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Original Article

An Energy Efficient Model to Forecast Solid Waste Generation using Green Artificial Intelligence Methodology

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Abstract - *Forecasting Municipal Solid Waste Generation (MSWG) is the need of the hour all around the world. Every day, researchers are developing numerous models to accurately predict waste generation to take immediate action. The models have been constructed using neural networks that require powerful GPUs or TPUs to compute. These machines exhibit high carbon footprints and harmful gases. Accurate prediction is a must; on the other hand, controlling Greenhouse Gas (GHG) emissions is in high demand. Keeping this as the objective, in this article, a study was conducted to identify an efficient model that effectively forecasts the MSWG, which is resilient to the number of incoming features. Most of the researchers have used XGBoost, Long Short-Term Memory (LSTM), and Temporal Convolutional Networks (TCNs) to predict and made these models the base models for predictive analytics. Hence, these models were compared with the Spike Neural Networks (SNNs), a mimic of the human membrane working principle. The effectiveness of these models is evaluated using the Peru MSWG dataset, and the results showed 99% accuracy by all 4 models on a Google Colab T4 GPU environment. The computational time and Carbon dioxide (CO_2) emission were recorded. The SNNs are very good in prediction with less computational time, but they emitted considerable CO_2 emissions when compared to all three other models. For future deployment efficiency on edge computing, SNNs may show promising results on a Neuromorphic hardware.*

Keywords - *Energy Efficient Model for prediction, Forecasting Solid Waste Generation, Green AI, Municipal Solid Waste Generation, Spike Neural Networks.*

1. Introduction

[1] The authors have discussed the impact of “Red-AI”, which primarily focuses on high-performance models, in terms of accuracy rather than efficient models, focusing on less carbon emission. [2] Has given a brief overview of Green in AI and Green by AI that has led towards this research. Constructing hybrid models is always in high demand, and at the same time, it is computationally intensive. Researchers have started to develop models that are efficient and give accurate predictions [3, 4].

Almost all the domains where predictive analytics is needed have moved to effective forecasting methods, and MSWG is no exception. The prediction of MSWG attracts researchers worldwide, since the volume of waste generation becomes too high each day. All the developed countries started to migrate towards a ‘zero-waste’ policy. [5] Has given a survey on MSWG and has predicted the amount of global waste generation by 2050. Since the number is alarming, it is time for densely populated countries in the Asian Continent to find means to greatly reduce the waste. [6] List the different types of waste that could be generated in an urban area. Among them, household waste generation is inevitable. [6-8] Discusses household wastes and their categories briefly. [9] A suggested list of methods in which household waste alone can be controlled, and effective recycling strategies were discussed. It has been identified that, based on the geographical regions, household wastes vary drastically. In connection with this, the corresponding municipality’s policy also changes. Therefore, a model that is designed for one region cannot be used blindly in another region. Henceforth, researchers develop models based on the dataset they collected and train their models to predict the waste generation for that region. It is still a challenging task to create a generic model that accommodates different varieties of datasets from various countries to train and predict. [6, 7] Consolidated the various types of waste generated in developed and developing countries, and how those countries are using their GDP to grow from that waste. It further investigated the methodologies countries use to predict waste generation.

The primary focus of this article is the solid waste that is generated in semi-urban and urban areas. It consists of the following sections:

- A review of literature
- Proposed Model
- Discussion on the result obtained
- Future Enhancement

2. Literature Review

A variety of hybrid models were constructed and tested in real-time. Most of the models have given promising results for the study area taken, but need more inputs to predict accurately. This survey has consolidated the models and the parameters that the authors have disclosed to the real world. The models were constructed using Machine learning, Deep learning, and Ensemble techniques based on the demand of objectives set by the authors. Some models demand powerful Graphics Processing Units (GPUs) to compute and predict the results.

[10] The author's objective is to concentrate on the factors influencing the MSWG and its prediction models. A hybrid model is constructed that combines Mutual Information (MI) with Shapley Additive Explanations (SHAP) for optimal feature selection. This approach enhances the accuracy in predicting MSWG by selecting optimal features when more features are available. Austin, Ballarat, and Boralesgamuwa datasets were used to train and test the model. Population, income, and the Consumer Price Index (CPI) are acknowledged as the crucial parameters. In Austin, the Feed Forward Neural Network (FFNN) achieved an R^2 of 0.7226 during training and 0.6529 during testing. In Ballarat, for training, the R^2 is 0.7037, and for testing, the R^2 is 0.6941. Data limitations in Boralesgamuwa led to improper predictions.

[11] Here, the author has concentrated on the MSWG in Macau. To identify which factor, either the household or the tourism, increases the MSWG, they have constructed a Generalised Additive Model (GAM), which was chosen for its flexibility and interpretability to handle seasonal data. This model was then compared with 6 models, such as Multiple Linear Regression (MLR) and Autoregressive Integrated Moving Average (ARIMA), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forest (RF), and GAM. The dataset of Macau has been collected from the official government sources for the period of 2010 to 2021. Household-related demographic parameters and tourism-related parameters, such as Average proportion of hotel occupancy (Hotel), monthly gaming revenues (Gaming), Tourists' Consumption of non-tradable goods and Services (TCS), and Tourists' Consumption of Products (TCP), have been used for the prediction. Larger households (four or more members) were found to generate significantly more MSW compared to smaller households (three members or fewer), and Tourism activities, particularly tourists' spending on non-tradable goods and services, positively affected MSW generation.

[12] Here, the author has constructed a Multi-layer Machine learning framework to predict the abnormal growth of solid waste generation. Dimensionality reduction is done using Principal Component Analysis (PCA), K-means clustering to identify distinct waste-generation groups, SHapley Additive exPlanations (SHAP) for feature explainability, and Adaptive Neuro Fuzzy Inference systems (ANFIS) combined with Grid Partitioning (GP) clustering based on PCA-transformed input, outperformed other models. The framework is tested with the South African Waste generated dataset for the period from 2015 to 2022. The ANFIS model with GP clustering, based on PCA-transformed inputs, showed superior performance with RMSE, MAE, MAPE, and R^2 values of 0.1939, 0.1655, 21.31, and 0.8943, respectively, during training. The waste generation patterns of the provinces were identified with this framework, which helped in flexible waste management strategies.

[13] To focus on data collection, preprocessing, and data mining, the author has come up with a generic framework that concentrates on all the above-mentioned steps. Moreover, an agent-based model is constructed that handles each dwelling as corresponding to a specific agent with attributes like address, dwelling type, and a socio-demographic profile. This model is tested at Gatineau, a Canadian city where the population produces an average of 8.0 kg of mixed waste per dwelling per week. Although the model seems to be generic, it requires adjustments for regional variations and specific waste characteristics in other areas. Limited socio-economic parameters lead to poor prediction of this framework.

[14] In Lima, Peru, during the year 2023, around 10000 metric tons of MSW were generated, and only 2% of it was valorised, which leads to illegal dumping sites. This proliferates air-borne, land, and water-borne diseases around the city. To handle this serious issue, the author has come up with a Random Forest model to effectively forecast the MSWG and successfully tested with an $R^2 = 0.55$ and a lowest Mean Squared Error (MSE). Strong policy implementation and granular data collection are needed for any model to forecast effectively.

When the Random Forest model can effectively forecast with an $R^2 = 0.55$, these authors in [15] have used the XGBoost model to predict the MSWG with an open dataset from Kaggle. They have given insight that around 2.1 billion metric tons of waste were generated by 2016, and are estimated to rise by 70% by 2050. Factors like urbanisation, increased consumerism, and inadequate infrastructure exacerbate the problem. Using XGBoost and an advanced Regularisation technique, a model is constructed to predict the MSWG. XGBoost achieved an R^2 value of 0.985 and an

RMSE of 0.056, making it the most accurate predictor of MSWG. On the test dataset, XGBoost achieved an R^2 value of 0.996 and an RMSE of 2.014, surpassing RF, LightGBM, and Decision Trees (DT).

[16] Accurate prediction of MSWG suffers from insufficient data, high computational difficulty, and unreliable or inaccurate predictions, hindering effective decision-making and waste management processes. Existing forecasting models also often fail to achieve optimal output and lack accurate temporal information extraction. The authors have integrated spatial-temporal factors within the waste data and constructed a Lightweight GraphFormer model to enhance the accuracy and efficiency of MSWG prediction. The dataset is collected from the World Bank Database, and the Malaysian Department of Statistics provided input data, specifically MSW data, from 2010 to 2020, which were used to test the constructed model. The proposed Lightweight GraphFormer model demonstrated better performance compared to other existing research articles, achieving a forecasting accuracy of 98.76%, a correlation coefficient of 0.982, and an RMSE of 0.078. The model effectively addresses gaps in existing models by providing an efficient approach to handle temporal and spatial dependencies, while maintaining low computational complexity, which is crucial when data is limited.

Another framework has been developed by the authors that wraps all the phases of predictive analytics, which finally suggests that strict policy making is needed to reduce the growth of MSWG in Madurai, a city in India, as suggested in [17]. Here, the author has collected the population census data, MSWG data from Madurai municipality corporation, cleaned the dataset, and used 6 predictive machine learning models, such as linear and polynomial Regression, Random Forest (RF), Support Vector Machines (SVM), and XG Gradient Boosting. K-fold cross-validation (k=5) was used for validation. Results indicate that XG Gradient Boosting generated the most precise outcomes, forecasting organic waste with an R^2 of 0.91 and inorganic waste with an R^2 of 0.91. This surpassed traditional Linear Regression models, which reported R^2 values of 0.867 for organic and 0.577 for inorganic waste. Ensemble methods, like Gradient Boosting, were found to be superior for complex urban waste patterns. While the model performed well, the R^2 value of 0.577 for inorganic waste prediction suggests room for improvement in model fit and predictive capacity for this waste stream.

[18] Deals with MSW Optimisation by introducing a Data-Driven Framework. The authors talk about waste prediction, policy making, and planning by analysing the 2019-2023 range of Socio-economic, Geographic, and waste management in Erode city. Supervised Machine Learning (ML) models like Support Vector Machine (SVM), Random Forest (RF), and Naïve Bayes (NB) were trained and tested. SVM outperformed with a high accuracy of 96%, with a latency time of 0.67 seconds. This paper identifies two different categories: 1. Waste category: A household Waste's key contributors are plastic and organic waste; 2. Socio-economic Factor: Household size and its Total income are the key predictors of MSWG.

It is estimated that around 3.4 billion tons of MSW will be generated annually by 2050, and requires severe steps to control the generation. Henceforth, the authors [19] used statistical and machine learning models to forecast and reduce waste generation and increase recycling. Statistical models such as Autoregressive Integrated Moving Average with Exogenous variables (ARIMAX) and Machine learning models such as Random Forest (RF), Support Vector Regression (SVR), and XGBoost have been used. Hybrid models were also constructed by combining these individual models to achieve higher accuracy and lower error rates. The dataset was collected from the Department for Environment, Food and Rural Affairs, United Kingdom, in 2023. Finally, the best performing model, called the hybrid ARIMAX-XGBoost model, outperformed all other models.

[20] Like all other developing countries, Jordon also suffers from an inefficient MSWG management system due to rapid urbanisation, illegal dumping, and incineration, which contributes 0.06% of greenhouse gas emissions on a global average. There is a need for strict policy makers, local awareness, and an increase in allocation of financial resources to transform the Jordon MSWG management system. The MSW treatment strategies were identified using the Multi-Criteria Decision Analysis (MCDA) model, which incorporates the Analytic Hierarchy Process (AHP). The dataset was collected from population figures, annual Municipal Solid Waste (MSW) volumes, GHG emissions, and official reports less than 5 years old. Demographic data from the Department of Statistics (DoS) was used to forecast the population and solid waste quantities for 2030. This article finds that proper recycling, legal dumping, and composting are the best methods to reduce MSWG.

While the whole world is intimidated regarding Waste growth, [21] Talks about key reductive factors that decline the Solid waste generation in the Circum-Bohai-Sea (CBS) area of China. Geographical and Temporal Weighted Regression (GTWR) identifies population along with an age limit of 15-59, and financial factors are the dominant keys that reflect Waste Generation. It also analysed the geographical factor, and inferred that 1% of the Shrinking Population leads to 141.6% of garbage reduction in urban areas, and 1% of the Ageing Population leads to 19.7% of garbage reduction in rural areas. Even though this reduction cannot be sustained, the waste growth in the future can be handled only if the smart city technology balances both the Urban and Rural areas with proper sanitation strategies. [22] In this article, the authors suggested that accurate prediction of MSWG is important to implement any framework that is designed to mitigate

MSWG. Machine Learning (ML) algorithms, particularly Decision Tree (DT) models, suffer from overfitting issues. Authors have made a study on a variety of ML models, such as Tree-based ML algorithms, specifically Decision Tree (DT), Random Forest (RF), and Gradient Boosting (GB), built the models using a Guwahati city dataset, incorporating solid waste quantities with socio-economic and demographic features. Forecasting approaches, namely Moving Average (MA) approaches, including Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA), were used for predicting the MSWG rate. MSWG rate data for validation were procured from the Central Pollution Control Board (CPCB), Government of India, covering the period from 1991 to 2016. The Gradient Boosting (GB) model demonstrated the best performance among the tree-based ML algorithms, with a Root Mean Squared Error (RMSE) of 3.01, a Mean Absolute Error (MAE) of 2.86, and an R^2 of 0.99. It also showed a correlation coefficient (r) of 0.82 between observed and predicted values. With exponential MA, the forecasted RMSE and R^2 for GB were 2.12 and 0.981, respectively, outperforming RF (RMSE 3.63, R^2 0.972) and DT (RMSE 4.22, R^2 0.967). The study successfully mitigated overfitting issues in DT models using a grid-based search, 10-fold cross-validation (a hyper-tuning approach), and an MA-based forecasting method.

The significance of optimising the hyperparameters was discussed in [6]. Singapore Waste Dataset collected from "data.world" includes time-series records of waste category, generation volume, recycling percentage, total material recycled, and total disposal tonnage. Among 13 diversified waste categories, the author took 3 predominant waste types: paper, plastic, and food scraps, for prediction. The timeline-based train-test split was taken to construct the models Extra Trees, SVR, kNN, catBoost, and XGBoost. Even though XGBoost outperformed with a lower Mean Absolute Percentage Error (MAPE), an enhanced version was introduced by using the Grid Search Optimisation (GSO) technique for hyperparameter tuning. The result was superior, reducing the MAPE by 40% for Paper/Cardboard waste, 18.33% for Plastic Waste, and 14.20% for Food scrap Waste, confirming GSO-XGBoost as the robust model.

The advantage of integrating Sensors, Statistical Models, and optimization techniques is demonstrated by implementing a project by [7]. This involved an 8-month dataset of hourly collected data from 3640 ultrasonic sensors deployed in containers across six municipalities in the Netherlands. Seasonal features such as holidays, weather, and event schedules were also collected. Narrowing down, the waste was also categorised into 6 types and analysed individually. The benchmark Seasonal Naïve Model is compared with advanced models, such as Error, Trend, and Seasonality models with external variables, the Ensemble approach (ETSX), and Quantile Regression with external variables. It identified that ETSX performed well with a lower RMSE. The author stressed the possibility of adaptive, effective waste routes that adjust to time-based changes and external forces. As Socio-Demographic parameters play a vital role in MSWG, from Malaysia's statistical dataset of duration 2012-2020, GDP, Population, 3 categories of Age group, Employability, and Electricity Demand in kWh were taken as factors to predict solid waste quantity in [23]. After a wide range of analyses of data across four Gaussian Process Regression (GPR) models with distinct stationary kernel family: Rational Quadratic, Matérn 5/2, Squared Exponential and Exponential, Ensemble: Bagging and Boosting trees, and Width-based and Depth-based Neural Networks, the author concluded that even though both GPR and NNs' efficiency were better than Ensemble trees, GPR stands first in its accuracy.

Saensuk Municipality of Thailand, a popular tourism spot, suffers from serious MSWGM practices and expects an accurate prediction strategy to combat the issue. The authors of [24] used three models to achieve the objective, namely Support Vector Regression (SVR), Multiple Linear Regression (MLR), and Long Short-Term Memory (LSTM). During the execution, they identified that the Multiple Linear Regression (MLR) model was the most suitable algorithm for optimal solid waste generation prediction in Saensuk Municipality, demonstrating an R2 value of 0.74623. The input solid waste data have been collected from the respective municipalities, spanning from 2009 to 2019. In addition to this data, five hyperlocal factors were used as independent variables: Tourists (person/year), Average monthly household income (Bath/year), Population (person/year), and Student Enrollment (person/year). Solid waste (ton/month) was the dependent variable. The LSTM model was not suitable for this dataset. Pearson Correlation analysis revealed that population, tourist numbers, and average monthly household expenses are influential variables for MSWG in Saensuk.

The LSTM-based Deep Learning Time Series Forecasting (DLTSF) framework was proposed in [8], focused on three socio-economic zones: poor, social, and privileged of Al-basaten, a district in East-Cairo, Egypt. The 100-day garbage collection was categorised into plastic, glass, paper, carton, and organic waste. The 61:49 Train-Test split is done to compute the model. The author concludes that waste generation scales directly with living standards, with the proof of performance metric mean RMSE of 0.03371.

[25] Here, the authors constructed an Elman Neural Network model to mitigate the MSWG that had an abnormal growth due to rapid urbanisation and economic growth in China. The reason behind using this model is its ability to process fuzzy nonlinear relation data accurately. The main input elements for the model include permanent population, passenger volume, gross domestic product, total investment in fixed assets, consumption level of urban residents, and electricity consumption, with MSW generation as the output. The municipal solid waste data were obtained from the

Chinese Statistical Yearbook, covering the period from 2003 to 2016. To train the model, data from 2003 to 2015 were used, while data from 2016 served as validation data. The Elman neural network model demonstrated good applicability and accuracy in predicting Shanghai's MSW generation, with an absolute average accuracy of 0.048%. The error between predicted and actual values was less than 1% in 2016. This model has been compared with the BP model and outperformed it. Finding an optimal number of hidden nodes was challenging, and that has been compromised by using a trial-and-error method.

The growing rate of migration towards urban areas increases the MSWG, doubling every decade. The Lack of practices to reduce and recycle MSW results in the release of toxic gases that pollute the air, water, and land. A framework is constructed by the authors of [26] for smart cities, which interconnects three main elements: Infrastructure for Product Lifecycle Data Collection, Novel Business Models, and Intelligent and Sensor-Based Infrastructure.

Data from the "Monitor E-waste Transparency" project was used, which tracked 205 devices, including LCDs, from various starting regions to ending regions, providing details on travel duration and distance. Long-distance travelling and random trajectories were recorded in tracking e-waste items, which include sensor reports from international borders. The illegal export of e-waste to developing regions often occurs and ends up in informal facilities and dump sites rather than formal recycling centres. Future work needs to address policy regulations to handle MSWG.

It is observed from the survey that, regardless of the model, users expect high throughput. Hence, it is time for researchers to develop models that support high throughput as well as optimal utilisation of resources to support green AI. Based on the survey made in [1], the proposed model uses the Spike Neural Networks (SNNs) for prediction. [27] Has given an in-depth analysis of SNNs over ANNs. From the above lists, it is known that the researchers have used various forms of LSTMs, TCNs, RF, XGBoost, Light GBM, etc., to predict the MSWG. This article makes use of SNNs to predict the short-term frequencies, i.e., for the next year and so on. The work extends with the implementation of the widely used models, such as XGBoost, LSTM, and TCN models on the same data, and the final comparison is made to evaluate their accuracy and efficiency metrics.

3. Proposed Model

The survey has provided clear insights into the models developed, the input parameters the models require, the records they expect to train and test, and, lastly, the policies governments should follow for accurate predictions. Normally, models require significant computational power as datasets grow. Any model that accurately predicts with a reasonable computation time can be treated as the best model. To identify this parameter, a model is constructed, which is shown in Figure 1. It consists of 3 phases.

- Data Preparation phase
- Prediction phase
- Result Analysis phase

3.1. Data Preparation Phase

An intense study is made to identify a dataset that has enough features to forecast, and finally, the Peru MSWG dataset has been officially retrieved from [28]. The dataset has been collected for the duration of 2014-2023 with 13 features and 18759 records. The entire country has been divided into 4 major regions with 1891 area codes.

In the preprocessing phase, it has been identified that for around 17 area codes, the MSWG has been collected from 2021 onwards; those 17 areas have been omitted, and only 1874 area codes had reasonable data, which also demanded a data imputation technique. To balance the dataset across all 1874 area codes, including filling missing values, the Multiple Imputation by Chained Equations (MICE), a powerful iterative imputation technique, has been used. It used the Random Forest Regressor to predict the missing values for both the population and waste generated features. For faster convergence and stability of results, scaling and normalisation of the data values are implemented. Figure 2 shows the correlation among the features to predict the solid waste generation. It clearly depicts that the population feature has the highest correlation to predict the MSWG.

An Exploratory Data Analysis (EDA) is performed to show the interaction and influence among the four variables. It is done by the Split scatter plot method that combines the Regression line and Hue Encoding. In Figure 3(a), the flattened relationship against the features (Period, Waste_Generated) and the third variable AreaCode indicates a weak binding; whereas in Figure 3(b), the slope line against the features (Population, Waste_Generated) depicts a strong, positive relationship. It includes, regardless of AreaCode, that Population growth becomes the dominant predictor, which implicitly models Waste_per_capita and strongly suggests that population growth is the main factor in waste generation.

3.2. Prediction Phase

To identify the energy-efficient forecasting model, the cleaned dataset has been forwarded to the 4 forecasting models, such as XGBoost, LSTM, TCN, and SNN, and executed individually. All 4 models were trained and tested using standard procedures.

3.2.1. XGBoost

An ensemble model that makes use of many 'weak' models for predicting accurate results, has proved its ability in almost all the State-of-the-Art benchmark datasets, and is used to forecast the MSWG in the Peru dataset. Due to its in-built ‘learn from mistakes’ methodology, it has gained wide attraction in the research arena. The model is constructed using a histogram-based tree method with 1000 estimators, a 0.05 learning rate to make it generalised, and uses 341 epochs to forecast the result.

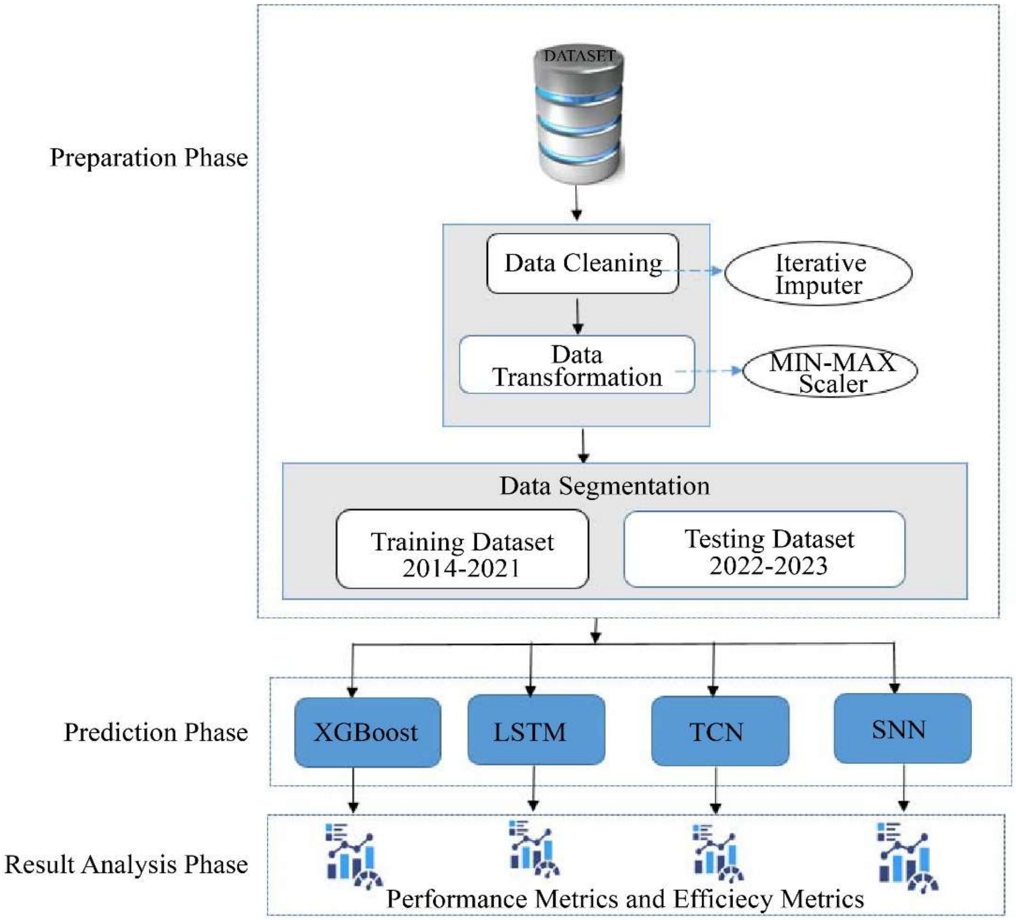


Fig. 1 Proposed Framework

3.2.2. LSTM

A shallow, low complexity model with standard practices like small batch size and early stopping techniques were implemented to enhance the best balance between low training error and low-test error. This model has been constructed with a ‘relu’ activation function with a batch size of 8 and early stopping, having a patience of 10 to reduce the use of time and electricity for training.

3.2.3. TCN

Compared to LSTM, TCN is computationally cost-effective. A well-structured four-layer stack of sequentially dilated convolutional layers was constructed for better performance. The impact of TCN is its ability to identify the long-range dependencies effectively and faster than LSTM.

3.2.4. SNN

The main bottleneck of a Deep Learning Model is cost efficiency and temporal data processing. Spike Neural Network, as an enhancing model, consumes low energy and produces high performance. So, SNN with a sigmoid surrogate gradient is employed for forecasting the waste generation.

This model was constructed with a simple Leaky Integrate-and-Fire (LIF) mechanism, having a beta value of 0.99 to retain its membrane potential, which leads to slow leakage. The actual vs predicted values made by all four models are shown in Figures 4, 5, 6, and 7, respectively. Table 1 shows the evaluation metrics for all four models.

3.2.5. Result Analysis Phase

In this phase, predictions made by the 4 models were compared. The efficiency metrics, such as the number of parameters, training time (in seconds), inference time (in seconds), and estimated memory (in MB) of all 4 models, are shown in Table 2, and Figure 8 portrays them.

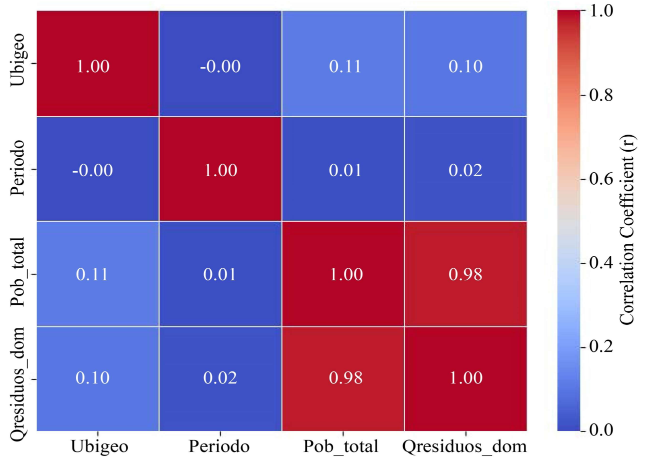
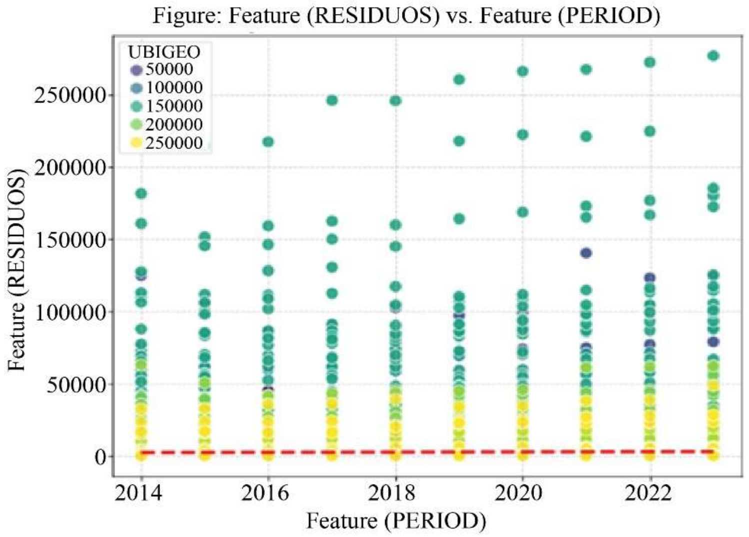
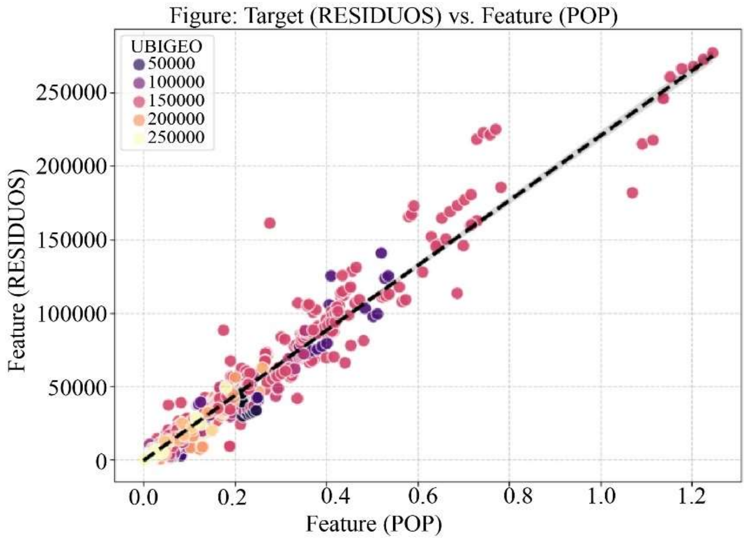


Fig. 2 Correlation matrix heatmap



Waste_generated vs Period across areacode
Fig. 3(a) Conditional scatter plot



Waste_generated vs Population across areacode
Fig. 3(b) Conditional scatter plot

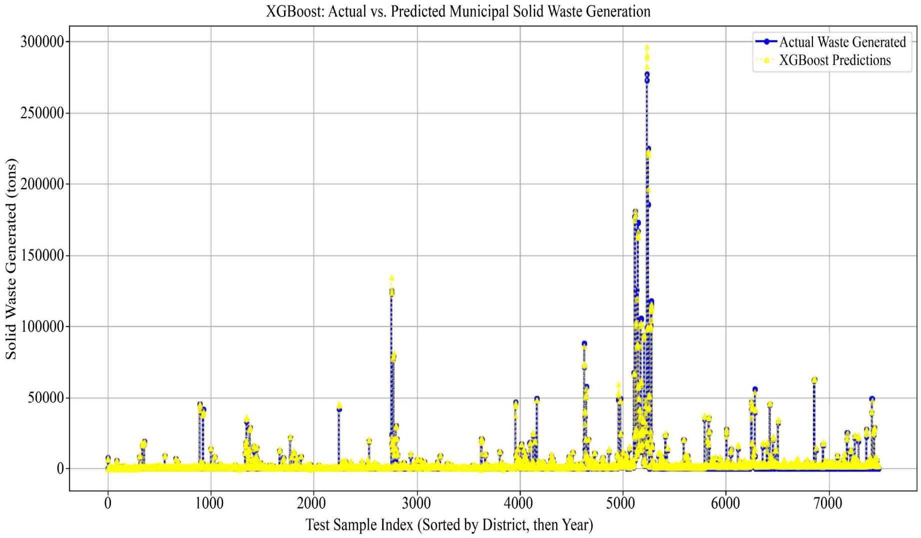


Fig. 4 XGBoost: Actual Vs Predicted municipal solid waste generation

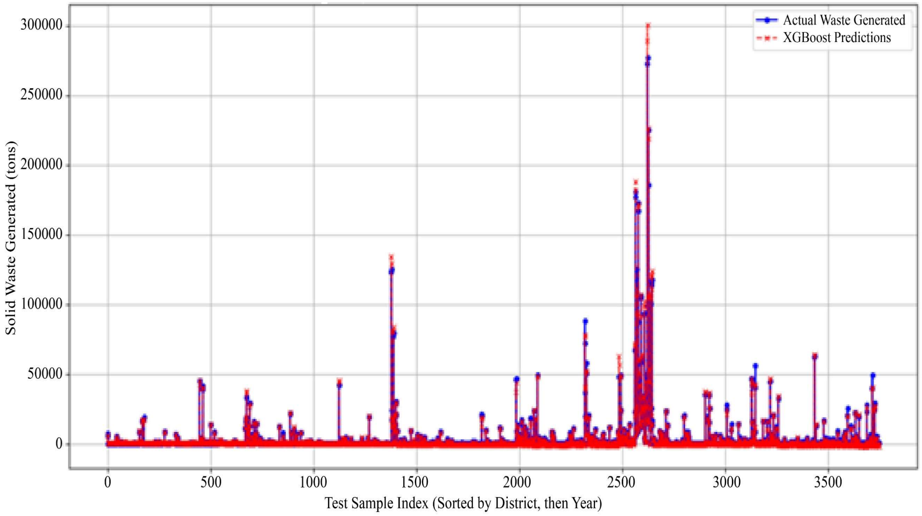


Fig. 5 LSTM: Actual Vs Predicted municipal solid waste generation

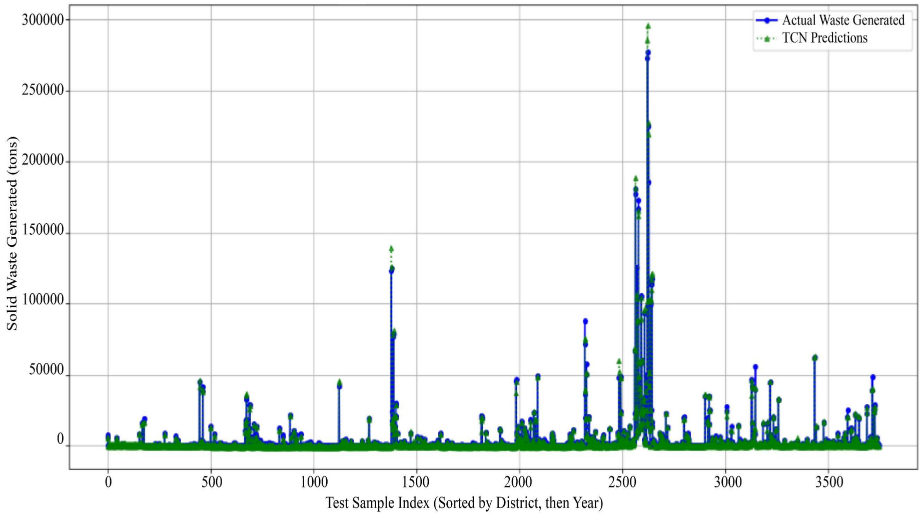


Fig. 6 TCN: Actual Vs Predicted municipal solid waste generation

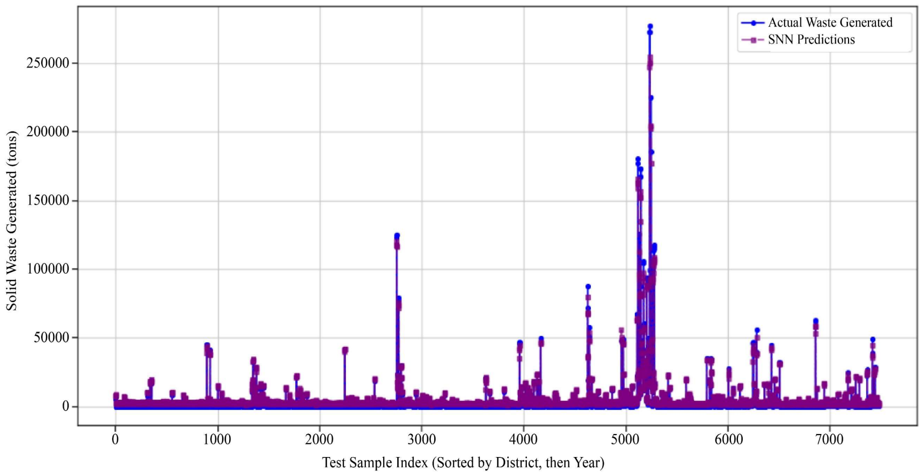


Fig. 7 SNN: Actual Vs Predicted municipal solid waste generation

Table 1. Model evaluation metrics

Model	MAE	RMSE	R^2
XGBoost	801.23	1523.01	0.99
LSTM	770.32	1518.70	0.99
TCN	685.71	1414.29	0.99
SNN	668.11	1503.59	0.99

Table 2. Model efficiency metrics

Model	Parameters	Training Time (s)	Inference Time (s)	Estimated Memory (MB)
XGBoost	6400	130.09	0.08	0.01
LSTM	1361	149.34	1.22	0.01
TCN	58881	138.40	1.94	0.22
SNN	1793	219.59	0.09	0.01

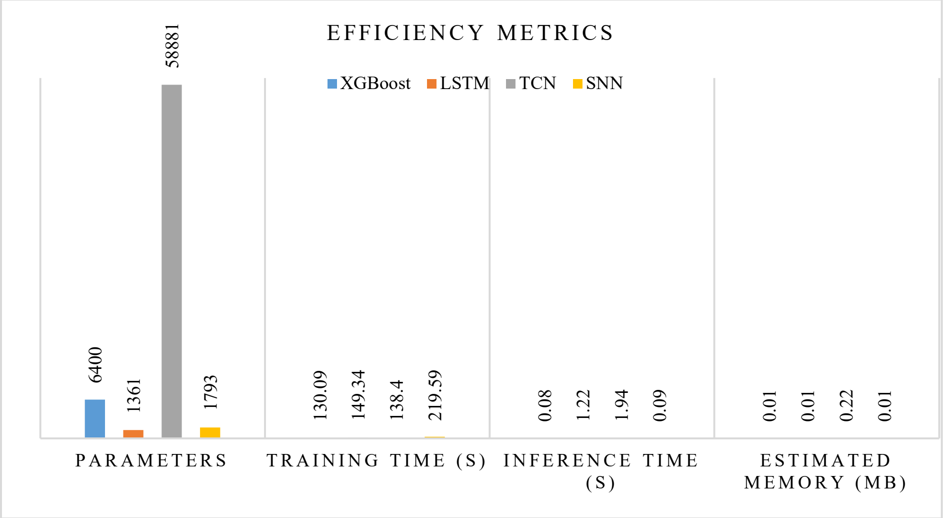


Fig. 8 Efficiency metrics

Table 3. Model emission metrics

Model	Emissions (gCO2)	Activity Sparsity	Epochs
XGBoost	0.0846	0.0007	341
LSTM	1.5101	0.0087	100
TCN	1.4002	0.0091	20
SNN	1.4903	0.0211	20

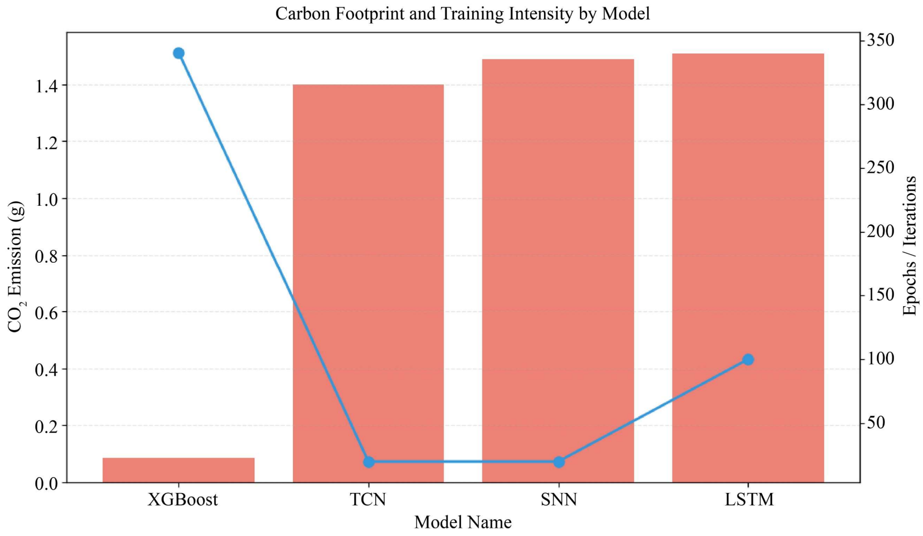


Fig. 9 Emission metrics

4. Discussion & Conclusion

It has been inferred that all 4 models' forecasting have reached an R^2 of 99% with low MSE and MAE. But the objective is to identify the model that predicts the output with the least carbon footprint, which should be considered. From Table 3 and Figure 9, we have ranked the models from the top to the least as follows: XGBoost, TCN, SNN, and LSTM. The inferences are made by running these models in a GPU environment with standard procedures. The carbon emission by each model is calculated, and from Table 3, it is noted that SNN is compared with all three other non-spiking architectures.

Thereby, the activity sparsity column denotes the sparsity for each model. XGBoost spiking style is calculated by the path sparsity based on its decision depth, whereas LSTM spiking style is calculated by the gate sparsity based on its gate behaviour, and for TCN, it is calculated by layer sparsity based on its convolutional filters selection. Finally, in the spiking architecture SNN, the binary spike is calculated as the firing rate. Although SNNs have been ranked third for the task taken, these models demand a Neuromorphic hardware environment to show promising results, which will be in high demand for edge computing.

5. Future Enhancement

The proposed model has conducted a comparative study on 4 models that used population features as the dominant ones to forecast MSWG. In the future, these models can be generalised by incorporating features such as demographic, socio-economic, spatial-temporal, and geographic features that must be properly collected and can enhance predictions more accurately for any given dataset.

The study reveals that the implementation of the models in the right infrastructure also plays a crucial role in carbon emissions. To conclude, it clearly depicts that irrespective of the models being developed for forecasting the MSWG, it is up to humankind to concentrate on reducing the solid waste generation to mitigate abnormal environmental changes.

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