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A Survey of PCB Defect Detection Algorithms

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Abstract
Printed circuit boards (PCBs) are the first stage in manufacturing any electronic product. The reliability of the electronic product depends on the PCB. The presence of manufacturing defects in PCBs might affect the performance of the PCB and thereby the reliability of the electronic products. In this paper, the various challenges faced in identifying manufacturing defects along with a review of various learning methods employed for defect detection are presented. We compare the various techniques available in the literature for further understanding of the accuracy of these techniques in defect detection.

Keywords PCB defects · Open defects · Soldering defects · Image processing · Learning algorithms

1 Introduction

PCBs are the building blocks for all electronic products. The reliability of electronic products is mainly influenced by the PCBs included in the product. The presence of any defects in the PCBs leads to the malfunctioning of the product leading to a loss of brand value. To avoid such situations, all electronic products go through stringent testing procedures right from the component level to the completed product. The overall cost of manufacturing is dependent on which stage the defects are identified. If these are identified at early stages, replacing the components will be cheaper than identifying a defect at later stages of manufacturing. Traditionally defects in a PCB were detected manually. An expert goes over the manufactured board to detect the defects. The manual method is effective if the density of components is less or spacing between the components is more. As the PCBs are getting denser and more compact, manual inspection is becoming ineffective. To overcome these difficulties various image processing techniques have been used for defect detection. The main challenge with image processing techniques is the processing time. To overcome the limitations of processing time, machine learning algorithm based techniques have been proposed which will reduce the processing time with low complexity as well as increase the reliability of the defect detection. Recently, Artificial Intelligence (AI) based defect detection is gaining popularity. In this paper, we review the various methods existing for assembled PCB defect detection.

The paper is organised as follows. In Section 2, we discuss various types of defects and some of the challenges in PCB manufacturing. In Section 3, we review the learning algorithms that exist for defect detection. We compare the existing algorithms in Section 4 and conclude the paper in Section 5.

2 Overview of PCB Defects

2.1 Different Types of Defects

Fabrication of PCBs consists of a series of mechanical and chemical processes that cannot be controlled with 100% accuracy. The variations that occur in the fabrication process due to the mechanical and chemical processes lead to various fabrication defects. In [41], we reviewed the various types of defects that occur in PCB manufacturing. The defects that occur in PCB manufacturing are classified in the Fig. 1. As seen from the figure the defects are majorly classified as Bare PCB defects and Component Mounted

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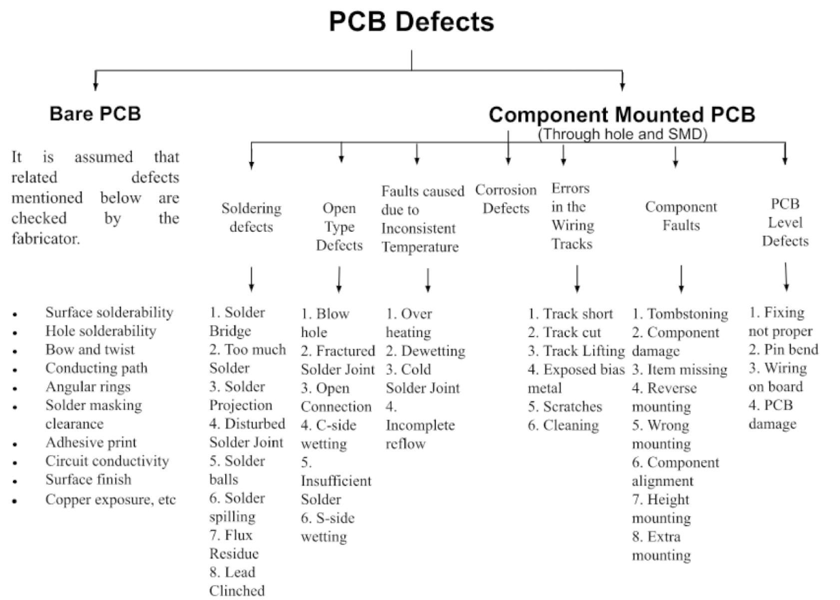


Fig. 1 Defects Classification Tree [41]

PCB defects. The Component Mounted PCB defects are again classified as Soldering defects, Open Type defects, Faults caused due to Inconsistent temperature, Corrosion defects, Errors in the Wiring Tracks, Component Faults, and PCB Level defects, with each having a respective subclass of defects. The detailed information of all the defects including images are studied in our reference [41].

These defects can occur at the Bare PCB level or the component Mounted PCB stage. We are assuming that defects such as surface solderability, Hole solderability, etc., that occur during the creation of Bare PCB are checked by the fabricator. The defects in the Component Mounted PCB (Through hole and Surface Mount Device (SMD)) are classified as soldering faults and non-soldering faults. Further, the faults can be classified into these sub-groups- solder, open, faults due to inconsistent process temperature, corrosion defects, errors in wiring tracks, component faults, and PCB level defects. To improve the classification of faults either image processing or Machine learning techniques can be used. In this survey, we focus on various algorithms to detect defects that occur in component mounted PCBs.

Of all the faults the probability of open fault occurrence is the highest at about 34%. Short faults and component shift faults constitute about 15% of each of the faults [32]. Open faults can be further sub-grouped into blow hole defects, fractured joint defects, an open connection, c-side wetting defects, insufficient solder, and s-side wetting defects. Open faults lead to electrical failure reducing the reliability of the board. Solder faults can be further sub-grouped into solder bridge defect, too much solder, solder projection defect, disturbed solder joint, solder ball defect, solder spilling defect, flux residue, and lead clinched defects. Short faults will lead to either logic modification of the circuit or electrical failure. The faults due to inconsistent process temperature can be sub classified as overheating faults, Dewetting faults, cold solder joints, and incomplete flow defects. The various track defects can be further subdivided into track shorts, track cuts, track lifting, exposed bias metal, scratches, and cleaning defects. Tombstoning, component damage, item missing, reverse mounting, wrong mounting, component alignment, height mounting, and extra mounting defects can be classified as component errors. PCB board-level defects are further sub classified as fixing not proper defects, pin bends, the wiring on the board, and PCB damage.

2.2 Challenges Involved in Defects Detection

To improve the efficiency and accuracy of defect detection, the process has to be automated instead of using manual inspection. Various techniques based on image processing, Machine Learning (ML) have been proposed in the literature to automize defect detection. In these techniques, the defect is identified by either comparing the image of the PCB with the golden PCB image or checking the PCB if any PCB layout rule has been violated. In the first technique, the quality of the image has to be good for comparison and the process has to follow grid comparison, so the images have to be divided into smaller grids and then compared. In the second technique, some of the defects might not be identified in their distorted appearance [5].

Images that we capture from the camera have degraded quality such as irregular lightning, changing background, shifting, and rotation. To solve the irregular lightning, and changing background problems, the images are preprocessed to a strong binary by dividing with a threshold obtained from the cumulative histogram. For the shifting and rotation of images, intensities of images and tolerance value are determined using *K* means clustering [28]. The images are divided into *K* non overlapping clusters segmented by grids. It is observed that the greater the grids lesser the tolerance value using the intensities of clustered images resulting in images with the defects marked. In some cases, Images are first Gaussian filtered to remove noise and converted to a grayscale image. Then for registration, a Recurrent Spatial Transform Network (RSTN) is used with the STN cell using the output as the input image for further steps. In this, the predefined reference image is used and weights of the cell are shared in the recurrent stages to further reduce the parameters. This is followed by image subtraction and then median filtering and binarization of the resultant image [16].

In [30], to solve the problem of labeling the data sets for training which costs time and money, a reference based method based on deep autoencoders is proposed that detects defects using only defect-free samples for training. For smooth images, data augmentation is done and for images with textured backgrounds, multiple images are used for testing. Then the images are converted to grayscale, if the color information is not required, followed by data normalization. The resulting image is used for small defect detection. Then the similarity is measured using L_2-distance metric.

3 Survey of Papers

PCB defect detection and classification can be done using various techniques such as Image processing, Transfer learning, Object detection, Auto-encoders, etc., Image processing techniques such as denoising, segmentation, and morphological process are used in [3–5, 10, 12, 20, 25, 31, 51] for defect detection. Machine learning algorithms such as clustering and classification are used in [22, 26, 28, 42, 44–46] for defect detection. In [21, 29, 30], authors used convolutional autoencoders. In [2, 6, 8, 9, 11, 14, 15, 36, 37, 40, 43, 47, 48], Neural Networks are used, and in [39, 49] Transfer learning methods are used for defect detection and classification. Object detection algorithms are used in [1, 7, 17, 23, 33, 35], whereas a combination of YOLO along with Machine learning algorithms is used in [7, 19] and YOLO with Neural Networks are used in [1] for defect detection. In [16, 34], authors used Recurrent Neural Networks (RNN) for defect detection. Image processing for feature extraction followed by Neural Networks are used in [17, 38, 50]. Optical Character Recognition (OCR) is used in [18] and Hypothesis Testing Strategy [24] for PDB defects detection.

In [5], authors used reference based method for defect detection and classification in PCB. The input image along with the reference image is preprocessed, segmented, and compared to detect defects in the input image as shown in Fig. 2 and a rule based defect classification methods are proposed. In order to remove salt and pepper noise in the image, a Median filter is used and for denoising, a Gaussian low pass filter is used and segmented using histogram thresholding and morphology operations. Also, the authors used the image registration method to eliminate the effect of rotation and transformation of the input image with respect to the reference image. Reference based method for defect detection of Surface Mount Technology (SMT) components in assembled PCB is proposed in [3]. In this paper, the authors used the Contour analysis technique for identifying shifting components, the OCR technique for recognizing component values, and the pixel subtraction technique for identifying missing components. These three types of defects are identified in a small portion of PCB using the Labview environment which can be extended to various other defects detection.

Image matching strategy for gray image, color image, and feature statistical histogram are proposed for PCB defect detection in [25]. A secondary matching error algorithm is used for gray image and color images whereas to describe the statistical histogram of image, features histogram matching is used. The reference-based method is used in [51] and proposed different algorithms for defect detection and identification based on defect characteristics. The authors used Wavelet transform for image denoising, Histogram

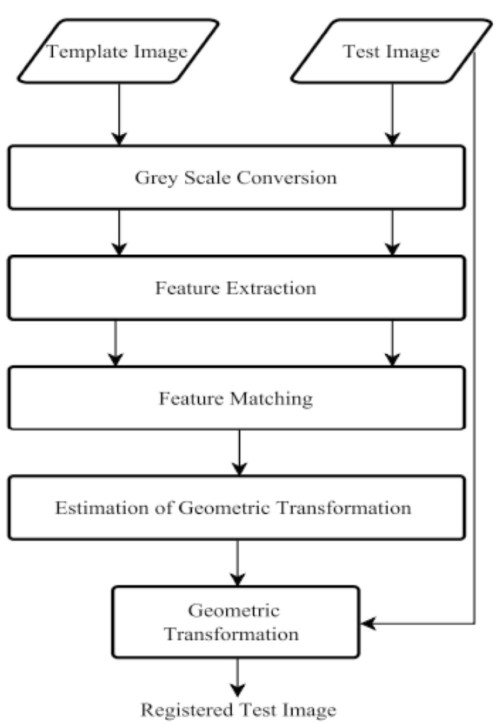


Fig. 2 Flowchart of Approach [5]

equalization for image enhancement and Hough transform method for image registration. Otsu segmentation and morphological processing are used for defect identification. In [4], authors proposed an image processing algorithm to detect and classify defects in PCBs. In this, the Background subtraction method is used for defect detection and background modeling is done using the Mixture of Gaussian (MoG) method.

Soldering defects are identified by using template based computer vision technique with joint contact information is studied in [31]. In this Fuzzy C-means clustering technique is used to determine and box the solder joints. Then a joint template-based inspection is done on the close joints that are not interconnected by circuit paths for rapid. The Image difference method is used for defect detection in [12]. In this paper, various defects are identified and classified by using image complement. First images are preprocessed by resizing, gray scaling and removing noise. The image difference technique is used to obtain positive and negative images. Then flood fill operation on Grayscale images of test and reference images, and their different subtractions are combined.

Text characters such as punctuation, digits, letters, etc., on PCB, are classified using the OCR algorithm in [18]. A hypothesis testing based detection method is presented in [24] for detecting fractures on the tracks of flexible PCBs. In this strategy, the region sandwiched between any two track broken ends is hypothesized to be the candidate. Then these breaks in tracks are detected using hypothesis testing and the Language semantic judgment (LSJ) algorithm is used for testing hypothetically connected tracks. A visual inspection based on corrosion and false soldering failures in PCBs are analyzed in [13] and concluded that high failure risk error is due to soldering PCB connection among all other defects.

A clustering based approach such as K-Means clustering and Hierarchical clustering is used to identify PCB defects in [28]. In this paper, a binary image is used for comparison purposes and clustering approaches help in overcoming the effects of small shifting and deviation of routine paths and contact sizes and coordinates of PCB connections. Whereas in [7], considered methods of defect localization and classification using You Only Look Once (YOLO), clustering approaches in PCB. Based on active and semi-supervised learning concepts, authors proposed a binary defect classification method using SVM classifier and K-means clustering to reduce labeling workload by automatically labeling the parts of unannotated samples in the training phase with a small error rate as shown in Fig. 3.

Inspection of dies attachment on PCB is performed using various ML techniques such as Support Vector Machine (SVM) with different kernels, decision trees, random forest, naive Bayes, logistic regression, multi-layer perceptron (MLP) and gradient Boosting (GB) classification using Monte Carlo simulation at different settings of hyperparameters in [42]. As shown in Fig. 4, the Feature selection is done using preprocessing techniques such as mutual information, feature importance that is based on extra tree classifier, principle component analysis (PCA), etc. and the extracted features along with PCB fault annotated images are given as input to the different ML algorithms for the fault recognition of PCB.

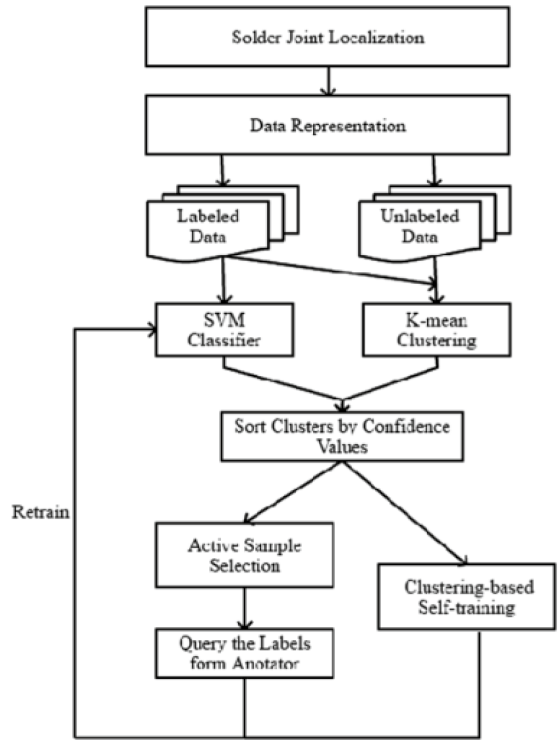


Fig. 3 Defects Classification Method [7]

An ML based PCB defect inspection framework, as shown in Fig. 5, is proposed in [26]. In this paper, the preprocessing black-white image is obtained by Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) features. A Combined HOG and LBP features via Bayes fusion as an input to SVM for defect classification. The Median and Mean filter is used for denoising purposes. PCB defect detection by segmenting copper and non-copper parts with the use of SVM is identified in [22]. As shown in Fig. 6 for the copper part, Hough circle transform with SVM and for the non-copper part 3D non-uniform color histogram with polynomial kernel SVM was used. Decisions from the two SVMs are logically combined to obtain a final conclusion about the type of defect and the defect image along with copper region and non copper region is shown in Fig. 7.

In [44], PCB defect detection using decision trees and ensemble method of random forest is used by considering Color and geometry features for decision making. Random forest based classification technique proposed in [45] for

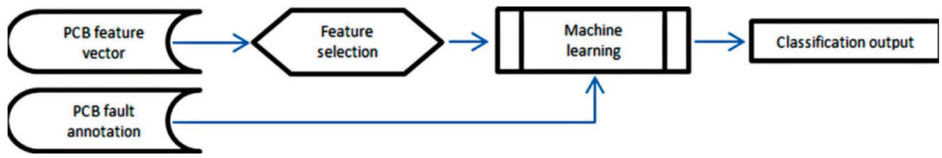


Fig. 4 Flow of Die inspection [42]

defect detection as shown in Fig. 8. Features are obtained through the Speeded-Up Robust Features (SURF) method that describes fault information. After learning fault patterns and probability from random forests, Kernel Density Estimation is used for estimating density weighted by probabilities. Later defects are classified with the threshold method.

Denoising convolutional autoencoders are used for detecting defects of PCB in [21] is shown in Fig. 9. Autoencoder is trained with Normal PCBs and corrupted PCBs that are corrupted by salt-pepper noise. Structural similarity measure that is the difference between test PCB image and autoencoder output image along with threshold metric is used to identify various defects in PCB. In [30], authors proposed a method of defect detection in PCB using deep autoencoders. When a single reference image is available, then training of the autoencoder is done using augmented images of the reference image. At the test stage, they compared test image features with reference image features via L_2 Norm metric and identification of defects performed using the threshold method.

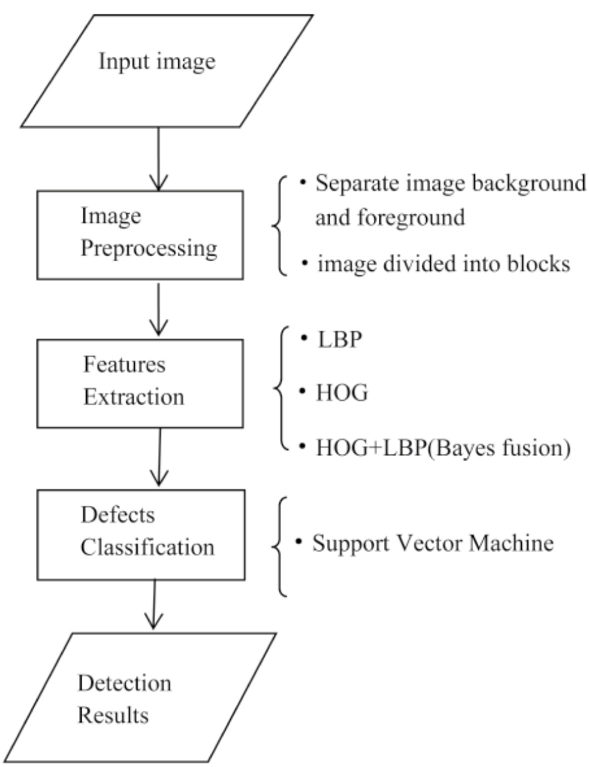


Fig. 5 Framework for PCB defect inspection [26]

A deep learning enabled image detection method is proposed for PCB defect detection in [15]. The authors used ResNet50 with Future pyramid network as a backbone for feature extraction and GARPN for improving prediction accuracy. Faster Region-based Convolutional Neural Network (RCNN) is used for building a new network.

A transfer learning based fault detection of patch components in PCB is proposed in [39]. In this paper, the authors used AlexNet, ResNet-50, and GoogleNet for comparison purposes. When the results of all three models are compared, AlexNet gives the best recognition with the fastest convergence speed and shortest training time. In [49], also authors used transfer based learning for fault detection. A deep convolutional neural network such as Visual Geometry Group (VGG)-16 is used for feature extraction with the extracted features are transferred to the Dense layer to avoid overfitting. And then the sliding window approach is used for defect localization.

In [35], the authors proposed the Deep ensemble method, as shown in Fig. 10, to identify defects in PCB. The model consists of ensemble methods of hybrid YOLOv2 (YOLOv2 detector and Resnet-101 as a classifier) and FRRF model (combination of Faster RCNN, Resnet-101, Feature pyramid network (FPN)). A tiny defect in PCB is detected by using a novel Single shot object detection algorithm, as shown in Fig. 11, is proposed in [23]. The authors proposed a semantic ascending module such that high level rich semantic information is passed to the shallow features and benefits for tiny defect detection. In order to learn the relationship of the features to be fused across channels, an attention mechanism is used whereas to eliminate the aliasing effect after fusion, a shuffle module is used.

A reference based approach is used for inspection of defects and Convolutional Neural Networks (CNN) based approach is used for classification of defects in [17]. As shown in Fig. 12, a preprocessed test and template image are compared to locate the errors, and then located defects are used to train a neural network to obtain classification results. The input image is grayscaled, registration is done using the SURF algorithm, and then using the adaptive threshold segmentation method performed binarization for comparison purposes. textcolorredAfter this, 2D geometric transform, median filtering, and mathematical morphological processing are done followed by CNN. In this paper, Densenet is

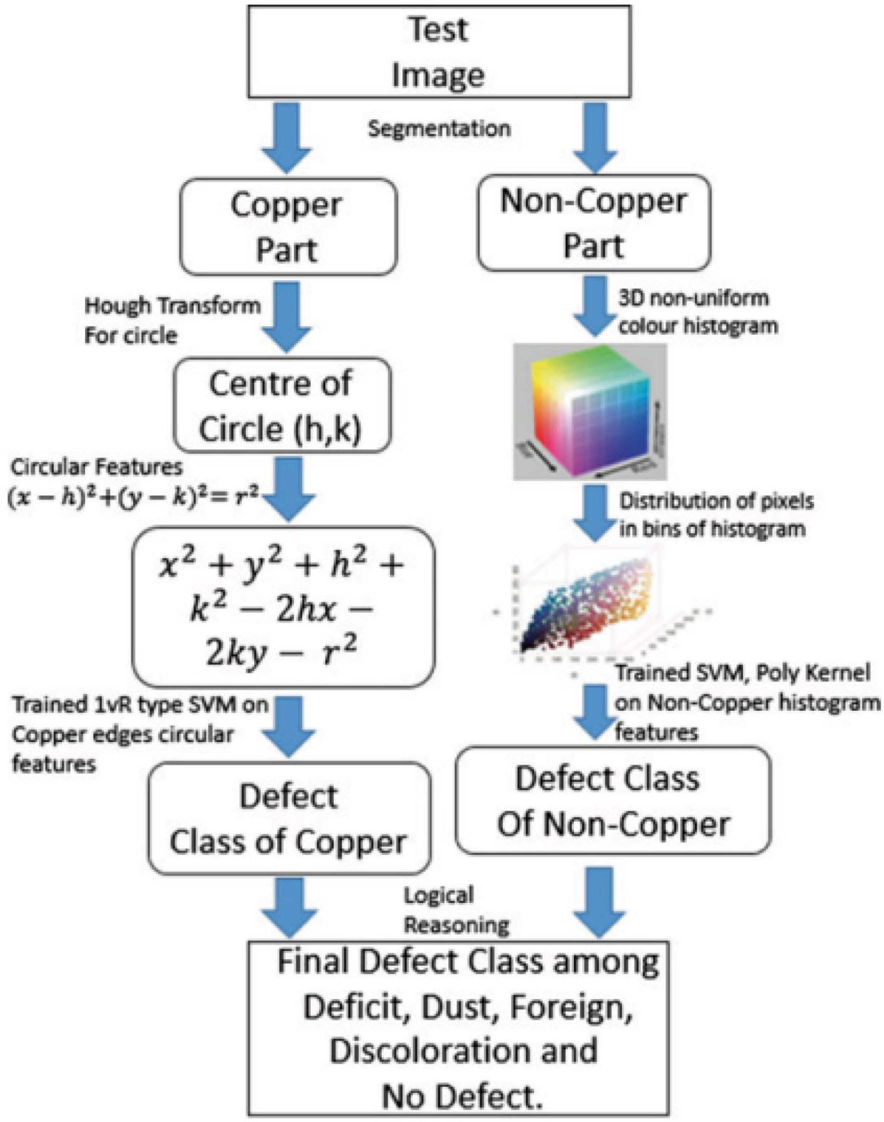


Fig. 6 PCB defect detection method [22]

used for the classification of defects. YOLO(v2) along with the CNN classification method is used to improve localization of defects along with high classification accuracy is presented in [1].

In [16], RSTN along with the referential comparison method is used for PCB defect detection. An improved RSTN is proposed for image registration and referential comparison method, where referential and registered images

Fig. 7 Defect Image, Copper Region, Non Copper Region [22]

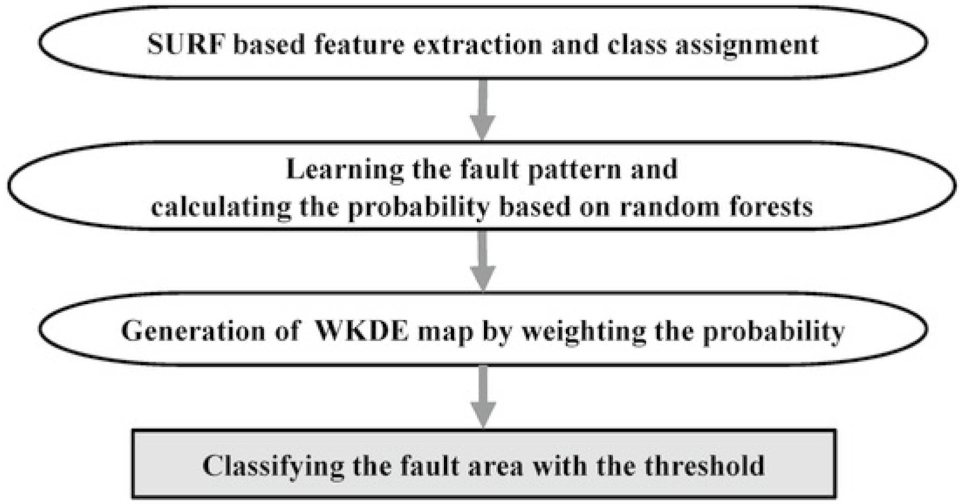


Fig. 8 Random forest based classification method [45]

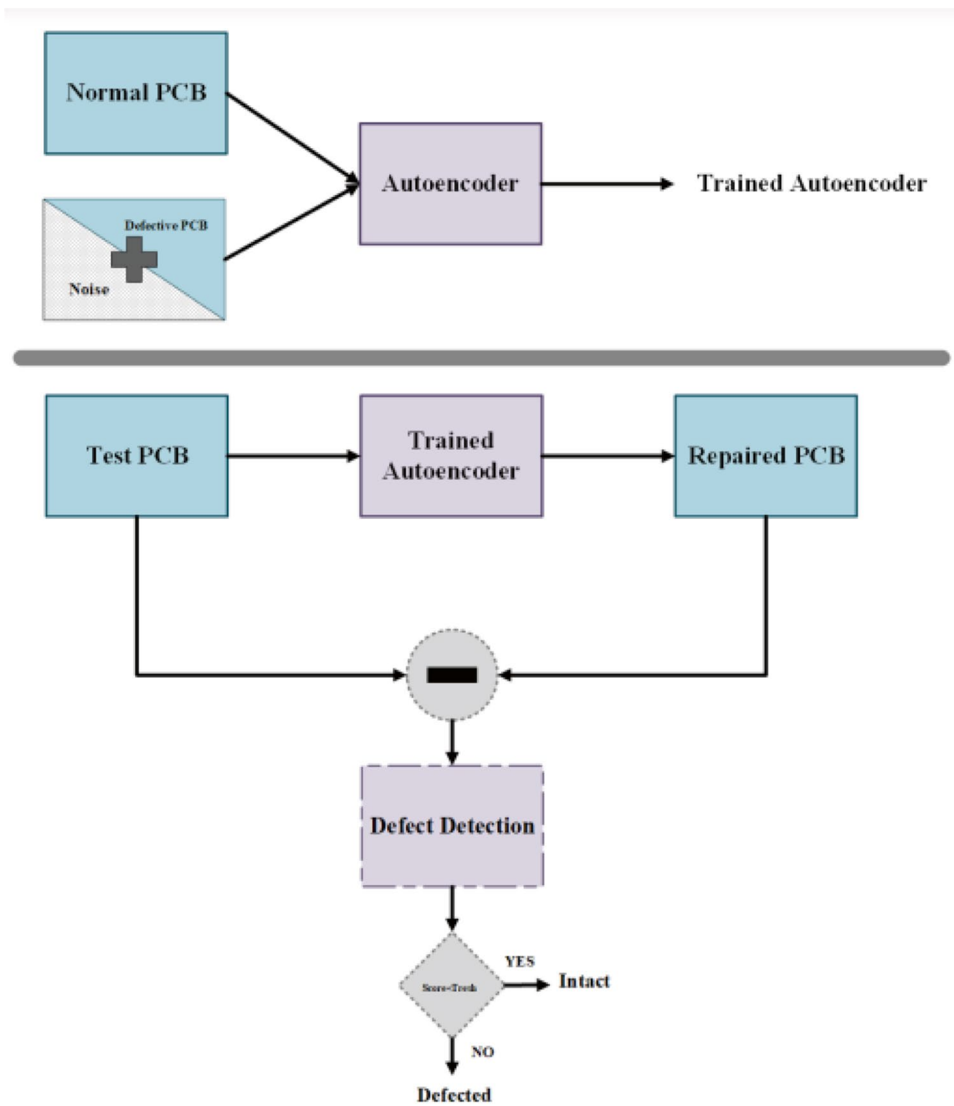


Fig. 9 Autoencoder method [21]

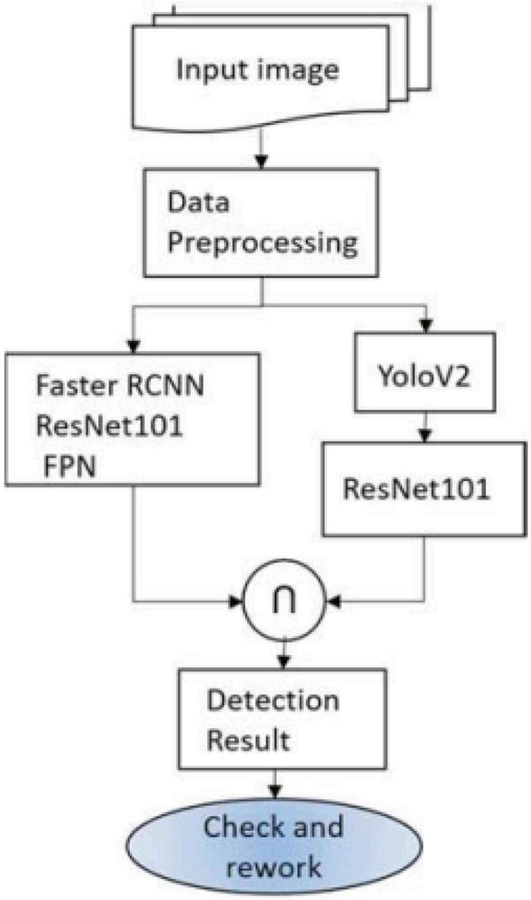


Fig. 10 Deep ensemble method [35]

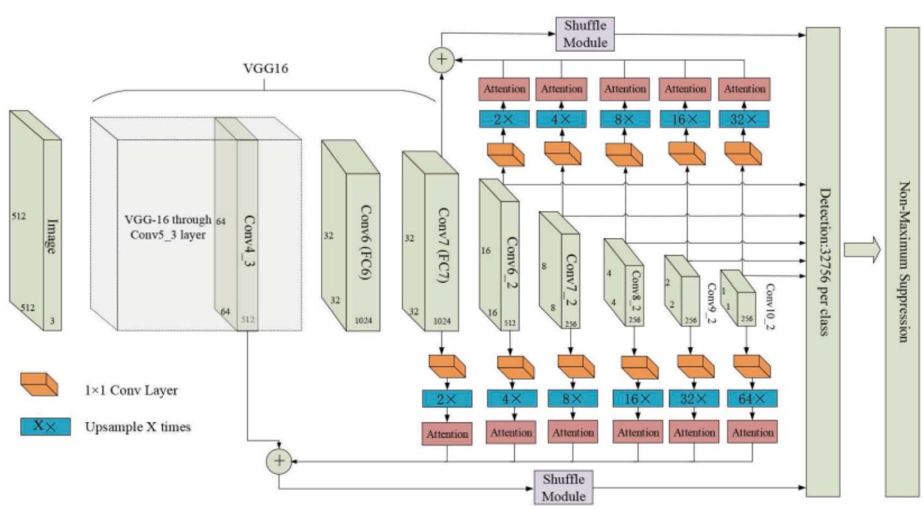
are preprocessed and subtracted, is for defect detection. An investigation of various ML algorithms used for PCB defect detection is reviewed in [46]. This review focuses on defect detection for SMT assembly lines. An Artificial Neural Network based defect detection mechanism known as Auto-VRS (Verify and Repair System) is proposed in [8] with the main aim of decreasing both false alarm rate and operator's overload. In this proposed system, to find accurate defect regions of interest using fast circuit comparison and classify different defects using CNN for feature extraction and fully connected Neural Networks are used along with CNN.

In [47], authors posed the PCB defect detection problem as multi-label classification problem and solved using the CNN model. In this, features of the cropped input image are used as an input to CNN and converted multi-label learning problem into multiple binary classification problem for defect detection. A neural network based defect detection in PCBs assembled in SMT is presented in [11]. As shown in Fig. 13, the features of an input image are passed through a feature selection block, which contains a back propagation (BP) network, that selects dominant features and a Neural network is used for defect classification. A CNN based non-reference approach for the classification of defects in PCB is presented in [2]. In this paper, authors considered good, confused, and damaged classes of defects. In the first stage good and confused are separated then in the later stage they are classified as confused into good and damaged. A confused class is introduced since this kind of PCB looks good but has some small scratches or external dirt attached to it.

In [36], authors proposed Multi-input CNN for classifying defects as weather true defects or pseudo defects. It takes input as two test images under different illumination conditions. Two models have been proposed, the first CNN is at the output layer and the second is at the input layer. Also, this proposed approach does not need a reference image.

An adaptive template matching algorithm is proposed in [10] for solder joint defect detection in PCBs. As shown in Fig. 14, first X-ray images are formed, then ROI is extracted and feature based template matching is performed based on edge and counter features using a Canny edge detector. In [40], a novel group pyramid pooling module is proposed for

Fig. 11 Tiny Defect Detection [23]



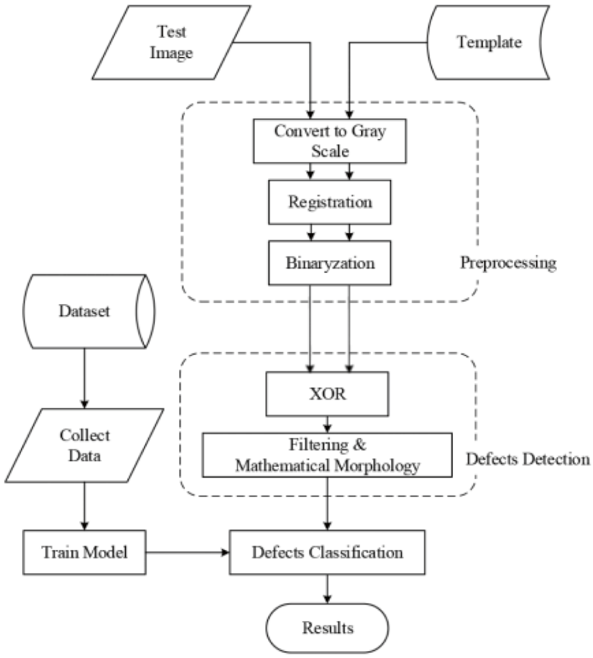


Fig. 12 CNN Based Approach [17]

the efficient extraction of features in a large range of resolutions for PCB defect detection. A CNN module such as VGG-16 or ResNet18 is used as a backbone network. A reference based defect detection algorithm is proposed in [33]. In this paper, the type of PCB is identified using the Fast Approximate Nearest Neighbor search library (FLANN) for SURF features and a Brute force technique by finding

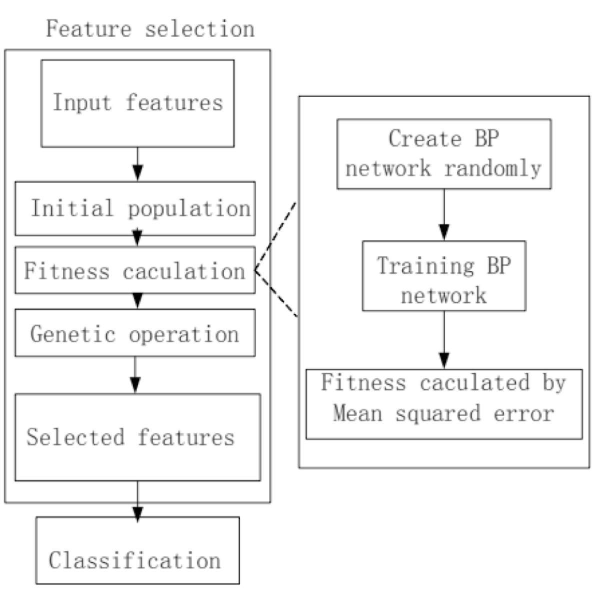


Fig. 13 Neural networks Based Approach [11]

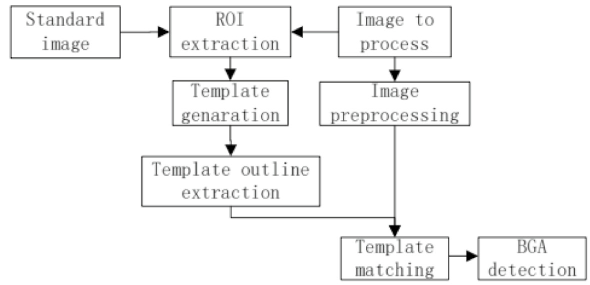


Fig. 14 Adaptive template matching algorithm [10]

Hamming distance for Oriented FAST and rotated BRIEF (ORB), a fast robust local feature detector, points. Detection and classification of PCB defects to distinguish between true and pseudo defects is proposed in [38]. The SURF algorithm is used to obtain key points and then a cropped image is generated from key points and fed to CNN and classification model for defect detection. In this paper, an SVM classifier with linear kernel and RBF kernel is used for classification purposes. A deep learning based PCB solder joint defect detection for X-ray based images is proposed in [50]. In the framework, a CNN module is used for feature extraction, and extracted features are fed to Long Short-Term Memory (LSTM), and then the classification is done using a classifier composed of two fully connected layers. LSTM is used to capture relationships within features of the input image.

An unsupervised learning approach is proposed in [29] for surface level PCB defect detection. A deep autoencoder is used for feature extraction and the similarity matching technique is used for defect detection. An object detection algorithm such as Faster RCNN and lightweight feature extraction using PeleeNet is proposed in [34] for defect detection. In this paper, the authors also performed character recognition using the Spatial transformer network, RNN layer, and Attention Mechanism technique. Classifying the defects of electronic boards into true and pseudo defects using CNN without the requirement of the reference image is presented in [19]. As shown in Fig. 15, the authors judged whether a defect exists or not using Dense Scale-Invariant Feature Transform (SIFT) and SVM classifier. Then CNN is used to classify between true or pseudo defects. The SIFT algorithm is used to extract key points from the input image and to generate a feature vector.

A transfer learning along with an unsupervised learning based algorithm is proposed for defect detection in [43]. The feature extraction is performed by transfer learning based VGG16 model and unsupervised learning is used to fine tune and describe the defects. In this framework, the RotNet model is used to extract complex semantic features from unlabelled images. A tree based supervised learning algorithm is proposed [20] for PCB defects that use

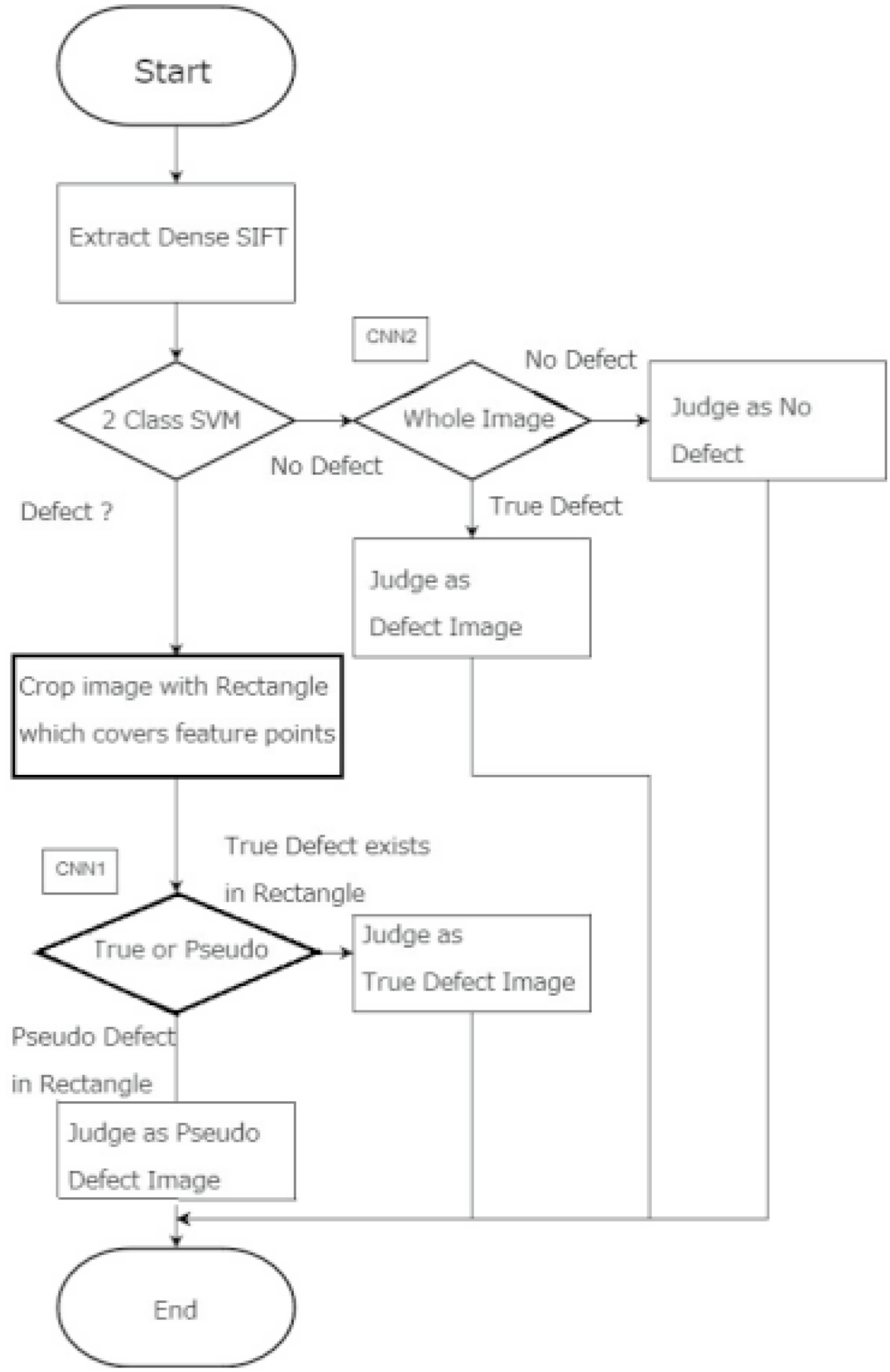


Fig. 15 CNN Based Approach [19]

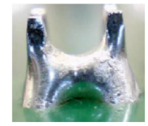
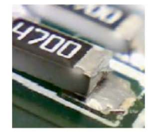
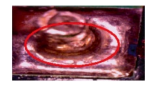
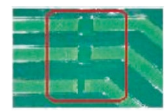
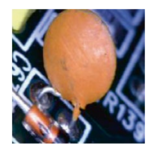
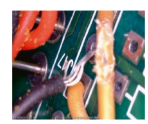
SMT. Tree based algorithms such as Classification And Regression Tree (CART), Random Forest, AdaBoost, and XGBoost for classifying defects into good, false call, and real defects.

A transfer learning based approach with pre-trained models such as VGG-16, DenseNet68, and Inception V3 are used for defect recognition and classification is studied in [6]. For defect localization, a faster R-CNN model is used.

4 Comparison

Table 1 summarizes the type of defects, studied in reference papers, defects that were not detected in aparticular type of defects, and one of the corresponding images. It is observed from the table that the least number of papers [11] studied for Tombstone, the wrong component, component shifted in the category of Faults caused due to inconsistent temperature. More papers studied defect identification in the

Table 1 Different types of errors with studied papers

S. No.	Defect type	Studied in papers	Defects Not Detected	Image of the Defect
1.	Soldering defects	[10, 13, 15, 23, 29–31, 42, 44, 50]	Solder Projection, Disturbed Solder Joint, Solder Spilling, Lead Clinched	
2.	Open Type defects	[5, 11, 12, 15, 23, 28, 37, 40, 44, 48, 51]	Fractured Solder Joint, C-side Wetting S-side wetting	
3.	Faults caused due to inconsistent temperature	[11]	Over Heating, De wetting, Incomplete Reflow	
4.	Corrosion defect	[13, 19, 22, 36]	All are detected	
5.	Errors in the wiring Tracks	[5, 8, 9, 12, 15, 17, 19, 24, 26–30, 33, 35–40, 43, 45, 47–49, 51]	Track Lifting, Exposed Bias Metal	
6.	Component faults	[3, 4, 6, 11, 18, 27, 29, 30, 33, 34, 39, 44]	Component Damage, Height Mounting, Extra Mounting	
7.	PCB level defects	[22, 43, 48]	Fixing not proper, Pin Bend, Wiring on Board	

category of errors that occur in wiring tracks such as a missing hole, open and short circuit, spurious copper, spur, etc., All defects due to corrosion are detected in [13, 19, 22, 36]. It is seen that there is no single algorithm that can be used for detecting all types of errors in PCB and identification of algorithms is dependent on the availability of dataset, type of error, error size, etc.

Different algorithms are used in the papers to detect the defect types, classified according to the table. To detect the Solder type defects, improved faster RCNN with feature pyramid network is used in [15], and CNN with LSTM structures is employed in [50]. Deep autoencoders are used in [30] and [29]. Papers [42, 44] propose ML models and ensemble learning approaches respectively for the detection purpose. Template matching method is used in [10, 31] and single shot object detector (SSDT) in [23]. Out of all these papers [10, 23, 31] and [50] aimed at only solder joint defects.

To detect open type defects, [28] used K means and image processing technique, and paper [40] used CNN and image processing. Other papers which employed an image processing approach are used in [5, 12, 51]. In [15], proposed an RCNN model, and [23] used the SSDT model. The neural network approach is used in other papers [11, 48] and the Ensemble method is proposed in [44] and [37] came up with a data mining approach.

The defect caused due to temperature parameters is detected only in [11] which employed a Neural Network with a Genetic algorithm model. Corrosion defect is detected in [22] using SVM and the CNN model is proposed in [36]. In [19], the authors came up with a combination of SIFT, SVM, and CNN models for defect detection.

The Wiring track defects are detected in multiple papers, of which Neural Network (NN) approaches are used in [8, 9, 15, 17, 36, 38, 40, 47, 48] and [19], with some additional models employed in some papers. In [5, 27, 51] and [12] employed an image processing approach. Other papers that used the same approach along with some other models are [28] and [33]. In [35], uses a deep ensemble method and SSDT is used in [23]. In the paper [24] authors came up with a Hypothesis Testing Strategy. Deep autoencoders are used in [29, 30] and Data mining in [37]. In [26] proposed Bayes Feature Fusion model and SURF + Random Forest (ML) algorithm are employed in [45]. In the paper [43], the authors came up with a transfer learning approach for this defect detection. Of all these papers only [8, 38] could detect the 3 defects in this category.

Component faults are detected in [3, 4, 27] and [33] using the image processing approach. CNN algorithms are used in [6, 34, 39] and auto encoders are employed in [30, 47]. The paper [18] came up with (Object Character Recognition) OCR technique and [44] proposed ensemble learning. The paper [11] used NN with a genetic algorithm for defect detection. Only two papers [22, 48] could detect the PCB level defects and these used CNN + Feedforward Neural Network (FNN) and SVM models respectively.

It is observed from the survey papers that most of the papers use either traditional image processing techniques or Machine learning techniques such as SVM and Decision Trees or Deep Neural Networks (DNN) such as CNN, transfer learning methods, object detection techniques combined with classification. The image comparison method used in the image processing technique is not efficient due to the presence of noise in the image. Even though ML techniques give better performance even in noisy images compared to traditional image classification methods. The performance of ML techniques is less compared to DNN for image processing. As the computational complexity in DNN is very large due to the presence of Fully Connected Neural Networks (FCNN), the computational complexity can be minimized by replacing FCNN with traditional ML methods such as SVM.

It is also observed that some of the defects such as solder projection, solder spilling, lead clinched, C-side wetting, S-side wetting, Incomplete reflow, etc., are not detected by any of the referred papers may be due to the unavailability of data set or less important. We believe to make an automated defect detection device for PCB it is good to have algorithms for detecting all types of defects. We are not comparing the performance of algorithms based on accuracy metrics since different papers used different metrics on different defects for algorithm performance.

5 Conclusion

In this paper, a review of various techniques using learning methods for PCB defect detection has been reviewed. Various techniques based on image processing, and transfer learning which were explored in the literature have been reviewed and presented in this paper. Most of the techniques presented in the literature are effective for detecting a few sets of faults and a comprehensive method to identify all the faults has to be identified. Also, we can study the various algorithms that identify the defects that occur at the Bare PCB level.

Data Availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Conflict of Interest The authors declares no conflict of interests.

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