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AUTOMATED DEFECT DETECTION IN PRINTED CIRCUIT BOARDS BASED ON THE YOLOv5 NEURAL NETWORK

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ABSTRACT

In this paper, we consider the possibilities of applying the YOLOv5s deep learning model to the task of automating the process of detecting surface defects on printed circuit boards. Modern printed circuit boards are manufactured in large volumes and contain a significant number of elements. The manufacturing process of printed circuit boards is complex, which increases the likelihood of board wiring defects, such as short, open circuits, mouse bites, etc. These defects are superficial and can be detected by visual and optical inspection. Compared to other methods, this type of visual-optical inspection is easier to automate. It is proven that it is promising to use deep learning models to automate the process of detecting objects in images. Modern neural networks can automatically detect surface defects in printed circuit board images with high reliability. The paper considers the class of YOLO models. It is established that the YOLOv5 model has better performance and recognition accuracy than previous modifications. In this study, the YOLOv5s model was implemented and trained to test the effectiveness of this network in the task of automated detection of surface defects on printed circuit boards. The open dataset “PCB Defects” was used for training. A qualitative and quantitative analysis of the performance of the trained network on the test dataset was carried out. It was found that the network can detect surface defects of printed circuit boards with 92.5% reliability in terms of mAP50. Additionally, the results of the recognition of different classes of defects are analyzed and recommendations for further improvement of the system are given. In particular, it is promising to apply augmentation of training data and use a more complex architecture of the deep learning model.

KEYWORDS: PCB defects, object detection, deep learning, YOLOv5

INTRODUCTION

Automation of electronic module production is an important component in the modern production of electronic equipment. Ensuring the quality and reliability of electronic modules is a key stage in this process, and timely detection of defects is an extremely important task. The installation of defective electronic boards in end devices can result in higher overall costs for the production and maintenance of electronic equipment, as well as possible injury to the end user. Therefore, early detection of defects is extremely critical and is essential to ensure the perfect quality and safety of electronic devices.

In today’s environment, there is a tendency to reduce the size of electronic modules and components to make them more compact for the devices in which they will be used. Another important factor is the significant increase of the production of electronic devices. In this regard, there is a need to use the latest methods of automating the process of controlling defects in printed circuit boards. In terms of the optimal combination of information content, speed, and ease of automation, one of the most promising methods for detecting PCB defects is visual and optical inspection.

Visual and optical inspection provides the ability to detect a wide range of surface defects, such as component damage, misalignment or misconnection, soldering defects, and many others. This method provides objective results, which reduces the influence of the human factor. The use of computer vision, image processing algorithms, and machine learning allows the automation of the inspection process with high speed and reliability [1]. Due to this, the method is effectively used in the tasks of quality control of printed circuit boards, even at high production volumes.

Among computer vision methods, one of the most promising is the use of deep learning models. Deep neural networks can achieve high levels of confidence in detecting objects in images [2]. Thanks to the ability of neural networks to learn complex patterns and dependencies, they can effectively cope with the detection of even small and complex defects that can be difficult to identify using traditional methods.

ANALYSIS OF THE PROBLEM

Printed circuit boards are manufactured using a special technology. First, a circuit is designed, which includes components, connection paths, and other elements. This design is then transferred to a base material, which is usually a polymer board. This process creates the physical basis for the components and wires. After the circuit is transferred to the base material, a series of operations are performed to create the PCB. One of the steps is to apply layers of copper to the board. The copper layers form conductive tracks that provide electrical connections between components. After the copper is applied, the board is subjected to an exposure process that allows the contours of the paths and pads to be formed using photosensitive material and masks [3].

After exposure and removal of excess copper layers, the board passes through etching solutions that remove unwanted copper particles. This process allows the formation of clear path and pad outlines, ensuring proper PCB functionality. After etching, other processing steps are carried out, such as mounting component holes, applying a protective layer, and plating the board with solder. These steps provide corrosion protection, increase strength, and add durability to the PCB.

During the production, assembly, and use of printed circuit boards, various types of defects can occur that can affect their functionality and reliability. Conductor defects are among the most common problems on printed circuit boards. The main types of conductor defects are short, open circuit, mouse bite, spur, spurious copper, and missing hole [4]. Since these defects are superficial, they can be detected by visual and optical inspection. Examples of images of some of the listed defects types from the open data sources [5] are shown in Figure 1.

Visual and optical inspection has the important advantage of being an easy to automate process. Thanks to the use of computer vision, image processing algorithms, and machine learning, the software can be developed that can automatically analyze PCB images and detect defects. This significantly reduces the dependence on the human factor, increases the speed and accuracy of control, and reduces the cost of manual work.

The basic principle of deep learning methods is that a neural network is trained on a large set of PCB images that are already labeled with the presence or absence of defects and their positions. Once the training process is complete, the model can automatically analyze new images and perform defect detection. Deep neural networks can be used for a variety of PCB defect detection tasks, such as visual anomaly detection, defect classification, defect detection, and defect region segmentation.

Thus, neural networks are a powerful tool for detecting defects on printed circuit boards. They can learn complex dependencies, automatically identify diagnostic features, and work with large amounts of data. This makes it possible to automate the inspection process to a large extent. The use of neural networks helps to achieve high accuracy and reliability of defect detection, speeds up the inspection process, and reduces production costs.

Paper [6] is devoted to the control of printed circuit boards. The authors consider in detail the problems of quality control of printed circuit boards and propose methods of automated optical inspection to detect defects. The paper begins with an overview of existing methods for controlling defects on printed circuit boards and their limitations. It shows that traditional methods, such as visual inspection, have limited efficiency and can be costly and time-consuming. Therefore, the authors propose the use of automated optical inspection systems based on neural networks to improve the quality and speed of the defect inspection process.

The authors of [7] argue that due to the complexity of the PCB manufacturing environment, most previous work still uses traditional image processing algorithms for automated PCB defect detection. In their work, they proposed an improved approach to PCB defect detection by learning deep discriminant features. This significantly reduced the high requirements for a large data set for the deep learning method.

The results show better performance in defect classification than other traditional methods based on manual feature detection. According to the authors, the proposed method has the highest mean Average Precision (mAP) score of 99.59 %, which is 8 % higher than the second best method based on a combination of Alexnet and SVM. Such a significant increase demonstrates the high efficiency of deep learning in the tasks of detecting surface defects in PCBs. However, in this study, the network was trained on artificially generated training images. Therefore, in a real-world application, the inspection reliability indicators may differ.

Paper [8] argues that traditional algorithms, which are hampered by inefficiency and limited accuracy, do not meet the requirements of modern standards. In contrast, deep learning-based PCB defect detection algorithms demonstrate increased reliability and efficiency. This is

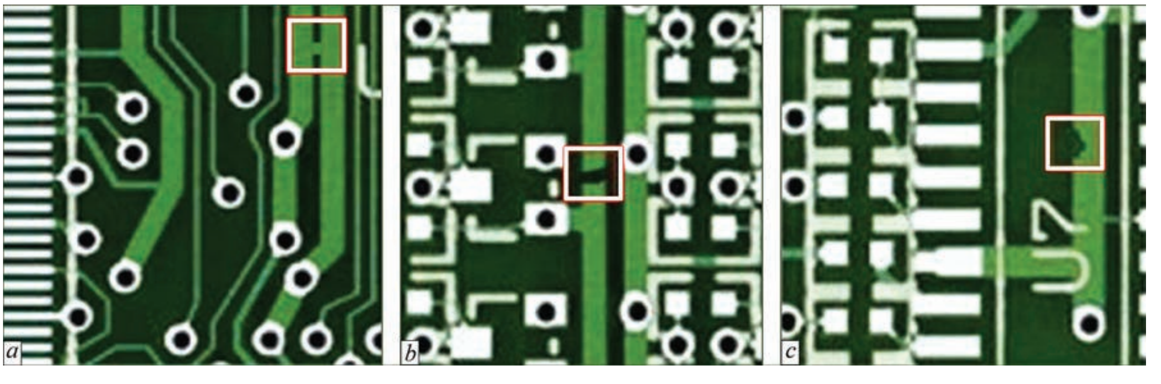

Figure 1. Examples of surface defects on printed circuit boards: *a* — short; *b* — open circuit; *c* — mouse bite

further supported by their ability to learn and recognize new types of defects. The study presents a comprehensive analysis of machine vision-based PCB defect detection algorithms that span the fields of machine and deep learning. The authors note that the introduction of free datasets for PCB defect detection improves the ability to evaluate the effectiveness of algorithms.

According to research, currently, the reliability of detection and correct classification of defects can exceed 95 % mAP with an Intersection over Union (IoU) of 0.5. To potentially improve the results, the authors identified promising areas for future research to solve existing problems in the automation of surface defect detection on printed circuit boards. According to the research results, among the existing deep learning models, the YOLO family of models demonstrates the best efficiency in detecting PCB defects.

In [9], a deep learning algorithm based on the "You Look Only Once" (YOLO) model is proposed for PCB quality control. In the proposed method, skilled quality control engineers first use a video interface to record and label defective PCBs. This data is then used to train a base YOLO model to detect surface defects. In this study, 11,000 training images were used. The neural network proposed by the authors consists of 24 convolutional layers and 2 fully connected layers. The model under consideration achieved a defect detection reliability of 98.79 % in terms of mAP. This result confirms the high efficiency of these models. However, the network architecture considered by the authors is currently outdated. Therefore, there is a need to study more modern modifications of YOLO.

The paper [10] also argues that the traditional method of manual defect detection of printed circuit boards may not meet the required production standards due to the high error rate. In this paper, the authors propose an improved algorithm based on the use of YOLOv4.

The study uses a dataset of PCB defects published by the Peking University Intelligent Robotics Laboratory. This dataset contains a large number of images of different types of defects, which significantly increases the reliability of the model. The authors analyze the distribution of CSPDarkNet53 structural layer features and the distribution of defect sizes in the dataset. At the preprocessing and data entry stage, the image is automatically divided according to the average defect size in the image. This increases the probability that a region contains a defect image. Experimental results show that the improved algorithm based on YOLOv4 has an mAP of 96.88 %.

Despite the benefits, researchers have noted some challenges and limitations of deep learning methods for PCB defect control. For example, the need for a large volume of pre-processed defect images to train models, as well as the difficulty of managing defect diversity and representativeness.

Overall, automated visual and optical inspection using deep learning models is a powerful tool for detecting surface defects on PCBs. Given the rapid progress in machine learning, we can expect further development of this approach for PCB defect inspection. One of the promising areas of research is the use of YOLO family models. These are the models that demonstrate the best results on different training data sets. Of particular interest is the YOLOv5 modification, whose effectiveness in automated PCB defect detection has not been sufficiently covered in scientific publications for today.

STATEMENT OF THE PROBLEM

This study aims to analyze the effectiveness of the YOLOv5 neural network in the task of automated detection of surface defects in printed circuit board images. This approach will allow to detect the location of defects in an automated mode and classify them by type. In a real system, the images of the object under inspection are sent to the intelligent digital processing unit from a special camera installed on the production line or directly above the product. The images are automatically processed by a neural network. The output of the neural network module is an image in which defects are framed and classified by type.

DESCRIPTION OF THE NEURAL NETWORK MODEL

YOLO is a neural network architecture for object detection and classification that has made significant advances in speed and accuracy over its predecessors. One of the main advantages of this model is that it has a high speed of image processing. This allows it to be used for real-time work on mobile devices. In addition, YOLO shows high accuracy in object detection on different datasets. The basic version of the YOLO architecture is described in [11].

However, the initial version of YOLO also has some drawbacks. For example, the architecture may have trouble detecting small objects or objects whose shape may change. There may also be problems with object localization, especially when objects overlap or have similar features. Therefore, this model has a large number of modifications that improve its performance.

YOLOv5 (You Only Look Once version 5) is an updated version of the YOLO algorithm that was introduced in 2020 [12]. YOLOv5 has several model sizes, such as YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, which differ in the number of layers and computing power. For example, the YOLOv5x model has about 88 million parameters. The generalized architecture of YOLOv5 is described in work [13] and shown in Figure 2.

YOLOv5 is also distinguished by its high object detection accuracy. For example, the YOLOv5x model

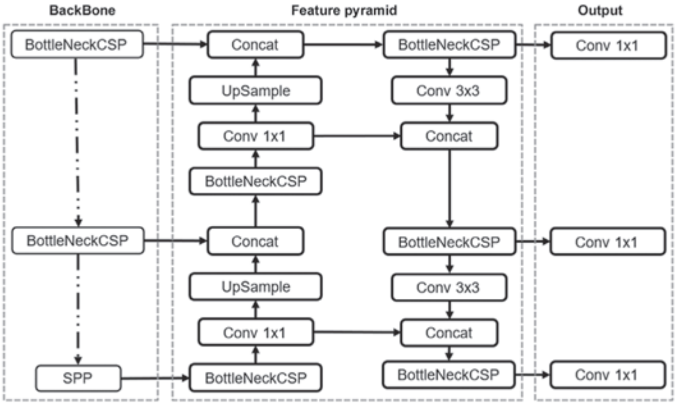

Figure 2. YOLOv5 architecture

achieves about 47 % mAP (Mean Average Precision) on the MS COCO dataset when using a 640×640 resolution and training for 300 epochs. Number of internal parameters: Depends on the model size, from XS (14 million parameters) to XL (177 million parameters). Performance may also vary depending on model size.

The YOLOv5 model uses the Mish activation function. The Mish activation function is a nonlinear function used to introduce nonlinearity in a neural network. It is defined by the following formula:

$$\mathrm{Mish}(x) = x \cdot \tanh(\mathrm{softplus}(x)). \quad (1)$$

The Mish activation function has a smooth gradient, which helps to avoid the problem of gradient decay that can occur in other activation functions such as Sigmoid or ReLU. It also allows more information to be retained in the output signal, which can improve model accuracy.

Compared to YOLOv1 and YOLOv3, YOLOv5 has better speed and accuracy. It also provides a simpler and easier to use architecture, making it a convenient option for developers and researchers. A comparison of the quantitative characteristics of the different YOLO modifications is shown in Table 1. All these models were trained and tested on the MS COCO dataset [14].

To summarise, YOLOv5 is a better choice than previous versions. It strikes a balance between accuracy and performance, making it a popular solution for a variety of object detection tasks.

METRICS FOR OBJECT DETECTION

The following metrics are used to compare and evaluate the performance of object detection algorithms. They help to determine how accurately and completely the objects are detected, as well as how the algorithm handles different object sizes and orientations. Using these metrics, you can assess the quality of the algorithm and compare it with similar solutions. The most popular metrics are IoU, Precision, Recall, mAP50, and mAP50-95 [15]. The value of all these metrics can range from 0 to 1, with 1 being the perfect result.

IoU (Intersection over Union) is a metric used to evaluate the overlap between two regions. In the context of object detection, IoU measures the degree of overlap between the predicted region (the detected object) and the reference region (the ideal or annotated region of the object).

$$\mathrm{IoU} = \frac{\text{Area of overlap}}{\text{Area of union}}. \quad (2)$$

Precision (P) — measures the proportion of objects detected by the algorithm that are correct. It is calculated as the ratio of the number of correctly detected objects to the total number of objects detected by the algorithm. A high P means a small number of incorrectly detected objects.

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \quad (3)$$

where TP is the number of correctly detected objects, FP is the number of incorrectly detected objects.

Recall (R) — measures the proportion of really present objects detected by the algorithm. It is calculated as the ratio of the number of correctly detected objects to the total number of actual objects. A high R means that the algorithm detects most of the objects.

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \quad (4)$$

where TP is the number of correctly detected objects, FN is the number of missed objects.

mAP (Mean Average Precision) at a threshold of 50 % IoU (mAP50) — measures the quality of classification of detected objects. mAP50 means that an object is considered to be correctly detected if its overlap with

Table 1. Comparison of YOLO modifications

Parameter	YOLOv1	YOLOv3	YOLOv5
Performance	45–60 FPS	20–30 FPS	20–40 FPS
Hyperparameters	45.0 M	61.0 M	85.0 M
mAP	63 %	57 %	70 %

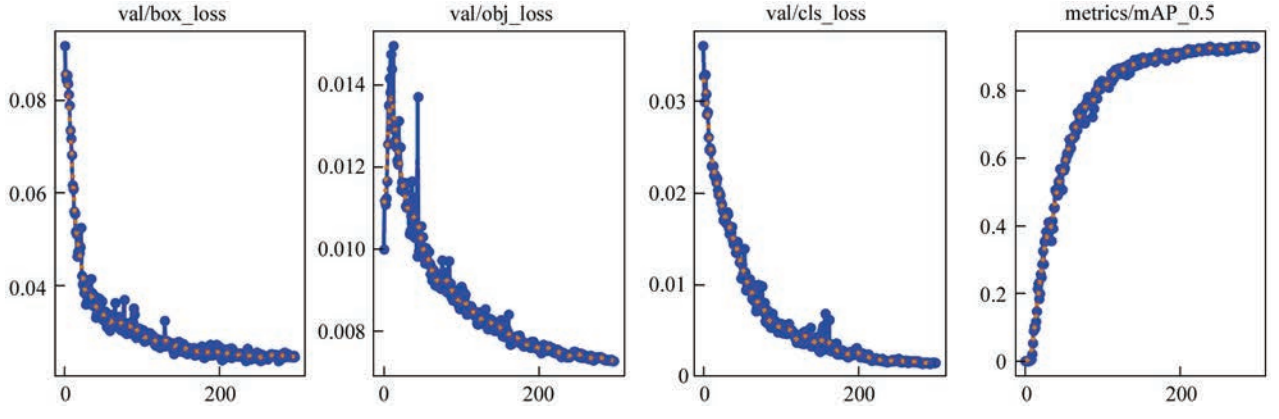

Figure 3. Graphs of the learning process

the predicted boundary (IoU) is at least 50 %. A higher mAP50 indicates better object classification accuracy.

$$\text{mAP50} = \frac{(\text{AP50\_1} + \text{AP50\_2} + ... + \text{AP50\_N})}{\text{N}}, \quad (5)$$

where AP is the average Precision across classes.

mAP in the range from 50 to 95 % IoU (mAP50-95) — measures the quality of object detection in the IoU range from 50 to 95 %. It evaluates the algorithm's ability to detect objects consistently at different levels of overlap. A higher mAP50-95 indicates better robustness of the algorithm to changes in object size and orientation.

$$\text{mAP50} - 95 = \\ = \frac{(\text{AP50-95\_1} + \text{AP50-95\_2} + ... + \text{AP50-95\_N})}{\text{N}}. \quad (6)$$

DESCRIPTION OF MODEL TRAINING PARAMETERS

The open dataset "PCB defects" was used to train the neural network. The initial dataset consists of 1386 images representing 6 types of defects on printed circuit boards: missing hole, mouse bite, open circuit, short circuit, spur, and parasitic copper. Each type of defect is evenly represented in the dataset, which allows for a variety of tasks related to defect detection. The dataset is described in detail in [5].

However, the original images in this set have too high a resolution. Therefore, it was decided to split each image into 600×600 pixels. The final training set contains 9920 images, while the testing set contains 2508 images.

The neural network is implemented using the PyTorch framework, which is one of the most popular and powerful tools for developing and training neural networks. PyTorch provides flexibility and simplicity in working with tensors, which makes it easy to build, train, and validate a neural network model.

The YOLOv5s model was trained using the following parameters: input image size — 416×416, batch size — 16, number of epochs — 300, weights of the trained model — yolov5s on the MS COCO set. Other hyperparameters are left by default for the base YOLOv5 network.

The learning curves are shown in Figure 3. It can be concluded that the training was completed successfully, with no signs of overlearning.

RESULTS AND DISCUSSION

Examples of the results of the trained network for detecting defects in images from the test set are shown in Figure 4. It can be seen that the network is able to successfully detect defects of different classes and sizes. In particular, even small defects are successfully detected. Since PCB images contain many different structural elements, finding defects manually would take considerable time and require a lot of attention and operator experience. Instead, the processing speed of one image by the neural network was 14.7 ms.

The evaluation of the neural network performance also includes quantitative metrics. The results of quantifying the model's performance on the test set are shown in Table 2.

The YOLOv5s model demonstrated high performance in detecting objects in images. The overall precision (P) is 0.941, which means that most of the detected objects are correct. However, the recall (R) is 0.894, which indicates that some objects may be missed or under-detected.

Among the specific defect classes, the missing hole demonstrates high precision (P = 1.000) and recall (R = 0.997), indicating that the model is able to detect this type of defect. Similar results are observed for the "short" class with precision P = 0.989 and recall R = 0.969. These results confirm the model's effectiveness in recognizing these specific defect classes.

At the same time, some classes, such as "open circuit", "spur" and "spurious copper", show lower precision and recall values. For example, "open circuit" has a value of P = 0.838 and R = 0.800. This may indicate that the model may need additional training or optimization to detect these types of defects.

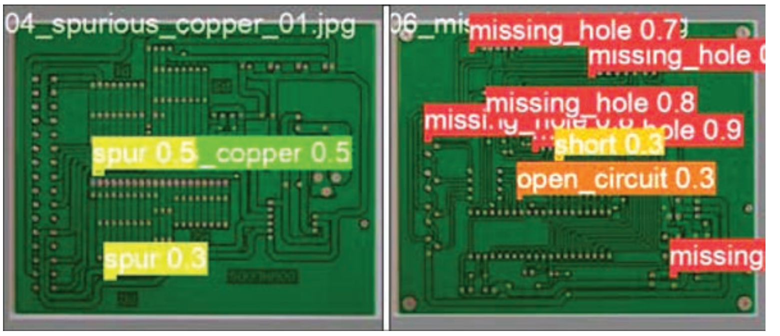

Figure 4. Examples of detecting different classes of defects

Table 2. Results of model evaluation

Defect class	Samples	P	R	mAP50	mAP50-95
All	596	0.941	0.894	0.925	0.459
Missing hole	105	1.000	0.997	0.995	0.561
Mouse bite	104	0.894	0.888	0.918	0.450
Open circuit	100	0.838	0.800	0.884	0.411
Short	90	0.989	0.969	0.981	0.487
Spur	98	0.953	0.829	0.861	0.424
Spurious copper	99	0.970	0.879	0.910	0.424

In addition, the mAP50 and mAP50-95 metrics also indicate the overall reliability of the defect classification. The value of mAP50 is 0.925, which indicates a good ability of the model to classify objects at IoU = 50 %. However, the value of mAP50-95 is 0.459. This means that the model decreases the proportion of correct classifications with increasing IoU.

Taking into account the qualitative evaluation, which shows good quality of object detection in images, and the quantitative evaluation, which indicates the speed and efficient use of resources, we can conclude that the YOLOv5s neural network is highly effective in detecting surface defects in PCB images.

Based on the data presented here, we can also suggest several ways to further develop automated systems for detecting surface defects in printed circuit boards. The first direction is to use more powerful models: It is worth considering the use of more advanced neural network architectures that have high object detection accuracy on standard datasets, such as MS COCO. Potentially, these models can provide better detection quality and the ability to recognize a wider range of objects.

Another area for further research is data augmentation. The use of various augmentation methods will expand the training dataset and improve the model's ability to generalize and recognize defects in different imaging conditions.

Finally, an important task is to optimize the hyperparameters of the selected deep learning model. It is worth conducting additional experiments to investigate the effect of batch size, activation functions, backpacks, and other parameters on the efficiency of defect detection. This will help to find the optimal values in terms of control reliability that will ensure better defect detection quality and model performance.

The choice of specific ways to improve the method of automated surface defect detection of printed circuit boards should depend on the context, resources, and development goals. The result will be influenced by the survey conditions, the characteristics of the object under inspection, the architecture of the deep learning model, etc.

CONCLUSIONS

The paper presents a detailed analysis of the effectiveness of automated detection of surface defects of printed circuit boards using the YOLOv5 neural network. Existing studies confirm the relevance of using artificial intelligence methods to automate the processing of data from visual and optical inspection of printed circuit boards. Compared to previous versions, the YOLOv5 modification has increased performance and reliability of the results.

The considered method of automated detection of surface defects of printed circuit boards based on the YOLOv5 neural network has shown high efficiency. The network is capable of detecting even small defects and classifying them with a reliability of mAP50 = 92.5 %. The study results indicate the system's potential for use in industrial environments. It should also be noted that the model was trained on images captured by a camera with a resolution of 8 MP. The minimum size of defects that the model can detect depends on a large number of factors, such as the shooting conditions, image clarity, model scale, selected model hyperparameters, etc.

The YOLOv5s model in question is the best at detecting critical defects such as hole skipping and short circuits. However, an important defect such as "rupture" is detected with lower reliability. This can be explained by the visual similarity between defective discontinuities and the required track discontinuities provided by the board design. For the same reason, defects such as "excess copper" may not be detected reliably. The "spur" defect is identified with the lowest reliability, but this type of defect does not have a significant impact on the reliability of the board under normal operating conditions. In general, the system under consideration only helps to detect defects in an automated manner. The final diagnostic decision on their criticality and impact on the stability of the board should be made by a qualified specialist.

Automation of visual and optical inspection of printed circuit boards remains an important area of research. The further development of new image processing algorithms, the use of artificial intelligence, and hardware improvements can significantly improve the speed, accuracy, and reliability of the inspection process. The latest YOLOv7 and YOLOX modifications are also currently available and will require further study in the future.

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CONFLICT OF INTEREST

The Authors declare no conflict of interest

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