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DETECTION AND CLASSIFICATION OF PCB DEFECTS USING DEEP LEARNING METHODS

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ABSTRACT:

Printed Circuit boards (PCBs) are one of the most important stages in making electronic products. A small defect in PCBs can cause significant flaws in the final product. Hence, detecting all defects in PCBs and locating them is essential. In this paper, we propose an approach based on denoising convolutional autoencoders for detecting defective PCBs and to locate the defects. Denoising autoencoders take a corrupted image and try to recover the intact image. We trained our model with defective PCBs and forced it to repair the defective parts. Our model not only detects all kinds of defects and locates them, but it can also repair them as well. By subtracting the repaired output from the input, the defective parts are located. The experimental results indicate that our model detects defective PCBs with high accuracy (97.5%) compare to state of the art works. Index Terms—PCB, defect detection, autoencoder, denoising convolutional autoencoders.We describe the complete model architecture and compare with the current state-of-the-art using the same PCB defect dataset. These benchmark methods include the Faster Region Based Convolutional Neural Network (FRCNN) with ResNet50, RetinaNet, and You-Only-Look-Once (YOLO) for defect detection and identification. Results show that our method achieves a 98.1% mean average precision(mAP[IoU = 0.5]) on the test samples using low-resolution images. This is 3.2% better than the state-of-the-art using low-resolution images (YOLO V5m) and 1.4% better than the state-of-the-art using high-resolution images (FRCNN-ResNet FPN). While achieving better accuracies, our model also requires roughly 3× fewer model parameters (7.02M) compared with the state-of-the-art FRCNN-ResNet FPN (23.59M) and YOLO V5m (20.08M). In most cases, the major bottleneck of the PCB manufacturing chain is quality control, reliability testing and manual rework of defective PCBs. Based on the initial results, we firmly believe that implementing this model on a PCB manufacturing line could significantly increase the production yield and throughput, while dramatically reducing manufacturing costs."

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INTRODUCTION:

A printed circuit board (PCB) mechanically supports the connection of electronic components via conductive tracks, pads, and soldering. PCB defects can cause malfunction and degrade the performance of the connected electronic components, which have a crucial impact on the performance of the entire system. Recently, in the mobile era, as the small mobile electronic product market has rapidly grown, more diverse and complicated PCB designs are required. This, in turn, produces PCB defect patterns that are difficult to detect by the human eye.

In general, PCB defect detection can be classified into two categories: direct inspection by a human operator and camera-based machine vision methods. Operator-based inspection allows operators to easily perform visual checks using simple instructions. However, operators can easily become fatigued by repetitive work and the detection results from each operator are not consistent. This is a fundamental limitation of human-based judgment and is the leading cause of defective products leaving the factory. To overcome these limitations, researchers have studied machine vision-based defect inspection, which consists of a camera, light source, and operation system. The main purpose of this approach is quality control using an automated optical inspection (AOI) system. The AOI system detects defects by acquiring high-quality images using an industrial camera such as Radiant vision camera, equipped with a charge-couples device (CCD) or complementary metal-oxide semiconductor (CMOS) image sensor. In the past, CCD was more used due to the fixed pattern noise (FPN) of the CMOS sensor. However recently, CMOS sensors have been widely used because of their improved performance and lower price compared to CCD.

There are three frequently used AOI approaches in PCB inspection: reference comparison, non-reference verification, and hybrid approaches. The reference comparison method compares the images to be detected with the template images to obtain defect areas. It is intuitive and easy to understand but requires high alignment accuracy and is sensitive to the light environment of the photographing process. The non-reference comparison method checks whether the traces and layout of the circuit board to be tested are reasonable according to the design rules; however, this method can easily miss large defects and distortion characteristics. The hybrid comparison method considers both advantages, but it is difficult to implement and has a large amount of computational complexity.

Not only the methods from the abovementioned literature studies but also a wide range of machine vision and image processing algorithms are available for developers to utilize . Ideally, an almost perfect AOI system can be developed if all the defect types are reported and studied in advance. However, one cannot guarantee that the system will encounter only preregistered defects. In a real production environment, new types of defects are always likely to be encountered and a typical machine vision-based detection system will not detect these correctly. In this case, the defect inspection system must be recalibrated using new sample data whenever the manufacturing conditions change . This can be a major disadvantage of traditional machine vision-based inspection systems because process changes occur every year in recent manufacturing environments.

Recently, the advent of deep learning techniques has enabled developers to obtain more generalized computer and machine vision solutions. In particular, convolutional neural networks (CNNs) have yielded significant improvements in the image recognition

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and detection field. A CNN can learn image features automatically and is advantageous in that it can operate without conjugating techniques for extracting features. AlexNet, a competitor in ImageNet LSVRC-2012 and one of the most popular CNN structures, won with an error rate 10% lower than that of the computer vision model that won in the previous year . In addition, the performances of CNNs appear to approach the levels of humans in recognition tasks .

Autoencoders are another line of neural network structures that compress the input data into a low-dimensional representation and expand it to reproduce the original input data . It is known that an autoencoder learns the structure of the image and reconstructs the original image from the corrupted input image. This motivated us to investigate the autoencoder as a PCB defect detection application. Herein, we propose a CNN-based autoencoder model that can effectively detect PCB defects by capturing images of the PCB with an industrial camera equipped with an image sensor such as a CMOS sensor without any prior knowledge of the defects or of the expert engineers' normal/defect assessments.

LITERATURE SURVEY:

A literature review of detection and classification of PC defects using deep learning methods would likely cover a range of research studies that have explored the use of deep learning techniques to identify and classify defects in printed circuit boards (PCBs). These defects can be caused by various factors, such as manufacturing errors, environmental conditions, or material degradation, and can have significant impacts on the performance and reliability of electronic devices.

One approach that has been used in the literature is to apply convolutional neural networks (CNNs) to detect and classify defects in PCB images. CNNs are a type of deep learning model that are particularly well-suited for image classification tasks, as they can learn to recognize patterns and features in images through multiple layers of processing.

In the context of PCB defects, researchers have used CNNs to classify different types of defects, such as cracks, voids, and contamination, based on images of the PCBs. Other studies have focused on using machine learning techniques, such as support vector machines (SMs) and decision trees, to detect and classify defects in PCBs. These methods can be used in combination with other techniques, such as image processing or data mining, to extract features from the PC images and improve the accuracy of the defect classification.

Overall, the use of deep learning methods for the detection and classification of PCB defects has shown promising results, with some studies achieving high levels of accuracy and sensitivity.

However, further research is needed to improve the robustness and generalizability of these techniques, and to address challenges such as variability in the appearance of defects and the limited availability of annotated training data. Another challenge in the use of deep learning methods for PCB defect detection and classification is the limited availability of annotated training data, which is necessary to train and validate the models. To address this issue, researchers have used various strategies, such as synthesizing synthetic data, collecting and annotating additional real-world data, or using transfer learning to adapt pre-trained models to the PCB defect classification task. 8In summary, the use of deep learning methods for the detection and classification of PCB defects has shown promising results, but there are still challenges to be addressed, such as the variability in the appearance of defects and the limited availability of annotated training data. Further research is needed to improve the robustness and generalizability of these techniques and to address these challenges.

EXISTING SYSTEM:

PCB defect detection schemes are divided into 2 main categories: image processing techniques and machine learning methods. Image processing techniques can be used to detect errors in PCBs and classify them. Dave et al proposed a reasonable PCB inspection system that detects defects in bar PCBs using image processing. This method can recognize commons defects such as missing holes or open circuits.

Wuetal developed an automated visual inception system for PCBs. This method subtracts a template PCB image from inspected images and uses an elimination process to locate defects in PCBs. To group all possible defects in PCBs, Kamalpreet et al presented a method using MATLAB image processing operations. This method groups 14 possible defects into 5 groups. In order to classify the PCB defects, Putera et al proposed a PCB defect detection and classification system using a morphological image segmentation algorithm and image processing theories. This system detects and classifies the defects on bar single layer PCBs. Ibrahim et al presented a scheme to locate any defects on PCBs automatically using a wavelet-based image difference algorithm. This scheme is more efficient compared to previous traditional methods.

Some of the researches used machine learning methods to improve the accuracy and efficiency of previous image processing techniques. Srimani et al proposed a hybrid approach to detect and classify defects in PCBs using soft computing techniques. This approach uses an adaptive genetic algorithm for feature selection and a neural network classifier. To tackle the problem of solder-balls occurrence in PCBs,

Kusiak et al developed a method that uses a data mining approach to identify the cause of these defects.

Deep Learning is a machine learning approach for recognizing patterns and classifying them. It works best with unstructured data and unlabeled datasets compare to other machine learning methods. Therefore, it is an impeccable approach for PCB defect detection.

METHODLOGY:

The various phase of the waterfall model includes

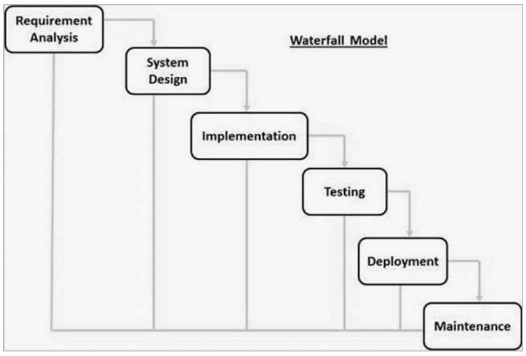

Figure: 3. Waterfall model of the system development life cycle.

PROPOSED SYSTEM ARCHITECTURE

In this section, a method for defect detection in PCBs is proposed. The proposed method not only detects defective boards and locates the possible defects, but also repairs the defective PCBs. The proposed method is based on denoising convolutional autoencoders, and it is a comprehensive method to detect all possible defects. As it shows an overview of the proposed method. As it is shown in Figure, the proposed autoencoder is trained with a dataset containing image pairs of defective and intact PCBs. We added salt-and-pepper noise to the defective

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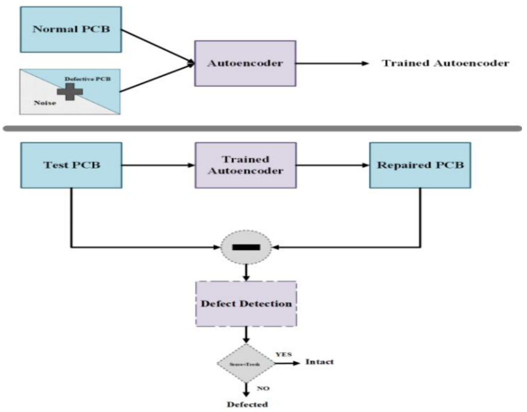

Figure 4. Proposed System Architecture

Architecture Components:

1. **Normal PCB:**

Printed circuit board is the most common name but may also be called "printed wiring boards" or "printed wiring cards". Before the advent of the PCB circuits were constructed through a laborious process of point-to-point wiring. This led to frequent failures at wire junctions and short circuits when wire insulation began to age and crack.

2. **Defective PCB:**

A defective printed circuit board (PCB) is a PCB that has one or more faults or defects that & prevent it from functioning correctly. Defects in PCBs can be caused by a variety of factors, including manufacturing defects, design flaws, and damage during handling or shipping. Some common types of defects in PCBs include open or shorted circuits, incorrect component placement, missing or incorrect components, and damage to the PCB material itself.

3. **Auto Encoder:**

An autoencoder is a type of artificial neural network used to learn efficient codings of unlabeled data (unsupervised learning).[1] The encoding is validated and refined by attempting to regenerate the input from the encoding. The autoencoder learns a representation (encoding) for a set of data, typically for dimensionality reduction, by training the network to ignore insignificant data ("noise").

4. **Testing PCB:**

There are several methods that can be used to test a defective printed circuit board(PCB). Some common methods include:

In-circuit testing: This involves using specialized test equipment to apply a known stimulus to the PCB and measure the response. This can help to identify defects in the PC's components or connections.

Functional testing: This involves testing the PCB in the context of a larger system to ensure that it is functioning correctly.

Burn-in testing: This involves running the PC under a high workload for an extended period of time in order to identify latent defects that may not be apparent during normal operation.

Figure 5. Sample Normal, Defective, Noisy Defective PCBs

RESULTS :

OUTPUT SCREENS

1. HOME SCREEN

A link is generated which redirects to the Web page,where its consists of two buttons named Browse and Upload.

Figure 23. Home Page

I. UPLOADING PCB IMAGE(A)

Figure 24. Uploading a PCB Image

Figure 25. Result of Uploaded Image

II. UPLOADING PCB IMAGE(B)

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Figure 26. Uploading a PCB Image

Figure 27. Result of Uploaded Image

CONCLUSION :

On the basis of our project study, this research came up with the following conclusions:
PCBs play a key role in producing electronic devices and the quality of the final product depends on its PCB. Therefore, the PCB should be flawless. In this paper, we proposed a defect detection method for PCBs based on denoising autoencoders. We trained the network with image pairs of the intact and defective PCBs. By learning the features of an intact PCB, our proposed method is able to repair the input and by subtracting the input from the output, the flaws are located. Our results proved the effectiveness of the proposed method. This paper presented a novel approach for defect detection in PCBs, however; the proposed method can be used to detect the defects in other kinds of products such as plastic injection molding products.
Moreover, the subtracting algorithm can be improved to achieve more accurate results in locating the defects. It is possible to use deep learning methods for the detection and classification of defects in printed circuit boards (PCBs. These methods have the potential to improve the efficiency and accuracy of defect detection and classification in PC manufacturing, as they can automatically learn and recognize complex patterns and features in the data. There are several different types of deep learning architectures that can be used for PCB defect detection and classification, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks. These architectures can be trained on large datasets of PC images and defects, and can learn to identify and classify defects based on their visual appearance.
One of the key challenges in using deep learning for PCB defect detection and classification is the need for a large and diverse dataset of PCB images and defects. This dataset must be representative of the types of defects that may occur in real-world PCB manufacturing, and must be carefully labeled to allow the deep learning model to learn from it. Overall, the use of deep learning methods for the detection and classification of PCB defects has
the potential to significantly improve the efficiency and accuracy of defect detection and classification in PCB manufacturing. It is an active area of research, and further improvements and developments are expected in the future.

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