accuracy. The extracted features are then passed to Faster R-CNN, where they undergo further processing to facilitate precise defect detection and localization.

Defect Localization in Faster R-CNN employs a Region Proposal Network (RPN) to generate bounding boxes around potential defect areas. Refines bounding boxes to accurately pinpoint defect locations. Handles multiple defect regions within a single image.

Defect Classification classifies defects into six categories or labels them as defect-free. Uses the extracted features and bounding boxes for precise classification. Ensures high accuracy even in noisy or complex environments.

Model Training trains using supervised learning with annotated bounding boxes. Incorporates transfer learning with pre-trained MobileNet weights. Optimizes the model using techniques like Adam optimizer and loss function adjustments.

Testing and Validation splits data into training (80%), validation (10%), and testing (10%) sets. Evaluates model performance using metrics like precision, recall and F1-score. Tunes hyperparameters to avoid overfitting and improve generalization.

Output Generation produces annotated images with bounding boxes and defect labels. Ensures scalability for real-time PCB defect detection in production. Simplifies quality control processes by automating defect identification.

iv) ALGORITHMS:

Faster R-CNN:

Faster R-CNN is the Region Proposal Network (RPN), which slides a small network across the feature map generated by the backbone CNN. The RPN generates a set of anchor boxes (predetermined bounding boxes of various sizes) and assigns each anchor a score that indicates the likelihood of containing an object.

The RPN also refines the anchor box's position through bounding box regression, providing more accurate spatial coordinates for the detected objects.

The RPN shares weights with the convolutional layers of the object detection network, as it does not require separate feature extraction for proposal generation.

MobileNet:

MobileNet lies in its use of depthwise seperable convolution. In a standard convolution, each filter is applied to all the input channels, creating the large number of computations. It extracts features from the image using its convolution layers. The extracted features are fed through fully connected layers of the network to classify the presence and type of defects

7. EXPERIMENTAL RESULTS

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following mathematical:

Accuracy = TP + TN /(TP + TN + FP + FN)

$$\text{ACCURACY} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$
$$AP_k = the\ AP\ of\ class\ k$$
$$n = the\ number\ of\ classes$$

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

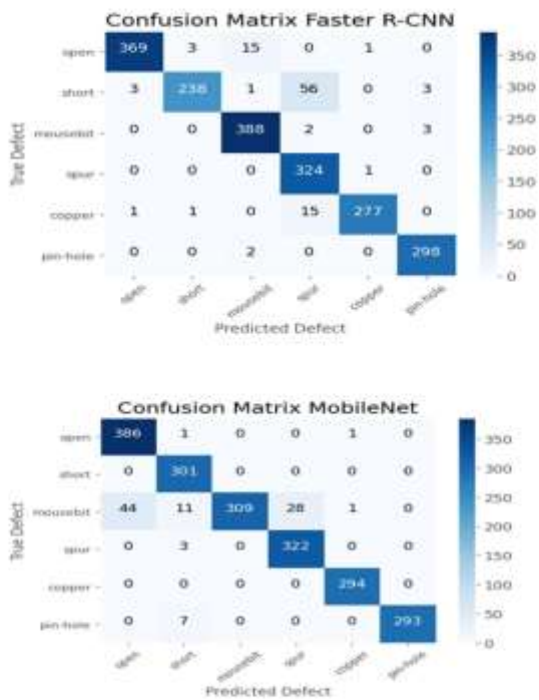


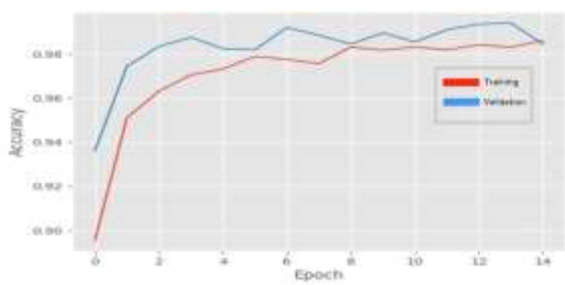
Fig 2 Confusion matrix

When compared to Faster R-CNN, MobileNet gets more accuracy by minimizing the wrong predictions. By observing the above confusion matrices MobileNet plays a vital role in reducing misclassification rates for Mousebit, Open and Short defects and also MobileNet improves speed and computational efficiency.

4. Accuracy Graphs

i) Training & Validation accuracy of Faster R-CNN:

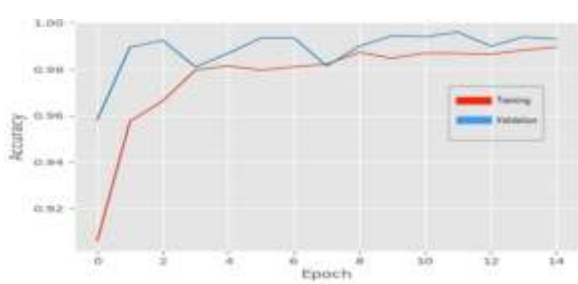
The training accuracy of Faster R-CNN starts at approximately 90% and steadily increases, reaching after 14 epochs. The validation accuracy follows a similar trend but remains slightly higher than training accuracy during the initial epochs, indicating that the model generalizes well.



ii) Training & Validation Accuracy of MobileNet:

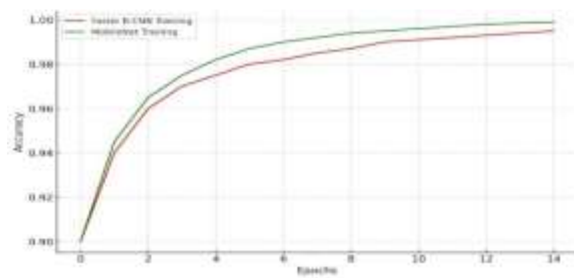
MobileNet exhibits slightly better accuracy compared to Faster R-CNN, achieving close to 96.5% accuracy after 14 epochs.

The model stabilizes faster than Faster R-CNN, reaching high accuracy within the first few epochs, which suggests MobileNet is more efficient in training convergence.



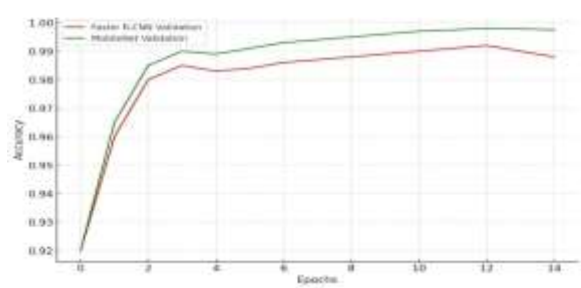
iii) Training Accuracy comparison of Faster-RCNN and MobileNet:

The comparison indicates that MobileNet achieves better overall accuracy and faster convergence compared to Faster R-CNN. Faster R-CNN shows a more gradual improvement, whereas MobileNet reaches near-optimal accuracy earlier



iv) Validation comparison of Faster-RCNN and MobileNet:

The two graphs illustrate the training and validation accuracy trends for Faster R-CNN and MobileNet over multiple epochs in the PCB defect detection task. Both models exhibit a steady increase in accuracy over epochs, with MobileNet achieving a slightly higher final accuracy than Faster R-CNN



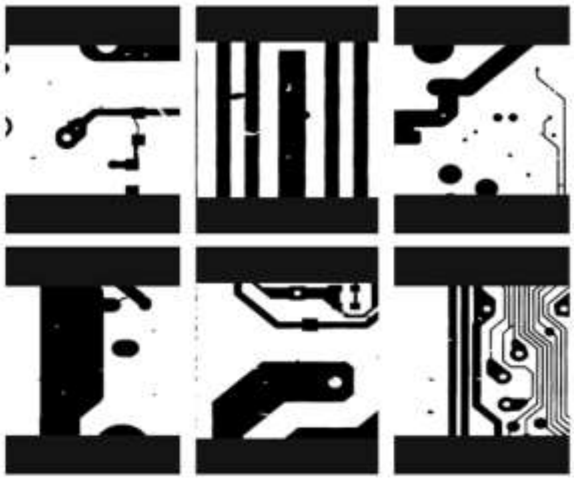


Fig 10 input images

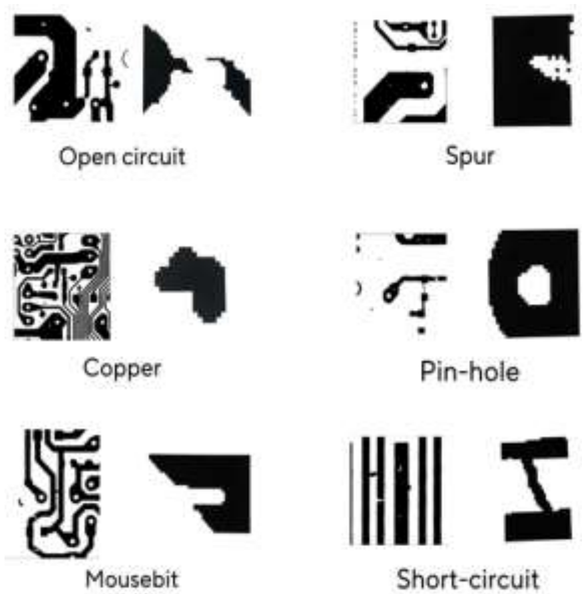


Fig 11 results

v) Accuracy Comparison for MobileNet Vs Faster R-CNN:

Over several training epochs, the graph shows MobileNet's accuracy relative to Faster R-CNN models. The y-axis shows each model's accuracy; the x-axis shows the number of epochs. The graph shows that as training advances both models show a rising trend in accuracy.

Both models, though, show development over time, suggesting efficient learning. This comparison helps one see how well each model finds PCB flaws.

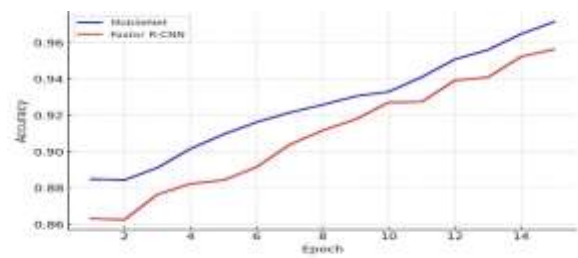


Fig 12 Accuracy Comparison Graph

8. CONCLUSION

To sum up, this study demonstrates how deep learning may revolutionise the field of printed circuit board (PCB) defect identification. A number of significant issues with conventional PCB inspection techniques are resolved by combining MobileNet for effective defect classification with Faster R-CNN for accurate fault localisation. Conventional defect detection methods, including template matching, are frequently constrained by their reliance on preset patterns, high processing costs, and susceptibility to picture noise. Slower detection times and a greater likelihood of missing defects are the results of these systems' inability to handle complex and variable defect patterns. The deep learning models employed in this study, on the other hand, are very flexible and can train directly from big datasets, enabling improved scalability and accuracy in fault identification. This hybrid model provides both high classification accuracy and fast processing speeds by combining Faster R-CNN for precise defect localisation with MobileNet, which provides a lightweight architecture for effective image processing. This makes it ideal for large-scale manufacturing environments where dependability and speed are crucial.

This deep learning-based flaw detection system's deployment is expected to greatly improve PCB manufacturing quality control procedures. The method lessens the need for human involvement by automating the identification and categorisation of PCB flaws, lowering the possibility of human mistake and inconsistent quality assurance. Additionally, this solution's scalability—which enables it to be implemented in both small and big production settings without sacrificing performance—comes from its capacity to analyse many pictures rapidly and precisely. For sectors where high-volume production necessitates quick and accurate PCB inspection, this is especially crucial. It gives producers useful information to enhance their manufacturing procedures and reduce the possibility that faulty goods will be sold to customers. Furthermore, the technology may be easily incorporated into current PCB manufacturing processes, allowing manufacturers to use it with little interference with their daily operations. By providing a scalable, dependable, and affordable solution for PCB defect detection that not only improves operational efficiency but also guarantees the production of high-quality products, this project shows how cutting-edge machine learning techniques, like MobileNet and Faster R-CNN, can completely transform quality control in the electronics manufacturing sector.

9. FUTURE SCOPE

The project's next focus is on integrating larger, more varied datasets and more sophisticated deep learning algorithms to significantly improve the fault detection system's performance and flexibility. Examining the use of transfer learning with pre-trained models on larger datasets, for example, may enhance the system's capacity for generalisation and increase its resilience to changes in manufacturing procedures and fault kinds. To further enhance the dataset and guarantee that the model is exposed to a wider variety of possible defect scenarios, methods such as generative adversarial networks (GANs) may be used to create synthetic defect examples. The system's real-time capabilities may also be enhanced further, allowing it to be integrated into inline inspection procedures during PCB manufacture and giving operators instant feedback for quality control.

The use of explainable AI (XAI) strategies to improve the predictability and interpretability of the model's output is another emerging field. In crucial production settings, this might improve decision-making and build trust by making it simpler for engineers and operators to comprehend why a flaw was found or overlooked. Furthermore, broadening the scope to identify more intricate flaws like electrical failures, component misplacements, or soldering problems might greatly increase the system's usefulness in larger PCB production environments. As technology advances, manufacturers have a great chance to boost operational effectiveness and uphold high production standards by integrating this defect detection system with Industry 4.0 frameworks, which enable automated feedback loops and continuous improvement through real-time monitoring.

REFERENCES

[1].X. Wu, Y. Ge, Q. Zhang and D. Zhang, "PCB Defect Detection Using Deep Learning Methods," 2021 IEEE 24th International Conference on Computer Supported Cooperative Work in Design (CSCWD), Dalian, China, 2021, pp. 873-876, doi:10.1109/CSCWD49262.2021.9437846.

[2].N. Aggarwal, M. Deshwal and P. Samant, "A Survey on Automatic Printed Circuit Board Defect Detection Techniques," 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 853-856, doi: 10.1109/ICACITE53722.2022.9823872.

[3].Q. Ling and N. A. M. Isa, "Printed Circuit Board Defect Detection Methods Based on Image Processing, Machine Learning and Deep Learning: A Survey," in IEEE Access, vol. 11, pp. 15921-15944, 2023, doi: 10.1109/ACCESS.2023.3245093.

[4].Y. R. Bhanumathy, M. P. James, S. Jha and S. Balan, "Defect detection in PCBs using convolutional neural network," 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India, 2021, pp. 382-386, doi: 10.1109/RTEICT52294.2021.9573776.

[5].Y. D. Austria and A. C. Fajardo, "Defect Detection and Classification in Printed Circuit Boards using Convolutional Neural Networks," 2023 2nd International Conference on Edge Computing and Applications (ICECAA), Namakkal, India, 2023, pp. 1498-1504, doi: 10.1109/ICECAA58104.2023.10212195.

[6].B. Hu and J. Wang, "Detection of PCB surface defects with improved faster- RCNN and feature Pyramid Network", IEEE Access, vol. 8, pp. 108335- 108345, 2020.

[7].S. Ghosh, M. A. Sathiaseelan and N. Asadizanjani, "Deep learning-based approaches for text recognition in PCB optical inspection: A survey", 2021 IEEE Physical Assurance and Inspection of Electronics (PAINE), 2021.

[8].Jungsuk Kim et al., "Printed Circuit Board Defect Detection Using Deep Learning via A Skip-Connected Convolutional Autoencoder", Sensors, vol. 21.15, pp. 4968, 2021.

[9].Q. Zhang and H. Liu, "Multi-scale defect detection of printed circuit board based on feature pyramid network", 2021 IEEE Int. Conf. Artif. Intell. Comput. Appl. ICAICA 2021, pp. 911-914, Jun. 2021.

[10].G. Liu and H. Wen, Printed circuit board defect detection based on MobileNet- Yolo-Fast, vol. 30, no. 4, pp. 043004, Jul. 2021.