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Development and Evaluation of a Computer Vision-Based System for Real-Time Defect Detection in Automated Assembly Line Manufacturing

Elena Moretti,
Italy.

Abstract

In recent years, the demand for higher production quality and reduced human error in manufacturing has accelerated the integration of intelligent systems into automated assembly lines. This paper presents the development and evaluation of a real-time computer vision-based system designed to detect product defects with minimal latency and high accuracy. Utilizing convolutional neural networks (CNNs), the system processes high-resolution video input from industrial-grade cameras, automatically identifying defects such as misalignments, surface deformities, and missing components. The proposed system demonstrates significant improvements in detection speed and consistency over traditional manual inspection methods. Our evaluation, conducted in a simulated industrial environment, reveals a detection accuracy of 96.3%, with processing latency under 120 milliseconds per frame.

Keywords: Computer Vision, Real-Time Defect Detection, Automated Assembly Line, Deep Learning, Quality Control, Industrial AI, CNN.

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1. INTRODUCTION

The rise of Industry 4.0 has fundamentally transformed modern manufacturing by integrating automation, data exchange, and smart systems. A major challenge within this paradigm is maintaining high product quality while reducing reliance on manual inspection, which is often inconsistent and labor-intensive. Real-time defect detection systems that leverage machine vision have emerged as vital solutions to address this gap.

This paper focuses on the design and evaluation of a computer vision-based inspection system capable of real-time performance on automated assembly lines. By incorporating deep learning models, the system can adapt to a variety of defect types and production environments. Our goal is to reduce false negatives while ensuring throughput remains unaffected.

2. Literature Review

Visual inspection using computer vision has been explored extensively, especially with the advent of machine learning. Traditional machine vision systems relied on rule-based algorithms to detect product inconsistencies; however, these were often brittle and sensitive to environmental changes. For instance, work by Ghorai et al. (2014) demonstrated that handcrafted feature extractors like SIFT and SURF could detect surface-level defects in textiles, but struggled under varying lighting and orientation.

With the rise of deep learning, particularly convolutional neural networks (CNNs), vision systems saw a drastic improvement in adaptability and performance. Tsai et al. (2018) showed that CNNs could be trained to detect defects in semiconductor wafers with accuracy surpassing 90%. Similarly, Babenko et al. (2020) applied ResNet-based models for automotive part inspection, achieving significant reductions in false positives. Despite these successes, many systems still lacked real-time responsiveness and required extensive pre-processing pipelines.

Another key issue discussed in literature is the challenge of dataset diversity. Many systems performed well on specific datasets but failed to generalize. To counteract this, Liu et al. (2019) proposed synthetic data augmentation techniques, improving defect detection robustness across multiple industrial domains. However, real-time implementation remained largely theoretical, with few deployments tested under full-scale production conditions.

3. System Architecture and Design

The proposed system integrates hardware and software components to form an efficient real-time defect detection pipeline. As illustrated in **Figure 1**, high-resolution cameras are installed above the assembly conveyor to capture continuous image streams of moving products.

The core of the system is a deep CNN model—based on a modified YOLOv5 architecture—trained to classify and localize defects. Pre-processing involves image normalization, contrast enhancement, and background subtraction to ensure consistency under variable lighting. The inference engine, optimized using TensorRT, operates on an NVIDIA Jetson AGX Xavier, allowing low-latency predictions.

The design also includes a graphical user interface (GUI) for operators to review flagged defects and override false alarms. The system logs inspection metadata and integrates with existing manufacturing execution systems (MES) for traceability.

4. Experimental Setup and Methodology

To evaluate the system, we conducted experiments in a simulated assembly line using three types of products: plastic enclosures, PCB modules, and mechanical fasteners. Each product batch included manually introduced defects (e.g., scratches, missing parts) to create a balanced dataset.

A total of 15,000 labeled images were used to train and validate the CNN model, split in an 80:10:10 ratio. The test environment consisted of a 12-meter conveyor system with an average product flow of 120 units per minute. Cameras recorded at 60 FPS, and detection latency was measured using embedded timestamps.

Performance was assessed using precision, recall, F1-score, and inference latency. The system was also tested under varying lighting and background noise to evaluate robustness.

Table 1. Dataset Composition and Defect Types

Product Type	Total Images	Defect Classes	Example Defects
Plastic Enclosures	5,000	4	Cracks, Warping
PCB Modules	5,000	5	Missing ICs, Solder Blobs
Mechanical Fasteners	5,000	3	Rust, Misalignment

5. Results and Performance Evaluation

The trained model achieved a mean Average Precision (mAP) of 95.2% on the test set. Real-time inference was achieved with an average latency of 117 milliseconds per frame, surpassing the industry benchmark of 150 ms. As shown in **Table 2**, precision and recall were consistently high across all product types.

Environmental tests revealed that performance dropped slightly under low-light conditions (mAP reduced to 91.4%), but remained within acceptable quality thresholds.

Table 2. Detection Performance Metrics

Product Type	Precision (%)	Recall (%)	F1-Score (%)	Latency (ms)
Plastic Enclosures	96.1	95.3	95.7	114
PCB Modules	95.9	96.7	96.3	119
Mechanical Fasteners	94.7	93.2	93.9	117

6. Limitations and Future Work

While the proposed system performs well under controlled conditions, several limitations remain. First, the model struggles with rare or novel defect types not seen during training. This highlights the need for continual learning frameworks or unsupervised anomaly detection modules to adapt to unforeseen cases.

Second, lighting variations and occlusions introduce variability that occasionally reduces accuracy. Future iterations will explore adaptive lighting and 3D imaging to overcome these challenges. Additionally, plans are underway to deploy the system in a live manufacturing facility for longitudinal performance analysis over time.

Another future direction is expanding the system to perform root-cause analysis by linking defect patterns with specific upstream process faults, thereby enhancing not just detection but also prevention.

7. Conclusion

This study demonstrates that deep learning-based computer vision systems can effectively deliver real-time, high-accuracy defect detection in industrial settings. By leveraging a modifiedYOLOv5 model and edge AI devices, the system meets the stringent latency and precision requirements of modern assembly lines. These findings support broader adoption of AI-driven quality control, with implications for cost savings, waste reduction, and improved product consistency.

Continued research into self-adaptive models and domain adaptation techniques will be critical for future industrial applications.

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