

Analysis of Red Bird's Eye Chili Price Dynamics in Surabaya Using an Optuna-Optimized ARIMA-LightGBM Model

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Article Info

Article history:

Received 2026-08-06

Revised 2026-09-11

Accepted 2026-10-05

Keyword:

ARIMA,
LightGBM,
Optuna, Prediction,
Red bird's eye chili.

ABSTRACT

Red bird's eye chili is one of the food commodities widely needed by the community and tends to experience price fluctuations. This situation can create difficulties for consumers, traders, and food business operators in planning purchases. This is due to rapid price fluctuations, which may delays the chili purchases while prices remain unstable. In Surabaya, high demand and limited local production contribute to price variability. This study aims to predict red bird's eye chili prices in Surabaya for a short-term horizon of 14 days by applying a hybrid ARIMA-LightGBM model optimized with Optuna. The data used in this study are historical red bird's eye chili price data from Genteng Market and Keputran Market. ARIMA is used to capture linear patterns in time series data, while LightGBM is applied to model the residual patterns that cannot be fully explained by ARIMA. Optuna optimization is used to obtain optimal hyperparameter configuration. The evaluation results showed that the Optuna-optimized ARIMA-LightGBM model achieved the lowest forecasting errors among the evaluated models. The model obtained a MAPE of 22.84% for Genteng Market and 23.55% for Keputran Market. The comparison with Seasonal Naive, ARIMA, and ARIMA-LightGBM without optimization demonstrated that the hybrid ARIMA-LightGBM model with Optuna optimization provides improved prediction performance for short term red bird's eye chili price prediction.



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I. INTRODUCTION

Agriculture remains important to Indonesia's economy and food supply, with its contribution to gross domestic product increasing from 9.52% in 2024 to 10.31% in 2025. Horticulture forms part of this sector through the production of vegetables, fruits, flowers, and ornamental plants [1]. Red bird's eye chili is one of the horticultural commodities widely consumed by households and food businesses. Its distinctive pungency is mainly associated with capsaicin, which also supports its use beyond daily food consumption. Therefore, it's availability and price affect not only household consumption but also traders and culinary businesses [2].

East Java contributed around 36.4% of the national output and became the largest producing province. However, the high production at the provincial level does not necessarily ensure sufficient local supply in Surabaya. The city requires approximately 4692 tons of red bird's eye chili annually,

while its local production is only about 42.9 tons [3]. This substantial gap indicates that Surabaya relies heavily on supplies distributed from other producing regions.

Red bird's eye chili prices experience fluctuations due to variations in production patterns and market demand. The seasonal nature of chili production may also lead to changes in price levels over different periods [4]. During 2025, the price decreased from approximately IDR 64000/kg to IDR 54000/kg in January before increasing to about IDR 79000/kg by the end of February. Prices also fell to around IDR 20000-30000/kg in November and rose again in December. These movements illustrate the high variability of red bird's eye chili prices in Surabaya. Therefore, an approach that can provide information about future price movements is needed to support anticipation of price changes [5].

Prediction can be used to provide early information on possible future price movements based on historical data. The resulting information may support transaction timing,

expenditure planning, inventory management, and distribution strategies [6]. Therefore, an appropriate prediction approach is needed to analyse the characteristics of red bird's eye chili prices in Surabaya.

Previous studies have applied different approaches to related prediction problems. Az-Zahra and Voutama used Single Moving Average (SMA) to predict daily red bird's eye chili prices in Bekasi Regency and produced the lowest Mean Absolute Error (MAE) of IDR 1781.22 [7]. However, the study only compared different SMA window size and did not examine whether a more adaptive approach such as a hybrid model.

Price movements in time-series data may contain patterns that cannot be represented adequately by a single forecasting method. Statistical models can describe temporal structures based on historical observations, whereas machine-learning models can learn more complex relationships from the remaining prediction errors. Combining both approaches allows one model to provide the initial forecast and another to correct the patterns that have not been captured. This approach was applied by Ma and Li through an ARIMA-LightGBM model for predicting handling complexity at automated terminals. ARIMA was used to produce the initial forecast, while LightGBM modelled the residuals generated by ARIMA. The hybrid model produced lower RMSE values than the other models across the evaluated characteristics [8].

The performance of LightGBM is influenced by the configuration of its hyperparameters. An unsuitable configuration may limit the model's ability to learn residual patterns, while manual selection requires repeated experiments. Optuna provides an automatic optimization process that searches for promising parameter combinations more efficiently. Wishnuwardana et al. applied Optuna to optimize LightGBM for identifying the most suitable solvent component in an acid gas removal unit. Optuna optimization further increased its performance by 0.4% and LightGBM initially achieved an accuracy of 98.4% [9]. These results indicate that Optuna can improve LightGBM performance by identifying a more suitable hyperparameter configuration. However, the study did not combine the optimized LightGBM model with ARIMA residual modelling or apply it to commodity price forecasting.

Based on these limitations, this study aims to develop an adaptive short term prediction approach for red bird's eye chili prices in Surabaya so that price changes can be anticipated more accurately. The analysis focuses on Genteng Market and Keputran Market. The study applies a hybrid ARIMA-LightGBM model, where ARIMA generates the initial forecast and LightGBM models the remaining residual patterns as correction values. Optuna is then applied to determine the most suitable LightGBM hyperparameter configuration. The resulting forecasts are expected to provide more reliable information for consumers, traders, and food business actors in planning purchases, inventories, and transactions. In addition, this study evaluates the contribution of each modelling component by comparing the proposed

approach with ARIMA, ARIMA-LightGBM without optimization, and seasonal naive forecasting. This comparison is conducted to determine whether the performance improvement is obtained from the hybrid modelling approach and hyperparameter optimization. The resulting forecasts are expected to provide more reliable information for consumers, traders, and food business actors in planning purchases, inventories, and transactions.

II. METHOD

This study employs a quantitative time series prediction approach to predict daily red bird's eye chili prices at Genteng Market and Keputran Market in Surabaya. Each market will be modelled separately because the price formation may produce distinct temporal patterns. The steps to be taken are shown in figure 1.

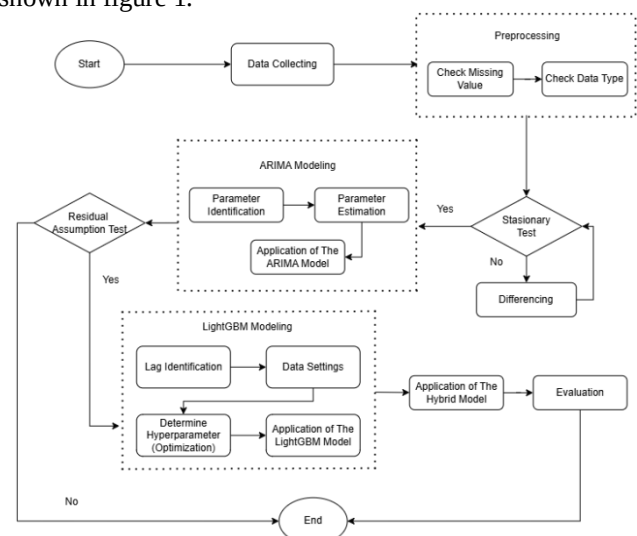


Figure 1. Workflow

A. Data Collecting

The dataset consists of daily red bird's eye chili prices from Genteng Market and Keputran Market in Surabaya. Both were selected because both are traditional markets included in the government's commodity price monitoring system for Surabaya. These markets provide relevant information on daily red bird's eye chili price movements for short-term forecasting analysis. The data were obtained from Sistem Informasi Ketersediaan dan Perkembangan Harga Bahan Pokok (SISKAPERBAPO). The observation period covers January 2021 to April 2026, with the data recorded at a daily frequency. Each observation contains a date and the corresponding price recorded at each market. The two market price series are analysed independently to preserve their respective price characteristics

B. Preprocessing

The preprocessing phase of this study included missing value checking and data type verification. A check was performed to ensure no missing values were present, ensuring that information essential for the analysis was retained.

Furthermore, the data type was verified to ensure it met the requirements of the Python module to be implemented. This process aims to minimize potential errors during modeling and making it ready for analysis.

C. Stationary Test

Before the modeling process, the data were tested to determine their stationarity. A stationary time series has a pattern that does not change significantly over time. In this study, stationarity was examined based on the variance and mean of the data. Variance stationarity was identified using the Box-Cox transformation, which was applied to stabilize changes in data variance [10]. The Box-Cox transformation is expressed as follows:

$$T(Y_t) = \frac{Y_t^\lambda - 1}{\lambda} \quad (1)$$

Where Y_t is the observed value at time t and λ is the Box-Cox transformation parameter. A lambda value close to one indicates that the variance is relatively stable, while a value far from one indicates that transformation is required.

After variance stabilization, mean stationarity was tested using the Augmented Dickey-Fuller test. The ADF test was used to determine whether the time series data contained a unit root. A p-value below 0.05 indicates that the data are stationary, while a p-value above 0.05 indicates that differencing is required [11]. The ADF Test is expressed as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^p \alpha \Delta Y_{t-i} + \varepsilon_t \quad (2)$$

Where β_1 is constant, β_2 is deterministic tren, δ is coefficient, $\sum_{i=1}^p \alpha \Delta Y_{t-i}$ is number of lags, and ε_t is error term.

D. ARIMA

Autoregressive Integrated Moving Average (ARIMA) is a prediction model that produces predictions based on patterns in historical data. ARIMA combines the autoregressive, integrated, and moving average components. This component represented by $AR(p)$ that uses previous observations, $I(d)$ that represents the differencing process, and $MA(q)$ that uses previous error values [10]. The ARIMA model is expressed as follows:

$$\phi_p(B)(1 - B)^d Y_t = \mu + \theta_q(B)a_t \quad (3)$$

Where Y_t is data value at time t , $(1 - B)^d$ is differentiation operator of order d , $\phi_p(B)$ is previous value association parameters, $\theta_q(B)$ is parameters that look at previous errors, and a_t is white noise term at time t .

The values of p and q were identified using the PACF and ACF plots. The PACF plot was used to identify the autoregressive order p , while the ACF plot was used to identify the moving-average order q . Meanwhile, the value of

d was determined from the number of differencing processes required to obtain stationary data. Several parameter combinations were then formed as candidate ARIMA models. The candidate models were compared using the Akaike Information Criterion (AIC). AIC is used to determine the model that provides a balance between its suitability for the data and its complexity. The model with the lowest AIC value was selected as the best ARIMA model [10]. The AIC value is calculated as follows:

$$AIC = 2m - 2\ln(L) \quad (4)$$

Where L is the likelihood value, m is the number of estimated parameters, and $\ln$ is the natural logarithm.

E. Residual Assumption Test

After the ARIMA model was obtained, residual assumption test was conducted to examine whether the remaining errors still contained certain patterns. Residuals are obtained from the difference between the actual values and the values estimated by the model. In this study, the residuals were examined using the Kolmogorov-Smirnov, Ljung-Box, and ARCH-LM tests. These tests were used to assess residual normality, autocorrelation, and variance stability, respectively. The test decisions were based on a significance level of 0.05.

1) Kolmogorov-Smirnov

The Kolmogorov-Smirnov test was used to examine whether the residuals followed a normal distribution. This test assumes that the distribution of the data being tested is continuous and the sample is random. It measures the largest difference between the cumulative distribution of the residuals and the theoretical normal distribution [12]. The Kolmogorov-Smirnov statistic is expressed as follows:

$$D = \max|F_n(x) - F(x)| \quad (5)$$

Where D is the Kolmogorov-Smirnov statistic, $F_n(x)$ is the cumulative distribution function of the residuals, and $F(x)$ is the cumulative distribution function of the theoretical distribution. A p-value greater than 0.05 indicates that the null hypothesis is not rejected, meaning that the residuals can be considered normally distributed.

2) Ljung-Box

The Ljung-Box test was used to determine whether autocorrelation remained in the ARIMA residuals. Residuals without significant autocorrelation are referred to as white noise, indicating that no temporal relationship remains unexplained by the model [10]. The Ljung-Box statistic is expressed as follows:

$$Q = n(n+2) \sum_{k=1}^K \frac{\hat{\rho}_k^2}{(n-k)} \quad (6)$$

Where Q is the Ljung-Box statistic, n is the number of residuals, K is the number of tested lags, and $\hat{\rho}_k$ is the residual autocorrelation at lag k . A p-value greater than 0.05 indicates that the null hypothesis is not rejected; therefore, the residuals do not contain significant autocorrelation and satisfy the white noise assumption.

3) ARCH-LM

The ARCH-LM test was used to determine whether the residual variance remained constant over time. This test identifies the presence of an ARCH effect by examining whether the current squared residual can be explained by squared residuals from previous periods. The ARCH-LM statistic is expressed as follows:

$$LM = nR^2 \quad (7)$$

Where LM is the ARCH-LM statistic, n is the number of residuals, and R^2 is the coefficient of determination obtained from the squared residual regression. A p-value greater than 0.05 indicates that the null hypothesis is not rejected, meaning that no significant heteroscedasticity is detected. Therefore, the residual variance can be considered constant [13].

F. LightGBM Modeling

LightGBM is a gradient-boosting decision-tree algorithm that builds trees sequentially to reduce the prediction error of the previous trees. Unlike level-wise tree growth, LightGBM applies a leaf-wise strategy by expanding the leaf that provides the greatest reduction in loss. This approach can improve learning efficiency, although model complexity must still be controlled through its hyperparameter [14]. The prediction update in LightGBM is expressed as follows:

$$\hat{y}_t^{(m)} = \hat{y}_t^{(m-1)} + \eta \cdot f_m(x_t) \quad (8)$$

Where $\hat{y}_t^{(m)}$ is the prediction at iteration m , $\hat{y}_t^{(m-1)}$ is the prediction from the previous iteration, η is the learning rate, and $f_m(x_t)$ is the decision tree added at iteration m .

The LightGBM hyperparameters were optimized using Optuna. Optuna is an automatic hyperparameter optimization framework that selects parameter combinations through a series of trials. In this study, Optuna used the Tree structured Parzen Estimator (TPE) sampler, which separates previous trial results into good and less-promising groups. The two probability distributions are expressed as follows:

$$l(x) = P(x|y < y^*) \quad (9)$$

$$g(x) = P(x|y \geq y^*) \quad (10)$$

Where x is a hyperparameter combination, y is the objective value obtained from a trial, and y^* is the threshold used to separate the trial results. Meanwhile, $l(x)$ represents the distribution of hyperparameter combinations that produce better objective values, while $g(x)$ represents the distribution of less promising combinations [15], [16]. The next hyperparameter combination is selected by maximizing the ratio between these distributions:

$$x^* = \arg \max_x \frac{l(x)}{g(x)} \quad (11)$$

G. Hybrid Prediction

Hybrid prediction was performed by combining the ARIMA predict and the residual predict produced by LightGBM. ARIMA was used to produce the main predict, while LightGBM was used to estimate the errors that remained from ARIMA. Combining these two predictions is expected to reduce the prediction error compared with using ARIMA alone. The hybrid ARIMA-LightGBM prediction is expressed as follows:

$$\hat{y}_t^{Hybrid} = \hat{y}_t + \hat{e}_t \quad (12)$$

Where $\hat{y}_t$ represents the initial prediction generated by ARIMA, and $\hat{e}_t$ represents the residual correction predicted by LightGBM.

H. Evaluation

The final stage was the evaluation of model performance. Evaluation was conducted to measure the difference between the actual red bird's eye chili prices and the prediction results. This study used, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Lower evaluation values indicate that the prediction results are closer to the actual data [17]. MAE used to measure the average absolute difference between the actual and predicted values. This metric represents the magnitude of forecasting errors in the same unit as the observed data, where lower MAE values indicate predictions that are closer to the actual values.

$$MAE = \frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t) \quad (13)$$

RMSE measures prediction error by giving a larger weight to larger differences. RMSE is expressed as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2} \quad (14)$$

Then, Mean Absolute Percentage Error measures the average prediction error as a percentage of the actual value. MAPE is expressed as follows:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \quad (15)$$

Where Y_t is the actual price, $\hat{Y}_t$ is the predicted price, and n is the number of test data [11]. Meanwhile, MAPE accuracy level criteria are explained in the following table I.

TABLE I
COLLECTED DATA

MAPE (%)	Criterion
<10%	Very Good
10-20%	Good
20-50%	Quite Good
>50%	Bad

III. RESULT AND DISCUSSION

This section presents the results obtained from each stage of the analysis and discusses their implications for red bird's eye chili price prediction. The discussion covers the dataset characteristics, stationarity testing, ARIMA model selection, residual diagnostics, LightGBM residual modelling, and the final evaluation of the hybrid model. Results for Genteng and Keputran Market are presented separately to show the performance of the model on each price series.

A. Dataset

TABLE II
COLLECTED DATA

Date	Genteng Market	Keputran Market
2021-01-01	60000	50000
2021-01-02	60000	50000
2021-01-03	60000	50000
:	:	:
2026-04-28	45000	45000
2026-04-29	40000	45000
2026-04-30	40000	45000

The dataset consisted of daily red bird's eye chili prices from Genteng Market and Keputran Market in Surabaya. The observation period covered January 2021 to April 2026, resulting in 1946 observations for each market. The dataset contained three variables, which is date, Genteng Market price, and Keputran Market price. The data were collected manually from the SISKAPERBAPO website by recording the daily price observations for both markets. The collected data were then compiled and stored in a Microsoft Excel file for further processing and analysis.

TABLE III
DATA CHECK

Column	Data Type	Missing Value
Date	Datetime	0
Genteng Market	Integer	0
Keputran Market	Integer	0

The data inspection showed that all observations were complete, with no missing values. The date variable was stored in datetime format, while both price variables were stored as integers. The absence of missing values allowed the complete time series to be used without an imputation process. The prices of the two markets were analysed separately because each market may have a different price formation process

B. Data Exploration

Before the modelling process, exploratory data analysis was conducted to identify the initial characteristics of red bird's eye chili price movements at Genteng Market and Keputran Market. The exploration included descriptive statistical analysis and time series visualization to examine the distribution, central tendency, price range, variability, and movement patterns of the observed prices.

TABLE IV
STATISTIC DESCRIPTIVE

Deskripsi	Pasar Genteng	Pasar Keputran
Rata-rata	47809.86	47015.93
Standar Deviasi	24098.38	22494.312
Nilai Minimum	15000.00	15000.00
Nilai Maksimum	140000.00	120000.00

Table IV presents the descriptive statistics of red bird's eye chili prices at Genteng Market and Keputran Market. The average price recorded at Genteng Market was IDR 47809.86/kg, while Keputran Market had an average price of IDR 47015.93/kg. The similarity between the average values indicates that both markets generally had comparable price levels during the observation period. Both markets also showed the same median price of IDR 40,000/kg, suggesting that most daily observations were concentrated around this value.

However, the distribution of prices showed differences in variability between the two markets. Genteng Market had a standard deviation of IDR 24098.38, which was higher than Keputran Market with IDR 22494.31. This difference indicates that price movements at Genteng Market were relatively more spread out from their average value. In addition, Genteng Market reached a higher maximum price of IDR 140000/kg, while the highest price at Keputran Market was IDR 120000/kg. Both markets had the same minimum price of IDR 15000/kg. These results indicate that although the two markets had similar average price levels, Genteng Market experienced more extreme price changes during the observation period.

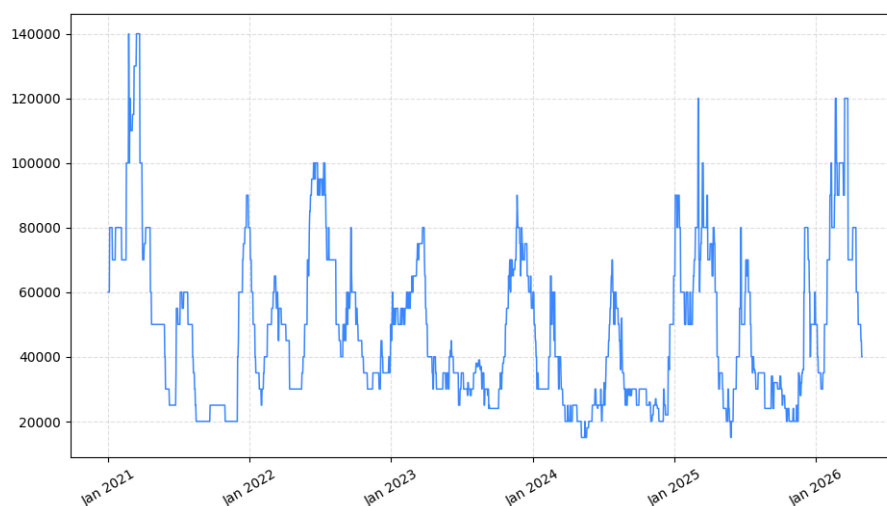


Figure 2. Genteng Market Price Time Series Plot

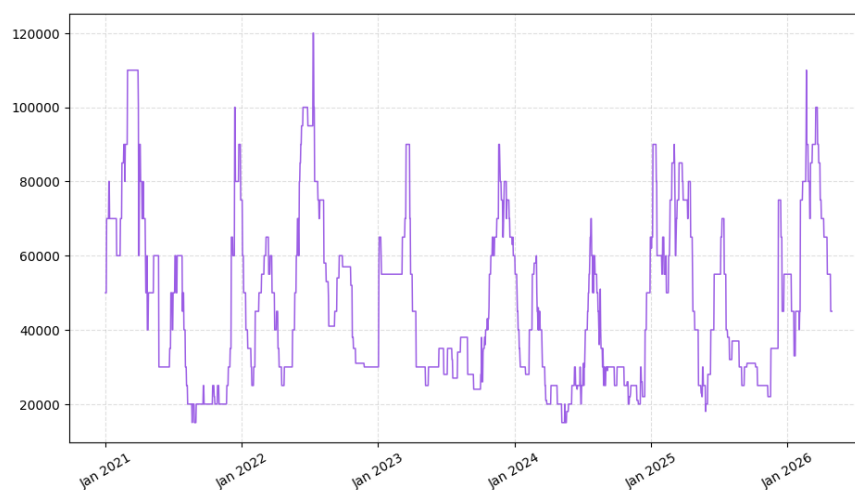


Figure 3. Keputran Market Price Visualization Time Series Plot

The time series plots in figure 2 and figure 3 show the price movements of red bird's eye chili at Genteng Market and Keputran Market during the observation period. The price movements in both markets fluctuate over time, with several periods of increasing prices followed by subsequent decreases. The series shows dynamic changes throughout the observation period without a consistent long-term trend. Several price increases appear around similar periods across different years, suggesting the presence of recurring price movements. However, the timing and magnitude of these increases vary between periods, indicating that the seasonal pattern is not constant throughout the series.

At Genteng Market, the price movement shows a wider variation, with several noticeable increases and decreases across the period. The highest price occurred at the beginning of 2021, reaching approximately IDR 140000. Several price increases can also be observed around the beginning of certain years, although the timing and magnitude vary between periods. Meanwhile, Keputran Market shows a similar fluctuation pattern with a lower price range, where the highest

price reached approximately IDR 120000. Some increases also appear around similar periods, but the magnitude differs across years. These patterns indicate that both markets have dynamic price movements with variations in short-term price changes.

C. Stationary Test

The data from each market were divided into training and testing sets. The final 14 observations, covering April 17-30, 2026, were used as testing data, while the preceding observations were used to estimate the ARIMA models. The 14-day forecasting horizon was selected to represent near future price conditions of red bird's eye chili. Considering its perishable characteristics and limited storage capability, price information within a short period may provide more insights into upcoming market conditions. Therefore, this study focuses on short-term forecasting to capture price movements within a practical time range.

After the data division process, stationarity testing was conducted to determine whether the price series met the

requirements for ARIMA modelling. The stationarity results were also used to determine the differencing order (d) in the ARIMA model.

TABLE V
BOX-COX RESULT

Market	Lamda (λ)	Lamda (λ) After Transformation	Interpretation
Genteng Market	-0.1564	1.0680	Stationary in Variance
Keputran Market	-0.0967	0.5033	Stationary in Variance

The stationarity test was conducted in two stages, beginning with variance stationarity using the Box-Cox transformation. The initial Box-Cox analysis produced lambda values of -0.1564 for Genteng Market and -0.0967 for Keputran Market. Since both values were far from one, the original price series were considered nonstationary in variance and required transformation. After the transformation, the lambda values became 1.0680 for Genteng Market and 0.5033 for Keputran Market. Both values were rounded to one, indicating that the variance of the transformed series had become relatively stable.

TABLE VI
STATIONARY TEST

Market	P-value	Interpretation
Genteng Market	0.000001	Stationary in mean
Keputran Market	0.000022	Stationary in mean

After the variance was stabilized, stationarity in mean was examined using the Augmented Dickey-Fuller test. Based on table VI, the transformed data produced p-values of 0.000001 for Genteng Market and 0.000022 for Keputran Market. Since both p-values were below 0.05, the null hypothesis of a unit root was rejected. Therefore, the transformed price series were statistically stationary in the mean.

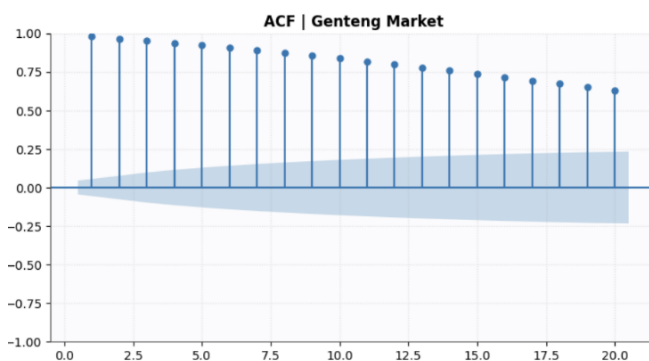


Figure 4. ACF Plot for Genteng Market Stationary Check

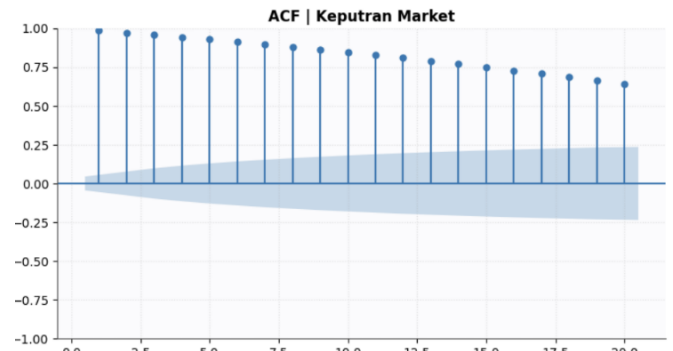


Figure 5. ACF Plot for Keputran Market Stationary Check

However, the ACF plots still showed large positive autocorrelation values that declined slowly across successive lags. This pattern indicated that the series retained strong temporal persistence despite the significant ADF results. Therefore, first order differencing was applied to reduce the remaining dependence and prepare the data for ARIMA parameter identification.

TABLE VII
STATIONARY TEST AFTER 1ST DIFFERENCING

Market	P-value	Interpretation
Genteng Market	0.000000	Stationary in mean
Keputran Market	0.000000	Stationary in mean

After first order differencing, both markets remained stationary, as indicated by p-values below 0.05. Showing that the strong persistence in the original transformed series had been reduced. The differencing process resulted in an ARIMA differencing order of $d=1$ for both Genteng Market and Keputran Market.

D. ARIMA

After the stationarity requirements were satisfied, the ARIMA model was developed as the baseline model to generate the initial price forecast based on historical price patterns. The autoregressive order (p) was identified using PACF plot, which indicates the relationship between current observations and previous lag values after removing the influence of intermediate lags. Meanwhile, the moving average order (q) was determined using ACF plot which describes the correlation between observations and their previous error terms. The differencing order (d) was set to 1 because both market series required one differencing process to reduce the remaining temporal dependence and achieve stationarity.

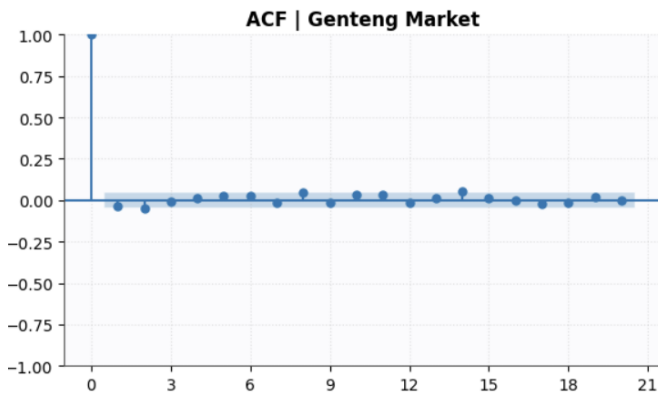


Figure 6. ACF Plot for Genteng Market

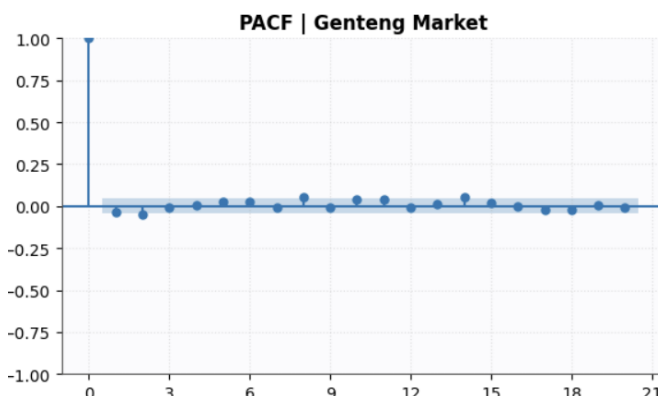


Figure 7. PACF Plot for Genteng Market

In Genteng Market, the ACF and PACF coefficients decreased rapidly and approached the confidence limits after the first lag. This pattern indicated that the temporal dependency of the series was mainly represented by the initial lag values. Therefore, candidate values of 0 and 1 were considered for the autoregressive order (p) and moving-average order (q), while the differencing order (d) was set to 1 based on the differencing process performed during the stationarity stage. Based on these combinations, four candidate models were evaluated, namely ARIMA(0,1,0), ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1).

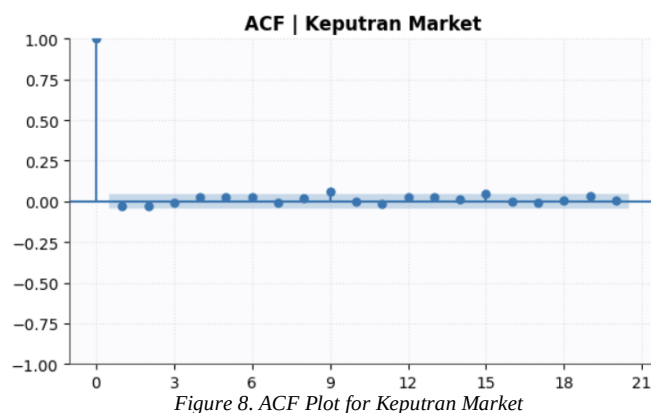


Figure 8. ACF Plot for Keputran Market

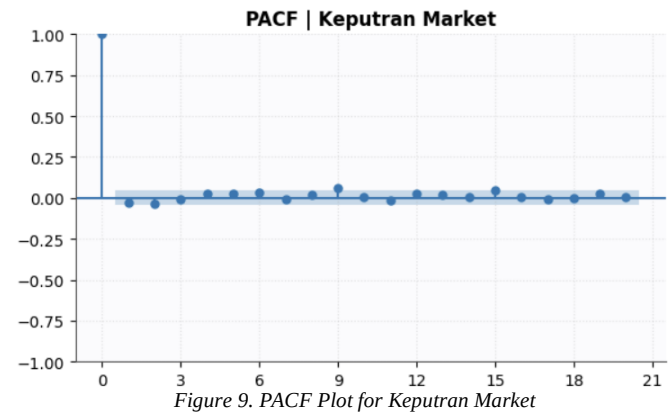


Figure 9. PACF Plot for Keputran Market

For Keputran Market, the ACF and PACF coefficients showed a similar pattern, with the values declining sharply and remaining within the confidence limits after the first lag. This indicated that the possible autoregressive and moving average orders were also concentrated around the first lag. Therefore, candidate values of 0 and 1 were considered for p and q , while $d=1$ was retained based on the differencing process identified during the stationarity evaluation. The candidate models for Keputran Market were ARIMA(0,1,0), ARIMA(1,1,0), ARIMA(0,1,1), and ARIMA(1,1,1).

Since ACF and PACF analyses only provide initial candidate orders, each ARIMA configuration was subsequently estimated and compared using the Akaike Information Criterion (AIC). The AIC comparison was conducted to select the model that provided the best balance between goodness of fit and model complexity. The model with the lowest AIC value was selected as the final ARIMA model for each market.

TABLE VIII
AIC ESTIMATION

Market	Model	AIC
Genteng Market	ARIMA(1,1,1)	-10208.89
	ARIMA(0,1,1)	-10208.20
	ARIMA(1,1,0)	-10207.87
	ARIMA(0,1,0)	-10206.97
Keputran Market	ARIMA(0,1,1)	-8057.14
	ARIMA(1,1,1)	-8057.13
	ARIMA(1,1,0)	-8057.01
	ARIMA(0,1,0)	-8056.11

Based on the AIC comparison in table VIII, ARIMA(1,1,1) was selected for Genteng Market because it produced the lowest AIC value of -10208.89. For Keputran Market, ARIMA(0,1,1) was chosen with the lowest AIC value of -8057.14. These results indicate that the most suitable ARIMA structure differed between the two markets. Based on the estimated coefficients, the ARIMA model for Genteng Market and Keputran Market can be expressed as:

$$\Delta Y_t = -0.4142\Delta Y_{t-1} + \varepsilon_t - 0.4647\varepsilon_{t-1} \quad (16)$$

$$\Delta Y_t = \varepsilon_t - 0.0333\varepsilon_{t-1} \quad (17)$$

The estimated ARIMA equations show that the price dynamics of the two markets were represented by different structures. For Genteng Market, the ARIMA(1,1,1) model indicates that the current differenced price is influenced by the previous differenced price and the previous error term. For Keputran Market, the ARIMA(0,1,1) model does not include an autoregressive component, meaning that the current differenced price is represented by the current error and the previous error term.

TABLE IX
ARIMA EVALUATION

Market	RMSE	MAPE
Genteng Market ARIMA(1,1,1)	12379.57	23.23%
Keputran Market ARIMA(0,1,1)	13363.06	24.39%

The selected ARIMA models were then used to forecast the 14-day testing period. Their performance was evaluated using RMSE and MAPE to measure the magnitude of prediction errors in rupiah and percentage terms. Based on the MAPE criteria, both models were categorized as having quite good forecasting performance because their MAPE values were within the 20%-50% range.

E. Result of Residual Test

After the best ARIMA model for each market was selected, was performed to examine whether the remaining errors still contained temporal patterns that could be further modelled.

TABLE X
RESIDUAL TEST

Market	Test	P-value	Interpretation
Genteng Market	Kolmogorov-Smirnov	0.0000	Not Normally Distributed
	Ljung-Box	0.1865	White Noise
	ARCH-LM	0.0136	Heteroskedastic
Keputran Market	Kolmogorov-Smirnov	0.0000	Not Normally Distributed
	Ljung-Box	0.1943	White Noise
	ARCH-LM	0.9953	Homoskedastic

Based on table X, The Kolmogorov-Smirnov test produced p-values below 0.05 for both markets, indicating that the residuals were not normally distributed. However, residual normality is not an essential requirement for obtaining forecasts. Normality is mainly useful for constructing prediction intervals based on the assumed error distribution. The Ljung-Box test produced p-values above 0.05 for both markets, indicating that no significant autocorrelation remained in the residuals. This condition is important because

ignoring residual autocorrelation may result in inconsistent or inefficient parameter estimates and inaccurate out of sample forecasts.

Meanwhile, the ARCH-LM test indicated heteroskedastic residuals for Genteng Market and homoskedastic residuals for Keputran Market. This difference indicates that the residual variance was dynamic at Genteng Market and relatively stable at Keputran Market. Since the ARCH-LM test specifically evaluates the variance structure of the residuals, both residual series remained suitable for subsequent modelling. Therefore, both residual series were retained for the next stage, in which LightGBM was developed to model the residuals and construct the final hybrid model.

F. Lag Feature

After obtaining the ARIMA residuals, feature construction was performed to prepare the input variables for the LightGBM model. Since LightGBM was used to model the remaining errors generated by ARIMA, the residual series was analyzed to identify whether previous residual values contained temporal information related to the current residual. Therefore, lag features were constructed from historical residual values and used as input variables for LightGBM.

The Partial Autocorrelation Function (PACF) was applied to identify significant residual lags. PACF measures the relationship between the current residual and previous residual values after removing the influence of intermediate lags. A lag was considered significant when its PACF value exceeded the confidence interval threshold. The identified significant lags were selected as candidate features for the LightGBM model.

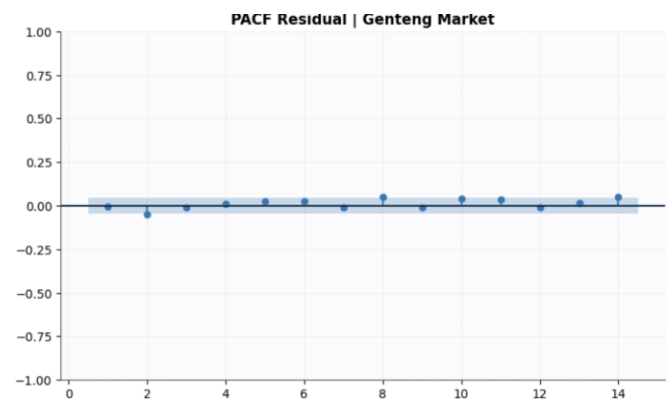
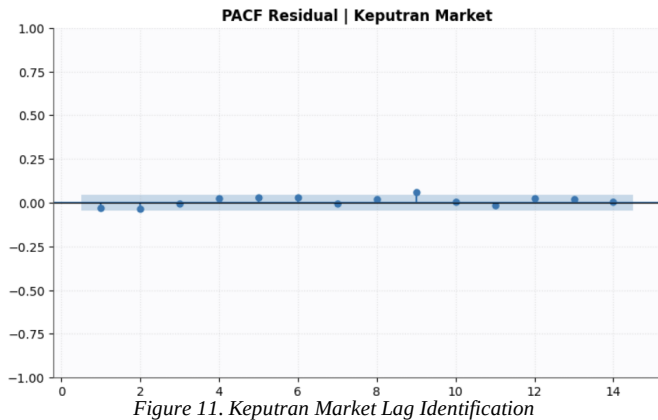


Figure 10. Genteng Market Lag Identification



The PACF plots of the ARIMA residual series for Genteng Market and Keputran Market are presented in figure 10 and figure 11. The lag features were identified by observing the PACF values that exceeded the confidence interval boundary in the plots. For Genteng Market, several lag values showed spikes beyond the confidence interval, while Keputran Market showed one lag value that exceeded the boundary. The significant lag values observed from the plots were then confirmed using their PACF values, as presented in table XI.

TABLE XI
FEATURE LAG

Market	Confidence Interval	Lag	Value
Genteng Market	0.0446	8	0.0524
		14	0.0500
Keputran Market		9	0.0618

The confidence interval threshold was calculated as 0.0446. For Genteng Market, lag 8 and lag 14 exceeded the threshold with PACF values of 0.0524 and 0.0500. Meanwhile, Keputran Market showed a significant lag at lag 9 with a PACF value of 0.0618. Therefore, lag 8 and lag 14 were selected as candidate features for Genteng Market, while lag 9 was selected for Keputran Market. These selected lag features were subsequently used as input variables for LightGBM to model the ARIMA residual patterns.

G. LightGBM Modelling

After the significant lag features were identified, LightGBM was developed to model the residual component generated by ARIMA. The selected lag values from the residual series were used as input features, while the current residual value was used as the prediction target. Through this approach, LightGBM was utilized to capture residual patterns that were not represented by the ARIMA model.

Optuna was then used to determine the most suitable LightGBM hyperparameters for each lag configuration. The optimization process was performed using the Tree-structured

Parzen Estimator (TPE) sampler with 100 trials. The optimized parameters included `n_estimators` (50-200), `learning_rate` (0.01-0.3), `num_leaves` (20-256), `max_depth` (1-15), and `min_child_samples` (5-30). The optimization objective was to minimize the RMSE of the resulting hybrid forecast.

TABLE XII
HYPERPARAMETER OPTIMIZATION RESULT

Market	N_estimators	Learning_rate	Num_leaves	Max_depth	min_child_samples
Genteng (Lag 8)	68	0.0155	227	15	23
Genteng (Lag 14)	103	0.0612	117	15	22
Keputran (Lag 9)	183	0.0379	123	7	13

Table XII shows that Optuna produced different LightGBM configurations for each residual lag configuration. These differences indicate that the optimal hyperparameter settings depended on the selected lag features used as input variables. Each optimized configuration was then evaluated based on its forecasting performance, and the results were compared with the standalone ARIMA model, as presented in table XIII.

TABLE XIII
RMSE LIGHTGBM RESIDUAL PREDICTION RESULT

Market	Lag	RMSE Before	RMSE After
Genteng Market	8	12379.57	12397.27
	14	12379.57	12185.30
Keputran Market	9	13456.48	12862.60

For Genteng Market, lag 14 produced the lowest hybrid RMSE of IDR 12185.30, corresponding to a reduction from the ARIMA RMSE. Therefore, lag 14 and its optimized hyperparameters were selected for the final Genteng LightGBM model. For Keputran Market, lag 9 produced a hybrid RMSE of IDR 12862.60, which was lower than the standalone ARIMA model. Thus, lag 9 was retained for the final Keputran LightGBM model. Using the selected lag and optimized hyperparameters, LightGBM was trained to estimate the residual component that had not been represented by the ARIMA forecast. The predicted residual from LightGBM was then added to the corresponding ARIMA forecast to obtain the final hybrid prediction.

H. Hybrid Prediction

The hybrid forecasting model combines the ARIMA forecast and LightGBM residual prediction to obtain the final price estimation. In this approach, ARIMA first generates the initial forecast based on the historical price series. The

difference between the actual values and the ARIMA predictions is calculated as the residual component. These residuals are then modelled using LightGBM with the selected lag features obtained from the PACF analysis. The final hybrid prediction is generated by adding the ARIMA forecast and the residual correction predicted by LightGBM.

TABLE XIV
GENTENG MARKET PREDICTION SUMMARY

Date	Actual	ARIMA	LightGBM - Optuna	Hybrid
2026-04-17	60000	60397.12	-896.97	59500.15
2026-04-18	60000	60562.51	-769.31	59793.20
:	:	:	:	:
2026-04-29	40000	60679.75	746.97	61426.72
2026-04-30	40000	60679.76	419.45	61099.20

Table XIV presents the prediction components for Genteng Market. The ARIMA forecasts remained relatively stable around IDR 60000, while the actual prices showed a declining movement during the testing period. The LightGBM residual predictions functioned as correction values for the initial ARIMA forecasts. Positive residual predictions increased the hybrid forecast, while negative residual predictions adjusted the forecast downward. Through this residual correction process, the hybrid prediction incorporated additional adjustments from the LightGBM residual estimation compared with the standalone ARIMA forecast.

TABLE XV
KEPUTRAN MARKET PREDICTION SUMMARY

Date	Actual	ARIMA	LightGBM - Optuna	Hybrid
2026-04-17	65000	65000	136.41	65136.41
2026-04-18	55000	65000	-263.38	64736.63
:	:	:	:	:
2026-04-29	45000	65000	95.59	65095.59
2026-04-30	45000	65000	-224.10	64775.90

Table XV shows a similar correction process for Keputran Market. The ARIMA forecasts remained close to IDR 65000 throughout the testing period, while the actual prices decreased during the testing period. The LightGBM residual predictions provided downward adjustments to the initial ARIMA forecasts, with larger negative residual values resulting in greater corrections. As the residual corrections were incorporated, the hybrid forecasts gradually approached the actual price values, with the closest prediction occurring on April 30. The forecasting results were further visualized by comparing the actual prices, ARIMA forecasts, and hybrid ARIMA-LightGBM predictions during the testing period. This visualization was used to observe how the residual correction from LightGBM affected the final prediction compared with the initial ARIMA forecast during the testing period.

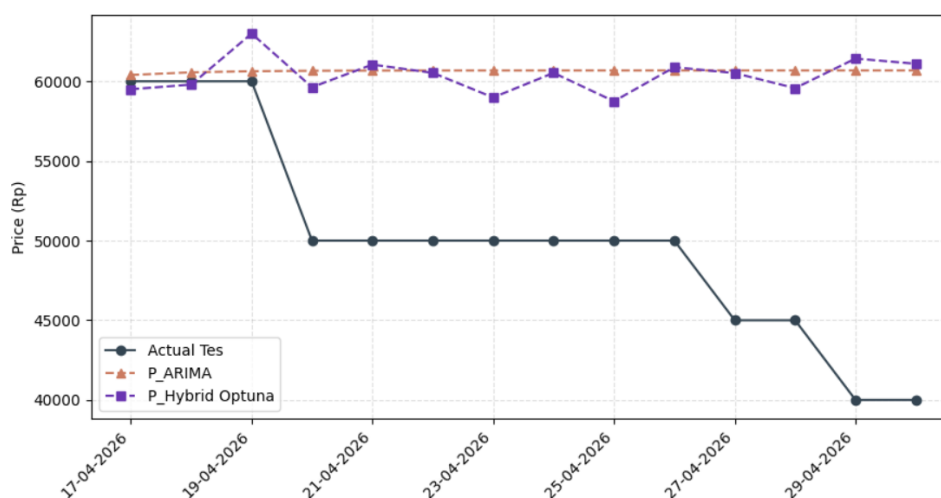


Figure 12. Visual Comparison for Genteng Market

Figure 12 presents the comparison between the actual prices, standalone ARIMA predictions, and hybrid ARIMA-LightGBM predictions at Genteng Market during the 14-day testing period. The ARIMA prediction remained relatively stable at approximately IDR 60000-61000/kg. Meanwhile,

the hybrid forecast showed more dynamic movements throughout the testing period due to the residual correction provided by the LightGBM component. These adjustments represent the additional information captured from the residual patterns after the initial ARIMA forecasting process.

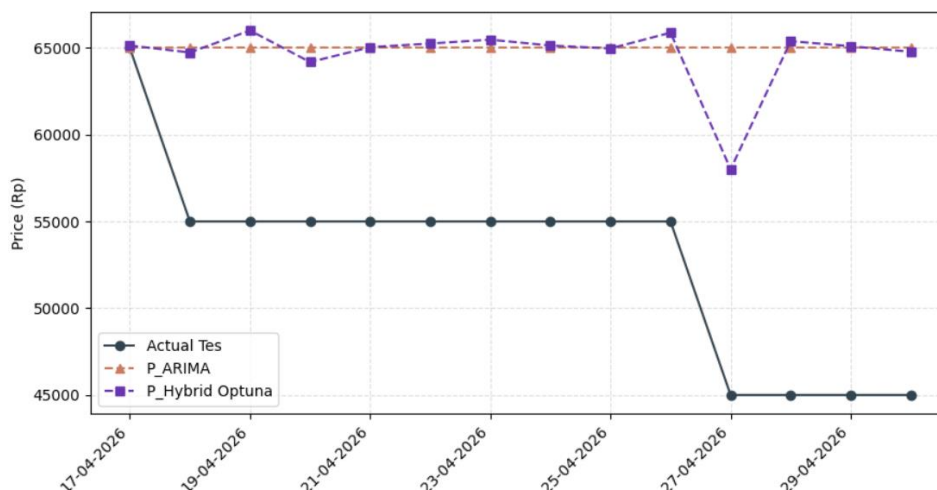


Figure 13. Visual Comparison for Keputran Market

A similar pattern was observed at Keputran Market. While the ARIMA forecast remained close to IDR 65000/kg, the hybrid model generated more varied predictions, including a noticeable adjustment during the latter part of the testing period. This variation shows that the LightGBM residual correction introduced additional variation into the ARIMA forecast during the testing period.

I. Evaluation

This section evaluates the performance of the forecasting models using MAE, RMSE, and MAPE as evaluation metrics. Four models were compared, including Seasonal Naive, ARIMA, ARIMA-LightGBM without optimization, and ARIMA-LightGBM with Optuna optimization. The comparison was performed to observe the contribution of LightGBM residual modelling and the effect of hyperparameter optimization on the forecasting results.

TABLE XVI
EVALUATION RESULT

Market	Model	MAE	RMSE	MAPE
Genteng	Seasonal Naive	24285.71	25565.04	49.68%
	ARIMA	10767.06	12379.57	23.23%
	ARIMA-LightGBM Default	10553.42	12243.64	23.00%
	ARIMA-LightGBM Optuna	10463.54	12181.08	22.84%
Keputran	Seasonal Naive	12142.86	13363.06	24.39%
	ARIMA	12068.05	13363.06	24.39%
	ARIMA-LightGBM Default	12068.05	13188.04	24.16%
	ARIMA-LightGBM Optuna	11791.62	12862.6	23.55%

Based on Table XVI, the forecasting performance varied across models and markets. Seasonal Naive was included as a baseline to evaluate whether the recurring seasonal pattern could represent the price movement of red bird's eye chili. At Genteng Market, Seasonal Naive produced the highest error with a MAPE of 49.68%, indicating that the price variation at this market could not be sufficiently captured only through seasonal repetition. Meanwhile, ARIMA achieved a lower MAPE of 23.23%, showing that modelling the temporal dependency of the price series provided a better representation of the observed pattern. At Keputran Market, Seasonal Naive and ARIMA produced similar MAPE values of 24.39%, suggesting that seasonal behaviour and historical dependency provided comparable forecasting information for this market.

The integration of LightGBM residual modelling further reduced the forecasting errors compared with the standalone ARIMA model. At Genteng Market, ARIMA-LightGBM Default reduced the MAPE from 23.23% to 23.00%, while the Optuna-optimized model achieved the lowest error with RMSE of 12181.08, MAE of 10463.54, and MAPE of 22.84%. A similar pattern was observed at Keputran Market, where the optimized hybrid model obtained the lowest error among the evaluated models, with RMSE of 12862.60, MAE of 11791.62, and MAPE of 23.55%. These results show that residual correction from LightGBM provided additional adjustment to the ARIMA forecast.

The comparison between ARIMA-LightGBM Default and ARIMA-LightGBM Optuna shows that hyperparameter optimization contributed to improving the forecasting results. Although the reduction in error was relatively limited, the optimized model consistently achieved lower MAE, RMSE, and MAPE values in both markets. This indicates that the Optuna-based parameter selection helped refine the LightGBM configuration for modelling the residual component in the hybrid forecasting framework.

IV. CONCLUSION

This study developed a short-term forecasting model for red bird's eye chili prices in Surabaya using a hybrid ARIMA-LightGBM approach optimized with Optuna. ARIMA was applied to capture the temporal patterns of the price series, while LightGBM was used to model the residual patterns using selected lag features. The evaluation was conducted by comparing Seasonal Naive, ARIMA, ARIMA-LightGBM without optimization, and ARIMA-LightGBM with Optuna optimization using MAE, RMSE, and MAPE.

The results showed that the Optuna optimized ARIMA-LightGBM model achieved the lowest forecasting errors among the evaluated models for both markets. The model obtained a MAPE of 22.84% for Genteng Market and 23.55% for Keputran Market. The optimized configuration improved the LightGBM residual modelling performance by providing a more suitable hyperparameter combination for each market. The different selected lag features and model configurations between markets also demonstrate that each market has distinct price movement characteristics, highlighting the importance of adapting forecasting models to individual market patterns.

The developed forecasting model is expected to support future applications by providing short-term price information for both consumers and market participants. The predicted price trends may help consumers anticipate changes in expenditure needs, while traders and market managers can use the information as a reference for procurement and supply planning.

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