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Machine Learning-Based Prediction of Cayenne Pepper Price Dynamics in Local Markets of East Lombok

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Abstract: Fluctuations in cayenne pepper prices in local markets are difficult to predict and often create uncertainty in farmers' decision-making. This study analyzes cayenne pepper price dynamics and develops a Random Forest-based prediction model using weekly price data (2021–2024) from four markets in East Lombok Regency: Pancor, Aikmel, Paok Motong, and Sakra. Predictor features included lagged prices (24 weeks), rolling mean and standard deviation (4-, 8-, and 12-week windows), and seasonal sine–cosine transformations. The dataset was split chronologically into training (80%) and testing (20%) sets to preserve temporal dependencies. The model achieved R^2 values of 0.86–0.93, with MAE of IDR 2,657–4,206 per kg and RMSE of IDR 3,519–4,946 per kg. It captured general price trends and seasonal patterns well but showed limited accuracy in predicting extreme price spikes, likely due to the inherent limitation of tree-based algorithms in extrapolating beyond historical training ranges and the absence of external variables such as supply volume. These findings indicate that cayenne pepper price dynamics follow learnable historical patterns, and the model has potential as a data-driven decision-support tool to help reduce, though not eliminate, market uncertainty and support local food security.

Keywords: Cayenne pepper; Local market dynamics; Price prediction; Random forest; Time series forecasting

Introduction

Cayenne pepper (*Capsicum frutescens* L.) is one of the horticultural commodities with high economic potential and is widely consumed by the public, leading to continuously increasing demand, particularly in the household sector (Rachmawati & Soegianto, 2025). This is also supported by previous studies, which indicate that chilli is a strategic food commodity with high consumption levels, significant price fluctuations, and contributes to food price inflation dynamics (Putri et al., 2025a). In addition, several cayenne pepper farmers in Lombok Timur Regency stated that cayenne pepper serves as their main source of income. Meanwhile, cayenne pepper prices at both the farmer and consumer levels often experience high fluctuations and are difficult to predict (Wibowo et al., 2025). Devianto et al. (2024) stated that chili price fluctuations are caused by several factors, such as seasonal effects, long-term historical price patterns, and market demand-supply dynamics. Yustitia & Charibaldi (2024) also noted that price fluctuations are strongly influenced by the balance between production and demand. These frequent price changes contribute to uncertainty in farming planning and marketing strategies for agricultural products (Helbawanti et al., 2021).

Fluctuations in cayenne pepper prices not only affect farmers' economic conditions but also influence food price stability and consumers' purchasing power, given that cayenne pepper is a strategic commodity that contributes to inflation (Putri et al., 2025a). Price instability in food commodities, particularly unexpected price increases, can affect food accessibility and affordability, as reflected in reduced consumption diversity and a higher share of household expenditure on food, thereby impacting food security (Amolegbe et al., 2021). Therefore, efforts to understand and predict

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cayenne pepper price movements are essential, not only from an economic perspective but also in supporting the stability of the food system (Komaria et al., 2023). Despite the growing body of research on agricultural price prediction, most existing studies operate at the regional or national level and rely on relatively simple modeling approaches, limiting their ability to capture the complex price dynamics that occur at the local market level in producing regions such as East Lombok Regency (Khaidir et al., 2025). This study addresses that gap through a locally grounded approach with comprehensive feature engineering that has not been previously explored in the context of cayenne pepper price prediction at the local market level in Indonesia.

Based on data from the Central Bureau of Statistics (BPS), cayenne pepper production in West Nusa Tenggara (NTB) Province reached 941,552 quintals (approximately 94,155 tons) in 2024. Of this total, Lombok Timur Regency contributed the largest share, with a production of 648,588 quintals (approximately 64,859 tons), accounting for approximately 68.8% of total provincial production, making it the primary cayenne pepper producing regency in NTB.

Cayenne pepper production in Lombok Timur Regency has experienced significant fluctuations over recent years. Based on data from the Central Bureau of Statistics (BPS), production reached 857,955 quintals in 2020, before declining sharply to 493,984 quintals in 2021 and further to 407,074 quintals in 2022. Production subsequently recovered to 550,147 quintals in 2023 and continued to increase to 648,588 quintals in 2024. This fluctuating yet recovering production trend indicates that although Lombok Timur has significant agricultural potential, production stability remains a challenge, particularly given its sensitivity to supply-demand imbalances that can lead to price volatility in the market (Putri et al., 2025a).

Although cayenne pepper production potential in Lombok Timur Regency is high, farmers' access to price information remains limited. Currently, farmers only receive price information through collectors or intermediaries based on interviews conducted with farmers in Lombok Timur Regency (Ruslan et al., 2024). In addition, farmers carry out farming and selling activities based solely on habitual practices without being supported by price data analysis, a pattern also observed in input-use decisions such as fertilizer application among cayenne pepper farmers (Athoriq et al., 2026). This limitation significantly affects the quality of decision-making in farming activities, particularly in determining planting time and harvesting marketing strategies (Bruns et al., 2022).

In addition to limited access to price information, farmers have not yet optimally utilized historical price data in their decision-making processes, a gap also reflected in the underutilization of technical and informational resources despite farmers' extensive farming experience (Azizi & Wibisonya, 2025). In fact, regularly available price data hold significant potential to be analyzed for identifying price movement patterns, such as trends and seasonality. Without the effective use of such data, decisions tend to be reactive and insufficiently informed, thereby increasing the risk of suboptimal timing in planting decisions as well as marketing strategies for harvested products (Anggarda et al., 2023). In this context, the development of a price prediction model based on historical data is intended to generate accurate and systematic price trend information at the local market level. The resulting prediction output can serve as an analytical foundation for a decision support system by the Food Security Agency, contributing to improved price information access and supporting more informed farming decisions (Rahayu et al., 2026).

Several previous studies have conducted agricultural price prediction using historical data analysis to identify price movement patterns over time (Harjanto et al., 2022). The development of such prediction models has been used as a basis for decision-making by farmers, traders, and policymakers in supply management and price stabilization (Sun et al., 2024). However, traditional models such as ARIMA have limitations in capturing non-linear price patterns and high price volatility, whereas machine learning approaches including Random Forest have demonstrated superior predictive performance for volatile agricultural commodities (Permana et al., 2026). Most existing studies still focus on price analysis at the regional or national level, while studies at the local market level, particularly in East Lombok Regency, remain limited. Therefore, this study aims to analyze the price patterns of cayenne pepper and to develop a Random Forest-based price prediction model across four major markets in East Lombok Regency, namely Pancor, Aikmel, Paok Motong, and Sakra, using actual price data systematically recorded by the Food Security Agency. The results are expected to serve as a practical analytical foundation for decision-making related to planting time, distribution planning, and marketing strategies, thereby contributing to improved understanding of cayenne pepper price dynamics at the local market level.

Method

This study employs a machine learning-based predictive modelling approach to analyze cayenne pepper price dynamics in four main markets in East Lombok Regency, namely Aikmel, Paok Motong, Sakra, and Pancor markets. The method used is the Random Forest algorithm, which is applied to historical cayenne pepper price data from 2021 to 2024. Random Forest is an ensemble-based machine learning method that improves prediction accuracy by combining multiple decision trees and is effective in handling complex data (Ardianto et al., 2025). Furthermore, the historical data are analyzed as a time series to identify price movement patterns over time and to develop a future price prediction model. This study consists of several stages, including data collection and preprocessing, feature engineering, data splitting into training and testing sets, model development, model evaluation, and visualization of prediction results. Figure 1 illustrates the prediction workflow.

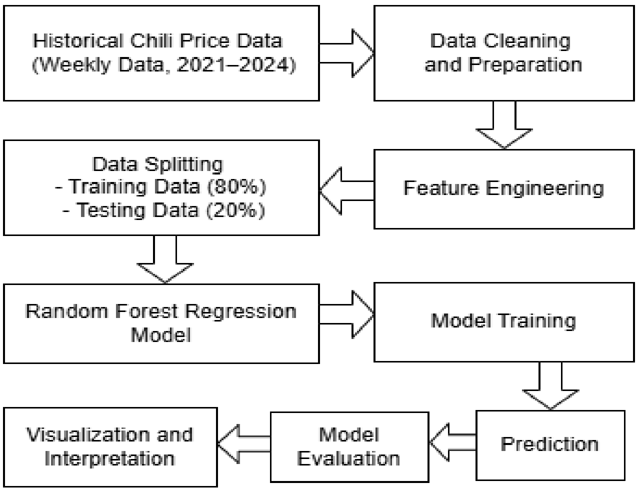

Figure 1. Flowchart of cayenne pepper price prediction process

Data Collection and Preprocessing

At the data collection and preprocessing stage, the data used in this study consist of weekly historical cayenne pepper price data from 2021 to 2024 obtained from the Food Security Office. The historical price data are structured into a weekly time series format so that weekly price changes can be observed sequentially. Data from each market is analyzed separately to identify price dynamics in each location. Prior to the prediction modelling stage, the data are sorted based on year and week, and a data cleaning process is conducted to ensure that no missing or empty values are present, so that the dataset meets the requirements of the prediction model (Putra & Suhartana, 2025).

Feature Engineering

The feature engineering stage is conducted to extract additional information from historical cayenne pepper price data so that the model can recognize price movement patterns over time. This study generates several features as follows:

Time Index

This variable is created to represent a continuous time sequence in historical price data. It helps the model capture long-term price trend patterns.

Lag Features

Lag features in this model are used to incorporate price information from previous weeks. In this study, 24 lag variables are used so that the model can consider the influence of past prices on the current week's price.

Rolling Mean

The rolling mean in this model is used to capture short-term price trends. This study applies several time windows, namely 4-week, 8-week, and 12-week rolling means. These features help the model understand the average price tendency over the recent weeks.

Rolling Standard Deviation

Rolling standard deviation in this model is used to measure the level of price volatility of cayenne pepper over a specific period. This feature helps the model identify whether the market conditions are stable or unstable.

Seasonal Features

Seasonal features in this model are used to capture seasonal patterns by utilizing sine and cosine functions of the weekly variable. These features aim to represent recurring annual price cycles. This representation is consistent with seasonal modelling approaches that use periodic components to capture recurring temporal patterns (Porcelli et al., 2025).

Training and Testing Data Splitting

The dataset was partitioned after all feature engineering processes had been completed. To preserve the temporal integrity of the time series data and prevent data leakage, the dataset was split chronologically without shuffling, where the first 80% of the data spanning from the first week of 2021 to mid-2024 was used for training, while the remaining 20% covering mid-2024 to December 2024 was used for testing. This approach aligns with the fundamental principles of machine learning modelling on time-series data, where the model is permitted to learn only from historical data and must not access information from the period being predicted. Consequently, the model was trained exclusively on data that temporally precedes the test period, ensuring that no future information leaked into the training process. This chronological separation between training and testing data ensures that the model's ability to generalize can be evaluated objectively, thereby providing a more representative picture of predictive performance under real-world conditions (Mustopa et al., 2025).

Prediction Model Development

Price prediction in this study uses the Random Forest Regressor algorithm. The model is built to learn the relationship between features generated through feature engineering and cayenne pepper price as the target variable. The processed data are separated into predictor and target variables. The target variable is the price column, and the predictor variables are obtained by removing the price, year, and week columns from the dataset, leaving only the features used for the prediction modelling process.

The Random Forest model is configured using several main parameters, including the number of decision trees set to 1500 ($n_{estimators}$ = 1500), maximum tree depth of 20 (max_{depth} = 20), minimum samples required to split a node of 5 ($min_{samples\ split}$ = 5), and minimum samples required at a leaf node of 2 ($min_{samples\ leaf}$ = 2) (Yasper et al., 2023). These parameters are used to improve the model's ability to capture complex patterns in price data while maintaining the stability of prediction results (Meda et al., 2025).

Prediction Model Training

The model training is conducted using the training data obtained from the previous stage. Before training, the model is configured with several parameters, including 1500 decision trees, a maximum depth of 20, a minimum number of samples required to split a node of 5, and a minimum number of samples at a leaf node of 2. The $random_{state}$ parameter is set to 42 to ensure that the training process produces consistent results across different runs. After the parameters are defined, model training is performed using the fit function, where the model learns the relationship between input features such as lag features, moving averages, and seasonal features with cayenne pepper prices in the training data. In this process, the Random Forest algorithm builds multiple decision trees independently from the training data and then aggregates their outputs to form an ensemble model that produces stable and accurate predictions (Putri et al., 2025b). Once the model is trained, the results are used to generate predictions on the testing data and to compute model performance evaluation metrics.

Model Testing and Evaluation

After the training process, the resulting model is used to generate predictions on the testing data. Predictions are performed using the predict function on the testing features (X_{test}), resulting in predicted cayenne pepper prices for periods that were not used during model training. The predicted values are then compared with the actual values (y_{test}) to evaluate the model's performance. Evaluation is conducted using error and accuracy metrics, namely the Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) (Hadi & Benedict, 2024).

Coefficient of Determination (R^2)

The coefficient of determination (R^2) is used to measure how well the model explains the variance in the actual data based on prediction results. The R^2 value is obtained by comparing the differences between actual and predicted values with the total variance of the actual values from their mean, thereby indicating the model's ability to represent the observed data. A higher R^2 value indicates better model performance in explaining data variability, which reflects improved predictive accuracy (Harsanyi et al., 2024).

$$R^2 = 1 - \frac{\sum_i^n (yi - \hat{y}i)^2}{\sum_i^n (yi - \bar{y}i)^2} \tag{1}$$

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |yi - \hat{y}i| \tag{2}$$

MAE is used to measure the average magnitude of prediction errors. It is calculated as the average of the absolute differences between predicted and actual values, providing a direct interpretation of the error magnitude relative to the true values. MAE is intended to assess prediction accuracy and to facilitate the understanding of model error magnitude (Maulita et al., 2024).

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (yi - \hat{y}i)^2} \tag{3}$$

RMSE is used to measure the magnitude of prediction errors by assigning a higher penalty to large errors. It is calculated as the square root of the average squared differences between predicted and actual values, making it more sensitive to outliers. A lower RMSE value indicates better model performance in prediction. A low RMSE suggests that the predicted values are closer to the actual values, reflecting good model accuracy in data modeling (Chicco et al., 2021).

Result and Discussion

Pepper Historical Price Trends

The analysis of historical price patterns indicates that cayenne pepper prices across all markets exhibit high volatility, with similar movement patterns across locations and time periods. The historical price patterns for each market are presented in Figures 2 to 5.

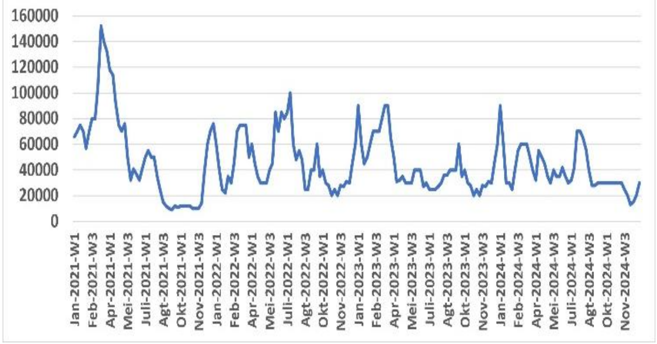

Figure 2. Cayenne pepper price trend in Pancor market (2021–2024)

The historical price trend in the Pancor market (Figure 2) shows that cayenne pepper prices during the period 2021–2024 exhibit high volatility and significant fluctuations. Price spikes occur each year following a similar pattern, with prices rising during certain periods and declining in others. The high level of volatility indicates that cayenne pepper price movements are highly dynamic and complex. This pattern suggests the presence of market dynamics influenced by seasonal factors and changes in the balance between supply and demand.

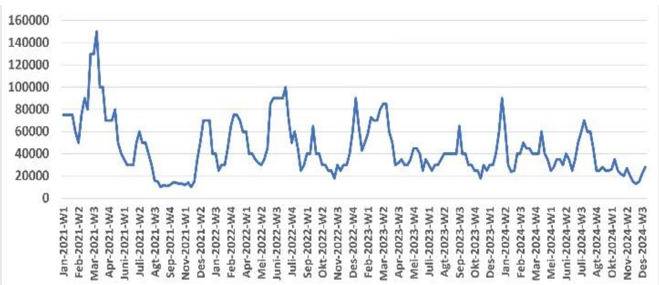

Figure 3. Cayenne pepper price trend in Aikmel market (2021-2024)

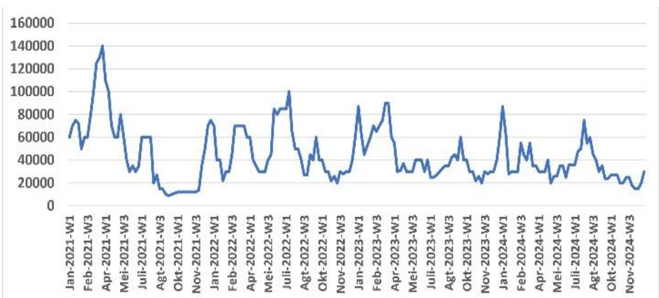

Figure 4. Cayenne pepper price trend in Paok motong market (2021–2024)

A similar pattern is also observed in the Aikmel market (Figure 3), where prices exhibit high fluctuations throughout the 2021–2024 period. Price spikes follow a pattern consistent with other markets, increasing during certain periods and declining in others. This condition indicates that price movements in the Aikmel market are also characterised by high volatility and complexity.

In the Paok Motong market (Figure 4), price fluctuations are observed throughout the 2021–2024 period, with dynamic week-to-week variations. Price spikes tend to occur at the beginning of 2021 and in the early periods of subsequent years, followed by a decline toward the middle and the end of the year. This pattern indicates a consistent annual cycle in price movements.

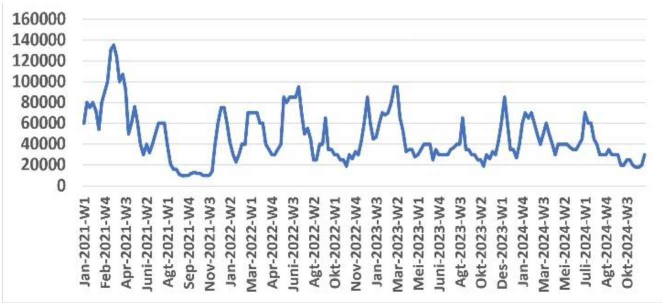

Figure 5. Cayenne pepper price trend in Sakra market (2021–2024)

Meanwhile, the analysis of price patterns in the Sakra market (Figure 5) reveals a trend consistent with the other three markets. Prices tend to increase at the beginning of each year and decline from mid-year toward the end of the year throughout the 2021–2024 period. The consistency of this pattern indicates a strong interconnection in cayenne pepper price dynamics across different markets.

Overall, the analysis of historical prices across all markets indicates that Pancor, Aikmel, Paok Motong, and Sakra share similar characteristics of high price volatility, with comparable movement patterns across periods. All markets experience price spikes at the beginning of the year, particularly a significant surge observed in 2021. This pattern recurs annually, although price levels vary across markets, with some markets occasionally exhibiting different magnitudes of price increases compared to others (Zaini et al., 2023). Overall, price fluctuations across these markets reflect complex market dynamics associated with the balance between supply and demand within the agricultural system (Sun et al., 2024). These findings highlight the importance of utilizing historical data to better understand price patterns and improve the accuracy of price predictions.

Feature Engineering Results

The feature engineering results show that historical cayenne pepper prices can be represented through several temporal features that capture the main characteristics of time series data. The 24 lag features indicate a relationship between past and current prices, suggesting that price movements are dependent on historical data. The rolling mean feature provides a short-term price trend representation and reduces the impact of extreme fluctuations, resulting in a more stable price pattern. The rolling standard deviation feature captures price volatility and variations across periods, reflecting dynamic market behaviour.

The seasonal feature, constructed using sine and cosine transformations on the weekly variable, indicates the presence of an annual cyclical pattern. This suggests that prices tend to increase during certain periods repeatedly each year, and similarly decrease during other periods. Overall, the features used are able to represent historical patterns, price trends, volatility, and seasonality, thereby providing a strong foundation for the model to learn the dynamics of cayenne pepper prices in the main markets of Lombok Timur Regency. To validate the contribution of each feature to the model's predictive performance, a feature importance analysis based on Gini Impurity was conducted for each market model (Lubis et al., 2026). The results are presented in Figure 6.

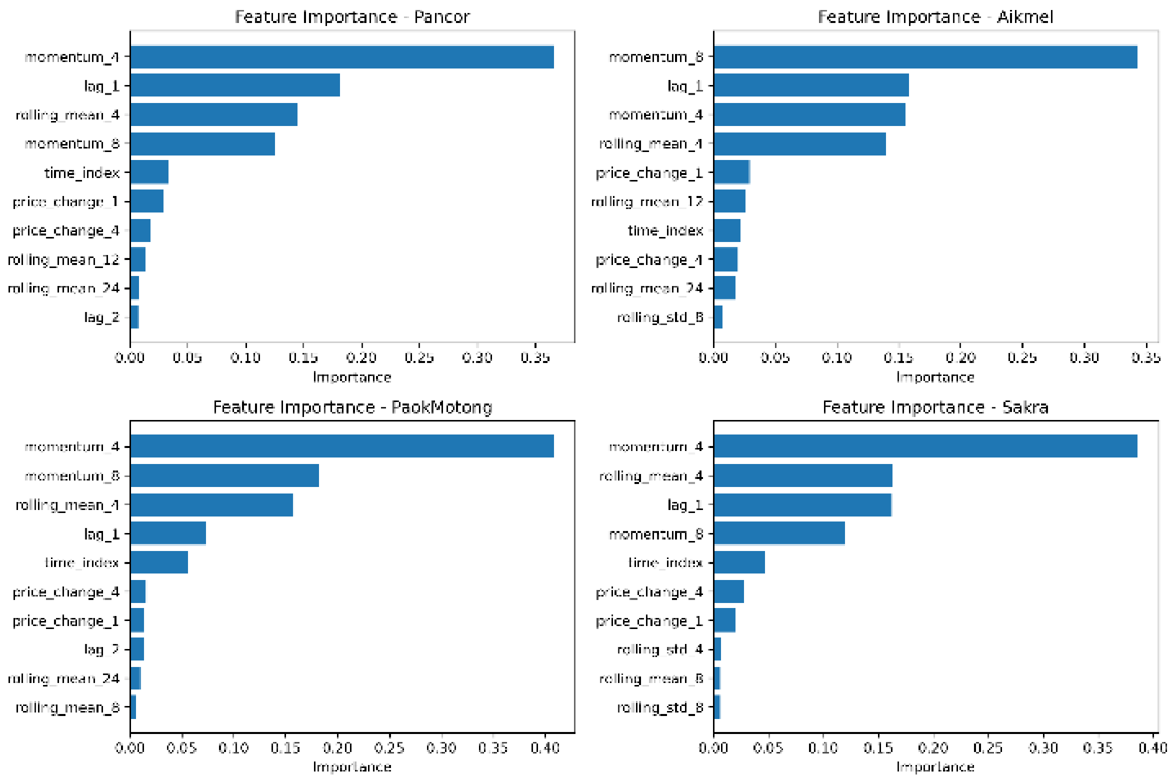

Figure 6. Feature importance analysis of Random Forest model for each market in East Lombok Regency

The feature importance analysis reveals consistent patterns across all four markets. Momentum_4 (4-week price momentum) emerges as the most dominant feature in Pancor, Paok Motong, and Sakra markets, with importance values ranging from 0.37 to 0.41, while momentum_8 ranks highest in the Aikmel market (0.34). This finding indicates that medium-term price momentum over the preceding four to eight weeks plays a critical role in determining current price levels. Lag_1 (previous week's price) consistently ranks within the top three features across all markets, confirming the strong short-term autocorrelation inherent in cayenne pepper price dynamics. Rolling_mean_4 also appears consistently in the top four features across all markets, reflecting the importance of short-term price trend representation in the model's decision-making process. Additionally, time_index ranks within the top five across all markets, suggesting the presence of a long-term temporal trend that the model successfully captures. These findings validate the feature engineering approach adopted in this study and demonstrate that both short-term price signals and medium-term momentum indicators are the primary drivers of cayenne pepper price prediction at the local market level in East Lombok Regency.

Random Forest Model Prediction Results

The prediction results for each market using the Random Forest algorithm show good performance, particularly in capturing upward and downward price trends. However, at certain points with very high fluctuations, the model is still unable to fully follow the actual price movements. The model performs more stably in capturing general patterns but has limitations in predicting sudden extreme price spikes (Salsabila et al., 2025). Nevertheless, overall, the model is able to represent cayenne pepper price movement patterns well during the testing period. The prediction results are shown in the following figure.

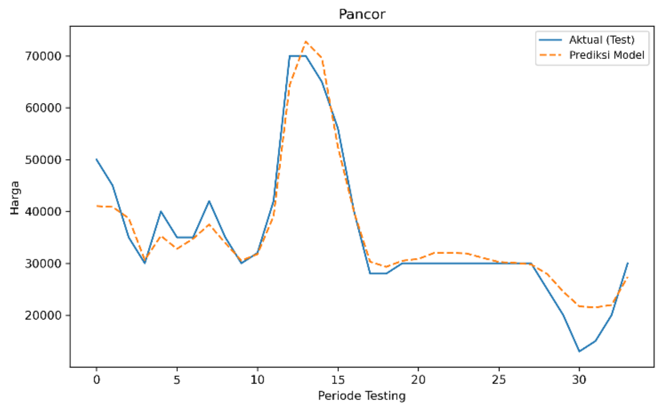

Figure 7. Actual and predicted cayenne pepper price comparison in Pancor market

The prediction results for the Pancor market (Figure 7) show a relatively good agreement between actual and predicted values across most periods. As illustrated in the figure, the model is able to follow the general pattern of actual prices reasonably well in several periods. However, in certain periods characterized by sharp fluctuations and steep declines, the model is not able to fully capture the magnitude of these changes. The evaluation is conducted using 20% of the total dataset, corresponding to approximately 30 to 35 weeks.

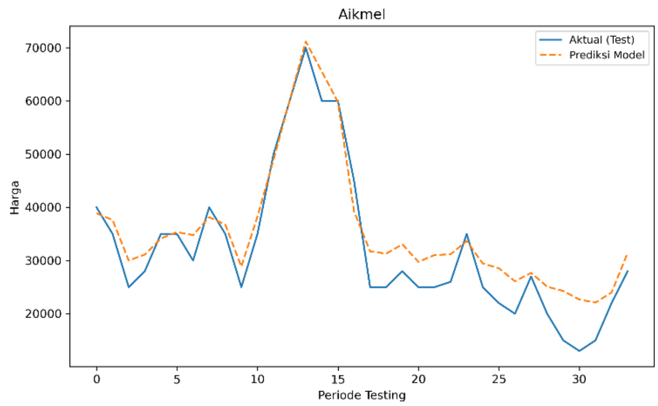

Figure 8. Actual and predicted cayenne pepper price comparison in Aikmel market

In the Aikmel market (Figure 8), the model demonstrates a good ability to follow the pattern of actual prices during the testing period. Price increases occurring in the latter phase of the testing period, corresponding to approximately mid-to-late 2024, are captured reasonably well by the model, and price declines are also reasonably represented. However, discrepancies between actual and predicted values remain at several points, particularly during periods of rapid price changes.

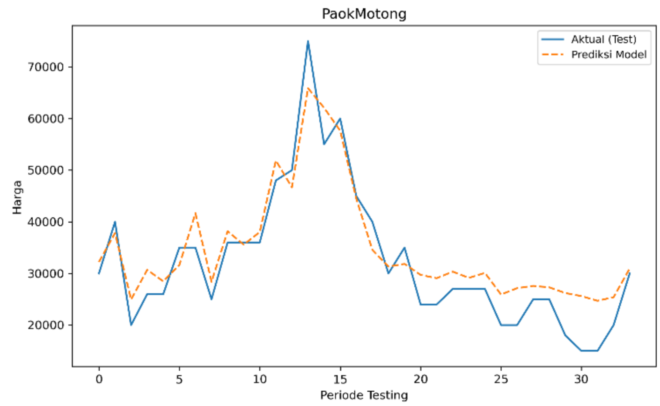

Figure 9. Actual and predicted cayenne pepper price comparison in Paok motong market

In the Paok Motong market (Figure 9), the results are consistent with those observed in the previous two markets. The model is able to follow the general pattern of actual prices and capture the upward trend occurring in the latter phase of the testing period, corresponding to approximately mid-to-late 2024. However, in this market, the model tends to underestimate prices compared to the actual values. This underestimation is more pronounced when compared to the Pancor and Aikmel markets.

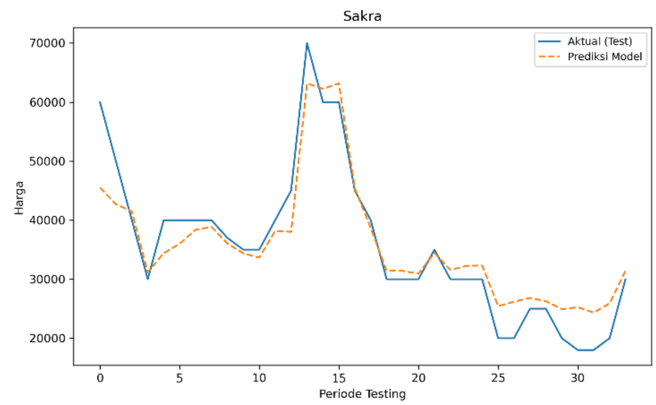

Figure 10. Actual and predicted cayenne pepper price comparison in Sakra market

Meanwhile, in the Sakra market (Figure 10), the model demonstrates the ability to capture the general pattern of price movements, particularly during price increases. However, the predicted peaks are slightly lower than the actual peaks. Based on the model's predictions across the four markets, it can be concluded that the model captures the overall movement of actual prices reasonably well, with price patterns in each market clearly represented.

Overall, the prediction results across the four markets in East Lombok indicate that the model is able to consistently capture the general pattern of cayenne pepper price movements. The model performs better under relatively stable price conditions and gradual price changes. However, across all markets, the model still exhibits limitations in capturing extreme price spikes, both during sharp increases and rapid declines. This suggests that, although the model can represent general patterns, the complexity of market dynamics remains a challenge for accurate price prediction. The underestimation of peak prices observed across all markets is primarily attributed to the inherent limitation of the Random Forest algorithm, which is unable to extrapolate beyond the maximum target values present in the training data. As a tree-based ensemble method, the splitting and averaging mechanism of Random Forest regression tends to produce systematic underestimation at extreme price ranges where training data points are scarce (Dwinanda et al., 2024). Consequently, when cayenne pepper prices in the testing period reached levels that had not been previously observed in the training data from 2021 to mid-2024, the model was mathematically constrained to predict values within the historical price range, resulting in systematic underestimation of extreme price spikes. This characteristic is a well-documented limitation of tree-based regressors and should be considered when interpreting the prediction results, particularly during periods of unprecedented price surges driven by supply shocks or seasonal disruptions (Jeong et al., 2016).

Evaluation of Model Performance

Table 1. Model performance evaluation results for each market

Market	R^2	MAE	RMSE
Pancor	0.931	2657.05	3519.34
Aikmel	0.884	3883.73	4647.86
Paok Motong	0.859	4205.98	4945.93
Sakra	0.877	3337.23	4475.5

The model evaluation results across all markets presented in Table 1 show that the Random Forest algorithm performs well in predicting cayenne pepper prices. The coefficient of determination (R^2) ranges from 0.86 to 0.93. The highest R^2 value is found in the Pancor Market at 0.931, indicating that the model is able to explain approximately 93.1% of the variance in actual prices within the dataset. Meanwhile, the lowest value is observed in the Paok Motong Market at 0.859.

The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) provide an overview of prediction errors across markets. To contextualize these error values, the MAE for each market is compared against the average cayenne pepper price across the 2021–2024 period. The Pancor Market shows the lowest error values, with a MAE of IDR 2,657.05 and an RMSE of IDR 3,519.34. Relative to the average price of IDR 45,436/kg, this corresponds to a relative error of approximately 5.85%, indicating a high level of prediction accuracy. In the Aikmel Market, the MAE and RMSE are IDR 3,883.73 and IDR 4,647.86 respectively, with an average price of IDR 48,448/kg, yielding a relative error of approximately 8.02%. The Paok Motong Market records a MAE of IDR 4,205.98 and an RMSE of IDR 4,945.93, corresponding to a relative error of approximately 9.46% against an average price of IDR 44,440/kg. Meanwhile, the Sakra Market records a MAE of IDR 3,337.23 and an RMSE of IDR 4,475.5, with a relative error of approximately 7.28% against an average price of IDR 45,860/kg. Overall, the relative error values across all four markets remain below 10%, confirming that the Random Forest model achieves high prediction accuracy in the context of cayenne pepper price dynamics in East Lombok Regency.

Overall, the differences in evaluation results across markets indicate that the price characteristics of each market influence model performance. Markets with more stable price patterns tend to have lower error values compared to markets with more volatile price fluctuations, which result in higher errors. In this study, although some values are still not fully captured by the model, overall, the Random Forest algorithm demonstrates good performance in predicting highly volatile cayenne pepper prices in Lombok Timur Regency. Therefore, this model is suitable to be used as a data-driven approach based on historical data for analyzing and forecasting cayenne pepper prices.

In addition, the evaluation results indicate that the model not only provides accurate predictions but also has potential as a data-driven decision support tool (Subangkit et al., 2026). Predicted price information can be used in production and distribution planning, thereby helping reduce market uncertainty (Rahmanta et al., 2020). In the long term, greater availability of more accurate price information may contribute to improved price stability, an essential component in supporting food security.

Interpretation of Prediction Results on Cayenne Pepper Price Dynamics

The prediction results indicate that cayenne pepper price movements at the local market level in Lombok Timur Regency exhibit patterns that can be learned from historical data. These results suggest that price dynamics are not random but follow specific recurring structures, particularly in the form of trends and seasonal cycles. The model's ability to follow gradual price changes indicates temporal dependencies, where prices at a given time are influenced by previous periods. These findings demonstrate that a time-series-based approach is relevant for modelling the dynamics of horticultural commodity prices, particularly cayenne pepper prices in this study.

The model's limitation in capturing extreme price spikes indicates that there are components of market dynamics that historical data cannot fully explain (Aryoso et al., 2025). Sudden price changes may be caused by external factors such as distribution disruptions, production changes, and imbalances between supply and demand in the market due to uncertainty shocks (Fu, 2026). Differences in model accuracy across markets also contribute to price dynamics. Markets with high price volatility tend to produce larger prediction errors, indicating that the price system in these markets is more complex, a pattern similarly observed for cayenne pepper compared to other commodities in prior modeling studies (Lestari et al., 2025).

Overall, the findings of this study indicate that the machine learning-based model can represent the general patterns of cayenne pepper price dynamics; however, it is not yet able to fully capture the complexity of the market system. Therefore, the prediction results should be interpreted within their proper context, taking into account external factors that influence price movements in real-world conditions.

These findings suggest that machine learning approaches, particularly Random Forests, have strong potential for application as data-driven decision-support systems in the agricultural sector. By leveraging historical data, the model can help reduce decision-making uncertainty, especially in determining optimal planting times and marketing strategies. This highlights that the integration of analytical technologies into agricultural systems can serve as a strategic approach to improving efficiency and strengthening food system resilience at the local level.

Conclusion

Based on the results of this study, it can be concluded that the Random Forest model is able to predict cayenne pepper price dynamics in local markets in Lombok Timur Regency with good performance, as indicated by a coefficient of determination (R^2) ranging from 0.86 to 0.93. The model can capture general price movement patterns, including trends and seasonal patterns. The model's inability to capture extreme price fluctuations suggests that cayenne pepper price dynamics are influenced not only by historical patterns but also by external factors. Nevertheless, the developed model continues to represent the main price movement patterns and remains relevant as a data-driven decision-support tool at the local market level. Furthermore, the model developed in this study has the potential to serve as a decision-support tool for data-driven decision-making, particularly in planning optimal planting schedules and distribution strategies. Accordingly, the utilisation of historical data-based price prediction models can enhance price stability and support sustainable food security at the local market level.

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Author Contributions
In this study, all authors contributed to the research process and manuscript writing. W.A. was responsible for data collection, processing, and analysis; E.A. and H.H. provided supervision, feedback, and contributed to the review and refinement of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest in this study.

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