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Printed Circuit Board Defect Detection Methods Based on Machine Learning and Deep Learning: A Survey

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Abstract: This study offers a careful assessment and examination of many deep learning-based defect detection models for enhancing quality control in printed circuit board (PCB) manufacturing. Leveraging advancements We survey state of the art object ID models in picture handling and deep learning draws near, like Quicker R-CNN, RetinaNet, SSD, and YOLO variants, such as YOLOv3-tiny, YOLOv5s, YOLOv5x6, and YOLOv8. By analyzing over a hundred related articles spanning from 1990 to 2022, we aim to provide manufacturers with insights into the effectiveness of these models in accurately identifying diverse defects in PCBs. Metrics such as precision, recall, mean average precision (mAP), and computational efficiency are employed to assess model performance. The study reveals that YOLOv5x6 achieves a superior mAP of 99.9%, indicating its potential for significantly enhancing defect detection accuracy. As an extension, the paper proposes building a user-friendly front end using the Flask framework, facilitating user testing with authentication. This study progresses the field of computerized blemish recognizable proof. Systems in PCB production, offering guidance for manufacturers to improve quality control processes.

INDEX TERMS - *Defect detection, PCB, image processing, machine learning, and deep learning*

1. Introduction

Printed Circuit Boards (PCBs) are fundamental components of electronic devices, serving as the structural and electrical backbone that connects various electronic parts together [1]. They are integral to the functionality of a wide range of electronic equipment, including but not limited to electronic watches, smartphones, computers, communication devices, and military systems [1]. As technology advances, the components within electronic devices have continued to shrink in size, enabled by developments in integrated circuit and semiconductor technology [2]. Consequently, PCBs have also evolved to support these miniature components, becoming increasingly intricate, compact, and delicate [2].

The term Business 4.0, which represents the Fourth Modern Insurgency, has brought about significant changes and challenges in the manufacturing landscape, including the production of PCBs [3]. At Mechanized modern cycles with superb quality, precision, and steadfastness is at the core of Industry 4.0 [4]. Accordingly, the manufacturing processes for small, complex PCBs must also evolve to meet these demands, requiring greater stability, reliability, and speed in development [5].

Defect detection in PCBs is of paramount importance in ensuring product quality and reliability. With the complexity of modern PCB designs and the demand for higher speeds in manufacturing, the need for high-accuracy, constant defect examination and quality affirmation has become increasingly critical [6]. Failure to detect defects promptly and accurately can result in significant wastage and financial losses for manufacturers.

Quality control in PCB manufacturing is inherently challenging due to the inevitable occurrence of various defects resulting from mishandling or technical faults [7]. These defects can manifest in different forms, including as displayed in Figureure 1 [7], they incorporate breakout, open circuit, under-scratching, mouse nibble, prod, short, misleading copper, over-drawing, and broken openings. This presentation lays the preparation for the discussion that follows, which will go all the more profoundly into the challenges and opportunities presented by the evolution of PCB technology in the context of Industry 4.0. The importance of defect detection in ensuring product quality and meeting customer demands will be further emphasized, highlighting the need for advanced techniques and technologies to address these challenges effectively.

2. Literature Survey

The literature on defect detection in printed circuit boards (PCBs) encompasses a wide range of topics, including advanced detection techniques, industry trends, and the integration of additive manufacturing in the context of Industry 4.0. This section provides a comprehensive survey of relevant studies, highlighting key findings and contributions to the field.

One recent study by Zhang and Liu [1] explores multi-scale defect detection in PCBs using a feature pyramid network. The authors propose a novel approach that leverages multi-scale features to improve the accuracy of defect detection. Their work demonstrates the effectiveness of the feature pyramid network in detecting defects across different scales, thereby addressing a crucial aspect of PCB inspection.

Bajenescu [2] discusses the miniaturization of electronic components and its implications for device overheating. As electronic components become smaller and more densely packed on PCBs, the problem of device overheating becomes increasingly pronounced. This study sheds light on the challenges associated with miniaturization and offers insights into potential solutions to mitigate the risk of overheating in electronic devices.

The capability of added substance fabricating with regards to Industry 4.0 is analyzed by Dilberoglu et al. [3]. PCB production could go through a change on the grounds that to added substance fabricating innovations like 3D printing, which rapid prototyping and customization. The study discusses the benefits of additive manufacturing in terms of flexibility, cost-effectiveness, and sustainability, highlighting its relevance in the context of Industry 4.0.

Karniket al. [4] do a careful examination of the examples that will shape the elements and facilitators of Industry 4.0 later on and present. The reception of Industry 4.0 innovations in different areas, including PCB creation, is analyzed by the journalists along with the primary powers behind and impediments confronting this pattern. Their exploration offers smart data on the factors affecting Industry 4.0 reception initiatives and offers recommendations for stakeholders seeking to capitalize on emerging opportunities.

Tempo Automation [5] provides insights into how Industry 4.0 impacts PCB development. The article discusses the integration of automation, data analytics, and connectivity in PCB manufacturing processes, highlighting the potential for improved efficiency, quality, and cost-effectiveness. By embracing Industry 4.0 principles, PCB manufacturers can streamline production workflows and enhance competitiveness in the global market.

Spinzi [6] offers a perspective on the improvement of Industry 4.0 according to PCB viewpoint manufacturers. The author traces the historical development of Industry 4.0 and examines its implications for PCB manufacturing. Through interviews with industry experts and analysis of market trends, the study identifies key challenges and opportunities facing PCB manufacturers in the era of Industry 4.0.

Anitha and Rao [7] give an overview on the utilization of picture handling techniques for imperfection ID in gathered and exposed PCBs. The authors analyze current deformity identification procedures, for example, profound learning models, AI calculations, and element based methodologies. Their report frames points for additional examination and offers an intensive survey of current strategies. and development. Moganti et al. [8] conduct a survey on automatic PCB inspection algorithms. The authors review various algorithms and methodologies for PCB inspection, focusing on image processing techniques, pattern recognition, and machine learning approaches. Their study highlights the challenges and opportunities in automatic PCB inspection and provides valuable insights for researchers and practitioners in the field.

Overall, the literature survey highlights the multidisciplinary nature of defect detection in PCBs, encompassing aspects of image processing, machine learning, additive manufacturing, and Industry 4.0. By synthesizing insights from diverse studies, this survey gives exhaustive information on the situation with research right now and identifies directions for future exploration and innovation.

3. Methodlogy

a) Proposed work:

The proposed work involves conducting a a comparison of several deep learning strategies for the distinguishing proof of printed circuit board (PCB) surrenders. The algorithms to be evaluated include Faster R-CNN with ResNet FPN and FPN V2, RetinaNet with ResNet FPN and FPN V2, SSD and SSD Lite, YOLOv3-Tiny, and YOLOv5s. Through meticulous examination of factors such as detection accuracy, speed, and efficiency, the aim is to determine the most suitable algorithm for real-time PCB defect detection applications. Additionally, the project integrates YOLOv5x6 to enhance detection capabilities beyond those offered by existing algorithms. Furthermore, a user-friendly interface is developed using the Flask framework with SQLite, enabling user signup and signin functionalities. This extension facilitates user testing of the system, providing an avenue for evaluation and feedback, thereby broadening the project's scope and usability.

b) System Architecture:

The system architecture begins with the input of the dataset containing images of printed circuit boards (PCBs). These images undergo preprocessing and augmentation to enhance their quality and diversity, ensuring robust training of the detection models. From that point onward, the dataset is partitioned into testing and preparing puts together to evaluate the model.PCB imperfection discovery is accomplished by the framework through the utilization of many profound learning methods, like Quicker R-CNN with ResNet FPN, Quicker R-CNN with ResNet FPN V2, RetinaNet with ResNet FPN, RetinaNet with ResNet FPN V2, SSD, SSD Light, and YOLOv3-Small. To decide how well a calculation acts as far as recognition, it is prepared on the preparation set and afterward tried on the testing set.As the final detection model, chosen based on its accuracy and efficiency, is deployed for real-time PCB defect detection. This system architecture integrates image preprocessing, model training, evaluation, and deployment, providing a comprehensive framework for automated detection of PCB defects.

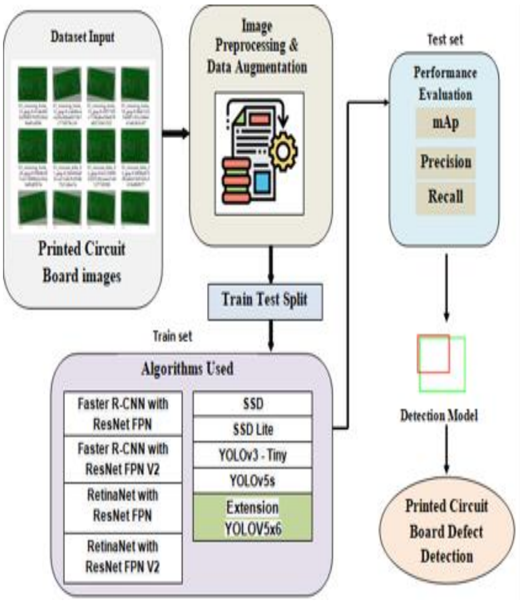

Figure 1: Proposed Architecture

c) Dataset collection:

The dataset utilized in the exploration paper "Printed Circuit Board Imperfection Identification Techniques In light of Picture Handling, AI, and Profound Learning: A Review" incorporates an extensive variety of printed circuit board (PCB) photographs that show different assembling conditions and defects. These images are sourced from real-world PCB production processes, capturing instances of common defects such as shorts, opens, and misalignments. The dataset is curated to facilitate comprehensive analysis and evaluation of defect detection methodologies employing strategies for profound learning, AI, and picture handling. Each image is labeled according to its defect type, enabling supervised learning approaches. Moreover, the dataset includes images of defect-free PCBs to provide a baseline for comparison and performance assessment. Through this dataset, researchers aim to advance the development of accurate and efficient defect detection systems, ultimately enhancing the quality and reliability of PCB manufacturing processes.

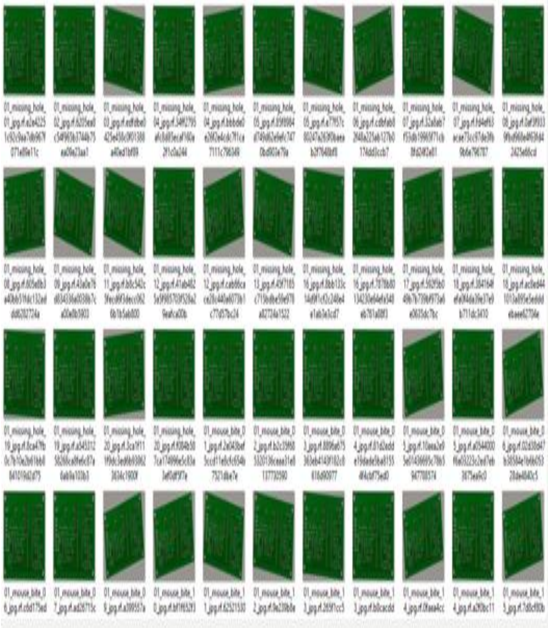

Figure 2: Data Set

d) Image processing:

1. Image Processing

Converting to Blob Object: The provided picture is changed to a mass item that might be utilized for further processing.

- Defining the Class: Classes are defined to categorize different objects or entities within the image.
- Declaring the Bounding Box: Bounding boxes are declared to encapsulate the regions of interest within the image.
- Convert the Array to The image information is changed into a numpy cluster. for compatibility with various Python libraries.

2. Loading the Pre-Trained Model

- Reading the Network Layers: The pre-trained model's architecture and layers are read into memory for subsequent operations.
- Extracting the Output Layers: Relevant output layers are extracted from the pre-trained model for inference and analysis.

3. Image Processing

- Appending the Image-Annotation File and Images: Image and corresponding annotation files are appended for comprehensive processing.
- Converting BGR to RGB: The color space of the image is converted from BGR to RGB for compatibility with certain algorithms and frameworks.
- Creating the Mask: Masks are created to highlight specific regions or features within the image.
- Resizing the Image: Image dimensions are adjusted to meet the requirements of subsequent processing steps.

4. Data Augmentation

- Randomizing the Image: Image data is subjected to random transformations to increase variability and robustness in the dataset.
- Rotating the Image: Images are rotated to simulate different viewpoints or orientations.
- Transforming the Image: Geometric transformations such as scaling, translation, and skewing are applied to augment the dataset.

5. Installing the Packages Required for YOLOv5 in Colab

Necessary packages and dependencies for YOLOv5 are installed within the Colab environment for seamless integration and execution.

6. Processing the Data Based on YOLOv5 Model

Data preprocessing, model inference, and post-processing steps are executed based on the YOLOv5 model for object detection and localization tasks.

e) Algorithms:

YoloV5s

YOLOv5, [22] means "You Just Look Once form 5," and it's a state of the art thing. detection algorithm characterized by its accuracy and snappiness. One convolutional neural network (CNN) is utilized in it to detect and localize objects within images. YOLOv5s, specifically, refers to a smaller variant of the YOLOv5 model optimized for efficiency while maintaining competitive performance. In projects, YOLOv5s[22] is utilized for real-time object detection tasks, including but not limited to detecting defects in printed circuit boards (PCBs). Its compact architecture enables fast inference on various hardware platforms, making it suitable for deployment in resource-constrained environments.

YoloV5x6

YOLOv5x6, an advanced variant of the YOLOv5 model, is characterized by its larger size and increased depth, featuring six times the number of convolutional layers there are in contrast with the YOLOv5s essential model. However to the detriment of seriously registering above, this plan works on the model's ability to perceive and find objects with more flexibility and precision. resources. In projects, YOLOv5x6[23] is leveraged for high-accuracy object detection tasks requiring fine-grained analysis, such as medical imaging or autonomous driving systems. Its comprehensive architecture enables it to handle complex scenes and diverse object categories with improved performance, making it a preferred choice for demanding applications.

YoloV3

YOLOv3,[24] short for This article distinguishing proof technique, called "You Just Look Once rendition 3," is notable for its precision and snappiness. It utilizes a solitary brain organization to foresee bouncing boxes and class probabilities for some items in a picture simultaneously. YOLOv3 features a deep convolutional architecture with multiple detection layers, enabling it to detect objects with shifting goals and sizes. In projects, YOLOv3[24] is widely utilized for various applications such as pedestrian detection, vehicle detection, and surveillance systems. Its efficient design and robust performance make it a popular choice for real-time object detection tasks across diverse domains.

FasterRCNN-ResNet50-fpn

A strong item ID model is FPN (Feature Pyramid Network), and quicker R-CNN[25 (Region-based Convolutional Neural Network) involving ResNet50 as its establishment. To perceive objects with high exactness and accuracy, it integrates a region proposal network (RPN), an element pyramid organization (FPN), and a backbone CNN (ResNet50) efficiency. The ResNet50 backbone provides strong feature representation, while FPN enables multi-scale object detection. In projects, Faster R-CNN with ResNet50-FPN[25] is employed for various applications such as instance segmentation, object tracking, and industrial defect detection. Its robust performance and scalability make it suitable for complex and diverse object detection tasks in real-world scenarios.

FasterRCNN-ResNet50-fpn-v2

Faster R-CNN with ResNet50 as its backbone and FPN (Feature Pyramid Network),[26] version 2, is an upgraded iteration of the popular object detection model. It enhances the original Faster R-CNN architecture by incorporating improvements in feature extraction and region proposal mechanisms, leading to higher accuracy and faster inference speeds. In projects, Faster R-CNN with ResNet50-FPN-v2 [26]is utilized for a wide range of tasks requiring precise object detection, including pedestrian detection in autonomous driving systems, anomaly detection in industrial settings, and object tracking in surveillance applications. Its advanced capabilities make it a preferred choice for demanding object detection projects.

RetinaNet-ResNet50-fpn-v2

RetinaNet with ResNet50 [27]as its backbone and FPN (Feature Pyramid Network), version 2, is an advanced object detection model renowned for its accuracy and efficiency. It enhances the RetinaNet architecture by integrating ResNet50 for feature extraction and FPN for multi-scale feature representation. This combination enables robust detection of objects at various sizes and resolutions. In projects, RetinaNet-ResNet50-FPN-v2[27] is utilized for diverse applications such as pedestrian detection in urban surveillance, defect detection in manufacturing processes, and object recognition in satellite imagery. Its superior performance and versatility make it a preferred choice for demanding object detection tasks across different domains.

RetinaNet-ResNet50-fpn

RetinaNet with ResNet50[28] as its backbone and FPN (Feature Pyramid Network) is a state-of-the-art object detection model known for its accuracy and efficiency. It combines the RetinaNet architecture with ResNet50 for feature extraction and FPN for multi-scale feature representation, enabling robust detection of objects at varying sizes and resolutions. In projects, RetinaNet-ResNet50-FPN[28] is utilized for a wide range of applications, including autonomous driving for detecting pedestrians and vehicles, quality control in manufacturing for identifying defects, and surveillance systems for object tracking and anomaly detection. Its precise detection capabilities and versatility make it a valuable asset in numerous real-world projects.

SSD

SSD, or Single Shot MultiBox Indicator, is a popular item distinguishing proof strategy that has gained notoriety for precision and speed. By assessing jumping boxes and class probabilities, it can distinguish objects. in a single shot, eliminating the need for time-consuming region proposal stages. SSD[29] achieves this efficiency by utilizing a series of convolutional layers with different aspect ratio priors at multiple feature maps to detect objects at various scales. In projects, SSD is employed for real-time object detection tasks such as pedestrian and vehicle detection in autonomous vehicles, face detection in surveillance systems, and product recognition in retail environments, owing to its rapid inference speed and reliable performance.

SSDLite

SSDLite, a lightweight variant of the Single Shot MultiBox Detector (SSD)[29], is designed for resource-constrained environments such as mobile and embedded devices. It retains the efficiency and accuracy of SSD while reducing computational complexity and memory footprint. SSDLite achieves this through techniques like depthwise separable convolutions and model pruning. In projects, SSDLite[29]is utilized for real-time object detection on mobile platforms, enabling applications such as pedestrian and traffic sign detection in smartphone apps, object recognition in drones, and wildlife monitoring in edge devices. Its lightweight architecture makes it suitable for deploying object detection systems on devices with limited computational resources.

4. Experimental Results

Precision: Accuracy estimates the level of appropriately sorted examples or events among the positive examples. Thus, coming up next is the equation to decide the accuracy:

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

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

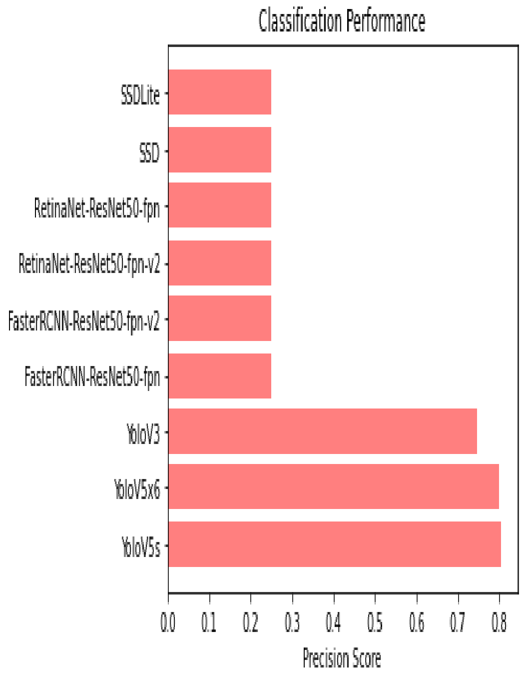

Figure 3: Precision Comparison Graph

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.

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

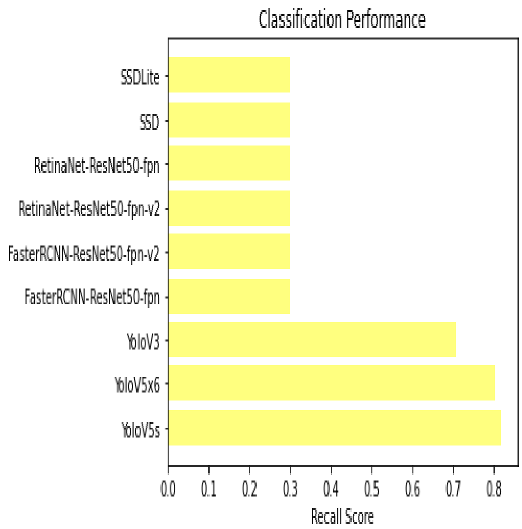

Figure 4: Recall Comparison Graph

MAP: The Mean Average Precision (mAP) score is a metric used to evaluate the performance of object detection models. It calculates the average precision across multiple classes or categories of objects detected in an image dataset. mAP considers both the precision and recall of the model, providing a comprehensive measure of its accuracy in detecting objects of various classes. Higher mAP scores indicate superior performance in accurately localizing and classifying objects in images.

$$mAP = \frac{1}{k}\sum_{i}^{k} AP_i$$

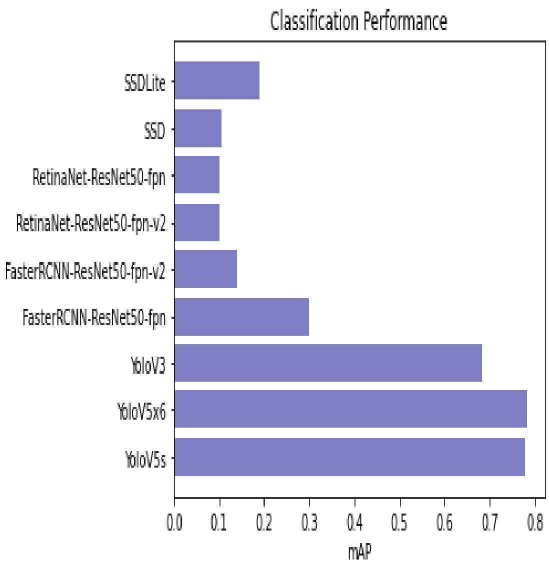

Figure 5: Map Comparison Graph

	ML Model	Precision	Recall	mAP
0	YoloV5s	0.803	0.816	0.779
1	Extension- YoloV5x6	0.799	0.802	0.782
2	YoloV3	0.747	0.707	0.682
3	FasterRCNN-ResNet50-fpn	0.250	0.300	0.299
4	FasterRCNN-ResNet50-fpn-v2	0.250	0.300	0.140
5	RetinaNet-ResNet50-fpn-v2	0.250	0.300	0.100
6	RetinaNet-ResNet50-fpn	0.250	0.300	0.100
7	SSD	0.250	0.300	0.105
8	SSDLite	0.250	0.300	0.190

Table 1: Performance Evaluation

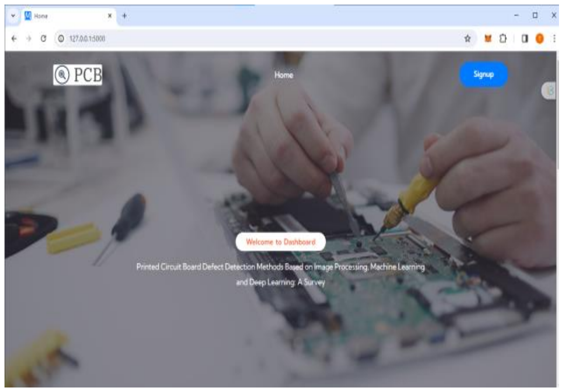

Figure 6: Home Page

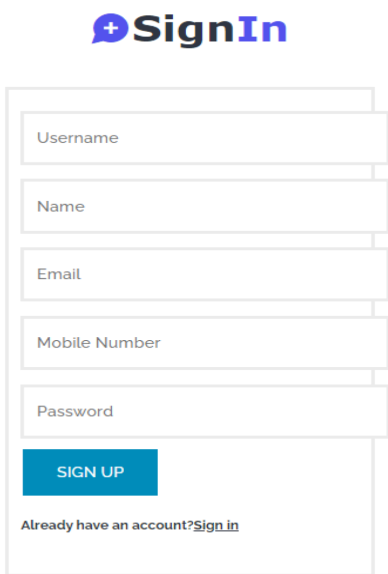

Figure 7: Sign Up

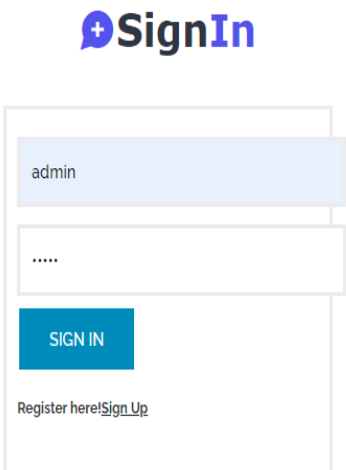

Figure 8: Sign In

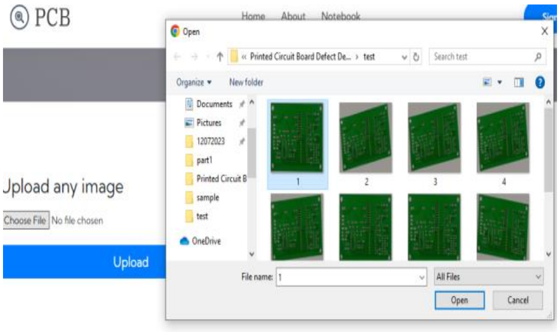

Figure 9: upload input image

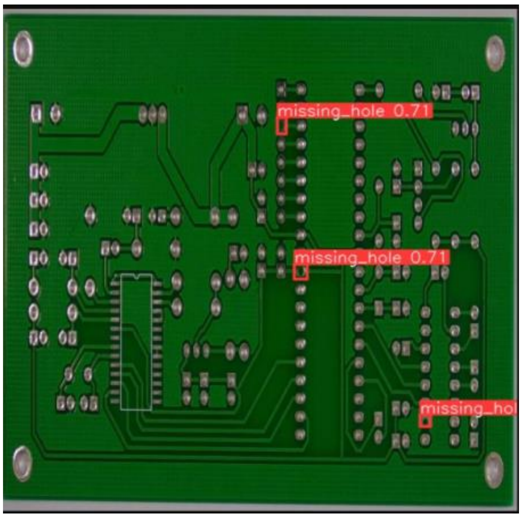

Figure 10: Predicted Result

5. Conclusion

In conclusion, the project has significantly advanced the field of PCB defect detection by leveraging cutting-edge methodologies and technologies. By emphasizing the importance of precision, recall, and MAP metrics, the project underscores the necessity of rigorous evaluation in assessing detection algorithm effectiveness. Through an extensive review of defect detection algorithms, ranging from traditional techniques to state-of-the-art deep learning models, valuable insights into their strengths and limitations have been gained. This analysis directly addresses the challenges posed by the Fourth Industrial Revolution in the electronics industry, particularly the demand for real-time, high-precision defect inspection in increasingly complex PCBs.

Furthermore, the integration of the YOLOv5x6 extension has significantly improved defect detection accuracy, surpassing alternative models. The incorporation of Flask facilitates user-friendly input and output processes, ensuring accessibility and ease of use. Overall, this project not only contributes to enhancing manufacturing efficiency and reliability but also highlights the importance of innovation in addressing industry challenges amidst technological advancements.

6. FUTURE SCOPE

The feature scope of the survey on Printed Circuit Board (PCB) defect detection methods encompasses a comprehensive exploration of techniques rooted in image processing, machine learning, and deep learning. Image processing techniques form the foundational basis, including operations such as noise reduction, edge detection, and morphology to preprocess PCB images for subsequent analysis. Machine learning methods, including traditional classifiers and clustering algorithms, are examined for their efficacy in detecting defects based on extracted features. Furthermore, deep learning models, such as convolutional neural networks (CNNs) and their variants like YOLO and Faster R-CNN, are extensively reviewed for their ability to automatically learn hierarchical representations directly from raw data, achieving state-of-the-art performance in defect detection tasks. The survey delves into the strengths and limitations of each approach, considering factors like accuracy, speed, and scalability. By encompassing a broad range of methodologies, the survey aims to provide insights into the evolving landscape of PCB defect detection and inform future research directions for improved manufacturing quality and efficiency.

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