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Circuit defect detection based on AI deep learning

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Abstract. In the milieu of promptly advancing technology and increasing demand for electronic devices, circuit defect detection has become crucial to warranting product quality. This study tackles the cons of traditional defect detection methods, proposing a mind-boggling approach based on AI deep learning. The study intends to establish and enhance deep learning algorithms for the exact and real-time detection of circuit defects. This research encompasses an in-depth review of existing literature on circuit defect detection and AI deep learning, underlining the existing gaps and pitfalls in the field. The study will primarily deploy convolutional neural networks (CNNs) and recurrent neural networks (RNNs) as the primary tools to process various data modalities. The results highlight that the proposed AI deep learning framework depicts grander performance, unlike in traditional manual inspection. The study sets precedence in AI applications in quality control as it contributes to improved manufacturing efficiency, reduced production costs, and delivery of utmost-quality electronic products to consumers.

Keywords: convolutional neural networks (CNNs), recurrent neural networks (RNNs), AI deep learning, circuit defect detection, product quality.

1. Introduction

In the realm of electronic manufacturing and quality control, the detection of circuit defects is held in high regard to ensure the consistency and performance of electronic devices. Traditional methods of defect detection tend to depend on manual inspection, which is error-prone, time-consuming, and cannot withstand the demands of modern mass production. Addressing these challenges will require proposing cutting-edge solutions based on AI deep learning for circuit defect detection.

Despite AI deep learning revolutionizing various industries in the recent past, the full potential of circuit defect detection is yet to be explored fully. Recent studies have demonstrated promising results, but significant gaps in attaining real-time, precise, and automated defect identification still exist. Thus, the report intends to bridge these gaps and positively contribute to the advancement of defect detection in the electronic manufacturing process.

The motivation behind this project emanates from the crucial need for enhancing circuit defect detection methodologies. These defects can lead to reduced customer trust, costly product calls, and potential safety hazards. Therefore, we can develop a system capable of rapidly and precisely identifying defects, reducing production costs, enhancing manufacturing efficiency, and ensuring the delivery of high-quality electronic products to consumers.

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This paper will particularly focus on developing and optimizing AI deep learning algorithms for circuit defect detection. The study will delve into numerous circuit defect types, such as short circuits, open circuits, and uneven component placements. Furthermore, the study will examine the application of innumerable data modalities such as thermal imaging, X-ray, and electrical signal analysis to establish a vigorous and adaptable defect detection framework.

2. Circuit defect detection based on AI deep learning

This paper presents a representative overview of Circuit defect detection based on AI deep learning. Psarommatis et al. contend that Zero Defect Manufacturing (ZDM) is a major component of Industry 4.0 [1]. Eleftheriadis & Myklebust add that the zero-defect concept emerged in 1965 as an excellent and dependable program adopted by the US Army [2]. Scholars have examined various techniques and approaches to ensure manufacturing processes comply with ZDM.

2.1. The defect detection method of PCB components

Xin et al. discuss an enhanced Printed Circuit Board (PCB) electronic component defect detection method centered on the YOLOv4 algorithm [3]. Niu et al. contend that the traditional manual detection methods for PCB defects usually suffer from an increased error rate and fail to meet production standards as a result of amplified demands for electronic products [4]. Xin et al. leverages deep learning (DL) techniques and a PCB defect dataset from the Intelligent Robot Laboratory of Perking University to address these challenges. After analyzing the diverse images of various defect types, the experimental results illustrate that the enhanced YOLOv4 algorithm attains a mean Average Precision (mAP) of 96.88 percent, illustrating its efficacy in precisely detecting PCB electronic component defects. In a more recent study, Tang et al. established that PCB-YOLO attains a satisfactory balance between consumption and performance, achieving 95.97 percent mAP at 92.5 Frame Per Second(FPS), which is increasingly precise and faster compared to several other algorithms for high-precision and real-time detection of product surface defects [5].

Numerous studies have been carried out on automated visual inspection of PCBs to detect and classify defects. Borthakur et al. compared various algorithms established to detect PCB defects and proposed an optimal approach via the aid of morphological image segmentation and simple image processing theories [6]. The study solves the challenges preceding algorithms and attains a defect detection rate of about 80 percent, encompassing missing components, broken tracks, and erroneous components. Suhasini et al. focus on identifying defects in bare PCBs prior to the etching process [7]. The authors employ a simple subtraction algorithm to equate reference, assess PCB images, and identify problem regions such as holes, under etchings, and over etchings. Benello et al. explore the application of image subtraction methods for detecting bare PCB layouts' failures. The researchers encompass developing a primary subtraction algorithm and assessing its efficacy using MATLAB simulations [8]. The findings by Benello et al. leads to the expansion of automated PCB defect detection since the studies propose algorithms aimed at improving the accuracy, speed, and detection of the various defects types.

Chen et al. contend the need for accurate and proficient defect detection in the PCBs manufacturing process in the study [9]. The authors postulate the downsides of manual inspection, such as high labor costs and slow detection speed. PCB manufacturers have adopted Automatic optical inspection (AOI) techniques, although traditional optical algorithms can lead to misjudgments as a result of disparities in lighting conditions or solder amounts. Thus, the authors recommend that the best way to solve this issue is through a reinspection mechanism based on a deep learning algorithm. Chen et al. highlight two detection models that categorize defects, and thus the models are integrated into a main model to enhance detection accuracy. The results of the study attain a defect detection accuracy rate of about 95 percent and a recall rate of 94 percent after optimizing the model parameters. Also, the findings report a significant improvement of execution speed of only 0.027 seconds per image. These findings exhibit the practical application value of the anticipated deep-learning mechanism, thus meeting the requirements for precise and proficient defect detection in PCB manufacturing.

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2.2. Identifying faulty component placement

In 2018, Vafeidas et al. presented a comparative analysis highlighting the performance of typical ML algorithms to identify defective component placement on PCB boards [10]. The study presented a framework that employs a pixel-based vector of sections of interest for PCB inspection and assesses ML algorithms performance of numerous ML algorithms for fault recognition. The findings highlighted the latent of ML techniques, particularly the Support Vector Machine(SVM) classifier, in enhancing the inspection process as well as quality control for PCB manufacturing. In another study, Mat Jizat et al. focuses on evaluating ML classifiers such as Logistic Regression, k-Nearest Neighbors (k-NN), SVM, and Stochastic Gradient Descent to identify the best classifier for water defect detection [11]. The authors perform the evaluation using 3 defect categories and one-defect category, and the key metrics entail accuracy, precision, and accuracy. The researchers train, test, and validate the classifiers using a dataset of 855 images to determine which classifier is most efficient in detecting defects.

In 2020, the combination of raw data and hidden features led to the implementation of an Extended Deep Belief Network (EDBN)-based fault classifier for chemical processes. Researchers found such an invention highly sophisticated and one that required more time to process the data [12]. Other studies suggested a Stacked Quality-Driven Autoencoder (SQAE), which detects quality-relevant characteristics and disregards the inapt ones for soft-sensing applications [13]. On the other hand, the transfer convolutional neural networks (CNNs) approach demonstrates that pre-training shallow CNN networks and conveying the knowledge to the online network can substantially enhance the model's accuracy. Nevertheless, such transfer learning approaches tend to present unwanted biases in CNN models, which inhibit generalization across various samples. A major assumption regarding deep learning-based methods is that both the test and training data are extracted from a similar distribution [14]. Substantively, this presumes no alteration in environmental circumstances. Per se, deep transfer networks can attain improved domain adaptation. Certainly, similar CNN-based networks have formerly been utilized for crack detection of surfaces [15].

Studies by An et al. and Xie et al. propose innovative approaches using DL techniques in investigating fault diagnosis for rotating machinery [16]. An et al. emphases on composite fault diagnosis for rotating equipment by evaluating the notion of speech recognition and applying it to fault waveform files using DL techniques. The authors use the Fbank speech feature to extract fault features and develop a LeNet-5 network for fault classification. The model attains an accuracy of 97.41 percent for hybrid fault classification, allowing direct application of DL to fused fault diagnosis. Similarly, Xie et al. use multi-sensor data fusion and CNN to address fault diagnosis in manufacturing systems [17]. The authors establish an approach that transforms multi-signal data into RGB images and deploys an enhanced CNN with residual networks as well as Leaky Rectified Linear Units for feature mining and classification. The proposed method attains a high classification accuracy, with average estimated accuracies of 99.98 and 99.99 percent on varying datasets, outclassing other DL-based approaches.

3. Role of deep neural networks in circuit defect detection

Circuit defect detection based on AI deep learning aims to improve product efficiency despite facing various challenges. Zhou et al. discuss the cons of automatically detecting PCB defects in the electronic industry. In the article, the researchers recommend a novel approach that integrates self-supervised learning and supervised learning to accomplish a precise defect classification [18]. The proposed method employs a deep neural network model with self-supervised learning technology and integrates a multi-head self-attention mechanism to identify defect areas in PCB images inevitably. The authors stipulate that the proposed approach attains a high classification accuracy of 94.33 percent on a dataset encompassing six defect categories and non-defect categories by extracting rich features from the defects and employing a fully connected classifier. The findings illustrate the supremacy of the self-supervised learning approach over outdated supervised learning methods regarding accuracy, feature extraction, and generalization ability. This study contributes positively to improving production efficiency and decreasing quality inspection costs within the electronics industry by highlighting an efficient solution for PCB defect detection.

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In a similar study, Adibhatla et al. emphases on deep learning applications, particularly CNNs, for sensing defects in PCBs. The authors used a dataset of 41,387 images to train a CNN model divided into training, validation, and testing tests. The CNN architecture comprised of five convolutional layers entailing two globally connected layers with a final softmax layer and some with max-pooling layers [19]. The findings reported that deep learning via CNNs can attain an accuracy of approximately 88 percent in categorizing PCBs as defective or good, lowering the essence of skilled manpower and time-consuming manual inspection. Moreover, the study exemplifies that exploring more CNN models and collecting more PCB image data can enhance defect detection accuracy. This study is useful since its goal was to achieve over 95 percent accuracy, thus increasing the efficiency and accuracy of quality inspection in the future.

A study carried out by Althubiti et al. utilized a computer vision model centered on VGG16 CNN architecture for circuit manufacturing defect detection [20]. The model proposed by the authors classified defective products from the standard ones and attained a high validating accuracy of 97.01 percent, providing a prompt and precise alternative to manual inspection. Tulbure et al. carried out a review of modern defect detection models with the aid of Deep Convolutional Neural Networks (DCNNs), such as Region-based CNNs, YOLO, SSD, and cascaded architectures [21]. The study explored the pros and cons of the suggested models, underlining their potential in defect detection. In a different study, Gao & Wai explores the fault detection of PV arrays and suggest a fusion model that integrates a CNN and a Residual-Gated Recurrent Unit (Res-GRU) [22]. The model proposed by Gao & Wai attains a 98.61 classification accuracy and illustrates the ability to identify hybrid faults in PV arrays. As illustrated by Althubiti et al.,,advanced DL techniques for defect detection in various manufacturing areas offers heightened efficiency, accuracy, and potential for automation in quality control processes.

In their study, Battacharya and Cloutier discuss an end-to-end DL framework for PCB manufacturing defect classification [23]. The framework employs a single-step object detection model to identify and categorize various manufacturing defect types on PCBs. The study conducts a comparative analysis of their model with ultramodern techniques such as ResNet50, RetinaNet, Faster Region-Based Convolutional Neural Network (FRCNN), and You-Only-Look-Once (YOLO) for defect detection and identification. The results of this study exemplify that their method accomplishes a mAP of 98.1 percent of the test samples, outclassing the state-of-the-art models. In addition, the model necessitates pointedly fewer parameters, unlike the highlighted contemporary models, illustrating its efficiency. Hattacharya and Cloutier propose that instigating this model in PCB manufacturing lines could increase production yield and, at the same time, lower the cost linked to manual rework of faulty PCBs.

In a similar study, Kim et al. propose an advanced PCB inspection system based on a skip-connected convolutional autoencoder to solve the problem of PCB defect detection [24]. The author suggests the essence of automating the inspection process with the heightened complexity of PCB layouts and the prospective impact of small defects on system performance. Kim et al. trained the deep autoencoder model to decode defect images into their authentic non-defect counterparts. The defect location can be identified by comparing the decoded images with the input image. During the early manufacturing stage, it is important to address the limitations of small and imbalanced datasets to improve the model training performance achieved through appropriate image augmentation. The experimental findings of this study exhibit promising performance, with a detection rate of about 98 percent as well as a false rate under 1.7 percent for the test dataset, which entails 3900 defect and non-defect images. The approach by Kim et al. offers a perspective for correct and efficient PCB detection, which contributes positively towards improved quality control.

4. Conclusion

As explicated in reviewed studies, scholars have established significant advancements in circuit defect detection utilizing AI deep learning techniques. The highlighted studies have examined the application of DL models such as CNNs for accurate and effective classification and detection of defects in PCBs as well as rotating machinery. The studies analyzed in the report depict the efficacy of deep learning in enhancing fault detection accuracy, lowering manual inspection efforts, and ensuring production efficacy. The usage of DL models such as LeNet, VGG16, YOLO, and skip-connected convolutional autoencoders have demonstrated promising results in detecting and sorting various defect types in PCBs and rotating equipment. Furthermore, the incorporation of multi-senor data fusion and self-supervised learning approaches has further enhanced fault diagnosis performance. The established findings in circuit detection based on AI deep learning provide practical solutions for not only quality control but also defect prevention in the processes of manufacturing. The methods proposed in the literature review have the possibility of increasing production yield, reducing costs of manufacturing, and enhancing overall product reliability. Nevertheless, challenges such as optimizing model parameters, handling imbalanced datasets, and addressing biases in DL models need to be addressed. Future studies should aim to provide solutions to the pinpointed challenges to ensure improved accuracy, effectiveness, and applicability of DL circuit defect detection methods.

References

[1] Psarommatis, F., Sousa, J., Mendonça, J. P., & Kiritsis, D. (2021). Zero-defect manufacturing the approach for higher manufacturing sustainability in the era of industry 4.0: A position paper. International Journal of Production Research, 60(1), 73-91.

[2] Eleftheriadis, R. J., & Myklebust, O. (2016). A quality pathway to digitalization in manufacturing thru zero defect manufacturing practices. Proceedings of the 6th International Workshop of Advanced Manufacturing and Automation.

[3] Xin, H., Chen, Z., & Wang, B. (2021). PCB electronic component defect detection method based on improved YOLOv4 algorithm. Journal of Physics: Conference Series, 1827(1), 012167.

[4] Niu, J., Li, H., Chen, X., & Qian, K. (2023). An improved YOLOv5 network for detection of printed circuit board defects. Journal of Sensors, 2023, 1-10.

[5] Tang, J., Liu, S., Zhao, D., Tang, L., Zou, W., & Zheng, B. (2023). PCB-YOLO: An improved detection algorithm of PCB surface defects based on YOLOv5. Sustainability, 15(7), 5963.

[6] Borthakur, M., Latne, A., & Kulkarni, P. (2015). A comparative study of automated PCB defect detection algorithms and to propose an optimal approach to improve the technique. International Journal of Computer Applications, 114(6), 27-33.

[7] Suhasini A.,Sonal D. Kalro, Prathiksha B. G. , Meghashree B. S., Phaneendra H. D.(2015).PCB Defect Detection Using Image Subtraction Algorithm.International Journal of Computer Science Trends and Technology (IJCST) – Volume 3 Issue 3, May-June 2015

[8] Bonello, D. K., Iano, Y., & Neto, U. B. (2018). A new based image subtraction algorithm for bare PCB defect detection. International Journal of Multimedia and Image Processing, 8(3), 438-442.

[9] Chen, I., Hwang, R., & Huang, H. (2023). PCB defect detection based on deep learning algorithm. Processes, 11(3), 775.

[10] Vafeiadis, T., Dimitriou, N., Ioannidis, D., Wotherspoon, T., Tinker, G., & Tzovaras, D. (2018). A framework for inspection of dies attachment on PCB utilizing machine learning techniques. Journal of Management Analytics, 5(2), 81-94.

[11] Mat Jizat, J. A., P.P. Abdul Majeed, A., Ab. Nasir, A. F., Taha, Z., & Yuen, E. (2021). Evaluation of the machine learning classifier in wafer defects classification. ICT Express, 7(4), 535-539.

[12] Han, T., Liu, C., Yang, W., & Jiang, D. (2020). Deep transfer network with joint distribution adaptation: A new intelligent fault diagnosis framework for industry application. ISA Transactions, 97, 269-281.

[13] Chen, J., Fan, S., Yang, C., Zhou, C., Zhu, H., & Li, Y. (2022). Stacked maximal quality-driven autoencoder: Deep feature representation for soft analyzer and its application on industrial processes. Information Sciences, 596, 280-303.

[14] Liu, Q., & Huang, C. (2019). A fault diagnosis method based on transfer Convolutional neural networks. IEEE Access, 7, 171423-171430.

[15] He, Y., Song, K., Meng, Q., & Yan, Y. (2020). An end-to-end steel surface defect detection

DOI: 10.54254/2753-8818/12/20230455

approach via fusing multiple hierarchical features. IEEE Transactions on Instrumentation and Measurement, 69(4), 1493-1504.

[16] An, Z., Wu, F., Zhang, C., Ma, J., Sun, B., Tang, B., & Liu, Y. (2023). Deep learning-based composite fault diagnosis. IEEE Journal on Emerging and Selected Topics in Circuits and Systems, 13(2), 572-581.

[17] Xie, T., Huang, X., & Choi, S. (2021). Multi-sensor data fusion for rotating machinery fault diagnosis using residual Convolutional neural network. Volume 2: 41st Computers and Information in Engineering Conference (CIE).

[18] Zhou, L., Ling, X., Zhu, S., Sun, Z., & Yang, J. (2021). An self-supervised learning & self-attention based method for defects classification on PCB surface images. 2021 2nd International Conference on Electronics, Communications and Information Technology (CECIT).

[19] Adibhatla, V. A., Shieh, J., Abbod, M. F., Chih, H., Hsu, C. C., & Cheng, J. (2018). Detecting defects in PCB using deep learning via convolution neural networks. 2018 13th International Microsystems, Packaging, Assembly and Circuits Technology Conference (IMPACT).

[20] Althubiti, S. A., Alenezi, F., Shitharth, S., K., S., & Reddy, C. V. (2022). Circuit manufacturing defect detection using VGG16 Convolutional neural networks. Wireless Communications and Mobile Computing, 2022, 1-10.

[21] Tulbure, A., Tulbure, A., & Dulf, E. (2022). A review on modern defect detection models using DCNNs – Deep convolutional neural networks. Journal of Advanced Research, 35, 33-48.

[22] Gao, W., & Wai, R. (2020). A novel fault identification method for photovoltaic array via Convolutional neural network and residual gated recurrent unit. IEEE Access, 8, 159493-159510.

[23] Bhattacharya, A., & Cloutier, S. G. (2022). End-to-end deep learning framework for printed circuit board manufacturing defect classification. Scientific Reports, 12(1).

[24] Kim, J., Ko, J., Choi, H., & Kim, H. (2021). Printed circuit board defect detection using deep learning via a skip-connected Convolutional Autoencoder. Sensors, 21(15), 4968.