X-RAY METHODS

APPLICATION OF NEURAL NETWORKS FOR CONTROL OF PRINTED CIRCUIT BOARDS USING 3D X-RAY MICROTOMOGRAPHY DATA

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Abstract. The article discusses a method for detecting PCB defects using neural networks. The analysis of various neural network architectures is carried out to identify the most effective one. An approach to filtering data simulating the operation of a microtomograph using convolutional autoencoders is also presented. To assess the quality of the proposed approaches, the mean Average Precision (mAP) metric for the YOLOv8 and Faster R-CNN models was used.

Keywords: *neural networks, printed circuit board, defects, data filtering*

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INTRODUCTION

In today's world, technology is advancing at a rapid pace and printed circuit boards are an integral part of many electronic devices. They are complex multilayer structures that require careful quality control before assembly and installation in the final product. One of the most effective tools used in finding defects in printed circuit boards are neural networks [1–4].

Neural networks are mathematical models based on the principles of biological neural systems (Fig. 1). They are able to train on large amounts of data and find complex dependencies in them. In the context of searching for defects on printed circuit boards, neural networks can be trained to recognize different types of defects such as short circuits, open circuits, soldering defects and others.

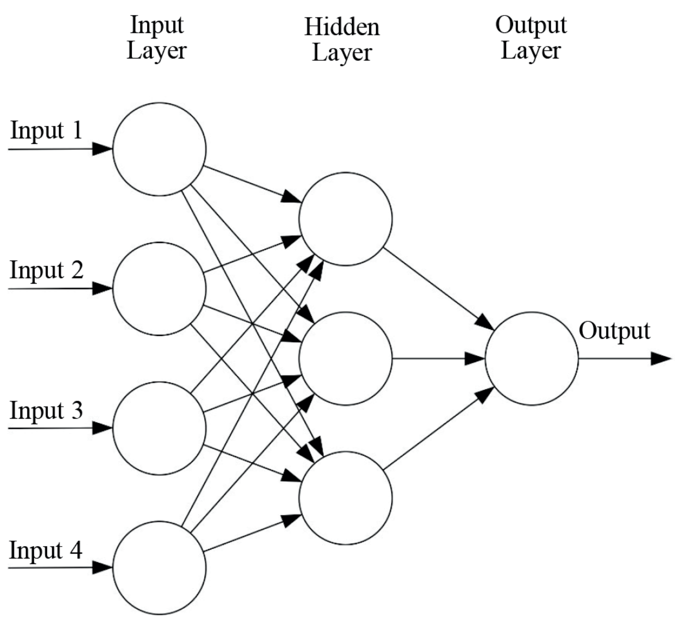

Fig. 1. Neural network model.

The purpose of this article is to review the existing methods of defect search using neural networks, analyze their advantages and disadvantages, as well as to develop and study new approaches to improve the efficiency and accuracy of detection and recognition of defects in printed circuit boards. The results of the study can be useful for specialists in the field of electronics, software developers and researchers involved in the automation of quality control processes, printed circuit boards and elements of radio-electronic equipment.

OVERVIEW

The development of deep learning has led to the development of non-contact automatic detection methods, which have become a popular area of research due to their high recognition adaptability and generalization ability [5]. Generally, neural networks suitable for use in the task of recognizing defects in images can be categorized into one-stage and two-stage networks. "You Only Look Once" (YOLO) – is one of the most popular model architectures and algorithms for detecting and recognizing objects in images or video stream (Fig. 2) [6–9]. It utilizes one of the best neural network architectures to provide high accuracy and overall processing speed, which is the main reason for its popularity. Examples of two-stage networks are Fast R-CNN and Faster R-CNN (Fig. 3) [10, 11], which are improved versions of an earlier model, R-CNN [12]. The main difference between these networks is that the one-stage network directly predicts the location and category of defects in the network after feature extraction, whereas the two-stage network first generates sentences that may include defects and then

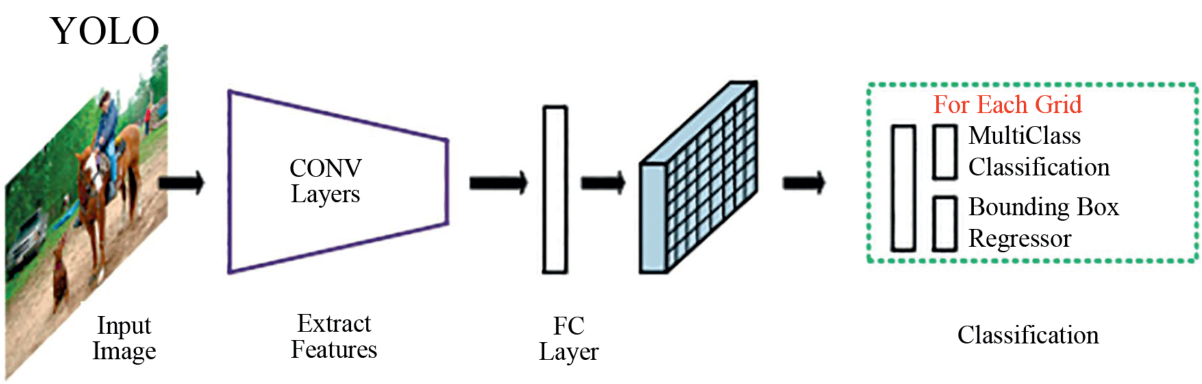

Fig. 2. YOLO architecture, the image is taken from "Deep Learning for Generic Object Detection: A Survey" [13].

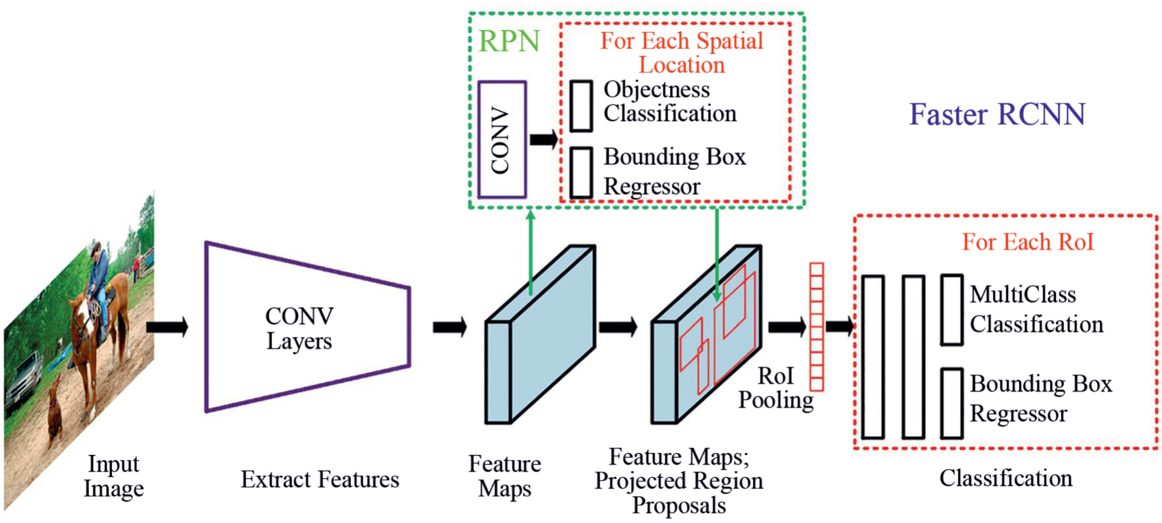

Fig. 3. Faster RCNN architecture, image taken from "Deep Learning for Generic Object Detection: A Survey" [13].

conducts the recognition process. Specifically, the two-stage network generates candidate blocks of different sizes that may contain defect features, and then performs target recognition to predict defect classes and locations. However, the recognition rate in such a case is quite slow due to the generation of multiple candidate frames. On the other hand, a one-stage network performs both training and recognition in a single network without the need to explicitly suggest potential regions, resulting in a higher recognition rate. In this paper, a one-stage network based on YOLOv8 and a two-stage Faster R-CNN are used.

DATA

Printed circuit boards were manufactured using the LUT (Laser-Uturn Technology) technology. The essence of the LUT method is that the image of the board is printed on glossy photo paper and burned to the board using an ordinary iron. Later the paper is soaked in water and rolled off the textolite. The ink that was previously on the paper remains on the textolite. The resulting piece of textolite is soaked in a solution of chlorine iron. The chlorine dissolves all the copper that is not located under the ink. When finished, the ink is washed off and the result is that we have preserved copper tracks underneath, as shown in Fig. 4.

A set of images of PCB sections collected from Shanghai Jiao Tong University [14] was used as training data. The LUT printed circuit boards were scanned using a micro-CT scanner [15–18], and a computer simulation of the micro-CT scanner was performed based on them by adding random noise and applying blurring to the images from the aforementioned dataset.

The procedure for creating a noisy image includes the following steps:

1. The original image is merged with a gray background using a specified level of transparency. Then brightness and contrast are changed, random noise is added and blur is applied.

2. In the final step, histogram equalization and global contrast normalization are performed to obtain the final image.

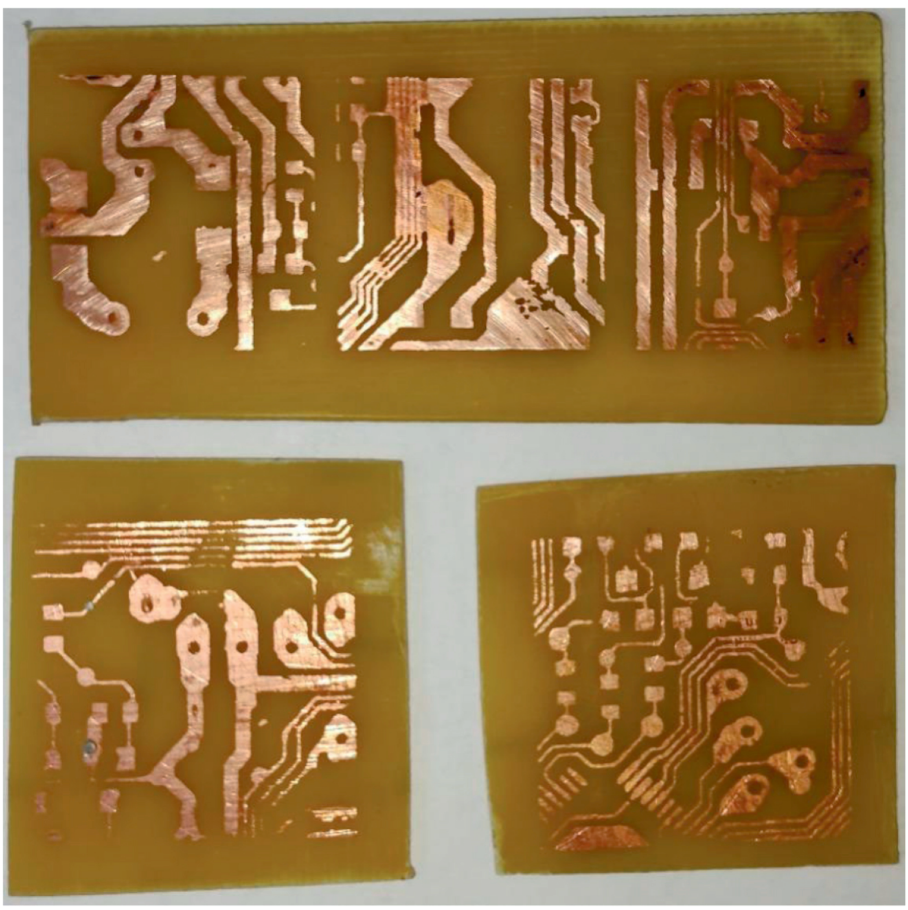

Fig. 4. Examples of fabricated printed circuit boards.

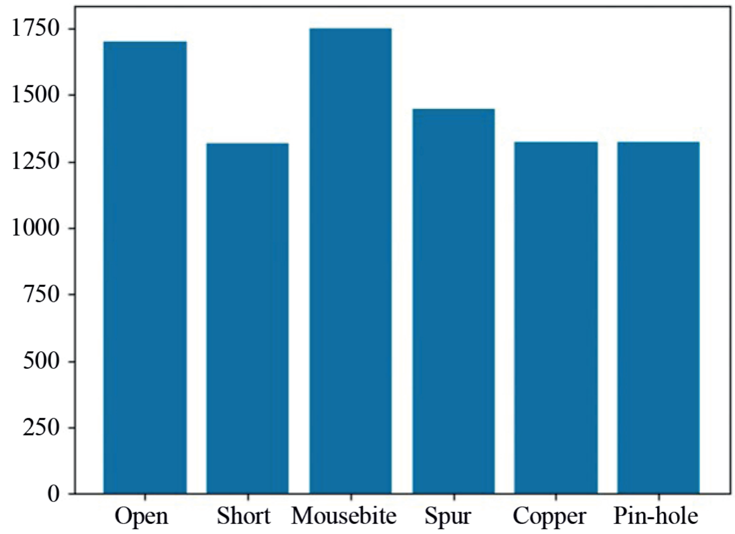

Fig. 5. Number of defects of each type in the presented dataset (here the abscissa axis shows the name of defects, and the ordinate axis shows the total number of defects of a particular type).

The presented set contains 1500 images of PCB sections, and each image has a resolution of 640 × 640 pixels. During training, the data were split into training and validation samples in the ratio of 4:1.

A total of 6 types of defects were presented:

- Open (gap);
- Short;
- Mousebite (excerpt);
- Spur (protrusion);
- Copper (island);
- Pin-hole.

MODELS

Two convolutional neural network architectures were chosen for comparison – YOLOv8 and Faster R-CNN (ResNet-50-FPN backbone). The models were trained on the same hardware – a personal computer with an Intel Core i9-12900kf processor and an NVIDIA RTX 3090 graphics card.

LOSS FUNCTIONS

As loss functions for YOLOv8 and Faster R-CNN model we used slightly different loss functions proposed by the authors of these architectures. Thus, for Faster R-CNN the loss function represented by the sum of the other four loss functions was used:

$$L = L_{classifier} + L_{box\_reg} + L_{objectness} + L_{rpn\_box\_reg}, \tag{1}$$

where $L_{classifier}$ – classification error; L_{box_reg} – regression error; $L_{objectness}$ – object recognition confidence error; $L_{rpn\_box\_reg}$ – regression error of a separate part of the neural network – Region Proposal Network (RPN), responsible for generating potential locations containing the searched objects.

For YOLOv8, the loss function is calculated as a weighted sum of three different functions:

$$L = w_1 \cdot L_{box} + w_2 \cdot L_{cls} + w_3 \cdot L_{dfl}, \tag{2}$$

whereL_{box} is regression error; L_{cls} is classification error; L_{dfl} is bounding box bias error; w_1, w_2, w_3 are their respective weights.

MODEL QUALITY METRICS USED

The mAP (Mean-Average-Precision) metric was used to compare the performance of the models. The mAP value is measured in the range of 0 to 1 and is equal to the average of the Mean-Average-Precision metric across all classes, and can be calculated as follows:

$$\text{mAP} = \frac{1}{n}\sum_{i=1}^{n} AP_i, \tag{3}$$

where AP_i is defined as the area under the precision-recall curve [19] for the class number i and n denotes the total number of classes. In this paper, the selected metric will be specified along with a number (e.g., mAP50 or mAP50-95) representing the IoU (Intersection over Union) value threshold. Intersection over Union is a number representing the ratio of the “intersection area” to the “union area” between the predicted and true bounding boxes of the object. Thus, in the further text of the paper, the entry “mAP50” will mean that the metric was calculated considering the IoU threshold of 0.5 (50%), and the entry “mAP50-95” will mean that the metric was calculated at different thresholds from 0.5 to 0.95 (50 to 95%) in steps of 0.05, and then the average value was found.

TRAINING AND RESULTS ON NOISY DATA

As a result of training both models on the described data, it was possible to obtain the following results shown in Table 1.

Table 1. Results of models on noisy data

Model	Class of defect	mAP50
YOLOv8	Open	0,9
	Short	0,76
	Mousebite	0,81
	Spur	0,82
	Copper	0,91
	Pin-hole	0,86
Faster R-CNN	Open	0,93
	Short	0,87
	Mousebite	0,86
	Spur	0,91
	Copper	0,95
	Pin-hole	0,94

DATA FILTERING

After analyzing the results, it was hypothesized that cleaning the data from noise can improve the quality of defect recognition.

The use of a convolutional autoencoder [20–23] was chosen as a tool for noise removal.

Using the Keras library [24], a convolutional autoencoder architecture was implemented, taking as input and providing as output images with a resolution of 320 × 320 pixels.

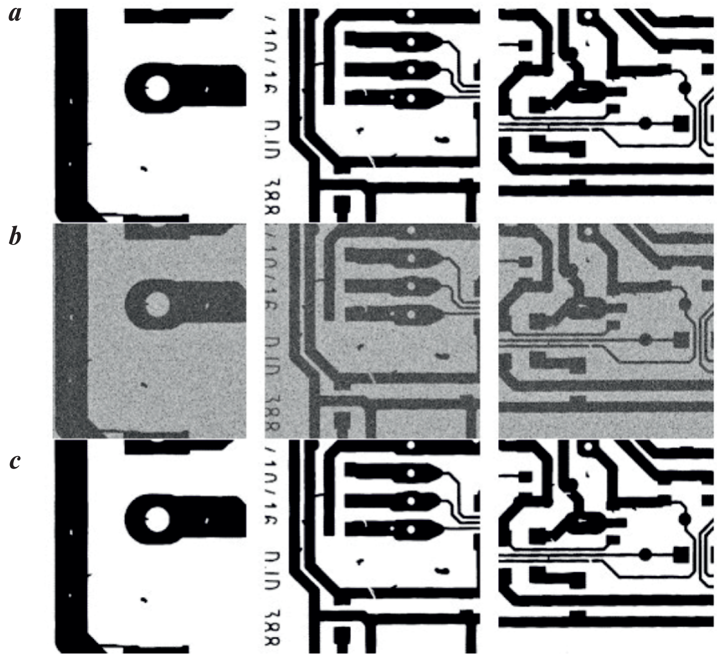

Fig. 6. Comparison of autoencoder results: *a* – original images; *b* – noisy images; *c* – images cleaned by autoencoder.

To process images of higher resolution than 320 × 320 pixels, we used an algorithm for splitting the image into a separate part, with their subsequent processing and back-joining with overlapping (to avoid unwanted artifacts at the junction boundary of the parts) [25].

The final structural diagram of the resulting software is shown in Fig. 7.

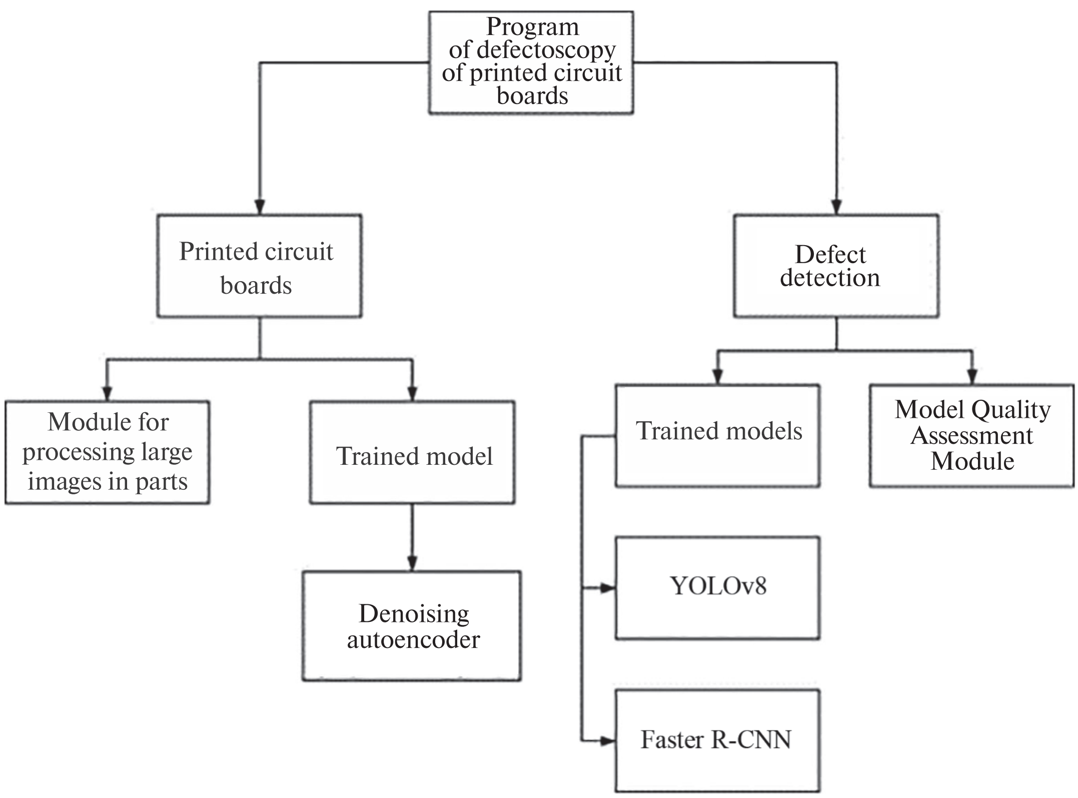

Fig. 7. Structural diagram of the software.

TRAINING AND RESULTS ON CLEANED DATA

The parameters of the models were exactly identical to those used for training on the noisy data. The results obtained are shown in Table 2.

Table 2. Results of models on cleaned data

Model	Class of defect	mAP50
YOLOv8	Open	0,98
	Short	0,96
	Mousebite	0,97
	Spur	0,97
	Copper	0,99
	Pin-hole	0,99
Faster R-CNN	Open	0,95
	Short	0,94
	Mousebite	0,93
	Spur	0,95
	Copper	0,97
	Pin-hole	0,97

Comparison of the results for the noisy and cleaned data are summarized in Table 3.

Table 3. Comparison of model results on noisy and cleaned data

Model	Data	mAP50	mAP50–95
YOLOv8	Noisy	0,84	0,46
	Cleaned	0,98	0,76
Faster R-CNN	Noisy	0,91	0,62
	Cleaned	0,95	0,70

CONCLUSION

The paper presents a method for recognizing PCB defects using YOLOv8 and Faster R-CNN neural networks. The experiments were conducted both on a set of unnoised images and on a set simulating noisy microtomography data.

For noisy data, the Faster R-CNN architecture performed slightly better, and on cleaned data both models showed a significant increase in results, with a slight advantage of the YOLO architecture. Therefore, we can speak about the applicability of the described method of image cleaning from noise to improve the quality of defect recognition.

Thus, it can be concluded that neural networks can be an effective tool for application in the task of quality control of electronic printed circuit boards.

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