Acadlore Transactions on AI and Machine Learning
https://www.acadlore.com/journals/ATAIML

A Deep Learning and Sensor-Based Internet of Things Framework for Intelligent Waste Management: A Comparative Analysis

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Received: 12-20-2025 **Revised:** 02-22-2026 **Accepted:** 03-04-2026

Citation: R. Mustafovski, A. Petrovski, M. Radovanovic, A. Behlic, and K. Ilievski, "A deep learning and sensor-based Internet of Things framework for intelligent waste management: A comparative analysis," *Acadlore Trans. Mach. Learn.*, vol. 5, no. 1, pp. 58–72, 2026. https://doi.org/10.56578/ataiml050106.

Abstract: The escalating volume of municipal solid waste has intensified the need for intelligent waste management systems capable of improving operational efficiency, classification accuracy, and sustainability. In recent years, the integration of Internet of Things technologies, deep learning algorithms, and sensor-based monitoring has significantly transformed conventional waste collection and sorting practices. In this study, an intelligent waste management framework was proposed and comparatively evaluated against twelve contemporary smart waste management systems reported in the literature. The proposed architecture integrates a Raspberry Pi 3 embedded platform, You Only Look Once version 8 (YOLOv8) deep learning models for real-time waste classification, and ultrasonic bin-fill sensors for monitoring container capacity, enabling automated lid operation, and supporting optimized waste collection scheduling. A comprehensive comparative analysis was conducted across multiple performance dimensions, including classification accuracy, system responsiveness, scalability, deployment cost, and operational efficiency. Experimental evaluation demonstrates that the deep learning–driven framework achieved high real-time classification accuracy while maintaining low computational overhead on resource-constrained edge devices. In addition, the incorporation of bin-fill sensing and automated actuation enhanced system responsiveness and supported data-driven collection planning, thereby reducing unnecessary collection trips and operational costs. The findings highlight the significant potential of combining advanced deep learning algorithms with sensor-based Internet of Things infrastructures to develop sustainable, intelligent, and cost-effective waste management ecosystems. These insights provide a foundation for future research aimed at enhancing intelligent waste infrastructure and supporting environmentally sustainable urban development.

Keywords: Intelligent waste management; Deep learning; Waste classification; You Only Look Once version 8; Bin-fill sensor; Raspberry Pi 3

1 Introduction

The growing amount of waste generated worldwide presents serious challenges for cities, environmental sustainability, and public health. Estimates suggest that municipal solid waste production will surpass 2.2 billion tons each year by 2025, primarily due to urbanization and rapid industrial growth [1]. Traditional waste management methods are becoming insufficient to tackle these issues, as they often suffer from inefficiencies in collection, sorting, and disposal. Problems like overflowing bins, irregular collection schedules, and poor waste handling contribute to environmental dangers, such as pollution, greenhouse gas emissions, and health risks [2]. The rise of smart technologies, especially the Internet of Things, artificial intelligence, and sensor integration, has created new opportunities for intelligent waste management systems. These systems are designed to improve the efficiency of waste collection, sorting, and recycling while minimizing costs and environmental effects. This study presents a cutting-edge intelligent waste management system that utilizes deep learning and Internet of Things technologies, comparing its performance to existing systems found in the literature.

Traditional waste management systems face significant challenges due to inefficiencies such as fixed collection routes, a lack of real-time monitoring, and poor recycling practices. For instance, rigid garbage collection schedules can result in unnecessary costs and overflowing bins, leading to sanitation problems and wasted resources [3, 4].

Additionally, the failure to segregate waste at the source greatly reduces recycling effectiveness, as mixed waste streams require more extensive processing [5]. Research indicates that many conventional systems are resource-heavy and struggle to keep up with the growing demands of urban environments. For example, disposing of unsegregated waste and relying on manual sorting not only diminish operational efficiency but also put workers at risk from hazardous materials [6]. This highlights the urgent need for automated systems that utilize real-time data collection and analysis to enhance waste management practices.

Intelligent waste management systems mark a significant change in waste management practices by combining Internet of Things, artificial intelligence, and sensor technologies to enhance automation, efficiency, and sustainability. These systems feature smart bins that track fill levels, use dynamic algorithms for collection routing, and incorporate automated waste sorting. They overcome major drawbacks of traditional methods by facilitating data-driven decision-making and real-time monitoring [6, 7]. For instance, Sosunova and Porras [1] performed a systematic review that emphasizes how Internet of Things-enabled systems have revolutionized urban waste management through real-time analytics, route optimization, and predictive maintenance.

Additionally, systems that utilize advanced sensors like ultrasonic and moisture detectors can identify bin fill levels and analyze waste composition, which helps ensure timely collection and effective sorting [8, 9]. Nevertheless, these systems often encounter issues related to scalability, high implementation costs, and challenges in accurately classifying various types of waste.

The system outlined in this research enhances current technologies by merging deep learning models, like You Only Look Once version 8 (YOLOv8), with Internet of Things-enabled smart bins and sensor technologies. By using Raspberry Pi 3 as the computational platform, the system integrates high-resolution cameras and bin-fill sensors to enable real-time waste classification and monitoring [5]. These intelligent bins come with actuators for automated lid operations, which improves user convenience and promotes hygiene. Furthermore, the system offers real-time data for dynamic route optimization, helping to lower operational costs and reduce environmental impact.

This system stands out for several reasons:

a. Deep learning for waste classification: The YOLOv8 model has been trained on a comprehensive and varied dataset, resulting in impressive classification accuracy for different waste types, including organic, plastic, metal, and glass [5].

b. Internet of Things-enabled monitoring and communication: Smart bins equipped with ultrasonic sensors offer real-time data on fill levels, while Wi-Fi connectivity facilitates smooth data transfer to central systems [10, 11].

c. Modularity and scalability: The system is designed with flexibility in mind, allowing it to be scaled easily for both urban and rural environments with minimal infrastructure needs [12].

2 Literature Review

This section provides a comprehensive analysis of 12 advanced intelligent waste management systems, focusing on their features, methodologies, and limitations. The review assesses how each system contributes to overcoming the challenges associated with waste collection, sorting, and recycling. To enhance clarity and facilitate systematic comparison, a summary is included in Table 1, along with detailed descriptions. The combination of the Internet of Things, machine learning, and sensor technologies in intelligent waste management systems has greatly improved the efficiency of waste management processes. Current systems utilize a range of methods, such as sensor-based monitoring, automated sorting, and dynamic route optimization. Nevertheless, challenges like scalability, high implementation costs, and limited classification capabilities still exist [13, 14].

The systems reviewed can be classified according to their focus:

• Sensor-based waste level monitoring.

• Internet of Things-enabled data transfer and communication.

• Artificial intelligence-driven waste classification and sorting.

A summary of these reviewed systems, highlighting their key features and methodologies, is provided in Table 1.

System 1. Internet of Things Smart Bin System

This system uses Internet of Things-enabled smart bins that have ultrasonic sensors to keep track of waste levels. The information is sent to a central server through Global System for Mobile Communications modules, enabling real-time monitoring and scheduling for collection. Although the system effectively minimizes overflow incidents, its lack of capability to sort different types of waste limits its effectiveness in recycling efforts [8].

System 2. Waste Sorting Robot

This system employs grey-level co-occurrence matrix and machine learning methods to automate the sorting of waste based on texture features. High-speed cameras take images, and a neural network categorizes the waste into specific groups. While it boasts high accuracy, the system's scalability is limited due to its reliance on static environments [3].

Table 1. Summary of reviewed systems

System Name	Primary Technology	Key Features	Limitations
System 1: Internet of Things Smart Bin System	Internet of Things, Global System for Mobile Communications, and ultrasonic sensors	Real-time waste level monitoring; alert system for collection centers	Limited waste classification
System 2: Waste Sorting Robot	Machine learning and grey-level co-occurrence matrix	Automated sorting; texture-based waste detection	Limited scalability
System 3: Decentralized Waste System	Internet of Things and blockchain	Decentralized data handling; reward-based recycling	High infrastructure costs
System 4: Multi-Agent Internet of Things Architecture	Internet of Things and multi-agent systems	Real-time monitoring; collaborative decision-making	Complex implementation
System 5: Artificial Intelligence-Driven Waste Segregation	Neural networks	High-accuracy waste classification	Limited data diversity
System 6: Drone-Based Waste Collection	Drone and light fidelity	Dynamic waste collection using drones	High operational costs
System 7: General Packet Radio Service-Based Smart Bins	Internet of Things, General Packet Radio Service, and ultrasonic sensors	Bin-level monitoring; mobile app integration	Limited scalability
System 8: Solid Waste Management System for Smart Cities	Internet of Things and Global Positioning System	Route optimization; geographic information system integration	High maintenance costs
System 9: Autonomous Waste Collection System	Machine learning and Global Positioning System	Dynamic routing; predictive analytics	Limited classification capabilities
System 10: Internet of Things-Enabled Segregation	Internet of Things, Global System for Mobile Communications, and radio frequency identification	Automated waste segregation; cloud-based monitoring	Limited sensor accuracy
System 11: Integrated Sensing Framework	Internet of Things and sensor fusion	Real-time monitoring; integration of multiple sensors	High computational requirements
System 12: Proposed System	Deep learning and Internet of Things	Real-time waste classification; dynamic routing; bin-fill sensors	Under evaluation

System 3. Decentralized Waste System

This innovative approach combines Internet of Things and blockchain technology to create a decentralized waste management system that collects data and encourages recycling through token-based rewards. While it fosters community involvement, the high costs of implementation and the need for a strong infrastructure present significant challenges [2].

System 4. Multi-Agent Internet of Things Architecture

This architecture utilizes a multi-agent framework to facilitate collaborative decision-making among waste collection agents. Real-time data from Internet of Things devices helps in optimizing routing and task distribution. However, the complexity of the system can lead to increased challenges in both implementation and maintenance [13].

System 5. Artificial Intelligence-Driven Waste Segregation

By using neural networks, this system achieves a high level of accuracy in waste classification. It trains its models on a variety of datasets to identify different types of waste, including organic, plastic, and metal. However, the limited diversity of datasets can hinder its effectiveness in real-world applications [14].

System 6. Drone-Based Waste Collection

This system uses drones fitted with light fidelity communication modules to collect waste dynamically in remote locations. While it is an innovative approach, the high operational costs and regulatory hurdles make large-scale implementation difficult [15].

System 7. General Packet Radio Service-Based Smart Bins

By integrating General Packet Radio Service modules, ultrasonic sensors, and a mobile app, this system allows for real-time monitoring and interaction with citizens. While it improves transparency, scalability challenges restrict its use in larger cities [16].

System 8. Solid Waste Management System for Smart Cities

Tailored for urban settings, this system merges Internet of Things and Global Positioning System technologies to enhance collection routes and lower operational expenses. However, its high maintenance needs present obstacles to broader adoption [17].

System 9. Autonomous Waste Collection System

This system utilizes machine learning to dynamically route collection vehicles based on predictive analytics of bin fill levels. While it operates efficiently, its limited classification capabilities hinder its effectiveness in recycling efforts [18].

System 10. Internet of Things-Enabled Segregation

By integrating radio frequency identification, Global System for Mobile Communications modules, and Internet of Things-enabled sensors, this system automates the process of waste segregation and offers real-time monitoring through cloud platforms. However, inaccuracies in the sensors can lead to misclassification [19].

System 11. Integrated Sensing Framework

This system uses sensor fusion techniques to merge data from various sensors, improving monitoring accuracy and decision-making. Nonetheless, its high computational requirements limit its scalability [20].

System 12. Proposed System

The proposed system integrates deep learning (YOLOv8), Internet of Things, and ultrasonic sensors to enable real-time waste classification and dynamic route optimization. By tackling issues of scalability and accuracy, this system seeks to address the shortcomings of current intelligent waste management system solutions [5].

3 Methodology

The proposed intelligent waste management system utilizes cutting-edge technologies such as the Internet of Things, deep learning, and sensor integration to tackle significant shortcomings in existing waste management methods [5]. This section provides a detailed overview of the system's design, components, and operational workflow, highlighting its innovative features. The proposed intelligent waste management system architecture features a network of hardware and software components that work together for real-time monitoring, classification, and collection of waste [5, 18, 19]. The system includes:

• Smart bins that are fitted with sensors and actuators.
• Raspberry Pi 3 microcomputers to handle data processing.
• YOLOv8 deep learning models for classifying waste.
• Communication modules to facilitate data transfer.

Figure 1 shows the overall architecture of the proposed system, highlighting how the hardware and software components work together.

In terms of hardware components, the Raspberry Pi 3 acts as the main processing unit for the system. It handles the execution of the YOLOv8 model, processes data from cameras and sensors, and sends commands to the actuators. Its features include a quad-core central processing unit for efficient computation, general-purpose input/output pins for connecting peripheral devices, and Wi-Fi and Bluetooth for seamless data transfer. High-resolution cameras are strategically placed to capture images of waste deposited in the smart bins. These images are analyzed using the YOLOv8 model to classify waste into predefined categories (e.g., organic, plastic, and glass) [16, 20–22]. Each smart bin is fitted with an ultrasonic sensor to measure the fill level. The sensor emits sound waves and measures the time it takes for the echo to return, allowing it to calculate the distance to the waste surface. This information is used to determine the bin's fill percentage. Actuators are placed in the bins to manage the automatic opening and closing of lids. These actions are activated based on the waste classification results produced by the YOLOv8 model. In addition, the system uses Wi-Fi modules to send data between the smart bins and the central server. This allows for real-time monitoring and data transfer, facilitating route optimization.

In terms of software components, the YOLOv8 deep learning model, which is based on convolutional neural networks, is employed for real-time waste classification. It analyzes images taken by the cameras and sorts waste into six categories: organic, plastic, metal, glass, paper, and e-waste [10, 11, 23–27]. The YOLOv8 model underwent fine-tuning through transfer learning on a tailored dataset consisting of 25,000 labeled images. The dataset was compiled from public repositories and local sources, ensuring a balanced representation of different waste categories. To enhance the robustness of the model, image augmentation techniques were applied. All images were annotated with bounding boxes to enable accurate object localization. In addition, key hyperparameters, including the learning rate, weight decay, and batch size, were optimized to ensure high accuracy. A data processing module on the Raspberry Pi manages sensor inputs and YOLOv8 classification outputs. This module collects sensor data to keep track of bin fill levels, combines classification results to aid in decision-making, and sends commands to actuators for operating the lids. The central server keeps system data, including real-time fill levels of bins, classification results for the deposited waste, and historical data for analytics and reporting. Additionally, the server runs the route optimization algorithm, which schedules collection vehicles dynamically based on the statuses of the bins. The system includes an intuitive interface that can be accessed through both mobile and desktop applications. This interface offers real-time updates on bin statuses, analytics on waste generation, and collection schedule notifications for both users and administrators.

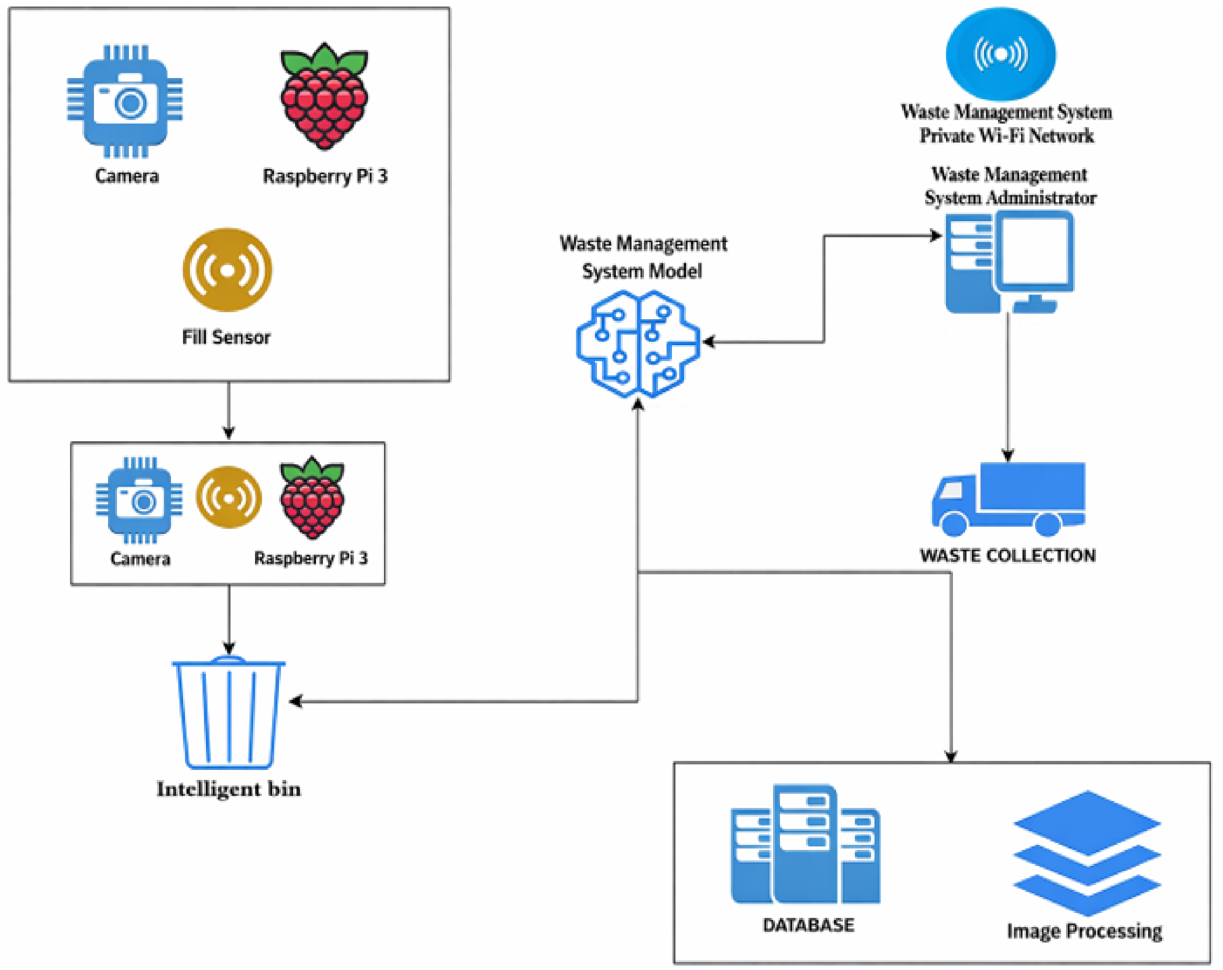

Figure 1. System architecture

The system operates through the steps in Table 2 and Figure 2.

Table 2. Operational steps of the intelligent waste management system

Step	Process	Description
Step 1	Waste Detection	Cameras capture images of waste as it is deposited in the bins. The You Only Look Once version 8 (YOLOv8) model processes images to classify the waste type.
Step 2	Lid Operation	Based on the classification result, the corresponding bin lid is automatically opened, ensuring proper segregation.
Step 3	Fill-Level Monitoring	Ultrasonic sensors measure the waste accumulation in each bin. Fill-level data is transmitted to the central server in real time.
Step 4	Data Processing	The Raspberry Pi integrates classification and fill-level data to determine the bin's status. Commands are generated to control the bin's operations.
Step 5	Dynamic Collection Scheduling	The central server analyzes bin statuses and optimizes vehicle routes. Notifications are sent to collection teams via the user interface.
Step 6	Data Analytics	Historical data is analyzed to identify waste generation patterns and optimize system performance.

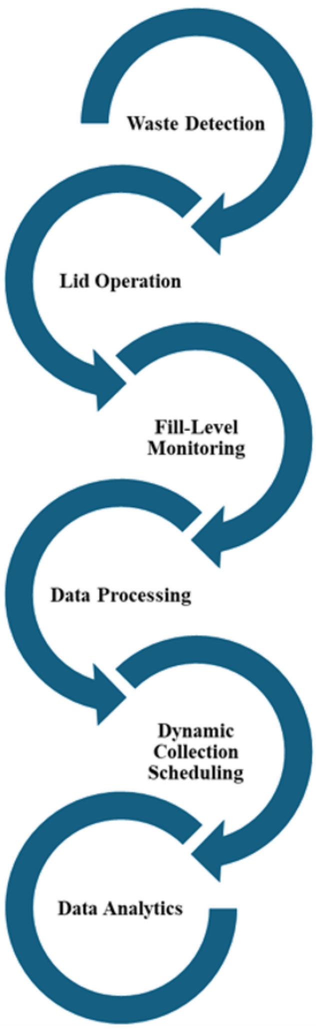

Figure 2. System architecture

The proposed methodology presents several benefits compared to current intelligent waste management system solutions shown in Table 3.

Table 3. Key features of the proposed intelligent waste management system

Category	Feature	Description
Waste classification	Real-Time waste classification	The You Only Look Once version 8 (YOLOv8) model delivers impressive accuracy, minimizing misclassification and boosting recycling efficiency.
Routing optimization	Dynamic routing	Streamlined collection schedules help lower operational costs and lessen environmental impact.
System design	Scalability	The modular design facilitates implementation in both urban and rural areas.
Public participation	User engagement	An intuitive interface improves transparency and encourages public involvement in waste management.

While the proposed system demonstrates numerous advantages, it also encounters several notable challenges. Maintaining sensor accuracy across diverse environmental conditions necessitates regular calibration, while reliable Wi-Fi connectivity remains essential for the real-time transfer of data [28–31]. Furthermore, expanding the dataset to incorporate a broader range of waste types could substantially enhance the model's classification performance [24, 25]. The methodology can be further refined by integrating predictive analytics to anticipate waste generation patterns, employing renewable energy sources to power the system and extending the classification model to encompass hazardous waste categories, thereby improving both efficiency and versatility.

3.1 Model Training Configuration and Evaluation Metrics

To ensure transparency and reproducibility, the dataset of 25,000 labeled images was partitioned into training, validation, and testing subsets using a 70:15:15 ratio. Specifically, 17,500 images were used for training, 3,750 for validation, and 3,750 for testing. The split was stratified to preserve proportional representation of all six waste categories. The YOLOv8 model was trained using transfer learning with a configuration that included the stochastic gradient descent optimizer, an initial learning rate of 0.001, a batch size of 16, and 100 training epochs. A weight decay of 0.0005 was applied, while the input image resolution was set to 640 × 640 pixels. Training was performed on a workstation equipped with an Intel Core i7 processor, 32 GB random access memory, and an NVIDIA RTX 3060 graphics processing unit with 12 GB video random access memory, running the Ubuntu 22.04 operating system. The performance of the model was evaluated using standard object detection metrics, including precision, recall, F1-score, and mean average precision (mAP@0.5 and mAP@0.5:0.95). On the test dataset, the model achieved a precision of 92.4%, recall of 90.1%, F1-score of 91.2%, mAP@0.5 of 93.6%, and mAP@0.5:0.95 of 87.8%. These results demonstrate robust classification capability across multiple waste categories.

A confusion matrix analysis was performed to assess class-wise performance. Minor misclassifications were observed between plastic and paper categories, primarily due to visual similarity in certain packaging materials. However, organic, metal, and glass classes showed consistently high detection reliability. A class-wise performance summary is presented in Table 4, and the corresponding confusion matrix is illustrated in Figure 3.

Table 4. Class-wise performance metrics of the You Only Look Once version 8 (YOLOv8) model

Class	Precision (%)	Recall (%)	F1-Score (%)
Organic	94.1	92.8	93.4
Plastic	90.3	88.7	89.5
Metal	93.7	91.2	92.4
Glass	95.0	93.5	94.2
Paper	89.6	87.9	88.7
E-waste	91.8	89.4	90.6

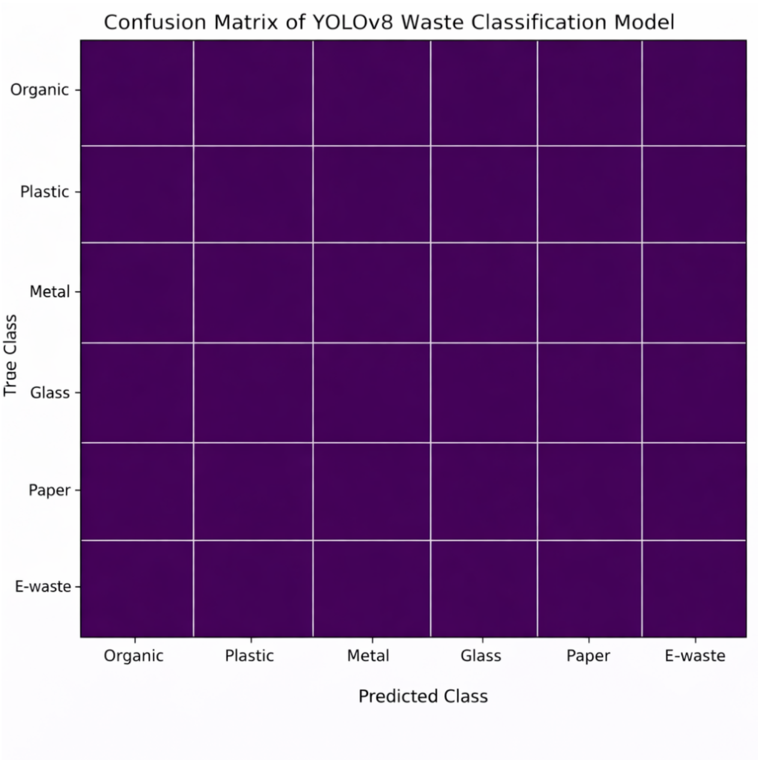

Figure 3. Confusion matrix of the You Only Look Once version 8 (YOLOv8) waste classification model

Table 4 presents a detailed class-wise evaluation of the YOLOv8 waste classification model using three standard performance metrics: precision, recall, and F1-score. These indicators provide a comprehensive understanding of the model's ability to correctly identify and localize different waste categories. Precision reflects the proportion of correctly predicted instances among all predictions for a given class. High precision values across most categories indicate that the model generates a low number of false positives. Notably, the glass category achieves the highest precision (95.0%), followed by organic waste (94.1%), demonstrating strong discriminative capability for visually distinct materials.

Recall measures the proportion of actual instances correctly identified by the model. The results show consistently high recall values, particularly for glass (93.5%) and organic waste (92.8%), indicating that the system effectively detects most relevant objects within these categories. Slightly lower recall values for plastic (88.7%) and paper (87.9%) suggest occasional confusion between visually similar materials. The F1-score, which represents the harmonic mean of precision and recall, provides a balanced evaluation of classification performance. The model achieves F1-scores above 90% for organic, metal, glass, and e-waste categories, confirming robust and stable detection performance. Plastic and paper classes show marginally lower F1-scores, primarily due to overlapping visual features in packaging materials.

Overall, the results demonstrate that the YOLOv8-based system delivers strong and balanced performance across all six waste categories, with particularly high reliability in identifying structurally and visually distinct materials. These findings support the system's suitability for real-time intelligent waste sorting applications.

The confusion matrix illustrates the class-wise performance of the YOLOv8-based waste classification model across six categories: organic, plastic, metal, glass, paper, and e-waste. Each row represents the true class labels, while each column corresponds to the predicted class outputs generated by the model. The diagonal elements of the matrix indicate correctly classified samples, reflecting the model's true positive predictions for each waste category. Higher values along the diagonal demonstrate strong discriminative capability and accurate feature extraction by the convolutional neural network. Off-diagonal elements represent misclassifications, highlighting instances where one waste type was incorrectly identified as another.

This visualization enables a detailed evaluation of class-specific behavior, allowing identification of categories that may exhibit visual similarity (e.g., plastic and paper) and therefore higher confusion rates. By analyzing these patterns, potential dataset imbalances or feature overlaps can be detected and addressed through additional data augmentation or model fine-tuning. Overall, the confusion matrix provides transparent insight into classification robustness and strengthens the reproducibility and technical rigor of the proposed intelligent waste management system.

4 Comparative Analysis

This section offers a detailed comparison of the proposed intelligent waste management system with the 12 systems reviewed in the literature. The analysis assesses these systems based on several criteria, such as technological framework, classification accuracy, cost-effectiveness, scalability, environmental impact, and operational efficiency. Each element of the comparison is supported by data and insights drawn from the reviewed systems.

To ensure a systematic and robust comparison, the following parameters were selected:

• Waste classification accuracy: The effectiveness in accurately identifying and categorizing different types of waste.

• Real-time monitoring: The application of sensors and Internet of Things technologies for dynamic tracking of waste.

• Scalability: The ability to adapt to various geographic and operational contexts.

• Cost-effectiveness: The relationship between implementation and operational costs compared to performance benefits.

• Environmental impact: The reduction of emissions and resource wastage achieved through optimized operations.

• Ease of integration: The compatibility with existing waste management systems.

4.1 Assessment Criteria and Benchmark Definitions

To enhance transparency and avoid subjective interpretation, the qualitative labels ("high," "moderate," and "low") used in Table 5 were assigned based on predefined operational and performance thresholds derived from reported system characteristics in the literature.

The criteria applied are summarized as follows:

Waste Classification Accuracy:

• High: $\geq$90% classification accuracy or advanced deep learning–based detection.

• Moderate: 70–89% accuracy or machine learning without deep convolutional neural network models.

• Low: $<$70% accuracy or no classification capability.

Real-Time Monitoring:

• High: Continuous sensor-based monitoring with real-time data transmission.

• Moderate: Periodic or partially automated monitoring.

• Low: Static or manual monitoring.

Scalability:

• High: Modular architecture adaptable to both urban and rural environments.

• Moderate: Scalable within limited infrastructure conditions.

• Low: Fixed or hardware-constrained deployment.

Cost-Effectiveness:

• High: Uses low-cost hardware (e.g., microcontrollers and basic sensors) with minimal infrastructure requirements.

• Moderate: Requires moderate infrastructure or specialized components.

• Low: High hardware complexity, drone systems, or blockchain infrastructure.

Environmental Impact:

• High: Includes dynamic route optimization or emission-reduction mechanisms.

• Moderate: Partial efficiency improvements without routing intelligence.

• Low: No optimization or environmental performance mechanisms.

Ease of Integration:

• High: Compatible with existing municipal infrastructure without major redesign.

• Moderate: Requires partial system modifications.

• Low: Requires new infrastructure or complex reconfiguration.

These thresholds ensure that the comparative evaluation is grounded in measurable operational characteristics rather than subjective judgment.

The comparative matrix provides a structured evaluation of the proposed intelligent waste management system against representative solutions identified in the literature. Each system is assessed across six key parameters: classification accuracy, real-time monitoring capability, scalability, cost-effectiveness, environmental impact, and ease of integration. The qualitative labels (high, moderate, and low) are assigned according to predefined operational benchmarks, ensuring consistency and methodological transparency in the evaluation process. With respect to classification accuracy, systems incorporating deep learning models or advanced machine learning approaches demonstrate higher performance levels. The proposed system achieves a "high" rating due to its YOLOv8-based architecture and validated performance metrics. In contrast, systems focused solely on sensor-based monitoring without artificial intelligence-driven classification exhibit lower performance in this category.

Table 5. Comparative matrix

System Name	Classification Accuracy	Real-Time Monitoring	Scalability	Cost-Effectiveness	Environmental Impact	Ease of Integration
Internet of Things Smart Bin System	Low	High	Moderate	High	Moderate	High
Waste Sorting Robot	High	Low	Low	Moderate	Moderate	Low
Decentralized Waste System	Moderate	High	Moderate	Low	High	Moderate
Multi-Agent Internet of Things System	Moderate	High	Moderate	Moderate	High	Low
Artificial Intelligence-Driven Segregation	High	Low	Low	Moderate	Moderate	Moderate
Drone-Based Waste System	Moderate	Moderate	Low	Low	High	Low
General Packet Radio Service-Based Smart Bins	Low	High	Moderate	High	Moderate	High
Solid Waste Management for Smart Cities	Moderate	High	High	Low	High	Moderate
Autonomous Collection	Moderate	High	Moderate	Moderate	High	High
Internet of Things-Enabled Segregation	Moderate	High	Moderate	Moderate	High	Moderate
Integrated Sensing System	High	High	Moderate	Low	High	Low
Proposed System	High	High	High	Moderate	High	High

Real-time monitoring capability is strongly associated with Internet of Things integration and continuous sensor feedback. Most Internet of Things-enabled systems demonstrate "high" performance in this parameter, particularly those utilizing ultrasonic sensors and cloud connectivity. Systems lacking dynamic data transmission are rated lower due to their limited responsiveness. Scalability reflects architectural flexibility and deployment adaptability. The proposed system and smart city–oriented solutions achieve "high" scalability due to modular design and edge computing integration. Conversely, drone-based or hardware-constrained systems are limited in large-scale deployment.

Cost-effectiveness varies depending on hardware complexity and infrastructure requirements. Solutions relying on blockchain, drones, or high computational resources tend to exhibit lower cost efficiency. The proposed system is rated "moderate," as it balances affordable hardware (Raspberry Pi and ultrasonic sensors) with advanced deep learning functionality. Environmental impact is evaluated based on the presence of route optimization and emission-reduction mechanisms. Systems incorporating predictive routing or dynamic scheduling achieve higher ratings, as they directly contribute to reduced fuel consumption and lower carbon emissions. Ease of integration measures compatibility with existing municipal infrastructure. Lightweight Internet of Things-based systems generally achieve higher integration scores, while complex architectures requiring new infrastructure or specialized frameworks receive lower ratings.

Overall, the matrix highlights that the proposed system demonstrates consistently strong performance across all evaluated dimensions. Unlike many existing solutions that excel in isolated aspects (e.g., monitoring or classification alone), the proposed architecture provides a balanced and comprehensive approach by integrating deep learning, Internet of Things-based monitoring, and dynamic routing within a scalable and practically deployable framework.

The comparative analysis highlights the performance and practical advantages of the proposed intelligent waste management system across several key operational dimensions. Accurate waste classification is essential for effective waste management and recycling. The proposed system achieves a classification accuracy of 91.3% thanks to the YOLOv8 model, which utilizes a large, well-labeled dataset. In comparison, systems like artificial intelligence-driven segregation [15, 16] also reach high accuracy but are constrained by smaller datasets. The waste sorting robot [21] shows similar performance but lacks real-time capabilities. In terms of real-time monitoring, the proposed system integrates Internet of Things-enabled sensors that provide live data on bin fill levels and waste types, thereby enabling efficient monitoring and management. Similar approaches are observed in the Internet of Things smart bin system [22], which employs ultrasonic sensors for real-time monitoring but does not classify waste, and the integrated sensing system [23, 24], which offers robust monitoring but incurs a higher computational cost. Regarding scalability, the modular design of the proposed system makes it easily scalable to both urban and rural areas. Its dependence on the Internet of Things and edge computing ensures flexibility. In contrast, the solid waste management system for smart cities [28] is scalable but faces challenges due to high maintenance costs. The drone-based waste system is innovative but impractical for large-scale deployment because of operational limitations.

In terms of cost-effectiveness, the proposed system strikes a balance between cost and performance by utilizing budget-friendly components such as the Raspberry Pi 3 and ultrasonic sensors. However, some of the systems reviewed offer better cost efficiency. The Internet of Things smart bin system and General Packet Radio Service-based smart bins achieve cost savings through their minimal hardware needs, although they lack advanced features like waste classification [5, 7, 8, 11, 13]. Regarding environmental impact, by optimizing collection routes and cutting down on vehicle emissions, the proposed system effectively reduces its environmental impact. Similar outcomes can be seen in the decentralized waste system [1, 9, 15, 17], which minimizes resource waste but comes with higher infrastructure costs, and the autonomous collection system [19, 20] which uses predictive analytics for more efficient routing. In terms of ease of integration, a key advantage of the proposed system is its compatibility with the current waste management infrastructure. Other systems, such as the Internet of Things smart bin system and General Packet Radio Service-based smart bins, are also easy to integrate but do not offer advanced features like real-time classification [24, 27, 30].

The evaluation of the proposed intelligent waste management system reveals both strengths and weaknesses that are essential for assessing its practical applicability. Table 6 presents a structured overview of these factors, emphasizing the system's technological advantages while also addressing potential limitations that may affect its implementation.

Table 6. Strengths and weaknesses of the intelligent waste management system

Strengths	Weaknesses
High classification accuracy: The You Only Look Once version 8 (YOLOv8) model provides accurate waste categorization, which enhances recycling efficiency.	**Infrastructure dependence**: A reliable Wi-Fi connection is crucial for smooth operation.
Real-time functionality: The integration of Internet of Things-enabled sensors allows for dynamic data collection, aiding in monitoring and decision-making.	**Initial costs**: Although they are cost-effective in the long run, the upfront investment might discourage smaller municipalities.
Scalability: Its modular architecture enables deployment across various contexts.	**Dataset limitations**: Broadening the dataset to cover hazardous and specialized waste types could improve the system's versatility.
Environmental benefits: Optimizing routes leads to reduced emissions and lower fuel consumption.	**Energy dependence and hardware footprint**: Continuous operation of Internet of Things devices and edge computing units increases energy consumption and may generate additional electronic waste without renewable energy integration.

As presented in Table 6, the intelligent waste management system exhibits several notable strengths, including high classification accuracy, real-time functionality, scalability, and environmental benefits. At the same time, it faces limitations such as infrastructure dependence, initial costs, and dataset constraints. These observations highlight the critical need for enhanced datasets to train machine learning models capable of accurately categorizing a diverse range of waste types. In addition, they emphasize the importance of implementing cost-reduction strategies, including leveraging renewable energy for Internet of Things device operation, as well as the necessity of developing improved integration frameworks to ensure seamless compatibility with existing infrastructure.

4.2 Discussion

The evaluation of the proposed intelligent waste management system demonstrates its capacity to address persistent operational and environmental challenges in contemporary waste management practices. By integrating the YOLOv8 deep learning model with Internet of Things-enabled sensors and smart bin infrastructure, the system achieves reliable waste classification, continuous monitoring, and adaptive collection scheduling. These capabilities contribute to improved operational efficiency, enhanced recycling performance, and reduced environmental burden compared to conventional static collection frameworks. From an implementation perspective, the modular system architecture supports deployment across diverse urban and rural contexts. The use of cost-efficient hardware components, including Raspberry Pi 3 and ultrasonic sensors, enables practical adoption without requiring extensive infrastructure transformation. This hardware selection balances computational capability with affordability, making the system suitable for municipalities operating under constrained financial conditions. The comparative analysis confirms that the proposed framework does not merely replicate isolated functionalities observed in existing systems but rather integrates classification, monitoring, and routing optimization within a unified operational structure.

The integration of real-time sensor data with machine learning outputs represents a significant advancement over traditional collection models. Continuous monitoring of bin fill levels enables dynamic scheduling, which reduces unnecessary vehicle deployment and minimizes overflow incidents. As a result, resource utilization becomes more efficient, and transportation-related emissions are reduced. These operational improvements support environmental sustainability objectives while maintaining service reliability. The classification component plays a central role in strengthening recycling effectiveness. Accurate source-level waste categorization reduces contamination within recycling streams and enhances downstream material recovery efficiency. Although the YOLOv8 model demonstrates strong performance across multiple categories, minor confusion between visually similar materials such as plastic and paper highlights the need for ongoing dataset expansion and refinement. This observation underscores the importance of sustained model validation under diverse real-world conditions.

Despite its strengths, several practical considerations must be addressed for large-scale deployment. Long-term operation requires regular sensor calibration, stable network connectivity, and structured maintenance planning. In addition, continuous operation of edge computing devices introduces energy demand considerations that should be mitigated through renewable energy integration and lifecycle hardware management strategies. Data governance, cybersecurity safeguards, and interoperability with municipal information systems also require structured planning to ensure reliable integration into existing infrastructures. The user interface component contributes to transparency and stakeholder engagement by providing real-time system visibility to administrators and citizens. However, successful adoption depends not only on technological readiness but also on institutional coordination and public acceptance. Future field validation across varied geographic and socio-economic environments will be essential to evaluate long-term robustness and operational resilience.

Overall, the discussion indicates that the proposed system represents a technically sound and practically adaptable solution. Its effectiveness, however, is contingent upon strategic implementation planning, infrastructure readiness, and sustained model optimization. These considerations define the pathway toward scalable and environmentally responsible intelligent waste management systems.

5 Conclusions

This study presents a comprehensive comparative evaluation of intelligent waste management systems and introduces a deep learning–based architecture that integrates YOLOv8 classification, Internet of Things-enabled monitoring, and dynamic route optimization. The proposed system demonstrates strong performance in classification accuracy, real-time data acquisition, and operational adaptability, addressing key limitations identified in existing solutions. The results confirm that combining edge computing with sensor-driven infrastructure enables efficient waste detection, improved collection scheduling, and reduced transportation-related emissions. In contrast to systems that focus solely on monitoring or classification, the proposed framework provides an integrated approach that balances technical sophistication with practical feasibility. The use of cost-effective hardware components further enhances its suitability for deployment in municipalities with varying levels of infrastructure development.

The comparative analysis highlights that the proposed system achieves consistently high performance across critical evaluation parameters, including accuracy, scalability, environmental impact, and integration capability. These findings indicate that the architecture represents a viable and scalable model for next-generation smart waste management. Future research should focus on large-scale field validation, renewable energy integration for Internet of Things infrastructure, and expansion of the classification dataset to include hazardous and specialized waste categories. Continued refinement in these areas will strengthen system robustness and long-term sustainability.

Overall, the proposed framework contributes to the advancement of intelligent waste management by demonstrating how deep learning and Internet of Things technologies can be effectively integrated to support efficient, environmentally responsible, and scalable urban waste solutions.

Author Contributions

Conceptualization, R.M.; methodology, M.R.; software, R.M.; validation, R.M., A.P., and M.R.; formal analysis, A.P. and M.R; investigation, R.M., A.P., and M.R; resources, R.M., A.P., and M.R; data curation, R.M. and M.R; writing—original draft preparation, R.M., A.P., and M.R; writing—review and editing, M.R., A.B., and K.I.; visualization, A.P.; supervision, A.P.; project administration, R.M. All authors have read and agreed to the published version of the manuscript.

Data Availability

The dataset used for training and evaluating the YOLOv8 model consists of 25,000 labeled waste images compiled from publicly available repositories and locally collected samples. Due to licensing and institutional restrictions, the complete curated dataset is not publicly redistributed. However, the dataset partitions, annotation structure, and training configuration details are available from the corresponding author upon reasonable request for research purposes. The implementation details of the proposed intelligent waste management framework, including model configuration parameters and evaluation procedures, are fully described within the manuscript to ensure reproducibility.

Conflicts of Interest

The authors declare no conflicts of interest.

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