Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, Number 2, May 2026
https://doi.org/10.47709/brilliance.v6i2.8704

Oil Palm Price Prediction Using Holt-Winters Exponential Smoothing at PT Ivo Mas Tunggal

Christoper Jodi Aman Sinaga[1*], Ari Purno Wahyu Wibowo[2]
[1,2]Widyatama University, Indonesia
[1*]christoper.sinaga@widyatama.ac.id, [2]ari.purno@widyatama.ac.id

open access

***Corresponding Author**

Article History:
Submitted: 30-05-2026
Accepted: 08-06-2026
Published: 26-06-2026

Keywords:
additive model; forecasting; Fresh Fruit Bunch (FFB) price; Holt-Winters Exponential Smoothing; Mean Absolute Percentage Error; time series.

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ABSTRACT

Fluctuations in oil palm Fresh Fruit Bunches (FFB) prices over time have created challenges in planning and decision-making processes within plantation companies, including at Nenggala Plantation of PT Ivo Mas Tunggal. Price instability affects production planning, marketing strategies, and risk management, making accurate forecasting essential for supporting managerial decisions-maing. Therefore, this study aims to predict oil palm Fresh Fruit Bunches (FFB) prices using the Holt-Winters Exponential Smoothing method and compare the performance of additive and multiplicative models. This study applies a time series forecasting using historical oil palm FFB price data from January 2020 to September 2024. The research process includes data preprocessing, splitting the dataset into training and testing sets, and forecasting using additive and multiplicative Holt-Winters models. Model performance was evaluated using Mean Absolute Percentage Error (MAPE). The results showed that the additive Holt-Winters model achieved better forecasting accuracy than the multiplicative model, with a MAPE value of 10.08% compared to 11.98%. The forecasting results also indicated that the additive model was able to follow the historical trend and seasonal patterns of oil palm FFB prices effectively. The Holt-Winters Exponential Smoothing method with an additive approach is effective for predicting palm oil prices and can support production planning and managerial decision-making at the plantation level. Future studies are recommended to incorporate external variables and compare the Holt-Winters method with other forecasting approach to improve prediction performance.

INTRODUCTION

Oil palm is one of the most important plantation commodities in Indonesia, demonstrating strong competitiveness and contributing significantly to national income as well as plantation company (Ardiyanto, Tarigan, Widyastuti, Nugroho, & Rivai, 2026). The stability of oil palm Fresh Fruit Bunches (FFB) prices plays a crucial role in supporting production planning, marketing strategies, and managerial decision-making. However, in practice, oil palm FFB prices tend to fluctuate over time due to various factors such as market demand, supply conditions, and economic dynamics. These fluctuations create uncertainty and make it difficult for companies to determine appropriate strategies, particularly at the operational level.

This phenomenon is also observed at Nenggala Plantation of PT Ivo Mas Tunggal, where historical data indicates that oil palm FFB prices change irregularly from month to month. Such instability directly affects the company's ability to plan production, manage risks, and optimize operational performance. Therefore, the ability to accurately predict price movements becomes essential in order to reduce uncertainty and support more effective decision-making processes.

Several forecasting methods have been applied in previous studies to address similar problems. Methods such as Moving Average and Fuzzy Time Series have been widely used to predict commodity prices. However, these approaches have limitations in capturing seasonal patterns and long-term trends, which are common characteristics of time series data. In contrast, the Holt-Winters Exponential Smoothing method provides a more comprehensive approach by considering level, trend, and seasonal components simultaneously. Previous research conducted by (Rahmadeni, R. and Egianta, 2021) demonstrated that the additive Holt-Winters model achieved good accuracy with a Mean Absolute Percentage Error (MAPE) value of 7.63% in predicting oil palm production in Riau.

Although previous studies have demonstrated the effectiveness of Holt-Winters model in forecasting palm oil-related variables, most studies focused on production forecasting or regional-scale datasets. Limited studies have examined the comparative performance of additive and multiplicative Holt-Winters model using real company-level oil palm FFB price data. Therefore, there remains a gap in understanding which model performs better in handling fluctuating planatation price data for operational decision-making.

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Therefore, this study aims to apply the Holt-Winters Exponential Smoothing method to predict oil palm Fresh Fruit Bunch (FFB) prices at Nenggala Plantation of PT Ivo Mas Tunggal, to compare the performance of additive and multiplicative models and evaluate prediction accuracy using Mean Absolute Percentage Error (MAPE). The contribution of this study lies in providing a data-driven prediction model that can support decision-making at the plantation level, as well as offering empirical insights into the effectiveness of different Holt-Winters approaches in handling fluctuating price data.

LITERATURE REVIEW

A study conducted by Yendra, Rahman, Riyan (Yendra et al., 2025) analyzed the forecasting of oil palm Fresh Fruit Bunches (FFB) prices in Riau Province using the Holt-Winters Exponential Smoothing method. The study demonstrated that the Holt-Winters method was capable of capturing both trend and seasonal patterns in time series data, resulting in relatively accurate forecasting performance. Furthermore, the comparison between additive and multiplicative models indicated that the multiplicative model achieved slightly better accuracy based on Mean Absolute Error (MAE), making it more suitable for datasets with varying seasonal patterns.

Research conducted by Al-Khowarizmi, Syah, Nasution, and Elveny (Al-Khowarizmi, Syah, Nasution, & Elveny, 2021) discussed forecasting Crude Palm Oil (CPO) prices using the K-Nearest Neighbor (K-NN) method. The study aimed to measure the sensitivity of Mean Absolute Percentage Error (MAPE) by combining it with the Detection Rate (DR) approach. The dataset used consisted of global CPO price data from January 2010 to August 2020, with a total of 2,365 data points divided into 2,200 training data and 165 testing data. The result showed that the K-NN method achieved a MAPE value of 0.013526%, while the MAPE sensitivity combined with Detection Rate produced a value of 0.000361%. These findings indicate that the combination of MAPE and Detection Rate provides a very high level of forecasting accuracy.

In addition, Peng, Zhang, and Tian (Peng, Zhang, & Tian, 2023) analyzed crude oil price forecasting using a hybrid approach combined Variational Mode Decomposition (VMD) and deep learning models. The results showed that the proposed model effectively handled complex and non-stationary time series data, achieving higher forecasting accuracy compared to traditional methods such as ARIMA, SARIMA, and Holt-Winters Exponential Smoothing. Similarly, Jayanth and Manimaran (Jayanth & Manimaran, 2024) proposed a hybrid forecasting model that integrates Double Exponential Smoothing with a Dual Attention Encoder-Decoder based Bi-GRU enhanced by Bayesian Optimization. Their findings showed that combining traditional time series methods with deep learning techniques significantly improved forecasting accuracy and better captured complex data patterns.

Moreover, Sabri, Khalid, Azam, and Sarmidi (Sabri, Khalid, Azam, & Sarmidi, 2022) examined the impact of external shocks on Malaysian crude palm oil (CPO) prices using the Structural Vector Autoregressive (SVAR) method. The study revealed that palm oil prices were highly influenced by external factors such as economic uncertainty and global crises, including the COVID-19 pandemic. The findings indicated that external variables contribute more significantly than internal factors in explaining price fluctuations, highlighting the importance of incorporating external factors into forecasting models.

Furthermore, Handika and Satwika (I Putu Susila Handika & I Kadek Susila Satwika, 2023) proposed an enhancement to the Holt-Winters Exponential Smoothing method by integrating Modified Improves Particle Swarm Optimization (MIPSO) to determine the optimal values of smoothing parameters, namely alpha (α), beta (β), and gamma (γ). The results showed that the optimized model achieved better computational efficiency compared to manual parameter tuning.

Trull, Gracia-Diaz, and Troncoso (Trull, García-Díaz, & Troncoso, 2020) investigated the initialization methods for multiple seasonal Holt-Winters forecasting models and highlighted that forecasting accuracy is highly dependent on proper initialization of level, trend, and seasonal components. The study proposed several initialization techniques designed for multiple seasonal patterns and demonstrated that appropriate initialization significantly improves model performance, particularly in models with additive trends.

Theoretical Foundation

Prediction

Prediction and forecasting methods are approaches used to estimate future values by analyzing historical data patterns and supporting decision-making processes (Dewi, Nurwati, & Rahayu, 2022). Prediction is a process used to estimate future conditions by analyzing historical data patterns to support decision-making. The purpose of prediction is not to provide absolute certainty bur to generate estimates that are as close as possible to future outcomes (Ainiyah & Bansori, 2021).

Prediction is a process of systematically estimating events that are most likely to occur in the future based on past information and current conditions, with the aim of minimizing the error between predicted results and actual outcomes. Prediction does not aim to provide absolute certainty, but rather to produce estimates that are as close as possible to future conditions (Roza, Fauzan, & Rahayu, 2020).

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In general, prediction has a similar meaning to forecasting or estimation. According to the Kamus Besar Bahasa Indonesia (KBBI), prediction is the results of an activity that estimates or forecasts future value using historical data (Roza et al., 2020). Prediction can be carried out using scientific approaches or subjective judgment, depending on the context and the problem being addressed. The benefits of prediction include understanding future conditions, supporting planning activities in areas such as production, marketing, finance, and other business sectors, as well as assisting companies in making investment decisions (Woro Isti Rahayu, 2020).

Oil Palm Prices

Oil palm prices, particularly in the form of Fresh Fruit Bunches (FFB), are an important indicator in determining farmers' income levels and the performance of the oil palm plantation industry. These prices are dynamic in nature and tend to fluctuate over time due to various factors, such as the price of Crude Palm Oil (CPO), global market demand, as well as weather conditions and production levels (Yendra et al., 2025).

Holt-Winters Exponential Smoothing

Holt-Winters Exponential Smoothing is a time series forecasting method that extends simple exponential smoothing by incorporating both trend and seasonal components. This method is particularly effective for data that exhibit systematic trends along with recurring seasonal patterns. It can be implemented in either additive or multiplicative forms, depending on whether the seasonal variations remain constant or change proportionally with the level of the series (Devanathan, Varshitha, Kumar, Lakshmanan, & Prakash, 2025).

Seasonal exponential smoothing in the Holt-Winters method can be applied in two forms namely additive and multiplicative. This approach is commonly referred to as the seasonal exponential smoothing strategy. The selection of the appropriate model depends on the characteristics of the seasonal pattern in the data, specifically whether the seasonal fluctuations remain relatively constant over time (additive) or vary proportionally with the level of the series (multiplicative). Therefore, the choice of model is determined based on the nature of seasonal variation present in the data (Taksana, Janjamraj, Romphochai, Bhumkittipich, & Mithulananthan, 2024).

The Holt-Winters method is an extension of the Holt exponential smoothing approach designed to incorporate seasonal component. This method consists of two forms, namely the additive and multiplicative models. The multiplicative model is applied when the magnitude of seasonal variations changes proportionally with the level of the data (Yendra et al., 2025).

- Multiplicative Seasonality

  The Holt-Winters method is applied when the plotted data exhibit fluctuating seasonal patterns. The corresponding equations are presented as follows (Yendra et al., 2025):

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(Lt-1+b_{t-1}) \quad (1)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-y)S_{t-s} \quad (3)$$

$$F_{t+m} = (L_t + B_t m)S_{t-s+m} \quad (4)$$

- Additive Seasonality

  The additive seasonal form of the Holt-Winters method is used when the original data exhibit relatively constant seasonal fluctuations. The corresponding equations for the additive model are presented as follows (Yendra et al., 2025):

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (5)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (6)$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \quad (7)$$

$$F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (8)$$

Description:

L_t = Level estimate of the data set at time t
L_{t-1} = Level estimate of the data set at time t – 1
b_t = Estimated trend of the data set at time t
b_{t-1} = Estimated trend of the data set at time t – 1
S_t = Seasonal estimate of the data series at time t
S_{t-s} = Seasonal estimate of the data series at time t – s
Y_t = Actual data at period t
S = Number of periods in one season cycle
t = Time period
m = Number of future periods to be forecasted
S_{t-s+m} = Seasonal estimate of the data series at time t – s + m

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F_{t+m} = Forecast Value at time t + m
α = Level smoothing parameter (0 < α < 1)
β = Trend smoothing parameter (0 < β < 1)
γ = Seasonal smoothing parameter (0 < γ < 1)

Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a widely used evaluation metric that measures the accuracy of forecasting models by calculating the average percentage difference between actual observations and predicted values, making it scale-invariant and independent of measurement units. It is calculated as the average of absolute percentage error. As an evaluation metric, a lower MAPE value indicates better forecasting performance, meaning that the model produces more accurate predictions (Safi & Sanusi, 2021). Mean Absolute Percentage Error (MAPE) is a commonly used metric to evaluate forecasting accuracy by measuring the average absolute percentage deviation between actual and predicted values. Its percentage-based representation makes it easy to interpret and enables comparison across dataset with different scales (Andi et al., 2026).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Y_t - F_t}{Y_t} \right| x\ 100\% \quad (9)$$

Description:
Y_t = Actual value at time t
F_t = Forecast value at time t
n = Number of observations

METHOD

Problem Identification

The price of oil palm Fresh Fruit Bunches (FFB) at Nenggala plantation of PT Ivo Mas Tunggal exhibits significant fluctuations over time. These fluctuations create challenges in planning production, determining marketing strategies, and supporting managerial decision-making. Therefore, an appropriate forecasting method is required to predict future price movements accurately.

To address this problem, this study applies the Holt-Winters Exponential Smoothing method, which is capable of capturing both trend and seasonal patterns in time series data. The performance of the model is evaluated using Mean Absolute Percentage Error (MAPE) to determine the level of prediction accuracy.

The research procedure began with problem identification, followed by data collection and processing. Subsequently, the dataset was divided inti training and testing data. The Holt-Winters Exponential Smoothing model was then implemented using both additive and multiplicative approaches. Finally, forecasting results were evaluated using MAPE to determine the most accurate model. The overall research procedure used in this study is presented in Figure 1 to provide a clear overview of the forecasting process.

Data Collection

The data used in this study are secondary data obtained from Nenggala plantation of PT Ivo Mas Tunggal. The dataset consists of monthly oil palm FFB prices from January 2020 to September 2024. Each data record includes the time period (year and month) and the corresponding price value (Rp/Kg).

Data Preprocessing

Data preprocessing is performed to ensure data quality before modeling. The preprocessing steps include:

- Data Cleaning
  Converting price data into numerical format and removing unnecessary characters such as commas or spaces.
- Handling Missing Values
  Missing value are handled using imputation techniques such as replacing with the mean or using previous values to maintain data continuity.
- Time Series Transformation
  The dataset is transformed into a time series format by indexing the data based on chronological order (month and year).

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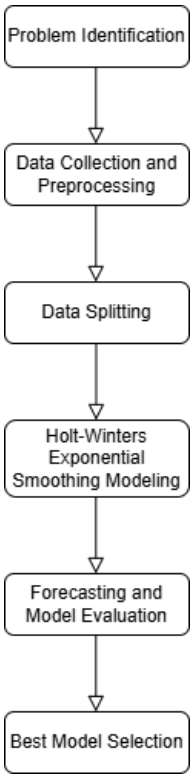

Figure 1. Research Flow Diagram

Data Splitting

The dataset is divided into two parts: training data and testing data. The training data (80%) is used to build the model, while the testing data (20%) is used to evaluate the model performance. The data splitting is performed sequentially without randomization to preserve the time series structure.

Holt-Winters Exponential Smoothing Model

This study applies the Holt-Winters Exponential Smoothing method, which consists of three main components: level, trend, and seasonal. Two types of models are used:

- Additive Model
  Used when seasonal variations remain constant over time.
- Multiplicative Model
  Used when seasonal variations change proportionally with the data level.

The smoothing parameters α (alpha), β (beta), and γ (gamma) are automatically optimized to obtain the best model performance.

Model Evaluation

The accuracy of the forecasting model is evaluated using Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Y_t - F_t}{Y_t} \right| x\ 100\% \qquad (10)$$

A lower MAPE value indicates better prediction accuracy. The model with the smallest MAPE value is selected as the best model for forecasting oil palm prices.

RESULT

The dataset used in this study consists of monthly oil palm Fresh Fruit Bunches (FFB) prices obtained from Nenggala plantation PT Ivo Mas Tunggal from January 2020 to September 2024. Historical price data were transformed into time series format and analyzed to identify trends and seasonal patterns before the forecasting process was conducted. Figure 1 illustrates the historical movement of oil palm FFB prices during the observation period.

Based on Figure 2, oil palm prices exhibited fluctuating movements over time with noticeable trend and seasonal characteristics. The existence of these patterns indicates that the Holt-Winters Exponential Smoothing method is appropriate for modeling and forecasting the dataset.

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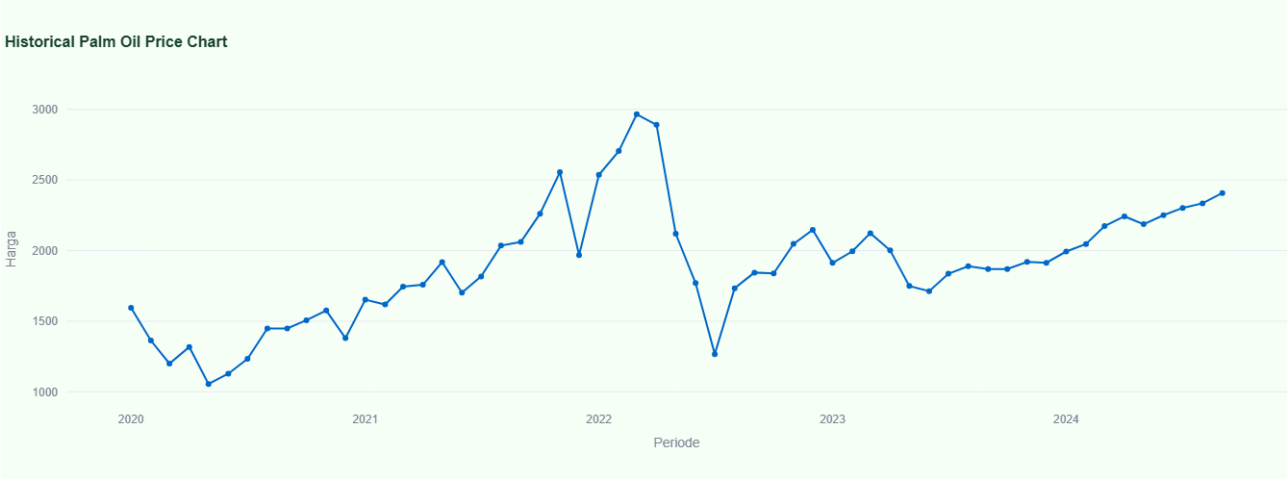

Figure 2. Historical Oil Palm FFB Price Trends

As shown in Figure 3, the forecasting results generally followed the overall movement pattern of the actual oil palm FFB prices. The predicted values successfully captured the upward and downward trends observed in the historical dataset. Although slight differences between actual and predicted values occurred in several periods, the forecasting model was able to maintain relatively close predictions. These deviations may be influenced by sudden market changes and price volatility that cannot be fully captured by historical patterns alone.

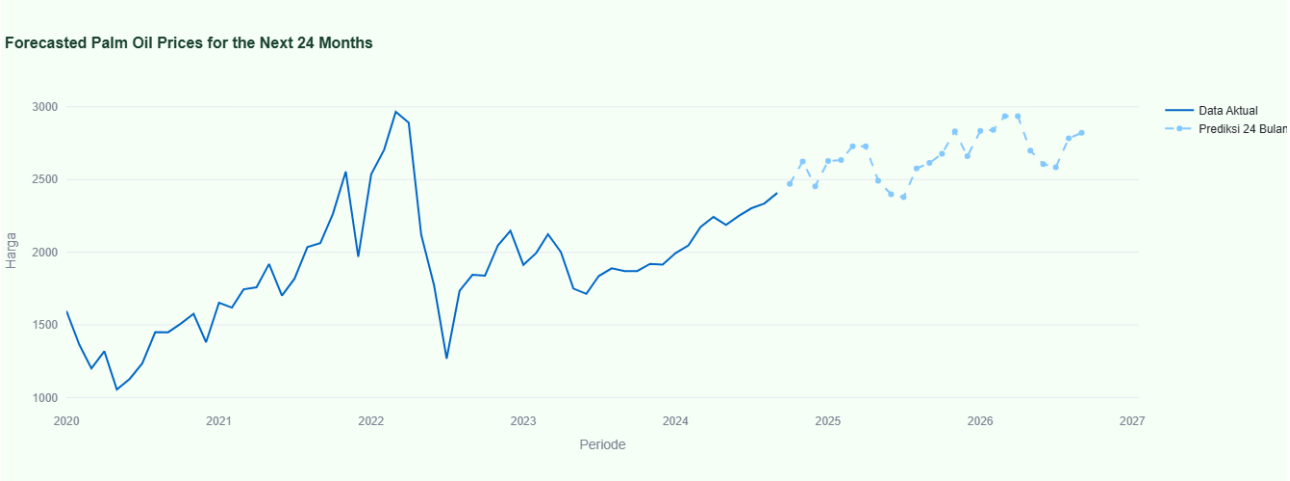

Figure 3. Comparison between actual and forecasted oil palm prices using the Holt-Winters model.

To quantitatively assess forecasting performance, the prediction results were evaluated using Mean Absolute Percentage Error (MAPE). MAPE was used because it expresses prediction errors in percentage form, making the results easier to interpret and compare across different forecasting models. The comparison of forecasting accuracy for both models is presented in Table 1.

Table 1. Comparison of forecasting accuracy using MAPE

Model	MAPE
Additive Model	10.08%
Multiplicative Model	11.98%

Based on the evaluation results, the Holt-Winters Additive model achieved a lower MAPE value of 10.08% compared to the Multiplicative model, which obtained a MAPE value of 11.98%. Since lower MAPE values indicate higher forecasting accuracy, the additive model demonstrated superior performance for predicting oil palm FFB prices in this study. These findings suggest that the seasonal variations in the dataset tend to remain relatively stable over time, making the additive approach more suitable than the multiplicative approach. Therefore, the Holt-Winters Additive model was identified as the most appropriate forecasting model for the oil palm price dataset used in this research.

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DISCUSSION

Based on the result of this study, the Holt-Winters Exponential Smoothing method was able to forecast oil palm Fresh Fruit Bunches (FFB) prices by effectively capturing both trend and seasonal patterns contained in the historical data. The evaluation results indicated that the additive model achieved a lower MAPE value compared to the multiplicative model, suggesting better forecasting performance for the dataset used in this study. This findings indicates that the seasonal fluctuations in oil palm FFB prices tend to remain relatively constant over time rather than increasing proportionally with the data level. Therefore, the additive model was more appropriate for representing the characteristics of the observed dataset.

The forecasting graph shown in Figure 2 demonstrates that the predicted values generally followed the movement pattern of the actual data. Although some deviations occurred during several periods due to price fluctuations, the forecasting model was still capable of maintaining the overall trend pattern of oil palm prices. This result suggests that the Holt-Winters method can provide relatively stable forecasting performance for seasonal time series data. The ability of the model to capture trend and seasonality simultaneously contributes to reducing prediction errors and improving forecasting reliability. Therefore, the implementation of forecasting techniques in this study can assist management in understanding future oil palm price movements more effectively.

Compared to previous studies, the findings of this research are consistent with the study conducted by (Yendra et al., 2025), which reported that the Holt-Winters method was effective in forecasting oil palm prices with seasonal patterns. Similarly, (Trull et al., 2020), explained that proper handling of seasonal components in Holt-Winters models can improve forecasting accuracy. In addition, compared to more complex forecasting approaches such as hybrid deep learning and ARIMA-based model proposed by (Peng et al., 2023), the Holt-Winters method used in this study provides a simpler forecasting process while still producing relatively good prediction accuracy.

The forecasting results generated in this study can support production planning, marketing strategies, and managerial decision-making at plantation Nenggala PT Ivo Mas Tunggal. By understanding future price trends, management can prepare more appropriate operational strategies and reduce uncertainty caused by oil palm price fluctuations. Furthermore, the graphical visualization of forecasting results makes the prediction output easier to understand by management and stakeholders.

However, this study still has several limitations. The forecasting process only used historical oil palm price data without considering external factors such as weather conditions, export demand, inflation, exchange rates, or global economic conditions that may influence oil palm price fluctuations. In addition, the dataset used in this study was limited to compare the Holt-Winters method with other forecasting methods such as ARIMA, LSTM, or hybrid forecasting models in order to obtain more comprehensive forecasting performance results.

CONCLUSION

Based on the results and discussion of this study, it can be concluded that the Holt-Winters Exponential Smoothing method was successfully implemented to forecast oil palm Fresh Fruit Bunches (FFB) prices at Nenggala plantation PT Ivo Mas Tunggal. The findings showed that the additive model achieved better forecasting performance than the multiplicative model, producing a lower Mean Absolute Percentage Error (MAPE) value of 10.08%. This result indicates that the seasonal variations within the dataset tend to remain relatively constant over time, making the additive approach more suitable for forecasting oil palm price data. Furthermore, the forecasting model was able to effectively capture the trend and seasonal characteristics contained in the historical dataset.

The contribution of this study lies in demonstrating the applicability of the Holt-Winters Exponential Smoothing method for company-level oil palm price forecasting using real plantation data. In addition, this study provides empirical evidence regarding the comparative performance of additive and multiplicative Holt-Winters models in handling fluctuating oil palm price data. The forecasting results generated in this study can support production planning, marketing strategies, and managerial decision-making processes related to oil palm price fluctuations.

This study has several limitations because the forecasting process only considered historical price data and did not include external variables such as weather conditions, inflation rates, export demand, exchange rates, and global economic factors. Therefore, future studies are recommended to incorporate additional variables and compare the Holt-Winters method with other forecasting approaches such as ARIMA, LSTM, or hybrid forecasting models to obtain more comprehensive forecasting performance results.

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