JITEL (Jurnal Ilmiah Telekomunikasi, Elektronika, dan Listrik Tenaga) p-ISSN: 2774-7972
Vol. 6, No. 1, Maret 2026, pp. 23-34 e-ISSN: 2775-6696
DOI: https://doi.org/10.35313/jitel.v6.i1.2026.23-34

AIoT-enabled automated waste classification and real-time capacity monitoring system for smart waste management

Ginanjar Suwasono Adi[1], Dodit Suprianto[2*], Atik Novianti[3], Khurnia Fiddiana Rohmah[4], Elka Faizal[5], Mochammad Junus[6], Riona Ihsan Media[7]
[1,2,3,4,5,6]Department of Electrical Engineering, Politeknik Negeri Malang
Jl. Soekarno Hatta No. 9, Malang, Indonesia
[7]Department of Manufacturing Design Engineering, Politeknik Manufaktur Bandung
Jl. Kanayakan No. 21, Bandung, Indonesia
[1]ginanjar.adi@polinema.ac.id, [2*]dodit.suprianto@polinema.ac.id, [3]atiknovianti@polinema.ac.id, [4]2031130061@student.polinema.ac.id, [5]elka.faizal@polinema.ac.id, [6]mochammad.junus@polinema.ac.id, [7]rio_sanmed@polman-bandung.ac.id

ABSTRACT

Population growth and urbanization have increased waste generation and intensified global waste management challenges. In Indonesia, national waste generation reached 38.4 million tons in 2023, with 38.38% remaining inadequately managed. This study aims to develop an Artificial Intelligence of Things (AIoT)-based system for automatic waste classification and real-time bin capacity monitoring. The system integrates the YOLOv8n model to identify four waste categories (organic, inorganic, hazardous/B3, and others) with ultrasonic sensors for capacity measurement, coupled with a web platform for data visualization. Model evaluation yielded a Macro F1-Score of 63.9%, with the best performance in the organic class (91.33%), followed by inorganic (68.37%), and hazardous/B3 (31.92%). Ultrasonic sensors demonstrated a near-linear relationship between waste height and capacity percentage (4.5% per cm), validating their reliability for real-time monitoring. The developed system proves the feasibility of AIoT integration for automated waste sorting, although further optimization is required to improve classification accuracy for minority classes. This research contributes to the development of intelligent solutions supporting more efficient and sustainable urban waste management.

Keywords: AIoT, YOLOv8n, automated waste classification, capacity monitoring, ultrasonic sensor

ABSTRAK

Pertumbuhan populasi dan urbanisasi telah meningkatkan timbulan sampah serta memperberat tantangan pengelolaan sampah secara global. Di Indonesia, timbulan sampah nasional pada tahun 2023 mencapai 38,4 juta ton per tahun, namun 38,38% masih belum terkelola dengan baik. Penelitian ini bertujuan mengembangkan sistem berbasis Artificial Intelligence of Things (AIoT) untuk klasifikasi sampah otomatis dan pemantauan kapasitas tempat sampah secara real-time. Sistem mengintegrasikan model YOLOv8n untuk mengidentifikasi empat kategori sampah (organik, anorganik, B3, dan lainnya) dengan sensor ultrasonik untuk pengukuran kapasitas, serta platform web untuk visualisasi data. Evaluasi model menunjukkan Macro F1-Score sebesar 63,9%, dengan performa terbaik pada kelas organik (91,33%), diikuti anorganik (68,37%), dan B3 (31,92%). Sensor ultrasonik menunjukkan hubungan near-linear antara tinggi sampah dan persentase kapasitas (4,5% per cm), memvalidasi keandalannya untuk pemantauan real-time. Sistem yang dikembangkan membuktikan kelayakan integrasi AIoT untuk pemilahan sampah otomatis, meskipun diperlukan optimalisasi lebih lanjut untuk meningkatkan akurasi klasifikasi pada kelas minoritas. Penelitian ini berkontribusi pada pengembangan solusi cerdas untuk mendukung pengelolaan sampah perkotaan yang lebih efisien dan berkelanjutan.

Kata kunci: *AIoT, YOLOv8n, klasifikasi sampah otomatis, pemantauan kapasitas, sensor ultrasonik*

1. INTRODUCTION

Waste is a pervasive global challenge, with population growth and urbanization continuously increasing municipal solid waste generation and straining existing management systems [1], [2]. This escalation exacerbates environmental pressures, demands greater infrastructure investment, and underscores the urgent need for smarter, more sustainable waste management solutions worldwide [1-3].

Naskah diterima tanggal 26 November 2025, disetujui tanggal 12 Maret 2026
*E-mail korespondensi

In Indonesia, this global trend is particularly pronounced. Data from the National Waste Management Information System (SIPSN) indicates that national waste generation reached 38.4 million tons in 2023, based on reports from 367 regencies/cities. Alarmingly, only 61.62% (23.6 million tons) of this waste was adequately managed, leaving 38.38% (14.7 million tons) unmanaged and posing significant environmental and public health risks. Inadequate waste management practices have been scientifically linked to air, soil, and water pollution, as well as adverse effects on human health and ecosystem sustainability [1], [2], [4]. Waste accumulation creates breeding grounds for disease vectors and can destabilize local ecosystems, necessitating coordinated action from governments, environmental agencies, businesses, and communities.

Indonesia's Law Number 18 of 2008 concerning Waste Management formally mandates this multi-stakeholder approach, assigning responsibilities to central and local governments, businesses, and the public. However, at the household level—the critical first step in the waste management chain—low source-segregation rates remain a primary bottleneck for effective recycling and processing, as recyclate quality heavily depends on user-level sorting practices [5], [6]. Research consistently identifies knowledge gaps, environmental awareness, policy support, and system convenience as key determinants of household waste sorting behavior [5], [6]. The situation is compounded by the continued reliance of most final processing sites (TPA) on environmentally hazardous open dumping methods, which elevate pollution and public health risks [1], [4].

Recent technological advancements offer promising avenues for addressing these challenges. Numerous studies have proposed IoT and AI-based automated waste monitoring and sorting systems [2], [3]. The integration of sensors, data communication protocols, and intelligent analytics enables real-time bin capacity monitoring, route optimization, and enhanced operational efficiency in waste management [3], [7], [8]. Within this domain, computer vision approaches leveraging deep learning particularly the YOLO (You Only Look Once) family of algorithms, have demonstrated robust performance in automated waste identification and classification [2], [8], [9]. Successive YOLO iterations have shown progressive improvements in detection accuracy for specific waste management scenarios [9]. Nevertheless, the literature acknowledges persistent limitations in scalability, partial implementation, and real-world deployment of many intelligent waste management systems [3].

Addressing these gaps, this research proposes the development of an automated waste sorting platform utilizing Artificial Intelligence of Things (AIoT) technology—a synergistic integration of AI and IoT. This approach offers a comprehensive solution for enhancing sorting efficiency, monitoring capabilities, and overall waste management effectiveness [2], [3]. The proposed system employs the YOLOv8n deep learning model for automatic waste classification, positioning object detection as a core component of smart waste management infrastructure [2], [8], [9]. Complementing this, ultrasonic sensors provide real-time bin capacity monitoring through an integrated web application. By enabling automated identification and segregation of waste into organic, inorganic, hazardous (B3), and other categories, this system aims to support recycling initiatives, improve operational efficiency, and mitigate environmental pollution risks.

2. RESEARCH METHODOLOGY

This research falls within the category of scientific and technological development, as the study focuses on the design and implementation of an intelligent device capable of automatically identifying and classifying waste types [2], [10], [11]. The research process commenced with problem identification by determining the primary issue to be addressed, namely waste classification. Subsequently, a literature review was conducted to explore various references related to classification methods, image processing, and the technologies employed. The research then proceeded to the system design phase and dataset collection. Following the system design, implementation was carried out, encompassing hardware development and the assembly of necessary components. The constructed system subsequently underwent testing. Should obstacles be encountered, troubleshooting was performed, wherein problems within the system were identified and resolved.

2.1 System Design

Figure 1 presents the system pipeline, providing a detailed representation of the waste monitoring and classification system architecture utilizing machine learning, along with cloud services to support more efficient waste management. This system comprises several main components. The bin is equipped with various devices, including an infrared sensor serving as a trigger to detect objects when waste is disposed, and an ESP32 functioning as a microcontroller to process data from the infrared sensor and ultrasonic sensor. The ESP32 also controls actuators in the form of stepper motors, manages data communication with the cloud system via the MQTT protocol, and receives and transmits information. The bin is also equipped with a camera for video streaming to the temporary holding area and for capturing images of detected waste objects. Additionally, a motor driver is present to convert control signals from the ESP32 into higher current to drive the stepper motors used for moving waste to the appropriate compartment based on classification results. Ultrasonic sensors are also employed to measure the fill level of each waste compartment.

The Edge Service constitutes the data processing and communication layer situated in proximity to the physical devices. Its primary functions include acting as an RTSP server to manage video streaming from the camera, receiving commands from the ESP32 via MQTT, triggering the camera to capture images, and transmitting these images to the server. Subsequently, the Cloud Base Service acts as the central hub for data storage, processing, and management. Its main components include a model deployment server that receives and stores images from the Edge Service, performs image classification, and sends the classification results to both the ESP32 and the database. The database is utilized to store image classification results and fill-level data from the ultrasonic sensors. Google Firebase serves as a backend service providing user authentication and data integration from the database.

This system also employs MQTT as the communication protocol for managing message transmission between the ESP32 and the Raspberry Pi. The selection of MQTT is justified by its suitability as 'a standard protocol for machine-to-machine or IoT communication with low overhead data packets and low power consumption [12], making it ideal for resource-constrained edge devices in IoT applications. Furthermore, sockets are utilized as a communication protocol for transmitting captured image data from the Raspberry Pi to the Server, as well as for sending fill-level data from the server to the website. The website functions to receive fill-level data from Firebase, display this information to users, and provide an interface for accessing data in real-time. This system is designed to ensure efficiency and full integration between components, thereby supporting more intelligent and centralized waste management.

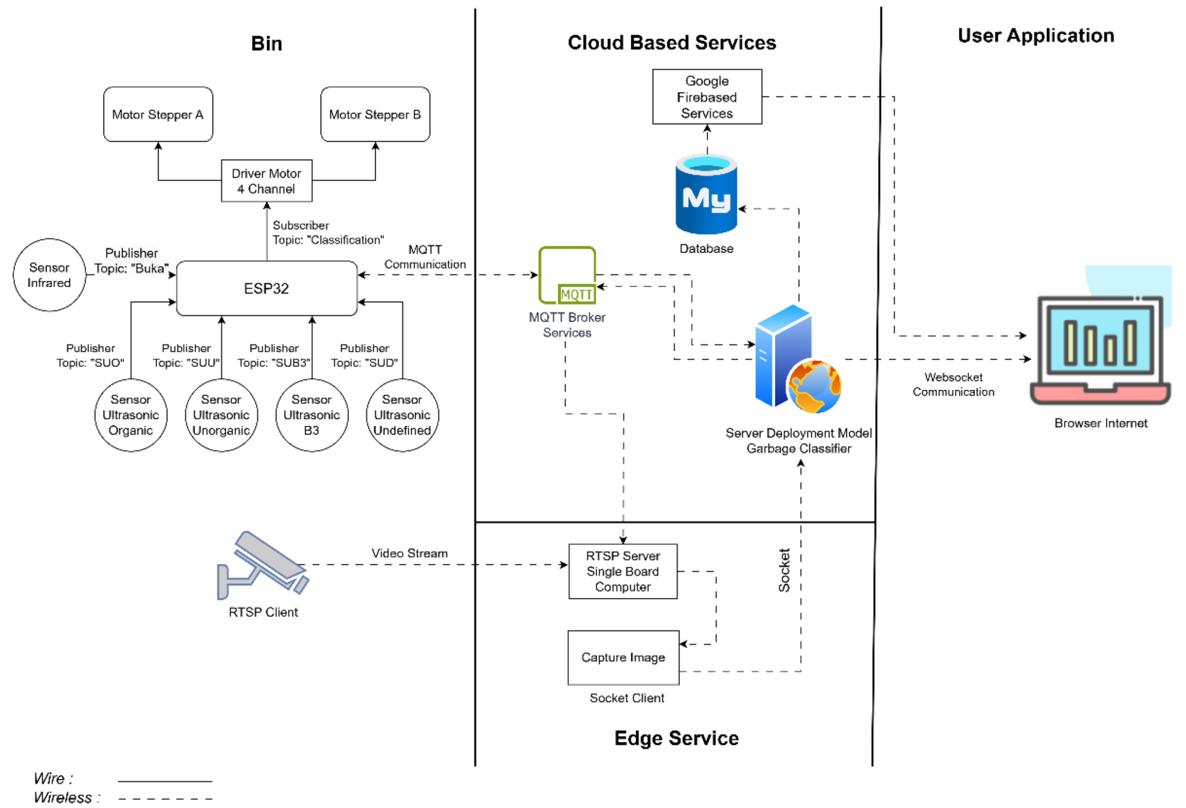


Figure 1. Automated waste sorting system pipeline

2.2 Model Training

The workflow of the processes undertaken to train, validate, and test the model is illustrated in Figure 2. Model training is the process by which a model is programmed to recognize specific patterns based on provided data. It begins with determining the dataset, which constitutes the source of information from which the model will learn to recognize particular patterns. The dataset employed in this waste classification testing comprises a collection of image data consisting of four waste categories: organic, inorganic, hazardous (B3), and other waste (categories outside these three classes).

This dataset was compiled from several sources, including public datasets available on open-source platforms and manual collection through documentation of waste images in the surrounding environment. The utilization of open-source datasets and field documentation represents a common approach, as it can enrich data variety and enhance the model's generalization capability [2], [9], [11]. Previous studies have also indicated that one of the primary challenges in waste classification is the variation in shape, color, lighting, background, as well as class imbalance in data quantity. Currently, the dataset consists of 3,900 images distributed across 14 waste categories, which were subsequently grouped into three main classes: Organic (1,500 images), Inorganic (1,400 images), and B3 (1,000 images).

The total dataset, comprising 3,900 raw images with varying resolution sizes, was divided into three main partitions. The division of the dataset into training, validation, and testing sets constitutes a standard procedure in machine learning and deep learning to ensure that the model not only learns from the training data but is also capable of generalizing to new data [9], [10], [11]. The training set, comprising 70% of the data (1,702 images), was used to train the model. Images in the training set are utilized by the model to learn to recognize patterns and features from various types of waste. The validation set, comprising 20% (1,461 images), was used to evaluate model performance during the training process. By employing 20% of the total dataset, the validation set serves to monitor model performance during training and assist in detecting overfitting, whereas the testing set is used to objectively assess the final model performance [9], [11]. The testing set, allocated 10% (737 images), was employed after training completion to evaluate the final model performance on new, previously unseen data.

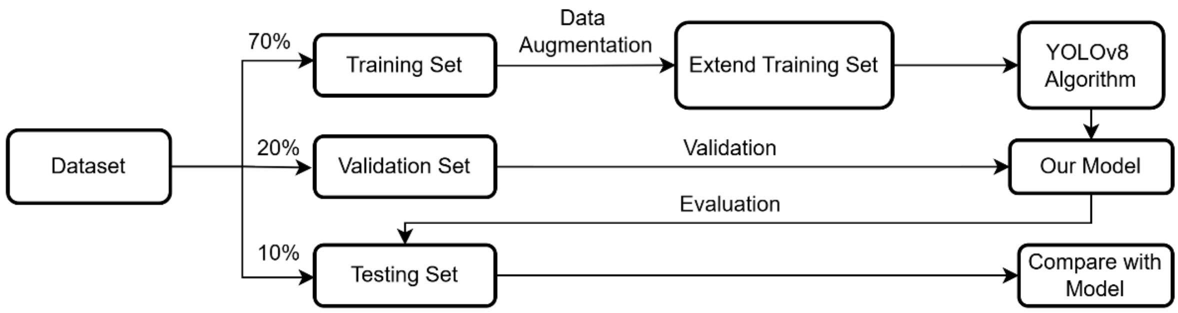


Figure 2. Model training process workflow

For the training set, the application of data augmentation techniques, such as rotation, lighting adjustments, and image flipping, is highly relevant in the context of waste classification, as these methods can enhance the diversity of training data and assist the model in becoming more robust to variations in real-world conditions [9], [10], [11]. The result of this augmentation is referred to as the extended training set. Subsequently, the YOLOv8n algorithm was employed to train the model on the extended training set. In this study, the training process was conducted using the following hyperparameters: image size of 640, 100 epochs, and a batch size of 16. During the training process, periodic evaluation using the validation set was necessary to assess the progression of model learning and to prevent degradation of generalization capability [9], [11]. Following the completion of training, the use of the testing set to evaluate the final model performance on previously unseen data constitutes a crucial step to ensure that the model is genuinely capable of functioning in real-world implementation scenarios [2], [10], [11]. Compare with model, the results from testing using the testing set are compared with the model to ensure the model performs effectively on new data.

2.3 Software Design

Figure 3 presents the main dashboard interface of the monitoring website, which displays real-time waste bin fill-level data via a WebSocket connection. The interface explicitly indicates WebSocket connectivity status, providing users with immediate feedback on system communication integrity. Fill-level data is visualized through dynamically updating bar charts that refresh automatically upon detecting changes in bin capacity. To facilitate multi-bin monitoring across different locations, a "Select Location" dropdown menu enables users to filter and view data for specific waste bins.

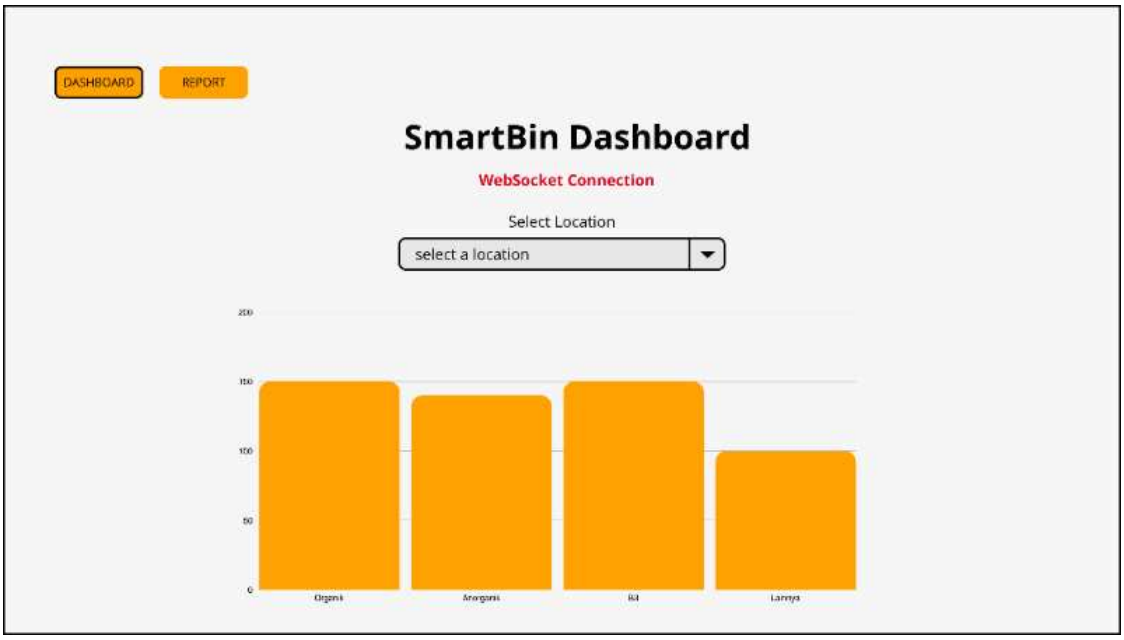


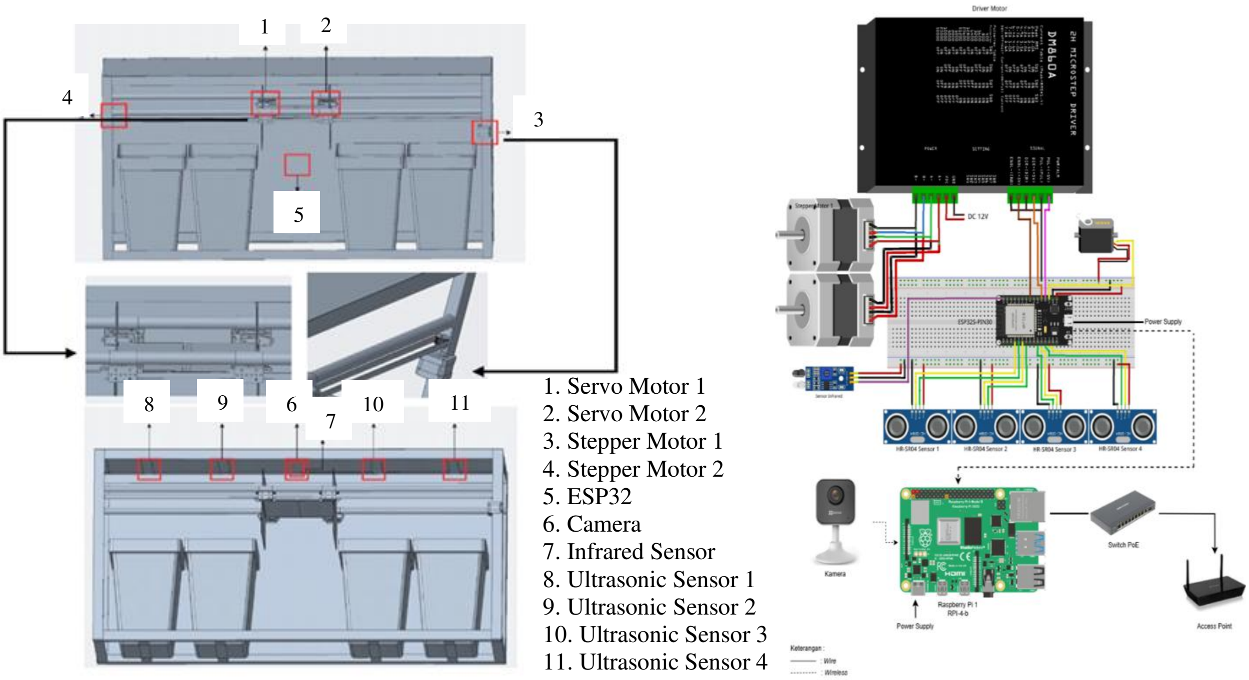
Figure 3. Main page (Dashboard) design

Figure 4. Report page design

Figure 4 illustrates the Report page interface, designed to present detailed historical transaction records of waste bin fill-level data. Users can filter data by specific time periods using a date selection feature with "dd/mm/yyyy" format and an accompanying "Filter" button. Transaction data is systematically organized in a four-column tabular format, displaying: (1) timestamp, (2) location identifier, (3) waste type classification, and (4) corresponding waste bin capacity percentage.

2.4 Hardware Design

The prototyping-stage software implementation—specifically the web-based monitoring dashboard for real-time fill-level visualization—aligns with established digitalization paradigms in smart city and smart waste management frameworks [7], [13]. The corresponding hardware architecture is presented in Figure 5(a). The automated waste sorting system comprises interconnected hardware components engineered to facilitate real-time object detection, classification, and actuation. Figure 5(b) provides a detailed wiring diagram illustrating the system's hardware architecture and component interconnections.



(a) (b)

Figure 5. (a) Hardware architecture of the automated waste sorting system, (b) System wiring diagram

3. RESULT AND DISCUSSION

3.1 Prototype Development Results

The developed prototype, shown in Figure 6, represents the culmination of integrating sensing, data communication, processing, and monitoring components into a unified AIoT architecture. The physical implementation demonstrates the functional interconnection of infrared trigger sensors, ESP32 microcontrollers, ultrasonic fill-level sensors, cameras for image acquisition, stepper motors for mechanical sorting, and the associated motor drivers. This integration enables the prototype to perform automated waste classification and simultaneous capacity monitoring—core functionalities aligned with contemporary smart waste management paradigms.

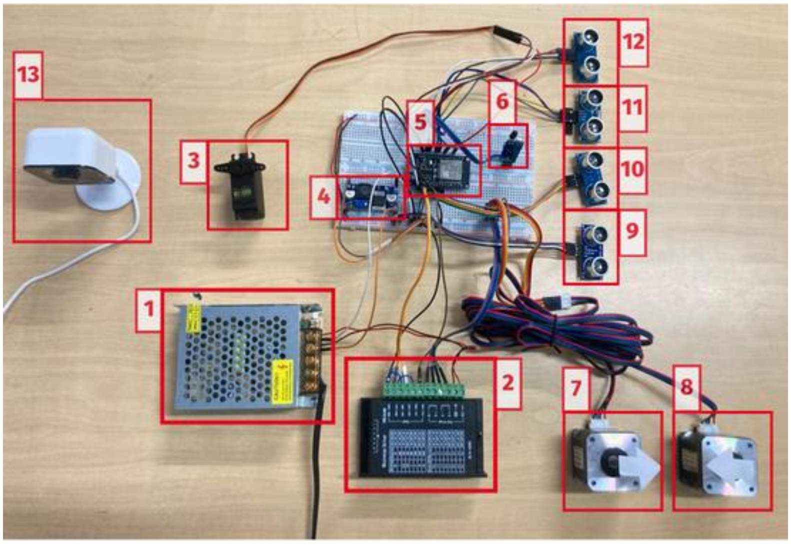
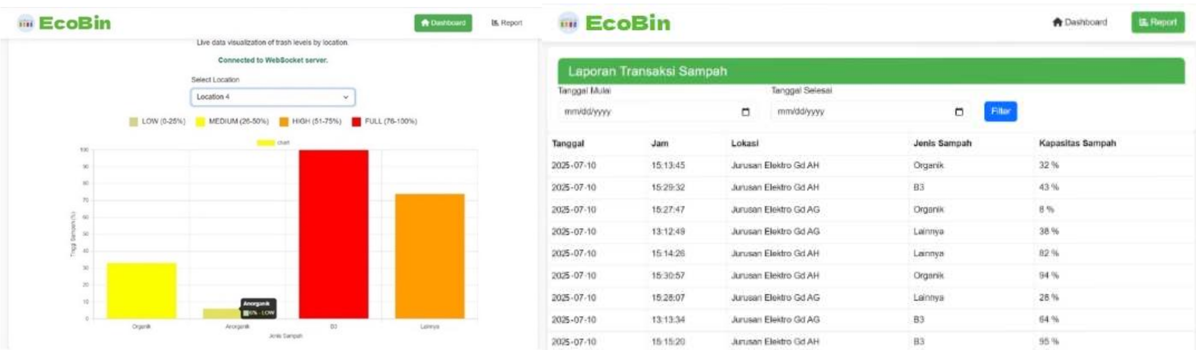


Figure 6. Completed prototype of the AIoT-based automated waste sorting system

This integrated approach reflects established principles in the literature, which emphasize that effective smart waste management systems typically emerge from the convergence of smart bins, communication gateways, cloud servers, and real-time monitoring interfaces [14], [15]. Such integration enables continuous bin status surveillance and supports data-driven operational decision-making. Furthermore, the validation of working prototypes is critically important, as it permits empirical testing of sensor fusion, network communication protocols, microcontroller coordination, and user interface responsiveness under conditions approximating real-world deployment scenarios [16]. The successful operation of this prototype validates the feasibility of the proposed AIoT architecture for automated waste sorting applications.

3.2 Website Development Results

The Smartbin dashboard interface, presented in Figure 7(a), visualizes waste capacity data through intuitive bar charts. The interface employs a color-coded alert system to indicate four distinct fill-level conditions: LOW (0-25%) displayed in light green, MEDIUM (26-50%) in yellow, HIGH (51-75%) in orange, and FULL (76-100%) in red. This visual encoding enables rapid status assessment and facilitates timely waste collection interventions.



(b) (b)

Figure 7. (a) Website dashboard interface showing real-time bin capacity monitoring, (b)Transaction report interface with date filtering capability

The waste transaction report page, depicted in Figure 7(b), presents systematically organized historical data retrieved from the database. Each tabular entry includes transaction timestamp, waste management location, waste type classification (organic, inorganic, B3, or other), and corresponding fill capacity percentage. The integrated date filtering functionality allows users to query data within specified temporal ranges, supporting longitudinal analysis and operational planning.

3.3 Model Evaluation

Quantitative evaluation of the YOLOv8n model's classification performance employed standard object detection metrics: Precision, Recall, F1-Score, and Mean Average Precision (mAP) [17], [18]. Precision and Recall quantify the model's effectiveness in minimizing false positives and false negatives, respectively, while the F1-Score provides a balanced measure of both. mAP offers an aggregate performance indicator across all waste categories.

The confusion matrix presented in Figure 8 reveals the model's class-wise prediction patterns. Overall Precision and Recall were both 0.674, indicating that 67.4% of positive predictions were correct and that the model successfully identified 67.4% of all actual positive instances. The equivalence of these values suggests a balanced error distribution between false positives and false negatives, with no systematic bias toward either error type.

Per-class F1-Score analysis reveals substantial performance variation across waste categories. The organic class achieved the highest F1-Score (91.33%), demonstrating robust feature learning and accurate classification. The inorganic class showed moderate performance (68.37%), indicating reasonable but improvable accuracy. The hazardous (B3) class exhibited the lowest F1-Score (31.92%), reflecting significant classification challenges with elevated false positive and false negative rates.

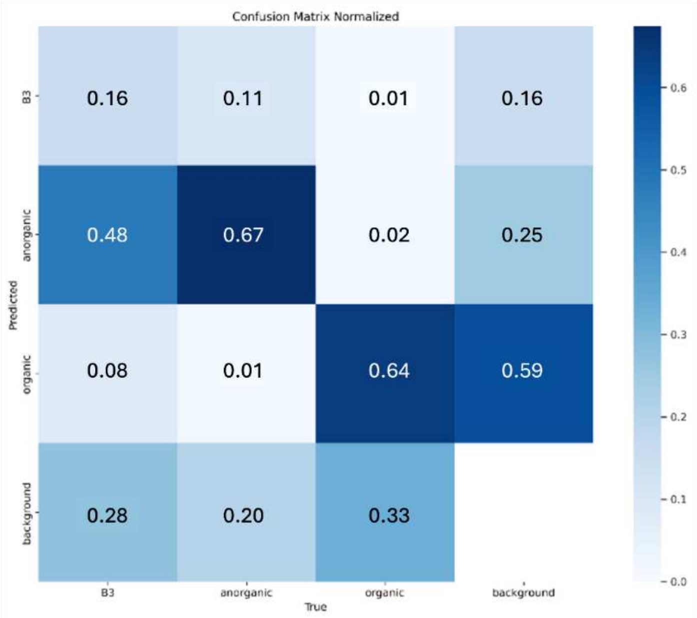


Figure 8. Confusion matrix for YOLOv8n classification results

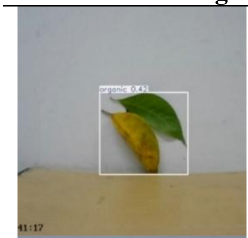
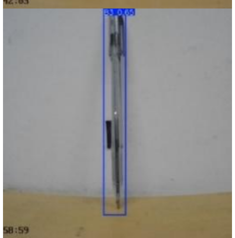
The aggregate Macro F1-Score of 63.9% confirms suboptimal overall performance and identifies substantial room for improvement, particularly in minority classes. This performance disparity aligns with recent literature documenting class imbalance as a pervasive challenge in waste classification datasets [11]. Common categories such as organic waste (paper, food scraps) typically dominate training data, while specialized hazardous waste categories remain underrepresented [11]. This imbalance 'biases model learning toward majority classes, compromising generalization to minority classes with limited or less diverse training samples'; a finding that directly corresponds with the performance degradation observed in our B3 class, which had the fewest training samples (1,000 images) compared to organic (1,500) and inorganic (1,400).

3.4 YOLOv8n Model Detection Analysis

Qualitative examination of detection results (Table 1) corroborates the quantitative findings. The inorganic class demonstrated consistently accurate detection across test samples, reflecting adequate feature representation and sufficient training data. However, systematic misclassifications were observed: several organic waste instances were incorrectly identified as inorganic, and B3 waste items were frequently misclassified as inorganic.

These error patterns are attributable to two primary factors. First, the dataset imbalance between organic (1,500 images), inorganic (1,400 images), and B3 (1,000 images) classes predisposes the model to prioritize the more numerous inorganic class during prediction. Second, visual feature overlap between categories—particularly the resemblance of white face masks (B3 class) to paper waste (inorganic class)—creates inherent ambiguity that challenges discrimination, especially for classes with limited training diversity [11], [17]. This phenomenon underscores the importance of both quantitative balance and qualitative diversity in training data for robust multi-class waste classification.

Table 1. YOLOv8n Detection Results

Test Image	Model Prediction	Actual Class	Description
	Organic	Organic	Correct Prediction
	Organic	Organic	Correct Prediction
	Inorganic	Inorganic	Correct Prediction
	Inorganic	Inorganic	Correct Prediction
	B3	B3	Correct Prediction
	Inorganic	B3	Incorrect Prediction

3.5 Ultrasonic Sensor Capacity Monitoring Validation

Sensor validation employed a single-unit testing protocol based on the assumption that all three system sensors shared identical specifications and underwent uniform calibration procedures, thus ensuring measurement consistency. Testing involved mounting the ultrasonic sensor at the bin's top to measure distance to the waste surface, with measurements converted to fill percentage.

The measurement data in Table 2 reveal a clear monotonic relationship between waste height and fill percentage, approximating linearity with approximately 4.5% capacity increase per centimeter of waste accumulation. This pattern is consistent with established smart bin implementations where top-mounted distance sensors measure the decreasing distance to accumulating waste [19], [20]. The near-linear relationship validates the conversion methodology and supports the sensor's suitability for real-time fill-level monitoring in this prototype.

Table 2. Ultrasonic sensor fill-level measurement results

No	Waste Height (cm)	Waste Bin Capacity (%)
1	5	23
2	7	32
3	9	41
4	11	50
5	12	55
6	15	68
7	16	73
8	18	82
9	20	91
10	22	100

However, recent studies caution that ultrasonic volume estimation accuracy can be compromised by irregular waste surface topography, heterogeneous material composition, and environmental noise interference [10]. While the single-sensor results demonstrate promising linear response, comprehensive validation would benefit from multi-sensor testing, broader waste-type variation assessment, and advanced calibration procedures to enhance system reliability across diverse operating conditions. Nevertheless, the current results confirm that waste bin capacity can be reliably estimated from ultrasonic height measurements, enabling effective real-time fill-level monitoring.

3.6 Limitations and Future Work: IoT Communication Performance

While the proposed AIoT system demonstrates satisfactory performance in waste classification accuracy and sensor-based capacity monitoring, several aspects of the communication infrastructure warrant further investigation. The current implementation prioritizes functional validation of the YOLOv8n model and ultrasonic sensor reliability, with less emphasis on quantitative evaluation of network-induced latency and data transmission reliability [12].

In real-time IoT applications, communication performance parameters such as end-to-end delay and jitter significantly influence system responsiveness and operational efficiency. As noted in previous studies on IoT-based control systems, "reducing delay can enhance the responsiveness of the control system, which is crucial for maintaining stability and operational efficiency in dynamic conditions" [10]. For smart waste management applications, excessive latency in transmitting fill-level data or classification results could lead to delayed collection responses and suboptimal route planning.

The MQTT protocol employed in this system offers configurable Quality of Service (QoS) levels to balance reliability and speed. Research on similar IoT architectures has demonstrated that MQTT with QoS level 2 can achieve end-to-end delays ranging from 21.72 ms to 55.61 ms under varying payload sizes, with jitter values between 1.17 ms and 33.89 ms [12]. These benchmarks provide useful references for evaluating the suitability of MQTT for time-sensitive waste monitoring applications.

However, comprehensive characterization of communication performance in the specific context of this waste sorting system remains to be conducted. Future work will therefore focus on:

1. End-to-end latency measurement: Quantifying the complete data pipeline from sensor acquisition at the edge to visualization on the web dashboard under various network conditions.
2. QoS optimization: Experimentally determining the optimal MQTT QoS configuration that balances message reliability with real-time responsiveness.

3. Scalability assessment: Evaluating communication performance when scaling from single-bin prototypes to multi-bin deployments with concurrent data streams.
4. Network resilience testing: Validating system behavior during intermittent connectivity and assessing local data buffering mechanisms.

Addressing these communication performance aspects will complement the classification accuracy and sensor validation presented in this study, advancing the proposed AIoT system toward robust, real-world deployment in smart city waste management infrastructure.

4. CONCLUSION

This research successfully developed and validated an AIoT-based automated waste sorting system integrating YOLOv8n deep learning classification with ultrasonic sensor-based capacity monitoring. The system demonstrates functional feasibility for real-time waste categorization and fill-level tracking, contributing to the growing body of smart waste management technologies. Quantitative evaluation revealed that the YOLOv8n model achieved a Macro F1-Score of 63.9%, with marked performance variation across waste categories: organic (91.33%), inorganic (68.37%), and hazardous/B3 (31.92%). This disparity highlights the critical challenge of class imbalance in waste classification datasets and underscores the need for targeted data acquisition strategies for minority categories. The ultrasonic sensor validation confirmed effective real-time capacity monitoring with near-linear response, supporting its integration into operational waste management systems. Several limitations should be acknowledged. First, the dataset imbalance disproportionately affected classification performance for the hazardous waste category, limiting the model's practical utility for this critical waste stream. Second, single-sensor validation, while indicative, does not fully characterize multi-sensor system reliability under varied field conditions. Third, the prototype's mechanical sorting mechanism was not extensively tested for long-term operational durability. Fourth, while the system employs MQTT for IoT communication, quantitative evaluation of network-induced latency and data transmission reliability has not been conducted, leaving the characterization of real-time communication performance for future investigation. Future research directions include: (1) comparative evaluation of alternative deep learning architectures (e.g., YOLOv9, YOLOv10, transformer-based detectors) to identify optimal models for waste classification; (2) acquisition of larger, more balanced primary datasets encompassing greater visual diversity across all categories, particularly hazardous waste; (3) multi-sensor validation studies under varied environmental conditions; (4) comprehensive QoS analysis of MQTT communication to quantify end-to-end delays, jitter, and optimal QoS configurations; and (5) field deployment trials to assess system performance in real-world operational contexts.

ACKNOWLEDGMENTS

The authors express their gratitude to P3M Politeknik Negeri Malang for funding support through the DIPA Budget for Fiscal Year 2025 under Number: SP DIPA-139.03.2.693474/2025, enabling this research to be successfully conducted.

REFERENCES

[1] W. Czekała, J. Drozdowski, and P. Łabiak, "Modern Technologies for Waste Management: A Review," *Appl. Sci.*, vol. 13, no. 15, 2023, doi: 10.3390/app13158847.
[2] B. Fang *et al.*, *Artificial intelligence for waste management in smart cities: a review*, vol. 21, no. 4. Springer International Publishing, 2023. doi: 10.1007/s10311-023-01604-3.
[3] S. Nesmachnow, D. Rossit, and P. Moreno-Bernal, "A Literature Review of Recent Advances on Innovative Computational Tools for Waste Management in Smart Cities," *Urban Sci.*, vol. 9, no. 1, pp. 1–61, 2025, doi: 10.3390/urbansci9010016.
[4] M. M. Siddiqi *et al.*, "Exploring e-waste resources recovery in household solid waste recycling," *Processes*, vol. 8, no. 9, pp. 1–13, 2020, doi: 10.3390/pr8091047.
[5] Y. M. Elmosaad *et al.*, "Self-Reported Household Waste Recycling and Segregation Practices among Families in Eastern Region of Saudi Arabia: A Cross-Sectional Study," *Int. J. Environ. Res. Public Health*, vol. 20, no. 3, pp. 1–16, 2023, doi: 10.3390/ijerph20031790.
[6] B. Chen and J. Lee, "Household waste separation intention and the importance of public policy," *Int. Trade, Polit. Dev.*, vol. 4, no. 1, pp. 61–79, 2020, doi: 10.1108/itpd-03-2020-0008.

[7] J. Prata, C. L. Simões, and R. Simoes, "Improvements to Municipal Solid Waste Collection Systems Using Real-Time Monitoring," *Sustain.*, vol. 17, no. 4, pp. 1–16, 2025, doi: 10.3390/su17041405.

[8] S. Thaseen Ikram, V. Mohanraj, S. Ramachandran, and A. Balakrishnan, "An Intelligent Waste Management Application Using IoT and a Genetic Algorithm–Fuzzy Inference System," *Appl. Sci.*, vol. 13, no. 6, 2023, doi: 10.3390/app13063943.

[9] D. Voskergian and I. Ishaq, "Smart e-waste management system utilizing Internet of Things and Deep Learning approaches," *J. Smart Cities Soc.*, vol. 2, no. 2, pp. 77–98, 2023, doi: 10.3233/scs-230007.

[10] T. Gelar, S. Fitriani, and S. Rachmat, "A Systematic Literature Review of YOLO and IoT Applications in Smart Waste Management," *Green Intell. Syst. Appl.*, vol. 5, no. 2, pp. 123–139, 2025, doi: 10.53623/gisa.v5i2.706.

[11] F. Fotovvatikhah, I. Ahmedy, R. M. Noor, and M. U. Munir, "A Systematic Review of AI-Based Techniques for Automated Waste Classification," *Sensors*, vol. 25, no. 10, 2025, doi: 10.3390/s25103181.

[12] D. Suprianto, G. S. Adi, R. Agustina, N. Hidayati, and A. M. Imammuddin, "Hybrid Multi-Servo Motor Controller Within an IoT-Enabled Smart Mechatronics Framework," vol. 10, no. 2, pp. 121–128, 2025, doi: 10.25139/inform.v10i2.10100.

[13] T. J. Sheng *et al.*, "An Internet of Things Based Smart Waste Management System Using LoRa and Tensorflow Deep Learning Model," *IEEE Access*, vol. 8, pp. 148793–148811, 2020, doi: 10.1109/ACCESS.2020.3016255.

[14] M. A. Al Mamun, M. A. Hannan, A. Hussain, and H. Basri, "Theoretical model and implementation of a real time intelligent bin status monitoring system using rule based decision algorithms," *Expert Syst. Appl.*, vol. 48, pp. 76–88, 2016, doi: 10.1016/j.eswa.2015.11.025.

[15] J. John *et al.*, *Smart Prediction and Monitoring of Waste Disposal System Using IoT and Cloud for IoT Based Smart Cities*, vol. 122, no. 1. 2022. doi: 10.1007/s11277-021-08897-z.

[16] R. Alnanih, L. Elrefaei, and A. Al-Ahwal, "Advancing Sustainability Through an IoT-Driven Smart Waste Management System with Software Engineering Integration," *Sustain.*, vol. 17, no. 21, pp. 1–28, 2025, doi: 10.3390/su17219803.

[17] A. Arishi, "Real-Time Household Waste Detection and Classification for Sustainable Recycling: A Deep Learning Approach," *Sustain.*, vol. 17, no. 5, 2025, doi: 10.3390/su17051902.

[18] Y. Ren, Y. Li, and X. Gao, "An MRS-YOLO Model for High-Precision Waste Detection and Classification," *Sensors*, vol. 24, no. 13, 2024, doi: 10.3390/s24134339.

[19] K. Pardini, J. J. P. C. Rodrigues, O. Diallo, A. K. Das, V. H. C. de Albuquerque, and S. A. Kozlov, "A smart waste management solution geared towards citizens," *Sensors (Switzerland)*, vol. 20, no. 8, pp. 1–15, 2020, doi: 10.3390/s20082380.

[20] L. M. Pires, J. Figueiredo, R. Martins, and J. Martins, "IoT-Enabled Real-Time Monitoring of Urban Garbage Levels Using Time-of-Flight Sensing Technology," *Sensors*, vol. 25, no. 7, 2025, doi: 10.3390/s25072152.