



Forecasting Patchouli (*Pogostemon Cablin Benth*) Production in North Kolaka Using ARIMA, LSTM and Hybrid ARIMA-LSTM

¹ Sri Muslihah Bakhtiar



Actuarial Science Study Program, Universitas Muhammadiyah Kolaka Utara

² Nurhikmah Fajar



Computer Engineering Study Program, Universitas Muhammadiyah Kolaka Utara

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ABSTRACT

Patchouli (*Pogostemon cablin* Benth.) is one of Indonesia's most economically valuable essential oil commodities. This study forecasts patchouli production using ARIMA, LSTM, and a hybrid ARIMA-LSTM model, emphasizing the novelty of applying machine learning techniques to essential oil production forecasting, an understudied area. Weekly production data from ARS Atsiri North Kolaka (January 2022-July 2025, 187 records) were analyzed. ARIMA was applied to capture linear patterns, LSTM to model nonlinear dynamics, and the hybrid model to combine both characteristics. Model performance was evaluated using MSE, RMSE, and MAPE. The ARIMA (2,1,1) model performed best among the linear approaches, while LSTM with normalization, windowing, and 50 hidden units achieved the highest overall accuracy (MSE = 251.22, RMSE = 321.67, MAPE = 0.238%). The hybrid model did not outperform LSTM, likely due to the limited dataset and the dominance of nonlinear patterns, thus confirming LSTM as the most effective model.

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Corresponding Author:

Sri Muslihah Bakhtiar,
Actuarial Science Study Program,
Universitas Muhammadiyah Kolaka Utara
Email: srinuslihahb17@gmail.com

1. INTRODUCTION

Patchouli (*Pogostemon cablin* Benth) is a superior essential oil producing plant in Indonesia which has a high economic value [1]. In international market, patchouli oil has long become a reliable export commodity which gave a significant foreign exchange for the country [2]. The significance of patchouli oil lies not only in its economic value but also in its diverse applications. It is widely used as a raw material in the perfume, cosmetic, pharmaceutical, and aromatherapy industries. In the perfume industry, patchouli oil functions as a fixative that prolongs fragrance and enhances product quality [3]. In healthcare field, patchouli oil is known to have healing potential for wounds, inflammation, and antibacterial agent [4]. Besides that, patchouli oil is also used in effective insecticides production, adding the dimension of its application in agriculture sector [5]. However, one of the challenges faced currently is the uncertainty in patchouli production, which could be due to various factors like weather, pests, plants' disease, and a non-optimal cultivation management [6]. Such fluctuations pose serious challenges: they complicate production planning, reduce farmers' income, disrupt supply chain stability, and

weaken Indonesia's competitiveness in the global essential oil market. Therefore, accurate forecasting methods are urgently needed to ensure production stability and support the sustainable development of the patchouli industry[7].

Various forecasting methods have been applied in agriculture [8][9], ranging from classical statistical models such as regression to advanced machine learning techniques like Support Vector Machines and Decision Trees[10]. However, ARIMA and LSTM are considered particularly relevant for time series forecasting. Previous studies have widely applied these models to crops such as rice, maize, and tea[11], demonstrating their effectiveness in capturing both linear and nonlinear dynamics. Despite these advances, research on essential oil commodities, particularly patchouli, remains very limited, especially in the context of hybrid approaches[12]. This comparative gap highlights the novelty of the present study, which applies and evaluates ARIMA, LSTM, and a hybrid ARIMA-LSTM model for patchouli production forecasting.

Forecasting is a process to estimate future values based on past data [13]. Forecasting model will be more beneficial if it is able to give a more accurate forecast, since the result can be used as the basis for decision-making. One of the popular statistical models is ARIMA (Autoregressive Integrated Moving Average) [14], which is effective to handle linear data pattern within a time series. However, ARIMA has some limitations in detecting complex nonlinear pattern [15]. To handle the limitation, other machine learning model such as Long Short-Term Memory (LSTM) [16] is used, which is a type of artificial neural network specifically designed to handle time series data. LSTM is very good to capture nonlinear pattern and the long term connection within data[17]. However, LSTM also has a weakness to model linear data efficiently [12]. Therefore, ARIMA-LSTM hybrid method became a good alternative solution, since it could combine the strength of both, ARIMA for linear pattern and LSTM for nonlinear pattern.

The ARIMA-LSTM hybrid approach has been widely applied in various forecasting studies, including rice yield prediction [18], sugarcane production and energy demand forecasting[19]. These studies demonstrate the effectiveness of the hybrid model in capturing both linear and nonlinear dynamics in complex time series data. However, despite patchouli's high economic value and its role as a key essential oil commodity, research applying the ARIMA-LSTM hybrid model to patchouli production forecasting remains very limited, particularly in Indonesia.

This study therefore aims to evaluate and compare the forecasting performance of ARIMA, LSTM, and a hybrid ARIMA-LSTM model for patchouli production forecasting, and to determine the most accurate approach among them. The findings are expected to provide practical benefits for farmers, local governments, and business owners in improving production planning, seedling distribution, harvest scheduling, and export strategies. In addition, this study contributes to the academic literature by integrating actuarial, agricultural, and data science perspectives in the context of essential oil production forecasting

The main issue in patchouli production management lies in the uncertainty and fluctuations caused by climate variability, pests, diseases, and cultivation practices [20]. These challenges directly affect cultivation planning, farm management, and market value, creating instability for both farmers and industry stakeholders. Although various forecasting models have been applied, their performance often suffers from high error rates and limited accuracy in capturing both linear and nonlinear patterns of production data. The main research problem addressed in this study is how to develop a forecasting model capable of reducing prediction errors by integrating ARIMA and LSTM approaches, thereby improving forecasting accuracy. This improvement is expected to provide a reliable basis for short-, medium-, and long-term decision-making in patchouli production management.

2. RESEARCH METHOD

2.1 Autoregressive Integrated Moving Average (ARIMA)

Time series Y_t is said to follow Autoregressive Integrated Moving Average model if the ARIMA[21][22] process is done with the difference to $W_t = \nabla^d Y_t$ within stationary ARIMA [22], [23]. If W_t follows the ARMA(p, q) model, then it can be said that Y_t is ARIMA(p, d, q). Generally, The ARIMA model can be mathematically represented as shown in equation (1) [2]:

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B) a_t, \quad (1)$$

where

- ϕ_p = p-th autoregressive parameter coefficient,
- θ_q = q-th moving average parameter coefficient,
- B = Backshift operator,
- d = Differencing,
- a_t = Remainder at t,
- p = Autoregressive (AR) parameter,
- q = Moving average (MA) parameter.

2.2 Long Short-Term Memory (LSTM)

Long short-term memory [24] type recurrent neural network (RNN) model was first developed by Sepp Hochreiter and Jurgen Schmidhuber on 1997[25]. The main strength of LSTM is its ability to keep pattern information from observation data by studying which part of the data that needed to be maintained and which part that could be omitted[26]. This is possible because each unit of LSTM is accompanied with several gates which is used to regulate the memory flow within the unit[27] [28]. The main structure of LSTM is categorized as a nonlinear model because each gate employs activation functions such as sigmoid and tanh, which created nonlinear connection within data processing. The Overall architecture and gate mechanism of the LSTM are illustrated in Figure 1.

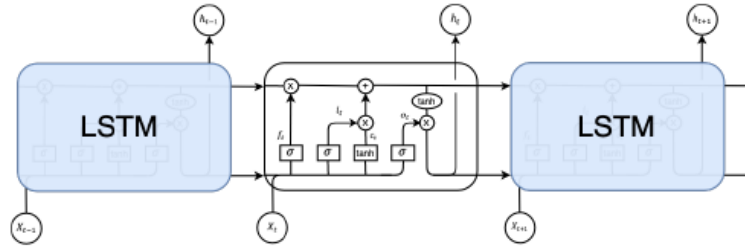


Figure 1. Long Short-Term Memory Architecture

The architecture of the LSTM model is illustrated in Figure 1. It consists of an input layer that receives the time series data, one hidden layer with 50 units designed to capture nonlinear dependencies, and an output layer that generates the forecasted production values. The cell state and gating mechanisms (input, forget, and output gates) enable the model to retain relevant information across time steps while filtering out noise. This structure is particularly suitable for modeling patchouli production data, which exhibits nonlinear and fluctuating patterns due to climate variability and cultivation practices.

The data processing mechanism within the LSTM network is mathematically represented in Equations (2)-(7). These equations describe the operations of the input gate, forget gate, output gate, and cell state updates that collectively govern the nonlinear dynamics of the LSTM model. [3]:

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

$$f_t = \sigma(W_f[h_{t-1} + Z_t] + b_f), \quad (3)$$

$$o_t = \sigma(W_o[h_{t-1} + Z_t] + b_o), \quad (4)$$

$$\tilde{c}_t = \tanh(W_c[h_{t-1} + Z_t] + b_c), \quad (5)$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t, \quad (6)$$

$$h_t = o_t * \tanh(c_t), \quad (7)$$

where

i_t	= Input gate
f_t	= Forget gate
o_t	= Output gate
$\tilde{c}_t$	= Cell state candidate value
c_t	= Cell state
σ	= sigmoid activating function
$W_{i,o}$	= Weight (input, forget, output) gate
h_{t-1}	= Hidden state vector of the following period
$b_{i,o,c}$	= Bias
Z_t	= Input data
W_c	= Cell state weight
$\tanh$	= tanh activating function

In this research, the steps of the LSTM model [29] are

a. Data Normalization

The first preprocessing step was normalization to address the significant differences in data scales. This study applied the MinMaxScaler function from the scikit-learn library, which rescales feature values into the range [0,1] to accelerate convergence and stabilize the LSTM training process. MinMax scaling was chosen because it is simple, efficient, and particularly suitable for neural networks that are sensitive to input scale. Prior to normalization, the dataset was examined for missing values, outliers, and anomalies to ensure data quality.

b. Data Splitting

Data was split into two parts, i.e. 80% training data and 20% testing data.

c. Training dan Evaluation

The LSTM model was trained using the processed training data. As part of the Recurrent Neural Network (RNN) family [30], LSTM requires careful parameter selection to balance accuracy and computational efficiency. In this study, the model was trained for 50 epochs. This number was chosen after preliminary trials, which indicated that extending training beyond 50 epochs did not significantly reduce error but increased the risk of overfitting.

The timestep was set to 5, meaning that the model considered information from the previous five weeks to forecast future production. This window size was selected because it effectively captured short-term fluctuations while avoiding excessive noise. Furthermore, only one hidden LSTM layer with 50 units was used. This architecture was considered sufficient to capture nonlinear patterns in the relatively small dataset (187 records), while deeper or more complex structures risked overfitting and computational inefficiency. After training, the model was evaluated on testing data to assess its predictive performance.

2.3 Hybrid (ARIMA-LSTM)

The hybrid ARIMA-LSTM model consists of two main steps[31]. In the first step, ARIMA is applied to identify and capture the linear patterns within the data. However, because ARIMA cannot fully represent nonlinear structures, its residuals still contain valuable nonlinear information [15]. In the second step, these residuals are further modeled using LSTM, which is effective in capturing nonlinear dependencies and long-term dynamics. By combining both methods, the hybrid model is expected to deliver more accurate forecasts than either model alone [32], as each component compensates for the other's weaknesses

Although other time series forecasting models, this study focuses on ARIMA, LSTM, and their hybrid due to their proven relevance and widespread use in agricultural time series forecasting. This focus allows a more in-depth evaluation of the hybrid's capability in addressing the specific challenges of patchouli production data.

2.4 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a statistical indicator used to measure the absolute error average percentage within a forecasting method. The calculation of MAPE is done by taking the absolute value of the difference between the prediction result and the actual data on each period, then divide it with the corresponding actual value. MAPE is used as the measurement of prediction accuracy by comparing the forecasted result to the real observation data. Low MAPE value indicated that the forecast model has a high accuracy, while high MAPE value indicated that the model has a relatively big prediction mistake. Mathematically, the Mean Absolute Percentage Error (MAPE) can be expresses as shown in equation (8) [33]:

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{n} \times 100\%, \quad (8)$$

where

y_t = actual value at the period t ,
 $\hat{y}_t$ = prediction value at the period t ,
 n = Number of observation period.

3. RESULT AND ANALYSIS

3.1 Data Description

Data used for this research is the production data from ARS ATSIRI North Kolaka. This company runs on manufacturing and marketing of essential oils from patchouli plant (*Pogostemon cablin* Benth), which is one of superior commodities in the area. The data were collected as secondary records directly from the company's production log, covering the period from January 2022 to July 2025, with a total of 187 weekly observations. While this dataset provides valuable real-world insights, its relatively small size poses challenges for training deep learning models such as LSTM. To address this limitation, a simple k-fold cross-validation was applied to evaluate model stability across different partitions of the data. The results consistently showed that LSTM outperformed ARIMA and the hybrid model, indicating that its superior performance was not dependent on a specific train-test split. In addition, robustness was assessed by repeating the experiments with different random initializations, which yielded similar accuracy levels. These checks strengthen confidence in the findings despite the limited dataset size. The overall pattern and fluctuation of the dataset are illustrated in the time series plot shown in Figure 2.

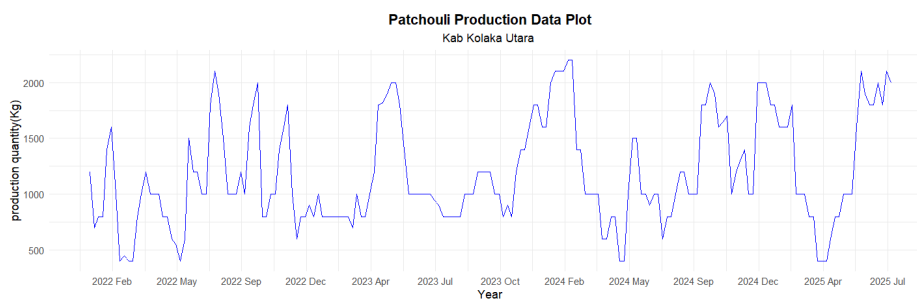


Figure 2. Time Series Data Plot

The production data of patchouli of ARS ATSIRI in North Kolaka during the period of January 2022 to July 2025 showed the fluctuating pattern with the estimate of production around 500 to 2,000 kg per month. The production experienced ups-and-downs, where the period of production logged at the end of 2023 and mid-2024 with the total over 2,000 kg. This pattern suggests the presence of seasonal dynamics that may be influenced by external factors such as raw material availability, climatic conditions, and distillation capacity. However, external variables such as weather conditions or pest outbreaks were not explicitly incorporated into the forecasting models, which represents a limitation of this study and an opportunity for future research. Overall, despite the fluctuations, production in 2025 tended to be higher than at the beginning of the observation period, making this dataset an important basis for future production forecasting.

3.2 Data Training and Data Testing

The patchouli production data from January 2022 to July 2025 was divided into a training set and a testing set as illustrated in Figure 3. The training set consisted of 130 observations covering the period from January 1, 2022 to July 22, 2024, while the testing set comprised 57 observations from June 29, 2024 to July 26, 2025. This division was intended to evaluate model performance and assess its ability to generalize to unseen data.

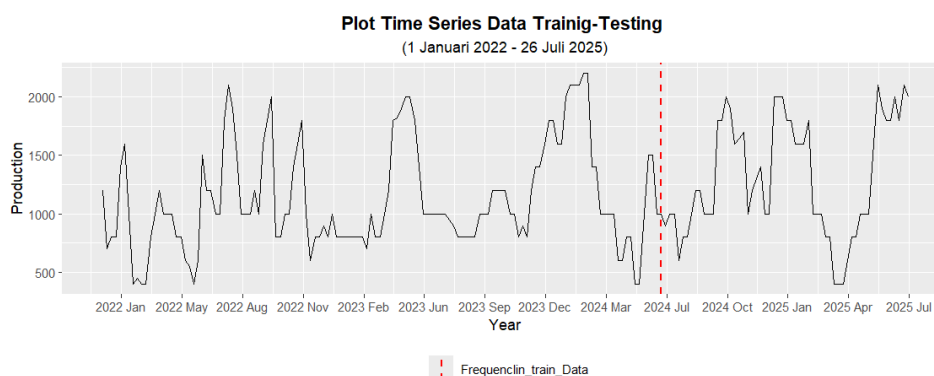


Figure 3. Time Series Plot of Training-Testing Data

3.3 ARIMA Method

Time series visualization plays an important role in ARIMA modeling, as it helps identify patterns, fluctuations, and potential seasonal dynamics in the data. In this study, the time series plot of patchouli production is presented in Figure 4 to illustrate these characteristics.

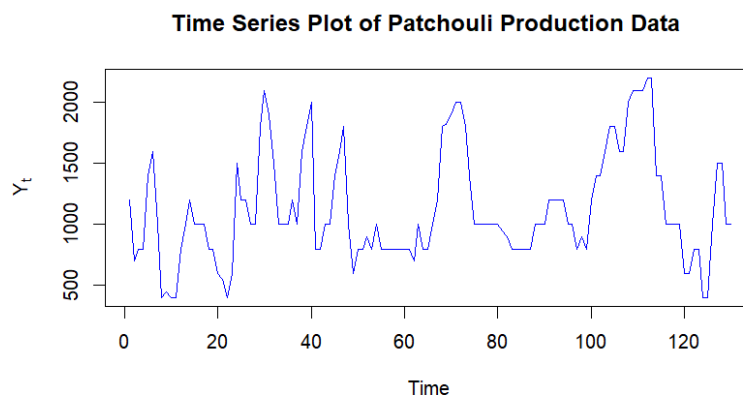


Figure 4. Time Series Plot of Patchouli Production-Train

According to the time-series plot of the training data, the series exhibited sharp fluctuations and non-constant variance over time. This indicates the presence of heteroscedasticity, i.e., changing variance as time progresses, which can undermine the validity of time-series models. The movement pattern also suggested non-stationarity, as both the mean and variance were not constant across the observation period. To satisfy the basic assumptions of time-series modelling, the data were transformed using the Box-Cox transformation to stabilize the variance. After this step, differencing was applied to remove trends or seasonal components that contributed to non-stationarity.

Stationary Test of Data

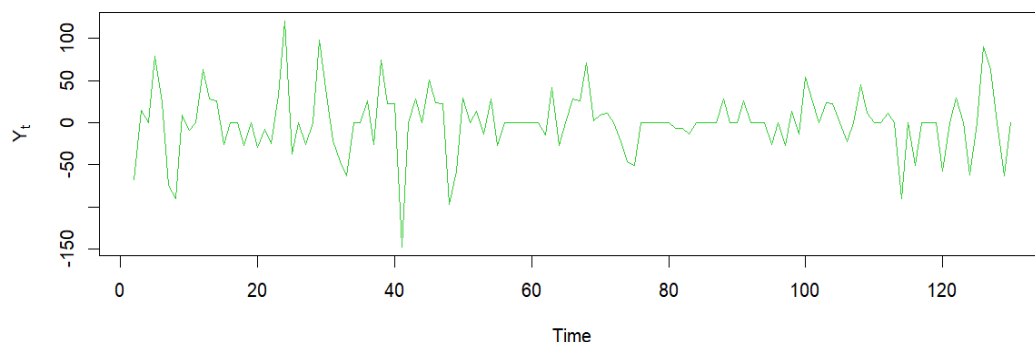


Figure 5. Time Series Plot of Patchouli Production Data with Diff=1

According to Figure 5, after first order differencing was done on the patchouli production data, it successfully stabilized the pattern of the data which showed a more stationary characteristic. This was shown by the time series graph in the figure which did not show a clear trend. Furthermore, the results of the Augmented Dickey-Fuller (ADF) test, as presented in Table 1, also confirm the stationarity of the differenced series.

Table 1. Augmented Dickey-Fuller Test

Dickey-Fuller	Lag Order	P-Value	Alternative Hypothesis
-6.3985	5	0.01	Stationary

The Augmented Dickey-Fuller (ADF) test yielded a p-value of 0.01, which is below the 5% significance level, and a test statistic of -6.3985. These results allow the rejection of the null hypothesis of a unit root, confirming that the patchouli production data became stationary after first-order differencing. This step provides the basis for specifying the ARIMA model with a differencing order of one ($d = 1$).

ACF and PACF Plots

In order to further identify the appropriate ARIMA model specification, the ACF and PACF plots of the differenced series are presented in Figure 6.

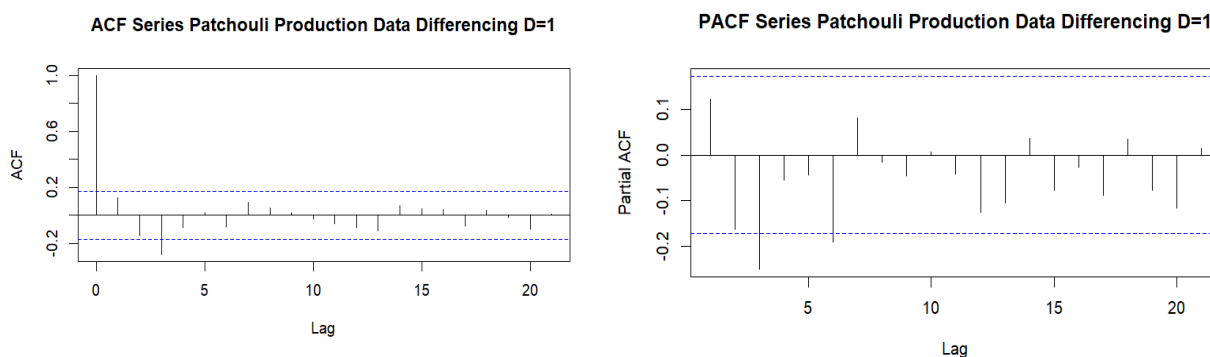


Figure 6. ACF and PACF Series with Diff=1

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots in Figure 6 described the characteristic of patchouli production data after first order differencing was done. ACF result showed a strong autocorrelation on the first lag, then decreased rapidly and all the following lags lied within the reliable boundary. This showed that the autocorrelation only had significant effect for the first lag. Meanwhile, the PACF plot did not show a significant jump outside the reliable boundary, which indicated that there was no dominant partial autocorrelation on a specific lag. The pattern gave the clue that the data has reached stationarity after differencing

was done, as well as could become a basis for selecting the ARIMA model by considering the autoregressive order (p) and the moving average (q).

ARIMA Model Parameter Estimation

Based on the ACF plot in Figure 6, it showed that there exists a negative autocorrelation which was significant on the first lag, meanwhile the autocorrelation value for the following lags were considerably small and lied within the significance boundary. This pattern indicated that the first order moving average was sufficiently dominant on the data. Meanwhile, for the PACF plot, it showed that the significance rate for the first and second lag with the following lags decreased and lied within the significance boundary. This pattern was interpreted as the effect of Autoregressive (AR) up to the second lag. Based on the result, then the ARIMA model which could be considered tentatively lies on Table 2.

Table 2. Tentative Model Parameter Estimation

No	Tentative Model	Parameter	Coefficient	P-Value	Conclusion
1	ARIMA(1,1,1)	ϕ_1	-0.11511	0.7294	Insignificant
		θ_1	0.26162	0.4078	Insignificant
2	ARIMA(1,1,2)	ϕ_1	0.710053	2.2×10^{-16}	Significant
		θ_1	-0.736134	1.137×10^{-14}	Significant
		θ_2	-0.263866	0.003967	Significant
		ϕ_1	0.996451	2.2×10^{-16}	Significant
3	ARIMA(2,1,1)	ϕ_2	-0.250327	0.003474	Significant
		θ_1	-1.000000	2.2×10^{-16}	Significant
		ϕ_1	0.966585	6.269×10^{-5}	Significant
		ϕ_2	-0.226538	0.2584	Insignificant
4	ARIMA(2,1,2)	θ_1	-0.967891	6.502×10^{-5}	Significant
		θ_2	-0.032106	0.8937	Insignificant

Based on Table 2, parameter estimation on a few tentative models offered that the model ARIMA(1,1,2) and ARIMA(2,1,1) showed the whole parameters were significant with the p-value which was smaller than the significance rate of 5%. Therefore, it can be concluded that these models were the best considerable model.

Selecting the Best Model

The selection of the best model used AIC (Akaike Information Criterion) value. The AIC values based on the tentative models are given in Table 3.

Table 3. AIC Value

Model	AIC
ARIMA(1,1,1)	1831.398
ARIMA(1,1,2)	1817.529
ARIMA(2,1,1)	1816.528
ARIMA(2,1,2)	1818.511

The best model could be chosen by considering the lowest AIC value. Model estimation result showed that ARIMA(2,1,1) has the lowest AIC value, which is 1,816.528 compared to other models. Therefore, ARIMA(2,1,1) is the best model.

3.4 LSTM Model

The formulation process of Long Short-Term Memory (LSTM) model was done through a few main steps, where the first is data pre-processing step to make sure the model performed optimally. First step is data normalization, knowing that LSTM is very sensitive to input value scale. A large range of values could cause gradient instability during backpropagation through time process. Therefore, Min-Max Scaling method was used to map the values into the range of $[-1,1]$ so that the value distribution became more uniform and the network learning process could be more stable. Next, sequential data formation (windowing) was done as the requirement for LSTM input which required that the data structure was in timesteps. For this research, the length of timesteps were made to be 5, which means each observation input consisted of five previous data to forecast the next value. Determining the timesteps was based on the consideration that LSTM had to capture the short-term temporal connection as well as keeping the computation efficiency. Therefore, the pre-processed data structure made possible for LSTM to study the time-dependency pattern more effectively.

Next process was to divide the research data into 80% training data and 20% testing data. Then, the data was

transformed into sequential format suitable for LSTM. The constructed model used one layer of LSTM with 50 units and ReLU (Rectified Linear Unit) activation function, as well as one dense layer with one neuron to create prediction. Optimization was done by using Adam algorithm with 0.001 learning rate and MSE as loss function. Training process was run for timestempepochss with the batch size of 16, where the parameter configuration was proven to give accurate prediction for inflation based on evaluation and testing.

To illustrate the performance of ARIMA-LSTM hybrid model in predicting patchouli production, comparison between actual data and prediction result was made on the training data. This visualization was made to show how capable the model was to follow fluctuation pattern on actual data as well as detecting the production dynamics from time to time

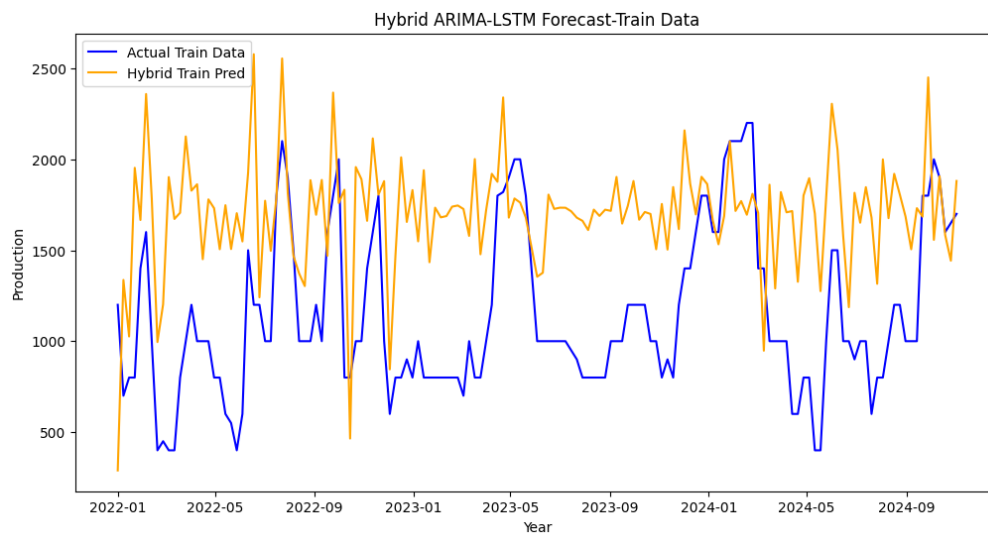


Figure 7. Visualization of ARIMA-LSTM Hybrid with Actual Data vs. Training Data

Figure 7 showed that the prediction result of ARIMA-LSTM hybrid model has a relatively in line pattern with the actual data. This indicated that the model was succeeded in capturing the main characteristic of the data, whether for periods with increasing trend or decreasing trend. Even though there exist a few deviations between actual data and prediction result, generally, the model was able to represent the temporal pattern well. These findings strengthen the argumentation that the ARIMA-LSTM hybrid approach was more adaptive in handling linear and nonlinear pattern on the patchouli production data.

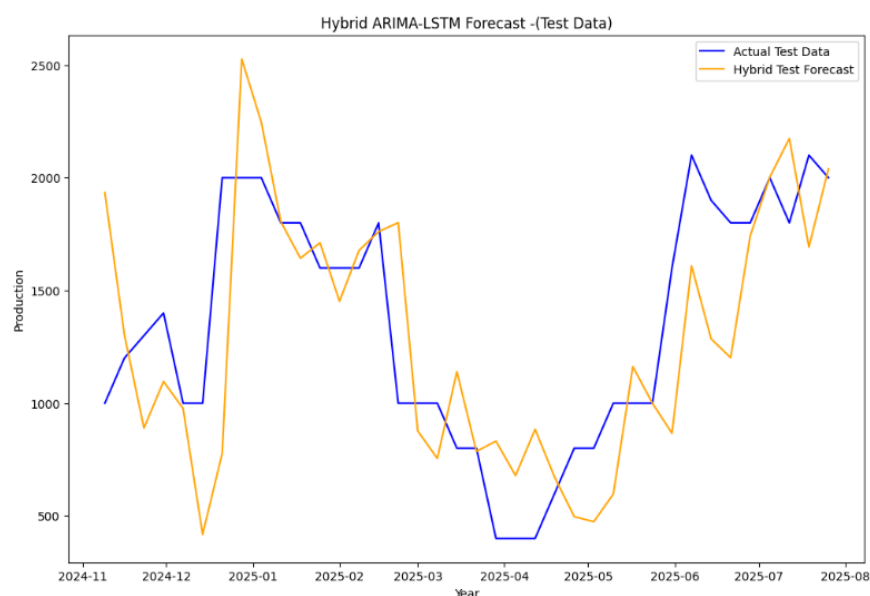


Figure 8. Visualization of ARIMA-LSTM Hybrid with Actual Data vs Testing Data

Based on Figure 8, it showed that the comparison results between the actual production data with the testing data within the test period (blue graph) with the prediction result of ARIMA-LSTM hybrid. Generally, the prediction pattern of the hybrid model was able to follow the trend of actual data, whether in increasing trend or decreasing trend. This showed that the model could represent the temporal dynamics of the production very well on the data that was not used for training.

3.5 ARIMA-LSTM Hybrid Model Forecast

After the best ARIMA model, which could represent the linear pattern of the data, was obtained, ARIMA(2,1,1) model was made the basis to develop the ARIMA-LSTM hybrid model. The hybrid approach was made by combining linear prediction from ARIMA with LSTM ability to capture nonlinear pattern. Data given by Figure 9 was the development of the number of patchouli production during the period of January 2022 to July 2025 as well as the forecast of the next 10 periods.

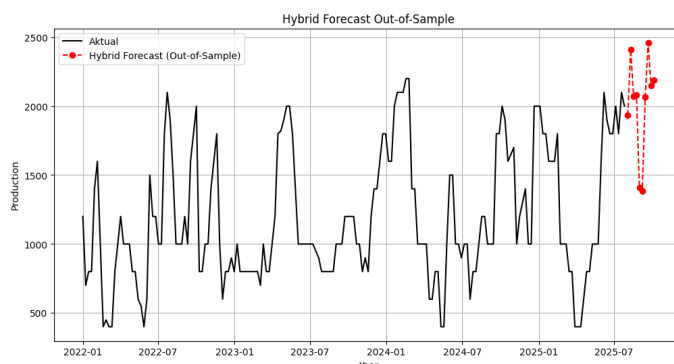


Figure 9. Forecast Result of ARIMA-LSTM Hybrid Model

Based on Figure 9, it presented the patchouli production forecast result using ARIMA-LSTM hybrid model for the next 10 periods. Black lines represented actual data, while red lines showed the model's prediction result. The pattern showed that the model was able to capture the fluctuation trend of the production within the previous periods as well as giving relatively close estimation from the actual value. This indicated that the hybrid model had the great ability to anticipate the dynamics of data outside the training data sample. The development of patchouli production can be seen in Table 4.

Table 4. Patchouli Production Forecast for the Next 10 Periods

Date	Estimation
August 3, 2025	2,046.990526
August 10, 2025	2,513.519544
August 17, 2025	2,192.738501
August 24, 2025	2,172.525151
August 31, 2025	1,473.794123
September 7, 2025	1,372.451830
September 14, 2025	2,001.342352
September 21, 2025	2,466.915554
September 28, 2025	2,277.355265
October 5, 2025	2,347.993956

Based on Table 4, it showed the estimation of patchouli production forecast by using ARIMA-LSTM hybrid model within the period of August to the beginning of October 2025. The estimation values presented showed significant variants during the weeks. For example, on August 10, 2025, the production is estimated to be 2,513 kg, meanwhile at the end of August (August 31, 2025), it showed a sharp decline to 1,473 kg. Next, the production was supposed to increase in mid-September with 2,466 kg as the highest value on September 21, 2025, before it lies around 2,347 kg on October 5, 2025. The fluctuation pattern showed that the model was able to capture the production dynamics from time to time, thus the forecast result could be used as the reference for planning and decision-making regarding the production in the future.

3.6 Accuracy Comparison of ARIMA and ARIMA-LSTM Hybrid Model

To give a picture about the model's performance, accuracy evaluation was done on two different forecast approach, i.e. ARIMA model and ARIMA-LSTM hybrid model with three methods, i.e. Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), which represented the mean square error rate and the root mean square error of the prediction result on the actual data. The smaller

values of MSE, RMSE, and MAPE showed that the model had a lower prediction error rate and thus was more accurate. The comparison of accuracy value of the models is presented on Table 5 and Figure 10.

Table 5. Accuracy Value Comparison

Method	MSE	RMSE	MAPE
ARIMA(2,1,1)	444.128100	530.656500	0.378550
LSTM	251.225299	321.672370	0.238164
ARIMA-LSTM Hybrid	401.404073	489.733339	31.099958

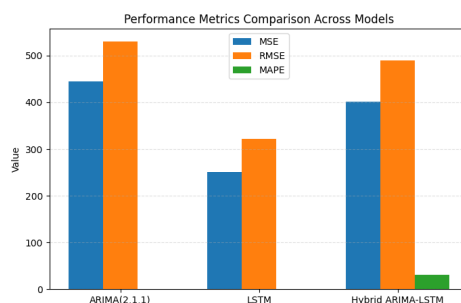


Figure 10. Accuracy Value Comparison

Based on the evaluation result on Table 5 and Figure 10, it was seen that the LSTM model has the best performance compared to ARIMA or ARIMA-LSTM hybrid. This was shown by the MSE (251.22), RMSE (321.67), and MAPE (0.238%) values which were lower, which marked the low prediction error rate and higher accuracy. Meanwhile, the ARIMA (2,1,1) model produced a greater error (MSE = 444.13, RMSE = 530.65, MAPE = 0.379%), which reflected its limitation in capturing the nonlinear data pattern. On the other side, the ARIMA-LSTM hybrid model did not provide better results, with a very high MAPE value (31.10%). This poor performance was likely influenced by the relatively small dataset, which limited the hybrid model's ability to balance linear and nonlinear components effectively. In addition, residual instability from ARIMA may have propagated into the LSTM stage, reducing overall accuracy. These factors suggest that the hybrid structure was not optimal for this data condition. Therefore, it can be concluded that the LSTM model was the most effective approach for forecasting in this research.

Although the LSTM model outperformed the ARIMA and hybrid models, it is important to acknowledge the potential risk of overfitting, particularly given the relatively small dataset used in this study. Overfitting may occur when the model captures noise instead of underlying patterns, thereby reducing its generalizability to unseen data. To mitigate this issue, early stopping and dropout regularization were applied during training. In addition, validation loss was monitored throughout the training process. The learning curves showed that both training and validation losses converged after approximately 30 epochs, with no significant divergence, indicating that overfitting was limited. Nonetheless, the possibility of overfitting cannot be entirely excluded due to the relatively small dataset, and this remains a limitation that should be considered when interpreting the results.

While the evaluation results highlight the accuracy of the forecasting models, their practical implications are equally important. The forecasting outcomes can support production planning by helping distillers and farmers anticipate fluctuations in raw material supply, optimize labor and resource allocation, and schedule distillation operations more efficiently. Moreover, by anticipating potential declines or peaks in production, stakeholders can make better-informed decisions regarding inventory management, market supply strategies, and financial planning. Thus, beyond demonstrating technical accuracy, the results of this study provide actionable insights that can be directly applied to the day-to-day operations of patchouli producers.

4. CONCLUSION

Based on the accuracy comparison (Table 5; Figure 10), the LSTM model achieved the best forecasting performance, producing the lowest errors compared to ARIMA and the ARIMA-LSTM hybrid. The limited improvement of the hybrid model may be due to the relatively small dataset and the dominance of nonlinear dynamics, which were effectively captured by LSTM alone. Beyond methodological insights, these findings have practical implications: accurate forecasting can support better production planning, reduce supply chain disruptions, and strengthen Indonesia's competitiveness in the global essential oil market. Nevertheless, this study is limited by its relatively small dataset, short observation period, and the absence of external variables such as climate, raw material availability, distillation capacity, or pest outbreaks. Future research should address these limitations by incorporating larger and more diverse datasets. Moreover, the proposed approach has potential applicability not only to patchouli but also to other essential oils and agricultural commodities, thereby broadening its relevance for sustainable agricultural development.

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