Printed Circuit board defect detection using machine language

[1]V.Jamuna

Department of Electronics and Communication Engineering

V.S.B. Engineering College, Karur, India

Abstract: As innovation propels, printed circuit sheets (PCBs) include more components and alter their format. One of the most critical quality control methods is PCB surface review, as little absconds in flag follows can cause major harm to the framework. Due to the impediments of manual checking, incredible endeavors have been made to computerize filtering utilizing high-resolution CCD or CMOS sensors. In conventional machine vision approaches, it is continuously troublesome to decide pass/fail criteria based on little disappointment illustrations. The advancement of progressed sensor innovation. To fathom this issue, we propose a progressed PCB review arrangement based on a jump-related convolutional auto encoder. A profound autoencoder show is prepared to partitioned blemished pictures from imperfect ones. To begin with generation, scaled the redress representation to move forward the execution of preparing tests through a little and lopsided database. The printed circuit board (PCB), which is the essential structure for electronic gadgets, is exceptionally vital to the gadgets industry. This consider presents a unused machine learning (ML) strategy for PCB blame discovery. To naturally distinguish absconds, we utilize progressed ML models such as Convolutional Neural Systems (CNNs) on a expansive database of PCB pictures stamped for abandons. To give solid and exact location comes about, our investigate centers on information planning, highlight extraction, demonstrate determination and vigorous approval. It comes about appear that ML-based PCB imperfection discovery is compelling, which empowers way better quality control and hardware fabricating industry. The execution of our framework has been carefully assessed, appearing great exactness and effectiveness in identifying abandons utilizing exact approval strategies. This investigate is an imperative step towards mechanizing PCB review, moving forward the unwavering quality of electronic items and decreasing generation costs. It moreover laid the basis for propels in quality control and imperfection avoidance in hardware fabricating. Included ML-based PCB surrenders these discoveries are anticipated to revolutionize quality confirmation strategies as the hardware industry advances and open the entryway to more productive, error-free and cost-effective hardware fabricating.

Keywords— Defect detection, PCB, image processing, Machine learning, CNS, **CMOS.**

I INTRODUCTION

The printed circuit board (PCB) is one of the most important components in electrical and electronic equipment. PCBs are divided into two categories: bare PCBs and assembled PCBs, also called PCBAs. Single-sided, double-sided or multi-layer bare PCBs are all possible.[1] The casting process is the most critical step in the creation of bare PCBs and an improperly placed PCB board can have defects such as overworking or etching. There are two types of PCBA components: active components and passive components.[2] Screen printing, component assembly and soldering are steps in the PCBA manufacturing process. Defects during manufacturing can include missing and misaligned components, as well as solder connections. PCB and PCBA testing is essential to make the PCB nearly perfect.[3] Most PCB defect detection is done manually by skilled technicians, which is tedious, expensive and time-consuming. In addition, it creates high waste and does not guarantee quality. Automated Optical Inspection (AOI) systems are used in many industries to inspect PCBs, eliminating the disadvantages of manual inspection.[4] However, most PCB manufacturers do not have the opportunity to buy AOI's main equipment. Finally, cheaper automated PCB inspection methods should be developed. However, the iterative operator can quickly become lost, and the consistency of the results of detecting each operator is another problem.[5] The basic flaw in human perception, which is the main reason for defective goods leaving the factory, must be overcome.[6] To overcome these limitations, researchers are looking for machine vision-based defect inspection that uses cameras, light sources, and operating systems.[7]Quality control is the main focus of this strategy using automated optical inspection (AOI) systems. AOI systems capture high-quality images using industrial cameras such as Radiant Vision cameras to detect defects.[8] Deep learning algorithms have recently enabled developers to create more comprehensive computer and machine vision solutions. In particular convolutional neural networks (CNNs) have made significant progress in the field of image recognition and detection.[9] CNN has the advantage of working without using the feature extraction approach and can automatically learn visual features. Alex Net, one of the most popular CNN constructs, competed in the Image Net LSVRC-2012 competition and took place first with a 10% error lower than the computer vision model that took place first last year.

The performance of CNNs in recognition tasks is comparable to humans.[10] Another neural network architecture called autoencoders, expands the compressed input data to reproduce the original input data after the data is compressed in a low-dimensional form. It is well known that autoencoders learn the image structure and generate the original image from the corrupted input image.[11] The autoencoder as a PCB fault detection program. Here, we propose that the CNN-based autoencoder model can successfully detect PCB defects when used with industrial cameras equipped with image sensors. Almost all electronic devices use PCBs which play an important role in electronic components.[12] However due to the limited technology used in PCB manufacturing 100% quality cannot be guaranteed. From time to time manufactured products have short circuits, circuit breaks, cracks and other defects. So the PCB industry is urgently needed to learn how to check products that do not meet the requirements and ensure that the quality of the final product is reliable. Today, many companies use AOI equipment together with artificial visual inspection techniques in the PCB production line but the high-end equipment is expensive and the artificial cost increases the operating cost. Other AOI pixel rate comparisons are used for slower detection with higher false positive rates and artificial detection learning cycles. Printed circuit boards (PCBs) are an integral part of modern electronic devices serving as the backbone for connecting and integrating various electronic components.[13]This complex board may be subject to defects during manufacturing or assembly, which may cause the final electronic product to malfunction or degrade performance. Defect detection on PCBs is an important quality control to ensure reliable and efficient electronic devices. Conventional visual inspection methods are time-consuming, labor-intensive, and cannot accurately detect subtle defects.

To overcome this challenge, the integration of machine learning techniques for PCB defect detection has emerged as a promising solution. The use of machine learning in PCB defect detection leverages the power of advanced algorithms to automatically classify and identify defects on PCBs with greater accuracy and efficiency. Instead of manual inspection methods.[14] Machine learning algorithms learn patterns and features from large databases of PCB images and use this knowledge to detect defects in real-world manufacturing environments.[15]This revolutionary approach has the potential to significantly improve the manufacturing process by reducing defects, reducing downtime, and ultimately improving the reliability and quality of electronic products. Image processing algorithms are important in these computer vision based systems.[16]For image processing with conventional detection algorithms, it is often necessary to select human features. Machine learning algorithms can be trained to achieve high accuracy in defect detection. Because you can learn identify features that indicate a defect, even if these features are subtle or difficult to detect with the naked eye.[17] Machine learning algorithms can be used to detect defects quickly and efficiently. This is because images can be prepared for real-time processing. Machine learning algorithms can be scaled to handle large image databases. This makes them suitable for use in high volume production environments. Compared with conventional feature extraction algorithms, CNN-based models have achieved success in various visual recognition tasks, such as image classification, object detection, and semantic segmentation. It can accurately record the details of defects, even in the presence of shadows or highlights, without the need for additional information. With this obvious advantage, the CNN-based object detection algorithm has consistently updated the entire object detection competition and has taken a leading position in the field of object detection.[18]Electronic circuits designed using surface mount technology

(SMT) have components mounted or mounted directly on a printed circuit board (PCB). PCBs are boards with tracks, lines, and tracks that electrically connect electronic components.[19] A copper-plated substrate connects these channels, allowing electrical energy to flow from one part to another. The solder paste solution is printed on the board using a solder paste printing process to cover the component on the board.

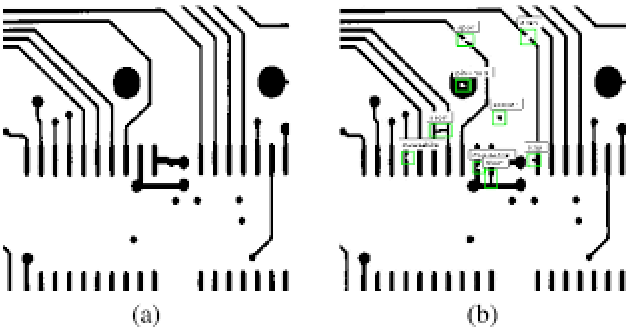

Fig.1.1

Screen printing, component assembly and soldering are all part of the manufacturing process. Defects include missing or misaligned components, incorrect solder connections, including bridges (where solder melts together), loose solder connections, excess solder connections, and insufficiently or tightly soldered soldered points. Example of soldering on defective PCBs. All these defects can damage the board or seriously damage it.[20]It is necessary to build an efficient, high-precision automatic detection module to check various defects in the PCB manufacturing process. The main goal is to create an automatic and scalable solution that can handle the complexities and variations present in real PCB design. Through machine learning, we are trying to create a reliable system that can accurately detect various defects such as shorts, open circuits, errors and other common manufacturing anomalies.

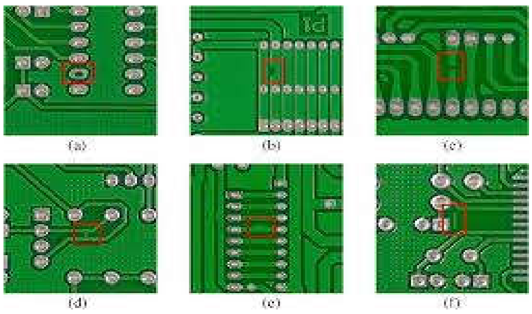

Fig.1.2

II. LITERATURE SURVEY

A. Related works

Ismail Ibrahim proposed a new algorithm for PCB defect classification. Image contrast includes widely used standard operations such as image subtraction and image addition. Five different defects can be successfully identified. Unwanted noise is reduced by solving problems related to translation and rotation matching between the template image and the defect image. At noise levels of 0.01, 0.02, and 0.03, the hybrid technique described by Swagata Ray et al. In addition to identifying defects, divide this into five groups.S. Burak Gokturk and others introduced a method to find circles and lines connecting them. These include graph matching, edge tracking, edge detection, edge joining, joint-based path determination, and edge detection. Results for different lighting conditions include the percentage of bottomless circles, missing radius, and missed links. The subtraction method was proposed by Wen-Yen et al., who divided defects into seven groups based on three indicators: the type of object detected, the difference in the number of objects, and the difference in the background number between the reference and the test. Picture these defects include absorption problems, deformation, short cuts, pits and holes. Hanang Hanlin et al. split the image of the standard board and expectations into pieces. The properties of each sub-block are enhanced by linear transformation and gray-scale statistical comparison is used to determine whether the image sub-blocks are missing or not. Defect detection on a 150*144 image took 19.7 milliseconds. T. J. A modified image comparison method with three subtraction operations proposed by Mateo Sanguino and others allows more work to be done in the error detection process. The triple subtraction process uses PCB and CAD files as input. Depending on the output value, the output can be divided into three categories: excess particles, loss of particles, and wide space (board, copper, excess copper, and loss of copper).

1.Single Layer PCB

A single layer of copper forms the simplest form of PCB. Various research projects have been done on synthetically produced (artificial) PCB images and real PCB images. Through-holes, printed circuit boards, and surface Mount PCB designs are among the prototypes, which are computer-generated PCB designs from three different boards. The actual image is taken directly from the camera on the PCB and is real or natural.

a. A picture of the actual PCB:

In this method, an artificial single-layer bare PCB image with no defects is compared with an artificial PCB image with 14 defects, such as open, short, exit, through-hole, over- and under-conductor. together, mouse bites, swelling, missing holes, wrong-sized holes, missing leads, faulty copper and shorter.

b. Real PCB image: This method compares an image of a real PCB without defects with an image of a damaged real PCB to identify defects.

2) Double layer and multi-layer PCB:

Single-layer and single-sided PCB are extensions of each other. Multilayer PCBs have more than two layers, which reduces component space and provides higher component density. In this multilayer board, it is difficult to detect defects in the intermediate layer after PCB fabrication because the intermediate layer is buried or replaced. Therefore, using image processing techniques to identify problems before sanding, pressing, and printing will help reduce waste while increasing production.

An algorithm for detecting defects in the inner layers of printed circuit boards was developed by Rau H et al. Image reduction, defect segmentation, and defect classification are all included in the algorithm. The technology only detects eight different types of defects. The inner layer of the PCB does not have open, short, mouse bites, holes, lossy conductors, whistles, excess copper and holes. An outer boundary tracing approach is used to isolate each defect area. A boundary state transition approach is proposed to classify various defects. Mechatronic Systems and X-ray Image Processing Techniques, Shui Fa Chuang et al. developed a special system to check the layer mismatch of laminated multilayer PCBs. Copper concentric circle output, compression, and offset values are examples of error errors.

a. Built-in PCB*:*

EK Teoh et al. Five separate algorithms have been developed to identify missing components, faulty components, faulty parts and bad solder joints. PCB alignment is important for accuracy. By reducing the background, K Sundaraj developed an algorithm that can only find missing and faulty capacitors and ICs. Most foreground pixels will show problems in predictable locations. This approach is not satisfactory if the color of the component is the same as the background color of the PCB.

To extract PCB components, Zhou Zeng developed an algorithm based on the color distribution of different areas. A combination of solder joint extraction and protective coating extraction is used to locate and identify components. Solder joint extraction involves the detection and removal of false discriminant components using color distribution features based on chromatic coordinates, as well as the identification of different regions using specular detection components. GMM takes a long time to model key pixels. Future research can be focused on improving the efficiency of the algorithm. PCBA, Ganavi, etc. to identify and classify defects. presented three methods: wavelet transformation, template matching, and background reduction. This method successfully detects faults such as mountains, tombstones, sides, missing, missing and misaligned parts.

b. PCB and PCBA*:*

An approach to detect defects developed by Du Ming et al. using the Eigen value of the covariance matrix. Based on the image information extracted from the gray level distribution, the board can be classified as defective or non-defective [Quantile-quantile (Q-Q) plot-based defect detection method developed by Du-Ming et al. A Q-Q plot compares the quanta in the probe image with the quanta in the template image. Defect detection only in bare PCB and PCBA reported in the results of the aforementioned method General algorithm developed by Mohit. Borthakur to identify defective PCB and PCBA. Filtering, zooming, zooming, histogram, wavelet transform and subtraction are used as image processing .

III.MATERIALS AND METHODS

A. Dataset preparation

After receiving the PCB image, we manually removed the PCB image using Photoshop, an image editor developed by Adobe Systems. This approach divides defects into six different categories: no holes, mouse bites, open circuits, shorts, pinches, and faulty copper. Each intelligently labeled image consists of three to five defects of the same class found in different areas. The general configuration of the PCB database is listed.[6] The database contains 693 images of PCB defects, of which 2953 are correctly identified. All cropped images, made from 2953 images, were cropped into 400400 dimensional, areas containing the defect.

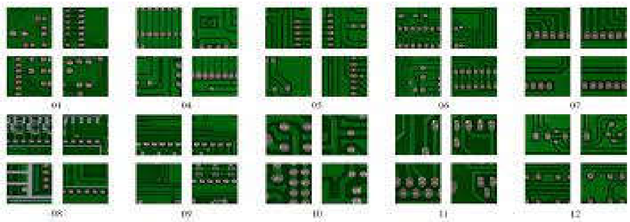

Fig.1.3

B. preprocessing

The performance of the neural network model is determined by the quality of the training data, which is done by pre-processing the data. The original PCB dataset is processed by image contrast enhancement and noise reduction in pre-processing to improve image quality. In the last step of processing, the PCB image is divided into 400x400 pixel image patches and image patches with defects are grouped separately to improve the data. Industrial grade cameras are used to collect high resolution images. it leads to a lot of computing power and a long training procedure for deep neural networks. It is designed to automatically extract a special patch image of size 400x400 from the original image, as well as pre-processing for image contrast and noise rejection.

C. Data Augmentation

For deep neural networks, the hyperparameters are very large, Preparing them requires a lot of training information. However, it is inevitable that defective products occur only occasionally during production, and the type of defects may differ from mass production. Since the deep neural network-based error detection system needs a verification mechanism that is accepted before mass production, this data inconsistency problem can be a limitation of this system. Gaussian random noise function to generate this noise is used to train the neural network model. Applying this imbalanced data to deep neural network models can cause a number of problems, including over processing and reduced performance. To avoid this problem, we use a small amount of error data to fill and improve the data to improve the performance of the model. Geometry correction and noise injection are used to account for the redundancy of the magnified image. By changing the size, orientation, or location of component features, geometric transformation is an effective method of adjusting positions in training data. Random rotation and random displacement are used to correct the positional bias in the PCB data. To help neural network models learn more robust features, noise injection is a technique that involves adding or multiplying a matrix of random values from a noise distribution. convolutional neural network and autoencoder.

*A*n autoencoder is a network that attempts to encode and encode the input into a low-dimensional hidden space. Using unsupervised learning algorithms, features from unlabelled data can be useful. Autoencoder consists of two components, an encoder that converts the input data into a low-dimensional latent vector and a decoder that multiplies the latent vector to produce the original input data. Data compression [19,20], denoising [21,22,23] and anomaly detection [24,25,26,27] are often used for them. Convolutional layers (Conv) are used to deal with 2D image data, because fully connected autoencoders are conventional autoencoders that ignore the two-dimensional (2D) image structure. filter and Convolution layer are the main components of this CNN. When the input data passes through the Convolution layer, a voltage operation is applied to the width and height of the input volume to calculate the resistance between the filter and the input data, and a two-dimensional feature map is generated by the corrected activation function. . linear unit (ReLU) and sigmoid function. It offers model adaptability.

$$aout = \max(an \times ninu(n,n))$$

The main function of the pool layer is to save space by reducing the resolution of the feature map, which enables efficient learning by reducing the computational load by reducing the data size.

Let X1 and X2 be the outputs of the corresponding encoder layer and decoder layer, respectively. The input to this decoder layer is calculated as:

$$(X1,2) = X1 \oplus X2$$

D. Image subtraction

It is also known as pixel reduction. It is the process of subtracting an image from another image using the complex numerical value of each pixel or the whole image. This is done in one of two ways: either by smoothing uneven parts of the image, such as wide shadows, or by looking at the differences between the two photos. This ability to see changes can be used to distinguish whether any object in the image has moved. It is commonly used in fields such as astrophotography to help in the electronic search for space rocks or Kuiper belt objects where the object is moving and still in one image.

E. Defect classification

Customers must contribute defects to be tested. This project has been covered in four different ways the disadvantages are as Open circuit: It is called open circuit on PCB because it creates an open circuit on PCB.An electrical fault occurs when at least two wires should not touch each other.An abnormally high current can flow through the circuit the result of lack.

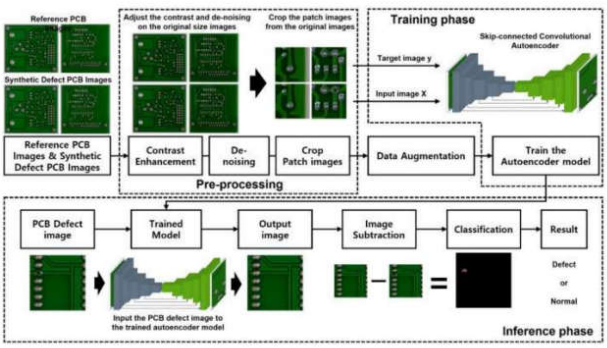

Fig.1.4

F. Performance Evaluation

The input image is subtracted from the flawless output image that produces our model. In this image subtraction method, the digital value of the entire image is subtracted from the value of other images.This method allows you to determine the difference between two photos, and this point of difference can be used to detect defects. Finally, the higher output image quality indicates that our model is better, and this performance indicator determines how similar the target image is. The peak signal-to-noise ratio (PSNR) and the mean squared error (MSE), which calculates the absolute similarity and difference of pixel values, are two metrics used by SSIM to evaluate structural data degradation. The main metric used to evaluate the performance of detection and classification models is accuracy. Estimating the exact performance can be difficult because the overall accuracy does not take into account the class inequality in the data. Therefore, different measures should be considered when evaluating the prediction accuracy of each class. In this study dealing with imbalanced data, the index is commonly used for sample estimation. Accuracy, true positive rate (TPR), true negative rate (TNR), precision, F1 score, and balanced classification rate (BCR) were used in this study. All these indicators have percentage values between 0 and 1, with values closer to 1 indicating greater productivity. The elements of the confusion matrix drawn are used with each performance indicator. NG stands for All Handicapped, Good for No Handicapped. In this analysis, the disability class is considered positive.The most important statistic for model evaluation is accuracy. This shows the ratio of total data accurately predicted by the model.

$$\text{Accuracy} = TP + TNTP + FN + TN + FP$$
$$\text{Accuracy} = TPTP + FP$$
$$\text{Accuracy} = TPTP + FP$$

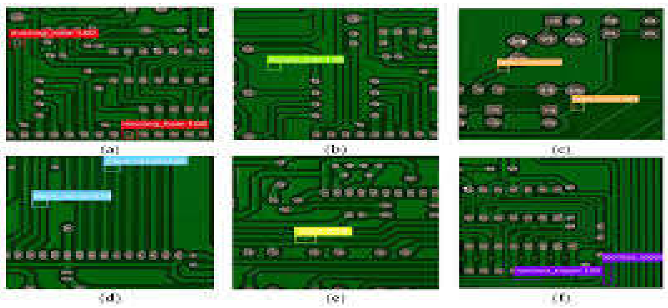

Fig.1.5

IV. RESULTS AND DISCUSSION

This paper used data mining to train the model. Study period for assessment performance of both training models during training. The test database contains 3900 patch images, of which 2000 are defective images and 1900 are normal images. The learning model is built without errors image using the test data, then reduce the image used to determine whether the generated image is different from the input image. Test pattern with six test images. If the output image is the same as the input image, the classification performance of the model will be adversely affected, because the difference between the two pairs of images is a sign of defects or abnormal locations, depending on the number of differences. Image thresholding to improve image quality to remove excess noise and identify defects.

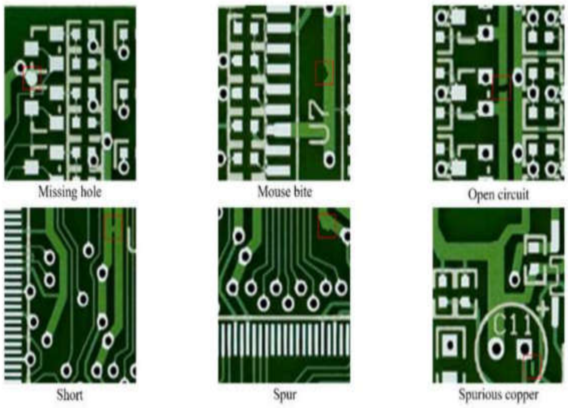

Fig.1.6

This paper has presented an analysis of each step in the supervised machine learning method and compare the performance of different pre-trained models. The lowest defect detection rate in the "Incremental/Hole Washer" category. All misplaced holes are found in this category. Areas where there is a washing machine but not a washer can sometimes be difficult to detect with the human eye, and training the model with dozens of cases is not enough to extract the information needed to detect this problem. There may be additional factors that contribute to this decline. A common threshold is used for all 66 classes. We can assume that the threshold for detecting defects should be adaptive and small if it is a normal group.

For class K, there is a smaller hand width (for example, for the class including washing elements). This loss drops quickly and reaches zero during the first ten periods. The accuracy of the classifier improved significantly at the same time time then gradually increased to 95% in the last 30 periods. In 15 epochs, the average number of matching boxes between RPN and ground truth reached 12 and began to fluctuate slightly thereafter. In the first 20 periods total loss decreases from 6.63 to 0.32, which is significant. With 40k bets and minimal data, the results are decent. Since capacitors are similar in size to resistors and have several unlabeled components, it would be better if there were more components to increase the level of accuracy.

V. CONCLUSION

This paper has provided a comprehensive overview of the latest methods of PCB defect detection. Focusing on this approach, several ways have found to detect PCB defects using machine learning techniques. Although the method has been positive for the detection of PCB defects, machine learning can be used to predict the possibility of PCB defects before the solder is printed. The PCB database is preprocessed to reduce the image using a popular imaging algorithm and resize it by removing unwanted space and improve image quality. CNN can identify and classify PCBs with a respectable level of accuracy. Overall accuracy of 85% is in classifying PCB defects. Future work will focus on improving the identification and classification of data. Hence, CNN-based fault detection the algorithm has overcome such problems and achieved significant gains in accuracy and speed

REFERENCES

[1] H. S. Cho, J. G. Yoo, J. S. Kim and S. H. Kim, “Samsung electro mechanics Co Ltd. official gazette of the United States patent and trademark. printed circuit board,” US Pat. US, vol. 8, no. 159, pp. 824, 2012.

[2] H. Matsubara, M. Itai and K. Kimura, “NGK spark plug Co Ltd. patents assigned to NGK spark plug. printed circuit board,” U.S. Patent US6,573,458, issued September 12, 2003.

[3] A. P. S. Chauhan and S. C. Bhardwaj, “Detection of bare PCB defects by image subtraction method using machine vision,” in The World Congress on Engineering (WCE 2011London, U.K., pp. 6–8, 2011.

[4] N. K. Khalid “An image processing approach towards classification of defects on printed circuit board,” Ph.D. dissertation, Universiti Teknologi Malaysia, Malaysia, 2007.

[5] K. Kamalpreet and K. Beant, "PCB defect detection and classification using image processing," International Journal of Emerging Research in Management & Technology, vol. 3, no. 8, pp. 1–10, 2014.

[6] W. Y. Wu, M. J. J. Wang and C. M. Liu, "Automated inspection of printed circuit boards through machine vision," Computers in Industry, vol. 28, no. 2, pp. 103–111, 199

[7] P. Wei, C. Liu, M. Liu, Y. Gao and H. Liu, "CNN-Based reference comparison method for classifying bare PCB defects," Journal of Engineering, vol. 2018, no. 16, pp. 1528–1533, 2018.

[8] K. P. Anoop, N. S. Sarath and V. V. Kumar, "A review of PCB defect detection using image processing," International Journal of Engineering and Innovative Technology, vol. 4, no. 11, pp. 188–192, 2015.

[9] C. T. Su, T. Yang and C. M. Ke, "A neural-network approach for semiconductor wafer post-sawing inspection," IEEE Transactions on Semiconductor Manufacturing, vol. 15, no. 2, pp. 260–266, 2002.

[10] D. B. Perng and S. H. Chen, "Directional textures auto-inspection using discrete cosine transform," International Journal of Production Research, vol. 49, no. 23, pp. 7171–7187, 20

[11] F. L. Chen and S. F. Liu, "A neural-network approach to recognize defect spatial pattern in semiconductor fabrication," IEEE Transactions on Semiconductor Manufacturing, vol. 13, no. 3, pp. 366–373, 2000.

[12] D. M. Tsai and B. Hsiao, "Automatic surface inspection using wavelet reconstruction," Pattern Recognition, vol. 34, no. 6, pp. 1285–1305, 2001.

[13] W. C. Li and D. M. Tsai, "Wavelet-based defect detection in solar wafer images with inhomogeneous texture," Pattern Recognition, vol. 45, no. 2, pp. 742–756, 2012.

[14] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

[15] A. S. Chivukula and W. Liu, "Adversarial deep learning models with multiple adversaries," IEEE Transactions on Knowledge and Data Engineering, vol. 31, no. 6, pp. 1066–1079, 20

[16] T. S. Li, "Applying wavelets transform, rough set theory and support vector machine for copper clad laminate defects classification," Expert Systems with Applications, vol. 36, no. 3, pp. 5822–5829, 2009.

[17] D. Ciregan, U. Meier and J. Schmidhuber, "Multi-column deep neural networks for image classification," in IEEE Conf. on Computer Vision and Pattern Recognition (CVPR 2012Providence, Rhode Island, pp. 3642–3649, 2012.

[18] T. H. Chan, K. Jia, S. Gao, J. Lu, Z. Zeng et al., "PCANet: A simple deep learning baseline for image classification" IEEE Transactions on Image Processing, vol. 24, no. 12, pp. 5017–5032, 2015.

[19] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 8, pp. 1798–1828, 2013.

[20] A. J. Crispin and V. Rankov, "Automated inspection of PCB components using a genetic algorithm template-matching approach," International Journal of Advanced.