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Visual and electrical approaches for automated verification of electronic components

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ABSTRACT

Reliable inspection and sorting of electronic components have become pivotal along the path of electronic manufacturing toward higher density and automation. Automated optical inspection systems at present depend on visual assessment methods because they do not include electrical testing capabilities, which results in a component verification reliability gap. In spite of recent advances, largely due to the fact that most automated optical inspection systems still abide by visual evaluation, verification of the actual electrical behavior of components became quite impossible. This paper is focused on bridging this gap through the introduction of a unified inspection framework whereby visual analysis is executed along with programmable electrical validation under a single automated process in conformity with Industry 4.0 practices. The system's synchronized workflow includes vision-based detection, optical character recognition, resistor color-band parsing, surface defect analysis, and electrical testing in real time. The component localization task uses YOLOv5, while EasyOCR with a convolutional neural network-long short-term memory (CNN-LSTM) structure and HSV-based segmentation delivers exact value extraction results. The testing system achieved 98.4% classification accuracy, 98.9% value recognition accuracy, and 94.9% overall sorting accuracy when tested on 3,000 photos and 400 physically inspected components at a throughput rate of seven components per minute.

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1. INTRODUCTION

The demand for faster electronics manufacturing requires highly precise and reliable quality control as component density and miniaturization increase. The verification of material and product quality used traditional visual inspection methods but manual assessment techniques now fail to meet standards because of their slow operation time and their own operator fatigue and their risk of human errors [1]–[3]. The presence of undetected defects in high-throughput environments leads to decreased yield and system reliability problems according to findings. Industry 4.0 has enabled intelligent and adaptive manufacturing through automation, real-time data exchange, robotics, and artificial intelligence (AI) [4]. Deep learning detectors that operate through YOLOv5 and YOLOv8 have proven ideal for implementing automated optical inspection (AOI) systems in electronics production [5], [6]. However, the majority of AOI pipelines are still purely visual and handle tasks such as optical character recognition-based (OCR) marking identification, surface defect detection, and color-band decoding separately [7]–[9]. This modular separation reduces the overall efficiency and fails to verify the actual electrical functionality of the components [10]. Most current techniques handle printed circuit boards (PCB) level inspection and visual sorting tasks because they lack electrical validity assurance [11], [12]. The study presents a complete visual-electrical verification system which uses deep learning vision systems and OCR-based value extraction and programmable electrical testing to create automated testing for small and medium-sized manufacturing operations. Major contributions of this work: i) The system develops a small inspection platform that validates passive and active components using YOLOv5-based vision and standard commands for programmable instruments (SCPI)-controlled inductance-capacitance-resistance (LCR) verification; ii) The system creates a hybrid pipeline by combining various technologies, such as vision, OCR, color decoding, and quantitative electrical measurement; and iii) Through experimental validation, the study shows that dual-domain verification improves classification reliability.

The architecture can support small production lines and medium production lines through its modular feeder system which enables scalability. The proposed framework specifically targets low-cost, modular automation which laboratories and small-to-medium enterprises (SMEs) can use but not high-end industrial solutions.

2. RELATED WORKS

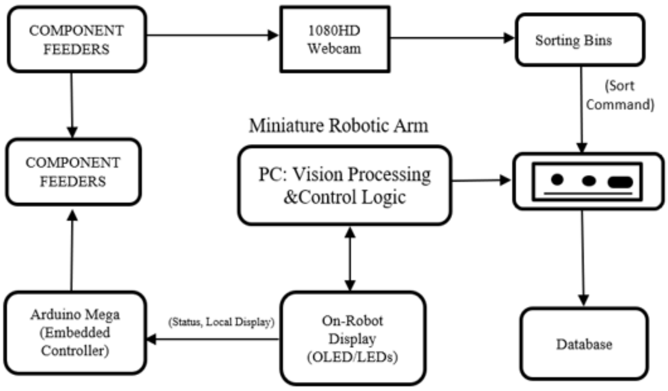
Mohsin *et al.* [13] developed an automated waste printed circuit board (WPCB) disassembly system which uses edge computing and Internet of Things (IoT) technology to achieve 94% accuracy while showing that distributed intelligence can successfully recycle electronic waste. The method works to recover components that have reached their end of life but does not function as a verification method for industrial product quality control. Murshed *et al.* [14] built a Raspberry Pi automatic level-crossing safety system which achieves 92% detection accuracy in real-time with a response time that takes less than five seconds to show how low-cost embedded vision technology can create effective safety systems. The system can process at high speed but its capacity to conduct full electronic inspection becomes limited because of its basic detection system and its restricted computing power. Petruse and Vlad [15] discovered that robot helpers enable workers to achieve better ergonomic conditions which reduce operator strain by 30% while increasing their task performance. The research proves useful for workplace improvement, but it fails to provide solutions for automated vision-based component inspection together with advanced sensing technology needs. The system designed by Sharma and Kumar [16] uses convolution neural network (CNN) technology for actual WPCB component identification which achieves 96% accuracy in controlled laboratory settings. The research needs to study how industrial environments which include dust and dark spaces and old machinery impact system performance. Sun *et al.* [17] created a thermal optimization method which improved cooling performance by 20% through their research on AI-based PCB enclosure design using simulation testing. The research study chooses to examine mechanical and thermal packaging elements instead of its two fault detection methods and electrical verification methods. Integrated verification frameworks remain essential because recent vision research and AI inspection improvements demonstrate their need according to research findings from [18], [19].

3. SYSTEM DESIGN AND METHODOLOGY

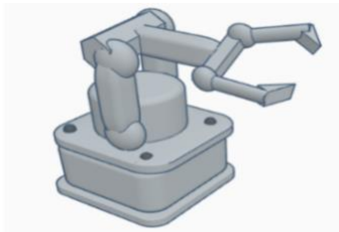
The automated visual–electrical verification platform for testing resistors and capacitors and dual inline package integrated circuits (DIP ICs) uses robotic systems together with computer vision technology and programmable electrical testing to create a complete inspection process [20]. The system consists of four components which include a high-resolution vision module and an adaptive feeder and a Cartesian robotic arm that has interchangeable end-effectors and an electrical verification test jig. The centralized control unit [21] manages all aspects of robotic mobility and image processing and measurement procedures and final sorting decisions. Figure 1 provides a comprehensive overview of the proposed automated inspection system. Specifically, the complete layout of the system appears in Figure 1(a) which shows all system components. Furthermore, Figure 1(b) illustrates the robotic manipulator equipped with a parallel gripper that is used to execute the automated pick-and-place operations.

The robotic manipulator system uses a five-axis Cartesian design with multiple gripping tools and a vibratory feeder system to perform accurate electronic component pick-and-place tasks for the mechanical subsystem operation [22]. The electrical subsystem tests IC logic functionality through two methods which include passive component impedance testing with a modular pogo-pin test jig and SCPI-controlled LCR meter [23]. The Arduino Mega tests integrated circuits through predefined test patterns while assessing resistance inductance and capacitance according to the evaluation method defined in (1). The electrical testing setup and IC verification circuit are illustrated in Figure 2. Figure 2(a) illustrates Arduino-based unit interfaced with LCD and TCS3200 sensor, while Figure 2(b) IC testing circuit illustrating input–output logic validation.

$$z = \sqrt{R^2 + \left[\omega L - \frac{1}{wC}\right]^2} \quad (1)$$

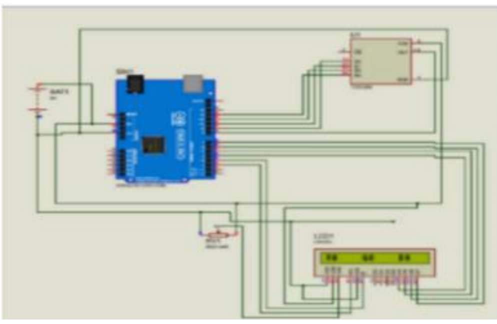


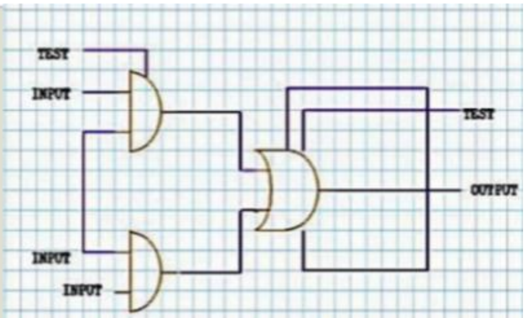
(a)



(b)

Figure 1. Overview of the proposed automated inspection system: (a) complete system architecture illustrating the integration of vision, robotic handling, and electrical verification modules; and (b) robotic manipulator with parallel gripper used for automated pick-and-place operations





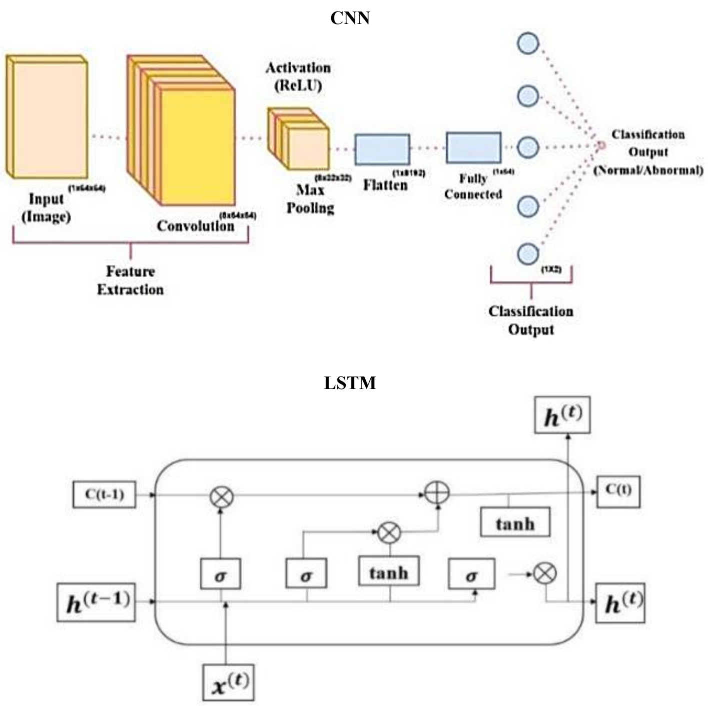
(a) (b)

Figure 2. Electrical verification module configuration: (a) Arduino-based unit interfaced with LCD and TCS3200 sensor and (b) IC testing circuit illustrating input–output logic validation

The vision subsystem includes component detection, value extraction, defect inspection based on a 1080p Logitech C920 camera with controlled LED illumination. Component detection is performed using YOLOv5m trained with more than 3,000 annotated images. Resistor values are decoded through color segmentation based on HSV mapped to EIA-96 standards [24]. Capacitor and IC recognition is performed using EasyOCR (convolution neural network-long short-term memory (CNN-LSTM)) after skew correction and contrast normalization [25]. Surface defects are assessed by performing an SSIM-based comparison with reference images (an acceptable condition will be given SSIM values of ≥ 0.85). YOLOv5 detection and EasyOCR text extraction are illustrated in Figure 3. Surface-level defects such as cracks, pin misalignment, and contamination are detected using a structural similarity index measure (SSIM) algorithm.

$$SSIM\ (x, y) = \frac{[(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)]}{(\mu_x{}^2 + \mu_y{}^2 + C_1)(\sigma_x{}^2 + \sigma_y{}^2 + C_2)} \tag{2}$$

It quantifies the similarity metrics in luminance, contrast, and structural patterns in the reference image and captured component images, shown in (2). The unified EasyOCR–YOLOv5 processing framework is shown in Figure 4.



(b)

Figure 3. Framework for component feature extraction and text recognition

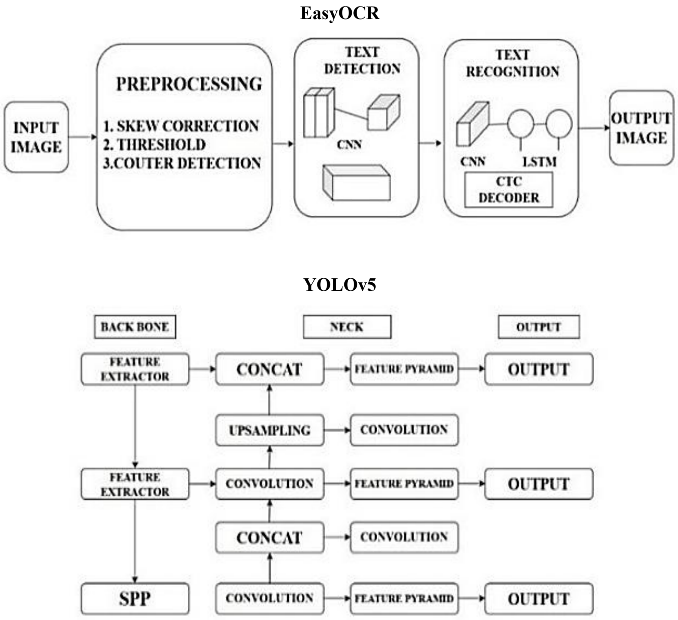


Figure 4. Integrated framework showing interaction between EasyOCR (text extraction) and YOLOv5 (object detection) for component identification

The computer vision pipeline starts with sequential component detection which is followed by preprocessing and value extraction and defect analysis work before it sends validated outputs to the central decision module. The CNN–LSTM feature extraction and sequence recognition structure is presented in Figure 5. The process of extracting resistor bands begins with HSV segmentation which uses adaptive thresholding and morphological filtering as its next step while pixel normalization in (3) enhances contrast and EIA mapping in (4) computes resistance values. PyTorch 2.1 (Python 3.10) served as the training platform for the model which used YOLOv5m for detection and EasyOCR (CNN–LSTM) for text recognition. The training process lasted for 100 epochs at a batch size of 16 while using an NVIDIA RTX 3060 (12 GB) to process 640 × 640 images with a dataset consisting of 2100/600/300 train–validation–test samples. The system provides reliable validation of component functionality.

$$P_{out}(x,y) = (P_{in}(x,y) - min(P)) \times \frac{255}{\max(P)-\min(P)} \tag{3}$$

$$R = (D_1 \times 10 + D_2) \times M \pm T \tag{4}$$

4. RESULTS AND DISCUSSION

The testing of the proposed system used mixed samples that included resistors and capacitors and DIP ICs. The framework achieved 98.4% classification accuracy and 98.9% value recognition accuracy and 94.9% overall sorting accuracy at an average throughput of seven components per minute. The research demonstrates that their proposed hybrid visual-electrical inspection method achieves successful outcomes because it combines electrical verification with visual inspection to reduce the occurrence.

4.1. Experimental setup

The prototype, depicted in Figure 5, was constructed on a 2020-series aluminum frame with modular electrical, mechanical, and visual subsystems. The motion stage employs a five-DOF Cartesian robot powered by NEMA 17 stepper motors to move quick-change grippers capable of vacuum suction and parallel-jaw. Fiducial markings and a vibratory feeder aid in determining component orientation, while a Logitech C920 HD camera with regulated illumination is used for visual examination. Electrical validation uses a SCPI-controlled Keysight U1282A multimeter to test passive components and an ESP32-based logic tester to evaluate ICs. System coordination uses UART and the RS-232 connections which is the Python control interface on industrial PC controls. The evaluation tested 3,000 labeled images and 400 physical components under different conditions according to the dataset details in Table 1.

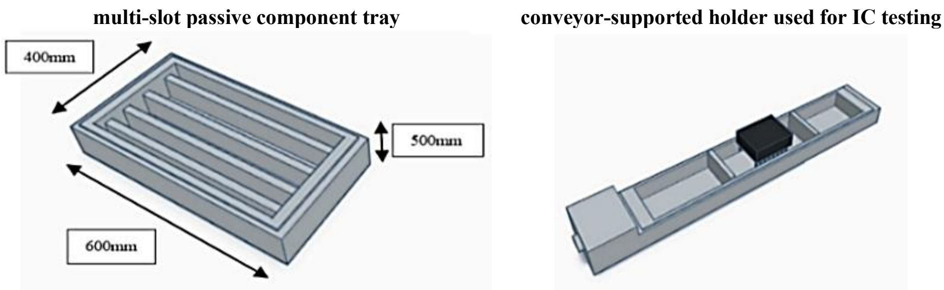


Figure 5. Prototype hardware arrangement of the inspection system

Table 1. Dataset distribution and physically tested components

Component Type	Training Images	Validation Images	Testing Images	Physically Tested Parts
Resistors	800	200	100	120
Capacitors	600	150	75	90
ICs	700	180	90	110
Total	2100	600	300	400

4.2. Performance metrics

The extensive testing process showed that all component types provide strong classification results. The YOLOv5 detector achieved 98.3% accuracy for resistors 97.6% for capacitors and 93.5% for DIP ICs with the slight reduction for ICs mainly caused by glare and pickup misalignment. The EIA-96 bands achieved 98.5% accuracy through resistor decoding which used HSV-based techniques while EasyOCR showed 97.0% accuracy for capacitor and IC marking recognition. The electrical verification process confirmed LCR parameters and IC logic functionality which resulted in 94.9% sorting accuracy. Table 2 presents complete performance metrics together with a comparison of inspection modes.

The categorization confusion matrix. It almost shows high true positive values in all the class, as seen in Figure 6. Through its three testing techniques—electrical testing, component traceability, surface irregularity detection, and optical recognition—the integrated system improves reliability. The figure illustrates prediction accuracy and misclassification patterns across different component categories

Table 2. Performance comparison of component-wise metrics and inspection modes

Category	Type/Mode	Vision Accuracy (%)	Mean Deviation (%)	Electrical Pass Rate (%)	Sorting Accuracy (%)
Component	Resistor	98.3 (value decoding)	0.8	98.5	97.0
Component	Ceramic Capacitor	97.0 (OCR)	1.2	97.0	95.5
Component	Electrolytic Capacitor	97.6 (OCR)	1.5	95.0	92.0
Component	DIP IC	96.0 (OCR)	—	96.0 (functional test)	95.0
Mode	Vision-only	—	—	—	98.4
Mode	Electrical-only	—	—	—	97.0

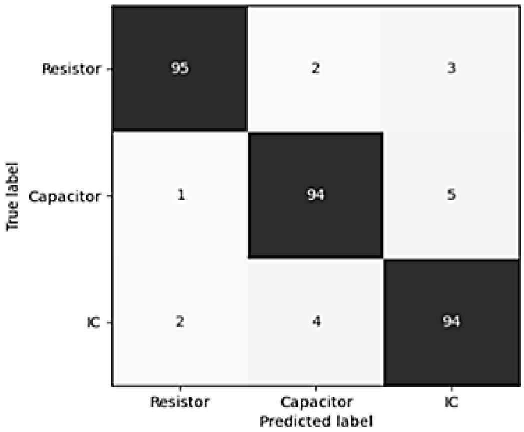


Figure 6. Performance of the vision model classification: Confusion matrix displaying prediction accuracy for IC, resistor, and capacitor categories.

Table 3 presents specific categorization metrics together with throughput characteristics for different component types. The system achieves precise color-band segmentation which enables accurate resistance measurement as shown in Figure 7 while OCR-based capacitor detection maintains its effectiveness across different font styles and lighting conditions. The most recognition errors occur because color fading and surface glare and poor print quality create visibility problems The main factors that cause recognition errors include poor IC printing which accounts for 2.5% and glare-related OCR errors which represent 2.2% according to the information presented in Table 4.

Table 3. Classification performance and throughput analysis of the proposed system

Component Type	Precision (%)	Recall (%)	F1-score (%)	Avg. Cycle Time (s)	Throughput (components/min)
Resistor	98.5	98.0	98.25	7.2	8.3
Ceramic Capacitor	97.0	96.5	96.75	8.5	7.0
Electrolytic Capacitor	96.0	95.0	95.5	—	—
DIP IC	96.5	95.5	96.0	10.1*	5.9

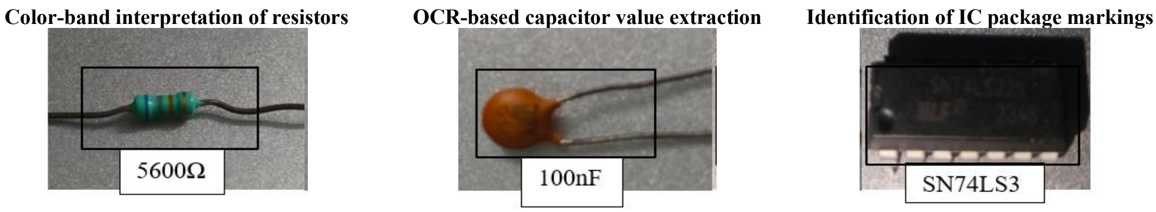


Figure 7. Results of component value and marking recognition

Table 4. Major visual and electrical error sources

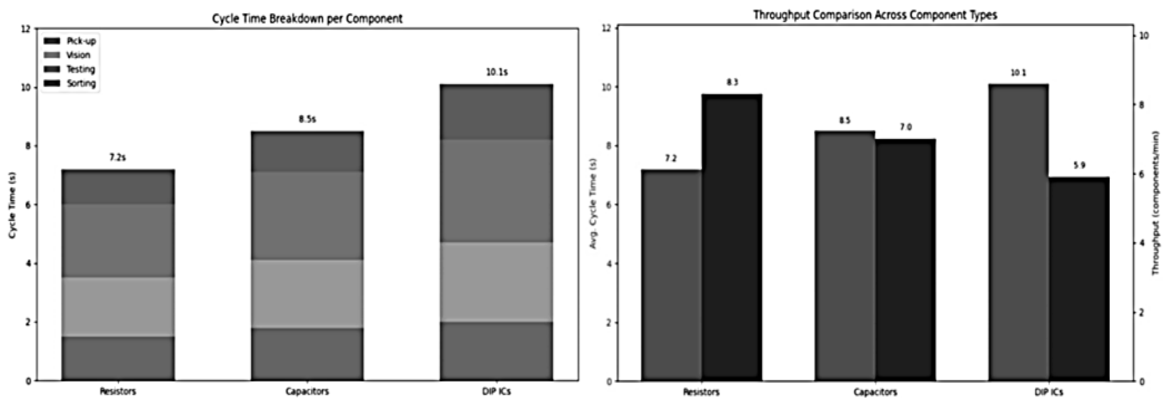
Error Source	Impact	Occurrence (%)
Faded resistor bands	Wrong value detection	1.8
Glare and reflections	OCR misreads, false negatives	2.2
Poor IC print quality	Partial/incorrect OCR	2.5
Component misalignment	Bounding box/label errors	1.5
Pogo pin inconsistencies	High contact resistance, signal noise	2.0
ESR variability in electrolytics	Capacitance deviation	2.5
Pin misalignment in ICs	Incorrect logic outputs	1.8
Signal instability	Measurement fluctuations	1.0
Loose test jig fixtures	Intermittent contact failures	1.2

Measurement of electrical parameters was automated by SCPI commands, facilitating setting impedance mode and test frequency, thereby measuring repeatability without manual intervention. The mean deviation in impedance values for 200 resistors was 0.8%, the deviations being 1.2% for ceramic capacitors and 1.5% for electrolytic capacitors, consistent with the anticipated tolerance ranges. Functionality verification of ICs using the ESP32-based logic tester provided a pass rate of 96.0% for the tests performed. The majority of electrical problems were related to contact variability and ESR which happened in small percentages and were primarily fixed by shielding and pogo-pin alignment improvements.

This function defines throughput as the reciprocal of the average cycle time and reflects the number of components processed from the minute, illustrated in (5). Thus, relating to system efficiency. The proposed system provides an affordable option for industrial use which competes with expensive inspection systems. The current throughput capacity fulfils the requirements of small and medium production facilities but advanced production lines need companies to develop better motion planning skills and parallel test execution capabilities.

$$T_p = \frac{60}{Average\ Cycle\ Time\ (seconds/component)}\ components/minute \qquad (5)$$

The cycle time for DIP ICs reaches its maximum value at 10.1 seconds while capacitors take 8.5 seconds and resistors require 7.2 seconds with testing and sorting processes consuming most of the time as demonstrated in Figure 8(a). The result shows DIP ICs produce the lowest throughput value of 5.9 components per minute while resistors create the highest throughput value of 8.3 components per minute according to the data presented in Figure 8(b). Capacitors show performance levels which fall between moderate and balanced. The proposed AOI system achieves almost double the throughput of manual inspection which processes 3 to 4 components per minute while maintaining complete reliability and traceability. The results in Table 5 show that the proposed approach adds electrical verification. To further evaluate detection efficiency, a comparative benchmarking of object detection models is presented in Table 6.



(a) (b)

Figure 8. Throughput and cycle-time evaluation of the proposed system: (a) component-wise cycle time distribution and (b) comparative throughput for DIP ICs, resistors, and capacitors

Table 5. Previous work with related systems

System description	Methodology	Accuracy (%)	Throughput	Limitations
Evaluation of PCB surface defect identification	Machine vision survey and methods [5]	Not applicable (review)	Not applicable	Review only; no testing in the real world
Identification of waste electronic components under occlusion	YOLO-based dynamic channel focusing [11]	~96.7%	High-speed detection	PCB-specific and computationally demanding
Identification of components in real time from waste PCBs	Computer vision and image processing [16]	~95% recognition accuracy	Not specified	PCB waste components only; no electrical verification
Robotic arm with TCS3200 sensor for color sorting	Microcontroller and color sensing [9]	~92% color classification	Prototype-level	Limited detection range and sensitivity to ambient lighting
Robotic pick-and-place operations using tolerance analysis	Optimization of tolerance through simulation [21]	>95% repeatability in placement	Not specified	Only simulation; no integration of real-time vision or sensors
Visual and Electrical Examination Robot for electronic parts	YOLOv5 + HSV decoding + OCR + LCR testing	98.4% (Visual), 98.9% (Value), 94.9% (Sorting)	7 components/min	Time bottleneck in the IC test cycle

Table 6. Comparative benchmarking of object detection models

Model	mAP (%)	Inference Time (ms)	GPU Memory Usage (GB)	FPS	Remarks
YOLOv5m (proposed)	84.0	27	3.2	40	Optimal speed–accuracy trade-off
YOLOv8-n	86.0	57	6.7	22	Higher accuracy but slower
EfficientDet-D0	79.0	68	5.8	18	Lower throughput
Detectron2(R-CNN)	68.0	120	7.3	9	Computationally heavy

5. SYSTEM LIMITATIONS AND FUTURE WORK

The proposed system demonstrates excellent inspection performance but it still has multiple existing deficiencies. The current prototype operates at seven components per minute which requires further optimization to achieve high-speed industrial operations. Pogo-pin contact and the current design which supports through-hole components cause the main measurement differences which require design changes to support surface-mount device SMD usage. The upcoming research will concentrate on developing parallel visual–electrical systems and bettering robotic movement control and creating contact systems that adjust to different conditions. Machines that work with conveyor systems for inspection and edge-AI acceleration will create an effective production system for smart manufacturing at high output levels. The present situation of industrial settings which operate at high-speed still encounters challenges because their systems need to scale up.

6. CONCLUSION

This work presents an automated visual–electrical verification system integrating a multi-stage AI vision pipeline with modular electrical testing for comprehensive electronic component quality control. The framework accomplishes 98.4% classification accuracy and 96% value recognition accuracy and 94.9% sorting accuracy at a throughput rate of seven components per minute through its use of YOLOv5 and HSV segmentation and EasyOCR and functional electrical validation methods. The Industry 4.0-compliant modular architecture provides cost-effective automated inspection because it enables repeated testing while reducing human errors which occur during manual inspections. The system functions as a dependable and scalable alternative to these conventional vision-only AOI systems which have limited capacity to test the ICs and assess their measurement accuracy.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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