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Article

Artificial Intelligence in Smart Waste Management: A Systematic Review of Algorithms, Integrated Architectures, and Future Research Directions

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Abstract: Urbanization, industrial development and changing consumption patterns have also been factors in ongoing growth of municipal solid waste (MSW) generation, which places extreme pressure on urban infrastructure, environmental quality and public health. Yet, traditional waste management approaches that focus predominantly on fixed collection times and manual sorting face challenges in contexts where the volume of production is fluid – resulting in overflowing bins, poor segregation of waste streams, ineffective routing of vehicles and higher emissions. These limitations have been addressed by smart waste management systems which have shifted from IoT monitoring (fill-level sensing) to AI systems that can be predictive, adaptive, and self-optimizing. This paper summarizes the available literature on various Artificial Intelligence (AI) technologies used for smart waste management, with a particular focus on detection/classification, fill level estimation, monitoring and operational decision-making. To be transparent and reproducible, a PRISMA-guided screening process was used: 780 records were identified, 602 records after duplicates, 450 records were screened, 150 were full texts and after final synthesis 128 studies were included. Results indicate research is typically spread out across individual components, and there is a lack of standardization in datasets, benchmarking and widespread implementation of real-world validation, which calls for an integrated architecture. Therefore, this study suggests a YOLOv8-based smart waste framework that integrates real-time waste detection/classification, waste bin fill-level estimation (empty/half-full/full) and monitoring/decision layer, which can be delivered at edge or hybrid (edge–cloud) architecture for low latency operation and scalability. The direction of the proposed concept is towards designing a unified system to increase the efficiency of the operations, decrease manual efforts, and increase sustainable, data-driven waste management in cities.
Keywords: Smart waste management; Artificial intelligence; Computer vision; YOLOv8; Waste detection; Waste classification; Bin fill-level estimation; Edge–cloud computing; IoT-enabled monitoring

1. Introduction

The quick growth of urban populations, industrial development and changes in consumption habits have contributed to a substantial rise in the generation of municipal solid waste (MSW) all over the world [1]. The World Bank estimates that waste production in the world will continue to grow at a significant rate in the future, putting strain on the municipal systems, environmental systems and public health systems [2]. Traditional waste management systems, often relying on set routines, manual sorting, and post-failure approaches have proven to be less effective in tackling the evolving nature of waste generation [3]. These factors cause operational inefficiencies, as well as health hazards, environmental pollution and greenhouse gas emissions due to overflowed bins, segregation issues, inefficient routing, fuel consumption, and late disposal[4].

In order to overcome these issues, Smart Waste Management (SWM) has been recognized as an important part of the smart city ecosystem[5]. Smart waste systems are built on digital technologies, sensors, communications networks and data analytics to improve monitoring and operational control[6]. Initial smart waste management applications mainly concentrated on introducing sensing mechanisms using the Internet of Things (IoT), such as ultrasonic or weight-based fill-level sensors that are embedded in the waste bins[7]. These systems gave real-time visibility, but were not equipped with predictive capability and autonomous decision-making intelligence[8].

The use of Artificial Intelligence (AI) in waste management systems is a game-changer[9]. Data-driven optimization, predictive modelling, automated classification and intelligent resource allocation are all areas in which AI can help[10]. Technologies such as Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), reinforcement learning and evolutionary optimization algorithms are becoming more widespread and used throughout the waste management cycle[11]. The AI-based systems can make waste management operations predictive, adaptive, and self-optimizing, unlike traditional systems[12].

The system of waste management is cyclic and interconnected and consists of collection, transportation, recovery, recycling/disposal and analytical evaluation[13]. The operational phases are interrelated, and as shown in Figure 1, the phases mutually shape a wider socio-ecological impact. Waste distribution by geographic area may change due to changes in collection frequency or routing[14]. Changes in the characteristics of waste can affect the prevalence of infections and risks to workers during public health crises, such as an increase in biomedical or hazardous waste material[15]. Changes in disposal timing affect emissions to the environment and landfill capacity utilization[16]. Therefore, waste management actions have cascading consequences beyond the operational logistics[17].

The systemic relationship, as depicted in Figure 1, between the waste management operations and the overall impacts on waste, such as the change in waste distribution, infection rate, disposal frequency, waste composition, safety risks and the volume of waste. These complex, multi-dimensional relationships highlight the need for smart control solutions that can process massive amounts of data and make effective decisions in real-time[18].

The role of Artificial Intelligence in this intelligence is played in the following ways:

- Computer Vision Models (e.g., CNN, YOLO): Support waste classification and segregation in an automated way to enhance recycling efficiency and prevent contamination[19], [20].
- Predictive Analytics (e.g., LSTM, Random Forest, XGBoost): Make predictions of waste generation patterns and changes in fill level for spatial regions.
- Optimization Algorithms (e.g., Genetic Algorithm, Particle Swarm Optimization, Reinforcement Learning): Create the most economical and efficient routes for fuel collection[21].
- Anomaly Detection Systems (ADS): Recognize abnormal waste trends or potential health risks of waste.

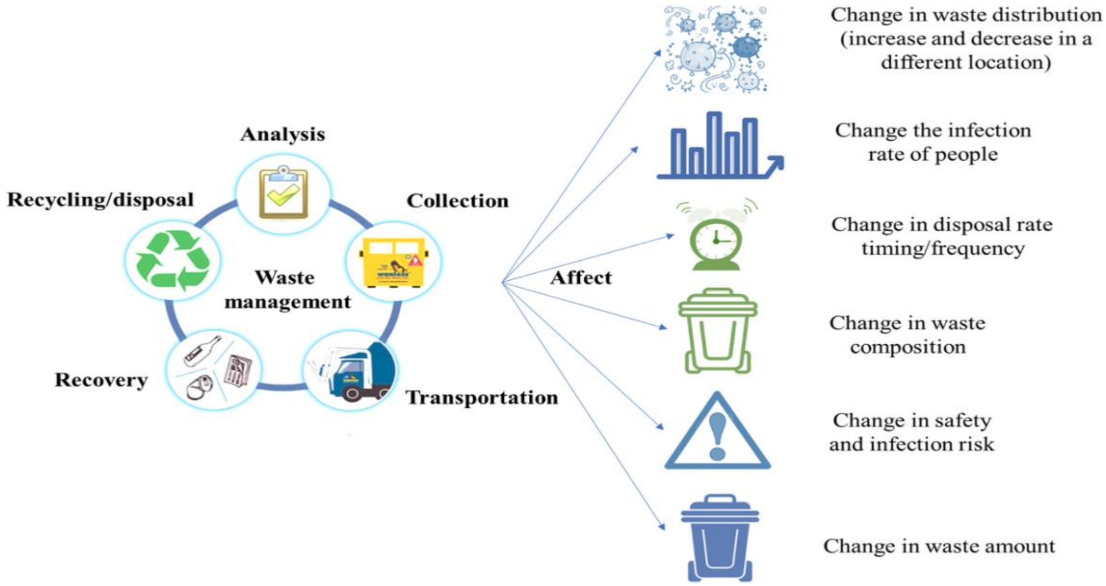

Figure 1. Integrated Waste Management Cycle and Its Dynamic Impacts

https://link.springer.com/article/10.1007/s10311-023-01604-3

For instance, during epidemics, when biomedical waste increases, the composition of biomedical waste and the risk of infection change. AI-powered predictive systems can adapt the disposal schedule and routing, reducing exposure[22]. Likewise, spatial predictive models can identify the spatial patterns in waste deposits in a district ahead of time, which allows the deployment of resources to address the distribution of waste before it overflows[17], [23].

While there has been significant progress, the current research on AI in waste management is scattered. Research in many studies is limited to the waste classification accuracy and does not consider system scalability and deployment[24]. Some focus on routing optimization and ignore predictive fill-level modelling. Also, there are no standardized datasets and benchmarking frameworks available, nor a common architectural model that combines sensing, analytics, optimization, and governance layers[25]. The vast majority of experimental validations take place in controlled contexts, and hence have only limited transferability to large-scale municipal settings[26].

Furthermore, there has been little work in the field to explore the impacts of AI interventions on other environmental and public health metrics, as described in concept in Figure 1. Waste management is not just an operational issue, but one that has a significant impact on the infection risk, occupational safety, emission levels and sustainability indicators. Thus, an analytical view at the system level is needed[27]. To address these gaps, this review gives an exhaustive and systematic summary on Artificial Intelligence applications in Smart Waste Management. Suggest further research ideas towards scalable, sustainable, and intelligent waste ecosystems[28].

This review, therefore, seeks to offer a structured pathway for the transition of the existing waste management infrastructure to a smart, resilient and data-driven urban system with the aim of combining technological, operational and systemic perspectives[29]. The results represent progress towards next-generation AI-powered smart cities that are not only capable of coping with waste but can be optimised and recovered as part of a circular economy[30].

2. Research Methodology

2.1 Research Design and Review Framework

This research uses a systematic literature review (SLR) to investigate the concept of a Smart Waste Management system by using Artificial Intelligence (AI), focusing specifically on the computer vision models that have been used by other researchers, including the YOLO architecture and AI-based monitoring systems. A methodological approach was followed to ensure reporting based on PRISMA (Preferred Reporting Items for

Systematic Reviews and Meta-Analyses) framework aiming at transparency and reproducibility. By employing the PRISMA model, this review follows four phases — Identification, Screening, Eligibility Assessment and Final Inclusion. This is an structured process which will assists in minimising selection bias and that guarantees that all relevant literature on Waste Management systems ingenstructed with the aid of help of AI.

2.2 Data Sources and Search Strategy

Academic databases such as Scopus, Web of Science, IEEE Xplore, ScienceDirect and SpringerLink were searched for relevant studies. The search was carried out with the help of predefined Boolean expressions, which are the combinations of the searched key terms "Smart Waste Management," "Artificial Intelligence," "Machine Learning," "Deep Learning," "Computer Vision," "YOLO," and "Waste Detection." To reflect the most recent developments in AI-based urban waste systems, the search was limited to peer-reviewed journal articles from 2015 and 2025. A total of 780 records came back from the first search of the database. These records were the main data source to further filter in the PRISMA framework.

2.3 Screening Process

After identifying, duplicate records from the databases were eliminated and 602 articles were obtained. The following studies were screened for title and abstract to see if the study was relevant to the AI-based waste monitoring, detection, classification, and optimization system. Only those AI-related studies that had both policy and computational validation elements were included during this step, as were those with at least computational modeling without policy or qualitative discussion. Studies that did not involve implementing Artificial Intelligence or did not include computational validation, studies that emphasized only policy or qualitative discussion without technical modeling, or studies that were not related to municipal solid waste systems were excluded.

Following the initial screening, 450 records were kept for further consideration and 300 records were discarded because they were irrelevant or did not match the set criteria.

2.4 Eligibility Assessment

In the eligibility phase, 150 articles were analyzed in detail. The studies were assessed based on the use of AI, ML, DL, or optimization algorithms; experimental validation on real or simulated data; reporting of performance metrics such as Accuracy, Precision, Recall, F1-score, Mean Average Precision (mAP), Root Mean Square Error (RMSE), or computational efficiency; and direct application in the smart waste management lifecycle.

In this phase studies that were not clearly related to smart waste systems, did not have clear relevance, were not methodologically clear, did not have experimental rigor or nor did they have a quantifiable evaluation were excluded.

2.5 Final Inclusion and Data Extraction

All the inclusion and exclusion criteria were applied and 128 studies were selected for final consideration for the systematic review. The studies were grouped into thematic blocks: waste detection and classification with AI, waste generation prediction, estimation of waste quantities in bins, route optimization, valorization of waste in circular economy by AI.

Structured data extraction was conducted for all the included studies to capture key characteristics including algorithm description, data characteristics, performance measures, deployment (simulation, pilot, or real-world implementation), and limitations. These extracted data were then analyzed in terms of the taxonomy to identify research trends, performance benchmarks, scalability considerations and existing research gaps.

2.6 PRISMA Flow Summary

The selection process for this study was summarized as follows: 780 records were identified by searching the databases, 602 records were identified after removal of duplicates, 450 records were screened based on the title and abstract, 300 records were excluded during the screening process, 150 full-text articles were assessed for eligibility, and 128 studies were included in the systematic review. This method of filtering provides transparency of the filtering process and increases the credibility of the findings of the review.

Figure 2: PRISMA Model

3. Literature Review

3.1 Artificial Intelligence in Global Waste Management

Along with other issues, waste management has become one of the most critical issues in sustainability at global level due to the rapid urbanization, industrialization and over-consumption trend. By 2050, the quantity of municipal solid waste (MSW) generated is expected to be around 3.4 billion tonnes, creating severe environmental pollution, reliance on landfills, and health threats [31]. To address these challenges, Artificial Intelligence (AI) has been identified as a transformative technological enabler that can support the improvement of efficiency, accuracy and sustainability of waste ecosystems.

Olawade et al. (2024) offers an extensive overview of the use of AI throughout the waste management lifecycle, ranging from collection and sorting to waste-to-energy (WTE) processing, to logistics optimization, to the detection of illegal dumping and recovery of resources [32]. The results of their study prove that AI-assisted logistics optimization can cut transportation distance by up to 36.8%, operational costs by around 13.35% and the time used by 28.22%. Moreover, AI waste identification and sorting systems can achieve more than 72.8% to 99.95% accuracy of waste classification, which is better than the manual waste segregation system. The study also highlights the need for incorporating AI with chemical analysis methods to enhance the optimization of plastic pyrolysis, carbon emission estimation, and energy conversion processes.

Likewise, Fang et al. (2023) mentions the contribution of AI in smart bins, waste sorting robots, forecasting of waste generation, monitoring systems and smart city waste governance[31]. The review highlights the impact of AI in increasing the efficiency of the recycling process, mitigating pollution, and optimizing processes. Both studies, however, point to data quality, privacy issues, costs, and ethical issues as challenges in scaling up use.

3.2 Evolution of AI and IoT Integration in Smart Waste Systems

Smart waste management has been evolving with the use of the Internet of Things (IoT) technologies, in combination with machine learning and deep learning models. The use of IoT-based sensor networks is a key factor in enhancing operational visibility as it enables real-time monitoring of bin fill levels, temperature, humidity, and gas emissions [33]. The IoT systems, however, are mainly monitoring and are not inherently smart. These systems can be made intelligent by integrating AI models, enabling them to perform predictive analytics and adaptive control. Sinthiya et al. (2022) reviewed 40 studies on smart waste management with the help of AI published in between 2001 and 2021[34]. They have classified the various AI applications into different waste domains such as municipal, medical, construction, industrial and domestic waste management. The study emphasizes on the wide applications of the machine learning and deep learning algorithms in classification, forecasting, and optimization applications. Notably, it outlines future research avenues concerning scalability, real-time processing, and integrated smart frameworks.

Despite all these developments, research is still limited, focusing on one of the three aspects (classification, monitoring, routing) independently from the others, without a systems view.

3.3 AI-Based Waste Detection and Classification

Waste classification is one of the most studied fields in waste management based on AI. In the field of waste recognition, Convolutional Neural Networks (CNNs) have shown great success in identifying categories of waste that can be recycled, organic, and hazardous waste [35]. New object detection architectures like YOLO have also improved real-time detection, allowing for the detection of both location and type in a single inference.

High accuracy real-time waste classification at scale is still challenging, however [36]. The robustness of the models is still affected by variability in lighting conditions, complexity of background, occlusion, and class imbalance. Moreover, there are alternative views on how best to deploy. There are also studies proposing using CNN for edge deployment to reduce latency and network dependence (A Smart Recycling Bin Using Waste Image..., 2022), or for cloud-based deployment to take advantage of the central computing power [37]. This debate highlights other concerns about the scaling, computational expense, and real-time performance compromises.

3.4 Optimization, Logistics, and System Efficiency

Some of the largest costs of waste management are associated with collection and transportation. In this paper, Artificial Intelligence approach is to minimize huge searching points cost, therefore various optimization algorithm are used for route optimizing process like Genetic Algorithm, Particle Swarm Optimisation and reinforcement learning [38]. According to Olawade et al. AI-driven logistics systems are expected to significantly reduce transportation distances, fuel consumption, and time spent in 2024 [32].

Additionally, system configuration and parameter optimization are executed harnessing metaheuristic optimization approaches [39]. The systems intelligence acquired from predictive fill-level estimation and classification can be fused with these techniques to realize holistic system intelligence. However, there remain issues integrating different hardware setups together with communications protocols and very limited integration between municipal systems.

3.5 Identified Research Gaps

Significant steps have been made, but still some questions remain unanswered. Conducting studies separately on detection, monitoring and optimization is common, but it can be hard to realize system-wide integration. Second, data on waste classification is still not uniform enough to benchmark and can thus give rise to a problem when comparing performances. And thirdly, there are few human real-world studies assessing the size for most of those which are laboratory based.

The authors of Olawade et al. The need for AI in sustainable solutions requires better data quality, protection of privacy, ethics and cost-effectiveness (Zhang et al. (2024)). Without addressing the issues mentioned, the promise of AI in waste management could be partially unattainable. The ongoing damage to the environment, poor recycling systems with linked costs of operations and progressively expensive bill for landfill have signified the demand for the sustainable, holistic and energy efficient AI based solutions at scale[32].

3.6 Purpose and Contribution of the Present Review

Hence, the objective of this systematic review is to providesan overview of recent studies on the use of artificial intelligence (AI) and Internet of Things (IoT)-enabled smart waste management focusing specifically on system integration and classification accuracy, operational efficiency [40]. This review aims to address the needs that were highlighted in the reviewed research by providing a systematic and comprehensive examination of existing modeling methods, identifying technical hurdles, and recommending future research paths. The findings of this research will benefit in merging the scattered research results and highlight the importance of scalable design of the architectural elements, thus enabling the creation of intelligent, accurate, and energy-efficient smart waste management systems that enable sustainable urban development and circular economy goals.

Table 1. Comparative Analysis of AI-Based Smart Waste Management Studies

Author & Year	Application Domain	AI Technique Used	Key Quantitative Findings	Identified Limitations	Research Gap Highlighted

Olawade et al., 2024	Waste logistics, sorting, waste-to-energy, monitoring	Machine Learning, Deep Learning, AI + Chemical Analysis	Transportation distance reduced up to 36.8%; cost savings up to 13.35%; time savings up to 28.22%; sorting accuracy 72.8–99.95%	Data quality issues, privacy concerns, high implementation cost, ethical considerations	Need for scalable, privacy-aware, cost-effective AI frameworks
Fang et al., 2023	Smart bins, robotic sorting, forecasting, smart city integration	ML, DL, AI-based optimization	Improved operational efficiency and recycling performance	Lack of standardized evaluation benchmarks; scalability concerns	Integration of AI models across lifecycle stages required
Sinthiya et al., 2022	Systematic review of AI-based waste systems	ML & DL algorithms (CNN, ANN, hybrid models)	Categorized AI use in MSW, medical, industrial waste domains	Fragmented frameworks; limited real-world validation	Need for unified and integrated AI architecture
Feng et al., 2022	Waste image classification	Deep CNN models	High classification accuracy in controlled environments	Dataset imbalance; sensitivity to lighting conditions	Robust real-time detection models needed
White et al., 2020; Longo et al., 2021	Cloud-based smart waste analytics	Centralized ML systems	Enhanced large-scale analytics capability	High latency; network dependency; infrastructure constraints	Edge–cloud balance required for real-time monitoring
Duhayyim et al., 2022; Mishra et al., 2022	Route optimization & system efficiency	Genetic Algorithm, PSO, Metaheuristic optimization	Reduced routing cost and fuel consumption	Weak integration with real-time detection systems	Need for detection + optimization integration

4. Proposed YOLOv8-Based Smart Waste Framework

4.1 System Overview

Existing AI-based waste management systems face several challenges, such as poor integration, lack of real-time capabilities, and scalability, which is why this study introduces an integrated YOLOv8-based Smart Waste Management Framework. It integrates object detection, image-to-waste classification modeling using deep learning, waste level detection in bins based on images, and real-time monitoring functionalities to facilitate intelligent decision-making and automated waste classification in urban settings.

The proposed system is intended to be real-time and to provide accurate support of waste detection and segregation, while being efficient enough to be deployed in the edge or hybrid edge–cloud environments. The system combines computer vision and smart monitoring technologies to achieve more efficient operations, minimize human involvement, and boost recycling accuracy.

4.2 Architectural Design

The framework we propose comprises five layers that are connected:

4.2.1 Image Acquisition Layer

This layer is used for gathering images of trash by using smart bins equipped with cameras or monitoring systems. Images are obtained under a range of environmental settings, lighting and background complexity and types of waste. Data is preprocessed in distinct ways like resizing, normalizing data augmentation and remove noise to improve the diversity of dataset and robustness of model.

4.2.2 YOLOv8-Based Detection and Classification Layer

The YOLOv8 Object Detection framework is an essential part of the structure. YOLOv8 is adept at identifying multiple waste categories in one forward pass. This ability makes it capable of detecting different types of waste from an image in real-time.

A set of annotated waste images (bounding box coordinates and classes) is used to train the model. Performance is assessed in terms of standard metrics such as:

- Precision
- Recall
- F1-score
- Mean Average Precision (mAP)
- Inference time

YOLOv8 is chosen for its enhanced feature pyramid networks, anchor-free detection approach, optimized loss functions, and the backbone architecture, all of which offer better accuracy-speed trade-offs than previous versions of YOLO.

4.3 Bin Fill-Level Estimation Module

The proposed framework also includes an image-based bin fill level estimation mechanism, besides waste classification. In this module, the spatial occupancy in bin images is analyzed to classify the bins into three statuses to represent three operational states:

- Empty
- Half-full
- Full

The proportion of bin space taken up by the waste objects detected is calculated using feature extraction and bounding box area estimation techniques. This approach avoids the need of extra ultrasonic sensors which removes dependence on hardware and reduces the cost. The classification and fill-level estimation features facilitate dynamic scheduling and overflow prevention.

4.4 Decision and Monitoring Layer

The detection results are sent to a monitoring dashboard or cloud-based platform for visualization and decision making. This layer performs:

- Real-time waste statistics aggregation
- Classification distribution analysis
- Fill-level alerts generation
- Historical trend storage

Municipal management can use this data for deciding resources and optimizing collection frequency. This framework can be integrated with route optimization algorithms, and facilitates smart collection planning.

4.5 Edge–Cloud Deployment Strategy

The proposed system uses a hybrid edge–cloud architecture for a better trade-off between latency and scalability. Edge devices can perform detection inference for classification in real-time (with low latency), whereas the cloud can be used for the storage and the analysis of historical data, as well as for model updates. Therefore, a hybrid solution can provide a real-time responsive system, with scalable computation.

4.6 System Workflow

The steps involved in the proposed system operation are summarized below:

1. Image capture from smart bin camera.
2. Preprocessing and normalization of image input.
3. YOLOv8-based waste detection and classification.
4. Fill-level estimation based on bounding box coverage.
5. Data transmission to monitoring dashboard.
6. Generation of alerts and decision recommendations.

The user benefits from automatic segregation, better visibility of the process, detection of overflow, etc.

4.7 Expected Contributions and Advantages

There are multiple advantages of the suggested YOLOv8 based framework when compared with existing Conventional AI based frameworks:

- High real-time detection accuracy
- Reduced manual sorting dependency
- Elimination of additional fill-level sensors
- Improved scalability via hybrid deployment
- Enhanced operational efficiency and cost-effectiveness

The proposed framework simultaneously tackles detection accuracy, real-time performance, and system integration, thereby advancing towards scalable, intelligent, and sustainable smart waste management systems.

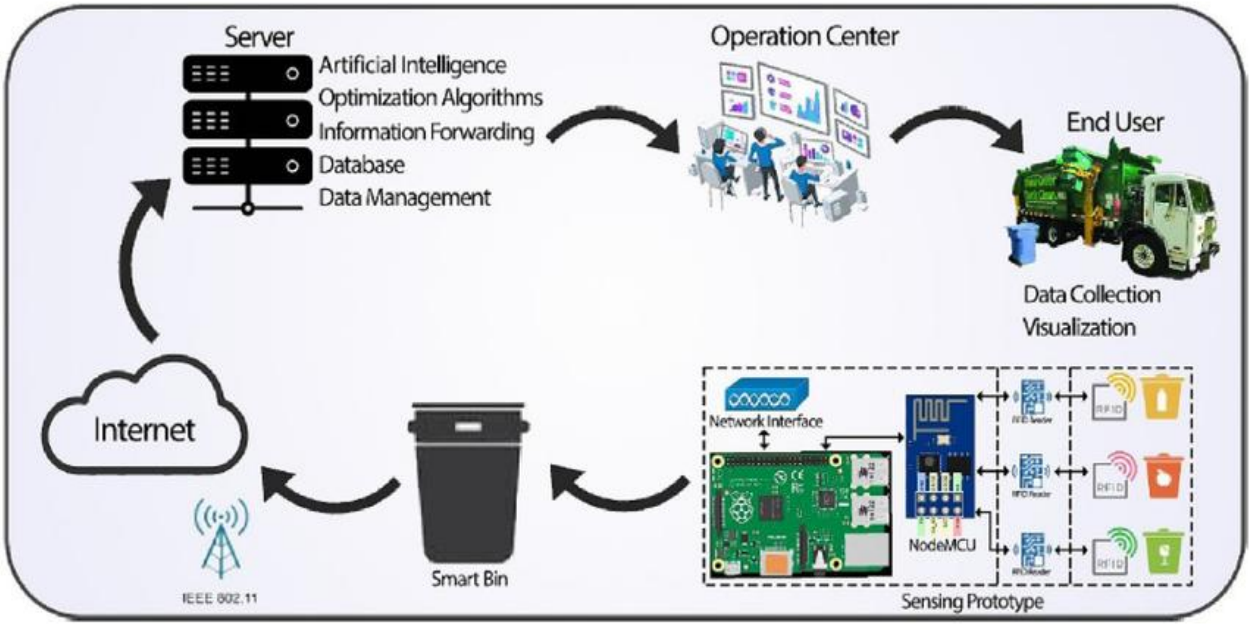

Figure 2: YOLOv8-Based Smart Waste Management System

5. Challenges and Future Research Directions

This section requires analysis rather than description, and should focus instead on your YOLOv8-based framework.

5.1 Technical Challenges

AI-based smart waste management has advanced significantly, but there are still several challenges that need to be overcome before this technology can be adopted at scale. There are many challenges, such as dataset variability and imbalance. Images collected in the real world show significant variation in lighting, background noise, occlusion and superposition of objects. Such variations make it more difficult to generalize the models, especially in real-time urban applications. In addition, there are limited number of available waste image datasets, which are not adequately represented or lack standardized annotation formats, causing model performance to be biased.

The other significant issues are computational efficiency. While YOLOv8 offers better speed–accuracy compromises, it is challenging to deploy deep learning models to edge devices with constrained hardware capabilities. For sustainable deployment in smart bins and embedded systems, memory constraints, energy consumption and model size optimization are key factors to consider.

Further, there may be issues with the fill-level estimation of waste levels in bins where the distribution of waste is not uniform, or where the waste is not visible in the image, or the image contains a partial view. To achieve better accuracy in estimation, robust spatial modeling techniques and depth-aware vision approaches could be needed.

5.2 System Integration and Scalability Issues

Previous studies have concentrated on either classification or routing optimization, but not comprehensive systems. Seamless interoperability between AI detection modules, IoT networks, municipal dashboards and route optimization engines remain complex.

Scalability also is a big concern. The smarter bins that roll through urban areas, the more bandwidth of data transmission, centralized analytics and cloud storage may be at risk of performance bottlenecks. Some of these problems can be addressed by hybrid edge–cloud architectures, but there is no standard architecture or communication protocol.

Furthermore, with the different levels of technological readiness and the different infrastructures of the cities, there are further integration problems.

5.3 Data Privacy, Security, and Ethical Considerations

There are privacy and cybersecurity issues with AI-powered smart waste systems, given the ongoing process of capturing images and transmitting data. Unauthorized access to surveillance data or model manipulation, or system intrusion, may lead to loss of operational integrity. The ethical issues on image collection in the public space need also to be discussed.

Encrypting communication channels, employing federated learning approaches, and establishing secure model update protocols are essential for responsible AI deployment in future implementations.

5.4 Economic and Sustainability Constraints

While the benefits of AI systems in reducing operational costs and transportation distances are measurable, the initial implementation costs are still significant. Financial investment is necessary for the installation, operation of the cloud infrastructure, training of the model, maintenance, and regular updates.

Another contributing factor to concerns over environmental footprints is energy usage for models from deep learning. To support smart waste systems to become sustainable, lightweight and energy efficient AI architectures have to be developed.

5.5 Future Research Directions

To address the challenges that were identified, some research directions are suggested:

1. Development of Standardized Waste Image Datasets

In future, a benchmark dataset on a larger scale with standardized formats of annotations in multiple cities will be developed to facilitate the fair comparison of the performance of the different models and enhance the generalization performance.

2. Lightweight and Energy-Efficient AI Models

Model compression, knowledge distillation, pruning, and quantization could be explored to improve the feasibility of deploying models on the edge and still achieve high detection accuracy.

3. Multi-Modal Sensing Integration

Using computer vision, depth sensors, ultrasonic and weight sensors to combine these data can enhance the robustness of the fill-level estimation and decrease the uncertainty in complex environments.

4. Federated Learning for Privacy Preservation

Decentralized AI training on multiple smart bins can be achieved with Federated AI frameworks, which can help to improve privacy and security by not sending raw image data.

5. Integration with Route Optimization and Smart City Platforms

Future systems should integrate outputs of real-time detection with dynamic routing algorithms and city decision-support systems to develop fully autonomous waste management ecosystems.

6. Explainable and Ethical AI

The development of explainable AI models will enhance the safety and trust of AI-based segregation decisions. This is especially true in terms of public acceptance and regulatory requirements.

7. Digital Twin and Predictive Simulation

Digital twins can assist in the modeling of diverse urban situations to analyze waste and predict system performance to better manage and optimize infrastructure.

5.6 Summary

AI-driven waste management systems that incorporate YOLOv8 show great potential, especially regarding detection accuracy, operational efficiency, and sustainability. However, issues relating to dataset robustness, computing requirements, system integration, privacy, and costs remain obstacles. The potential for Transformative Smart Cities through Intelligent Waste Management Systems has yet to be realized. Research should focus on AI frameworks that emphasize scalability and energy efficiency, with a focus on ethics.

6. **Conclusion**

The world is facing an increasing amount of municipal solid waste (MSW), causing environmental, economic, and public health burdens that demand innovative and adaptive solutions. Conventional waste management systems rely on human-initiated separation and scheduled collections of waste. These systems are struggling to adapt to the evolving patterns of waste in metropolitan areas. The first of its kind, Artificial Intelligence has enabled waste detection, classification and management optimization at every stage within the waste management process.

This study systematically mapped recent advances in smart waste management using AI and the Internet of things (IoT) systems and identified the most significant technology patterns, performance metrics and research deficiencies. The literature suggests the presence of many benefits beyond the traditional scope of cost and time with the implementation of AI-based systems. Operational efficiency increases and waste classification accuracy can be achieved at rates greater than 99%. Shorter transportation distances achieve reduced operational costs. Persistent hurdles of data quality and system privacy, as well as several other integration and deployment challenges remain.

To address these limitations, this paper proposes a framework for smart waste management built on YOLOv8 that integrates real-time object detection, image-to-image estimation of bin fill levels, hybrid edge/cloud deployment, and automated intelligent frameworks. The proposed framework enhances detection accuracy, minimizes latency, eliminates the need for additional hardware-based level sensors, and is designed to scale to the urban level. The framework harnesses deep learning-based waste identification, real-time automated monitoring, and even optional route-optimization within the framework, to move closer to a fully autonomous waste management ecosystem.

The findings of this research stress designing future smart waste systems around AI elements at the systems level rather than the individual level. For a sustainable, long-term implementation of smart waste systems, what is required are standardized benchmark datasets, light model optimizations, privacy-preserving learning, and energy-efficient deployment optimizations. There is a need for the further integration of researchers, municipal bodies, and policymakers to implement ethical, secure, and cost-effective AI solutions.

The development of AI-enabled smart waste management systems that leverage cutting-edge object detection models are a highly sought-after urban solution. If implemented in sustainable and scalable systems, they are likely to improve recycling rates focus on reducing the negative impacts on the environment, provide a major contribution to the circular economy, and integrate seamlessly with smart city solutions.

REFERENCES

1. I. R. Abubakar et al., ‘Environmental Sustainability Impacts of Solid Waste Management Practices in the Global South’, IJERPH, vol. 19, no. 19, p. 12717, Oct. 2022, doi: 10.3390/ijerph191912717.
2. Z. Zhang et al., ‘Municipal solid waste management challenges in developing regions: A comprehensive review and future perspectives for Asia and Africa’, Science of The Total Environment, vol. 930, p. 172794, Jun. 2024, doi: 10.1016/j.scitotenv.2024.172794.
3. M. A. Hannan et al., ‘Waste collection route optimisation model for linking cost saving and emission reduction to achieve sustainable development goals’, Sustainable Cities and Society, vol. 62, p. 102393, Nov. 2020, doi: 10.1016/j.scs.2020.102393.

4. S. Ahmad, Imran, F. Jamil, N. Iqbal, and D. Kim, ‘Optimal Route Recommendation for Waste Carrier Vehicles for Efficient Waste Collection: A Step Forward Towards Sustainable Cities’, IEEE Access, vol. 8, pp. 77875–77887, 2020, doi: 10.1109/ACCESS.2020.2988173.
5. C. Xin, T. Zhang, S.-B. Tsai, Y.-M. Zhai, and J. Wang, ‘An Empirical Study on Greenhouse Gas Emission Calculations Under Different Municipal Solid Waste Management Strategies’, Applied Sciences, vol. 10, no. 5, p. 1673, Mar. 2020, doi: 10.3390/app10051673.
6. R. Alshaikh and A. Abdelfatah, ‘Optimization Techniques in Municipal Solid Waste Management: A Systematic Review’, Sustainability, vol. 16, no. 15, p. 6585, Aug. 2024, doi: 10.3390/su16156585.
7. W. Xia, Y. Jiang, X. Chen, and R. Zhao, ‘Application of machine learning algorithms in municipal solid waste management: A mini review’, Waste Manag Res, vol. 40, no. 6, pp. 609–624, Jun. 2022, doi: 10.1177/0734242X211033716.
8. P. Latha, N. S. Benni, M. G. Asuti, and K. Thamaraiselvi, ‘Smart and efficient waste management through wireless IoT-enabled deep learning’, Sci Rep, vol. 16, no. 1, p. 11118, Apr. 2026, doi: 10.1038/s41598-026-43827-8.
9. I. Sosunova and J. Porras, ‘IoT-Enabled Smart Waste Management Systems for Smart Cities: A Systematic Review’, IEEE Access, vol. 10, pp. 73326–73363, 2022, doi: 10.1109/ACCESS.2022.3188308.
10. S. Fuqaha and N. Nursetiawan, ‘Artificial Intelligence and IoT for Smart Waste Management: Challenges, Opportunities, and Future Directions’, J. Fut. Artif. Intell. Tech., vol. 2, no. 1, pp. 24–46, Apr. 2025, doi: 10.62411/faith.3048-3719-85.
11. F. S. Alsubaei, F. N. Al-Wesabi, and A. M. Hilal, ‘Deep Learning-Based Small Object Detection and Classification Model for Garbage Waste Management in Smart Cities and IoT Environment’, Applied Sciences, vol. 12, no. 5, p. 2281, Feb. 2022, doi: 10.3390/app12052281.
12. C. Liu et al., ‘A Domestic Trash Detection Model Based on Improved YOLOX’, Sensors, vol. 22, no. 18, p. 6974, Sep. 2022, doi: 10.3390/s22186974.
13. X. Cai, F. Shuang, X. Sun, Y. Duan, and G. Cheng, ‘Towards Lightweight Neural Networks for Garbage Object Detection’, Sensors, vol. 22, no. 19, p. 7455, Sep. 2022, doi: 10.3390/s22197455.
14. S. Thaseen Ikram, V. Mohanraj, S. Ramachandran, and A. Balakrishnan, ‘An Intelligent Waste Management Application Using IoT and a Genetic Algorithm–Fuzzy Inference System’, Applied Sciences, vol. 13, no. 6, p. 3943, Mar. 2023, doi: 10.3390/app13063943.
15. A. Bari, O. Arshi, and S. Mondal, ‘Advancements in waste management: a comprehensive review of Artificial Intelligence applications in smart cities’, Smart Constr. Sustain. Cities, vol. 4, no. 1, p. 7, Mar. 2026, doi: 10.1007/s44268-026-00088-8.
16. I. Dawar, A. Srivastava, M. Singal, N. Dhyani, and S. Rastogi, ‘A systematic literature review on municipal solid waste management using machine learning and deep learning’, Artif Intell Rev, vol. 58, no. 6, p. 183, Mar. 2025, doi: 10.1007/s10462-025-11196-9.
17. A. Alourani, M. U. Ashraf, and M. Aloraini, ‘Smart waste management and classification system using advanced IoT and AI technologies’, PeerJ Computer Science, vol. 11, p. e2777, Apr. 2025, doi: 10.7717/peerj-cs.2777.
18. B. Ali, M. A. Javed, A. A. K. Alharbi, S. Alotaibi, and M. Alkhathami, ‘Internet of Things-Assisted Vehicle Route Optimization for Municipal Solid Waste Collection’, Applied Sciences, vol. 14, no. 1, p. 287, Dec. 2023, doi: 10.3390/app14010287.
19. W.-L. Mao, W.-C. Chen, C.-T. Wang, and Y.-H. Lin, ‘Recycling waste classification using optimized convolutional neural network’, Resources, Conservation and Recycling, vol. 164, p. 105132, Jan. 2021, doi: 10.1016/j.resconrec.2020.105132.
20. S. Kumar, D. Yadav, H. Gupta, O. P. Verma, I. A. Ansari, and C. W. Ahn, ‘A Novel YOLOv3 Algorithm-Based Deep Learning Approach for Waste Segregation: Towards Smart Waste Management’, Electronics, vol. 10, no. 1, p. 14, Dec. 2020, doi: 10.3390/electronics10010014.
21. N. C. A. Sallang, M. T. Islam, M. S. Islam, and H. Arshad, ‘A CNN-Based Smart Waste Management System Using TensorFlow Lite and LoRa-GPS Shield in Internet of Things Environment’, IEEE Access, vol. 9, pp. 153560–153574, 2021, doi: 10.1109/ACCESS.2021.3128314.
22. Y. Ren, Y. Li, and X. Gao, ‘An MRS-YOLO Model for High-Precision Waste Detection and Classification’, Sensors, vol. 24, no. 13, p. 4339, Jul. 2024, doi: 10.3390/s24134339.
23. S. Shahab and M. Anjum, ‘Solid Waste Management Scenario in India and Illegal Dump Detection Using Deep Learning: An AI Approach towards the Sustainable Waste Management’, Sustainability, vol. 14, no. 23, p. 15896, Nov. 2022, doi: 10.3390/su142315896.

24. M. E. Bamisaye, B. O. Ajayi, and I. Sereewatthanawut, ‘Sustainable waste management of construction materials: Mathematical modelling and analysis’, Resources, Conservation & Recycling Advances, vol. 27, p. 200274, Sep. 2025, doi: 10.1016/j.rcradv.2025.200274.
25. K. Y. Chau, M. Moslehpour, S.-H. Pan, and A. Akhundzada, ‘Advanced predictive modeling of municipal solid waste management using robust machine learning’, Sci Rep, vol. 15, no. 1, p. 43247, Dec. 2025, doi: 10.1038/s41598-025-27237-w.
26. K. S. Al Yarubi, S. O. F. Khairy, S. M. E. Hossain, and G. Hayder, ‘Internet of Things-Driven Waste Management: Paving the Way for Sustainable Smart Cities’, Processes, vol. 13, no. 4, p. 1140, Apr. 2025, doi: 10.3390/pr13041140.
27. T. Anh Khoa et al., ‘Waste Management System Using IoT-Based Machine Learning in University’, Wireless Communications and Mobile Computing, vol. 2020, pp. 1–13, Feb. 2020, doi: 10.1155/2020/6138637.
28. J.-S. Lee and D.-C. Shin, ‘Prediction of Waste Generation Using Machine Learning: A Regional Study in Korea’, Urban Science, vol. 9, no. 8, p. 297, Jul. 2025, doi: 10.3390/urbansci9080297.
29. F. Alqahtani, Z. Al-Makhadmeh, A. Tolba, and W. Said, ‘Internet of things-based urban waste management system for smart cities using a Cuckoo Search Algorithm’, Cluster Comput, vol. 23, no. 3, pp. 1769–1780, Sep. 2020, doi: 10.1007/s10586-020-03126-x.
30. N. Baras, D. Ziouzios, M. Dasygenis, and C. Tsanaktsidis, ‘A cloud based smart recycling bin for waste classification’, in 2020 9th International Conference on Modern Circuits and Systems Technologies (MOCAST), Bremen, Germany: IEEE, Sep. 2020, pp. 1–4. doi: 10.1109/MOCAST49295.2020.9200283.
31. B. Fang et al., ‘Artificial intelligence for waste management in smart cities: a review’, Environ Chem Lett, vol. 21, no. 4, pp. 1959–1989, Aug. 2023, doi: 10.1007/s10311-023-01604-3.
32. D. B. Olawade et al., ‘Smart waste management: A paradigm shift enabled by artificial intelligence’, Waste Management Bulletin, vol. 2, no. 2, pp. 244–263, Jun. 2024, doi: 10.1016/j.wmb.2024.05.001.
33. M. M. Ahmed, E. Hassanien, and A. E. Hassanien, ‘IoT-based intelligent waste management system’, Neural Comput & Applic, vol. 35, no. 32, pp. 23551–23579, Nov. 2023, doi: 10.1007/s00521-023-08970-7.
34. N. J. Sinthiya, T. A. Chowdhury, and A. K. M. B. Haque, ‘Artificial Intelligence Based Smart Waste Management—A Systematic Review’, in Computational Intelligence Techniques for Green Smart Cities, M. Lahby, A. Al-Fuqaha, and Y. Maleh, Eds, in Green Energy and Technology. , Cham: Springer International Publishing, 2022, pp. 67–92. doi: 10.1007/978-3-030-96429-0_3.
35. Z. Feng, J. Yang, L. Chen, Z. Chen, and L. Li, ‘An Intelligent Waste-Sorting and Recycling Device Based on Improved EfficientNet’, IJERPH, vol. 19, no. 23, p. 15987, Nov. 2022, doi: 10.3390/ijerph192315987.
36. H. Abdu and M. H. Mohd Noor, ‘A Survey on Waste Detection and Classification Using Deep Learning’, IEEE Access, vol. 10, pp. 128151–128165, 2022, doi: 10.1109/ACCESS.2022.3226682.
37. E. Longo, F. A. Sahin, A. E. C. Redondi, P. Bolzan, M. Bianchini, and S. Maffei, ‘A 5G-Enabled Smart Waste Management System for University Campus’, Sensors, vol. 21, no. 24, p. 8278, Dec. 2021, doi: 10.3390/s21248278.
38. S. Mishra, L. Jena, H. K. Tripathy, and T. Gaber, ‘Prioritized and predictive intelligence of things enabled waste management model in smart and sustainable environment’, PLoS ONE, vol. 17, no. 8, p. e0272383, Aug. 2022, doi: 10.1371/journal.pone.0272383.
39. M. Al Duhayyim, ‘Modified Cuttlefish Swarm Optimization with Machine Learning-Based Sustainable Application of Solid Waste Management in IoT’, Sustainability, vol. 15, no. 9, p. 7321, Apr. 2023, doi: 10.3390/su15097321.
40. A. Namoun, A. Tufail, M. Y. Khan, A. Alrehaili, T. A. Syed, and O. BenRhouma, ‘Solid Waste Generation and Disposal Using Machine Learning Approaches: A Survey of Solutions and Challenges’, Sustainability, vol. 14, no. 20, p. 13578, Oct. 2022, doi: 10.3390/su142013578.