A Comparative Analysis of Printed Circuit Boards Defect Detection Leveraging Deep Learning Approaches

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Abstract. Printed circuit boards (PCBs) are the foundations of modern industry. Their prevalence across electronic industries is explicit, ranging from computers and smartphones to televisions, digital cameras, and other devices. However, during the production process of PCBs, defects are inevitable, leading to substandard products, hence the detection of defects is a crucial task. Deep learning offers significant advantages over conventional machine learning approaches. These advantages include but not limited to the capacity to automatically extract complex embeddings from input samples, leading to improved accuracy and performance. Fueled deep learning, algorithms designed for PCB defect detection are anticipated to deliver superior precision and efficiency, attributed to their capability to recognize novel defect patterns. This article provides a comprehensive analysis of these algorithms, separated into three major categories, including Transformer-based solutions, one-stage, and two-stage approaches. Improvement methods and advantages of these algorithms are detailed. Finally, prospective future research is pinpointed to tackle existing challenges within the algorithms.

Keywords: Deep learning; printed circuit boards; defect detection.

1. Introduction

In recent years, fueled by the strong advancement of the information technology and the global economy, electronic products have achieved widespread adoption, with the consumer electronics sector experiencing exponential growth. Whether it's a television remote control or a mobile phone, whether it's a building elevator or an airplane, electronic products are everywhere. The core component is the printed circuit board (PCB). It offers the essential circuit interconnections needed for the diverse components integral to device design. With the continuous upgrading and enhancement of electronic products, high quality PCBs products are strongly required. Even small defects in PCBs may reduce the performance of electronic devices. In addition, if defects are found in the PCB after assembling all electronic components, simply discarding the electronic device is not cost-effective. As the foundation and key component of electronic products, PCB must demonstrate strong stability, obvious anti-interference ability, and excellent performance in high-speed transmission, higher integration, and compact size. However, due to the reduction in component size, the increase in component density, and the complexity and diversity of PCB manufacturing, PCBs are easily affected by a series of factors during the production process. Such factors are prone to inducing a range of defects, including missing and broken holes, open circuits, scattered copper, and mouse bites.

If these defects are ignored, it may reduce the performance of electronic devices. This may result in expenditure losses. Therefore, detecting PCB related faults in the early stages of PCB manufacturing is of great importance. Early manual inspection exists, but its technology is not very accurate. In the realm of PCB inspection, the majority of industries rely on Automatic Optical Inspection (AOI) systems. This system can automatically detect issues to reduce labor costs. Yet, the principal AOI machinery is prohibitively costly, putting it out of reach for many manufacturers. Consequently, there is an ongoing effort among researchers to design an economical automatic PCB defect detection solution.

This article systematically analyzes and comprehensively synthesizes previous works on PCB defect detection. The primary focus is on previous works leveraging deep learning or Transformer-powered approaches to increase the robustness and effectiveness of defect detection in PCB industry. This work provides a comparative analysis of the effectiveness and influence of these algorithms in PCB-related applications. In addition, based on existing literature, popular algorithms were reviewed and deliberated, while assuming potential development paths in the field.

2. Deep Learning-based PCB Defect Detection Approaches

2.1. One-stage-based PCB Defect Detections

The characteristic of the one-stage algorithm is to directly predict the target on the original image without the need for region proposal steps. Common representative algorithms include You Only Look Once (YOLO), RetinaNet, and Single Shot MultiBox Detector (SSD). These algorithms typically use deep learning techniques to extract image features using Convolutional Neural Networks (CNNs) and predict target positions and categories within the same network. Due to the omission of the region proposal step, one-stage algorithms typically have high detection speeds and are suitable for real-time application scenarios.

A large number of scholars have proposed different solutions to the problem of insufficient stability and limited accuracy of models designed for defect detection of PCB. For tackling the challenge of detecting small defects in PCBs, Jiang et al. improved the SSD model via merging coordinated attention to process positional information in shallow layers, resulting in significant improvements for smaller volume targets [1]. Zhang and colleagues have integrated a dual attention mechanism to bolster the identification of minor defects. By fusing this design with a Feature Pyramid Network (FPN) in the bottleneck of the model, the capacity for feature extraction has been significantly amplified [2, 3]. And MobileNetV2 lightweight backbone neural network was used instead of ResNet101, thus achieving a reduction in model parameters. The improved model effectively improves detection accuracy while reducing inference time. Moreover, a new PCB-based object detection dataset is proposed for solving the detection problem related to anchor frame size [4]. They performed an in-depth examination of the effective receptive field (ERF) for the output layer and devised an ERF-driven anchor frame allocation strategy to tackle the issue of anchor frame dimensions [5]. At the same time, they leveraged an enhanced Atrous Spatial Pyramid Pooling (ASPP) design. To further improve the capacity of the module, the authors incorporate channel attention mechanisms and enriches the feature maps with contextual data, thereby addressing the difficulties associated with pinpointing minute and elusive defects [6, 7]. Wu et al. proposed improved YOLOv5, which integrates lightweight networks with dual attention mechanisms [8]. This work reduces the model's parameter count and floating-point operations via introducing dual attention mechanisms are integrated into the network, thereby improving accuracy and detection speed. Xuan et al. improve backbone network for more precise performance via attention mechanisms and inverted residual blocks. These additions are capable of advancing the model's resolution for recognizing tiny defects in PCB images [9]. Zhao, Y. et al. integrates a new multi-level module to YOLOv5 for enhanced feature fusion capacity [10, 11]. Moreover, it enhances the capacity of gaining more informative details by appending an advanced global attention mechanism (GAM) [12]. A previous work introduces an enhanced full model by applying continuous convolution modules to MobileNetV2 [13]. Compared to the other backbones models, this enhanced skip connection helps to reduce detection time. Yu and coauthors use a lightweight model for identifying small defects of PCB [14]. The authors designed Diagonal Feature Pyramid (DFP), which is a low-cost mechanism for fusing and extending features. This design is helpful for detecting small defects. At the same time, they also designed a multi-scale mechanism to adapt to defects of various scales.

In summary, the aforementioned studies have designed several promising approaches for defect detection based on PCV images through one-stage solutions, encompassing several innovative approaches, attention mechanisms, and pioneering backbone architectures. These methodologies have been extensively implemented in the detection of PCB defects within imagery, yielding remarkable outcomes across various metrics. Nevertheless, one-stage algorithms still have their drawbacks, such as the poor performance when facing diversified defect contexts, a pronounced reliance on a restricted dataset, and the imperative for additional refinement to handle disparities in defect size, orientation, and lighting conditions.

2.2. Two-stage-based PCB Defect Detections

The two-stage method divides the PCB defect detection problem into two stages. Firstly, several candidate boxes are extracted from input iamges. Then these candidate boxes are classified and regressed to achieve the final outcomes. Common two-stage approaches include Faster R-CNN and Mask R-CNN. This type of method usually has high detection accuracy, but correspondingly increases computational complexity and time overhead.

Although single-stage algorithms provide faster performance, two-stage algorithms are significantly better than them in terms of detection accuracy. A representative work called Tiny Defect Detection Network (TDD-Net), is proposed for detecting micro defect [15]. Due to the fact that the defect area occupies a small portion of the entire image, traditional solutions are not sensitive enough for detecting small defects. Therefore, the author applied k-means to the boundary boxes to identify reasonable anchor scales unsupervisedly. To mitigate the effects of diminutive and unbalanced datasets on the precision of detection, the technique of online hard example mining is implemented. This online solution is conducted during the learning process, aiming to enhance the precise recognizing bounding box candidates [16]. Latter, a new model is proposed for detecting defects on PCB surface [17]. In this work, a residual neural network and Faster R-CNN are applied as the foundational architecture. This design is deployed to serve as the detection mechanism for the input image. Using FPN to fusefeatures of different depthes and ShuffleV2 light weighted module, the computational complexity of the entire network was successfully reduced. In order to enhance the expressive power of the network, a feature pyramid-based network that integrates the Squeeze-and-Excitation (SE) module in ResNet-101 is proposed. It introduces a top-down structure to improve the overall feature level and uses Region of Interest (ROI) Align instead of pooling to reduce the misalignment [18].

In summary, compared to one-stage algorithms with higher operational efficiency, there is relatively little research literature on two-stage algorithms. Nevertheless, it's clear that two-stage algorithms offer considerable benefits to detection precision. Given the prevalent nature of real-time applications, one-stage algorithms have gained prominence to satisfy the demands of real-time detection time. Compared with two-stage algorithms, although there is a gap in detection accuracy, the difference between the two is not enough to compensate for the gap in detection speed. Consequently, there is a relatively limited pool of researchers dedicated to this area. Nonetheless, for specialized tasks demanding elevated levels of detection accuracy and tailored datasets, the utilization of two-stage algorithms remains a beneficial option.

2.3. Transformer-based PCB Defect Detections

The Transformer framework has marked a pivotal innovation in the field of Natural Language Processing (NLP). Conventional sequential models frequently grapple with issues like gradient vanishing and exploding when they process extensive sequences. In stark contrast, the Transformer architecture tackles these obstacles by incorporating self-attention mechanisms, which significantly bolster its capacity to apprehend a broad spectrum of interdependencies across sequences. Later, researchers extends its application to the computer vision field, such as Vision Transformer (ViT) [19, 20]. Specifically, in PCB defect detection, the diminutive size of defects often renders conventional detection methods ineffectual. Over the past few years, Transformer models have demonstrated increased sensitivity to minute targets and intricate defects across various conditions, positioning them as more apt for the task of PCB defect identification. Consequently, the employment of Transformer models could potentially elevate the detection efficacy.

An et al. introduced ViT (LPViT) for enhancing label robustness and plaque correlation [21]. This model emphasizes resilience and makes comprehensive use of the diverse areas within the PCB image, capturing their inter-image relations. Moreover, it incorporates a technique where specific modules are randomly obscured to foster a deeper understanding across diverse parts of the image. In another study, Chen applied a new method to generate anchor frames allowing convenient identification of defect in PCB dataset by incooporaing an enhanced clustering algorithm [22]. Moreover, the features used for learning is extrated by a Transformer module. In addition, convolution mechanism and attention mechanism are integrated to advance the capacity of extracting informative features from the network.

These cutting-edge Transformer models have been applied to large visual modeling, leveraging multi-scale features for tackling dense prediction tasks. Such tasks are intrinsic to the field of defect detection in PCB industry when employing transformer-based approaches. It is anticipated that the application of these pioneering Transformers will enhance the capabilities of current models on defect detection of PCB.

3. Further Perspective

In recent years, deep learning-based technologies have demonstrated outstanding capabilities in various fields, especially for computer vision. In the above sections, representative works of PCB defect detection are summarized. In the future, several key problems are waiting to be handled.

Overcoming challenges and problems: Despite the remarkable strides made by deep learning, several challenges persist in defect detection of PCB. Firstly, the inherent diversity and complexity of PCB defects present a formidable challenge for the development of robust deep learning models capable of identifying a wide array of anomalies. The varied nature of defects, with their distinct attributes and manifestations, complicates the task of enhancing the models' ability to generalize across different scenarios. Additionally, the issue of data imbalance, coupled with the scarcity of defective samples, hampers both the training process and the model's capacity to generalize effectively, necessitating the implementation of robust countermeasures. Lastly, enhancing the interpretability of these models stands as a critical research avenue in this field, particularly for applications that demand stringent and reliable model decision-making processes.

Future development prospects: Compared to traditional PCB defect detection methods, deep learning-based approaches have several advantages. The models could autonomously extract informative features, which minimizes the dependency on manual feature engineering. As hardware continues to advance and large-scale datasets become more accessible, the capabilities of these models become increasingly evident. In the future, researchers can concentrate on exploring more effective data augmentation, enhancing more robustness models, and sample generation methods to tackle challenges related to diversity and data scarcity. Additionally, integrating crack analysis is also essential for detecting PCB defects, since neural networks can accurately identify tiny cracks on PCB surfaces that are usually hard to notice by human. This capability is helpful for defect identification and significantly contributes to enhancing the quality PCBs. Furthermore, improving the interpretability of the model, increasing the transparency of model decisions, and combining other techniques can further improve the performance of PCB defect detection.

In conclusion, the application of deep learning to PCB defect detection holds promise for future advancements and practical applications. As technological innovates, significant strides are anticipated in the quality control mechanisms and augmenting the efficiency of PCB manufacturing processes. The innovations could lead to higher standards of product reliability and performance.

4. Conclusion

In this paper, the author points out the prevailing applications and cutting-edge research within the realm of deep learning for defect detection of PCB. Drawing upon the one-stage and two-stage algorithms, as well as the Transformer-based methodologies, the author distills several key insights: (1) Deep learning is a promising solution: Models propelled by deep learning have marked significant advancements in the detection of PCB defects. This progress is attributed to their robust capabilities in feature learning and representation. CNNs adeptly harness a series of convolutional and pooling layers to distill both local and global features from raw images, progressively abstracting the content. While Transformers have made their mark in NLP, their adaptability in computer vision tasks is equally commendable. These models capitalize on self-attention mechanisms to seize global insights while retaining an acute focus on local details, offering an inherent edge in PCB defect detection. (2) Representative detection methods have been introduced: Deep learning-driven PCB defect detection techniques are categorically introduced from three perspectives. The one-stage algorithm facilitates real-time predictions by directly ascertaining the location and category of defects within the original image. Conversely, the two-stage algorithm operates by initially delineating potential regions of interest, followed by a classification phase that refines the localization of defects. Moreover, Transformer-based approaches are demonstrating promise, as they enables the capture of multi-scale and multi-level features, thereby enhancing PCB defect detection achievements.

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