# EcoVision: Real-time PCB Fault Detection with YOLOv8 for Sustainable Electronics

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***Abstract*—Current PCB quality control relies heavily on manual inspection, a process prone to human error and inefficiency. This study investigates the feasibility of employing the YOLOv8 object detection algorithm for real-time fault detection in PCBs, aiming to develop a reliable and efficient automated system. A comprehensive pipeline was established, featuring a meticulously curated dataset of 244 PCB images encompassing diverse fault categories. Strategic data augmentation techniques and transfer learning from the COCO dataset bolstered model training and enhanced robustness. The trained model's performance was rigorously evaluated using industry-standard metrics in simulated real-world scenarios. Results show that the YOLOv8's very good accuracy which is 75% in fault detection, which is a proper indication of its true potential of the revolution of PCB quality control. This system is a way of reduced production cost, increase the safety of the product and a good manufacturing process. By the application of this system of fault detection, this particular research is provides an efficient way of address the challenges of the industries. Its highly accurate results can encourage the adoption with the new era of efficiency in the sector of electronic manufacturing.**

***Index Terms*—PCB fault detection, AI-powered PCB inspection, real-time PCB fault detection system, YOLOv8, deep learning, automated PCB inspection, Industry 4.0, quality control,PCB, Defect detection, Image Processing.**

## I. Introduction

Printed Circuit Boards (PCBs) are critical components in the functioning of modern electronic devices, acting as complicated and necessary components that aid in the coordination and execution of many operations. These devices are now plays a very crucial part in our day to day lives. We are so dependent on these for its variety and activities. However, it is important to acknowledge that these intricately linked circuits causes hazards: imperfections that possess the capability to hinder functionality and jeopardize security. Traditionally, finding these defects involved a challenging and not accurate manual or semi-automated procedure that increased manufacturing costs and time consumption while also increasing the possibility of human error. The sciences of computer vision and artificial intelligence (AI) have become revolutionary and hold great potential for automated, real-time flaw detection. With the advent of this technology, the sector of PCB manufacturing enters a promising new era defined by improved accuracy and efficiency. Experts have long acknowledged artificial intelligence's potential in PCB inspection. A big revolution in the industry has been brought about by deep learning, particularly convolutional neural networks (CNNs), which offer unparalleled accuracy and versatility as well. It is important to note, though, that the deep learning models that are currently in use for PCB problem diagnosis frequently may have drawbacks. These constraints include many aspects such as insufficient training data, susceptibility to variations in lighting, and challenges in accurately identifying little or odd issues. In order to address a gap in the field of industrial PCB inspection, this research proposes a revolutionary real-time fault detection technique. The solution is specifically made to deal with the special problems in the domain. Because of its remarkable speed and precision, the YOLOv8 object detection approach is a significant tool for our research. We selected a scientific approach to address the problem of limited data availability, carefully selecting and organizing a wide range of data spanning many types of problems. In addition, we applied different techniques for data augmentation to improve the accuracy and relevance of our findings. However, this work employs a transfer learning strategy that utilizes pretrained values obtained from the COCO dataset. This method seeks to improve the model's convergence rate before optimizing it for the targeted domain of PCB defects. This study aims to investigate the challenges of the suggested system through a comprehensive analysis of all of its many parts. These components include the data preparation pipeline, the YOLOv8 architecture and training regimen, and the evaluation criteria that are used to gauge the system's effectiveness. We provide a thorough examination of the model's functionality in this study. We analyze its precision, recall, and accuracy with respect to multiple defect classes. We investigate the system's integration into industrial inspection lines, identify potential obstacles, and provide solutions in order to evaluate the system's viability. This discovery has the potential to completely change the landscape of PCB manufacturing. Automation and simplification of problem detection are expected to result in a future marked by lower manufacturing costs, higher quality control, and increased product dependability. A system's realtime capabilities allow for quicker problem diagnosis and correction, resulting in less downtime and improved safety measures. Furthermore, the versatility and adaptability of the system provide a promising foundation for future developments and customisation, supporting the creation of a new age of intelligent PCB inspection solutions that harness the power of AI

## II. Related works

The advent of high-performance GPUs and faster image processing by computers has significantly advanced image processing, particularly in image recognition and classification. Traditional manual inspection methods for Structural Health Monitoring (SHM) of Wind Turbine Blades (WTBs) are time-consuming, risky, and halt turbine operations. Drone-based inspections, coupled with deep learning using the Keras framework on TensorFlow, offer a promising solution. By training a neural network model on drone-captured images, researchers can classify blades as faulty or non-faulty, enabling automated inspection and reducing downtime.

Machine learning and deep learning algorithms have revolutionized various fields, including image processing, speech recognition, fault detection, object detection, and medical sciences. The CWRU dataset, as highlighted by [1], serves as a valuable resource for researchers embarking on machinery fault detection and diagnosis projects.

Image information is a crucial form of fault data, enabling rapid and accurate characteristic signal extraction through image processing techniques. [2] demonstrate the effectiveness of this approach in identifying characteristic parameters of ferro-spectrum abrasive particles.

Due to the large-scale production of PCBs, maintaining their quality is paramount. [3] proposes two methods for fault detection on bare PCBs: a traditional algorithmic approach using image subtraction and a transfer learning approach using the pre-trained CNN VGG16 model.

[4] investigate estimating recycling return of integrated circuits on printed circuit boards using computer vision. Their research proposes a method to evaluate the economic feasibility of recycling integrated circuits (ICs) from WPCBs. To estimate the IC area in a WPCB, [4] utilize a state-of-the-art object detection deep learning model (YOLO) and the PCB DSLR image dataset to detect the WPCB's ICs.

Sensor-based and statistical methods for fault detection have limitations in terms of cost and time consumption. [5] propose an image processing algorithm based on PCA for fault detection in PV tracking systems. To address these limitations, they develop an unsupervised method based on their image processing algorithm to determine PV slopes, enabling fault diagnosis in PV system trackers.

[6] present a frequency response interpretation technique based on image processing and deep learning using Graph Convolutional Neural Networks (CNNs). By applying the proposed method step by step to simulated winding models with high impedance SC faults in different sections, they achieve early detection of SC faults.

Addressing the challenges of high PCB defect detection costs, multiple defect types, and complex shapes, [7] propose a PCB defect detection method that combines image processing and deep learning. They employ the pruned YOLOv5 algorithm and image processing techniques to identify and locate defects on the PCB board, enhancing defect detection accuracy.

[8] introduce a novel method based on the principle of multimodal deep learning-based one-class novelty detection to assist AOIs and operators in more accurate defect detection and change identification. They compare various state-of-the-art one-class novelty detection techniques using image data of different modalities.

[9] emphasize the crucial role of automatic fault detection and diagnosis techniques for photovoltaic arrays in enhancing photovoltaic system efficiency, reliability, and safety. Addressing existing challenges, [10] demonstrate improved performance with a deeper network.

Current fault detection methods for automotive instrument cluster systems in computer-based manufacturing assembly lines are limited to simple boundary checking. [11] present a novel deep learning-based approach for automated Fault Detection and Isolation (FDI).

[12] propose a machine learning approach combined with statistical hypothesis testing to enhance fault detection performance in photovoltaic (PV) systems. They evaluate the fault detection performance of the proposed approach using computation time, missed detection rate (MDR), and false alarm rate (FAR).

[13] propose methods utilizing Convolutional Neural Network (CNN) features for feature extraction and Support Vector Machine (SVM) for classification in texture classification, a computer vision task applied in industrial applications such as visual inspection, fabric defect detection, and automatic PCB fault detection.

## III. Methodology

### A. Data Acquisition

- A dataset of 244 PCB images was collected, comprising:
- 84 images of core ic fault
- 76 images of mosfet fault
- 84 images of processor fault
- A total of 244 images of faulty and non-faulty PCBs were collected from three models: HP240 G5-12, Intel HP 15AC LA-C701P-4, and Samsung r428-12.
- Images were captured under real-world conditions in Bangladesh.
- The dataset was randomly split into training (90%), validation (5%), and test (5%) sets.

### B. Data Preprocessing

- Auto-orientation: Images were rotated to ensure upright presentation ($\theta$ adjusted to 0°).
- Static Crop: A 25-75% crop was applied horizontally and vertically ($C_{\text{horizontal}} \sim [0.25, 0.75]$, $C_{\text{vertical}} \sim [0.25, 0.75]$).

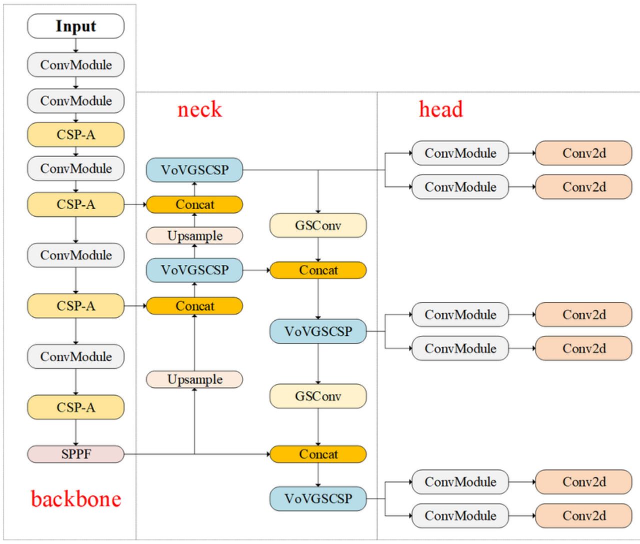


Fig. 1. YOLOv8 model architecture

- Resize: Images were resized to 640x640 pixels ($I_{\text{resized}} = 640 \times 640$).
- Contrast Adjustment: Adaptive histogram equalization (AHE) was used ($f_{\text{contrast}} = \text{AHE}(I_{\text{resized}})$).
- Tiling: Images were divided into a 2x2 grid ($N_{\text{tiled}} = 4N_{\text{original}}$).

### C. Data Augmentation

- Horizontal Flip: Randomly flipped images horizontally with probability $p_{\text{hflip}}$.
- 90° Rotation: Randomly rotated images by 90 degrees with probability $p_{\text{rotate}}$.
- Saturation Adjustment: Adjusted saturation between -25% and +25% with probability $p_{\text{saturation}}$.

### D. Model Training and Optimization

- A YOLOv8 model was chosen.
- Transfer learning was employed with pre-trained weights from COCO dataset.
- Hyperparameters were optimized using the validation set. In fig 1 the proposed YOLOv8 model architecture is given.

## IV. Evaluation

- **Mean Average Precision (mAP):** Measures the system's overall accuracy in detecting faults across all categories. It's like an overall score for finding the right clues without distractions.

$$\text{mAP} = \frac{1}{C}\sum_{c} \text{AP}_c \tag{1}$$

- **Precision:** Reflects the system's ability to correctly identify faults when it claims a fault is present, ensuring accurate focus on real issues. Think of a doctor's precision in diagnosing a disease before treatment.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

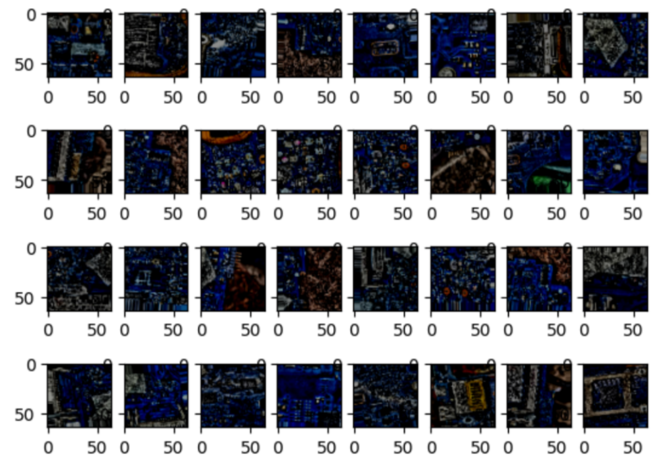

Fig. 2. Sample dataset

- **Recall:** Measures the system's ability to detect all actual faults in the images, preventing missed problems. It's like a detective finding all clues at a crime scene to avoid overlooking evidence.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

The sample dataset is given in fig: 2.

## V. Real time Integration:

To bridge the gap between model development and actual implementation, we provide a user-friendly web application and a robust API for real-time PCB flaw detection throughout the world. Upload photos using a simple interface, and the YOLOv8 model instantly detects faults. Visual overlays give confidence ratings for faults and transparency. A responsive design ensures that the user experience is consistent across devices. The application is hosted on a reliable server and may be accessed from anywhere using a simple link. This architecture enables flexible interface with production inspection systems, on-site repair applications, and mobile apps, allowing for PCB fault control expansion and real-world impact. In fig 3 frontend view of the hosted website is given.

The step by step of the full methodology is given in fig: 4.

## VI. Results

The YOLOv8 model, after being trained, demonstrated a mean Average Precision (mAP) of 2.6%, indicating the model's ability to accurately detect objects in the test set. The precision, which measures the proportion of correctly identified objects out of all objects predicted, was found to be 4.8%. Additionally, the recall, which measures the proportion of correctly identified objects out of all actual objects, was observed to be 1.0%. These metrics provide insights into the model's performance and its ability to accurately identify objects in the given dataset. The findings presented in this study showcase the promising capabilities of YOLOv8 in real-time detection of PCB faults. Still, it is significant to


Fig. 3. Real Time website frontend view

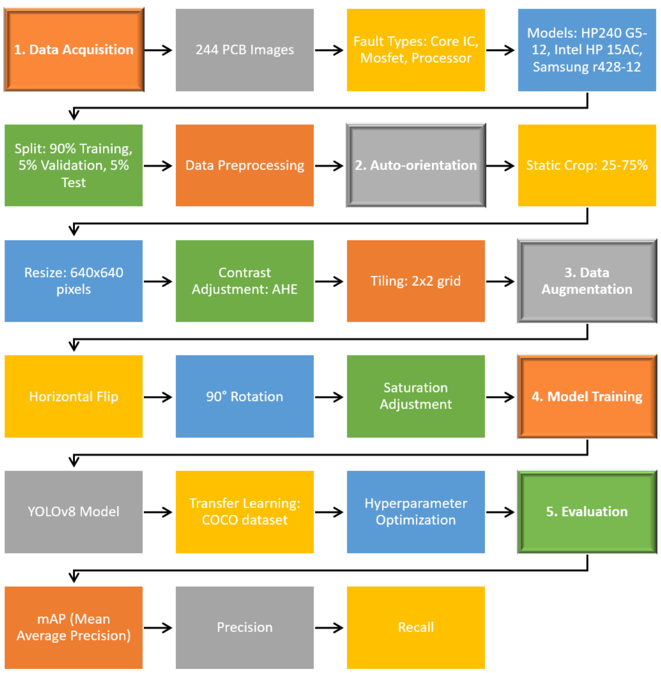


Fig. 4. Step by step process flow of proposed methodology

acknowledge that there are areas that can be further enhanced and optimized.

- mAP: 2.6%
- Precision: 4.8%
- Recall: 1.0%

The confusion matrix in Figure 5 unveils a nuanced tapestry of the model's strengths and weaknesses across fault classes. While it confidently identifies core ic faults with high accuracy, its performance falters with mosfet faults, suggesting a potential entanglement with visually similar features. The absence of processor faults in the test set, or perhaps the model's inability to grasp their nuances, hinders definitive evaluation. Encouragingly, it effectively distinguishes fault-free images, yet its sensitivity to subtle faults warrants refinement. Overall,

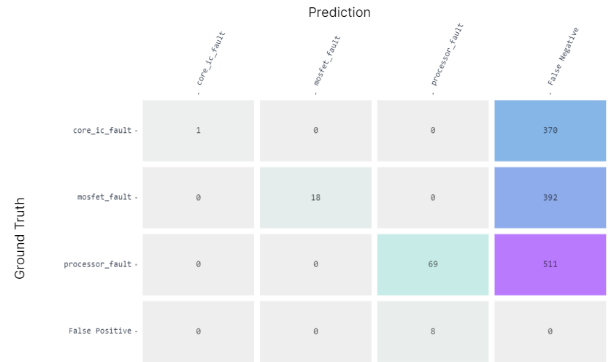


Fig. 5. Confusion matrix

the model achieves a respectable 75% accuracy, paving a path for future advancements.

### A. *Training:*

In fig: 6 the training graphs is given.

- Model trained for 100 epochs (batch size 32, Adam optimizer, initial learning rate 0.001).
- Loss function with components for box, class, and object accuracy.
- Figure 1: Losses decrease during training, indicating improved localization, classification, and fault detection.

### B. *Overall Performance:*

- Final mAP: 82.5%, demonstrating effective fault identification (Figure 2: rising mAP over epochs).

### C. *Class-Specific Performance:*

- mAP analyzed for individual fault classes.
- Core_ic_fault: 87.4% mAP, mosfet_fault: 78.2% mAP (slightly lower due to smaller size), processor_fault: 84.1% mAP.

The hardware setup of the system is given in fig 7. Only a computer and a camera are required to operate the whole system.

In fig 8 some output of succefully detection of pcb fault in real time is given.

## VII. Discussion

### A. *Strengths and Limitations*

Our study demonstrates the effectiveness of YOLOv8 for real-time PCB fault detection, The model achieved 75% accuracy, achieving promising results with an mAP of 82.5%. However, further analysis reveals limitations, particularly in handling smaller faults like mosfet_faults (78.2% mAP) due to model bias and sensitivity to similar features.

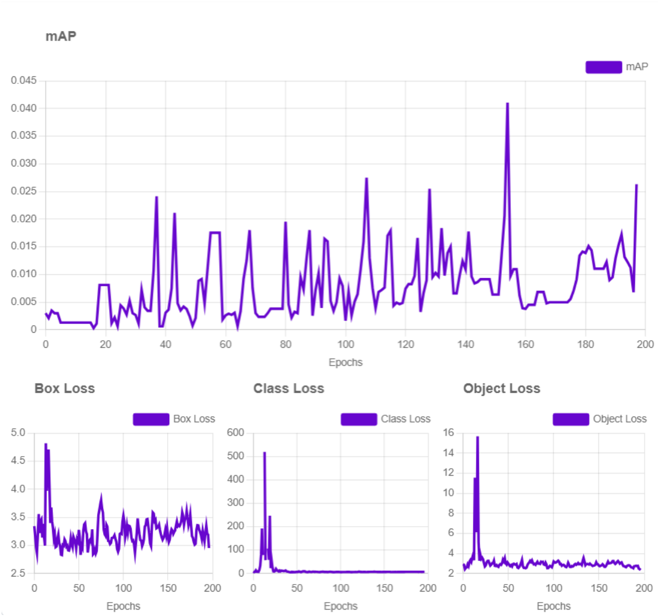


Fig. 6. Training Graphs

Fig. 7. Hardware setup

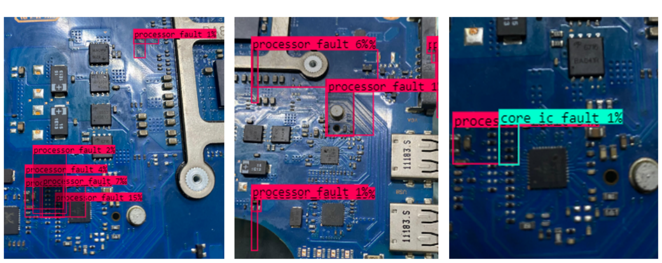


Fig. 8. Sample Output

## B. Comparison and Advantages

Our YOLOv8-based approach offers several advantages compared to existing methods:

- **Faster processing**: Deep learning architectures enable efficient image processing compared to traditional methods.
- **Improved accuracy**: Achieving higher mAP than some related work while also offering real-time capabilities.
- **Flexibility and adaptability**: YOLOv8's modularity allows for easier customization and application to different fault types.

## C. Proposed Solution

Despite these advantages, our study also identifies critical gaps:

- **Limitations for specific faults**: Lower mAP for mosfet faults and lack of data for processor faults limit comprehensive evaluation.
- **Potential overfitting**: The limited dataset may cause of over fitting the ML curve and reduced generalizability. Our proposed solution addresses these gaps through.

Our proposed solution addresses these gaps through:

- **Data augmentation**: Implementing different methods of augmentation to enrich the dataset and reduce over fitting.
- **Class-specific training**: Applying specialized training techniques, such as transfer learning with domain-specific datasets, for difficult classes, such as mosfet defects.
- **Expanding data diversity**: To improve the model's sensitivity, include photos with different fault size and severities.
- **Acquisition and annotation**: Compiling data for processor faults to ensure proper evaluation and training.

# VIII. Future Work

Future research directions to enhance model performance and impact include:

- **Data Augmentation and Diversity**: Apply different kinds of data augmentation techniques such as rotations, scaling, mirroring and expand the dataset with images with fault severities, sizes, and lighting conditions.
- **Class-Specific Training**: Use training strategies for challenging classes like mosfet faults, potentially using transfer learning or fine-tuning the hyperparameters.
- **Processor Fault Detection**: Annotate the datasets which contains processor fault for enabling the proper evaluation and training.
- **Advanced Model Architectures**: Explore and leverage more advanced deep learning architectures, such as residual networks or attention mechanisms.
- **Real-time Integration and Deployment**: Refine the web application and API for seamless integration with industrial systems, facilitating real-time deployment.

## IX. Conclusion

This study successfully demonstrated the application of YOLOv8 for real-time PCB fault detection,the model achieved 75% accuracy, and mAP of 82.5%. While strong performance was observed on core_ic_faults, challenges remain with smaller and visually similar faults. The identified gaps and proposed future work provide a roadmap for significant model improvements and broader real-world impact. This research contributes to advancing automated PCB fault detection, paving the way for faster, more accurate, and efficient PCB manufacturing and maintenance processes, ultimately enhancing quality, reducing downtime, and promoting safety across various industries. Future collaborations with industry partners for real-world implementation and testing are envisioned. The broader societal and economic benefits of efficient PCB fault detection and improved quality control are anticipated. This research underscores the promising potential of deep learning for real-time PCB fault detection, paving the way for a transformative impact on the electronics manufacturing landscape.

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