International Journal of Advances in Applied Sciences (IJAAS)
Vol. 14, No. 4, December 2025, pp. 1155~1165
ISSN: 2252-8814, DOI: 10.11591/ijaas.v14.i4.pp1155-1165

Design and implementation of an internet of things-based automatic waste sorting system

Akhmad Taufik[1,3], Paisal[1,3], Muhammad Ruswandi Djalal[2,4], Zahran Atha Dillah[1,3], Haryono Ismail[1,3]
[1]Department of Mechanical Engineering, Faculty of Mechatronics Engineering, Politeknik Negeri Ujung Pandang, Makassar, Indonesia
[2]Department of Mechanical Engineering, Faculty of Energy Engineering, Politeknik Negeri Ujung Pandang, Makassar, Indonesia
[3]Department of Mechanical Engineering, Centre for Mechatronics and Control Systems (CMCS), Politeknik Negeri Ujung Pandang, Makassar, Indonesia
[4]Department of Mechanical Engineering, Center for Sustainable Energy and Smart Grid Application (CoSESGA), Politeknik Negeri Ujung Pandang, Makassar, Indonesia

Article Info

Article history:

Received Jul 8, 2025
Revised Oct 19, 2025
Accepted Nov 4, 2025

Keywords:

Automation
Internet of things
Real-time monitoring
Smart sorting
Waste management

ABSTRACT

This paper presents the design and development of an internet of things (IoT)-based automatic waste sorting system that classifies waste into four categories: organic, non-organic, metal, and others. The system integrates an Arduino Mega for control, multiple proximity sensors (inductive, capacitive, and infrared), and ultrasonic sensors for level detection, and a NodeMCU ESP8266 for real-time monitoring via the Blynk platform. A total of 100 tests (25 per bin) were conducted. Classification success rates were 92% (metal), 80% (inorganic), 84% (organic), and 100% (others), resulting in an overall accuracy of 89%. The main contribution is a combined automatic sorting and IoT monitoring framework suitable for campus-scale deployment.

Corresponding Author:

Akhmad Taufik
Department of Mechanical Engineering, Faculty of Mechatronics Engineering
Politeknik Negeri Ujung Pandang
Makassar, Indonesia
Email: akhmad_taufik@poliupg.ac.id

1. INTRODUCTION

The motivation for this project arises from the serious challenges faced in waste management in Indonesia. Despite various initiatives, such as waste-to-energy (WTE) plants and the recycling of materials like glass, paper, and metal, waste management in Indonesia still faces significant obstacles [1]. Improperly managed waste leads to environmental pollution, making collective awareness and community involvement crucial for fostering a culture of cleanliness, which should be an integral part of Indonesia's identity and character [2]. Schools are among the largest waste producers, along with markets, households, industries, and offices [3]. Waste accumulation in non-standard or illegal landfills results in soil and water pollution [4].

Currently, waste management poses a challenge for both developing and developed countries. Slow transportation of waste from temporary disposal sites to final disposal sites using garbage trucks can lead to waste accumulation. Therefore, a system is needed to promptly notify officers to empty full trash bins and transport the waste to the final disposal site [5]. By utilizing sensor technology and automation systems, this trash bin simplifies the waste sorting process. Additionally, the project incorporates internet of things (IoT) technology to enhance the involvement and monitoring of waste management officers. Through an integrated trash bin capacity monitoring system connected to a smartphone, individuals can easily check whether a trash bin is full or has available space. IoT is a concept that enables physical devices to connect to the internet, collect data, and act on that data [6]–[8]. Devices connected to the IoT are referred to as smart objects [9], [10].

Some applications of IoT technology in waste management systems include a study [11] that discusses waste management in urban areas and proposes an IoT-based smart waste management system for homes affected by coronavirus disease 2019 (COVID-19) in India. The implementation of this system improves waste management by creating a sterile environment and enhancing comfort during the pandemic. The researcher [12] examines the impact of IoT technology and environmental monitoring systems on waste reduction in the food and beverage sector in Indonesia. The results offer valuable insights for industry stakeholders and policymakers aiming to enhance sustainability measures within the Indonesian food and beverage industry. In paper [13], a smart waste management model for smart cities was developed using two technologies: IoT and a fuzzy inference system. This model aims to provide an ideal waste management solution. The implementation results indicate that the system can read, collect, and process information intelligently through a fuzzy inference engine, which dynamically determines how to manage waste collection. Additionally, remote IoT waste monitoring can be conducted in real time using an Android application. The researcher [14] discusses the optimization of waste management as part of efforts to establish a smart eco campus through the application of highly efficient, effective, and user-friendly wireless communication technology. IoT applications serve as tools to raise awareness about the importance of waste sorting, helping to maintain cleanliness in the campus area. As shown in [15], the collection and decomposition of waste in an intelligent manner within IoT-based households aims to maximize the benefits of waste while efficiently minimizing actual waste.

However, most prior works remain limited in scope, either by focusing on monitoring only or by restricting sorting to two categories. For example, [16] presented a NodeMCU IoT-based prototype with HC-SR04 and proximity sensors that could only distinguish between metal and non-metal waste, more recent small-scale systems have likewise targeted binary tasks. In particular, [17] developed an IoT-enabled sorter that provided remote monitoring but was limited to organic and non-organic classification, while [18] demonstrated a proximity sensor-based organic and non-organic classification without networked telemetry. Other IoT studies emphasized either monitoring for hygiene during COVID-19 [11], sustainability in the food and beverage industry [12], smart city optimization using fuzzy inference [13], eco campus awareness [14], or household-level IoT decomposition [15].

Unlike these works, the present study advances the field by integrating multi-sensor material classification (inductive, capacitive, and infrared proximity sensors), ultrasonic level detection, and mechanical actuation (servo and stepper motors with automatic bin locking), combined with real-time IoT monitoring via NodeMCU and Blynk. The system sorts waste into four categories (organic, non-organic, metal, and others) and was experimentally validated in 100 trials, achieving 89% overall accuracy. This combination of extended material classification, practical hardware routing, and campus-ready IoT visualization distinguishes the proposed system from prior monitoring-only and limited sorting approaches. Beyond device-level innovation, the proposed system is designed to support operational integration with campus or municipal waste-management workflows by providing real-time fill-level telemetry and routing logs that can inform collection scheduling and resource allocation. Such data-enabled integration can help align the device with local waste-reduction policies and source-segregation programs.

2. METHOD

The automatic waste sorting system developed in this study integrated multiple sensing modalities, microcontrollers, actuators, and an IoT monitoring module to enable on-device material classification and continuous bin-level monitoring. This integrated architecture allows each subsystem, ranging from proximity-based material detection to mechanical routing and ultrasonic-based capacity measurement, to operate in a coordinated and repeatable manner throughout the sorting cycle. Furthermore, the methodical structure of this section outlines the component specifications, dataset construction, calibration and thresholding procedures, testing protocol, IoT communication workflow, and reliability considerations, ensuring that the overall system can be reproduced, evaluated, and improved in future research.

2.1. Hardware configuration and specifications

Table 1 summarizes the main hardware components, typical model examples, quantities used in the system, operating voltage, and brief notes on their function. The wiring and power schematic of the system is shown in Figure 1, illustrating the interconnection between sensors, actuators, and microcontrollers. Figure 2 provides an overview of the assembled IoT-based automatic waste sorting system, showing the sensor chamber, control electronics, and four collection bins. Implementations combining inductive and capacitive proximity sensors for on-device sorting have been demonstrated in recent small-scale sorter designs, supporting the sensor choices adopted in the present system [19], [20].

Table 1. main hardware components

Component	Model	Qty	Operating voltage	Notes
Controller	Arduino Mega 2560 (ATmega2560)	1	5 V	Primary control and actuator interface
IoT module	NodeMCU (ESP8266)	1	3.3-5 V	Wi-Fi telemetry to Blynk/dashboard
Inductive proximity sensors	LJ12A3-4-Z/BY	6	6-36 V	Metal detection (nominal sensing ≈4 mm)
Capacitive proximity sensors	LJC18A3-H-Z/BX	6	6-36 V	Organic/dielectric detection
Infrared reflective sensors (IR)	E18-D80NK	7	5 V	Optical cues for non-metallic items (adjustable threshold)
Ultrasonic sensors	HC-SR04	8	5 V	Level and presence detection; range 2-400 cm; full threshold ≤15 cm
Servo motors	MG996R	6	5 V	Front door servos, top cover, disposal mechanism
Stepper motor+driver	NEMA-17+TB6600 driver	1	12 V	Indexed routing: NEMA-17+TB6600 positions the disposal gate/sensor chamber over the target bin with precise, repeatable steps and returns to home.
DC step-down modules	LM2596	4	12 VDC (in)→5 VDC (out)	LM2596 DC–DC buck module. Input range 4.5-40 V; adjustable output 1.25-37 V. In this system, the module was set to 5.00 V to supply components requiring 5 V. Typical module current rating was ~2-3 A (module dependent).
Power supply	AC→DC switching adapter	1	220 VAC (in)→12 VDC (out)	Main voltage source in the system

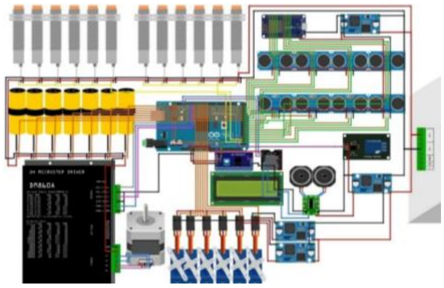

Figure 1. Component wiring schematic

Figure 2. System overview of the IoT-based automatic waste sorter

2.2. Ultrasonic and presence sensing behavior

Ultrasonic sensing in the system was used for two distinct purposes: local actuation safety and remote level monitoring. The system used eight ultrasonic transducers in total, configured as two sensors per bin for actuation/presence control and four sensors (one per bin) for fill-level monitoring. The Arduino Mega reads all eight sensors to perform presence checks and final actuation decisions. These readings were filtered by computing an averaged value over 5 samples (10 ms interval) using the firmware routine getFilteredDistance().

In parallel, four of the ultrasonic sensors (one per bin) were read by the NodeMCU ESP8266 for dashboard visualization. The ESP converted measured distance (cm) into a fill percentage using the implemented mapping: distances ≤15 cm→100% (full), distances ≥45 cm→0% (empty), with linear interpolation for intermediate values (map(distance, 15, 45, 100, 0)). Both the numeric thresholds used for mapping and the presence threshold on the Mega (implemented as detectDistance=10 cm) were documented for reproducibility. Note that the Mega's presence threshold (detectDistance=10 cm) was used for conservative safety/actuation checks, while the dashboard 'full' mapping used ≤15 cm to provide earlier operator alerts; these distinct thresholds serve different operational roles. Ultrasonic fill level sensing and empirical distance to level mappings are standard practice in IoT bin research and are employed here following published guidance [21], [22]. System performance testing is conducted under various conditions to evaluate sorting accuracy, processing time, and the effectiveness of IoT monitoring. Measurements are taken to ensure that the system operates efficiently across different waste sorting and monitoring scenarios.

2.3. IoT dashboard and Blynk integration

Real-time bin level monitoring was implemented on a NodeMCU (ESP8266) using the Blynk platform. The ESP read four ultrasonic sensors (one per bin) and converted measured distance (cm) into a fill percentage using an empirical mapping: distances ≤15 cm are mapped to 100% (full), distances ≥45 cm are mapped to 0% (empty), and intermediate values are linearly mapped (map(distance, 15, 45, 100, 0)). The computed fill percentages (level values) were transmitted to the Blynk dashboard via virtual pins (V0-V3) using Blynk.virtualWrite(...), and were rendered on four-gauge widgets, one gauge per bin. NodeMCU-based telemetry with cloud/dashboard visualization is a common lightweight architecture for bin-level monitoring and remote alerts [23]. Telemetry update occurred at approximately 1 Hz (the ESP loop includes a 1 s delay between measurements). The ESP code established Wi-Fi connectivity at startup (WiFi.begin(...)) and used the Blynk client for ongoing communications. Therefore, the ESP must remain connected to the network to provide real-time updates; if connectivity is lost, the dashboard will not receive new measurements.

2.4. Actuation and mechanical sequence

Actuation was executed after the classification decision and enforced a single item processing cycle. In the system, the top cover was initially open to allow an item to be dropped into the sensor chamber. Once an object was detected and classified, the controller first verified bin presence and lock state, then closed the top cover to prevent additional items from entering during the sorting operation. Next, the stepper motor drove the sensor chamber to the target bin. Once in position, the disposal servo was actuated to release the item. After release, the stepper returned the sensor chamber to its home position, and the top cover was reopened to accept the next item. The firmware required sensor stability before actuation to avoid false triggers, ensuring reliable one item per cycle operation. Indexed mechanical routing using stepper motors and release servos was consistent with prior smart bin routing implementations requiring precise, repeatable motion [24]. The classification and actuation logic are summarized in the flowchart shown in Figure 3.

2.5. Data acquisition and dataset structure

Data acquisition was performed by both controllers: the Arduino Mega was the primary logger for classification events and actuator actions, while the NodeMCU (ESP8266) provided periodic level telemetry for dashboard visualization. During experimental runs, the Arduino Mega streamed diagnostic output to the serial console (viewed via the Arduino IDE Serial Monitor at 9600 baud); this output included classification results, sensor readings, actuation timestamps, and status flags. These observations were recorded during testing for subsequent analysis. The NodeMCU wrote fill level values to Blynk virtual pins (V0-V3) at ≈1 Hz. These values were logged on the Blynk server and were used to cross-check level measurements.

2.6. Calibration and thresholding procedures

Sensor calibration and filtering procedures were as follows. Digital/proximity sensors were debounced by double sampling (two reads with 5 ms separation) and only accepted when stable. The Arduino implemented a stability counter such that classification or actuation proceeded only after requiredStabilityCount=10 consecutive stable cycles. Ultrasonic filtering differed by controller: the Mega used a 5-sample averaged window (10 ms spacing) for presence/actuation decisions, while the ESP performed single measurements per loop for level display and mapping. These different filtering choices reflected distinct requirements: the Mega prioritized actuation robustness (5-sample averaging+stability counter) to avoid false triggers, whereas the ESP prioritized dashboard responsiveness and therefore used single sample readings at ≈1 Hz for near real-time visualization. The ESP distance→level mapping was map(distance 15,45,100,0); the Mega's presence threshold (detectDistance) was set to 10 cm. Techniques for improving ultrasonic distance accuracy, such as Kalman filtering and multi-sample averaging, are commonly reported in the literature and motivate the filtering choices adopted in the present study [25].

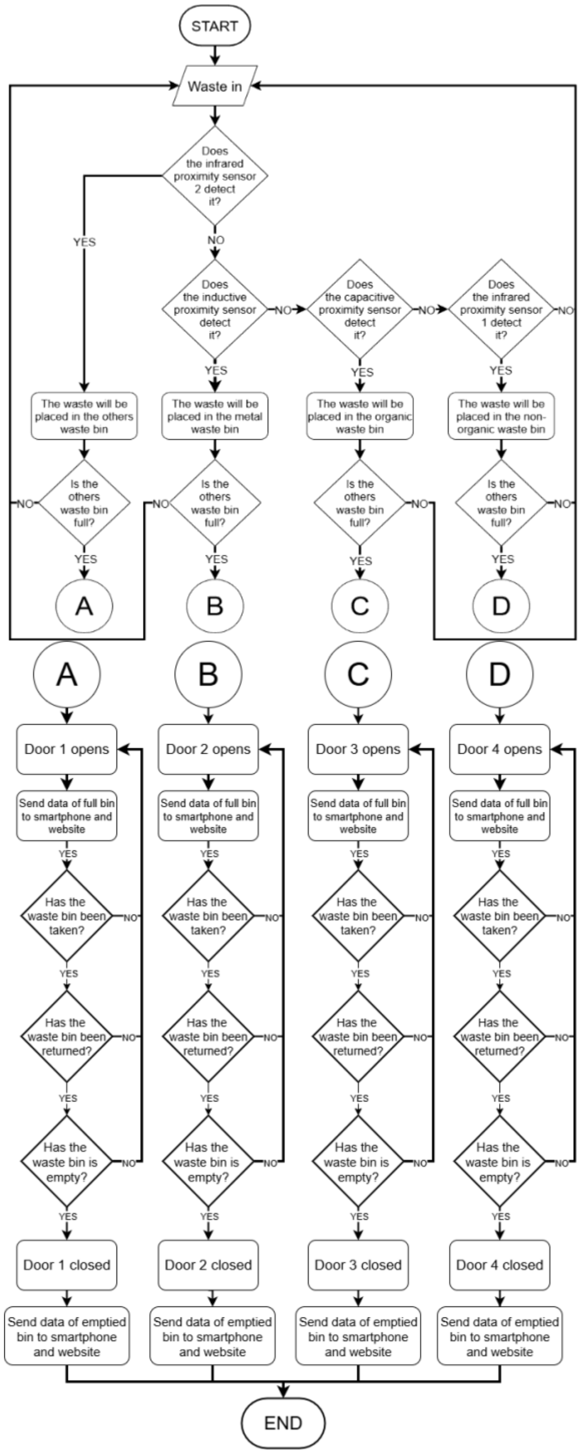

Figure 3. Waste sorting mechanism flowchart

2.7. Testing protocol and evaluation metrics

Trials were randomized to avoid order effects. A total of 100 randomized trials were performed (25 trials per class: organic, non-organic, metal, and others). For each trial, an operator placed a single sample into the open top cover. The controller then polled sensors, the on-device classifier issued a decision, actuators routed the item, and a human observer verified the routing outcome before the trial result was recorded. Trials proceeded only after the sensor stability condition described in subsection 2.6 was satisfied.

We defined the following evaluation metrics and logging procedures. Overall accuracy was computed as total correct routings divided by the total number of trials. Per-class performance was reported as precision, recall, and F1-score. Classification outcomes were summarized using a 4×4 confusion matrix (counts and percentages). Timing measurements comprised: i) sensor response time, defined as the elapsed time from initial detection to classifier decision, and ii) transit/operation time, defined as the elapsed time from detection to completion of mechanical actuation (item release and return to home). Mechanical failures were monitored visually by the test operator and were defined as actuator or door malfunctions (e.g., servo stall, stepper missed index, or misaligned door).

2.8. Environmental and reliability considerations

The system's sensing and actuation performance depended on environmental conditions and hardware robustness; therefore, the experimental evaluation accounted for common field factors. Ultrasonic sensors proved sensitive to temperature, humidity, and to highly absorbent or irregular surfaces; inductive sensors depended on metal proximity and geometry; capacitive sensors were affected by moisture and material permittivity; and infrared detectors could be influenced by ambient lighting and reflective surfaces. Mechanical components (servos, stepper motors, and linkages) were subject to wear, misalignment, and torque limitations under load. To mitigate this issue, the firmware implemented stability and safety checks (averaged/filtered ultrasonic readings on the Mega, requiredStabilityCount, presence threshold detectDistance=10 cm, and a timeout mechanism using millis()).

3. RESULTS AND DISCUSSION

The experimental evaluation measured the performance of the integrated IoT-enabled waste sorting system across classification, timing, and telemetry dimensions. The following subsections summarize the randomized trial protocol, overall outcomes, classification results with per-class metrics, timing and throughput measurements, and IoT dashboard behavior. They also analyze failure modes and discuss comparative implications.

3.1. Experimental summary

A set of 100 randomized trials was conducted to evaluate the integrated IoT-enabled waste sorting system (25 trials per class: metal, non-organic, organic, and others). Each trial consisted of an operator placing a single sample into the device, automatic material classification, mechanical routing and disposal, and human verification of the outcome. The following sections present classification results, per-class performance metrics, and timing measurements derived from these trials.

3.2. Classification results

Table 2 reports the 4×4 confusion matrix (ground truth vs. predicted). Overall, the system correctly classified 89 out of 100 samples, yielding an overall accuracy of 89.0%. Most metal samples were correctly routed (23/25); misclassifications for metal were rare and were routed to non-organic bins. Non-organic items exhibited the highest confusion: 5 non-organic samples were misrouted (1→organic; 4→others). Organic items were largely correctly classified (21/25), with four cases confused as non-organic. The 'others' category was perfectly recognized in our trials (25/25).

3.3. Per-class performance

Table 3 summarizes per-class precision, recall, and F1-score. Key observations are: i) metal attains the highest precision (100.0%) with a recall of 92.0%, indicating reliable positive predictions for metal, ii) non-organic shows the lowest precision (76.9%) and moderate recall (80.0%), reflecting false positives to other bins, iii) organic achieves strong precision (95.5%) and acceptable recall (84.0%), and iv) the 'others' class exhibits perfect recall (100.0%) and high precision (86.2%). These class level metrics highlight where the sensor fusion and thresholding logic perform well and where further improvements (e.g., additional sensing modalities or threshold tuning) would reduce confusion. Figure 4 illustrates the overall success rate for each waste category, providing a visual comparison of the system's classification performance and highlighting variations in accuracy among metal, non-organic, organic, and others.

Table 2. Confusion matrix (counts) for 4-class sorting

Ground/predicted	Metal	Non-organic	Organic	Others	Support
Metal	23	2	0	0	25
Non-organic	0	20	1	4	25
Organic	0	4	21	0	25
Others	0	0	0	25	25
Total (counted)	23	26	22	29	100

Table 3. Per-class performance metrics

Class	TP	FP	FN	Precision	Recall	F1-score	Support (n)
Metal	23	0	2	1.0000 (100.00%)	0.9200 (92.00%)	0.9583 (95.83%)	25
Non-organic	20	6	5	0.7692 (76.92%)	0.8000 (80.00%)	0.7843 (78.43%)	25
Organic	21	1	4	0.9545 (95.45%)	0.8400 (84.00%)	0.8936 (89.36%)	25
Others	25	4	0	0.8621 (86.21%)	1.0000 (100.00%)	0.9265 (92.65%)	25
Accuracy					89.0%		

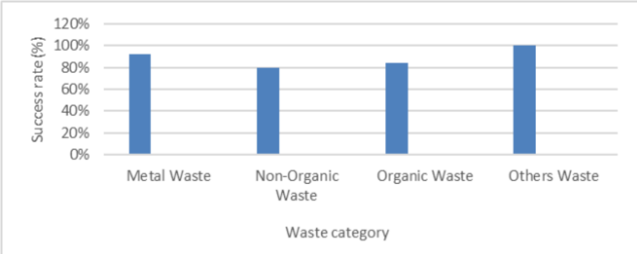

Figure 4. Success rate of waste sorting

3.4. Timing and throughput

Table 4 presents cycle-time and sensor-response statistics (mean±standard deviation). Overall mean cycle time was 11.50±2.20 s per item, yielding a theoretical throughput of approximately 3600/11.50≈313 items per hour under continuous operation. Sensor response (classification latency) averaged 4.37±1.09 s. Per-class timing shows metal items required the longest cycle times (13.55±1.07 s) and the longest sensor response (5.12±0.77 s), while the 'others' class was fastest (9.82±1.02 s cycle time; 3.64±0.69 s sensor response). The timing results reflect both the implemented stability checks in firmware and the mechanical travel distance required for indexing to target bins.

Table 4. Timing and throughput statistics (mean±standard deviation, seconds)

Class	Support (n)	Cycle time mean (s)	Cycle time std (s)	Sensor response mean (s)	Sensor response std (s)
Metal	25	13.55	1.07	5.12	0.77
Non-organic	25	12.57	1.74	4.01	1.03
Organic	25	10.83	2.17	4.67	1.14
Others	25	9.82	1.02	3.64	0.69
Overall	100	11.50	2.20	4.37	1.09

3.5. IoT telemetry and dashboard visualization

During experiments, the dashboard served two purposes: i) remote visualization of bin fill levels to confirm system behavior, and ii) a secondary logging endpoint for cross-checking measured values. The NodeMCU established Wi-Fi connectivity at startup (WiFi.begin(...)) and used the Blynk client for ongoing communication. Figures 5 and 6 show the web and mobile dashboard views used during the trials. These views were used only for monitoring and did not participate in the real-time actuation logic, which remained under the control of the Arduino Mega.

3.6. Failure analysis

We inspected misclassified trials to identify root causes. Based on the confusion matrix as shown in Table 2, the principal failure modes were: i) ambiguous sensor readings due to object orientation or mixed materials, ii) off-center or tilted item drops that prevented representative sensor signals, iii) variation in object shape and size, and iv) inherently mixed/ambiguous waste items. Further analysis showed that the four non-organic items routed to the other bin were primarily the result of imperfect drop position. Because sensors did not receive representative readings, these items could not be confidently classified as non-organic. Although these events counted as classification failures for the non-organic class, the presence of the fourth “others” bin prevented incorrect routing to sensitive categories (e.g., metal) and thus acted as an effective safety buffer. This behavior demonstrated that the other bin functioned as intended; it safely captured ambiguous items (25/25 success for tested large shape items) and reduced the risk of problematic misroutes. As immediate mitigations, we had implemented software-level stability checks (requiredStabilityCount=10) and a 5-sample averaging window for ultrasonic readings to reduce false triggers. During the 100 randomized trials, no mechanical failures were observed that prevented the system from completing its sorting cycles. This conclusion was based on direct operator observation and inspection of diagnostic serial output recorded during testing.

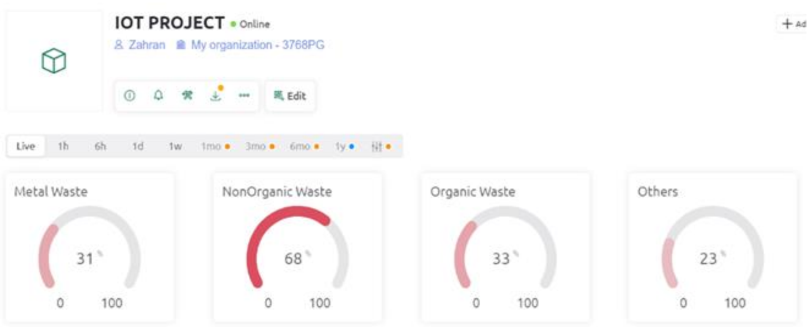

Figure 5. Monitoring system interface on Blynk website

Figure 6. Monitoring system interface using Blynk application

3.7. Comparative discussion

Table 5 summarizes representative sorter systems and their reported performance. Compared to the cited works, the present system handled a larger classification (four categories) and was validated on a substantially larger test set (n=100), yielding 89.0% reported accuracy. The other two studies reported 100% accuracy; however only addressed binary sorting tasks (metal vs non-metal or organic vs non-organic) with much smaller trial counts (n=10 and 8), which reduces the statistical strength of those claims. From a policy and operations viewpoint, the system's telemetry could be fed into campus facilities management or municipal waste dashboards to trigger collection events and prioritize high-fill locations, thereby reducing unnecessary truck trips and associated emissions. Pilot deployments should therefore include stakeholder engagement (facilities, waste contractors, and local authorities) to determine integration interfaces and data-sharing protocols.

Table 5. Comparative summary of smart waste sorting systems

Study (ref)	Year	Categories handled	Key sensors/method	IoT monitoring	Trials (reported)	Reported accuracy
This work	2025	4 (metal, non-organic, organic, and others)	Inductive+capacitive+IR+ultrasonic; Arduino Mega (classification and actuation)+NodeMCU (telemetry); NEMA-17+servos	Yes (Blynk)	100	89.0%
Rumansyah *et al.* [16]	2022	2 (metal vs non-metal)	Inductive+capacitive+ultrasonic; NodeMCU (classification, actuation and telemetry); servo	Yes (Blynk)	10	100%
Ismail *et al.* [17]	2023	2 (non-organic vs organic*)*	Capacitive+ultrasonic; Arduino Uno (classification and actuation)+NodeMCU (telemetry); servo	Yes (Blynk)	8	100%
Santoso *et al.* [18]	2021	2 (non-organic vs organic)	Capacitive+inductive; Arduino Nano (classification and actuation); servo	NO	20	80%

3.8. Limitations and future work

The sensor chamber design was not optimal, causing some items to fall tilted or off-center; this produced ambiguous sensor readings and was a primary cause of several classification errors. In addition, the limited number and placement of sensors reduced the system's tolerance to variations in object orientation and size. Real-time bin-level monitoring depended entirely on a Wi-Fi connection: when the NodeMCU lost network access, telemetry was not delivered to the dashboard, and levels could not be monitored online, which limits monitoring reliability in locations with unstable networks. The sorter also relied on a wired 220 V AC mains supply; this dependence on a local power outlet restricts deployment options and makes off-grid operation infeasible. Moreover, the device was not designed for outdoor use or water exposure. Without a waterproof enclosure and proper sealing/drainage, the electronics and actuators are vulnerable to rain and environmental ingress; therefore, the current system is suitable only for indoor or sheltered installations.

Recommended improvements include a mechanical redesign of the chamber (e.g., chamber or guide rails) and re-positioning or addition of proximity sensors to improve reading robustness and reduce orientation sensitivity, together with local telemetry buffering to tolerate intermittent network outages. For outdoor deployment, we recommend a waterproof enclosure with appropriate sealing and drainage. As an alternative or complementary approach, adding a camera with lightweight on-device image processing (e.g., compact convolutional models) could substantially improve material discrimination, that's because their performance generally increases as the amount and diversity of labeled training data grow. However, image-based classification requires a labeled dataset, additional compute and power budget, and careful attention to privacy and lighting conditions. To remove reliance on mains power for field or off-grid deployments, future work should evaluate solar-powered operation with battery buffering and power budgeting. Additional extensions could include simple carbon accounting (e.g., estimating avoided collection trips from telemetry) and embedding the device into campus educational programs to promote source-segregation behavior.

4. CONCLUSION

This study presented an IoT-integrated automatic waste sorting system that combined multi-sensor material classification (inductive, capacitive, and infrared proximity sensors), ultrasonic level sensing, and indexed mechanical routing with real-time telemetry (NodeMCU+Blynk). The system was experimentally validated in 100 randomized trials and achieved an overall accuracy of 89.0% (n=100) with a mean cycle time of 11.5±2.2 s per item. Key strengths are the on-device rule-based classification across four categories and campus-ready IoT visualization. Main limitations included chamber/drop positioning sensitivity, dependency on Wi-Fi for remote monitoring, and lack of weatherproofing (indoor use only). For deployment, we recommend field piloting, mechanical guides, and extra complementary sensors (or optional lightweight image processing), and enclosure weatherproofing. Overall, the work demonstrated a practical, low-cost approach suitable for campus trials while identifying clear, prioritized improvements for production use.

ACKNOWLEDGMENTS

The author would like to express gratitude to all the lecturers, staff, and technicians of the Department of Mechanical Engineering at Politeknik Negeri Ujung Pandang for their guidance and assistance in completing this research.

FUNDING INFORMATION

The authors would like to thank Politeknik Negeri Ujung Pandang for providing funding through the 2023 Applied Engineering Research Program under contract number 954/P/2023.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Akhmad Taufik	✓	✓	✓	✓	✓	✓		✓	✓	✓		✓	✓	✓
Paisal		✓		✓		✓		✓	✓	✓	✓	✓		
Muhammad Ruswandi Djalal	✓		✓		✓	✓	✓	✓	✓	✓	✓		✓	
Zahran Atha Dillah	✓		✓			✓			✓	✓			✓	
Haryono Ismail	✓		✓		✓		✓			✓		✓		✓

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

The authors declare no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] Y. A. Fatimah, K. Govindan, R. Murniningsih, and A. Setiawan, "Industry 4.0 based sustainable circular economy approach for smart waste management system to achieve sustainable development goals: a case study of Indonesia," *Journal of Cleaner Production*, vol. 269, 2020, doi: 10.1016/j.jclepro.2020.122263.

[2] N. Hayat, R. Rahmawati, I. Razak, and M. N. Bendly, "Inequality of social problems related to the management and utilization of household waste: seen from the perspective of family education," *Gagasan Pendidikan Indonesia*, vol. 4, no. 2, 2023, doi: 10.30870/gpi.v4i2.23163.

[3] R. Haniva, S. B. Butar, and N. Ambarita, "Waste management in schools as part of sustainable development," *Journal of Sustainability, Society, and Eco-Welfare*, vol. 1, no. 2, pp. 126–148, 2024, doi: 10.61511/jssew.v1i2.2024.325.

[4] B. C. Hohl *et al.*, "Community identified characteristics related to illegal dumping; a mixed methods study to inform prevention," *Journal of Environmental Management*, vol. 346, no. June, 2023, doi: 10.1016/j.jenvman.2023.118930.

[5] T. Juwariyah, L. Krisnawati, and S. Sulasminingsih, "Design of IoT-based smart bins integrated monitoring system using Blynk," *IOP Conference Series: Materials Science and Engineering*, vol. 1125, no. 1, May 2021, doi: 10.1088/1757-899X/1125/1/012078.

[6] K. O. M. Salih, T. A. Rashid, D. Radovanovic, and N. Bacanin, "A comprehensive survey on the internet of things with the industrial marketplace," *Sensors*, vol. 22, no. 3, pp. 1–31, 2022, doi: 10.3390/s22030730.

[7] R. A. Mouha, "Internet of things (IoT)," *Journal of Data Analysis and Information Processing*, vol. 09, no. 02, pp. 77–101, 2021, doi: 10.4236/jdaip.2021.92006.

[8] M. S. I. M. Zin, M. A. K. Mustafah, F. Arith, A. A. M. Isa, L. Barukang, and G. Markarian, "Development of low-cost IoT-based wireless healthcare monitoring system," *Przeglad Elektrotechniczny*, vol. 1, no. 1, pp. 222–227, 2022, doi: 10.15199/48.2022.01.48.

[9] R. Chataut, A. Phoummalayvane, and R. Akl, "Unleashing the power of IoT: a comprehensive review of IoT applications and future prospects in healthcare, agriculture, smart homes, smart cities, and industry 4.0," *Sensors*, vol. 23, no. 16, 2023, doi: 10.3390/s23167194.

[10] N. Costa, N. Rodrigues, M. A. Seco, and A. Pereira, "SL: a reference smartness level scale for smart artifacts," *Information (Switzerland)*, vol. 13, no. 8, pp. 1–18, 2022, doi: 10.3390/info13080371.

[11] S. Saha and R. Chaki, "IoT based smart waste management system in aspect of COVID-19," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 9, no. 2, Jun. 2023, doi: 10.1016/j.joitmc.2023.100048.

[12] M. Bakhar and E. Budihartono, "Impact analysis of the use of IoT technology and environmental monitoring systems on waste reduction in the food and beverage industry in Indonesia," *West Science Interdisciplinary Studies*, vol. 1, no. 11, pp. 1213–1220, 2023, doi: 10.58812/wsis.v1i11.380.

[13] S. T. Ikram, V. Mohanraj, S. Ramachandran, and A. Balakrishnan, "An intelligent waste management application using IoT and a genetic algorithm–fuzzy inference system," *Applied Sciences (Switzerland)*, vol. 13, no. 6, 2023, doi: 10.3390/app13063943.

[14] A. G. Permana and J. Raharjo, "Integrated waste management system with IoT-based centralized control towards a Smart Eco Campus-Telkom University," *International Journal of Energy Economics and Policy*, vol. 13, no. 2, pp. 322–333, 2023, doi: 10.32479/ijeep.14048.

[15] S. Dubey, P. Singh, P. Yadav, and K. K. Singh, "Household waste management system using IoT and machine learning," in *Procedia Computer Science*, 2020, vol. 167, pp. 1950–1959, doi: 10.1016/j.procs.2020.03.222.

[16] J. A. Wardana, A. C. Chen, R. S. Jaelani, L. Leonardo, and B. Juarto, "Smart trash cans for waste management using NodeMCU and ultrasonic sensor," in *2022 4th International Conference on Cybernetics and Intelligent System (ICORIS)*, Oct. 2022, pp. 1–5, doi: 10.1109/ICORIS56080.2022.10031466.

[17] Ritzkal *et al.*, "Using circular economy to manage organic and inorganic waste with internet of things-based monitoring system," *Instrumentation Mesure Métrologie*, vol. 24, no. 1, pp. 53–62, Feb. 2025, doi: 10.18280/i2m.240106.

[18] M. M. Ali, H. CHVS, G. S. Teja, B. V. Jyothi, and L. S. Kumar, "Intelligent waste sorting system: leveraging Arduino for automated trash identification and categorization," *International Journal of Computer Information Systems and Industrial Management Applications*, vol. 16, pp. 648–663, 2024.

[19] V. T. Widyaningrum, A. S. Romadhon, and R. Safitri, "Automatic waste sorter machine using proximity sensor," in *Proceedings of Himbep 2020*, 2021, pp. 264–270, doi: 10.5220/0010331102640270.

[20] R. Wulandari, M. R. Ariwibowo, T. Taryo, and G. Ananda, "Design smart trash based on the inductive proximity sensor," *International Journal of Multidisciplinary Approach Research and Science*, vol. 2, no. 01, pp. 194–200, 2023, doi: 10.59653/ijmars.v2i01.394.

[21] P. Zoumpoulis, F. K. Konstantinidis, G. Tsimiklis, and A. Amditis, "Smart bins for enhanced resource recovery and sustainable urban waste practices in smart cities: a systematic literature review," *Cities*, vol. 152, no. May, 2024, doi: 10.1016/j.cities.2024.105150.

[22] A. Addas, M. N. Khan, and F. Naseer, "Waste management 2.0 leveraging internet of things for an efficient and eco-friendly smart city solution," *PLoS ONE*, vol. 19, no. 7 July, pp. 1–23, 2024, doi: 10.1371/journal.pone.0307608.

[23] A. K. Lingaraju *et al.*, "IoT-based waste segregation with location tracking and air quality monitoring for smart cities," *Smart Cities*, vol. 6, no. 3, pp. 1507–1522, 2023, doi: 10.3390/smartcities6030071.

[24] M. Shreya, V. N. Yughan, J. Katyal, and R. Ramesh, "Technical solutions for waste classification and management: a mini-review," *Waste Management and Research*, vol. 41, no. 4, pp. 801–815, 2023, doi: 10.1177/0734242X221135262.

[25] M. H. Setiawan, A. Ma'arif, H. M. Marhoon, A. N. Sharkawy, and A. Çakan, "Distance estimation on ultrasonic sensor using Kalman filter," *Buletin Ilmiah Sarjana Teknik Elektro*, vol. 5, no. 2, pp. 210–217, 2023, doi: 10.12928/biste.v5i2.8089.

BIOGRAPHIES OF AUTHORS

Akhmad Taufik was born in Wonomulio, Indonesia, in April 1976. He earned his Bachelor's and Master's degrees in Electrical Engineering from Hasanuddin University, Makassar, Indonesia, in 1999 and 2018, respectively. He completed his doctoral program in 2016 at Ehime University, Japan. He is a member of the Centre for Mechatronics and Control Systems (CMCS) Research Group and currently serves as a lecturer in the Department of Mechanical Engineering at Politeknik Negeri Ujung Pandang. His research interests include flying robots, sensors, and image processing. He can be contacted at email: akhmad_taufik@poliupg.ac.id.

Paisal was born in Ambon, Indonesia, in June 1981. He earned his Bachelor's and Master's degrees in Mechanical Engineering from Hasanuddin University, Makassar, Indonesia, in 2004 and 2012, respectively. He is a member of the Centre for Mechatronics and Control Systems (CMCS) Research Group and currently serves as a lecturer in the Department of Mechanical Engineering at Politeknik Negeri Ujung Pandang. His research interests include fluid mechanics and mechanical engineering. He can be contacted at email: paisal@poliupg.ac.id.

Muhammad Ruswandi Djalal was born in Ujung Pandang, Indonesia, in March 1990. He received his bachelor's degree in Energy Engineering from Politeknik Negeri Ujung Pandang, Makassar, Indonesia, in 2012, and his master's degree from the Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia, in 2015. In 2025, he completed his doctoral degree in the same department at ITS, Surabaya. He is a member of the Center for Sustainable Energy and Smart Grid Application (CoSESGA) research group and a lecturer in Energy Engineering in the Department of Mechanical Engineering at Politeknik Negeri Ujung Pandang. His research interests include power system stability, renewable energy, and artificial intelligence. He can be contacted at email: wandi@poliupg.ac.id.

Zahran Atha Dillah is a 2020 undergraduate student in the Mechatronics Engineering program, Department of Mechanical Engineering, Politeknik Negeri Ujung Pandang, Makassar, Indonesia. In 2024, he completed his Bachelor's degree. His research interests include internet of things (IoT) technology. He can be contacted via email: zahranathad@gmail.com.

Haryono Ismail is a 2020 undergraduate student in the Mechatronics Engineering program, Department of Mechanical Engineering, Politeknik Negeri Ujung Pandang, Makassar, Indonesia. In 2024, he completed his Bachelor's degree. His research interests include internet of things (IoT) technology. He can be contacted via email: haryono.is@gmail.com.