<u>*Araştırma Makalesi*</u>   <u>*Research Article*</u>

Detection of Defects in Printed Circuit Boards with Machine Learning and Deep Learning Algorithms

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ATIF/REFERENCE: Kaya, V., & Akgül, İ. (2022). Detection of Defects in Printed Circuit Boards with Machine Learning and Deep Learning Algorithms. *European Journal of Science and Technology*, (41), 183-186.

Abstract

Printed Circuit Boards (PCBs) are electronic boards that hold electronic components together and provide the electrical connection between these components. Printed circuit boards offer many advantages over traditional wired circuits, such as durability, less heat, minimal wiring, and ease of assembly. Correct design and production of printed circuit boards significantly affect the quality and efficiency of printed circuit boards. In this study, a defect detection system based on machine learning and deep learning algorithms is proposed to help produce printed circuit boards accurately and minimize the error rate. In the proposed system, missing hole, mouse bite, open circuit, short, spur, and spurious copper defects on the printed circuit have been determined. According to the results obtained, According to the results obtained, success accuracies of 74.62% were obtained with YOLO-v4, 47.83% with HOG+SVM, and 39.86% with HOG+KNN. It has been seen that the algorithms discussed in the study are applicable in the detection of defects in printed circuit boards.

Keywords: Artificial intelligence, Machine learning, Deep learning, Printed circuit board.

Makine Öğrenmesi ve Derin Öğrenme Algoritmaları ile Baskı Devre Kartlarındaki Kusurların Tespiti

Öz

Baskı devre kartları (PCB), elektronik bileşenleri bir arada tutan ve bu bileşenler arasındaki elektrik bağlantısını sağlayan elektronik devre kartlarıdır. Baskı devre kartları, dayanıklılık, daha az ısınma, minimum kablo kullanımı ve montaj kolaylığı gibi geleneksel kablolu devrelere göre birçok avantaj sunmaktadır. Baskı devre kartlarının doğru tasarımı ve üretimi baskı devre kartlarının kalitesini ve verimliliğini önemli ölçüde etkilemektedir. Bu çalışmada baskı devre kartlarının doğru bir şekilde üretilmesine ve hata oranının en aza indirilmesine yardımcı olmak için makine öğrenmesi ve derin öğrenme algoritmalarına dayalı kusur tespit sistemi önerilmiştir. Önerilen sistemde baskı devre üzerinde yer alan eksik delik, fare ısırığı, açık devre, kısa devre, çıkıntı ve sahte bakır kusurları tespit edilmiştir. Elde edilen sonuçlara göre YOLO-v4 ile %74.62, HOG+SVM ile %47.83, HOG+KNN ile %39.86 başarı doğrulukları elde edilmiştir. Çalışmada ele alınan algoritmaların baskı devre kartlarında kusur tespitinde uygulanabilir olduğu görülmüştür.

Anahtar Kelimeler: Yapay zeka, Makine öğrenmesi, Derin öğrenme, Baskı devre kartı.

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1. Introduction

Today, printed circuit boards (PCBs), which are included in the structure of electronic components and hold electronic components together, play an important role in the construction of electronic devices. Printed circuit boards are the basic component of electronic devices (Tsai & Huang, 2018; Zhang et al., 2018). Printed circuit boards offer many advantages over traditional wired circuits due to their low cost, durability, smaller footprint, minimization of cable usage, and ease of assembly. These advantages positively affect the physical dimensions, mass production, and repair of electronic devices.

Thanks to technological advances, the widespread use of electronic devices has been reduced to very small sizes and this has made the printed circuit boards more complex (Adibhatla et al., 2018; Zhang et al., 2018; Hu & Wang, 2020; Fung & Yung, 2020).

Problems caused by the error in the printed circuit board during the production of electronic devices or errors that occur during the mounting of electronic components on the surface either interrupt the production or cause the tests to fail (Sezer & Altan, 2021). For this reason, early detection of missing components or defects on the printed circuit board is important for electronic devices (Hu, & Wang, 2020). Therefore, detecting defects in printed circuit boards is extremely important in quality control (Volkau et al., 2019).

Artificial intelligence methods, which have been widely used in recent years with the developing technology, have also been effective in the field of defect detection by providing significant success in the industry (Deng et al., 2018; Santoso et al., 2022). In this study, missing hole, mouse bite, open circuit, short, spur, and spurious copper defects caused by the production of printed circuit boards used in the production of electronic devices or the assembly of electronic components on printed circuit boards have been detected using machine learning and deep learning algorithms.

The rest of the work is detailed as follows. In Chapter 2, studies on the detection of defects in printed circuit boards are reviewed. In Chapter 3, detailed information about materials and methods for defect detection is presented. In Chapter 4, experimental results, analysis and discussions are given. In Chapter 5, information about the results obtained in the study and future studies is given.

2. Related Works

In this section, artificial intelligence-based studies on defect detection in printed circuit boards are examined.

Ding et al. A defect detection network is proposed to detect the quality and defects of printed circuit boards. In the proposed method, k-means clustering, low-level structural information, and online hard example mining are used. Defect detection on printed circuit boards in the proposed model reached an mAP value of 98.90% (Ding et al., 2019).

Hu and Wang proposed a deep learning-based Faster RCNN-based method to detect defects in printed circuit boards. In the proposed method, ResNet50, ShuffleNetV2 and GARPN structures were preferred in order to better detect the defects in the printed circuit boards. According to the results obtained, it

reached 94.2% mAP and 0.08s/img detection speed with the proposed model (Hu & Wang, 2020).

Adibhatla et al. used a convolutional neural network-based method to detect defects in printed circuit boards and achieved a classification success rate of 85% (Adibhatla et al., 2018).

Hua et al. proposed an algorithm to extract efficient features of printed circuit board images In the proposed method, feature detector (GFTT) and feature descriptor (SURF) are combined to obtain accurate image registration. In addition to these, it was concluded that the in the printed circuit boards can be detected by adding the cross-correlation method (Hua et al., 2018).

Tang et al. have proposed a deep learning model that accurately detects defects in printed circuit boards using images that have been tested incorrectly. In the proposed model, a dataset including open, short, mouse bite, spur, copper, and pin-hole PCB defects was used and a 98.6% mAP@62 FBS result was obtained (Tang et al., 2019).

Liu and Wen proposed a detection network based on MobileNet-Yolo-Fast to detect defects in printed circuit boards. In the proposed model network, they detected defects in the printed circuit boards using the k-means clustering algorithm to obtain anchors boxes, the MobileNetV2 model for the backbone network, and the spatial pyramid pooling structure to increase the image receptive area (Liu & Wen, 2021).

Adibhatla et al. proposing a deep learning algorithm based on YOLO architecture to detect defects in printed circuit boards achieved an error detection accuracy of 98.79% (Adibhatla et al., 2020).

3. Material and Method

3.1. System Configuration and Acquisition of Image Data

In this section, the structure of the systems used to detect defects in printed circuit boards and the acquisition of images are discussed in detail. In this study, machine learning and deep learning algorithms were used. These algorithms were trained and tested in the Python programming language using Keras and TensorFlow libraries in the cloud-based Google Colaboratory (Colab, 2022) environment.

In the study, a dataset containing 6 different printed circuit defects was used to detect defects in printed circuit boards (Kaggle, 2022). This dataset contains 693 printed circuit images with a total of 2,953 defective regions in RGB format and different pixel sizes. In the dataset, there are 115 missing holes containing 497 defects, 115 mouse bites containing 492 defects, 116 open circuits containing 482 defects, 116 shorts containing 491 defects, 115 spurs containing 488 defects, and 116 spurious coppers containing 503 defects (Huang & Wei, 2019). Images containing 6 different printed circuit defects in this dataset are shown in Figure 1.
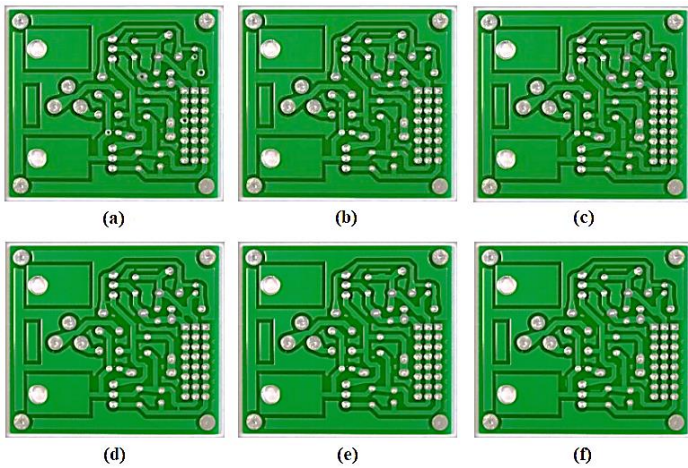
Figure 1. Images of defects in the dataset (a) missing hole (b) mouse bite (c) open circuit (d) short (e) spur (f) spurious copper

3.2. Training and Testing

In the study, HOG (Dalal & Triggs, 2005), SVM (Boser et al., 1992), KNN (Cover & Hart, 1967) machine learning algorithms, and YOLO-v4 (Bochkovskiy et al., 2020) deep learning algorithm were used to extract the characteristics of defects in printed circuit boards. For the training and testing of the algorithm structures, a dataset containing 6 different types of defects (missing hole, mouse bite, open circuit, short, spur, and spurious copper) commonly occurring in printed circuit boards was used. Printed circuit defect images in this dataset are reserved for training and testing of the algorithms used in the study, and detailed information is given in Table 1.

Table 1. The number of defect images allocated in the dataset for training and testing of algorithms

Type of defects	number of dataset images		
	Train (80%)	**Test (20%)**	**Total (100%)**
missing hole	92	23	115
mouse bite	92	23	115
open circuit	93	23	116
short	93	23	116
spur	92	23	115
spurious copper	93	23	116
Total	**555**	**138**	**693**

4. Results

Experimental analyses were performed to verify the validity of the HOG, SVM, KNN and YOLO-v4 algorithms discussed in the study in detecting defects on printed circuit boards. In the experiments, the dataset images reserved for the training and testing of machine learning and deep learning algorithms were used and the training of the algorithms was performed. The training of HOG+SVM, HOG+KNN, and YOLO-v4 algorithms was applied separately to extract the features of the defects on the printed circuit and to perform a successful classification process. The average success metrics obtained from the algorithms as a result of the training are given in Table 2.

Table 2. Average success metrics obtained as a result of training the algorithms

Model	Precision	Recall	F1-Score	Accuracy
HOG+SVM	0.50	0.48	0.48	0.48
HOG+KNN	0.39	0.40	0.38	0.40
YOLO-v4	0.61	0.79	0.69	0.75

In addition, the success rates in detecting missing hole, mouse bite, open circuit, short, spur, and spurious copper defects in the dataset were examined separately by using the proposed algorithm structures and shown in Figure 2.
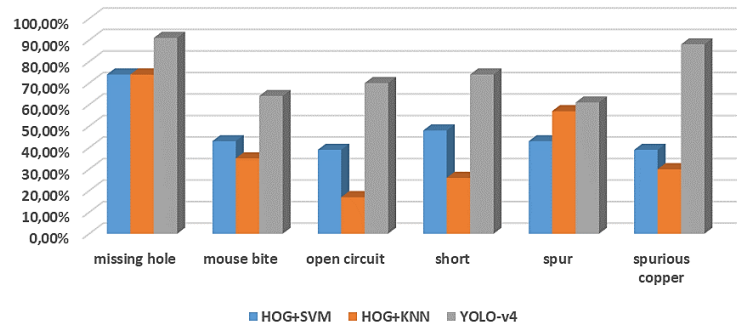

Figure 2. The success rate graph of algorithms in defect detection

According to the experimental analyses obtained, it has been seen that the defective areas on the printed circuit boards are difficult and complex to detect. Therefore, it is seen that the detection of defective regions is achieved with the YOLO-v4 deep learning algorithm with a success rate of 74.62%. In addition, 47.83% success rate was achieved with HOG+SVM and 39.86% with HOG+KNN.

5. Conclusions

In this article, HOG, SVM, and KNN machine learning algorithms and YOLO-v4 deep learning algorithm are used to detect defects in printed circuit boards. HOG+SVM, HOG+KNN, and YOLO-v4 algorithms were trained in order to extract and classify the features of the defects on the printed circuit board images of the algorithm structures. As a result of the training, 6 different types of printed circuit board defects (missing hole, mouse bite, open circuit, short, spur and spurious copper) discussed in the study were classified by success rates of 74.62% with YOLO-v4, 47.83% with HOG+SVM, and 39.86% with HOG+KNN.

As a result, it has been seen that the deep learning algorithm is more successful when compared to the machine learning algorithms in detecting the defects in the printed circuit boards. In the future, higher success rate will be achieved by collecting printed circuit board images containing more types of defects and using different machine learning and deep learning algorithms.

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