A Review on Machine Learning Approaches for Solid Waste Management

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***Abstract*—The rapid increase in population and the ongoing expansion of urban regions have resulted in a substantial growth in municipal solid waste generation, creating serious challenges for environmental protection and urban management. In response to these problems, recent research has increasingly focused on technological solutions, among which machine learning has gained considerable attention. Machine learning can capture complex nonlinear patterns and is therefore widely applied across various stages of municipal solid waste management to enhance sustainable and efficient waste handling. This review examines over one hundred research studies published between 2000 and 2022, with the objective of analyzing how machine learning techniques have been employed throughout the waste management process, including waste generation prediction, collection scheduling, transportation optimization, and disposal planning. The study systematically explores prevailing research trends, identifies methodological limitations, and highlights promising future research directions, offering conceptual understanding and practical guidance for subsequent investigations. In contrast to previous review studies, this research specifically focuses on the waste generation and disposal stages, highlighting how individuals, households, and municipal authorities employ advanced computational techniques to minimize waste volume and improve management efficiency. The findings indicate that most existing studies focus on waste classification, regional estimation of waste quantities, and prediction of bin fill levels. Nevertheless, several important challenges remain, such as the lack of real-time time-series datasets, limited model robustness and generalization capability, the absence of unified benchmarking standards, and the difficulty of achieving reliable long-term forecasting of waste generation.**

***Keywords*—Municipal solid waste management; machine learning; modeling; optimization; solid waste generation; disposal**

I. Introduction

Urbanization and industrial development are accelerating worldwide, and according to projections by the United Nations, nearly 65% of the global population is expected to reside in urban areas by 2050 [117]. Municipal solid waste (MSW) refers to the solid and semi-solid materials regularly produced in urban areas, encompassing waste from residential, commercial, industrial, institutional, as well as construction and demolition sources [91]. Owing to accelerated urbanization, economic advancement, and population growth, the volume of MSW generated has risen significantly over the past few decades [79]. It is estimated that global MSW production will reach approximately 3.40 billion tons per year by 2050.

The efficiency of municipal solid waste management (MSWM) differs considerably across countries. In low-income nations, nearly 20% of public expenditure is allocated to MSWM-related operations, whereas in high-income countries, this share is approximately 4% [65]. Numerous studies have reported that the rapidly increasing volume of MSW poses a serious threat to urban ecosystems and surrounding environments [38], leading to problems such as illegal dumping, land degradation, and water and air pollution. Consequently, MSW is widely recognized as a major global environmental concern, particularly in developing regions [53]. To safeguard natural resources, protect ecosystems, and ensure public health, effective MSWM practices are essential [29]. However, the environmental challenges associated with MSW are often difficult to resolve due to the heterogeneous composition and complex behavior of waste streams [23].

Municipal solid waste management (MSWM) comprises a sequence of interconnected activities [1], such as waste minimization, generation, storage, collection, transportation, recycling, resource recovery, and ultimate disposal. Among these components, the disposal stage poses the greatest environmental risk, as it may lead to persistent adverse effects through the release of toxic gases and leachate. In contrast, waste generation marks the starting point of the MSWM process, and numerous source-reduction strategies have been introduced to limit waste production at the level of individuals, households, and communities. For these reasons, this survey places particular emphasis on intelligent methods applied at the waste generation and disposal stages. It has been reported that household waste accounts for approximately 55–80% of total waste generation in developing countries [138].

On average, each individual produces about 0.74 kg of waste per day, whereas in North America, per capita waste generation reaches nearly 800 kg annually [122]. Although high-income countries represent only 16% of the global population, they contribute about 34% of the world's total waste. Fig. 1 illustrates that low-income countries generate approximately 5% of global waste while accounting for 9% of the world's population [7].

Fruits, vegetables, and other green garbage make up 44% of all waste produced, whereas paper, plastic, glass, cans, and other dry recyclable debris account for 38% of all waste produced globally [4].

Additionally, regional differences exist in global trash disposal trends. Only 19% of waste is recycled, while a considerable 40% is dumped directly into landfills. Fig. 2

illustrates that in low-income countries, nearly 93% of waste is disposed of through open dumping practices, including roadside dumping and uncontrolled burning, whereas in high-income countries, only about 2% of waste is managed in this manner [4].

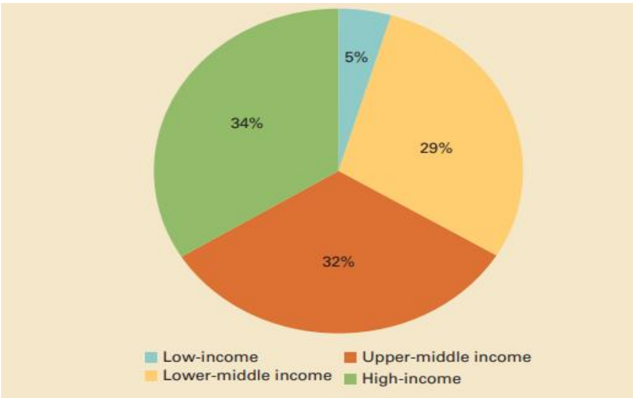

Fig. 1. Global waste generation distributed by income [4].

Traditional MSWM frameworks exhibit notable limitations, primarily because they are unable to adequately represent the complex, dynamic, and nonlinear relationships inherent in municipal solid waste systems [35]. As a result, machine learning (ML) approaches are gaining prominence as powerful tools for modeling, forecasting, and optimizing MSW-related operations. Prior studies have explored the role of information technologies in construction and demolition waste management [75], while others have conducted comprehensive reviews of artificial intelligence (AI) applications in solid waste management. Unlike these earlier works, the present study specifically emphasizes the role of ML algorithms in MSWM and provides a comprehensive perspective examining 140 scholarly articles published between 2000 and 2022 [128] that span the entire waste management lifecycle. The key strengths and limitations of commonly used ML algorithms in MSWM are summarized in Table I.

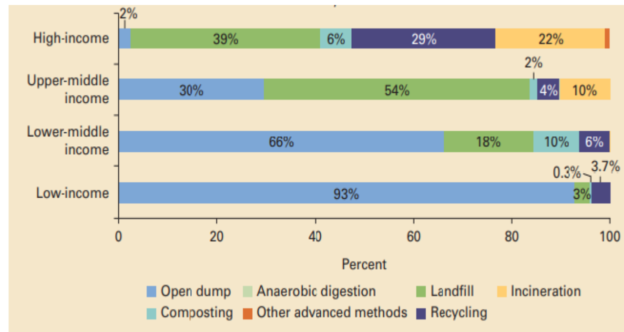

Fig. 2. Methods of waste disposal based on income [4].

TABLE I. STRENGTHS AND LIMITATIONS OF ML & DL ALGORITHMS IN MSWM

Algorithms	Strengths	Limitations
Artificial Neural Networks (ANN)	Suitable for any nonlinear relationship.	Lot of parameters are required.
Support Vector Machine (SVM) / Support Vector Regression (SVR)	Suitable for small sample problems.	Sensitive to missing data.
Decision Trees (DT)	Extremely interpretable.	Prone to overfitting.
K-Nearest Neighbor (KNN)	No assumption for input data.	Requires extensive calculation.
Adaptive Neuro Fuzzy Inference System (ANFIS)	Combine the benefits of neural networks and fuzzy reasoning	Unsuitable for features with higher dimensions.
K-means	Simple to use and quick convergence.	Sensitive to noise
Random Forest (RF)	Reduces model variance	For attribute data with varying values, not applicable.
Gradient Boosted Decision Trees (GBDT) / Gradient Boosted Regression Trees (GBRT)	Rank feature importance.	Parallel training is challenging.
Convolutional Neural Networks (CNN)	Able to automatically extract features.	Need parameter tuning.
Recurrent Neural Network (RNN) / Long Short-Term Memory Networks (LSTM)	Effective for sequence data.	Need large amount of calculation.

II. METHODOLOGY OF LITERATURE SURVEY

A. Motivating Research Questions

This review aims to compile and clarify the available empirical evidence on machine learning–driven waste management models developed for predicting waste generation patterns and optimizing disposal processes. Artificial intelligence and deep learning models are added to broaden the understanding of the computationally intelligent methods used in this discipline.

To structure and guide this survey, the following three fundamental research questions (RQs) are formulated:

- Which machine learning methods and algorithms are most frequently applied to enhance and optimize solid waste generation and disposal processes?
- What key independent variables (features) are utilized to predict societal attitudes and behavioral patterns related to waste disposal in urban environments?
- What major challenges and limitations are encountered when modeling and forecasting waste disposal behaviors and trends?

III. ARTIFICIAL INTELLIGENCE FOR MANAGING GARBAGE

The integration of artificial intelligence has the potential to significantly transform municipal solid waste management by enhancing the efficiency of waste collection, processing, and classification. AI-driven solutions such as smart waste bins, automated sorting robots, predictive analytics models, and wireless sensing technologies enable real-time monitoring of bin status, accurate forecasting of waste generation, and improved operational performance of waste treatment facilities. Through the adoption of these intelligent systems, municipalities can reduce operational costs, improve workplace safety, and minimize the environmental impacts associated with conventional waste management practices.

Traditionally, solid waste management has relied heavily on manual labor and labor-intensive processes. However, recent advancements in artificial intelligence, computer vision, robotics, and related digital technologies have created new opportunities to modernize waste management systems. These technologies support automated decision-making, reduce human exposure to hazardous environments, and improve service efficiency, ultimately contributing to better public health outcomes and enhanced quality of urban life. Fig. 3 presents an optimized conceptual framework summarizing the key research themes addressed in this review.

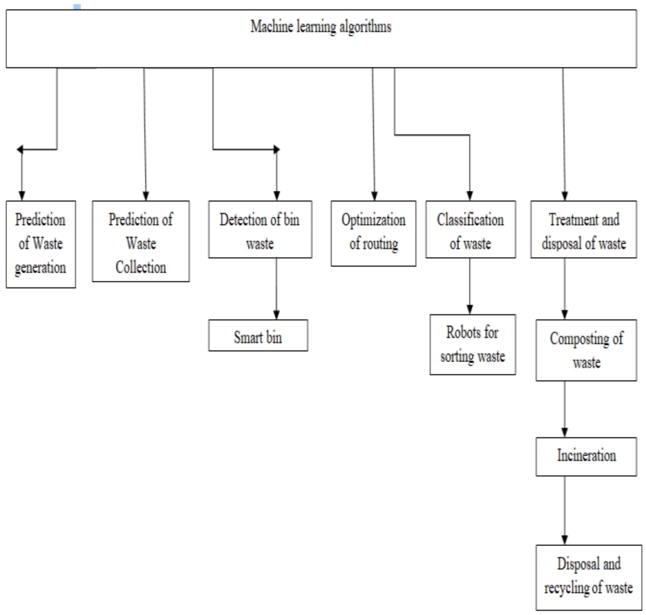

Fig. 3. Optimized schematic illustrating the key thematic areas addressed in this review.

A. Machine Learning Algorithms in the Solid Waste Management Process

1) Prediction of waste generation: The literature review related to the prediction of waste generation using ML models is summarized in Table II. Forecasting municipal solid waste generation remains a central challenge in integrated waste management systems, particularly in developing regions where long-term and reliable datasets are limited. To address this problem, a wide range of machine learning techniques have been explored, including artificial neural networks, support vector regression, decision trees, ensemble learning, and deep learning models.

Early studies demonstrated that backpropagation neural networks and support vector regression are effective for short- and medium-term waste forecasting, with neural networks often providing slightly higher accuracy in nonlinear settings [92]. Hybrid models further improved performance by combining dimensionality reduction and learning algorithms. For example, principal component analysis integrated with support vector machines reduced data redundancy and enhanced predictive stability in weekly waste forecasting tasks [66, 88].

Artificial neural networks remain the most widely adopted models for municipal solid waste prediction across different geographical scales. Regional modeling strategies have been shown to significantly improve forecasting accuracy compared to global models, as demonstrated in large-scale studies across multiple regions in China [123] and Europe [17]. Socio-economic and demographic variables such as population, income, household size, and urbanization level are consistently identified as dominant predictors [6,73,77].

In recent years, deep learning models have gained increasing attention for time-series waste forecasting [12]. Long short-term memory networks have shown superior performance in capturing temporal dependencies in household and construction waste generation when compared to traditional regression and shallow neural networks [37,59]. These models are particularly effective for multi-site and long-horizon forecasting under non-stationary conditions.

Beyond city-level forecasting, fine-grained prediction at the building and neighborhood levels has become feasible with the availability of large-scale administrative datasets. Gradient boosting and neural network models trained on multi-source data have achieved high accuracy in estimating daily and weekly waste generation for individual buildings in major metropolitan areas [67,62]. Such high-resolution forecasts enable dynamic collection planning and localized policy interventions.

Several studies have also focused on specialized waste streams, including hospital waste, packaging waste, and construction and demolition waste. Decision tree models, adaptive neuro-fuzzy systems, and hybrid PCA-based neural networks have been successfully applied to improve prediction accuracy for small and heterogeneous datasets [31,32,36,96]. Hybrid approaches combining wavelet transforms with support vector machines further addressed noise and uncertainty in time-series waste data [4].

From a methodological perspective, existing studies can be broadly categorized into short-term, mid-term, and long-term forecasting according to the prediction horizon [128]. While short-term models generally achieve high accuracy, long-term forecasting remains challenging due to socio-economic uncertainty, data scarcity, and model generalization issues. The lack of standardized benchmarking datasets and uncertainty quantification frameworks continues to limit fair comparison among competing models.

Overall, the literature demonstrates that machine learning-based models, particularly artificial neural networks, support vector machines, and deep learning architectures, significantly outperform traditional statistical methods such as multiple linear regression and ARIMA in most forecasting scenarios [20,21,50]. However, future research must address data availability, model interpretability, and robustness to support reliable long-term planning and policy decision-making.

TABLE II. SUMMARY OF MUNICIPAL SOLID WASTE GENERATION MODELS

Ref no	Year	Authors	Type of waste	Forecast period	Dataset	Algorithm	Performance evaluation	Advantage
[88]	2009	Noori R, Abdoli MA, Ghasrodashti AA, et al.	Municipal Solid Waste	Weekly time series (2005-2008)	Mashhad city	Improved SVM combined with Principal Component Analysis (PCA)	Potential tool for predicting waste generation	Advantages over the traditional model
[123]	2020	Wu F, Niu D, Dai S, et al.	Municipal Solid Waste	short-term prediction (from weekly to monthly), mid-term prediction (months to 3-5 years), and long-term prediction (many years in the future)	mainland China	Artificial Neural Networks (ANN)	Regional difference has huge impact on MSW prediction.	The accuracy of the MSW forecast would rise from 0.916 in R2 and 59.3 in Rooted Mean Squared Error (RMSE) to 0.968/0.946/0.943 in R2 and 6.4/9.7/17.6 in RMSE for the southern/northern/western region
[92]	2021	Oguz-Ekim P	Municipal Solid Waste	-	Turkey	BackPropagation Neural Network (BPNN), Support Vector Regression (SVR), and general regression neural network	BPNN is slightly better	-
[3]	2016	Abbasi M and El Hanandeh A	Municipal Solid Waste	monthly waste generation	Logan City Council region in Queensland, Australia	support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN) and k-nearest neighbours (kNN)	ANFIS system produced the most accurate forecasts of the peaks	Artificial intelligence models have good prediction performance and could be successfully applied to establish municipal solid waste forecasting models.
[67]	2018	Kontokosta CE, Hong B, Johnson NE, et al.	Municipal Solid Waste	weekly and daily waste generation	750,000 residential properties using daily collection data from 609 New York City Department of Sanitation (DSNY) sub-sections over ten years	Gradient boosting regression trees and neural network models	accurately estimates the generation of garbage at the building level after cross-validation and a two-stage spatial validation	Predicting building-level waste generation wit h a high degree of accurac y.
[37]	2020	Cubillos M	household waste	2011 and 2018.	historical data of weekly waste weights from households in the municipality of Herning, Denmark,	multi-site Long Short-Term Memory (LSTM) Neural Network	LSTM approaches can effectively improve the results by 85% on average compared with traditional methods such as ARIMA.	-
[59]	2020	Huang L, Cai T, Zhu Y, et al	Urban constructio n waste	1986 to 2016	two datasets of construction waste data from Shanghai and Hong Kong	three-layer long short-term memory (LSTM) network	LSTM-based forecasting model is effective and accurate in predicting construction waste generation.	The forecasting of construction waste generation enables local governments to manage construction waste landfill and formulate construction waste management policies.
[20]	2021	Ayeleru OO, Fajimi LI, Oboirien BO, et al.	Municipal Solid Waste	Projection was made up to 2050.	historical data obtained from Statistics Sout h Africa (STAT	artificial neural network (ANN) and supported vector machine (SVM)	10 neurons structure (ANN10) performed best with a determination coefficient (R2) of	Machine learning algorithm is effective for the development of models for MSW forecasting.

					S SA)		99.9%, while in the SVM models, the linear model performed best with R2 of 98.6%.	
[113]	2019	Solano Meza JK, Orjuela Yepes D, Rodrigo-Ilarri J, et al.	urban solid waste	2012-2016	city of Bogotá	Decision trees, Support Vector Machine, Recurrent Neural Networks	support vector machines are the most appropriate model for this type of analysis.	A possible decision-making strategy was explored and implemented to plan and design technologies for the stages of collection, transport and final disposal of waste in cities
[63]	2018	Kannangara M, Dua R, Ahmadi L, et al.	Municipal Solid Waste	-	220 municipalities in the province of Ontario, Canada	decision trees and neural networks	machine learning algorithms can be successfully used to generate waste models with good prediction performance	Demonstrates the feasibility of creating tools that helps in regional waste planning by means of sourcing, pre-processing, integrating and modeling of publically available data from various sources.
[36]	2020	Coskuner G, Jassim MS, Zontul M, Karateke S	construction and demolition (C&D) wastes	1997 to 2016	Askar Landfill site in the Kingdom of Bahrain.	multi-layer perceptron artificial neural network (MLP-ANN)	MLP-ANN models exhibited strong accuracy in predictions with high R^2 and low MSE values.	cost-effective approach for planning integrated MSW management systems.
[32]	2020	Cha G-W, Moon HJ, Kim Y-M, Hong W-H, Hwang J-H, Park W-J, Kim Y-C	construction and demolition (C&D) wastes	-	-	random forest (RF) algorithm	RF is an adequate machine learning algorithm for a small dataset consisting of categorical data	proposed RF model can predict DW (Demolition Waste) generation using a small amount of data
[31]	2022	Cha G-W, Moon HJ, Kim Y-C	Demolition waste	-	buildings in redevelopment areas in South Korea	artificialneural network (ANN), K-nearest neighbors (KNN), linear regression (LR), random forest (RF), andsupport vector machine (SVM)	The selection of various ML algorithms and HPs is important in developing optimal ML models for WG management.	ANN-ReLu, SVM-polynomial, ANN-logistic) are the best ML models for predicting the DWGR (Demolition Waste Generation Rate)
[30]	2017	Cha GW, Kim YC, Moon HJ, Hong WH	Demolition waste	-	-	chi-squared automatic interaction detection (CHAID), which is a decision tree (DT) method	the CHAID model for concrete classifies approximately 98.9% of the concrete generation correctly	The CHAID model can assist construction companies and building demolition contractors in decision making.
[96]	2013	Owusu-Sekyere E, Harris E, Bonyah E	solid waste	2005 to 2010	Kumasi Metropolitan Area (KMA)	Autoregressive Integrated Moving Average (ARIMA) time series model	ARIMA (1, 1, 1) was the best model for forecasting solid waste generation in the KMA.	Autoregressive Integrated Moving Average (ARIMA) time series model to explore the dynamics of solid waste generation
[62]	2017	Johnson NE, Ianiuk O, Cazap D, Liu L, Starobin D, Dobler G, Ghandehari M	municipal solid waste	2005 to 2011	New York City Department of Sanitation (DSNY) was used in conjunction with other datasets related to New York City	Gradient Boosting Regression Model	Accurately (R2>0.88) forecast weekly MSW generation tonnages for each of the 232 geographic sections in NYC across three waste streams of refuse, paper and metal/glass/plastic.	The model is able to capture very short timescale fluctuations associated to holidays, special events, seasonal variations, and weather related events.
[123]	2020	Wu F, Niu D, Dai S, et al.	municipal solid waste	-	mainland China	artificial neural network (ANN)	ANN one of the most well-liked non-	-

							linear models, have been effectively used to predict municipal solid waste	
[93]	2019	Oliveira V, Sousa V, Dias-Ferreira C	household packaging waste	-	-	artificial neural network (ANN) model using genetic algorithms	ANN has a significantly higher explanatory power than traditional regression techniques	ANN makes it a valuable tool in the definition of strategies to increase recycling and achieve circular economy goals.
[21]	2016	Azadi, S., Karimiashni, A.,	municipal solid waste	2009–2010	Fars province, Iran	Artificial Neural Network (ANN) and Multiple Linear Regression (MLR)	The MLR, as a conventional model, showed poor prediction performance.	In order to develop a more cost-effective strategy for waste management in the future, the ANN model could be used to predict the mean Seasonal Municipal Solid Waste Generation (SMSWG) rate.
[4]	2012	Abbasi M, Abduli MA, Omidvar B, Baghvand A	municipal solid waste	January 2006–December 2011	weekly time series of municipal solid waste generation (MSWG) in Tehran and Mashhad cites	support vector machine (SVM), and hybrid of wavelet transform (WT) and support vector machine (WT - SVM)	WT - SVM model had more robustness than SVM and had a lower sensitivity to change of input variables.	-
[6]	2011	Abdoli M A, Nezhad M F, Sede R S, Behboudian S	solid waste generation (SWG)	2000–2010	city of Mashhad	multivariate regression model and ANN	ANN can reduce uncertainties and lead to noticeable increase in the accuracy of the long-term forecasting	Different socioeconomic and environmental factors are assessed, and the most effective ones are used as input variables.
[17]	2013	Antanasijevic D, Pocajt V, Popovic I, Redzic N, Ristic M	municipal waste generation (MWG)	-	Bulgaria and Serbia	artificial neural networks (ANN)	ANNs can be applied successfully to modeling and forecasting MWG on a national scale.	the scope for possible application of the model is broad
[73]	2011	Lebersorger S, Beigl P	municipal solid waste	-	542 municipalities in the Province of Styria	regression model	The model explains 74.3% of the MSW variation and the model assumptions are met.	The resulting regression model included municipal tax revenue per capita, household size and the percentage of buildings with solid fuel heating systems.
[77]	2007	Liu G, Yu J	municipal living refuse (MLF)	1990 to 2003	city of Shanghai	gray correlation coefficient	among the selected seven factors, consumption of gas, water and electricity are the largest three factors affecting MLF generation, and GLPM(1) is the optimized model to predict MLF generation	The methods and results developed in this paper can provide valuable information for MLF management and related municipal planning projects.
[50]	2019	Golbaz S, Nabizadeh R, Sajadi HS	hospital solid waste (HSW)	2016	eight single-specialty hospitals in Karaj metropolis in Iran	Multiple Linear Regression (MLR) along with several machine learning methods including Artificial Neural Networks (ANN), Fuzzy Logic - Artificial Neural Networks (ANFIS), Support Vector Regression	The machine learning methods could interpret the relationship between waste generation rate and model inputs, appropriately.	The machine learning methods may play an effective role in developing cost-effective methods for suitable HSW management.

						(SVM), Least Squares Support Vector Regression (LSSVM), Fuzzy Logic - Support Vector Regression (FSVM)		
[49]	2022	Geetha, S., Saha, J., Dasgupta, I., Bera, R., Lawal, I. A., &Kadry, S.	Organic waste can be either an orange peel or hospital waste.	2527 labeled images	Trash image datasets	Neural Networks	The proposed method achieved an accuracy of at least 90%	A novel method for waste detection and classification to address the challenges of waste management.
[70]	2020	Kulisz M and Kujawska J	municipal waste generation (MWG)	2003–2019	Poland	Artificial Neural Network	The ANN models exhibited high accuracy of forecasts at high *R* values and low *MSE* values.	ANN models are effective in predicting the amount of waste and can be considered a cost-effective approach to planning integrated waste management systems.
[5]	2019	Abbasi M, Rastgoo MN and Nakisa B	municipal solid waste (MSW)	1991–2013.	Tehran	radial basis function (RBF) neural network, adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) models.	RBF was the best-performing model for monthly and seasonal forecasting of MSW generation.	RBF network can be applied for forecasting and modeling MSW generation on a national scale.
[39]	2020	Dai, F.; Nie, G.; Chen, Y.	municipal s olid waste (MSW)	-	Huangshi, a ci ty of Hubei pr ovince in Chi na,	fuzzy information granulation (FIG) method, genetic algorithm (GA-SVR), ARIMA model, Kriging interpolat ion method	the FIG–GA-SVR prediction mod el proposed in this study is suitable for interv al prediction and has good generalization ability	This model can not only be applied to the prediction of MSW generation, but also can be applied for prediction in other fields.
[10]	2020	Ahmad, S.; Iqbal, I.N.; Jamil, F.; Kim, D.	municipal s olid waste (MSW)	2017-2019	residential grids in Jeju Island.	regression model	The analysis, coupled with prediction algorithms allows the policy-makers to generate a waste profile specific to a residential grid.	The study aims to suggest the number of resources which lead to a minimum cost and also ensure a certain level of hygiene in the area.

2) Prediction of waste collection: Waste collection represents one of the most commonly delivered services at the municipal level. Around the world, various garbage collection service models are in use [105]. Door-to-door collection is the most typical type of garbage pickup. In this scenario, rubbish outside of homes is collected on a regular basis using trucks or small vehicles. Communities may place rubbish in a central container or a collection station in some areas, where the municipality will pick it up and transfer it to final disposal facilities. As illustrated in Fig. 4, waste collection coverage in North America and other high-income regions approaches nearly 100%. In contrast, collection rates decline to approximately 51% in lower-middle-income countries and about 39% in low-income nations. In areas where formal collection services are limited, households often manage waste independently, typically through open burning, uncontrolled dumping, and, in some cases, small-scale composting. Enhancing waste collection systems is therefore a critical intervention for mitigating environmental pollution, improving public health, and potentially reducing urban traffic congestion associated with inefficient disposal practices.

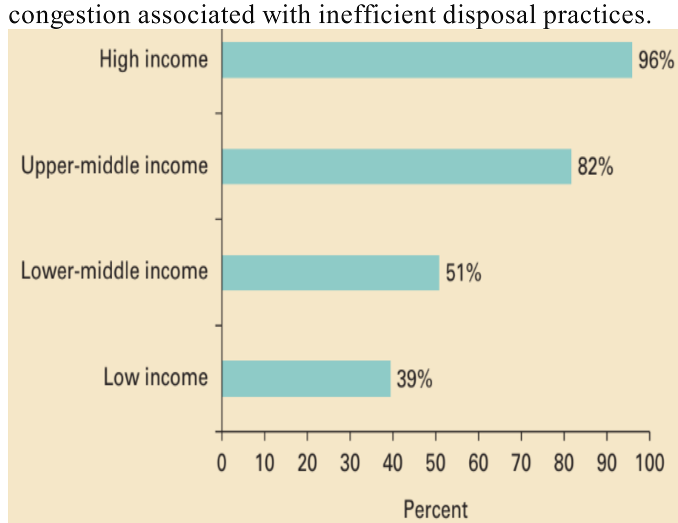

Fig. 4. Waste collection rates by income level [4].

Since municipal waste services are predominantly concentrated in urban centers, collection coverage in cities is generally much higher than in rural areas. In lower-middle-income countries, urban waste collection rates are reported to be more than double those observed in rural regions [4].

3) Detection of bin waste

a) Smart bin: Traditional garbage bins require manual inspection by sanitation workers to assess the quantity of waste present, making routine monitoring inefficient and highly labor-intensive. To address this limitation, several studies have proposed smart bin systems that operate autonomously using embedded sensors and wireless communication modules. Typical implementations employ ultrasonic sensors to estimate the fill level of bins, while microcontrollers such as ESP8266, Arduino, and NodeMCU manage sensing and data transmission. Automatic lid-opening mechanisms based on proximity detection have also been introduced to minimize human contact and improve hygiene conditions [100].

Overflowing garbage containers are a major cause of unsanitary environments and are associated with the spread of infectious diseases. To mitigate this problem, many smart bin designs incorporate real-time alert mechanisms that notify municipal authorities when the bin reaches a critical fill level. These alerts are commonly transmitted using Wi-Fi or GSM modules and published on web dashboards for continuous monitoring. Such mechanisms enable timely collection and help maintain cleaner residential surroundings [104].

Several cost-effective smart bin prototypes have been developed for small-scale and resource-constrained environments. These systems combine ultrasonic sensors with compact microcontroller boards and GSM modules to send short message alerts when the bin is full. Renewable energy sources, such as solar panels and rechargeable battery units, are often integrated to ensure uninterrupted operation in outdoor deployments [108].

Beyond basic monitoring, advanced smart bins integrate automatic segregation mechanisms to separate metallic and non-metallic waste. Continuous uploading of bin status data to cloud platforms enables large-scale analysis and decision support. Mathematical models have also been proposed to optimize the spatial distribution of bins in public spaces such as parks, schools, and tourist locations in order to improve collection efficiency and coverage [109].

The uncertainty associated with the actual fill levels of distributed bins frequently leads to inefficient collection schedules and unnecessary vehicle trips. To overcome this issue, sensor-based monitoring has been combined with optimization algorithms that determine optimal collection routes. In particular, ant colony optimization and capacitated arc routing formulations have been employed to minimize transportation costs while maximizing waste collection efficiency [97], [118].

Image-based approaches have also been investigated for estimating bin fill levels and classifying waste content. Feature extraction methods such as the Hough transform and the grey level co-occurrence matrix (GLCM) have been applied to derive structural and textural features from bin images. Machine learning classifiers, including feedforward neural networks, multilayer perceptrons, and k-nearest neighbor algorithms, are then used to categorize bin status automatically [52], [18].

Recent research has investigated deep learning and few-shot learning approaches for waste detection and classification tasks [69]. To enhance identification performance, particularly in scenarios with limited labeled datasets, advanced strategies such as feature fusion techniques and attention-driven architectures have been introduced to improve model robustness and generalization. These models enable flexible detection of multiple waste categories with fewer than 30 training samples per class, making them suitable for real-world deployments [139].

Several city-scale implementations have demonstrated the feasibility of IoT-enabled waste management platforms [28, 45]. In these systems, bins are equipped with sensors to measure fill level, temperature, and gas concentration, and all data are transmitted to centralized servers. Geographic Information Systems (GIS) and spatial databases are integrated to support bin placement planning and demand estimation, while optimized collection routes are delivered to drivers through mobile devices [95], [64].

Cloud-based architectures further enable real-time access to bin status information by municipal authorities and waste contractors. Route planning and path selection modules utilize current bin conditions to reduce fuel consumption and collection time. Some platforms have demonstrated the ability to manage thousands of bins simultaneously, indicating good scalability for smart city environments [27], [48], [2], [71].

In addition to monitoring, predictive analytics has been introduced to estimate future garbage levels. Time-series forecasting models and deep learning approaches, such as long short-term memory (LSTM) networks, have been applied to predict bin fill-up times and air quality indicators [89]. These predictive capabilities support proactive scheduling and reduce the risk of overflow events [60], [115], [72].

More comprehensive smart bin systems integrate multiple sensors, including ultrasonic, gas, infrared, and energy sensors, to monitor waste level, hazardous gas emission, and power status. Additional features such as voice control, photovoltaic power supply, and SMS alerts have been incorporated to enhance usability and sustainability, particularly in regions with limited infrastructure [74], [11], [82].

Overall, research on smart garbage bins has primarily focused on automated fill-level detection, real-time communication, and intelligent decision support for waste collection. These systems significantly improve operational efficiency, reduce health risks, and contribute to cleaner urban environments. However, the high initial deployment cost remains a major barrier to large-scale adoption, especially in developing countries. Government subsidies and policy support may play a critical role in accelerating the widespread implementation of smart bin technologies [2], [71].

4) Optimization of routing: The Priority Considered Green Vehicle Routing Problem (PCGVRP) model explicitly incorporates environmental objectives by jointly minimizing conventional waste management costs and greenhouse gas emissions. To enable dynamic routing and improve the economic efficiency of waste transportation, the waste filling level (WFL) of bins is integrated into the routing decision process. A local search hybrid algorithm is employed, in which an initial solution is first obtained using particle swarm optimization and subsequently refined through simulated annealing to exploit both global and local search capabilities [124].

The impact of waste composition on collection route duration, travel distance, and associated atmospheric emissions has been examined through the integration of artificial neural network–based waste forecasting with geographic information system (GIS)–driven route optimization techniques. Utilizing historical datasets from Austin, Texas, a nonlinear autoregressive neural network model was constructed to predict recycling and solid waste quantities across multiple sub-regions. This predictive framework supports more efficient planning and optimization of waste collection operations [55].

Accurate estimation of household packaging waste generation rates is essential for determining appropriate collection frequencies. To support short-term operational planning, multiple linear regression and artificial neural network models have been developed to generate seasonally adjusted forecasts that guide the scheduling of collection services and allocation of logistics resources [47].

Clustering-based optimization approaches have also been proposed to group waste bins and customers in a manner that minimizes transportation costs within and between depots. A mathematical clustering model assigns customers to clusters by balancing demand variation and mean demand levels, and experimental results demonstrate its effectiveness in improving collection efficiency for small-scale networks [15].

A bi-objective optimization framework has been formulated for residential waste transportation in Sousse, Tunisia, with the dual goals of reducing operational costs and minimizing environmental impact. A hierarchical "cluster-first, route-second" strategy is adopted to generate near-optimal solutions with moderate computational complexity, while simultaneously determining vehicle routes and bin allocation locations [61].

Beyond routing, sensor-based tracking technologies have been introduced to monitor plastic waste movement. The TRACKPLAST system represents a non-GPS solution that uses a LoRa-based wireless sensor network and cloud infrastructure to trace plastic bottles from inland sources toward marine environments, enabling visualization and source identification of plastic leakage pathways [99].

Geospatial analysis has been applied to characterize spatial patterns of household plastic waste generation. By integrating geographic information systems and GPS data, spatial variations in daily per capita plastic waste generation are mapped and analyzed to support improved collection planning and recycling infrastructure design [54].

Metaheuristic algorithms have been widely adopted to address vehicle routing problems in waste management. Using real-world data from Istanbul, an ant colony optimization–based routing strategy achieved a 13% improvement in route efficiency compared to existing schedules, demonstrating its potential for reducing travel distance and operational costs [13].

Since collection and transportation account for a major share of municipal solid waste management budgets, linear programming models have been proposed to redesign routing schedules and reduce collection frequency. A case study in Sanliurfa, Turkey, shows that optimized routing can significantly lower operational expenditures in dense urban neighborhoods [106].

Given the NP-hard nature of vehicle routing problems, simulated annealing has been extensively used as an efficient solution technique. In a large-scale Iranian case study involving 43 recycling nodes, a simulated annealing–based approach reduced total system cost by more than 13%, confirming its suitability for large urban networks [22].

Genetic algorithms integrated with geographic information systems have also been proposed to optimize waste collection routes. By combining a modified Dijkstra algorithm with evolutionary search, the proposed spatial genetic algorithm achieved more than 28% reduction in vehicle travel time, highlighting the benefit of hybrid GIS–metaheuristic frameworks [16].

Advanced routing variants, such as the collection vehicle routing problem of garbage facilities (CVRPGF), have been addressed using parallel simulated annealing. The proposed algorithm reduces both the number of vehicles and total travel time in benchmark and real-world instances, although its performance is constrained by fixed vehicle speed assumptions [137].

Smart bin–assisted routing has further improved collection efficiency. A modified backtracking search algorithm is introduced to solve capacitated vehicle routing problems by incorporating threshold waste levels to avoid unnecessary bin emptying. The resulting scheduling model demonstrates reductions in travel distance, fuel consumption, and carbon dioxide emissions [14].

In the context of electronic waste, hybrid optimization frameworks have been developed to enhance collection efficiency. Harmony search–based routing algorithms outperform several competing methods, while redesigned vehicle body architectures further improve loading efficiency and packing density during collection operations [90].

More recently, hybrid intelligent frameworks combining machine learning and graph theory have been proposed to automate recycling and minimize collection distance [103]. These systems integrate artificial intelligence with network optimization to support sustainable waste management strategies [46, 130].

Overall, the rapid advancement of artificial intelligence has led to the emergence of intelligent waste monitoring and routing platforms. In these systems, sensor data are continuously collected and transmitted to centralized servers, where learning algorithms are trained to predict waste generation, optimize routing decisions, and support real-time operational planning. Such platforms provide effective tools for improving environmental monitoring, pollutant tracing, and decision-making in modern waste management systems.

5) Classification of waste: Artificial intelligence–based technologies have been increasingly applied to improve the efficiency and reliability of waste classification and recycling processes. In addition to automating material identification, intelligent systems are capable of detecting anomalies in recycling workflows, such as improper sorting and material contamination, and notifying operators to enable timely corrective actions.

The rapid growth of industrial activity in urban regions has significantly increased the volume of solid waste, including paper, plastics, metals, glass, and wood. Landfilling remains the dominant disposal method, although it is costly, environmentally harmful, and associated with serious health risks for nearby populations. Incineration, another widely adopted method, releases toxic pollutants that may contribute to respiratory diseases and cancer. Consequently, recycling has become a critical strategy for protecting both environmental quality and human health, and effective classification of recyclable municipal solid waste is essential for supporting circular economy practices [94].

Because different waste types require distinct treatment and recovery processes, accurate waste classification is a fundamental step in modern waste management systems. Recent deep learning–based models have demonstrated promising performance; however, classification accuracy remains limited by architectural complexity and dataset constraints. To address this issue, a hybrid model that integrates VGG19, DenseNet169, and NASNetLarge has been proposed to improve ImageNet-based feature learning and enhance classification accuracy [58].

Mobile-based waste reporting applications have also been introduced to encourage public participation in waste monitoring. The Spot Garbage system uses fully convolutional networks to detect and coarsely classify garbage regions in geo-tagged images captured by users. Trained on the GINI dataset, the model achieves a mean accuracy of 87.69% and enables community-driven environmental supervision [86].

Beyond visual imaging, deep learning has been applied to near-infrared spectroscopy for textile waste classification. By constructing a normalized spectral dataset and extracting multidimensional features through convolution and pooling layers, an automated fabric composition recognition system has been developed to support intelligent textile sorting [78,107].

Edge-based artificial intelligence platforms have further enabled large-scale street cleanliness monitoring. Images captured by vehicle-mounted cameras are processed in real time by deep learning models to detect and classify diverse types of litter, such as leaves, bottles, and branches, thereby supporting continuous urban sanitation assessment [98].

To improve convolutional neural network performance, genetic algorithms have been applied to optimize fully connected layers. In particular, a GA-optimized DenseNet121 model significantly improves classification accuracy on the TrashNet dataset by fine-tuning network hyperparameters [80].

Large-scale waste image datasets have facilitated the development of specialized classification networks. The VN-trash dataset, comprising over 5900 images categorized into organic, inorganic, and medical waste, has been used to train an enhanced ResNeXt-based deep neural network that improves prediction performance in real-world scenarios [119].

Transfer learning–based classification frameworks have also been widely adopted. MobileNet models trained on ImageNet and fine-tuned using waste image datasets successfully classify waste into six major categories, including glass, paper, plastic, and metal, demonstrating the effectiveness of lightweight deep networks for embedded systems [102].

Residual network architectures augmented with self-monitoring modules have further improved recyclable waste recognition. These models integrate global receptive fields with channel-wise feature fusion and outperform conventional classifiers on the TrashNet benchmark [135].

Two-stage recognition–retrieval frameworks have been proposed for hierarchical waste sorting. In these systems, a recognition model first classifies waste into fine-grained subcategories, which are subsequently mapped to broader disposal classes by a retrieval model, enabling accurate multi-level segregation [136].

Hierarchical deep learning pipelines have also been developed for detecting and classifying waste in food trays. By combining object detection with high-resolution classification within bounding boxes, these models outperform standard deep learning baselines in both detection and classification accuracy [114].

To address the limitations of existing public datasets, the NWNU-TRASH dataset has been introduced with improved diversity and balanced class distribution. Transfer learning–based DenseNet169 models trained on this dataset achieve faster convergence and higher classification accuracy under realistic conditions [134].

Simplified convolutional architectures have been proposed to reduce computational complexity while maintaining high accuracy. The multilayer hybrid CNN achieves over 92% accuracy on the TrashNet dataset with fewer parameters than conventional VGG-based models [112].

Real-time industrial waste sorting systems have also been developed using conveyor belt imaging. CNN-based classifiers trained on on-site datasets achieve more than 92% accuracy under realistic operating conditions, demonstrating their suitability for automated sorting facilities [140].

Near-infrared qualitative identification systems using CNNs and PaddlePaddle have enabled online classification of more than 13 categories of waste textiles, providing high-speed and accurate textile sorting in industrial environments [43].

Automated plastic waste sorting systems based on deep learning and computer vision have been proposed for both industrial and household applications. These systems classify plastic into multiple categories using CNN-based object detection frameworks [26].

Hybrid feature extraction pipelines combining autoencoders, CNNs, ridge regression, and support vector machines have achieved extremely high classification accuracy, exceeding 99% in controlled experimental settings [116].

Integrated mechanical sorting systems combine CNN-based visual recognition with robotic actuators to separate metal and non-metal waste on conveyor belts. Multilayer perceptrons provide binary classification, while CNNs perform fine-grained recognition, achieving high accuracy during training and validation [51].

Lightweight CNN–ELM hybrid models, referred to as LitterNets, have been proposed to reduce training time while maintaining competitive classification performance compared with standard transfer learning models [132].

Object detection–based waste segregation systems using YOLOv5 have further improved real-time classification accuracy and enabled automated grouping of waste materials captured by camera-based sensors [101].

Hybrid deep transfer learning frameworks with dual-stream architectures have been designed to perform coarse-to-fine waste classification by first separating waste into broad groups and then refining predictions at the class level [131].

Cloud-assisted deep learning platforms have enabled large-scale waste classification with high accuracy and low latency. Among several evaluated networks, MobileNetV3 demonstrates the best trade-off between accuracy, model size, and inference speed [121].

Efficient Net-based classifiers achieve state-of-the-art performance on the TrashNet dataset, reaching accuracy levels close to 98%, while also reducing model size and computational cost. The construction of larger, standardized datasets further improves generalization performance [83].

In developing countries, manual waste sorting exposes workers to severe health risks. Automated classification systems based on deep learning have been introduced to replace manual segregation by identifying biodegradable and non-biodegradable waste in real time, thereby improving safety and efficiency [40].

Integrated computer vision and composting systems combine YOLO-based detection with biological treatment methods to enable simultaneous waste segregation and rapid composting of biodegradable materials [57].

Artificial intelligence has also been applied to hazardous waste detection. Real-time video analysis using CNNs, Keras, and OpenCV enables the classification of hazardous and non-hazardous materials with approximately 90% accuracy, supporting safer recycling workflows [24].

Overall, extensive experimental evidence demonstrates that deep learning–based waste classification systems, particularly those built on convolutional neural networks, provide high accuracy and robustness in identifying diverse waste categories. These intelligent models play a crucial role in enabling automated segregation, improving recycling efficiency, and supporting sustainable municipal solid waste management.

a) Robots for sorting waste: Autonomous robots for recycling construction and demolition (C&D) waste have emerged as effective tools for conserving resources; however, the highly unstructured environments and the large diversity of waste objects on construction sites pose significant challenges for navigation, perception, and manipulation. To address these issues, a robotic system integrating simultaneous localization and mapping (SLAM) has been developed to enable real-time navigation and recycling operations. Deep learning–based recognition and high-precision three-dimensional grasping strategies are further employed to ensure stable pickup of waste items, and experimental results demonstrate robust recognition performance under varying lighting and spatial density conditions [125].

Robotic systems have also been introduced to enhance the handling of recyclable materials in industrial waste-processing facilities. Because sorting environments are highly dynamic and unpredictable, these robots require advanced visual perception and manipulation capabilities. An autonomous robotic platform has been proposed that physically separates recyclables into multiple material categories using a low-cost deep learning–based computer vision module for object detection and classification [34].

Artificial intelligence techniques have been further applied to construction waste reuse through predictive modeling of recycled material properties. Specifically, machine learning approaches have been employed to predict the ultrasonic pulse velocity of concrete incorporating ceramic waste powder. These models utilize decision tree algorithms and ensemble-based techniques such as bagging, Extreme Gradient Boosting (XGBoost), and Adaptive Boosting (AdaBoost) to enhance predictive accuracy and reliability. The prediction performance is evaluated using statistical metrics such as the coefficient of determination, root mean squared error, and mean absolute error, demonstrating the feasibility of AI-assisted material quality assessment [68].

Novel robotic manipulators have been designed to support high-speed and energy-efficient waste sorting. A parallel robot architecture with three translational degrees of freedom and an additional gripper degree of freedom enables simultaneous positioning and grasping operations. The integrated gear-driven gripper is directly actuated by base-mounted motors, providing fast and precise control for industrial sorting applications [127].

Deep learning and computer vision technologies have also been adopted to improve household waste recognition. To enhance object detection performance, a You Only Look Once version 3 (YOLOv3) model is trained using the TrashNet dataset to recognize waste items under constrained training conditions. Although each training image contains only a single object, the proposed framework demonstrates improved recognition capability in automated sorting systems [74].

Automatic sorting robots based on hyperspectral imaging have been proposed to eliminate the need for manual labeling during training. By combining height maps with near-infrared hyperspectral images, the system identifies regions of interest and performs online pixel-level classification. Scale-sensitive and scale-insensitive feature extraction strategies are employed to capture both amplitude and trend information from spectral data, leading to more consistent sorting outcomes [81].

Substantial efforts have also focused on improving convolutional neural network–based object detectors for municipal waste recognition. Various single-shot detectors and region proposal network architectures have been fine-tuned on the TrashNet dataset to achieve fast and accurate detection. The best-performing model has been deployed on an autonomous mobile robot capable of identifying and collecting waste directly from the ground [85].

Overall, robotic waste-sorting systems have demonstrated strong potential to enhance operational efficiency, reduce labor requirements, and improve the accuracy of material separation. Nevertheless, high installation and maintenance costs remain major obstacles to large-scale deployment. To address these limitations, ongoing research explores low-cost hardware designs, modular robotic architectures, and adaptable platforms capable of operating in diverse environments. Continued advances in robotic structure, sensing technologies, classification algorithms, and manipulation mechanisms are expected to play a critical role in the future development of intelligent waste-sorting systems.

6) Treatment and disposal of waste

a) Composting of waste: Composting is a useful process for treating organic waste. Composting can be viewed as a practical alternative for disposing of MSW because organic matter makes up the majority of it. Through composting, municipal solid waste (MSW) is converted into stable, hygienic, and odour-free humus, thereby supporting key objectives such as environmental safety, volume reduction, and resource recovery. The complex biological and physicochemical processes involved in composting—including maturity assessment, parameter control, and process optimization—can be effectively modeled and monitored using machine learning algorithms [120].

Samples of sewage sludge that had been composted with rapeseed straw are collected. Pictures of the composted material using VIS, UV-A, and MIX light are obtained.25 convolutional neural networks with various numbers of filters are created. The classification errors ranged from 0.51% to 17.77% for the developed model [69].

The influence of key operational parameters during the composting of vegetable trimming residues—namely aeration rate, moisture content, particle size, and composting duration—has been investigated in relation to the resulting physico-chemical properties of the final compost, including pH, organic matter content, Kjeldahl nitrogen, and the C/N ratio. Additionally, the temporal variations of temperature, pH, and CO_2 emissions throughout the composting process were analyzed. To determine the optimal processing conditions that yield favorable temperature profiles, balanced pH levels, controlled CO_2 evolution, and high-quality compost output, an adaptive network-based fuzzy inference system (ANFIS) was implemented. This modeling framework incorporates the four primary input variables—aeration, moisture content, particle size, and composting time—to identify the most suitable composting configuration [41].

The viewpoints and difficulties of machine learning (ML) and its key algorithms, including Deep Neural Networks (DNNs), Adaptive-Network-Based Fuzzy Inference Systems (ANFIS), Random Forest (RF), and Artificial Neural Networks (ANNs), which are utilized in the composting process, are examined. The research also highlighted the specific flaws and deficiencies of the measures that are employed as error or performance criteria. It has been observed that Artificial Intelligence (AI)–based optimization techniques, such as Genetic Algorithms (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO), are primarily employed to fine-tune the hyperparameters of machine learning (ML) models rather than to directly adjust their internal model parameters [19].

There are, however, few computer techniques for precisely forecasting carbon dioxide emissions from the composting of green waste. Based on the data gathered, unique machine learning algorithms are created to forecast the production of carbon dioxide from composting green waste and compared six ways. The Random Forest model achieved superior performance in the regression analysis, recording a root mean square error (RMSE) of 23.3. In the classification task, it reached a highest prediction accuracy of 88% after the exclusion of extreme outliers from the dataset. Total organic carbon, which accounts for around 59% of the Gini index, is the most important aspect and can offer recommendations for lowering carbon emissions from composting green waste [76].

The optimal proportions of floral waste (1325 g) and cattle dung (500 g) for vermicompost production were determined using a Central Composite Design (CCD) and subsequently compared with predictions obtained from an Artificial Neural Network (ANN) model. The optimized mixture yielded vermicompost with a pH of 7.10, electrical conductivity of 3.39 mS/cm, total organic carbon of 34.01%, a C:N ratio of 13, phosphorus content of 5.31 g/kg, and potassium concentration of 14.45 g/kg. In this study, Response Surface Methodology (RSM) and ANN were evaluated for predicting compost maturity parameters, with both approaches achieving coefficient of determination (R^2) values approaching unity [111].

In conclusion, artificial neural networks can optimize compost maturity and carbon dioxide and heavy metals can be predicted using machine learning models.

b) Waste treatment process- incineration: Waste incineration remains a widely adopted disposal method; however, improper operation can lead to serious environmental and operational problems. The modeling of incineration processes is particularly challenging due to strong nonlinearity, complex coupling among variables, long system delays, and high thermal inertia, which make accurate prediction and control difficult.

The lower heating value (LHV) is a key parameter used to estimate the amount of recoverable energy in municipal solid waste subjected to thermochemical conversion. To predict LHV for the municipal waste of Santo André, two regression-based models have been developed using samples collected from 36 garbage trucks over a five-month period. Multiple linear regression with the least squares method is applied to establish predictive relationships between waste composition and energy content [42].

Online estimation of the heating value of municipal waste has also been proposed as a rapid and cost-effective alternative to laboratory analysis. In this framework, multiple nonlinear machine learning techniques—such as multilayer perceptron (MLP) neural networks, support vector machines (SVM), adaptive neuro-fuzzy inference systems (ANFIS), and random forest models—are developed to estimate heating values. Model performance is further enhanced through the application of optimization techniques to tune hyperparameters and improve generalization accuracy [129].

Because municipal solid waste is a highly heterogeneous fuel, reliable operation of waste-to-energy plants requires accurate time-resolved characterization of its physical and chemical properties. Gaussian process regression models have been developed using historical operational data combined with meteorological and calendar information to estimate the daily LHV of incoming waste streams. Both baseline and hyperparameter-optimized GPR models demonstrate superior prediction accuracy compared with previously reported approaches [25].

Deep learning has also been applied to model complex incineration processes in waste-to-energy facilities. Output variables related to safety, operational stability, and economic performance are first identified, and mechanism-based analysis is used to select relevant candidate inputs. The Lasso method is then employed to eliminate redundant and insignificant variables. Utilizing the established input–output configuration, a multi-input, multi-output deep learning architecture is developed and subsequently evaluated in comparison with traditional approaches, including least squares support vector machines (LSSVM), convolutional neural networks (CNN), and long short-term memory (LSTM) networks [33].

In industrial symbiosis settings, waste incineration plants supply low-cost steam and energy to neighboring process industries. To support such collaborations, it is essential to monitor and predict boiler performance accurately. Since conventional artificial neural networks are often criticized for their lack of interpretability, hybrid machine learning and deep learning models have been proposed to capture the complex relationships governing boiler operation while improving transparency and predictive reliability [110].

c) Disposal and recycling of waste: Geographic Information System (GIS)–based techniques have been applied to identify suitable waste disposal sites in Dejen town by considering ten key criteria, including proximity to settlements, roads, and streams; land use patterns; geological and geomorphological characteristics; slope; wind speed and direction; lineament density; and elevation. To assess the relative unsuitability of each criterion in developing the suitability map, the researchers structured the influencing factors hierarchically within a decision matrix and transformed the qualitative assessments into quantitative scores [133].

Utilizing machine learning, a cloud-based classification system for automated equipment in recycling industries is provided. A MobileNet model that can categorize five different kinds of garbage is trained. On a cloud server, the inference can be executed in real-time. The classification accuracy is improved using a variety of methods, including data augmentation and hyperparameter tuning. Custom data transmission protocols and security features are used to support and connect a number of industrial stations. Experimental findings showed that a cloud server can achieve good performance with 96.57% accuracy [141].

The increasing demand for automated e-waste recycling is examined as a crucial requirement to manage the rapidly expanding e-waste stream, and the role of artificial intelligence in supporting the recycling process through smart classification of devices, with the smartphone being implemented. By fine-tuning the output layers of AlexNet as a pre-trained model and performing the implementation on a small dataset containing 12 classes from 6 smartphone brands, transfer learning is used as a particular technique of artificial intelligence [8].

For the first time, methane generation was predicted using three machine learning models: artificial neural networks, adaptive neuro-fuzzy inference systems, and support vector machines. Results showed that for predicting methane generation, the support vector machine model outperformed both the adaptive neuro-fuzzy inference system and artificial neural network models. The support vector machine (SVM) model successfully explained approximately 90% of the variability in methane emissions for landfills with leachate recirculation and about 82% for those without recirculation [84].

Key determinants of leachate production were identified, and multiple AI-driven models were developed to predict leachate generation rates. These approaches included support vector machine (SVM)–based regression time series models and artificial neural network (ANN)–multilayer perceptron (MLP) architectures with both single and double hidden layers. Feature selection results indicated that three variables—waste disposal volume, rainfall intensity, and gas emissions—were sufficient for effective modeling of leachate generation. Initial performance evaluation demonstrated that the ANN-MLP model with two hidden layers (ANN-MLP2) achieved the highest predictive accuracy, followed by the single hidden-layer ANN-MLP1 model, whereas the SVM approach exhibited comparatively lower performance [9].

A fresh method for choosing a landfill location scientifically and managing waste sustainably in Aligarh, India is presented. This might be accomplished by gathering pertinent data, choosing appropriate models for criterion weighting, and validating the models. Using a GIS-based ensemble FAHP-SVM and FAHP-RF model, an appropriate landfill site selection map is created. A total of 18 theme layers (decision criteria) are chosen by taking into account the features of the study region, the characteristics of prior studies, and other factors [87].

Artificial neural network (ANN) models have been developed to estimate emission rates from landfill sites, which release significant levels of odorous compounds from their active surfaces. These models incorporate meteorological parameters—such as temperature, humidity, and atmospheric pressure—along with waste composition characteristics, including protein, fat, carbohydrate, ash, and moisture content, to enhance prediction accuracy. By contrasting and training with various structural configurations, the best structures and performances of the ANN models are identified. The performance of ANN models with genetic algorithm (GA) optimization is superior to that of ANN models without GA [126].

Using a backpropagation (BP) neural network implemented in MATLAB, projections indicate that municipal solid waste (MSW) generation in 2025 will reach approximately 1251.22 million tonnes in Beijing, 704.71 million tonnes in Guangzhou, and 71.040 million tonnes in Lhasa. The findings suggest that key drivers of MSW generation across these cities include economic growth, population size, and levels of governmental investment. By analyzing both the influencing factors and projected waste quantities in selected representative cities, the study provides valuable insights into the escalating MSW management challenges faced by different economic regions in China [44].

The Levenberg-Marquardt optimization approach and the hyperbolic tangent sigmoid activation function are combined with a feed-forward back propagation neural network. Based on available weighbridge records, the ANN-driven solid waste forecasting model demonstrated strong predictive capability, achieving coefficients of determination (R^2) of 0.85 for the training phase and 0.86 for testing. The developed model can be effectively integrated with weighbridge management systems to estimate incoming waste quantities at landfill sites. The findings further indicate that the proposed ANN-based approach for landfill area estimation, when combined with optimized final disposal strategies, can support improved planning and operational management of landfill facilities [56].

IV. Conclusion

This review examined 140 studies that applied machine learning techniques to different stages of municipal solid waste management. The reviewed studies indicate that machine learning techniques have been applied throughout the full spectrum of the waste management lifecycle. These applications range from forecasting waste generation and monitoring bin fill levels to optimizing collection routes and automating waste classification, covering stages from generation and segregation to transportation, processing, and final disposal. In recent years, research interest in applying machine learning to MSWM has grown rapidly, as reflected by the sharp increase in the number of published studies. Artificial neural networks remain the most widely used models, with feedforward, backpropagation, radial basis function, and autoregressive variants frequently reported. A smaller but growing body of work has explored long short-term memory networks for time-series waste prediction. More recently, deep learning approaches, particularly convolutional neural networks, have gained increasing attention for automated waste classification tasks.

Despite this progress, the large-scale and mature deployment of machine learning in real-world waste management systems remains limited due to the inherent complexity of MSWM. At present, only a few applications, such as intelligent waste classification and automated identification systems, have reached practical implementation. For example, deep learning–based waste sorting robots developed by commercial vendors are already in operation in several countries. However, most existing studies remain exploratory in nature, and broader industrial adoption is expected to emerge gradually as technologies mature and infrastructure improves.

The growing body of research on intelligent waste management also raises several new challenges and research questions. Inefficient waste disposal leads to severe environmental degradation, high operational costs, and inadequate governance in both developed and developing countries. In this context, artificial intelligence offers promising computational tools to improve treatment efficiency, reduce environmental impacts, and support more intelligent decision-making. Practical applications such as smart bin systems, robotic sorting platforms, and predictive monitoring models illustrate the potential of artificial intelligence to enhance hazardous waste handling, reduce illegal dumping, recover valuable resources, and support medical waste management during public health emergencies.

Artificial intelligence also plays an important role in improving waste logistics and transportation by reducing travel distances, lowering fuel consumption, and increasing collection efficiency. In addition, learning-based models have been applied to optimize treatment technologies, including recycling, composting, land filling, and incineration. Deep learning and machine learning approaches have been used to simulate incineration processes, predict heavy metal concentrations in compost, and improve waste classification accuracy. Nevertheless, environmental factors such as temperature, humidity, and lighting conditions may affect model performance and introduce uncertainties. Even with these limitations, artificial intelligence has strong potential to reshape waste management systems toward more efficient, economical, environmentally sustainable, and intelligent operations.

Although artificial intelligence technologies have become increasingly prevalent in waste management, several critical limitations remain. Insufficient and low-quality data, the lack of customized models tailored to specific waste management contexts, and the gap between theoretical performance and real-world effectiveness continue to restrict practical deployment. Limited scalability and reduced robustness in complex operational environments are additional barriers. Future progress will depend on a deeper understanding of model behavior, improved integration with sensing and communication technologies, and the coordinated use of multiple learning paradigms.

Machine learning models are opening new opportunities for intelligent solid waste management, but their success strongly depends on data quality and algorithmic reliability. Learning models must be trained using representative real-world datasets that accurately reflect the operational environment and target applications. Reliable data acquisition, preprocessing, and continuous model updating are therefore essential prerequisites for effective intelligent decision-support systems.

Based on the findings of this review, machine learning has demonstrated clear potential for addressing key challenges in solid waste management, particularly in optimizing collection routes, improving sorting accuracy, and supporting predictive planning. The study highlights the importance of adopting machine learning–based decision tools to determine optimal collection schedules and disposal strategies.

To maximize the potential of machine learning in waste management, it is crucial to consolidate existing data sources, address fragmented information systems, and encourage seamless data exchange across all stages of the waste management value chain. Establishing integrated data acquisition and monitoring mechanisms throughout the disposal process can facilitate more responsive, precise, and adaptive decision-making. Such a coordinated framework would elevate waste management from a conventional service operation to an intelligent, data-driven system, thereby enabling the development of advanced smart waste management infrastructures.

Conflicts of Interest

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