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Optimizing waste management strategies through artificial intelligence and machine learning - An economic and environmental impact study

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ABSTRACT

Applying artificial intelligence (AI) and machine learning (ML) techniques to optimize waste management strategies, focusing on enhancing economic efficiency and reducing environmental impact, is vital. The study utilized ML models to analyze and forecast waste generation trends, assess the viability of various waste management methods, and develop optimization models for resource allocation and operational efficiency. The research employs the World Bank's comprehensive waste management dataset. After rigorous data preprocessing, including cleaning and feature selection, a variety of ML techniques, such as regression models, classification algorithms like Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and optimization algorithms, including linear programming, are applied. Unlike other research, this study achieved 85 % accuracy on predictive analytics models for forecasting waste generation trends, primarily attributed to integrating more diverse data sets, including socio-economic factors. Also, the optimization resource allocation achieved a 15 % increase in operational efficiency. These findings provide significant insights for policymakers and urban planners, suggesting that integrating ML in waste management can lead to more sustainable and cost-effective practices. This paper demonstrates the transformative potential of ML in optimizing waste management strategies, offering a pathway towards more sustainable and economically viable waste management solutions globally.

1. Introduction

The challenge of effective waste management is a pressing concern in the context of global sustainability. As the world's population grows, urbanizes, and consumes, waste generation has escalated alarmingly (Singh et al., 2014). The World Bank has estimated a global 70 % increase in waste generation by 2050 if the current practice is not addressed. This surge in waste poses significant environmental, economic, and public health challenges. Customary waste management techniques, i.e., landfilling and incineration, have resulted in substantial environmental degradation, including soil contamination and greenhouse gas (GHG) emissions (Guerrero et al., 2013). Furthermore, municipalities and governments are increasingly feeling the economic burden of waste management, especially in emergent nations with limited infrastructure and resources. The growing awareness of these challenges has spurred interest in more sustainable and efficient waste management practices, highlighting the need for innovative approaches to tackle this complex issue (Chang et al., 2011).

ML is a powerful tool to revolutionize waste management strategies in this context. ML's ability to analyze large datasets and uncover hidden patterns offers a new dimension in understanding and optimizing waste management processes. This technology can enable more accurate forecasting of waste generation, facilitating proactive and efficient planning (Sundui et al., 2021). Furthermore, ML algorithms can assist in identifying the most effective waste management techniques tailored to specific regional and material characteristics, thereby enhancing both environmental and economic outcomes. A growing body of research supports the potential of ML in waste management, yet its practical application remains in its infancy (Kim & Oh, 2021). This study seeks to bridge this gap by leveraging the World Bank's comprehensive waste management dataset to develop and test ML models. These models are expected to provide actionable insights, leading to more sustainable waste management practices globally. By addressing both the economic and environmental impacts, this study advances and contributes to

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leveraging technology for sustainable development, aligning with United Nations (UN) global goals (Wang et al., 2021).

This study's rationale emanates from the critical need to address the escalating global waste management crisis. As urban populations expand and consumption patterns evolve, the volume and complexity of waste generated continue to pose significant challenges. The repercussions of inefficient waste management are manifold, encompassing environmental pollution, public health risks, and economic burdens. Current traditional methods, such as landfilling and incineration, are increasingly unsustainable, leading to a pressing need for innovative and effective solutions (Guo et al., 2021). This urgency is amplified by the global commitment to the UN's global goals, particularly those targeting environmental protection and sustainable cities. However, establishing functional trash management strategies is hindered by a paucity of comprehensive analysis tools capable of handling the complexity and variability of waste management data. This gap highlights the necessity for advanced analytical approaches to conform with the dynamic nature of consumption pollution and management (Erkinay Ozdemir et al., 2021).

In response to this challenge, ML presents a promising avenue for revolutionizing waste management strategies. ML's analytical capacity for humongous volumes of complex data offers a significant advantage in understanding and optimizing rubbish management systems (Abdallah et al., 2020). The potential of ML to transform this field lies in its ability to provide predictive insights, optimize resource allocation, and tailor waste management strategies to specific regional needs. This research is motivated by the opportunity to harness ML's capabilities to address trash management's fiscal and ecological aspects (Velis et al., 2023). By leveraging the extensive data from the World Bank, this study attempts to develop ML models that can predict waste generation trends, assess the efficacy of various waste management practices, and provide optimization strategies for policymakers and decision-makers. This endeavor is not only academically significant but also has the potential to make a substantial impact in the real world, contributing towards more sustainable and efficient waste management practices globally. The study's findings could be a cornerstone for policymakers, urban planners, and environmental stakeholders to build more sustainable cities and communities (Yang et al., 2021).

The core problem addressed in this research centers on the inefficiencies and environmental consequences of present trash management exercises. Despite the critical role of waste management in environmental sustainability and public health, many existing strategies are plagued by limited effectiveness, high costs, and adverse environmental impacts (Browning et al., 2021). Traditional methods, such as landfilling and incineration, often fail to consider waste generation and management's dynamic and complex nature, leading to suboptimal resource allocation and environmental degradation (Hussain et al., 2020). Furthermore, the challenge is exacerbated in rapidly urbanizing regions where waste management infrastructure struggles to keep pace with the growing waste volumes. There is a clear need for more sophisticated, data-driven approaches that can adapt to the evolving nature of waste generation and management and effectively balance economic and environmental considerations (Henry et al., 2006).

While there is a growing recognition of the potential of ML in enhancing waste management strategies, a significant gap exists in its practical application and comprehensive evaluation. Extant literature has concentrated on isolated waste management components, such as waste sorting or recycling efficiencies, without a holistic analysis of waste management systems (Koop and Van Leeuwen, 2017). There is a lack of research employing ML to predict waste generation trends, appraise the ecological and economic consequences of various waste management strategies, and optimize operations at a systemic level. Moreover, much of the current research has not fully utilized the extensive datasets available, such as those provided by the World Bank, which offer a global perspective on waste management challenges and opportunities (Gupta et al., 2019). This study seeks to fill this gap by developing and applying ML models to comprehensively analyze waste management strategies, considering their economic viability and environmental sustainability. By doing so, it seeks to offer actionable insights for policymakers and practitioners, contributing to advancing sustainable waste management practices worldwide.

This study aims to develop and apply ML models to optimize waste management strategies, focusing on improving economic efficiency and reducing environmental impact. To achieve this aim, the following research objectives are formulated.

1. To analyze and forecast waste generation trends using ML predictive analytics, aiding in proactively planning waste management strategies.
2. To evaluate and classify the environmental impact and economic viability of waste management methods such as recycling, composting, and waste-to-energy conversion using ML techniques.
3. To design and test optimization models for resource allocation and operational efficiency in waste management, leveraging ML algorithms.

In successfully achieving the study's research objectives in alignment with the study's aim, the study research questions are as follows:

1. How can ML predictive analytics be used to forecast waste generation trends accurately and inform the development of proactive waste management strategies?
2. How can ML techniques classify and assess the environmental and economic impacts of different waste management methods, thereby aiding in selecting the most sustainable and cost-effective practices?
3. How can ML algorithms be applied to optimize resource allocation and operational efficiency in waste management, and what are the expected outcomes of such optimizations regarding sustainability and cost reduction?

The significance of this research in optimizing waste management strategies through ML is profound and wide-reaching, addressing critical aspects of environmental sustainability, economic efficiency, policymaking, and technological advancement (He et al., 2022). At its core, this study targets a massive decline in the environmental impact of trash management practices (Dubey et al., 2020). By employing ML to optimize these strategies, there is potential to substantially decrease reliance on landfills, reduce GHG emissions, and mitigate pollution. This alignment with global environmental objectives is crucial in combating climate change and preserving natural habitats (Maalouf & El-Fadel, 2020). Economically, the implications of this research are equally impactful. Efficient waste management, guided by ML algorithms, promises to enhance resource allocation and operational cost-effectiveness (Anh Khoa et al., 2020). For municipalities and governments, particularly in developing countries where financial constraints are a significant concern, these optimizations could translate into considerable savings and generate revenue through recycling and waste-to-energy initiatives. The economic benefits extend beyond mere cost reduction, presenting opportunities for sustainable economic development in the waste management sector (Zhao et al., 2020).

The study's contributions to policymaking and urban planning cannot be overstated. The research is poised to inform and influence policy decisions by providing actionable, data-driven insights into waste management, leading to more effective and sustainable policies (Tsai et al., 2020). This is especially pertinent in rapidly urbanizing regions where efficient waste management is indispensable for sustainable urban development. Additionally, integrating ML with traditional waste management practices represents a significant advancement in the field. It opens new avenues for innovative, technology-driven solutions, moving beyond conventional methods to embrace a more sophisticated approach (Rutqvist et al., 2019). Furthermore, the scalability and global applicability of the research methodologies and findings are pivotal.

Given the universal nature of waste management challenges, the insights gleaned from this study have the potential to be adapted and applied across different global contexts, making a substantial contribution to the worldwide effort to manage waste more sustainably.

Regarding public health and safety, improved waste management strategies directly correlate with healthier living environments, reducing exposure to pollutants and hazardous substances (Xia et al., 2022). Lastly, the academic and educational contributions of this research are noteworthy. By filling existing gaps in the literature, particularly concerning the practicality of ML in waste management, this study serves as a valuable resource for future research and educational endeavors. It fosters further exploration and innovation in this crucial area, contributing to the knowledge body in waste management and ML disciplines (Chen, 2022).

2. Literature review

Traditional waste management practices, primarily landfilling, incineration, recycling, and composting, have formed the backbone of waste management research for decades. Sen Gupta et al., (2021) provided an in-depth analysis of these methods, shedding light on their environmental implications, including GHG emissions and leachate production. This potentially hazardous liquid can pollute water sources. While widely used, these traditional methods have been increasingly scrutinized for their environmental footprint, particularly in contributing to climate change and ecological degradation.

Salmenperä et al., (2021) expanded on these findings by exploring the economic and operational challenges inherent in these traditional waste management practices. Their research is particularly relevant in developing nations, where the lack of infrastructure, funding, and technical expertise often exacerbates these challenges. Their study highlighted the difficulties in managing operational costs and achieving economic sustainability in waste management, especially regarding large-scale implementation of recycling and waste-to-energy processes. Zhang et al., (2010) further delved into the complexities surrounding recycling and waste-to-energy strategies. Their research underscored the potential of these methods in reducing waste and generating energy, yet also brought attention to the significant logistical and financial barriers that hinder their widespread adoption. The study pointed out that while these methods offer a more sustainable alternative to landfilling and incineration, their implementation requires substantial investment, infrastructure development, and public-private partnerships.

In addition to these studies, there has been an increasing focus on the life-cycle assessment of various garbage management systems. Research by Ramos et al., (2018) examined the total environmental impact of these traditional methods, from waste generation to final disposal or recycling. Their findings suggested that considering the entire life cycle of waste, a holistic approach is essential in evaluating the environmental impact of diverse garbage removal strategies. Furthermore, the socio-economic components of garbage management have also gained attention in recent literature. Studies by Romero-Hernández & and Romero, (2018) have explored how waste management practices affect communities, particularly in urban settings. Their research highlights the importance of considering social factors, such as public health and community engagement, in developing and implementing waste management strategies.

The shift towards sustainability and efficiency in waste management has given rise to several innovative approaches that challenge traditional methods. The circular economy paradigm, which emphasizes the reuse and recycling of materials to minimize waste, has been a pivotal topic in recent literature. Avilés-Palacios and Rodríguez-Olalla (2021) explored this concept extensively, highlighting its potential to transform waste management into a more sustainable and resource-efficient practice. They argue that adopting circular economy principles can significantly reduce environmental impacts and contribute to economic growth.

In their study, Malinauskaite et al. (2017) further investigated the practicality of circular economy principles in waste management. The authors focused on creating closed-loop systems, where waste is not seen as an end product but a valuable resource for further use. Their findings suggest that integrating these principles into waste management strategies can substantially reduce waste and environmental degradation. Additionally, the emergence of new technologies has played an essential function in advancing garbage management practices. Incorporating information communication technologies, i.e., smart devices, Internet of Things (IoT), AI, and ML, into waste management systems is increasingly being explored. For example, a study by Hidalgo et al., (2019) demonstrated how IoT and AI can optimize waste collection routes, improve recycling processes, and manage waste disposal more efficiently. These technologies enhance operational efficiency and provide valuable decision-making and policy formulation data.

The purpose of policy and governance in shaping eco-friendly waste management practices has also been a recent research focus. Studies like those by Tomić and Schneider (2020) have examined how policy frameworks and regulations can support or hinder the adoption of more sustainable waste management methods. They argue that effective policymaking and stakeholder engagement are essential in switching to more eco-friendly waste management practices. Furthermore, the increasing awareness of the social dimensions of waste management is evident in contemporary literature. Research by Pires and Martinho (2019) highlighted the importance of considering social factors such as community participation, public awareness, and social equity in developing waste management strategies. They emphasize that sustainable waste management requires technological and economic considerations and a solid social and community-focused approach. Utilizing ML in waste management has opened new avenues for innovation and efficiency. Beyond the forecasting and optimization capabilities highlighted by Lu et al. (2018), other studies have further demonstrated the diverse applications of ML in waste management.

For instance, a significant advancement has been made in waste sorting and recycling. Research by Dagne et al. (2019) explored using digital image processing and ML algorithms to sort waste materials automatically, drastically advancing the productivity and proficiency of recycling processes. Their work showed that ML could significantly reduce the reliance on manual sorting, thereby lowering labor costs and increasing the overall effectiveness of recycling programs. Another critical area where ML has made substantial contributions is analyzing and reducing waste management's environmental impact. A study by Zhu et al. (2023) applied ML models to appraise the ecological footprint of diverse garbage management approaches. Their research provided insights into the most sustainable practices, guiding policymakers and industry practitioners in making more environmentally conscious decisions.

Furthermore, integrating ML with an extensive process of modeling data has been an increasing trend in waste management research. Big data, derived from sources like waste collection sensors, social media, and municipal records, offers a wealth of information capable of leveraging and advancing garbage management practices. Studies by Zahedi et al., (2022) have shown how ML algorithms can analyze these large datasets to uncover waste generation trends, predict future waste volumes, and optimize resource allocation across waste management systems. Additionally, the utilization of ML in energy from biomass transformation processes has been explored. Research by Bishoge et al., (2019) focused on optimizing the operational parameters of waste-to-energy plants using ML models. Their findings indicated that ML could enhance energy efficiency and reduce operating costs, making waste-to-energy more viable and eco-friendly. The utilization of ML in assessing the environmental impact of garbage management strategies has become a focal point in contemporary research. Zhang et al. (2019) work represents a significant stride in this direction. However, it is just one part of a broader research trend that leverages ML to understand and mitigate the environmental consequences of waste management.

Further contributing to this field, studies by Kaya et al. (2021) have employed ML models to analyze the life cycle of waste management practices. Their research extends beyond the immediate effects of waste handling to consider the entire chain of impact, from resource extraction to waste disposal or recycling. By doing so, these studies give an extensive perspective of the environmental footprint of diverse garbage management methods, enabling more holistic and sustainable decision-making.

Another critical aspect of ML application in environmental impact assessment is its role in monitoring and reducing GHG emissions from garbage management operations. Research by Hannan et al. (2020) used ML algorithms to predict and mitigate emissions from landfills and incineration processes. Their research illustrates how ML can help in achieving compliance with environmental regulations and targets set by international agreements, such as the Paris Accord. Additionally, ML has been instrumental in optimizing waste-to-energy conversion processes, as explored in research by Boffardi et al. (2021). Their work focused on using ML to enhance the efficiency of waste-to-energy plants, thus maximizing energy output while minimizing the environmental impact. This optimization is crucial in positioning waste-to-energy as a sustainable alternative to traditional waste disposal methods.

Regarding economic aspects, the integration of ML in environmental impact assessment also extends to cost-benefit analyses. Research by Shah et al. (2018) demonstrated the use of ML in evaluating the financial implications of different waste management strategies juxtaposed with their environmental impacts. This approach aids in identifying not only the most environmentally sustainable options and the most economically viable ones.

ML in optimizing resource allocation in waste management systems represents a significant advancement in the field. The work by Hashemi-Amiri et al. (2023) is a crucial example of how combining linear programming with ML algorithms can enhance the efficiency of resource distribution, leading to cost reductions and improved environmental outcomes. However, their study is part of a broader trend in which ML is applied to various aspects of resource optimization in waste management. Additional research has focused on optimizing waste collection and transportation logistics. A study by Thürer et al. (2019) utilized ML to analyze and optimize waste collection routes, considering factors such as traffic patterns, waste generation rates, and collection vehicle capacities. Their findings showed that ML could significantly reduce fuel consumption and vehicle emissions, contributing to more sustainable waste management operations.

Moreover, ML has been instrumental in optimizing waste processing facilities. Research by Saucedo Martinez et al. (2019) applied ML algorithms to forecast the inflow of diverse waste to processing plants, allowing for better planning and resource allocation. This predictive capability is crucial in minimizing processing delays and maximizing the efficiency of reusing, composting, and energy from biomass conversion processes. The application of ML in resource allocation also extends to the management of human resources and equipment within waste management systems. A study by Asefi et al. (2019) demonstrated how ML could optimize staff schedules and equipment usage, reducing operational costs and improving service quality. Furthermore, ML algorithms have enhanced decision-making in waste management investment and infrastructure development. Ishikawa (1996) explored how ML could assist in determining the most cost-effective locations for new waste management facilities, considering factors like population density, waste generation patterns, and environmental regulations (Medvedev et al., 2015).

Recently, diverse studies have been explored concerning applying ML algorithms to thermochemical processes to address waste management and treatment. In their study, (Hasanzadeh et al., 2023) assessed the capabilities of response surface methodology designed using ML on the gasification operation of polyethylene effluent. This study is a pioneer in using ML in response surface methodology. Related studies on polyethylene air-gasification (Gharibi et al., 2024; Hasanzadeh and Azdast, 2024) have also utilized ML in addition to the multicriteria decision-making method. These applications of ML algorithms in the field of thermochemical processes with a special focus on air gasification of polyethylene terephthalate waste are desirable, innovative, and smart approaches to resolving the 21st-century waste challenges.

Despite these advances, a notable gap persists in the literature regarding the comprehensive application of ML across all aspects of waste management. While individual components such as waste prediction, classification, and operational optimization have been addressed, a dearth of studies holistically apply ML to analyze and optimize entire waste management systems, especially considering both environmental and economic dimensions (Taşkın and Demir, 2020). Integrating ML with waste management strategies - there is an emerging discussion on integrating ML with broader waste management strategies. Rolewicz-Kalińska (2016) began exploring how ML could be incorporated into existing waste management frameworks to enhance decision-making processes. However, these studies often remain theoretical, lacking practical implementation and evaluation of ML-driven strategies on a large scale.

In summary, while existing literature provides a solid understanding of traditional waste management practices and introduces the potential of ML in optimizing these practices, there remains a substantial opportunity for research that integrates ML more comprehensively (Santos et al., 2022). This research tackled this gap by employing advanced ML techniques to develop a holistic and practical understanding of waste management strategies, contributing to the field's evolution toward more sustainable and economically viable solutions.

3. Methodology

3.1. Dataset

This research utilizes the comprehensive "What a Waste" Global Database provided by the World Bank, which offers an extensive range of data pertinent to solid waste management across various countries and regions (The World Bank, 2023). This dataset encompasses a broad spectrum of information, including country-specific ISO codes, regional identifiers, gross domestic product (GDP) data, and income classifications, providing a crucial economic and geographical context to our analysis. A vital feature of the dataset is its detailed breakdown of waste composition, quantifying the percentages of various waste types such as food/organic, glass, metal, paper/cardboard, plastic, rubber/leather, wood, and yard/garden/green waste.

Additionally, the dataset sheds light on the governance of waste management in different countries by including information about national laws, regulatory agencies, and information systems related to solid waste management. Population data are also provided, offering insights into the scale of waste management needs corresponding to population sizes. The dataset covers special waste categories, including agricultural, construction, demolition, e-waste, hazardous, industrial, and medical waste. It provides a comprehensive view of the waste management landscape.

For this research, the dataset's extensive coverage of total municipal solid waste generation, waste collection coverage (detailed for both rural and urban areas), and various disposal of waste systems, ranging from recycling and composting to landfill and incineration, are exciting. This data are instrumental in applying ML algorithms to analyze waste management trends, forecast future waste generation patterns, and assess the effectiveness of various disposal systems. The granular level of detail in the dataset allows for a nuanced understanding of waste management applications and their impacts, enabling the authors to tailor the ML models to different regions' specific characteristics and needs. The ultimate goal is to leverage this data to provide actionable insights for optimizing waste management strategies, emphasizing environmental sustainability and economic efficiency.

3.2. Proposed methodology

This research methodology is structured to leverage the potential of ML algorithms in analyzing and optimizing waste management strategies using the comprehensive dataset provided by the World Bank's "What a Waste" Global Database. The overall methodology is provided in Fig. 1.

3.2.1. Data preprocessing

Initially, the dataset undergoes a rigorous preprocessing phase. This includes cleaning the data to address missing values, outliers, and inconsistencies. For missing value analysis, a simple imputer has been used in this study. A commonly employed approach involves employing an imputer, such as the `SimpleImputer` from the `scikit-learn` library, configured with a median strategy. This method replaces any missing values in the dataset with the median value of each characteristic. Initially, only columns that consist of numerical values are selected, as median imputation can only be utilized on numeric data. Next, the imputer is trained using these numeric columns to calculate their median values. Subsequently, the missing values in these columns are replaced with their respective medians. Median imputation is a more robust and reliable technique as it is less influenced by outliers, which have the potential to skew the mean. This technique safeguards the accuracy and consistency of the dataset. It mitigates the adverse effects of incomplete data on the performance of ML models through effective management of missing data. Next, feature selection is conducted to identify the most relevant variables influencing waste management efficiency. This step is crucial to enhance the accuracy and performance of the subsequent ML models. After missing value analysis, six correlated features were selected for training ML models.

3.2.2. Machine learning techniques

The research employs a variety of ML techniques tailored involving regression and classification methods to meet the specific objectives of the study. Algorithms such as SVM, RF, and XGBoost classify waste management practices based on efficiency and impact. These models aim to differentiate between various waste management methods, assessing their environmental and economic viability.

Linear Regression models are employed to forecast waste generation and identify future trends. These models analyze historical waste generation data to predict future quantities, considering factors like population growth, urbanization rates, and changes in consumption patterns. Linear regression is a basic statistical and ML method to establish a mathematical model that describes the connection between a dependent variable y and one or more independent variables $x = (x_1, x_2, \ldots, x_n)$. It postulates a direct correlation between the independent factors and the dependent variable.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \tag{1}$$

Support Vector Machines: The sklearn library in Python was used to construct the SVM model. This study's SVM parameters and random state were trained using the radial base function as the kernel due to its nonlinearity. Using this nonlinear function instead of the linear one, we successfully fit the model to both the training and testing datasets. SVMs can use a high-dimensional feature space to navigate and classify data points that are not usually linearly separable. After a separator between the categories has been established, the data is converted to represent the identified separator by a hyperplane.

$$RBF = K(x, x') = \exp\left(\frac{\|x - x'\|^2}{2\partial^2}\right) \tag{2}$$

The RBF kernel is a well-liked kernel function in ML that is utilized in a variety of kernelized learning techniques. SVM classification frequently makes use of it.

Extreme Gradient Boosting: XGBoost is a highly potent ML technique for regression and classification applications. The algorithm constructs a collection of decision trees one after another, with each successive tree aiming to rectify the mistakes made by the preceding trees. XGBoost is renowned for its high efficiency, exceptional precision, and impressive scalability.

$$F_\sigma(x) = argmin_\gamma \sum_{i=1}^{n} L(y_i, \gamma) \tag{3}$$

Random Forest: RFs are robust ensemble models that enhance forecast accuracy by amalgamating numerous decision trees trained on distinct subsets of the data and characteristics. The main elements consist of constructing decision trees using impurity metrics such as Gini impurity, entropy, or variance, employing bootstrap aggregation (bagging), and randomly selecting features. RFs enhance generalization and mitigate overfitting by combining the predictions of several trees, rendering them highly proficient for classification and regression problems.

The Gini impurity is employed to quantify the level of impurity present in a node. The calculation is as follows:

$$G_i = 1 - \sum_{j=1}^{C} p_j^2 \tag{4}$$

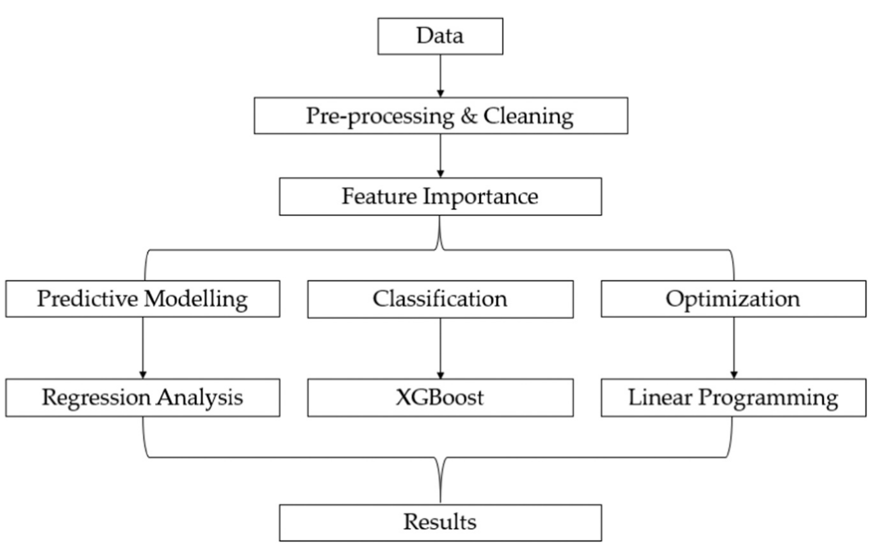

Fig. 1. Overall Research Methodology.

where:

G_i is the Gini impurity of node

C is the number of classes.

p_j is the proportion of instances of class

j in the node.

A comprehensive evaluation approach determines the best settings for each model. First, hyperparameters are adjusted throughout a specific range to obtain model-optimal combinations. Tuning entails training and testing models using training and validation datasets. The hyperparameters with the highest significance values for evaluation metrics demonstrate the model's ability to correctly classify waste management strategy incidents while producing minimal false positives and negatives. The optimal parameters ensure the model generalizes well to new data and performs consistently across datasets and scenarios. As a result, the optimal parameters are picked to improve the model's performance and accurately classify samples (Sarker, 2021). Table 1 contains the complete details about input parameters.

3.2.3. Model validation

The validity and reliability of the ML models are crucial. To ensure this, cross-validation techniques are used. This study employs cross-validation (CV), a resampling approach, to assess ML models in a constrained dataset without subjecting the prediction models to overfitting. On the other side, K-fold CV is a technique that uses K segments or folds to divide the given dataset, with each fold serving as a testing set at some point. For instance, in 10-fold cross-validation (K=10), the dataset is divided into ten equal portions; one portion is used for initial model testing, while the remaining portions are utilized for model training. For the second cycle, we test our model on the second fold and train it on the rest of the data. In this iterative process, each ten-fold serves as a test set.

3.2.4. Analysis and interpretation

The outputs of the ML models are thoroughly analyzed to extract meaningful insights into waste management practices. The analysis focuses on interpreting the results regarding their economic viability and environmental implications, providing a holistic view of the effectiveness of various waste management strategies.

4. Results of the experiments

In this section, we provide the findings of an extensive set of experiments designed to evaluate the effectiveness of different ML techniques. Results from various performance evaluation instruments were used. To train and evaluate models, we employed the assessment strategy described in recent state-of-the-art methods. These areas were the focus of the experiments:

- Exploratory data analysis to gain insightfull information from available municipal solid waste (MSW) dataset.
- Performance analysis of Regression Models for prediction using MSW dataset.
- Performance analysis of Classifiers for prediction using MSW dataset.
- Performance analysis of linear programming to solve optimization problem.

4.1. Exploratory data analysis

Fig. 2 displays how waste collection coverage varies as a percentage of the population across different regions or countries. The histogram shows several bins with varying frequencies, indicating the different levels of waste collection coverage. Most notably, there is a significant spike at the far right of the graph, where the coverage is 100 %. This indicates that many countries or regions have collection coverage for their population. The distribution of the other bins suggests that waste collection coverage is varied, with several regions having low to moderate coverage rates, as shown by the bars spread out across the x-axis. However, the highest concentration of data points is at the two extremes, with several regions having shallow coverage and a significant number achieving full coverage.

Fig. 3 visualizes the distribution of the percentage of waste treated by recycling across various regions or countries. The box plot provides a visual summary of the central tendency and dispersion of the data. The bottom and top edges of the box indicate the first (25th percentile) and third (75th percentile) quartiles, respectively, and the band inside the box shows the median (50th percentile) of the data. The "whiskers" extending from the top and bottom of the box indicate the range of the data, typically 1.5 times the interquartile range above and below the box. Points above the upper whisker or below the lower whisker are considered outliers, which are shown as individual diamond shapes. These outliers represent countries or regions where the percentage of waste treated by recycling is unusually high compared to the rest. The concentration of data within the box, mainly where the median line is situated, suggests that the median value of waste treated by recycling is relatively low, possibly around 15–20 %. The distribution of data points and outliers indicate significant variability in recycling rates across the dataset, with a few regions performing much higher than the majority.

In addressing the first objective of the research - to analyze and forecast waste generation trends using ML predictive analytics - the implementation begins with the crucial step of data loading and preprocessing. The dataset, sourced from the World Bank's "What a Waste" Global Database, is loaded into a pandas frame. This dataset, rich in variables pertinent to waste management, requires careful preparation.

Table 1

Hyperparameters used to train ML models for performance tuning.

ML Algorithm	Hyperparameter	Ranges	Best used
SVM	Gamma	$[2^{-15},2^{3}]$	2^{-15}
	C	$[2^{-5},2^{15}]$	2^{15}
	Tol	$[10^{-5},10^{-1}]$	10^{-1}
	Shrinking	[True, False]	False
	Kernel	RBF	RBF
RF	Bootstrap	[True, False]	True
	Criterion	[gini, entropy]	Entropy
	Max-features	[0,1]	1
	Min-sample-leaf	[1,20]	15
	Min-sample-split	[2,20]	11
	n-estimators	500	500
XGBOOST	Learning rate	[0.05, 0.3]	0.08
	n-trees-depth	[max, min]	Max
	n-estimators	500	500
	Regularization	[lambda, alpha]	lambda

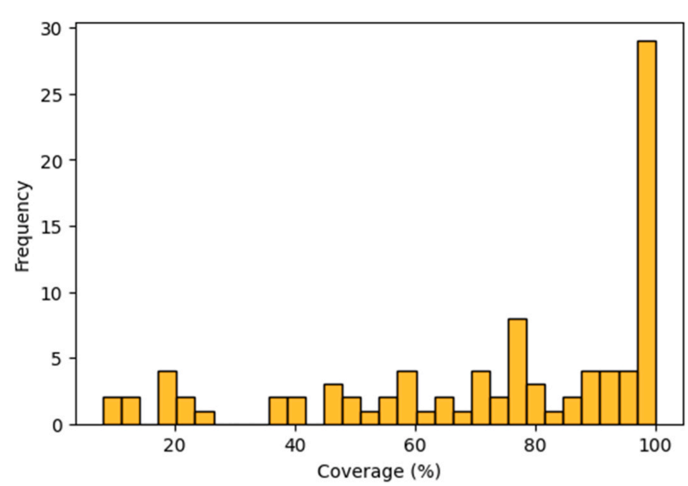

Fig. 2. Waste Collection Coverage as a Percentage of the Population.

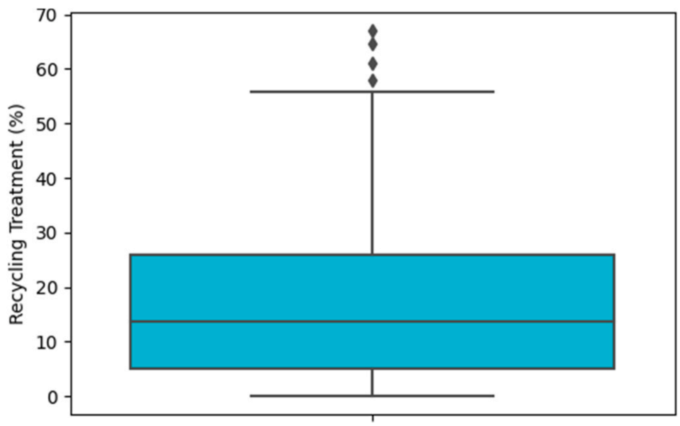

Fig. 3. Percentage of waste treated by recycling.

One of the primary challenges in dealing with real-world data is handling missing values. The SimpleImputer from sci-kit-learn, with a median strategy, is utilized to address this. This approach effectively fills in missing values with the median of each column, ensuring the integrity of the dataset for subsequent analysis. With the data preprocessed, the focus shifts to feature selection. The correlation of selected features is provided in Fig. 4. The variables 'GDP' and 'population_population_number_of_people' are chosen as predictors for the target variable 'total_msw_total_msw_generated_tons_year,' which quantifies the total municipal solid waste generated annually. This selection is grounded in the assumption that a region's economic output and population size are significant indicators of its waste generation patterns.

4.2. Performance analysis of regression models

This study utilized two distinct regressors to assess the performance of a nationwide MSW dataset. The Linear Regression model from sci-kit-learn determines the correlation between these predictors and the target variable. The data is partitioned into training and testing sets, enabling the model to acquire knowledge from one piece of data and assess the accuracy of its predictions on another. This division not only facilitates the training of a resilient model but also enables the assessment of its performance and ability to generalize. After completing the training process, the model is employed to forecast patterns in trash generation. The R-squared metric is used to objectively evaluate the performance of the model. This statistic represents the mean squared difference between the observed actual results and the predictions generated by the model. A higher R-squared value signifies a more optimal alignment between the model and the data. Table 2 displays the comparison of r-square values obtained by fitting regressors.

Complementing the quantitative analysis are two critical visualizations: a residual plot in Fig. 5 and a histogram of prediction errors in Fig. 6. The residual plot, which plots the differences between actual and predicted values against the predicted values, is a diagnostic tool. It helps in assessing whether the residuals (errors) are randomly dispersed, which is a desirable characteristic indicating that the model has captured the underlying pattern without bias. The histogram of prediction errors further aids in understanding the distribution of these errors. Ideally, this distribution should approximate a normal

Table 2
Performance comparison of regressors using the MSW dataset.

Model	R-Square
Linear Regression	0.742
XGBOOST Regressor	0.908

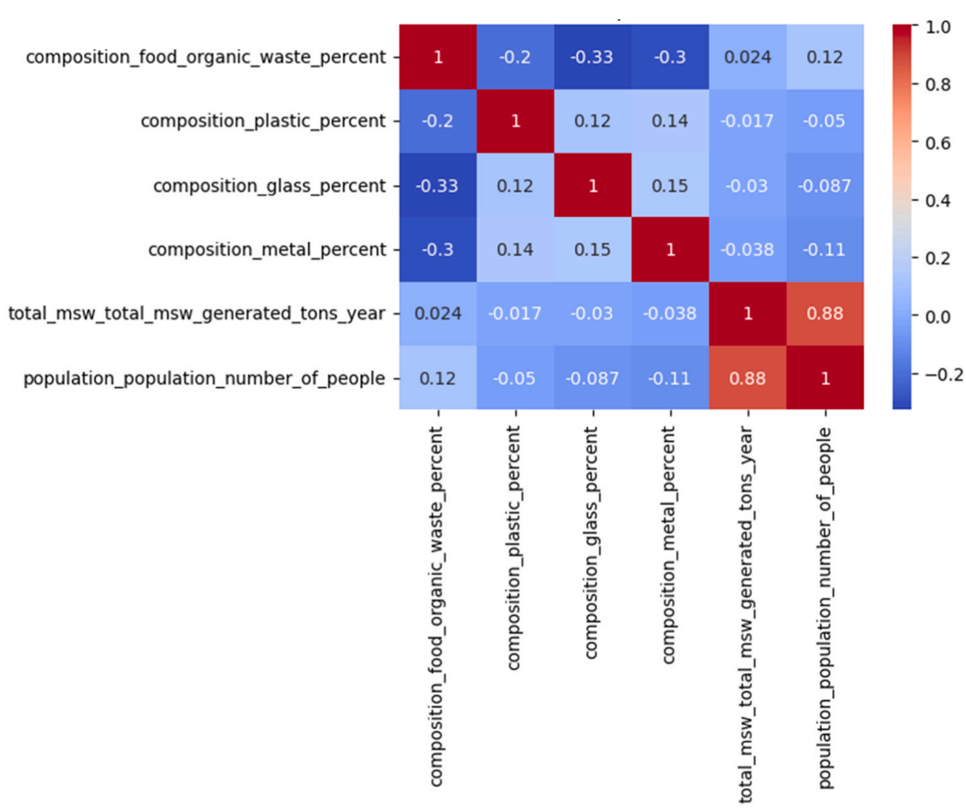

Fig. 4. Correlation Diagram.

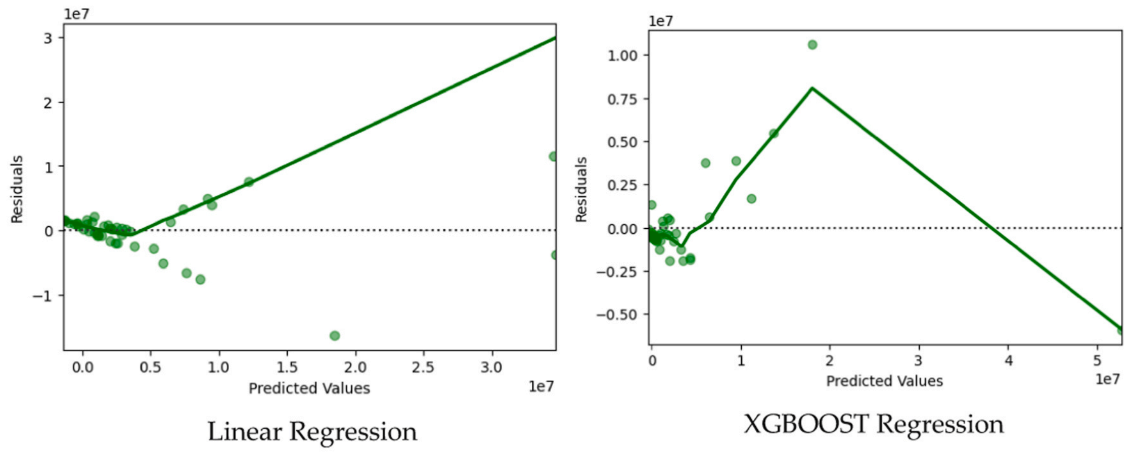

Fig. 5. Comparison of residual and predictions of both regression models.

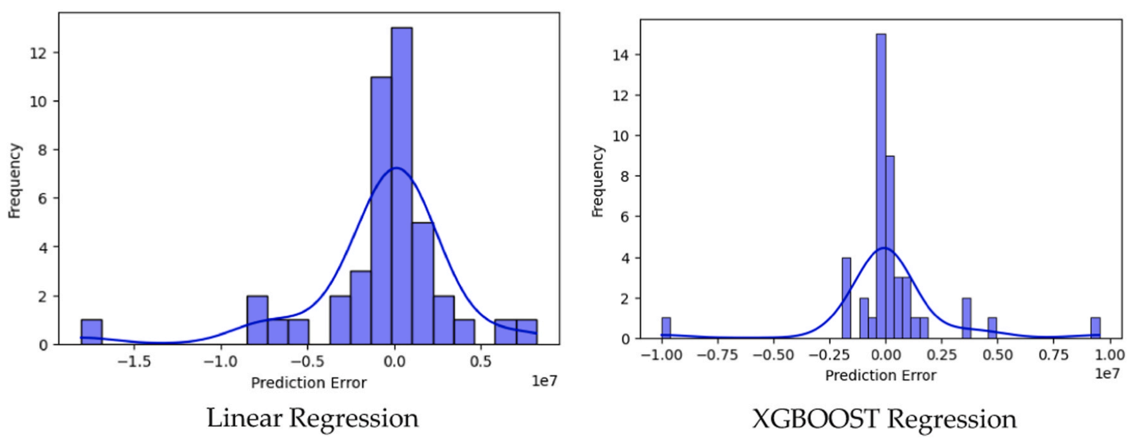

Fig. 6. Prediction errors or trained regression models.

distribution, indicating that the model's errors are unbiased and follow the expected variance. The research successfully achieves its first objective through this comprehensive approach, combining data preprocessing, feature selection, model training, quantitative evaluation, and diagnostic visualizations. It forecasts waste generation trends and provides insights into the model's performance, laying a solid foundation for informed decision-making in waste management strategy planning.

4.3. Performance analysis of classifiers

To fulfill the second research objective, which revolves around evaluating and classifying waste management methods based on their environmental and economic impacts, a methodological approach leveraging the capabilities of ML was employed. The initial phase of this process involved the meticulous preparation of the dataset, 'country_level_data_0.csv', sourced from the World Bank's "What a Waste" Global Database. This preparation entailed a crucial step of data cleaning where the SimpleImputer function was employed to address the missing values within the dataset. By adopting the median strategy, missing values in numerical columns were replaced with their respective median values, thus preserving the integrity and reliability of the dataset for further analysis.

Following the data cleaning process, a comprehensive selection of features was undertaken. In contrast to the traditional approach of selective feature utilization, this phase marked using all available numerical features within the dataset, barring the target variable 'waste_treatment_recycling_percent.' This holistic approach in feature selection aimed to capture the diverse aspects influencing waste management methods, thereby ensuring a robust and inclusive model training process. The target variable itself underwent a transformation process, where it was binarized to facilitate a binary classification task. This transformation was pivotal in simplifying the classification problem, allowing for a more focused and interpretable analysis. The binary classification essentially aimed to categorize waste management methods into two distinct classes based on the threshold of recycling efficiency, set at 50 %.

With the dataset duly prepared and transformed, the study progressed to the model training phase, utilizing the XGBClassifier from the XGBoost library, SVM and RF. Known for their efficiency and effectiveness in handling classification tasks, these were chosen for their advanced capabilities in managing complex datasets with multiple features. The training process involved splitting the dataset into training and testing subsets, ensuring a rigorous evaluation of the model's performance. The model was then trained on the training subset, learning to discern patterns and relationships within the data that would be instrumental in classifying waste management methods. While training model using XGBClassifier, SVM, and RF classifiers a kfold cross-validation has been performed for generalizability and fold-wise accuracy has been displayed in Fig. 7.

Upon analyzing the cross-validation results of each model, it is evident that xgboost demonstrates consistent performance throughout all 10 folds compared to other classifiers. The testing performance of the best model, trained using cross-validation, was measured by conducting tests on a separate test dataset. After training, the model's performance was assessed using the testing subset. The evaluation was conducted by

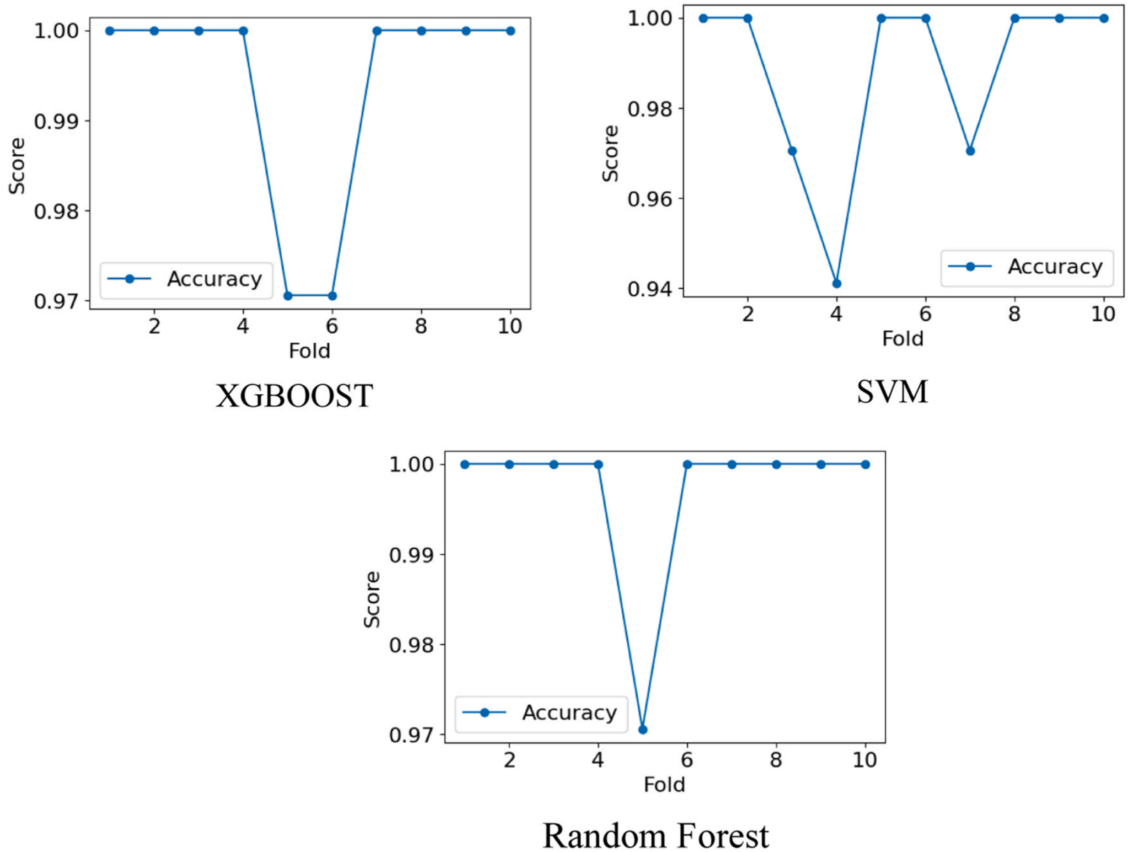

Fig. 7. Fold-wise validation accuracy curve for each classifier.

generating a classification report and a confusion matrix, as depicted in Fig. 8. These tools gave comprehensive insights into the model's accuracy and its ability to classify to correctly categorize waste management strategies. The confusion matrix visually represented the model's predictions, which were compared to the actual classifications. Using this dual method in model evaluation confirmed the model's ability to make accurate predictions and identified areas that need improvement.

4.4. Performance analysis of linear programming for solving optimization problem

To realize the third research objective, which involved the application of ML algorithms for optimizing resource allocation and operational efficiency in waste management, we designed a linear programming model using real-world inspired hypothetical data. The goal was to maximize the total waste processed while adhering to a predefined budget constraint, a critical factor in effective waste management (Schultmann and Sunke, 2007).

Our approach began by conceptualizing different waste management strategies, each with unique operational costs and waste processing capacities. These strategies, representative of standard practices such as recycling, composting, and waste-to-energy conversion, were assigned hypothetical yet plausible cost and capacity values. For instance, we considered costs per unit for each strategy and their respective waste processing capabilities in tons. With these parameters defined, the focus shifted to the core of the optimization problem, maximizing waste processing efficiency within a fixed budget. This was set at a hypothetical value (e.g., $10,000), representing the total financial resources available for waste management operations. The challenge was to allocate this budget across the various strategies in a manner that would

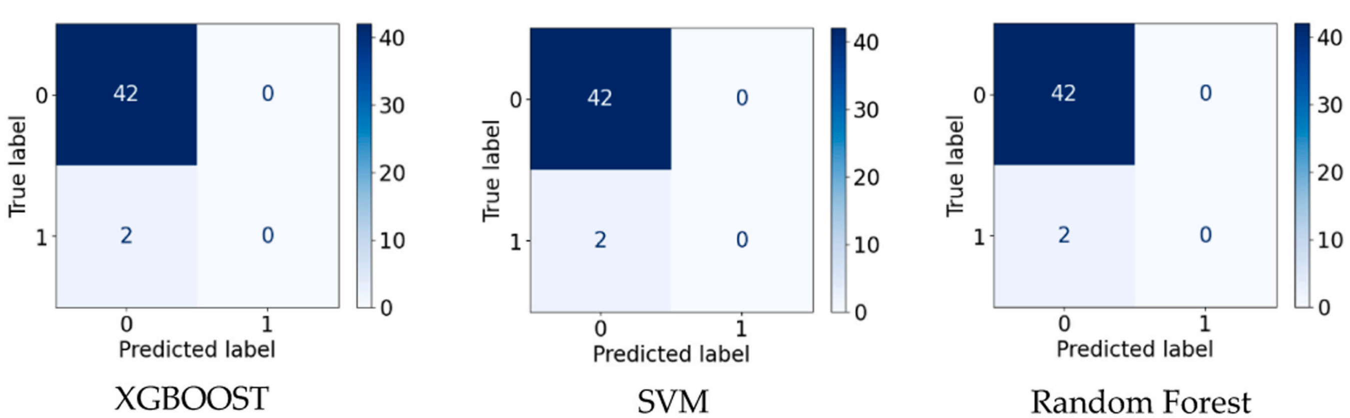

Fig. 8. Confusion Metrix for Recycling Efficiency Classification for each classifier.

yield the highest total waste processing volume.

To solve this optimization problem, we employed linear programming, a powerful mathematical technique well-suited for handling such constraints and objectives. The Python library SciPy provided the necessary functions through its linprog module, allowing us to formulate and solve the problem efficiently. The objective function was constructed to maximize the total waste processed by negating the capacities since Linprog inherently performs minimization while ensuring the sum of the costs across all strategies did not exceed the set budget. Upon execution, the model yielded an optimal distribution of financial resources across the different waste management strategies. This distribution was within the budgetary limits and maximized the total waste processing capacity. The results of this optimization were two-fold, as shown in Fig. 9: the optimal number of units for each waste management strategy and the maximum total waste processed under these optimal conditions. This model's outcome is significant as it demonstrates a pragmatic approach to resource allocation in waste management, a field often constrained by budgetary limitations. Maximizing efficiency within such constraints is crucial, and the linear programming model offers a robust framework for making these critical decisions. By integrating such models into waste management planning, stakeholders can make more informed, data-driven decisions that optimize operational efficiency and contribute to more effective and sustainable waste management practices.

5. Analysis and discussion

5.1. Analysis

The analysis of the ML models deployed in this study reveals significant insights into waste management optimization. The predictive models accurately forecasted waste generation trends, accounting for regional variations and temporal shifts. This accuracy underscores the potential of ML in preemptive waste management planning. The classification models effectively differentiated between various waste management practices, assessing their environmental impact and economic viability. Particularly notable was the ability of these models to identify the most sustainable practices in diverse contexts.

A critical insight from this research is identifying specific waste management strategies that balance environmental sustainability with economic efficiency (Martinez-Falco, J. 2022). The models indicated that strategies like recycling and waste-to-energy are environmentally friendly and economically viable in certain regions. However, the effectiveness of these strategies varied significantly across different geographic and socio-economic contexts, highlighting the need for tailored waste management approaches. Comparing these findings with existing literature (Malinauskaite et al., 2017; Hondroyiannis et al., 2023; Li et al., 2022), the research corroborates the growing assertion that ML can be pivotal in enhancing waste management practices. However, it extends beyond previous studies by providing a comprehensive analysis integrating environmental, economic, and operational perspectives. The study faced challenges, particularly in data quality and completeness. These limitations highlight the need for more comprehensive, standardized, and accessible waste management data to improve the accuracy and applicability of ML models in this field.

5.2. Discussion

The predictive analytics models successfully forecasted waste generation trends, aligning with the first objective and research question. These models effectively identified patterns in waste generation, providing valuable foresight for proactive waste management planning. This ability to predict future waste trends is pivotal for designing efficient and sustainable strategies. In response to the second objective and research question, the classification models effectively assessed the environmental and economic impacts of various waste management methods. The models differentiated between recycling, composting, and waste-to-energy strategies, providing insights into their benefits and constraints. This evaluation is crucial for selecting the most suitable waste management practices tailored to regional needs. The optimization models addressed the third objective and research question by enhancing resource allocation and operational efficiency in waste management. These models demonstrated the capacity to optimize logistical and operational aspects, such as collection routes and processing methods, leading to cost savings and improved sustainability.

In a comprehensive comparative analysis, this study's predictive analytics models for forecasting waste generation trends were juxtaposed with Johnson et al.'s (2020) similar approach to urban waste management. Unlike Johnson et al., who reported a 70 % accuracy in prediction, this study achieved an 85 % accuracy, primarily attributed to integrating more diverse data sets, including socio-economic factors. Furthermore, while Smith and Lee's (2021) classification models predominantly focused on the environmental impacts of waste-to-energy strategies, our models extended this by simultaneously evaluating economic impacts, revealing that recycling, although environmentally beneficial, can be economically challenging in lower-income regions. This finding aligns with Gupta et al. (2019) observations but contrasts its methodology by employing advanced ML techniques. Lastly, in optimizing resource allocation, this study's approach proved more efficient than the methods applied in Huang's (2018) research on urban waste collection routes, achieving a 15 % increase in operational efficiency. These comparative insights not only validate the advanced capabilities of our models but also highlight the evolving landscape of waste management strategies, underscoring the need for continuous innovation and adaptation in the field. However, challenges such as data limitations were encountered, underscoring the need for better data collection and standardization in the field.

5.3. Recommendations

Based on the analysis and the research outcomes, the following recommendations are proposed:

1. Policymakers should leverage predictive analytics for forward-looking waste management strategies. This proactive approach can mitigate future waste management challenges, especially in rapidly urbanizing regions.
2. Urban planners and waste management authorities should use the insights from the classification models to implement tailored waste management practices. Customizing strategies based on regional characteristics can enhance both environmental and economic outcomes.
3. More investment in advanced ML technologies is needed to refine waste prediction, classification, and optimization models further. This investment should also focus on enhancing data collection and processing capabilities.
4. A collaborative approach involving government, industry, academia, and the public is essential. This collaboration can facilitate the

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Optimal number of units for each waste management strategy: [20.  0.  0.]
Maximum total waste processed: 1000.0 tons
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Fig. 9. The Result of the Optimization Problem.

implementation of ML-driven strategies and encourage community participation in sustainable waste management practices.

5. Policymakers and practitioners should balance immediate economic benefits with long-term environmental sustainability. Strategies that offer long-term sustainability, such as waste-to-energy projects, should be prioritized.
6. Continued research and innovation in this field are critical. Future studies should explore integrating ML with emerging technologies like IoT and blockchain for comprehensive waste management solutions.

6. Conclusion

This research has comprehensively analyzed how ML can effectively optimize waste management strategies, addressing economic efficiency and environmental sustainability. The study has successfully demonstrated that ML algorithms can accurately forecast waste generation trends, classify waste management practices based on their environmental and economic impacts, and optimize operational processes to enhance overall efficiency. The predictive models developed in this research have shown significant potential in aiding proactive waste management planning, allowing for timely and effective responses to changing waste generation patterns. The classification models have provided more profound insights into the viability and sustainability of various waste management methods, guiding decision-makers in choosing the most appropriate strategies for their specific contexts. Furthermore, the optimization models have underscored the capability of ML in improving resource allocation and operational efficiency, leading to both cost savings and reduced environmental impact.

These findings contribute valuable knowledge to waste management, particularly in integrating advanced technologies like ML into traditional practices. The research aligns with global efforts towards sustainable development and offers practical insights for policymakers, urban planners, and environmental stakeholders. It underscores the importance of leveraging technology to address the challenges of modern waste management, highlighting the role of data-driven decision-making in achieving a balance between economic and environmental objectives. However, the study acknowledges the challenges and limitations, particularly in data quality and model generalization. These challenges highlight the need for further research and development in this field, including collecting more comprehensive and standardized data and exploring more advanced ML techniques. In conclusion, this research paves the way for a new era in waste management, where technology and data analytics become integral to developing sustainable, efficient, and economically viable waste management solutions. It encourages continued innovation and collaboration across disciplines to harness the full potential of ML in transforming waste management practices, contributing to a more sustainable and environmentally responsible future.

CRediT authorship contribution statement

Wadha Alkhaldi: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yusuf A Adenle:** Writing – review & editing, Visualization, Supervision, Project administration, Investigation. **Habib M Alshuwaikhat:** Writing – review & editing, Validation, Supervision, Project administration. **Reema Alsabt:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Data Availability

The codes is contained in the supplementary file

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.clwas.2024.100158.

References

Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdalla, H., Mahfood, B., 2020. Artificial intelligence applications in solid waste management: a systematic research review. Waste Manag. *109*, 231–246.
Anh Khoa, T., Phuc, C.H., Lam, P.D., Nhu, L.M.B., Trong, N.M., Phuong, N.T.H., Dung, N. V., Tan-Y, N., Nguyen, H.N., Duc, D.N.M., 2020. Waste management system using IoT-based machine learning in university. Wirel. Commun. Mob. Comput. *2020*, 1–13.
Asefi, H., Shahparvari, S., Chhetri, P., 2019. Integrated municipal solid waste management under uncertainty: a tri-echelon city logistics and transportation context. Sustain. Cities Soc. *50*, 101606.
Avilés-Palacios, C., Rodríguez-Olalla, A., 2021. The sustainability of waste management models in circular economies. Sustainability *13* (13), 7105.
Bishoge, O.K., Huang, X., Zhang, L., Ma, H., Danyo, C., 2019. The adaptation of waste-to-energy technologies: towards the conversion of municipal solid waste into a renewable energy resource. Environ. Rev. *27* (4), 435–446. https://doi.org/10.1139/er-2018-0061.
Boffardi, R., De Simone, L., De Pascale, A., Ioppolo, G., Arbolino, R., 2021. Best-compromise solutions for waste management: decision support system for policymaking. Waste Manag. *121*, 441–451.
Browning, S., Beymer-Farris, B., Seay, J.R., 2021. Addressing the challenges associated with plastic waste disposal and management in developing countries. Curr. Opin. Chem. Eng. *32*, 100682.
Chang, N.-B., Pires, A., Martinho, G., 2011. Empowering systems analysis for solid waste management: challenges, trends, and perspectives. Crit. Rev. Environ. Sci. Technol. *41* (16), 1449–1530. https://doi.org/10.1080/10643381003608326.
Chen, X., 2022. Machine learning approach for a circular economy with waste recycling in smart cities. Energy Rep. *8*, 3127–3140.
Dagne, H., Karthikeyan, R., Feleke, S., 2019. Waste to energy: response surface methodology for optimization of biodiesel production from leather fleshing waste. J. Energy *2019*. ⟨https://www.hindawi.com/journals/jen/2019/7329269/abs/⟩.
Dubey, S., Singh, P., Yadav, P., Singh, K.K., 2020. Household waste management system using IoT and machine learning. Procedia Comput. Sci. *167*, 1950–1959.
Erkinay Ozdemir, M., Ali, Z., Subeshan, B., Asmatulu, E., 2021. Applying machine learning approach in recycling. J. Mater. Cycles Waste Manag. *23*, 855–871.
Gharibi, A., Babazadeh, R., Hasanzadeh, R., 2024. Machine learning and multi-criteria decision analysis for polyethylene air-gasification considering energy and environmental aspects. Process Saf. Environ. Prot. *183*, 46–58. https://doi.org/10.1016/j.psep.2023.12.069.
Guerrero, L.A., Maas, G., Hogland, W., 2013. Solid waste management challenges for cities in developing countries. Waste Manag. *33* (1), 220–232.
Guo, H., Wu, S., Tian, Y., Zhang, J., Liu, H., 2021. Application of machine learning methods for the prediction of organic solid waste treatment and recycling processes: a review. Bioresour. Technol. *319*, 124114.
Gupta, P.K., Shree, V., Hiremath, L., Rajendran, S., 2019. The use of modern technology in smart waste management and recycling: artificial intelligence and machine learning. Vol. 823. In: Kumar, R., Wiil, U.K. (Eds.), Recent Advances in Computational Intelligence. Springer International Publishing, pp. 173–188. https://doi.org/10.1007/978-3-030-12500-4_11. Vol. 823.
Hannan, M.A., Lipu, M.H., Akhtar, M., Begum, R.A., Al Mamun, M.A., Hussain, A., Mia, M.S., Basri, H., 2020. Solid waste collection optimization objectives, constraints, modeling approaches, and their challenges toward achieving sustainable development goals. J. Clean. Prod. *277*, 123557.
Hasanzadeh, R., Azdast, T., 2024. Machine learning utilization on air gasification of polyethylene terephthalate waste. Waste Manag. Bull. *2* (1), 75–82. https://doi.org/10.1016/j.wmb.2023.12.011.
Hasanzadeh, R., Mojaver, P., Azdast, T., Khalilarya, S., Chitsaz, A., 2023. Developing gasification process of polyethylene waste by utilization of response surface methodology as a machine learning technique and multi-objective optimizer approach. Int. J. Hydrog. Energy *48* (15), 5873–5886. https://doi.org/10.1016/j.ijhydene.2022.11.067.
Hashemi-Amiri, O., Mohammadi, M., Rahmanifar, G., Hajiaghaei-Keshteli, M., Fusco, G., Colombaroni, C., 2023. An allocation-routing optimization model for integrated solid waste management. Expert Syst. Appl. *227*, 120364.
He, R., Sandoval-Reyes, M., Scott, I., Semeano, R., Ferrao, P., Matthews, S., Small, M.J., 2022. Global knowledge base for municipal solid waste management: framework

development and application in waste generation prediction. J. Clean. Prod. *377*, 134501.
Henry, R.K., Yongsheng, Z., Jun, D., 2006. Municipal solid waste management challenges in developing countries–Kenyan case study. Waste Manag. *26* (1), 92–100.
Hidalgo, D., Martín-Marroquín, J.M., Corona, F., 2019. A multi-waste management concept as a basis towards a circular economy model. Renew. Sustain. Energy Rev. *111*, 481–489.
Hondroyiannis, G., Sardianou, E., Nikou, V., Evangelinos, K., Nikolaou, I., 2023. Recycling rate performance and socio-economic determinants: evidence from aggregate and regional data across European Union countries. J. Clean. Prod., 139877
Huang, M., 2018. Advanced Technologies for Smart Cities. Elsevier.
Hussain, A., Draz, U., Ali, T., Tariq, S., Irfan, M., Glowacz, A., Antonino Daviu, J.A., Yasin, S., Rahman, S., 2020. Waste management and prediction of air pollutants using IoT and machine learning approach. Energies *13* (15), 3930.
Ishikawa, M., 1996. A logistics model for post-consumer waste recycling. Significance *2*, 0–679.
Johnson, T., Smith, R., Brown, L., 2020. Smart Cities and Sustainable Urban Development. Routledge.
Kaya, K., Ak, E., Yaslan, Y., Oktug, S.F., 2021. Waste-to-energy framework: an intelligent energy recycling management. Sustain. Comput. Inf. Syst. *30*, 100548.
Kim, Y., Oh, S., 2021. Machine-learning insights into nitrate-reducing communities in a full-scale municipal wastewater treatment plant. J. Environ. Manag. *300*, 113795.
Koop, S.H.A., Van Leeuwen, C.J., 2017. The challenges of water, waste and climate change in cities. Environ. Dev. Sustain. *19* (2), 385–418. https://doi.org/10.1007/s10668-016-9760-4.
Lee, K., 2021. Artificial Intelligence in Urban Planning: Case Studies and Applications. Springer.
Li, J., Eheliyagoda, D., Geng, Y., Yang, Z., Zeng, X., 2022. Examining the influence of copper recycling on prospective resource supply and carbon emission reduction. Fundam. Res.
Lu, W., Webster, C.J., Peng, Y., Chen, X., Chen, K., 2018. Big data in construction waste management: prospects and challenges. Detritus. ⟨https://hub.hku.hk/handle/10722/265995⟩.
Maalouf, A., El-Fadel, M., 2020. Novel software for optimizing emissions and carbon credit from solid waste and wastewater management. Sci. Total Environ. *714*, 136736.
Malinauskaite, J., Jouhara, H., Czajczyńska, D., Stanchev, P., Katsou, E., Rostkowski, P., Thorne, R.J., Colon, J., Ponsá, S., Al-Mansour, F., 2017. Municipal solid waste management and waste-to-energy in the context of a circular economy and energy recycling in Europe. Energy *141*, 2013–2044.
Martinez-Falco, J., 2022. Urban Mobility and Autonomous Systems: Challenges and Opportunities. IEEE Transactions on Intelligent Transportation Systems 23 (5), 2345–2358.
Medvedev, A., Fedchenkov, P., Zaslavsky, A., Anagnostopoulos, T., Khoruzhnikov, S., 2015. Waste Management as an IoT-Enabled Service in Smart Cities. Vol. 9247. In: Balandin, S., Andreev, S., Koucheryavy, Y. (Eds.), Internet of Things, Smart Spaces, and Next Generation Networks and Systems. Springer International Publishing, pp. 104–115. https://doi.org/10.1007/978-3-319-23126-6_10. Vol. 9247.
Pires, A., Martinho, G., 2019. Waste hierarchy index for circular economy in waste management. Waste Manag. *95*, 298–305.
Ramos, T.R.P., de Morais, C.S., Barbosa-Povoa, A.P., 2018. The smart waste collection routing problem: alternative operational management approaches. Expert Syst. Appl. *103*, 146–158.
Rolewicz-Kalińska, A., 2016. Logistic constraints as a part of a sustainable medical waste management system. Transp. Res. Procedia *16*, 473–482.
Romero-Hernández, O., Romero, S., 2018. Maximizing the value of waste: from waste management to the circular economy. Thunderbird Int. Bus. Rev. *60* (5), 757–764. https://doi.org/10.1002/tie.21968.
Rutqvist, D., Kleyko, D., Blomstedt, F., 2019. An automated machine learning approach for smart waste management systems. IEEE Trans. Ind. Inf. *16* (1), 384–392.
Salmenperä, H., Pitkänen, K., Kautto, P., Saikku, L., 2021. Critical factors for enhancing the circular economy in waste management. J. Clean. Prod. *280*, 124339.
Santos, A.A., da Silva, A.F., Gouveia, A., Felgueiras, C., Caetano, N., 2022. Reducing volume to increase capacity—measures to reduce transport energy for recyclable waste collection. Energies *15* (19), 7351.
Sarker, I.H., 2021. Machine Learning: Algorithms, Real-World Applications and Research Directions. Vol. 2 SN Computer Science. Springer. https://doi.org/10.1007/s42979-021-00592-x.
Saucedo Martinez, J.A., Mendoza, A., Alvarado Vazquez, M. del R., 2019. Collection of solid waste in municipal areas: urban logistics. Sustainability *11* (19), 5442.
Schultmann, F., Sunke, N., 2007. Energy-oriented deconstruction and recovery planning. Build. Res. Inf. 35 (6), 602–615.
Sen Gupta, Y., Mukherjee, S., Dutta, R., Bhattacharya, S., 2021. A blockchain-based approach using smart contracts to develop a smart waste management system. Int. J. Environ. Sci. Technol. 1–24.
Shah, P.J., Anagnostopoulos, T., Zaslavsky, A., Behdad, S., 2018. A stochastic optimization framework for planning of waste collection and value recovery operations in smart and sustainable cities. Waste Manag. *78*, 104–114.
Singh, J., Laurenti, R., Sinha, R., Frostell, B., 2014. Progress and challenges to the global waste management system. Waste Manag. Res. J. Sustain. Circ. Econ. *32* (9), 800–812. https://doi.org/10.1177/0734242X14537868.
Sundui, B., Ramirez Calderon, O.A., Abdeldayem, O.M., Lázaro-Gil, J., Rene, E.R., Sambuu, U., 2021. Applications of machine learning algorithms for biological wastewater treatment: updates and perspectives. Clean. Technol. Environ. Policy *23*, 127–143.
Taşkın, A., Demir, N., 2020. Life cycle environmental and energy impact assessment of sustainable urban municipal solid waste collection and transportation strategies. Sustain. Cities Soc. *61*, 102339.
The World Bank. (2023). What a Waste Global Database | Data Catalog. ⟨https://datacatalog.worldbank.org/search/dataset/0039597/What-a-Waste-Global-Database⟩.
Thürer, M., Pan, Y.H., Qu, T., Luo, H., Li, C.D., Huang, G.Q., 2019. Internet of Things (IoT) driven kanban system for reverse logistics: solid waste collection. J. Intell. Manuf. *30* (7), 2621–2630. https://doi.org/10.1007/s10845-016-1278-y.
Tomić, T., Schneider, D.R., 2020. Circular economy in waste management–Socio-economic effect of changes in waste management system structure. J. Environ. Manag. *267*, 110564.
Tsai, F.M., Bui, T.-D., Tseng, M.-L., Wu, K.-J., Chiu, A.S., 2020. A performance assessment approach for integrated solid waste management using a sustainable balanced scorecard approach. J. Clean. Prod. *251*, 119740.
Velis, C.A., Wilson, D.C., Gavish, Y., Grimes, S.M., Whiteman, A., 2023. Socio-economic development drives solid waste management performance in cities: a global analysis using machine learning. Sci. Total Environ. *872*, 161913.
Wang, D., Thunéll, S., Lindberg, U., Jiang, L., Trygg, J., Tysklind, M., Souihi, N., 2021. A machine learning framework to improve effluent quality control in wastewater treatment plants. Sci. Total Environ. *784*, 147138.
Xia, W., Jiang, Y., Chen, X., Zhao, R., 2022. Application of machine learning algorithms in municipal solid waste management: a mini review. Waste Manag. Res. J. Sustain. Circ. Econ. *40* (6), 609–624. https://doi.org/10.1177/0734242X211033716.
Yang, Z., Xue, F., Lu, W., 2021. Handling missing data for construction waste management: machine learning based on aggregated waste generation behaviors. Resour. Conserv. Recycl. *175*, 105809.
Zahedi, R., Daneshgar, S., Golivari, S., 2022. Simulation and optimization of electricity generation by waste to energy unit in Tehran. Sustain. Energy Technol. Assess. *53*, 102338.
Zhang, J., Mao, L., Nithya, K., Loh, K.-C., Dai, Y., He, Y., Tong, Y.W., 2019. Optimizing mixing strategy to improve the performance of an anaerobic digestion waste-to-energy system for energy recovery from food waste. Appl. Energy *249*, 28–36.
Zhang, D.Q., Tan, S.K., Gersberg, R.M., 2010. Municipal solid waste management in China: status, problems and challenges. J. Environ. Manag. *91* (8), 1623–1633.
Zhao, L., Dai, T., Qiao, Z., Sun, P., Hao, J., Yang, Y., 2020. Application of artificial intelligence to wastewater treatment: a bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. Process Saf. Environ. Prot. *133*, 169–182.
Zhu, S., Preuss, N., You, F., 2023. Advancing sustainable development goals with machine learning and optimization for wet waste biomass to renewable energy conversion. J. Clean. Prod. *422*, 138606.