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COMPARING FORECASTS OF AGRICULTURAL SECTOR EXPORT VALUES USING SARIMA AND LONG SHORT-TERM MEMORY MODELS

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ABSTRACT

Indonesia's agricultural sector plays a crucial role in the national economy, with significant export potential and supporting the livelihoods of the majority of the population. As part of the government's vision to make Indonesia the world's food barn by 2045, increasing the volume and value of agricultural product exports is a primary focus, making export value forecasting essential for supporting strategic decision-making. Sequential data analysis is an important approach in analyzing data collected over a specific period. This study aims to compare two popular methods in forecasting the export value of the agricultural sector, namely the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model and the Long Short-Term Memory (LSTM) model. Monthly agricultural export data from West Java Province from January 2013 to February 2024 were used as the dataset. The best SARIMA model generated was (1,1,1)(0,1,1)12, while the optimal parameters for the LSTM model were neuron: 50, dropout rate: 0.3, number of layers: 2, activation function: relu, epochs: 500, batch size: 64, optimizer: Adam, and learning rate: 0.01. Evaluation was performed using the Root Mean Squared Error (RMSE) method to measure the accuracy of both models in forecasting the export value of the agricultural sector. The results showed that the LSTM model outperformed the SARIMA model, with a lower RMSE value (SARIMA: 4182.133 and LSTM: 1939.02). This research provides valuable insights for decision-makers in planning agricultural sector export strategies in the future. With this comparison, it is expected to provide better guidance in selecting forecasting methods suitable for the characteristics of the data.

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1. INTRODUCTION

Indonesia is known as an agrarian country, where a significant portion of the population earns their livelihood and generates a substantial part of the Gross Domestic Product (GDP) from the agricultural sector. This gives Indonesia considerable export potential, which can boost the nation's economy. Exports and imports play a crucial role in Indonesia's economic growth. In addition to the mining and industrial sectors, agriculture is also a significant export sector. The importance of agriculture in Indonesia's economy cannot be overlooked, as the majority of Indonesians depend on this sector for their livelihoods. The agricultural sector is key in overcoming economic crises, as it can provide significant recovery. The reliability and substantial potential of the agricultural sector make it one of the main drivers of national economic recovery [1]. To realize the vision of Indonesia as the world's food barn by 2045, the government is actively encouraging the increase of export volumes and values of agricultural products.

Forecasting export values in the agricultural sector becomes important to support efficient decision-making in planning long-term strategies and managing supply chains optimally. Sequential data analysis is a statistical technique employed to examine data gathered over a designated timeframe. Its aim is to detect patterns and trends within the dataset, which can subsequently be utilized to predict future occurrences or to comprehend the fundamental processes influencing the data [2]. In sequential data analysis, these patterns are divided into three types: trend, cyclical, and seasonal patterns. The seasonal pattern is marked by repetitive variations in data over a defined period. With the development of sequential data modeling and its applications, sequential data models are increasingly used for modeling and forecasting. Forecasting is a technique used to project future values based on historical data. The selection of a forecasting method is tailored to the type of analysis required. One commonly used method is Autoregressive Integrated Moving Average (ARIMA) [3].

ARIMA is a model that explains sequential data based on observations and can forecast future values. The application of ARIMA to various time series shows patterns free from random white noise and without seasonal patterns. This model was first introduced by Box and Jenkins in 1970. When generating short-term forecasts, ARIMA has shown greater efficiency than complex structural models. In ARIMA, future value predictions are derived from a linear combination of past values and errors [4].

Seasonal Autoregressive Integrated Moving Average (SARIMA) extends the ARIMA model by incorporating seasonal patterns in the data. This model is well-suited for sequential data that exhibit seasonal patterns, such as agricultural export data that may be influenced by seasonal factors like planting and harvesting seasons. SARIMA uses parameters such as autoregressive (AR), differencing (I), and moving average (MA) to model and forecast sequential data. SARIMA leverages past and present information on the variable to provide accurate short-term estimates. To effectively implement this model, it is necessary for the sequential data to be stable in both its mean and variance [5]. On the other hand, Long Short-Term Memory (LSTM) is a variety of recurrent neural network that is highly effective for sequential data analysis. It is capable of capturing complex patterns and forecasting future outcomes. LSTM is an evolution of Recurrent Neural Networks (RNNs), designed to address long-term dependency issues and the vanishing gradient problem with additional mechanisms [6][7].

Forecasting export volumes has already been conducted by several researchers, such as the study conducted in [8]. This research utilizes data on Indonesia's oil and gas export and import volumes, sourced from the Central Bureau of Statistics of Indonesia, spanning the years 1996 to 2016, using the Artificial Neural Network (ANN) method. According to the findings of the research, it is deduced that the model architecture of 12-5-1 demonstrates a prediction accuracy of 83%.In addition, research on forecasting in the agricultural export sector has also been conducted in [9]. This study uses monthly data on the export value of Indonesian coffee from January 2005 to April 2020. The forecasting uses the ARIMA method. Based on the research results, the ARIMA(1,3,1) model is used to predict the movement of Indonesia's coffee export value.

The study conducted in [10] used data on sunflower prices (January 2014 – December 2018) and soybean prices (January 2011 – December 2016), utilizing both ARIMA and ANN methods. Based on the results obtained by comparing the ANN and ARIMA models using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Percentage Error (RMSPE) to measure model accuracy, the findings indicate that ANN is better at predicting agricultural commodity prices.

Comparisons between SARIMA and LSTM have been conducted several times, including research conducted in[11] using point of sale data from four perishable products sold in over 90 stores in selected regions of leading retailers in Austria over a three-year period from January 2017 to December 2019. Based on the results, it was found that SARIMA and LSTM have similar accuracies for salad and tomato products, but SARIMA performs better for cucumbers, while LSTM is better for potatoes. LSTM is suitable for stable data without many external factors, while SARIMA is better for seasonal patterns.

A separate investigation was conducted in [12] utilizing sales data sourced from the download section of the excel.com website. The dataset comprised approximately 1 million sales records, spanning a timeframe of 46 years (1972–2017). Based on the results presented, LSTM showed the best performance with an accuracy of around 97.01%, surpassing ARIMA (93.84%) and SARIMA (94.378%). However, this is balanced with higher execution time and computational costs. SARIMA could be a more efficient alternative for large but not overly complex datasets with seasonality.

Most studies related to agricultural export forecasting in Indonesia are still limited to traditional forecasting methods such as ARIMA or ANN, and there has been little comparison of the performance of modern deep learning methods like LSTM with traditional statistical methods in the context of seasonal agricultural export data. Additionally, while some studies have addressed the forecasting of export volumes for specific agricultural products like coffee, there is a scarcity of research examining aggregate export data from a single province, which could provide broader insights into the export conditions in that region. This study aims to fill this gap by utilizing monthly agricultural export data from West Java Province from 2013 to 2024 and comparing the performance of the SARIMA and LSTM models, thereby offering new and relevant contributions in the context of agricultural export forecasting in Indonesia, as well as evaluating the performance of both models in generating future export value forecasts.

2. RESEARCH METHODS

2.1 Data Set

The data utilized in this study consists of monthly agricultural export values from the West Java province for the period January 2013 to February 2024, measured in Thousand USD, totaling 134 data points. These data were be divided into a training set comprising 120 data points and a test set comprising 14 data points. The data was collected from the Central Bureau of Statistics (BPS) of West Java Province.

2.2 ARIMA Model

The ARIMA model, also known as the Box-Jenkins model, is a widely used method in sequential data analysis [13]. The ARIMA model, an extension of the Auto Regressive Moving Average (ARMA) model, is capable of handling non-stationary sequential data. Unlike ARMA, which assumes stationarity, ARIMA requires transforming the data to remove seasonality and trends before making predictions. This involves isolating the signal from noise to generate predictions for the subsequent time period. The ARIMA model is relatively accurate for short-term forecasts, but it tends to be less effective for long-term forecasts, as the predictions often become flat [14]. The general form of the ARIMA model (p,d,q) can be expressed as follows:

$$\boldsymbol{\phi_p(B)(1-B)^d X_t = \theta_0 + \theta_q(B)e_t} \tag{1}$$

With:

$\phi_p(B)$	: Autoregressive (AR) polynomial indicating the dependence of X_t on previous values
$(1-B)^d$	: Differencing operator used to make the data stationary
θ_0	: Constant in the model
$\theta_q(B)$	: Moving average (MA) polynomial indicating the dependence of X_t on past random errors.
e_t	: Random error or noise at time t

2.3 Seasonal-ARIMA Model

The Seasonal-ARIMA model is an ARIMA model that exhibits seasonal patterns in its data [15]. SARIMA is typically denoted as ARIMA$(\mathbf{p},\mathbf{d},\mathbf{q})(\mathbf{P},\mathbf{D},\mathbf{Q})^{\boldsymbol{s}}$, where (p,d,q) represents the non-seasonal order of the model, and (P,D,Q) represents the seasonal order. In this notation, P represents the order of the seasonal autoregressive (AR) component, D signifies the number of seasonal differences, Q indicates the order of the seasonal moving average (MA) component, and s denotes the number of periods in a season[16]. The general form of the SARIMA model (p,d,q) can be formulated as follows:

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D X_t = \theta_q(B)\Theta_Q(B^S)e_t \tag{2}$$

With :

$\phi_p(B)$: This represents the non-seasonal autoregressive (AR) polynomial of order p
$\Phi_P(B^S)$: The seasonal autoregressive (AR) polynomial of order P with a seasonal lag S
$(1-B)^d$: This is the non-seasonal differencing operator of order d
$(1-B^S)^D$: This is the seasonal differencing operator of order D with a seasonal lag S
$\theta_q(B)$: This represents the non-seasonal moving average (MA) polynomial of order q
$\Theta_Q(B^S)$: The seasonal moving average (MA) polynomial of order Q with a seasonal lag S
e_t : Random error or noise at time *t*

2.4 Kwiatkowski Phillips Schmidt Shin (KPSS) Test

Forecasting using the Box-Jenkins method requires the assumption of stationary data. Therefore, testing on the data is necessary. One of the tests that can be performed is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test. The hypothesis of the KPSS test is as follows:

H_0: The Data is Stationary
H_1: The Data is non-Stationary

2.5 Long Short-Term Memory (LSTM)

LSTM, short for Long Short-Term Memory, is a type of RNN that can remember previous values for future use, while RNNs have a weakness in maintaining long-term information due to activations resulting in information loss over time. This makes RNNs less effective in capturing long sequences [17]. RNNs face issues with very long data sequences, where the gradient values for updating new weights can become zero, commonly referred to as the vanishing gradient problem. LSTM was developed to address the shortcomings of RNNs. The LSTM architecture consists of a cell and three gates: input, output, and forget, which can overcome the problem of vanishing gradients [18].

Long Short Term Memory has proven to be a highly effective solution for tackling the issue of long-term dependencies in RNN models, with nearly all major advancements in research being attributed to LSTM [19].

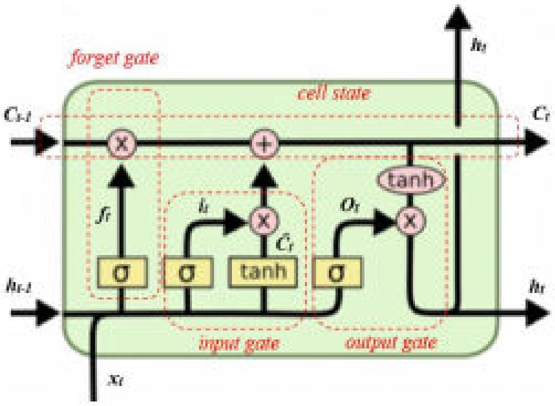


Figure 1. LSTM Architecture

Based on Figure 1, LSTM has several stages in the learning process. The stages of LSTM learning are as follows:

1. Calculating the LSTM output using Equation (3)-Equation (7) (forward learning process). These equations can be explained as follows.

$$a(t_i) = \sigma(w_a x(t_i) + w_{ha} h(t_{i-1}) + b_a) \tag{3}$$
$$f(t_i) = \sigma(w_f x(t_i) + w_{hf} h(t_{i-1}) + b_f) \tag{4}$$
$$c(t_i) = f_t \times c(t_{i-1}) + a_t \times \tanh(w_c x(t_i) + w_{hc} h(t_{i-1}) + b_c \tag{5}$$

$$o(t_i) = \sigma(w_o x(t_i) + w_{ho} h(t_{i-1}) + b_o) \quad (6)$$
$$h(t_i) = o(t_i) \times \tanh(c(t_i)) \quad (7)$$

with:

$x(t_i)$: input data
$a(t_i)$: output of the input
σ and $tanh$: activation functions
$f(t_i)$: output of the forget gate
$c(t_{i-1})$ and $c(t_i)$: cell state at time t-1 and t
$o(t_i)$: output data of the output gate
$h(t_{i-1})$ and $h(t_i)$: output data at time t-1 and t
w_a, w_o, w_f, w_c : weight matrices for the input gate, output gate, forget gate, and cell state
$w_{ha}, w_{ho}, w_{hf}, w_{hc}$: recurrent weights

2. Calculating the discrepancy between the generated data and the input data from each layer.
3. Backpropagating this error into the input gate, cell, and forget gate.
4. Using an optimization algorithm to adjust the weights of each gate based on the error terms.
5. Repeating steps 1-4 iteratively for multiple iterations until the biases and weights reach their optimal values [20].

2.6 Model Evaluation

The importance of the model's appropriateness for forecasting underscores the need for evaluation. One method for evaluating forecasting models is by using Root Mean Squared Error (RMSE). The formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - Y_t')^2} \quad (8)$$

With :

n : the total number of observations or data points in the dataset
Y_t : the actual value of the dependent variable at time t or the observed data point
Y_t' : the predicted value of the dependent variable at time t from the model or forecasted data point.

2.7 Research Method

Figure 2 describes the stages of research to compare two time series forecasting models, SARIMA and LSTM. This research includes data collection and processing, the development of SARIMA and LSTM models, and model evaluation based on RMSE to determine the best model. Finally, the model with the highest accuracy is selected to make predictions on future data.

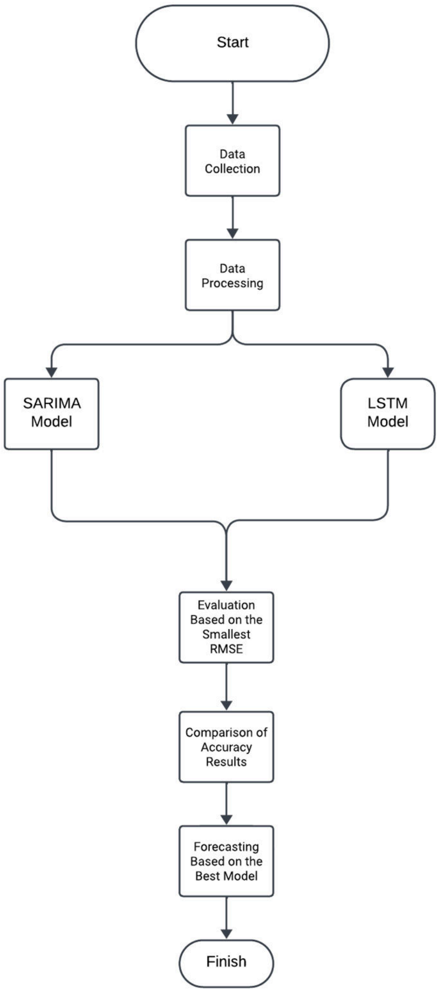


Figure 2. Flowchart of Research Methodology

3. RESULTS AND DISCUSSION

Based on the original data of agricultural sector export values available on the West Java BPS website, it can be observed that the data pattern is non-stationary in nature and exhibits a trend. The highest spike occurs in September 2022 (data point 117), reaching a value of over 27,600. It appears as shown in **Figure 3** below.

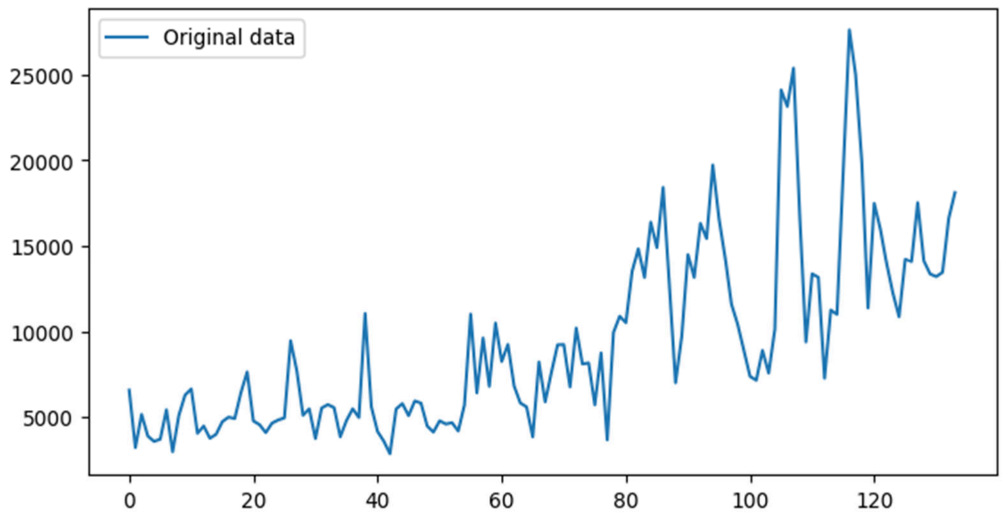


Figure 3. Visualization of Agricultural Sector Export Value Data from January 2013 to February 2024

3.1 SARIMA Model

The seasonality of the SARIMA model can be identified from the decomposition of data containing seasonality, as shown in Figure 4:

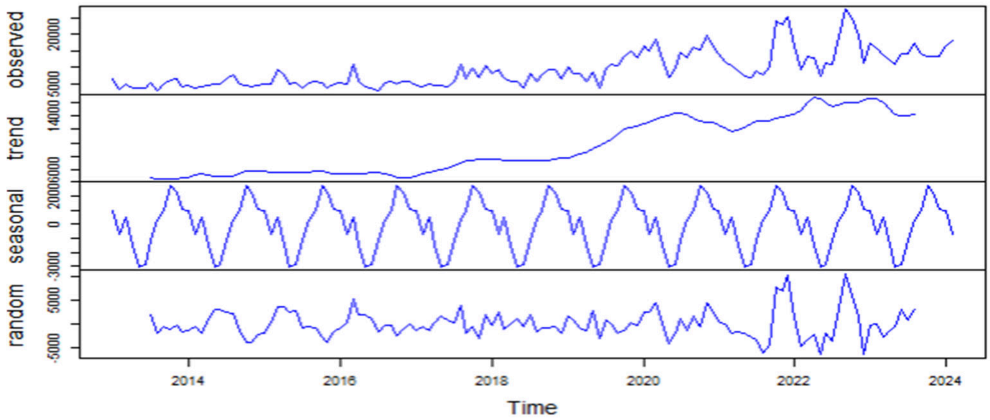
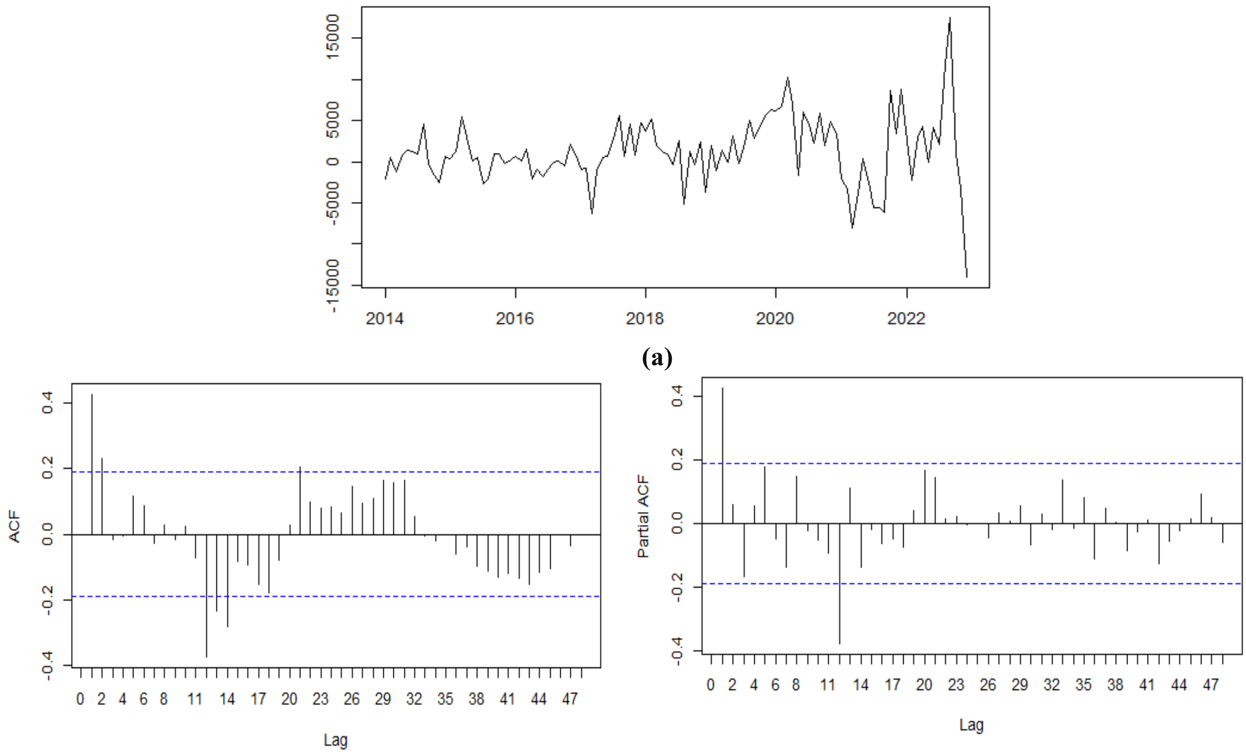


Figure 4. Decomposition Plot

Model SARIMA is a sequential data modeling where the dataset must be stationary both in terms of mean and variance. To assess the stationarity of the data in terms of mean, the KPSS test can be used. After conducting the KPSS test on the data, a p-value of 0.01 is obtained, indicating that the data is non-stationary. Next, differencing was performed to make the data stationary in terms of mean.



(a)

(b) **(c)**

Figure 5. (a) Data Plot After Differencing, (b) ACF Plot After Differencing, (c) PACF Plot After Differencing

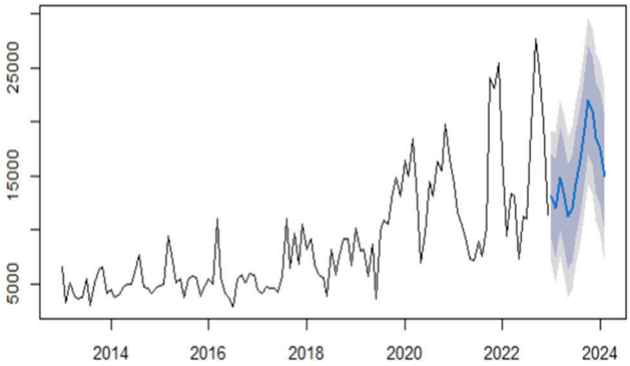
SARIMA model generally notated as SARIMA (p,d,q)(P,D,Q)s, where (p,d,q) is non seasonal order, p is AR component, d is differencing and q is MA component. While (P,D,Q) is seasonal component. Based on Figure 5, initial model can be obtained is (1,1,1) (1,1,1)12. Then we can modified initial model into some models and conduct assumption test and we got two models that are SARIMA (1,1,1)(0,1,1)12 and SARIMA(0,1,1)(0,1,1)12.

Assumption test we used for residual checking such as autocorrelation test (mostly known as white noise check). White noise check mostly used Ljung-box test, p-value for SARIMA (1,1,1)(0,1,1)12 model is 0.896 > 0.05 (α), so with 95% confidence there is no autocorrelation of residuals. While p-value for SARIMA (0,1,1)(0,1,1)12 model is 0.8018 > 0.05 (α), so with 95% confidence there is no autocorrelation of residuals After analyzing some models, two models are obtained, as shown in **Table 1**.

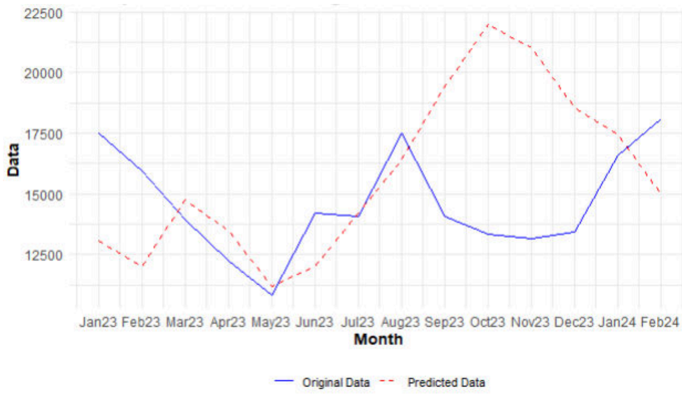
Table 1. The Best SARIMA Model

(p,d,q)(P,D,Q)s	RMSE
(1,1,1)(0,1,1)12	4182.133
(0,1,1)(0,1,1)12	5457.370

Based on the RMSE value, the model with the smallest RMSE is ARIMA (1,1,1)(0,1,1)12. **Figure 6** shows the SARIMA forecasting plot based on the best model.



(a)



(b)

Figure 6. (a) Visualization of SARIMA(1,1,1)(0,1,1)[12] Model, (b) Comparison between Original Data and Predicted Test Data

The values from the visualization above, when converted into numerical form, appeared as shown in **Table 2**.

Table 2. Comparison between Original Data and Forecasted Data

Month and Year	Export Values	Forecasting Export Values
January 2023	17482.24	13063.42
February 2023	15957	12036.99
March 2023	13946.83	14781.19
April 2023	12226.46	13468.20
May 2023	10841.69	11203.82
June 2023	14216.69	12040.52
July 2023	14057.64	14199.34
August 2023	17523.01	16409.96
September 2023	14092.39	19421.14
October 2023	13331.53	21990.90
November 2023	13182.98	21021.29
December 2023	13429.1	18556.44
January 2024	16610.99	17479.92
February 2024	18114.12	14992.81

3.2 LSTM Model

In forecasting using the LSTM model, it is necessary to divide the data into training data and test data. Thus, the forecasting process using this LSTM model can be performed using these separated training and test data. There are several parameters related to this LSTM model, such as the number of neurons, dropout rate, number of layers, activation function, epochs, batch size, optimizer, and learning rate. The initialization of LSTM parameters constructed can be seen as shown in **Table 3**.

Table 3. LSTM Model Parameters

Parameters	Values
Neuron	50, 100,150,200

Dropout Rate	0.3
number of Layers	1 dan 2
Activation Function	Relu
Epochs	100, 300, 500
Batch Size	64 dan 128
Optimizer	Adam dan RMSprop
Learning Rate	0.1, 0.01, 0.001

Based on the combination of parameters above, the smallest RMSE value for the test data is 1939.02 with the following parameters: neurons: 50, dropout rate: 0.3, number of layers: 2, activation function: relu, epochs: 500, batch size: 64, optimizer: Adam, and learning rate: 0.01. Figure 7 is a visualization of the overall prediction of the data using the best LSTM model compared to the original data. The blue line represents the actual data, while the orange line represents the overall prediction using the best model. This figure shows that the LSTM model effectively captures the general trend and seasonal patterns of the export data. Although some discrepancies appear, especially during sudden spikes or drops, the forecast line closely follows the actual data in most areas. This indicates that the model is reasonably accurate in predicting the data, with some room for improvement in capturing extreme fluctuations.

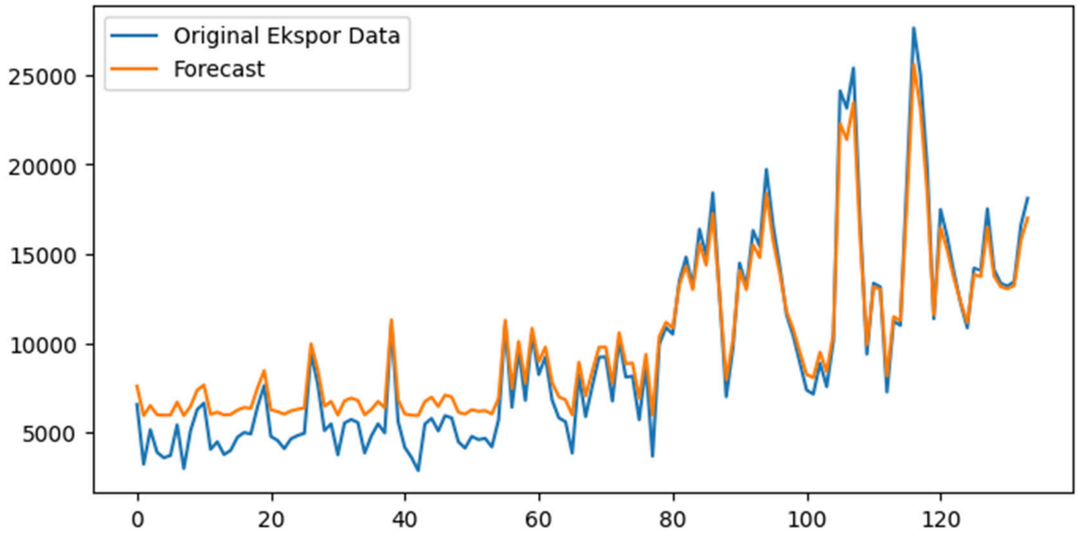


Figure 7. Visualization of LSTM Model

3.3 Forecasting

From the two models that have been conducted, namely SARIMA and LSTM, based on the smallest RMSE value, LSTM is the best model for forecasting. Next, a forecast for the next 12 months is performed, and the forecasted data using the best LSTM model is obtained as shown in Table 4.

Table 4. 12-Month Forecast of Export Values Using LSTM Model

Month and Year	Forecasting Export Values
March 2024	17008.19
April 2024	16088.97
May 2024	15336.66
June 2024	14728.77
July 2024	14242.64
August 2024	13857.10
September 2024	13553.35
October 2024	13315.29
November 2024	13129.48
Desember 2024	12984.91
January 2025	12872.71
February 2025	12785.80

The data above was visualized in Figure 8, represented by a dashed green line:

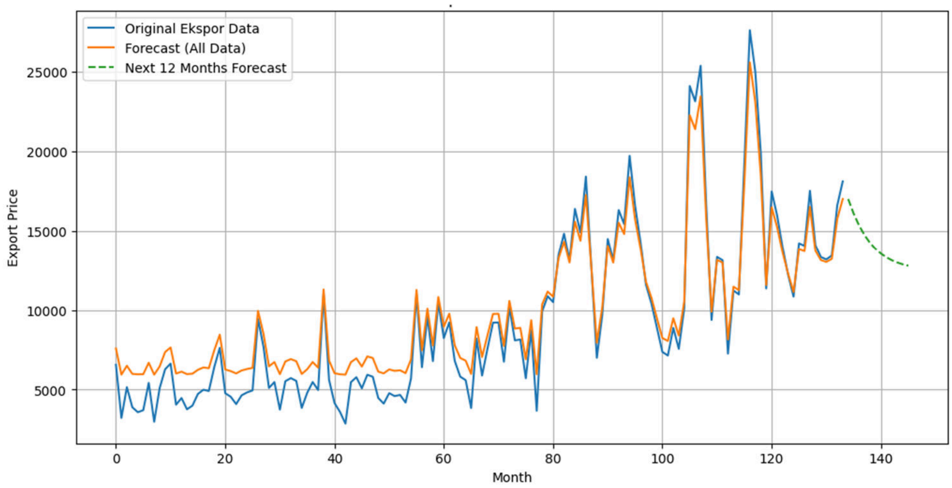


Figure 8. Visualization of the Forecasted Data for the Next 12 Months

This graph shows the export price forecast for the upcoming months, with the blue line representing the actual export price data and the orange line representing the prediction using all available data. It is evident from the graph that the forecasting model is quite accurate in capturing price fluctuation patterns, especially during periods with significant changes, demonstrating its ability to predict past trends.

The strength of this study lies in the model's ability to capture export price fluctuations well, especially during periods of significant changes, making it suitable for short-term analysis with a high confidence level. The graph visualization also helps provide a clear comparison between the actual data, predictions, and future projections.

However, a limitation of this study appears at the end of the graph, where the dotted green line shows a 12-month projection with a predicted decline in export prices. Long-term forecasts like this are highly uncertain due to external factors, such as economic policy changes or global market conditions, which are not accounted for in the model. Therefore, these results should be interpreted cautiously, and additional analysis is necessary to consider other factors that may influence prices in the future.

4. CONCLUSIONS

Based on the analysis conducted on the agricultural sector export data from the West Java BPS, it is concluded that the data pattern shows a significant trend and is non-stationary in nature. The LSTM model outperforms the SARIMA model in forecasting the agricultural sector export values. Although both models are capable of handling trends and seasonal patterns in the data, LSTM yields a lower RMSE value, indicating a smaller forecasting error. Further recommendation includes parameter optimization in the LSTM model to enhance forecasting accuracy. Additionally, research could explore hybrid approaches that combine the strengths of LSTM and SARIMA models to produce a stronger forecasting model. Parameter optimization and the use of hybrid methods are expected to improve the performance and relevance of the forecasting model in the context of agricultural sector exports.

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