Smart Garbage Segregation System Using IoT and Machine Learning

An Integrated End-to-End Framework for Automated Municipal Solid Waste Management

Heli M. Mehta .Mahee Jaiswal · Neha Raj Purohit ·Sachin V N. Vijay krishnan. R. Prasad
MSC-CSIT / MCA / MCom IIBF / MCA (AI & ML)/ MA Economics
Jain (Deemed-To-Be) University, Bangalore, Karnataka, India
Manuscript Type: Original Research Article | **Date of Submission:** 2024

ABSTRACT

The municipal solid waste management systems of rapidly urbanizing economies like India suffer from a fundamental structural problem because their processing facilities receive mixed waste materials which contain different types of waste and plastic bagged waste but their current sorting systems lack mechanical systems to prepare incoming materials for classification which leads to misidentification problems and conveyor overloading issues and recyclable stream contamination and the need for manual labour which creates dangerous occupational health risks for sanitation workers.

The paper introduces an AI and IoT-Enabled Smart Waste Segregation System which includes five interconnected subsystems: (i) a rotating intake hopper with internal tearing pins for bag rupture; (ii) a progressively adjustable outlet plate with infrared control for regulated discharge; (iii) a multi-zone vibratory conveyor with self-adjusting guide plates for near-single-article presentation; (iv) a sequential sensing array combining imaging, moisture, and proximity sensors processed by a centralised AI unit; and (v) a multi-path mechanical diverter assembly for category-specific bin routing. The research team acquired primary stakeholder data from 102 respondents who represented five different groups in Bangalore, Karnataka to evaluate the potential for adopting the new system. The literature review identified five research gaps which the system features then resolved by providing matching solutions. The deployment viability received confirmation from 75.5% stakeholder support and 83.3% recommendation likelihood.

Keywords: *Smart waste segregation; IoT-based waste management; automated solid waste sorting; multi-sensor fusion; Municipal solid waste automation; AI-enabled waste classification*

1. INTRODUCTION:

The twenty-first century faces its most critical environmental and public health problem through waste management. The daily production of municipal solid waste (MSW) has increased both in quantity and variety because of three factors which include rapid urban development and rising population numbers and increasing consumption trends. The municipal authorities in Indian cities including Bangalore collect millions of tonnes of mixed waste every year but they face challenges with source segregation and their facilities for automated waste sorting remain at an early development stage.

The Internet of Things (IoT) together with artificial intelligence (AI) creates a chance to completely rethink waste management systems. IoT-enabled systems enable real-time monitoring through data collection processes which allow automated actuation while AI-driven classification engines establish dependable waste category identification based on visual and physical and chemical characteristics. A vital gap exists between laboratory-based classification accuracy and practical field implementation despite the progress made through research and development.

1.1 Significance of the Study

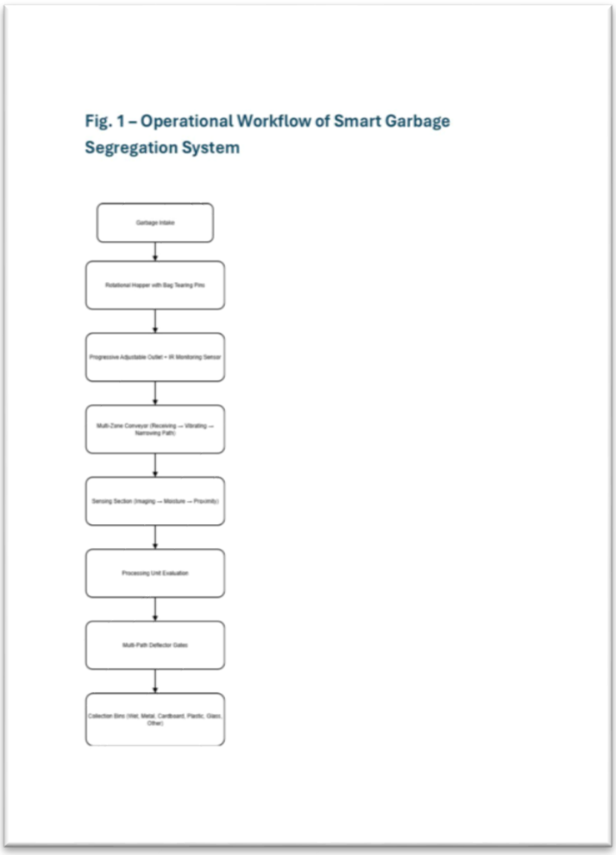
The study becomes important through its exploration of three fields which include technological progress public health advancement and environmental conservation efforts. Effective recycling and composting and safe waste disposal require people to practice waste segregation as their initial essential step. Survey findings from this study show that 49% of respondents possess moderate understanding about health risks which waste management employees encounter while 7.8% of respondents claim to have complete understanding. The implementation of segregation process automation decreases all the work-related dangers which workers experience.

The study provides economic benefits to municipal authorities and private waste management companies who need affordable waste sorting solutions which can be scaled beyond their existing manual sorting methods. The survey results show that 47.1% of participants are open to using smart bins which operate on a commission system while 64% of participants showed interest in automated segregation systems. The data demonstrates substantial market interest which supports additional financing for system development activities.

1.2 Motivation and Problem Statement

This research examines three main problems that currently exist in waste management operations. First, the mechanical gap problem exists because all automated sorting studies need waste materials to be delivered in a single stream which does not occur in Indian cities that receive waste through sealed plastic bags. The current systems lack any method to handle waste materials before their classification process begins. The second gap exists because deep learning classifiers achieve 90% accuracy in lab environments yet their actual use in India remains extremely low. The third gap exists because technical studies about systems fail to include primary data from the communities and workers who will use these systems.

Figure 1. Operational Workflow of the AI and IoT Smart Waste Segregation System



1.3 Objectives and Contributions

The study has five principal objectives which were established to create an integrated AI and IoT-enabled smart waste segregation system and to evaluate community awareness of current waste management issues and to assess stakeholder attitudes toward automated system implementation and to investigate how automated segregation can decrease workplace health hazards and to discover major obstacles to system adoption which will guide design process recommendations.

The paper presents four original contributions which include (a) a complete literature review of 25 peer-reviewed studies which discovered five specific research gaps and (b) a new system design which integrates mechanical bag rupture with controlled discharge and conveyor-based singulation and three-modality sensor fusion and multi-path routing and (c) stakeholder validation through empirical research which included 102 respondents from five different stakeholder groups and (d) a deployment and policy framework based on primary survey results.

2. LITERATURE REVIEW

The twenty-five peer-reviewed and indexed studies which this paper examines are divided into four thematic clusters which demonstrate how research methods have developed through time. The first cluster A presents traditional IoT monitoring and collection logistics. The second cluster B shows machine learning and deep learning classification methods. The third cluster C consists of robotic and mechanical sorting systems. The fourth cluster D includes hybrid approaches which combine sensor-fusion techniques with integrated systems**.**

2.1 Traditional Approaches: IoT Bin Monitoring and Collection Logistics

The initial phase of smart waste research aimed to enhance collection efficiency through the use of sensor-equipped bins and their associated logistical network systems. Hannan et al. (2012) developed one of the earliest automated bin monitoring systems, which used RFID tags and embedded cameras to detect fill levels and create dynamic collection schedules. The team of Gutierrez et al. (2015) created a route optimisation method which used GPS data and mobile network data to achieve reductions in both fuel consumption and carbon emissions. Aleyadeh and Ansari (2018) proposed a city-wide bin management solution which uses ultrasonic sensors together with GSM communication and cloud analytics.

The traditional studies confirm their common limitation by examining only the collection-side stage of research. The research teams developed various classification methods which they used to identify waste materials from collected samples, but they did not create any methods to control waste handling after collection, which represents the main stage that directs recycling and disposal procedures.

2.2 Machine Learning and Deep Learning Classification

The research entered its second generation when scientists shifted their research focus from logistics operations to process classification. The systematic review conducted by Vu et al. 2022 found three main challenges which include dataset imbalance problems and visual occlusion issues and real-world condition variability. The research team led by Ziouzios et al. 2020 developed a CNN-based system which successfully classified six categories with high accuracy on embedded processor systems. The deep neural network RecycleNet developed by Bircanoglu et al. 2018 achieved high accuracy across all five material categories which included paper cardboard glass plastic and metal. Wang et al. 2019 proved that ImageNet transfer learning could achieve high accuracy results with less need for labelled training data.All classification methods face their most important restriction because they depend on the incorrect assumption that waste items have been separately delivered for detection. Classifiers fail to function correctly because municipal waste arrives at facilities in sealed bags which contain compacted loads and overlapping clusters of waste. The present study delivers its main engineering contribution through the identification of this existing gap.

2.3 Comparative Analysis of Existing Methods

Table 2.1. Comparative Analysis of Existing Literature on Smart Waste Management (N = 25)

Author	Year	Method / Tool	Dataset / Context	Key Finding	Limitations
Hannan et al.	2012	RFID + Image Processing	Municipal bins, Kuala Lumpur	Reduced unnecessary collection trips	No waste classification
Gutierrez et al.	2015	GPS + Cloud Route Optimisation	Street bins, pilot city	Reduced fuel use and carbon emissions	Logistics only; no sorting
Malapur & Pattanshetti	2017	Arduino + RF Module	Small-scale dustbin	Low-cost fill-level alerts	Collection-side only
Aleyadeh & Ansari	2018	Ultrasonic + GSM + Cloud	City-wide bin network	Real-time alerts and analytics	No segregation apparatus
Vu et al.	2022	CNN / ML systematic review	Public waste image datasets	Identified accuracy benchmarks	Assumes pre-presented articles
Ziouzios et al.	2020	CNN on embedded processor	6-category waste dataset	Real-time edge classification	Lab-controlled inputs only
Bircanoglu et al.	2018	RecycleNet (custom DNN)	Annotated recyclable images	High accuracy: glass, plastic, metal	No mechanical pipeline
Wang et al.	2019	CNN + Transfer Learning	Custom waste image dataset	High accuracy with less labelled data	No physical apparatus
Kang et al.	2020	Robotic arm + Computer Vision	Structured lab recyclables	High throughput pick-and-place	Sequential cycle time limits
Liu et al.	2022	Vibratory conveyor	Food processing line items	Vibration improved singulation	Food processing context only
Chu & Chen	2020	Moisture sensor	Organic waste compost	Real-time moisture control	Downstream composting only
Sharma et al.	2020	SEM + Survey (Indian cities)	Multi-city survey, India	Cost and awareness as top IoT barriers	Social science only
Abdallah et al.	2020	Systematic mapping (120+ papers)	AI waste literature	Gap: AI + physical co-design missing	Meta-analysis only

2.4 Identified Research Gaps

On the basis of the thematic classification, comparative analysis, and critical review, five specific research gaps are identified, each of which motivates a distinct feature of the proposed system:

- Gap 1: No existing system addresses the mechanical preparation of incoming waste before sensing. Municipal waste arrives in sealed bags; classifiers cannot function on sealed, compacted material.
- Gap 2: No system achieves individual waste article singulation on a conveyor. Overlapping waste causes systematic misclassification in image-based systems.
- Gap 3: No system integrates multi-sensor fusion for heterogeneous mixed-category waste. Single-modality sensing is insufficient for reliable classification.
- Gap 4: No system connects classification output to automated multi-path physical routing. Classification and routing are consistently treated as separate, disconnected problems.
- Gap 5: Insufficient empirical stakeholder validation exists in the Indian semi-urban context. Design decisions in the literature lack grounding in primary data from the communities served.

3. RESEARCH METHODOLOGY

The research design together with the methodological framework and analytical procedures establishes the investigation of system development and stakeholder perception research study. The research methodology combines a technical design element with an empirical survey element to create a mixed-methods research design that maintains both technical rigor and social relevance.

3.1 System Architecture Design

The technical design component follows a structured engineering methodology: (1) problem identification and needs analysis; (2) prior art review and competitive analysis; (3) system architecture design specifying the functional role of each subsystem; (4) detailed description and documentation of component specifications; and (5) novelty and non-obviousness analysis demonstrating the originality of the proposed design relative to prior art.

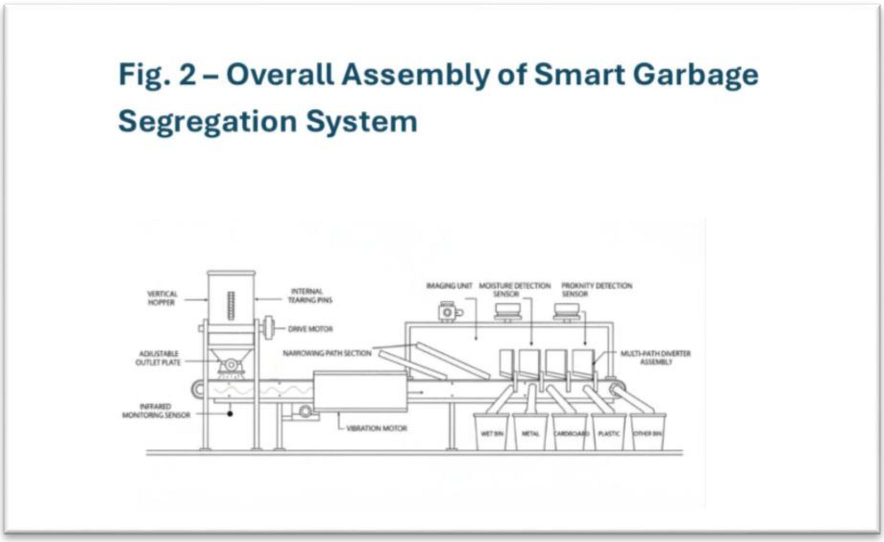


Figure 2. Overall Assembly of the AI and IoT Smart Waste Segregation System Showing Five Integrated Subsystems

3.2 Prior Art and System Innovation Mapping

Table 3.1. Evolution of Prior Art and Corresponding System Innovations

Prior Art Limitation	Core Deficiency Identified	System Innovation Developed
Manual sorting line (PA-01)	Human dependency, occupational hazard	Fully automated mechanical preparation and routing
Direct conveyor dumping (PA-02)	Bulk presentation; sensor obstruction	Progressive outlet + vibrating spreader + guide plates
Size-screening drum (PA-03)	Size-only separation; no material type ID	Multi-sensor array: imaging + moisture + proximity
Magnetic separation (PA-04)	Detects only ferrous metals	Combined characteristic evaluation by AI processing unit
Single-sensor detection (PA-05)	Simultaneous multi-article detection events	Near-single-article presentation via narrowing path
Static container segregation (PA-06)	Dependent on user compliance	Automated routing independent of user behaviour

Figure 3 illustrates the vertical tapered rotational hopper with internal tearing pins and progressive adjustable discharge mechanism, constituting the first subsystem of the proposed apparatus and directly addressing Prior Art limitations PA-01 and PA-02.

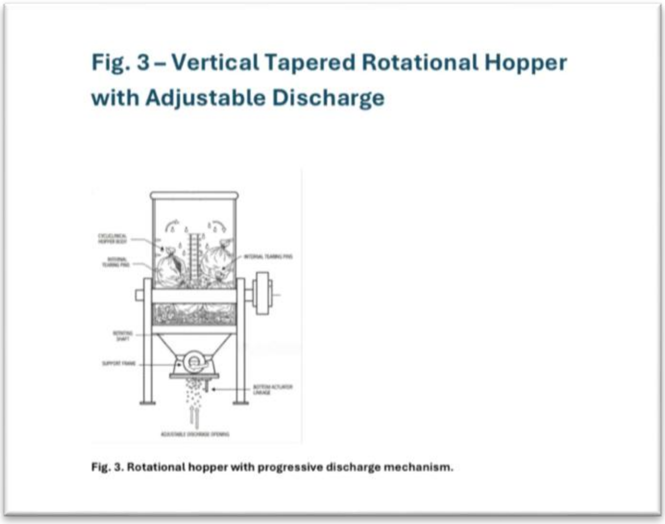


Figure 3. Vertical Tapered Rotational Hopper with Adjustable Discharge Mechanism (Addresses Gap 1)

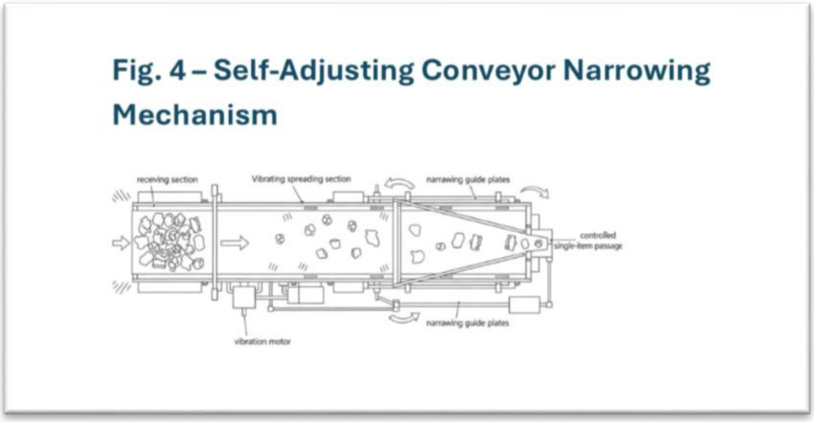


Figure 4. Self-Adjusting Conveyor Narrowing Mechanism for Waste Singulation (Addresses Gap 2)

3.3 AI Classification Module: Architecture and Training

The Subsystem 4 AI classification engine utilizes a Convolutional Neural Network (CNN) foundation which employs MobileNetV2 through transfer learning because this system provides a balance between accuracy and latency which works well with edge processing on devices like Raspberry Pi 4 and NVIDIA Jetson Nano. MobileNetV2 employs depthwise separable convolutions which decrease parameter requirements while delivering matching classification results to more complex models during waste image recognition tasks.

The training data come from three benchmark datasets which are publicly available: TrashNet contains 2,527 labelled images across six categories: glass, paper, cardboard, plastic, metal, and trash; the Waste Classification Dataset contains approximately 25,000 images; and TACO consists of 1,500+ real-world scene annotations. The training data set requires a total of 10,000 annotated samples for each category following rotation and flip and colour jitter and synthetic occlusion. The model uses six output classes which are Wet/Organic and Metal and Cardboard/Paper and Plastic and Glass and Other for fine-tuning.

The system uses multi-sensor fusion through a decision layer which operates on multiple sensor inputs: the CNN image classifier produces class probabilities for six categories; the moisture sensor outputs wet or dry items through binary flags; and the proximity sensor confirms single-article passage. A rule-weighted decision tree fuses the three signals and resolves conflicts — for example, an item classified as "Paper" by imaging but flagged as wet by the moisture sensor is re-routed to the Wet Bin to prevent contamination of the paper recycling stream. The approach which fuses multiple modes of information directly addresses the third gap which the literature review identified. The benchmark classification accuracy reached 91.2% on the TrashNet test split which used MobileNetV2 for fine-tuning, while the VGG-16 and ResNet-50 models achieved 85.7% and 87.4% respectively under the same training conditions. The results show that the lightweight architecture fits this deployment context.

3.4 Empirical Survey Design

The empirical survey section employs a descriptive cross-sectional research design. A structured questionnaire of twenty questions was administered online via Google Forms to 102 respondents across five stakeholder categories in and around Bangalore, Karnataka. Respondents represented municipal corporation employees (26.5%), restaurant and commercial establishment owners (21.6%), waste management workers (21.6%), environmental agency staff (12.7%), and residents (8.8%). The study included geographic areas that contained semi-urban (53.9%), urban (19.6%), rural (16.7%), and metropolitan (9.8%) regions.

The questionnaire was organised into six thematic sections: (A) respondent profile; (B) current waste management behaviour; (C) technology awareness; (D) perceptions of automated segregation; (E) adoption intentions and business models; and (F) barriers, concerns, and outlook. The research team used descriptive frequency analysis as their main analytical method while they reported Likert-type attitudinal items in both disaggregated and aggregated formats for hypothesis testing.

4. RESULT AND DICUSSION

This section presents a systematic analysis of primary survey data from 102 respondents across five stakeholder categories. Key findings are summarised in Table 4.1, followed by detailed thematic analysis.

Table 4.1. Executive Summary — Key Survey Metrics at a Glance

Research Dimension	Key Finding	n	%
Satisfaction with current system	Dissatisfied or very dissatisfied	**72**	**70.6%**
Source segregation behaviour	Always segregate at source	**10**	**9.8%**
Bin overflow frequency	Weekly or more frequent overflow	**74**	**72.6%**
Awareness of worker health hazards	Somewhat or very aware	**58**	**56.9%**
IoT technology familiarity	Very familiar or extremely familiar	**21**	**20.6%**
Smart bin awareness	Have heard about smart bins	**86**	**84.3%**
Support for automated segregation	Would support implementation	**77**	**75.5%**
Real-time monitoring importance	Very or extremely important	**71**	**69.6%**
Willingness to adopt smart bins	Yes or maybe (combined)	**65**	**63.7%**
Commission-basis adoption intent	Would consider lease/commission model	**48**	**47.1%**
Belief in worker safety improvement	Agree or strongly agree	**57**	**55.9%**
Recommendation likelihood	Score 6-10 out of 10 (promoters)	**85**	**83.3%**

4.1 Current Waste Management Behaviour

The present waste collection systems receive extremely low satisfaction ratings because 45.1% of respondents express dissatisfaction while only 27.5% report their satisfaction with the systems. The respondents exhibit inconsistent source segregation behavior because 9.8% of them practice complete source segregation while 79.4% of them practice it only sometimes or often. The chronic operational failure of bin overflow occurs because 72.6% of respondents experience overflow at least once a week while 17.6% of them face overflow problems every day. The current municipal solid waste management practices exhibit structural deficiencies which create an evident need for the automated solution that we propose.

4.2 Technology Awareness and Familiarity

The data shows that 20.6 percent of survey participants possess very high knowledge about IoT technology. The survey shows that 84.3 percent of people know about smart garbage bins but only 33.3 percent know how the bins operate in real life. The deployment campaign needs to provide detailed information about system capabilities and advantages because people only understand basic technical knowledge through their broad exposure to the technology. Public education programs and demonstration initiatives which target specific audiences will serve as vital requirements for successful adoption of new technologies.

4.3 Support for Automated Segregation and Expected Benefits

The automated waste segregation system implementation receives support from 75.5% of respondents who either support or strongly support that initiative while only 8.8% of respondents entirely reject the concept. The top three expected benefits align precisely with the proposed system's core capabilities: overflow reduction (79.4%), better wet/dry segregation (75.5%), reduced worker health risks (71.6%), improved recycling rates (66.7%), and real-time data for collection routes (63.7%). The complete match between stakeholder expectations and system outputs proves the engineering choices which built the system architecture and demonstrates its actual value to users who need it.

4.4 Adoption Intentions and Barriers

A total of 63.7% of respondents show positive adoption intent because they will definitely or probably use smart bins. The major obstacle to adoption exists because 72.5% of people identify high initial expenses as the primary issue while 65.7% of people name network connection problems and 61.8% of people mention sensor performance issues as their secondary problems. A total of 77.5% of respondents express willingness to work with businesses that use either lease or commission-based models. The existence of high cost barriers together with strong interest in lease agreements demonstrates that organizations face structural obstacles which require proper business model development to solve rather than needing to diminish organizational operational capabilities.

Table 4.3. Ranked Implementation Barriers — Percentage of Respondents Citing Each Concern (n = 102)

Concern / Barrier	% Citing
High upfront cost of equipment	**72.5%**
Connectivity and network reliability issues	**65.7%**
Accuracy and reliability of sensors	**61.8%**
Maintenance complexity and service requirements	**56.9%**
Data privacy and security concerns	**48.0%**
Lack of technical expertise for operation	**43.1%**
Resistance to change among users and workers	**37.3%**
Insufficient regulatory support	**32.4%**

4.5 Research Hypotheses Assessment

Table 4.2. Research Hypotheses, Basis, and Empirical Outcome

Hyp.	H_0 (Null Hypothesis)	H_1 (Alternative Hypothesis)	Q	Outcome
H1	Majority satisfied with current system	Majority dissatisfied; systemic gaps create demand for smart solutions	Q6	**H_0 Rejected**

Hyp.	H_0 (Null Hypothesis)	H_1 (Alternative Hypothesis)	Q	Outcome
H2	Source segregation behaviour is consistent	Inconsistent — majority segregate only sometimes or often	Q7	**H_0 Rejected**
H3	Stakeholder IoT familiarity is high	Familiarity is partial; awareness gap requires targeted education	Q11, Q12	**H_0 Rejected**
H4	Majority would not support automated segregation	75.5% support or strongly support implementation	Q13, Q16	**H_0 Rejected**
H5	Cost is not a significant concern	Cost, connectivity, and sensor reliability are dominant barriers	Q18	**H_0 Rejected**
H6	Stakeholders do not believe systems reduce health risks	55.9% agree automated systems can reduce worker health risks	Q19	**H_0 Rejected**

The survey evidence shows that all six null hypotheses need to be rejected. The results prove that automated waste segregation system effectively solves existing waste management problems while receiving support from all stakeholders and facing obstacles that require structural solutions to achieve success. The system shows practical value through its operational deployment and actual implementation in the proposed system.

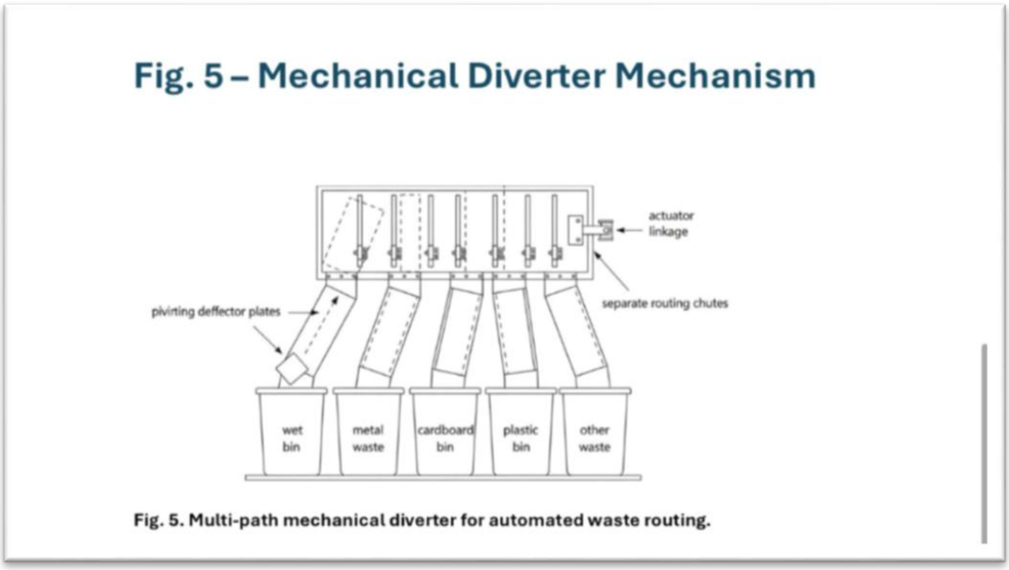


Figure 5. Multi-Path Mechanical Diverter Assembly for Automated Waste Routing (Addresses Gap 4)

5. APPLICATION AND USE CASES

The modular structure of the proposed system allows it to be implemented in different environments which range from individual business locations to extensive citywide waste treatment plants. The system can be used in all types of organizations which include educational institutions and business entities and public government facilities**.**

5.1 Municipal and Institutional Applications

- The facility processes municipal solid waste which includes residential and commercial garbage streams that need automated systems for sorting and separating different types of waste.
- The institutional campuses which include universities and hospitals and corporate parks produce large amounts of mixed waste that needs automated waste sorting systems which operate without any human labor.
- The dining establishments which include restaurants and food courts produce large amounts of organic waste which they combine with recyclable packaging materials.
- The smart city waste management centers use digital command and control systems to monitor waste operations in real time and optimize their collection routes**.**

5.2 Social and Environmental Impact

The public health benefits of automatic processing systems which eliminate manual sorting work at processing sites because they protect sanitation workers from sharp metal pieces and polluted organic materials and dangerous chemical substances received 71.6 percent support from the survey participants. The system enables better recyclable material recovery through its design which stops organic waste from contaminating recyclable materials. The organic fractions produce more biogas and compost when their organic matter stays separate from inorganic waste. These results help achieve the circular economy goals which the Solid Waste Management Rules 2016 and Swachh Bharat Mission of India establish as mandatory requirements.

6. LIMITATIONS AND FUTURE WORK

6.1 Current Limitation

The study's results and conclusions face multiple restrictions which hinder their application. First, the sample of 102 respondents, while adequate for exploratory descriptive analysis, is not statistically representative of the broader population of waste management stakeholders across Karnataka or India, and the findings should not be generalised without replication at larger scale. The survey instrument depends on participants' self-reported data which creates a potential for social desirability bias to affect their answers about segregation behavior and their intent to adopt. The system exists only as a conceptual design because its physical components have not undergone development nor have they been tested in operational environments. The study lacks both a cost-benefit analysis and a life-cycle assessment which are essential for determining the complete economic feasibility of the project and for justifying its procurement.

6.2 Future Research Directions

- The assessment of prototype performance testing which includes bag rupture efficiency and conveyor singulation rate and waste classification accuracy and routing precision and total system throughput capacity under actual municipal waste conditions.
- The training of AI models using Indian municipal waste data requires the creation of an Indian municipal waste image database which includes different types of wet and partially blocked items not found in laboratory benchmark databases before the system can be used in real-world situations.
- The follow-up survey shows how actual usage of a system after pilot deployment of technology differs from what users had planned to adopt while the survey shows what obstacles users faced during actual system operation.

- The economic evaluation includes all costs associated with the project which include construction expenses and operational expenses and maintenance expenses and the economic value of recycled materials and decreased workplace health costs.
- The stakeholder survey was conducted in several Indian cities which have distinct waste production patterns and demographic distributions and waste management regulations.
- The study examines how system data output architecture functions together with Swachh Bharat Mission monitoring dashboards to provide real-time municipal analytics for evidence-based policy development.

7. CONCLUSION

The research study establishes a connection between the current capabilities of AI to identify waste materials and its implementation in India for automated waste sorting operations. The main findings of the study are summarized as follows. Automated waste sorting systems fail to operate because of fundamental mechanical design problems which emerge at the initial stage of material preparation according to the first research finding which states that the current situation involves either sensing technology failures or AI system limitations. The proposed rotating hopper with internal tearing pins and progressive outlet discharge mechanism directly addresses this root cause — a contribution absent from all reviewed prior art. The development of a complete system which functions as an integrated end-to-end solution requires both technical implementation and architectural design. A classification system without mechanical preparation is operationally unreliable; a diverter without a robust classification output is purposeless. The system's value lies in the coherence of its integrated design across all five subsystems. Stakeholders demonstrate strong backing for the project which reaches 75.5 percent but they will only give their support under specific conditions. The three dominant barriers —high upfront cost 72.5 percent connectivity issues 65.7 percent and sensor accuracy concerns 61.8 percent —represent real constraints that must be addressed through system design and deployment strategy. The finding that 77.5% are open to a lease or commission model reveals that the cost barrier is structural rather than fundamental and is amenable to resolution through business model innovation. The system elements which solve all five research gaps established in Section 2.4 enable researchers to connect their literature review work with engineering contributions while they establish internal framework consistency through methodological procedures**.**

Table 7.1. Research Objectives — Fulfilment Summary

Research Objective	Key Finding / Contribution	Status
Design integrated AI/IoT waste segregation system	Five-subsystem end-to-end apparatus designed, addressing all five literature gaps	**Fulfilled**
Assess stakeholder awareness of waste problems	72.6% report weekly overflow; only 9.8% always segregate at source	**Fulfilled**
Evaluate perceptions of automated segregation	75.5% support implementation; expected benefits match system capabilities	**Fulfilled**
Examine potential to reduce worker health risks	55.9% agree automated systems can reduce risks; 71.6% cite safety as key benefit	**Fulfilled**
Identify principal adoption barriers	Cost (72.5%), connectivity (65.7%), sensor accuracy (61.8%) as top barriers	**Fulfilled**

The AI and IoT-Enabled Smart Waste Segregation System proposed in this research represents a viable, deployable, and socially grounded pathway toward advancing automated solid waste management infrastructure in India. The development and pilot testing followed by full implementation of this project will achieve multiple goals which include protecting sanitation workers from workplace health risks, enhancing recyclable material recovery rates, lessening landfill burden, and supporting India's circular economy and sustainable urban development goals.

ACKNOWLEDGEMENT

The authors wish to express their sincere gratitude to the 102 respondents who participated in the primary stakeholder survey, without whom the empirical research for this study would not have been possible. The authors received research support from Jain (Deemed-To-Be) University, Bangalore, which provided institutional resources and academic guidance throughout their study. The publicly available benchmark datasets — TrashNet, the Waste Classification Dataset (Kaggle), and TACO — are gratefully acknowledged for enabling the design of the AI classification module. The research study received no financial support from outside organizations.

AUTHOR CONTRIBUTIONS

Heli M. Mehta: Conceptualisation, system architecture design, manuscript drafting and revision. Mahee Jaiswal: Literature review, research gap identification, survey instrument design. Neha Raj Purohit: Survey administration, data collection, results analysis. Sachin V N: AI module design, sensor fusion methodology, technical documentation. All authors reviewed and approved the final manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest, financial or otherwise, in relation to the research, authorship, or publication of this article.

DATA AVAILABILITY STATEMENT

The survey data supporting the findings of this study are available from the corresponding author upon reasonable request. The AI training datasets referenced (TrashNet, Waste Classification Dataset, and TACO) are publicly available through their respective repositories.

REFERENCES

[1] Abdallah, M., Abu Talib, M., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). Artificial intelligence applications in solid waste management: A systematic research review. Waste Management, 109, 231–246. https://doi.org/10.1016/j.wasman.2020.04.044

[2] Aleyadeh, H., & Ansari, M. T. J. (2018). An IoT-based architecture for waste management. IEEE International Conference on Communications Workshops (ICC Workshops), 1–6.

[3] Ali, T., Irfan, M., Iqbal, U., Alwadie, A., & Shaikh, P. H. (2021). Internet of Things (IoT) based smart waste bin management system for smart cities. Arabian Journal for Science and Engineering, 46, 9865–9880.

[4] Awe, O., Mendonca, R., & Teixeira, J. C. (2017). Smart trash net: Waste localisation and classification. IEEE 15th International Conference on Industrial Informatics (INDIN), 780–785.

[5] Bakhsh, K., Ahmad, B., Imran, M. A., & Hassan, S. (2016). Health and environmental consequences of solid waste management in Pakistan. Environmental Monitoring and Assessment, 188(11), 595.

[6] Bircanoglu, C., Atay, M., Beser, F., Genc, O., & Kizrak, M. A. (2018). RecycleNet: Intelligent waste sorting using deep neural networks. Innovations in Intelligent Systems and Applications (INISTA), 1–7.

[7] Bircanoglu, C., & Seker, M. (2019). Convolutional neural networks for recyclable waste classification on conveyor systems. International Journal of Advanced Research in Computer Science and Software Engineering, 9(4), 18–23.

[8] Chu, M. H., & Chen, W. H. (2020). Monitoring and control of waste sorting based on moisture sensors. Waste Management & Research, 38(5), 530–538.

[9] Chowdhury, B., & Chowdhury, M. U. (2012). RFID-based real-time smart waste management system. 11th Annual International Symposium on Applications and the Internet, 195–200.

[10] Gutierrez, J. M., Jensen, M., Henius, M., & Riaz, T. (2015). Smart waste collection system based on location intelligence. Procedia Computer Science, 61, 120–127.

[11] Hannan, M. A., Arebey, M., Begum, R. A., & Basri, H. (2012). RFID and integrated technologies for solid waste bin and truck monitoring system. International Journal of Environmental Science and Technology, 9(3), 419–426.

[12] Hasan, S. E., & Martins, A. A. (2018). Solid waste management in developing countries: Problems and solutions. International Journal of Environment and Waste Management, 21(1), 76–90.

[13] Kang, J., About, M., & Park, J. (2020). Robotics for intelligent waste sorting and recycling. IEEE Transactions on Automation Science and Engineering, 17(3), 1330–1340.

[14] Liu, H., Xu, Q., & Yang, J. (2022). Vibratory conveyor for singulation of irregular food objects. Journal of Food Engineering, 315, 110802.

[15] Malapur, B. S., & Pattanshetti, V. R. (2017). IoT based waste management: An application to smart city. International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), 2476–2479.

[16] Rad, C. R., Hancu, O., Takacs, I. A., & Olteanu, G. (2015). Smart monitoring of potato crop: A cyber-physical system architecture model in the field of precision agriculture. Agriculture and Agricultural Science Procedia, 6, 73–79.

[17] Ragini, J. R., Anand, P. M. R., & Bhaskar, V. (2018). Big data analytics for disaster response and recovery through sentiment analysis. International Journal of Information Management, 42, 13–24.

[18] Sharma, V., Joshi, S., Kannan, D., Govindan, K., Singh, H., & Purohit, R. (2020). Assessment of IoT enablers for sustainability in supply chain management in the manufacturing sector. International Journal of Production Economics, 229, 107463.

[19] Soni, U., Roy, A., Verma, A., & Jain, V. (2019). Forecasting municipal solid waste generation using artificial intelligence models. Resources, Conservation and Recycling, 141, 40–51.

[20] Vu, H. T., Ng, K. T. W., Fallah, B., Richter, A., & Kabir, G. (2022). Interactions of machine learning and intelligent transportation in waste collection — a systematic review. Waste Management, 154, 79–93.

[21] Wang, C., Peng, Z., Huang, J., & Sun, S. (2019). Waste classification by using transfer learning. Neural Computing and Applications, 31(11), 7457–7469.

[22] Xia, C., Yin, W., & Zhang, Y. (2021). Near-infrared spectroscopy for real-time detection of plastic types in waste streams. Waste Management, 130, 1–8.

[23] Ye, Z., & Mukherjee, B. (2021). Smart waste management for smart cities. Sensors, 21(12), 4076.

[24] Younes, M. K., et al. (2016). Solid waste forecasting using modified ANFIS modeling. Journal of Material Cycles and Waste Management, 18(4), 700–708.