International Journal of Environmental Impacts
Vol. 8, No. 1, February, 2025, pp. 41-51
Journal homepage: http://iieta.org/journals/ijei

MSW-DeepStack: Innovative Municipal Solid Waste Prediction Model for Informed Decision-Making

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https://doi.org/10.18280/ijei.080105

Received: 9 September 2024
Revised: 9 November 2024
Accepted: 2 December 2024
Available online: 28 February 2025

Keywords:
municipal solid waste, machine learning, deep learning, stacking, Gated Recurrent Units (GRU), XGBoost, Random Forest (RF)

ABSTRACT

Municipal solid waste (MSW) is a fundamental problem in today's urban environments, as its composition and quantity are constantly shifting due to many different influences. Sustainable waste management solutions could not be developed without reliable estimates of future waste generation. Predicting the amount of waste generated might assist authorities with decision-making and new technological approaches, such as machine learning and deep learning. In this study, a stacking ensemble of three models, namely, Grid Search Optimized XGBoost (GSO-XGBoost), Gated Recurrent Units (GRU), and Random Forest (RF) was proposed. The proposed MSW-DeepStack model outperforms the state-of-the-art algorithms by obtaining the highest R^2 values ranging between 0.61 and 0.9. Furthermore, the MSW-DeepStack model obtained the lowest error rates: MAPE (0.1%-10.6%), MAE (0.0163-0.1182), RMSE (0.0014-0.1225), and ME (0.0022-0.213). The proposed MSW-DeepStack model has superior results compared to the state-of-the-art models, thereby demonstrating its efficiency and sturdiness. Further, the proposed model predicted that Singapore would generate around seven million metric tons of MSW by 2030. This estimation would aid in improving the MSW management methods and assist the authorities in making well-informed choices by shedding light on long-term trends in waste production.

1. INTRODUCTION

Waste management is a global problem that impacts every single individual on the planet. Humans and animals alike have been dependent on Earth's natural bounty ever since the inception of human civilization. Consumption and secondary use of resources result in waste, which poses serious problems for communities. Waste has become inevitable as a result of a greater population, increased wealth, and higher levels of education [1-3]. Poor waste management has far-reaching impacts, including threats to ecosystems, human health, and biodiversity [4]. Hence, waste management has become an urgent environmental problem requiring quick attention and viable solutions. Agricultural, biomedical, chemical, radioactive, inert, and municipal solid wastes are some of the potential waste classifications. Among them, Municipal solid waste (MSW) is a major issue because of the sheer volume with which it is generated. According to the Global Waste Management Outlook 2024 report by the UN Environment Programme, global municipal solid waste generation is expected to grow from 2.1 billion tonnes in 2023 to 3.8 billion tonnes by 2050 [5]. Such massive waste production necessitates in-depth research and innovative approaches to manage MSW.

The city-state of Singapore serves as the focus of our investigation; it covers a total area of around 728.6 square kilometers and is home to about 6 million people. The economy of Singapore has flourished since it became independent in 1965, with the country recording low inflation and a positive balance of payments [6]. Therefore, the country now has one of the highest GDP per capita figures globally. Waste management is a significant issue despite a prosperous economy and an expanding population. During the late 1990s, Singapore experienced severe impacts on its air quality due to deteriorating conditions that affected the entire region, resulting in the infamous haze of September 1997 [7]. Concurrently, the nation's burgeoning industrial activities and individual prosperity contributed to an escalating waste management predicament. In response to these pressing environmental challenges, Singapore established the National Environment Agency (NEA) in 2002, with a primary focus on addressing these issues and fostering a greener and cleaner living environment. The disposal of waste and environmental preservation fall within its purview.

One of the significant initiatives undertaken by the NEA was the development of a Public Waste Collection (PWC) scheme. This scheme was devised to cater to the waste disposal needs of both domestic and trade premises across Singapore, which were strategically divided into geographical sectors. Waste is segregated at the source itself and sent for recycling. The non-recyclable waste is sent to the landfill. Despite its small land area, Singapore has found solutions for its landfill management. One of Singapore's primary approaches to waste management is generating energy by incinerating waste [8]. Semakau Landfill, the last remaining landfill site in Singapore, receives ash from the incinerator and other wastes that cannot be either recycled or incinerated. Semakau landfills and incineration have played crucial roles in waste management, but they have also raised challenges that need to be carefully considered and addressed [9]. Due to land scarcity and the possible negative effects of incineration emissions and ash disposal, the current waste management strategy of the state needs careful examination. A more circular economic model requires addressing the sources of waste production, thereby encouraging waste minimization and recycling efforts [10].

The purpose of this study is to examine and forecast the overall waste production rate of Singapore, with an emphasis on MSW. To accomplish this, cutting-edge Machine Learning (ML) and Deep Learning (DL) techniques were utilized to analyze complex datasets and create accurate models of waste generation. Even before two decades, researchers used time series prediction to better handle the MSW generations [11, 12]. To improve the efficiency of the prediction model, a combination of ML and DL models was executed on the univariate time series dataset. The rest of the article is structured as follows: Section 2 describes the related works; the dataset is described under Section 3; Section 4 visualizes the descriptive analytics, while the proposed methodology is explained under Section 5. The results are discussed in Section 6, and Section 7 explains the conclusion of the study.

2. LITERATURE SURVEY

This section explores the latest advancements and applications of ML and DL in predicting the MSW generation rate, paving the way for more sustainable and viable solutions. The municipal solid waste generation in Thailand was predicted using the grey model (GM) by Li et al. [13]. Multivariate and univariate applications of GM were performed, with factors like population density, GDP per capita, household expenditure, and household size taken into account. The models with the smallest Mean Absolute Percentage Error (MAPE) were GM(1,1) and GM(1,3), with values of -0.1 and 2.124, respectively. The study estimates a 10–25% rise in garbage generation from 2018 to 2030. MSW was quantified by Mensah et al. [14] using data gathered from both residential and commercial locations in Ethiopia. When compared to other models, the Multi-Linear Regression model fared the best with a coefficient of determination of 0.72. The GDP per capita is inversely proportional to the number and size of municipal solid waste disposal facilities, according to research by Khanal [15]. The facility type most desired varies from region to region, with some areas preferring incineration and others preferring landfills. The study highlights the need for updated waste management policies, procedures, technology, and administration in China.

The Waste Management Output Index (WMOI), the Diversion Gross Domestic Product (DGDP) ratio and the Current spending per ton handled (CuPT) were applied to evaluate the efficiency of waste management systems in Canada [16]. To facilitate the comparison of jurisdictions, an additive weighting technique was adopted. The study observed increasing WMOI tendencies in most regions aside from Nova Scotia and decreasing DGDP ratio tendencies across all jurisdictions except for Nova Scotia. In addition, CuPT tendencies showed that Saskatchewan and Alberta were more productive than other provinces. Kathmandu Metropolitan City (KMC) in Nepal utilized linear regression analysis to examine the rising trend of the MSW generation rate [17]. There is a strong relationship between population size and the amount of trash produced. Using Artificial Neural Network Multi-Layer Perceptron (ANN-MLP), Support Vector Regression (SVR), and Random Forest (RF) with an autoencoder (AE), Islam et al. [18] proposed a hybrid ML model to forecast demolition waste management. The hybrid model, especially the AE-ANN model, significantly improved the performance of the ANN model, reducing the error rate by 27%.

A comprehensive survey analyzed ML techniques implemented for managing waste within smart cities, focusing on waste generation and disposal phases [19]. The survey exposed various challenges in this field, including the lack of real-time data availability, the absence of standardized benchmarking tests for evaluating ML models, and the need for well-defined long-term waste management plans. Islam et al. [18] conducted a study to predict yard waste generation in Winnipeg, Canada, using quarterly data [20]. They implemented the grey models GM(1,1) and GM(1, N) to predict individual and multivariate factors, respectively. Both models outperformed linear and non-linear models, achieving low MAPE values. The MAPE for in-sample data ranged from 0.06% to 10.39% for GM(1,1) and from 5.64% to 7.54% for GM (1, N). Lu et al. developed the WGMod, an advanced ML model to predict MSW generation in China [21]. WGMod identified key influencing factors such as annual precipitation, population density, and annual mean temperature, achieving an R^2 value of 0.939.

Bayesian-optimized ANN models with ensemble uncertainty analysis were used to predict heterogeneous MSW generation rates [22]. The study demonstrated a correlation between MSW physical composition and other indices, resulting in more reliable predictions with lower relative standard deviations. The study report suggests that 42,873 tons per day (t/d) of municipal solid waste will be produced in Malaysia by 2030, with 44% of it being food waste. Wu et al. [23] proposed an optimized ANN coupled with the Particle Swarm Optimization (PSO) algorithm to forecast waste quantities in Poland. The ANN-PSO model outperformed the conventional ANN model in terms of the coefficient of efficiency (CE)-0.11. In Vietnam, the solid waste generated from selected residential areas was evaluated using six different ML models [24]. Among them, Random Forest (RF) and k-nearest neighbors (KNN) performed better with an R^2 of 0.96-0.97.

Cubillos [25] developed and optimized an ANN model to predict municipal solid waste (MSW) generation rates in mainland China, considering regional variations. The study found that regional differences had a major impact on MSW prediction and suggested that building out regional models independently might improve predictive capability. After dividing the regions into southern, northern, and western, the outcome improved from R^2 0.916 and RMSE 59.3 to R^2 0.968/0.946/0.943 and RMSE 6.4/9.7/17.6, respectively. In Nagpur, India, the monthly data was analyzed using non-linear autoregressive neural models [26]. A couple of NAR models were set with different hidden layers, and both models performed better with lower absolute maximum errors of 6.45% and 3.05%. A multi-site Long Short-Term Memory (LSTM) neural network was utilized to analyze historical data of weekly waste weights from households in Herning, Denmark [27]. The study demonstrated that the adoption of a multi-site approach enhances the forecasting performance of the LSTM model by an average of 28%. Moreover, the LSTM models outperformed traditional methods such as ARIMA, demonstrating an average improvement of 85%.

Kannangara et al. [28] compared six different ML models to forecast MSW in India. A hybrid model of Genetic Algorithm (GA) and ANN was found to be the best performer with an R^2 value of 0.87. The fuzzy logic method was utilized to investigate the socio-economic components of MSW generation in China [29]. Due to the limited dataset, the GM (1, 1), Linear Regression, and ANN models were chosen for accurate forecasting. The GM (1, 1) model is suitable for short datasets as it accounts for the lack of social and other predictor values, while Linear Regression performs well on larger historical datasets. On the other hand, ANN is effective for short datasets, capturing patterns and data relationships to generate outputs. The ANN model and Decision Tree (DT) were implied to evaluate MSW, paper, leaf, yard, and kitchen organic wastes, along with socio-economic factors [30]. The ANN model performed better with the R^2 of 0.72 for MSW, and the population, education and income were highly correlated with the waste generation rate. To predict the generation of MSW, a waste prognostic tool, regression, and time series analysis were employed [31]. The authors concluded that the biodegradable waste content would be the fraction with the highest percentage.

To tackle the escalating issue of MSW, it is evident that ML and DL techniques have become indispensable instruments. These approaches offer a comprehensive array of tools to enhance the precision of waste prediction and uncover fundamental influencing elements. By employing these methodologies to navigate intricate datasets, scholars are striving to unveil intricate correlations between waste generation and diverse socio-economic and environmental variables.

3. DATASET DESCRIPTION

The National Environment Agency (NEA) provides a comprehensive historical dataset on the total amount of solid waste generated in Singapore. The solid waste data from 2003 to 2023 was sourced from the site "data world" and NEA's official site [32, 33]. The dataset offers valuable year-on-year information, including the total waste generated, waste disposed of, waste recycled, and corresponding recycling rates. It covers both domestic and non-domestic types of municipal solid waste, encompassing categories like ash and sludge, construction and demolition debris (C&D), ferrous metals (FM), food waste, glass, horticultural waste, non-ferrous metals, paper and cardboard (P&C), plastics, scrap tyres, stones, ceramics, rubber, textiles and leather, used slag, and wood and timber. However, to ensure the relevance and effectiveness of the analysis, certain attributes that did not significantly impact the study were removed during the preprocessing phase.

The final MSW dataset is made up of a total of fourteen datasets, each of which contains year-on-year records, and the associated total waste generated, measured in tons for the aforementioned waste categories. This dataset serves as a valuable resource for studying and understanding solid waste trends and recycling rates over time. The dataset is univariate time series data focusing on annual waste generation. Table 1 summarizes the key attributes of the dataset, including the year of data collection and the total waste generated each year.

Table 1. Dataset description

S. No.	Parameter	Data Type
1	Year	Date
2	Total Waste Generated (TWG) in tons	Integer

4. DESCRIPTIVE ANALYSIS

Despite the challenges caused by digitization and the COVID-19 pandemic, all fourteen datasets exhibited a downward trend. However, they remain a major factor in the production of MSW. Figure 1 shows the total waste generation from 2003 to 2023, while Figure 2 shows the average annual rate of recycling. Over this period, both garbage generation and recycling rates rose gradually from 2003 until 2013, after which they leveled off. In 2013, the global recycling rate peaked at 62%. By 2014, however, both waste produced and recycling rates had decreased by 4.3% and 7.4%, respectively. In the same year, there was a significant drop in the amount of construction and demolition (C&D) waste recycled, which accounted for 25% of the overall decline in recycling compared to that of 2013. This drop was the first in a decade, and it was the result of the NEA's persistent advocacy for waste recycling programs.

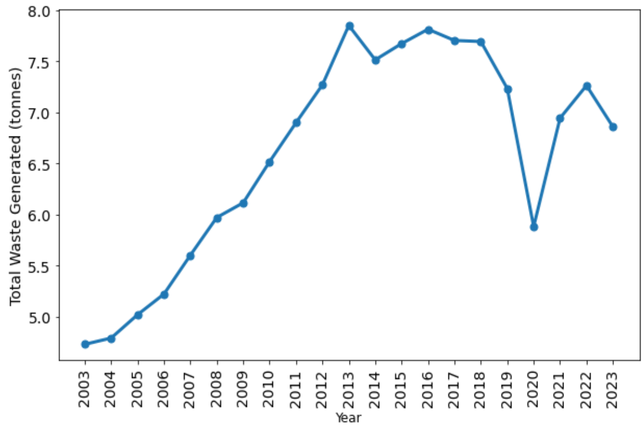

Figure 1. Total waste generated in Singapore between 2003 and 2023

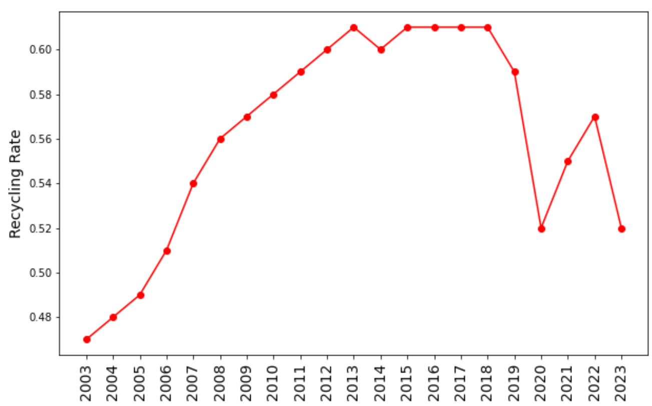

Figure 2. Average waste recycling rate of Singapore between 2003 and 2023

Due to extrinsic factors such as the COVID-19 pandemic, subsequent years witnessed additional fluctuations. Solid waste generation in Singapore fell for the second year in a row in 2020, down to about 5.88 Million Metric Tons (MMT) from 2019. This represented a 19% decrease from 2019. The total amount was almost identical to that which was discarded in 2008. There was a decline from 73% in 2019 to 68% in 2020 in the non-domestic sector and a decline from 17% to 13% in the domestic sector over the same time. The worldwide outbreak created an economic slowdown in 2020, which in turn affected the generation and recycling of ferrous metal scrap and construction and demolition debris.

In contrast, the production of waste reached 6.94 MMT in 2021, an 18% increase over 2020. The rise was attributed to the increase in economic activity. While the aggregate recycling rate for waste generated in 2021 increased to 55% from 52% in 2020, it did not reach the 2019 level before the pandemic. In the year-on-year analysis, the non-domestic sector envisioned its recycling rate rising from 68% to 70%, while the domestic sector remained at 13%. More waste was generated in Singapore in 2022, the second consecutive year of increase as economic activity continued to pick up. Both non-domestic and residential waste production rose from 2021 to 2022, from 5.12 Mt to 5.53 Mt and 1.82 MMT to 1.86 MMT, correspondingly. In 2022, the recycling rate increased to 57% from 55% the previous year. This rise is attributable to the greater amounts of construction and demolition waste generated by an increase in demolition projects. Thus, these inferences highlight that the waste generation rate would increase in tandem with the economy and population.

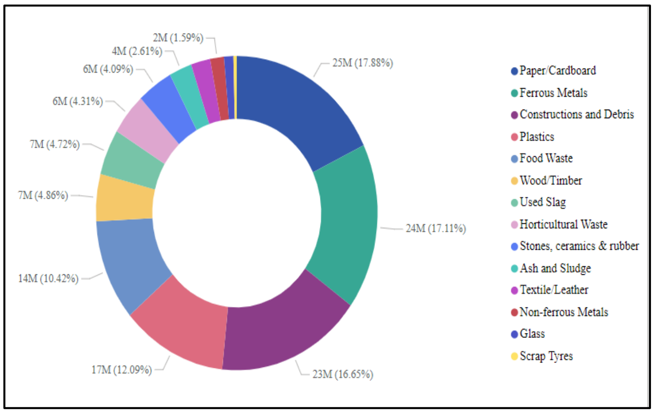

Figure 3. Total waste generated based on the category

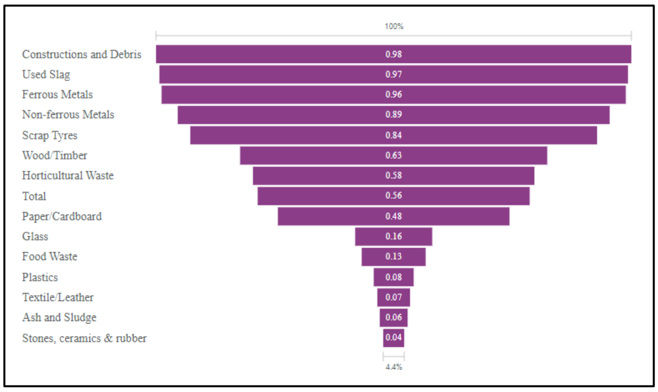

Figure 4. Average waste recycling rate based on the category

Upon analyzing Figure 3 and Figure 4, it becomes apparent that Paper & Cardboard (P&C) waste constitutes a significant portion, amounting to approximately 25 MMT. However, only half of this waste is recycled, while the rest is either sent to landfills or waste-to-energy convertible plants. Similarly, the quantities of ferrous metals and C&D waste are almost equal, each contributing around 22 MMT. Subsequently, their recycling rates are also similar, at approximately 96% and 98%, respectively. On the other hand, used slag demonstrates a high recycling rate of 97%. Out of a total waste generation of 6.54 MMT, a substantial amount (6.3 MMT) is being recycled, showcasing efficient recycling practices for this waste material. Additionally, plastic waste accounts for an estimated 16.75 MMT of total waste production, of which only 1.67% was recycled during the 20 years.

Despite the issue of food insecurity affecting a segment of the population, it is noteworthy that the overall food waste in Singapore remains significant at approximately 14 MMT. However, only 13% of the food waste was recycled, indicating that a considerable amount of food is being discarded and wasted. The recycling rate of wood and timber waste is 63%, with a total waste production of 6.73 MMT, almost 4.67 MMT of which is recycled. The horticultural waste production rate was 6 MMT, of which 2.4 MMT of waste was sent to landfills. Similarly, stones, ceramics, and rubber wastes were produced in a lesser amount of 5.66 MMT, of which only 4% were recycled. This waste type has the lowest recycling rate among both domestic and non-domestic waste, as it includes a mix of miscellaneous waste categories that require distinct management and recycling approaches.

Among the waste types, ash and sludge waste have the second lowest recycling rate, with only 6% of the total production of 2.65 MMT being recycled. The overall waste production from the textile and leather sector is 3.06 MMT, and although the amount of waste is less, it has been growing significantly in the modern era. Non-ferrous metal waste is produced in a relatively small amount of 2.19 MMT, but due to its higher recycling rate, approximately 89% of the total waste produced is recycled. Meanwhile, glass waste has a recycling rate of 16% and a total production of 1.48 MMT, making it the second least produced waste type. Scrap tires are the least produced waste type, with only 0.52 MMT of waste generated, of which almost 84% is recycled.

The insight produced by the descriptive study indicates that addressing the challenges in MSW is necessary. The suboptimal recycling rates of various waste types, such as stones, ceramics and rubber, ash and sludge, and textile waste emphasize the demand for novel forecasting techniques to direct the waste management strategies. Hence, to effectively deal with the escalating problems in handling waste, research on waste generation forecasting is vital.

5. PROPOSED METHODOLOGY

The proposed MSW-DeepStack model is a stacking-based algorithm. Stacked generalization is an ensemble learning technique that combines multiple algorithms to enhance predictive performance. Stacking aims to learn from the predictions of several base models by training a meta-model on top of them. The meta-model takes the outputs of the base model as input and provides the final prediction. In the MSW-DeepStack model, at the initial level, the predictions are generated by the eXtreme Gradient Boosting (XGBoost) and

Gated Recurrent Unit (GRU) models while the Random Forest (RF) model acts as the meta-regressor. Since the Grid Search Optimized-XGBoost (GSO-XGBoost) model surpassed the standard XGBoost model [34-36], it was adapted. The flow diagram of the proposed MSW-DeepStack model is depicted in Figure 5.

The implied datasets follow a univariate time sequence, where the temporal data pattern varies with time, resembling nonlinearity. Thus, the XGBoost model was employed as it performs better with non-linear data patterns. Additionally, the XGBoost model is a parallelized and optimized version of the gradient boosting model. It excels by using an ensemble of weak learners to generalize other models, optimizing arbitrary differential loss functions. To prevent overfitting, the XGBoost model incorporates Lasso (L1) and Ridge (L2) regularization methods. The objective function of XGBoost combines a loss function, measuring the disparity between predicted and actual values tailored to the specific task, with a regularization term controlling model complexity. Eq. (1) outlines the objective function that needs minimization at each iteration to find optimal weights for weak learners:

$$Obj^{(i)} = \sum_{a=1}^{m} l\left(y_a, \hat{y}_a^{(i)}\right) + \sum_{a=1}^{i} \Omega(f_a) \tag{1}$$

Calibrating the complexity of this objective function is crucial for tuning the bias/variance trade-off. The regularization term, represented by Eq. (2), incorporates parameters λ and γ and depends on the number of leaves (T) in the tree:

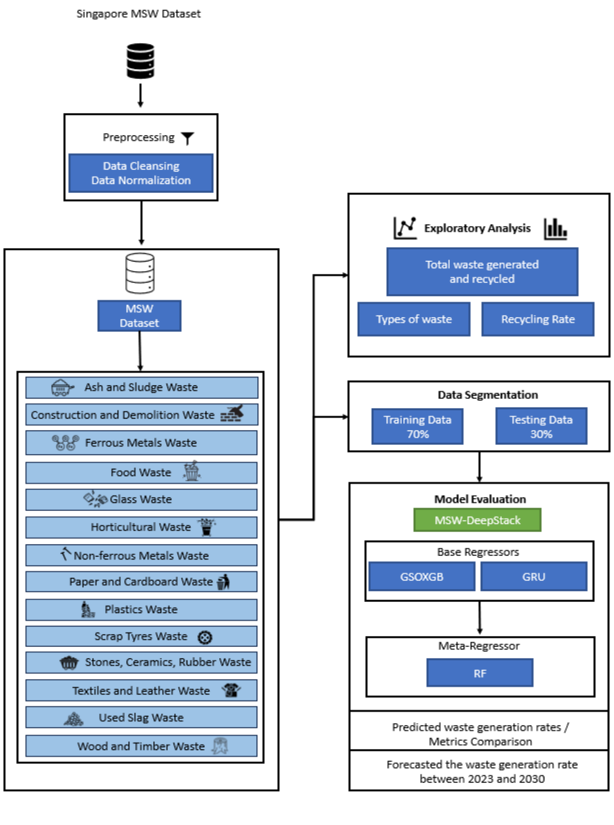

Figure 5. Flow diagram of the proposed MSW: DeepStack model

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{b=1}^{T} (w_b)^2 \tag{2}$$

As the error is often a complex and non-linear function, second order Taylor's expansion is used to linearize it. The specific objective at iteration i, which becomes the optimization goal for the new tree, is represented in Eq. (3).

$$Obj^{(i)} = \sum_{a=1}^{m} \left[g_a f_i(x_a) + \frac{1}{2} h_a {f_i}^2(x_a) \right] + \Omega(f_i) + c \tag{3}$$

Here, g_a and h_a are first and second-order derivatives of the loss function, respectively. $f_i(x_a)$ is the output of the i^{th} weak learner for the data point x_a and $\Omega\ (f_i)$ denotes the regularization term. The optimal leaf value $w_b^* = -\frac{G_b}{H_b + \lambda}$ concerning the objective function, where G_b and H_b represent the sum of gradient and Hessian of training points attached to the node b. The reduction in the objective function with this optimal parameter is denoted as $obj^* = -\frac{1}{2}\sum_{b=1}^{M} \frac{{G_b}^2}{H_b + \lambda} + \gamma T$. The choice of the right split value involves a brute force approach, pruning approaches with gain less than γ. The predicted value from the XGBoost model is stored as $W\_XG(x)$ using Eq. (4).

$$Gain = -\frac{1}{2}\left[\frac{G_l}{H_l + \lambda} + \frac{G_r}{H_r + \lambda} - \frac{(G_l + G_r)^2}{H_l + H_r + \lambda}\right] - \gamma \tag{4}$$

Grid Search Optimization (GSO) systematically explores parameter spaces for univariate time series forecasting. The model is fitted for various parameter combinations, and performance is assessed using metrics to identify optimal parameters. Therefore, in this research, the hyperparameterized XGBoost (GSO-XGBoost) model is used as the first base layer. Hyperparameters such as n_estimators and max_depth are optimized using GSO. The GSO model identified the optimum max_depth as 3, and n_estimators as 100 for the MSW dataset.

The second base model, GRU, is chosen for its efficiency with smaller datasets (Kostadinov, 2019). GRU incorporates update and reset gates to address vanishing gradient problems. The update gate (U_g) and reset gate (R_g) are calculated using sigmoid functions. The final memory at the current timestep (h_t) is determined by combining information from the update and the candidate hidden state H_{cand} using Eq. (5).

$$h_t = \left(1 - U_g\right) \odot H_{cand} + U_g * h_{prev} \tag{5}$$

The predictions obtained from both base models are combined to create a stacked dataset. Subsequently, the meta-regressor is applied to this combined dataset. Random Forest is a meta-estimator that fits several decision trees on various sub-samples of the dataset and employs averaging to enhance predictive accuracy while controlling overfitting issues. Therefore, Random Forest models were selected as the meta-regressor for the proposed MSW-DeepStack model. The Random Forest model is initiated as a meta-regressor by creating an empty list, RF, to store decision trees (Rastogi, 2020). For each tree (t), a bootstrap sample B(t) is formed by randomly selecting samples with replacements from the combined dataset. Decision trees are created by recursively dividing the data based on optimal features and split points, controlled by parameters like max_depth and min_samples_split. Trained trees are added to the RF list, forming the final Random Forest model. Predictions on the combined data are made by each decision tree, and the outputs are averaged to create W_RF(x). The MSW-DeepStack model combines these outputs to generate stacked predictions, MSW-DeepStack(x), as the final result.

6. EXPERIMENTS AND RESULTS

The attribute "total waste generated" for each data type was measured in tons. The dataset was cleansed by converting duplicate names into unique ones and eliminating redundant entries. To facilitate easier access and computation, this attribute was normalized by dividing the column with all its values by one million. The MSW dataset was then prepared in a suitable format for time series forecasting, where the data is divided into input sequences and target values using a rolling window approach. When the lookback is specified, the function forms input sequences with 1 past time step, adding a time step dimension to each sample. As a result, the original 2D arrays representing the input data are transformed into 3D arrays with the additional time step dimension, which is required for certain forecasting models like GRU. The MSW dataset was then split into two segments: 14 years (2003-2017) allocated for training, and 6 years (2018-2023) designated for testing, following a 75:25 ratio. Since the rolling window approach was utilized, the last data point of the MSW dataset was omitted.

The architecture MSW-DeepStack model analyzes the most prevalent categories of MSW, and employs a fusion of Machine Learning (ML) and Deep Learning (DL) techniques. These methods were employed to extract meaningful patterns and insights from the data. The architecture of the MSW-DeepStack model is structured as a two-tiered framework. In particular, the performance of the model was significantly elevated by integrating the Grid Search Optimized XGBoost model (GSO-XGBoost) as opposed to the conventional XGBoost model [37-40]. In light of this enhancement, the initial phase entailed applying the GSO-XGBoost model to all fourteen MSW datasets. Thus, the GSO-XGBoost and GRU models were coupled for optimal performance in the first tier. The key output of this combination was the column stacking of GSO-XGBoost prediction and GRU prediction. This stacked columnar data was meticulously constructed to be used as the input for the subsequent tier. A meta-regressor, in this case a Random Forest (RF), is used in the second phase of the model. This RF model operates on the column-stacked predictions obtained from the first tier. The role of the RF model in this architecture is to utilize the combined predictive power of the initial GSO-XGBoost and GRU models, thereby refining the overall predictive accuracy of the MSW-DeepStack model. Overall, the innovative architecture of the MSW-DeepStack model capitalizes on the strengths of GSO-XGBoost, GRU, and RF models, resulting in a comprehensive solution for addressing the challenges of MSW quantity prediction. Each of the fourteen unique MSW datasets was run through the MSW-DeepStack model to improve the quantity of waste forecasting.

6.1 Evaluation metrics

The key performance indicators such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Maximum Error (ME), and R-Squared error (R^2) were utilized to mathematically represent the above-mentioned KPIs (refer to Eqs. (6)-(10)).

$$MAPE = \left[\frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_a, \hat{y}_a}{y_a}\right|\right] * 100 \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_a, \hat{y}_a| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_a, \hat{y}_a)^2} \tag{8}$$

$$ME = Max_a|y_a, \hat{y}_a| \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_a, \hat{y}_a)^2}{\sum_{i=1}^{N}(y_a, \bar{y})^2} \tag{10}$$

where, y_a is the actual value at time a, $\hat{y}_a$ is the predicted value at time a, $\bar{y}$ is the Mean target value, and N is the number of data points.

The observed pattern of ash and sludge waste reached a high in 2016, pointing to a considerable rise in trash creation that could most likely be linked to industrial activity or development. Since then, the pattern has stabilized, suggesting a constant output of trash (refer to Figure 6). Significantly, the GRU model had the highest MAPE, at 13%, of all models. The MAPE values of 3.75% and 3.45% were recorded by the Random Forest and GSO-XGBoost models, respectively, indicating moderate performance. The proposed MSW-DeepStack model performed exceptionally well, with a MAPE of 0.27%.

As shown in Figure 7, C&D debris increased over time, though this trend was slowed by the pandemic. RMSE values of 0.5070, 0.4255, and 0.5117 were attained by the GSO-XGBoost, Random Forest, and GRU models, respectively, indicating inadequate performance. In contrast, with an RMSE of 0.1225, the MSW-DeepStack model substantially outscored the other models. A similar upward trend was seen in Figure 8 which displays the ferrous metal wasted over time. ME values of 0.34 and 0.44 were seen in the GRU, Random Forest and GSO-XGBoost models, while the ME value of 0.1 was observed in the proposed model, which is a significant improvement. Tables 2 (a)-(d) represent results obtained from the employed models.

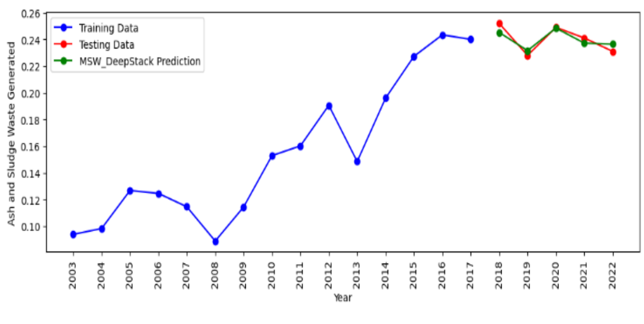

Figure 6. Ash and sludge waste

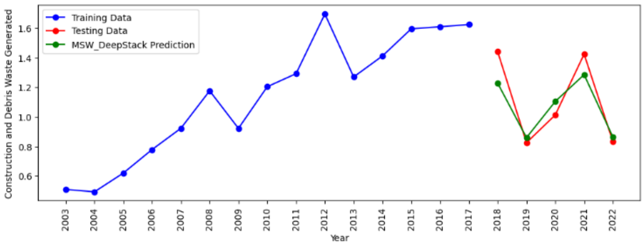

Figure 7. Construction and debris waste

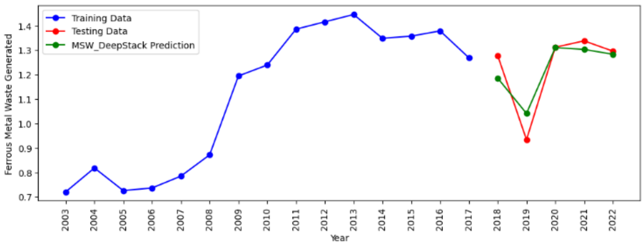

Figure 8. Ferrous metal waste

Table 2. (a) Results of GSO-XGBoost

	MAPE	MAE	RMSE	ME
Ash and Sludge	0.03450	0.0082	0.0093	0.0128
Construction and Debris	0.4491	0.4116	0.5070	0.7724
Ferrous Metals	0.1444	0.1524	0.2156	0.4498
Food Waste	0.0937	0.0695	0.0828	0.1289
Glass	0.0842	0.0060	0.0068	0.011
Horticultural Waste	0.3378	0.0831	0.1384	0.2982
Non-Ferrous Metals	0.3115	0.0276	0.0334	0.0603
Paper and Cardboard	0.0656	0.0733	0.0854	0.1203
Plastics	0.1263	0.1217	0.1303	0.1751
Scrap Tyres	0.2534	0.0064	0.0073	0.0114
Stones, ceramics & rubber	0.2166	0.0466	0.0583	0.0978
Textile and Leather	0.2041	0.0429	0.0528	0.0974
Used Slag	0.8634	0.1193	0.1230	0.1657
Wood and Timber	0.1925	0.0740	0.0917	0.1748

Table 2. (b) Results of GRU

	MAPE	MAE	RMSE	ME
Ash and Sludge	0.13	0.0317	0.0345	0.0497
Construction and Debris	0.3814	0.3596	0.4255	0.6299
Ferrous Metals	0.1340	0.1481	0.2122	0.3422
Food Waste	0.0755	0.0567	0.0712	0.126
Glass	0.0521	0.0037	0.0038	0.0044
Horticultural Waste	0.1345	0.0354	0.0448	0.0867
Non-Ferrous Metals	0.1475	0.0131	0.0157	0.0294
Paper and Cardboard	0.078	0.0861	0.0960	0.1334
Plastics	0.0628	0.0610	0.076	0.1377
Scrap Tyres	0.22	0.0062	0.007	0.0117
Stones, Ceramics & rubber	0.181	0.0383	0.0484	0.0858
Textile and Leather	0.1761	0.0362	0.0465	0.0878
Used Slag	0.6413	0.0873	0.0941	0.1274
Wood and Timber	0.1897	0.073	0.0883	0.1335

Table 2. (c) Results of RF

	MAPE	MAE	RMSE	ME
Ash and Sludge	0.0375	0.0091	0.01	0.016
Construction and Debris	0.433	0.3914	0.5117	0.7934
Ferrous Metals	0.1644	0.1794	0.2409	0.4421
Food Waste	0.094	0.0695	0.0818	0.1296
Glass	0.0865	0.0063	0.0068	0.0109
Horticultural Waste	0.2693	0.0675	0.0971	0.205
Non-Ferrous Metals	0.2598	0.0216	0.0333	0.0697
Paper and Cardboard	0.0606	0.0674	0.0811	0.1243
Plastics	0.1142	0.1103	0.1196	0.1637
Scrap Tyres	0.2142	0.0054	0.0064	0.0118
Stones, Ceramics & rubber	0.2121	0.0452	0.0565	0.0986
Textile and Leather	0.2013	0.0424	0.0527	0.0977
Used Slag	0.9148	0.1269	0.1303	0.1733
Wood and Timber	0.1707	0.0667	0.087	0.1541

Table 2. (d) Results of MSW-DeepStack

	MAPE	MAE	RMSE	ME
Ash and Sludge	0.004	0.0168	0.0045	0.0068
Construction and Debris	0.1016	0.0828	0.1225	0.213
Ferrous Metals	0.0498	0.0448	0.0654	0.1071
Food Waste	0.02	0.0266	0.0205	0.0251
Glass	0.0011	0.0163	0.0014	0.0022
Horticultural Waste	0.0214	0.0748	0.0245	0.0348
Non-Ferrous Metals	0.0066	0.0689	0.0075	0.0115
Paper and Cardboard	0.0423	0.0383	0.0485	0.0786
Plastics	0.017	0.018	0.0182	0.0255
Scrap Tyres	0.0013	0.0473	0.0019	0.0033
Stones, Ceramics & rubber	0.0086	0.0398	0.0094	0.0133
Textile and Leather	0.0213	0.1182	0.0246	0.0357
Used Slag	0.0144	0.1043	0.0152	0.0223
Wood and Timber	0.0347	0.0967	0.0355	0.048

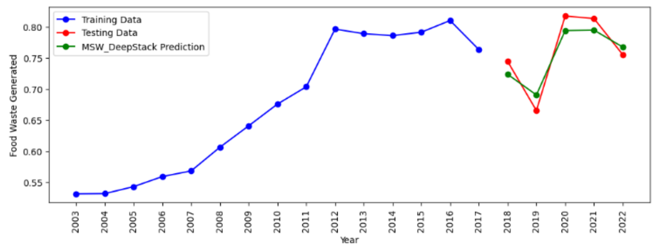

Figure 9. Food waste

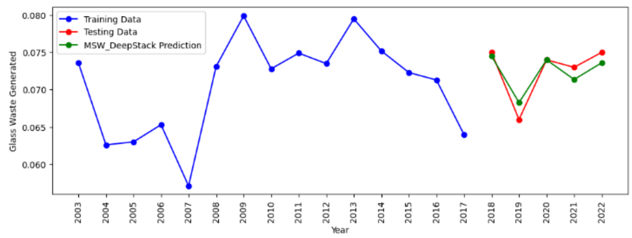

Figure 10. Glass waste

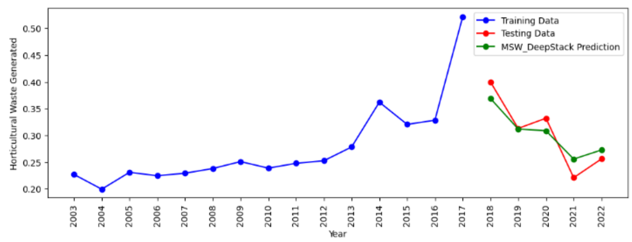

Figure 11. Horticultural waste

Regarding food waste (see Figure 9), the MAPE values for the optimized XGBoost and Random Forest models hover around 9.3%, while the MAPE for the GRU model is closer to 7.5%. The proposed MSW-DeepStack model performed exceptionally well, with a much lower MAPE than the state-of-the-art model. As consumer and production practices shift, so do the seasonal patterns of glass debris which are represented in Figure 10. The MSW-DeepStack fared best of all used models, with an MAE of 0.0163, an RMSE of 0.0014, and a ME of 0.0022. While the GSO-XGBoost model showed a ME of 0.011, the RF model only dropped to 0.0109. The GRU model outperformed GSO-XGBoost and RF, however, it was still inferior to the proposed model as its ME was only 0.0044. In 2017, there was an uptick in the rate of discarded garden materials, but the trend has since leveled off (refer to Figure 11). The RMSE values for the GSO-XGBoost, RF, and GRU models ranged from 0.1384, 0.0448, and 0.0971, which is comparable but not remarkable. The proposed MSW-DeepStack model, on the other hand, was superior, with an RMSE of 0.0245. This further demonstrates its superiority in reducing discrepancies between forecasted and observed values.

The statistics shown in Figure 12 represent a seemingly random trend for non-ferrous metal waste. Compared to other models, both GSO-XGBoost and RF showed moderately higher ME values (0.06 and 0.069, respectively). With an ME of 0.029, the GRU model outperformed GSO-XGBoost and RF in terms of prediction accuracy. Meanwhile, the MSW-DeepStack model emerged as the most favourable choice, achieving a negligible ME of 0.0115. P&C waste illustrated in Figure 13 denotes a complex pattern in numbers. The proposed MSW-DeepStack model achieved the highest MAPE (4.2%) among the models appraised. The MAPE values for the GSO-XGBoost, GRU and RF models, on the other hand, were 6.5%, 6% and 7.8%, respectively.

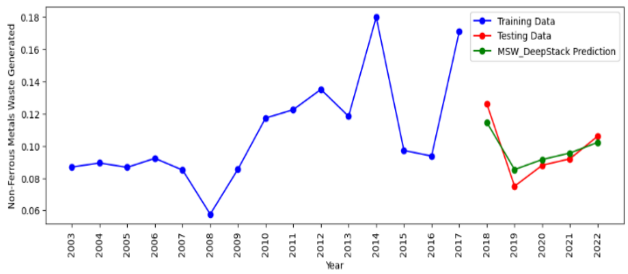

Figure 12. Non-ferrous metal waste

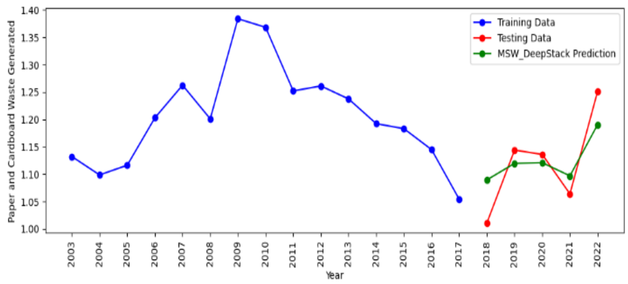

Figure 13. Paper and cardboard

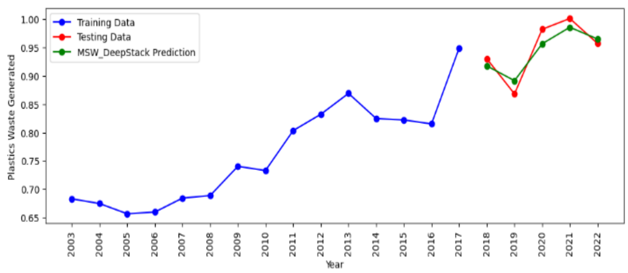

Figure 14. Plastics

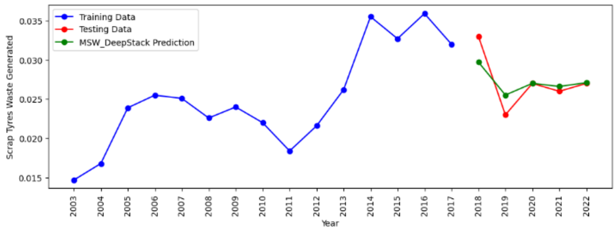

Figure 15. Scrap tyres

Over the past decade, there have been distinct trends in the data on plastic trash (refer to Figure 14). The GSO-XGBoost and RF models performed moderately, with MAPE values of 12.7% and 11.4%, respectively, while the GRU model performed better, with a MAPE value of 6.2%. Particularly, the proposed MSW-DeepStack model performed the best of all models tested, with a MAPE of 1.7%. Although scrap tyres are discarded in modest numbers, the associated data structure is intricate (as illustrated in Figure 15). Compared to the other models, MSW-DeepStack performed the best, with a ME of 0.0033. GSO-XGBoost, RF, and GRU all produced ME values of 0.0114, 0.0117, and 0.0118, respectively.

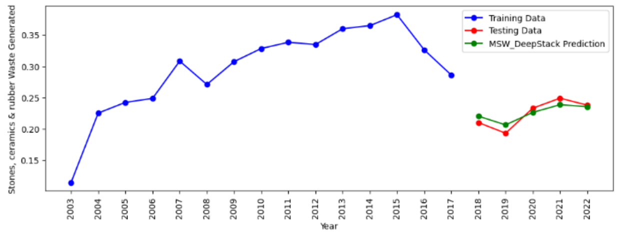

Figure 16. Stones, ceramics & rubber

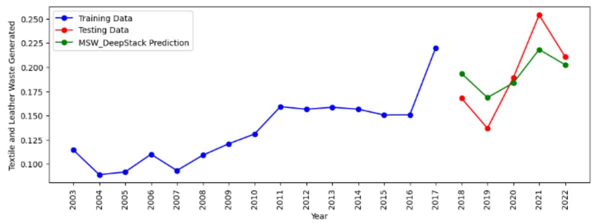

Figure 17. Textile and leather

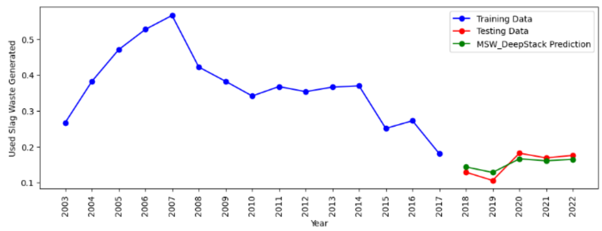

Figure 18. Used slag

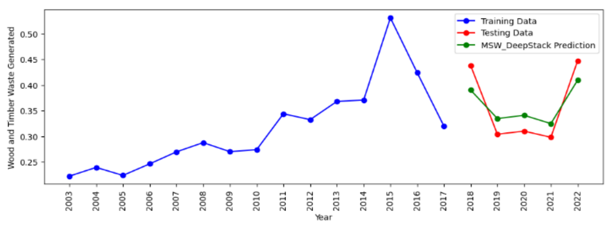

Figure 19. Wood and timber

Waste quantities of stones, ceramics, and rubber showed a linear trend until 2017, then declined, as displayed in Figure 16. When compared to the GSO-XGBoost, RF, and GRU models, the proposed model's predictions for this type of waste had the lowest MAPE (8.6%), MAE (0.0398), RMSE (0.0094), and ME (0.0133). Waste materials from the textile and leather industries, as well as used slag and timber and wood, exhibited seasonal patterns (refer to Figures 17-19). The MSW-DeepStack model worked quite well, with lower RMSE values of 0.0246, 0.0152, and 0.0355, even for waste with such seasonal data patterns. Comparatively higher RMSE, MAPE, MAE, and ME values indicated that the performance of the remaining models was merely average.

The MSW-DeepStack model exhibits better accuracy and reduced error rates in several metrics, such as RMSE, MAPE, MAE, and ME. Reliability in capturing actual waste generation numbers is improved by a reduced MAE, which indicates that the model regularly makes smaller average errors. The decreased ME emphasizes forecasting stability by showing fewer extreme prediction deviations. Furthermore, a lower RMSE indicates less error variation, which aids in precisely simulating data oscillations. In the same way, the suggested model's exceptionally low MAPE demonstrates its great accuracy in identifying genuine waste generation trends with little departure from actual values. Together, these metrics illustrate the MSW-DeepStack model's robustness, making it a valuable tool for precise municipal solid waste management predictions.

Table 3. R^2 Value obtained by MSW-DeepStack model

Waste Type	R^2 Score (MSW-DeepStack)
Ash and Sludge	0.8
Construction and Debris	0.8
Ferrous Metals	0.81
Food Waste	0.86
Glass	0.9
Horticultural Waste	0.84
Non-Ferrous Metals	0.81
Paper and Cardboard	0.64
Plastics	0.84
Scrap Tyres	0.7
Stones, ceramics & rubber	0.8
Textile and Leather	0.61
Used Slag	0.74
Wood and Timber	0.72

Further, the R^2 values for the MSW-DeepStack model were superior for all used datasets, falling between 0.6 to 0.9 as represented in Table 3. The best R-squared value was 0.9, and it was found in the glass waste dataset, which exhibits a linear trend. The second-highest R^2 value of 0.86 was achieved for food waste, indicating strong predictive accuracy for this dataset. Both horticultural waste and plastic waste datasets secured the third-highest R^2 value of 0.84. In contrast, lower R^2 values were recorded for certain complex datasets. For example, paper and cardboard waste and textile and leather waste had R^2 values of 0.64 and 0.61, respectively, reflecting the complexity of their data patterns. Used slag and ferrous metal waste datasets achieved reasonably good R^2 values of 0.74 and 0.81, respectively. Similarly, scrap tyres and wood and timber datasets showed moderate performance with R^2 values of 0.7 and 0.72, respectively. Other datasets such as stones, ceramics, and rubber, and non-ferrous metals achieved R^2 values of 0.8 and 0.81, respectively, demonstrating stable performance. The ash and sludge and construction and debris datasets also recorded an R^2 value of 0.8, signifying good predictive results. Across a wide range of datasets with varying data patterns, the proposed approach consistently outperforms the state-of-the-art methods. As the next step, MSW-DeepStack model showed the least amount of error when applied to the MSW dataset. Subsequently, it was used to forecast the rate of waste production between 2023 and 2030.

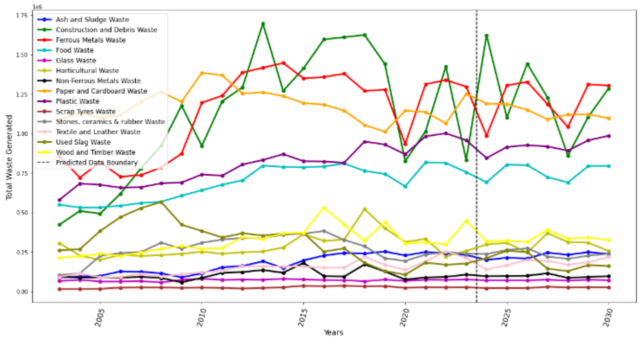

Figure 20. Historical (2003-2023) and predicted data (2024-2030)

Figure 20 illustrates the historical and projected trends in garbage generation from 2003 to 2030. After a period of reduction during the pandemic, waste production has resumed its upward trend and shows no signs of slowing down until either consumption or production patterns undergo radical changes. C&D would surpass ferrous metal waste and P&C waste as the most common types of waste in the country by 2030. Notably, despite considerable efforts, it is anticipated that plastic trash will increase by almost 7 MMT by the year 2030. One further interesting conclusion drawn from MSW-DeepStack is that waste generation will grow between 2026 and 2028. Overall, the rate of waste formation is rising across the board, except for used slag.

Considering the essential roles played by waste reduction and responsible consumption in the Sustainable Development Goals (SDGs) proposed by the United Nations, attaining sustainable waste management is consistent with the SDGs. The results stress the need for comprehensive strategies that address waste minimization, recycling, circular economy, and specific regulatory changes. Collectively pursuing these measures is crucial in changing the course, marking a concrete step toward a future with sustainable waste practices and the actualization of the broader SDGs. Though Singapore utilizes incineration, waste-to-energy techniques and recyclability, the waste generation rate must be minimized to maintain a sustainable environment. Waste shipped to Semakau should be reduced by at least 30 percent daily until 2030 since the landfill is expected to reach capacity by 2035. It would aid in keeping Semakau Landfill in operation past the year 2035 [41]. Hence, these findings would aid the authorities in making the appropriate decisions with the predicted waste generation rate for the various categories of municipal solid waste.

7. CONCLUSIONS

The United Nations has embarked on a revolutionary path toward sustainable development, with the end goal of 2030 in sight. Effective management of waste holds paramount importance for the health of the environment and the economy.

This issue is extremely important to address because of its widespread effects on our ecosystem, economy, and culture. The present research used a stacking model to estimate the annual municipal solid waste (MSW) production in the island nation of Singapore. The proposed MSW-DeepStack model outperformed others with the lowest MAPE MAPE (0.1%-10.6%), MAE (0.0163-0.1182), RMSE (0.0014-0.1225), and ME (0.0022-0.213), along with the highest R^2 rates ranging between 0.61 and 0.9 for employed datasets. In addition, the MSW-DeepStack model predicts that, if the current scenario continues, trash generation will increase substantially by generating 7 MMT across various categories of municipal solid waste by 2030. MSW contributes to a huge amount of waste generation since it handles both domestic and industrial waste. Population, GDP, household income, and educational attainment are a few of the variables that influence the amount and type of trash generated. As part of future work, we aim to enhance waste generation forecasts by integrating socio-economic factors. This comprehensive approach is consistent with the underlying goal of ensuring sustainable waste management and offers a promising way to resolve the challenges posed by waste generation and its impact on the environment and society.

AUTHOR CONTRIBUTIONS

Vaishnavi Jayaraman: Conceptualization, Methodology, Data Curation, Visualization, Investigation, Software and Writing-Original draft preparation. Arun Raj Lakshminarayanan: Supervision, Validation, Reviewing and Editing. A. Abdul Azeez Khan: Manuscript editing. K. Javubar Sathick: Validation.

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