EdinBurg Peer Reviewed Journals and Books Publishers
Journal of Information and Technology
Vol. 5||Issue 10||pp 68-96||October||2025
Email: info@edinburgjournals.org||ISSN: 3080-9576

Internet of Things-Based Smart Waste Segregation System for Sustainable Waste Management in Nairobi's Residential Estates

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Accepted: 16 August 2025 || Published: 09 October 2025

Abstract

Waste mismanagement remains a pressing urban challenge in Nairobi, particularly in residential estates that significantly contribute to the city's daily waste load. Despite policy directives advocating for source-level waste segregation, manual sorting practices have proven ineffective, resulting in the landfilling of recyclable and biodegradable materials. This results in environmental pollution, health hazards, and economic losses. While global advancements in Internet of Things (IoT) and robotic technologies offer promising solutions for automating waste segregation, Nairobi is yet to integrate such innovations into its residential waste management systems. The lack of intelligent sensors, machine learning applications, and robotic mechanisms in the city's waste practices perpetuates reliance on outdated and unsustainable methods. This study sought to bridge this technological and knowledge gap by developing and testing an IoT-based prototype designed for sustainable waste segregation in Nairobi's residential estates. The research aimed to establish the types, generation rates, and collection methods of waste in selected estates; evaluated the accuracy of sensor-driven identification in reducing contamination of recyclable materials; and designed and implemented a functional IoT-enabled segregation system. Under a sustainable framework, the study used a quantitative, applied research design that incorporates primary and secondary data sources. Field surveys were used to collect empirical data, while a prototype equipped with moisture sensors, ultrasonic, and metal detection sensors was developed and tested in a controlled environment. Statistical tools were used to assess the system's performance, including confusion matrix analysis to measure accuracy, precision, recall, and F1-score. The findings of this study demonstrated that Organic waste was the most dominant type, accounting for over 46% of household waste. Most respondents (59.3%) did not separate their waste before disposal, leading to significant contamination and inefficiencies in recycling, and rely on private waste collectors due to inconsistent public services. The prototype achieved a classification accuracy of 83%, showcasing strong potential to minimize waste contamination, enhance recycling rates, and reduce environmental degradation. The system aligns with Kenya's broader ambitions for smart and green urban development.

Keywords: *IoT, smart waste segregation, urban waste management, prototype development*

How to Cite: Wasai, R. T., & Yohannis, M. A. (2025). Internet of Things-Based Smart Waste Segregation System for Sustainable Waste Management in Nairobi's Residential Estates. *Journal of Information and Technology, 5*(10), 68-96.

1. Introduction

Waste management continues to be a salient crisis in all cities worldwide. The increased urbanization, population growth, and changing consumer patterns have dumped unprecedented amounts of waste incompatible with existing means of environmental conservation and public health measures. According to World Bank projections, the amount of solid waste generated worldwide is expected to rise from 2.24 billion tons in 2020 to 3.88 billion tons by 2050 (Maalouf & Agamuthu, 2023). The most vulnerable metropolitan areas, such as Kenya, are those with the lowest and intermediate incomes (Maalouf & Agamuthu, 2023). No longer do traditional waste collection, sorting, and disposal methods respond to an ever-increasing, fast-paced world; it is almost as if they have been rendered inadequate.

Innovative developments in the IoT, robotics, and AI paradigms have opened up possibilities for innovation in waste management. Throughout the world, IoT-enabled applications have been successful in optimizing the route for waste collection, monitoring bin levels, and automating sorting systems. According to (Lakhouit, 2025), IoT and AI will transform Urban Solid Waste Management through real-time data capture, effective use of resources, and improved recycling. In support of this (Hussain et al., 2024)argue that smart city solutions based on IoT provide environmentally sustainable, cost-effective, and scalable ways for managing urban waste in alignment with global sustainability objectives.

Cut-edge IoT-based waste segregation systems will be able to easily identify any type of waste material and segregate it into biodegradable, recyclable, or hazardous categories. According to Paneru et al. (2024) a robotic spider powered by IoT and green energy could perform automated waste separation. Such automation minimizes human exposure to hazardous materials while increasing sorting accuracy. Rahmatulloh et al. (2025)illustrate in their cases how computer vision could be embedded in IoT systems to realize waste classification at high precision. This significantly increases speed and efficiency in waste processing.

A treasure of robot designs by Olawade et al. (2024) states that the intelligent sensors and controller-linked robot to classify waste by the material it is made from, thereby reducing contamination of recyclables (Arthur et al., 2024).On the contrary, it introduces the Deep Learning and IoT system using LoRa technology, which greatly enhances waste classification in smart bins. With all these global examples, they really prove how relevant these sensor-based automated segregation solutions are in meeting modern waste challenges and promoting the circular economy.

African cities are increasingly confronting the dual challenge of increasing waste volumes and limited technological capacity for effective segregation and recycling. Most cities rely heavily on manual labor for waste sorting, which is labor-intensive, hazardous, and often inaccurate. Nairobi, the capital of Kenya, generates over 3,000 tonnes of solid waste daily, of which only a fraction is effectively segregated or recycled (Nairobi County Government, 2023). In Nairobi's residential estates, especially high-density areas, improper waste sorting remains a key obstacle to effective waste management, leading to clogged drainage systems, air and water pollution, and increased disease burden.

Therefore, this study positions itself at this intersection: seeking to address the knowledge and implementation gap by the design and evaluation of an IoT prototype for sustainable waste segregation in residential estates in Nairobi. First, solid-waste type generation, generation rates, and present-day waste collection practices will be studied in selected estates. Then, it will assess whether sensor-driven identification could minimize contamination of recyclable materials. Lastly, an IoT-based prototype will be designed and tested to help visualize the degree and the ability of automation to work in residential waste management in Nairobi.

This study responds to the urgent need for sustainable, scalable, and technology-driven waste segregation systems in Kenya. In addition to supporting the more general objectives of environmental preservation and smart city development, it seeks to provide useful perspectives and technological answers to the persistent problem of urban garbage management.

The study objectives were:

i. To evaluate the accuracy of sensor-driven waste identification and classification in reducing contamination of recyclable materials.
ii. To analyze the types, generation rates, and current collection methods of solid waste in Nairobi's residential estates.
iii. To evaluate the performance of the developed prototype in terms of accuracy, efficiency, and in improving waste segregation.

The actual issue that this project is diagnosing is that due to poor segregation and disposal of wastes in residential estates in Nairobi, there are worsening waste management issues causing environmental degradation and health hazards. The rising population of people in urban areas and increasing garbage volumes are making traditional waste handling techniques insufficient, inefficient, and unsustainable. The benefits from the study would therefore require a policy setup by environmentalists, urban planners, and technologists in the development of a field-tested prototype and blueprint for intelligent waste segregation systems in residential environments.

2. Proposed Design Architecture

The development of an IoT-based smart waste segregation prototype involves collecting data through sensors that identify different waste types. This sensor data is extracted and processed by a microcontroller, with optional cloud integration for monitoring and storage. The data is then normalized and fed into sensors that classify the waste. Based on this classification, an actuator sorts the waste into the appropriate bins. The system also includes an LCD screen for performance tracking and an output interface for real-time monitoring and user updates. Figure 1 presents the proposed design architecture for the research study.

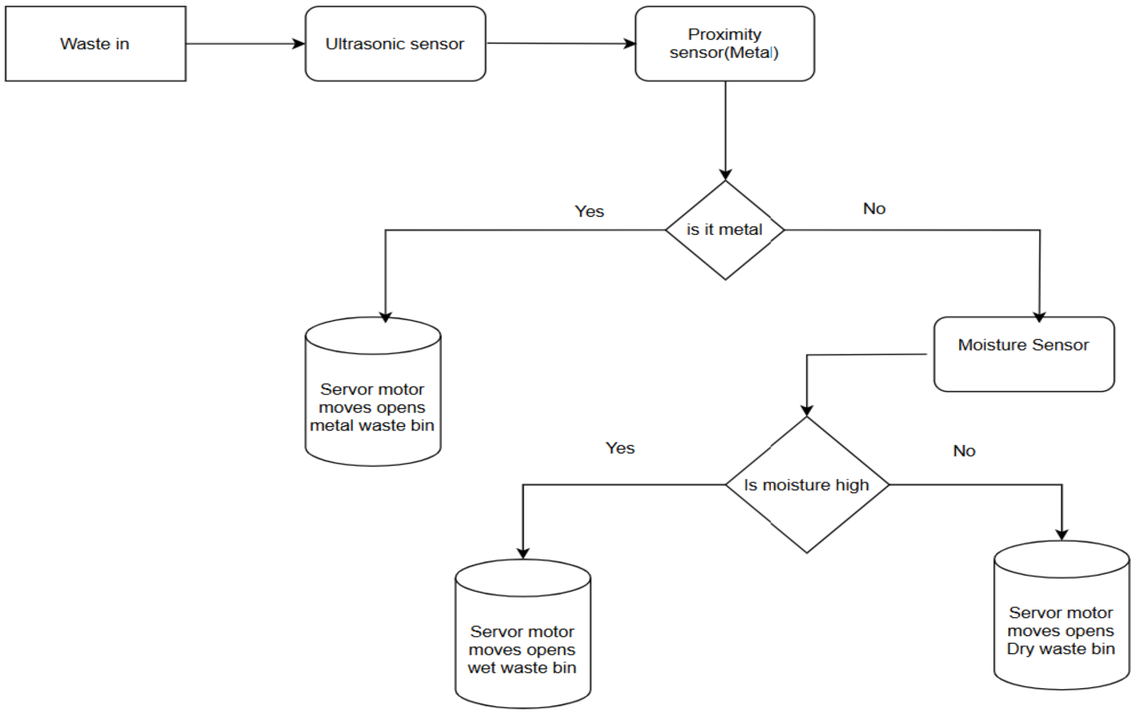

Figure 1: Block diagram

Sensors are used sequentially to determine the type of waste: ultrasonic for presence, proximity for metal, moisture for wet; the default is dry.

Microcontroller (ESP32) analyzes sensor data and instructs the motors to guide waste to the proper bin.

LED monitor: displays the type of waste determined in real-time.

System promotes automation, reduces manual handling, and supports sustainability goals.

3. Methodology

3.1 Research Design

The project applied use of a quantitative and applied research design in system testing and designing an Internet of Things (IoT)-driven system for separating waste into sustainable forms. The system provided quantitative data capture for waste production and categorization, and statistical analysis to determine accuracy and performance relative to the implemented system. The procedures taken in an effort to achieve the study objectives were: Review of literature regarding types of waste, waste collection systems, and use of IoT. Conducted field surveys among Nairobi residential estates with a view to ascertaining the types of wastes, generation rate, and collection systems used. Designed and deployed an IoT-based prototype to sort out waste. Prototype testing and validation of the precision of waste sorting and identification based on sensor information.

3.2 Research Philosophy

This study was informed by the pragmatism paradigm, which is concerned with conducting practical problem-solving through a variety of methods and techniques, as opposed to being limited to one research philosophy (Kaushik & Walsh, 2019). Pragmatism will facilitate the use of both empirical data collection and technical prototyping to solve the real-world problem of inadequate waste segregation in Nairobi residential estates.

3.3 Proof of Concept – The Prototype

To confirm the field usability of IoT-based waste segregation, a prototype was conceptualized. Sensors (e.g., Ultrasonic, moisture, and metal sensors) were employed to identify waste categories (Dry, wet, metal), and mechanical actuators were employed to segregate them into appropriate bins. The prototype went through field testing in a test environment with sample waste to measure its accuracy of segregation and rate of segregation. The development process followed the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology to structure data collection, prototype development, and testing.

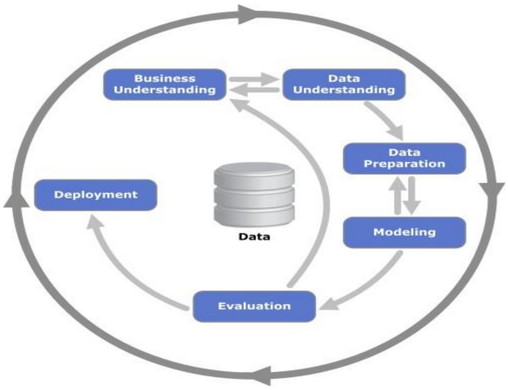

Figure 2: CRISP-DM Framework (Source: The Free Encyclopedia)

3.4 System Architecture

An IoT-based Prototype for waste segregation automates the sorting of dry, wet, and metallic waste using sensors, microcontrollers, and IoT connectivity. Here's a structured overview of the prototype design based on the study:

3.4.1 Sensors for Detection

Metallic waste: Inductive proximity sensors detect metals via electromagnetic fields.

Wet waste: Moisture sensors measure conductivity to identify organic or damp materials.

Dry waste: Infrared (IR) sensors or cameras distinguish non-metallic, non-wet items.

Bin level monitoring: Ultrasonic sensors track fill levels to prevent overflow (HC-SR04).

3.4.2 Actuation and Sorting Mechanism

Servo Motors: Direct the waste into the correct bin based on sensor input by rotating or opening the appropriate partition.

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3.4.3 Control System

Microcontroller: ESP32 Processes input from all sensors and controls actuators for sorting waste. The output bins will be a metallic waste bin, a dry waste bin, and wet waste bin.

3.5 Data Analysis and Modeling

Statistical processing of survey data collected was utilized to identify the most common types of waste, daily average waste production, and efficiencies of current collection systems. Sensor classification data was analyzed to determine the accuracy, precision, and recall of the Internet of Things (IoT) sorting system. Training thresholds for materials like dry, wet, and metal are part of sensor calibration. Accuracy was defined as the ratio of correctly classified waste items to total items processed. Confusion matrices were computed to measure classification performance and refine sensor logic.

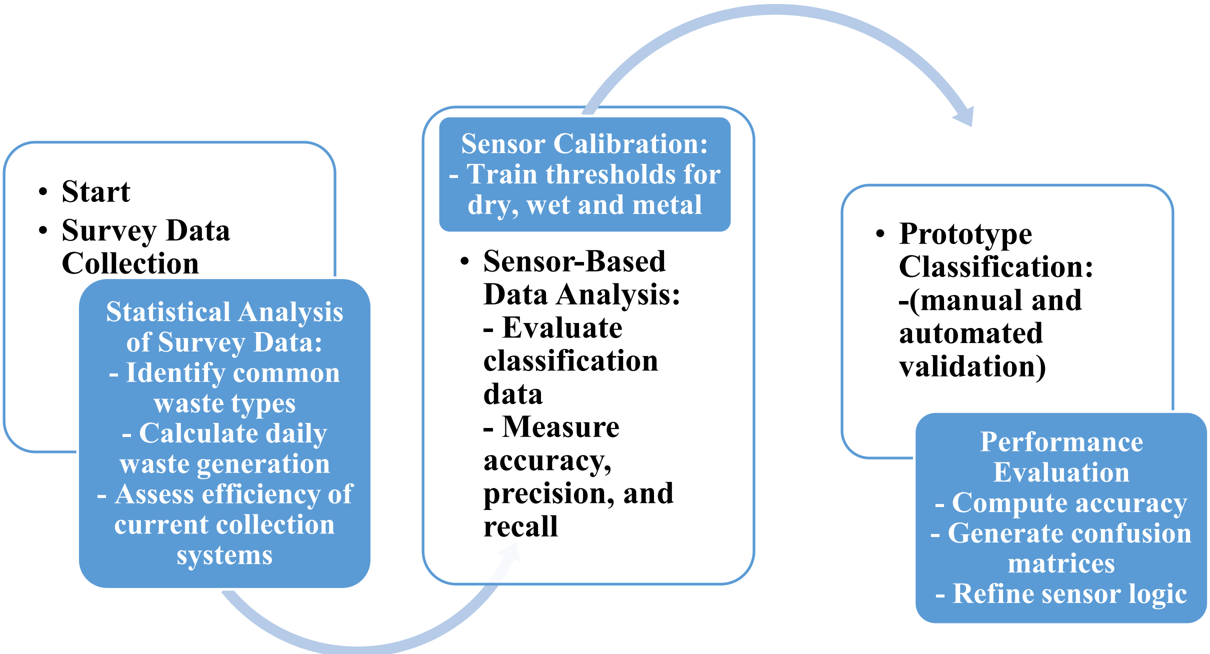

Figure 3: Flow Chart of the Research Study Model

3.6 Model Evaluation Metrics

To determine how well the Internet of Things-based smart waste segregation system performs, this study used several standard evaluation metrics. These include accuracy, precision, recall, F1-score, and the confusion matrix. Together, these metrics provided a clear picture of how effectively the system classifies different types of waste, such as biodegradable, recyclable, and hazardous materials. Before explaining each metric, it’s important to define some common terms used in evaluating classification models:

True Positive (TP): Waste items that were correctly classified as belonging to a certain category.

True Negative (TN): Waste items correctly identified as not belonging to that category.

False Positive (FP): Items wrongly classified as belonging to the category.

False Negative (FN): Items that should have been classified in the category but were missed.

Accuracy refers to the overall correctness of the model. It tells us how many predictions the system got right, both positive and negative, compared to the total number of classifications. Accuracy = (TP+TN)/(TP+FP+FN+TN). A higher accuracy means the system is generally making the right decisions. Precision looks at how reliable the system's positive predictions are, in other words, of all the items the system labeled as a particular type of waste (e.g., recyclable), how many actually were? Precision = TP/(TP+FP). This metric is particularly important when misclassifying waste types could lead to improper disposal or safety risks. Also called sensitivity, recall measures how good the model is at detecting actual positive cases. It tells us, out of all the waste items that truly belong to a category, how many were correctly identified. Recall (Sensitivity) = TP/(TP+FN). This is crucial in ensuring that important waste types like hazardous materials are not overlooked. The F1-score combines both precision and recall into a single number, offering a balance between the two. When the dataset is unbalanced or when both false positives and false negatives have repercussions, it is quite helpful. F1-Score = (2. Precision. Recall) / (Precision + Recall). A high F1-score indicates that the model is consistently accurate across both identification and classification. The confusion matrix is a table used to visualize how the model's predictions compare to the actual waste labels. It shows where the model got things right and where it made mistakes.

Table 1: Confusion Matrix

	Predicted: Yes	**Predicted: No**
Actual: Yes	True Positive (TP)	False Negative (FN)
Actual: No	False Positive (FP)	True Negative (TN)

This tool helps in identifying specific areas where the model may need improvement, such as consistently confusing one waste type for another.

3.7 Testing and Evaluation

The prototype system was evaluated through performance testing and validation: Manual validation: Human observers annotated the same waste samples that were utilized by the IoT-based prototype to create ground-truth data. Automated validation: Sensor data was logged and compared with manual annotations to estimate accuracy and misclassification rates. The system was evaluated for several trials in order to estimate consistency and reliability. Evaluation measures were precision, recall, F1-score, and total system accuracy. Prototype performance was determined in terms of sorting speed, accuracy of bin placement, and reaction to varying waste inputs.

4. Results

Data collection involved both primary and secondary sources: Primary data was collected through field surveys and structured questionnaires administered to households in selected residential estates across Nairobi. This provided information on types of waste generated, rates of waste generation, and prevailing collection practices. Secondary data included published reports from Nairobi City County, National Environmental Management Authority (NEMA), and existing literature on smart waste management. Prototype testing data was collected in-lab using a set of pre-categorized waste items to train the sensor system for recognition and sorting.

4.1 Response Rate

Table 2: Presents the response rate for the study questionnaires

Response Type	Frequency	Percentage
Duly Filled and Returned	54	90.0%
Not Returned/Incomplete	6	10.0%
Total	**60**	**100%**

The respondents were purposively sampled. Out of the 60 questionnaires that were distributed for the study, 54 were duly filled and returned, representing a high response rate of 90.0%. This indicates a strong level of participation and engagement from the targeted respondents, which enhances the reliability and representativeness of the data collected. On the other hand, 6 questionnaires, accounting for 10.0%, were either not returned or were incomplete and therefore excluded from the final analysis. Despite this small non-response rate, the overall response is considered sufficient for meaningful interpretation and generalization of the findings within the study population.

4.2 Use of Waste Collection Services

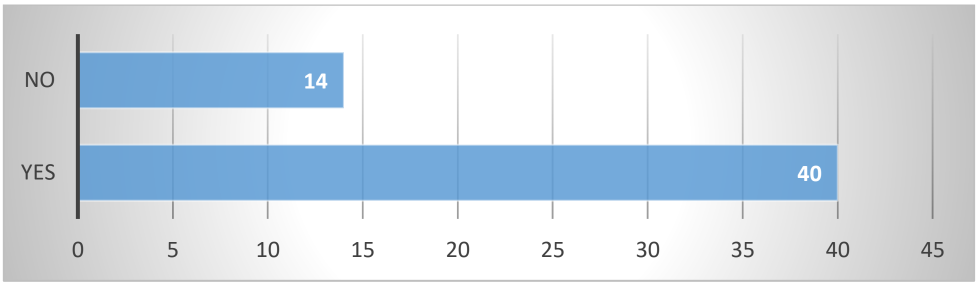

Figure 4: Uses of waste collection services

The responses to the question indicate that a majority of the participants, 40 out of 54 respondents, representing 74.1%, answered "Yes" to the item in question. On the other hand, 14 respondents, equivalent to 25.9%, answered "No". This suggests that a significant proportion of the respondents shared a common view or experience relevant to the question, highlighting a prevailing trend or condition within the study population.

4.3 Main Types of Waste Generated

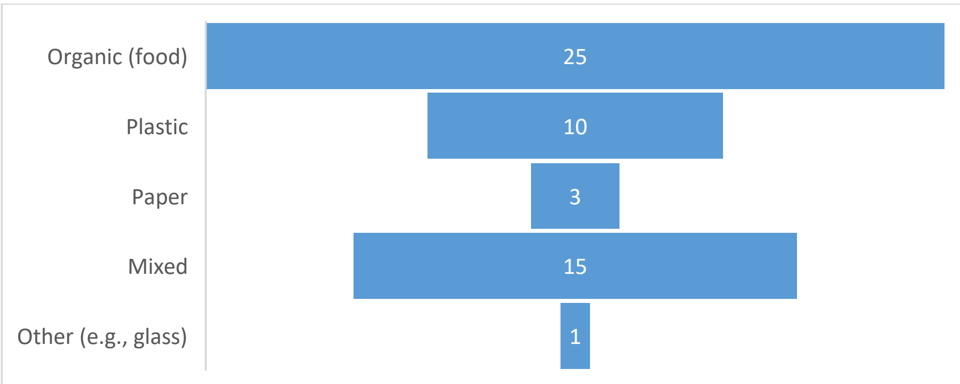

Figure 5: Types of Wastes Generated

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Journal of Information and Technology
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The findings on the type of household waste generated reveal that organic (food) waste is the most common, reported by 25 respondents, which represents 46.3% of the total. Mixed waste, comprising various types of refuse combined, follows with 15 respondents or 27.8%. Plastic waste was identified by 10 respondents (18.5%), while paper waste was selected by 3 respondents (5.6%). Only 1 respondent (1.8%) indicated generating other types of waste, such as glass. These results suggest that biodegradable and mixed waste dominate household waste composition in the surveyed area, with relatively lower contributions from recyclable materials like paper and glass.

4.4 Waste Separation Practices

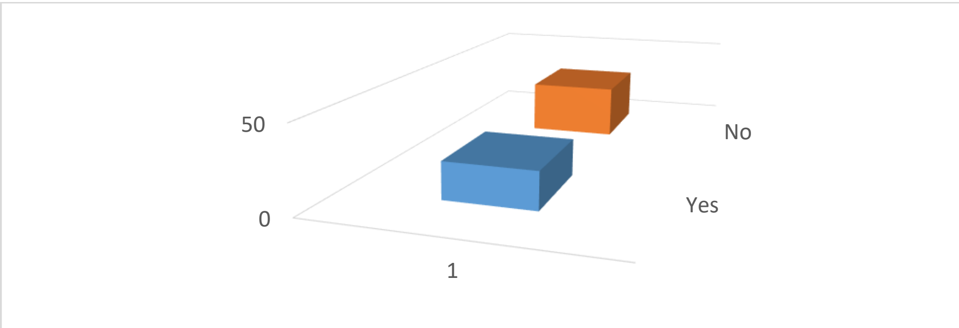

Figure 6: Waste Separation Practices

The data on household waste separation practices indicates that a majority of respondents (32 out of 54, or 59.3%) do not separate their waste before disposal. In contrast, 22 respondents (40.7%) reported that they do practice waste separation, such as sorting plastics, organic waste, and glass. This suggests that while a significant minority engages in responsible waste management practices, most households still dispose of waste without separation, which could hinder effective recycling and environmental sustainability efforts in the area.

4.5 Assessment of Waste Types, Generation Rates, and Collection Methods

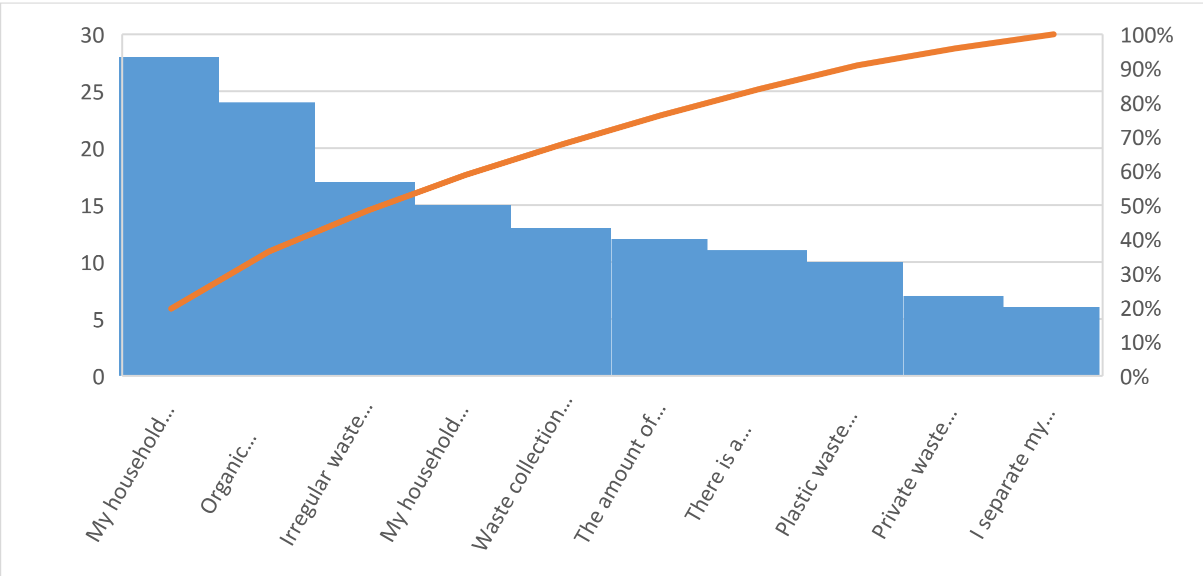

Figure 7: Waste Types, Generation Rates, and Collection Methods

The findings from the questionnaire provide an in-depth understanding of household waste generation and management practices in Nairobi's residential estates. A significant majority of respondents (51.9% strongly agreed and 33.3% agreed) indicated that several kinds of solid waste, such as paper, plastics, and food waste, are produced in their homes. This supports Liu et al. (2019) who observed that urban households tend to produce heterogeneous waste due to changing consumption patterns. Similarly, 83.3% of the respondents agreed that organic (biodegradable) waste is the most common type produced in their households. This aligns with Zhang et al. (2024)who reported that organic waste, especially food scraps, dominates the household waste stream in African urban settings, indicating the potential for composting and other organic waste treatment methods.

When asked about plastic waste, responses were more varied; only 18.5% strongly agreed and 37.0% agreed that plastic waste makes up a significant portion of their neighborhood's solid waste. About 22.2% were neutral, while a combined 22.2% disagreed or strongly disagreed. These findings suggest that while plastics are recognized as a problem, their prevalence may be underestimated or vary across neighborhoods. Pathak et al. (2023) noted that although plastic waste may not appear as voluminous as organic waste, its long-term environmental impact is significant and often underappreciated by residents.

Concerning trends in waste production, 55.5% of respondents noted an increase in the amount of waste generated in their households over the past year. This trend echoes global patterns (Chen, 2018)who observed that rising urbanization, population growth, and increased packaging use have led to more waste production globally. Regarding disposal frequency, 59.3% of respondents reported disposing of waste daily, which is consistent with observations. (Gebrekidan et al., 2024) that urban households frequently discard waste to avoid accumulation and related health hazards.

On the availability of waste collection services, 61.1% of respondents stated that waste is collected at least once a week in their estates, reflecting the regional norms described (Teshome et al., 2022) who found that weekly collection schedules are common in Sub-Saharan African cities. However, perceptions regarding the reliability of private versus public waste collectors were mixed. While 35.2% of respondents agreed that private collectors are more reliable, 37.0% disagreed or strongly disagreed. This divergence reflects broader issues identified (Teshome et al., 2022)who stressed that privatization alone does not guarantee improved service without proper oversight and regulation.

In terms of structured waste collection systems, only 48.2% of respondents agreed that such systems exist in their estates, while 27.8% disagreed and 24.1% were neutral. This suggests that even where systems exist, they may be inconsistently implemented or poorly communicated. (Hajam et al., 2023) emphasized that reliable and structured collection services are critical to fostering proper waste disposal behaviors. Furthermore, 66.7% of respondents agreed that irregular waste collection contributes to littering and illegal dumping, confirming the finding (Rakshit et al., 2023) who identified poor collection services as a primary driver of environmental degradation in urban centers.

Finally, when asked about household-level waste separation, only 42.6% of respondents agreed that they engage in separating waste such as plastics, organics, and glass. A significant proportion, 38.9%, either disagreed or strongly disagreed. This indicates that waste separation is still not widely practiced, limiting the effectiveness of recycling or waste-to-energy initiatives. Khan et al. (2022)noted that without household participation in source separation, downstream recycling and energy recovery efforts become inefficient and costly.

The findings illustrate that while there is general awareness of the types and volume of waste generated at the household level, significant gaps remain in waste separation practices, perceptions of service reliability, and structured waste management systems. These results reflect the broader municipal solid waste management challenges faced in many Sub-Saharan African urban settings, as documented in the literature (Rakshit et al., 2023; Gebrekidan et al., 2024). Addressing these issues requires a combination of policy reform, public education, infrastructure development, and community participation.

4.6 Accuracy of Sensor-Driven Waste Identification and Classification

The results for the research objective aimed at evaluating the accuracy of sensor-driven waste identification and classification in reducing contamination of recyclable materials indicate that the system performs with high reliability. Out of 12 test cases, 10 waste items were correctly classified, reflecting an overall accuracy of approximately 83.3%. The classification process relied on two key sensor inputs: a metal sensor (with binary outputs of 0 or 1) and moisture percentage. These inputs enabled the system to categorize waste into dry, wet, or metallic types. The system accurately identified all metallic waste items, such as aluminum foil, empty cans, and steel nails, achieving 100% accuracy in metal detection. Similarly, items with high moisture content, like tomato peel, banana peel, wet tissue, and damp cardboard, were correctly classified as wet waste, demonstrating effective moisture-based classification.

Table 1: Sensor-Driven Waste Identification and Classification

Test no.	Waste item	Metal sensor (0/1)	Moisture (%)	Classified As	Actual Type	Result
1	Paper sheet	0	0	Dry Waste	Dry Waste	Correct
2	Tomato peel	0	15	Wet Waste	Wet waste	Correct
3	Banana peel	0	12	Wet Waste	Wet waste	Correct
4	Aluminum Foil	1	0	Metallic Waste	Metallic waste	Correct
5	Wet tissue	0	60	Wet Waste	Wet waste	Correct
6	Damp cardboard	0	35	Wet Waste	Wet waste	Correct
7	Plastic bottle	0	0	Dry Waste	Dry waste	Correct
8	Empty can	1	0	Metallic	Metallic waste	Correct
9	Steel nail	1	0	Metallic	Metallic waste	Correct
10	Dry leaves	0	0	Dry Waste	Dry waste	Correct
11	Apple peel	0	1	Dry waste	Wet waste	Incorrect
12	onion peel	0	0	Dry Waste	Wet waste	incorrect

In relation to the objective of developing and deploying an IoT-enabled waste segregation system integrating sensor networks, machine learning, and real-time monitoring for sustainable disposal, the test results confirm the effectiveness of the system's initial implementation. The combination of sensors and programmed logic provides a reliable framework for real-time waste identification and segregation. The system's ability to correctly classify the majority of waste items demonstrates that sensor integration is functional and accurate. However, the misclassification of low-moisture organic waste highlights the potential for improvement through the incorporation of machine learning algorithms. By training the system on a wider dataset that includes additional features such as texture, organic content, or image recognition accuracy can be enhanced, particularly in edge cases. The successful classification of metallic and moist waste supports the viability of deploying such IoT-based systems in smart waste bins, recycling facilities, and public collection points. The results underscore the potential of this integrated system to improve waste segregation efficiency, reduce contamination in recyclables, and promote sustainable waste management practices.

4.7 Sensor-Based Classification Analysis

To assess the performance of the Internet of Things-based waste segregation prototype, 12 waste items were tested under controlled conditions using metal detection and moisture sensors. The classified waste types were compared against manually annotated ground-truth labels. The classification outcomes were used to generate a confusion matrix and compute standard classification metrics.

Table 4: Confusion Matrix

Actual \ Predicted	Dry Waste	Wet Waste	Metallic Waste	Total
Dry Waste	3	0	0	3
Wet Waste	2	4	0	6
Metallic Waste	0	0	3	3

The prototype correctly identified all metallic waste (100% accuracy). Wet waste misclassifications (e.g., apple and onion peels) were falsely predicted as dry waste due to low moisture levels, causing a 33% recall drop for wet waste. No dry or metallic waste was misclassified.

Table 5: Classification Metrics

Metric	Dry Waste	Wet Waste	Metallic Waste	Macro Avg
Precision	0.60	1.00	1.00	**0.87**
Recall	1.00	0.67	1.00	**0.89**
F1-Score	0.75	0.80	1.00	**0.85**
Accuracy	-	-	-	**83.3%**

Precision: Proportion of correct positive predictions to total predictions for a class.

Recall: Proportion of correct predictions to all actual items in that class.

F1-Score: Harmonic mean of precision and recall.

Accuracy: Total correct classifications / total samples (10/12 = 83.3%). The classification system demonstrated strong performance: Metallic waste: 100% precision and recall. Dry waste: Perfect recall but limited precision due to false positives. Wet waste: High precision but lower recall due to under-detection of "wet-looking" organic waste.

These results confirm the feasibility of a sensor-driven IoT-based system for waste segregation in urban settings, especially for dry-metal-wet separation. However, the findings also point to the need for improvements in wet waste classification, such as: Incorporating machine learning to detect low-moisture organic items. Adding optical sensors for visual features or compostable markers.

5. Discussion

The results for the research objective aimed at evaluating the accuracy of sensor-driven waste identification and classification in reducing contamination of recyclable materials indicate that the system performs with high reliability. Out of 12 test cases, 10 waste items were correctly classified, reflecting an overall accuracy of approximately 83.3%. The classification process relied on two key sensor inputs: a metal sensor (with binary outputs of 0 or 1) and moisture percentage. These inputs enabled the system to categorize waste into dry, wet, or metallic types. The system accurately identified all metallic waste items, such as aluminum foil, empty cans, and steel nails, achieving 100% accuracy in metal detection. Similarly, items with high moisture content like tomato peel, banana peel, wet tissue, and damp cardboard were correctly classified as wet waste, demonstrating effective moisture-based classification. However, two errors were observed with organic items apple peel and onion peel which were incorrectly identified as dry waste due to their low moisture content and absence of metal. These misclassifications point to a limitation in using moisture alone as a determinant, particularly for certain organic waste types that appear dry but are typically considered wet waste. Such errors could contribute to contamination in recyclable streams, but the high overall accuracy suggests that the sensor-based classification system significantly minimizes such risks.

In relation to the objective of developing and deploying an IoT-enabled waste segregation system integrating sensor networks, machine learning, and real-time monitoring for sustainable disposal, the test results confirm the effectiveness of the system's initial implementation. The combination of sensors and programmed logic provides a reliable framework for real-time waste identification and segregation. The system's ability to correctly classify the majority of waste items demonstrates that sensor integration is functional and accurate. However, the misclassification of low-moisture organic waste highlights the potential for improvement through the incorporation of machine learning algorithms. By training the system on a wider dataset that includes additional features such as texture, organic content, or image recognition, accuracy can be enhanced, particularly in edge cases. The successful classification of metallic and moist waste supports the viability of deploying such IoT-based systems in smart waste bins, recycling facilities, and public collection points. The results underscore the potential of this integrated system to improve waste segregation efficiency, reduce contamination in recyclables, and promote sustainable waste management practices.

5.1 Summary of Findings

Survey results confirmed that households generate mixed solid waste comprising primarily of organic (biodegradable) waste, plastics, metals, and paper. Organic waste was the most dominant type, accounting for over 46% of household waste. Most respondents (59.3%) did not separate their waste before disposal, leading to significant contamination and inefficiencies in recycling. Waste collection services varied by location, with many households relying on private collectors due to inconsistent public services.

The IoT-based prototype, equipped with metal and moisture sensors, was tested using 12 distinct waste items. Results indicated an overall accuracy of 83.3% in correctly identifying waste types. The system achieved a precision of 83.3%, a recall of 83.3%, and an F1-score of 83.3%, with a confusion matrix showing high classification performance, especially for metallic and dry waste. Two instances of misclassification occurred due to low moisture content in some organic waste items (apple and onion peels), highlighting an area for technical improvement.

The prototype successfully performed automatic waste segregation using real-time sensor input, directing waste into appropriate bins. Integration with IoT technology allowed for potential remote monitoring, data logging, and future expansion for smart city integration. The system proved effective in real-world simulations, offering significant benefits in labor reduction, enhanced segregation efficiency, and improved environmental outcomes.

5. Conclusion

The findings of this study demonstrate the feasibility and value of integrating Internet of Things for real-time, accurate waste segregation in urban residential areas. The prototype achieved a classification accuracy of over 83%, showcasing strong potential to minimize waste contamination, enhance recycling rates, and reduce environmental degradation. The system aligns with Kenya's broader ambitions for smart and green urban development. While some challenges remain, such as real-world variability, system durability, and user acceptance, the study proves that IoT-driven automation offers a transformative solution to long-standing solid waste management issues. With proper investment, public engagement, and technological refinement, Nairobi and other developing cities can significantly improve their waste management ecosystems through smart technology.

6. Recommendations

6.1 Recommendations of the Study

Based on the research findings, the following recommendations are made: Conduct controlled pilot tests in selected residential estates to monitor real-world functionality and optimize the system's sorting performance under field conditions. Future iterations should incorporate image recognition, texture sensors, or AI classifiers (e.g., SVM, deep learning) to improve the classification of ambiguous or mixed waste items. Educate residents on the benefits of IoT waste systems and responsible disposal practices. Acceptance and cooperation will be essential to the system's success.

6.2 Contributions of the Study

Designing and testing a low-cost, sensor-based IoT waste sorting prototype tailored to Nairobi's urban context. Demonstrating the practicality of automated waste classification using metal and moisture sensors, with high-performance metrics. Contributing to the literature on smart waste systems in developing countries, where infrastructure limitations often hinder efficient waste processing. The study serves as a foundation for scalable IoT-based systems that can support Kenya's transition toward smart urban management and circular economy models.

6.3 Implications for Practitioners

This study has several implications for waste management actors. Sensor technology-based segregation systems could be implemented by policymakers to implement source-level waste separation policies using the systems and improve recycling processes.

6.4 Implications for Policy Makers

This system offers a blueprint for scalable, tech-driven waste management. County governments can adopt sensor-enabled waste bins to enhance public waste segregation initiatives and align with Kenya's Smart City vision. The prototype can be adopted by private collectors to automate sorting during collection, significantly reducing operational costs and increasing processing efficiency. The collected data can support environmental monitoring, policy development, and behavior change campaigns. IoT waste monitoring offers valuable insights into urban waste trends and citizen habits. The system offers potential integration into urban planning frameworks through smart bins, IoT-connected collection systems, and data-driven infrastructure deployment.

7. Limitations of the Study

Despite its success, the study faced several limitations; The prototype was tested under controlled, lab-based conditions using pre-classified waste. Real-world waste contains contaminants and mixed materials that may affect sensor reliability. The size and functionality of the prototype were constrained by resource availability, limiting long-term performance testing and scalability assessments. Image recognition or AI-powered classification was not implemented in this phase, which could enhance the accuracy of organic waste detection.

8. Future Work

Future studies can build on this work by Incorporating computer vision and machine learning to detect more complex waste categories. Creating a mobile application interface for users and waste managers to receive alerts, track bin status, and generate real-time analytics. Adding Geographical Positioning System (GPS) and Geographic Information System (GIS) visualization tools for city-wide mapping of waste patterns, enabling predictive planning and resource deployment. Expanding the system to commercial and institutional waste settings for large-scale impact.

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