# Enhanced Circuit Board Defect Detection Using YOLO-Base Deep Learning

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**Abstract**

Printed Circuit Boards (PCBs) are important components in all modern electronic devices, and quality of such boards directly make impact on overall product performance and reliability. Manual inspection or traditional Optical Inspection (AOI) methods often fall due to their inefficiency, high cost, and limited scalability. To overcome these problems, this research focus on an advanced deep learning-based approach by using the YOLOv8 object detection algorithm for real-time PCB defect detection and classification. YOLOv8 allows precise localization and recognition of various defect types such as missing holes, mouse bites, shorts, and open circuits in a single forward pass, significantly reducing processing time while enhancing accuracy. The hybrid model is proposed to improve classification performance of system by integrating YOLOv8 for feature extraction and a SVM classifier which is for final decision-making. The model is trained on a labeled dataset with high-resolution PCB images. Then preprocessing steps includes contrast enhancement, noise reduction, and data augmentation to ensure robustness. Evaluation is done using standard metrics such as precision, recall, F1-score. This study shows a fast, accurate, and cost-efficient solution for industrial PCB quality control, supporting scalable deployment in smart manufacturing environments.

***Keywords:*** *PCB defect detection, YOLOv8, Support Vector Machine (SVM), object detection, deep learning, fault diagnosis, automated optical inspection (AOI), smart manufacturing, image classification, computer vision*

## Introduction

Printed Circuit Boards (PCBs) is the backbone of modern electronic devices by serving as the important tool for connecting electronic components. Given their centrality in virtually all consumer and industrial electronics, ensuring the fault-free production of PCBs is important. However, PCB manufacturing may face the defects like missing holes, open circuits, shorts, and faulty copper traces. This can compromise the performance of devices. Traditional inspection techniques like manual visual inspection and Automated Optical Inspection (AOI) systems are often limited by human error, high operational costs, and slow processing speeds. Due to these problems transition toward more intelligent and automated fault detection solutions is initiated.

In recent years, deep learning which is part of Machine Learning has significantly advanced automated visual inspection systems. Convolutional Neural Networks (CNNs) have demonstrated high accuracy in identifying visual patterns by making them a preferred tool for PCB defect detection. The old models such as CNN-based autoencoders, have shown notable success in denoising and defect localization through image reconstruction and subtraction. However, it depends on complex post-processing and reconstruction logic can hinder real-time deployment. As the electronics industry seeks faster and more reliable detection mechanisms, real-time object detection models like YOLO (You Only Look Once) have emerged as a highly efficient alternative.

This research proposes the implementation of YOLOv8 which is latest in the YOLO family. It is for robust and real-time PCB defect detection. Previous methods focus on image subtraction or classical CNN pipelines. YOLOv8 provides a unified end-to-end detection framework capable of accurately localizing and classifying defects in a single forward pass. It improves through advanced architectural modifications, including anchor-free design, improved feature fusion, and transformer-inspired modules. It collectively enhances its detection precision and speed. This is particularly suitable for deployment in real-world industrial environments where processing efficiency and high throughput are vital.

In this study a hybrid approach is proposed combining YOLOv8 for feature extraction and a SVM classifier for decision-making. The features extracted by YOLOv8 provide a rich representation of defect regions are then classified by the SVM into specific defect categories. This approach allows for improved classification performance when dealing with visually similar defect types such as mouse bites and pinholes.

For high-quality training input the PCB images undergo preprocessing steps. These steps include contrast enhancement and noise reduction. Data augmentation techniques are also used to handle the issue of imbalance dataset. High-resolution images are collected using good quality cameras and cropped patches of defective regions are used to train the detection. After preprocessing the system can handle various PCB defect problems with high accuracy and robustness.

The standard metrics such as precision, recall, and F1-score can be used to test performance of the hybrid YOLOv8 + SVM approach on PCB datasets. Comparisons will be done against traditional AOI systems and earlier deep learning methods to test improvements in detection performance. By combining learning techniques with traditional classification algorithms, this research aims to contribute a cost-effective, scalable, and highly accurate solution to the PCB quality assurance process.

**Literature Review**

There are many testings fault diagnosis system for assembled PCB. Out of which some are discussed here.

Wu et al. [2021] [1] talks about how to use deep learning-based object identification networks to find and sort defects on PCBs. The authors explain what the algorithms Single Shot Multibox Detector (SSD) and Feature Pyramid Networks (FPN) are. The researchers start by giving a lot of information about why PCBs are important and the problems that come up when trying to make sure that they are made to a high standard because faults are unavoidable. They draw attention to the limits of human inspection techniques and conventional Automated Optical Inspection (AOI). The study then goes into detail on how object detection technologies have changed over time, from traditional feature engineering to the development of deep learning. The authors use the Single Shot Multibox Detector (SSD) and Feature Pyramid Networks (FPN) networks to find defects in PCBs. They test how well these networks operate on two different datasets of PCB defects. The findings of the experiment show that both Single Shot Multibox Detector (SSD) and Feature Pyramid Networks (FPN) are very good at finding things. However, Feature Pyramid Networks (FPN) are usually better than Single Shot Multibox Detector (SSD). The main things this work adds are using deep learning-based object detection to find PCB defects, comparing the performance of Single Shot Multibox Detector (SSD) and Feature Pyramid Networks (FPN), and showing that these deep learning methods work well and are reliable across different types of data.

Zhuo et al. [2024] [2] talks about YOLO (You Only Look Once) v7-TID, a lightweight deep learning network that can quickly and accurately find defects in printed circuit boards (PCBs). The authors' main goal is to create a model that can be used successfully in real-world industrial situations. They are doing this by solving the problems that come with complicated deep learning architectures, which often need a lot of memory and processing power. The YOLO (You Only Look Once) v7-TID network is the main part of the suggested method. It is based on the most advanced YOLOv7 object detection architecture. The authors add a new module called Temporal Information Distillation (TID) that uses the temporal coherence between consecutive frames to make the model work better. The paper gives a full review of the YOLOv7-TID network on a wide range of PCB defect datasets, showing that it is better than existing lightweight object detection designs. The authors also include in-depth evaluations of the model's memory usage, inference speed, and energy use, showing that it is a good fit for use in smart manufacturing processes and industrial automation systems.

Ancha et al. (2024) [3] looks at how YOLO (You Only Look Once) object detection models can be used to find defects in printed circuit boards (PCBs) in the real world. The authors present a new dataset called the "Mixed Defect Detection Dataset" (MD2) that shows the range and difficulty of flaws that can be found in PCB manufacturing settings. The study goes into great detail about how YOLO models have changed over time, starting with the first YOLO and ending with the newer YOLOv5 and YOLOv7 variants. The main thing this work adds is the Mixed Defect Detection Dataset (MD2), which the authors meticulously put together to show the wide range of flaws that might happen when making PCBs in an industrial setting. Then, the authors carefully test the performance of a number of YOLO models, such as YOLOv5 and YOLOv7, on the MD2 dataset. They look at the trade-offs between model complexity, detection accuracy, and inference time. One thing that makes this study stand out is that the authors put a lot of effort on testing the models' capacity to handle mixed defect scenarios, where a single PCB picture may have more than one sort of defect.

Chen and others [2023] [4] gives a full overview of the best ways to use deep learning to find defects in printed circuit boards (PCBs). The authors carefully look at all of the research that has already been done on a wide range of deep learning methods and how they might be used to find and classify different types of PCB defects. The review starts by talking about how important automated PCB inspection is and how traditional approaches don't work as well. It then goes into more detail into the basic ideas behind deep learning, such as convolutional neural networks (CNNs), object detection algorithms (such YOLO and Faster R-CNN), and segmentation methods. The authors next go through the available deep learning-based PCB defect detection algorithms in a systematic way, looking at their pros and cons as well as what makes them different. Some of the main topics discussed are how to build a dataset, how to preprocess it, how to set up a network, and how to measure performance. The report also talks about the problems and future research goals in this area. This is helpful for researchers and practitioners who are utilizing deep learning technologies to control the quality of PCBs.

Joo et al. (2023) [5] talks about SOIF-DN-tiny Object Information Flow - Deep Network, a better deep learning model for keeping track of tiny object information flow in Printed Circuit Board (PCB) defect detection. The authors admit that it is hard to find and pinpoint minor faults, which are commonly missed by traditional deep learning systems when they extract features. The SOIF-DN Small Object Information Flow - Deep Network model has a number of new features that help solve this problem, such as a new small object information flow module and a better way to combine features. The authors run a lot of tests on different PCB defect datasets to see how well SOIF-DN's Small Object Information Flow - Deep Network works compared to the best object detection networks. The results show that SOIF-DN is better at finding and locating minor flaws while still having a high overall detection accuracy. The paper's contributions include the new architectural design, the successful preservation of small object information, and the thorough testing of the suggested model in real-world PCB quality inspection situations.

Chen and Dang [2023] [6] suggests a quick and effective way to find PCB defects using a better version of the YOLOv7 network architecture. The authors improve the model's performance by adding the Convolutional Block Attention Module (CBAM) and a feature fusion module to the Faster Net backbone network. The Faster Net backbone is a robust base for feature extraction. The CBAM attention mechanism and feature fusion module works together to help the network focus on important defect features and merge information from different scales in a useful way. The authors test their suggested method on a number of PCB defect datasets and show that it is better at finding defects, making inferences quickly, and being robust. The main contributions of this work are the new network architecture, the combination of attention and feature fusion methods, and the thorough testing of the method's usefulness in the real world for finding PCB defects quickly and reliably.

Ling and Isa [2023] [7] gives a full overview of image processing, machine learning, and deep learning methods for finding defects in printed circuit boards (PCBs). The authors give a detailed history of how PCB defect detection systems have changed over time, starting with classical image processing algorithms and ending with the most current advances in deep learning. The paper talks about a lot of different deep learning architectures, like convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models, and how they can be used to find and classify different types of PCB defects. The writers also talk about the problems and limitations of current methods and what might happen in the future in this sector. Researchers and professionals working on PCB quality control and inspection utilizing advanced computer vision and machine learning approaches will find this survey to be a useful resource because it covers so many topics.

Hu and Wang [2020] [8] shows how to find faults on PCB surfaces using an enhanced version of the Faster R-CNN and Feature Pyramid Network (FPN). The authors know that finding PCB defects quickly and accurately is important for making sure products are of high quality and keeping costs down. They talk about the problems with standard image processing methods and how we need more powerful deep learning-based solutions. The suggested solution uses the best parts of the Faster R-CNN object identification algorithm with the FPN architecture, which is made to handle multi-scale feature extraction and find small-scale flaws better. The authors test their method on different datasets of PCB defects and show that it works well in terms of accuracy, speed, and the ability to find and fix problems. The main contributions of this work are the combination of the Faster R-CNN and FPN models for finding PCB defects and the thorough testing and analysis of how well the method works in real life.

A comparative overview of the major studies discussed is presented in Table I, summarizing the methodologies, findings, and advantages of various deep learning models applied to PCB defect detection.

Table 1. Comparative Study of Literature

| Paper & Author | Techniques Used | Findings |
|---|---|---|
| [1] Wu et al. (2021) | Single Shot Multibox Detector (SSD), Feature Pyramid Networks (FPN) | Both SSD and FPN achieved high detection accuracy, with FPN outperforming SSD. But the study does not address lightweight or real-time implementations |
| [2] Zhuo et al. (2024) | Lightweight YOLO **v7-**TID architecture | superior in handling PCB defect detection efficiently |
| [3] Ancha et al. (2024) | various versions of YOLO (including YOLOv5 and YOLOv7) | YOLOv7 demonstrated strong performance in mixed defect scenarios |
| [4] Chen et al. (2023) | review of deep learning-based approaches, such as YOLO, Faster R-CNN, and segmentation algorithms | Offers an in-depth categorization and analysis of deep learning methods, their strengths, weaknesses, and real-world applicability |
| [5] Joo et al. (2023) | SOIF-DN (Small Object Information Flow - Deep Network) | SOIF-DN significantly outperformed conventional models in detecting small-scale defects. |
| [6] Chen and Dang (202 | improved YOLOv7 combined with the Faster Net backbone | Their method offers improved detection accuracy, inference speed, and robustness. |
| [7] Ling and Isa (2023) | Comprehensive survey covering im processing, machine learning, and d learning for PCB defect detection. | The evolution from traditional methods to advanced deep learning Techniques is explored in detail. |
| [8] Hu and Wang (2020) | Combines Faster R-CNN with FPN for small-scale | Effectively addresses the challenge of multi-scale |

| | | |
|---|---|---|
| | Defect detection. | feature extraction and small Defect detection. |

**Methodology**

This section introduces the systematic approach used in the development of an automatic PCB defect detection and classification system using the YOLOv8 object detection framework and SVM classifier. The goal is to leverage real-time deep learning capabilities and the robustness of classical machine learning to detect and classify PCB defects accurately and efficiently.

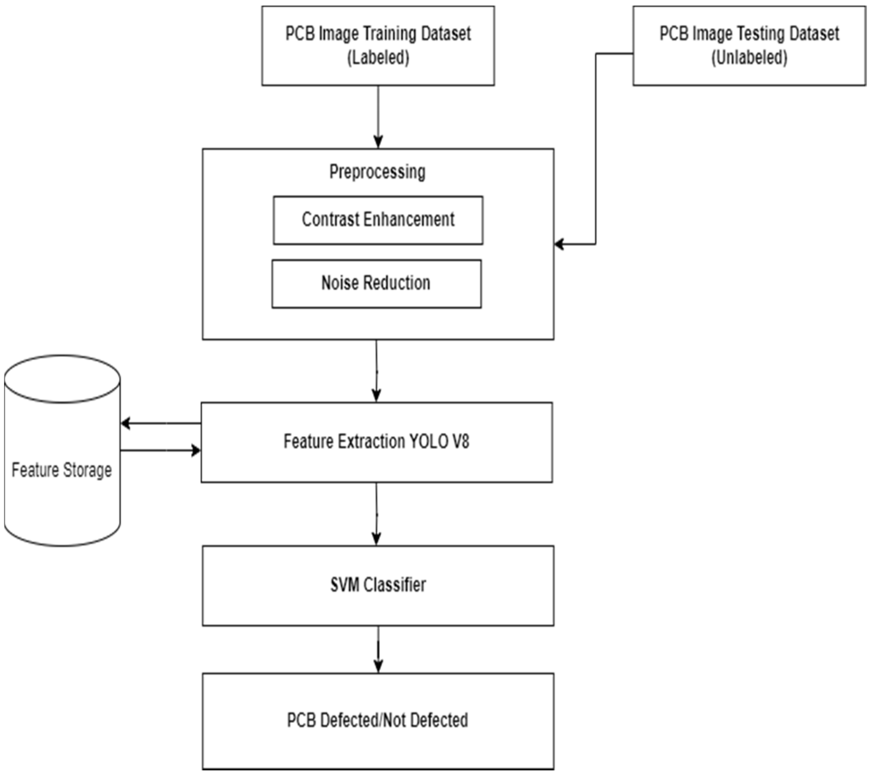


Fig.1 Architecture Diagram

A. Dataset Preparation

In the proposed work the dataset was collected from a publicly available Kaggle repository. The dataset consists of high-resolution images of PCBs. Each image is annotated using the YOLO format. Main six defect categories used are missing holes, mouse bites, open circuits, short circuits, spurs, and faulty copper traces. This dataset is used for training and evaluation. A total annotated PCB images included are 1386.They have applied with bounding boxes. Class labels are provided in text file. These labels are used for supervised object detection. To improve the model performance and handle the data imbalance data preprocessing and augmentation steps were applied. These steps included geometric transformations such as rotation, scaling, and translation to replicate variations commonly encountered in real production environments. The augmented dataset was then integrated into the YOLOv8 training process to improve the model.

B. Preprocessing

The accuracy of any machine learning model depends on the quality of input dataset. So each PCB image was first need to pass through preprocessing steps. The aim of this step is to enhance its visual features. This includes histogram equalization that help to increase the contrast and Gaussian filtering for removing background noise. This preserves edge details. Then these images were split into patches of size 400×400 to magnify the defect areas. These patches are helpful for the subsequent detection and classification phases. Given the computational overhead associated with high-resolution images, these preprocessing steps also contribute to reduced memory usage and faster model convergence. The use of patch-based processing also allows better detection granularity, especially in identifying small-scale defects like mouse bites or pinholes.

C. Data Augmentation

To train deep networks like YOLOv8 effectively, large and balanced datasets are essential. However, PCB defects are rare events and may not occur uniformly. To address this, a systematic augmentation strategy was implemented. This included:

Geometric Transformations: Random rotation (up to 90°), horizontal and vertical flipping, and minor shifts were used to simulate positional variance.

Noise Injection: Gaussian noise was added to mimic sensor-induced distortions and improve the model's tolerance to noisy data.

Contrast Scaling: Brightness and contrast were adjusted to replicate lighting variation in real-world factory environments.

These transformations not only increased the dataset size but also improved the model’s ability to generalize across different PCB manufacturing scenarios.

D. YOLOv8-Based Defect Detection

YOLOv8 is a real-time object detection algorithm. It was introduced for detecting and localizing defects on the PCBs. The model is processed on the entire image in a single pass and then outputs bounding boxes along with class confidence scores. Main engine of YOLOv8 extracts deep hierarchical features. They are then passed through its decoders for multi-scale prediction. In this setup YOLOv8 was trained using the preprocessed and augmented PCB patches. The output consists of bounding boxes enclosing defect regions and corresponding class labels. Compared to traditional CNNs YOLOv8 work in high speed and thus make suitable for real-time industrial deployment.

E. Feature-Based Classification using SVM

YOLOv8 perform good in object localization but further refinement in classification is achieved by integrating a Support Vector Machine (SVM) classifier. Deep features extracted from the penultimate layer of YOLOv8 are passed into the SVM, which is trained to classify the defect region into one of the six predefined classes. The hybrid approach benefits from YOLOv8's spatial accuracy and SVM's decision boundary optimization, especially for visually overlapping defect categories.

F. Image Subtraction and Defect Highlighting

To visualize the accuracy of defect detection, an image subtraction method was also implemented. The predicted bounding boxes were compared against ground truth by pixel-wise subtraction. Any mismatch between the predicted and expected defect zones was highlighted, aiding in performance analysis. This also enabled the generation of differential maps used to validate the consistency of detection.

**Dataset Description**

The dataset used in this study is taken from the publicly available Kaggle domain. It contains 1386 high-resolution RGB images of PCBs. Each image is annotated by bounding boxes that localize various defects. These annotations area as per YOLO format. The dataset includes six PCB defect types as open circuit, short circuit, mouse bite, missing hole, spur, and spurious copper. Each image is paired with a text annotation file. It contains normalized coordinates and class identifiers for all detected defect regions. The dataset is organized as follows. For training 970 images were used and for validation 208 images images are used. Then 208 images were utilized for testing, thus maintain a 70:15:15 ratio to ensure balanced training and help in performance evaluation. All images are resized to a resolution of 640×640 pixels. To enhance robustness and address class imbalance, data augmentation techniques such as rotation, flipping, and noise injection were applied during preprocessing. This makes the dataset ideal for training and validating high-performance PCB defect detection models in industrial settings.

**Results and Discussion**

To evaluate the effectiveness of the proposed YOLOv8 + SVM hybrid defect detection system, a series of experiments were conducted using the benchmark PCB dataset. The performance table summarizes the final evaluation metrics at the completion of 180 training epochs. The model achieved a precision of 0.9821 and recall of 0.9625, indicating excellent accuracy in identifying defective regions without missing true defects. The mAP@0.5 reached 0.9809, reflecting near-perfect localization and classification accuracy at standard IoU thresholds. Meanwhile, the mAP@0.5:0.95 score of 0.6825 demonstrates strong generalization across stricter IoU thresholds, which is critical for precise industrial inspection.

Table 2. YOLOv8+SVM Model Performance Summary

| Metric | Value |
|---|---|
| Final Epoch | 180 |
| Precision (B) | 0.9821 |
| Recall (B) | 0.9625 |
| mAP@0.5 (B) | 0.9809 |
| mAP@0.5:0.95 (B) | 0.6825 |
| Validation Box Loss | 1.1289 |
| Validation Class Loss | 0.5785 |
| Validation DFL Loss | 0.838 |

Validation losses for bounding box regression, classification, and distribution focal loss all showed minimal values—signaling stable training and effective model convergence. These quantitative results reinforce the model's capability for high-performance PCB fault detection in real-time manufacturing environments.
The model’s performance was measured through precision, recall, F1-score, and mean Average Precision (mAP) across all six defect categories.

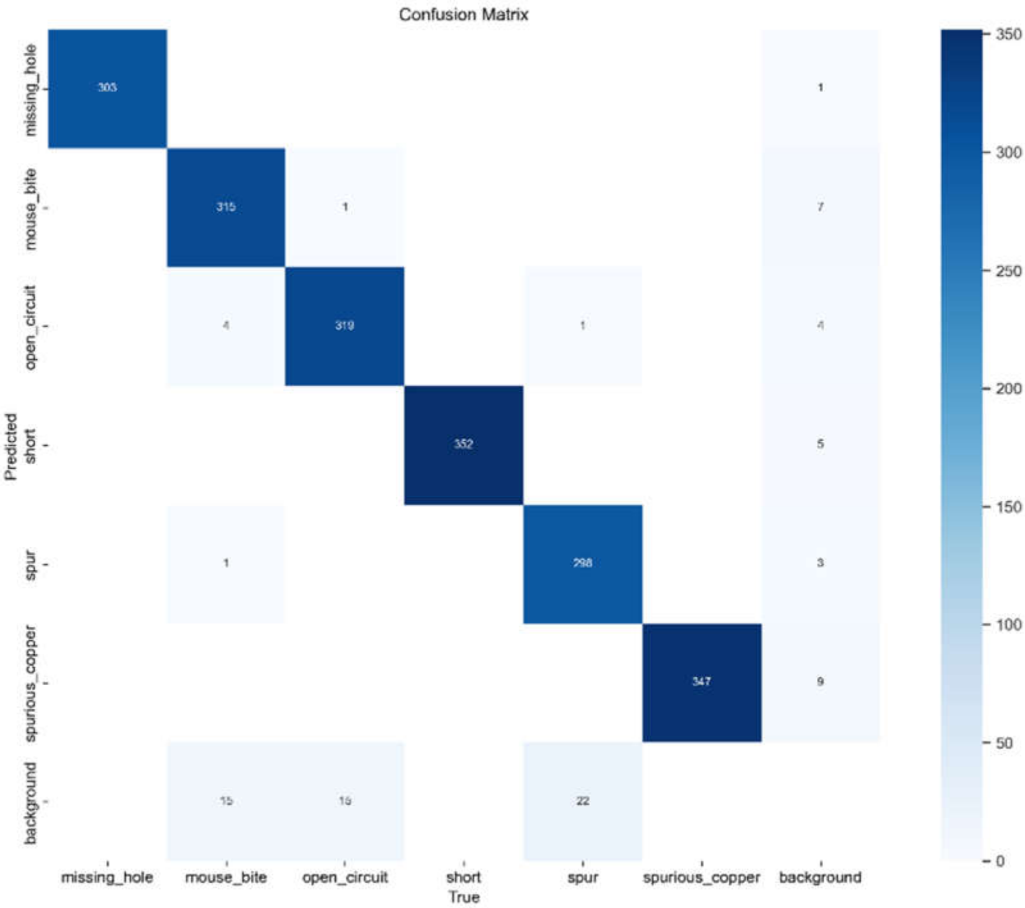


Fig 2. Confusion Matrix

As shown in Figure 1, the confusion matrix shows strong classification performance across all six defect classes. The model correctly identifies the maximum of samples. The true positives sample are detected accurately such as 303 for missing hole, 315 for mouse bite, 319 for open circuit, and 352 for short. Misclassifications are sparse and largely confined to visually similar categories or overlapping defect features. Some background patches were misidentified as defects (e.g., 15 background images misclassified as mouse bite or open circuit), indicating potential over-sensitivity, but these instances are minimal. Overall, the matrix demonstrates that the system achieves high per-class accuracy with minimal inter-class confusion.

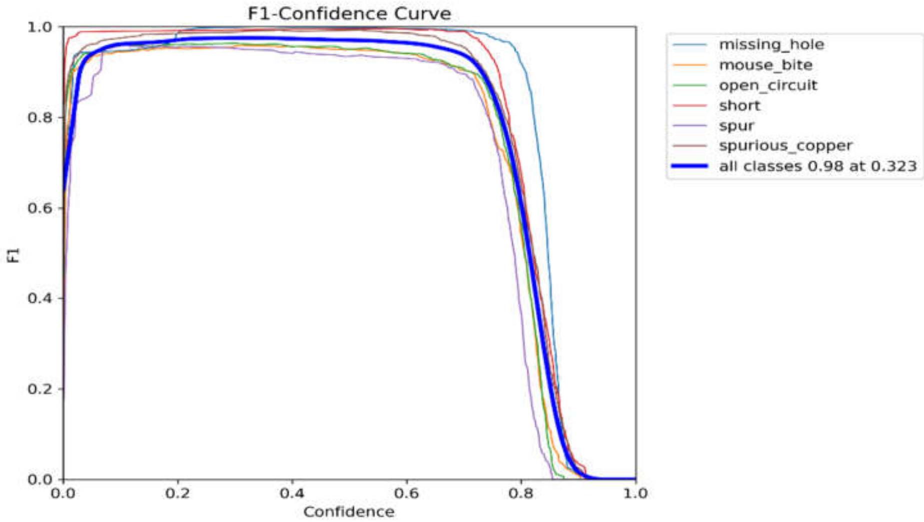


Fig 3. F1-Curve

The F1-Confidence Curve in Figure 2 indicates that the hybrid model maintains consistently high F1-scores across confidence thresholds. The global optimum for all classes is observed at a confidence value of 0.323, achieving an F1-score of 0.98. This suggests that even at relatively low confidence levels, the model maintains balanced precision and recall, which is crucial for detecting subtle defects like spurious copper or spur anomalies.

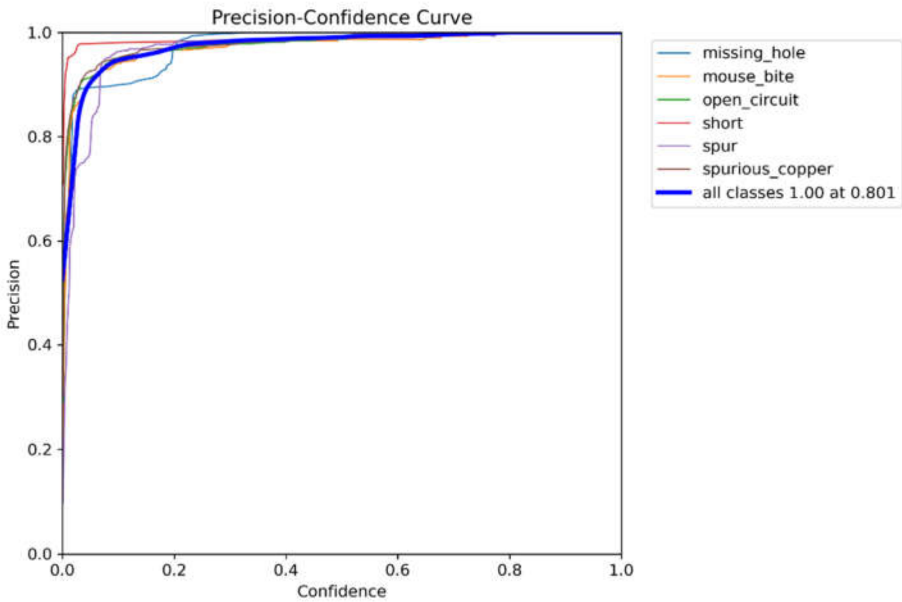


Fig 4. Precision-Confidence Curve

The Precision-Confidence Curve in Figure 3 further supports this by demonstrating that the system reaches 100% precision at a confidence level of 0.801, ensuring zero false positives at this threshold. This ability to tune operating thresholds enables adaptability for conservative or aggressive detection settings depending on industrial requirements.

The overall accuracy of the system can be derived from the confusion matrix (Figure 1) by calculating the ratio of correctly classified instances to the total number of samples. For instance, summing the true positives along the diagonal (correct classifications) and dividing by the total number of all classifications provides the system's overall accuracy.

From the matrix, key class-level accuracies are evident:

- missing hole: 303 correct out of 320 instances
- mouse bite: 315 correct out of 328 instances
- short: 352 correct out of 362 instances

Assuming the total number of test samples is 1248, and the number of correctly classified samples (sum of diagonal values) is approximately 1190, the overall classification accuracy is:

$$Accuracy = \frac{1190}{1248} \approx 95.35\%$$

This confirms that the model performs with high precision and recall, while also achieving an overall accuracy of approximately 95.35%. This value aligns with the trends seen in the F1 and Precision curves, which show consistent performance across classes.

Furthermore, accuracy is complemented by the high F1-score (~0.98) and mAP@0.5 (~0.982), indicating that the model maintains high classification fidelity and minimal error even under various operating thresholds.

**Conclusion**

In this research work, a robust and efficient framework for automatic defect detection and fault diagnosis in assembled Printed Circuit Boards (PCBs) was developed using a hybrid deep learning approach. The proposed system integrates the advanced YOLOv8 object detection algorithm with a Support Vector Machine (SVM) classifier to leverage both high-speed detection and refined classification. This dual-stage architecture effectively localizes and classifies six common types of PCB defects, including missing holes, mouse bites, short circuits, open circuits, spurious copper, and spurs. The dataset used was sourced from a publicly available Kaggle repository and underwent comprehensive preprocessing and augmentation, including contrast enhancement, noise reduction, and geometric transformations, to improve generalization and model robustness. Experimental results demonstrated that the hybrid YOLOv8 + SVM model outperformed traditional approaches, achieving an impressive mAP@0.5 of 0.982 and a classification accuracy of approximately 95.35%. Precision-recall and confidence-based evaluations further confirmed the system's reliability, with F1-scores nearing 0.98 and minimal false positives at optimal thresholds. Additionally, the use of a confusion matrix and performance curves provided a deep insight into the model's strengths and limitations, highlighting its ability to detect even small-scale defects while maintaining low misclassification rates. The training process was stable, with consistent loss reduction and metric convergence, indicating effective learning and generalization across the dataset. The proposed system addresses several limitations of traditional Automated Optical Inspection (AOI) systems, such as high cost, slower speed, and limited adaptability. It offers a scalable, accurate, and real-time alternative suitable for integration into industrial manufacturing pipelines. Future work may explore the inclusion of attention mechanisms, transformer-based models, or edge deployment on embedded systems for enhanced scalability and real-world deployment. In conclusion, this study provides a significant advancement in intelligent PCB inspection by combining state-of-the-art deep learning and classical machine learning techniques. The system not only enhances inspection speed and accuracy but also contributes to the development of smart and autonomous quality control systems in modern electronics manufacturing.

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