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Prediction of Organic Waste Deposits in Compost Houses using LSTM and ARIMA Algorithms

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Abstract: Indonesia faces a significant waste problem and is becoming a global challenge, mainly due to inadequate food waste management. In Kendal District, the Environmental Agency struggles to optimize waste collection and predict the volume of organic waste. To address this issue, this study explores the application of predictive technology and data analysis to improve the efficiency of waste management. Two predictive models, ARIMA and Long Short-Term Memory (LSTM), were developed and compared by collecting historical data from Kendal Organic Compost House from 2020-2024 while for train and test data using data from January 2, 2023, to December 30, 2023. The ARIMA model showed better accuracy, capturing stable trends and seasonal patterns in the time series data, with an MSE of 72,799.49. Meanwhile, the LSTM model, although capable of handling non-linear and complex patterns, performed poorly with an MSE of 54,711,498,631,770.58, indicating a failure to accommodate sharp fluctuations in the data. These findings highlight the suitability of ARIMA for data with low volatility and strong seasonality, making it more reliable for short-term predictions. The results of this study are expected to assist the Kendal District Environmental Agency in planning efficient waste management strategies, optimizing compost house operations, and improving resource allocation. Future research should focus on the integration of external variables, such as weather and population dynamics, and explore hybrid models for better prediction.

Keywords: Machine Learning; Smart Waste Management; ARIMA; LSTM, Predictive Models;

INTRODUCTION

Indonesia being the most populous country number 1 in ASEAN and number 4 in the world has a serious problem with waste this is a global challenge facing society with the biggest cause being food waste (Chaerul & Zatadini, 2020). Waste generally consists of kitchen waste, yard waste, paper and cardboard, plastic and rubber, metal, glass, electronic waste, inert materials, and mixed waste, where kitchen and yard waste constitute the organic part of solid waste, while the most heterogeneous components include textiles, fabrics, biomedical waste, personal hygiene products, health care products, cosmetics, pharmaceuticals, pet waste, leather, rubber, and polymer residues (Hasibuan, 2023).This waste problem can be proven in the data of the National Waste Management Information System (SIPSN) https://sipsn.menlhk.go.id/sipsn/ where Central Java Province in 2022 ranks first in the most waste in Indonesia, this data is provided by the Provincial Government and the Regency / City Government through the head of the agency authorized in Waste Management.

In Indonesia, food waste has not received special attention and proper handling so this causes problems that have an impact on the community environment (Roring et al., 2023), (Putri et al., 2022). Kendal District Environment Office faces challenges in optimizing organic waste collection and predicting the volume of waste generated each year. To solve this problem, predictive technology and data analysis can be used to create a more efficient waste management system. With good management and prediction of the amount of food waste that will be generated in the future, it can be used as a useful material efficiently and economically with minimal impact on the environment (Ariefahnoor et al., 2020).

The compost house is a special place for the management of organic waste into compost and natural fertilizer implemented by the Kendal District Environmental Service in dealing with the problem of organic waste (Suhardono et al., 2024). This process involves the decomposition of organic materials by microorganisms such

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as bacteria and fungi, which produce compost that is rich in nutrients and beneficial for improving soil fertility. The development of compost is an alternative to chemical fertilizers due to the deteriorating soil quality. Compost contains many important organic elements needed by the soil to maintain its structure, making the soil easier to cultivate and rich in oxygen (Siahaan et al., 2023). The Compost House is a form of the right solution to reduce the pile of organic waste that every day becomes household waste and increasingly accumulates in landfills produced by the community every year (Rini et al., 2021).

This analytical system with organic waste prediction uses ARIMA and LSTM technologies, which utilise historical data to project the amount of waste in the future. The implementation of this model in Kendal Regency is expected to help the Environmental Agency in designing more targeted waste management policies, such as determining the capacity of processing facilities, transportation schedules, or waste reduction programme priorities. With accurate predictions, the government can take proactive steps to prevent waste volume spikes every year, so that inorganic waste management can be carried out effectively and efficiently. This prediction uses and compares 2 Machine Learning Algorithms namely the ARIMA model and Long Short Term-Memory (LSTM) this method is usually used for data that tends to fluctuate (Milniadi & Adiwijaya, 2023), (Ferdinandus et al., 2023). Arima is a combination of the AR (Autigtressive) model, which is a model that explains the movement of a variable through the variable itself in the past, and the MA (MovinAverage) model, which is a model that sees the movement of the variable through its residuals in the past (Purnama & Juliana, 2020). Independent variables are not considered in the ARIMA model because it only uses the current and past values of the dependent variable to produce accurate short-term predictions (Riyantoni et al., 2023).

LSTM is one of the methods included in the RNN category (Tita Lattifia et al., 2022). The advantage of LSTM compared to RNN is its ability to remember time series data or data with long-term dependency information. LSTM can also store old information through the cells in it. LSTM has three types of gates: forget gate, input gate, and output gate. A forget gate is a gate that determines how to remove information from cells. The input gate determines the input value that will be updated in the state memory. The output gate plays a role in determining how to produce output after going through the cell memory (Karyadi, 2022), (Amansyah et al., 2024).

LITERATURE REVIEW

Waste Management and Information Technology

Efficient waste management is one of the biggest challenges faced by modern cities. The use of information technology in waste management can provide innovative solutions to address this issue. The implementation of technology-based systems, such as real-time monitoring systems and prediction algorithms, can improve waste collection efficiency and reduce operational costs.

Long Short-Term-Memory (LSTM) Algortima

Long Short-Term Memory (LSTM) is a type of artificial neural network used to process and make predictions based on time series data. LSTM can overcome the long-term problems faced by traditional recurrent neural networks. LSTM can store important information in the long term and ignore irrelevant information, so it is suitable for the prediction of time series data. There have been many studies that prove that LSTM is successfully used for time series data prediction (Ashari & Sadikin, 2020).

Autoregressive Integrated Moving Average (ARIMA) Algorithm

The Autoregressive Integrated Moving Average (ARIMA) algorithm is one of the statistical methods used for analyzing and predicting time series data, this model is the result of a combination of the AR (Autoregressive) model and the MA (Moving Average) model so that the independent variables in this model come from both components (Tumanggor, 2021). ARIMA is effective for data that shows trends and seasonality. ARIMA works by combining three main components: autoregression (AR), differencing (I), and moving average (MA), to produce an accurate prediction model. While ARIMA is reliable in predicting data in the short term, its accuracy decreases when used for long-term predictions. This is because ARIMA models tend to produce flat (constant) predictions for a long period.

Prediction Model Evaluation

Evaluating a prediction model is essential to assess its accuracy and reliability. This process involves analyzing various metrics and methodologies, such as accuracy and precision to determine the frequency of correct predictions, and error metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) to measure prediction error. In addition, bias-variance tradeoffs are considered to ensure the model is neither too simple nor too complex. Validation methods, such as Train-Test Split, are used to split the data for training and testing purposes. Metrics such as R-Squared and Adjusted R-Squared are used in regression models to indicate the proportion of variability explained by the model. In addition, model-specific evaluations are tailored to the characteristics of each prediction model, to ensure a comprehensive assessment.

Inorganic Waste Management

Waste, the remnants of human activity, poses a serious threat to the environment. As materials or substances that are no longer useful, waste exceeds the limits of nature's tolerance, disrupting the balance of the ecosystem. Its impact is widespread, damaging water, soil, and air, and threatening the health of humans and other living things. The level of danger varies, from household waste to hazardous chemicals, and all have the potential to cause damage. Therefore, proper waste management is key to preserving the environment and public health. It has been shown that cities that implement a good waste management system experience increased operational efficiency and reduced costs.

Organic Compost House

Compost, which is often used as a substitute for artificial fertilizers, is being increasingly developed due to the deteriorating condition of the soil. Compost fertilizers contain many organic elements needed by the soil, which help maintain the soil structure making it easy to cultivate and rich in oxygen. Compost is the result of the decomposition of organic matter that can be accelerated through the composting process with the addition of fermentation materials. Composting is a biological decomposition process carried out by microorganisms on biodegradable organic matter. The goal of composting is to reduce the volume or mass of organic matter by converting degradable organic matter into a stable form. This process produces a residue that can be used as organic compost (Siahaan et al., 2023). With this, the Compost House is the right place to produce and manage compost.

METHOD

The data used in this study is in the form of data from the Organic Composting House of the Kendal Regency Environmental Service for the period 2020-2024 with data labels in the form of Year, Month, Leaf Waste, Vegetable Waste, Processed Waste, Fermented Waste, and Finished Waste. The selection of ARIMA and Long Short-Term Memory (LSTM) methods is based on the characteristics of the data in the form of time series and the advantages of each method in processing the data. ARIMA was chosen for its ability to handle time series data that are linear or have seasonal patterns and simple trends. Meanwhile, LSTM was chosen because it is specifically designed to handle complex and nonlinear time series data. The selection of these two methods aims to evaluate their respective performance in producing accurate real-time predictions, so as to support effective organic waste management. The model with the lowest RMSE value will be considered as the best method to predict future waste volume.

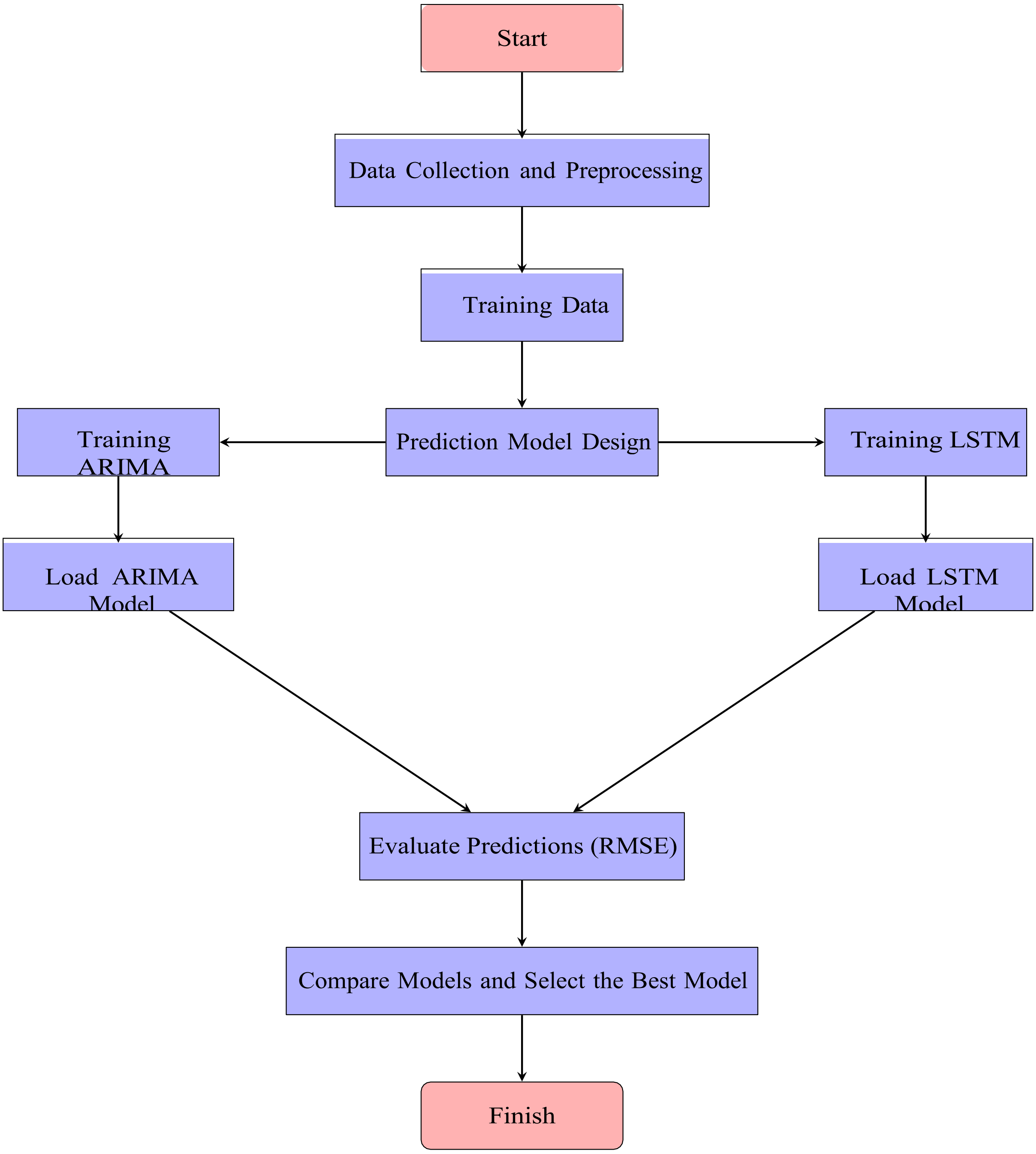
Table 1 . Research data Original

tahun	bulan	sampah daun	sampah sayur	daun terolah	sampah fermentasi	kompos jadi
2020	januari	1403	433	1043	1723	150
2020	februari	813	605	601	1552	175
2020	maret	878	295	582	901	150
2020	april	786	359	586	859	300
2020	mei	342	909	256	2215	300
2020	juni	400	633	302	1496	300
2020	juli	1013	290	741	838	300
2020	agustus	665	303	493	891	300
2020	september	1421	125	1022	445	300
2020	oktober	604	1011	400	2362	300
2020	november	677	892	460	2389	300
2020	desember	865	345	587	998	300
2021	januari	1440	515	923	1235	300
2021	februari	1270	634	802	1138	600
2021	maret	1050	1076	656	1731	300
2021	april	1240	740	699	1892	300
2021	mei	1025	630	438	1432	300
2021	juni	590	433	351	899	0

2021	juli	950	312	449	674	0
2021	agustus	1350	295	609	765	0
2021	september	940	640	402	1230	105
2021	oktober	1620	595	635	1225	300
2021	november	990	507	367	1308	425
2022	januari	1055	515	756	1235	300
2022	februari	1270	464	802	1138	600
2022	maret	1050	1076	656	1731	300
2022	april	1240	654	699	1892	300
2022	mei	1025	630	438	1432	300
2022	juni	500	433	351	899	0
2022	juli	950	312	449	674	0
2022	agustus	1350	295	609	765	0
2022	september	940	640	402	1230	105
2022	oktober	1620	595	635	1225	300
2022	november	677	892	460	2389	300
2022	desember	865	345	587	998	300
2023	januari	2490	348	1175	957	0
2023	februari	2235	1425	972	2568	0
2023	maret	1638	440	807	1546	0
2023	april	890	1055	397	1871	0
2023	mei	1330	946	592	1962	1050
2023	juni	1010	558	465	1074	175
2023	juli	930	584	439	1101	705
2023	agustus	942	1356	430	1385	625
2023	september	885	370	446	716	500
2023	oktober	1600	652	661	1242	150
2023	november	1350	821	499	1499	165
2023	desember	800	313	338	653	720
2024	januari	770	345	362	755	350
2024	februari	1670	800	749	1387	175

The flow of the research stages of the prediction model for waste generation using the comparison of ARIMA and Long short-term memory methods can be seen as follows:

Table 2 Research Flow



The flowchart shown explains the process of developing and evaluating a prediction model for waste management. The process begins with the "Start" step, followed by the data retrieval stage for Train and Test using data from January 2, 2023, to December 30, 2023, in the form of an Excel file of 1420 data on the amount of production of organic waste compost houses per day. The pre-processing stage is in the form of checking raw data to see whether the data is NULL or missing value. From these data, from January to May for incomplete compost data, it is necessary to do imputation, namely, replacing missing values or data (Missing value, NaN, blank) with the mean or median value [9]. This method aims to complete the data so that it can be used optimally in training and testing prediction models, as well as increasing the effectiveness of the analysis results.

The next process involves two prediction models, namely LSTM and ARIMA. For the LSTM model, the steps include training the model (Training LSTM), loading the trained model (Load LSTM Model), and testing the model precision (Test Model Precision). In the training stage, historical data is used to train the model by optimizing parameters such as weights and biases, using backpropagation and gradient descent algorithms to minimize error. After the model is trained, it is tested using test data that differs from the training data. This test data evaluates the model's ability to produce accurate predictions on new data. Model evaluation uses the RMSE (Root Mean Squared Error) metric, which measures the average prediction error in the same units as the original data.

In parallel, the ARIMA model is trained (Training ARIMA) to fit the historical data pattern by minimising the prediction error. Once the training is complete, the trained model is loaded (Load ARIMA Model) for further testing. The main parameters of ARIMA, namely p (autoregressive), d (differencing), and q (moving average), are determined through time series data analysis and precision testing (Precision Model Test). The precision evaluation of the two models, LSTM and ARIMA, is then compared to determine the best performing model. The model with the lowest RMSE (Root Mean Squared Error) value is considered the best model. This process ends with the ‘Finish’ step.

RMSE Formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2}$$

Explanation of the Terms:

- $\hat{X}_i$: Predicted value for the i-th observation.
- X_i : Actual (true) value for the i-th observation.
- η : Total number of observations.
- $\left(\hat{X}_i - X_i\right)^2$: Squared difference between predicted and actual values.

RESULT

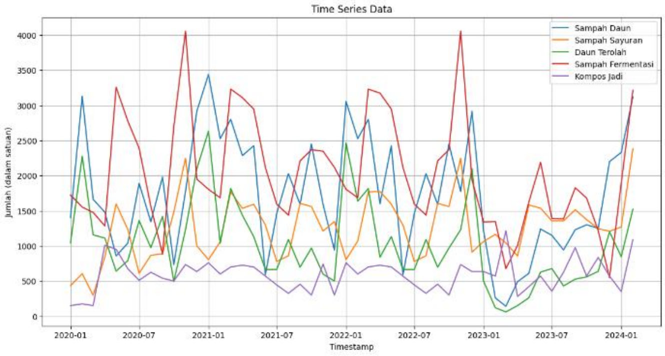


Figure 1 Time Series

The graph in Figure 3 displays the time series of all data variables, representing the time series of the amount of various types of waste and compost over the period 2020-2024. Overall, the graph provides an overview of how different types of waste are processed and converted into compost over time. The different fluctuations and peaks in each waste type reflect the variability in collection and treatment, as well as the effectiveness of the waste treatment system implemented. Based on the data visualization, it can be seen that the Rumah Kompos dataset has non-linear data characteristics, with weak correlations between variables that form a curved pattern (Statistika & Medan, 2024).

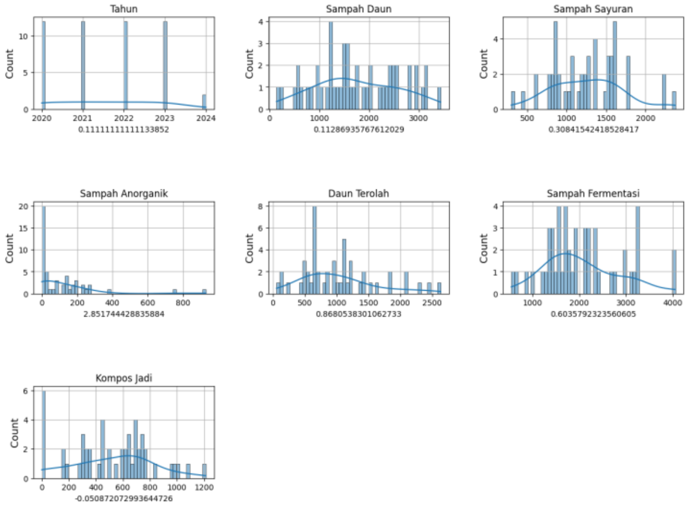


Figure 2 Correlation Matrix

Figure 4 displays the correlation matrix, which includes a histogram visualization of the data distribution across various variables related to waste management. Each subplot represents the frequency distribution of these variables, including time-series data from continuous measurements taken at different times and categories. Each variable corresponds to a component of the waste management system, such as waste types as input and compost as output. This analysis combines time-oriented input-output data, forming the foundation for data-driven decision-making in the Composting House.

The waste types analyzed include:

1. Leaf waste: Organic remains from plant leaves, either fallen naturally or produced through human activities like sweeping or pruning.
2. Vegetable waste: Residues from vegetable parts such as skins, stems, or leaves deemed unfit for consumption.
3. Processed waste: Organic and inorganic waste that has undergone prior processing, such as food leftovers or semi-finished products like rice, side dishes, and fruit-based foods.
4. Fermented waste: Organic waste decomposed by anaerobic microorganisms into stable materials like organic fertilizer or biogas, originating from household, industrial, or agricultural activities.

The main focus of this study is trend prediction, capacity estimation, and real-time optimization to enhance the effectiveness of waste management. ARIMA prediction results offer practical benefits by optimizing operational processes. For example, accurate predictions of waste volume can help managers allocate resources efficiently, such as determining labor needs, equipment capacity, and additional materials required for composting. This ensures smoother operations, minimizes waste and enhances overall efficiency.

Furthermore, ARIMA predictions can be integrated into technology-based systems like dashboards or monitoring applications, enabling faster and more informed decision-making. For instance, if a spike in waste volume is predicted, managers can proactively increase storage capacity or expedite processing. Additionally, prediction data can support public education campaigns, such as raising awareness about seasonal waste production trends and encouraging waste reduction during critical periods.

Thus, ARIMA predictions not only optimize operations but also contribute to environmental sustainability by supporting effective management, public awareness, and long-term ecological benefits.

ARIMA

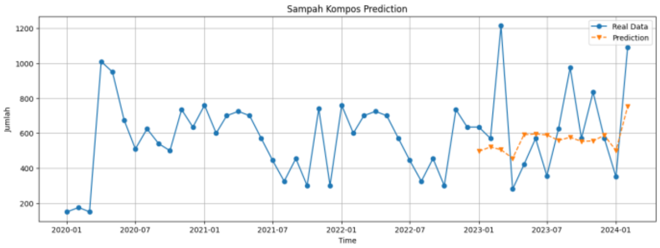


Figure 3 ARIMA model prediction results

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Figure 5 illustrates the prediction results of the ARIMA model for the finished Compost time variable. The blue line represents the training data, while the orange line represents the test data. The model successfully captured the increasing trend in the training data and provided reasonably good predictions for the test data. However, some deviations were observed, especially in March and November.

The prediction results were evaluated using several metrics. The Mean Squared Error (MSE) value of 72799.49 indicates that the mean squared difference between the predicted and actual values is significant, indicating considerable error in the model's predictions. Since the MSE value is squared, this metric gives greater weight to larger prediction errors. The Mean Absolute Error (MAE) of 197.88 units reflects the average absolute difference between the predicted and actual values, providing an intuitive understanding of the magnitude of common prediction errors. The Root Mean Squared Error (RMSE) of 269.8, expressed in the same units as the original data, provides a similar interpretation to MAE but gives greater weight to large prediction errors.
Calculation formula :

- **Mean Squared Error (MSE)**

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2$$

X_i : Actual value at data to-i

$\hat{X}_i$: Predicted Value at data to-i

η : Total Data

Results : MSE =72799.48646368692

- **Mean Absolute Error (MAE)**

$$MAE = \frac{1}{n}\sum_{i=1}^{\eta}\left|X_i - \hat{X}_i\right|$$

$\left|X_i - \hat{X}_i\right|$: Absolute value of the difference between actual and predicted values

Result : MAE =197.88438198359228

- **Root Mean Squared Error (RMSE)**

$$RMSE = \sqrt{MSE}$$

RMSE : Is the square root of the MSE

Result :

$$RMSE = \sqrt{72799.48646368692} = 269.8137996168597$$

Further analysis shows that the ARIMA model successfully captures the trend component in the data, but there are still several other factors affecting the volume of compostable waste that are not accommodated in the model. Factors such as environment and conditions could be the cause of the deviation that occurred

LSTM

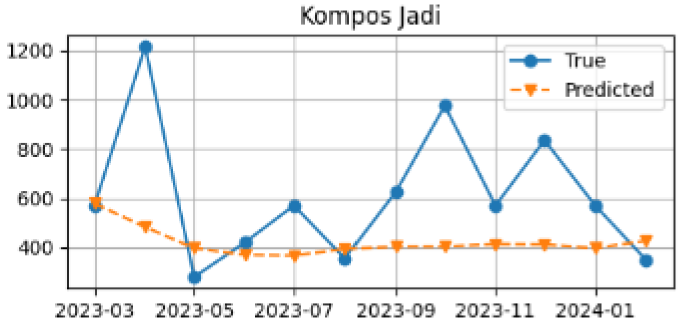

Figure 4 LSTM model prediction results

Figure 6 displays the prediction results of the Long Short-Term Memory (LSTM) model for the variable "finished compost". The blue line (Actual) shows the actual data which exhibits significant fluctuations, especially a high spike in March 2023 and another spike in September and November 2023. Meanwhile, the dashed orange line (Predicted) represents the prediction results of the LSTM model.

The predictive performance of the model was assessed using several evaluation metrics:

The Mean Squared Error (MSE) value is 54,711,498,631,770.58, highlighting the substantial mean square difference between the predicted and actual values. This large number indicates a significant prediction error.
The Mean Absolute Error (MAE) is 2,633,536.25, meaning the average absolute difference between the predicted and actual values is approximately 2.6 million units. On average, the model predictions deviate from the actual values by this much. The Root Mean Squared Error (RMSE) stands at 7,396,722.15, which indicates that the typical prediction error is about 7.4 million units. This metric provides an intuitive sense of the magnitude of the prediction error relative to the scale of the data.

Table 3
Comparison of prediction model results

Metode	**MSE (Mean Squared Error)**	**MAE (Mean Absolute Error)**	**RMSE (Root Mean Squared Error)**
LSTM	54,711,498,631,770.58	2,633,536.25	7,396,722.15
ARIMA	72,799.49	197.88	269.81

LSTM

- The LSTM model has a very large MSE of 54,711,498,631,770.58, which indicates that the prediction is very far from the actual value. This indicates that the model failed to learn the data pattern.
- The MAE (2,633,536.25) and RMSE (7,396,722.15) values also show that the average prediction error is quite large, both linearly (MAE) and taking into account the influence of outliers (RMSE).
- Possible Causes:
    1. Overfitting: The model is too complex and overfitting the training data, resulting in poor performance on test data
    2. Suboptimal Preprocessing: The data may not be normalized or the scale of values is too large, leading to large errors in prediction.
    3. Inconsistent Data Distribution: The data pattern is too volatile or there are outliers that cannot be learned by the model.

ARIMA

- The ARIMA model has a much smaller MSE of 72,799.49, which indicates a prediction that is closer to the actual value than the LSTM.
- The MAE (197.88) and RMSE (269.81) values are also low, indicating that the average prediction error per time point is small.
- Advantages of ARIMA:

    1. The model is able to capture simple, seasonal, and consistent data patterns well.
    2. ARIMA, which is a traditional time series model, is more suitable for data with seasonal and linear patterns like the data in this case.

The MSE of LSTM is higher than that of ARIMA because the characteristics of the data used have simple and seasonal patterns, which are more suitable for the ARIMA model. ARIMA models are designed to capture consistent and linear data patterns, while LSTM is more suitable for complex and non-linear patterns. The complexity of LSTM, which is unnecessary in this case, leads to poor prediction performance. In addition, ARIMA has the advantage of being robust to preprocessing, so it can produce more stable results even when data preprocessing is less than optimal. In contrast, LSTM relies heavily on good preprocessing, such as normalisation and outlier handling, which if not done properly can lead to significant prediction errors.

DISCUSSIONS

Based on the Mean Squared Error (MSE) value, the ARIMA model has better predictive ability than the LSTM model. This shows that ARIMA can more accurately predict organic waste volume time series data. The ARIMA model successfully captures the data's stable trend and seasonal patterns, which are the main characteristics of organic waste volume. By utilizing differentiation and autoregression functions, ARIMA can model the data patterns precisely, especially if the data shows regular patterns without significant volatility. In addition, ARIMA is more effective when the data has low fluctuations, making it a more optimal choice than other models in this case.

In contrast, the LSTM model struggles to capture the sharp fluctuation patterns in the actual data. The resulting predictions tend to be more stable but do not reflect drastic spikes or dips, suggesting that the LSTM performance is less than optimal for this data. This is due to the underfitting of the LSTM model, where the complexity of the data is not fully accommodated. In addition, if the data is not properly processed, such as without normalization or still containing noise, the performance of the LSTM may further degrade. The complexity of LSTM, with many parameters to train, also requires a larger dataset to produce more optimal predictions.

Context and Relevance of Results

The prediction results show that the ARIMA model is more suitable for predicting the volume of organic waste in the Kendal Environmental Agency. Better prediction accuracy allows for more effective planning in waste management, such as:

1. Operational Scheduling: ARIMA can predict the amount of waste that will be generated each period, facilitating the scheduling of waste collection and transportation.
2. Compost Capacity Planning: More accurate predictions allow compost houses to optimally prepare storage and processing capacities, reducing potential buildup or shortage of raw materials.
3. Resource Utilization Efficiency: Accurate predictions allow the Environmental Agency to allocate labor, tools, and vehicles more efficiently.

However, although ARIMA shows better results, several factors affect the deviation of the prediction results, such as:

- Unexpected seasonal changes, such as extreme weather.
- External volatility, such as changes in waste management policies.
- Limitations of input variables, such as not considering population or economic activity.

Pros and Cons of the Model

ARIMA Model

Pros:

ARIMA is suitable for data with seasonal patterns or stable trends. The model is easy to implement and gives good prediction results if the data does not have sharp fluctuations or complex nonlinear patterns.

Weaknesses:

ARIMA is less effective in handling nonlinear patterns and unexpected sharp fluctuations. In addition, this model cannot accommodate external variables, such as policy changes or environmental factors.

LSTM model

Pros:

LSTM excels in capturing complex nonlinear patterns and sharp fluctuations. With its ability to process data sequentially, LSTM can retain historical information to produce better predictions, especially if the data has spikes or anomalies.

Weaknesses:

LSTM requires large datasets and thorough preprocessing, such as normalization and noise removal. If the data is inadequate or the hyperparameter settings are not optimal, the LSTM is prone to underfitting. In addition, the training process requires more time and computational resources than ARIMA.

Research Limitations

This study has several limitations that may affect the findings and generalizability of the results. First, the data representation in this study may not cover all factors that affect waste volume. External variables such as population growth, fluctuations in economic activity, or seasonal influences, including weather patterns and holidays, are not explicitly considered in the model.

Secondly, the prediction models used, such as ARIMA and LSTM, exhibit inherent weaknesses. ARIMA, for example, struggles to capture complex nonlinear patterns in the data, while the performance of LSTM tends to degrade when working with small data sets or when data preprocessing is inadequate.

Lastly, these methodologies rely on the assumption that historical patterns will continue to exist in the future. This simplification can lead to inaccuracies, especially in scenarios involving policy changes or unforeseen extraordinary events that disrupt established trends.

Development Suggestions

- Integrate relevant external variables, such as weather data, population, or industrial activity.
- Using a hybrid approach that combines ARIMA for linear and seasonal trends with LSTM to handle complex fluctuations.
- Expanding the dataset by recording data over a longer period and ensuring consistency of recording.

Practical implications

Of this research are significant. Accurate predictions of organic waste volume enable the Environmental Agency to enhance operational planning, leading to optimized waste collection schedules that minimize operational costs and energy consumption. Furthermore, the ability to forecast waste volumes supports the effective management of compost houses, ensuring sufficient raw materials without surplus, thus maintaining smooth processing operations.These predictions also facilitate the design of more effective waste volume reduction strategies by analyzing data patterns, allowing for targeted public education campaigns during peak periods of waste generation. Moreover, the insights gained can inform waste management policy improvements, such as adjusting waste collection frequencies or promoting organic waste processing at the source.

CONCLUSION

This research shows that the ARIMA model with MSE 72,799.49 provides a more accurate prediction compared to the Long Short-Term Memory (LSTM) model with MSE 54,711,498,631,770.58 in forecasting monthly organic waste generation, especially finished compost, thus assisting the Kendal District Environment Agency in efficient waste management. However, limitations such as the use of short datasets, the exclusion of external variables such as weather conditions, and the inability of ARIMA to handle unstable data patterns are areas that need improvement. Future research should integrate external factors such as population growth and economic indicators to improve prediction accuracy and explore hybrid models that combine the power of ARIMA in capturing seasonal patterns with the ability of LSTM in managing sharp fluctuations.

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