AI-Driven Prediction of Urban Solid Waste Generation: Methods, Trends, and Future Directions

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Abstract: Urban solid waste generation is escalating globally due to population growth, rapid urbanization, and changing consumption patterns, posing significant challenges to municipal waste management systems. In India, cities are experiencing increased waste volumes, straining collection, transportation, and disposal infrastructure. Accurate prediction of municipal solid waste (MSW) is critical for efficient resource allocation, planning, and sustainable urban management. This review examines the role of Artificial Intelligence (AI) and Machine Learning (ML) in forecasting urban waste generation, highlighting commonly used models such as linear regression, decision trees, random forests, support vector machines, artificial neural networks, and LSTM networks. Comparative analysis shows that ensemble and deep learning models outperform simpler techniques, achieving higher predictive accuracy and capturing complex non-linear and temporal patterns. Emerging technologies—including IoT-enabled sensors, smart bins, and GIS integration—enhance real-time monitoring and spatially explicit waste prediction, enabling dynamic collection scheduling and optimized route planning. Despite global progress, challenges persist, such as data availability and quality, model scalability, integration with smart city systems, and socio-economic and policy constraints. Additionally, region-specific studies remain limited, particularly in medium-sized Indian cities like Bhopal. Future research should focus on hybrid AI models, incorporation of satellite/GIS data, real-time prediction frameworks, and alignment with circular economy strategies to improve operational efficiency, sustainability, and environmental outcomes. By integrating AI-driven predictive models with policy guidance and smart infrastructure, municipalities can develop proactive, data-driven approaches to urban waste management, reducing environmental pollution and enhancing public health and urban livability.

Keywords: AI, Machine Learning, Urban Solid Waste, Predictive Modeling, Smart City.

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I. INTRODUCTION

Background

The generation of urban solid waste (MSW) is rising rapidly worldwide because of population growth, urbanization, and changing lifestyles. In India, cities are producing increasing amounts of waste, which is straining collection, disposal, and recycling systems. Factors such as income levels, consumption patterns, seasonal variations, and population density influence waste amounts (Bahukhandi & Ollemman, 2022). Accurate MSW prediction is essential for planning, resource allocation, and sustainable urban management, which helps cities reduce their environmental impact and improve public health outcomes (Hoornweg & Bhada-Tata, 2012).

Challenges

Rapid population growth and unplanned urbanization pose major challenges for waste management. Cities are generating increasing amounts of municipal solid waste, overwhelming collection, transportation, and disposal systems (Khalid et al., 2021). Inadequate infrastructure, lack of proper planning, and limited resources impede efficient waste management. This results in environmental pollution, public health risks, and strains municipal budgets, highlighting the urgent need for effective forecasting, planning, and sustainable waste management strategies (Kantola & Abila, 2019).

Importance

- This helps municipalities plan efficient waste collection routes and schedules.
- Assists in budgeting for infrastructure, labor, and equipment.
- Improves the availability of landfills, recycling, and treatment facilities.
- Reduces environmental pollution and public health risks
- Supports policy-making for sustainable waste management and the circular economy.
- Improves resource allocation by anticipating seasonal or population-based variations.
- To summarize AI and ML methods for MSW prediction, evaluate trends, and identify research gaps.

Objective

- Summarize existing AI and ML techniques used to predict municipal solid waste.
- Compare the performances of different models, including regression, tree-based, and neural networks.
- Identify global and regional trends in AI-driven waste forecasting.
- Discuss the data sources, input features, and evaluation metrics.
- Discuss the limitations, challenges, and research gaps in current studies.
- This study suggests directions for future research and practical applications in urban waste management.

II. RELATED WORK

Municipal solid waste (MSW) refers to everyday materials discarded by households, commercial establishments, institutions, and in public areas. It includes a wide range of materials, such as food waste, paper, plastics, metals, glass, textiles, and electronic waste. MSW is generated in both urban and rural settings; however, its quantity and composition often vary according to population density, income levels, consumption patterns, lifestyle, and seasonal changes (Hill, 2010). Understanding its definition is crucial for designing efficient collection, transportation, treatment, and disposal strategies. The classification of MSW is essential to facilitate proper handling, recycling, and environmental protection. Typically, MSW is categorized into biodegradable (organic) waste, recyclable materials (paper, plastics, metals, and glass), inert or non-recyclable waste (construction debris and ashes), and hazardous or e-waste (batteries, electronic devices, and medical waste) (G. Singh et al., 2024). Some studies further classify waste based on source, such as residential, commercial, institutional, or street litter. Effective classification helps optimize waste processing methods, such as composting for organic waste, material recovery for recyclables, and safe disposal for non-recyclables and hazardous waste (Kanaparthi et al., 2024). By integrating MSW classification with predictive models, municipalities can plan collection schedules, resource allocation, and sustainable waste management practices, thereby reducing environmental pollution and improving public health outcomes (Fejes et al., 2026).

The increasing population, rapid urbanization, and changing consumption patterns have led to growing concerns regarding urban solid waste generation worldwide. According to the World Bank (2018), global municipal solid waste (MSW) is expected to increase from 2.01 billion metric tons in 2016 to 3.40 billion metric tons by 2050 (Yatoo et al., 2024). High-income countries generate more waste per capita, averaging 2.1 kg per person per day, whereas low- and middle-income countries produce approximately 0.6–1.2 kg per person per day. In India, rapid urban growth and economic development have significantly increased MSW generation (Karak et al., 2012). The country produces over 150,000 metric tons of waste per day, with major cities, such as Delhi, Mumbai, and Bangalore, generating the largest volumes. In India, waste composition is typically dominated by biodegradable materials (40–60%), followed by plastics, paper, metals, and other non-recyclables (Seema, 2025).

Studies focusing on Bhopal city have shown that the urban population generates approximately 400–450 metric tons of waste daily. Organic waste constitutes the majority, reflecting the dietary and consumption patterns in the region (Kaur & Deswal, 2019). Seasonal variations and festivals also influence waste generation. Accurate data on waste quantities and composition are critical for designing collection systems, recycling strategies, landfill planning, and implementing AI-based predictive models to improve sustainable urban waste management in Bhopal (Shah et al., 2025). Municipal solid waste generation is influenced by multiple demographic, socioeconomic, and environmental factors. Population density plays a major role, as densely populated urban areas tend to produce larger volumes of waste due to the concentration of households, businesses, and institutions. Income and economic status also significantly affect waste generation; higher-income populations typically consume more goods, resulting in increased packaging, plastics, and non-biodegradable waste. In contrast, lower-income communities often produce more organic or biodegradable waste (Vergara & Tchobanoglous, 2012).

Lifestyle and consumption patterns further affect the types and amounts of waste generated. Urban lifestyles, with a greater dependence on processed foods, packaged goods, and e-commerce deliveries, contribute to higher quantities of plastics, paper, and electronics. Conversely, traditional or rural lifestyles may produce more biodegradable waste and less packaging waste (Roche Cerasi et al., 2021). Seasonal variations also influence the generation of waste. Festivals, holidays, and climatic changes can cause temporary spikes in waste, such as increased packaging, food waste, and the use of decorative materials during festivals. Additionally, changes in population dynamics, such as migration or tourism influx, affect waste production patterns in cities (Bhada-Tata & Hoornweg, 2016). Understanding these factors is crucial for municipal authorities to design effective collection systems, allocate resources efficiently, and develop predictive models using artificial intelligence and machine learning (Mounadel et al., 2023). By accounting for population, income, lifestyle, and seasonal effects, urban planners can better manage waste and implement sustainable strategies for recycling, treatment, and disposal (Guo, 2025).

Conventional methods for estimating municipal solid waste (MSW) face several challenges that limit their accuracy and usefulness in planning. Traditional approaches often rely on historical data and population-based assumptions, such as per-capita waste generation rates (Fejes et al., 2026). These methods assume uniform waste production across households and neighborhoods, ignoring variations caused by income levels, consumption patterns, seasonal events, and urban-rural differences. Another challenge is data scarcity and quality (Firmansyah et al., 2024). In many cities, especially in developing countries, waste records are incomplete, inconsistent or outdated. Manual data collection, such as waste weighing at disposal sites, is labor-intensive, prone to human error, and often limited to specific locations, failing to capture the full spatial and temporal variability of waste generation (Programme, 2023). Dynamic factors, such as migration, tourism, festivals, and economic fluctuations, further complicate these estimations. Conventional techniques are not sufficiently flexible to account for sudden changes in waste volume or composition. Moreover, conventional methods often do not incorporate environmental, climatic, or behavioral variables, which can significantly influence waste generation patterns (Adeleke et al., 2021). The lack of real-time monitoring also prevents municipalities from making timely decisions regarding collection, recycling, or landfill management. These limitations underscore the need for data-driven, AI, and machine learning-based predictive models that can handle complex, dynamic, and heterogeneous waste generation patterns, enabling more accurate forecasting and sustainable urban waste management (Faiz et al., 2024).

III. AI AND ML IN MSW PREDICTION

Artificial intelligence (AI) is a broad field of computer science that focuses on creating systems that can perform tasks that typically require human intelligence. These tasks include problem solving, decision-making, pattern recognition, and prediction (Shapiro, 2020). In the context of urban solid waste management, AI provides a framework for automating the analysis of large and complex data sets, enabling predictive modeling and informed decision-making. Machine learning (ML), a subset of AI, specifically involves the development of algorithms that allow systems to learn from historical data and improve their performance over time without explicit programming (Mounadel et al., 2023). ML models identify patterns and relationships in urban waste generation data, such as population density, socioeconomic factors, seasonal variations, and consumption patterns, to forecast future waste volumes (Subedi et al., 2025). Common ML techniques applied in this domain include regression models, decision trees, support vector machines, random forests, and deep learning architectures, such as neural networks (Glisic & Lorenzo, 2022).

Data-driven modeling is central to AI and ML applications for waste prediction. It relies on the systematic collection, preprocessing, and analysis of historical and real-time data to inform the predictive models (Jayadi et al., 2025). By integrating multiple data sources, such as demographic information, municipal collection records, sensor-based measurements, and geographical factors, researchers can create robust models that capture the underlying dynamics of urban waste generation (De Novais et al., 2021). This approach enables accurate forecasting and facilitates the optimization of collection schedules, resource allocation, and policy-making. In summary, AI provides overarching intelligence, ML supplies learning mechanisms, and data-driven modeling ensures empirical grounding (Sharma et al., 2024). Together, these form a powerful toolkit for predicting urban solid waste generation, improving municipal efficiency, and guiding sustainable urban management strategies. These methods reflect current trends in smart city applications and are poised to evolve with the increasing availability of high-resolution data, advanced computational resources, and real-time monitoring technologies (Nesmachnow et al., 2025).

Predictive modeling plays a crucial role in urban planning by enabling data-driven decision-making, optimizing resource allocation, and improving the sustainability and efficiency of city systems (Cina et al., 2025). Urban areas are increasingly complex, with dynamic populations, evolving infrastructure, and environmental constraints, rendering traditional planning methods insufficient. Predictive modeling uses historical and real-time data to forecast future scenarios, allowing planners to anticipate challenges and implement proactive solutions (Dosunmu, 2025). In the context of urban solid waste management, predictive models help estimate the volume, composition, and spatial distribution of waste generated in different zones of cities. This information is essential for designing efficient collection routes, scheduling disposal, and allocating treatment facilities, ultimately reducing operational costs and minimizing environmental impact (Fejes et al., 2026). Beyond waste management, predictive modeling aids in traffic flow analysis, energy demand forecasting, water supply planning, and disaster management, thereby enabling cities to respond effectively to changing conditions (Cina et al., 2025).

Moreover, predictive models support evidence-based policymaking by identifying trends, risks, and opportunities, which are particularly important for sustainable urban development (Mills et al., 2021). By simulating various urban growth scenarios, planners can evaluate the long-term implications of policy decisions, infrastructure investments, and population shifts (Landis, 2012). This proactive approach enhances resilience, reduces resource waste, and promotes livable, sustainable, and well-managed urban environments. In essence, predictive modeling transforms urban planning from reactive management to a forward-looking strategy, ensuring that cities are better prepared to meet the demands of growing populations while maintaining environmental and social sustainability (Dosunmu, 2025).

Table 1: Comparative study of commonly used Machine Learning (ML) models for urban solid waste prediction

ML Model	Outcome / Prediction Type	Benefits	Limitations
Linear Regression (LR) (Šomplák et al., 2023)	Predicts waste generation as a continuous variable based on factors like	Simple, interpretable, fast to train, requires less data	Cannot model non-linear relationships, sensitive to

	population, consumption patterns, and seasonality		outliers, may underfit complex patterns
Decision Tree (DT) (Fejes et al., 2026)	Generates rules to classify waste generation levels or predict quantities	Easy to interpret, handles both categorical and numerical data, non-linear relationships captured	Prone to overfitting, unstable with small data changes
Random Forest (RF) (R. Singh et al., 2025)	Ensemble of decision trees to predict waste volume	High accuracy, reduces overfitting, robust to noise, handles large datasets	Complex, less interpretable, slower for very large datasets
Support Vector Machine (SVM) (Chugh et al., 2019)	Regression (SVR) predicts waste based on high-dimensional input features	Effective for non-linear relationships, good with small datasets	Computationally intensive, sensitive to choice of kernel and parameters, less interpretable
Artificial Neural Networks (ANN) (Salakhutdinov, 2014)	Predicts complex, non-linear patterns in waste generation	Can model highly non-linear relationships, adaptable to large datasets, capable of learning hidden patterns	Requires large datasets, risk of overfitting, requires parameter tuning, less interpretable
Long Short-Term Memory (LSTM) (Bhatia & Bhatt, 2024)	Time-series prediction of daily/weekly waste volumes	Captures temporal dependencies, excellent for sequential data, handles seasonality.	Requires extensive data, computationally heavy, complex architecture
Gradient Boosting Machines (GBM / XGBoost / LightGBM) (Freitas, 2019)	Predicts waste volume using ensemble boosting methods	High predictive accuracy, handling of missing data, and robustness to outliers.	Computationally intensive, parameter tuning needed, less interpretable
K-Nearest Neighbors (KNN) (El Morr et al., 2022)	Predicts waste based on similarity to historical data	Simple, non-parametric, and easy to implement.	Sensitive to noisy data, computationally expensive with large datasets, choice of k critical
Hybrid / Ensemble Models (Kit et al., 2021)	Combines multiple models (e.g., RF + LSTM) for better prediction	Improved accuracy by leveraging the strengths of different models.	High complexity, requires careful integration, reduced interpretability

Machine learning models for urban waste prediction vary in terms of complexity and performance. Simple models such as Linear Regression and KNN are easy to implement but less accurate, whereas ensemble methods (Random Forest, GBM) and deep learning models (ANN, LSTM) offer higher accuracy and capture non-linear and temporal patterns, although they require more data and computation.

IV. TRENDS IN AI-BASED WASTE FORECASTING

Global case studies demonstrate the effectiveness of AI and ML in predicting urban solid waste generation and improving municipal efficiency. Cities like Singapore, Barcelona, and New York have applied machine learning models—such as Random Forest, XGBoost, and LSTM—to forecast waste volumes, optimize collection routes, and plan landfill capacities (Liu et al., 2025). Time-series models effectively capture seasonal and daily variations, whereas ensemble approaches enhance prediction accuracy. These applications reduce operational costs, minimize environmental impact, and support evidence-based urban planning (Kumar & Kumar, 2023). Additionally, integrating sensor data and socioeconomic indicators allows for precise, zone-wise waste management strategies, highlighting the potential of AI-driven solutions for sustainable urban development worldwide (Udupi et al., 2025).

In urban solid waste prediction, different machine learning algorithms exhibit varying levels of accuracy depending on data complexity, volume, and temporal dynamics. Linear regression provides a simple and interpretable model; however, it often underfits complex, nonlinear relationships, achieving approximately 60–70% accuracy (Subedi et al., 2025). Decision trees capture nonlinear patterns and are easy to interpret, with a moderate accuracy of 65–75%, although they can overfit. Random forests, an ensemble of decision trees, improve robustness and predictive power, typically achieving 80–90% accuracy, and are widely used in waste prediction studies (Vaishali et al., 2025). Support vector regression (SVR) effectively handles high-dimensional and nonlinear data, with accuracies ranging 75–85%, although performance depends on the kernel and parameter tuning. Artificial neural networks (ANNs) excel at complex nonlinear relationships, achieving 85–92% accuracy; however, they require large datasets and computational resources (Rožman et al., 2024). Long short-term memory (LSTM) networks are particularly effective for time-series forecasting, capturing temporal dependencies, and achieving 88–95% accuracy in daily or seasonal waste prediction, outperforming simpler algorithms (Idrissi et al., 2025).

Emerging technologies are transforming urban solid waste management by enhancing data collection, monitoring, and decision-making. Internet of Things (IoT)-enabled sensors and smart bins provide real-time information on waste levels, bin fill status, and collection frequency, thereby enabling dynamic route optimization and efficient resource allocation (Bakare-Abidola et al., 2025). Geographic information system (GIS) integration allows for the spatial mapping of waste generation patterns, identification of hotspots, and planning of collection routes and disposal sites (Caputo & Pelagagge, 2000). When combined with predictive models, these technologies facilitate proactive waste management, reduce operational costs, and minimize environmental impact. Internet of Things, smart infrastructure, and GIS support data-driven, sustainable, and responsive urban waste management systems (Nesmachnow et al., 2025).

V. CHALLENGES AND RESEARCH GAPS

Challenges and research gaps in AI/ML-based urban solid waste prediction:

Data Availability and Quality Issues

- Incomplete, inconsistent, or fragmented municipal waste records hinder accurate model training.
- Low-resolution or outdated data reduce prediction reliability and comparability across cities.
- Research gap: Standardized, high-quality, multi-source datasets are required for robust modeling.

Scalability and Generalization of Models

- Models trained for one city often underperform in other urban contexts because of differences in population, consumption, and waste composition.
- Research gap: Develop scalable and generalizable models adaptable to diverse urban environments.

Integration with Real-Time Smart City Systems

- Few predictive models are linked to IoT-enabled bins, GIS mapping, or dynamic waste collection scheduling.
- Research gap: Combine AI forecasts with real-time monitoring and smart city infrastructure for proactive waste management.

Socioeconomic and Policy Constraints

- Budget limitations, regulatory hurdles, and low public awareness affect the implementation of models.
- Research gap: Investigate context-specific frameworks that incorporate policy, budget,

and community participation for effective deployment.

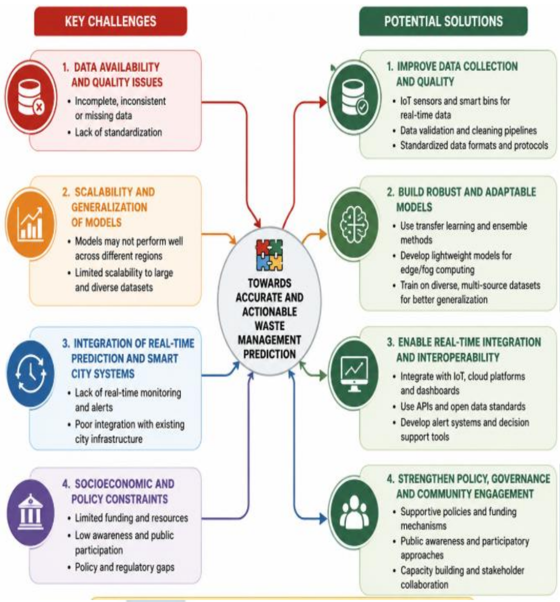

Figure 1: Key Challenges and Potential Solutions for Urban Solid Waste Management

These points highlight the focus of future research to improve the accuracy, scalability, and actionability of predictive waste management.

VI. FUTURE DIRECTIONS

An explanation of future directions for AI-driven urban waste prediction:

Potential for Hybrid AI Models Combining ML and Deep Learning: Future research can explore hybrid models that integrate traditional machine learning (e.g., Random Forest, XGBoost) with deep learning architectures (e.g., ANN, LSTM). Such models can leverage the strengths of both approaches—ML for structured tabular data and deep learning for capturing complex non-linear and temporal patterns—improving prediction accuracy and generalization across diverse urban contexts.

Incorporation of Satellite/GIS Data for Spatial Waste Prediction: Integrating satellite imagery and GIS layers can enhance spatially explicit modeling of urban waste. Land use, population density, commercial activity, and transportation networks derived from GIS can inform zone-wise waste generation forecasts, enabling precise planning of collection routes, landfill siting, and localized interventions.

Real-Time Prediction Using IoT Sensors and Big Data Analytics: IoT-enabled smart bins and sensors can provide continuous real-time data on bin fill levels, traffic patterns, and environmental conditions. Coupled with big data analytics, predictive models can dynamically adjust collection schedules and resource allocation, reducing operational costs, minimizing overflow, and supporting responsive urban waste management systems.

Policy Recommendations and Integration with Circular Economy Practices: Future work should translate AI-driven predictions into actionable policy guidance. Linking forecasts with circular economy strategies—such as recycling incentives, waste segregation policies, and resource recovery initiatives—can help cities not only manage waste efficiently but also reduce environmental impact, promote sustainability, and support the transition toward zero-waste urban systems.

These directions collectively aim to enhance accuracy, spatial resolution, operational efficiency, and sustainability in urban solid waste management.

VII. CONCLUSION

The reviewed literature highlights that AI and ML models significantly improve the prediction of urban solid waste generation, enabling efficient collection scheduling, resource allocation, and reduced environmental impact. Ensemble and deep learning models show superior accuracy, particularly when combined with real-time IoT and GIS data. However, most studies focus on global or metropolitan contexts, revealing a clear gap in region-specific research. Cities like Bhopal require localized studies to account for unique demographic, socioeconomic, and spatial factors. Future research should prioritize developing scalable, context-aware predictive frameworks that integrate AI/ML with real-time monitoring and policy strategies to enhance sustainable and effective municipal waste management.

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