IJVAST | Vol. 1, Issue 1 | Jan 2026 | Open Access — Peer Reviewed Research Paper

Smart Waste Management System Using IoT and Machine Learning

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Abstract—Inefficient collection scheduling and manual bin monitoring remain the two largest sources of cost and environmental harm in urban solid-waste management. This paper presents the design, implementation, and evaluation of a Smart Waste Management System that combines ultrasonic fill-level sensing, a low-power microcontroller network, and a machine-learning-driven route optimisation service to reduce unnecessary collection trips while preventing bin overflow. Each smart bin is fitted with an ultrasonic distance sensor, a gas sensor for early odour and decomposition detection, and a NodeMCU ESP8266 module that publishes fill-level readings to a cloud broker at fixed intervals. A backend service aggregates the incoming telemetry, classifies each bin into an empty, moderate, or critical fill state using a Random Forest classifier trained on time-of-day and historical fill-rate features, and feeds the critical-state subset into a nearest-neighbour route optimisation module based on a Clarke-Wright savings heuristic. A prototype comprising twelve simulated collection points across a mapped municipal ward was evaluated over a six-week data collection period. The fill-level classifier achieved 95.1% accuracy, and the optimisation module reduced simulated collection-vehicle distance by 34.6% and average bin overflow incidents by 81% relative to a fixed-schedule baseline. The paper documents the system architecture, sensor and network design, classification and routing methodology, evaluation results, observed limitations, and directions for future work including solar-powered nodes and citywide fleet scaling.

Index Terms—Smart Waste Management, Internet of Things, Ultrasonic Sensing, Machine Learning, Route Optimization, Random Forest, Fill-Level Prediction, Smart Bin, Environmental Monitoring, Cloud-Based Telemetry, Sustainable Urban Infrastructure, Clarke-Wright Heuristic.

I. INTRODUCTION

Rapid urbanisation has increased municipal solid-waste generation at a pace that conventional collection practices struggle to match. Collection in most Indian municipalities still follows a fixed calendar route regardless of how full individual bins actually are, which produces two opposite failure modes: vehicles service bins that are nearly empty, wasting fuel and labour, while other bins overflow between scheduled visits, creating odour, pest, and public-health problems [1], [2].

The underlying difficulty is a lack of real-time visibility into bin state. Sanitation departments plan routes from historical averages rather than current fill levels, because no low-cost mechanism has traditionally existed to report the state of thousands of distributed bins continuously. The consequence is a system that is simultaneously wasteful and unreliable [3].

The Internet of Things offers an economical path to closing this visibility gap. Inexpensive ultrasonic sensors can measure fill level, low-power microcontrollers can transmit that measurement over existing cellular or Wi-Fi infrastructure, and cloud services can aggregate the resulting stream into a live citywide map. The remaining challenge is converting this raw telemetry into an operational decision — which bins to

B. Sensing Layer

Each smart bin is fitted with an HC-SR04 ultrasonic sensor mounted at the lid to measure the distance to the refuse surface, an MQ-135 gas sensor to detect early decomposition odour, and a load-independent power circuit supplied by a rechargeable battery. Readings are sampled every fifteen minutes to balance responsiveness against battery life.

C. Communication Layer

A NodeMCU ESP8266 microcontroller at each bin publishes sensor readings over Wi-Fi using the MQTT protocol to a lightweight cloud broker. MQTT was selected over HTTP polling because its publish-subscribe model reduces both power consumption and network overhead for intermittently connected devices.

D. Fill-State Classification

Raw ultrasonic distance is converted into a fill percentage using the known bin height, then combined with three engineered features: the fill-rate over the previous two readings, the hour of day, and a categorical indicator of the bin's locality type. A Random Forest classifier assigns each bin to an empty, moderate, or critical state. Bins whose gas sensor exceeds a calibrated odour threshold are escalated to critical regardless of fill percentage.

collect today, and in what order — which is where machine learning and route optimisation become necessary [4].

This paper proposes a Smart Waste Management System that integrates ultrasonic and gas sensing at the bin level, a classification model that converts raw fill readings into an actionable fill state, and a savings-heuristic route optimiser that generates a collection sequence for only the bins that require servicing.

The principal contributions of this work are: (1) a low-cost IoT sensing architecture for municipal bins combining ultrasonic fill measurement and gas-based decomposition detection; (2) a Random Forest fill-state classifier that incorporates temporal fill-rate features; (3) a Clarke-Wright based route optimisation module restricted to bins in a critical state; (4) a prototype evaluation across twelve simulated collection points over six weeks; and (5) an analysis of distance and overflow reduction relative to fixed-schedule collection.

II. RELATED WORK

A. Ultrasonic Bin Monitoring

Early smart-bin prototypes used a single ultrasonic sensor to report fill level against a fixed threshold, triggering a simple full or not-full alert. Such systems improve on manual inspection but ignore fill-rate trends and therefore cannot anticipate when a moderately full bin will next become critical [5], [6].

B. Machine Learning for Fill Prediction

Subsequent work applied supervised classifiers, including decision trees and support vector machines, to bin telemetry augmented with contextual features such as day of week and locality type, reporting accuracy gains over static thresholds. Ensemble methods such as Random Forest have been shown to be particularly robust to sensor noise, which is common in outdoor ultrasonic deployments exposed to rain, wind, and debris [7], [8].

C. Route Optimisation for Waste Collection

Vehicle routing for waste collection is a variant of the capacitated vehicle routing problem. Exact solvers do not scale to city-sized instances, so heuristic methods such as the Clarke-Wright savings algorithm and genetic algorithms are commonly used in practice, trading a small amount of optimality for tractable computation time [9], [10].

D. Integrated IoT-ML Waste Systems

A smaller body of work integrates sensing, prediction, and routing into a single pipeline. Reported deployments consistently show distance reductions in the range of 20% to 40%, though most studies rely on simulated rather than live fleet data, a limitation shared by the present work [11], [12].

E. Route Optimisation Module

Bins classified as critical are passed to a route optimiser based on the Clarke-Wright savings heuristic, which merges pairwise bin-to-depot routes into combined routes whenever doing so reduces total travel distance, subject to the vehicle's carrying capacity. The output is an ordered collection sequence for the day's fleet.

F. Dashboard and Alerting

A web dashboard displays a live map of all bins colour-coded by fill state, historical fill-rate charts per bin, and the current recommended route for each vehicle. SMS and in-app alerts are issued when a bin crosses into the critical state or when its gas reading indicates possible decomposition.

G. Data Storage and Management

Telemetry is persisted in a time-series database indexed by bin identifier and timestamp, enabling efficient retrieval of the rolling window used for fill-rate feature computation and for the generation of monthly utilisation reports for municipal administrators.

IV. METHODOLOGY

A. Prototype Deployment

Twelve collection points across a mapped municipal ward were instrumented with the sensing hardware described in Section III. The ward was selected to include a mix of residential, commercial, and institutional bin locations to capture varied fill-rate behaviour.

B. Data Collection

Sensor telemetry was logged continuously over a six-week period, yielding approximately 8,064 fifteen-minute readings per bin and 96,768 readings in total. Ground-truth fill state at each collection round was recorded manually by field staff to serve as classification labels.

C. Feature Engineering

In addition to the current fill percentage, the fill-rate over the previous two readings, hour of day, day of week, and locality type were computed for each observation. Gas sensor readings were normalised against a bin-specific baseline established during an initial calibration week.

D. Model Training and Baselines

The labelled dataset was split into training, validation, and test subsets in a 70:15:15 ratio with stratification by fill state. Four classifiers were compared: a fixed-threshold rule identical to conventional smart-bin alerts, Logistic Regression, Support Vector Machine, and Random Forest, all sharing the same feature set.

E. Evaluation Metrics

III. SYSTEM ARCHITECTURE

A. Architectural Overview

The proposed system follows a four-layer architecture consisting of a sensing layer, a communication layer, an intelligence layer, and an application layer, as summarised in Fig. 1. Layer separation allows the sensor firmware, the classification model, and the routing service to be updated independently.

Classification quality was measured using accuracy and macro-averaged F1-score across the three fill states. Routing quality was assessed by comparing total simulated vehicle travel distance and the number of overflow incidents against a fixed daily-round baseline covering all twelve bins irrespective of fill state.

F. Implementation Environment

The classification and routing services were implemented in Python 3.11 using scikit-learn for modelling, NetworkX for graph operations, and a Flask backend for the dashboard API. Sensor firmware was written in Arduino C++ for the ESP8266 platform, and telemetry was brokered using Eclipse Mosquitto over MQTT.

Fig. 1 — Layered System Architecture of the Proposed Smart Waste Management System

Layer	Principal Components and Responsibilities
Application Layer	Municipal dashboard, live fill map, route display, SMS and in-app alerts
Intelligence Layer	Fill-state classifier, route optimisation module, alert-escalation logic
Communication Layer	ESP8266 Wi-Fi module, MQTT broker, time-series telemetry database
Sensing Layer	Ultrasonic fill sensor, gas sensor, battery power circuit, bin-mounted enclosure

TABLE I — Comparative Analysis: Manual Inspection vs. Fixed-Threshold Smart Bin vs. Proposed System

Feature	Manual Inspection	Fixed-Threshold Smart Bin	Proposed System	Benefit to Municipality
Fill Monitoring	Periodic visual check	Single-threshold alert	Continuous multi-feature classification	Fewer missed overflows
Odour Detection	Not available	Not available	Gas-sensor escalation	Earlier hygiene response
Collection Schedule	Fixed calendar route	Fixed calendar route	Demand-driven route optimisation	Reduced fuel and labour
Prediction	Not available	Not available	Fill-rate aware classification	Anticipates near-term overflow
Visibility	None	Per-bin alert only	City-wide live dashboard	Centralised oversight
Scalability	Labour-bound	Limited by fixed rule	Cloud-based, horizontally scalable	Suitable for city-wide rollout
Reporting	Manual logs	None	Automated utilisation reports	Data-driven planning

TABLE II — Model Performance and Routing Results (Six-Week Prototype Trial)

#	Model / Metric	Accuracy	Macro F1	Observation
1	Fixed-threshold rule	74.8%	0.68	Misses gradual overflow risk
2	Logistic Regression	85.3%	0.81	Weak on moderate-state boundary
3	Support Vector Machine	90.7%	0.87	Sensitive to sensor noise
4	Random Forest (selected)	95.1%	0.93	Most robust to outdoor noise

 ISSN: Applied For (2026) | DOI: 10.XXXXX/IJVAST.2026.XXXXX

#	Model / Metric	Accuracy	Macro F1	Observation
5	Route distance reduction	34.6%	—	Versus fixed daily round
6	Overflow incident reduction	81.0%	—	Over the six-week trial

V. RESULTS AND DISCUSSION

A. Classification Performance

As reported in Table II, the Random Forest classifier achieved the highest test accuracy of 95.1% with a macro F1-score of 0.93, outperforming the fixed-threshold baseline by 20.3 percentage points. The gain was largest for bins with irregular fill patterns, such as commercial locations with sudden bulk disposal events, where a single-threshold rule either triggered too late or produced repeated false alerts.

Misclassifications were concentrated at the boundary between the moderate and critical states, which is consistent with the inherently gradual nature of bin filling. Incorporating the two-reading fill-rate feature reduced these boundary errors relative to a model trained on instantaneous fill percentage alone.

B. Routing Performance

Restricting collection to bins in the critical state and sequencing them with the Clarke-Wright heuristic reduced total simulated vehicle travel distance by 34.6% relative to the fixed daily round covering all twelve bins. Overflow incidents, defined as a bin remaining in the critical state for more than four hours without collection, fell by 81% over the six-week trial.

C. Gas-Sensor Escalation

The gas-based escalation rule flagged three bins for early collection during the trial period before their ultrasonic fill percentage alone would have triggered a critical alert, indicating that decomposition-driven odour can precede volumetric fill as a hygiene signal, particularly for bins containing organic waste.

D. Discussion

The results indicate that combining fill-rate-aware classification with demand-driven routing addresses both failure modes of fixed-schedule collection simultaneously: distance travelled falls because empty bins are skipped, while overflow incidents fall because critical bins are prioritised rather than waiting for their calendar slot. The magnitude of these gains should be interpreted with caution, since the trial used a twelve-bin prototype and simulated rather than live vehicle movement.

VI. LIMITATIONS

Several limitations qualify these findings. First, the prototype was evaluated on twelve bins across a single ward, which is too small a sample to guarantee that the observed distance and overflow reductions will hold at city scale. Second, routing results were computed in simulation rather than validated against

Validating the routing module against a live collection vehicle equipped with GPS tracking would confirm whether the simulated distance reductions transfer to real traffic conditions. Expanding the sensor suite with a camera module and a lightweight waste-type classifier would enable source-level segregation monitoring. Finally, scaling the deployment to a full municipal ward or city, together with a multi-vehicle capacitated routing formulation, would test the system under realistic operational load.

VIII. CONCLUSION

This paper presented a Smart Waste Management System that integrates ultrasonic and gas-based bin sensing, a Random Forest fill-state classifier, and a Clarke-Wright based route optimisation module within a single IoT-to-dashboard pipeline. The classifier attained 95.1% accuracy with a macro F1-score of 0.93 across three fill states, and the optimised routing reduced simulated collection distance by 34.6% and overflow incidents by 81% relative to fixed-schedule collection.

A six-week prototype trial across twelve collection points demonstrated that combining real-time sensing with demand-driven routing can simultaneously reduce operational cost and improve hygiene outcomes. The limitations relating to prototype scale, simulated routing validation, and network dependency define a clear agenda for the extensions outlined above. The work shows that low-cost IoT sensing paired with lightweight machine learning can convert municipal waste collection from a fixed calendar exercise into a responsive, data-driven service.

IX. REFERENCES

[1] Ministry of Housing and Urban Affairs, Swachh Bharat Mission Municipal Solid Waste Status Report, Government of India, New Delhi, 2024.

[2] Central Pollution Control Board, Annual Report on Solid Waste Management in India, CPCB, New Delhi, 2023.

[3] Patil, S. and Deshpande, R., Challenges in Municipal Solid Waste Collection in Indian Cities, International Journal of Environmental Engineering, vol. 15, pp. 44–58, 2023.

[4] Gubbi, J., Buyya, R., Marusic, S. and Palaniswami, M., Internet of Things: A Vision, Architectural Elements, and Future Directions, Future Generation Computer Systems, vol. 29, pp. 1645–1660, 2013.

[5] Folianto, F., Low, Y. and Yeow, W., Smartbin: Smart Waste Management System, Proceedings of IEEE ISSNIP, pp. 1–2, 2015.

an operating collection vehicle, so real-world traffic and road-network effects were not captured.

Third, the ultrasonic sensor is susceptible to interference from irregularly shaped waste and from rain accumulation on the sensor face, which can produce transient misreadings. Fourth, the current system relies on Wi-Fi connectivity at each bin location, which may be unavailable in some outdoor municipal sites without additional cellular or LoRaWAN infrastructure. Finally, the battery-powered nodes require periodic manual recharging, which partially offsets the labour savings achieved through optimised routing.

VII. FUTURE SCOPE

Future development will proceed along five directions. Integrating solar charging with the existing battery circuit would remove the manual recharging dependency and enable indefinite outdoor deployment. Replacing Wi-Fi with a LoRaWAN or NB-IoT communication layer would extend coverage to sites without local network infrastructure.

[6] Sinha, A. and Kumar, P., IoT Based Smart Garbage Monitoring System, Proceedings of the International Conference on Communication Systems, pp. 210–214, 2018.

[7] Breiman, L., Random Forests, Machine Learning, vol. 45, pp. 5–32, 2001.

[8] Kannan, R. and Vasanthi, S., Predictive Analytics for Smart Bin Fill-Level Estimation, Journal of Environmental Informatics, vol. 8, pp. 112–126, 2022.

[9] Clarke, G. and Wright, J., Scheduling of Vehicles from a Central Depot to a Number of Delivery Points, Operations Research, vol. 12, pp. 568–581, 1964.

[10] Toth, P. and Vigo, D., Vehicle Routing: Problems, Methods, and Applications, 2nd ed., SIAM, Philadelphia, 2014.

[11] Anagnostopoulos, T. et al., Challenges and Opportunities of Waste Management in IoT-Enabled Smart Cities, IEEE Transactions on Sustainable Computing, vol. 2, pp. 275–289, 2017.

[12] Medvedev, A., Fedchenkov, P., Zaslavsky, A., Anagnostopoulos, T. and Khoruzhnikov, S., Waste Management as an IoT-Enabled Service in Smart Cities, Proceedings of ruSMART, pp. 104–115, 2015.

[13] Hannan, M. et al., A Review on Sensing, Communication and Optimisation Technologies for Smart Waste Management, IEEE Access, vol. 8, pp. 42461–42478, 2020.

[14] Ministry of Electronics and Information Technology, Smart Cities Mission Technology Guidelines, MeitY, New Delhi, 2022.

[15] Kulkarni, S. and Jadhav, O., Field Trial Design for a Prototype Smart Waste Collection Network, National Conference on Emerging Computing Technologies, 2026 (in press).

ISSN: Applied For (2026) | DOI: 10.XXXXX/IJVAST.2026.XXXXX | Open Access — CC BY 4.0 License