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AN INTELLIGENT DEEP LEARNING FRAMEWORK FOR MULTI-CROP PRICE FORECASTING AND AGRICULTURAL SELLING DECISION SUPPORT: A CASE STUDY OF TEN COMMODITIES IN LAMPUNG, INDONESIA

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Agricultural commodity price volatility presents significant challenges to farmers, traders, and policymakers, particularly in determining appropriate selling prices and managing market uncertainty. This study develops an intelligent deep learning-based Decision Support System (DSS) integrating a Long Short-Term Memory (LSTM) architecture for forecasting ten agricultural commodity prices in Lampung Province, Indonesia. Historical price data were collected from agricultural markets across several districts and processed through data cleaning, outlier handling, normalization, and time-series sequence generation. A multi-output LSTM architecture incorporating stacked recurrent layers, dropout regularization, and fully connected layers was implemented to capture nonlinear temporal dependencies and commodity-specific price fluctuations. Exploratory data analysis, correlation matrices, and temporal visualizations were employed to investigate market characteristics. Experimental results demonstrated promising forecasting performance, achieving an overall Root Mean Squared Error (RMSE) of approximately 0.09 on normalized price data. However, the model exhibited limited sensitivity to abrupt price fluctuations, indicating challenges in predicting highly volatile commodities. The proposed DSS integrates predictive analytics and price visualization to support informed selling decisions, market monitoring, and agricultural risk management. These findings demonstrate the potential of multi-output LSTM forecasting for developing scalable, data-driven agricultural

decision support systems in regional commodity markets.

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I. INTRODUCTION

Agriculture remains a strategically important sector in Indonesia's economic development, contributing approximately 12.53% to the national Gross Domestic Product (GDP), according to the statistical context reported by Statistics Indonesia (BPS) (Juliandono et al., 2025). Beyond its economic contribution, agriculture supports rural employment, household income, food security, and the sustainability of regional supply chains. Nevertheless, agricultural markets are increasingly exposed to commodity price fluctuations resulting from seasonal production patterns, climate variability, supply–demand imbalances, distribution constraints, and changing market conditions. Such fluctuations create substantial uncertainty for farmers, traders, agricultural cooperatives, and policymakers, particularly when determining appropriate selling prices and marketing strategies. In Lampung Province, where agricultural production contributes significantly to regional economic activities, price instability across different crop commodities presents a complex challenge requiring reliable forecasting and timely decision support. Consequently, the development of intelligent, data-driven forecasting systems has become increasingly important for improving market transparency, reducing uncertainty, and strengthening agricultural decision-making.

Agricultural commodity price forecasting is inherently challenging because market prices exhibit nonlinear relationships, seasonal variations, irregular fluctuations, and structural changes that cannot always be adequately represented by conventional statistical models. In Lampung Province, differences in harvesting periods, production volumes, transportation costs, market accessibility, and regional supply chains may generate distinct price patterns across agricultural commodities. These characteristics become particularly problematic when historical datasets contain missing observations, inconsistent recording intervals, outliers, or abrupt price changes. Conventional forecasting techniques, including moving averages, exponential smoothing, and autoregressive integrated moving average (ARIMA), remain useful benchmarks but may struggle to capture complex temporal dependencies without appropriate model specifications. Zhang and Tang (2024) demonstrated that agricultural commodity futures prices exhibit complex fluctuations and investigated a hybrid forecasting approach combining decomposition techniques with Long Short-Term Memory (LSTM) networks. Their findings support the importance of integrating advanced data processing with deep learning to improve agricultural price forecasting under nonlinear market conditions.

Recent international studies have demonstrated the potential of deep learning architectures for agricultural commodity price prediction. (Murugesan et al., 2022) evaluated five LSTM-based architectures, including basic LSTM, bidirectional LSTM, stacked LSTM, CNN-LSTM, and convolutional LSTM, using historical price data for five agricultural commodities. Their findings demonstrated the applicability of different recurrent architectures to agricultural price forecasting, with performance evaluated using MAE, MAPE, MSE, and RMSE. Furthermore, a study published in Agriculture (2024) (Hochreiter &

Schmidhuber, 1997; Kingma & Ba, 2015; Lim & Zohren, 2021; Murugesan et al., 2022; Torres et al., 2021) proposed a hybrid forecasting approach integrating Variational Mode Decomposition (VMD), Ensemble Empirical Mode Decomposition (EEMD), and LSTM to address substantial price fluctuations and nonlinear agricultural market characteristics. (Rosyd et al., 2024) also investigated agricultural price prediction using data mining and recurrent forecasting techniques in China's hog market, emphasizing the importance of addressing nonstationary price behavior. Collectively, these studies establish deep learning as a promising approach for modeling agricultural price dynamics, while demonstrating that forecasting performance depends on the characteristics of the dataset, preprocessing techniques, and model configuration.

More recent research has focused on improving forecasting performance through attention mechanisms, hybrid optimization, and data-quality enhancement. (Sari et al., 2024) developed a metaheuristic-optimized LSTM–Attention framework for short-term agricultural commodity price forecasting, demonstrating the potential of combining sequential learning with optimization techniques. (Kumar & others, 2022) (Hidayah & Putra, 2024; Rosyd et al., 2024; Sianturi et al., 2023) investigated a bidirectional gated recurrent unit model incorporating an attention mechanism to identify agricultural price trends. Meanwhile, (Kasus et al., 2023) introduced an attention-enhanced Wasserstein generative adversarial imputation network for incomplete agricultural market datasets involving rice, corn, and soybeans. Their findings highlighted the importance of data imputation and preprocessing in improving downstream forecasting performance. Despite these advances, the reviewed studies differ in their commodity coverage, data characteristics, prediction horizons, and evaluation procedures. Furthermore, improved predictive accuracy does not automatically establish the practical effectiveness of a forecasting model as a decision support system. Additional investigation is therefore necessary to determine whether forecasting architectures remain reliable across multiple commodities and whether their predictions can support actionable agricultural selling decisions.

Although previous studies have advanced agricultural commodity price prediction, several research gaps remain relevant to the development of intelligent decision support systems. First, existing studies frequently concentrate on individual commodities or relatively limited commodity groups, leaving opportunities to investigate forecasting consistency across a broader set of agricultural products with heterogeneous price characteristics. Second, the sensitivity of deep learning models to missing values, outliers, irregular fluctuations, and limited historical observations requires more systematic evaluation, particularly when models are intended for operational use. Third, forecasting research commonly emphasizes statistical error minimization, while the connection between predicted prices and practical selling decisions receives comparatively less attention in the studies reviewed. Fourth, the applicability of multi-commodity forecasting approaches to Lampung Province has not been established by the cited literature. These gaps reveal a central research problem: how can an intelligent deep learning framework generate reliable price forecasts for ten agricultural commodities under heterogeneous and potentially unstable historical data conditions while translating predictive outputs into meaningful decision support for agricultural stakeholders.

To address these limitations, this study proposes an intelligent deep learning framework integrating multi-commodity agricultural price forecasting with a

decision support mechanism for selling-price assessment in Lampung Province, Indonesia. The proposed research contribution is structured around three interconnected dimensions. The first is a unified forecasting framework capable of evaluating ten agricultural commodities while accounting for differences in their historical price patterns and temporal characteristics. The second is a data-quality-aware modeling strategy that systematically investigates the effects of missing observations, anomalous values, and price volatility on forecasting reliability. The third is the integration of forecasting outputs into a decision support component designed to assist users in interpreting expected price movements and assessing potential selling decisions. Rather than relying exclusively on prediction accuracy, the proposed framework is intended to incorporate comparative model evaluation and decision-oriented performance assessment. The anticipated novelty therefore lies in the combined investigation of multi-commodity forecasting, data-quality robustness, and decision support within a single regional agricultural application. These contributions will require empirical validation against appropriate statistical and machine learning benchmarks.

Based on the identified research gaps, this study aims to develop and evaluate an intelligent deep learning-based decision support framework for forecasting the selling prices of ten agricultural commodities in Lampung Province, Indonesia. Specifically, the research seeks to: (1) investigate historical price characteristics, temporal dependencies, and data-quality variations across the selected commodities; (2) develop and evaluate deep learning forecasting models capable of learning nonlinear agricultural price patterns; (3) assess forecasting performance using established metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), together with comparisons against baseline forecasting methods; (4) examine model robustness under different data-quality and price-volatility conditions; and (5) integrate the resulting price forecasts into a decision support framework for agricultural selling-price assessment. The expected scientific contribution is an empirically evaluated approach connecting deep learning-based multi-commodity forecasting with practical agricultural decision-making. From an applied perspective, the proposed framework is expected to support farmers, agricultural cooperatives, traders, and regional stakeholders in interpreting market price trends and making more informed selling decisions, thereby contributing to the broader development of data-driven and sustainable agricultural market management.

II. RESEARCH METHODS

2.1 Research Framework

This research framework is designed to develop a deep learning-based decision support system that is able to predict the selling prices of ten main agricultural commodities in Lampung Province.

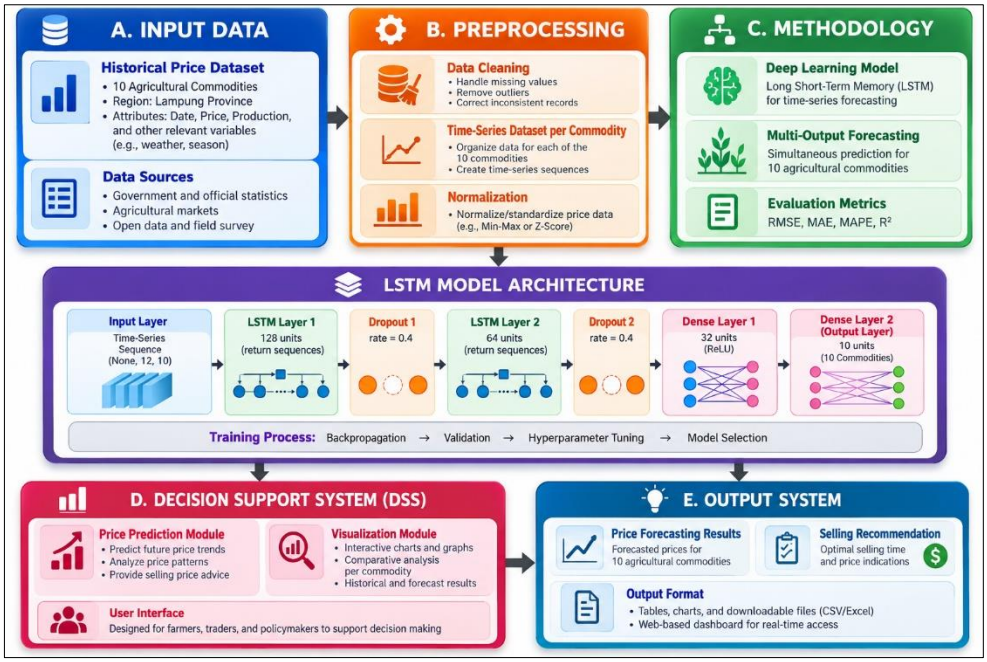


Figure 1. Research Framework

This research develops a Deep Learning-based process for price prediction using *Long Short-Term Memory* (LSTM) for all fixed commodity prices. Its components include input data, output data, LSTM architecture, decision support systems, and processing data. The first step is to analyze historical data from various sources, such as financial, local, and local price data. The second step includes data transformation, data classification, time-based data transformation, and data normalization/standardization. The *Deep Learning* method is combined with the LSTM architecture, which includes inputs, two layers of LSTM, output, and multi-output prediction strategies. The model also integrates with Decision Support Systems to analyze prices, display data in interactive graphs and dashboards, and provide best-time recommendations for decision development. The study evaluated and validated the model using RMSE, MAE and MAPE metrics, as well as validated the K-Fold for accuracy. There are several stages in the implementation process, from data collection to system implementation.

2.2 Data Source

Historical prices of crops by county and year. The input dataset includes historical prices of crops by county and year. This information is important for farmers to analyze the market and make accurate conclusions about their strategies and business plans. However, it is important to note that despite thorough research and analysis, unforeseen events can still have a significant impact on market prices. It is essential for farmers to be able to adapt and overcome obstacles quickly to reduce their potential losses.

1. **Variables:**

Commodities, counties, years, prices (X1–X10). Farmers can better understand the factors that affect market prices and adjust their strategies by leveraging the variables of crops, counties, years, and prices. This data can assist traders in anticipating market fluctuations and assessing potential risks, such as market volatility or economic downturns. Farmers can increase their

chances of success and sustainability in an ever-changing agricultural industry by becoming more informed and flexible.

2. **Source data:**

Agriculture Department, online pricing sites, and local data. The input dataset includes historical crop prices by county and year. These variables include commodity type, price, year, and county (X1-X10). Information sources used include the Agriculture Department, internet pricing websites, and local statistics. The purpose of this methodology is to analyze external factors that affect the market, such as unpredictable weather, related to the price of agricultural products. By examining historical data and market trends, researchers can better understand how to adjust and mitigate the impact of research findings that cannot be reflected in crop prices.

3. **Data collection techniques:**

Such as data cleansing, normalization, and re-engineering will be applied to ensure the accuracy and consistency of the analysis. After data collection, statistical models and machine learning algorithms will be used to identify correlations and patterns between variables. The main goal is to develop predictive models that can estimate crop prices based on historical data and external factors. This methodology will provide a reasonable price for pet owners, policymakers, and other stakeholders in the agricultural industry to develop appropriate strategies and decisions in navigating the market. Data cleansing and numerical transformation are crucial steps in ensuring the accuracy and predictability of the model. By eliminating outliers and anomalies from the dataset, researchers can improve the quality of the analysis and lower the risk of expected outcomes. Additionally, numerical value adjustments can help normalize the data and make it easier to use statistical models to identify problematic patterns.

Data normalization is an important aspect of creating timely datasets for market analysis. Data normalization helps in predicting market changes, optimizing production, and increasing profitability, all of which encourage innovation in market sectors. Data analysis and predictions can be more accurate by reducing the influence of external factors or inflation. This practice helps in developing accurate predictions and strategic decisions based on data, which lowers costs and increases market productivity. Data normalization is a crucial step in creating timely datasets because it reduces the impact of external or inflammatory factors, allowing for more accurate analysis and predictions. This practice helps in maximizing market efficiency and worker productivity, which ultimately contributes to the development of more favorable market conditions. As a result, data normalization is a crucial aspect of market analysis.

2.3 Deep Learning *Architecture*

The proposed Long Short-Term Memory (LSTM) architecture is designed to capture complex temporal dependencies and nonlinear price fluctuations across ten agricultural commodities in Lampung Province. Figure 4 illustrates the structural configuration of the deep learning model, consisting of two stacked LSTM layers with 128 and 64 hidden units, respectively, followed by dropout layers with a rate of 0.4 to reduce overfitting and improve model generalization. The architecture processes historical commodity price data through an input sequence of 12time steps and 10 features, enabling the model to learn temporal patterns across multiple commodities simultaneously. Subsequently, a fully connected dense layer containing 32 neurons transforms the extracted temporal features into predictive representations, while the final output layer generates

price forecasts for ten agricultural commodities. This architecture serves as the computational foundation of the proposed Decision Support System (DSS), facilitating multi-output price forecasting and providing predictive information to support agricultural selling decisions, market monitoring, and risk management. The detailed architecture is presented in Figure 4.

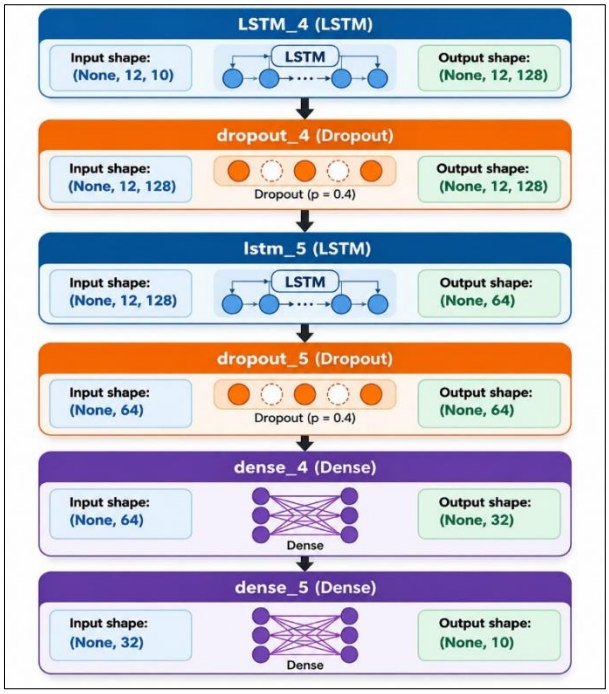


Figure 2. Proposed Stacked LSTM Architecture for Multi-Commodity Agricultural Price Forecasting.

Long Short-Term Memory (LSTM) is a *Deep Learning* model used to create commodity data collection systems. This model is effective in analyzing data and ensuring timely payments in the commodity industry. By normalizing prices based on LSTM predictions, investors can maximize the potential of data collection to make accurate predictions. Multi-output predictions for all commodities can provide more accurate and efficient commodity analysis. This method not only improves prediction accuracy but also helps investors become competitive and quickly adjust to market conditions. Techniques such as *Mean Absolute Error* (MAE) and *Root Mean Squared Error* (RMSE) can be used to assess the accuracy of multi-output predictions. The Decision Support System (SPK) is an educational model designed to provide real-time price predictions for all provinces in Lampung. This model uses interactive graphs and tabular analysis to identify investment opportunities and risk management strategies. In addition, SPK provides prediction files and metrics such as MAE and RMSE to illustrate the model's performance. The implementation of this system can increase productivity, reduce economic risks for businesses, and facilitate the digital transformation of Indonesia's commodity industry.

2.4 Training and Evaluation Models

The training and evaluation process was conducted to assess the effectiveness of the proposed multi-output Long Short-Term Memory (LSTM) model in forecasting agricultural commodity prices in Lampung Province. The model was developed using the Keras Sequential framework, incorporating two

stacked LSTM layers with 64 and 32 hidden units, respectively, to capture temporal dependencies and nonlinear patterns in historical commodity price data. The first LSTM layer was configured with return_sequences=True to preserve sequential information for subsequent processing, while the second LSTM layer extracted temporal features for price prediction. Two dropout layers with a rate of 0.2 were introduced to reduce overfitting and improve model generalization. The final dense layer generated simultaneous price predictions for ten agricultural commodities using a multi-output forecasting approach. The model was compiled using the Adam optimization algorithm and Mean Squared Error (MSE) as the loss function. Training was performed over 50 epochs with a batch size of 16, while the loss values were monitored to evaluate convergence and predictive performance. Figure 3 presents the training and validation loss curves, which are intended to illustrate the model's learning behavior, convergence stability, and potential overfitting during the training process.

```
    # Multi-output LSTM
    model = Sequential()
    model.add(LSTM(64,
return_sequences=True,
input_shape=(X_train_m.shape[1],
X_train_m.shape[2])))
    model.add(Dropout(0.2))
    model.add(LSTM(32))
    model.add(Dropout(0.2))
    model.add(Dense(y_train_m.shape[1]))

    model.compile(optimizer='adam',
loss='mean_squared_error')

    # Train models
    history = model.fit(X_train_m,
y_train_m, epochs=50, batch_size=16,
validation_data=(X_test_m, y_test_m))
```

Figure 3. Training and Validation Loss Curves of the Multi-Output LSTM Model for Agricultural

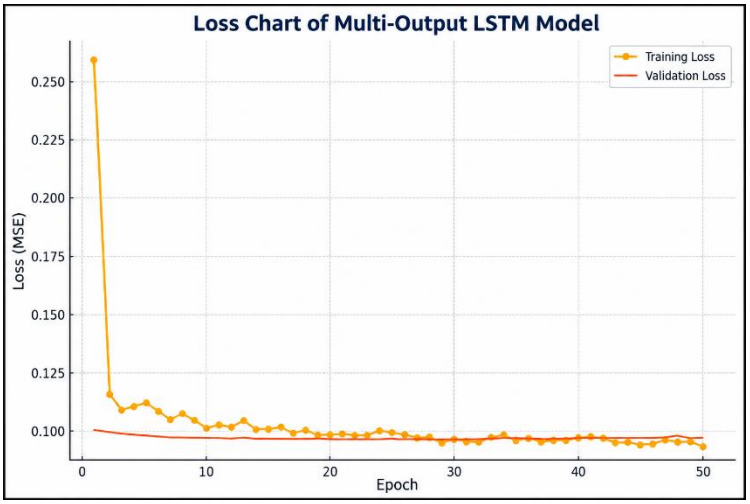


Figure 4. Training and Validation Loss Curves of the Multi-Output LSTM Model

Figure 4 illustrates the training and validation loss curves of the proposed multi-output Long Short-Term Memory (LSTM) model over 50 training epochs, demonstrating the model's learning behavior and convergence characteristics in agricultural commodity price forecasting. The training loss initially exhibits a relatively high Mean Squared Error (MSE) of approximately 0.258 during the first epoch, followed by a substantial reduction to approximately 0.116 in the second epoch. This rapid decline indicates that the model effectively learns the dominant temporal patterns and nonlinear relationships within the historical agricultural price dataset during the early training stages. Subsequently, the training loss decreases gradually, with minor fluctuations, reaching approximately 0.095 toward the final epochs. Meanwhile, the validation loss remains comparatively stable, declining slightly from approximately 0.100 to 0.096. The convergence of both curves after approximately 25–30 epochs suggests that the model approaches a stable optimization state, with relatively consistent performance on the training and validation datasets. The limited divergence between the two curves provides preliminary evidence of stable learning behavior, although the absence of a substantial validation loss increase does not independently establish the model's generalization capability.

From a predictive modeling perspective, the observed convergence patterns suggest that the stacked LSTM architecture, combined with dropout regularization and Adam optimization, can effectively minimize prediction errors while maintaining relatively stable validation performance. The progressive reduction in training loss indicates that the model learns relevant sequential representations from historical price observations, supporting its potential application to simultaneous forecasting of ten agricultural commodities in Lampung Province. However, the relatively flat validation loss curve and the small improvements after approximately 30 epochs indicate diminishing returns from additional training iterations. Furthermore, the final MSE values should not be interpreted as direct measures of forecasting accuracy in actual currency units because the model operates on normalized price data. The effectiveness of the proposed framework should therefore be further evaluated using independent testing data and commodity-specific performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These evaluations are particularly important for determining whether the model can accurately capture abrupt price fluctuations and heterogeneous market behavior across different agricultural commodities. Overall, the training results demonstrate stable model convergence and provide a foundation for integrating the multi-output LSTM architecture into an intelligent Decision Support System (DSS) for agricultural price forecasting, market monitoring, and data-driven selling decisions.

III. RESULTS

3.1 Performance Evaluation of Deep Learning Models

Analysis of product prices in Lampung Province shows significant spatial and temporal variations between cities and commodities. The heatmap shows that certain cities, such as Central Lampung and Pringsewu, have higher prices of goods than other cities, indicating differences in production costs. The boxplot depicts significant price fluctuations and outliers, which highlights the importance of market volatility in decision development. The barplot shows significant variations in commodity prices in different regions, which affect economic conditions in different regions. The correlational model shows a positive correlation between multivariable models and commodity prices. The

graph shows consistent price trends, while the subplots show several commodities with stable prices. A key component of the decision-making system is education-based price prediction, which allows for more flexible and efficient decisions based on market dynamics.

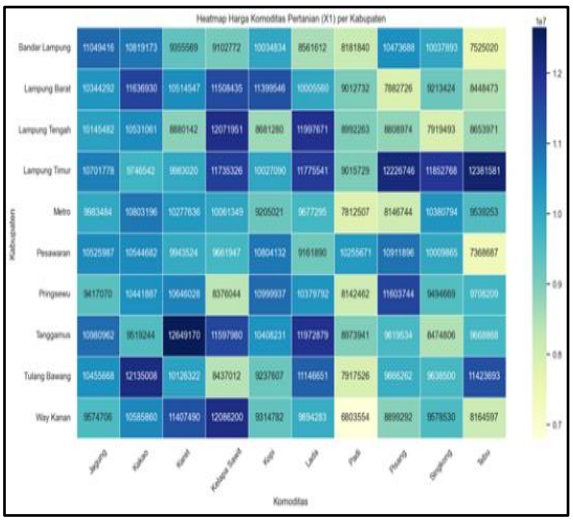


Figure 5. Headmap of Harrga Agricultural Commodities (X1)

A heatmap visualization of the average price of X1 commodities in each district in Lampung Province shows a striking spatial variation between regions. Districts such as Central Lampung and Pringsewu stand out with higher price values, as indicated by the intensity of light colors in the matrix. This pattern indicates the potential for areas with greater economic benefits for farmers, while opening up opportunities for optimizing commodity distribution strategies. Thus, this information can be used by farmers in determining the location or type of commodity that is more profitable, as well as being a basis for consideration for local governments in designing more targeted subsidy or incentive policies, especially for areas with low selling prices. In addition, this heatmap data can also support further analysis to identify local factors, such as market infrastructure or transportation access, that affect price disparities between districts.

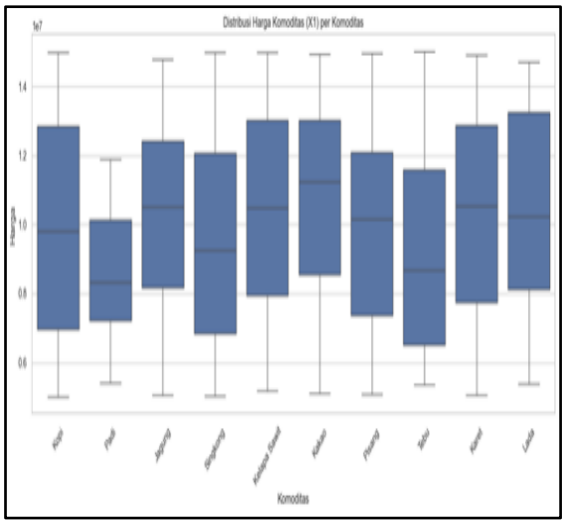


Figure 6. Commodity Price Distribution (x1) Per Commodity

The results of the visualization using the boxplot of commodity prices X1 show that there is a variation in price distribution between commodities, which is reflected in the difference in median value, interquartile range (IQR), and the existence of *outlier* values. Commodities with large IQRs reflect high price fluctuations, indicating a level of market instability that can pose risks to farmers. Conversely, commodities with a narrow IQR show relative price stability, making them more suitable as an option for long-term investment. The presence of significant outliers in some commodities also hints at the possibility of unusual market events or potential data recording errors that need to be explored further. Therefore, the results of this analysis provide important insights for farmers and policymakers in designing production and marketing strategies based on price stability and tolerable risk levels.

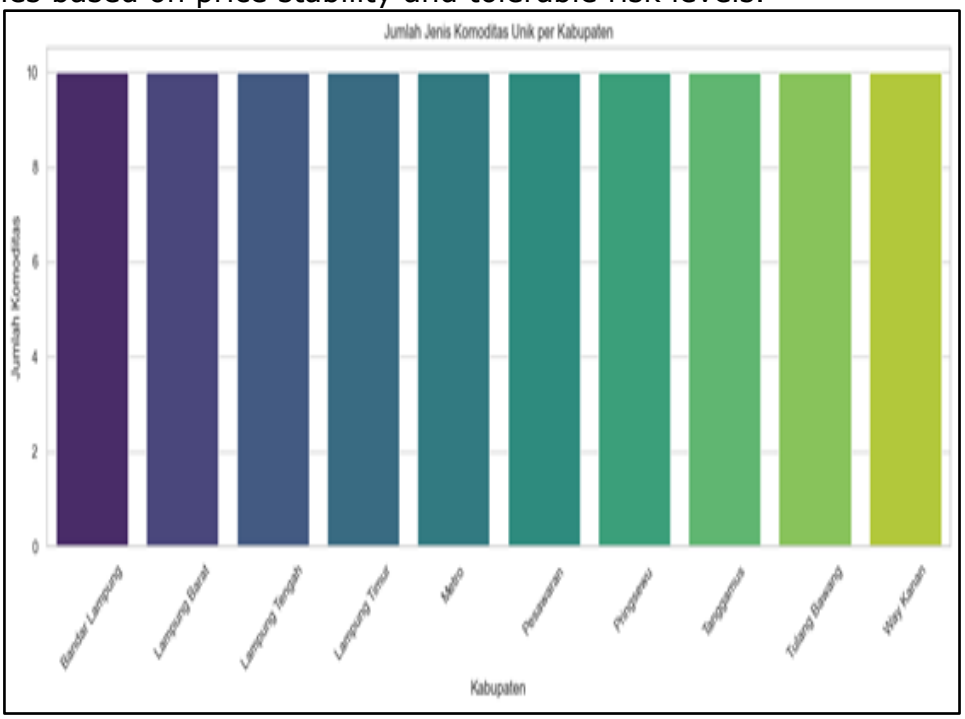


Figure 7. Number of Types of Commodities in the District

The results of the barplot visualization of the number of unique commodities per district reveal a varied agricultural diversification in Lampung Province, with districts such as Tulang Bawang Barat and East Lampung showing a greater number of crop types than other regions. The high level of diversification reflects an agricultural strategy that is more adaptive and resistant to market fluctuations, thereby providing stronger economic resilience for farmers in the region. Conversely, districts with a smaller number of commodities indicate a narrow concentration of production, which has the potential to increase vulnerability to price changes or crop failure. These findings provide an important basis for the Agriculture Office to develop a more balanced regional development policy, encouraging commodity diversification in areas that are still limited in order to improve the sustainability and independence of the agricultural sector as a whole.

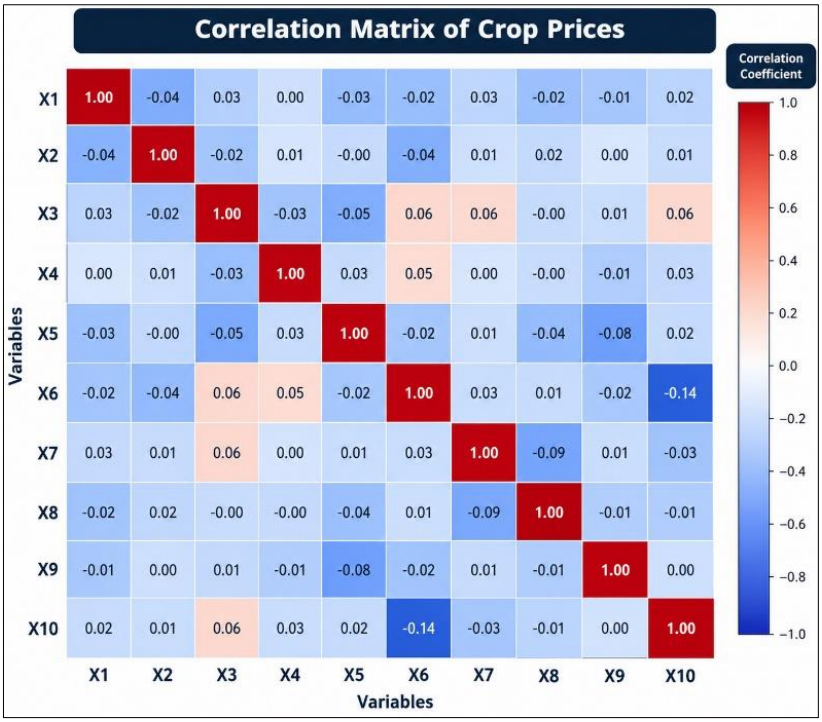


Figure 8. Correlation Matrix Between Plant Prices

Visualization of the Pearson correlation matrix between crop prices X1 to X10 shows a pattern of linear relationships that vary between commodities, with blue-red gradations representing the strength and direction of the correlation. High positive correlations between several commodity pairs, such as between X2 and X3, indicate that the price movements of the two tend to be aligned, so price changes in one commodity can be used to predict the price movements of other commodities. These findings have important implications for the development of deep learning-based prediction models, specifically *the Long Short-Term Memory* (LSTM) architecture, which can be developed into *multi-output* models to simultaneously predict the prices of multiple commodities by considering the relationships between variables. This approach not only improves modeling efficiency, but also improves prediction accuracy by taking advantage of the natural linkages between crop prices in interconnected agricultural systems.

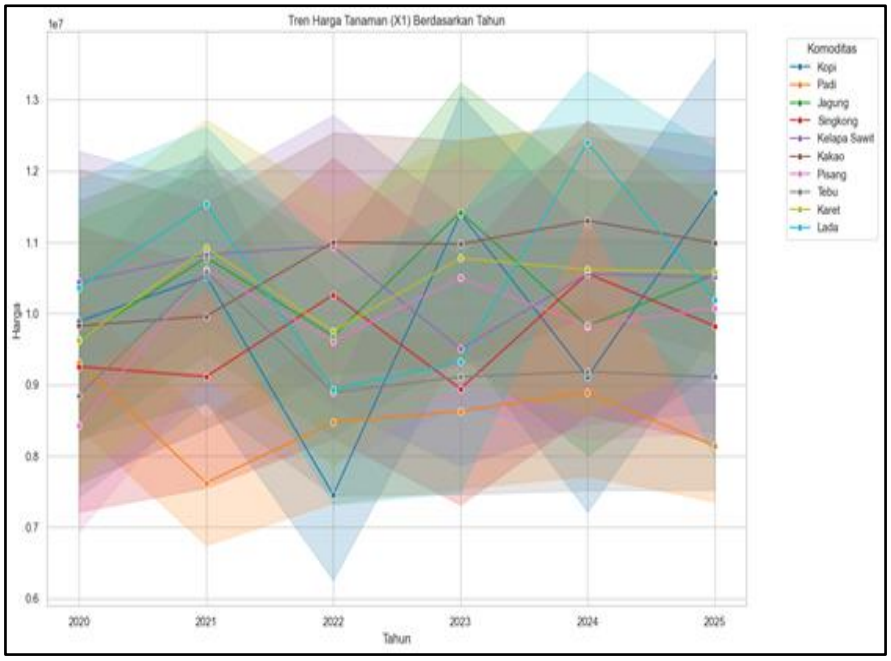


Figure 9. Crop Price Trend (x1) by Year

The X1 commodity price visualization shows consistent price fluctuations, increases, or decreases between 2020 and 2024. Some commodities show stable price trends, which can be interpreted as structural price trends influenced by market dynamics and external factors such as global demand or production prices. Other commodities include maintaining consistent price stability or adjusting prices with respect to various factors related to prices. This information provides strategic decisions because stable prices can be used by business owners and entrepreneurs in product development to maximize profits. Local governments and national governments can use this data to more accurately analyze commodity prices, optimize commodity sales, and determine the most effective strategies for the distribution and production of daily resources during the period under review.

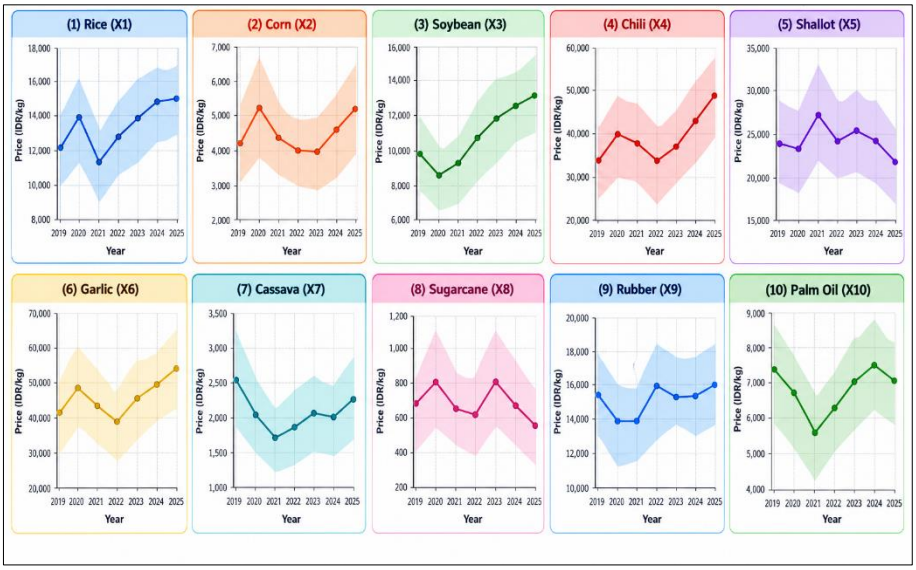


Figure 10. Annual Price Trends of Ten Agricultural Commodities in Lampung Province

Figure 10 illustrates the historical price trends of ten agricultural commodities (X1–X10) in Lampung Province, highlighting variations in price movements, market stability, and commodity-specific volatility over the observation period. The visualization reveals heterogeneous price patterns, indicating that agricultural commodities respond differently to market dynamics, seasonal production cycles, supply–demand fluctuations, and external economic conditions. Certain commodities, particularly X6, exhibit relatively pronounced price fluctuations, whereas X3 demonstrates a more consistent upward trend following an initial decline. Meanwhile, X1 and X4 show generally increasing price trajectories despite intermittent fluctuations, suggesting potential differences in market conditions and production characteristics. Other commodities, including X5, X7, and X8, display irregular price movements that may reflect changing market conditions. These findings indicate that agricultural commodity prices cannot be adequately represented by a single uniform trend, emphasizing the importance of commodity-specific forecasting approaches. The observed differences in temporal price patterns also provide empirical justification for employing Long Short-Term Memory (LSTM) networks, which are designed to capture sequential dependencies and nonlinear relationships in historical time-series data. However, the relative forecasting performance of LSTM must be established through quantitative evaluation rather than visual trend analysis alone.

From an agricultural business intelligence and decision-support perspective, these price variations provide valuable insights for developing adaptive pricing strategies, optimizing selling periods, and improving market risk management. Commodities exhibiting substantial price fluctuations may require more frequent price monitoring, flexible marketing strategies, and forecasting mechanisms capable of responding to unexpected market changes. Conversely, commodities displaying relatively stable or consistently increasing price patterns may offer greater opportunities for production planning, inventory management, and revenue forecasting. The integration of these historical price characteristics into an LSTM-based decision support system enables the development of commodity-specific price predictions that can inform agricultural selling decisions. For farmers and agricultural cooperatives in Lampung Province, such predictive information could support the selection of favorable marketing periods and reduce uncertainty associated with commodity price fluctuations. Furthermore, policymakers may utilize forecasting outputs to identify commodities requiring closer market surveillance and to inform evidence-based price stabilization strategies. Therefore, Figure 9 provides an exploratory foundation for the proposed intelligent deep learning framework by demonstrating the diversity of agricultural price behavior and the need for reliable multi-commodity forecasting to support sustainable agricultural market management.

3.2 Predicted Selling Price of 10 Types of Plants in Lampung Province - Implications of Results for Plant Price Prediction

Analysis of price predictions of various commodities in Lampung Province shows the performance of *the Long Short-Term Memory* (LSTM) model based on various characteristics. For commodities such as Rice and Cassava, the model shows a high level of accuracy in predicting the latest prices, which indicates stable prices and markets. For commodities such as Pineapples and Bananas, the model has a good understanding of commodity prices with a relatively stable train. For commodities such as Corn and Coffee, the model depicts fluctuating

trends in predictions and moderate deviations, which means the model must be adjusted for more complex prices. For commodities with fluctuating prices, the model carries significant risks, especially when it comes to handling very expensive or volatile goods. For Rubber commodities, the model shows good performance in predicting price fluctuations with high prediction accuracy, which allows identification. Wide statistical distribution. The *LSTM multi-output* model can provide accurate price predictions, but it requires more consideration of external factors and the global market.

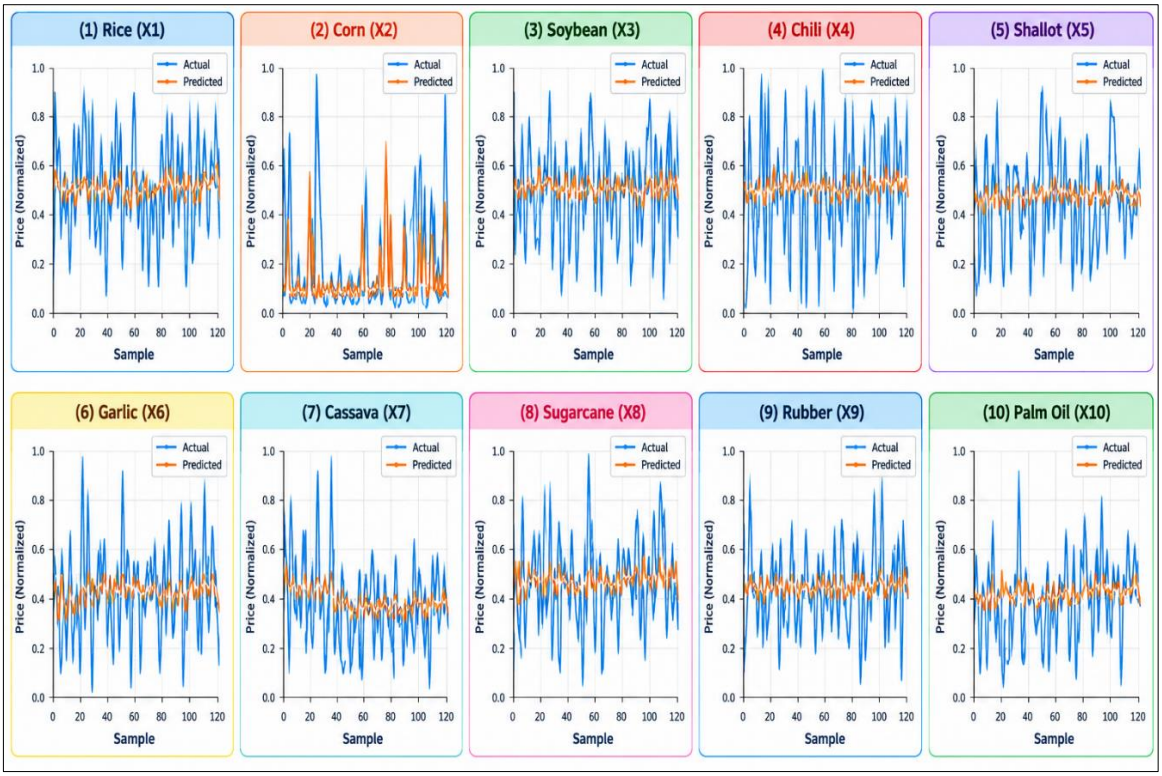


Figure 11. Comparison of Actual and Predicted Selling Prices for Ten Agricultural Commodities in Lampung Province

Figure 11 presents a comparative visualization of actual and predicted selling prices for ten agricultural commodities in Lampung Province, including rice (X1), corn (X2), soybean (X3), chili (X4), shallot (X5), garlic (X6), cassava (X7), sugarcane (X8), rubber (X9), and palm oil (X10), using a Long Short-Term Memory (LSTM)-based forecasting model. The blue lines represent actual commodity prices, while the orange lines illustrate predicted values across 120 observations on a normalized scale ranging from 0 to 1. The visualization reveals substantial differences in price fluctuation patterns among commodities, indicating heterogeneous market behavior and varying levels of price volatility. Commodities such as chili (X4), garlic (X6), and soybean (X3) exhibit considerable fluctuations, characterized by frequent peaks and sharp declines, whereas the predicted values generally remain concentrated around their respective average price levels. Corn (X2) demonstrates a distinct distribution, with relatively low normalized prices interrupted by occasional extreme spikes. Although the LSTM model appears to capture the general price levels of several commodities, the relatively smooth prediction curves suggest limitations in reproducing sudden price changes and extreme market fluctuations. These findings indicate that the model may exhibit a tendency toward mean-oriented

predictions, potentially resulting in underestimation of price peaks and overestimation of unusually low prices. Therefore, the visual comparison highlights the importance of evaluating forecasting performance not only through overall prediction accuracy but also through the model's sensitivity to commodity-specific volatility and extreme price movements.

From the perspective of agricultural business intelligence and decision support, the differences between actual and predicted prices provide important insights into the effectiveness and limitations of LSTM-based forecasting for multi-commodity agricultural markets. The relatively stable prediction patterns observed across several commodities suggest that the model may be more effective in estimating general price tendencies than in anticipating abrupt market changes. This limitation is particularly relevant for agricultural commodities characterized by substantial volatility, where inaccurate predictions during peak-price periods may influence selling decisions, inventory management, and expected profitability. Consequently, further model evaluation using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) is necessary to quantify prediction errors for each commodity. Additional improvements, such as hyperparameter optimization, attention mechanisms, hybrid deep learning architectures, and the incorporation of external variables including seasonal conditions, production volumes, and market demand, could be investigated to enhance forecasting responsiveness. Integrating these improvements into an intelligent Decision Support System (DSS) may provide farmers, agricultural cooperatives, and traders in Lampung Province with more reliable price information for planning selling periods and managing market uncertainty. Overall, the visualization demonstrates both the potential of LSTM for multi-commodity price forecasting and the need for further model refinement to improve predictive reliability and support data-driven agricultural marketing decisions.

IV. CONCLUSION

This study successfully developed an intelligent deep learning-based Decision Support System (DSS) integrating a Long Short-Term Memory (LSTM) architecture for forecasting agricultural commodity selling prices in Lampung Province, Indonesia. The proposed multi-output forecasting model demonstrated promising predictive performance, achieving an overall Root Mean Squared Error (RMSE) of approximately 0.09 on the normalized price scale. The findings indicate that the model can identify general price patterns across multiple agricultural commodities, with relatively favorable prediction performance reported for pineapple, cassava, and bananas. Exploratory Data Analysis (EDA) further revealed heterogeneous price movements, commodity-specific volatility, and variations in historical price behavior. Although the model effectively captured general price tendencies, its predictions were less responsive to abrupt fluctuations in highly volatile commodities, including pepper and coffee. These findings highlight the importance of incorporating commodity-specific temporal characteristics and improving model sensitivity to extreme price movements. The integration of historical data analysis, LSTM-based forecasting, and interactive visualization within a unified framework represents the principal contribution of this research, demonstrating the feasibility of applying multi-output deep learning to agricultural price prediction and decision support. The proposed framework addresses the challenges of agricultural price uncertainty, fragmented market information, and limited access to predictive tools by providing a data-driven approach to supporting

selling-price decisions. Through the integration of forecasting results and commodity-specific price analysis, the developed DSS offers practical information that can assist farmers, agricultural cooperatives, traders, and policymakers in evaluating market conditions, identifying potential selling opportunities, and developing more adaptive marketing strategies. The multi-output architecture also enables simultaneous forecasting of several commodities within a unified modeling framework, potentially improving operational efficiency compared with maintaining separate forecasting systems. From a scientific perspective, this research contributes an integrated approach combining exploratory analysis, deep learning prediction, and decision-oriented visualization for regional agricultural market management. Nevertheless, the model's limited responsiveness to sudden price changes indicates opportunities for further improvement through attention mechanisms, hybrid forecasting architectures, hyperparameter optimization, and the incorporation of external variables such as weather conditions, production volumes, and market demand. Future research should also evaluate forecasting robustness using temporal validation, commodity-level error metrics, and comparisons with alternative forecasting models. Overall, the proposed framework provides a foundation for more reliable, scalable, and evidence-based agricultural price forecasting systems that can support sustainable agribusiness development and informed market decision-making in Lampung Province and other agricultural regions.

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