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Rice Price Prediction with Long Short-Term Memory (LSTM) Neural Network

Rahmat Hidayat[1*], Irawan Wibisonya[2]
[1]Computer Science, Sains and Technology, Universitas Putra Bangsa, Kebumen, Indonesia
[2]Agribisnis, Sains and Technology, Universitas Putra Bangsa, Kebumen, Indonesia
[1]ayat150190@gmail.com, [2]irawanwibisonya@gmail.com

Abstract

Rice is a crucial commodity, especially in countries that rely on rice as a staple food. Fluctuations in rice prices can impact inflation, purchasing power, and economic stability. Therefore, an effective method for forecasting rice prices is essential for timely decision-making. This study aims to develop a rice price forecasting model by incorporating weather variability. Using Long Short-Term Memory (LSTM) neural networks, the model is expected to provide accurate predictions and guide decision-making in rice trading. LSTM is effective in analyzing time-series data. In this study, LSTM was used to examine the relationship between weather variability, crop yields, and land area with rice prices. Daily data from 2015 to 2023 were collected to build a model capable of predicting future rice prices. The results showed that the LSTM model achieved a Root Mean Squared Error (RMSE) of 0.054, indicating high prediction accuracy. This model allows stakeholders, including farmers, traders, and government officials, to better understand future rice price movements. This, in turn, helps them implement more effective strategies in managing rice supply and stabilizing prices.

Keywords: *prediction; variability; long short-term memory; artificial neural networks*

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1. Introduction

In the era of globalization and digitalization, climate change and weather variability have become important factors affecting the production and distribution of various commodities, including rice. Rice prices are highly sensitive to weather variability, such as changes in temperature, humidity, and rainfall, which can affect crop yields and market availability[1]. A very high increase in rice prices occurred in February 2024 according to news excerpts published by BBC News Indonesia, where the price of premium rice reached Rp.18.000 per kilogram, the highest price in Indonesian history. The high price of rice is one of the impacts of many farmers who failed to harvest due to El Nino weather changes[2].

Weather variability, such as rainfall, temperature, and humidity, has a significant impact on rice production and quality. The uncertainty of weather patterns can lead to significant disruptions in agricultural practices, including changes in cropping patterns, fertilizer use, and pest control, which ultimately impact rice yields and supplies. Compounded by global climate change, this makes agricultural production and price forecasting increasingly challenging [3].

With the advancement of technology, rice prices can be predicted using annual data as well as factors affecting prices [4]. Accurate and effective forecasting methods are crucial to anticipate rice price fluctuations. One promising method in rice price forecasting is Long Short-Term Memory (LSTM) Neural Networks [5]. LSTM is a type of neural network that can recognize patterns, account for long-range dependencies in data, and predict future trends.

Previous research [6], [7] has shown that LSTM-based models are able to provide accurate forecasts in agricultural commodity price forecasting. However, the gap remains in applying LSTM to predict rice prices while integrating weather variability as a key variable. Therefore, this research aims to fill the knowledge gap by developing a forecasting model using LSTM Neural

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Networks that integrates weather variability data and price history as the main features in predicting rice prices. This approach is expected to make a significant contribution in improving the accuracy of rice price forecasting, thus supporting more effective agricultural, trade, and social welfare policies.

Several previous studies have used statistical and artificial intelligence methods to forecast agricultural commodity prices, including rice prices. These methods include linear regression[8], [9], [10], [11] from research using linear regression using price history as the main variable, obtained quite good results with RMSE (Root Mean Squared Error) 0.559861633 which means prediction with linear regression is quite accurate. While the use of ARIMA (Autoregressive Integrated Moving Average) implemented in research [12], [13] also uses the price history variable as the main variable as well as other artificial neural network techniques used in research [14], [15], [16]. Although the results obtained using these two methods are quite good, the use of main variables that are not diverse certainly does not strengthen that the method is good to implement. The Use of LSTM in Forecasting LSTM Neural Networks have been widely used in various fields, including in forecasting stock prices, demand for goods, and weather. Additionally, there are studies that apply LSTM to rice price prediction[1], [4], [5], [17], [18], [19], [20]. However, the use of LSTM in forecasting rice prices based on weather variability and price history as the main variables has not been specifically studied. The integration of weather variability and rice price history is a key novelty of this research, utilizing both variables as the primary features in forecasting rice prices.

2. Research Methods

Figure 1 is the stages that are the main guidelines in this research, namely:

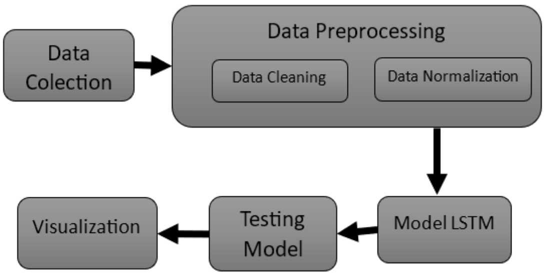

Figure 1. Research Method

Data collection is a crucial early stage in this research. The data collected includes daily rice prices, weather variables (rainfall, temperature, humidity), crop yields, and land area from 2015 to 2023. Data sources were obtained from government agencies such as the Meteorology, Climatology, and Geophysics Agency (BMKG), the Central Bureau of Statistics (BPS), and the Industry and Trade Office. The quality of the data collected was ensured by addressing the issues of missing data and interpolation of incomplete data.

Once the data is collected, it cannot be used in the model right away. A preprocessing step is essential to ensure that the data is ready for analysis.

Data Cleaning: Removing or filling in missing data using the average value of the same month in the previous year. This is done to avoid distortions in the prediction results.

Data Normalization: Weather and rice price data that have different scales are normalized using the min-max scaling method. This is important so that the LSTM model can work optimally without bias from variables with larger scales.

Once the data is cleaned and normalized, the next step is to build and train the Long Short-Term Memory (LSTM) model[21]. An LSTM is a type of neural network specifically designed to handle sequential data, such as time series, which is particularly suitable for price prediction over time. These models learn patterns in past data, and then use those patterns to make predictions about the future. LSTMs are renowned for their ability to remember both long- and short-term data, making them suitable for problems involving historical trends and seasonal changes. In this research, modeling and testing predictions are carried out using the python programming language. The frameworks used are Keras and Tensorflow, and the python libraries used are Scikut-learn, pandas, matplotlib, numpy, and seaborn.

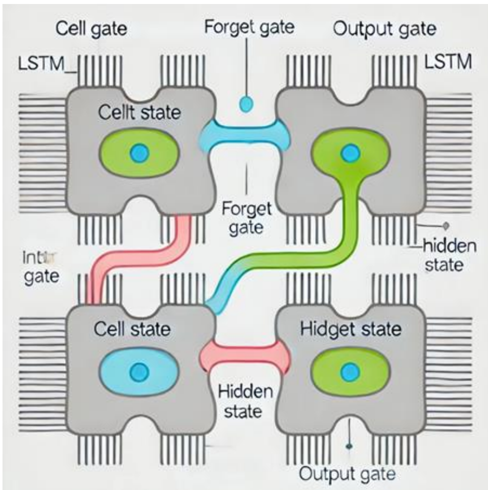

Figure 2. LSTM Structure

Figure 2 is an LSTM structure that includes Forget Gate, Input Gate, and Output Gate, as well as the flow of information displayed through the cell state and hidden state[22].

Forget gate: This gate decides which information from the cell state should be discarded. By using the current input and the previous hidden state, this gate generates a value between 0 and 1 for each element in the cell state. A value of 0 means that the information is completely removed, while a value of 1 means that the information is fully retained. The equation for the Forget Gate is expressed as Equation 1.

$$f_t = \sigma\left(W_f \cdot \left[h_{\{t-1\}}, x_t\right] + b_f\right) \quad (1)$$

Input gate: After determining which information to forget, the Input Gate controls the new information that will be added to the cell state. This gate also uses the current input and the previous hidden state to generate a value that determines how much new information will be allowed. The equation for the Input Gate is Equation 2.

$$i_t = \sigma\left(W_i \cdot \left[h_{\{t-1\}}, x_t\right] + b_i\right) \quad (2)$$

Output gate: This gate determines the information that will be output at a specific time step. The Output Gate takes the current cell state and decides which information will be used to generate the next output. The equation for the Output Gate is Equation 3.

$$o_t = \sigma\left(W_o \cdot \left[h_{\{t-1\}}, x_t\right] + b_o\right) \quad (3)$$

Cell state: The update of the cell state takes into account the new information permitted by the Input Gate and the information retained from the previous cell state. This update is expressed as seen in Equation 4.

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \quad (4)$$

Hidden state: The hidden state is obtained from the updated cell state, expressed as Equation 5.

$$h_t = o_t * \backslash tanh(C_t) \quad (5)$$

The cell state (*Ct*) retains long-term information carried over from the previous time step. The cell state can be considered as memory that holds important information from processed inputs. The hidden state (*ht*) is the output of the LSTM at a particular time step, which carries the most relevant current information for future predictions. The hidden state is also used as input for the next time step in the modeling process. The flow of information in the LSTM begins with processing the input through the Forget Gate and Input Gate, contributing to the update of the cell state. Thus, LSTM is capable of retaining important information over the long term while discarding irrelevant information, which is highly beneficial for forecasting rice prices based on weather variability.

Once the LSTM model has been trained, it must be tested using separate data that the model has never seen before. This stage is important to evaluate how well the model does in making predictions on unfamiliar data. A commonly used evaluation method is error measurement such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE), which helps measure how far the model's prediction is from the actual data[22]. If the model makes accurate predictions, it can be used to predict future prices. Otherwise, the model needs to be improved or retrained.

Formula for Root Mean Squared Error (RMSE) is shown in Equation 6.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2} \quad (6)$$

The formula for Mean Absolute Error (MAE) is shown in Equation 7.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}| \quad (7)$$

The last stage in this research is visualization of results. Visualization is used to compare the prediction results with the actual data. Usually, these results are visualized in the form of a graph so that it can easily see the trends and patterns of the predictions compared to reality. For example, you can create a line graph showing the actual price and the predicted price, so that the difference or error in the prediction can be clearly seen. This visualization is also important for conveying the results to stakeholders or readers of the study, so that they can understand the model's performance intuitively.

3. Results and Discussions

3.1 Exploratory Data

In this study, data on rice prices, yields and weather were analyzed from 2015 to 2023. The data used is 3287 data which can be seen in Table 1. The next step is to visualize the data to understand the pattern of price changes and the influence of weather conditions, crop yields and land area. However, some data had missing values, especially in some periods for rice price data. To overcome this, missing data was filled in by using the average value of the same month in previous years. As for the yield data obtained from BPS and in the form of annual yields, and land area, to overcome this, interpolation was carried out to obtain data in daily form. This step is important to ensure that the data used in the prediction model is complete and accurate.

Table 1. Dataset

Time	Price (Rp)	Rain	Land Area	Crop Yield
1/1/2015	8.750	Light	2386,84	1309,06
2/1/2015	8.750	Light	2386,84	1309,06
…….	……..	……..	……	………
1/1/2016	9.500	Not Raining	2376,87	1201,47
…….	……..	……..	………	………
30/12/2023	13.500	Light	2436,84	1084,37
31/12/2023	13.500	Medium	2436,84	1084,37

The rain variable used in the dataset is data obtained from BMKG, where the rain status reflects the actual monitored conditions, not the predicted results. In this study, the rain variable is used because rice is a crop that is highly dependent on irrigation. In the Kebumen region, irrigation of rice fields is highly dependent on water flowing from dams. The dam will only be opened when the water discharge increases, as the main priority is power generation. Therefore, the level of irrigation in the rice fields of the Kebumen region is highly dependent on rainfall. The next step is to visualize the

Table 2. Normalization Data

Time	Price (Rp)	Rain Numeric	Land Area	Crop Yield
1/1/2015	0,166	0,3	0,0335	0,6889
2/1/2015	0,166	0,3	0,0335	0,6889
…….	……..	……..	……	………
1/1/2016	0,285	0	0,0046	0,4503
…….	……..	……..	………	………
30/12/2023	0,920	0,3	0,1787	0,1929
31/12/2023	0,920	0,6	0,1787	0,1929

dataset used as can be seen in Figure 3. This is done to see the price pattern as well as the rain pattern that occurs in a certain period of time as shown in Figure 4.

Figure 3. Price Visualization

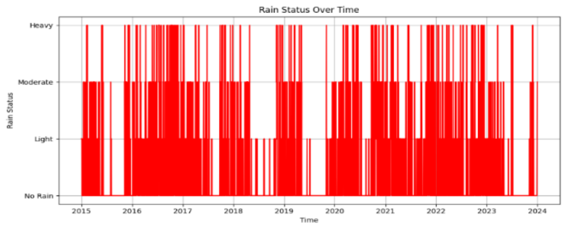

Figure 4. Raining Visualization

The next stage is data normalization. Data normalization is done to ensure that all variables are on the same scale, especially when using algorithms such as Neural Network that are sensitive to scale differences. If not normalized, variables with a large range of values can dominate the learning process, causing the model to be unable to capture patterns properly. In addition, normalization helps speed up the convergence of optimization algorithms during training and reduces the risk of numerical problems that may lead to unstable or less accurate results. In this research, the normalization process was applied to all variables in the dataset, including Price (Rp), Rain, Land Area, and Crop Yield. This was done using the min-max scaling technique, which converts the values of the variables into a range between 0 and 1, making them comparable in scale. The formula used for normalization is shown in Equation 8.

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{8}$$

For example, in Tabel 2: Normalization Data, the rice price of 13,500 Rupiah on December 30, 2023, is normalized to 0.920. Similarly, the rainfall variable, which originally had values like "Light" or "Not Raining," was converted into numerical values, with "Light" being represented by 0.3. Other variables, such as Land Area and Crop Yield, were also normalized to ensure that all features in the dataset contribute equally to the learning process.

The result of this normalization process is shown in Tabel 2, where all the variables are now on a comparable scale, ranging between 0 and 1. This step is critical to the success of the model training, as it ensures that no single variable disproportionately influences the model's learning, leading to more accurate predictions.

3.2 Price prediction with LSTM

In this study, the parameters were adjusted to achieve more accurate prediction results. The model used involves dividing the data into training and testing data with a ratio of 80:20 and 70:30. In addition, testing was conducted using epochs of 100 and 200, as well as a neural network model consisting of 4 layers, each with 256, 128, 64, and 32 neurons. The purpose of this parameter setting and testing scenario is to find the best model in predicting rice prices. Based on these scenarios, the following results were obtained in Table 3.

Table 3. Scenario

Training-Testing	Epoch	Layer	RMSE
80-20	100 200	256,128,63,32	0.065 0.063
70-30	100 200	256,128,63,32	0.054 0.059

The test results in Table 3 show that:

At 80:20 split, with 100 epochs, the model produced an RMSE value of 0.065, and when the number of epochs was increased to 200, the RMSE decreased to 0.063.

At a 70:30 split, better results were obtained. With 100 epochs, the resulting RMSE value was 0.054, while with 200 epochs, the RMSE value slightly increased to 0.059.

One of the main novelties of this research is the integration of multiple key variables, including weather conditions such as rainfall, crop yield, and land area, along with price history in the LSTM model. This combination has not been widely used in rice price prediction studies, which commonly rely only on historical price data. The results of this research show that by incorporating these additional variables, the accuracy of predictions improves significantly, as evidenced by the lower RMSE values compared to previous methods.

Overall, the 70:30 data split scenario with 100 epochs produced the best performance, characterized by the lowest RMSE value of 0.054. This shows that the model provides the most accurate rice price prediction compared to other scenarios. Once the best scenario is found, the next step is to visualize the comparison between the actual price and the predicted price based on the dataset.

The graph in Figure 5 shows the results of rice price prediction using the LSTM model. In the graph, the blue line represents the rice price data used to train the model (training data), while the orange line illustrates the actual data used to test the model (testing data). The green line shows the rice price prediction generated by the LSTM model. From this graph, it can be observed that the LSTM model is able to follow the rice price trend pattern quite well on the testing data, although there are slight differences at some points. The alignment between the green line (predicted price) and the orange line (actual price on the test data) demonstrates the model's ability to capture the spikes and drops in rice prices with a high level of accuracy.

Additionally, while there are minor deviations between the predicted prices and actual prices at certain points, the overall trend is well-captured. The pattern of steady price increases, especially towards the end of 2023 and into early 2024, is predicted accurately, indicating a continued upward trend in rice prices. This demonstrates the robustness of the LSTM model in capturing complex, real-world pricing behaviors over an extended period.

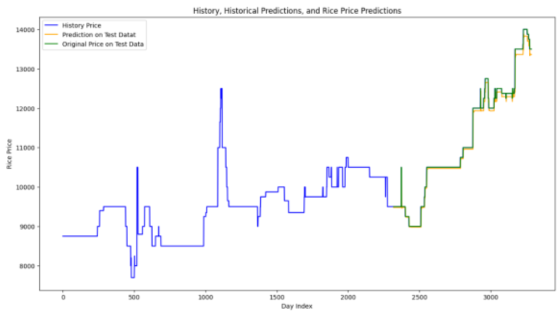

Figure 5. Rice Price Prediction Using LSTM

Furthermore, Figure 5 shows the model's ability to adapt to seasonal price fluctuations and highlights its capability to generalize well on unseen data (test data), with only minimal error, as evidenced by the close tracking between the green and orange lines. The visualization effectively illustrates the prediction's performance over the entire dataset, making it clear that the model successfully identifies both short-term fluctuations and long-term trends.

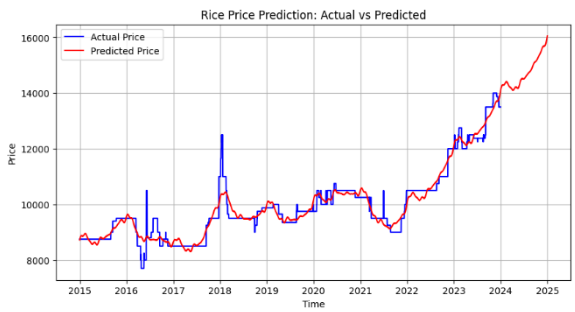

Figure 6. Rice Price Prediction at 2024

The graph in Figure 6 shows the comparison between the actual rice price (blue line) and the rice price predicted by the model (red line) for the period from 2015 to 2024. From this graph, it can be seen that the model is able to capture the general pattern of rice prices, following the price fluctuations quite well. Notably, the model manages to track both short-term price spikes and more stable periods, reflecting its ability to adjust to different market behaviors.

Although there are some deviations at certain points, the overall trend and major fluctuations are aligned between the predicted and actual prices. The pattern of steady price increases is especially noticeable towards the end of 2023 and the beginning of 2024, indicating a continued upward trend in prices. Moreover, the model's ability to predict the long-term trend suggests it is effectively capturing the underlying drivers of rice price increases.

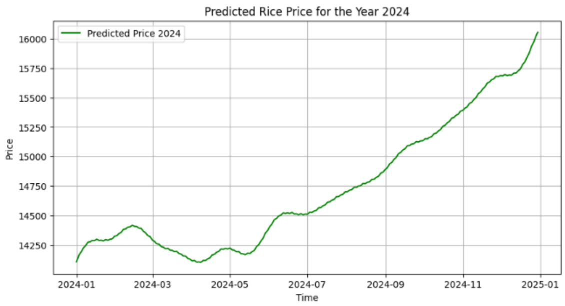

Figure 7. Rice Price Prediction at 2024

Meanwhile, the graph in Figure 7 displays rice price predictions specifically for the year 2024. The green line illustrates the trend of rice price predictions throughout the year. At the beginning of 2024, the model shows some price volatility, capturing potential seasonal effects or market dynamics that affect rice prices. There is a seasonal pattern with slight fluctuations at the beginning of the year, but overall, rice prices are predicted to continue increasing throughout the year, reaching a peak at the end of 2024. This long-term upward trend suggests that external factors, such as increased demand or reduced supply, might be influencing the rise in prices. Table 4 is a table of predicted premium rice prices that will occur in 2024.

Table 4. Rice Price Prediction in 2024

Time	Price
Januari	Rp. 14.262
February	Rp. 14.372
Maret	Rp. 14.205
April	Rp. 14.156
Mei	Rp. 14.226
Juni	Rp. 14.496
Juli	Rp. 14.600
Agustus	Rp. 14.779
September	Rp. 15.043
Oktober	Rp. 15.254
November	Rp. 15.553
December	Rp. 15.792

Table 4 shows the predicted rice price per month for 2024, generated from the prediction model. In January, the price of rice is predicted to reach IDR 14,262, and will increase slightly to IDR 14,372 in February. The price then tends to stabilize in March and April, with prices of IDR 14,205 and IDR 14,156 respectively. In May, the price of rice rose slightly again to IDR 14,226. Midway through the year, there was a more significant increase, with prices reaching IDR 14,496 in June and IDR 14,600 in July. The price increase continued in August, reaching IDR 14,779. By the end of the year, predictions show a sharper upward trend in prices. In September, prices are expected to reach IDR 15,043, and continue to rise to IDR 15,792 in December. These price increases suggest a steady upward trend in rice prices throughout 2024, with a sharper increase towards the end of the year.

4. Conclusions

The Long Short-Term Memory (LSTM) model used in this study proved to be able to predict rice prices with high accuracy, as shown by the RMSE value of 0.054. The predictions show an upward trend in rice prices throughout 2024, especially at the end of the year. This provides important insights for the government, farmers, and market players to plan measures to maintain rice supply and price stability. Given the LSTM model's ability to capture seasonal patterns and long-term trends, it can be further developed by adding variables such as government policies and economic factors to improve prediction accuracy. The results of this study can be used as a basis for strategic decision-making regarding rice prices and supply in the future. Based on the research results, there are several suggestions that can be considered for further development. First, the LSTM model used can be improved by adding additional variables such as rice import policy, market demand fluctuations, and macroeconomic factors such as inflation. By adding these variables, the prediction model can provide more accurate and comprehensive results. In addition, it is recommended to expand the use of weather data at the regional level, so that predictions can be more specific to certain regions. Hybrid methods that combine LSTM with statistical models such as ARIMA or SARIMA can also be explored to capture more complex seasonal patterns and trends. Finally, a long-term evaluation of the model's performance should be conducted using data from future years to ensure the robustness of the model in the face of dynamic market and weather conditions.

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