Comparison of Artificial Neural Network and Long Short-Term Memory for Modelling Crude Palm Oil Production in Indonesia

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***Abstract*—Indonesia is one of the largest producers and exporters of Crude Palm Oil (CPO), making CPO production crucial to the country's economic stability. Accurate forecasting of CPO production is essential for effective inventory management, export-import strategy, and economic planning. Traditional time series methods like ARIMA have limitations in modeling nonlinear data, leading to the adoption of machine learning approaches such as Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM). This study compares the performance of ANN, a general neural network, and LSTM, a neural network specifically designed for time series data, in predicting CPO production in Indonesia. Data from 2003 to 2022 were used to train and evaluate both models with various hyperparameter tuning configurations. The results indicate that while both models provide excellent forecasting accuracy, with MAPE values below 10%, the LSTM model achieved a lower out-of-sample MAPE of 5.78% compared to ANN's 6.87%, suggesting superior performance by LSTM in capturing seasonal patterns in CPO production. Consequently, LSTM is recommended as the preferred model for CPO production forecasting due to its enhanced ability to handle temporal dependencies and nonlinear patterns in the data.**

Keywords—Artificial Neural Network (ANN); Crude Palm Oil (CPO); Long Short-Term Memory (LSTM)

I. Introduction

Indonesia is the largest agrarian country in Southeast Asia and one of the world's largest producers of Crude Palm Oil (CPO). According to data from the United States Foreign Agricultural Service, Indonesia's CPO production reached 47 million metric tons as of March 2024. This achievement places Indonesia as both the largest producer and exporter of crude palm oil (CPO) globally. Crude Palm Oil (CPO) is unrefined palm oil extracted from the mesocarp of the oil palm fruit, which remains in a raw state and requires further processing and refining to become pure palm oil [1]. CPO has many derivative products used in daily life, including cooking oil, margarine, biodiesel, soap, and detergent. [2].

As a primary producer in the international CPO market, crude palm oil is a major commodity that supports Indonesia's economy. According to data from the Central Statistics Agency (BPS), CPO contributes significantly and consistently to Indonesia's export value, accounting for around 12-13% during the period from 2020 to 2022. Thus, the CPO industry makes a substantial contribution to national income through export activities. The export value plays a crucial role in the country's economic stability, as higher export values lead to an appreciation of the domestic currency. Currency appreciation can lower import prices, reducing inflationary pressures. Conversely, currency depreciation can increase import prices, triggering inflation [3]. Therefore, CPO production is a potential factor in the country's economic development.

Based on data from the Central Statistics Agency of Indonesia, CPO production fluctuated significantly from 2021 to 2022, with the lowest production occurring in February 2022, leading to a shortage of cooking oil that caused concern among the public. CPO is one of the largest contributors to the nation's export revenue. Therefore, fluctuations in CPO production can lead to instability in export income. A decline in export income could result in a trade balance deficit and depreciation of the domestic currency, which in turn may increase import prices and trigger inflation, negatively impacting the economy as a whole [3]. One way to manage and anticipate this risk is by forecasting CPO production. With accurate forecasting, the government and industry players can plan more effective export-import policies, manage inventory and prices more stably, and adjust investment strategies to reduce economic uncertainty, ensuring the optimal contribution of the palm oil sector to economic growth and national stability.

A commonly used forecasting method for modeling time series data is the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA is a time series model derived from the Autoregressive Moving Average (ARMA) model, which combines non-stationary Autoregressive and Moving Average processes requiring differencing to achieve stationarity [4]. The ARIMA model is quite flexible in modeling time series data patterns because it can capture random data patterns, trends, seasonal, and even cyclical characteristics in the time series data. However, studies indicate that ARIMA is less suitable for modeling nonlinear time series data [5]. Recent advancements in technology have led to the use of machine learning methods, which are more suitable for addressing the limitations of traditional time series models. Machine learning algorithms excel in discovering and representing complex structural patterns in data, enabling better future forecasting based on these patterns [6]. Machine learning methods, especially deep

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learning, have become powerful tools for handling time series data with nonlinearity or complexity factors [7]. The most commonly used deep learning method is the Artificial Neural Network (ANN). Artificial Neural Network (ANN) is a computational system inspired by the structure and operation of neural cells in the brain, modeling biological neural networks. ANN is a non-linear model with a flexible functional form and several parameters that cannot be interpreted. This characteristic enables ANN to solve unstructured and hard-to-define problems [8].

As technology advances, various deep learning methods have emerged. One deep learning method specifically designed for time series data is Long Short-Term Memory (LSTM) [9]. LSTM, a variant of Recurrent Neural Network (RNN), is widely used in time series data modeling. LSTM's architecture was developed to address the vanishing gradient problem often encountered in conventional RNNs. LSTM uses two key mechanisms, the forget gate and input gate, allowing the model to learn which information should be retained or forgotten at each time step. This advantage makes LSTM more flexible in managing its internal memory, which can be useful when working with complex or nonlinear data. Additionally, LSTM has a better ability to capture data patterns over longer periods, making it more suitable for applications requiring deeper and more accurate temporal dynamics modeling.

This study introduces a novel contribution to the field by focusing on the application and comparative analysis of two advanced neural network methods—Artificial Neural Network (ANN) and Long Short-Term Memory (LSTM)—for forecasting crude palm oil (CPO) production in Indonesia. While ANN has been widely utilized for various predictive tasks, this research leverages the specialized capabilities of LSTM in handling sequential and time-series data, addressing the unique temporal patterns, seasonality, and variability inherent to Indonesia's CPO production. By tailoring these methods to the specific characteristics of Indonesia's agricultural sector, this study not only provides valuable insights into their effectiveness and limitations but also establishes a robust framework for improving forecasting accuracy in a critical industry that significantly impacts the country's economy.

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II. RELATED WORK

Time series forecasting has been extensively explored using both traditional statistical models and modern machine learning techniques. To better understand the strengths and limitations of these approaches, various studies have compared their performance across different domains. The Table I below summarizes key findings from relevant studies, highlighting the application of ARIMA, ANN, and LSTM models in diverse sectors and the insights gained from these comparisons

TABLE I. RESULTS OF CRUDE PALM OIL (CPO) PRODUCTION IN INDONESIA MODELLING WITH ANN

Domain	Key Findings	References
Various Sectors (Finance, Healthcare, Weather, Utilities)	Machine learning methods like ANN outperform ARIMA in scenarios with non-linear or complex patterns.	[10]
Energy Consumption (Commercial Buildings)	ANN is more reliable for non-linear datasets, capturing intricate dependencies and variability, while ARIMA is effective for linear and stationary data.	[11]
Global Crude Palm Oil (CPO) Prices	LSTM achieves superior accuracy (MAPE: 2.33%, RMSE: 34.708), better capturing complex temporal dependencies compared to ARIMA and hybrid models.	[12]
Economic and Financial Indicators (GDP Growth)	LSTM outperforms ARIMA in long-term forecasting for non-linear and non-stationary data, addressing ARIMA's limitations.	[13]
Stock Price Prediction (Real Estate)	LSTM provides better accuracy for non-stationary, complex, and cyclical data, while ARIMA performs better for linear and stationary datasets.	[14]

Conventional methods like ARIMA have been widely utilized for time series forecasting due to their ability to capture trends, seasonality, and cycles in data. However, ARIMA has notable limitations in addressing non-linear and complex data, such as the patterns of CPO production in Indonesia, which are influenced by various factors including seasonality, policy changes, and international price fluctuations. These studies collectively highlight the evolution of time series forecasting techniques, showcasing the growing prominence of machine learning methods like LSTM and ANN in overcoming the limitations of traditional models such as ARIMA. ANN excels in modeling non-linear and unstructured relationships, while LSTM, a variant of Recurrent Neural Networks (RNN), is specifically designed to handle temporal dynamics and long-term dependencies in time series data. However, a research gap persists in exploring the application of these models in integrated or hybrid approaches tailored for specific domains, such as agriculture and commodity price forecasting. This study aims to address this gap by applying and comparing ANN and LSTM for forecasting CPO production in Indonesia, to capture the intricate characteristics and variability of the data more effectively while providing a robust framework for planning and decision-making in the CPO industry.

III. METHODOLOGY

The methodology diagram (Fig. 1) illustrates the key stages in modeling and forecasting Crude Palm Oil (CPO) production in Indonesia using Artificial Neural Network (ANN) and Long

Short-Term Memory (LSTM) models. Initially, the data is divided into training and testing subsets, ensuring a robust evaluation of the models. To achieve this, several data splitting ratios, such as 70:30, 80:20, and 90:10, are explored to analyze the impact of data availability on the training process.

In the model design and training phase, ANN and LSTM models are configured with specific hyperparameters to capture the unique patterns in the data. These configurations include batch sizes of 8 and 16, neuron counts of 50 and 100, hidden layers of 1 and 2, epochs of 50 and 100, and learning rates of 0.001 and 0.01. The use of a six-month window size for LSTM is particularly emphasized to account for the seasonal characteristics of CPO production. Adam optimization is applied to update the model weights effectively, ensuring optimal learning from the data.

During the evaluation stage, the models are assessed using the Mean Absolute Percentage Error (MAPE) metric to validate their forecasting accuracy. The systematic exploration of data splits and hyperparameter combinations ensures a comprehensive understanding of the models' capabilities in forecasting CPO production. The final step occurs in the output gate component, where the sigmoid activation function (σ) is applied to produce the output value o_t and process the cell state (C_t) with tanh activation.

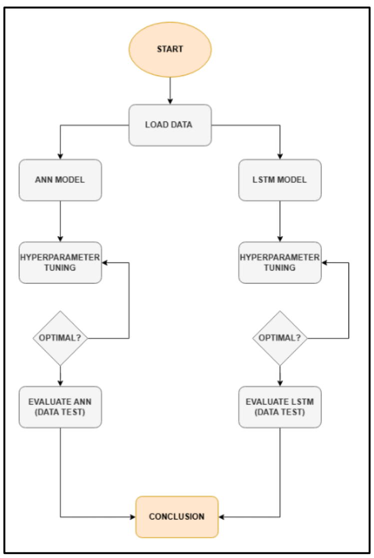

Fig. 1. Methodology diagram.

IV. Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a computational system inspired by the structure and function of neural cells in the brain, essentially modeling biological neural networks. ANN is an example of a non-linear model with a flexible functional form and several parameters that cannot be interpreted, similar to parametric models. However, this allows ANN to tackle unstructured and challenging-to-define problems. The process within an ANN begins with input data received by neurons, which are grouped into layers. Information received from the input layer is passed sequentially through the layers in the ANN until it reaches the output layer. Layers positioned between the input and output are known as hidden layers. A Neural Network is determined by three main components: the pattern of relationships between units (network architecture), the method for updating weights in connection links (training method or algorithm), and the activation function [8].

A. Components of ANN

This form of artificial intelligence is developed to mimic the workings of the human biological nervous system (neurons). Each component of an ANN system can be analogized to parts of the human neuron system, such as dendrites (parts that receive input/signals), the cell body (processes inputs), and the axon (transmits this input to other neurons/outputs) [15] (Fig. 2).

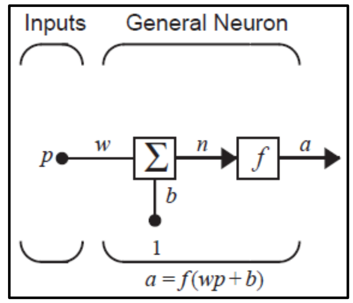

Fig. 2. Components of ANN.

Each piece of information received by the dendrites (input) is summed and sent through the axon to the dendrites (output) of another neuron. This information will only be received by the other neuron if it meets a certain threshold value. Neurons that receive information and transmit it to other neurons are considered to be activated. Neurons receive information from other neurons in the form of values known as weights, which also indicate the strength of the connection between neurons.

B. ANN Architecture

ANN architecture is the pattern of relationships between neurons. Neurons that share the same weight pattern and activation function are grouped in the same layer. Information usually flows from the input layer to the output layer, often passing through hidden layers. Some neural network architectures include:

1) Single-layer network

This network has only one layer containing weights connected to each other. There is no hidden layer in this type of network, and all input units are connected to every output unit (Fig. 3).

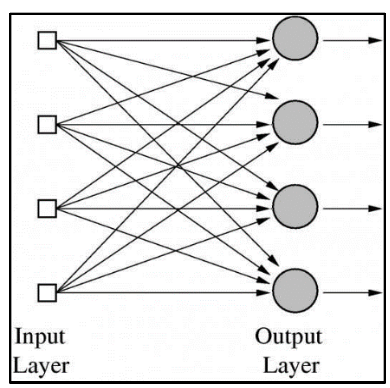

Fig. 3. Single-layer network.

2) Multi-layer network

This network has one or more layers (hidden layers and weights) between the input layer and the output layer. A multi-layer network can solve more complex problems than a single-layer network (Fig. 4).

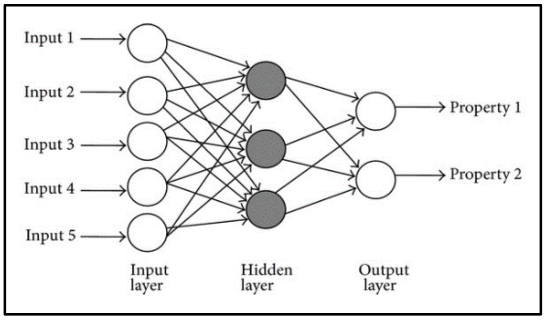

Fig. 4. Multi-layer network.

V. LONG SHORT TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) is a neural network architecture that shares similarities with Recurrent Neural Networks (RNNs) [16]. LSTM was first introduced by Hochreiter and Schmidhuber in 1997. LSTM falls within the category of Recurrent Neural Networks (RNNs), where it has repeating units that function similarly to neural network sequences [17]. LSTM was designed to overcome the limitations of conventional RNNs, specifically the vanishing gradient problem. The vanishing gradient problem occurs when gradient values decrease significantly towards the last layers, preventing weight updates and causing the model to struggle to improve or converge. Unlike conventional RNNs, LSTM uses additional signals passed from one time step to the next, known as the cell state. LSTM has strong generalization capabilities and effective learning abilities for both large and small datasets. It is particularly advantageous in processing non-linear data, which enhances forecasting accuracy [18].

LSTM's design makes it particularly suitable for solving complex problems that involve sequential or time-dependent data. For instance, in forecasting tasks where patterns such as seasonality, trends, or temporal dependencies play a critical role, LSTM excels by learning these non-linear relationships. Its strong generalization capabilities and ability to learn from both large and small datasets make it highly effective for addressing real-world challenges. By leveraging its strengths, LSTM has been successfully applied in various domains, such as financial time-series prediction, speech recognition, and production forecasting. For example, in modeling Crude Palm Oil (CPO) production, LSTM can identify seasonal trends and long-term dependencies, enabling more accurate and reliable forecasts. These features make LSTM a powerful solution for problems where conventional methods often struggle, ensuring better decision-making and planning in dynamic environments.

The LSTM architecture consists of memory cells, an input gate, a forget gate, and an output gate. The LSTM cell can store data for a specific duration. Intuitively, the input gate controls the extent to which new information can enter the cell, while the forget gate controls how much information remains within the cell, and the output gate manages which information exits the cell to calculate the activation of the LSTM model [16]. Below are descriptions of the gates in an LSTM (Fig. 5).

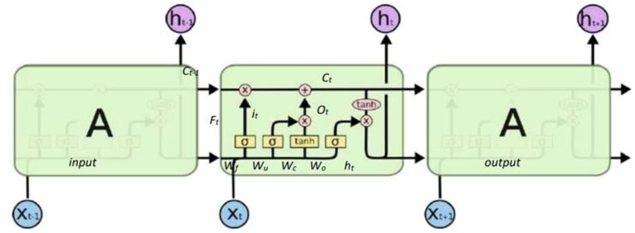

Fig. 5. Architecture of LSTM.

VI. RESULT

This section begins by discussing the characteristics of the Crude Palm Oil production in Indonesia, modeling with ANN, modeling with LSTM, and a comparison of the results from the ANN and LSTM models.

A. Crude Palm Oil in Indonesia

The production data of Crude Palm Oil (CPO) in Indonesia is very important, especially for the government. The government requires information on Crude Palm Oil (CPO) production in Indonesia to assist in the effective planning and management of CPO supplies, reduce economic risks due to fluctuations in CPO production, and devise better export-import strategies for CPO to enhance the stability of the national economy. The characteristics of the CPO production data in Indonesia are illustrated in Fig. 6.

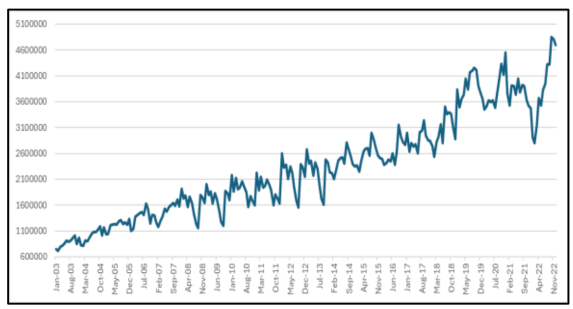

Fig. 6. Time series plot Crude Palm Oil (CPO) production in Indonesia.

Fig. 6 shows that the production of Crude Palm Oil (CPO) in Indonesia from January 2003 to December 2022 exhibits a seasonal pattern. CPO production in Indonesia from 2003 to 2013 showed a tendency to decline sharply at the end of the year, particularly in September, and had a tendency to rise sharply at the beginning of the year, especially in January. In other words, there tends to be a decrease at the end of the year, followed by a rise at the beginning of the year. This is supported by the characteristics of oil palm, which grows well during the end of the rainy season, where the rainy season in Indonesia usually starts in November and ends between January and March. However, from 2014 to 2022, the production of Crude Palm Oil (CPO) in Indonesia has shown a new seasonal pattern, characterized by a tendency to decrease at the beginning of the year and an increase at the end of the year. This is believed to be due to increasingly unpredictable climate conditions year after year. Overall, the production of Crude Palm Oil (CPO) in Indonesia has shown an increasing trend during this period, indicating a consistent rise in production year after year. The lowest production of Crude Palm Oil (CPO) in Indonesia was recorded at the beginning of the observation period, specifically in February 2003, while the highest production occurred at the end of the observation period, specifically in October 2022.

B. Forecasting CPO Production Using Artificial Neural Network

The process in an Artificial Neural Network (ANN) begins with the input received by neurons, which are grouped in layers. The information received from the input layer is sequentially passed to the subsequent layers in the ANN until it reaches the output layer. The determination of inputs in modeling the production of Crude Palm Oil (CPO) in Indonesia using ANN is based on Fig. 7.

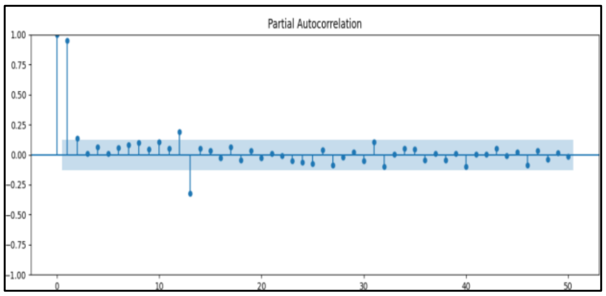

Fig. 7. PACF Crude Palm Oil (CPO) production in Indonesia.

Fig. 7 shows that the production of Crude Palm Oil (CPO) in Indonesia during period x_t has a strong relationship with production in periods x_{t-1}, x_{t-2}, x_{t-12}, and x_{t-13}. Based on this relationship, the Artificial Neural Network model uses the CPO production data from Indonesia during periods x_{t-1}, x_{t-2}, x_{t-12}, and x_{t-13} as inputs to predict CPO production in Indonesia for x_t period. This study will utilize several combinations of hyperparameters, namely a batch size of 8 and 16, neuron counts of 50 and 100, hidden layers of 1 and 2, epochs of 50 and 100, and learning rates of 0.001 and 0.01. Adam optimization will be used to update the weights of the ANN network, and MAPE out-of-sample will be employed to determine the best ANN model. In addition to these hyperparameters, this study will also use data splitting ratios to divide the dataset into training and testing subsets. Data splitting ratios refer to the proportion of data allocated for each subset, for example 80% for training, where the model learns from the data, and 20% for testing, where the model's performance is evaluated on unseen data. This approach helps to prevent overfitting and ensures the model's effectiveness on new data. The results of the modeling using the Artificial Neural Network with several data partitioning scenarios and hyperparameter tuning are presented in Table II.

TABLE II. RESULTS OF CRUDE PALM OIL (CPO) PRODUCTION IN INDONESIA MODELLING WITH ANN

Split Ratio	Batch Size	Neurons	Hidden Layers	Epochs	Learning Rate	MAPE
70 : 30	8	150	2	150	0,01	6,87%
80 : 20	8	120	2	150	0,01	7,92%
90 : 10	8	150	2	150	0,01	6,94%

Table II shows that the best Artificial Neural Network model for predicting Crude Palm Oil (CPO) production in Indonesia is the model with a data partitioning ratio of 70:30, a batch size of 8, 150 neurons, 2 hidden layers, 150 epochs, and a learning rate of 0.01. This model achieves an out-of-sample MAPE value of 6.87%, which falls within the criteria for very good forecasting, as it is less than 10%. The best models in Table II indicate a trend that increasing the number of hidden layers and epochs reduces the model's error rate. Conversely, a smaller batch size tends to produce models with a lower error rate.

C. Forecasting CPO Production Using Long Short Term Memory

LSTM is a form of neural network. One important component in the formation of LSTM networks is the determination of the inputs used. This study will use the window size feature, or time steps, as input. The window sizes used in this research are variations of three, four, and six, representing quarterly, triannual, and semiannual periods. In addition to the input, another crucial component is the hyperparameters. This study will utilize several combinations of hyperparameters, namely a batch size of 8 and 16, neuron counts of 50 and 100, hidden layers of 1 and 2, epochs of 50 and 100, and learning rates of 0.001 and 0.01. Adam optimization will be used to update the weights of the LSTM network, and MAPE out-of-sample will be employed to determine the best LSTM model. In addition to these hyperparameters, this study will also use data splitting ratios to divide the dataset into training and testing subsets. Data splitting ratios refer to the proportion of data allocated for each subset, for example 80% for training, where the model learns from the data, and 20% for testing, where the model's performance is evaluated on unseen data. This approach helps to prevent overfitting and ensures the model's effectiveness on new data. The results of the modeling using Long Short-Term Memory with several data partitioning scenarios and hyperparameter tuning are shown in Table III.

TABLE III. RESULTS OF CRUDE PALM OIL (CPO) PRODUCTION IN INDONESIA MODELLING WITH LSTM

Split Ratio	*Window Size*	*Batch Size*	*Neurons*	*Hidden Layers*	*Epochs*	*Learning Rate*	MAPE
70 : 30	3	8	120	2	100	0,01	6.141%
	4	16	150	1	150	0,01	6.28%
	6	8	150	1	150	0,001	6.33%
80 : 20	3	8	150	1	150	0,001	5.81%
	4	16	120	1	100	0,01	5.85%
	6	16	120	2	150	0,001	5.78%
90 : 10	3	8	120	2	150	0,001	6.15%
	4	8	150	2	150	0,01	6.17%
	6	8	150	2	150	0,001	6.01%

Table III shows that the best Long Short-Term Memory (LSTM) model for a 70:30 data partitioning ratio is with a window size of 3 and a hyperparameter combination of a batch size of 16, 120 neurons, 2 hidden layers, 100 epochs, and a learning rate of 0.01. This LSTM model with the specified window size and hyperparameter combination achieves an out-of-sample MAPE of 6.14%. The best LSTM model for an 80:20 data partitioning ratio is with a window size of 6 and a hyperparameter combination of a batch size of 16, 120 neurons, 2 hidden layers, 150 epochs, and a learning rate of 0.001. This LSTM model achieves an out-of-sample MAPE of 5.78%. The best LSTM model for a 90:10 data partitioning ratio is with a window size of 6 and a hyperparameter combination of a batch size of 8, 120 neurons, 1 hidden layer, 150 epochs, and a learning rate of 0.001. This LSTM model achieves an out-of-sample MAPE of 6.01%. Therefore, the best model to be used in the dashboard to be developed is with an 80:20 data partitioning ratio, a window size of 6, and a hyperparameter combination of a batch size of 16, 120 neurons, 2 hidden layers, 150 epochs, and a learning rate of 0.001.

Table III also indicates that there is no definitive pattern of hyperparameters that consistently yields the best model. The best model obtained is the one with a window size of 6, which aligns with the seasonal pattern of Crude Palm Oil (CPO) production in Indonesia. For example, from 2003 to 2013, there was a tendency for production to decrease in September and increase in February, which corresponds to a time gap of six months from September to February.

D. *Comparison of Artifical Neural Network and Long Short Term Memory*

The results of modeling Crude Palm Oil (CPO) production in Indonesia using general neural network methods, namely Artificial Neural Network (ANN), and neural networks specifically designed for time series data, namely Long Short-Term Memory (LSTM) are presented in Table IV.

TABLE IV. COMPARISON ANN AND LSTM MODEL

Metode	MAPE
Artificial Neural Network (ANN)	6,87%
Long Short Term Memory (LSTM)	5,78%

Table IV shows that the modeling of Crude Palm Oil (CPO) production in Indonesia using the general neural network method, namely Artificial Neural Network (ANN), and the neural network method specifically designed for time series data, namely Long Short-Term Memory (LSTM), yields out-of-sample MAPE values of 6.87% and 5.78%, respectively. Based on the out-of-sample MAPE values, both methods can be classified as capable of modeling CPO production in Indonesia very well, as the MAPE values are both below 10%. When comparing the two methods, the Long Short-Term Memory (LSTM) method provides a lower out-of-sample MAPE compared to the Artificial Neural Network (ANN), indicating that the LSTM method has a better model performance than the ANN.

VII. DISCUSSION

The findings of this study demonstrate the effectiveness of ANN and LSTM in predicting CPO production in Indonesia. Both models performed exceptionally well, with MAPE values below 10%, indicating their suitability for time series forecasting. However, LSTM showed superior performance with a MAPE of 5.78%, outperforming ANN, which achieved a MAPE of 6.87%. This suggests that LSTM's ability to process sequential data and capture long-term dependencies allows it to model the complex and dynamic seasonal variations in CPO production more effectively. While ANN is proficient at handling non-linear relationships, its focus on shorter-term dependencies may have limited its adaptability to the shifts in seasonal patterns observed during the study period.

The seasonal trends in CPO production, driven by climatic factors and the oil palm growth cycle, emphasize the importance of models that can capture long-term temporal dynamics. From 2003 to 2013, CPO production typically decreased toward the end of the year and increased at the start of the following year, but after 2014, these patterns shifted due to changing and unpredictable climate conditions. The LSTM model's use of a six-month window size proved effective in addressing these shifts, reflecting its ability to align with seasonal cycles. Furthermore, the study underscores the importance of optimizing hyperparameters to improve model performance. For ANN, better results were achieved with smaller batch sizes, a larger number of neurons, and deeper network layers. In contrast, for LSTM, the optimal configuration included a six-month window size, a batch size of 16, and specific combinations of hidden layers, neurons, and learning rates.

The practical applications of these findings are significant for the CPO industry and policymakers. Accurate forecasts can support decision-making in inventory management, price stabilization, and export-import planning, thereby enhancing economic stability. The superior performance of LSTM makes it particularly useful for addressing the challenges posed by evolving seasonal patterns and climate variability in CPO production. Nonetheless, the study has certain limitations, such as relying solely on historical production data without incorporating external factors like market demand, policy changes, or global price fluctuations. Future research could explore hybrid approaches that combine ANN, LSTM, and other machine learning techniques to further improve accuracy. Moreover, integrating exogenous variables, such as weather conditions or economic indicators, could lead to more comprehensive forecasting models. Overall, this research demonstrates the potential of advanced neural network models in tackling complex forecasting challenges in the agricultural sector and provides a strong foundation for future studies.

VIII. CONCLUSION

The LSTM model demonstrates superior performance compared to the ANN model in modeling and forecasting Crude Palm Oil (CPO) production in Indonesia. This conclusion is supported by a comparative analysis of Mean Absolute Percentage Error (MAPE) values, where the LSTM model achieved a notably lower MAPE (5.78%) in out-of-sample predictions compared to the ANN model (6.87%). The lower MAPE value highlights the LSTM model's enhanced capability to minimize the deviation between predicted values and actual observations, ensuring higher predictive accuracy. The superior performance of LSTM is attributed to its architectural design, which is specifically optimized to capture long-term dependencies and temporal patterns in sequential data. This makes LSTM particularly effective in handling the seasonal fluctuations and nonlinear trends inherent in agricultural production processes like CPO. For example, the LSTM model successfully identified seasonal production trends and temporal dependencies, such as increased production during harvest periods and decreases during off-seasons, which the ANN model struggled to replicate. In contrast, while the ANN model performs well in general-purpose predictive tasks, it lacks the specialized mechanisms to account for sequential and temporal dynamics. Consequently, its predictions are less robust when applied to CPO production data with complex seasonality and long-term patterns.

These findings emphasize the importance of selecting appropriate modeling techniques tailored to the characteristics of the dataset. By leveraging the strengths of LSTM, stakeholders in the CPO industry can achieve more reliable forecasts, allowing for improved planning, efficient resource allocation, and informed decision-making to strengthen Indonesia's position as a global leader in palm oil production. Future research could explore the use of more recent and extensive datasets to validate the robustness of the LSTM model over a longer period. Additionally, investigating other advanced machine learning models, such as Transformers or hybrid models, could provide further improvements in forecasting accuracy. Incorporating external factors like climate change, government policies, and global market prices into the models may also enhance their predictive capabilities. Furthermore, optimizing hyperparameters using advanced techniques like Bayesian Optimization and testing the models in real-world inventory management and export-import strategies could provide valuable insights for practical applications. Finally, conducting similar studies in other major CPO-producing countries could help generalize the findings and adapt the models to different conditions.

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DATA AVAILABILITY

The data supporting the findings of this study are openly accessible and can be retrieved using the following link: https://doi.org/10.17632/8smrcwbggx.1. All relevant datasets used and analyzed during the research have been thoroughly documented to ensure transparency and reproducibility.

CONFLICT OF INTEREST STATEMENT

The authors state that they have no conflicts of interest related to the publication of this article. Each author has been involved in the research and manuscript development without any financial, professional, or personal ties that could compromise the integrity of the findings or their interpretation.

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