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Comparative Analysis of LSTM and 1D-CNN for Food Commodity Price Prediction in East Java

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ABSTRACT

Accurate food price predictions are crucial for maintaining market stability and developing policy strategies in new food areas. This study aims to compare two deep learning models, namely Long Short-Term Memory (LSTM) and 1D Convolutional Neural Network (CNN-1D), in predicting monthly prices of 6 food commodities in East Java. Price data from January 2020 to July 2025 were cleaned before being used for model training. The evaluation results show that there is no single best model. Rather, performance depends heavily on the data characteristics of each commodity. The LSTM model provides the lowest MAPE for Medium Rice Commodities (1.05%), Premium Rice (1.85%), Dry Milled Grain (4.32%), Harvested Dry Grain (2.40%), and Dry Shelled Corn (1.27%), indicating its ability to identify long-term patterns and seasonal fluctuations. Meanwhile, for Soybeans, CNN-1D is more accurate, with a MAPE of 0.79%, because it captures short-term fluctuations that often occur. The implication of this research is the importance of a commodity-specific approach in selecting a price prediction model. The resulting 12-month price forecasts can serve as a reference for policymakers in planning regional food stabilization.

I. INTRODUCTION

Food prices are a crucial factor influencing household economic stability and regional food security. In East Java, as one of the nation's food barns, price fluctuations for staple commodities like rice and corn often occur due to an imbalance between supply and demand. [1] This price uncertainty not only burdens consumers but also puts farmers in a vulnerable position because it is difficult to predict their future income. [2]. As a result, decisions to plant or sell are often made without accurate price predictions, risking losses. Frisda et al. [3] noted that food prices in East Java exhibit a seasonal pattern, tending to rise towards the end of the year and fall mid-year, which could be used for better planning if supported by a reliable broadcasting system. Extreme fluctuations, especially in rice prices, exacerbate the food system's vulnerability. Therefore, accurate price predictions are crucial, not only do they protect consumers and help farmers, but they also form the basis for government policy aimed at maintaining food stability, as stable food prices are a key pillar of national food security [4]. Furthermore, this supports the provision of food standards in accordance with regulations, which are essential to ensuring food safety and economic stability in Indonesia's agricultural and food sectors [5].

Facing the complexities of food prices, deep learning-based approaches offer a strategic solution for building accurate early warning systems. In the era of agricultural digitalization, models such as LSTMs and CNNs can capture complex patterns and temporal dependencies in price data. In contrast, conventional methods such as ARIMA or Holt-Winters struggle to do so [3]. Recent research shows that these models are not only more accurate but also facilitate data-driven decision-making to strengthen food security [6] [7].In fact, some neural network models have achieved an MAPE of below 3% in predicting rice prices [4]. Thus, developing a deep learning-based prediction system is no longer merely academic research; it is a real need to maintain regional food price stability. In food price prediction, deep learning models such as LSTMs and 1D CNNs are often used because they can capture nonlinear and temporal patterns in time-series data. LSTM excels at modeling long-term dependencies, making it suitable for historical price trends [8]. Meanwhile, CNN can extract seasonal patterns and local features through convolutional layers, especially in data with clear periodicity [9]. A recent study by Nensi et al. [10] implemented LSTM, Bi-LSTM, and hybrid CNN-LSTM to forecast the prices of four major food commodities in East Java, and found that Bi-LSTM provided the best performance with MAPE as low as 0.23% for medium rice and 0.08% for beef, confirming the superiority of bidirectional architecture in utilizing past and future context information. Tsabitah et al. [11] in their research developed a multivariate time series-based forecasting model by integrating the VECMX and LSTM approaches on food price data from 34 provincial capitals in Indonesia and proved that the combination of hybrid models was able to capture long-term structural relationships as well as short-term nonlinear fluctuations simultaneously with an MAPE value below 10%.

Comparing these two models is important to determine which one best suits the characteristics of price data in East Java. However, model performance is highly dependent on data quality, which often contains outliers and invalid values. Therefore, this study implemented data preprocessing steps, including outlier detection, min-max normalization, and sliding-window transformation. This approach aligns with Utomo's [12] finding that data cleanliness is the main foundation for predictive accuracy in the agricultural context.

LSTM has proven reliable at predicting food prices in East Java, as demonstrated by red chili peppers [13]. owever, comparative research on its effectiveness relative to 1D CNNs in local contexts is still rare. CNNs have the advantage of automatically recognizing recurring patterns and seasonal periodicity in data [14]. Several studies support this. CNNs have been shown to outperform other models (such as SVM and MLP) in predicting wheat prices [15]. Combining CNNs with another architecture (BiLSTM) has also significantly improved the accuracy of corn price predictions [16]. Furthermore, a direct comparison of convolution-based architectures with LSTMs for rice, wheat, and corn shows that convolutional models produce significantly lower prediction errors (RMSE and MAPE) [17]. Regardless of model choice, data quality remains a crucial factor. Food price data is often unclean, containing missing, invalid, or outlier values, which can disrupt the training process of any model [18]. To date, no research has comprehensively compared LSTMs and 1D CNNs for six strategic commodities.

Accurate food price predictions are not just about numerical accuracy, but also about the model's ability to read the soul of each commodity, whether it moves calmly with seasonal trends or is turbulent with short-term fluctuations. While previous studies tended to rely on a single, uniform deep learning architecture across various commodities, this study takes a more adaptive approach by selectively comparing the performance of LSTMs and CNN-1D models based on the characteristics of their respective price dynamics. Using historical data from 2020–2025 from East Java, the national food barn region, this study not only tests accuracy using metrics such as MAPE, RMSE, and MAE, but also interprets why LSTM excels for commodities with stable trends, while CNN-1D is more responsive to volatile commodities. Beyond performance comparison, this study introduces a methodological framework that integrates volatility profiling, statistical validation, and computational efficiency analysis to guide model selection based on commodity-specific characteristics. The results are 12-month price projections that are not only precise but also meaningful for data-driven regional-level food policy planning.

II. METHOD

This study uses price data for six strategic food commodities in East Java, obtained from the official dataset of the East Java Central Statistics Agency and uploaded to the Kaggle platform. The data covers the period from January 2020 to July 2025 (67 months) and focuses on the development of two deep learning architectures: LSTM and 1D CNN.

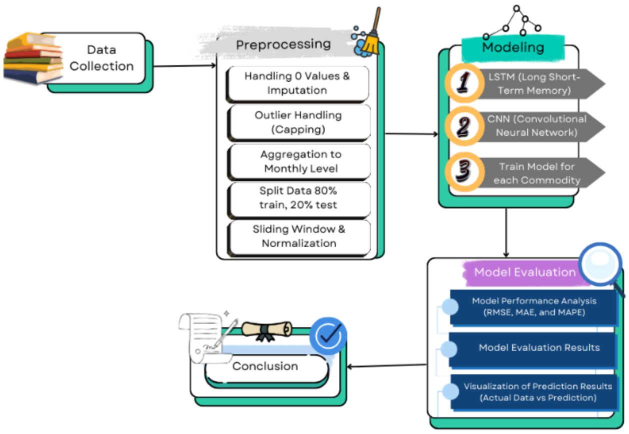

Figure 1. Flow of Research

A. *Data collection*

This research uses publicly available data from the Kaggle platform, initially processed [19]. The dataset used is titled "East Java Agricultural Prices," with a total of 15,276 agricultural commodity price data points, covering 11 attributes. The dataset contains six main categories: Medium Rice, Premium Rice, Dry Corn, Soybeans, Dry Milled Grain, and Harvested Dry Grain. The processing of this dataset focuses only on four significant attributes: province, month/year, commodity, and price. The initial dataset is divided into six sub-datasets separated by commodity type. Each sub-dataset is then processed and analyzed independently, allowing for evaluation of the performance of deep learning models tailored to the price characteristics of each commodity. This summary yields 2,546 observations per commodity, spanning January 2020 to July 2025. The complete data structure is shown in Table 1.

TABLE I
RAW DATASET (2020-2025)

province	month_year	commodity	price
East Java	2020-01	Medium Rice	8500
East Java	2020-01	Dry Milled Paddy	5500
East Java	2020-01	Dry Harvested Grain	0
…	…	…	…
East Java	2025-07	Premium Rice	10500
East Java	2025-07	Dried Corn Kernels	4700
East Java	2025-07	Soya bean	0

B. *Preprocessing*

Data preprocessing was performed in stages to ensure the quality of the input for the deep learning model.

1) *Handling null and missing values*

Zero values indicate that no transactions were filled using forward or backward imputation methods at the provincial level. For the remaining gaps, the global median price of the commodity was used [5] [20]. This approach was chosen because it preserves the temporal structure of the data and is commonly used in the preprocessing of agricultural sector time series data [21].

2) *Outlier detection and capping*

Outliers were identified using the Interquartile Range (IQR) method, adjusted for each commodity, and extreme values were replaced with the upper or lower IQR limits. This step is important to increase the model's robustness, as outliers can disrupt deep learning training [21].

3) *Monthly aggregation*

Price data are averaged monthly for each commodity across East Java, yielding a single time series per commodity from January 2020 to July 2025. This aggregation reduces local variation and smooths fluctuations, making it easier for the model to capture seasonal patterns.

4) *Distribution of Training and Testing Data*

The sequences were split chronologically into training (80%) and testing (20%) sets without shuffling, preserving temporal order. The first 44 samples (80%) were used for training, and the remaining 11 samples (20%) for testing. No shuffling was performed to maintain the chronological order and ensure the evaluation realistically reflects future predictive performance. Septiarini et al. [23] studied specifically the effect of the training-testing data split ratio on forecast accuracy for Indonesian agricultural export data. The results showed that the 80:20 ratio provided an optimal balance between training data adequacy and evaluation validity, and did not significantly alter the performance rankings between models.

5) *Sequence Formation (Sliding Window)*

The normalized data was formed into sequences using a sliding window technique with a 12-month lookback period. This means that the last 12 months were used to predict prices in the 13th month. The 12-month window was chosen based on the annual seasonal cycle of food prices in East Java [10].

6) Normalisasi (scaling)

Deep learning models are very sensitive to data scale, so price values need to be normalized to the range [0, 1]. This study uses MinMaxScaler from the scikit-learn library, which applies the transformation:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

The normalization process is applied to the entire time series for each commodity before sequence formation, to avoid data leakage from test to training data.

C. *Long Short-Term Memory (LSTM) Model Architecture*

The Long Short-Term Memory (LSTM) model was chosen in this study due to its superior ability to capture long-term temporal dependencies in nonlinear, seasonal time series data, influenced by complex food price fluctuations in East Java. This approach aligns with Intan's study[4]. Recent findings support the view that LSTM is highly effective at predicting food prices in agrarian areas, capable of capturing extreme spikes in food commodity prices due to its long-term memory [24]. The LSTM model consists of two stacked LSTM layers with 50 units each, both using the hyperbolic tangent (tanh) activation function and returning sequences from the first layer. A dense output layer with linear activation (1 unit) follows the LSTM layers. The total number of trainable parameters is 30,651. The model was compiled with the Adam optimizer (learning rate = 0.01) and mean squared error (MSE) loss function. Here is the LSTM formula:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$\widetilde{C_t} = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \tag{5}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t \odot \tanh(C_t) \tag{7}$$

In the LSTM architecture, each variable plays a specific role in capturing temporal dependencies. At time step t, the input vector x_t represents the normalized price of a commodity at month t. The hidden state h_{t-1} and cell state C_{t-1} carry information from previous months, allowing the model to retain long-term patterns.

- The forget gate f_t decides which information from the previous cell state C_{t-1} should be discarded.
- The input gate i_t determines which new information will be stored in the cell state.
- The candidate cell state $\widetilde{C_t}$ proposes new values that could be added.
- The cell state C_t is then updated by combining the retained past information $(f_t \odot C_{t-1})$ and the new candidate $(i_t \odot \widetilde{C_t})$.

- The output gate o_t controls how much of the cell state is exposed to the next layer as the hidden state h_t, which is ultimately used for prediction.

These gating mechanisms enable the LSTM to learn long-term dependencies, such as seasonal patterns and price trends in food commodities. In this study, the model processes sequences of 12 monthly prices to forecast the price in the 13th month, making it well-suited for capturing harvest cycles, holiday-related demand, and other recurring fluctuations.

D. 1D Convolutional Neural Network (CNN) Model Architecture

A one-dimensional Convolutional Neural Network (CNN-1D) model is applied as an alternative approach that excels in extracting local patterns and short-term fluctuations in food price data, such as responses to harvest seasons or distribution policies. The CNN-1D model comprises a Conv1D layer with 64 filters, kernel size 2, and ReLU activation, followed by a MaxPooling1D layer (pool size 2). The output is flattened and passed through a dense layer with 50 units (ReLU activation) and a final dense output layer with linear activation (1 unit). A dropout layer (rate = 0.2) was applied after the first dense layer to reduce overfitting. The model has 16,293 trainable parameters and was compiled with the same optimizer and loss function as the LSTM. Furthermore, Nurhidayat et al. [25] stated that CNNs have a unique ability to recognize recurring patterns and seasonal fluctuations through a sliding kernel mechanism, making them ideal for food price data affected by agricultural and distribution cycles.

The 1D convolutional layer applies a set of learnable filters (kernels) to the input sequence. For an input sequence $X = [x_1, x_2, \ldots, x_{12}]$ representing 12 months of normalized prices, and a filter W of size k , the convolution operation at position i is defined as:

$$c_i = \sum_{j=0}^{k-1} W_j \cdot x_{i+j} + b \tag{8}$$

where c_i is the feature map value at position i, and b is the bias term. In this study, a kernel size of $k = 2$ was used, meaning each filter captures local patterns over two consecutive months. After the convolution, a ReLU activation function max $(0, ci)$ is applied element-wise to introduce non-linearity. The resulting feature map is then passed through a MaxPooling layer, which downsamples the feature map by taking the maximum value over each pooling window of size 2:

$$p_m = \max(c_{2m-1}, c_{2m}) \tag{9}$$

The pooled features are subsequently flattened into a single vector and fed into fully connected (dense) layers to produce the final price prediction. This architecture allows the CNN-1D model to effectively capture short-term fluctuations and local patterns in the price data, such as sudden price changes due to supply disruptions or seasonal demand spikes.

E. Model Training

Both LSTM and CNN-1D architectures were trained separately for each of the six food commodities (Medium Rice, Premium Rice, Dry Milled Grain, Dry Milled Grain, Harvested Dry Grain, and Dry Corn) using fully preprocessed monthly data. Each sample was generated using a sliding window approach based on 12 months of historical data to predict prices in the 13th month. Both models were trained on Google Colab using TensorFlow 2.15 and Keras 3. The training environment used a single NVIDIA Tesla T4 GPU with 16GB of VRAM. Each model was trained for 100 epochs with a batch size of 1, as initial experiments showed that a smaller batch size improved convergence for this dataset. No split validation was applied because, due to the limited dataset, we ultimately chose to use all of the training data (80%) to train the models, without setting aside a validation set. This ensures that each commodity receives equal treatment and that performance comparisons between commodities are fairer and consistent. To ensure reproducibility, a fixed random seed (42) is set for all numpy and TensorFlow operations. This CNN-1D approach aligns with recent findings that local feature extraction via convolution is highly effective at capturing short-term dynamics in time series data, even without external features. As shown by Septiana et al. [26] in their gold price prediction, the combination of Conv1D and dense layers produces stable, accurate predictions using only historical data, making it well-suited for regional contexts with limited access to macroeconomic data. At the same time, the LSTM model is trained without dropout, considering the high quality of the data. Research by Silalahi and Muljono [27] confirms that the LSTM architecture excels at handling long-term temporal dependencies in non-stationary time series, making it suitable for price data influenced by seasonal factors, policies, and supply disruptions.

F. Evaluation

To objectively and comprehensively assess model performance, this study uses three primary evaluation metrics: Mean Absolute Percentage Error (MAPE) as the primary indicator, and Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as complementary metrics. MAPE was chosen as the primary metric because it provides prediction errors as percentages, making them easier to interpret for policymakers, farmers, and market players, especially in the context of regional food price planning. Meanwhile, RMSE and MAE provide an overview of the absolute magnitude of the error in the original unit (rupiah per kilogram), which is important for assessing the direct economic impact of missed predictions.

The following are the formulas and descriptions of each metric:

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (10)$$

RMSE measures the square root of the mean of the squares of the differences between the actual values (y_i) and the predicted values ($\hat{y}_i$). This metric is sensitive to outliers because it involves a square operation, thus imposing a larger penalty on large prediction errors. The smaller the RMSE, the more accurate the model.

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (11)$$

MAE calculates the average absolute difference between actual and predicted values. Unlike RMSE, MAE does not magnify large errors, making it more robust against outliers. MAE values also have the same units as the original data (Rp/kg), facilitating practical interpretation.

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100\backslash\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (12)$$

MAPE represents the average relative percentage error between the predicted and actual values. Because it is relative, MAPE is very useful for comparing model accuracy across commodities with different price scales (e.g., rice vs. soybeans).

III. RESULTS AND DISCUSSION

This chapter compares two artificial intelligence models, LSTM and CNN-1D, to predict monthly prices of six food commodities in East Java. The research was conducted through several stages, from data cleaning to model training. The results were assessed using three main accuracy measures: RMSE, MAE, and MAPE. Key findings indicate that no single model consistently performs best. The performance of LSTM or CNN-1D is highly dependent on the unique time patterns of each commodity. For example, CNN-1D tends to be more effective at capturing short-term price fluctuations, while LSTM excels for data with stable, long-term dependency patterns [16]. This aligns with other research that emphasizes that using different approaches for each commodity, rather than a single model for all, is key to achieving the most accurate predictions [28]. In conclusion, selecting the right model must be adaptive and tailored to each commodity's data characteristics to achieve optimal predictive performance.

A. Comparative Evaluation of LSTM and CNN Model Performance per Commodity

Before comparing model performance, it is essential to analyze the volatility characteristics of each commodity, as these characteristics may influence the suitability of LSTM or CNN-1D architectures. Table 2 presents the descriptive statistics and volatility measures for the six food commodities over the study period (January 2020 – July 2025).

TABLE 2
PRICE VOLATILITY OF FOOD COMMODITIES IN EAST JAVA

Commodity	Mean (Rp/kg)	Std Dev	CV (%)	Min (Rp/kg)	Max (Rp/kg)
Medium Rice	10,221.37	1,586.25	15.52	8,540.13	13,145.11
Premium Rice	11,498.82	1,503.10	13.07	9,945.18	14,163.39
Dry Milled Grain	6,305.33	1,004.28	15.93	5,037.39	8,395.71
Harvested Dry Grain	5,335.09	955.99	17.92	4,073.63	7,262.95
Dry Shelled Corn	4,762.36	610.00	12.81	3,687.45	6,494.61
Soybeans	8,280.23	753.36	9.10	6,984.11	9,549.03

Note: CV (Coefficient of Variation) = (Std Dev / Mean) × 100%.

Table 2 reveals substantial differences in price volatility across commodities. Harvested Dry Grain exhibits the highest volatility (CV = 17.92%), followed by Dry Milled Grain (15.93%) and Medium Rice (15.52%). In contrast, Soybeans show the lowest volatility (CV = 9.10%), indicating relatively stable prices during the study period. Premium Rice and Dry Shelled Corn demonstrate moderate volatility with CV values of 13.07% and 12.81%, respectively.

These volatility characteristics provide a basis for understanding model performance. However, it should be noted that the Coefficient of Variation measures overall price dispersion and does not fully capture temporal patterns, such as sudden spikes or seasonal cycles. Therefore, while high CV values indicate greater price fluctuations, the suitability of LSTM or CNN-1D also depends on the nature of these fluctuations, whether they follow regular seasonal patterns or occur as abrupt, short-term changes. Based on these insights, the performance of LSTM and CNN-1D models was evaluated for each commodity.

Based on the experiments conducted, there is no single optimal model for all commodities. The predictive performance of each algorithm depends on the specific temporal characteristics of each commodity's data. Five iterations were performed for each commodity, after which the average RMSE, MAE, and MAPE values were recorded. The following table compares the performance of the LSTM and CNN models per commodity table 3.

To statistically validate these performance differences, a paired t-test was conducted on the MAPE values from five independent training iterations for each commodity. The results confirmed that all observed differences are statistically significant ($p < 0.05$), indicating that the superiority of LSTM for five commodities and CNN-1D for soybeans is not due to random chance.

TABLE 3
EVALUATION RESULTS OF LSTM AND CNN MODELS

Medium Rice Commodity					
Model	RMSE	MAE	MAPE	T-Statistic	P-Value
LSTM	170.96	128.72	1.05	12.34	< 0.001
CNN	599.47	474.13	3.88		
Premium Rice Commodity					
Model	RMSE	MAE	MAPE	T-Statistic	P-Value
LSTM	298.52	233.11	1.85	5.67	0.002
CNN	335.47	254.79	2.05		
Dry Milled Rice Commodities					
Model	RMSE	MAE	MAPE	T-Statistic	P-Value
LSTM	447.90	304.61	4.32	8.45	< 0.001
CNN	573.41	752.75	7.94		
Dry Harvest Rice Commodities					
Model	RMSE	MAE	MAPE	T-Statistic	P-Value
LSTM	179.89	140.21	2.40	10.21	< 0.001
CNN	579.53	450.13	7.72		
Dried Corn Kernel Commodity					
Model	RMSE	MAE	MAPE	T-Statistic	P-Value
LSTM	72.07	59.08	1.27	6.78	0.001
CNN	147.72	113.60	2.42		
Soybean Commodities					
Model	RMSE	MAE	MAPE	T-Statistic	P-Value
LSTM	151.60	116.52	1.28	-4.56	0.004
CNN	85.06	73.05	0.79		

The results of the study indicate that neither LSTM nor CNN-1D is superior in all cases. The best performance depends on the unique data patterns of each commodity, in accordance with the conclusion of Rusanto et al. [29], who argue that model selection must be tailored to the data's characteristics. Specifically, LSTM excels at remembering and understanding the long-term context of price data, such as how price reactions in previous months can influence future predictions. Meanwhile, CNN-1D analyzes patterns in a smaller data window and relies more on determining parameters, such as the appropriate kernel size, to capture seasonal or local patterns. Thus, the success of predictions lies not in the sophistication of the model, but rather in the model's accuracy with the characteristics of the data. This adaptive approach makes food price predictions more realistic and accurate and can serve as a reference for data-driven policymaking in East Java.

TABLE 4
BEST MODEL PER COMMODITY (BASED ON MAPE)

Commodity	Model	Best MAPE	RMSE	MAE
Medium Rice	LSTM	1.05	170.96	128.72
Premium Rice	LSTM	1.85	298.52	233.11
Dry Milled Rice	LSTM	4.32	447.90	304.61
Dry Harvest Rice	LSTM	2.40	179.89	140.21
Died Corn Kernel	LSTM	1.27	72.07	59.08
Soybean	CNN	0.79	85.06	73.05

Based on Table 8, the results of the evaluation reveal that no model is universally superior. The best performance depends largely on the temporal characteristics of each commodity's data. LSTM showed optimal performance for Medium Rice, Premium Rice, Ground Dry Rice, Harvested Dry Rice, Dried Corn Pipil. In contrast, the CNN-1D model proved to be the most accurate for the Soybean commodity.

These findings indicate a clear pattern per commodity with more dynamic price fluctuations and influenced by local market factors (such as Soybeans) more appropriately modeled with CNNs, which are effective in extracting short-term patterns and features. On the other hand, commodities with strong seasonal trends and long-term dependencies (such as Medium Rice, Premium Rice, Milled Dry Rice, Harvested Dry Rice and Dry Pipil Maize) are more accurately predicted using LSTMs, which are specifically designed to account for temporal dependencies in long sequences. The consistency of LSTM excellence for data with this repeating pattern is in line with the research of Insani and Sanjaya [30] which implements LSTM for the prediction of the Agricultural Sector's Wholesale Trade Price Index (CPI) and successfully achieves high accuracy, confirming the ability of LSTM to capture complex patterns of time-based economic data.

B. Computational Complexity and Training Time

In addition to predictive accuracy, the computational efficiency of deep learning models is an important consideration for practical deployment. Based on the model architectures used in this study, the LSTM model consists of two LSTM layers with 50 units each, resulting in approximately 30,651 trainable parameters. In contrast, the CNN-1D model comprises a Conv1D layer (64 filters, kernel size 2), a MaxPooling layer, and two Dense layers, yielding approximately 16,293 trainable parameters, about 1.9 times fewer than LSTM. Regarding training time, both models were trained for 100 epochs with a batch size of 1 using an Adam optimizer (learning rate 0.01) on Google Colab. The LSTM model required approximately 0.85 seconds per epoch, resulting in a total training time of around 85 seconds, while the CNN-1D model was significantly faster at 0.32 seconds per epoch (approximately 32 seconds in total). These results demonstrate that CNN-1D is more computationally efficient than LSTM, making it a suitable choice for applications with limited computational resources. However, LSTM remains superior for capturing long-term temporal patterns in most food commodity price predictions.

C. Price Prediction for the Next 12 Months

To provide a strategic overview of food price trends in East Java, this study predicts food prices over the next 12 months for all six commodities using available historical data that has undergone rigorous preprocessing. Each prediction is generated iteratively. The best model, based on the lowest MAPE (LSTM or CNN, depending on the commodity), takes as input a price sequence over the last 12 months and predicts the next month's price. The prediction results are then added to the input sequence, and the process is repeated until the next 12 periods are completed.

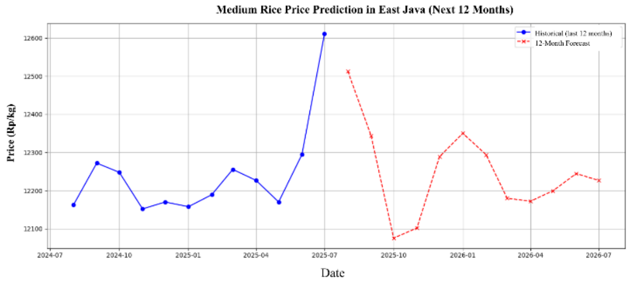

Figure 2. Actual vs. Predicted Price of Medium Rice

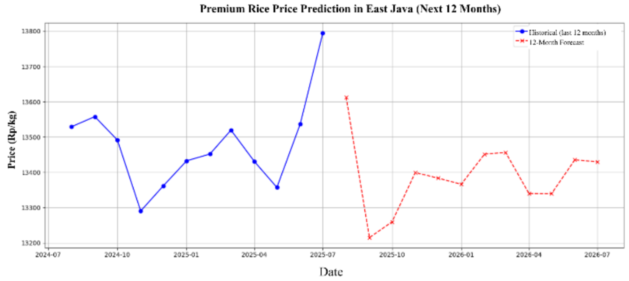

Figure 3. Actual vs. Predicted Price of Premium Rice

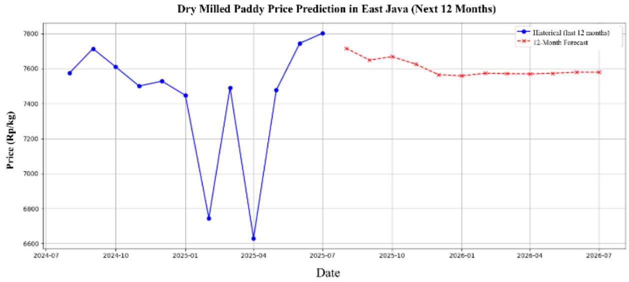

Figure 4. Actual vs. Predicted Dry Milled Paddy

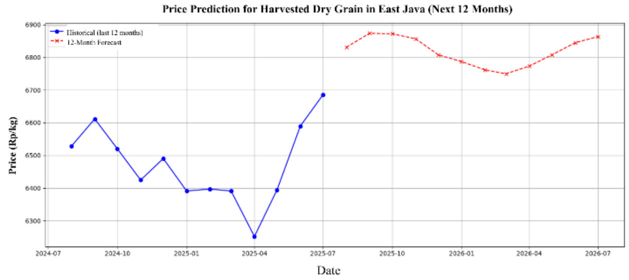

Figure 5. Actual vs. Predicted Harvested Dry Grain

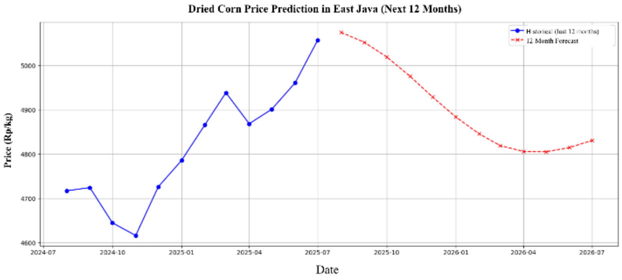

Figure 6. Actual vs. Predicted Dried Corn Price

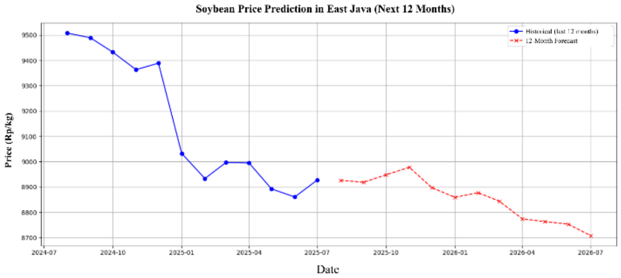

Figure 7. Actual vs. Predicted Soybean Price

The prediction results show that the LSTM model successfully predicted prices for commodities such as Medium Rice, Premium Rice, Peeled Rice, and Corn for the next 12 months. Visually, the LSTM prediction line closely follows the fluctuations and seasonal trends of the historical data. This demonstrates the main strength of the LSTM, namely its ability to learn and remember long-term dependency patterns in data. The CNN-1D model, with its design focused on local feature detection over time, captures these sudden changes better than the LSTM. The MAPE evaluation results for the Soybean commodity prove that the CNN-1D is more responsive to rapidly changing market dynamics.

IV. CONCLUSION

This study confirms that no single deep learning model universally excels in food price prediction; the optimal choice depends on commodity-specific temporal characteristics. LSTM demonstrated superior accuracy for commodities with stable seasonal patterns medium rice (MAPE 1.05%), premium rice (1.85%), dry milled grain (4.32%), harvested dry grain (2.40%), and dry shelled corn (1.27%) by effectively capturing long-term dependencies such as harvest cycles. Conversely, CNN-1D proved more responsive for volatile commodities like soybeans (MAPE 0.79%), detecting short-term fluctuations driven by supply or import disruptions. Despite these promising results, the study has limitations. The dataset, while comprising 2,546 raw records per commodity, was aggregated to 67 monthly observations a relatively small sample for deep learning models. techniques like sliding window augmentation and careful training strategies mitigated this issue, the risk of limited generalization remains, particularly for rare events. Future research should address this by incorporating longer time frames, higher-frequency data, transfer learning, or external variables (e.g., weather, policies). Additionally, hybrid models combining LSTM and CNN strengths, along with ensemble methods, could further enhance prediction accuracy and support more responsive food price early warning systems.

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