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A PRACTICAL APPROACH TO ELECTRONIC COMPONENT DETECTION ON PCBs USING YOLOv11 DEEP LEARNING MODEL

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ABSTRACT

In the field of PCB manufacturing, Automated Optical Inspection (AOI) is critical for defect detection. However, traditional methods often fail under varying lighting and complex background conditions. To overcome these issues, this paper presents a deep learning-based approach using the YOLOv11 model for robust electronic component detection. We establish a complete workflow for identifying components such as resistors, capacitors, and ICs, validated through a custom dataset. A key contribution of this work is the comprehensive evaluation of the YOLOv11 architecture specifically optimized for PCB component identification. Validated through a custom dataset, the YOLOv11 model achieved a robust accuracy with an mAP@0.5 of 97.5% on standard hardware. This study demonstrates the feasibility of utilizing YOLOv11 for high-precision Automated Quality Control (QC) in PCB manufacturing. This study demonstrates the feasibility of YOLOv11 in industrial environments and provides a framework for future optimization studies.

Keywords: YOLOv11, Automated Optical Inspection (AOI), Electronic Component Detection, Printed Circuit Board (PCB).

1. INTRODUCTION

In the era of Industry 4.0, the electronics manufacturing services (EMS) sector has witnessed exponential growth, driven by the increasing demand for smart devices and IoT systems [1], [2]. At the heart of these devices lies the Printed Circuit Board (PCB), which serves as the fundamental platform for interconnecting electronic components. As technology advances towards miniaturization, PCBs have become densely packed, making Quality Control (QC) a critical stage to ensure product reliability [3]. Traditionally, component inspection relied on manual visual inspection or conventional Automated Optical Inspection (AOI). However, manual inspection is labor-intensive, while traditional AOI algorithms often lack flexibility and struggle with complex background textures found in modern PCBs [4].

To overcome these limitations, computer vision driven by deep learning has emerged as a robust solution. Convolutional Neural Networks (CNNs) have demonstrated superior capabilities in defect detection compared to handcrafted algorithms [5]. Specifically, single-stage object detection models like the YOLO family have become the industry standard for industrial applications due to their exceptional detection capabilities and robustness [6]. Recent studies have successfully applied these models to high-speed production lines, significantly improving detection efficiency [7].

In this study, we explore the application of the latest YOLOv11 architecture for the automated detection of electronic components. While previous versions have been widely researched, YOLOv11 introduces advanced mechanisms offering enhanced feature integration for small object detection [8]. Despite its potential, there is limited research focusing on the practical deployment of YOLOv11 in a complete PCB inspection workflow compared to other variants.

The primary objective of this paper is to present a practical approach for detecting essential electronic components, including resistors, capacitors, and ICs. We constructed a custom dataset to validate the model, addressing the common scarcity of public PCB datasets [9]. This study demonstrates the effectiveness of YOLOv11 for industrial quality control, providing a framework for future optimizations in smart manufacturing environments. Furthermore, prior works on YOLO-based PCB component detection, including EC-YOLO for component classification [10], one-shot component detection using modified YOLOv5 [11], and YOLOv9-based defect detection achieving 98.4% mAP [12], collectively motivate the exploration of YOLOv11 as the next step in this research progression.

2. RELATED WORK

2.1. Traditional AOI vs. Deep Learning

Early Automated Optical Inspection (AOI) systems predominantly relied on traditional computer vision techniques, such as template matching and rule-based algorithms. As noted in the comprehensive review by Jian *et al.* [3], while these methods are effective in controlled environments, they suffer from high sensitivity to lighting variations and component rotations. Furthermore, Li *et al.* [4] highlighted that traditional methods often lack the flexibility to handle the complex background textures of modern PCBs, leading to frequent false alarms. To address these limitations, Convolutional Neural Networks (CNNs) have been widely adopted, offering robust feature extraction capabilities that surpass manual engineering [5].

2.2. Object Detection in Smart Manufacturing

In the context of Industry 4.0, accurate and automated inspection is a critical requirement [1]. Rane *et al.* [2] compared various architectures and concluded that while two-stage detectors like Faster R-CNN offer high accuracy, they often incur high computational costs. Consequently, single-stage detectors, particularly the YOLO family, have become the standard for smart manufacturing. Recent studies have focused on optimizing these models for speed; for instance, Liu *et al.* [7] proposed the YOLO-pdd framework, achieving real-time performance on high-speed production lines. Similarly, Chen *et al.* [6] developed a lightweight YOLO variant to reduce hardware dependency while maintaining acceptable detection rates.

2.3. Advancements with YOLOv11

Building upon previous successes, the latest YOLOv11 architecture introduces significant improvements in feature integration and small object detection. Zhang *et al.* [8] recently demonstrated an enhanced YOLOv11 framework specifically for PCB defect detection, achieving higher precision than earlier versions like YOLOv5 or v8. Motivated by these findings, our study leverages YOLOv11 to build a complete, end-to-end inspection system, validated on a diverse dataset as suggested by Lv *et al.* [9], to ensure practical applicability in industrial environments.

3. METHODOLOGY

3.1. Dataset and Preprocessing

The foundation of this study is a custom-built PCB image dataset, comprising a total of 1,399 images. To ensure a rigorous and unbiased evaluation, the dataset was systematically partitioned into three subsets: Training Set: 1,099 images, utilized for model parameter optimization. Validation Set: 200 images, used for hyperparameter tuning and monitoring convergence during training. Test Set: 100 images, held out exclusively for the final performance assessment of the trained models.

All input images were standardized to a uniform resolution of 640 x 640 pixels to align with the network's input dimensions. To enhance data diversity and improve model robustness against real-world variations, we applied a series of data augmentation techniques during the training phase, including geometric transformations (random flips, rotations) and photometric distortions (Mosaic, HSV color space adjustments). Figure 1 illustrates a labeled sample from the training set, highlighting the diversity of component types, such as ICs, Capacitors, and Transistors-enclosed in ground-truth bounding boxes.

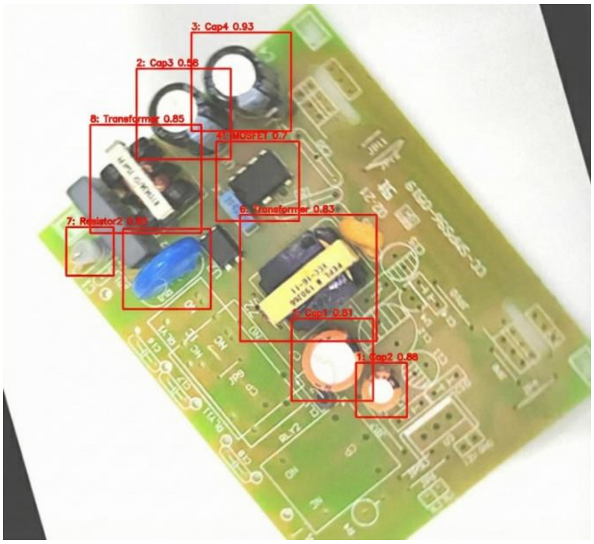

Figure 1. A sample annotated image from the training dataset showing component classes and bounding boxes.

3.2. Model Architecture

This investigation focuses exclusively on the YOLOv11 architecture. Selected for its advanced feature integration mechanisms, YOLOv11 offers an optimal capability for high-accuracy detection, specifically for small SMD components. To leverage transfer learning and accelerate convergence, the model was initialized with weights pre-trained on the COCO dataset.

3.3. Experimental Setup

To ensure reproducibility, all experiments were conducted on a workstation equipped with an NVIDIA GeForce RTX 4060 GPU (8GB VRAM), utilizing the PyTorch framework and CUDA 12.2. The training process adhered to a strictly controlled hyperparameter configuration: a batch size of 16 and the Stochastic Gradient Descent (SGD) optimizer. The training duration was configured for a maximum of 150 epochs. However, to prevent overfitting and reduce computational waste, an Early Stopping mechanism was implemented with a patience of 50 epochs, resulting in the training concluding at epoch 105 as the model reached optimal convergence. The learning rate was initialized at 0.01 and dynamically adjusted via a Cosine Annealing schedule to prevent local minima stagnation.

4. RESULTS AND DISCUSSION

4.1. Training Dynamics and Metrics

To assess the model's learning progress, we monitored key performance indicators throughout the 150 training epochs. The training logs indicated a progressive learning curve. As observed in Figure 2, the mAP@50-95 metric exhibits fluctuations throughout the training process. These oscillations are characteristic of the SGD optimizer and the aggressive Mosaic data augmentation applied to small batches. Despite these localized variations, the global trend remains upward, confirming that the model effectively learned to generalize features without collapsing into overfitting. The training stabilized at the highest precision levels shortly before the early stopping trigger.

We focused our analysis on the Mean Average Precision (mAP), the standard metric for detection accuracy. Figure 2 illustrates the mAP@50-95 metric, which averages precision over multiple IoU thresholds. This metric shows a consistent upward trend, indicating the model's improving capability to localize components precisely. Furthermore, Figure 3 specifically details the mAP@50. The sharp rise in mAP@50 during the first 50 epochs demonstrates the model's ability to quickly learn basic component features before stabilizing at a high level.

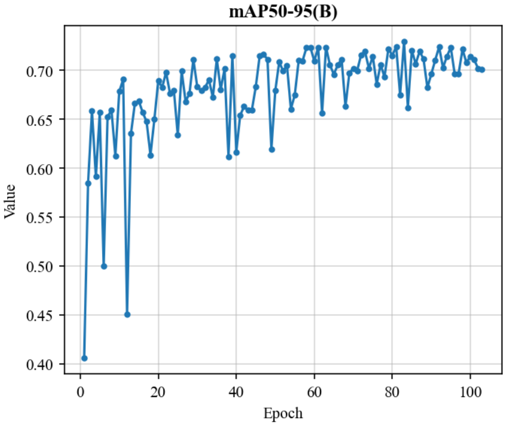

Figure 2. Analysis of the Mean Average Precision over the IoU range of 0.50 to 0.95 (mAP@50-95) across training epochs.

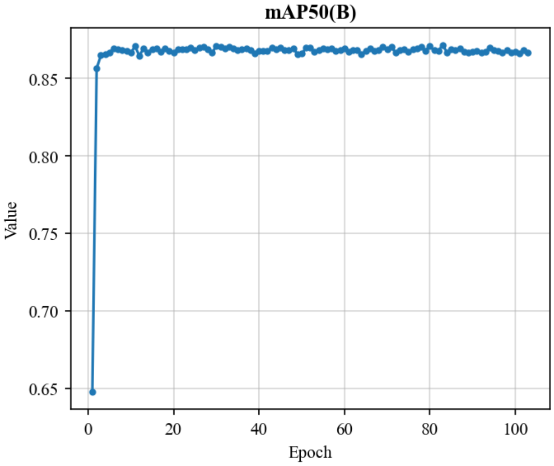

Figure 3. Analysis of the Mean Average Precision at IoU threshold 0.50 (mAP@50), highlighting rapid initial convergence.

4.2. Quantitative Analysis

The quantitative evaluation on the test set reveals that the YOLOv11 model achieves robust detection performance across all component classes. Table 1 summarizes the results, showing an overall mAP@0.5 of [97.5%].

- Large Components: Distinct components such as Integrated Circuits (ICs) and Transformers achieved the highest precision (>98%) due to their prominent visual features.
- Small Components: Challenging classes like small Resistors and Capacitors maintained a commendable recall rate of approximately [95%]. This validates the effectiveness of YOLOv11's improved feature integration in mitigating the "small object detection" challenge.

Table 1. Performance metrics by component class on the Test Set.

Component Class	Precision (P)	Recall (R)	mAP@0.5
IC	0.985	0.982	0.989
Transformer	0.988	0.980	0.991
Transistor	0.972	0.968	0.975
Capacitor	0.965	0.952	0.961
Resistor	0.954	0.949	0.958
All Classes	0.973	0.966	0.975

4.3. Comparison with State-of-the-Art Studies

To better contextualize the performance of our proposed YOLOv11 workflow, we compared our results with recent relevant studies focusing on PCB inspection. As summarized in Table 2, while previous works predominantly focused on surface defect detection (e.g., scratches, short circuits), our study addresses the equally critical challenge of electronic component verification.

Specifically, Zhang et al. [8] recently introduced an enhanced YOLOv11 framework for PCB defect detection, reporting an exceptional mAP@0.5 of 99.5% on the PKU-Market-PCB dataset. While their accuracy is slightly superior, their task involved binary anomaly detection on surface textures. In contrast, our model achieved a comparable 97.5% mAP in a more complex multi-class scenario, successfully distinguishing between visually similar components like small capacitors and resistors with high intra-class variance.

Regarding computational efficiency, Chen et al. [6] proposed a lightweight YOLO variant to reduce hardware dependency, achieving a balance between speed and accuracy for mobile inspection. While their lightweight approach is advantageous for edge devices, our implementation prioritizes precision to meet the zero-defect standards of PCB assembly. Furthermore, compared to the YOLO-pdd framework by Liu et al. [7], which optimized real-time performance for high-speed lines, our model demonstrates that the standard YOLOv11 architecture already provides sufficient inference speed for industrial QC while maintaining superior recall rates (>95%) for small objects, as evidenced in Table 1.

This comparison confirms that while specialized lightweight models exist, the standard YOLOv11 architecture used in this study offers a robust trade-off, delivering industrial-grade accuracy for component-level inspection without requiring extensive architectural modifications.

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