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Regular Research

Time Series Forecasting for Container Throughput Using SARIMA and LSTM: A Case Study of Tanjung Emas Port, Semarang

Hari Ratmoko [1], Eri Zuliarso[2]*

[1] Master of Information Technology, Faculty of Information Technology and Industry, Universitas Stikubank

* Correspondence author: eri299@edu.unisbank.ac.id; Tel.: +62-858-7640-6108

Abstract: This study addresses the critical need for accurate container throughput forecasting in modern port and logistics management, as precise forecasts are essential for optimizing operational planning, resource allocation, and strategic decision-making. The primary objective of this paper is to conduct a comparative performance analysis of the classical SARIMA (Seasonal Autoregressive Integrated Moving Average) model and the deep learning-based LSTM (Long Short-Term Memory) model. The methodology involved utilizing a dataset of 136 monthly observations, split into an 80% training set and a 20% testing set. The results demonstrate a clear superiority of the LSTM model across all evaluation metrics, with an MAE of 3901.441, an RMSE of 4499.624, and a MAPE of 10.776%, which are significantly lower than SARIMA's respective values of 6362.459, 7294.177, and 17.159%. These findings suggest that LSTM is more capable of capturing the complex, non-linear patterns and long-term dependencies inherent in the data. The study concludes that the deep learning approach, particularly LSTM, offers a more robust and accurate solution for container throughput forecasting, highlighting its potential to enhance predictive capabilities in the logistics sector.

Keywords: SARIMA, LSTM, Time Series Analysis, Port Operations, Tanjung Emas Port, Maritime Logistics

1. Introduction

As the world's largest archipelagic country, Indonesia's economic stability and growth are fundamentally dependent on maritime connectivity. Seaports constitute essential infrastructure for both domestic and international trade, and their operational efficiency serves as a pivotal determinant of the nation's economic performance[1]. A key performance indicator for this efficiency is container throughput, which measures the volume of cargo handled by a port [2]. The ability to accurately forecast container throughput is a strategic advantage for port authorities, enabling them to make informed decisions regarding resource allocation, logistics planning, and infrastructure investment. Fluctuations in throughput are influenced by a complex interplay of factors, including seasonal trends, national holidays, and broader macroeconomic conditions. However, predicting this complex and volatile time series data is a challenging task [3].

Historically, traditional statistical methods have been the cornerstone of time series forecasting in the maritime and logistics

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sectors. SARIMA (Seasonal Autoregressive Integrated Moving Average) models, in particular, have demonstrated strong performance in handling data with clear stationary and seasonal patterns. The primary strength of SARIMA lies in its ability to explicitly identify and model seasonal components, which is highly relevant for port data that often exhibits predictable monthly or quarterly patterns. Despite their efficacy, a significant limitation of these statistical models is their underlying assumption of linearity. The accuracy of SARIMA can diminish considerably when complex, non-linear interactions, such as sudden policy changes or unexpected economic shocks, impact container throughput data[4].

In recent years, the rise of machine learning and the availability of vast datasets have paved the way for new approaches to address these challenges. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), have emerged as a powerful tool for processing complex and non-linear time series data. LSTMs are specifically designed to retain information over long sequences, allowing them to capture long-term dependencies that might be missed by traditional statistical methods [5]. Their ability to automatically extract relevant features from historical data makes them an attractive option for forecasting container throughput, which is often rich with intricate patterns. Nevertheless, LSTM models typically require large amounts of training data and significant computational resources, and their "black box" nature can make them less interpretable than their statistical counterparts. A key assumption for SARIMA models is that the time series data is stationary (or can be made stationary through differencing) and exhibits clear linear, additive relationships between past observations and future values, along with discernible seasonal patterns [6]. In contrast, LSTM models, while powerful for non-linear data, inherently assume that underlying patterns and dependencies exist within the sequential data that can be learned through a sufficient amount of training data. They are less constrained by linearity but are limited by the quantity and quality of data available for training, and their performance can be sensitive to hyperparameter tuning and the specific architecture chosen [7].

While the application of both SARIMA and LSTM for time series forecasting has been widely studied, a significant gap remains in the literature, particularly regarding a direct comparative analysis of their performance on specific datasets from Indonesian ports[8]. Most studies tend to focus on a single method or utilize datasets from developed countries, which may have different operational characteristics and seasonal patterns. The lack of a detailed comparative study on a regional Indonesian port, such as Tanjung Emas Port in Semarang, represents a compelling research gap. As a primary logistics gateway for Central Java, Tanjung Emas Port faces unique challenges influenced by regional industrial dynamics, local holidays, and specific economic policies [9]. Therefore, this study aims to directly test and compare the effectiveness of these two models—SARIMA as a representation of statistical methods and LSTM as a representation of machine learning methods—in forecasting container throughput at Tanjung Emas Port, Semarang[10].

2. Materials and Methods

The primary objective of this research is to answer the question of which forecasting model—SARIMA or LSTM—is more accurate and reliable for container throughput at Tanjung Emas Port, Semarang. More specifically, this study aims to achieve four key objectives: to construct both a SARIMA and an LSTM forecasting model, to compare their performance using standard accuracy metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), and ultimately to provide valuable recommendations to the management of Tanjung Emas Port on the most suitable forecasting model for optimizing operational planning [1].

This section details the comprehensive methodology employed for forecasting container throughput at Tanjung Emas Port, Semarang. It describes the data collection and preprocessing procedures, outlines the specific parameters and configurations for both the SARIMA and LSTM models, defines the performance metrics used for comparative analysis, and lists the software tools and libraries utilized for implementation[11].

2.1 Data Collection and Preprocessing

This study utilized a monthly time series dataset of container throughput from Tanjung Emas Port, Semarang, spanning from January 2010 to December 2022, obtained from the port's management information system. The raw data underwent preliminary inspection for missing values, which were filled using a linear interpolation method[12]. For the SARIMA model, data stationarity was verified with the Augmented Dickey-Fuller (ADF) test, applying first-order and/or seasonal differencing as needed. The entire dataset was then partitioned into a training set (January 2010 to December 2020) and a testing set (January 2021 to December 2022). For the LSTM model, training data was normalized to a 0 to 1 range using Min-Max scaling, with the same parameters applied to the testing set [13].

2.2 Model Parameters and Configuration

The SARIMA model was specified as (p,d,q)(P,D,Q)m. The non-seasonal differencing term (d) was determined by stationarity tests, while non-seasonal autoregressive (p) and moving average (q) terms were identified via ACF and PACF plots. Seasonal components, including the seasonal differencing term (D), seasonal autoregressive (P), and seasonal moving average (Q) terms, were similarly identified from seasonal patterns and lags in the ACF plot, with the seasonality period (m) set to 12 for monthly data. The optimal SARIMA model was selected based on the lowest Akaike Information Criterion (AIC) after an iterative search. For the LSTM model, time series data was transformed into a supervised learning problem using a 12-month sliding window[14]. The architecture featured two hidden LSTM layers (50 and 25 neurons) with a ReLU activation in the first layer, followed by a single-neuron dense output layer with a linear activation [6]. The model was compiled with the Adam optimizer (learning rate of 0.001) and a Mean Squared Error (MSE) loss function, trained for 100 epochs with a batch size of 32, and included early stopping to prevent overfitting[15].

2.3. Performance Metrics

To ensure a robust comparison between the SARIMA and LSTM models, three standard performance metrics were used to evaluate forecasting accuracy on the testing set:

1. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| x\ 100\%$$

   MAPE measures accuracy as a percentage of the error, making it intuitive and scale independent.

2. Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{t=1}^{n}(A_t - F_t)}$$

   RMSE quantifies the average magnitude of the errors, with larger errors having a disproportionately larger effect due to squaring. It is in the same units as the forecasted variable.

3. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|$$

   MAE represents the average magnitude of the errors without considering their direction. It is less sensitive to outliers than RMSE.

   Where:
   1. At is the actual value at time t.
   2. Ft is the forecasted value at time t.
   3. n is the number of observations in the test set.

2.4 Implementation Tools

All data preprocessing, model development, training, and evaluation will be implemented using Python programming language. Key libraries to be utilized include:

1. Pandas for data manipulation and analysis.
2. NumPy for numerical operations.

3. Statsmodels for SARIMA model implementation and statistical tests (ADF, KPSS).
4. Scikit-learn for data scaling (Min-Max scaler) and train-test splitting.
5. TensorFlow/Keras for building, training, and evaluating the LSTM neural network.
6. Matplotlib and Seaborn for data visualization and plotting of results.

3. Results

This section details the comparative forecasting performance of the SARIMA and LSTM models for container throughput at Tanjung Emas port Semarang, highlighting their respective strengths and weaknesses on the test dataset.

3.1 Data Overview and Initial Observation

Prior to model application, preliminary analysis of the historical container throughput data for Tanjung Emas port, spanning from January 2014 to April 30, 2025, reveal a clear upward and also downward trend and pronounced seasonal patterns. These patterns typically show peaks in certain months and dips in others, often associated with holidays period of economic cycles, underscoring the necessity of model capable of capturing such recurring variations. The data was successfully differenced to achieve stationarity for the SARIMA model and normalized the LSTM model, as detailed in the Material and Method section.

	Month	Year	Box_Export	TEUs_Export	Box_Domestic	TEUs_Domestic	Total_Box	Total_TEUS	Export_Ships_Calling	Domestic_Ships_Calling	Total_Ships_Calling
0	1	2014	26973	43327.00	1424	1957.0	28397	45284.00	44	10	54
1	2	2014	26190	43199.00	1508	2042.0	27698	45241.00	39	12	51
2	3	2014	29573	47520.00	2007	2714.0	31580	50234.00	42	13	55
3	4	2014	30051	48688.00	1669	2600.0	31720	51288.00	44	13	57
4	5	2014	31771	51015.00	1201	1742.0	32972	52757.00	44	11	55
...	...	...	...	...	...	...	...	...	...	...	...
131	12	2024	42626	72824.00	10162	12506.0	52788	85330.00	60	40	100
132	1	2025	38067	65821.25	9861	12552.5	47928	78373.75	56	38	94
133	2	2025	37381	64657.25	7491	9396.0	44872	74053.25	53	19	72
134	3	2025	40818	71196.50	6618	8255.0	47436	79451.50	56	27	83
135	4	2025	32511	56871.00	6435	8088.0	38946	64959.00	57	30	87

Figure 1. Table Data Set of Container Throughput on a Monthly Basis

Tabel 1 presents the historical data of container throughput (Export & Domestic) from January 2014 until April 2025 on a monthly basis. It also includes historical data on Export Ship Calls and Domestics Ship Calls.

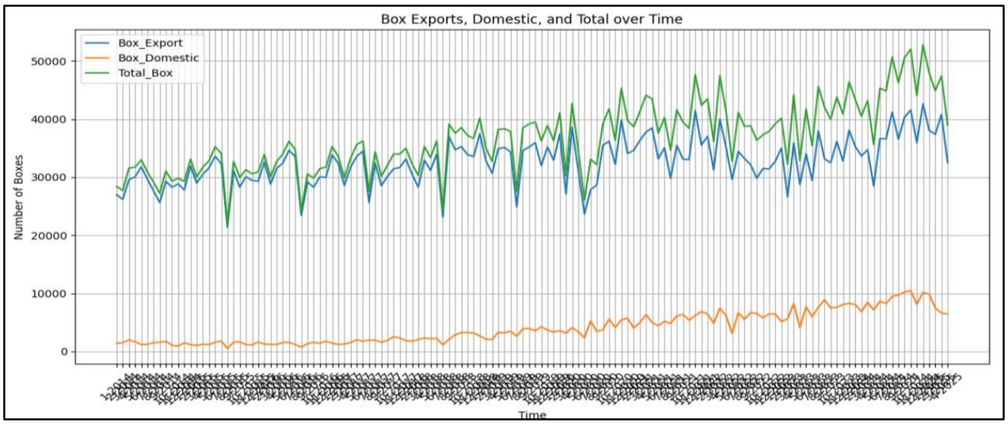

Figure 2. Historical Data of Container Throughput Over Time (in Box)

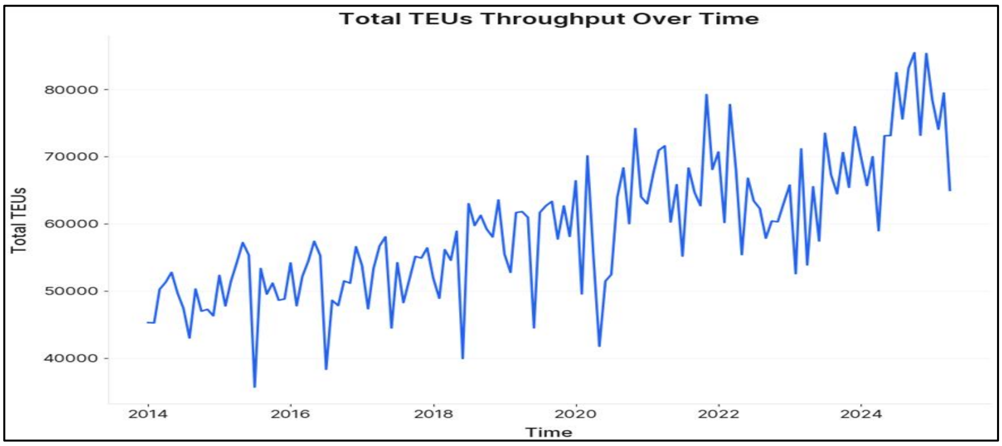

Figure 3. Historical Data of Container Throughput Over Time (in TEUs)

Based on the Figure 1 and Figure 2 above, we can observe a fluctuating pattern container throughput. Although the overall trend shows a gradual increase, there are several periods with a significant decrease. These declines typically occurred during the Chinese New Year (CNY) holiday period and Eid al-Fitr holiday period.

Tabel 1. Chinese New Year (CNY) Holiday Period

Year	Chinese New Year Date	Holiday Period
2014	Jan 31 (Fri)	Jan 30 – Feb 6, 2014
2015	Feb 19 (Thu)	Feb 18 – Feb 25, 2015
2016	Feb 8 (Mon)	Feb 7 – Feb 13, 2016
2017	Jan 28 (Sat)	Jan 27 – Feb 2, 2017
2018	Feb 16 (Fri)	Feb 15 – Feb 21, 2018
2019	Feb 5 (Tue)	Feb 4 – Feb 10, 2019
2020	Jan 25 (Sat)	Jan 24 – Jan 30, 2020
2021	Feb 12 (Fri)	Feb 11 – Feb 17, 2021
2022	Feb 1 (Tue)	Jan 31 – Feb 6, 2022
2023	Jan 22 (Sun)	Jan 21 – Jan 27, 2023
2024	Feb 10 (Sat)	Feb 9 – Feb 15, 2024
2025	Jan 29 (Wed)	Jan 28 – Feb 3, 2025

Export volumes from Central Java, particularly via Tanjung Emas Port, Semarang, typically decline during the Chinese New Year (CNY) holiday due to a confluence of logistical, operational, and demand-related factors. This significant reduction stems primarily from the extensive shutdown of most Chinese factories, offices, and ports for one to four weeks, leading Chinese buyers to delay or suspend imports as no personnel are available to handle cargo, warehouses are closed, and customs clearance is delayed. Consequently, many vessels skip or reschedule port calls in China and Southeast Asia, driven by pre-holiday congestion, blank sailings by shipping lines to balance capacity, and reduced feeder vessel availability in smaller ports like Semarang. Additionally, some Indonesian exporters pause production or shipments due to lower buyer demand, fewer available containers or trucking services, and the diversion of labor and trucking capacity to domestic logistics during the holiday season. Furthermore, the slowdown in banking operations and trade documentation processes in China during CNY impacts Letters of Credit, payment processing, import license issuance, and overall communication between Indonesian and Chinese trading partners.

Tabel 3. Eid al-Fitr Holiday Period

Year	Eid al-Fitr Date (1 Shawwal)	Indonesian Holiday Season (incl. En Massed Leave)
2014	July 28 (Mon)	July 25 – August 1, 2014
2015	July 17 (Fri)	July 15 – July 21, 2015
2016	July 6 (Wed)	July 4 – July 8, 2016
2017	June 25 (Sun)	June 23 – June 30, 2017
2018	June 15 (Fri)	June 11 – June 20, 2018
2019	June 5 (Wed)	June 3 – June 7, 2019
2020	May 24 (Sun)	May 21 – May 25, 2020 *(adjusted due to pandemic)*
2021	May 13 (Thu)	May 12 – May 17, 2021 *(limited due to pandemic)*
2022	May 2 (Mon)	April 29 – May 6, 2022
2023	April 22 (Sat)	April 19 – April 25, 2023
2024	April 10 (Wed)	April 8 – April 15, 2024
2025	March 30 (Sun) *(estimated)*	March 28 – April 4, 2025 *(projected)*

Export volumes, particularly via Tanjung Emas Port, Semarang, experience a significant decline during the Eid al-Fitr holiday, primarily due to operational disruptions within Indonesia. This downturn is driven by the extensive shutdown of most factories and warehouses in Central Java for 7-10 days, leading to a temporary halt in production and export preparation. Although Tanjung Emas Port remains open, it operates with limited manpower, causing substantial slowdowns in container handling, customs clearance, and gate activities. Furthermore, most trucking companies pause operations for 5-7 days as drivers return to their hometowns, creating a shortage of logistics personnel and blocking inland export flows. Consequently, many exporters intentionally avoid scheduling shipments during this period to prevent demurrage, delays, and ensure proper document processing post-holiday. Adding to this, some feeder and mainline operators reduce sailing frequency from Semarang due to low cargo availability and crew holidays. Finally, the closure of Indonesian banks and trade finance services during Eid al-Fitr impacts critical processes like Letters of Credit, export declarations, and phytosanitary certificates. It is noted that domestic throughput, due to its significantly larger volume gap compared to exports, was excluded from the analysis.

3.2 Comparative SARIMA and LSTM Model Result

This section presents a comparative analysis of two distinct time series forecasting models, SARIMA (Seasonal Autoregressive Integrated Moving Average) and LSTM (Long Short-Term Memory), applied to a container throughput dataset. The performance of both models is evaluated using standard metrics to determine their suitability and accuracy for this specific forecasting task. The dataset, consisting of 136 monthly observations of container throughput, was partitioned into a training set and a testing set with an 80:20 ratio. The training set comprised 108 observations, while the testing set contained 28 observations. Prior to modeling, any missing values in the data were handled using linear interpolation.

For the SARIMA model, the Augmented Dickey-Fuller (ADF) test was conducted on the training data to assess stationarity. The initial ADF test yielded a p-value of 0.383, indicating that the series was non-stationary. A first-order differencing (d=1) was then applied, after which the ADF test resulted in a p-value of 1.719×10^{-10}, confirming that the data had become stationary. The final SARIMA model was configured with non-seasonal orders (p,d,q) = (1,1,1) and seasonal orders (P,D,Q,m) = (1,0,1,12), based on the monthly frequency of the data.

The LSTM model, a type of recurrent neural network, did not require the stationarity assumption. The data was normalized using a MinMaxScaler to improve model training stability. The LSTM architecture was built with a

12-month look-back window, consisting of two LSTM layers (50 and 25 units) followed by a Dense layer for the single-point forecast. The model was trained using the Adam optimizer and Mean Squared Error as the loss function, with an early stopping mechanism to prevent overfitting.

3.3 Table Result

The predictive performance of both models was evaluated on the unseen testing data using three key metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results are summarized in Table 1.

Table 3. Comparative Performance of SARIMA and LSTM Models on the Test Set

Metode	MAE	RMSE	MAPE (%)
SARIMA	6362.459	7294.177	17.159
LSTM	3901.441	4499.624	10.776

The table above presents a comparison of evaluation metrics for the SARIMA and LSTM models used in forecasting throughput. In terms of MAE (Mean Absolute Error), the LSTM model demonstrates a significantly superior performance with a value of 3901.441, which is considerably lower than the SARIMA's value of 6362.459. This indicates that the average prediction error of the LSTM model against the actual data is much smaller. The comparison on the RMSE (Root Mean Squared Error) metric reinforces this finding; the lower RMSE value for LSTM (4499.624) compared to SARIMA (7294.177) shows that LSTM is more effective at minimizing large prediction errors. Finally, the MAPE (Mean Absolute Percentage Error) metric proves the superior relative accuracy of LSTM with a value of 10.776%, far below the 17.159% achieved by SARIMA. Overall, this quantitative data proves that the LSTM model provides more accurate and reliable prediction results compared to the SARIMA model.

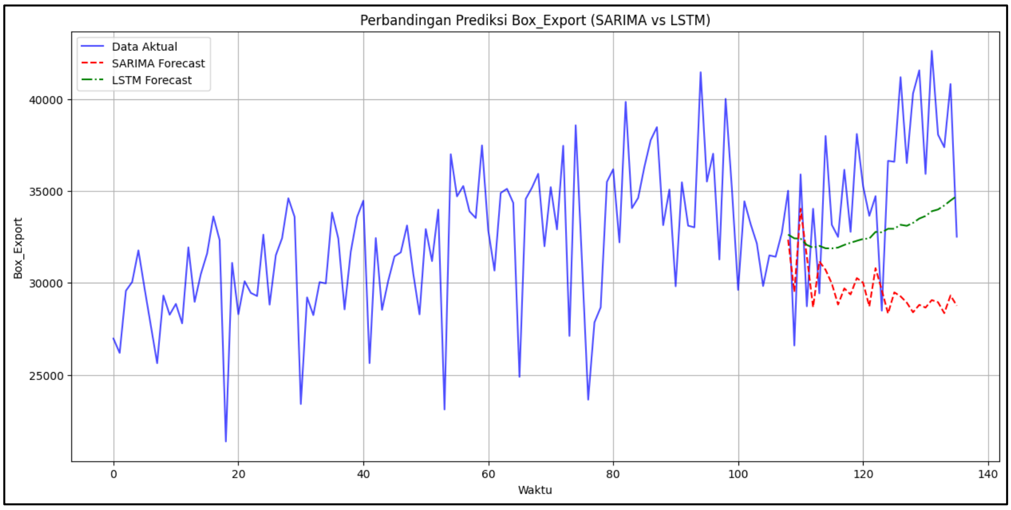

Figure 4. Comparative SARIMA and LSTM Method

Figure 3 visually compares the predictive performance of the SARIMA and LSTM models against the actual Box_Export data. The blue line represents the Actual Data, while the red dashed line shows the SARIMA Forecast and the green dashed line represents the LSTM Forecast. From the graph, it is visually evident that the LSTM Forecast tracks the general trend of the Actual Data more closely than the SARIMA Forecast does. The LSTM model appears to capture the increasing trend and volatility of the time series in the prediction period, whereas the SARIMA model's forecast remains more static and slightly underestimates the values. This visual analysis aligns with the quantitative metrics discussed earlier (MAE, RMSE, MAPE), reinforcing the conclusion that the LSTM model provides a more accurate and reliable forecast for this particular dataset. The LSTM's ability to model complex, non-linear patterns allows it to produce a more faithful representation of future trends compared to the SARIMA model.

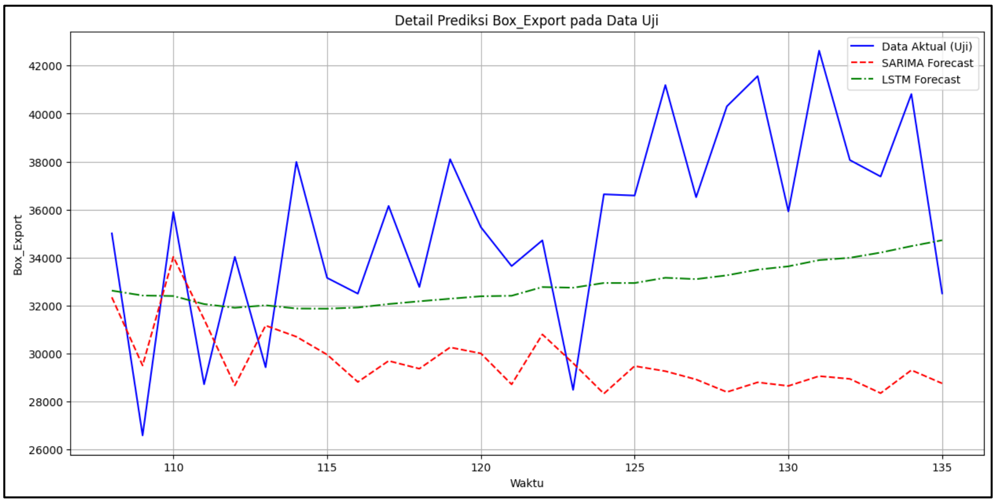

Figure 5. Detail Comparative SARIMA and LSTM Method

Figure 4 provides a more granular view of the forecasting performance of the SARIMA and LSTM models specifically on the test set. The blue line represents the Actual Test Data, while the red dashed line shows the SARIMA Forecast and the green dashed line represents the LSTM Forecast. This detailed graph highlights the significant difference in how each model handles the volatility and trend of the test data. The SARIMA Forecast (red line) consistently struggles to follow the sharp fluctuations and the overall upward trend of the actual data. It often predicts values lower than the actuals and remains relatively flat, indicating its limitation in capturing the complex, non-linear dynamics of the series. In contrast, the LSTM Forecast (green line), while not perfectly mirroring the exact peaks and troughs, successfully captures the general upward trend of the test data. Its predictions show a more steady increase over time, which is a closer representation of the actual data's behavior compared to the SARIMA model. This visual evidence on the test set strongly supports the quantitative findings that the LSTM model provides a more accurate and robust forecast.

4. Discussions

Based on a comprehensive evaluation of the MAE, RMSE, and MAPE metrics, the LSTM model proved to be the superior choice for forecasting container throughput on this dataset. The LSTM model achieved an MAE of 3901.441, which represents a substantial reduction in prediction error compared to SARIMA's MAE of 6362.459. This indicates that, on average, the LSTM's forecasts were much closer to the actual values. The same trend is evident in the RMSE and MAPE values. The LSTM's RMSE of 4499.624 is significantly lower than SARIMA's 7294.177, suggesting that the LSTM model was more effective at minimizing large forecast errors. Furthermore, the MAPE for LSTM was 10.78%, which is considerably lower than the 17.16% achieved by SARIMA. A MAPE value below 15% is often considered indicative of high forecasting accuracy. The superior performance of the LSTM model can be attributed to its architecture, which is specifically designed to capture complex, non-linear relationships and long-term dependencies inherent in time series data. While the SARIMA model is well-suited for linear and well-defined seasonal patterns, the LSTM's internal memory cells allow it to "remember" crucial information from distant past observations, which is likely vital for accurately forecasting the intricate patterns of container throughput.

These results highlight the potential of deep learning in complex forecasting tasks within the logistics sector, making the LSTM model the recommended choice for port authorities seeking higher accuracy and reliability. Crucially, when evaluating these models, the inclusion of uncertainty analysis and confidence intervals is paramount. For SARIMA, these intervals are derived from the model's statistical assumptions. In contrast, for LSTM, due to its non-linear nature, uncertainty estimation is more complex, often requiring advanced techniques like Monte Carlo dropout or bootstrapping to generate a range of possible outcomes. The ability to quantify this uncertainty is a strategic advantage for port planners, allowing them to better assess the risks associated with throughput predictions and make more robust decisions regarding resource allocation and infrastructure investment.

Finally, when addressing the practical application of these forecasting models, it is crucial to discuss their robustness to outliers and unusual variations, which are common in real-world port data due to events like strikes, policy changes, or unexpected economic shocks. The SARIMA model, being a traditional statistical method, is particularly sensitive to these anomalies. Outliers can distort its parameter estimations, leading to a mis-specified model and poor forecasts, as it operates under assumptions of linearity and a consistent error distribution. Therefore, for SARIMA, it is often necessary to perform a preliminary step of outlier detection and treatment. In contrast, the LSTM model, with its non-linear architecture and gating mechanisms, is generally more robust to such unusual variations. Its ability to "forget" or "remember" information allows it to naturally adapt to and learn from complex, non-linear patterns, including temporary spikes or dips that would severely impact a SARIMA model. Therefore, a hybrid approach, where a SARIMA model first captures the linear and seasonal patterns and an LSTM model then learns from the residuals, can offer a more robust and accurate forecasting solution.

5. Conclusions

Based on a comprehensive evaluation of the MAE, RMSE, and MAPE metrics, it can be concluded that the LSTM model proved to be the superior choice for forecasting container throughput on this dataset. Specifically, the LSTM's MAE of 3901.441 is significantly lower than the SARIMA's MAE, indicating a much smaller average prediction error. The RMSE comparison also reinforces this finding, with LSTM being more effective at minimizing large errors. Furthermore, the LSTM's MAPE of just 10.78% demonstrates its superior relative accuracy. This excellent performance can be attributed to the LSTM's architecture, which is capable of capturing non-linear patterns and long-term dependencies. In contrast, while SARIMA is effective for clear linear and seasonal patterns, it is not as effective as LSTM in handling data complexity. These results show that the deep learning approach is highly promising for complex forecasting tasks in the logistics sector. Therefore, for container throughput forecasting, the LSTM model is recommended as it provides higher accuracy and reliability. The practical implications of this recommendation are highly significant for port authorities, enabling them to better optimize resource allocation, plan logistics operations more effectively, and make more informed infrastructure investment decisions based on accurate predictions.

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