Forecasting Rice Price Volatility Utilizing BiLSTM-SHAP to Ensure National Food Stability

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***Abstract*—Rice price volatility in Indonesia remains a persistent economic issue, partly driven by climate variability and fluctuations in national rice production, prompting the government to resort to substantial annual imports. However, the extent to which domestic production factors and weather conditions influence future rice prices has not been quantitatively evaluated. This study aims to forecast short-term rice prices in Indonesia by integrating multiple time-series features, including rice prices, harvested area, paddy production, and weather features, using a Bidirectional Long Short-Term Memory (BiLSTM) network. Daily data from 2013 to 2024 were collected from the National Statistics Agency, Food Price Panel, and the Meteorology and Climatology Agency. Chronological split was applied for training, validation, and testing to preserve temporal dependency. The optimal model predicts rice prices seven days ahead using 256 hidden units, achieving MAE of 128.84 IDR, RMSE of 157.98 IDR, and R^2 of 0.694. SHAP analysis shows that historical rice prices have the strongest contribution with a SHAP value of 0.969652, significantly higher compared to other features. The results demonstrate that integrating agricultural and climatic inputs improves predictive performance while providing interpretable insights into price-forming factors.**

Keywords: BiLSTM, Deep Learning, Food Prices, Rice Price Forecasting, SHAP

I. INTRODUCTION

Rice constitutes an internationally traded commodity, with only six nations functioning as the world's principal suppliers [1]. In Indonesia, domestic demand for rice is frequently fulfilled through importation; for instance, in 2024, the nation imported 4.52 million metric tons of rice, representing an approximate 47.38% increase relative to the preceding year [2]. This situation underscores the criticality of food policy in safeguarding price stabilization and supply availability. Consequently, rice price volatility adversely affects agricultural producers, traders, and the general populace [3].

Rice price volatility in Indonesia, which is the focus of this research, is influenced by various interrelated factors. These include government policy and intervention [4], diminished production resulting from agricultural land conversion [5], climate change and natural disasters [7-8], as well as the influence of macroeconomic factors such as inflation and both local and global market dynamics [7]. In economic theory, volatility reflects unexpected price movements. However, seasonal patterns can still be identified within food price fluctuations, indicating recurring patterns during specific periods.

Research on rice price prediction has been conducted using various approaches, including statistical methods, fuzzy logic, artificial neural networks, and deep learning. Within statistical methodologies, the problem of rice price prediction is treated as a linear issue. Several statistical models employed include Linear Regression [9-12], Exponential Smoothing [12], and ARIMA (Autoregressive Integrated Moving Average) [8, 14, 15]. Other research has utilized a Chen model based on fuzzy logic with historical rice price data, under the assumption that identical patterns will recur in the future. This approach is highly dependent on the appropriate initial selection of the fuzzy set; consequently, if this selection is suboptimal, prediction accuracy can decrease significantly [15]. Nevertheless, both approaches face difficulties in accounting for external factors [16].

To address non-linear and dynamic pattern changes, approaches utilizing artificial neural networks and deep learning have been developed, which mimic the human brain's method of processing information [17]. Compared to conventional artificial neural networks, deep learning approaches such as Long Short-Term Memory (LSTM) demonstrate superior accuracy in understanding long-term patterns and overcoming the vanishing gradient problem that frequently occurs in traditional neural networks [17, 19]

A recent study applied LSTM to predict rice prices by considering features such as weather, harvest area, and crop yield [19]. The results indicated a high level of accuracy and provided an outlook on the upward trend of rice prices throughout 2024. Nevertheless, this study also emphasized the importance of testing other features that might influence rice prices. Furthermore, LSTM has a limitation in comprehending broader contexts due to its operational nature, which focuses solely on understanding data patterns in a forward direction [20].

To overcome the limitations of previous LSTM, an LSTM variant, namely Bidirectional Long Short-Term Memory (BiLSTM) exists. It possesses an additional backward layer, allowing it to understand data context more effectively as it provides information regarding the end of the sequence, which

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is useful for predicting subsequent data [21]. Furthermore, SHAP analysis is employed to provide a more complete interpretation related to the features that most influence rice prices [22].

Compared to previous studies, this research introduces several distinct contributions. First, we apply the BiLSTM architecture to replace standard LSTM models, enhancing temporal pattern recognition. Second, we integrate numerical weather features (rainfall, humidity, temperature), which contrasts with other studies that have utilized weather data in a categorical format. Third, we provide a novel contribution by focusing on the North Sumatra region, an area not extensively explored in previous forecasting literature. Finally, we add SHAP analysis to facilitate a detailed and interpretable breakdown of rice prices and the most influential features.

II. METHODOLOGY

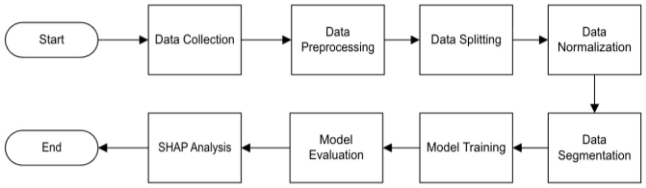

Fig. 1. Research methodology

A. Data Collection

The data used in this study consisted of rice price (IDR), paddy production (tons), harvested area (ha), and weather features comprising rainfall (mm), humidity (%), and average temperature (°C), which were considered crucial for the analysis. Rice price data was sourced from the Badan Pusat Statistik (BPS) and Panel Harga Pangan (BPN) by crawling daily data. To ensure data validity, cross-verification was conducted using news reports regarding rice prices at specific times in North Sumatra. Paddy production data was also collected from BPS, with harvested area and paddy production serving as representative features for agricultural output. Lastly, weather data was retrieved from the Badan Meteorologi Klimatologi dan Geofisika (BMKG) of the North Sumatra Station. The entire dataset was then consolidated into a single master dataset spanning the period from 2013 to 2024, enabling the identification of long-term patterns and fluctuations in rice price movements.

TABLE I. DATASET SAMPLE

Date	Rice Price	Paddy Production	Harvested Area	Rainfall	Humidity	Temperature
2013-01-01	9664.00	3727681.00	742968.00	0.0	83.0	28.1
2013-01-02	9664.00	3727681.00	742968.00	6.2	79.0	27.6
2013-01-03	9664.00	3727681.00	742968.00	2.8	88.0	25.5
2013-01-04	9664.00	3727681.00	742968.00	0.0	85.0	27.4
2013-01-05	9664.00	3727681.00	742968.00	0.0	87.0	26.2
…	…	…	…	…	…	…
2024-12-27	15250.00	2204875.51	419463.48	0.0	84.0	27.2
2024-12-28	15250.00	2204875.51	419463.48	0.0	85.0	27.8
2024-12-29	15250.00	2204875.51	419463.48	0.0	88.0	27.6
2024-12-30	15250.00	2204875.51	419463.48	0.0	92.0	26.2
2024-12-31	15250.00	2204875.51	419463.48	6.1	91.0	26.5

B. Data Preprocessing

The rice price, paddy production, and weather data underwent a preprocessing stage to ensure consistency and reliability prior to modeling. This process included handling missing values and, specifically for weather data, handling irregular entries such as "-", "8888", and "9999". Any missing data points were imputed using the forward-fill method, where the last known valid observation is carried forward. Such preprocessing steps were undertaken to reduce potential biases arising from incomplete records and to improve the quality of the dataset for subsequent analysis.

C. Data Splitting

The dataset was partitioned chronologically into three subsets: 80% training data, 10% validation data, and 10% testing data. This sequential splitting method was employed to maintain the temporal dependencies inherent in the time-series data. This allocation was informed by previous LSTM-based rice price studies and is deemed sufficient for model training while retaining a representative portion for evaluation. The data splitting proportion plays a critical role in determining model performance, as it influences the model's learning capacity and its ability to generalize to unseen data.

D. Data Normalization

The normalization process was carried out by transforming the values of each feature into a range between 0 and 1 using the MinMaxScaler technique. This step was intended to preserve computational stability and improve efficiency during model development, ensuring that all features contributed proportionally within the learning process of the BiLSTM model.

E. Data Segmentation

Each dataset, including the training, validation, and testing sets, was subjected to segmentation before being processed by the model. This segmentation, also known as windowing, is an essential step for BiLSTM as the model is designed to operate on sequential data. In this study, two window sizes were applied, 7 days and 30 days, to compare weekly and monthly rice price movements. The 7-day and 30-day window sizes were selected to represent two different temporal cycles: a short-term cycle and a medium-term cycle. The segmentation was performed by designating 'rice price' as the target column to be predicted.

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F. Model Training

Upon completing the preprocessing and segmentation stages, the data was subsequently trained using a single-layer BiLSTM model. The hyperparameters applied in this process are detailed in Table II, which provides a comprehensive overview of the model configurations employed in this study.

TABLE II. HYPERPARAMETER

Hyperparameter	Value
Neuron	64, 128, 256, 512
Dropout Rate	0.2
Optimizer	adam
Loss Function	mae
Epoch	100
Batch Size	32

Scenarios for both the 7-day and 30-day segmentations were trained using the same base hyperparameter set, but with varied neuron counts to observe their effect on model capability. This approach was designed to ensure consistency across experiments, allowing the analysis to focus on the distinct impacts of segmentation length and neuron quantity. As a result, a total of 8 scenarios were generated, which are presented in Table III to outline the detailed experimental design.

TABLE III. RESEARCH SCENARIOS

Scenario	History	Neuron
1	7 days	64
2	7 days	128
3	7 days	256
4	7 days	512
5	30 days	64
6	30 days	128
7	30 days	256
8	30 days	512

In the implementation stage, early stopping was also applied by monitoring the validation loss (val_loss). Training was halted if the model did not show any improvement within 10 consecutive epochs. This mechanism was introduced to prevent overfitting and to optimize computational efficiency during the training process.

G. Model Evaluation

To assess the predictive performance of the model, several error metrics were employed. One of the key measures is the Mean Absolute Error (MAE), which calculates the average absolute difference between the actual and predicted values. A lower MAE value indicates higher prediction accuracy. The formula for MAE is given as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

Where

y_i : represents the actual value

$\hat{y}_i$: the predicted value

n : the total number of observations.

In addition, the Root Mean Squared Error (RMSE) was also utilized as a complementary evaluation metric. RMSE measures the square root of the average of the squared differences between the actual and predicted values. This metric is particularly sensitive to large errors, making it a robust indicator of model performance in the presence of significant deviations. The formula is expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

Finally, R^2 (R-squared) was applied to measure the percentage of variance in the target feature that is explainable by the input features, with a value range of 0 to 1. A higher R^2 value indicates that the model better fits the data. The formula is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (3)$$

All three metrics provide valuable perspectives: MAE offers a direct interpretation of the average error magnitude, while RMSE highlights the impact of larger errors in the same scale as the target feature, and R^2 quantifies the model's goodness-of-fit by explaining the proportion of variance captured.

H. SHAP Analysis

In this study, SHAP analysis was performed to interpret the predictions generated by the best-performing BiLSTM model. After obtaining the outputs from the trained model, SHAP values were computed on the test dataset to decompose each prediction into the additive contributions of its constituent features. The input features included historical rice prices, paddy production indicators, and weather data. By applying SHAP, it was possible to quantify how each feature influenced the model's output across different timesteps.

SHAP values are presented numerically. A positive SHAP value indicates that a feature contributed to shifting the prediction higher, while a negative SHAP value indicates a contribution that shifted the prediction lower. This approach proved particularly valuable for detecting patterns across the two segmentation schemes, offering deeper insights into how short-term versus long-term sequences affected the BiLSTM model's decision-making process. Furthermore, these insights can be used to inform feature selection in future model development.

III. RESULTS AND DISCUSSION

In this study, the BiLSTM model was constructed using six features: rice price, paddy production, harvested area, rainfall, humidity, and temperature. These features were selected to represent both economic and environmental factors that may influence rice price fluctuations. To evaluate the model's performance, a set of experiments was designed by systematically varying two parameters: the length of the historical input (history) and the number of hidden units. Each parameter configuration was intended to capture the model's sensitivity to temporal dependency, model capacity, and regularization.

A. Model Result

The results of these experiments are summarized in Table IV, which reports the MAE, RMSE, and R^2 values for each scenario. This comparison allows for the identification of the most optimal configuration and provides an analysis of how the interplay between segmentation length and neuron count impacts the predictive accuracy of the BiLSTM model. The metrics in Table IV will also be used to select the best-performing model for subsequent SHAP analysis.

The experimental results indicate that the choice of history length has a notable impact on the BiLSTM model's performance. Models trained with a 7-day history (scenarios 1-4) consistently achieved superior MAE, RMSE, and R^2 values compared to those trained with a 30-day history (scenarios 5-8).

TABLE IV. COMPARISON OF EACH SCENARIO

Scenario	MAE	RMSE	R^2
1	264.5753	287.7497	-0.4787
2	263.2334	285.2669	-0.4498
3	128.8351	157.9808	0.6940
4	184.3486	209.0940	0.3136
5	273.6352	297.0893	-0.8358
6	294.2785	314.3758	-1.0796
7	148.5102	177.2618	0.4753
8	223.2996	248.8883	-0.2288

This finding suggests that short-term historical information is more relevant for rice price prediction, as extending the history window did not yield substantial performance gains. Moreover, these results imply that price fluctuations are more sensitive to short-term dynamics and that longer horizons may introduce additional noise into the learning process rather than improving predictive accuracy.

Furthermore, the number of hidden units played a crucial role in determining model performance. Configurations with 256 units yielded the best results compared to 64, 128, and 512, based on MAE and RMSE values. Notably, based on the R^2 values, only the 256-unit configurations produced positive results, indicating they were the only models to effectively fit the rice price data. Consequently, the optimal BiLSTM model in this study was identified as Scenario 3, which utilized a 7-day history and 256 hidden units. To further facilitate the interpretation of this optimal model, additional relative metrics MAPE and Normalized RMSE were calculated. The results yielded a MAPE of 0.8517%, indicating that the model's predictions were, on average, less than 1% different from the actual prices. Similarly, the Normalized RMSE was 1.0522%, confirming that the overall error magnitude remained exceptionally low relative to the average price.

The optimal BiLSTM model's results were further evaluated by comparing the actual rice price values with the model's predictions and by graphically analyzing the distribution of prediction errors. These two approaches were selected as they provide a comprehensive understanding of the model's performance, assessing both its ability to capture temporal patterns and the magnitude of the resulting prediction errors.

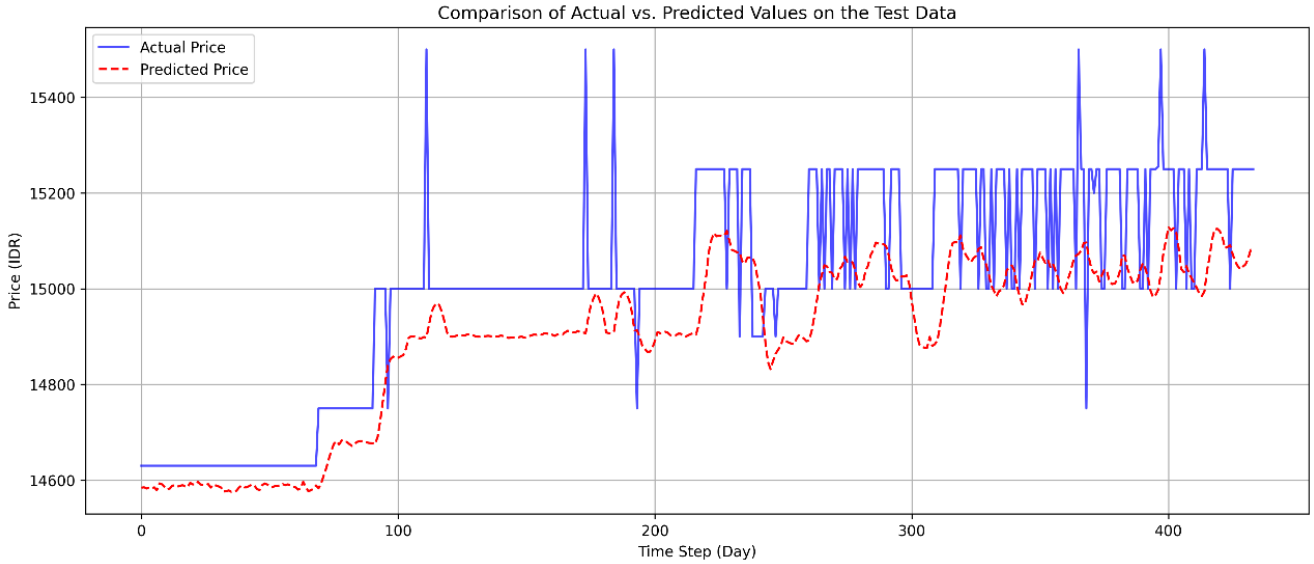

Fig. 2. Comparison on actual vs predicted price

Fig. 2 presents a comparison between actual rice prices (blue line) and predicted prices (red dashed line) on the test dataset. Overall, the predicted values closely follow the general trend of rice price movements over time. Although certain sharp fluctuations in the actual data were not fully captured by the model, the predictions remain stable and consistent with the overall trajectory of price changes. This indicates that the model demonstrates a strong generalization capability in recognizing temporal dynamics of rice prices.

Fig. 3 illustrates the distribution of prediction errors, defined as the difference between predicted and actual values. The concentration of errors primarily between 0 and 150 (IDR) indicates that most predictions closely approximate the actual prices. Furthermore, the distribution exhibits a slight positive skew, as positive errors (overestimations) are more frequent than negative errors. This suggests the model has a mild systematic tendency to over-predict the actual price. However, the presence of several large outliers confirms that while generally stable, the model is not infallible.

Considering the consistency of the predictive patterns with the actual data (Fig. 2) and the error distribution centered near zero (Fig. 3), this scenario was identified as the best-performing configuration.

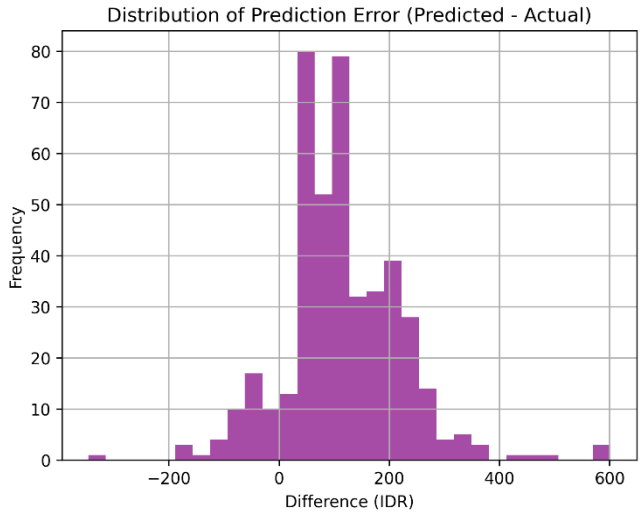

Fig. 1. Distribution of prediction error

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This combination of findings demonstrates that the model not only captures the overall trend of rice prices but also minimizes prediction errors in a stable manner, thereby representing the most optimal configuration among all those tested.

B. SHAP Analysis

To complement the performance evaluation of the best-performing model, an interpretability analysis was conducted by comparing the correlation matrix and SHAP (SHapley Additive exPlanations) values, as presented in Table V. This approach contrasts the simple linear relationships identified by the correlation matrix with the actual predictive contributions learned by the model, as revealed by SHAP.

TABLE V. CORRELATION MATRIX AND SHAP OF EACH FEATURE

Features	Correlation Matrix	SHAP
Rice Price	1.000000	0.969652
Paddy Production	-0.683082	0.100713
Harvested Area	-0.703393	0.105333
Rainfall	0.071428	0.091103
Humidity	-0.183933	0.091130
Temperature	0.296472	0.094396

The primary finding is that the model is predominantly autoregressive. The Rice Price feature (SHAP: 0.969) is the most influential predictor by an absolute margin, indicating that historical price movement is the primary factor the model learned for forecasting. The most compelling finding, however, emerges from the exogenous features. Although their SHAP values are substantially smaller than that of historical price, all external features were found to provide a meaningful contribution (SHAP > 0). Furthermore, the model regards the importance of fundamental economic features Harvested Area (0.105) and Paddy Production (0.100) as nearly equivalent to the importance of climatic factors, such as Temperature (0.094), Humidity (0.091), and Rainfall (0.091).

This finding reveals a significant contradiction when compared to the standard linear correlation matrix. In the correlation analysis, Harvested Area (-0.703) and Paddy Production (-0.683) exhibited a strong negative linear relationship, while climatic features like Temperature (0.29) and Rainfall (0.07) showed very weak correlations. This discrepancy is a core finding of this study: the BiLSTM model is capturing more than just simple linear relationships, a fact quantitatively validated by the SHAP analysis.

Furthermore, these results stand in contrast to a previous study on economic factors affecting rice price fluctuations in the same North Sumatra region, which employed descriptive analysis and Vector Auto Regression (VAR) [23]. That study concluded that paddy production accounted for 60% of the influence on rice price, with the remainder attributed to economic factors such as inflation. In our research, the inverse appears to be true, with the autoregressive Rice Price feature being the dominant driver. However, the aforementioned study also emphasized that economic factors are indeed the most influential in the short term, a point our findings partially support through the identification of Harvested Area and Paddy Production as the most significant exogenous features.

IV. CONCLUSION

This study demonstrates that the BiLSTM model, when applied to rice price forecasting, is capable of producing accurate and interpretable predictions. Among the 8 scenarios, the best-performing configuration achieved a Mean Absolute Error (MAE) of 128.8351, a Root Mean Squared Error (RMSE) of 157.9808, and an R^2 of 0.6940, utilizing a 7-day historical window and 256 hidden units. Additional relative metrics, MAPE and Normalized RMSE, were applied to facilitate interpretation, yielding a MAPE of 0.8517% and a Normalized RMSE of 1.0522%. These results confirm the model's ability to effectively capture short-term temporal dependencies in price movements. Furthermore, the integration of SHAP analysis provided an additional layer of interpretability, clarifying the relative influence of each feature on the prediction process and strengthening the practical value of the findings [24-25]. Specifically, this analysis confirmed the model's predominantly autoregressive nature, with Rice Price (SHAP: 0.969) as the dominant predictor, while economic and climatic features provided nearly equivalent secondary contributions.

This research has several methodological limitations that should be noted. The use of a fixed 80/10/10 sequential data split, while common, is methodologically less robust than time-series cross-validation techniques, such as a rolling-window approach. Furthermore, the hyperparameter tuning process (e.g., neuron count and history size) was conducted manually, which may not have yielded the most optimal configuration. The data scope is also a constraint, as testing was performed only on data from North Sumatra; consequently, the model's generalizability to other regions or a national level remains unconfirmed. Finally, the employed feature set did not include crucial external macroeconomic features, such as inflation, import policies, or fuel prices, limiting the model's ability to account for systemic economic shocks.

Future work will focus on four main areas to address these limitations. First, automated hyperparameter optimization using techniques such as Bayesian Optimization or Grid Search should be employed to replace manual tuning and identify the most robust model architecture. Second, feature enrichment by integrating relevant macroeconomic data (e.g., inflation and import data) is the next crucial step. Third, the enriched model should then be re-validated using a rolling-window cross-validation methodology and benchmarked against baseline models (like SARIMA or Random Forest) to objectively measure its performance. Finally, as practical implementations, exploring the use of real-time data for very short-term forecasting and testing the model's generalizability on data from other provinces will be essential next steps.

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