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Through-Hole Technology (THT) Component Sorting and Fault Detection Using Image Processing

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Abstract

The increasing volume of electronic waste (e-waste) presents challenges in efficient component recovery, particularly in developing countries such as the Philippines. This study proposes an automated system for Through-Hole Technology (THT) component sorting and fault detection to address the limitations of manual visual inspection and multimeter-based testing. The system integrates a Raspberry Pi 5 and an Arducam 64MP Pi Hawk-eye camera to perform image-based component recognition using YOLOv8 and OpenCV for identifying resistors, capacitors, and LEDs. An ATmega328P microcontroller manages dedicated test circuits for electrical validation of component functionality. Experimental results show identification accuracies of 100% for LEDs, 82.5% for resistors, and 65–75% for capacitors, while fault detection achieved 93% accuracy for resistors and 90% for LEDs, comparable to manual multimeter testing. The proposed system also doubled sorting speed for small batches. Although limitations were observed in capacitor polarity detection, the modular design demonstrates a scalable framework for improving automated component recovery and supporting sustainable e-waste management.

Keywords: Through-Hole Technology (THT), Image Processing, YOLOv8, OpenCV, Fault Detection

INTRODUCTION

The rapid growth of electronic waste (e-waste) has become a major environmental and public health concern worldwide. In the Philippines, approximately 32,664 metric tons of e-waste were generated in 2019, making the country one of the leading producers of e-waste in Southeast Asia. Improper disposal practices contribute to environmental degradation, including water pollution and biodiversity loss, while limited public awareness and inadequate recycling infrastructure continue to hinder effective waste management (Ong, 2023). Although initiatives involving the Philippine Ecological Solid Waste Management Act and the United Nations Industrial Development Organization (UNIDO) have promoted the establishment of e-waste treatment facilities, challenges in developing sustainable recycling systems remain.

Recent studies have emphasized the recovery and reuse of valuable materials and components from waste printed circuit boards (WPCBs). Unlike conventional recycling methods that primarily extract metals such as copper and gold, advanced approaches focus on dismantling and sorting components to maximize material recovery and improve sustainability (Maurice et al., 2021). Efficient component identification and management are particularly important because electronic components exist in large quantities and possess diverse characteristics that complicate storage and utilization (Uysal, 2025).

Sorting and testing electronic components remain labor-intensive processes in educational laboratories, repair shops, and manufacturing industries. Conventional methods rely on manual visual inspection and multimeter-based measurements, making them time-consuming and prone to human error. Sequential processing further limits productivity, particularly in environments requiring rapid handling of diverse components (Ravindran and Ramesh, 2020). In practice, repair shops, electronics retailers, and engineering students often avoid testing and organizing individual through-hole technology (THT) components because the process is tedious and time-consuming. Consequently, reusable components are frequently discarded or remain unsorted, contributing to resource wastage and increasing e-waste management.

Commercial component testers have improved the identification of capacitors, diodes, and transistors, providing measurement accuracy comparable to standard multimeters. However, these systems still require manual placement of components and exhibit limitations when dealing with small-value components, thereby restricting their applicability in automated sorting applications (KAI, 2015). Similarly, modern testing approaches, including in-circuit testing and advanced component analyzers, enhance fault detection accuracy but continue to depend on human intervention during component handling (Abbas, 2024).

Several studies have explored automated component recognition techniques to reduce electronic waste and improve sorting efficiency. Labade et al. (2014) demonstrated resistor classification using image-processing techniques such as Gaussian filtering, k-means clustering, and Laplacian operators. More recent developments in automated inventory management and tracking systems have shown that intelligent solutions can significantly reduce human error and improve component handling efficiency (Salih et al., 2023). Nevertheless, most existing systems are limited to single-component classification or still require manual testing procedures.

To address this gap, this study proposes an automated system for the identification, fault detection, and sorting of THT electronic components, specifically resistors, capacitors, and LEDs. By combining image-based component recognition, automated electrical testing circuits, and mechanical sorting mechanisms, the system aims to improve efficiency, reduce human error, and support sustainable electronic component recovery. The research is guided by the following objectives:

1. Develop an automated system to accurately detect and classify faulty electronic components, ensuring quality control, reducing production defects, and minimizing e-waste.

2. Implement an image-based identification algorithm to differentiate component types, reducing the need for manual inspection.

3. Integrate specialized test circuits for precise fault detection, improving accuracy and speed in component testing.

4. Automate component placement and sorting based on testing outcomes, reducing the time-consuming nature of the manual method and labor intensity.

LITERATURE REVIEW

The Global and Local Challenge of E-Waste Waste Electrical and Electronic Equipment (WEEE), or e-waste, is currently the fastest-growing waste stream globally (Procedia Environmental Sciences, 2016). In 2014, global generation reached approximately 41.8 metric kilotonnes (Procedia Environmental Sciences, 2016). In the Philippines, the management of this waste is governed by the Ecological Solid Waste Management Act of 2000 (RA 9003), which mandates the diversion of solid waste through reuse and recycling to protect human health and the environment (EX Corporation, 2008). Despite these regulations, many Printed Circuit Boards (PCBs) end up in the informal sector, where "malpractices" such as open burning and acid leaching are used to recover metals, leading to toxic residues in landfills (Procedia Environmental Sciences, 2016).

Traditional recycling frameworks often focus on bulk material recovery, yet literature suggests a significant opportunity in the reuse of individual Electronic Components (EC). Research indicates that when electronic equipment becomes obsolete, the internal components, specifically resistors, transistors, microcontrollers, and integrated circuits often remain "unaltered" and functional (Procedia Environmental Sciences, 2016). Also, Electronic components are rich in precious metals such as gold, copper, platinum, and palladium (Okoro, 2019). Recovering these through reuse or targeted recycling reduces the energy-intensive need for destructive mining and decreases greenhouse gas emissions (Okoro, 2019).

Existing commercial recycling processes primarily utilize physical and chemical methods for bulk extraction. In the Philippines, industry leaders like HMR Envirocycle engage in manual dismantling of e-items (EX Corporation, 2008). However, these current methods are often labor-intensive (manual sorting), which limits the ability to efficiently identify and preserve functional Through-Hole Technology (THT) components for the circular economy (Procedia Environmental Sciences, 2016).

The use of image processing to automate the sorting of THT components and detect faults is supported by several foundational needs identified in literature. Status-Based Identification: Literature mandates that electronic components be reused "based on their status" (Procedia Environmental Sciences, 2016). Image processing can provide a non-destructive primary filter to assess the physical condition of a component, detecting visible faults such as burn marks or physical degradation before components move to intensive electrical testing. Automated systems can be trained to recognize the visual signatures of functional components. (Procedia Environmental Sciences, 2016).

Integrating image processing into e-waste management shifts the paradigm from simple base metal recovery to a circular economy model that preserves the higher functional and economic value of electronic components (Procedia Environmental Sciences, 2016; Okoro, 2019).

METHODS

This study employed a technological applied research to design, develop, and evaluate an automated system for identifying, testing, and sorting Through-Hole Technology (THT) electronic components. The research focused on developing a functional prototype that integrates image processing, electrical testing, and automated mechanical sorting to improve the efficiency of reusable component recovery from electronic waste.

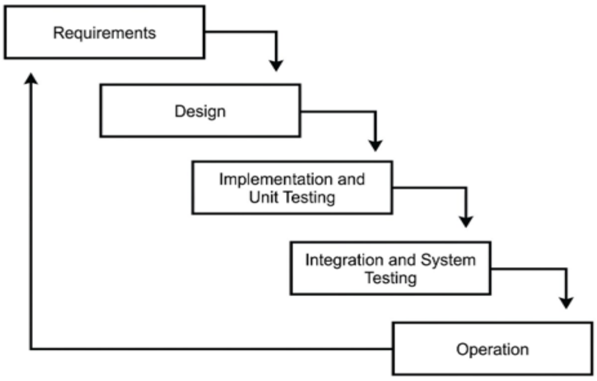

Figure 1
Incremental Model

The system was developed using an incremental development model, as illustrated in Figure 1. This model divides system development into sequential phases, where each module is developed, tested, and validated before integration with other components. Such an approach enables early detection of design issues, facilitates iterative refinement, and ensures reliable system integration.

The system architecture, as shown in Figure 2, consists of four main modules: power supply, component detection, separation and sorting, and circuit testing.

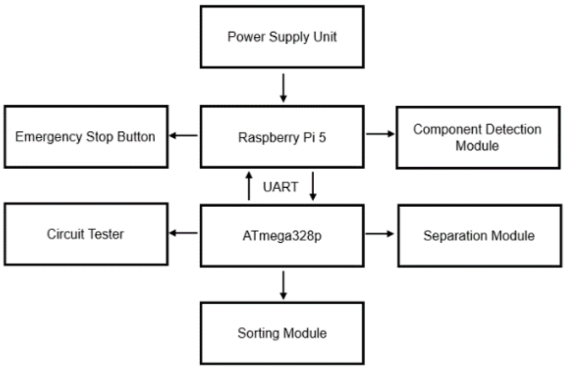

Figure 2
System Architecture

A DC-DC buck converter regulates the system power supply to maintain stable voltage. The component detection module utilizes a Raspberry Pi 5 connected to an Arducam Pi Hawk-eye camera and touchscreen interface to capture component images and perform classification using image processing algorithms.

The separation module, controlled by an ATmega328P microcontroller, employs a vibration motor driven by a relay and L298N motor driver to ensure that components enter the system individually. The sorting module uses a NEMA 17 stepper motor with a DRV8825 driver, a VL53L1X proximity sensor, and a PCA9685 servo controller to position and sort components into designated bins.

A separate circuit tester module, also managed by an ATmega328P, measures electrical properties such as resistance and capacitance to determine component functionality. The integration of image recognition and electrical testing enables automated identification and classification of THT components.

The operational workflow is illustrated in Figure 3. The process begins with system initialization followed by the placement of components such as resistors, capacitors, and LEDs in the input tray. The components will pass through the separation module to ensure proper component positioning for inspection. The camera module captures images of each component and image processing techniques are then employed to identify the component type and estimates its nominal value based on visual features.

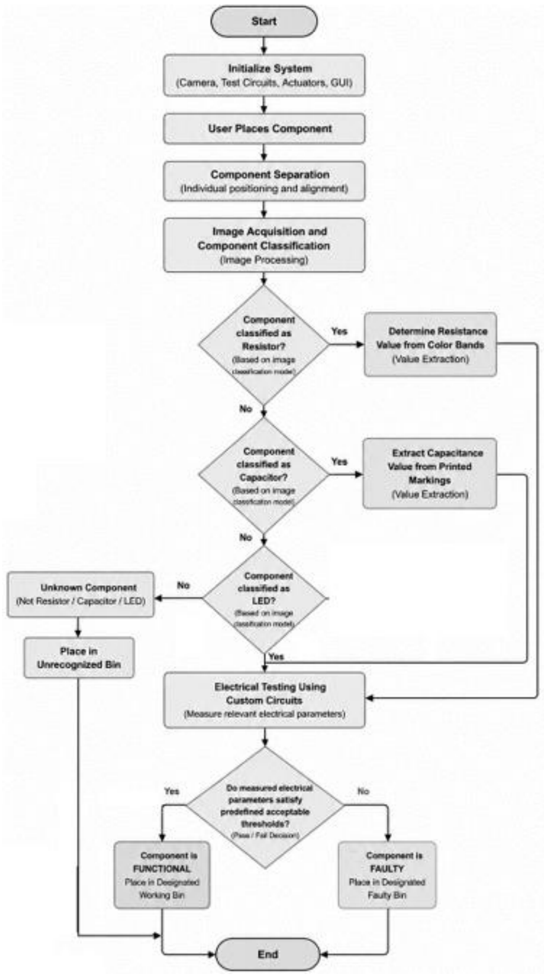

Figure 3
Process Flowchart

If it classifies the component as a resistor, it will then determine the value through color-band recognition. If the component is a capacitor, its value is extracted from the printed markings. Components that do not match any of the predefined categories are automatically directed to the unrecognized bin.

After the component identification and value extraction, the components undergo electrical evaluation using custom fault detection circuits to determine their operational condition. Functional components are sorted into the designated working bin for reuse while defective one is separated into designated faulty bin for disposal.

A custom dataset consisting of 4,409 images and 56,525 bounding boxes across 39 classes was developed to train the YOLOv8 architecture for THT sorting and defect classification. The annotated dataset was divided into training (70%), validation (20%), and testing (10%) subsets while maintaining representative samples from all 39 component classes. The YOLOv8 object detection network was trained using input images resized to 640 x 640 pixels. The core architectural and dataset distribution metrics are summarized in Table 1.

Table 1
Dataset Characteristics and YOLOv8 Training Configurations.

Parameter / Metric	Design Specification
Dataset Scale	4,409 images / 56,525 annotations
Component Classes	39 distinct categories (including nominal and faulty)
Acquisition Resolution	640 x 480 pixels
YOLOv8 Input Resolution	640 x 640 pixels
Dataset Split (Train / Val / Test)	70% / 20% / 10% (Class-representative)
Average Object Density	12.8 objects per image (range: 2–21)

The prototype design, shown in Figure 4, consists of a vibratory bowl feeder, camera module, test circuit module, and servo-driven sorting mechanism. The vibratory bowl feeder ensures the sequential separation and delivery of individual components, enabling consistent positioning for subsequent inspection. As each component passes beneath the camera module, image acquisition and visual identification are performed to determine the component type and extract relevant characteristics. Based on the classification results, a servo-actuated mechanism routes the component to the corresponding test circuit for electrical validation. The system evaluates the operational condition of the component and performs automated sorting accordingly. Functional components are directed to the designated working bin, while defective components are separated into a faulty bin. Measurement results and system status are displayed through an LCD-based graphical user interface (GUI) to provide real time feedback to the user.

Figure 4
3D Model

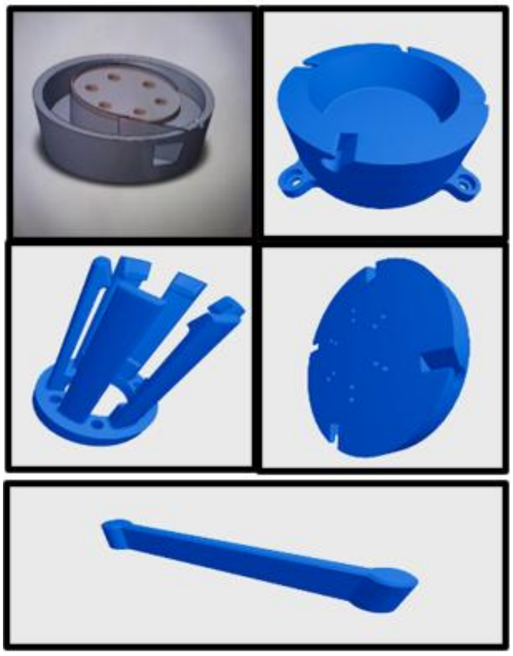

Figure 5
Separation Module

The separation module, shown in Figure 5, is designed to regulate the flow of components and ensure their individual presentation to the sensing and testing stages. The module consists of a vibratory bowl feeder and a set of custom-designed 3D-printed guiding components that facilitate the orderly movement and orientation of through-hole components. By preventing component accumulation and overlap, the separation mechanism minimizes measurement errors and enhances the reliability of the image acquisition and electrical testing processes.

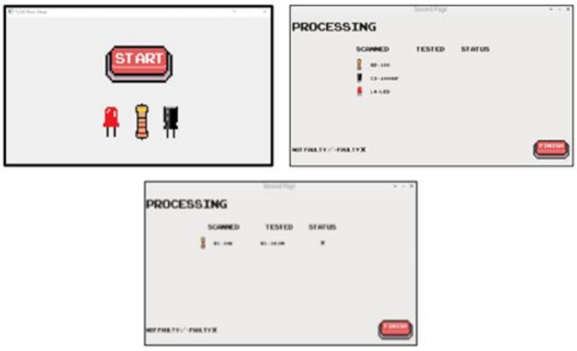

Figure 6
GUI of the System

The graphical user interface (GUI), shown in Figure 6, serves as the primary platform for user interaction and system monitoring. It displays real-time system status indicators, component identification results, and electrical measurement data, allowing users to track the progress and performance of the sorting and fault detection process. In addition, the GUI provides control options for system operation and configuration, enabling efficient user supervision and facilitating seamless interaction with the automated system.

System performance was evaluated using several quantitative metrics.

$$x = \frac{\text{CR}}{\text{TR}} \text{ X } 100 \qquad (1)$$

$$Error = 100\% - X \qquad (2)$$

$$Separation\ Accuracy = \frac{\text{Correctly Separated}}{\text{Total Components Fed}} \text{ X } 100\% \qquad (3)$$

$$Avg.Time = \frac{\text{Total Time Taken}}{\text{Total Components Tested}} \qquad (4)$$

Figure 7
Formulas

The accuracy of the component identification module was calculated by the formula, shown in Figure 7, (X) = (CR/TR) × 100%, where CR is the number of correctly identified components, and TR is the total number of components testing.

An additional measure was calculated as Error = 100% – X, as it quantifies the percent of components that were incorrectly classified or could not be classified at all.

In order to measure the separation module's performance, a Separation Accuracy (S) = (CS/TS) × 100%, where CS = correctly separated components and TS = total components presented to the vibratory bowl feeder was evaluated.

In the evaluation of component identification unit testing, average time per second will be defined as Average Time = Total time taken / Total components tested.

Sorting performance was assessed by comparing manual sorting and automated sorting using identical component sets. Fault detection accuracy was validated by comparing the results of the automated circuit tester with measurements obtained using a standard digital multimeter, which served as the reference instrument.

A dataset of THT components including resistors, capacitors, and LEDs was prepared for system evaluation. The dataset included both functional and intentionally faulty components to test classification reliability. Each component underwent image-based identification, automated electrical testing, and sorting.

The collected data included identification accuracy, separation accuracy, sorting time, and fault detection performance.

The developed system was evaluated using the ISO/IEC 25010:2012 Product Quality Model, which provides a standardized framework for assessing software and system quality. The evaluation focused on four key characteristics: functional suitability, performance efficiency, reliability, and safety. These criteria were used to assess technical attributes such as component identification accuracy, sorting speed, electrical validation consistency, and system durability.

Evaluation was conducted by domain stakeholders, including electronics technicians, engineers, and electronic component retailers, who possess practical experience in component testing and handling. Participants assessed the system using a structured questionnaire based on ISO/IEC 25010 evaluation criteria. Responses were recorded using a four-point Likert scale, enabling the collection of quantitative feedback for performance assessment and system improvement.

For performance validation, a dataset consisting of Through-Hole Technology (THT) components, including resistors, capacitors, and LEDs, was prepared. The dataset included both functional and intentionally faulty components to evaluate identification accuracy, separation performance, sorting speed, and fault detection reliability. Automated circuit tester measurements were also compared with readings from a standard digital multimeter, which served as the reference instrument for electrical validation.

Ethical considerations were observed throughout the evaluation process. Participation of evaluators was voluntary, and all participants were informed of the purpose of the study prior to providing feedback. No personally identifiable information was collected, and responses were recorded anonymously to ensure confidentiality and data privacy. The evaluation focused solely on system functionality and usability, posing no physical or psychological risk to participants, and all collected data were used exclusively for research purposes.

RESULTS AND DISCUSSION

The researchers developed The Through-Hole Technology (THT) Component Sorting and Fault Detection System. Though system testing was made to ensure its functionality. It was further evaluated by experts for its acceptability in terms of its functionality, efficiency, reliability and safety.

Unit testing results (Table 2) compare manual detection and image processing for LEDs, resistors, and capacitors. Manual detection achieved 100% accuracy for LEDs and capacitors, while resistors averaged 90%, with processing times ranging from 2 to 21 seconds. Image processing maintained high accuracy for LEDs (100%) and resistors (90–95%) with significantly reduced processing times (2–3 seconds).

Table 2

Component Detection Module Unit Testing

Methods	Component Types	Component Quantity	Expected Values	Accuracy (%)	Avg. Time (sec)
Manual Detection	LED	5	Red	100%	2 sec
		5	Blue	100%	2 sec
		5	Green	100%	2 sec
		5	White	100%	2 sec
	Resistor	10	10R – 470R	90%	18 secs
		10	510R – 10K	90%	20 secs
		10	20K – 1M	90%	21 secs
	Capacitor	5	0.22µF – 2.2 µF	100%	3 secs
		5	4.7 µF – 33 µF	100%	3 secs
		5	47 µF – 470 µF	100%	3 secs
	Faulty	5	N/A	90%	4 secs
	Unknown	5	N/A	90%	4 secs
Image Processing	LED	5	Red	100%	2 secs
		5	Blue	100%	2 secs
		5	Green	100%	2 secs
		5	White	100%	2 secs
	Resistor	10	10R – 470R	95%	3 secs
		10	510R – 10K	95%	3 secs
		10	20K – 1M	90%	3 secs
	Capacitor	5	0.22 µF – 2.2 µF	70%	3 secs
		5	4.7 µF – 33 µF	65%	3 secs
		5	47 µF – 470 µF	75%	3 secs
	Faulty	5	N/A	90%	3 secs
	Unknown	5	N/A	90%	3 secs

However, capacitors showed lower accuracy (65–75%), indicating challenges in automated visual identification due to reflective surfaces and subtle markings. Unlike the standardized color bands on resistors, capacitor specifications rely on alphanumeric text printed on cylindrical bodies. This geometry introduces severe specular reflections, illumination sensitivity, and rotational occlusion of the polarity stripe, causing conventional image processing and OCR templates to fail when component orientation is inconsistent. Automated optical inspection (AOI) studies similarly report that capacitor recognition accuracy is highly dependent on viewing angle and component orientation, necessitating more advanced recognition methods than simple template matching or OCR. (Fang, 2020)

Table 3 presents batch-based separation testing using manual sorting and a vibrating bowl feeder. Manual sorting maintained 100%

accuracy across all batch sizes but required progressively longer processing times (10–20 s). The vibrating bowl feeder was faster (6–15 s) but accuracy declined with batch size (100% for 3 components, 70% for 10).

Table 3
Separation Module Testing

Methods	Batch Size	Correctly Separated	Accuracy (%)	Error (%)	Avg. Time (sec)
Manual Sorting	3	3	100%	0%	10 secs
	5	5	100%	0%	15 secs
	10	10	100%	0%	20 secs
Vibrating Bowl Feeder	3	3	100%	0%	6 secs
	5	4	80%	20%	12 secs
	10	7	70%	30%	15 secs

Automated sorting using a servo motor (Table 4) achieved 100% accuracy for small quantities (10 components) but declined to 70% for 30 components, whereas manual sorting remained consistently accurate. While servo-driven sorting improved throughput for small batches, larger quantities revealed limitations due to component accumulation, mechanical misalignment, or timing errors.
These findings are consistent with industrial robotic sorting studies, which show that increased throughput often reduces accuracy without adaptive feedback mechanisms (Patel et al., 2019).

Table 4
Sorting Module Testing

Methods	Components Quantity	Correctly Sorted	Accuracy (%)	Error (%)	Avg. Time (sec)
Manual Sorting	10	10	100%	0%	10 secs
	20	20	100%	0%	15 secs
	30	30	100%	0%	20 secs
Servo Motor	10	10	100%	0%	9 secs
	20	16	80%	20%	13 secs
	30	21	70%	30%	17 secs

Table 5 compares traditional multimeter testing with the automated circuit tester. Multimeter accuracy was higher (resistors 98%, LEDs 94%, capacitors 90%) and faster (4 s per measurement). The automated tester achieved competitive results for resistors (93%) and LEDs (90%) but could not reliably test capacitors due to polarity and mechanical orientation challenges.

The circuit tester's inability to evaluate capacitors stems from two fundamental challenges: First, the software complexity required to bypass electrolytic capacitor polarity during testing as these components require proper charging before capacitance measurement Second, mechanical limitations in consistently orienting polarized capacitors for proper contact, as random orientation during feeding prevents reliable testing (Common Issues with Capacitors and How to Fix Them, 2025).

Table 5
Fault Detection Module Testing

Methods	Component	Expected Values	Accuracy (%)	Error (%)	Avg. Time (sec)
Multimeter	Resistor	10R – 1M	98%	2%	4 secs
	Capacitor	0.22 µF – 1000 µF	90%	10%	4 secs
	Led	1.5V – 3.9V	94%	6%	4 secs
Circuit Tester	Resistor	10R – 1M	93%	7%	6 secs
	Capacitor	0.22 µF – 1000 µF	--	--	--
	Led	1.5V – 3.9V	90%	10%	6 secs

Experts assessed functionality, efficiency, reliability, and safety (Table 6). The system scored highly for efficiency (95.83%) and safety (91.67%), with slightly lower reliability (83.33%) due to occasional feeding or alignment errors.
These results support hybrid automation-human approaches, especially for critical components prone to misalignment or visual misreading (Zhang et al., 2022).

Table 6
Evaluation of Experts

Criteria	Equivalent Percentage	Verbal Interpretation
Functionality	85.42	Functional
Efficiency	95.83	Highly Efficient
Reliability	83.33	Reliable
Safety	91.67	Highly safe

The Through-Hole Technology (THT) Component Sorting and Fault Detection System demonstrated high performance, achieving 100% accuracy in LED detection, 82.5% for resistors, and 70% for capacitors strongly demonstrates the feasibility of AI-assisted component recognition. The system improved the efficiency by doubling the sorting speed for small batches compared to manual method, reducing the time and labor required for component sorting and recovery. Fault detection for resistors (93%) and LEDs (90%) was comparable to multimeter measurements, highlighting the system's reliability and potential to reduce diagnostic time from hours to minutes, supporting sustainable e-waste management. Limitations included reduced capacitor testing accuracy due to polarity and alignment issues, declining sorting accuracy for larger batches, and decreased feeder reliability with higher component volumes. The system's modular design provides a scalable prototype and can be deployed in a resource-limited workshops supporting the establishment of low-cost and accessible e-waste processing solutions. The system contributes to sustainable e-waste management reuse and recirculation of functional components that would otherwise be discarded. By extending THT component lifespan and reducing the dependence on newly manufactured parts. The system supports circular economy principles, minimizes electronic waste generation and helps conserve raw materials and energy associated with component production.

Conclusion. This study developed and evaluated an automated Through-Hole Technology (THT) component sorting and fault detection system that integrates image processing, electrical testing, and mechanical sorting to address inefficiencies in manual recovery practices. Guided by four objectives, the system successfully demonstrated automated identification of resistors, capacitors, and LEDs, fault detection through custom circuits, and automated placement into designated bins. Results showed high accuracy for LEDs and resistors, competitive fault detection compared to multimeter testing, and improved sorting speed for small batches, though capacitor recognition remained limited due to polarity and orientation challenges. These findings highlight both the promise and current constraints of AI-driven component recovery. By reducing reliance on manual inspection, the system advances quality control, minimizes production defects, and supports sustainable e-waste management by enabling reuse of functional components. While scalability issues emerged with larger batches, the modular design provides a foundation for adaptive improvements such as guided alignment and feedback mechanisms. Overall, the prototype demonstrates that integrating image-based recognition with electrical validation can significantly enhance efficiency, reliability, and sustainability in component recovery, offering a practical pathway toward circular economy practices in electronics and contributing to reduced environmental impact.

Recommendation. Future work should prioritize enhancing both the image processing and hardware subsystems to improve the accuracy and reliability of THT component sorting and fault detection. For capacitor inspection, optical polarity verification using image preprocessing techniques such as adaptive thresholding, edge detection, and color segmentation should be integrated to accurately identify polarity markings. To increase inspection consistency, a guided alignment mechanism or servo-controlled positioning fixture should be implemented to ensure that components are presented to the vision system in a uniform orientation prior to image acquisition. On the hardware side, the feeder mechanism should be redesigned with anti-jamming features, vibration-assisted feeding, and closed-loop servo control to improve component handling reliability. Additionally, the system can be expanded to support Surface-Mount Technology (SMT) components through higher-resolution imaging and precision pick-and-place mechanisms.

Author contributions. Asil Kastle S. Dela Cruz: conceptualization, system design, supervision, institutional ethics, analysis, revision of the manuscript, and compliance with journal formatting standards | Kristine E. Pineda: conceptualization, system design, supervision, manuscript drafting and revision | Gabriel Anthony Manlutac: conceptualization, software and hardware design, manuscript drafting and revision | Kyle Francis P. Pantig: software and hardware design, development and implementation | Nathaniel B. Pangalinan - software and hardware development and implementation | Cris Jaylord T. Menodza - data collection, unit testing | John Louie C. Manalang - data collection, unit testing.

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Data availability statement. All data supporting the findings of this study are included within the manuscript and its supplementary materials.

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