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Enhanced Printed Circuit Board defect detection through Adaboost Classifier Integration

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ABSTRACT

A printed circuit board (PCB) connects multiple electronic components using tracks or pathways etched from copper sheets. Using the proposed method to forecast the defect type is the project's main objective. Various kinds of errors are located using the proposed approach. The suggested model can detect spur, short, copper, and mouse bite defects. The input image removes its noise first using a median and mean filter. The next step is registration, which involves aligning the input image and obtaining the registered image using the Surf and Sift feature. The next step is pinpointing the error and creating a custom boundary box containing it. Features were extracted in order to gather data regarding the defects. The Ad Boost classifier identifies PCB defects in the image and classifies four different types of defects.

Keywords: Adaboost; PCB Design; Deep Learning; Machine Learning.

1. Introduction

The mechanical support and electrical connection of electronic components are both supported by printed circuit boards, which serve as platforms for these components. The components are positioned in their respective positions in a composite sandwich structure composed of conductive and non-conductive layers [1]. The circuitry on these boards has been meticulously defined and engineered. Copper is the most common metal used for the conductive layer; other metals such as aluminum, nickel, chrome, and others can also be utilized in this capacity. In most cases, the non-conductive layer is made up of a composite material that is made up of epoxy and glass fiber [2]. As the complexity of printed circuit boards (PCBs) continues to rise, the difficulties associated with identifying and categorizing defects are also becoming more challenging in comparison to times gone by [3]. Furthermore, numerous methodologies suggested in published papers have relied on proprietary images, which have hindered the ability of other researchers to effectively compare their novel approaches. Currently, there is a restricted quantity of publicly accessible datasets on the internet that are specifically associated with PCB. Manufacturing printed circuit boards (PCBs) is a complex process [4], with the etching stage being the most important component of the PCB manufacturing process.

Etching is a process that primarily removes any extraneous copper that is exposed and is not a part of the desired circuit pattern [5]. Early-stage inspection is required to reduce the amount of scrap produced due to improper etching of a PCB panel. However, all inspections take place after the etching process has been completed. During this process, any faulty printed circuit board (PCB) discovered is considered non-functional and discarded without delay [6]. Because the etching process accounts for seventy percent of the total cost associated with producing printed circuit boards, it is not feasible to throw away defective PCBs. When manufacturing printed circuit boards (PCBs), manual visual inspection is typically one of the most expensive expenditures [7]. Recent studies have shown that to identify and categorize defects on the image being tested accurately, it is necessary to analyze both a template that is free of defects and an image that has been tested with defects. There is no requirement for any physical interaction when using this method, which is a time-honored technique. However, image-based algorithms for detecting PCB defects frequently face challenges. This is simply because there is not sufficient data available with detailed annotations to confirm the effectiveness of these algorithms. In addition, the lack of data makes it difficult for researchers to develop a sophisticated detector, such as a neural network [8]. Boards for printed circuit boards (PCBs) can be classified into a number of different types, including single-layer, double-layer, multi-layer, rigid, aluminum, high-frequency, and flexible. Mouse bite, short circuit, spur, and copper defects are among the most common types of defects that can occur on a printed circuit board with a single layer [9].

2. Literature Survey

Ensuring the quality of printed circuit boards (PCBs) is crucial in manufacturing processes due to their vital role in electronic devices. Given the complex patterns of printed circuit boards (PCBs) and the need for exactness, it is challenging to identify flaws in PCBs. The Adaboost classifier is a highly prominent method that has proven effective for automating defect detection processes. Machine learning techniques have been recognized as highly efficient tools [10]. This literature review offers a comprehensive summary of the research conducted on identifying PCB defects using the Adaboost classifier. It emphasizes the crucial studies, methodologies, obstacles, and potential future paths.

This paper aims to investigate the application of ensemble learning techniques, such as Adaboost, to enhance the detection of printed circuit board (PCB) defects for manufacturing processes [11]. This paper compares and contrasts the performance of several machine learning algorithms, including Adaboost, in locating PCB faults based on their respective capabilities. The most important objective of the study is to determine the degree to which Adaboost is successful in this domain. The primary objective of [12] is to demonstrate how Adaboost can be utilized as a defect detection system in manufacturing printed circuit boards within real-time environments. Compared to other methods considered more conventional, the paper demonstrates that Adaboost is significantly more effective and precise. This study aims to investigate the impact of feature engineering on the accuracy of PCB defect detection when working in conjunction with Adaboost. Within this situation, the significance of feature extraction and selection techniques becomes readily apparent [13].

In order to enhance the performance of detecting defects in printed circuit boards (PCBs), this study aims to investigate the utilization of deep learning techniques with Adaboost. Additionally, the research demonstrates that these two methods are capable of cooperating with one another in an efficient manner.

At the beginning of the PCB defect detection research process, the primary methods utilized were rule-based systems and conventional image processing techniques.

Li et al. laid the groundwork for the implementation of machine learning strategies by establishing the importance of classifiers in defect detection. They were the ones who paved the way. In recent times, the Adaboost classifier, which is also known as Adaptive Boosting, has garnered much attention due to its capacity to construct influential ensembles by combining several weak classifiers. The field of machine learning underwent a significant transformation after Schapire and Freund presented the Adaboost algorithm in the year 1999 [14]. This was accomplished through the utilization of a cutting-edge boosting technique. The findings of the initial research conducted by Smith et al. demonstrated that the application of Adaboost to this kind of issue results in a significant improvement in the accuracy of PCB defect detection. Specifically, they highlighted that Adaboost performed more effectively than other available choices in certain circumstances. Although Adaboost has a number of benefits, it also has a few drawbacks, such as the fact that it is susceptible to being fooled by noisy data and that it requires careful parameter tuning. As a result of these limitations, you should pay close attention to the details. It may be difficult to achieve precise detection using Adaboost due to the complexity of printed circuit board (PCB) designs and the significant number of different types of defects that can be found [15].

Deep learning strategies, hybrid models, and feature engineering have been the focus of recent advancements in the field, to find ways to overcome the limitations of Adaboost [16]. The precision of defect detection was further improved by Wang et al. who proposed a hybrid approach to the problem. By taking this approach, Adaboost and CNCs are combined. Because of their research, this methodology was presented. The investigation of novel characteristics, the enhancement of classifier parameters, and the development of real-time defect detection systems are just a few of the potential avenues that could be pursued in future research.

To enhance manufacturing quality assurance procedures, the detection of PCB defects through the use of the Adaboost classifier has demonstrated promising results. Even though there are obstacles to overcome, such as noisy data and parameter tuning, ongoing research efforts are concentrated on overcoming these limitations and improving the efficiency of detection systems that are based on Adaboost. Adaboost continues to be an invaluable instrument in the field of PCB defect detection, thanks to the various advancements that have been made in feature engineering and the integration of deep learning.

3. Proposed System

An application of the median and mean filter in the spatial domain is utilized in the initial stage of the project in order to eliminate the noise in the image. Registration is the next step, and it is used to align an image that has not been aligned before.

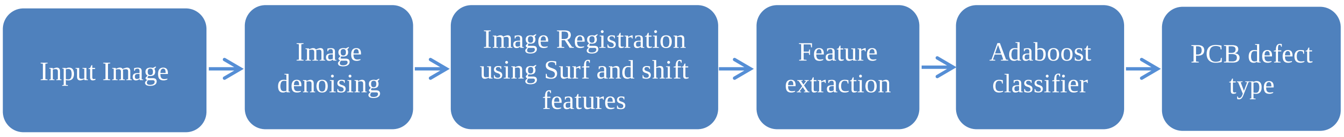

Figure 1. Architecture diagram of proposed system

Following that is the segmentation process, which divides the image into multiple objects by employing the canvases segmentation technique. It is necessary to XOR the original image and the reference image to locate the defects and extract the features. After that, the information is then provided to the Ad Boost classifier in order for it to classify the defects that are present in the image.

3.1. Dataset Description

We utilized the PCB Defect dataset that was available on the Kaggle online community, which is geared toward data scientists and users of machine learning. During the registration, segmentation, and classification tasks, this dataset includes one hundred images, each containing four different types of defects.

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3.2. Image Denoising

The method employs the mean and median filter at the beginning to effectively remove the noise from the input image. The principles of the convolutional and moving windows are the fundamental concepts behind the image-denoising process that utilizes these filters.

The mean filter, implemented through a sliding window spatial filter, replaces the central pixel value with the average value of all the pixels within the window. Smoothness in an image is attained by employing a filter that diminishes the intensity disparities between adjacent pixels. The median filter replaces the center value in the window with the median of all the pixel values within the window.

Median filters are commonly employed in image processing and time series processing to achieve smoothness. Median filtering exhibits considerably lower sensitivity to extreme values, commonly referred to as outliers, compared to the mean. One of the benefits of employing median filtering is that it offers this advantage. Consequently, it can effectively remove these anomalies without sacrificing the clarity of the image.

3.3. Image Registration

The subsequent action to be taken is image registration. In order to perform image registration, the initial step involves converting both images into grayscale. Analyze and juxtapose the attributes of the reference image with those of the original image.

The SURF and SIFT features are employed to provide both key points and their corresponding descriptors. The brute force matcher is employed to align the key points in both the reference and original images. In addition, it retrieves the image that is the most optimal match between the two images, while the BF Matcher retrieves the top K matches. The top k matches have been chosen, and the noisy matches between the two images have been removed. The homography transform has been applied to align the input image and obtain the registered image.

3.4. Feature Extraction

After the segmentation process, the defect in the image is precisely identified, and a bounding box is generated to enclose the entire defect area. Features have been extracted to gather information about the defect by considering the region's characteristics. The structural features employed in this work include area, width, height, and shape. The shape possesses the following attributes: convexity, solidity, orientation, length of major axis, length of minor axis, eccentricity, equivalent diameter, Crofton perimeter, perimeter, and filled area.

This type of representation may additionally encode information regarding the object's structure, or it may provide details about the components utilized in constructing the object.

3.5. ADABOOST classifier

The extracted feature is subsequently supplied to the Ad Boost classifier. AdaBoost, also called Adaptive Boosting, is an ensemble method utilized in machine learning. This method employs the fusion of multiple foundational models to produce an optimal unified predictive model. AdaBoost can utilize any classifier that produces suboptimal predictions, which it subsequently combines to construct a robust predictive model.

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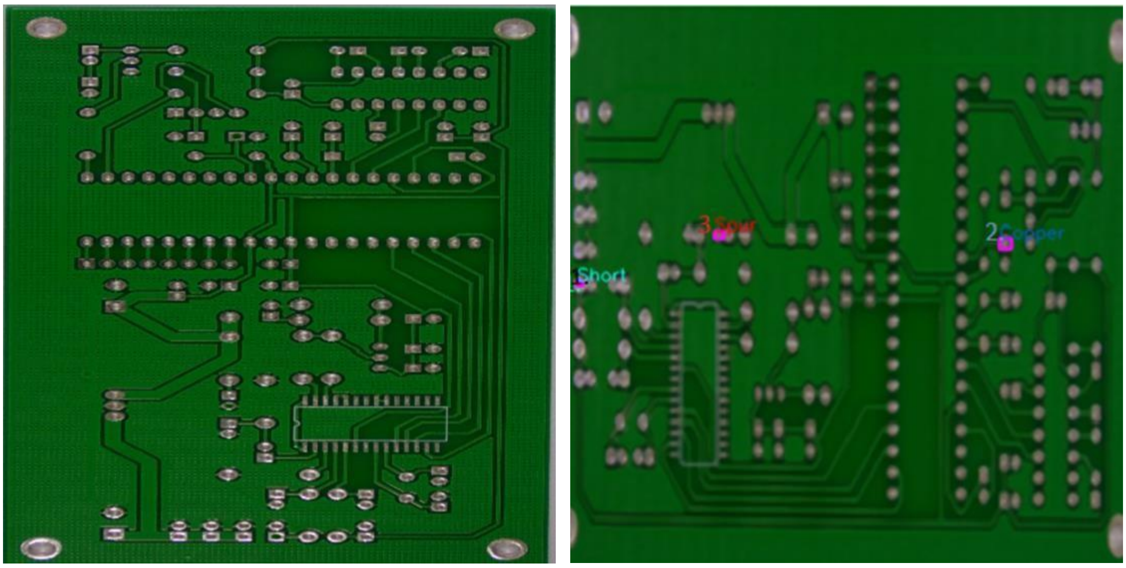

Figure 2. Input Images

The AdaBoost algorithm utilizes one-level Decision Trees, the prevailing form of classifier. These Decision Trees exhibit a single split at each level. These trees are commonly known as Decision Stumps. During the initial stages of the training process, the model assigns uniform weights to all data points in the dataset. After the initial iteration of training data is finished, the model will then assess the data points that have been classified incorrectly. Subsequently, the model allocates greater weight values to the data points that were inaccurately classified. Therefore, when we transmit the data to the subsequent model, it prioritizes the data points with greater weights over the other data points. This procedure will iterate until the error rate reaches a sufficiently low level. While training the model, we generated a template for every individual type of PCB defect found in the dataset of PCB defects.

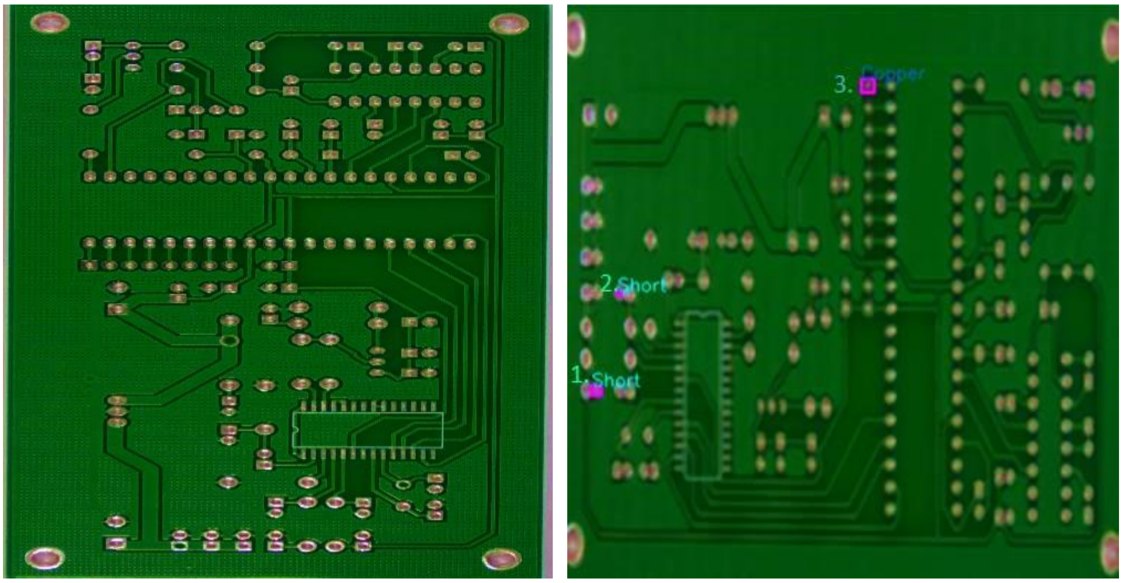

Figure 3. Output Image

Subsequently, the model was equipped with these templates during the testing phase. Ultimately, the model successfully detects and classifies various types of PCB defects, such as mouse bite, short, spur, and copper.

4. Experimental Results

There are four distinct categories of defects that are included in the dataset. Mouse bite, copper, spur, and short are some of the various defects that have been identified. The primary objective is to determine whether or not the input image contains defects. To put it another way, the image that is put in is used as the input.

Table 1. Performance Measures of the Proposed System

Method	Accuracy	Sensitivity	Specificity	Precision	F-Score
Mouse bite	0.923	0.943	0.948	0.958	0.966
Short circuit	0.987	0.945	0.976	0.987	0.953
Spur	0.921	0.964	0.989	0.964	0.928
Spurious Copper	0.939	0.981	0.932	0.974	0.983

The noise in the input image is eradicated through the use of mean and median filters. After the registration process, the input image is aligned to obtain the registered image. After that, isolation of the soldering joints is accomplished through the process of segmentation. The next step is to extract features and then supply them to the Ad Boost classifier to classify the four different types of defects present in the PCB board. In this step, we compute the shape features (area, width, and height) and examine the structural feature extraction performance measure. The subject is covered, and illustrations are included in Table 1.

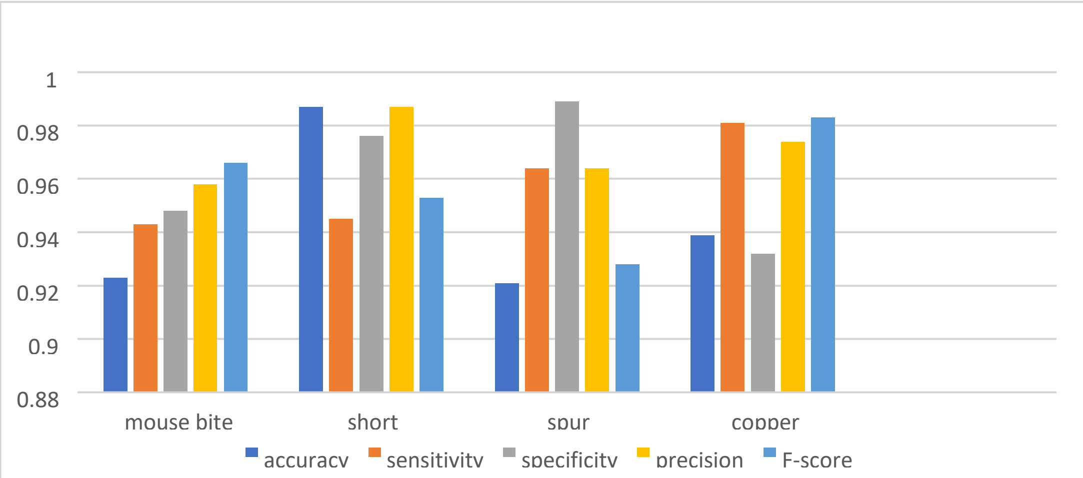

Figure 4. Graphical Representation of the proposed system

The accuracy of every flaw is displayed in the table. There are four types of defects: spur, spurious copper, mouse bite, and short circuit. Each defect's exact location is shown in the table.

The performance metric of the proposed system is displayed in Table 1. This measure is calculated based on the examination of confusion statistics. Figure 4 visually depicts the performance measures linked to the proposed system. The ROC analysis of the proposed system is presented in Figure 5. The proposed method yields the following average performance measures: 94.6% sensitivity, 93.6% specificity, 92.8% accuracy, 97.4% precision, and 96% f-score.

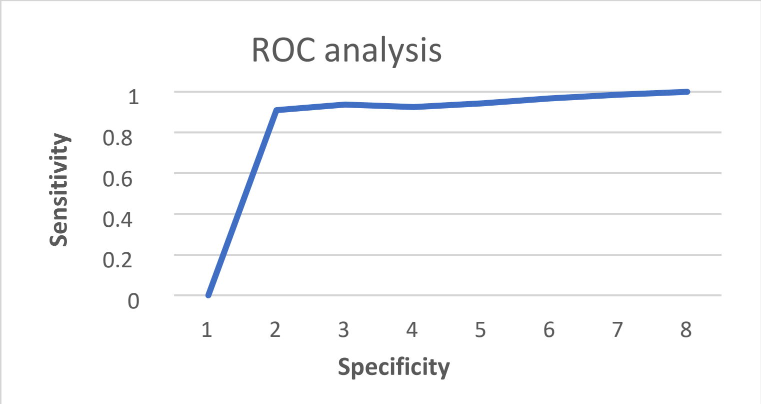

Figure 5. ROC Analysis representation of the proposed system

5. Conclusion

Based on this, we can conclude that the noise in the input image has been removed using a median and mean filter. Additionally, the unaligned image has been aligned through image registration to produce a final registered image. The soldering joints have been separated using segmentation, and the extracted features have been inputted into the Ad Boost classifier to identify image defects. We can construct, train, and test our model to achieve optimal efficiency and accuracy while minimizing the time and computational resources needed by utilizing the PCB dataset. As a result of our previously suggested approach, detecting defects in PCBs has been significantly enhanced.

Declarations

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This study did not receive any grant from funding agencies in the public or not-for-profit sectors.

Competing Interests Statement

The authors declare that there are no competing interests.

Consent for Publication

The authors declare that they consented to the publication of their original research work.

Authors' Contributions

All the authors took part in data collection, literature review, analysis, and manuscript writing equally.

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