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Enhancing Operational Efficiency in Domestic Cargo Handling at Tanjung Priok Port

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Abstract

Maritime transportation plays a crucial role in national development and population mobility in archipelagic countries like Indonesia. It is also key in encouraging Indonesia's economic growth, especially in frontier, outermost, and underdeveloped areas, as well as being a gateway to international trade. One of the important nodal points in sea transportation is the Port of Tanjung Priok in North Jakarta. This port is the largest and busiest, serving as the main gateway for the flow of export-import goods and the distribution of goods between islands. This research aims to analyze the loading and unloading activities of domestic goods at the Port of Tanjung Priok using secondary data from the official website of the Central Bureau of Statistics for the period from January 2007 to December 2023. The models used are Seasonal Autoregressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM). SARIMA is employed due to the presence of seasonal patterns in the data. Subsequently, the SARIMA model will be compared with the Long Short-Term Memory (LSTM) model, which uses a machine learning approach to evaluate and determine the most accurate model for predicting domestic cargo handling activities at Tanjung Priok Port. Based on the RMSE analysis, the LSTM model has a lower RMSE compared to the SARIMA model, indicating that LSTM provides more accurate predictions for this time series data. However, it is important to note that a lower RMSE does not always mean that one model is generally better. Additional evaluations, such as residual analysis, other statistical tests, or prediction consistency through cross validation, should also be considered to validate the model's superiority comprehensively. This analysis is expected to provide deeper insights into port capacity planning and operational management, enabling more precise and effective decision-making in response to future demand dynamics and operational trends.

1. INTRODUCTION

Maritime transportation has played an important role in promoting national development and the movement of people and goods, particularly in an archipelagic country like Indonesia. As the primary connectivity between islands and the entrance to worldwide trade, ports play an important role in driving economic growth [1] [2]. Tanjung Priok Port in North Jakarta is one of the ports that contributes to this effort. Known as Indonesia's largest and busiest port, it is critical to the flow of export-import products and inter-island distribution [3] [4]. Although Tanjung Priok Port has long served its purpose, operational efficiency issues still limit the port's potential, necessitating an investigation into the operational efficiency of domestic cargo processing at Tanjung Priok Port. In this context, understanding and analyzing cargo handling activities at this port over time is critical for developing long-term improvement initiatives. This study will examine domestic cargo handling activities at Tanjung Priok Port from 2007 to 2023. Using historical data from the last 16 years, it is planned to provide a thorough picture of cargo handling trends and patterns, as well as the factors that influence them. To accomplish this goal, two statistical and machine learning-based predictive models capable of accurately modeling time series data are used: the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and the Long Short-Term Memory (LSTM) model.

Evaluating these two models will provide vital information that port management and other stakeholders can use to make strategic decisions. Understanding the dynamics of cargo handling at Tanjung Priok Port allows for significant improvements in capacity planning and operational management, resulting in increased port efficiency and productivity, as well as the discovery of effective strategies to improve port performance, making Tanjung Priok

Port more advanced and adaptable to changing times and global demands. The findings of this study are also expected to contribute to the scientific literature on the use of predictive models in transportation and logistics, particularly in the context of ports, and to serve as a reference for strategic decision-making that will benefit the national economy, particularly by increasing the competitiveness and efficiency of the maritime sector. As a result, this study has larger implications for Indonesian transportation and logistics strategies and relevance to Tanjung Priok Port's growth. The impact of future government policies and the quantitative effects of applying predictive models on the performance of the national economy have not yet been thoroughly investigated in this study. Therefore, more investigation is required to determine how predictive models may aid in the decision-making process when it comes to the creation of marine policies and port infrastructure investments.

2. RESEARCH METHODS

The methodology employed in this study comprises multiple sequential stages, including data collection, exploratory data analysis, data partitioning, model development, model evaluation, and result interpretation. The research workflow is presented in Figure 1

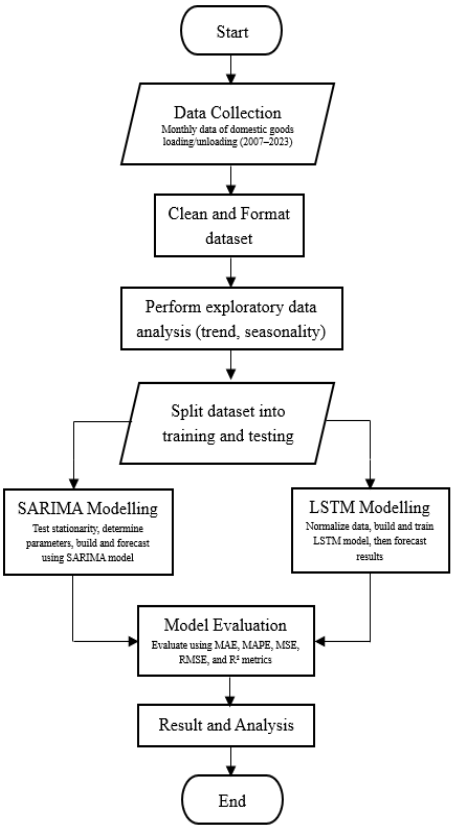

Figure 1. The Research Workflow

2.1 Data Collection

This study uses a quantitative method with a descriptive design to analyze domestic cargo handling activities at Tanjung Priok Port from 2007 to 2023. The total data used in this study consists of 204×3 data points, each for loading and unloading goods. The table below displays the data used.

	Tanggal	Barang	Barang_New
0	2007-01-31	383471	3.83471
1	2007-02-28	428255	4.28255
2	2007-03-31	567639	5.67639
3	2007-04-30	623092	6.23092
4	2007-05-31	573148	5.73148
...	...	...	...
199	2023-08-31	1306371	13.06371
200	2023-09-30	1290251	12.90251
201	2023-10-31	1253396	12.53396
202	2023-11-30	1394134	13.94134
203	2023-12-31	1410015	14.10015

Figure 2. The data of loading (left) and unloading (right) of domestic goods Tanjung Priok

The data sources were obtained from the Central Bureau of Statistics website, and the dataset used consists of daily data. Additionally, the dataset is a time-series dataset recorded by observation date as shown in the attached table, where each row represents one observation period consisting of three variables: Time (date), Number of Domestic Goods Loaded/Unloaded measured in tons, and the converted value in units of hundred thousand tons to simplify interpretation; thus, the primary unit of analysis is tons with an additional scaled unit used for visualization and comparison, and the tabular form of the data is presented in Figure 2 based on records obtained from the official website of the Central Bureau of Statistics (BPS). By obtaining data directly from the Central Bureau of Statistics website, it is expected that the dataset used is valid and reliable for analyzing domestic cargo handling activities at Tanjung Priok Port during this period. The data collection technique was carried out through browsing and scraping methods from the specified website. The data was then transferred to a CSV file using Microsoft Excel for further processing with Python. Python was used for modeling and displaying the model evaluation results. **Figure 3.** is a plot of the goods loaded and unloaded at Tanjung Priok Port.

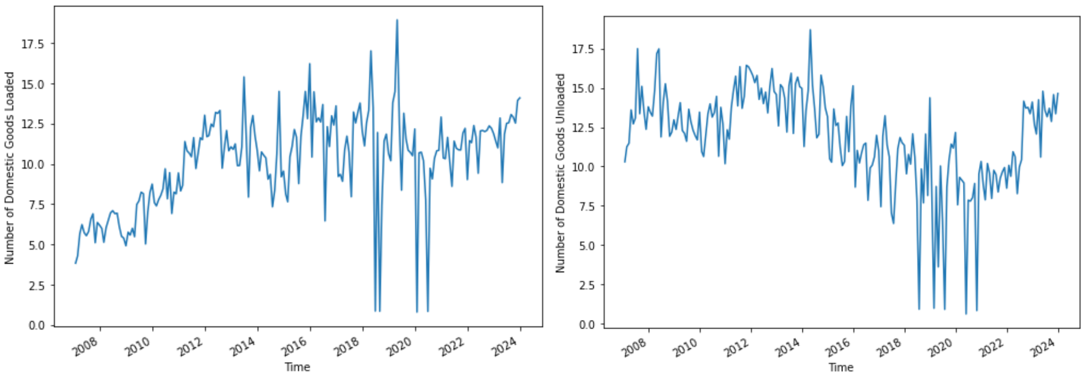

Figure 3. The plot of loading (left) and unloading (right) of domestic goods Tanjung Priok

2.2 Data Analysis

After going through the data collection method, the next step is to analyze the data to obtain a comprehensive picture of cargo handling trends and patterns, as well as the factors that influence them. There are 2 Time Series models used to analyze the data, namely *Seasonal Autoregressive Integrated Moving Average* (SARIMA) and *Long Short-Term Memory* (LSTM) model.

2.2.1 *Seasonal Autoregressive Integrated Moving Average (SARIMA)*

The *Seasonal Autoregressive Integrated Moving Average* (SARIMA) is a Time Series model that extends the non-seasonal ARIMA model to handle data with seasonal patterns. This model combines concepts from Autoregressive (AR), Integrated (I), and Moving Average (MA) models with seasonal components [5]. The general SARIMA (p, d, q, s)(P, D, Q, S) equation is as followed:

$$(1-B)^d.(1-B^S)^D.X_t = C + \sum_{i=1}^{p} \phi_i .B^i.X_t + \sum_{i=1}^{q} \theta_j .B^j.\varepsilon_t + \sum_{i=1}^{P} \Phi_i .B^{iS}.X_t + \sum_{i=1}^{Q} \Theta_j .B^{jS}.\varepsilon_t + \varepsilon_t \tag{1}$$

Where,

B: the operator lag
d: order of non-seasonal differencing to make Time Series Stationary
S: seasonal period
D: number of seasonal differences required to make the Time Series Stationary
X_t: value of time series at time t
p: order of the non-seasonal AR model
C: constant term
ϕ_i: coefficients for the non-seasonal AR terms
q: order of the non-seasonal MA model
θ_j: coefficients for the non-seasonal MA terms
Φ_i : coefficients for the seasonal AR terms
Θ_j.: coefficients for the seasonal MA terms
ε_t: the white noise error term at time t

The following are several discussions of other Time Series models that are related to the SARIMA model:

1. *Autoregressive/* AR, denoted by (p). This model uses Time Series data with the prediction of the current value as a linear combination of past values, indicating that the current value depends on previous values.
- AR Formula:

$$X_t = C + \textstyle\sum_{i=1}^{p} \phi_i.X_{t-1} - \varepsilon_t \tag{2}$$

2. *Moving Average/* MA, denoted by (q). This model utilizes forecast error in a regression approach to predict future observations for the next time point. This component uses past error values.
- MA Formula:

$$X_t = C + \textstyle\sum_{i=1}^{p} \theta_i.\varepsilon_{t-1} - \varepsilon_t \tag{3}$$

3. *Autoregressive Integrated Moving Average/* ARIMA, denoted by (p,d,q). This model is an extension of the ARMA model (combination of AR and MA) that includes a differencing process to make the data statio nary. This model is suitable for non-stationary data.
- ARIMA Formula:

$$(1-B)^d.X_t = C + \textstyle\sum_{i=1}^{p} \phi_i.B^i.X_t + \sum_{i=1}^{q} \theta_j.B^j.\varepsilon_t + \varepsilon_t \tag{4}$$

The following outlines the steps involved in SARIMA methods:

1. Decomposition
   The first step is decomposing the time series into smaller components, such as trend, seasonal, and residual. This helps to understand the seasonal and trend patterns in the data.
2. Stationarity Test

This test is conducted to check whether the time series data is stationary or not. One common test used is the Augmented Dickey-Fuller (ADF) test.

3. Differencing
   If the data is not stationary, differencing can be applied to transform the data into stationary. Differencing involves subtracting the previous value from the current value.
4. ACF and PACF Tests
   The ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) tests are used to identify the appropriate ARIMA model order, specifically, the number of autoregressive (AR) and moving average (MA) lags.
5. Ljung-Box Test
   The Ljung-Box test is used to check for autocorrelation in the residuals. This test helps to determine whether the resulting model is adequate or if there is still significant autocorrelation in the residuals.

2.2.2 *Long Short-Term Memory (LSTM)*

Long Short-Term Memory (LSTM) was first introduced in 1997 by Hochreiter and Schmidhuber and is a derivative of the *Recurrent Neural Network* (RNN) method, which is designed to handle sequential data[6]. The LSTM method was developed to address the vanishing gradient problem that occurs in Recurrent Neural Networks (RNN). Although the architecture of LSTM is similar to RNN, the difference lies in the use of four gates in the *hidden state* process, namely the *forget gate, input gate, cell state,* and *output gate*[7].

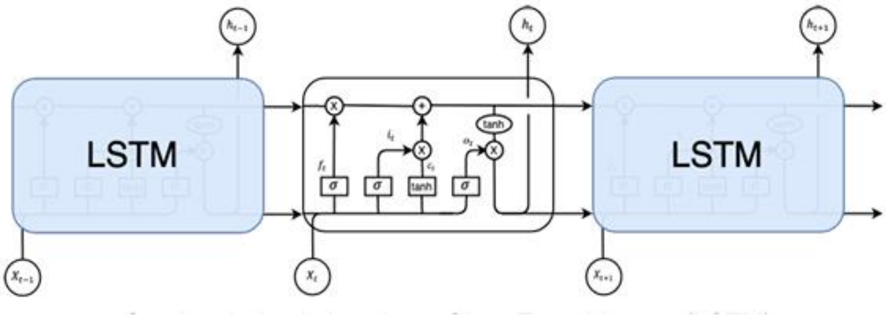

Figure 4. Architecture of LSTM

1. *Forget Gate* (f_t)
   In an LSTM, the *forget gate* is the first gate an input goes through. The input at time t and the output at time t - 1 are combined by this gate using the *sigmoid* activation function. The *sigmoid* function determines whether this gate's output is 1 or 0. When f_t equals 0, the information from the previous state is lost, and when f_t equals 1, the information is retained. The formula of Forget Gate (f_t) is given as follows:

$$f_t = \sigma(W_f S_{t-1} + W_f X_t) \tag{5}$$

   Where, σ: the *sigmoid* activation function, X_t: the input at time t, S_{t-1}: the prior state or the state at time t - 1, and W_f : the weight of the *forget gate.*
2. *Input Gate* (i_t)
   The second process in the *hidden state* is calculating the value of the *input gate*. The *input gate* is calculated using the *sigmoid* activation function (σ), as shown in the following equation:

$$i_t = \sigma(W_i[h_{t-1}, X_t] + b_i \tag{6}$$

   Where, (i_t): *input gate,* (X_t): *input values*, (W_i): weights, (b_i): bias, and (h_{t-1}): the previous *hidden state* value.

In the *input gate*, there is an additional process that involves calculating the candidate's new *cell state* value (C_t'). This value is obtained using the tanh activation function, as shown in the following equation:

$$C_t' = tanh(W_c.[S_{t-1}, X_t] + b_c \tag{7}$$

3. *Cell State* (C_t)
The *cell state* value can be derived by multiplying the product of the *input gate* (i) and the new candidate *cell state* (C_t') with the product of the *forget gate* ($f_t$and the prior *cell state* (C_{t-1}). This is done once the values for the *input gate, forget gate,* and new candidate *cell state* have been determined. The following is the formula:

$$C_t = (i_t * C_t' + f_t * h_{t-1}) \tag{8}$$

4. *Output Gate* (o_t)
The *output gate*, which employs the *sigmoid* activation function, is the subsequent procedure. Together with the *cell state*, a new *hidden state* value is generated using the value of this *output gate*. The following equation is used to obtain the *output gate*:

$$o_t = \sigma(W_O S_{t-1} + W_o X_t) \tag{9}$$

Using the tanh function, the output value of the *hidden state* is determined by the value of the *output gate*. As the equation illustrates, this *hidden state* is obtained by multiplying the *output gate* value by the *cell state* after it has been processed using the tanh function.

$$h_t = o_t * tanh(C_t) \tag{10}$$

The steps of LSTM are listed bellow:

1. Convert Data into Sequences
The first step is to convert the data into sequences that are suitable for LSTM input. These sequences enable the model to recognize patterns in sequential data, such as time series data.
2. Normalize Training and Testing Data
Normalization is done to improve the model's performance. By normalizing, the data will fall within a specific range (e.g., between 0 and 1), making it easier for the model to make predictions. Normalization is typically performed by subtracting the mean and dividing by the standard deviation. Normalization data formula [8]:

$$x' = \frac{x_i - min(x)}{max(x) - min(x)} \tag{11}$$

Where x_i: the i-th data value before normalization, x': the i-th data value after normalization, *min(x)*: the minimum value from the training data, *max(x)*: the maximum value from the training data.
3. Inverse Transform
After the model is trained and predictions are made, we need to return the normalized data to its original scale so that the prediction results can be correctly interpreted. This process is called inverse transform. Inverse Transform formula [9]:

$$d = x'(max(x) - min(x)) + min(x) \tag{12}$$

Where d: the i-th data value denormalization, x': the i-th data value normalization, *min(x)*: the minimum value from the training data, *max(x)*: the maximum value from the training data.

Following the analysis using the twi methods, the next step involves calculating the performance metrics namely MSE, MAE, MAPE, and RMSE.

1. Mean Squared Error (MSE) is an evaluation metric used to measure how accurately a regression method predicts numerical values [9]. The formula of MSE can be expressed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{13}$$

Where N: the number of data samples, y_i: the actual value of the i-th data point, dan $\hat{y}_i$: predicted value from the model for the i-th data point.

2. Mean Absolute Error (MAE) represents the difference between actual values and predicted values, serving as the average total change within the dataset [10]. The formula of MAE can be expressed as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i) \tag{14}$$

Where N: the number of data samples, y_i: the actual value of the i-th data point, dan $\hat{y}_i$: predicted value from the model for the i-th data point.

3. Mean Absolute Percentage Error (MAPE) is the average of the absolute differences between predicted values and actual values, expressed as a percentage of the actual values [11]. The formula of MAPE can be expressed as follows:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i-\hat{y}_i}{y_i}\right) \tag{15}$$

4. Root Mean Squared Error (RMSE) is a measure of the difference between the values predicted by a model and the actual observed values [12]. The formula of RMSE can be expressed as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{16}$$

3. RESULTS AND DISCUSSION

3.1 SARIMA Forecasting

The data used in this analysis consisted of the monthly loading and unloading of goods at Tanjung Priok Port from 2007 to 2023. Prior to forecasting, seasonal testing and decomposition were conducted to examine the presence and pattern of seasonality.

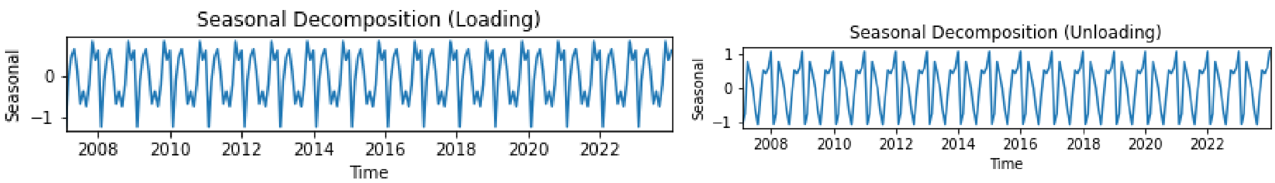

Figure 5. Seasonal Decomposition of Data on the Loading and Unloading of Domestic Goods

Based on the seasonal decomposition results presented in Figure 2, both loading and unloading data exhibit a clear and consistent seasonal pattern that repeats every 12 periods, indicating annual seasonality (s = 12). This means that fluctuations tend to recur in the same months each year, reflecting systematic increases and decreases within the 12-month cycle. The seasonal component shows regular peaks and troughs across corresponding periods, confirming the presence of strong seasonal effects in the time series. Therefore, the SARIMA model, which explicitly accounts for seasonal patterns with a seasonal period of 12, was selected as the appropriate forecasting method.

The stationarity of the data was examined using the Augmented Dickey–Fuller (ADF) test. Although the data exhibited seasonal patterns, stationarity in the mean is required to satisfy the assumptions of the time series model. The results of the ADF test for the loading data showed an ADF statistic of −5.2968 with a p-value of 0.00000556, which is lower than the 5% significance level. This value is also more negative than the critical values at the 1% (−3.4783), 5% (−2.8826), and 10% (−2.5780) significance levels. Therefore, the null hypothesis of a unit root was rejected, indicating that the differenced loading data is stationary. Similarly, the ADF test for the unloading data produced an ADF statistic of −3.2286 with a p-value of 0.0184, which is also lower than the 5% significance level and more negative than the critical values at all significance levels. This result indicates that the differenced unloading data is stationary.

Since both loading and unloading data achieved stationarity after first-order differencing, the integration order was determined as d = 1. After confirming stationarity, the next step was to identify the appropriate SARIMA model by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the autoregressive (AR), moving average (MA), and seasonal components of the model.

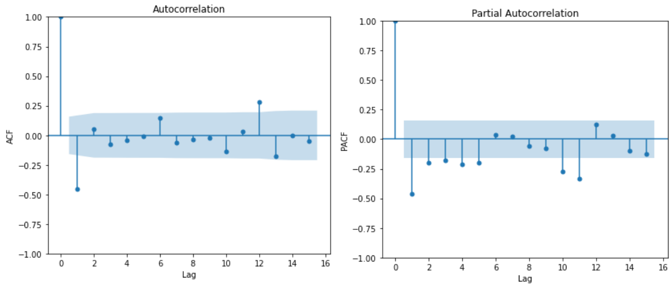

Figure 6. Plot ACF dan PACF of Data on the Loading of Domestic Goods

Based on Figure 4, the ACF plot of the loading data shows a significant negative spike at lag 1, followed by autocorrelation values that gradually decrease and remain within the confidence interval. This pattern indicates the presence of a moving average (MA) component. The PACF plot shows significant spikes at lag 1 and lag 2, followed by a gradual decline, which suggests the presence of autoregressive (AR) components up to lag 2. In addition, a significant spike is observed at lag 12 in the ACF plot, indicating the presence of a seasonal component with a period of 12 months. Therefore, the SARIMA$(2,1,1)(1,0,0)_{12}$ model was identified as an appropriate candidate model for the loading data.

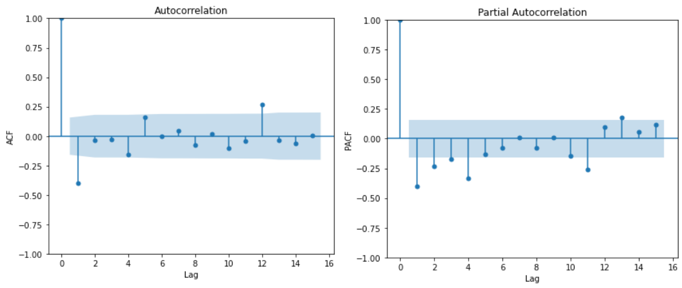

Figure 7. Plot ACF dan PACF of Data on the Unloading of Domestic Goods

Based on Figure 5, the ACF plot of the unloading data shows a significant spike at lag 1, followed by a rapid decline toward zero, indicating the presence of a moving average (MA) component. The PACF plot shows a significant spike at lag 1 and then gradually decreases, indicating the presence of an autoregressive component. Furthermore, a significant spike is observed at lag 12 in both ACF and PACF plots, confirming the presence of seasonal behavior with 12 months. Therefore, SARIMA$(0,1,1)(1,0,1)_{12}$ was selected as the most appropriate model for unloading data.

After model identification, parameter estimation was conducted using maximum likelihood estimation. The estimation results for the loading data model, SARIMA$(2,1,1)(1,0,0)_{12}$, showed that all estimated parameters were statistically significant, with p-values less than 0.05. Specifically, the non-seasonal autoregressive parameters AR(1) and AR(2), the moving average parameter MA(1), and the seasonal autoregressive parameter SAR(12) significantly contributed to the model. Similarly, for the unloading data, the SARIMA$(0,1,1)(1,0,1)_{12}$ model showed that all parameters, including the non-seasonal MA(1), seasonal AR(12), and seasonal MA(12), were statistically significant at the 5% significance level.

Diagnostic checking was then performed using the Ljung–Box test to evaluate whether the residuals satisfied the white noise assumption. For the loading model, the Ljung–Box test produced a p-value of 0.80, and for the unloading model, the p-value was 0.46. Since both p-values were greater than 0.05, the null hypothesis of no autocorrelation could not be rejected. This indicates that the residuals were independently distributed and did not exhibit significant autocorrelation. Therefore, both SARIMA models were considered adequate and appropriate for forecasting the loading and unloading data.

Finally, the actual and predicted results are plotted for visualization, showing the comparison between the actual and predicted number of loading and unloading goods on the test data. This plot provides a visual representation of how well the model predicts the number of loading and unloading items [11].

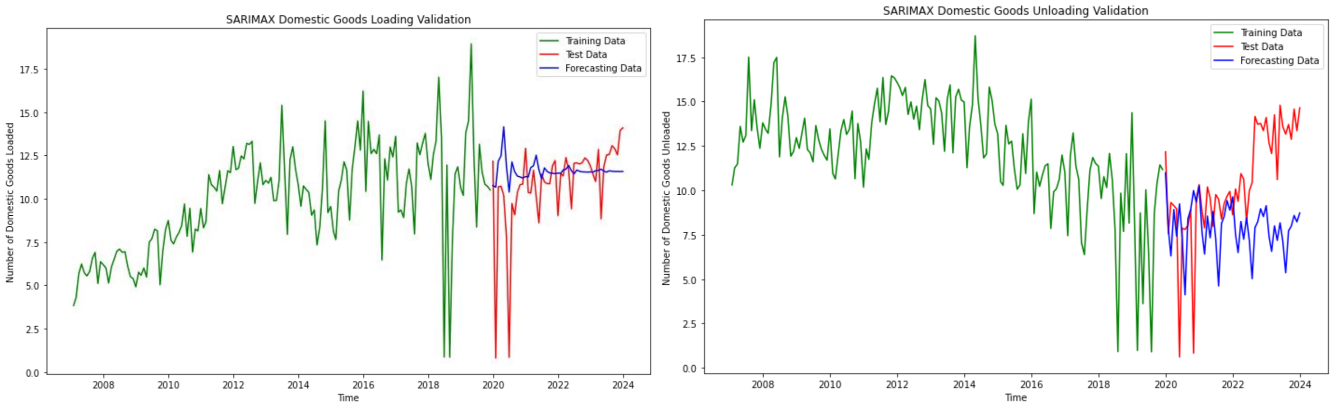

Figure 8. SARIMA Domestic Goods Loading and Unloading Validation

Based on Figure 5, the SARIMA forecasting results for both loading and unloading data generally follow the pattern of the actual data. For the loading data, the forecasted values are relatively close to the actual values, indicating that the model can capture the data pattern well. For the unloading data, the forecasted values also follow the general trend of the actual data, although there are larger differences compared to the loading data. This indicates that the model performance for unloading data is slightly lower than for loading data. These results suggest that the SARIMA model is able to perform forecasting reasonably well, especially for the loading data. This is supported by the error evaluation results, where the loading model produced lower MSE, MAE, and RMSE values compared to the unloading model.

3.2 LSTM Forecasting

The loading and unloading goods of data were also analyzed using an LSTM model. The first step involved normalizing the data to ensure it falls within the range of 0 and 1. This normalization is crucial to assist the neural network model, particularly LSTM, in training faster and more accurately [12]. Subsequently, the data was transformed into sequences of a specific length, in this case 10, where each sequence consists of 10 consecutive data points, with the target being the next data point.

The dataset was partitioned into training and testing sets based on chronological order. The training set consisted of data from January 2007 to December 2019 (76.47%), while the testing set consisted of data from January 2020 to December 2023 (23.53%). This approach preserves the temporal order of the data and allows the model to be evaluated using unseen future observations. Both sets of data are normalized separately. These two datasets are normalized separately. The sequence for the LSTM model is prepared from the normalized data and reshaped to fit the input required by the LSTM model. The LSTM model is constructed with two LSTM layers, each consisting of 50 units, followed by two Dense layers with 25 units each and 1 unit for the output. This model is then compiled using the Adam optimizer and the mean squared error loss function. The model is trained using the training data with validation on the testing data, with a batch size of 1, and trained for 100 epochs.

After the model is trained, predictions are made on both the training and testing sets. The predicted results and actual values are then transformed back to their original scale using the inverse transformation of the scaler. Finally, the actual and predicted results are plotted for visualization, showing the comparison between the actual and predicted quantities of loading and unloading goods on both the training and testing data. This plot provides a visual representation of how well the model predicts the quantities of loading and unloading goods.

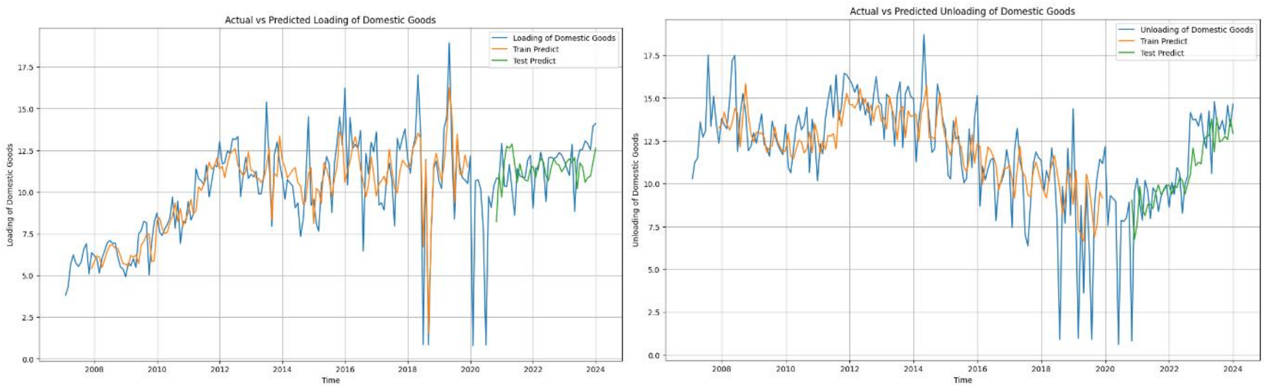

Figure 9. Actual vs Predicted Loading and Unloading of Domestic Goods with LSTM

Based on Figure 6, the LSTM model predictions generally follow the pattern of the actual data for both loading and unloading. For the loading data, the predicted values are relatively close to the actual values, indicating that the model is able to capture the data pattern well. For the unloading data, the predicted values also follow the overall trend of the actual data. This is supported by the error evaluation results, where the loading model produced lower MSE, MAE, and RMSE values compared to the unloading model. Overall, these results indicate that the LSTM model is able to provide good forecasting performance, particularly for the loading data.

3.3 Evaluation

Demonstrating the effectiveness of the model, the performance of the model was evaluated based on three metrics: Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). RMSE measures the difference between predictions and actual final values. The experimental results are shown in Table 1. Both SARIMA and LSTM achieve optimal performance overall. However, the LSTM model demonstrates better performance due to smaller error results, indicating that the testing outcomes closely align with predictions, suggesting superior forecasting capability. Additionally, dividing the data by one hundred thousand also impacts the error values produced.

Table 1. Performance comparison for two models (in hundred thousand)

Error Metrics	SARIMA		LSTM	
	Loaded	Unloaded	Loaded	Unloaded
MSE	6.264	17.428	2.396	4.066
MAE	1.581	3.316	1.186	1.337
RMSE	2.503	4.175	1.548	2.017

Based on the experiment, the performance of SARIMA and LSTM is relatively good in predicting the future. These models can be used to estimate the amount of loading and unloading goods at Tanjung Priok Port in the next period. The plot below also represents the estimated values for the period from January to December 2024. The plot shows that the amount of loading and unloading goods at Tanjung Priok Port tends to decrease.

The results of the SARIMA and LSTM models for forecasting loading and unloading goods at Tanjung Priok Port in 2024 are shown in Figures 6 and 7. The actual values are in green, and the forecasts for the next 12 months are marked in blue. From the results shown in the graphs below, it can be seen that the SARIMA model is quite far off in its forecasting, whereas the LSTM model closely resembles the actual data pattern.

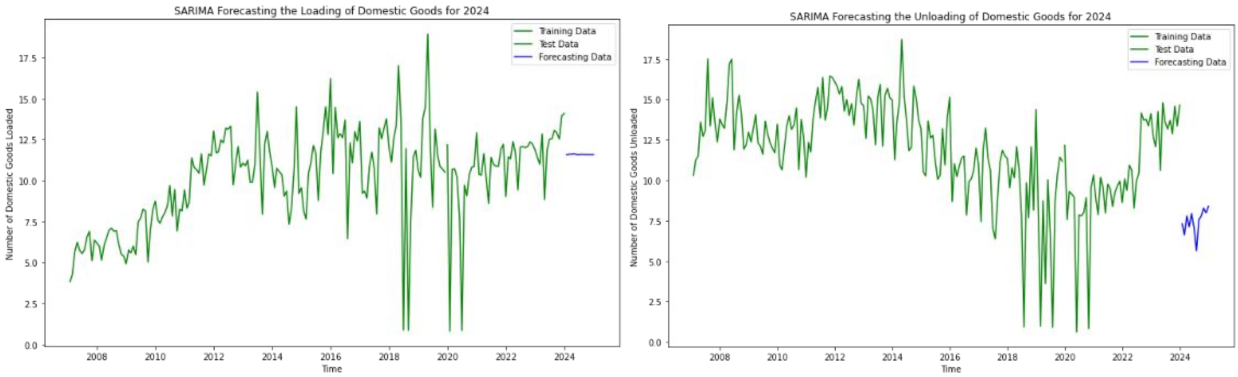

Figure 10. SARIMA Forecasting the Loading and Unloading of Domestic Goods for 2024

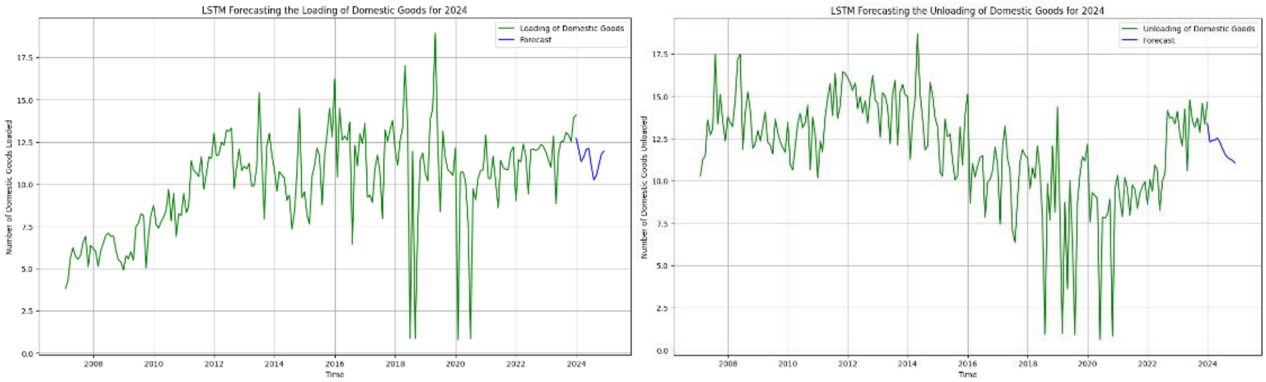

Figure 11. LSTM Forecasting the Loading and Unloading of Domestic Goods for 2024

For further analysis, here is the forecasting data for the SARIMA and LSTM models of loading and unloading goods domestic for 2024.

Table 2. The forecast of the loading and unloading goods for 2024 (in hundred thousand)

Time	SARIMA		LSTM	
	Loaded	Unloaded	Loaded	Unloaded
January	11.57568	7.305775	12.714358	14.345577
February	11.601381	6.616650	11.817123	14.451986
March	11.606799	7.795280	12.041165	14.593595
April	11.635557	7.121869	12.156153	14.855280
May	11.595730	7.937142	12.053276	15.025532
June	11.570865	7.076260	11.674550	15.110536
July	11.600775	5.630665	11.073468	15.104102
August	11.591049	7.562272	10.750775	15.153969
September	11.586777	7.787065	11.013126	15.259163
October	11.585984	8.275296	11.366182	15.381803
November	11.584781	7.979582	11.558536	15.494995
December	11.586359	8.390064	11.454896	15.559867

4. CONCLUSION

Research findings indicate that the Long Short-Term Memory (LSTM) model provides more accurate predictions compared to the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, as evidenced by lower Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) values.

Smaller errors indicate that the test results are closer to the predictions, reflecting a high-quality model in forecasting. It is important to note that these two methods differ fundamentally. LSTM, as a machine learning method, is superior in modeling due to its ability to continuously iterate and learn, thereby improving the model and minimizing errors. This superior predictive capability has significant implications given the increasing demands for efficiency and productivity in Indonesia's maritime sector. The application of LSTM can support the optimization of Tanjung Priok Port's performance, boost national economic growth, and enhance the competitiveness of the transportation and logistics sector in the future. This research not only has the potential to enhance the efficiency of Tanjung Priok Port but also makes a significant contribution to the scientific literature on transportation and logistics, providing a strong foundation for informed strategic decision-making.

REFERENCES

[1] Statistik Transportasi Laut 2020, Badan Pusat Statistik, 2021.

[2] "Transportasi Laut Pegang Peranan Strategis untuk Merajut Keberagaman Indonesia dan Mendorong Pertumbuhan Ekonomi," Kementrian Perhubungan Repbublik Indonesia, 2020. [Online]. Available: https://dephub.go.id/post/read/transportasi-laut-pegang-peranan-strategis-untuk-merajut-keberagaman-indonesia-dan-mendorong-pertumbuhan-ekonomi.

[3] A. F. Sopiah , "MENGENAL PELABUHAN TANJUNG PRIOK," 16 Desember 2019. [Online]. Available: https://seara.co.id/2019/12/16/mengenal-pelabuhan-tanjung-priok/.

[4] "IPC TERMINAL PETIKEMAS," Pelindo Terminal Petikemas IPC TPK, [Online]. Available: https://ipctpk.co.id/area-tanjung-priok/.

[5] "SARIMA (Rata-rata Pergerakan Terintegrasi Autoregresif Musiman)," 24 May 2024. [Online]. Available: https://www.geeksforgeeks.org/sarima-seasonal-autoregressive-integrated-moving-average/.

[6] L. Wiranda and M. Sadikin, "Penerapan Long Short Term Memory pada Data Time Series untuk Memprediksi Penjualan Produk PT. Metiska Farma," *JANAPATI,* vol. 8, no. 3, 2019.

[7] J. Cahyani, S. Mujahidin and T. P. Fiqar, "Implementasi Metode Long Short Term Memory (LSTM) untuk Memprediksi Harga Bahan Pokok Nasional," *Jurnal Sistem dan Teknologi Informasi,* vol. 11, no. 2, 2023.

[8] H. H. Nuha, "Mean Squared Error (MSE) dan Penggunaannya," *SSRN,* 2023.

[9] "Mean Absolute Error (MAE) is a metric that calculates the average magnitude of the absolute errors between the predicted and actual values.," ScienceDirect, 2022. [Online]. Available: https://www.sciencedirect.com/topics/engineering/mean-absolute-error.

[10] "The root mean square error is defined as the measure of the differences between values that are predicted by a model and values that are actually observed.," ScienceDirect, 2022. [Online]. Available: https://www.sciencedirect.com/topics/engineering/root-mean-square-error.

[11] M. I. Rizki and T. A. Taqiyyuddin, "Penerapan Model SARIMA untuk Memprediksi Tingkat Inflasi di," *Jurnal Sains Matematika dan Statistika,* vol. 7, no. 2, pp. 62-72, Juli 2021.

[12] "XGBoost vs LSTM: A Comparative Analysis of Time Series Forecasting for Stock Price Prediction," 5 September 2023. [Online]. Available: https://netanel.io/posts/xgb_vs_lstm/.