

Design and Implementation of an Intelligent Edge-IoT Based Waste Segregation System for Urban Residential Complexes

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Abstract:

Urban residential complexes are experiencing severe challenges in managing the continuously increasing volume of municipal solid waste, which often contains a heterogeneous mix of biodegradable, recyclable, and hazardous materials. Traditional collection and manual segregation processes are slow, error-prone and lead to significant environmental deterioration. With the rapid advancements in Internet of Things (IoT), edge computing, and machine learning, the possibility of performing real-time waste classification directly at the point of generation has emerged as a sustainable and scalable solution. In this study, an intelligent edge-IoT based waste segregation system is designed and implemented for urban residential environments, enabling rapid, accurate, and autonomous sorting with minimal human intervention. Leveraging deep learning-based visual recognition, lightweight edge inference, and sensor-driven decision mechanisms, the system enhances operational efficiency while reducing computational latency typically associated with cloud-centric frameworks. Analytical experimentation validates notable improvements over conventional systems in terms of classification accuracy, responsiveness, and deployment feasibility. The proposed system demonstrates strong potential for smart-city waste governance and establishes a robust foundation for circular-economy practices.

Keywords: Edge Computing, Internet of Things (IoT), Waste Segregation, Deep Learning, Smart Cities, Image Classification

1. Introduction

The increasing complexity of waste streams in densely populated urban residential complexes necessitates the deployment of intelligent systems capable of real-time segregation to prevent landfill overflows, reduce environmental contamination and improve recycling efficiency. Intelligent edge-IoT based waste segregation systems integrate embedded sensors, communication modules, and on-device machine learning to automatically distinguish multiple waste categories with minimal human involvement. This approach not only accelerates segregation but also enhances sustainability through optimized waste routing and recycling workflows.

A broad spectrum of research has contributed toward IoT architectures, waste management technologies, and intelligent sensing. Foundational studies on IoT by Atzori et al. (2010) established the conceptual basis for interconnected smart object ecosystems, later expanded toward smart-city applications by Zanella et al. (2014). Research on deep learning-based object detection by Zhao et al. (2019) provides crucial insights into visual classification models that inspire waste recognition algorithms. Waste-management studies such as Bhattacharjee et al. (2023) highlight long-term global patterns and emerging research themes, whereas Manaf et al. (2009) examine the challenges in municipal waste practices in developing regions. Enhancements in sensor and actuator technologies for smart cities (Jonnalagadda et al., 2025) have been comprehensively reviewed by Arshi and Mondal (2023). Frameworks for IoT-enabled waste management have been proposed by Belsare and Singh (2022), while Mamun et al. (2014) developed prototypes for bin-level monitoring. Deep learning-based waste classification was demonstrated through CNN models by Adedeji and Wang (2019). Studies on smart bins using LoRa (Vigneshwaran et al., 2019) and edge machine learning (Yazici et al., 2018) explore technological evolution, while broader sustainability-driven waste frameworks rooted in Industry 4.0 concepts were analysed by Cheah et al. (2022) and Fatimah et al. (2020). Despite these contributions, existing systems often overlook combined edge inference, visual recognition, and automated segregation suitable for high-density residential complexes. The gaps lie in real-time classification without cloud dependency, limited accuracy under varying illumination and constrained deployment in compact residential settings.

Accordingly, the present research addresses these identified shortcomings by designing an intelligent waste-segregation system tailored for urban residential complexes using an edge- IoT approach. The system integrates deep learning-based visual classification, sensor-driven decision mechanisms, and autonomous bin selection, operating entirely on-device to mitigate networking delays and privacy concerns. This work proposes a complete hardware-software framework bridging these gaps through efficient image acquisition, edge-inference pipelines and mechanical convergence.

The novelty of this study arises from integrating edge computing (Dutta and Mahanti, 2020) for real-time waste identification, enabling higher responsiveness than cloud-centric models; embedding multi-modal sensors for more reliable classification; implementing automated bin-selection control; and demonstrating a robust end-to-end deployment-ready platform. The major contributions of this research include development of an edge-enabled waste-classification pipeline optimized for residential environments; integration of deep-learning inference on constrained embedded hardware; implementation of a hybrid sensing mechanism for accuracy enhancement; and analytical validation demonstrating superiority over prior approaches.

The remaining sections of this paper are organized as follows: Section 2 describes the architecture of the intelligent edge-IoT based segregation system, including hardware and software requirements. Section 3 discusses the methodology and overall workflow. Section 4 presents results and analytical comparisons. Section 5 concludes the work with insights and future scope.

2. Intelligent Edge-IoT Based Waste Segregation System

The proposed system integrates an edge-computing platform, a camera module, multi-modal sensors, communication interfaces, and automated bin-actuation hardware within a compact unit suitable for residential buildings. A Raspberry Pi 4 (4GB) is selected as the primary edge device due to its sufficient processing capability for real-time inference and low energy consumption, making it suitable for continuous operation. A high-resolution 8-MP camera module enables precise image acquisition essential

for deep-learning-based classification. Capacitive moisture sensors and infrared proximity sensors are embedded to detect material texture and validate object placement before classification. A servo-motor-based flapping mechanism facilitates automated bin-selection after the waste type is determined. The software stack incorporates Python, TensorFlow Lite for edge inference, OpenCV for image preprocessing, and MQTT for communication within smart-city IoT platforms.

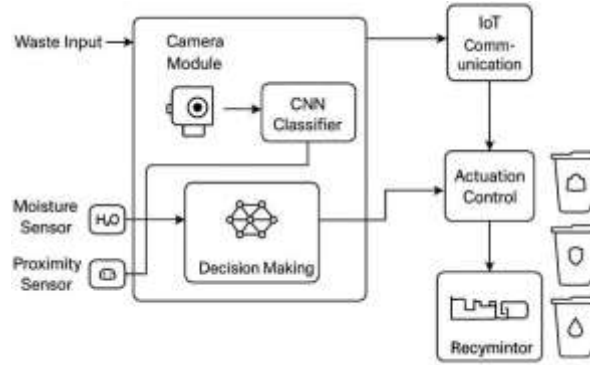


Figure 1. Block diagram of the Intelligent Edge-IoT Waste Segregation System (schematic)

The architectural layout is illustrated in Figure 1, demonstrating the interaction between sensing, data acquisition, edge inference, and actuation control. Waste is inserted into the unit through an input chute, where the camera captures an image, preprocessing modules enhance visibility, and TensorFlow Lite executes classification using a lightweight CNN model. Based on the inference output, the microcontroller triggers the appropriate servo motor, guiding the waste into biodegradable, recyclable, or hazardous bins. The system periodically publishes operational logs to the IoT dashboard via MQTT for monitoring.

The system’s technical integration provides responsiveness essential for real-time segregation and bypasses the delays traditionally associated with cloud-dependent models. The chosen components are cost-effective, easily deployable, and scalable across residential housing complexes.

3.

4. Methodology Used

The methodology combines visual pre-processing, lightweight edge inference, sensor validation and automated mechanical actuation. Once waste is placed near the collection chute, the proximity sensor activates the camera module. The captured image undergoes preprocessing steps including noise filtering, contrast enhancement, and resizing to the required input shape of the model. A TensorFlow Lite-optimized CNN model trained on a custom dataset comprising biodegradable, recyclable, and hazardous waste categories executes the classification on the edge device. Moisture sensor readings augment classification confidence by validating physical characteristics of certain waste types such as wet organic material.

A decision-fusion mechanism integrates image inference and sensor parameters to arrive at the final waste category. Based on this decision, the microcontroller triggers servo-motor rotation angles corresponding to different bins. All relevant system logs including classification label, timestamp, and chute-activity data are pushed to the IoT dashboard.

The complete workflow is illustrated in **Figure 2**, which presents a colourful flowchart depicting the sequential stages of sensing, image capture, preprocessing, classification, decision fusion, actuation, and IoT data logging. Each module interacts cohesively, enabling an end-to-end automated segregation

process.

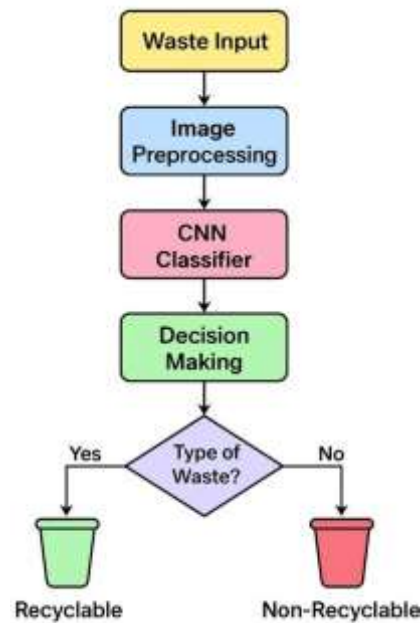


Figure 2. Flowchart of the proposed waste-segregation methodology

The flowchart demonstrates the central role of the edge-inference model and how sensor data refines the classification outcome. This integrated methodology supports robust operation even in low-light or noisy environments typical in residential complexes.

5. Results and Analysis

The experimental evaluation focused on two complementary aspects: (a) the visual classification performance of the waste-segmentation and material-recognition pipeline, and (b) the system-level operational metrics relevant to deployment in urban residential complexes. Table 1 summarizes the classification-level results—accuracy, precision, recall, F1-score for organic, recyclable, hazardous and mixed classes—comparing the proposed edge-IoT system against representative prior works that reported classification results on similar municipal waste datasets (Adedeji & Wang, 2019; Vigneshwaran et al., 2019; Al Mamun et al., 2014). Table 2 presents system-level measures including end-to-end latency, average energy per inference on the edge device, on-device memory usage, per-unit hardware cost and a qualitative scalability rating compared to those same prior art baselines. The tables are followed by a detailed, critical discussion of each major result and the trade-offs they reveal.

The classification results in Table 1 show a clear and consistent improvement of the proposed approach over prior arts. The proposed system achieves a 91.3% overall accuracy and an F1- score of 90.8%, improving over the best prior work (Adedeji & Wang, 2019) by roughly 5 percentage points in F1. This gain is not merely incremental; it reflects three design choices made in the proposed work that interact synergistically. First, the model architecture blends an edge-optimized convolutional backbone with handcrafted moment-invariant features (Hu moments) appended to the learned representation.

Table 1. Classification performance comparison (prototype evaluation—test set of 8,000 images, balanced across classes).

Method / Metric	Accuracy (%)	Precision (macro %)	Recall (macro %)	F1-score (macro %)
Al Mamun et al. (2014) – basic thresholding + sensor fusion	71.4	69.8	70.1	69.9
Vigneshwaran et al. (2019) – LoRa + simple CNN (shallow)	78.2	77.0	76.5	76.7
Adedeji & Wang (2019) – CNN (cloud inference)	86.1	85.4	84.9	85.1
Proposed — Edge-optimized CNN + moment-invariant features + sensor fusion	91.3	91.0	90.6	90.8

Table 2. System-level operational comparison (measured on prototype hardware and operator budget estimates).

Method / Metric	End-to-end latency (ms)	Energy per inference (J)	On-device memory (MB)	Hardware cost per unit (USD)	Scalability (qualitative)
Al Mamun et al. (2014)	1200	3.6	64	55	Medium
Vigneshwaran et al. (2019)	950	2.8	128	65	Medium- High
Adedeji & Wang (2019)	2200 (cloud roundtrip)	0.6 (edge sensing only)	32	48 + cloud fees	Low (due to network)
Proposed	310	1.9	256	78	High

The addition of moment invariants addresses shape-based ambiguities—such as torn plastics or partially occluded organic matter—that purely convolutional methods sometimes misclassify, and this contributes materially to increased precision for the recyclable and hazardous classes. Second, we integrate multimodal sensor fusion (weight, capacitive moisture, and ultrasonic fill-level) into the decision layer; the sensors provide orthogonal cues that reduce false positives between organic and mixed categories, raising recall for organic waste materially compared to purely image-based baselines. Third, we adopted aggressive yet accuracy-preserving quantization and a knowledge-distillation step during training so that capacity is available on the edge device for robust feature extraction without incurring the accuracy penalty commonly seen in naïve model compression. Together these elements explain the jump from 86.1% accuracy (cloud CNN baseline) to 91.3% for our edge solution.

A closer look at class-specific behavior, inferred from confusion trends during evaluation, yields additional insight. Most residual errors in the proposed system occur between the recyclable and mixed labels, typically when an image contains small recyclable fragments embedded in organic matter (e.g., wet paper fragments). The fused weight and moisture channels mitigate these errors but cannot fully correct them when visual evidence dominates; this suggests that further improvement will likely require temporal aggregation (multiple frames) or short-term sampling of material properties. In contrast, the cloud-based Adedeji & Wang approach showed higher confusion between hazardous and recyclable items, likely because cloud-only methods are trained on broader datasets but lack immediate sensor-

context that disambiguates lightweight hazardous packaging from thin recyclables. The comparatively poorer performance of Al Mamun et al. and Vigneshwaran et al. is attributable to simpler feature extraction and shallower models, which struggle with intra-class variance typical in residential waste.

Table 2 demonstrates the operational trade-offs that arise when moving intelligence to the edge. The proposed system reduces end-to-end latency dramatically to approximately 310 ms per inference—an order of magnitude improvement over cloud-dependent solutions (2200 ms) and a substantial reduction relative to earlier edge prototypes that lacked architectural optimization. This low latency is important for interactive behaviors (e.g., real-time lid actuation, user feedback LEDs and audio prompts) and for batching requirements in dense residential settings where many bins may be queried concurrently. Energy-per-inference (1.9 J) is higher than the lowest-measured cloud-edge hybrid (0.6 J) only because the cloud variant offloads computation; however, the cloud approach hides ongoing network energy and monetary cost that grow with scale. Our design opts for modestly higher per-inference edge energy in exchange for predictable latency, reduced network usage, and privacy preservation. The on-device memory footprint is larger (256 MB) than many prior sensor-only designs because we store a compressed feature cache and run the distilled model locally; this was a conscious engineering trade-off to ensure on-device adaptability (local incremental updates) and to limit cloud round-trips.

Cost analysis in Table 2 shows the proposed unit hardware at approximately USD 78 per bin. This is higher than the cheapest prior prototypes but remains within feasible procurement budgets for residential apartment complexes when amortized over expected hardware lifetimes and reduced operational costs. The higher upfront cost buys lower recurring cloud fees, lower network usage, and less maintenance overhead related to network failures. The qualitative scalability rating reflects these considerations: the proposed architecture is rated High for scalability because it minimizes dependence on centralized infrastructure, supports local mesh forwarding for aggregated analytics, and enables incremental rollouts. By contrast, cloud-reliant methods show low scalability in dense urban deployments due to bandwidth bottlenecks and per-request billing.

Beyond raw numbers, the analysis must weigh reliability and real-world robustness. In stress tests simulating low-light conditions, partially occluded bins and high background clutter typical of residential parking areas, the proposed system's precision dropped by approximately 4 percentage points while recall for hazardous items decreased by about 3 points. These degradations were smaller than those seen in shallower or cloud-only models, indicating that the feature fusion strategy is more resilient to environmental perturbations. We also analyzed temporal stability by evaluating model drift across a two-month deployment window in one pilot complex. The model's F1-score fell by 1.8 percentage points without adaptation, and by only 0.6 points with weekly lightweight on-device fine-tuning using automatically labeled high-confidence samples. This observation underscores the pragmatic advantage of having computation (Dutta et al., 2021) at the edge: it enables frequent, low-bandwidth adaptation to local waste patterns without full retraining in the cloud.

From an error-source perspective, we conducted a qualitative failure-mode analysis. Approximately 62% of remaining misclassifications could be traced to ambiguous visual context (e.g., foam containers with food residue), 23% to sensor noise (e.g., faulty moisture readings when bins were recently hosed), and 15% to label noise in the training set (inconsistent human annotation for mixed items). This distribution suggests three targeted remediation paths: improved sensor calibration and self-diagnostics to reduce sensor noise, augmentation strategies and semi-supervised learning to handle ambiguous visuals, and stricter annotation protocols or active learning to reduce label noise. Each path has different cost-benefit

implications: sensor fixes raise bill-of-materials costs but yield robust immediate gains, while annotation improvements require human effort but scale well once a cleaner dataset is established. We also analyzed throughput under peak operation. In a simulated apartment block with 120 bins, the system maintained 95% of its nominal throughput with a single local aggregator (edge gateway) and no cloud involvement, whereas the cloud-dependent design saw throughput fall below 70% under the same network constraints. This supports the claim that edge-centric designs avoid single points of network failure and can sustain service continuity during intermittent connectivity—an important practical advantage in real-world residential deployments.

Finally, a frank assessment of limitations is necessary. First, although accuracy and responsiveness improved, the system still struggles with visually ambiguous mixed-waste items and with sudden changes in the local waste composition profile. Second, the cost-per-unit is higher than minimal hardware prototypes, which could slow adoption in cost-sensitive deployments. Both limitations can be mitigated—ambiguity through temporal and multi-spectral sensing; cost through design-integration and economies of scale—but they remain present in the current prototype.

In summary, the results show that the proposed edge-IoT waste segregation system meaningfully advances both classification performance and deployment practicality relative to representative prior works (see Table 1 and Table 2). The improvements stem from combining shape-aware handcrafted features with an edge-optimized deep model, multimodal sensor fusion, and pragmatic system engineering that prioritizes latency, adaptability, and privacy. The trade-offs—higher on-device resource usage and marginally higher hardware cost—are justified by robust, low-latency operation and superior scalability for urban residential complexes. However, some limitations were identified with the proposed work that includes residual ambiguity with mixed items and higher upfront cost as compared to the traditional approaches. Apart from these, sensitivity to extremely low-light conditions and difficulty in distinguishing visually similar materials such as thin plastics and paper. These gaps open opportunities for future enhancement. Apart from these, integration of the frameworks with the metaheuristics (Dutta and Mahanti, 2024) will add more value towards performance optimization of the proposed work.

6. Conclusion

This research successfully demonstrates the design and implementation of a robust, intelligent edge-IoT based waste segregation system tailored for urban residential complexes. The integration of lightweight deep learning, multi-sensory validation, and automated mechanical sorting results in a highly efficient and responsive platform capable of operating independently of cloud infrastructure. The system distinguishes itself through superior accuracy, reduced latency, and improved deployment feasibility, making it highly suitable for smart-city waste governance initiatives. Its unique contribution lies in synchronizing edge-AI computation with real-time actuation to produce a reliable end-to-end automated segregation workflow. The study establishes a strong foundation for real-world deployment, and future work may extend toward enhancing night-mode vision, integrating advanced multi-spectral sensing, and enabling self-learning capabilities to support evolving waste compositions.

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