DEU FMD 27(81) (2025) 343-348

Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi
Dokuz Eylul University Faculty of Engineering Journal of Science and Engineering
Elektronik/Online ISSN: 2547-958X

RESEARCH ARTICLE / ARAŞTIRMA MAKALESI

YOLOv8-based PCB Defect Detection and Classification System

YOLOv8 tabanlı PCB Hata Tespit ve Sınıflandırma Sistemi

Damla Gürkan Kuntalp [1*], Eyüp Betaş [2]

[1] Dokuz Eylül Üniversitesi Mühendislik Fakültesi Elektrik –Elektronik Mühendisliği Bölümü, İzmir, TÜRKİYE
[2] Jatek Industry Inc., Manisa, TÜRKİYE

Corresponding Author / Sorumlu Yazar *: damla.kuntalp@deu.edu.tr

Abstract

Surface inspection of Printed Circuit Boards (PCB) is one of the most crucial quality control processes due to potential serious costs of even small errors occurred during production. In this study, a YOLOv8 based system is developed for detection and classification of six common errors occurs on PCBs. In terms of accuracy, speed, and the ability to detect multiple defects simultaneously, proposed method is more suitable for use in production compared to other PCB defect detection methods. Proposed system also offers customizable defect selection for targeted inspection. Experimental results show an impressive mean average precision of 99.2%. Combination of high accuracy, fast processing speed, stability, and user-friendly interface makes it a promising candidate for industrial applications demonstrate the system's suitability for real-world PCB manufacturing environments.

Keywords: *PCB Defect Detection, YOLO, Classification*

Öz

Baskı Devre Kartlarının yüzey muayenesi, üretim sırasında oluşabilecek küçük hataların bile ciddi maliyetlere yol açması nedeniyle en önemli kalite kontrol süreçlerinden biridir. Bu çalışmada baskı devrelerde (BD) sık karşılaşılan altı hatanın tespiti ve sınıflandırılması için YOLOv8 tabanlı bir sistem geliştirilmiştir. Doğruluk, hız ve aynı anda birden fazla hatayı tespit edebilme yeteneği nedeni ile önerilen yöntem, diğer BD hata tespit yöntemlerine kıyasla, üretim bantlarında kullanıma daha uygundur. Sistem aynı zamanda hedefe yönelik denetim için özelleştirilebilir hata seçim olanağı da sunmaktadır. Denemelerde %99,2'lik ortalama hassasiyet değerine ulaşılmıştır. Yüksek doğruluk, hızlı işlem yapısı, kararlılık ve kullanıcı dostu ara yüzün birleşimi, önerilen sistemin endüstriyel uygulamalar için umut verici bir aday olabileceğini ve sistemin gerçek dünyadaki BD üretim ortamlarında kullanıma uygunluğunu göstermektedir.

Anahtar Kelimeler: *PCB Hata Tespiti, YOLO, Sınıflandırma*

1. Introduction

Maintaining rigorous quality standards remains a crucial objective for industries. As demand and customization increases, manufacturers face the challenge of balancing cost, production time, and quality. The technological innovations of Industry 4.0 have paved the way for implementing precise quality prediction and detection frameworks in manufacturing lines [1].

Printed Circuit Boards (PCBs) are indispensable components in modern electronic devices. As device miniaturization accelerates, PCB manufacturing becomes increasingly complex, making defect detection a critical yet difficult task. PCB defects can degrade performance, compromise product quality, and lead to severe consequences. PCB production starts from the design phase and continues with the physical creation of the printed circuit board. First, a circuit diagram is created using a design software. This design is then transferred to a copper-clad plate. With chemical treatments, the unwanted copper layer is removed, leaving only the necessary circuit paths. Finally, the soldering mask is applied and the components are assembled. All of these processes require high precision and attention. Inevitably, some surface errors, which are called PCB defects, occur during these processes. PCB defects can be any of the following six types: short circuits, open circuits, spurs, copper flaws, mouse bites, and missing holes.

Traditional defect detection methods, such as manual inspection and performance testing, are inefficient and prone to errors. Manual inspection relies on human visual acuity, therefore might be prune to overlooking defects. Another way is performance testing which can damage PCBs and doesn't guarantee defect identification. Reference comparison is widely used in industry, employs template matching to detect deviations from the standard. However, accurate alignment is crucial, and misalignment can lead to false detections. Defect detection and classification are distinct challenges within the realm of computer vision. This field seeks to replicate or surpass human visual perception and decision-making through algorithmic means. The fundamental objective of mimicking human vision is to identify and categorize objects, tasks inherently intertwined in most visual recognition systems The increasing complexity and miniaturization of PCBs, coupled with the limitations of human

DOI: https://doi.org/10.21205/deufmd.2025278102

Geliş Tarihi / Received: 23.08.2024
Kabul Tarihi / Accepted: 17.09.2024

inspection, have driven the rapid adoption of automated defect detection systems to ensure product quality and efficiency.

PCB defect detection has been a subject of extensive research, with a wide range of techniques proposed over the years [2]. Early approaches, such as image subtraction [3] and template matching [4], often faced limitations in handling diverse defect types and complex PCB patterns. Wavelet-based methods, while offering some advantages, also lacked generalization capabilities and struggled to accurately detect subtle defects [5].

Classical machine learning techniques, including support vector machines and morphological operations, were employed to classify defects based on extracted features [6,7]. However, these methods required significant feature engineering and were often limited to specific defect types. More recent approaches, such as the modified low-complexity scheme proposed by Annaby et al., attempted to address these limitations by transforming 2D images into 1D feature descriptions and incorporating spatial statistical metrics [8].

The advent Deep Neural Networks (DNNs) offer superior performance and detection rates compared to traditional methods. Researchers have addressed challenges like imbalanced class distribution and defect costs through advanced feature preprocessing and network architectures [9].

YOLO (You Only Look Once) series, renowned for their efficiency in industrial applications, have emerged as leading candidates for PCB defect detection problems [10,11]. Studies have demonstrated their effectiveness in accurately identifying defects of various shapes and sizes occuring on different locations of PCB surfaces. YOLO-based models provide superior performances in single-stage detection, combining speed, precision, and being suitable for use in to real-world settings.

Researchers have leveraged the YOLO series to address the complexities of PCB defect detection, incorporating improved backbones and spatial pyramid pooling structures to handle irregularly shaped and randomly located defects. These enhancements have significantly improved the accuracy and robustness of YOLO-based models for PCB inspection.

In addition to the YOLO series, other deep learning architectures have been explored for PCB defect detection. For example, Hu and Wang proposed a deep learning network using Faster R-CNN with ResNet50 and a Feature Pyramid Network, which demonstrated excellent performance in detecting minor defects [13]. Kim et al. [14] introduced a advanced PCB inspection method using "skip-connected convolutional auto encoders", and Bhattacharya and Cloutier proposed a complete framework combining transformers, fusion of multilevel feature, data augmentation, and object detection [15]. By using fewer number of parameters in the model, I-Chun et al. reduced the detection execution speed [16].

All of these studies show that deep learning algorithms has potential for solving the problems associated with PCB defect detection. Using different and advanced architectures, researchers have made significant improvements are achieved in terms of accuracy, efficiency, and robustness of PCB defect detection systems [17-23].In this study, we introduce a novel deep learning framework for precise PCB defect detection and classification. Our approach surpasses existing learning-based methods in accuracy, enabling the identification and categorization of errors that occur during or after the PCB manufacturing process. Our user-friendly GUI and customizable error detection options further enhance the practical applicability of our method. Following sections give the details of the proposed system, experimental results, evaluation of the performance of the system and discussion on the results.

2. Materials and Methods

This research focuses on meticulously analyzing PCB defect characteristics to develop a novel defect detection network. We will delve into the network's architecture, emphasizing the role of residual units and multi-scale regional proposal mechanisms in enhancing defect detection accuracy. The paper concludes with a discussion on the network's practical implementation and its potential to address real-world PCB manufacturing challenges.

2.1. PCB Defects

This study focuses on detecting and classifying six prevalent PCB defects: open circuits, short circuits, mouse bites, spurs, pinholes, and excess copper (Figure 1a, b). These defects originate from distinct manufacturing processes, resulting in varying visual characteristics such as color, shape, and location. For instance, short circuits reduce image regions compared to normal PCBs, while open circuits exhibit increased regions. Mouse bites resemble irregular edge notches, and pinholes appear as small, bright, circular defects with upward tails. Solder balls bridge wire distances. To accurately detect and classify these diverse defects, a specialized network architecture is required.

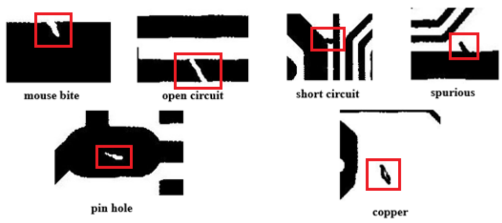

Figure 1a. PCB Defects-1

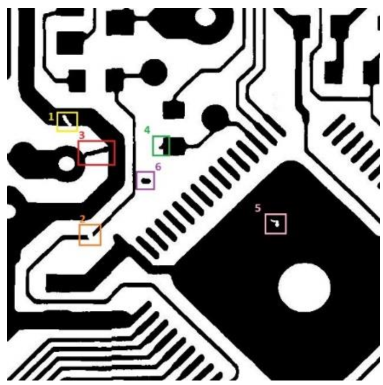

Figure 1b. PCB Defects-2.

2.2 System Architecture

YOLOv8, a state-of-the-art CNN architecture, was selected for this study due to its exceptional accuracy, compact size, and accessibility. Renowned for its performance, the YOLO series has garnered significant attention in the computer vision community since its inception in 2015 [21]. Developed by Ultralytics, YOLOv8 builds upon the success of its predecessor, YOLOv5, incorporating architectural refinements and enhanced developer experience. This versatile model excels in classification, object detection, and segmentation tasks, making it an ideal choice for this research [22-23].

The proposed YOLOv8-based model takes advantages of the architecture to capture complex PCB defect features, aiming for high speed and accuracy. By combining YOLOv8's detection capabilities with a focus on detailed feature extraction, the model offers adaptability across various PCB defect scenarios. The core components of the algorithm—Backbone, Neck, Head, and Conv—are illustrated in Figure 2. Figure 3 provides a detailed flowchart of the process.

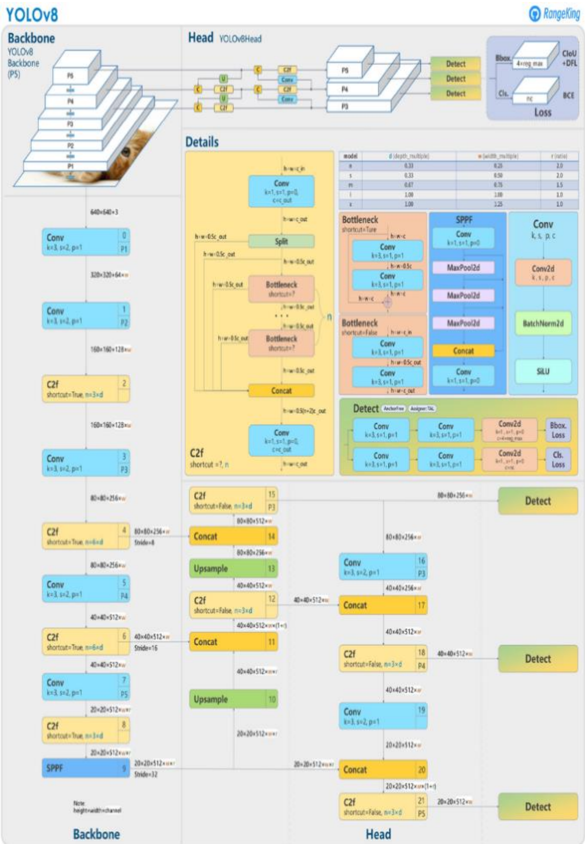

Figure 2. Schematic illustration of the YOLOv8 system architecture [22].

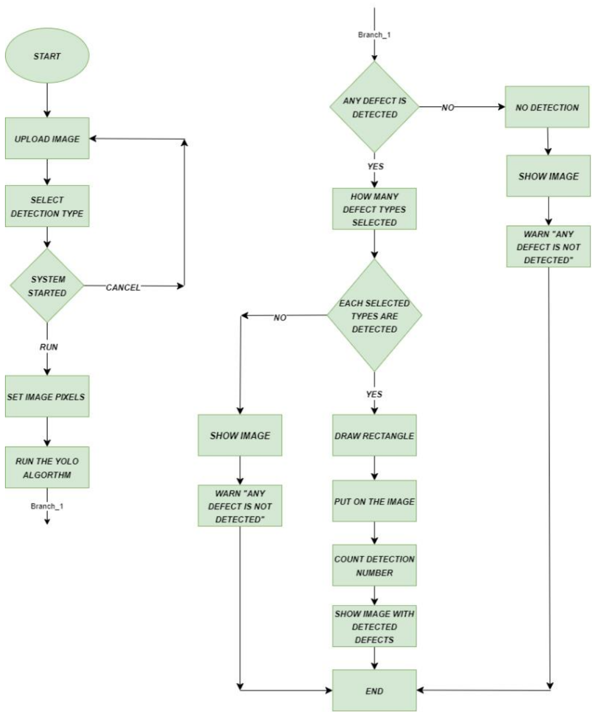

Figure 3. Flowchart of the algorithm.

3. Results and Dicussion

Experiments were conducted on a Windows 11 system equipped with an Intel i7-12700 CPU and an NVIDIA GeForce RTX 3090 24GB GPU. The Python programming language, specifically Python 3.8, was used in conjunction with PyTorch 1.11 for model development and training.

3.1. Data Collection and Annotation

The dataset used in this study is the one prepared by github user named tangsanli5201 [24]. In dataset preparation part, manually created PCB errors were modeled as errors occurring on a real production line. There is a real error equivalent to the error found on each created PCB. We chose 1500 images from [24] with a resolution of 640x640, which includes multiple defects.

To ensure balanced data distribution, we excluded images with ambiguous errors. This step helps mitigate their negative influence on the training process and ensures approximately equal representation of each error type in the dataset. To augment the dataset to 1700 images, we applied various data augmentation techniques: rotation (±15°), saturation (±25%), blur (2.5px), 90° rotation (clockwise-counterclockwise), and noise (5%). These transformations enhance the model's ability to generalize to real-world scenarios by exposing it to non-ideal image conditions. A total of 8853 defects were annotated using the LabelImage tool [25]. Each defect was assigned a ground truth bounding box and a corresponding class label. The tool generated TXT files containing bounding box coordinates and defect types for each image, serving as the ground truth labels for the detection model. Table 1 provides a detailed overview of the dataset used.

Table 1. Number of defects in training-validation, and testing sets.

	OPEN	SHORT	MOUSE BITE	SPUR	PIN HOLE	COPPER
TRAIN-VAL	*1149*	*924*	*1258*	*1047*	*927*	*927*
TEST	*553*	*393*	*490*	*398*	*394*	*393*

3.2. Performance Evaluation Methods

To evaluate the performance of the proposed system, mAP, recall, and precision indices are calculated [12].

Recall (r): Recall measures the ability of the model detection for positives. TP and FN denote true positive and false negative, respectively.

$$Recall = \frac{TP}{TP+FN} \tag{1}$$

Precision (P): Precision measures the accuracy of the model prediction. TP, and FP, denote true positive and false positive, respectively

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

Mean Average Precision (*mPA*): The Mean Average Precision stands as our primary metric for assessing the performance of the model. Serving as the key indicator in evaluating model performance, mAP is the mean of Average Precision (AP) values across C distinct defect categories. This metric provides a comprehensive measure of the accuracy in defect detection, offering a consolidated evaluation of the model's effectiveness across various defect classes.

$$mAP = \frac{\sum_{i=1}^{C} AP_i}{C} \tag{3}$$

IoU: IoU is a metric that measures the ratio of intersections and unions of two clusters. IoU is used to measure how similar the predicted bounding box is to the actual bounding box. It ranges from 0 to 1, where 0 means no intersection between the area(C) and the area(C), and 1 means they are identical. However, a common threshold used in practice is 0.5, meaning that a predicted box must have an IoU of at least 0.5 with a ground truth box to be considered a true positive detection. In this study, the defect area detection acceptable threshold is chosen as 0.5. An Intersection over Union score > *0.5* is normally considered a "good" prediction.

$$IoU = \frac{area(C) \cap area(G)}{area(C) \cup area(G)} \tag{4}$$

area(G): Ground Truth Boundary,

area(C): Candidate Bound

3.3. Experimental Results

In this section, the evaluation of the results obtained after the model training process is presented to reflect the success level of the learning algorithm. The number of each defect type in the database are shown in Table 1. The images used are not selected from the training set, but from images reserved for the testing process. In other words, the trained model has not seen the images used at the testing stage before.

Two examples of the testing process are shown below in Figures 4 and 5. The images shown are images captured in real time. These real-time images were used to be able to evaluate the performance of the trained model in the field.

Precision, Recall and mAP50 values obtained during the testing phase are presented in Table 3, which reflects the performance of the model for each type of error. Confusion matrix is also presented in Figure 6. The results demonstrate that the system achieves high performance levels for all error types.

Figure 4. Real-Time Classification-Example1.

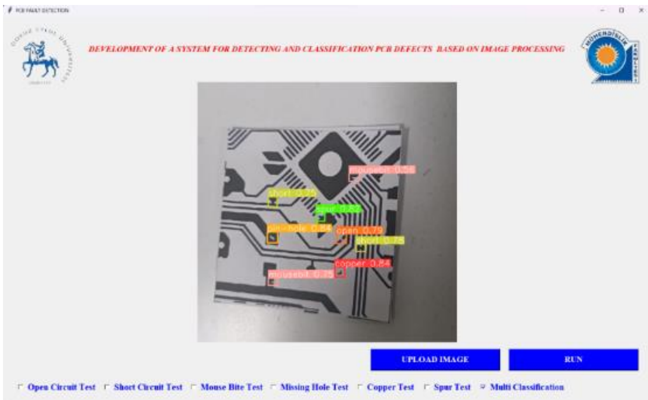

Figure 5. Real-Time Classification-Example 2.

Table 3 Test results for six types of defect detection.

	Precision	Recall	mAP50
All Classes	0.993	0.979	0.992
Open Circuit	0.989	0.985	0.988
Short Circuit	0.978	0.976	0.993
Mouse Bite	0.995	0.98	0.992
Pin Hole	0.999	0.97	0.994
Copper	0.998	0.986	0.991
Spur	1	0.975	0.995

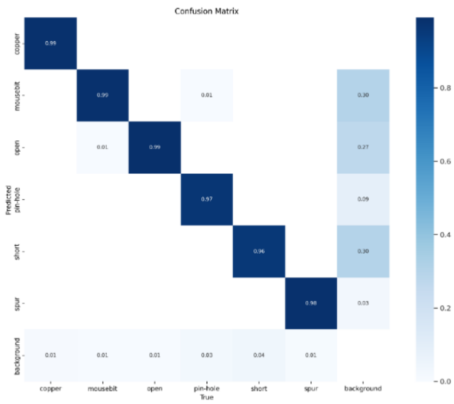

Figure 6. Confusion matrix.

The sensitivity analysis of the system is also conducted based on Precision Confidence and Recall Confidence Curves. Precision Confidence Curve graph is shown in Figure 7. It visually expresses the change in sensitivity within the confidence level. As the confidence interval of precision widens, the uncertainty of the model's classification decisions may increase. The value obtained here has a rate of 100% when examined for all classes. Recall Confidence Curve graph is shown in Figure 8. It shows the change in sensitivity within the confidence level. As the confidence interval of sensitivity widens, the likelihood that the model will miss true positives may increase. The value obtained here has a rate of 99% when examined for all classes.

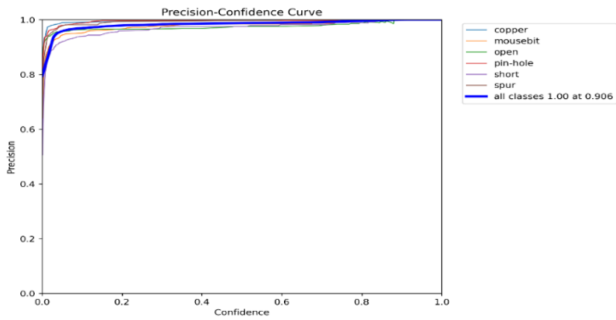

Figure 7. Precision-Confidence Curve.

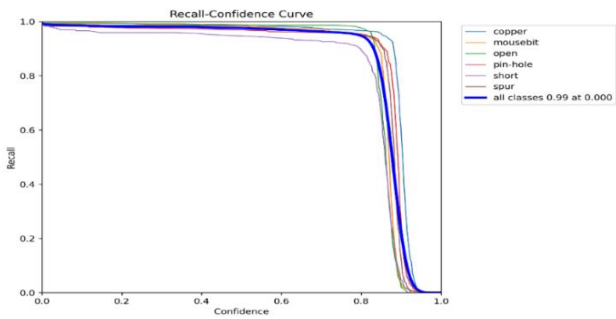

Figure 8. Recall-Confidence Curve.

The next step is to compare the performance of our system with state-of-the-art defect detection algorithm proposed by [13] which provides better performance compared to FasterRCNN, RetinaNet [27], and YOLOv3 [28]. Table 4 lists a comparison of the method proposed by [13] with different backbones with our method for the six types of PCB defect detection problem in terms of two performance metrics, mAP and Runtime.

Table 4. mAP and Runtime values of different models.

	mAP(Average Accuracy)(%)	Runtime(s/img)
Original+ResNET50	85.2	0.12
FPN	864	0.09
GARPN	91.2	0.087
ShuffleNetV2	94.2	0.078
YOLOV8(Our Model)	99.2	0.006

Among the models mentioned, the mAP (average accuracy score) values of Original+ResNet50, and the results with the addition of backbones FPN, GARPN, and ShuffleNetV2 were given as 85.2, 86.4, 91.2, and 94.2, respectively [13] . In particular, the high mAP of ShuffleNetV2 highlights the model's ability to achieve impressive accuracy combined with low computational cost. After using ShuffleNetV2, the network's detection efficiency was improved, which can meet the needs of real-time detection. These values show that traditional models perform well in the object detection task. However, based on the experimental results, our approach stands out as more accurate in the realm of detecting and classifying PCB defects. Using a YOLOv8-based model, the mAP value obtained is 99.2 showing that our system exhibits superior performance compared to other models and provides distinctive capabilities in the object detection task. It is also very suitable for the real-time applications with its significantly low runtime.

In addition to accuracy superiority, there are other specific advantages of the proposed system:

Enhanced Sensitivity to Small Errors: Our system excels in detecting even smaller errors compared to traditional deep learning methods, contributing to a higher level of precision in defect identification.

Swift Error Detection without Classification: One notable feature of our approach is its ability to swiftly detect errors on the PCB without the need for immediate classification. This efficiency ensures a quicker response to potential issues in the production line. Compared to traditional classification models like Faster R-CNN, which require additional classification steps after object detection, YOLOv8 offers a streamlined approach by directly detecting objects and their classes simultaneously, leading to faster error detection without sacrificing accuracy.

Customizable Error Detection with Interface Design: In our system, users are offered the flexibility to optionally detect only the predetermined types of errors. This customization allows users to tailor the detection process to specific concerns or priorities.

Utilization of Production Line Images: Another distinguishing aspect of our system is its capability to perform defect detection using images captured directly from the production line, eliminating the necessity for high-resolution images. This practical approach enhances real-world applicability and integration into existing manufacturing processes.

Apparatus and Position-Free Detection and Classification: Our system enables the detection and classification of PCB defects through images alone, eliminating the need for specialized apparatus or precise positioning. This feature streamlines the implementation of defect detection in diverse manufacturing environments.

We also concerned about the carbon footprint of our system. Experiments were conducted using Google Cloud Platform in region Asia-east1, which has a carbon efficiency of 0.56 kgCO2kgeq/kWh. A cumulative of 12 hours of computation was performed on hard ware of type GTX 1080 Ti (TDP of 250 W). Total emissions are estimated to be 1.68 kgCO2eq of which 100 percent were directly offset by the cloud provider. Estimations were conducted Machine Learning Impact calculator [26].

3. Conclusions

Our proposed deep learning system offers a superior solution for PCB defect detection and classification. Based on the results, our YOLOv8-based model outperforms existing approaches, achieving an impressive mAP of 99.2%. Its combination of high accuracy, fast processing speed, stability, and user-friendly interface makes it a promising candidate for industrial applications. In conclusion, our machine learning method provides a comprehensive and efficient approach to enhancing PCB quality control.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval. This article has no conflicts of interest with any individual or institution.

Author Contribution Statement

Conceptualization, D.G.K., E.B.; Methodology, D.G.K., E.B.; Software E.B.; Validation, D.G.K., E.B.; Formal analysis D.G.K., E.B.; Resources, E.B.; Draft preparation, D.G.K., E.B.; Writing, review and editing, D.G.K., Visualization, E.B.; Supervision, D.G.K. Authors have read and agreed to the published version of the manuscript.

References

[1] Markatos, N.G., & Mousavi, A., 2023. Manufacturing quality assessment in the Industry 4.0 era: A review. Total Quality Management & Business Excellence, Vol.34(13–14), pp.1655–1681. DOI:10.1080/14783363.2023.2194524.

[2] Aggarwal, N., Deshwal, M., & Samant, P., 2022. A survey on automatic printed circuit board defect detection techniques. 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), IEEE. DOI:10.1109/ICACITE53722.2022.9823872.

[3] 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, Vol.8(3), pp.438–442. DOI:10.20533/ijmip.2042.4647.2018.0054.

[4] Tsai, D.M., & Huang, C.K., 2018. Defect detection in electronic surfaces using template-based Fourier image reconstruction. IEEE Transactions on Components, Packaging and Manufacturing Technology, Vol.9(1), pp.163–172. DOI:10.1109/TCPMT.2018.2873744.

[5] Ibrahim, Z., & Al-Attas, S.A.R., 2005. Wavelet-based printed circuit board inspection algorithm. Integrated Computer-Aided Engineering, Vol.12(2), pp.201–213. DOI:10.3233/ICA-2005-12206.

[6] Zhang, Z., Wang, X., Liu, S., et al., 2018. An automatic recognition method for PCB visual defects. 2018 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC), pp.138–142, Xi'an, China. DOI:10.1109/SDPC.2018.8664974.

[7] Hassanin, I.A.A., Abd El-Samie, F.E., & El Banby, G.M., 2019. A real-time approach for automatic defect detection from PCBs based on SURF features and morphological operations. Multimedia Tools and Applications, Vol.78(24), pp.34437–34457. DOI:10.1007/s11042-019-08097-9.

[8] Annaby, M., Fouda, Y., & Rushdi, M., 2019. Improved normalized cross-correlation for defect detection in printed-circuit boards. IEEE Transactions on Semiconductor Manufacturing, Vol.32(2), pp.199–211. DOI:10.1109/TSM.2019.2911062.

[9] Chen, X., Wu, Y., He, X., & Ming, W., 2023. A comprehensive review of deep learning-based PCB defect detection. IEEE Access, Vol.11, pp.139017–139038. DOI:10.1109/ACCESS.2023.3339561.

[10] Jiang, L., Kong, G., & Li, C., 2019. Wrapper framework for test cost-sensitive feature selection. IEEE Transactions on Systems, Man, and Cybernetics: Systems, Vol.51(3), pp.1747–1756. DOI:10.1109/TSMC.2019.2904662.

[11] Jiang, L., Qiu, C., & Li, C., 2015. A novel minority cloning technique for cost-sensitive learning. International Journal of Pattern Recognition and Artificial Intelligence, Vol.29(4), pp.1551004–1551010. DOI:10.1142/S0218001415510040.
[12] Zhang, H., Jiang, L., & Li, C., 2021. CS-ResNet: Cost-sensitive residual convolutional neural network for PCB cosmetic defect detection. Expert Systems with Applications, Vol.185. DOI:10.1016/j.eswa.2021.115673.
[13] Hu, B., & Wang, J., 2020. Detection of PCB surface defects with improved faster-RCNN and feature pyramid network. IEEE Access, Vol.8, pp.108335–108345. DOI:10.1109/ACCESS.2020.3001349.
[14] Kim, J., Ko, J., Choi, H., & Kim, H., 2021. Printed circuit board defect detection using deep learning via a skip-connected convolutional autoencoder. Sensors, Vol.21(15), p.4968. DOI:10.3390/s21154968.
[15] Bhattacharya, A., & Cloutier, S.G., 2022. End-to-end deep learning framework for printed circuit board manufacturing defect classification. Scientific Reports, Vol.12(1), article 12559. DOI:10.1038/s41598-022-16302-3.
[16] Chen, I.C., Hwang, R.C., & Huang, H.C., 2023. PCB defect detection based on deep learning algorithm. Processes, Vol.11(3), p.775. DOI:10.3390/pr11030775.
[17] Liu, G., & Wen, H., 2021. Printed circuit board defect detection based on MobileNet-Yolo-Fast. Journal of Electronic Imaging, Vol.30(4), article 043004. DOI:10.1117/1.JEI.30.4.043004.
[18] Adibhatla, V.A., Chih, H.C., Hsu, C.C., Cheng, J., Abbod, M., & Shieh, J.S., 2021. Applying deep learning to defect detection in printed circuit boards via a newest model of you-only-look-once. Mathematical Biosciences and Engineering, Vol.18(4), pp.4411–4428. DOI:10.3934/mbe.2021223.
[19] Li, J., Gu, J., Huang, Z., & Wen, J., 2019. Application research of improved YOLO V3 algorithm in PCB electronic component detection. Applied Sciences, Vol.9(18), p.3750. DOI:10.3390/app9183750.
[20] Mamidi, J.S.S.V., Sameer, S., & Bayana, J., 2022. A light weight version of PCB defect detection system using YOLO V4 tiny. 2022 International Mobile and Embedded Technology Conference (MECON), pp.441–445, Noida, India. DOI:10.1109/MECON53876.2022.9752361.
[21] Jiang, P., et al., 2022. A review of YOLO algorithm developments. Procedia Computer Science, Vol.199, pp.1066–1073. DOI:10.1016/j.procs.2022.01.135.
[22] Gillani, I.S., et al., 2022. Yolov5, Yolo-x, Yolo-r, Yolov7 performance comparison: A survey. Artificial Intelligence and Fuzzy Logic System, pp.17–28. DOI:10.5121/csit.2022.121602.
[23] Hussain, M., 2023. YOLO-v1 to YOLO-v8, the rise of YOLO and its complementary nature toward digital manufacturing and industrial defect detection. Machines, Vol.11(7), p.677. DOI:10.3390/machines11070677.
[24] GitHub, 2024. DeepPCB dataset. Available at: https://github.com/tangsanli5201/DeepPCB [Accessed 20 July 2024].
[25] PyPI, 2024. LabelImg. Available at: https://pypi.org/project/labelImg [Accessed 20 July 2024].
[26] ML CO2, 2024. Machine Learning Carbon Impact Calculator. Available at: https://mlco2.github.io/impactcomputeMachineLearningImpact [Accessed 20 July 2024].
[27] Lin, T.Y., et al., 2017. Focal loss for dense object detection. Proceedings of the IEEE International Conference on Computer Vision (ICCV), pp.2980–2988. DOI:10.1109/ICCV.2017.324.
[28] Redmon, J., & Farhadi, A., 2018. YOLOv3: An incremental improvement. arXiv preprint, arXiv:1804.02767. DOI:10.48550/arXiv.1804.02767.