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WASTEVISION: AN INTELLIGENT IoT AND AI-BASED FRAMEWORK FOR PREDICTIVE AND OPTIMIZED MUNICIPAL WASTE MANAGEMENT

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ABSTRACT

Efficient management of municipal solid waste is vital for public hygiene, environmental sustainability and the sensible use of civic resources. Conventional collection practices rely on fixed schedules and manual supervision, which leads to overflowing bins, slow response, needless collection trips and wasteful use of resources. Prior work has presented IoT-based smart bins, AI-based waste classification, predictive analytics, GIS-based analysis and citizen-oriented solutions, yet these capabilities are usually built as isolated systems. This paper proposes an integrated intelligent framework that combines IoT-based waste monitoring, AI/ML-based waste classification, waste-collection forecasting, GIS visualization, full-bin alerts and waste-related reporting. The framework gathers and analyses bin fill level, weight, location, timestamp, historical waste patterns and waste images, and presents the results on a centralized web platform that supports data-driven collection decisions. A prototype is developed to show how IoT, artificial intelligence, predictive analytics and spatial information can be combined into a practical municipal waste-management solution.

INDEX TERMS – *Smart Waste Management, Internet of Things, Artificial Intelligence, Machine Learning, Waste Classification, Waste Prediction, GIS, Smart Bin, Predictive Analytics.*

1. INTRODUCTION

Municipal solid waste management is a pressing problem for modern cities, since growing populations, urbanization and consumption produce ever larger quantities of waste. In developing countries, weak collection, transportation, segregation and disposal practices can harm the environment and public health, and studies of the Indian situation point to shortcomings in infrastructure, resources, collection systems and institutional management [8].

Traditional collection relies on predetermined schedules and manual observation. Under such a scheme, vehicles may visit bins that are not yet sufficiently full, while other bins overflow before the next scheduled pickup. This reactive practice raises the number of unnecessary trips and increases fuel consumption, labour requirements and the likelihood of overflowing waste.

The Internet of Things (IoT) offers a way to improve waste monitoring. Smart bins fitted with sensors can measure parameters such as fill level and send the readings to a monitoring system, and earlier smart-waste systems have shown how sensors, communication technologies and automated monitoring can make collection more effective [4], [6], [9].

Artificial Intelligence (AI) and Machine Learning (ML) widen these capabilities further. Image-based classification can recognize the type of waste, and predictive models can examine historical records to estimate future waste generation or bin-filling behaviour. In their survey of smart dustbin systems based on IoT and deep learning, Arthur et al. noted a growing convergence of sensing, AI and computer vision in this field [5].

Location matters as well, because waste generation differs from place to place. Imran et al. showed that descriptive and predictive analysis with Quantum GIS is useful for planning waste management [3]. GIS can thus be used to display bin locations, waste levels, hotspots and areas needing collection attention. AI has also been applied to detecting waste and illegal dumping: Shahab and Anjum put forward a deep-learning approach that detects and localizes illegal waste dumps and underlined the promise of AI for sustainable waste management [7].

Although each of these technologies is valuable, they are usually implemented in isolation: IoT systems concentrate on monitoring, AI systems on classification or detection, predictive systems on forecasting and GIS systems on spatial analysis. An integrated framework that brings these capabilities onto one platform is therefore needed.

This paper proposes an intelligent waste-management framework that combines IoT monitoring, AI-based waste classification, waste prediction, GIS visualization, full-bin alerts and waste-related reporting. The goal is to shift from purely reactive collection toward data-driven, predictive decision support. The remainder of the paper is organized as follows. Section 3 reviews the literature, Section 4 identifies the research gaps, Section 5 describes the methodology, Section 6 presents the implementation, Section 7 discusses the results, and Sections 8 and 9 give the conclusion and further works/limitations.

2. LITERATURE REVIEW

Municipal solid waste management has been studied from several angles, including management practices, IoT-based monitoring, artificial intelligence, predictive analytics, GIS and

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citizen-oriented reporting. The existing work forms a solid base for intelligent waste-management systems, but individual studies tend to address only one aspect of the overall problem.

Kumar et al. [8] discussed the main challenges and opportunities of waste management in India, drawing attention to difficulties in collection, infrastructure, resource utilization and management practice. Amasuomo and Baird [2] offered a broader conceptual account of waste and its management and stressed the need for systematic handling across the waste lifecycle.

IoT has been applied increasingly to bin monitoring. Nisarga et al. [6] proposed a system that uses integrated technologies and IoT to track the condition of waste bins, and Kadus et al. [9] presented an IoT-based smart waste-management system. Gupta [4] likewise explored a smart waste-management system built on IoT. These studies show that sensor-based monitoring can reduce reliance on manual inspection and supply information on bin conditions, but they mainly emphasize monitoring and smart-bin functionality.

AI and deep learning have been explored as well. Arthur et al. [5] surveyed smart dustbin systems that use IoT and deep learning and pointed to the potential of pairing sensing with intelligent analysis, while Shahab and Anjum [7] studied deep learning for illegal-dump detection, showing what AI-based image analysis can contribute to identifying waste-related problems. These works indicate that AI can support automated waste recognition and detection, but the capability is not necessarily combined with predictive collection planning and IoT monitoring on one platform.

GIS and predictive analytics form another important direction. Imran et al. [3] investigated descriptive and predictive waste-management analysis with Quantum GIS, showing how spatial information and prediction can support planning. GIS-based analysis could nonetheless be connected further with real-time bin monitoring, AI-based classification, alerts and citizen reporting to provide more comprehensive decision support. Nandhini et al. [1] presented an IoT-oriented smart waste-management approach in the context of sustainable development, again underlining the value of integrating technology into waste-management processes.

Prior work shows ensemble models such as Random Forest generally outperform Linear Regression and Decision Tree for waste forecasting, and our comparison agrees: Random Forest achieved the lowest error (MAE 1.29 tonnes, MAPE 3.45%) and highest R^2 (0.9790), followed by Linear Regression (R^2 0.9750) and Decision Tree (R^2 0.9688).

In summary, the literature shows that IoT provides real-time monitoring, AI supports classification and detection, predictive analytics supports future planning and GIS provides spatial decision support, but these capabilities are frequently handled as separate components.

3. Research Gaps

The literature review revealed the following principal gaps.

A. Fragmented Technology Solutions

Existing studies address IoT monitoring, AI-based classification, predictive analysis and GIS-based planning, but usually as stand-alone systems and not as parts of one integrated platform [3], [5].

B. Monitoring Rather Than Decision Support

Many smart-bin systems stop at sensing the present fill level and raising an alert once a threshold is crossed [4], [6]. Such real-time information is useful, but it does not necessarily involve analysis of historical patterns or prediction of future waste requirements.

C. Limited Integration of Waste Classification

Deep-learning and computer-vision methods can classify or detect waste in images [5], [7], yet classification is often treated as a separate computer-vision task and is not tied to bin monitoring, prediction and collection planning.

D. Limited Predictive Integration

Predictive analysis can reveal future waste generation or bin-filling needs, and the QGIS-based work of Imran et al. demonstrates its value for planning [3]. It can, however, be linked more closely to real-time monitoring and operational decision support.

E. Limited Citizen Reporting Integration

Citizens can contribute to waste-management platforms by reporting illegal dumping, overflowing bins and similar problems. Combining such reports with sensor and AI outputs would give a more complete picture of waste-management conditions.

F. Main Research Gap

The central gap addressed in this work is the absence of a practical integrated framework that combines IoT monitoring, AI waste classification, waste prediction, GIS visualization, alerts and citizen/waste reporting on a single centralized platform. The proposed framework therefore aims not merely to monitor waste conditions but to turn the collected data into predictive and actionable information.

4. Proposed Methodology

The proposed methodology follows the integrated data-processing workflow shown in Fig. 1. It has two parallel branches. The AI/ML model branch (primary) covers data collection from datasets; data preprocessing, comprising image preprocessing, data cleaning and feature extraction; model training for waste classification and future waste prediction; and model testing and evaluation on test data using accuracy, precision and recall. In the IoT data-collection branch (secondary), a smart dustbin collects data and sends it to the cloud, where a threshold check either continues monitoring or generates a notification (bin full, predicted collection request, alert). The outputs of both branches feed a list of full bins, followed by waste collection, a bin-status update and a cloud-database update. The dashboard/website then presents real-time bin status, waste category, predictions, alerts and notifications, and reports and analytics, which support the final step of decision making, namely system monitoring and collection planning.

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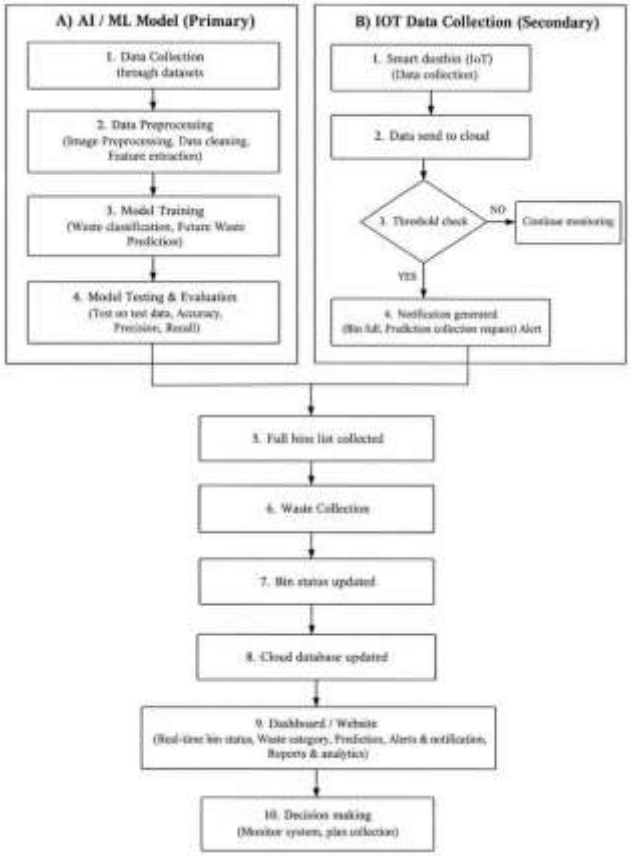


Fig. 1. Proposed flow for smart waste management.

A. Data Acquisition

The system uses four categories of waste-related data. The IoT data comprise the bin ID, bin location, fill level, weight, timestamp and bin status. The historical waste data include the waste quantity, date and time, location, previous fill levels and historical collection information. The image data consist of waste images that are used for AI-based classification wherever a suitable dataset is available. The reporting data, captured by the reporting module, comprise the complaint or report type, location, description, image or evidence, date and time, and status.

Waste Classification Dataset: Three datasets were merged: an original project dataset and two Kaggle datasets—Garbage Classification (12 Classes) by Mostafa Mohamed and Garbage Classification V2 by Suman Kunwar. Images were mapped into four classes: Hazardous, Non-Recyclable, Organic, and Recyclable. After removing duplicates, 16,298 images remained, split into training, validation, and testing sets in a 70:15:15 ratio.

Waste Prediction Dataset: The simulated dataset simulated_pune_daily_waste_forecasting.csv contains 18,144 records from 1 January 2023 to 12 December 2025. It includes ward, household, waste-generation, calendar, weekend, and festival features and was used to evaluate the Random Forest Regression model. It does not represent verified historical municipal data. Future validation may use real data from PMC, MPCB, and CPCB.

B. Data Preprocessing

The collected data are processed before being passed to the analytical and machine-learning modules. Structured data are cleaned by removing duplicate records, handling missing values, correcting invalid values and standardizing timestamps; numerical values are normalized where required and useful temporal features are created. Image data may be resized and normalized, augmented where appropriate, and split into training, validation and testing sets. The purpose of preprocessing is to make the data consistent and ready for reliable analysis.

C. Exploratory Data Analysis

Exploratory data analysis (EDA) is carried out to understand how waste is generated. It examines daily and weekly waste patterns, high-waste locations, bin-filling behaviour, overflow-prone areas, the relationship between time and waste quantity, and the spatial distribution of waste. The findings can be represented as graphs, charts, maps and dashboards.

D. IoT-Based Smart Bin Monitoring

The smart-bin component continuously monitors the condition of a bin with a sensor that measures the amount of waste inside it. The readings are passed to the application or database along the following path:

Sensor → Microcontroller → Communication → Database → Dashboard

Arduino or ESP32-based hardware can be used for the prototype implementation.

E. Full-Bin Alert Mechanism

A predefined fill-level threshold identifies the bins that need attention, according to the rule

If Fill Level ≥ Threshold → Generate Alert (1)

Each alert carries the bin ID, location, current fill level, time and priority/status. This allows the monitoring system to pick out bins that require collection instead of depending only on fixed schedules.

F. AI-Based Waste Classification

The AI module takes waste images and determines the corresponding waste category. The proposed categories are organic, recyclable, hazardous and non-recyclable, although the exact set can be adjusted to suit the selected dataset. The methodology adopts an EfficientNetB0-based approach for image-based waste classification, and the model is trained and evaluated with standard classification metrics: accuracy, precision, recall and F1-score. The use of AI for waste classification is supported by earlier research on deep-learning-based smart dustbin systems [5] and on waste detection using deep learning [7]. We selected EfficientNetB0 for its balance of high classification accuracy, low computational cost, and smaller model size. Comparing it with MobileNetV2 and ResNet50 can help justify its suitability for waste classification.

G. Waste Collection Prediction

Historical waste data are analysed to predict future waste generation or bin-filling needs, following the sequence

Historical Data → Feature Engineering → ML Model → Future Waste Prediction

Temporal features may include the day of the week, month, previous waste quantity, previous fill level and location. A machine-learning regression model such as Random Forest can be used for forecasting, and prediction performance is evaluated with the mean absolute error (MAE), root mean square error

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(RMSE), mean absolute percentage error (MAPE) and, where applicable, the R^2 score. Predictive analysis is particularly relevant because it supports planning before a bin actually reaches an overflow condition. Used Random Forest Regression because it handles complex, nonlinear relationships between household, ward, calendar, and waste-generation features while reducing overfitting through multiple decision trees. It provides reliable waste-generation predictions and supports evaluation using MAE, RMSE, MAPE, and R^2.

H. GIS-Based Visualization

GIS is used to display waste-related information spatially, showing bin locations, fill levels, overflow status, high-waste areas, collection priority and reported incidents. Map indicators distinguish normal, warning and high-priority locations. The use of GIS for waste-management planning is supported by the work of Imran et al. [3].

I. Waste/Illegal Dumping Reporting

The reporting module allows users or authorized personnel to submit waste-related incidents. A report holds the location, a description, an image, the date and time, and the type of problem, such as illegal dumping, overflowing waste, uncollected waste or a damaged bin. Although AI-based illegal-dump detection has been investigated earlier [7], the proposed system concentrates on a practical reporting workflow inside the larger waste-management platform.

J. Centralized Dashboard

All modules are linked through a centralized dashboard. It presents smart-bin status, fill-level information, alerts, waste-classification results, prediction results, the GIS map, reported complaints/incidents and collection-priority information, thereby providing a single interface for monitoring and decision support.

5. IMPLEMENTATION

The proposed framework is implemented as a prototype-level, web-based intelligent waste-management system.

A. System Architecture

The system consists of five layers. Layer 1 (data acquisition) receives IoT sensor data, waste images, historical waste records and reporting information. Layer 2 (data processing) cleans, transforms and prepares the collected data. Layer 3 (AI/ML) performs waste image classification, waste forecasting and pattern analysis. Layer 4 (monitoring and decision support) handles bin-status monitoring, full-bin alerts, collection priority and prediction results. Layer 5 (visualization) presents the processed information through the dashboard, charts, GIS maps, alerts, classification results and reports.

B. Software Implementation

The prototype is delivered as a web platform named WasteVision. Fig. 2 shows its home page, whose navigation gives access to the waste categories, predictions, waste reporting and dump-location pages.



Fig. 2. Home page of the WasteVision web platform.

C. Smart Bin Implementation

The smart-bin prototype uses sensors to determine how much waste the bin contains. A microcontroller transmits the sensor readings, the backend receives them and stores them in the database, and the dashboard retrieves the stored information to display the current status of the bin.

D. AI Classification Implementation

The classification module accepts an image as input and processes it through the sequence

Input Image → Preprocessing → AI Model → Predicted Category → Dashboard

Fig. 3 shows the classification interface, in which a photograph is submitted and the predicted waste category (organic in the example shown) is returned.



Fig. 3. Waste classification interface returning the predicted category for an uploaded image.

E. Prediction Implementation

Historical waste records are processed into features for the prediction model, which produces an estimated future waste quantity or expected bin-filling requirement. The forecast page of the platform is shown in Fig. 4.

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Fig. 4. Waste forecast page of the platform presenting a seven-day prediction for a selected ward.

F. Alert Implementation

When the monitored fill level reaches the defined threshold, the system generates an alert. The alert is stored and displayed on the dashboard together with the relevant bin information, which provides an additional layer of monitoring beyond fixed collection schedules.

G. Reporting Implementation

The reporting interface, shown in Fig. 5, allows a user to submit a waste-related problem. The information is stored in the database and displayed to the responsible user or administrator for further action, creating a communication link between waste-management monitoring and citizen participation.



Fig. 5. Citizen waste-reporting interface of the platform.

6. Results and Discussion

The framework was designed to demonstrate the integration of several waste-management technologies within a single platform. Table I summarizes the measured results, and the functional outcomes are then discussed module by module.

Table I
Evaluation Results of the Proposed Framework

Evaluation Metric	Actual Result
Classification Accuracy	91.88%
Classification Precision	85.27%
Classification Recall	89.81%
Classification F1-score	87.28%
Prediction MAE	1.1858
Prediction RMSE	1.5597
Prediction MAPE	3.07%
Prediction R^2	0.9834
Alerts (successful test cases)	Alerts sent successfully

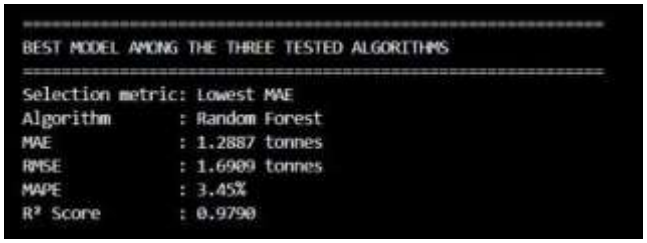


Fig. 6. Best model among the three tested algorithms (selection metric: lowest MAE).

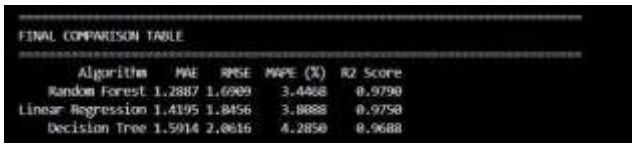


Fig. 7. Final comparison table of Random Forest, Linear Regression and Decision Tree.

A. IoT Monitoring

The IoT module monitors the condition of waste bins using sensor-generated information. Instead of relying entirely on manual inspection, the system can continuously present the current status of the monitored bins. This is consistent with earlier smart-bin research in which IoT technologies are used to monitor bin conditions and support collection activities [4], [6], [9].

B. Full-Bin Alerts

The alert module gives an immediate indication when a bin reaches the configured threshold. This makes overflowing or nearly overflowing bins more visible and yields information that can be used for collection planning. The main advantage is that collection attention can be based on the observed condition of the bin rather than only on a predetermined schedule. In testing, the alerts were sent successfully (Table I).

C. Waste Classification

The AI classification module identifies waste categories from images automatically, which serves the objective of introducing AI into waste-management operations. Existing research shows that deep-learning and computer-vision methods have considerable potential for waste classification and detection [5], [7]. On the test data, the classifier achieved an accuracy of 91.88%, a precision of 85.27%, a recall of 89.81% and an F1-score of 87.28% (Table I). As with any learned model, these figures should be re-verified when the classifier is applied to larger or different datasets.

D. Waste Prediction

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The prediction module uses historical waste information to estimate future waste requirements, and its main contribution is the transition from simple monitoring to predictive analysis. It obtained an MAE of 1.1858, an RMSE of 1.5597, a MAPE of 3.07% and an R^2 of 0.9834 (Table I). For example, a bin that is currently below the full-bin threshold may still be flagged as a priority if historical patterns indicate that it is likely to fill rapidly. This predictive approach complements the descriptive and predictive GIS-based analysis presented by Imran et al. [3].

E. GIS Visualization

The GIS component gives a geographical representation of waste-related information. Mapping bin locations and waste conditions makes it easier to identify areas with higher waste levels or repeated incidents, so GIS-based analysis complements sensor and predictive information by adding a spatial dimension to decision-making [3].

F. Waste Reporting

The reporting module records waste-related incidents together with their location and supporting information, which offers an additional source of information beyond automated sensor readings. It is particularly useful for problems such as illegal dumping or waste accumulation in areas that contain no smart bins, and earlier research has applied AI-based techniques to illegal waste detection [7].

G. Integrated System

The main outcome of the framework is the integration of several technologies in one platform. The overall system connects

IoT Monitoring → Alerts → AI Classification → Prediction → GIS → Reporting → Dashboard

and thereby addresses the fragmentation identified in the literature review. The framework is not intended to replace existing municipal waste infrastructure; rather, it is a prototype-level intelligent decision-support platform that demonstrates how data from different sources can be combined to improve waste-management operations.

7. Conclusion

This paper proposed an intelligent IoT and AI-based framework for improving municipal waste management through monitoring, classification, prediction, visualization, alerts and reporting. Traditional systems frequently depend on fixed collection schedules and manual observation, which can cause delayed response and inefficient use of resources. The proposed framework integrates IoT-based smart-bin monitoring with AI-based waste classification, waste forecasting, GIS visualization, full-bin alerts and waste-related reporting, giving a unified platform that turns waste data into useful monitoring and decision-support information.

The literature indicates that earlier studies have explored individual components successfully, namely IoT monitoring [4], [6], AI-based waste classification [5], predictive and GIS-based analysis [3] and illegal waste detection [7]. This work builds on those approaches by combining them in a common prototype framework. The system is intended as a prototype and not as a complete city-wide municipal deployment; its effectiveness can be established further through quantitative model evaluation, larger datasets, real-time IoT deployment and testing under real municipal operating conditions.

8. Further Works/Limitations

The framework can be extended in several directions.

A. Real-Time IoT Deployment

The prototype can be connected to a larger number of physical smart bins equipped with sensors and wireless communication modules.

B. Advanced Prediction Models

Future versions can investigate advanced time-series and machine-learning models to improve waste-generation and bin-filling prediction.

C. Improved Waste Classification

The classification module can be extended to recognize additional waste categories and can be trained on larger and more diverse datasets.

D. Dynamic Route Optimization

Future work can combine vehicle-routing algorithms with bin-priority information to generate optimized collection routes.

E. Mobile Application

A mobile application can be developed for citizens, waste collectors and municipal administrators.

F. Real-Time Notifications

SMS, email, push notifications or other communication mechanisms can be integrated for full-bin and complaint alerts.

G. Large-Scale GIS Integration

The system can be extended to larger geographical areas in order to identify waste hotspots and collection patterns across different zones.

H. Integration of Additional Data

Weather, traffic, population density, road conditions and historical collection information can be integrated to improve prediction and decision support.

I. Municipal-Level Deployment

After security, scalability, interoperability and privacy considerations have been addressed appropriately, the prototype can eventually be integrated with municipal databases and operational systems.

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