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Overview and comparison of neural network models for diagnostics and quality control in the production of printed circuit boards

The article reviews and analyzes modern solutions based on neural networks for diagnostics and quality control of printed circuit boards (PCB). Various convolutional neural network (CNN) models, including LeNet-5, AlexNet, VGGNet, ResNet, and others, are reviewed, and their advantages and disadvantages are discussed. The YOLO (You Only Look Once) model, which is capable of detecting objects in real time at high speed, is considered in more detail. First part gives a general overview of neural networks and their work in the context of working with visual data. Next, the article addresses individual CNN models and their use in the context of PCB diagnostics and control. The work provides a comparative analysis of actions and results of application of neural networks and traditional testing methods along with the challenges and prospects.

Key words: *quality control, defect detection, neural networks, artificial intelligence, printed circuit boards, YOLO, optical inspection*

Entry

In the modern world, where technological processes are becoming more and more complex, the relevance of new methods of control at all stages of production is growing significantly. This is especially true for production of printed circuit boards (PCB), since defects in them can lead to serious problems, such as failure of equipment responsible for diagnostics and quality control.

Even minor defects such as short circuits, tears, spurs, copper influxes, copper gaps and missing holes can significantly degrade the quality of the product (Fig. 1). In some cases, traditional methods, such as visual inspection or use of optical inspection systems, do not allow for detailed analysis of the structure or detection of microscopic defects. The first method to be mentioned is manual observation and detection of minor surface de-

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fects. This requires constant attention, which, over time, causes visual fatigue, and as a result, errors in the detection of defects caused by distraction. Inspection systems include methods such as optical inspection and X-ray inspection, which provide high efficiency and accuracy, but require expensive equipment.

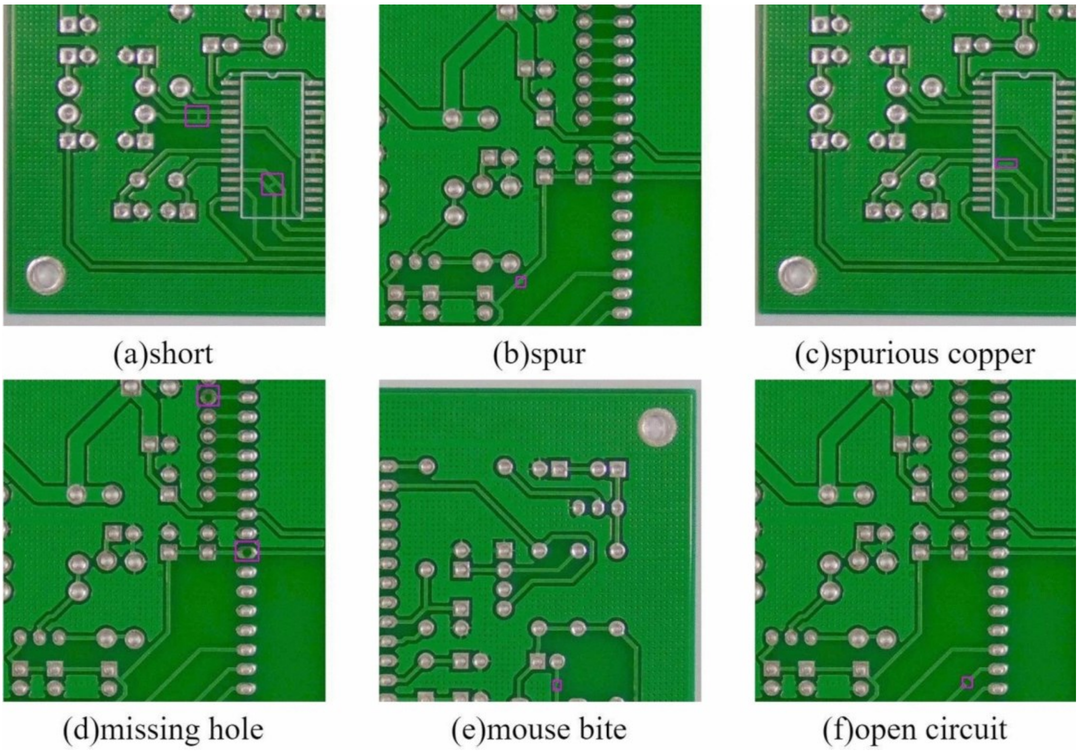

Fig. 1. Types of PCB defects [8]

The article provides an overview of modern methods of diagnostics and quality control of PCB using neural networks. Convolutional neural networks (CNNs) open up new possibilities for diagnosing defects in PCB manufacturing, due to their ability for highly accurate image processing and automatic learning. CNN models such as YOLO, ResNet, and others demonstrate real-time efficiency, which is essential for operational quality control tasks.

Reviewing and comparing different neural network models allows you to evaluate their advantages and disadvantages, adapt them to specific production requirements, and improve process efficiency. That is why the study of methods and tools for diagnosing PCB based on neural networks is relevant and timely.

Publication analysis

Over the past 5–10 years, research in the field of using neural networks for diagnostics and quality control of PCB has been significantly developed. This is due to the need to increase the efficiency of automation processes and improve methods for detecting defects.

A number of studies focus on the use of convolutional neural networks (CNNs) to analyze PCB images. In particular, the models of the YOLO (You Only Look Once) family have become one of the most popular approaches to detecting defects due to their speed and ability to work in real time. The article [9] provide examples of different versions of YOLO, such as YOLOv8, which demonstrates an optimal balance between speed and accuracy, which is especially important for automated manufacturing.

In addition, the YOLO-RRL model [2] was developed with an emphasis on ease and accuracy in detecting defects on PCB. It is optimized for use in environments of limited computing resources, providing efficiency and high performance. LW-YOLO also showed a significant advantage in defect detection tasks, outperforming other versions of YOLO in accuracy (97,1 %) and frame processing speed (141,5 FPS) [3].

In addition to YOLO, many studies look at other CNN models [10]. For example, we can mention ResNet [11], which, thanks to its deep bandwidth architectures, ensures high accuracy even in complex tasks, and EfficientNet [10], which offers balanced network scaling, making it suitable for different production conditions.

Overview of neural networks

The architecture of neural networks is one of the main directions in the development of artificial intelligence and machine learning. In this case, neural networks come from our main «analogues» — biological nervous systems. Neural networks have much less interconnected elements, which are neurons. Neurons together with the brain process input data, turning them into useful information. Each of them has its own properties and applications. CNN, or convolutional neural networks, represent one of the ways of machine learning organization/functioning. It is very efficient for image processing. The main feature of CNN is that they specialize in working with images, and, therefore, are able to detect patterns on visual data. Neural networks have different types of layers (Fig. 2), such as convolutional, subsampling (pooling), and fully coherent ones. Convolutional layers automatically process features, while subsample layers cut off the dimensionality of the data, leaving only important parts of this data [1].

Because of their architecture, CNNs are noted for their high accuracy in recognizing objects in images, so this makes them a unique tool/means for PCB quality control.

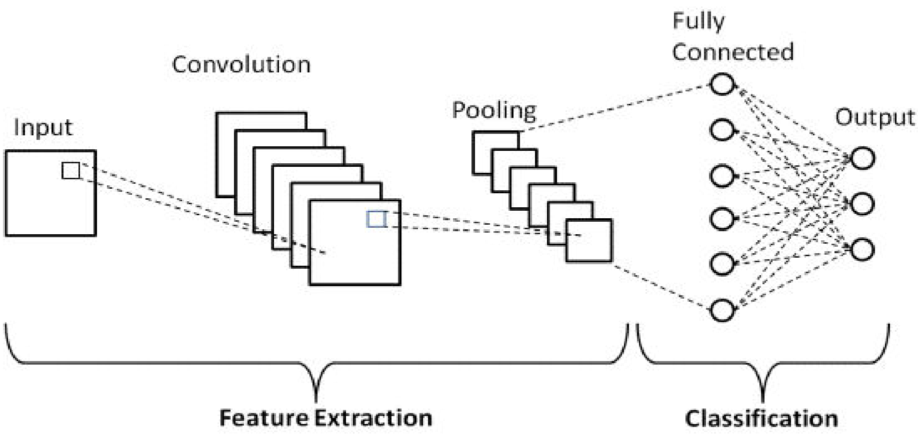

Fig. 2. Example of a basic CNN model

Popular CNN models

LeNet-5 is one of the first CNN models designed to recognize handwritten numbers. Despite its trivial design, it is still used for basic image classification tasks, namely when a small number of images of relatively simple patterns must be processed at the same time. LeNet-5 (Fig. 3) contains several convolutional and subsample layers, thanks to which the model can highlight the main features of an image, spending a minimum amount of computing resources.

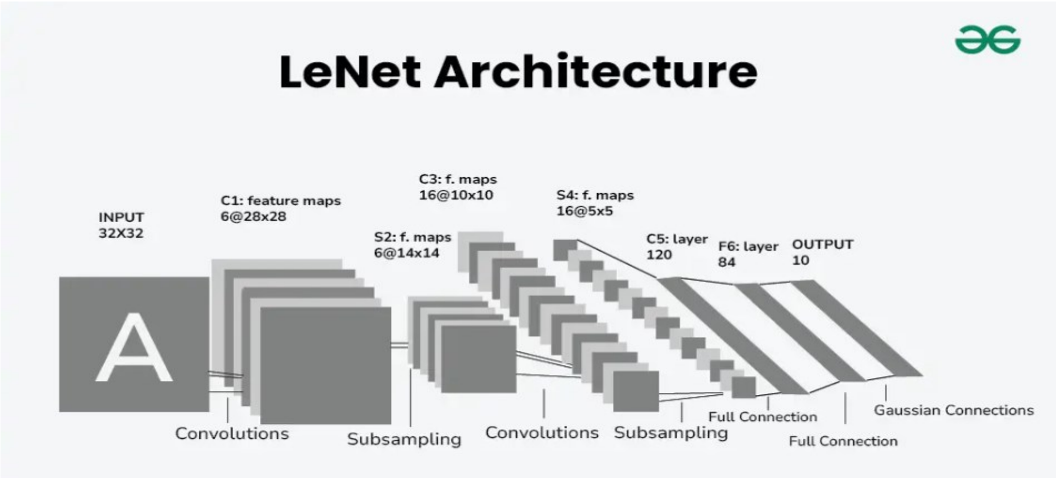

Fig. 3. LeNet-5 architecture

The overall architecture of LeNet-5, with a combination of convolution, subsampling, and fully linked layers, has been designed to be computationally efficient and good at capturing the hierarchical structure of handwritten digit images. Careful normalization of input values and structured arrangement of susceptible fields contribute to the network's ability to efficiently learn and summarize training data [4].

AlexNet, on the other hand, differs significantly from LeNet-5 (Fig. 3), as it performs well in the classification problems at the ImageNet competition. It has five convolutional layers and three fully linked layers (Fig. 4), thanks to which it can be used with more complex images.

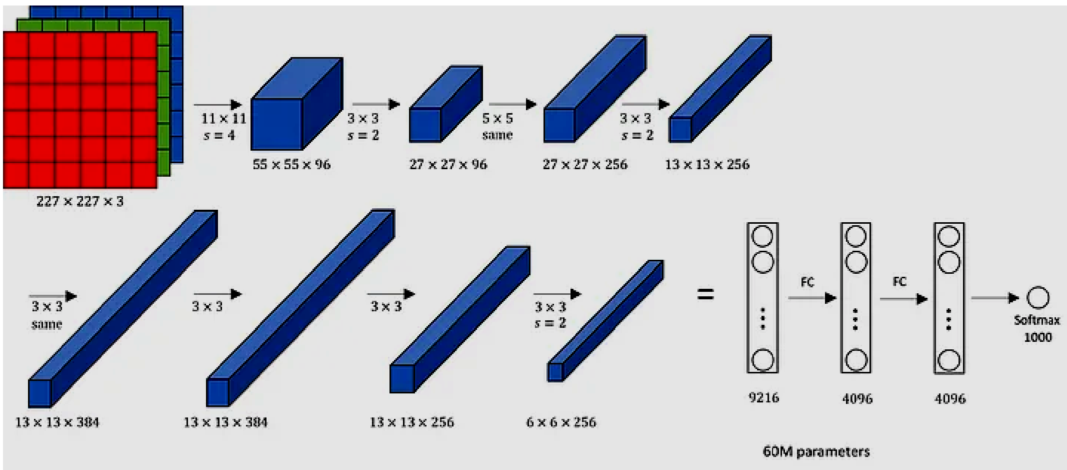

Fig. 4. AlexNet Architecture [5]

VGGNet is distinguished by the simplicity of its architecture, since only 3×3 convolutional layers are contained throughout the network (Fig. 5). It is more predictable and easier to set up. This model works well on various datasets, including classification of objects in complex images, including those of PCBs.

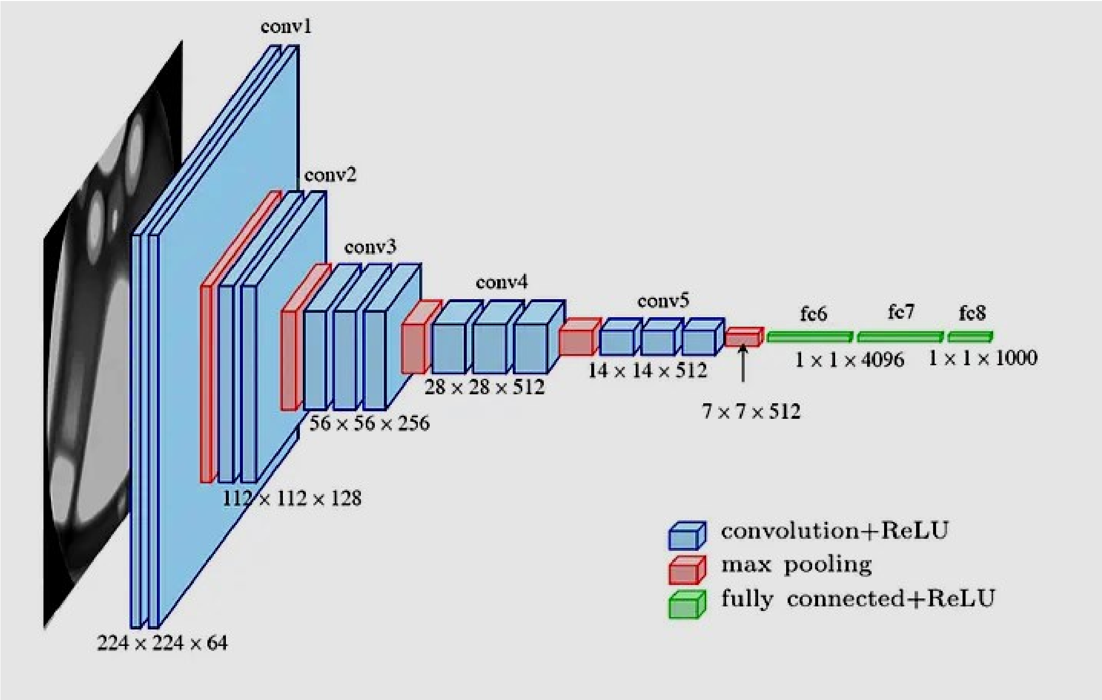

Fig. 5. VGGNet Architecture [6]

GoogLeNet, also known as **Inception**, has introduced a new approach to understanding modules. This allows the network to process information simultaneously at different scales, helping it highlight both large and small details in the image.

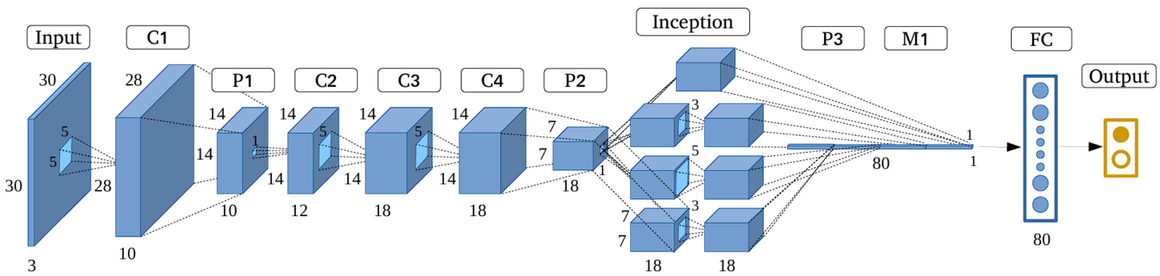

Fig. 6. GoogLeNet Architecture

GoogLeNet, or Inception v1, has made a significant contribution to the development of CNN with the introduction of the initial module. Usage of a variety of convolution filters in a single layer extended the network and 1×1 convolutions to reduce dimensionality (Fig. 6). Thanks to innovation, it won the ImageNet competition with a record low error rate. However, it shows researchers how they can develop a deeper model without significantly increasing computational requirements. As a result, its successors, such as Inception v2, v3, etc., created the basic ideas to achieve even greater performance and flexibility [7].

ResNet [10] was a breakthrough in the training of deep neural networks. Skip connections, which avoid gradient attenuation, made it possible to create very deep networks of up to 50 or up to 100 layers, which provides high accuracy in complex tasks of classification and detection of objects.

DenseNet [12] uses tight connections between layers, which allows you to better predict results and avoid data loss. This model is known for its high accuracy on complex tasks using a small number of parameters.

MobileNet [10] is designed specifically for mobile and embedded systems where computing resources are limited. Using depthwise separable convolutions, MobileNet is able to provide high speed image processing with minimal computational costs.

EfficientNet [10] is built on a balanced architecture that is able to scale the depth, width, and resolution of the network to improve accuracy, demonstrating high results in classification tasks with minimal computational overhead. This makes it versatile for a variety of applications, including PCB diagnostics.

Methodology for the application of neural networks

The use of neural networks for quality control of PCB is based on the ability of algorithms to analyze images in order to detect defects of varying complexity. The process of building and integrating such systems involves several key steps, each of which is critical to achieving efficiency and accuracy.

1. Data preparation

The first and most important step is to create a high-quality dataset. This involves collecting a large number of PCB images, which are labeled according to presence or absence of defects. The data must be representative, cover various types of defects, including short circuits, discontinuities, spurs, copper influxes, missing holes, etc. For example, synthetically generated images obtained by rotating, scaling, mirroring, or adding noise are added to the set. This makes the model less dependent on a limited number of initial samples and ensures its resistance to changes in production conditions.

2. Pre-processing of data

PCB images go through several stages of preparation before entering the neural network. The main processes include:

— **Scaling images** to a standard size that meets the requirements of the selected model. For example, for YOLO, these can be 416×416 pixel sizes;

— **Normalization** of pixel values, which improves stability of the model by reducing all values to a single range, usually from 0 to 1;

— **Filtering out noise and artifacts** that may appear due to optical distortion, dust, or uneven lighting. For this, smoothing or brightness equalization algorithms are used.

3. Choosing a model architecture

After preparing the data, the appropriate neural network architecture is selected.

This choice depends on the specifics of the task.

1. For real-time tasks that require high speed, YOLO models or its modifications (for example, YOLOv8, LW-YOLO) are suitable.

2. If the priority is maximum accuracy and speed is less important, deep architectures such as ResNet or EfficientNet are used.

4. Neural Network Training

Model training process involves optimization of its parameters based on the prepared data. For this, the following steps are taken:

— **Division of data** into training, validation, and test sets to check the generalization of the model;

— **Setting hyperparameters**: choosing the batch size, the number of epochs of training, the speed of training, etc;

— **Loss function**: For object detection tasks, functions that take into account both classification accuracy and localization quality, such as IoU (Intersection over Union), are often used.

5. Testing and validation

The trained model is evaluated on test data. The main metrics are:

— **Accuracy (Precision)** and **completeness (Recall),** which determine the ability of the model to correctly classify defects;

— **Average accuracy (mAP),** which is used to estimate the overall quality of a model in object detection problems;

— **FPS (Frames Per Second)** is the speed at which the model processes images, which is key for real-time operation.

6. Integration into the production process

The finished model is integrated into the production line, which includes image capture systems, data processing, and automated analysis of results. For example:

— the camera captures the image of the board, which is transmitted to the processing system;

— the neural network analyzes the image in real time and gives the result — the presence of defects, their type and location;

— the results are used to automatically sort, correct or reject defective boards.

When choosing neural networks for PCB quality control tasks, it is necessary to take specific features of the subject area into account. The formal criteria applicable to this field are as follows.

1. Accuracy of defect detection

The main purpose of the models is to provide high accuracy in identifying various types of PCB defects: short circuits, breaks, spurs, copper influxes, spaces, missing holes, etc. To do this, it is important that the model can:

— correctly distinguish defects on complex textures of printed circuit boards;

— ensure accuracy even in cases of microscopic defects typical of high-tech boards.

2. Image processing speed

PCB manufacturing requires real-time operation, so model speed (FPS) is a critical criterion. For example:

— high-performance lines require processing of several dozen boards per minute;

— models like the LW-YOLO [3], with a performance of 141.5 FPS, provide efficiency for mass production lines.

3. Working with small parts

PCBs contain small components and complex structures. The model should:

— have the ability to detect defects on elements with minimal dimensions;

— work with multiscale objects, which is typical for PCBs with complex designs.

4. Resistance to interference

Images of boards can have:

— poor quality due to lighting, dust or distortion of the optics;

— overlapping elements, which makes it difficult to detect defects. Models such as EfficientNet demonstrate high resistance to noise and interference.

5. Flexibility to adapt to new conditions

Different types of PCBs can vary in size, design, and materials. A neural network must be easily retrained to:

— detection of new types of defects;

— work with boards manufactured using different technologies (for example, SMD or PTH).

6. Scalability

The system must adapt to different conditions, including:

— high-resolution images for accurate detail analysis;

— the need to scale to a large number of objects for simultaneous analysis of multiple boards.

7. Computing resources

PCBs are usually tested in large volumes, which requires models to use hardware resources efficiently. High-performance models, such as the LW-YOLO, allow you to work on mid-range equipment, providing cost savings.

8. Reliability of work

The model must provide a minimum level of false positives and missed defects, which is critical for high-quality products. For example:

— a missed defect on the board may cause the device to fail;

— over-detection may result in unnecessary costs due to re-inspection or rejection.

9. Integration into the production process

The model must be easily integrated into existing production lines:

— support for various input formats from image capture systems;

— compatible with analysis and quality management software.

10. Deployment cost

The financial aspect is also important. The model has:

— work on available equipment;

— minimize the cost of retraining and maintaining the system.

YOLO: Features and Applications

YOLO (You Only Look Once) is one of the most effective models for real-time object detection. Its main advantage is its speed, since it processes the image holistically, dividing it into a grid and at the same time estimating the probability of the presence of objects and their coordinates. This makes YOLO suitable for integration into production processes where not only accuracy but also speed of analysis is important. This feature allows the model to operate at speeds of more than 100 FPS, even on mid-range equipment, making it an ideal solution for automated PCB quality control.

The features of YOLO make it unique in PCB analysis tasks. The ability to work with multiscale objects ensures the detection of both large and microscopic defects, such as short circuits, spurs, broken tracks or missing holes. The model shows consistent results even in difficult conditions, such as poor image quality due to noise, uneven lighting or overlapping elements. This makes it suitable for the analysis of complex multilayer PCB structures with high component density.

Practical applications of YOLO include real-time automation of defect detection. For example, LW-YOLO, one of the YOLO modifications, achieved an accuracy of 97,1 % and a speed of 141.5 FPS [3], allowing up to 60 boards per minute to be tested in high-performance production lines. In another study [9], YOLOv8 was integrated into an automated board sorting system, which significantly reduced the cost of manual inspection, while providing a high level of accuracy in detecting defects.

In addition to the standard versions of YOLO, modifications such as LW-YOLO and YOLO-RRL are used in industrial settings. LW-YOLO is focused on reduction of computational complexity, which allows it to be used on relatively cheap equipment, such as the NVIDIA Jetson Nano, without significantly losing the quality of the results. YOLO-RRL, in turn, was developed specifically for analysis of surface defects of printed circuit boards and is well adapted to work with various types of products [2]. These modifications provide the ability to choose a model depending on resources and production tasks.

The prospects for using YOLO in PCB quality control tasks remain extremely high. Further development of this architecture aims to improve accuracy, reduce computational requirements, and improve resilience to complex production conditions. For example, the integration of YOLO with other AI tools, such as self-learning systems, opens up new opportunities for automation and increased efficiency of production processes.

Conclusion

In conclusion, neural networks, especially CNNs, offer significant opportunities for diagnostics and quality control in PCB manufacturing. They provide high precision, speed, and process automation, making them an effective tool in modern manufacturing. However, for successful implementation, it is necessary to take into account the challenges associated with computing resources and the need for training data.

Having looked at many models of neural networks in detail, we can conclude that convolutional neural networks are the most optimal for detecting defects during PCB manufacturing. Namely, models based on LW-YOLO and YOLOv8.

It is important to continue research in this direction to ensure maximum efficiency and quality of PCB production in the future.

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