A Novel Ensemble Meta-Model for Predicting Demolition Solid Waste Generation

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ABSTRACT

Precise forecasting of Demolition Solid Waste (DSW) generation is essential for the development of sustainable waste management systems. This study uses ensemble machine learning models, such as Random Forest (RF), XGBoost, ANN, and LightGBM, and meta-learners to make predictions more accurate and reliable. The proposed stacked ensemble model shows excellent results, with an R^2 score of 0.99995 and very low errors in the training, validation, and test datasets, outperforming standalone learners and classic statistical baselines such as SARIMA and ETS. These gains suggest better generalization and stability and lead to practical advantages for operational planning (e.g., capacity sizing, logistics routing, resource allocation, and environmental impact mitigation) in demolition projects. The proposed meta-ensemble model serves as a platform for intelligent real-time decision-support tools, improving strategy selection and system performance in DSW management.

Keywords-waste prediction; ensemble meta-models; machine learning; solid waste management; hybrid models; environmental sustainability

I. INTRODUCTION

Prediction of Demolition Solid Waste (DSW) generation is essential to designing sustainable waste management systems. As waste generation across the world is on an upward trajectory, accurate forecasting is important for resource allocation, environmental preservation, and the efficient running of waste management processes. This study investigates the use of advanced Machine Learning (ML) and Deep Learning (DL) models, such as ensembles, to accurately predict DSW generation. The emphasis is on creating new ensemble meta-models that leverage the strengths of different algorithms to provide accurate and trustworthy predictions. Specifically, innovative ensemble meta-models combine advanced ML models, including Random Forest (RF), Artificial Neural Network (ANN), and XGBoost, to improve prediction accuracy in modeling DSW generation. These hybrid models outperformed both individual ML models and traditional statistical approaches, such as SARIMA and ETS, especially in terms of MSE (22.75), RMSE (4.77), and MAE (3.53).

Previous techniques, such as ANN and the Nonlinear Auto-Regressive network with Exogenous input (NARX), are inadequate, but modern techniques, such as Gaussian Process Regression (GPR), ensemble trees, and neural networks, provide more accuracy [1]. Waste picking can be improved with AI, as AI-based tools have been proposed for recycling, illegal dumping detection, carbon emissions, and smart city waste management. AI-based methods use ML and Deep Learning (DL) to keep costs low and improve efficiency, but there are challenges in their implementation [2]. A study of 42 papers (2010-2021) [3] surveyed the use of ML in smart cities, using demographic, image, and real-time data with ANN, CNN, and GBRT on long-term predictions to identify areas for further research. In developing countries, predicting the generation of Municipal Solid Waste (MSW) is difficult due to data limitations. In [4], Backpropagation Neural Networks (BPNN) and Support Vector Regression (SVR) were effective for this purpose, with BPNN being slightly better. This can lead developing countries to develop practical MSW strategies and avoid plans based on total dependence on foreign datasets.

In construction-based urbanization, building waste is produced as a result of failures, damage, breakage, or simply overload [5]. In [6], a weekly waste generation model used ensemble learning and Optuna meta-regression, achieving high accuracy (R^2 = 0.8, MPE = 0.26), providing effective results even with limited datasets. ML models have been proposed for integrated MSW-to-energy systems for hydrogen, oxygen, and power, achieving R^2 > 99.8% and showing potential for sustainable energy recovery [7]. Construction waste prediction using ML models has shown R^2 scores from 0.88 to 0.98 with aerial images in Saudi Arabia, supporting waste management methods to minimize environmental impact [8]. ML models such as ANN, LR, XGBoost, and RF can optimize MSW biogas prediction, with XGBoost and SVM (R^2 of 0.88 and 0.68) identifying the impact of discriminatory variables [9]. In [10], Construction and Demolition Waste (C&DW) generation was predicted using MLP and ANFIS, with ANFIS achieving the best results with an R^2 of 0.96 and an RMSE of 0.04209. This model can support policymakers in managing future C&DW.

In [11], MSW generation was estimated from 2020 to 2060 in China based on XGBoost and RF, indicating that GDP and population are important variables, highlighting policy reforms to reduce MSW as critical. In [12], a global overview of plastic waste management used Gradient Boost (GB) and RF on global datasets to predict plastic waste trends and help policy making. In [13], a BPNN model achieved an R^2 of 93.8% in determining key variables as major MSW predictors for the Shandong province. In Vietnam, the prediction of MSW generation with RF and KNN models performed really well with R^2 > 0.96 [14], and although data were available until October 2023, the models still provided reasonable forecast results. In [15], various ML approaches increased the operational efficiency by 15%, with 85% accuracy on forecasting the waste generation volume. These results indicate the potential of ML for a sustainable, effective, and shareable disposal of waste on a global scale. In [16], a new model combined ANN and Autoencoders (AE), showing significant improvements in performance measures such as MAE and R^2 (up to 49%). In [17], RF regression models were used to determine construction waste volumes based on a range of factors, such as project size, number of hours worked, and type of materials used. In [18], ensemble voting regressors were applied to five hospitals in Bahrain, achieving high accuracy (90.4%-91.7%). In [19], gradient boosting models (XGB, LGBM, AdaBoost) and the response surface method were used to predict and optimize biogas yield, with the best results achieved with XGB (R^2 = 0.999). The study in [20] described an MSW gasification system that could be integrated with Solid Oxide Fuel Cells (SOFC), with the model predicting energy outputs and emissions with R^2 > 94%.

II. PROPOSED METHODOLOGY

A. Proposed Architecture

Figure 1 describes the process of predicting HSW generation using different regression models such as SARIMA, NARX, LightGBM, KNN, SVR, ETS, RF, XGBoost, ANN, Linear Regression (LR), and Decision Trees (DT), including an ensemble meta-model, a hybrid optimized ensemble meta-model, and a fully optimized hybrid ensemble meta-model. Data preprocessing was applied along with feature normalization, and the dataset was split into a 60-20-20 ratio for training, validation, and testing. The models were trained on the data, and then predictions were generated and evaluated using metrics such as MSE, MAE, RMSE, MAPE, and R^2.

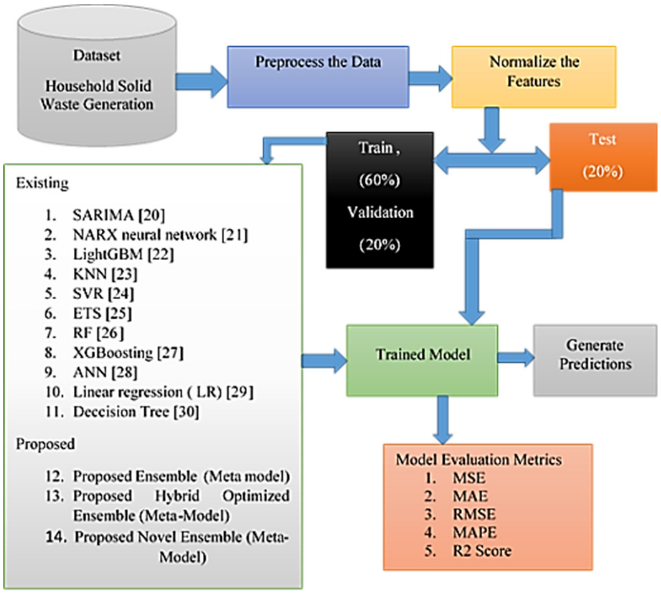

Fig. 1. Proposed architecture.

III. PROPOSED METHOD

This study aimed to develop a generalizable forecasting model for DSW under real settings. The input involved the plot size (m^2), and the output was the total DSW. Table I shows the base parameters for the baseline models.

TABLE I. MODEL ARCHITECTURE AND PARAMETERS

Model	Parameters
Linear Regression (LR)	Ordinary least squares, with fit_intercept=true
KNN regressor	N = 5, weights = 'distance', metric = 'Minkowski', p = 2
Decision Tree (DT) regressor	max_depth = 10, min_samples_split = 2, min_samples_leaf = 1, splitter = 'best'.
Random Forest (RF) regressor	n_estimators = 300, max_depth = None, min_samples_split = 2, min_samples_leaf = 1, max_features = 'sqrt ', bootstrap = True
XGBoost regressor	n_estimators = 600, learning_rate = 0.05, max_depth = 6, subsample = 0.8, colsample_bytree = 0.8, reg_lambda = 1.0, gamma = 0.0, objective = 'reg:squarederror'
LightGBM regressor	n_estimators = 600, learning_rate = 0.05, num_leaves = 31, feature_fraction = 0.8, bagging_fraction = 0.8, in_data_in_leaf = 20, objective = 'regression '
SVR (RBF)	C = 10, epsilon = 0.1, gamma = 'scale', with StandardScaler in pipeline
ANN (MLP)	Hidden layers = [64, 32] (ReLU), Dropout = 0.2 after each hidden layer, Output = 1 (linear); Optimizer = Adam (lr=1e-3), Loss = MSE, Batch = 32, Epochs = 200 with EarlyStopping (patience=20, restore_best_weights=True).

A. Ensemble Meta-Models for Predicting DSW

1) Data Preparation

The dataset contains total demolition waste (in MT) and its category splits (soil/sand/gravel, bricks/masonry, concrete, metal, wood, other), where each split is a fixed proportion of total derived from a published rule of thumb. The independent variable is plot size (m²).

2) Preprocessing

The features were normalized using MinMaxScaler. Then, the data was split into training, validation, and test sets (60:20:20).

3) Training and Testing Base Models

The models shown in Table I were trained on the training data. Evaluation was performed for the training, validation, and test sets for each model.

4) Combine Predictions

Predictions from the base models were stacked to create new feature sets (meta_train, meta_val, meta_test).

5) Meta-Models

Three ensemble models were examined for their performance. The first involved a linear regression model trained using the base model predictions as input. The second involved a Gradient Boosting Regressor (GBR) as a hybrid meta-model, trained on the outputs of RF, XGBoost, and SVR, to predict the target variable. The third was an optimized version of this hybrid meta-model to determine the influence of hyperparameter optimization on its performance. Table II describes the characteristics of these ensemble models.

The hyperparameter optimization involved Bayesian search (Optuna) over defined spaces:

- RF: n_estimators [100–1000], max_depth [None or 4–20], max_features {sqrt, log2}.
- XGB/LGBM: n_estimators [200–1000], learning_rate [0.01–0.2], subsample/ bagging_fraction [0.6–1.0], colsample/ feature_fraction [0.6–1.0], reg_lambda [0–10].
- SVR: C [0.1–100], epsilon [0.00001-0.001], gamma {scale, 0.0001-0.1}.
- Meta-GBR: n_estimators [100–800], learning_rate [0.01–0.1], max_depth [2–6], subsample [0.6–1.0].

6) Evaluation Metrics

The following evaluation metrics were used to assess the models: MSE, MAE, RMSE, MAPE, and R^2 score.

7) Insights and Innovations

The ensemble models combine the strengths of tree-based models, boosting algorithms, and kernel-based methods to improve predictive accuracy and minimize errors. Residuals help uncover systematic issues in predictions, enabling further refinements. The proposed models are suitable for complex datasets and diverse prediction tasks.

TABLE II. CHARACTERISTICS OF THE THREE PROPOSED ENSEMBLE MODELS

Features	Proposed ensemble meta-model	Proposed hybrid optimized ensemble meta-model	Proposed optimized ensemble meta-model
Base models used	RF, XGBoost, SVR	RF, XGBoost, SVR	RF, XGBoost, SVR
Meta-model	Linear	GBR	GBR
Optimization in meta-model	None	Hyperparameter tuning (learning rate, depth)	Additional hyperparameter tuning on base predictions
Feature combination method	Simple stacking	Optimized stacking with reduced complexity	Stacking with feature refinement
Feature scaling for base models	MinMaxScaler only for SVR	MinMaxScaler only for SVR	MinMaxScaler for all features
Hyperparameter optimization	Not applied	Applied to meta-model	Applied to meta-model and base models
Evaluation Metrics	MSE, MAE, RMSE, MAPE, R^2	MSE, MAE, RMSE, MAPE, R^2	MSE, MAE, RMSE, MAPE, R^2
Model complexity	Moderate	High	High
Scalability	Suitable for small to medium datasets	Suitable for large datasets with complex relationships	Suitable for large and feature-rich datasets
Residual analysis	Included	Included	Enhanced analysis with statistical tests
Performance emphasis	Balanced performance	Focus on reduced overfitting	Emphasis on robust predictions and interpretability
Implementation difficulty	Low	Moderate	High
Visualization support	Actual vs predicted and residual plots	Actual vs predicted and residual plots	Actual vs predicted and enhanced residual analysis
Target applications	General prediction tasks	Complex prediction tasks with optimization needs	High-stakes, interpretability-driven predictions

IV. IMPLEMENTATION SETUP

A. Dataset

The dataset [21] describes household solid waste generation rates and demolition waste rates for different plot sizes (m²). These include total demolition waste in metric tons and the breakdown of demolition waste in metric tons by categories, involving soil, sand and gravel, bricks and masonry materials, concrete materials, metals, wood, and other materials. The dataset was generated according to the thumb rule developed by the Technology Information, Forecasting and Assessment Council (TIFAC) [22]. The C&D waste generation ranges from 300 to 500 kg/m². C&D waste in India typically contains soil, sand, and gravel (36%), bricks and masonry (31%), concrete (23%), metal (5%), wood (2%), and other materials (3%).

B. Evaluation Metrics

- MSE is the mean of the squares of differences between actual and predicted values.
- MAE determines the average absolute difference between actual and predicted values.

- RMSE is the square root of MSE, indicating the standard deviation of the prediction error.
- MAPE gives the magnitude of error in terms of the percentage of the actual value.
- R^2 shows the proportion of variance in the target variable explained by the model.

V. RESULTS

Table II presents the performance results of various models on the training, validation, and test datasets. LR and ANN models give perfect R^2 scores (1.0) and extremely low errors. LR and KNN reach an R^2 of approximately 1 because the dataset is effectively deterministic and linearly generated. This study used the ensemble models not to outscore LR and KNN, but to validate a safe, out-of-fold stacked pipeline (preprocessing, tuning, meta-learning) that is reusable and deployment-ready. The novelty lies in this unified meta-ensemble stacking procedure, hyperparameter tuning, and calibration/diagnostics rather than incremental accuracy on a trivially linear case. In realistic DSW settings with heterogeneous, non-linear covariates and noise, such ensembles better capture interactions, reduce variance, and are more robust to shift and missingness than single models.

RF, XGBoost, and LightGBM show high R^2 scores (1.0) with low errors, and are therefore robust predictors. The novel ensemble and hybrid meta-models also maintain attractive R^2 scores of over 0.99995, with only a slight increase in errors. SVR has stable performance with high R^2 scores along with slightly increased errors. Due to negative R^2 values and high error metrics, SARIMA and ETS models do not yield reasonable predictions. The NARX neural network shows an outstanding validation accuracy (R^2 = 0.999999) but shows a mild drop in test performance. Ensemble meta-models provide the best accuracy with 1.0 R^2 scores in all datasets. These results highlight the advantages of the ensemble and neural approaches and the shortcomings of the SARIMA and ETS time-series models.

TABLE III. COMPARATIVE RESULTS OF EXISTING AND PROPOSED MODELS

Model	Set	MSE	MAE	RMSE	MAPE	R^2
Proposed ensemble meta-model	Train	21.078197	3.415599	4.591100	0.518650	0.999956
	Validation	22.711266	3.576473	4.765634	0.532063	0.999952
	Test	22.752051	3.532706	4.769911	0.514192	0.999952
Proposed hybrid ensemble meta-model	Train	0.069506	0.207071	0.263639	0.049005	1.000000
	Validation	0.142728	0.289168	0.377794	0.061085	1.000000
	Test	0.148884	0.297489	0.385855	0.057177	1.000000
Proposed optimized hybrid ensemble meta-model	Train	21.07819	3.415599	4.591100	0.518650	0.999956
	Validation	22.71126	3.576473	4.765634	0.532063	0.999952
	Test	22.75205	3.532706	4.769911	0.514192	0.999952
SARIMA [20]	Validation	475648.603787	598.081881	689.672824	182.000391	-0.000943
	Test	468484.358309	590.245959	684.459172	170.567880	-0.006250
NARX [21]	Validation	4.126559	1.397910	2.031393	0.179433	0.999999
	Test	18.110188	2.753241	4.255607	0.579487	0.999994
LightGBM [22]	Train	7.833605	2.345510	2.798858	0.493496	0.999984
	Validation	8.894943	2.498560	2.982439	0.494452	0.999981
	Test	8.533442	2.448192	2.921206	0.493100	0.999982
KNN [23]	Train	1.081563e-27	5.699503e-15	3.288713e-14	5.558795e-16	1.0
	Validation	3.192941e-02	8.673432e-02	1.786880e-01	1.698973e-02	1.0
	Test	3.876140e-02	9.268776e-02	1.968791e-01	1.734822e-02	1.0
SVR [24]	Train	1389.371091	29.746184	37.274268	7.640336	0.997077
	Validation	1443.587768	30.178196	37.994576	7.228131	0.996941
	Test	1445.492819	30.542335	38.019637	7.103704	0.996974
ETS [25]	Validation	536325.298019	621.311047	732.342337	218.100827	-0.128630
	Test	534889.665120	620.243077	731.361515	9.230871	-0.148881
RF [26]	Train	0.079061	0.220345	0.281178	0.045498	1.000000
	Validation	0.171194	0.316078	0.413756	0.062872	1.000000
	Test	0.179396	0.327713	0.423552	0.065066	-
XGBoost [27]	Train	7.914229	2.369606	2.813224	0.481427	0.999983
	Validation	8.709984	2.484514	2.951268	0.481636	0.999982
	Test	8.488302	2.465417	2.913469	0.471699	0.999982
ANN [28]	Train	0.019994	0.093862	0.141399	0.041860	1.000000
	Validation	0.017222	0.092735	0.131231	0.031758	1.000000
	Test	0.014239	0.090611	0.119329	0.026890	1.000000
LR [29]	Train	1.687521e-24	1.241639e-12	1.299046e-12	1.848982e-13	1.000000
	Validation	1.684221e-24	1.241368e-12	1.297775e-12	1.802456e-13	1.000000
	Test	1.703430e-24	1.249221e-12	1.305155e-12	1.775839e-13	1.000000
DTR [30]	Train	0.338546	0.475131	0.581847	0.096080	0.999999
	Validation	0.618354	0.640669	0.786355	0.126329	0.999999
	Test	0.638777	0.663461	0.799235	0.132298	0.999999

VI. CONCLUSION

The comparative assessment of multiple demolition solid waste generation prediction models reveals the superiority of ensemble-based techniques over conventional regression, ANN, and time-series models in terms of both accuracy and reliability. The proposed ensemble meta-models were robust and predictive, as they showed consistently low errors and high R^2 scores (~0.99995). However, traditional models such as SARIMA and ETS showed negative R^2 values and high errors, suggesting that they were not well-suited to the task. The R^2 score was nearly perfect for both ANN and NARX, neural models, but embraced the ensemble models for better generalization across the test dataset. Similarly, other high-performing models such as RF, XGBoost, and LightGBM demonstrated substantial predictive capabilities, further highlighting the potential of advanced algorithms in modeling complex waste management systems. In conclusion, ensemble meta-models hold great promise in facilitating precise, data-informed decision-making in the management of demolition waste generation, offering a pathway toward sustainable and efficient solutions.

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DATA AVAILABILITY

The dataset generated and analyzed in this study is available in [31].

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