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Performance Evaluation of ARIMA and ANN Models for Forecasting Oil Palm Production Trends

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Abstract: This study compares the performance of the Autoregressive Integrated Moving Average (ARIMA) model and an Artificial Neural Network (ANN) in forecasting annual palm oil production in Kampar Regency, using a univariate time series covering the period from 2013 to 2024. The forecasting aim is to support regional agricultural planning and decision-making in one of Riau Province's key oil palm-producing regions. The ARIMA model was developed using the Box–Jenkins approach, which involves stationarity testing, optimal model identification, parameter estimation, and residual diagnostics, including ACF/PACF, Shapiro–Wilk, Jarque–Bera, and Ljung–Box tests. A feedforward ANN with three lagged inputs, five hidden neurons, sigmoid activation, and backpropagation training was constructed for comparison. Model performance was evaluated using RMSE, MAPE, and R^2. The results indicate that the ARIMA (1,1,1) model yields more stable and reliable forecasts, with diagnostic tests confirming white noise residuals and no significant autocorrelation. Conversely, the ANN model produced higher errors and indications of overfitting, likely due to the limited number of observations and the sharp increase in production recorded in the final data year. While ANN captured a stronger upward trend, which may represent an optimistic scenario, ARIMA provided more conservative and statistically valid forecasts under constrained data conditions. Overall, the ARIMA(1,1,1) model proved more suitable for the short univariate palm oil production series, yielding lower forecasting errors (RMSE = 273.88; MAPE = 8.92%) than the ANN model (RMSE = 283.53; MAPE = 9.03%).

Keywords: ARIMA; Artificial Neural Network; forecasting; palm oil production; time series

1. INTRODUCTION

Palm oil (*Elaeis guineensis* Jacq.) is one of the most important plantation commodities supporting Indonesia's national economy, with Riau Province consistently recognized as the country's leading producer. Within Riau, Kampar Regency plays a strategic role due to its extensive plantation area and strong contribution to regional palm oil output. Accurate forecasting of palm oil production in Kampar is essential for guiding policy formulation, supply chain planning, and sustainable plantation management. However, production is strongly influenced by multiple agronomic and environmental parameters, such as rainfall, soil type, temperature, and water availability, which exhibit nonlinear relationships that are often difficult to capture using traditional statistical approaches.

Artificial Neural Networks (ANN) have emerged as a powerful tool for modeling complex nonlinear patterns in agricultural systems. Prior studies in Riau Province demonstrated ANN's strong predictive capability. Syarovy et al. (2022) reported a Mean Absolute Percentage Error (MAPE) of 10.52% with a correlation coefficient of 0.96, while (Ismanto et al., 2018) achieved an accuracy level of 99.97% for palm oil production prediction. These findings validate ANN's potential effectiveness for yield forecasting under diverse agroecological conditions. Commonly used predictive inputs include plantation area, total production, productivity, export volume, and climatic variables such as rainfall and temperature.

Environmental factors relevant to palm oil growth have also been well-studied. Hermantoro & Rudyanto (2018) emphasized that soil type, altitude, rainfall, temperature, and water deficit significantly affect palm oil yield, reinforcing the need for prediction models that incorporate climate-sensitive variables. Additional ANN architectures further demonstrate the method's flexibility: the NARX model achieved a correlation coefficient of 0.84 Harahap & Lubis (2018), while other configurations, such as networks with 11 input neurons and 3 hidden neurons, reported R^2 values as high as 0.98 (Hermantoro, 2009). Backpropagation-based ANN models have delivered strong performance, including mean square error (MSE) values as low as 0.0135873 (Akbar et al., 2025).

Beyond predictive performance, ANN-based systems have also been extended into operational tools. Putra & Harahap (2025) demonstrated the usefulness of real-time web-based monitoring systems for decision support in palm oil production, highlighting the practical applications of machine learning for plantation management. Accurate production forecasting can also support sustainability initiatives by helping producers anticipate environmental fluctuations and optimize resource use.

Although previous research provides robust evidence that ANN is effective for palm oil production forecasting at the provincial and national levels, no study has specifically focused on Kampar Regency, despite its status as one of Riau's most productive palm oil regions. Because palm oil productivity in Kampar is uniquely shaped by local microclimate, soil characteristics, plantation structure, and production practices, a regency-level ANN model is critically needed. Addressing this gap would enable more accurate production forecasting and support localized decision-making, ultimately improving the effectiveness of both government policies and private plantation management.

In addition to machine-learning approaches, classical statistical models such as the Autoregressive Integrated Moving Average (ARIMA) have long been used in agricultural time-series forecasting. ARIMA is particularly effective for modeling linear temporal patterns and short-term dependencies in production data. Several studies have shown that ARIMA can perform well when the time series is relatively stable or dominated by linear trends and seasonal components. For example, ARIMA models have been successfully applied in forecasting rice production, cocoa yields, and other commodity outputs under conditions where noise and fluctuations follow predictable temporal structures. However, ARIMA's performance tends to decline when the underlying data exhibit strong nonlinearities, abrupt changes, or interactions with external variables such as rainfall or temperature, conditions typical of palm oil production in tropical climates.

Comparative studies between ARIMA and ANN in the agricultural sector demonstrate a consistent pattern: ARIMA often provides reliable baseline forecasts, while ANN generally outperforms ARIMA when nonlinear environmental factors play a substantial role. Incorporating ARIMA into this study therefore provides an essential benchmark for evaluating whether the nonlinear learning capability of ANN offers significant advantages for forecasting palm oil production at the regency level.

To address this gap, the present study develops an Artificial Neural Network (ANN) model to predict palm oil production in Kampar Regency using ten years of historical data from BPS (2013–2024). Two modeling approaches; Artificial Neural Networks (ANN) and ARIMA, are implemented to evaluate their respective predictive performance. This study employs a univariate time-series approach using annual palm oil production as the sole input variable. Although factors such as plantation area, number of productive trees, and annual rainfall are known to influence palm oil yield, they were not incorporated into the models due to data availability constraints and the study's focus on evaluating the forecasting performance of ANN and ARIMA under limited information conditions.

2. METHOD

This study was conducted in Kampar Regency using secondary data from the Central Bureau of Statistics (BPS) of Riau and Kampar for the period 2013–2024 (BPS, 2025). The dataset used in this study comprised annual palm oil production (tons/year) as the sole variable of analysis. As the modeling focused exclusively on a univariate time series, no normalization procedures such as Min–Max scaling were applied.

2.1 ARIMA Modeling (Tunnicliffe Wilson, 2016)

The ARIMA model was developed using the Box-Jenkins methodology:

a. Stationarity check: First differencing achieved stationarity.
b. Model selection: Based on ACF and PACF patterns, ARIMA(1,1,1) was identified as optimal.
c. Parameter estimation: Maximum likelihood estimation was used.
d. Diagnostic checking:
    - ACF/PACF of residuals
    - Shapiro–Wilk and Jarque–Bera tests for normality
    - Ljung–Box test for autocorrelation

2.2 ANN Modeling (Dawson, 2018)

A feedforward Artificial Neural Network (ANN) was employed to model and forecast annual palm oil production using a univariate time-series approach. Due to the limited number of observations (12 annual data points from 2013 to 2024), a simple hold-out data partitioning strategy was adopted. Approximately 75% of the data (2013–2021) were used for model training, while the remaining 25% (2022–2024) were reserved for testing. A separate validation dataset was not employed in order to avoid excessive data fragmentation and instability during training. The ANN architecture consisted of three lagged production values as input neurons, a single hidden layer with five neurons, and a linear output layer. Sigmoid activation functions were applied in the hidden layer, and the network was trained using the backpropagation algorithm. Model performance was evaluated on the test set using RMSE and MAPE, allowing direct comparison with the ARIMA model under identical univariate data conditions.

A feedforward neural network was developed using:

a. Input: 3 lagged observations
b. Hidden layer: 5 neurons
c. Activation: sigmoid
d. Output layer: linear
e. Training: backpropagation

2.3 Forecasting Evaluation Metrics (Ali et al., 2020)

The predictive performance of both ANN and ARIMA models was assessed using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Lower RMSE and MAPE values and higher R^2 indicate better forecasting accuracy. A comparative analysis between ANN and ARIMA was then conducted to determine the most suitable method for forecasting palm oil production in Kampar Regency.

a. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{t=1}^{n} \lceil y_t - \hat{y}_t \rceil$$

Description:
n = number of observations
y_t = actual value at time t
$\hat{y}$ = forecasted value at time t

b. Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2$$

Description:
n = number of observations
y_t = actual value
$\hat{y}$ = predicted value

c. Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{MSE}$$

Description:
RMSE is the square root of MSE
- It provides an error measure in the same unit as the original data
- Lower RMSE values indicate better predictive accuracy.

3. RESULT AND DISCUSSION

3.1 Forecast Results of ARIMA and ANN Models

Table 1 shows the forecasted values for 2025–2027 derived from two different models: ARIMA(1,1,1) and a feed-forward Artificial Neural Network (ANN).

Table 1. Backtesting Result (2022–2024)

Year	Actual	ARIMA(1,1,1) Prediction	ANN Prediction
2022	2758.8	2828.21	2874.94
2023	2466.0	2852.52	2924.12
2024	3104.0	2837.89	2970.59

Prior to generating future forecasts, a backtesting procedure was conducted using production data from 2022 to 2024. Table 1 compares the actual production values with the predictions generated by the ARIMA and ANN models. The ARIMA model produced more conservative and stable estimates, while the ANN model tended to overestimate production, reflecting its sensitivity to recent fluctuations. Based on the backtesting performance shown in Table 1, future forecasts for the period 2025–2027 were generated using both models and are presented in Table 2.

Table 2. Forecasted Values (2025–2027)

Year	ARIMA(1,1,1) Forecast	ANN Forcast
2025	2543.51	3251.42
2026	2888.55	3502.98
2027	2676.14	3754.54

Based on the backtesting period from 2022 to 2024, the ARIMA(1,1,1) model achieved a lower forecasting error, with an RMSE of 273.88 and a MAPE of 8.92%, compared to the ANN model, which produced an RMSE of 283.53 and a MAPE of 9.03%. These results quantitatively demonstrate that ARIMA provides slightly more accurate and stable forecasts than ANN for short univariate annual production data.

The ARIMA model predicts a modest increase in 2026 after a dip in 2025, followed by a slight decline in 2027; whereas the ANN model projects a steady and substantial upward trend across the three-year horizon.

From the ANN projection, the value in 2027 is predicted to reach ~ 3754.5, which is substantially higher compared to the ARIMA projection of ~ 2676.1, indicating that the ANN "learned" a stronger upward trajectory, likely influenced by the spike in the last observed data (2024 = 3104.0).

Table 3. Forecast Accuracy Based on Backtesting

Model	RMSE	MAPE (%)
ARIMA(1,1,1)	273.88	8.92
ANN	283.53	9.03

Based on the backtesting period from 2022 to 2024, the ARIMA(1,1,1) model achieved a lower forecasting error, with an RMSE of 273.88 and a MAPE of 8.92%, compared to the ANN model, which produced an RMSE of 283.53 and a MAPE of 9.03%. These results quantitatively demonstrate that ARIMA provides slightly more accurate and stable forecasts than ANN for short univariate annual production data.

3.2 Interpretation and Comparative Assessment

3.2.1 Suitability for Annual Time Series Data

Given the relatively short length of the time series (12 data points, 2013–2024), the classical ARIMA model appears more robust. The ARIMA(1,1,1) model effectively captures the linear trend and short-term autocorrelation structure, and in diagnostic checks (residual behavior, autocorrelation tests) it meets the assumptions of a valid time series model. This suggests it is suitable for producing conservative and stable forecasts, especially when data is limited.

The ARIMA(1,1,1) model has been widely demonstrated to effectively capture linear trends and short-term autocorrelation structures, with numerous studies confirming its robustness across various time-series applications. Rahma & Dahda (2024) identified ARIMA(1,1,1) as the most accurate model for demand forecasting, producing the lowest error rates, while Wahyudi (2017) similarly selected the same model for stock price prediction based on rigorous statistical criteria such as Adjusted R-squared and the Akaike Information Criterion. Furthermore, Rakhmawati et al. (2022) showed its capability in managing complex financial data characterized by trends and non-stationarity. Its consistent ability to pass diagnostic evaluations, including residual analysis and autocorrelation tests, further strengthens the evidence that ARIMA(1,1,1) satisfies the assumptions of a valid and reliable time-series forecasting model (Mardesci et al., 2023).

In contrast, the ANN model, despite its flexibility and ability to model nonlinearities, may be less appropriate for such a small dataset. The strong upward forecast by ANN likely reflects over-fitting to the recent large jump (Micheal & Bolarinwa, 2025), rather than a stable underlying long-term pattern. In time series with limited observations, neural-network forecasts may overreact to recent outliers or volatility.

3.2.2 Implications of Divergent Forecasts

The divergence between ARIMA and ANN forecasts has practical implications:

- If used for decision-making under uncertainty and risk aversion (e.g. budgeting, planning, supply projections), the ARIMA forecast might be more reliable due to its conservative nature.
- If the objective is to anticipate optimistic growth scenarios or stress-test against high-growth conditions, the ANN forecast may serve as an upper-bound scenario, albeit with higher uncertainty.

However, decision makers should be cautious using the ANN forecast as a baseline, especially in cases where external shocks or structural breaks (e.g. policy change, environmental disruptions, market shifts) are possible. The steep growth predicted by ANN may not materialize if such conditions are not met (Aser & Firuzan, 2022; Micheal & Bolarinwa, 2025; Nikopoulus, 2010).

3.2.3 Limitations and Considerations

- The small sample size (annual data, only 12 points) limits the capacity of ANN to generalize robustly. Typically, neural networks perform better with larger datasets (many observations) to learn complex patterns.
- The ARIMA model assumes linear relationships and may miss any latent nonlinear dynamics; but given the data behavior and diagnostics, linear assumption appears acceptable.
- The ANN forecasts tend to be overly optimistic due to overfitting, which is primarily attributed to model overparameterization. With three lagged inputs and five hidden neurons, the ANN contains a relatively large number of trainable weights compared to the limited dataset of only 12 annual observations. This imbalance restricts the network's ability to generalize and causes the model to fit noise rather than the underlying production pattern. Consequently, the sharp increase observed in the final year disproportionately influences the network's weights, leading to upward-biased forecasts. .

Given these limitations, the ARIMA model is preferred for its statistical validity and conservative forecast; the ANN forecast can be considered as a supplementary scenario (Izudin et al., 2021; Khashei & Bijari, 2011; Velasco et al., 2019).

3.3 Recommendation for Future Use and Research

The comparative analysis indicates that the ARIMA(1,1,1) model provides more stable and accurate forecasts than the ANN model when applied to a short univariate annual production series. As demonstrated in the backtesting results (Table 1), the ANN model exhibits larger deviations between actual and predicted values, particularly in response to the sharp increase observed in the final year. This behavior reflects the model's sensitivity to limited data and its tendency toward overfitting due to overparameterization.

Therefore, for practical short-term forcasting and regional-level planning under data-scarce conditions, traditional time-series models such as ARIMA are recommended. However, future research should aim to enrich the dataset by extending the time span, increasing observation frequency, or incorporating additional explanatory variables (e.g., plantation area, productive tree count, and climatic factors). Such improvements would enhance the generalization capability of machine-learning models and allow ANN-based approaches to fully capture the underlying production dynamics.

4. CONCLUSIONS

This study demonstrates that the ARIMA(1,1,1) model outperforms the ANN model in forecasting annual palm oil production in Kampar Regency using a short univariate time series. ARIMA produced lower forecast errors and passed all diagnostic checks, confirming its suitability for modeling linear patterns in limited datasets. The ANN model, while capable of capturing nonlinear behavior, showed evidence of overfitting and produced less stable predictions due to the small number of observations. These findings indicate that ARIMA is more appropriate for baseline forecasting in regions with limited historical data, whereas ANN may require larger datasets or additional explanatory variables to perform effectively. Future research should explore longer time series, incorporate climatic and agronomic variables, and examine hybrid ARIMA–ANN approaches to enhance forecasting accuracy.

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