

# Prediction of the Number of Motor Vehicle Inspections using the Long Short-Term Memory (LSTM) Method as a Decision-Support Tool at the Transportation Agency of Langkat Regency

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## Abstract

Sustained population growth increases the demand for public services, including motor vehicle inspection or periodic testing (KIR). The Transportation Agency of Langkat Regency faces difficulty in accurately predicting the number of vehicles to be tested in a given period, which causes queue build-ups and inefficiency in resource allocation. This study aims to design and implement a prediction model for the number of motor vehicle inspections using the Long Short-Term Memory (LSTM) method as a decision-support tool. The data used are monthly historical data for the period from January 2023 to December 2025, comprising 36 data points. The data were normalized using Min-Max Scaling, formed into sequential samples with a timestep of three, and then divided into 80% training data and 20% testing data. The model was evaluated using the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) metrics. The evaluation obtained an MAE of 3, an MSE of 9, and an RMSE of 3 vehicles per month, indicating a high level of accuracy. The model projects a total of 916 vehicles in 2026 and 986 vehicles in 2027, with the testing peak occurring in July. These results can be used as a basis for resource planning and for improving the quality of public services.

**Keywords:** *Deep learning; Long short term memory; Decision making; Motor vehicle testing; Prediction*

## 1. Introduction

Indonesia's population continues to grow steadily every year. This growth rate is influenced by birth rates, migration, and death rates, and it indicates that the demand for public services, such as transportation and motor vehicle testing, keeps increasing as part of the provision of adequate public facilities [1]. As the number of residents and vehicles increases, the Transportation Agency of Langkat Regency faces various complex operational challenges in carrying out its duties.

One of the main challenges faced is the inability to accurately predict the number of vehicles that will undergo testing in a given period. Poorly predicted fluctuations in the number of vehicle inspections cause several problems, including vehicle queue build-ups in certain situations, inefficiency in allocating human resources (inspection officers), and suboptimal use of testing equipment. This condition ultimately leads to a decline in the quality of public services provided to the community.

Motor vehicle testing, also known as the KIR test, is the process of inspecting and testing various parts of a motor vehicle to ensure that the vehicle meets technical standards and is roadworthy, while also protecting the environment from pollution caused by vehicles that do not meet the standards [2]. The Long Short-Term Memory (LSTM) method is a variant of the Recurrent Neural Network (RNN) designed to overcome the shortcomings of traditional models in processing sequential data, particularly in understanding long-term dependencies. The LSTM structure, which has a memory cell allows the model to store and use past information more effectively, making it suitable for predicting time-series data [3].

In various studies, LSTM has been shown to be capable of understanding complex temporal patterns and providing fairly accurate estimates, for example in predicting air quality and inflation, evaluated using metrics such as the Root Mean Square Error (RMSE) [4]. Another study showed that LSTM has excellent predictive capability in time-series data modeling, achieving a precision of 97.433% in predicting rainfall and 99.018% in estimating maximum wind speed [5]. Evaluation results with relatively small error levels, namely an MAE of 0.141 and an RMSE of 0.205, also indicate the good predictive performance of LSTM [6].

Several previous studies reinforce the application of LSTM to various time-series prediction cases. LSTM has been used to predict sea transportation stock prices, emphasizing its potential as a prediction solution [7], to predict coffee prices with a low error rate using a

particular combination of learning rate and epoch [8], and to predict daily air quality with satisfactory evaluation values [9]. In addition, LSTM has also been applied to cryptocurrency prediction [10], the prediction of foreign tourist arrivals [11], the prediction of government spending as a decision-support tool [12], and time-series-based rainfall prediction [13]. These studies show that LSTM is able to capture temporal patterns from historical data with good accuracy.

Based on the above, this study focuses on the design and implementation of a prediction model for the number of motor vehicle inspections using the Long Short-Term Memory (LSTM) method at the Transportation Agency of Langkat Regency. The objective of this study is to design and implement the prediction model, from the data pre-processing stage, model architecture construction, and training, through to testing, and to analyze the model's performance using the Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) evaluation metrics. The prediction results are expected to serve as a basis for decision-making in optimizing resource allocation and improving the quality of public services.

## 2. Page Layout

The research method was arranged systematically using a literature review and the collection of data needed to analyze the system for predicting the number of motor vehicle inspections in Langkat Regency using the Long Short-Term Memory (LSTM) method. The overall research workflow is shown in Figure 1.

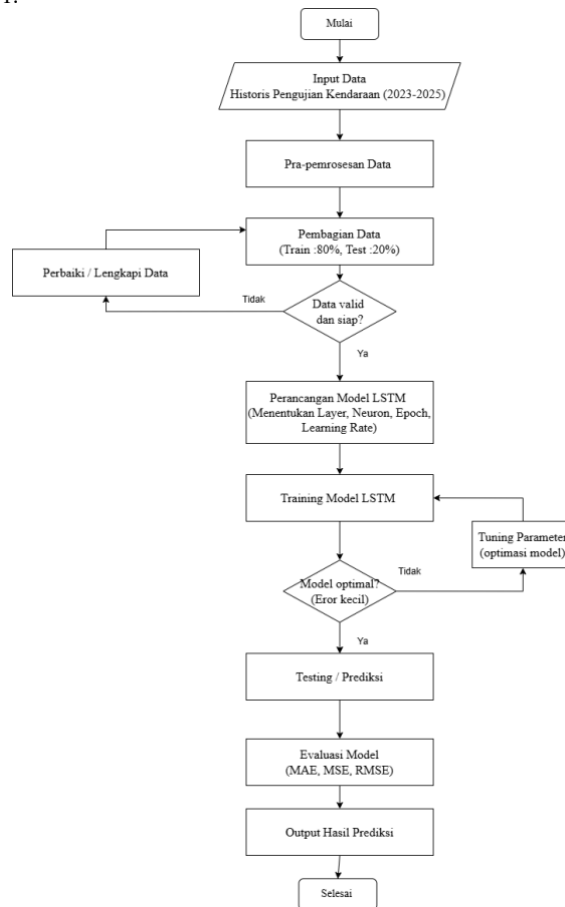


Fig. 1: Flowchart of the LSTM research algorithm

Based on Figure 1, the research begins with the input of historical motor vehicle inspection data for 2023–2025, followed by data pre-processing that includes data cleaning, aggregation into monthly data, and normalization using Min-Max Scaling. The data are then divided into training data (80%) and testing data (20%). Subsequently, the LSTM model architecture is designed, the model is trained using the training data, tested using the testing data, and its performance is evaluated using the MAE, MSE, and RMSE metrics, through to the analysis of the prediction results.

### 2.1. Research data

The data used are historical data on the number of motor vehicle inspections (periodic testing) at the Motor Vehicle Testing Implementation Unit of Langkat Regency, Transportation Agency of North Sumatra Province. The data were collected from the agency's official daily reports covering the period from January 2023 to December 2025. The daily data were then compiled and grouped into monthly data to form a time series used as input for the LSTM model, resulting in a total of 36 months of observations as presented in Table 1.

Table 1: Monthly motor vehicle inspection data of Langkat Regency

Month	2023	2024	2025
January	30	99	37
February	35	64	42

Month	2023	2024	2025
March	46	160	58
April	30	123	49
May	66	218	63
June	28	184	75
July	32	347	157
August	41	162	69
September	55	122	61
October	63	193	52
November	72	71	60
December	85	48	49
<b>Total</b>	<b>583</b>	<b>1791</b>	<b>772</b>
<b>Grand total</b>	<b>3,146 vehicles</b>		

Source: Transportation Agency of Langkat Regency (2023–2025)

Based on Table 1, the total number of vehicles that underwent periodic testing during the period from January 2023 to December 2025 is 3,146 vehicles. The maximum value was recorded in July 2024 at 347 vehicles, while the minimum value was recorded in June 2023 at 28 vehicles, with an average of 87.39 vehicles per month.

## 2.2. Long Short-Term Memory (LSTM)

*Long Short-Term Memory* (LSTM) is a model in *deep learning* developed from the *Recurrent Neural Network* (RNN) algorithm. This model was first introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997 and was later refined by Alex Graves in 2013 [14], [15]. LSTM is considered effective in prediction tasks because it can filter which information to retain and which to forget [16].

The LSTM architecture consists of several *gates*, namely the *forget gate*, *input gate*, *cell state*, and the *output gate*, each of which regulates the flow of information within the memory cell [17]. *Forget gate* determines the information to be forgotten, the *input gate* controls the new information to be added to memory, and the *output gate* regulates the information retrieved from memory to produce the output [18]. The equation for each *gate* is expressed as follows.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\bar{A}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

$$C_t = f_t \times C_{t-1} + i_t \times \bar{A}_t \quad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \times \tanh(C_t) \quad (6)$$

where  $f_t$ ,  $i_t$ , and the  $o_t$  respectively denote the values of the *forget gate*, *input gate*, and the *output gate*;  $W$  and  $b$  denote the weight and bias of each *gate*;  $\sigma$  is the sigmoid function;  $h_{t-1}$  is the *hidden state* from the previous step; and  $x_t$  is the input at time step  $t$ .

As an illustration, the forward computation at the first timestep uses the normalized input  $x_t = 0.0063$ , with the initial hidden state  $h_{t-1} = 0$  and the initial cell state  $C_{t-1} = 0$ . Substituting the initialized weights and biases into Equations (1)–(3) and (5) yields the gate activations:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) = \sigma(0.1033) = 0.5258$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) = \sigma(0.0524) = 0.5131$$

$$\bar{A}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) = \tanh(0.0038) = 0.0038$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) = \sigma(0.0028) = 0.5007$$

The cell state and hidden state are then updated using Equations (4) and (6):

$$C_t = f_t \times C_{t-1} + i_t \times \bar{A}_t = (0.5258)(0) + (0.5131)(0.0038) = 0.0019$$

$$h_t = o_t \times \tanh(C_t) = (0.5007) \times \tanh(0.0019) = 0.0010$$

The resulting hidden state  $h_t = 0.0010$  is then passed to the next timestep, and the procedure is repeated across the whole input sequence to produce the model output.

## 2.3. Data pre-processing

Data pre-processing is carried out to prepare the data so that it conforms to the format and value range required by the model. The daily data are aggregated into monthly data and then normalized using the *Min-Max Scaling* method to transform the data values into the range [0,1]. Normalization is needed to speed up the model's convergence and to avoid the dominance of large values during the training process [24]. The normalization formula is expressed in Equation (7).

$$x' = (x - x_{min}) / (x_{max} - x_{min}) \quad (7)$$

After training, the still-normalized model output is converted back to its original unit (number of vehicles) through the denormalization process in Equation (8).

$$x = x' \times (x_{max} - x_{min}) + x_{min} \quad (8)$$

Based on the data in Table 1, the values  $x_{min} = 28$  and  $x_{max} = 347$  were obtained. The normalized data were then formed into sequential samples through a *windowing* where  $timestep = 3$ , so that each sample consists of three input values ( $t-3, t-2, t-1$ ) and one target value ( $t$ ).

As an example of normalization using Equation (7), the January 2023 value of 30 vehicles is transformed into the range [0,1] as follows:  

$$x' = (30 - 28) / (347 - 28) = 2 / 319 = 0.0063$$

Conversely, denormalization using Equation (8) restores a normalized output to its original scale. For example, the model output 0.3950 for July 2025 is converted back as:

$$x = 0.3950 \times (347 - 28) + 28 = 0.3950 \times 319 + 28 \approx 154$$

which matches the predicted value for that month reported in Table 3.

### 2.4. Splitting of training and testing data

The normalized data were divided into training data (*training*) at 80% and testing data (*testing*) at 20%. From a total of 36 months of data, 29 months of training data (January 2023–May 2025) and 7 months of testing data (June 2025–December 2025) were obtained, as presented in Table 2.

**Table 2:** Splitting of training and testing data

Data group	Count	Period	Percentage
Data <i>training</i>	29 months	January 2023 – May 2025	80%
Data <i>testing</i>	7 months	June 2025 – December 2025	20%
<b>Total</b>	<b>36 months</b>	<b>January 2023 – December 2025</b>	<b>100%</b>

### 2.5. Model evaluation

Model evaluation aims to measure how well the model predicts the target values by comparing the predicted values with the actual values using error metrics (*error metrics*) [19]. In regression problems, the commonly used metrics are the *Mean Absolute Error* (MAE), *Mean Squared Error* (MSE), and the *Root Mean Squared Error* (RMSE), each of which has different characteristics in measuring prediction error [20]. MAE computes the average of the absolute differences and is not very sensitive to outliers [21], whereas MSE imposes a greater penalty on large errors because it squares the error [22]. RMSE is the square root of MSE, so it has the same unit as the original data. The three metrics are expressed in Equations (9), (10), and (11).

$$MAE = (1/n) \sum |y_i - \hat{y}_i| \tag{9}$$

$$MSE = (1/n) \sum (y_i - \hat{y}_i)^2 \tag{10}$$

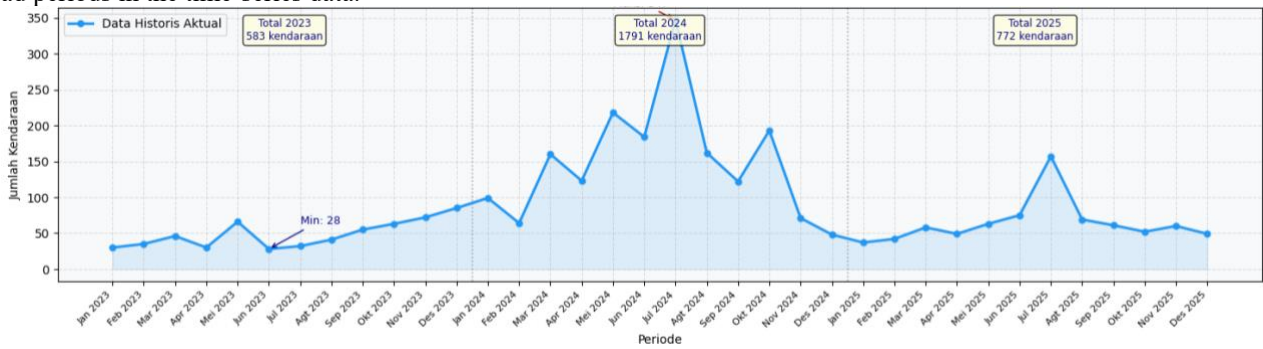
$$RMSE = \sqrt{(1/n) \sum (y_i - \hat{y}_i)^2} \tag{11}$$

where  $n$  is the number of data points,  $y_i$  is the actual value, and  $\hat{y}_i$  is the model's predicted value.

## 3. Results and Discussion

### 3.1. Historical vehicle inspection data

The monthly historical motor vehicle inspection data for the period from January 2023 to December 2025 are visualized as a line chart in Figure 2. This visualization makes it easier to identify fluctuation patterns, high-load (peak) periods, and low-load periods in the time-series data.



**Fig. 2:** Monthly historical motor vehicle inspection data for 2023–2025

Based on Figure 2, a recurring seasonal pattern is visible, with a tendency for the number of inspections to increase in the middle of the year. The highest spike occurred in July 2024 at 347 vehicles, while the lowest figure occurred in June 2023 at 28 vehicles. This historical pattern serves as the learning basis for the LSTM model in recognizing trends and seasonal patterns.

### 3.2. Model training and evaluation

The LSTM model was trained using the normalized training data and then tested on 7 testing data points (June 2025–December 2025). The prediction results on the testing data were compared with the actual values, and the error values were calculated to obtain the MAE, MSE, and RMSE metrics as presented in Table 3.

**Table 3:** Summary of LSTM model evaluation results on the testing data

Month	Actual (y <sub>i</sub> )	Output LSTM (x' <sub>i</sub> )	Prediction (ŷ <sub>i</sub> )	Error	Error <sup>2</sup>
June 2025	75	0,1567	78	3	9
July 2025	157	0,3950	154	3	9
August 2025	69	0,1379	72	3	9
September 2025	61	0,0940	58	3	9
October 2025	52	0,0658	49	3	9
November 2025	60	0,0909	57	3	9
December 2025	49	0,0564	46	3	9
<b>Total</b>				<b>21</b>	<b>63</b>

**MAE = 3 | MSE = 9 | RMSE = 3**

The three evaluation metrics are obtained by substituting the seven testing errors into Equations (9)–(11). Since each of the  $n = 7$  months has an absolute error of 3 and a squared error of 9, the results are:

$$MAE = (1/7)(3 + 3 + 3 + 3 + 3 + 3 + 3) = 21 / 7 = 3$$

$$MSE = (1/7)(9 + 9 + 9 + 9 + 9 + 9 + 9) = 63 / 7 = 9$$

$$RMSE = \sqrt{9} = 3$$

Based on Table 3, the LSTM model obtained an MAE of 3, an MSE of 9, and an RMSE of 3 vehicles per month. All seven testing data points produced predictions differing by only 3 vehicles from the actual values, indicating that the model is highly consistent and accurate. The comparison between the actual and predicted values on the testing data is visualized in Figure 3.



**Fig. 3:** Comparison of actual values and LSTM predicted values on the testing data

Figure 3 shows that the prediction curve of the LSTM model follows the trend and fluctuation pattern of the actual data very well. The difference between the actual and predicted values is relatively small and consistent with the RMSE of 3 vehicles per month, so the model is able to capture both seasonal patterns and short- and long-term trends in the vehicle inspection data.

### 3.3. Prediction results for 2026 and 2027

After being declared feasible, the model was used to predict the number of motor vehicle inspections in 2026 and 2027 using an iterative approach (rolling forecast), in which the prediction result of the previous period is used as input to predict the next period. A summary of the prediction results for both years is presented in Table 4.

**Table 4:** Prediction results for the number of motor vehicle inspections in 2026 and 2027

Month	2026 Prediction (vehicles)	2027 Prediction (vehicles)
January	52	56
February	57	61
March	70	75
April	63	67
May	77	83
June	88	95
July	172	186
August	82	88
September	72	78
October	66	71
November	71	77

Month	2026 Prediction (vehicles)	2027 Prediction (vehicles)
December	46	49
<b>Total</b>	<b>916</b>	<b>986</b>

Source: LSTM model prediction results (2026–2027)

Based on Table 4, the total predicted number of motor vehicle inspections in 2026 is 916 vehicles, with the highest prediction in July (172 vehicles) and the lowest in December (46 vehicles). In 2027, the total prediction increases to 986 vehicles, an increase of 70 vehicles (7.64%) compared with 2026, with a consistent peak in July (186 vehicles). A visual comparison of the two prediction years is shown in Figure 4.

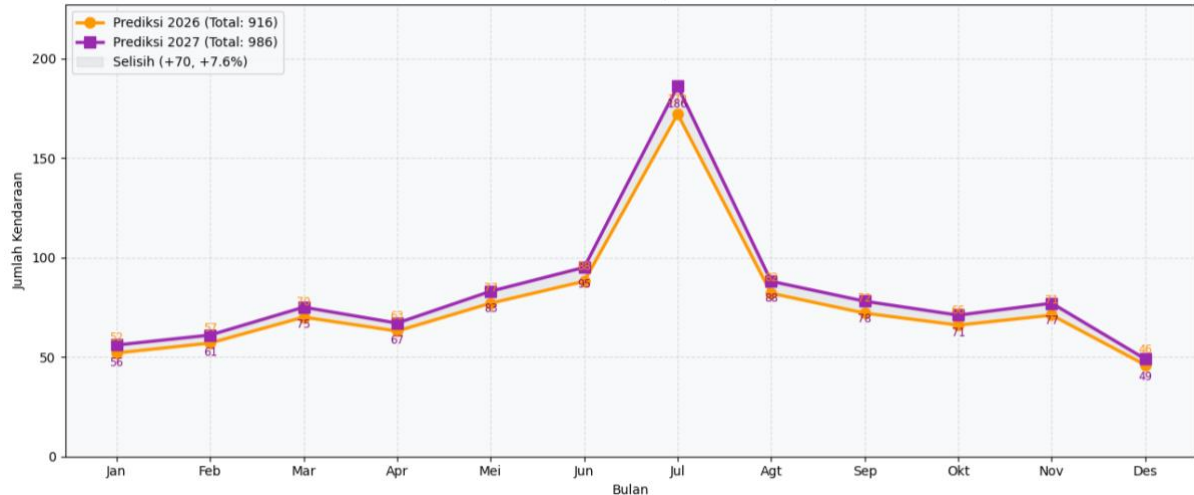


Fig. 4: Comparison of motor vehicle inspection prediction results for 2026 and 2027

Figure 4 shows that the 2027 prediction is generally higher than the 2026 prediction in almost every month, indicating a consistent growth trend in the number of vehicle inspections. Both years also display a similar seasonal pattern with a peak in July, confirming that the LSTM model successfully captured the recurring seasonal pattern in the data.

### 3.4. Discussion

The RMSE of 3 vehicles per month is equivalent to about 13.5% of the data average, which is still below the 20% threshold commonly used as a benchmark for the acceptability of a prediction model. This confirms that the developed LSTM model has good accuracy and is suitable for use. This result is consistent with previous studies demonstrating the reliability of LSTM in time-series data modeling across various domains [9], [12], [13]. In practical terms, the prediction results provide strategic value for the Transportation Agency of Langkat Regency in medium-term planning, including scheduling inspections, allocating inspection officers, and preparing testing equipment to anticipate the high-load periods predicted to occur in the middle of the year.

## 4. Conclusion

Based on the conducted research, the prediction model for the number of motor vehicle inspections at the Transportation Agency of Langkat Regency was successfully designed and implemented using the Long Short-Term Memory (LSTM) method with monthly historical data for the period from January 2023 to December 2025, comprising 36 data points. The model was trained using 80% training data and tested using 20% testing data with a timestep value of 3. The prediction results show a total of 916 vehicles for 2026 and 986 vehicles for 2027, with the testing peak occurring in July in both years.

The performance of the LSTM model yielded evaluation values of a Mean Absolute Error (MAE) of 3, a Mean Squared Error (MSE) of 9, and a Root Mean Squared Error (RMSE) of 3. This RMSE is equivalent to 13.5% of the data average, still below the 20% threshold, so the model is considered to have good accuracy and to be suitable for use as a decision-support tool. Future research is recommended to extend the range of historical data, add supporting variables such as the number of registered vehicles and national holidays, and compare the performance of LSTM with other methods such as the Gated Recurrent Unit (GRU), Bidirectional LSTM, or the hybrid CNN-LSTM model.

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