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Research Article

Integration of Statistical and Machine Learning Models for Time Series Forecasting in Optimizing Decision Making for Smart Waste Management

Carlos A. Villanueva[1], Thelma D. Palaog[2]
[1]College of Information Technology, University of the Cordilleras, Governor Pack Road, Baguio City 2600, Philippines
[2]College of Information Technology, University of the Cordilleras, Governor Pack Road, Baguio City 2600, Philippines

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ABSTRACT

Introduction: Smart decision-making for an efficient and effective waste management strategy involves the utilization of contemporary technologies such as predictive analytics and machine learning. They allow for effective planning of waste generation patterns, collection schedules and resource deployment. With the use of data-driven insights, municipalities can increase sustainability, lower operational expenses, and enhance environmentally friendly waste management strategies.

Objectives: The goal of this research is to create and contrast time series and machine learning models namely ARIMA, Random Forest, and XGBoost to predict the amount of biodegradable waste collected (weight_kg) over time. Utilizing both temporal patterns and structured features like year and population, the goal is to compare which modeling technique is most accurate and reliable in terms of forecast. Model performance is evaluated based on common measures like MAE, MSE, RMSE, MAPE, and R^2 score, aiming to choose the best method for producing short-term (1-year) predictions to inform data-driven waste management planning.

Methods: The machine learning workflow was adopted to research and forecast waste generation patterns, which involves data collection, preprocessing, feature selection, model training, testing, and validation to develop a predictive model

Results: Among the three models tested namely ARIMA, Random Forest, and XGBoost, ARIMA stood out with the lowest errors: MAE 0.62, MSE 0.71, RMSE 0.84, and MAPE 4.38%, and a positive pseudo-R^2 of 0.2254. Random Forest also had excellent performance (MAE 0.62, MSE 0.68, RMSE 0.82, R^2 0.23), following closely after ARIMA. XGBoost, on the other hand, was poor with high errors (MAE 1.41, MSE 3.58, RMSE 1.89) and a negative R^2 of -0.4312. Overall, ARIMA is the best model for this dataset.

Conclusions: ARIMA performed best with lowest errors and a positive R^2, followed very closely by Random Forest. XGBoost performed worse with greater error rates and a negative R^2. For further improvement in model performance, particularly for machine learning models, more features from the dataset (e.g., waste category, location, day of week, month, or type of collection service) may be added. These features may capture patterns and seasonal effects missed by simpler models, enabling more robust and generalizable forecasting. Integrating such variables may improve the predictive power of tree-based and deep learning models, potentially surpassing ARIMA in future iterations.

Keywords: lorem ipsum.

INTRODUCTION

Effective Decision-making is very crucial and has a great impact for the advancement of smart waste management systems, which is also are essential for addressing the gaps and growing challenges of urbanization and environmental sustainability. As cities expand and population increase, managing waste effectively and efficiently becomes more increasingly complex. The traditional waste management practices often struggle to keep pace with these demands, leading to inefficiencies, higher costs, and environmental impacts. Inefficient waste collection

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systems (Silva et al., 2023) rely on fixed schedules and poorly optimized routes, leading to unnecessary costs and resource waste. Trucks often collect half-empty bins or miss overfilled ones, wasting fuel, labor, and time, while also increasing operational costs and contributing to environmental harm through excess carbon emissions. The absence of real-time monitoring (Munir et al., 2023) means waste levels cannot be tracked accurately, resulting in overflows, unsanitary conditions, and inefficient resource allocation. These systems strain budgets, reduce service quality, and negatively impact both economic and environmental sustainability.

In recent years, the integration of advanced technologies has transformed how waste management systems operate. Among these advancements, predictive analytics and machine learning stand out as powerful tools that offer significant improvements in decision-making processes. Predictive analytics involves using historical data and statistical techniques to forecast future trends (Szpilko et al., 2023), while machine learning leverages algorithms to identify patterns and make data-driven predictions (Sengupta, N., & Chinnasamy, R, 2019). When combined, these technologies enable waste management systems to anticipate waste generation patterns, optimize collection routes, and improve recycling processes.

The integration of big data and predictive analytics in smart waste management enhances both environmental and economic performance (Nilashi et al., 2023) by optimizing waste collection routes and schedules, reducing unnecessary trips, fuel consumption, and vehicle emissions. This leads to lower operational costs and a smaller carbon footprint. Predictive models anticipate waste accumulation trends (Adewuyi et al., 2024), enabling more efficient resource allocation, such as trucks and personnel, further reducing waste management costs.

In order for a model to efficiently and effectively predict future waste generation, historical data must be prepared, and trained using machine learning techniques (Namuon et al., 2022). There was a significant increase in studies about machine learning to forecast waste patterns and trends (Alsabt et al., 2024). To provide accurate and reliable forecasts for waste generation, segregation, and collection, the system incorporates multiple machine learning methods (Pillai et al., 2023) such as decision trees, random forest and KNN. Likewise, a comparison on six machine learning (ML) models to predict municipal solid waste (MSW) generation from selected residential areas in Vietnam was also presented to test the reliable forecasting of the data on MSW generation (Nguyen et al., 2021).

OBJECTIVES

The main objective of this study is to create a model that can predict future waste generation based on historical data to optimize decision making. The study will utilize of series of machine learning and Statistical model to identify the most effective approach for enhancing decision-making in smart waste management. By applying and evaluating several models like ARIMA, Random Forest, and XGBoost, this aims to determine which model offers the best performance. Each model will be assessed based on its ability to predict waste generation patterns. This comparative analysis will provide valuable perceptions about the strong point and boundaries of different machine learning methods, ultimately guiding the selection of the most suitable algorithm (Arun et al., 2024) for improving decision-making processes in smart waste management systems.

METHODS

First, data collection was done through an interview with municipal officials tasked with gathering waste data, that will be served as the raw dataset required for model training for waste prediction.

Next, to have smooth and orderly model training, the machine learning workflow was considered as a structured and iterative process designed to enhance model accuracy and reliability. This workflow includes clearly defined steps such as "data preprocessing, feature selection, model selection, and evaluation". By adhering to this systematic approach, potential issues like data inconsistencies or overfitting are minimized, ensuring the development of a robust and effective predictive model.

The machine learning workflow was applied to develop a predictive model for waste generation. It is a structured process used to build and deploy predictive models that can analyze data, identify patterns, and make predictions (Kampezidou et al., 2024) or decisions without explicit programming. This workflow is essential for developing robust ML models across various applications, from waste management to healthcare and finance.

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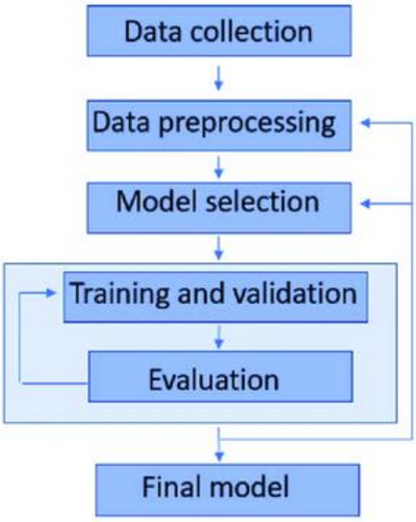

Figure 1. Machine Learning Workflow

Data Collection

The process began with collecting and preparing the data where historical waste generation data, along with external factors such as weather, population density, and socioeconomic variables, were gathered from municipal records. The datasets consist of daily waste collection from 2018-2023.

Data Preprocessing

After collecting the data, the next step is to analyze and comprehend it, preparing it to serve as input for the training process. After which the data was cleaned to identify and correct any anomalies resulting from errors in data entry or measurement. Next is the preprocessing stage, where valid and cleaned data is transformed into a format that is optimally suited for the requirements of the model.

As mentioned by (Borodkin et al., 2023) their research work ventures into the function and extent of data pre-processing methods in the development and implementation of Machine Learning models for prediction problem-solving in the field of education. Good data visualization methods are crucial in interpreting trends, patterns, and associations in the data, facilitating feature selection, model assessment, and explanation. The research work addresses several methods of enhancing data quality, including data cleaning, handling missing values, and data selection. We suppose that data quality and applying various preprocessing methods may have a strong influence on some machine learning models performance and quality.

The researcher prepared and transformed the data using an excel application. The raw data was processed and categorized based on different types of waste (such as biodegradable, recyclable, residual, and special waste). In addition to classifying the waste, the dataset was enriched by integrating various external variables that could influence waste generation. These variables included date, and population data.

Model Selection

In this stage, several processes were taken into consideration. First, a model selection was established to select suitable machine learning algorithms based on the nature of the data and the type of problem being addressed. Three models (Regression, Tree-Based and Time series) were selected to determine the performance of waste generation predictions. Specifically, the researcher selected Multiple Linear Regression, Random Forest, ARIMA, and XGBoost for waste generation prediction because each model brings distinct advantages suited to different aspects of the problem.

Training, Validation and Evaluation

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Training of the model was done through Google Colab, a cloud-based platform that provides a convenient and efficient environment for executing machine learning workflows. Using Colab allowed for access to powerful computational resources, such as GPUs and TPUs, which significantly accelerated the training process. Additionally, its collaborative features and seamless integration with Python libraries made it ideal for developing, testing, and refining the model in an organized and accessible manner.

Google Colaboratory (or Colab, as it is also known) is a cloud-hosted service on Jupyter Notebooks for machine learning research and education distribution, according to (Carneiro et al., 2018). It gives you an IDE that serves as a working place established for machine learning and free user access to an advanced GPU. This study offers a wide-ranging overview of Colaboratory on its hardware resources. Evalauation and review is achieved via use of Google Colab for fast-tracking machine learning on computer vision and other applications involving the GPU.

During the training, several attributes were considered (features might include factors like population size and day of the week) serves as an input variable (independent variables) and the target could be the actual amount of waste generated (dependent variables). In addition, the model receives the input features and, based on the current state of its parameters, it makes a prediction for the target. In waste generation prediction using factors like location, population, waste collected, and date, hyperparameter tuning plays a key role in optimizing model performance. It ensures the model accurately captures the relationships between these variables, improving prediction accuracy. By fine-tuning parameters like learning rate or regularization strength, the model can better generalize to different locations or population sizes, avoid overfitting, and effectively handle seasonal or temporal patterns in the data, leading to more reliable forecasts of waste generation.

Item Response Theory (IRT) enables ability measurement of Machine Learning models in relation to a human population. Yet, it becomes hard to develop an extensive dataset for training the ability of deep neural network models (DNNs). We suggest fine-tuning as a novel training process, in which a pre-trained model on an extensive dataset is fine-tuned using a small additional training set. We found that fine-tuning is effective in enhancing the performance of an advanced DNN model for Textual Entailment tasks (Lalor et al., 2017).

Several metrics are commonly used to evaluate the performance of a model, which is typically the type used for waste generation prediction (predicting continuous values such as tons of waste). These are the following:

(1) Mean Absolute Error (MAE), calculates the average absolute difference between the actual (true) waste amounts and the predicted waste amounts.
(2) Root Mean Squared Error (RMSE), is the square root of the MSE and is in the same unit as the predicted values (tons of waste). It measures prediction accuracy but gives more attention to voluminous errors by squaring the differences before averaging. A lower RMSE indicates fewer large prediction errors, making it more sensitive to outliers. RMSE is useful when larger errors are of greater concern, such as in extreme waste generation days.
(3) Mean Squared Error (MSE), This tperformance measurement computes the average of the squared errors between predicted and actual values. The smaller MSE indicates that predictions by the model are nearer to the true values.
(4) R-squared (R^2) – Coefficient of Determination, the R^2 indicates how closely the model's predictions are to the true data. It is the ratio of variance in the target variable (waste generated) that the model explains.

These performance evaluation metrics provide an inclusive thougth of model accuracy, understanding error distribution, and its effectiveness, allowing for more informed decisions about model optimization and improvement. This holistic evaluation ensures that the model can perform well in both typical and extreme cases, enhancing its reliability and usefulness in real-world applications.

During the working process a large number of experiments were performed and each test was evaluated with the mean square error (MSE) criteria, medium absolute error (MAE), root mean square error (RMSE) and R2 score. This research also opens the door to future research using regression models on the basis of machine learning. Correct validation and analysis of data can assist in healing and disease prevention at an early stage (Khan et al., 2021).

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Final Model

Through a systematic process and rigorous evaluation, the final model not only captures the complex relationships among various input factors but is also designed for real-time applications, empowering waste management authorities to make informed decisions on resource allocation and sustainability initiatives. This comprehensive approach has culminated in a reliable and effective tool for forecasting waste generation, ultimately contributing to improved waste management practices.

RESULTS AND DISCUSSION

Data Collection

Data were gathered from the municipality of Agoo, La Union that serves as the dataset comprises several tuples, and each entry is a piece of recorded data from a given location and time. Each tuple carries major features like the location, waste type (e.g., biodegradable, non-biodegradable), collection date, area population, and the weight of collected waste in kilograms.

Data Preprocessing

Following the initial collection, the raw data was preprocessed and cleaned to become consistent and relevant for model training. In this step, unwanted or incomplete records were eliminated, particularly retaining only the most important features. The resultant dataset comprises year and population as input features and the amount of waste collected in kilograms as the target variable. This more sophisticated organization enables the model to concentrate on important temporal and demographic variables that affect waste production, enhancing the predictive validity and reliability.

Model Selection

Three models were selected for waste generation prediction based on their individual strengths in handling different aspects of the problem. Random Forest is an ensemble learning model that excels in capturing complex, non-linear relationships between multiple variables, making it ideal for modeling the intricate factors that influence waste generation, such as population size, economic activity, and weather patterns.

ARIMA, on the other hand, is a time-series model well-suited for forecasting waste generation over time, as it can effectively account for trends, seasonality, and autocorrelation within the data. This is important because waste generation often exhibits periodic fluctuations and long-term trends. Lastly, XGBoost is a powerful gradient boosting model known for its high predictive accuracy and ability to handle complex interactions between variables. It also manages missing data and outliers effectively, which can be common in waste-related datasets.

The dataset was then separated into training (80%) and testing (20%) sets so that the model would be capable of learning from one set of data while it is tested on a completely different one. The stretchable ability at splitting of dataset is of vital importance to the structural integrity since load- and environment-induced tensile stresses are likely to cause issues. This endeavor examines the accuracy of innovative and collaborative machine learning models such as LightGBM, GBRT, XGBoost, and the like. Using a strong dataset that is split into training (80%) and test (20%) sets, we compared model performance based on R2, RMSE, and MAE scores (Al-Abdaly et al., 2024).

The model was then trained on the preprocessed data, during which it learned the patterns and relationships underlying the data. This training was done by fine turning parameters to reduce error and enhance accuracy based on the input data. This stage utilized fine turning parameters to fine-tune the performance of the model, considering the problem type and the available data type.

ARIMA Training, Validation and Evaluation

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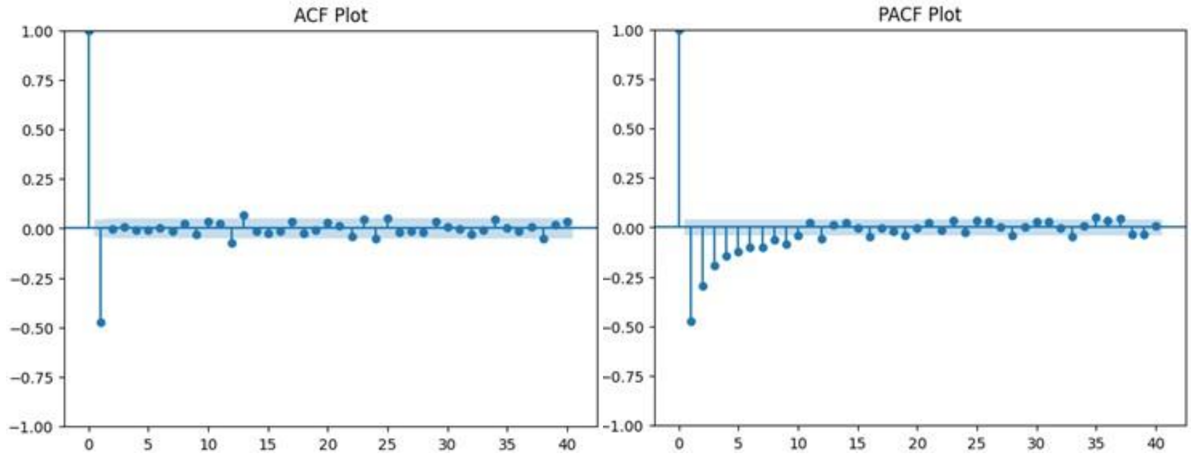

Figure 2. Autocorrelation Function

The ACF plot of the Autocorrelation Function reveals a tall spike at lag 1 that falls off very rapidly, and so it doesn't indicate very strong autocorrelation in the series after lag 1. The PACF plot also includes a large spike at lag 1, while other lags dwindle down, and hence an AR(1) process could be okay. These trends indicate that a low-order AR term simple ARIMA model could be suitable for the forecasting of this time series.

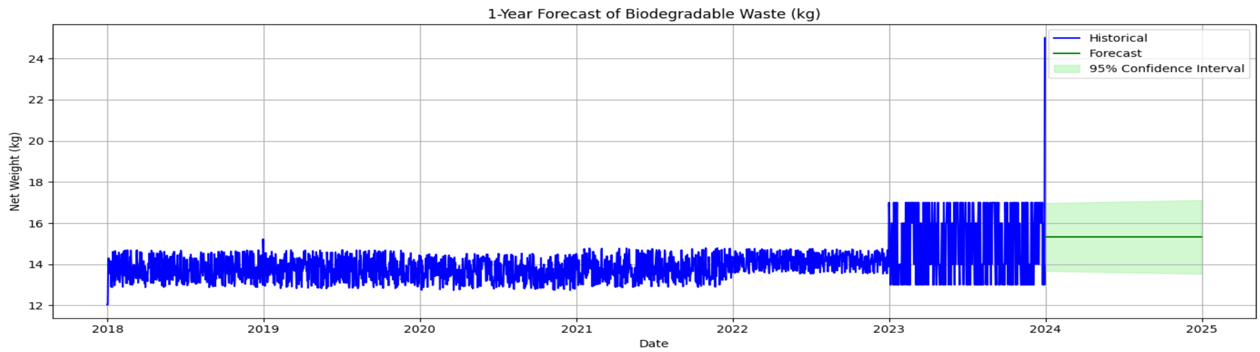

Figure 3. 1 year Forecast ARIMA

The graph illustrates a 1-year projection of biodegradable waste (in kg) based on past data between 2018 and 2023. Past observed values are depicted by the blue line, while the projected trend for 2024 is illustrated by the green line. The green area with shading gives the 95% confidence interval, illustrating the range of values expected. There is a small increasing trend indicated by the projection with moderate uncertainty.

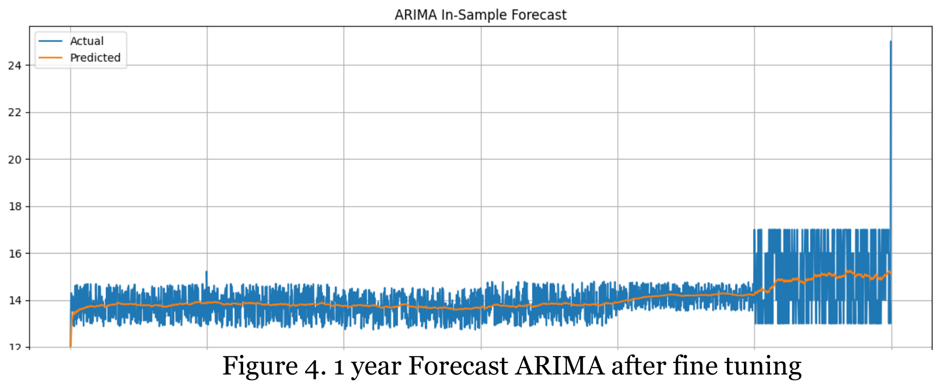

Figure 4. 1 year Forecast ARIMA after fine tuning

This prediction was made with the help of the auto_arima function from the pmdarima library, which selected the best (p, d, q) parameters automatically based on the time series. By allowing stepwise selection and hiding warnings,

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the model searched through various combinations efficiently to reduce error measures. The refined ARIMA model was then utilized to make precise predictions in line with observed trends in the data.

This graph shows the in-sample forecast of the ARIMA model by comparing actual biodegradable waste values (blue) with predicted values from the model (orange). The ARIMA model closely mimics the actual trend, particularly after 2020, suggesting that it caught the underlying pattern of the data well. Deviations can be seen during more volatile times, but the model generally fits the training data quite well.

Performance Evaluation (ARIMA)

The performance statistics reveal that the ARIMA model had a Mean Absolute Error (MAE) of 0.62 and a Root Mean Squared Error (RMSE) of 0.84, reflecting reasonably low prediction errors. The Mean Absolute Percentage Error (MAPE) of 4.38% indicates good accuracy in percentage terms. The pseudo R^2 value of 0.2254 reflects a modest level of variance explained by the model, as is usual for time series data where external variables are not present.

Random Forest Training, Validation and Evaluation

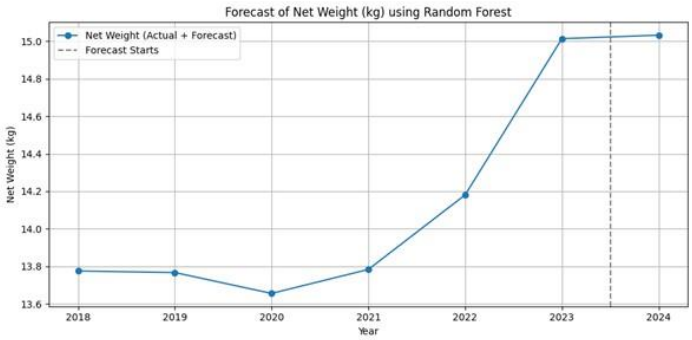

Figure 5. 1 year Forecast Random Forest

The graph illustrates the prediction of net biodegradable waste (kg) based on a Random Forest model, with past values from 2018 to 2023 and a prediction for 2024. The vertical dashed line indicates the start of the prediction period. The model foresees an increase in waste in 2024, maintaining the trend that has been observed since 2020. The graph indicates that biodegradable waste has been increasing steadily year by year, particularly from 2020 onwards. The Random Forest model anticipates this increasing trend to persist in 2024, implying increased waste. This may be an indication of increasing population, consumption, or waste management practice changes.

Performance Evaluation (Random Forest)

The Random Forest model has moderate performance with low error measures (MAE: 0.62, RMSE: 0.82), but a low R^2 of 0.23 means it only accounts for 23% of the variance in the data. This implies predictive ability, but accuracy could be enhanced with more features.

XGBoost Training, Validation and Evaluation

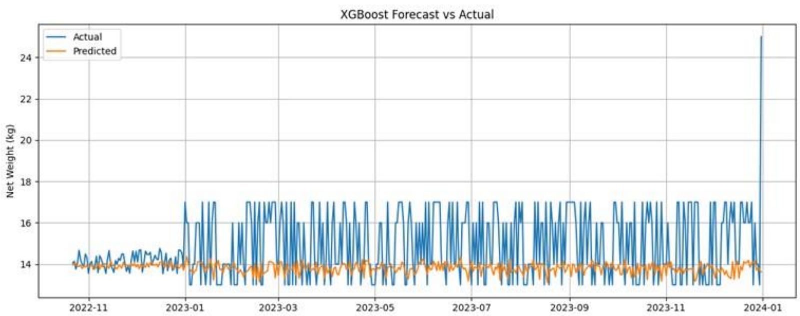

Figure 6. 1 year Forecast XGBoost

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The XGBoost forecast vs actual plot illustrates the accuracy of the model's prediction of daily net biodegradable waste weights. The orange line (predicted) tracks the blue line (actual) in general trend but falls below it in peak spikes, indicating the model captures the average trend but does not handle high variability or outliers well. XGBoost accurately follows long-term trends in biodegradable waste but fails to predict sudden spikes. Adding additional relevant features (e.g., weather, holidays, sources of waste) to the model may make it more accurate. data.

Performance Evaluation (XGBoost)

The XGBoost model performed poorly, with large MAE (1.41), RMSE (1.89), MAPE (8.82%), and a negative R^2 (-0.4312), indicating its predictions were not accurate and poorer than a simple average, and it was unable to explain the variance in the data.

Metric	ARIMA	Random Forest	XGBoost
MAE	0.62	0.62	1.41
MSE	0.71	0.68	3.58
RMSE	0.84	0.82	1.89
R^2	0.2254 (Pseudo)	0.23	-0.4312

Table 1. Model Comparison in Performance Evaluation

ARIMA and Random Forest were equally good and better in performance, with minimal errors (MAE, MSE, RMSE) and moderate explanatory ability (R^2 ~0.23). ARIMA was best at MAPE, so it was slightly more appropriate for percentage-based error measurement. XGBoost was worst, with much higher error values and a negative R^2, showing that it was not able to explain the variance in the data and it was worse than using the mean.

Final Model

ARIMA is the most consistent and well-balanced performance on all critical metrics. Lightest MAPE (4.38%), indicating it is most accurate in comparison to real values. Performance is almost the same as Random Forest in MAE and RMSE, but ARIMA is more interpretable with time series.

Predicting the continuous volume of waste for the years to come is critically necessary to assess the existing waste disposal system. Forecasting the future of waste increase between 2021 and 2028 for Bengaluru, the largest city of Karnataka, using time series forecast model ARIMA is commenced. Historical eight-year solid waste data from 2012 to 2020 are used for prediction (G & K, 2022). This data is preprocessed and time-specific only variables such as days, month, year and tons of waste are employed in this study to achieve precise prediction. The model is executed in python in Google Colab free cloud's Jupyter notebook. Since ARIMA is time-dependent, the prediction of the model is reliable and the performance of the model is measured by means such as Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Coefficient of Determination (R2).

Furthermore (Bagwan, 2023), based on his research exclusively on the Maharashtra state that by analysing historical and future inclinations through (ARIMA) models, commonly used in time series forecasting and analysis, the study foresees that the average E-waste processing load of 2023–2030 will be 163,563.15 Metric Tons, with expected values collectively growing gradually year after year up to 2030. Through rate of change in E-waste processing capacity of 2023–2030, there will be chances of 6.86 % annually. This is also putting in the limelight the scale of entrepreneurship in E-waste recycling businesses through determining mean growth of recyclers by 7.23 % each year. The study is centered on the role of policy and decision-making in handling this rapidly increasing waste stream from the perspective of environmental management and circular economic considerations.

CONCLUSION

Based on the provided dataset, ARIMA performed best with lowest errors and a positive R^2, followed very closely by Random Forest. XGBoost performed worse with greater error rates and a negative R^2. For further improvement in model performance, particularly for machine learning models, more features from the dataset (e.g., waste category, location, day of week, month, or type of collection service) may be added. These features may capture patterns and seasonal effects missed by simpler models, enabling more robust and generalizable forecasting. Integrating such variables may improve the predictive power of tree-based and deep learning models, potentially surpassing ARIMA in future iterations.

ARIMA is essentially a univariate model, it takes only the past values of the target variable and makes predictions based on them. But to improve performance and learn more complex patterns, you can either utilize alternative such as SARIMA that Captures seasonality (excellent for weekly/monthly waste patterns) and SARIMAX that Allows inclusion of exogenous variables (features).

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