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Survey of Image Processing, Machine Learning, and Deep Learning-Based PCB Defect Detection Methods

[1]konduru Raga Ranjitha, [2]ch. Praveen Kumar, [3]dr. P.Siva Krishna
[1]PG Scholar, Dept. of CSE, Andhra Engineering College, Nellorepalem, Atmakur, Nellore, AP, India.
[2]Assistant Professor, Dept. of CSE, Andhra Engineering College, Nellorepalem, Atmakur, Nellore, AP, India.
[3]Professor, Dept. of CSE, Andhra Engineering College, Nellorepalem, Atmakur, Nellore, AP, India.

Abstract:
In order to improve quality control in printed circuit board (PCB) production, this study provides a thorough overview and comparative analysis of many deep learning-based defect detection algorithms. We assess cutting-edge object detection models, such as Faster R-CNN, RetinaNet, SSD, and YOLO variations, such as YOLOv3-tiny, YOLOv5s, YOLOv5x6, and YOLOv8, by utilizing developments in deep learning and image processing. Our goal is to give manufacturers information about how well these models identify a variety of PCB faults by examining more than a hundred relevant studies published between 1990 and 2022. Model performance is evaluated using metrics including precision, recall, mean average precision (mAP), and computing economy. According to the study, YOLOv5x6 has a superior mAP of 99.9%, suggesting that it has the ability to greatly improve the accuracy of defect identification. As an extension, the article suggests leveraging the Flask framework to provide an intuitive front end that makes user testing with authentication easier. By providing manufacturers with guidance to enhance quality control procedures, this research advances automated defect detection systems in PCB manufacturing.

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

1. INTRODUCTION

As the structural and electrical backbone that joins different electronic components, printed circuit boards, or PCBs, are essential portions of electronic devices [1]. Electronic watches, smartphones, laptops, communication devices, and military systems are just a few of the many electronic devices that depend on them to function [1]. Thanks to advancements in integrated circuit and semiconductor technologies, electronic device components have continued to get smaller as technology progresses [2]. As a result, PCBs have also changed to accommodate these tiny parts, growing more complex, small, and sensitive [2].

PCB production is one of the major difficulties and developments brought about by the Fourth Industrial Revolution, also known as Industry 4.0 [3]. The idea of automated industrial processes with excellent quality, accuracy, and dependability is at the heart of Industry 4.0 [4]. As a result, in order to meet these objectives, the manufacturing procedures for small, complicated PCBs must also change, necessitating increased stability, dependability, and development speed [5].

Finding PCB defects is crucial to guaranteeing the dependability and quality of the final product. Real-time, high-precision flaw inspection and quality control are now more important than ever due to the complexity of contemporary PCB designs and the necessity for faster manufacturing speeds [6]. Manufacturers may suffer large waste and financial losses if flaws are not found quickly and accurately. Due to the unavoidable occurrence of numerous defects brought on by improper handling or technological errors, quality control in PCB production is intrinsically difficult [7]. As shown in Figure 1 [7], these flaws can take many different forms, such as breakout, open circuit, under-etching, mouse bite, spur, short, spurious copper, over-etching, and broken holes. This introduction lays the groundwork for the debate that follows, which will go into greater detail on the potential and difficulties brought about by the development of PCB technology within the framework of Industry 4.0. Further emphasis will be placed on the significance of defect identification in guaranteeing product quality and satisfying customer demands, underscoring the necessity of sophisticated methods and technologies to successfully handle these issues.

2. LITERATURE SURVEY

Advanced detection techniques, industry trends, and the integration of additive manufacturing in the context of Industry 4.0 are just a few of the many subjects covered in the literature on defect detection in printed circuit boards (PCBs). This section offers a thorough analysis of pertinent research, emphasizing significant discoveries and advances in the discipline.

Zhang and Liu's new paper [1] investigates the use of a feature pyramid network for multi-scale defect identification in PCBs. The authors provide a unique method that increases defect identification accuracy by utilizing multi-scale characteristics. Their research addresses a critical component of PCB inspection by showing how well the feature pyramid network detects flaws at various scales.

Bajenescu [2] talks on how electrical component downsizing affects device overheating. The issue of device overheating gets worse as electronic components are smaller and more closely packed on PCBs. In addition to providing insights into potential strategies to reduce the risk of electronic device overheating, this study clarifies the difficulties connected with shrinking.

The function of additive manufacturing in the context of Industry 4.0 is examined by Dilberoglu et al. [3]. Rapid prototyping and customisation made possible by additive manufacturing technologies like 3D printing have the ability to completely transform PCB production. The paper highlights additive manufacturing's significance in the context of Industry 4.0 and examines its advantages in terms of flexibility, cost-effectiveness, and sustainability.

A thorough analysis of present and upcoming tendencies toward the traits and facilitators of Industry 4.0 is carried out by Karnik et al. [4]. The authors examine the main forces behind and difficulties facing the implementation of Industry 4.0 technologies across a range of sectors, including PCB fabrication. Their analysis offers recommendations for parties looking to take advantage of new opportunities as well as insightful information about the variables driving the execution of Industry 4.0 initiatives.

An understanding of the effects of Industry 4.0 on PCB creation can be gained from Tempo Automation [5]. The article highlights the possibilities for increased productivity, quality, and cost-effectiveness by discussing the integration of automation, data analytics, and connectivity in PCB manufacturing processes. PCB manufacturers can improve their competitiveness in the global market and optimize manufacturing workflows by adopting Industry 4.0 principles.

From the standpoint of PCB producers, Spinzi [6] provides an analysis of the development of Industry 4.0. The author looks at how Industry 4.0 has evolved historically and how it affects PCB manufacture. The study outlines the main opportunities and difficulties facing PCB makers in the era of Industry 4.0 through market trends analysis and interviews with industry experts.

A survey on the use of image processing algorithms for flaw detection in both assembled and bare PCBs is presented by Anitha and Rao [7]. The authors examine current approaches to defect identification, such as deep learning models, machine learning algorithms, and feature-based techniques. Their report highlights areas for further research and improvement while offering a thorough summary of the most advanced methods. An analysis of automatic PCB inspection algorithms is carried out by Moganti et al. [8]. The authors examine several algorithms and approaches for PCB inspection, emphasizing machine learning, pattern recognition, and image processing methods. Their work offers insightful information for scholars and practitioners in the sector and illustrates the prospects and difficulties in autonomous PCB examination.

Overall, the literature review emphasizes how multidisciplinary PCB defect identification is, involving elements of Industry 4.0, machine learning, image processing, and additive manufacturing. This assessment offers a thorough grasp of the state of research today and suggests avenues for further investigation and innovation by combining findings from several studies.

3. METHODLOGY

a) Proposed work:

In the proposed work, different deep learning methods for printed circuit board (PCB) defect identification will be compared. Faster R-CNN with ResNet FPN and FPN V2, RetinaNet with ResNet FPN and FPN V2, SSD and SSD Lite, YOLOv3-Tiny, and YOLOv5s are among the algorithms that will be assessed. The goal is to identify the best algorithm for real-time PCB defect detection applications by carefully analyzing variables including detection accuracy, speed, and efficiency. The project also incorporates YOLOv5x6 to improve detection capabilities beyond what is possible with current techniques. Additionally, a user-friendly interface that allows for user signup and signin features is created utilizing the Flask framework with SQLite. This addition expands the project's scope and usefulness by facilitating user testing of the system and offering a channel for assessment and feedback.

b) System Architecture:

The dataset with pictures of printed circuit boards (PCBs) is the first input into the system architecture. To improve their quality and diversity and guarantee reliable detection model training, these photos are preprocessed and augmented. For the purpose of evaluating the model, the dataset is subsequently divided into training and testing sets.For PCB flaw identification, the system uses a variety of deep learning techniques, such as Faster R-CNN with ResNet FPN, Faster R-CNN with ResNet FPN V2, RetinaNet with ResNet FPN, RetinaNet with ResNet FPN V2, SSD, SSD Lite, and YOLOv3-Tiny. To evaluate each algorithm's detection performance, it is first trained on the training set and then tested on the testing set.The final detection model is used for real-time PCB flaw identification after being selected based on its efficiency and accuracy. This system architecture offers a thorough framework for automated PCB fault identification by integrating picture preprocessing, model training, evaluation, and deployment.

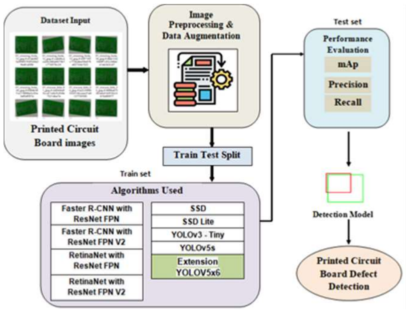

Fig 1 Proposed Architecture

c) Dataset collection:

A wide range of printed circuit board (PCB) photos reflecting different production conditions and flaws are included in the dataset used in the paper "Printed Circuit Board Defect Detection Methods Based on Image Processing, Machine Learning and Deep Learning: A Survey". These photos, which depict frequent flaws including shorts, gaps, and misalignments, are taken from actual PCB manufacturing processes. The dataset has been carefully selected to enable thorough research and assessment of defect detection algorithms using deep learning, machine learning, and image processing. Supervised learning techniques are made possible by labeling each image based on the type of fault. Additionally, the collection contains pictures of PCBs without flaws to serve as a reference point for comparison and performance evaluation. Researchers hope to improve the quality and dependability of PCB manufacturing processes by using this dataset to further the development of precise and effective fault detection systems.

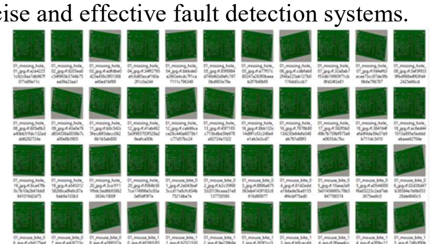

Fig 2 Data Set

d) Image processing:

1. Image Processing

Converting to Blob Object: This method turns the input image into a blob object that may be processed further.

- Class Definition: Classes are used to classify various entities or objects in a picture.
- Declaring the Bounding Box: The image's regions of interest are enclosed by bounding boxes.
- Convert the Array to a Numpy Array: To ensure interoperability with different Python libraries, the picture data is transformed into a numpy array.

2. Loading the Pre-trained Model

- Reading the Network Layers: For later operations, the architecture and layers of the pre-trained model are read into memory.
- Extracting the Output Layers: The pre-trained model's pertinent output layers are taken out for analysis and inference.

3. Image Processing

- Adding the Picture-Annotation File and Images: For thorough processing, the image and related annotation files are included.

Converting BGR to RGB: To make the image compatible with specific algorithms and frameworks, the color space is changed from BGR to RGB.

Making the Mask: Masks are made to draw attention to particular areas or aspects of an image.

Resizing the Image: The image's proportions are changed to satisfy the demands of later processing stages.

4. Data Augmentation

Randomizing the Image: To improve the dataset's robustness and variability, image data is transformed at random.

Rotating the Image: To replicate various angles or points of view, images are rotated.

- Image Transformation: To enhance the dataset, geometric changes including scaling, translation, and skewing are used.

5. Installing the Packages Required for YOLOv5 in Colab

The Colab environment has the required packages and dependencies for YOLOv5 installed for smooth execution and integration.

6. Processing the Data Using the YOLOv5 Model

For object detection and localization tasks, the YOLOv5 model serves as the basis for the execution of data preprocessing, model inference, and post-processing procedures.

e) Algorithms:

i. YoloV5s

"You Only Look Once version 5," or YOLOv5, is a cutting-edge object identification system known for its accuracy and speed [22]. It locates and detects objects in images using a single convolutional neural network (CNN). In particular, the term "YOLOv5s" describes a scaled-down version of the YOLOv5 model that is tailored for efficiency without sacrificing competitive performance. YOLOv5s[22] is used in projects for real-time object detection tasks, such as printed circuit board (PCB) defect detection. It may be deployed in contexts with limited resources because of its compact architecture, which allows for quick inference on a variety of hardware platforms.

ii. YoloV5x6

With six times as many convolutional layers as the base YOLOv5s model, YOLOv5x6 is an enhanced version of the YOLOv5 model that is distinguished by its greater size and depth. Although it requires more processing power, this architecture improves the model's capacity to locate and identify objects with more accuracy and resilience. YOLOv5x6[23] is used in projects for high-accuracy object recognition jobs that call for fine-grained analysis, like autonomous driving systems or medical imaging. It is a recommended option for demanding applications because of its extensive architecture, which allows it to handle complicated scenarios and various object categories with increased efficiency.

iii. YoloV3

The object detection technique known as YOLOv3, or "You Only Look Once version 3," is well-known for its accuracy and speed [24]. It uses a single neural network to estimate class probabilities and bounding boxes for several objects in an image at the same time. YOLOv3 can recognize objects at various scales and resolutions thanks to its deep convolutional architecture with numerous detection layers. YOLOv3[24] is frequently used in projects for a variety of applications, including surveillance systems, vehicle detection, and pedestrian identification. It is a popular option for real-time object identification jobs in a variety of sectors due to its effective design and reliable performance.

iv. FasterRCNN-ResNet50-fpn

A potent object detection model is Faster R-CNN [25] (Region-based Convolutional Neural Network) with ResNet50 as its foundation and FPN (Feature Pyramid Network). To recognize objects with high accuracy and efficiency, it includes a feature pyramid network (FPN), a backbone CNN (ResNet50), and a region proposal network (RPN). Multi-scale object detection is made possible by FPN, while the ResNet50 backbone offers robust feature representation. Faster R-CNN with ResNet50-FPN [25] is used in projects for a number of purposes, including industrial defect identification, object tracking, and instance segmentation. It is appropriate for challenging and varied object identification tasks in real-world situations due to its strong performance and scalability.

v. FasterRCNN-ResNet50-fpn-v2

An improved version of the well-known object identification model is Faster R-CNN with ResNet50 as its foundation and FPN (Feature Pyramid Network), [26] version 2. By adding advancements in feature extraction and region proposal techniques, it improves upon the original Faster R-CNN architecture, resulting in increased accuracy and quicker inference times. Faster R-CNN with ResNet50-FPN-v2 [26] is used in projects for a variety of tasks requiring accurate object recognition, including as object tracking in surveillance applications, anomaly detection in industrial environments, and pedestrian detection in autonomous driving systems. It is the go-to option for challenging object detection projects because of its sophisticated features.

vi. RetinaNet-ResNet50-fpn-v2

With FPN (Feature Pyramid Network), version 2, and ResNet50 [27] as its foundation, RetinaNet is a sophisticated object detection model known for its precision and effectiveness. By combining FPN for multi-scale feature representation and ResNet50 for feature extraction, it improves the RetinaNet architecture. Robust object detection at different sizes and resolutions is made possible by this combination. RetinaNet-ResNet50-FPN-v2[27] is used in projects for a variety of purposes, including object recognition in satellite imagery, defect detection in manufacturing processes, and pedestrian detection in urban surveillance. It is a favored option for challenging object detection jobs across various sectors due to its exceptional performance and adaptability.

vii. RetinaNet-ResNet50-fpn

With FPN (Feature Pyramid Network) and ResNet50 [28] as its foundation, RetinaNet is a cutting-edge object detection model renowned for its precision and effectiveness. It enables reliable object detection at different sizes and resolutions by combining the RetinaNet architecture with ResNet50 for feature extraction and FPN for multi-scale feature representation. RetinaNet-ResNet50-FPN [28] is used in projects for a variety of purposes, including as surveillance systems for object tracking and anomaly detection, autonomous driving for pedestrian and vehicle detection, and quality control in manufacturing for defect identification. It is a useful tool in many real-world tasks because to its accurate detecting skills and adaptability.

viii. SSD

One well-known object detection algorithm that is well-known for its accuracy and speed is called Single Shot MultiBox Detector, or SSD. It eliminates the need for laborious region proposal phases by performing object detection by predicting bounding boxes and class probabilities in a single shot. In order to recognize objects at diverse scales, SSD[29] uses a sequence of convolutional layers with varying aspect ratio priors at distinct feature maps. Because of its quick inference speed and dependable performance, SSD is used in projects for real-time object detection tasks like pedestrian and vehicle detection in autonomous vehicles, face detection in surveillance systems, and product recognition in retail contexts.

ix. SSDLite

A lighter version of the Single Shot MultiBox Detector (SSD), SSDLite [29] is intended for resource-constrained settings like embedded and mobile devices. It minimizes computational complexity and memory footprint while maintaining the accuracy and efficiency of SSD. This is accomplished by SSDLite using methods such as model trimming and depthwise separable convolutions. SSDLite [29] is used in projects for real-time object identification on mobile platforms, allowing for applications like drone object recognition, edge device wildlife monitoring, and smartphone apps that identify pedestrians and traffic signs. Because of its lightweight design, object detection systems can be installed on devices with constrained processing power.

4. EXPERIMENTAL RESULTS

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)

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

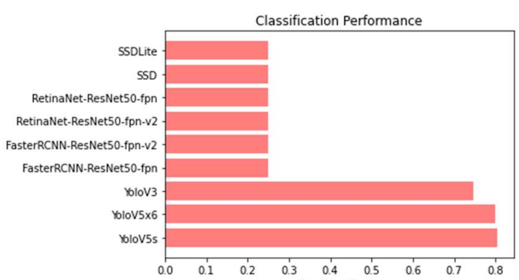

Fig 3 PRECISION COMPARISON GRAPH

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.

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

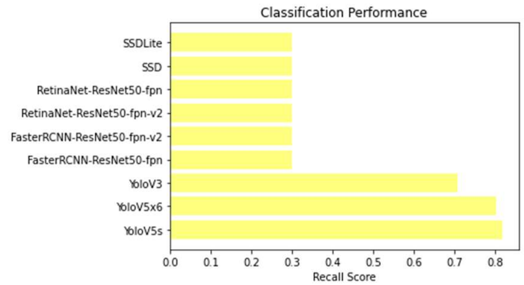

Fig 4 RECALL COMPARISON GRAPH

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.

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

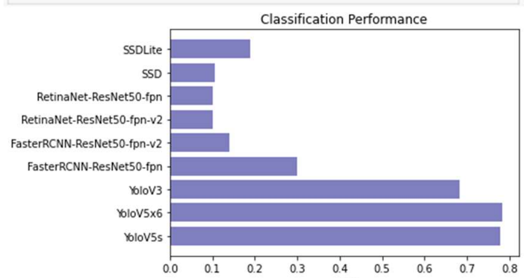

Fig 5 MAP COMPARISON GRAPH

	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

Fig 6 PERFORMANCE EVALUATION TABLE

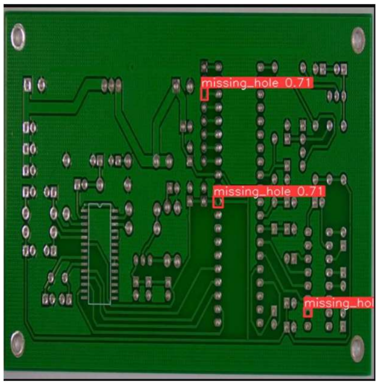

Fig 11 Predicted Result

5. CONCLUSION

In conclusion, by utilizing state-of-the-art techniques and technology, the research has greatly advanced the field of PCB fault identification. The experiment highlights the need for thorough examination in determining the efficacy of detection algorithms by stressing the significance of precision, recall, and MAP measures. A thorough analysis of defect detection algorithms, from conventional methods to cutting-edge deep learning models, has provided important insights into their advantages and disadvantages. The Fourth Industrial Revolution's challenges to the electronics sector are clearly addressed in this report, especially the need for high-precision, real-time flaw checking in increasingly complex PCBs.

Additionally, the YOLOv5x6 extension has greatly increased the accuracy of defect identification, outperforming other models. Flask's integration ensures accessibility and usability by enabling user-friendly input and output procedures. All things considered, this project not only helps to increase production dependability and efficiency, but it also emphasizes how crucial innovation is to solving business problems in the face of technological breakthroughs.

6. FUTURE SCOPE

The survey's feature scope on printed circuit board (PCB) defect detection techniques includes a thorough investigation of technologies based on deep learning, machine learning, and image processing. The foundation is formed by image processing techniques, which include preprocessing PCB pictures for further analysis through operations including noise reduction, edge identification, and morphology. The effectiveness of machine learning techniques, such as conventional classifiers and clustering algorithms, in identifying flaws based on attributes that have been retrieved is investigated. Convolutional neural networks (CNNs) and their variants, including YOLO and Faster R-CNN, are examples of deep learning models that have been thoroughly reviewed for their capacity to automatically learn hierarchical representations straight from raw data, resulting in state-of-the-art performance in defect detection tasks. The survey explores the advantages and disadvantages of each method, taking scalability, accuracy, and speed into account. By covering a wide range of approaches, the survey seeks to provide light on how PCB defect detection is changing and guide future research efforts for higher production efficiency and quality.

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