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Enhanced Long Short-Term Memory for Landfill Area Estimation Based on Domestic Solid Waste Prediction

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Abstract

A novel approach is presented to address the prediction challenge in domestic solid waste generation through the application of machine learning techniques. To overcome the limitations inherent in capturing intricate temporal patterns faced by conventional Long Short-Term Memory (LSTM) models de- signed for time series forecasting, an enhanced variant, termed e-LSTM, is introduced. This model incorporates crucial enhancements to rectify standard LSTM shortcomings. Introducing a hybrid activation function, SigmoRelu, bolsters the model's capacity to grasp complex time series patterns. Furthermore, the RAdam optimizer is employed to optimize the learning process and improve convergence. Dropout layers are seamlessly integrated within the LSTM architecture to counter overfitting, ensuring robust generalization to novel data. A series of comprehensive experiments is conducted to compare the performance of the e-LSTM model against standard LSTM and GRU models, showcasing its noteworthy advancements. Notably, the e-LSTM model demonstrates superior predictive accuracy in forecasting waste generation compared to standard long short-term memory (LSTM) and gated recurrent unit (GRU) models. In essence, the proposed e-LSTM model represents a significant stride in domestic solid waste prediction, effectively mitigating the limitations of traditional LSTM models. The synergistic integration of SigmoRelu activation, RAdam optimization, and dropout mechanisms results in a resilient and accurate predictive framework. Empirical results affirm the model's superiority, establishing it as a valuable tool for waste management applications and decision-making processes.

1. Introduction

As the urban population grows significantly over time, cities have numerous issues, particularly in terms of waste management. According to the world-bank, around 2.01 billion tons of waste were generated in 2016 as a result of urban population and economic expansion, and this number is expected to rise to 3.40 billion tons by 2050 [1]. Municipal the surge in municipal solid waste (MSW) has been a consequential outcome of rapid urbanization, economic progress, and population expansion, with projections estimating a global annual volume of 2.2 billion tons by 2025. This exponential growth poses a substantial threat to urban areas and their surrounding ecological landscapes, manifesting in issues such as illicit dumping and environmental contamination. Particularly pronounced in economically disadvantaged nations, MSW emerges as a formidable global environmental concern [2].

The imperative to institute effective municipal solid waste management (MSWM) strategies is paramount, not only for the preservation of resources but also for safeguarding the environment and public health. However, the intricate and diverse nature of MSW poses inherent challenges, rendering environmental issues associated with waste management notably intricate and demanding in their resolution[3].

Effective waste management and regulatory decision-making hinge on accurate waste forecasting. However, predicting domestic solid waste encounters challenges due to limited methods and historical data, impeding volume estimates and policy creation. Solid waste prediction play crucial roles in environmental planning, considering factors like population growth, historical trends, and socioeconomic aspects [4]. The current methods for predicting domestic solid waste encounter obstacles stemming from complex patterns, limited data availability, and evolving technologies. These challenges underscore the need to enhance prediction accuracy through advanced models and improved data quality [5]. Although intelligent techniques such as machine learning algorithms, data mining, GIS, and predictive analytics with IoT devices contribute to accurate waste prediction and resource allocation, there is still room for improvement. Recent advancements in deep learning research, particularly methods like Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), offer promising avenues for revolutionizing waste prediction [6]. In this context, Long Short-Term Memory (LSTM), a type of RNN, holds particular potential[7]. To address common challenges in waste forecasting, this paper introduces an enhanced version of LSTM known as e-LSTM. The e-LSTM model incorporates innovative solutions such as dropout layers to combat overfitting, the RAdam optimizer for optimization, and the SigmoReLU activation function to mitigate vanishing gradients [8]. These techniques empower e-LSTM for analyzing time-series data, and experimentation is essential for achieving optimal results.

2. Literature Review

2.1 Overview of Malaysian Domestic Solid Waste

An Overview of Scheduled Wastes Management in Malaysia discusses the challenges of solid waste management in the country. Malaysia faces solid waste issues due to urbanization, industrialization, and population growth. The nation has taken steps like 3R principles (Reduce, Reuse, and Recycle), waste segregation, and waste management facilities. Still, concerns persist, including infrastructure gaps and non-recyclable waste. Collaboration between government, industries, and the public is crucial for sustainable waste management and a greener future [4]. Malaysia aimed to predict solid waste generation accurately. Researchers used machine learning techniques and historical data to create models considering factors like population growth, urbanization, and policies. Results showed machine learning's effectiveness in predicting waste generation [2]. Models forecasted waste quantities with high accuracy, aiding municipal authorities and waste management agencies to allocate resources efficiently [9]. Machine learning is used to examine the influence of seasonal variation on municipal solid waste composition. Large datasets from different regions and times of the year are analyzed using advanced algorithms. The goal is to create a predictive model that forecasts waste composition accurately across changing climates. This research aids waste management strategies, guiding informed decisions for optimized waste handling and resource recovery [10].

2.2 Long Short-Term Memory (LSTM)

Various machine learning and deep learning methods have been used recently to predict the rates at which solid waste is generated, offering vital information for sustainable waste management. In order to attain high accuracy in waste generation prediction, researchers have utilized models including Random Forests (RF), Long Short-Term Memory (LSTM) networks, and Artificial Neural Networks (ANN) [11]. ANNs have been employed extensively because of their capacity to capture intricate nonlinear interactions, because of their memory capacity, these models are very good at processing time-series data, which makes them perfect for long-term trend prediction.

By averaging several decision trees, Random Forests, an ensemble learning technique, minimize overfitting and enhance generalization while producing reliable predictions [12]. Historical data on waste production, socioeconomic conditions, population increase, and other pertinent variables are used to train these models. Better planning and resource allocation for urban waste management systems have been made possible by the combination of these methodologies, which has greatly increased the precision of waste generation projections. Studies have demonstrated how well these models work in a variety of metropolitan environments and how well they adjust to changing regional features and data availability[5], [11].

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LSTM, a type of recurrent neural network (RNN) architecture, is well-suited for modeling sequential data and effectively addresses the vanishing gradient problem. No- table components of LSTM include memory cells, forget gate, input gate, output gate, and a well-maintained gradient flow **Fig. 1**. Widely applicable across various domains such as Natural Language Processing (NLP), speech recognition, and time series forecasting, LSTM networks involve forward propagation through three essential thresholds forget , input and output gate [13]. LSTM stands out in predicting both the generation and composition of solid waste, successfully capturing intricate temporal patterns in waste data. Leveraging memory cells and gating mechanisms, LSTM excels in handling short-term fluctuations and long-term dependencies inherent in time-series waste data. Its predictive capabilities extend to estimating waste generation rates, assessing composition variations, and facilitating tasks like collection scheduling, recycling strategy formulation, and planning treatment facilities. This makes LSTM a valuable tool for fostering sustainable waste management practices [14].

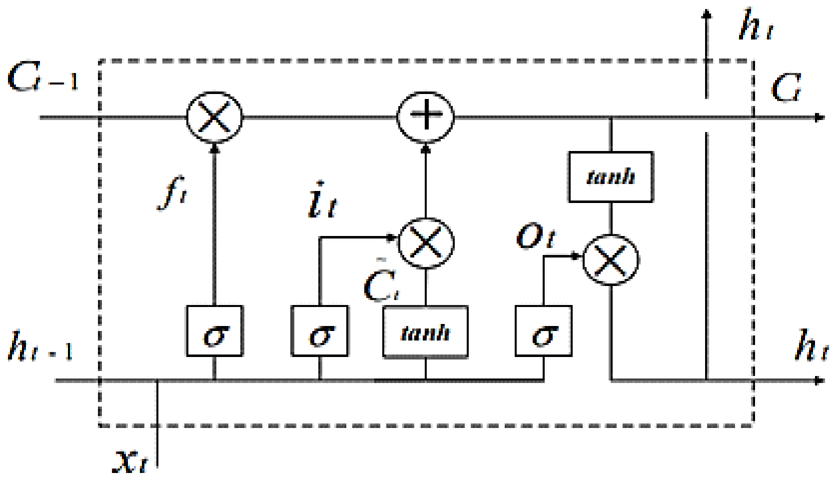

Fig. 1 *Long short-term memory network cell architecture*

3. Methodology

3.1 The Proposed Architecture of e-LSTM

In traditional LSTM networks, information processing relies on three critical components within the hidden-layer and the cell structure forget, input, and output gates. While effective in many applications, standard LSTM models face challenges, particularly in handling vanishing gradients [14]. To address these shortcomings, the e-LSTM model introduces innovative solutions. One key enhancement is the integration of a hybrid activation function called SigmoReLU, which combines features from both the Sigmoid (x) and ReLU functions. Where ReLU (Max (0, x)) function returns (x) if (x) is positive, otherwise return 0 as defined in Equation **(1)**. Furthermore, the Sigmoid(x) maps *(x)* to a value between (0 and 1) this provide a smooth gradient for both positive and negative (x), which helps with learning during backpropagation.

$$SigmoReLU\ (x) = max\ (0, x) + sigmoid(x) \tag{1}$$

Unlike the standard sigmoid activation function, which can lead to vanishing gradients, SigmoReLU offers improved performance [15]. Additionally, the e-LSTM architecture includes multiple layers, each utilizing the SigmoReLU activation function. Dropout layers are also incorporated to prevent overfitting, enhancing the model's robustness and ability to generalize to new data (refer to **Fig. 2**) [14]. Overall, these enhancements aim to address the limitations of standard LSTM models and improve the performance of e-LSTM in handling complex sequential patterns.

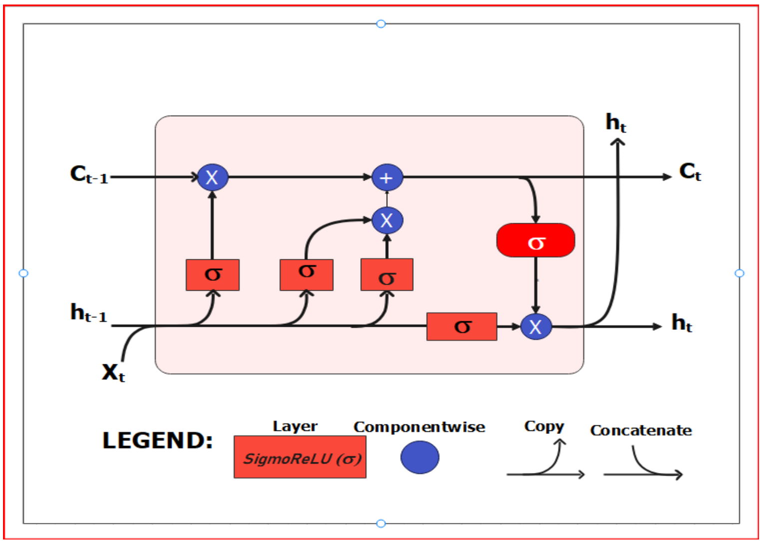

Fig. 2 *e-LSTM architecture*

3.2 Rectified Adam Optimizer (RADAM) and Dropout Mechanism

The e-LSTM model's efficiency and performance are significantly boosted by the implementation of the rectified Adam optimizer (RAdam) and dropout mechanism. RAdam contributes to adaptive learning rate adjustments, enhancing the model's convergence by dynamically adapting the learning rate for each parameter during training based on gradient history [16]. This adaptability proves valuable in handling noisy waste data patterns with irregular trends and variations commonly found in real-world waste generation data. The adaptive approach of RAdam is particularly beneficial for time series forecasting, such as domestic solid waste generation, resulting in improved e-LSTM model performance and more precise predictions [8]. The enhanced e-LSTM model architecture comprises an input layer integrating LSTM, activation, and dropout layers, three hidden layers each featuring activation and dropout layers, and an output layer consisting of dense and activation layers. The LSTM and activation layers facilitate the flow of information, ensuring the model's robust generalization. Dropout layers are strategically employed during training to exclude neural units and mitigate overfitting[14].

3.3 Hybrid Activation Function (SigmoReLU)

The hybrid activation function (SigmoReLU), a fusion of Rectified Linear Unit (ReLU) and sigmoid functions, was incorporated to enhance the e-LSTM model's predictive performance for domestic solid waste. SigmoReLU combines ReLU for non-negative values and sigmoid for values between (0 and 1) [15]. Introducing non-linearity to neural networks, enriching their capacity to learn complex input-output relationships. SigmoReLU mitigates the vanishing gradient problem through ReLU, stabilizing learning during back-propagation therefore combining ReLU and Sigmoid ensures numerical stability during training Equation (1), guarding against computational issues arising from extreme values [5]. This hybrid activation bolsters model representational power, activating neurons for specific input features while smoothly transforming inputs into probabilistic outputs [15]. The SigmoReLU hybrid activation boosts the e-LSTM in predicting domestic solid waste and improves the non-linearity, gradient handling, numerical stability and enhancing time series pattern capture. SigmoReLU incorporation further aids domestic solid waste rate prediction

3.4 Summary of the Dataset

The study's dataset was gathered from the Labis and Segamat landfill sites in the Johor region of Southern Peninsular Malaysia, covering a period of three years (2020–2023). It consists of daily measurements of domestic solid waste generation, represented as (Net WT). The dataset details are summarized in **Table 1**.

Table 1 *Summary of datasets*

Summary	Segamat Landfill	Labis Landfill
Total Rows	1069	1069
Missing Values	198 rows	169 rows

Mean (NET WT)	328,813.47	309,433.43
Standard Dev.	160,203.58	155,566.85
Minimum (NET WT)	9,070	613
25th Percentile	193,870	191,400
Median (50th %)	347,550	362,410
75th Percentile	467,205	415,952.5
Maximum (NET WT)	680,520	773,850

3.5 Model Training and Optimization Strategies

The study employed a train-test holdout validation scheme for conducting experiments. The dataset was divided using a 75–25 train-test split, meaning that it was split into two portions, with 75% of the data allocated for training and 25% for testing. As a result, the model was trained using 825 samples, and then its performance was evaluated on the remaining 270 samples. This approach ensured unbiased assessment on unseen data, emphasizing the model's generalization capabilities. To normalize data and facilitate effective pattern learning, Min-Max Scaling with MinMaxScaler was applied.

For time series forecasting of daily domestic solid waste income rates, the Time Series Generator method was employed, this technique allowed the e-LSTM model to capture temporal dependencies and historical context, improving predictive accuracy by considering historical trends **Fig. *3***. To prevent overfitting, a dropout layer was introduced between e-LSTM layers. Various dropout values, selected between (0.1 to 0.5) through a trial- and-error approach, were assessed **Table *2***. The dropout layer effectively reduced overfitting, minimizing the gap between training and test errors from (3.94% to 0.0019%). However, optimal dropout values should be carefully selected, as excessively large values may harm model performance and prediction accuracy [17].

Table 2 *Evaluate dropout value added to propose e-LSTM*

Value	RMSE	Training Error	Testing Error
0.1	0.0689	0.0090	0.0070
0.2	**0.0228**	**0.0021**	**0.0019**
0.3	0.129	0.0087	0.0045
0.5	0.341	0.0129	0.0220

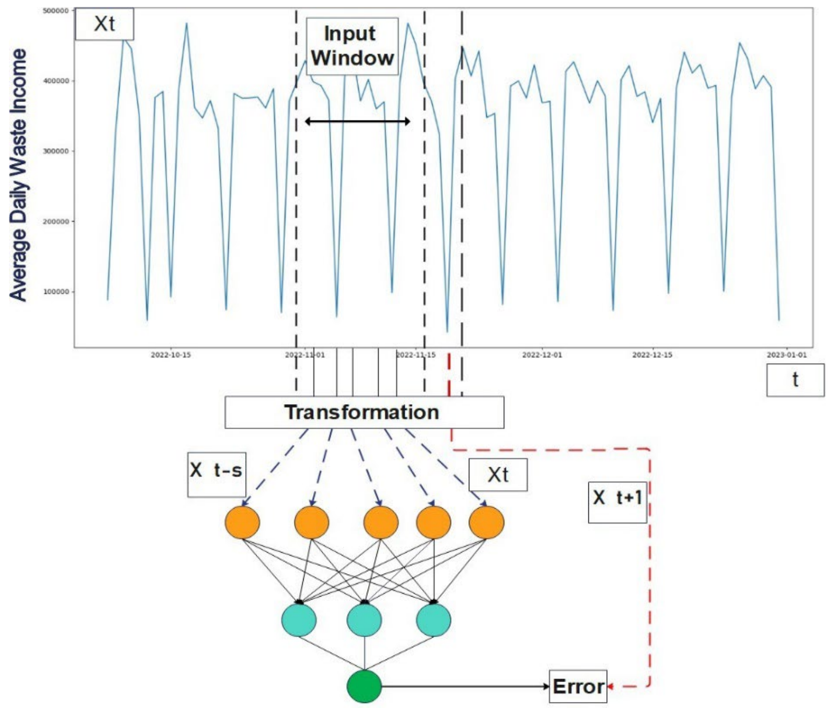

Fig. 3 *e-LSTM training procedure*

3.6 Evaluation Measures

In our study, we comprehensively evaluated the e-LSTM model against two common baseline models, standard LSTM and gated recurrent unit (GRU), for domestic solid waste income rate forecasting. We used various evaluation metrics, including MSE, MAE, RMSE, R-squared, and accuracy, to assess predictive performance and generalization capabilities. These measures facilitated a fair comparison, with lower MSE, MAE, RMSE and higher R-squared, and better accuracy indicating e-LSTM's superiority in forecasting. These findings have practical implications for waste management and related fields.

3.7 Performance Evaluation Measures

In this study we conducted a comprehensive assessment of the e-LSTM model by comparing it with standard LSTM and gated recurrent unit (GRU) models for predicting domestic solid waste generation rates. Various metrics, including mean score error (MSE), mean absolute error (MAE), RMSE, R2, and accuracy, were employed to ensure a fair comparison. Lower MSE, MAE, and RMSE, along with higher R2 and improved accuracy, collectively indicated the superior forecasting capabilities of the e-LSTM model, which holds practical applications in waste management and related fields. Additionally, the evaluation included specific performance measures such as training and testing loss, maximum residual error Equation (2), this equation computes the maximum absolute error between the actual (test) and predicted values (prediction), providing the worst-case error in the predictions. Variance score this score measures the proportion of the variance (var) in the actual data (test) that is predictable from the model (prediction). A score of 1 indicates perfect prediction, while a score of 0 indicates that the model does not explain any of the variability in the data Equation (3**)**.

The R^2, or the coefficient of determination, measures how well the predicted values approximate the actual data. It is the proportion of the variance in the dependent variable that is predictable from the independent variables where sum is summation function, summing over all *(n)* data points, test[i] represent the (*i*-th) actual observed value, prediction[i] represent the (*i*-th) predicted value and mean [test] represent the mean (average) of the actual observed values. An R^2 of 1 indicates perfect prediction, while an R^2 of 0 indicates that the model does not predict the data any better than the mean of the test data Equation (4). Therefore, model accuracy formal used to measure how close the predicted values are to the actual values, with 100% indicating perfect accuracy, which provided insights into the model's predictive precision, where (abs) is absolute value function, test is actual observed values and prediction is the predicted value by the model Equation (5). These evaluation metrics collectively validated the precision and reliability of the proposed e-LSTM predictive model.

$$Max\ Error = \ Max\ (abs(test - prediction\ )) \tag{2}$$

$$Explained\ Variance\ Score = \ 1 - \frac{var(test)}{var(test - prediction} \tag{3}$$

$$R2 = \int_{1}^{n} \ (test\ [i] - prediction\ [i])2/ \int_{i}^{n}(test\ [i] - mean[test])2 \tag{4}$$

$$\boldsymbol{Accuarcy} \ = \ [\mathbf{1} - \boldsymbol{abs}(\boldsymbol{test} - \boldsymbol{prediction}) \ / \ (\text{prediction})] * 100 \tag{5}$$

3.8 Modifying the e-LSTM for Future Prediction

The e-LSTM model is designed to forecast future domestic solid waste generation by analyzing recent data. It follows a loop mechanism to process input data and generate predictions for the upcoming days. During this process, the input data is reshaped, and the predictions are stored in arrays and lists. Each time step is iterated through, predicting the waste generation for the next day, and these forecasts are stored in a list. Additionally, arrays are used to represent both the original and predicted days. In essence, this model facilitates the forecasting and storage of future waste generation values based on historical data.

3.9 Estimation of Landfills Disposal Area

In this study, the implemented e-LSTM model is utilized to forecast the rate of domestic solid waste generation at landfill sites. This prediction holds significance in determining the required land area for waste disposal and assessing the potential capacity of proposed landfills. For the purpose of estimating landfill area size, a general formula is employed, which can be expressed in **Equation (6)**. Where the (Wr) represents the domestic solid waste generation rate, measured in kilograms per capita per year, (L) denotes the lifespan of the landfill, measured in years, (P) represents the population, indicating the number of people. Additionally, the (Pdensity) represents the total waste volume or waste bulk density, measured in kilograms per cubic meter. Lastly, (H) denotes the

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desired height of waste disposal at the landfill, measured in meters. The capacity of a landfill is significantly influenced by the landfill height. Reported waste heights at sanitary landfills can vary from 15 to 30 meters, with some instances reaching a maximum height of 50 meters. However, for waste heights surpassing 25 meters, special requirements are necessary to prevent waste slippage. In this specific study, the existing landfill height of 10 meters is taken into consideration[18].

$$Landfill\ Disposal\ Area = Wr * L * P * 1.5\ /(Pdensity * H) \quad (6)$$

The forecasted domestic solid waste collection rates at the landfill sites and the waste disposal options specified in the Johor waste management plan for 2025 are employed to calculate the required landfill area in the research. By utilizing the waste generation predictions generated by the e-LSTM model and incorporating the relevant parameters into the formula, researchers can estimate the land area needed for waste disposal and make informed decisions regarding landfill capacity requirements.

4. Results and Discussions

4.1 The e-LSTM Model Prediction

The e-LSTM predictions for both the Segamat and Labis landfill sites showcased impressive and precise forecast capabilities. Utilizing the e-LSTM model, the predictions effectively showcased the model's competence in capturing temporal patterns and variations in the daily generation of domestic solid waste. For the Segamat and Labis landfills site, the e-LSTM model exhibited remarkable predictive capabilities by generating forecasts that closely matched the real waste generation data, as depicted in (Fig. 5 and Fig. 6). The model's precision in its predictions was evident through its lower Mean Squared Error (MSE) and Mean Absolute Error (MAE) when compared to alternative models. Additionally, the Root Mean Squared Error (RMSE) values were minimized, indicating consistent proximity between the e-LSTM predictions and the observed values refer to Fig. *4*. This high degree of accuracy was further supported by the model's impressive R2 score, highlighting a strong correlation between the predicted and actual waste generation. The e-LSTM model demonstrated precise waste generation forecasts, reflected in lower MSE and MAE values. Reduced RMSE and increased R2 scores indicated accurate predictions. Compared to other models (refer to Table 3), the e-LSTM displayed superior accuracy highlighting its potential in waste management for precise trend. The e-LSTM model consistently aligns predicted values with actual ones, demonstrating strong correspondence. These predictions extend number of months ahead showcasing its accuracy in capturing waste generation trends (refer to Fig. *7* and Fig. 8).

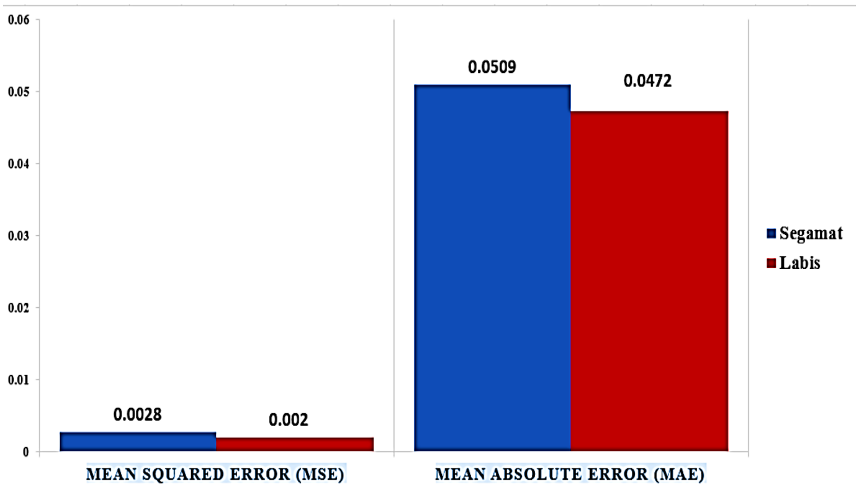

Fig. 4 *e-LSTM Performance evaluation: MSE and MAE comparison for Segamat and Labis landfills*

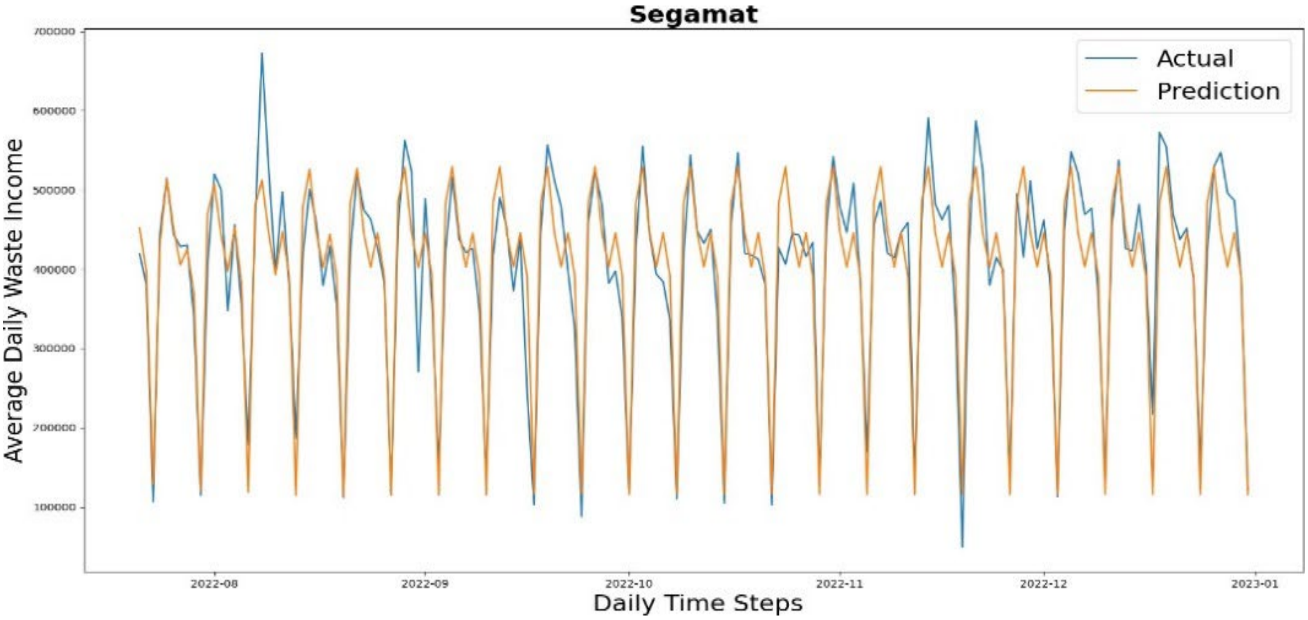

Fig. 4 *Domestic solid waste generation: testing vs. prediction for Segamat landfill sites*

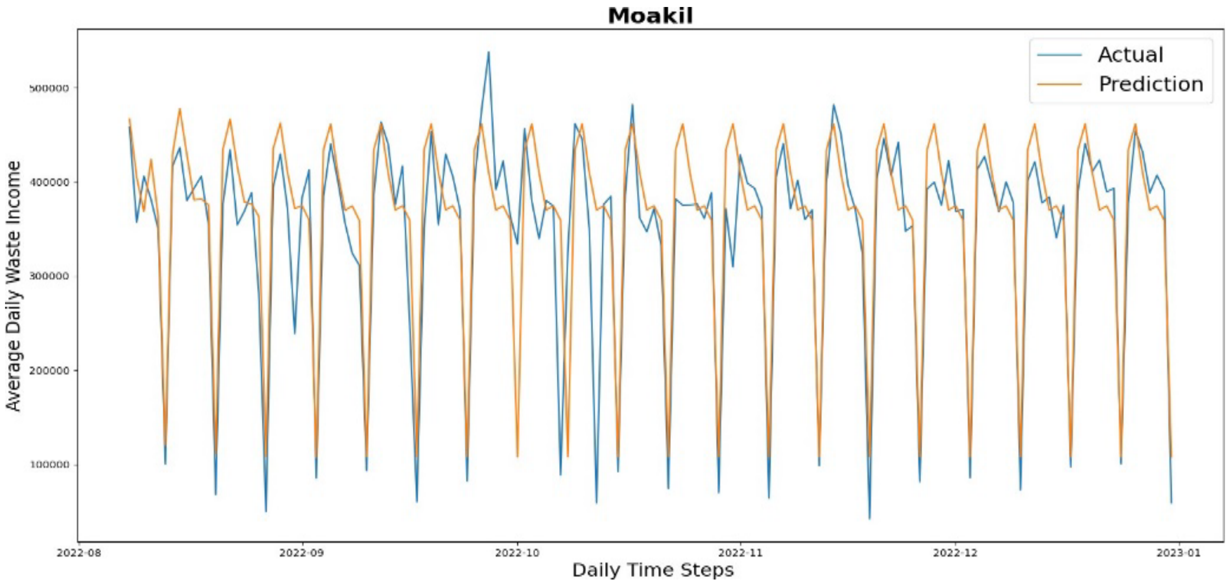

Fig. 5 *Domestic solid waste generation: testing vs. prediction for Labis forecasting at Segamat and Labis landfill sites*

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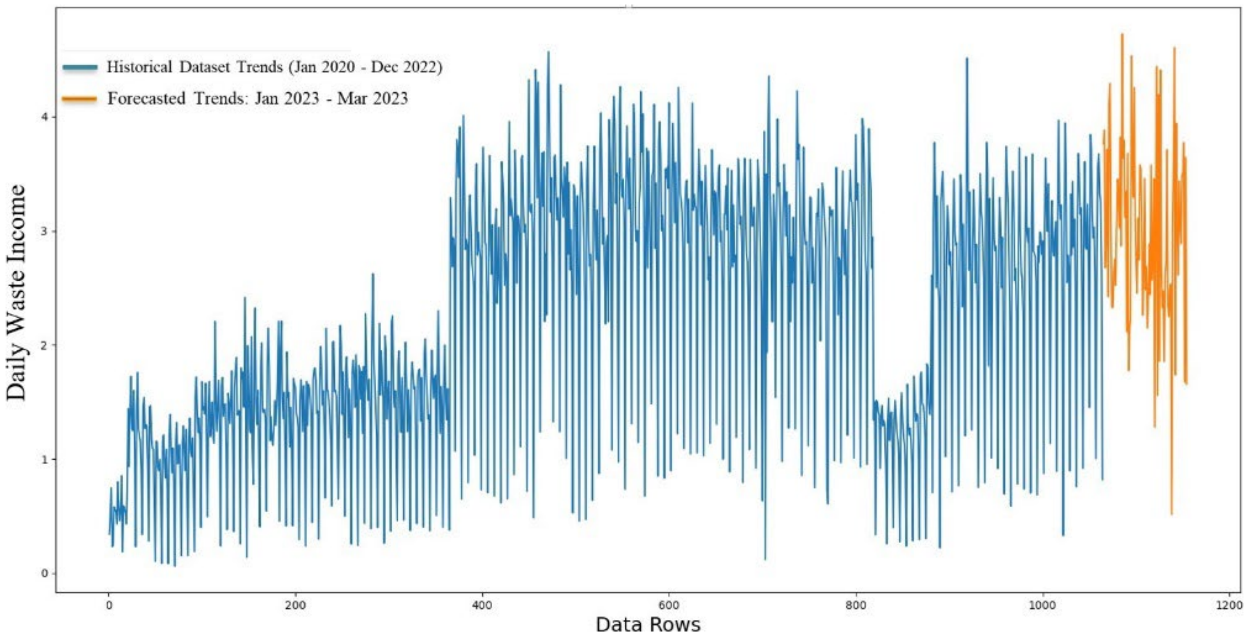

Fig. 6 *e-LSTM Predictions for the next 3 months (Jan 2023 - Mar 2023) for Segamat landfill*

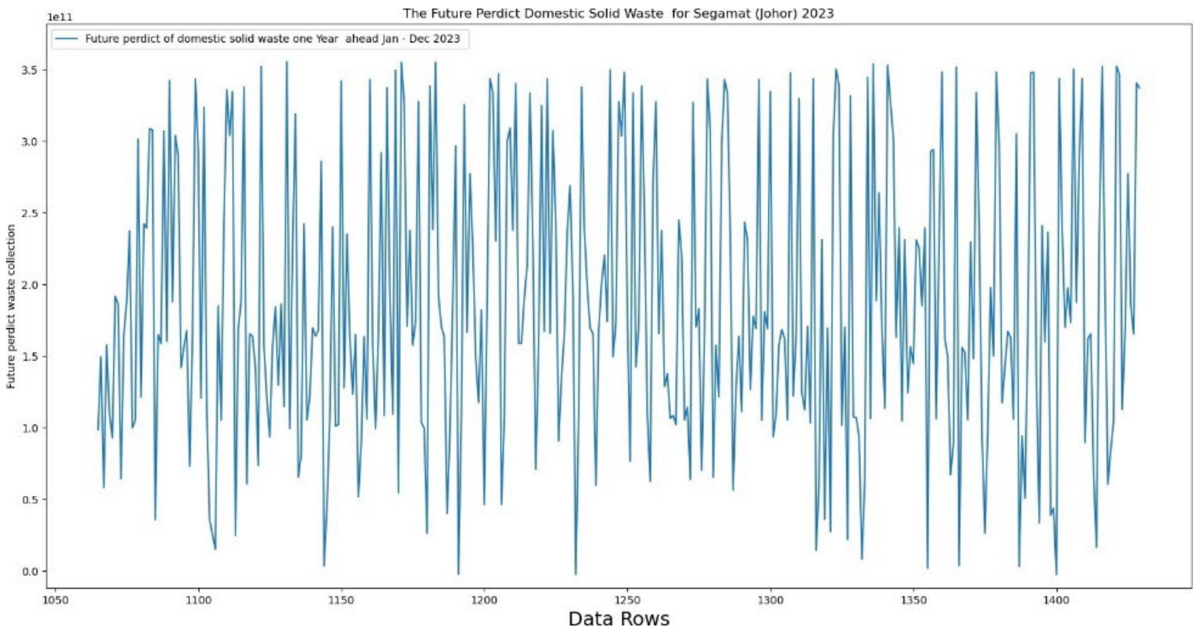

Fig. 7 *Forecasting the future: e-LSTM predictions for Segamat landfill in 2023*

4.2 Comparing e-LSTM with Alternative Machine Learning Models

The performance evaluation of the Enhanced Long Short-Term Memory (e-LSTM) model involved a comprehend-comparison with the standard LSTM and Gated Recurrent Unit (GRU) models, employing various metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), accuracy, and R-squared (R2) score. The outcomes underscore the significant advantages offered by the e-LSTM model in terms of predictive precision and generalization capabilities. Upon examining the performance of the three models, several key observations emerge from the results.

The e-LSTM model outperformed the standard LSTM and gated recurrent unit (GRU) models in a comprehensive performance evaluation using metrics like (MSE, MAE, RMSE, R2 score and accuracy). The results consistently showed significantly lower MSE and MAE values, indicating superior pattern and trend capturing **Fig.9**. The e- LSTM model exhibited higher accuracy, making a higher percentage of correct predictions, and lower RMSE values, depicting closer predictions to actual values and precise data variability representation. The higher

R2 score for e-LSTM suggests adeptness in capturing data variability and reliable representation of variable relationships Table 3.

Table 3 *Summary of comparison models performance*

Models	MSE	MAE	RMSE	MAX Error	Variance Score	R2	Accuracy
GRU	0.0187	0.0802	0.089	0.424	0.85	0.83	0.87
LSTM	0.0054	0.0587	0.074	0.263	0.87	0.85	0.88
e-LSTM	**0.0028**	**0.0409**	**0.065**	**0.231**	**0.90**	**0.92**	**0.93**

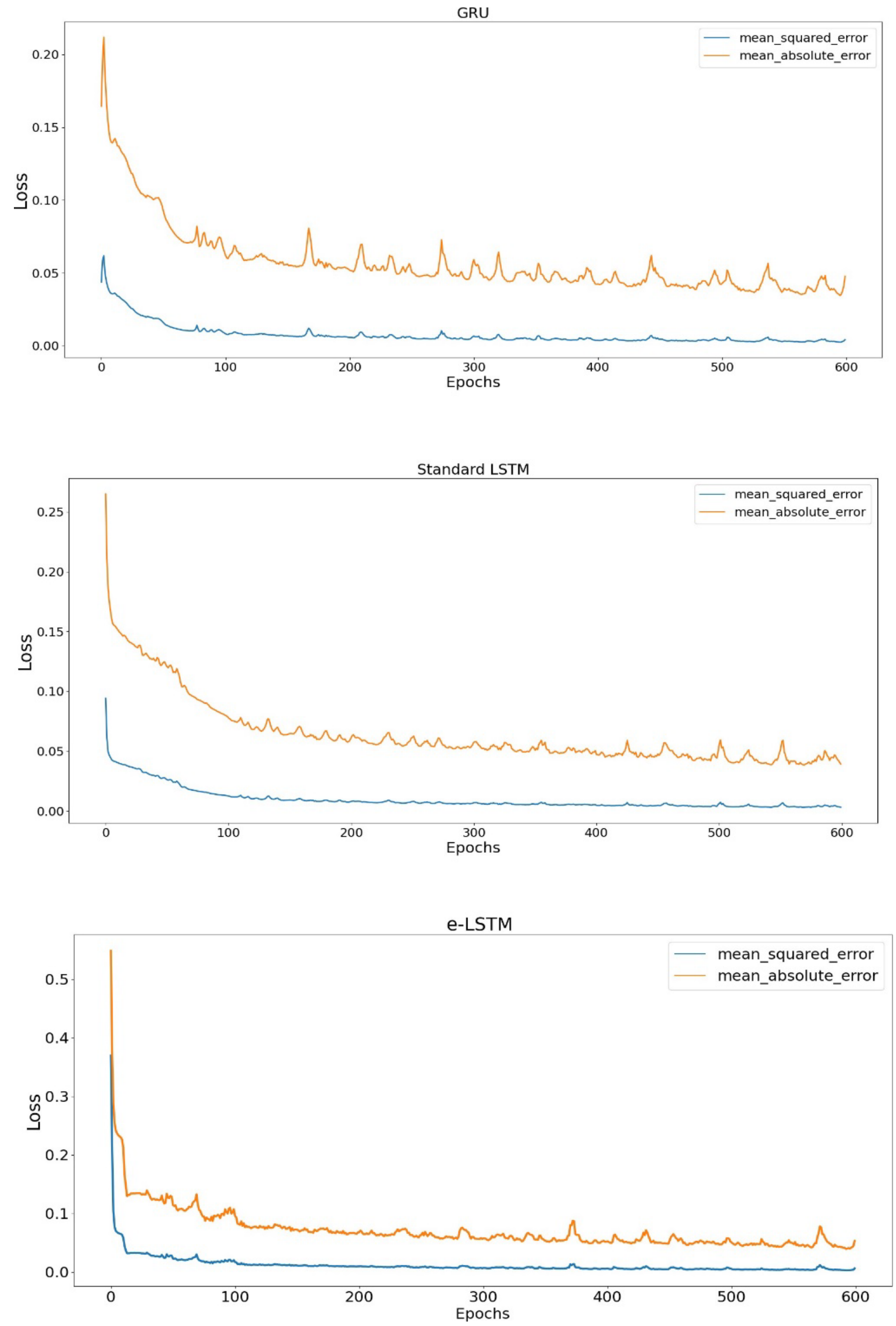

Fig. 8 *Comparative analysis of GRU, LSTM and e-LSTM models: MSE and MAE performance evaluation*

4.3 Landfill Disposal Area Estimation

This study estimates waste disposal area in southern Malaysia, focusing on Segamat and Moakil landfill sites. Waste density, crucial for accurate calculations, ranges from 655 kg/m^3 (uncompact) to around 761 kg/m^3 (compacted), in line with typical landfill densities (800 kg/m^3) [10]. Total waste volume is 34.1 million m^3, and landfill height is assumed at 15 meters, based on literature recommendations. Furthermore, it is imperative to consider the potential increase in waste height over time, as the required disposal area diminishes. In order to allow for the practical utilization of both daily and final domestic solid waste, an expansion of approximately 15–30% in the final landfill area is recommended to accommodate future waste input. We analyze a 31.60 hectare landfill area, using predictive modeling to forecast capacity usage up to 2030. These insights aid authorities in landfill management strategies.

This study uses a predictive model, considering historical waste rates, population growth, and relevant factors to estimate the landfill area's future utilization. The study goal is to predict when it will reach capacity. Currently, 26.21 hectares of the Segamat landfill area are used, with 5.39 hectares remaining, as shown in **Fig. 10**. For the Labis landfill, 22.92 hectares are used, and 8.68 hectares remain, as shown in **Fig. 11** . From the figures below where brown column represents the entire area allocated for landfilling, the green column indicates the portion of the total area already utilized for landfilling and the blue column represents the available space remaining for future landfilling. The results of this analysis serve as a crucial wake- up call for the waste management agencies responsible for the management of the landfill disposal area. The imminent filling of the landfill site by 2025 demands immediate attention and necessitates the development of robust strategies to handle the rising waste disposal demands beyond this point.

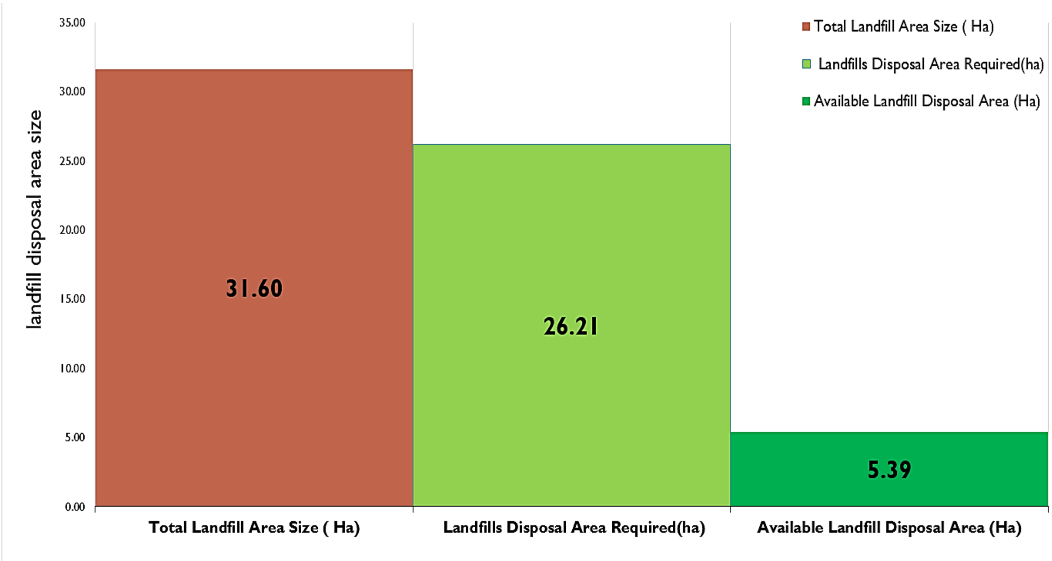

Fig. 9 *Estimation the landfills disposal area size for Segamat landfill*

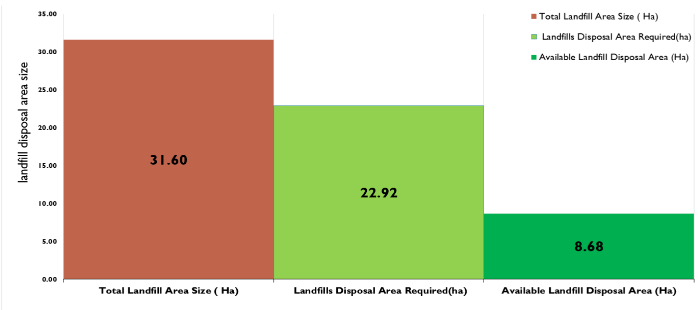

Fig. 10 *Estimation the landfills disposal area size for Labis landfill*

5. Conclusion

In conclusion, this model is a major step forward in overcoming the shortcomings of conventional LSTMs and improving the accuracy of waste prediction. The integration of innovative features, such as the dropout layers and the SigmoReLU activation function as well as the RAdam optimization, shows remarkable proficiency in predicting the generation of domestic solid waste. The ability to capture complex temporal patterns and solve problems such as overfitting or vanishing gradients is a major development in waste prediction technologies. With its high accuracy and precision, e-LSTM has great potential to optimize waste management strategies as well as to support sustainability initiatives.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Rozaida Ghazali, Abdulrahman Sharaf Fadhel;* ***data collection:*** *Mohd Razali Md Tomari, Lokman Hakim Ismail;* ***analysis and interpretation of results:*** *Abdulrahman Sharaf Fadhel, Rozaida Ghazali, Ahmed Khalaf Zager Alsaedi;* ***draft manuscript preparation:*** *Abdulrahman Sharaf Fadhel, Abdullahi Abdi Abubakar Hassan. All authors reviewed the results and approved the final version of the manuscript.*

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