DOI: 10.14421/ijid.2023.5129 IJID (International Journal on Informatics for Development), *e-ISSN: 2549-7448*
*Vol. 12, No. 1, 2023, Pp. 1-14*

# Price Forecasting of Chili Variant Commodities Using Radial Basis Function Neural Network

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**Article History**
Received April 19th, 2025
Revised May 3rd, 2025
Accepted May 5th, 2025
Published May, 2025

***Abstract*— This study addresses the challenge of price instability in chili markets, which can lead to economic losses and inflation. To mitigate this issue, we propose a machine learning model using Radial Basis Function Neural Networks (RBFNN) to predict prices of various chili variants. Our quantitative approach involves a comprehensive data preparation process, including preprocessing and normalization of time series data collected from 2018 to 2022. The RBFNN model is constructed with K-Means clustering for optimal hidden layer configurations and evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). The results demonstrate promising accuracy, with MAPE error rates below 20% and relatively low RMSE values for large red chili (10.37%, 4484) and curly red chili (14.77%, 5590). Our findings indicate the potential for creating a reliable forecast model for predicting chili prices over 7 days, enabling better supply and demand management. The study's results also suggest that increased training data enhances forecasting accuracy. This research contributes to the development of effective price forecasting models, providing valuable insights for policymakers and stakeholders in the chili industry.**

***Keywords*—chili markets; MAPE; price instability; RMSE; time series data**

## 1 INTRODUCTION

Every human has needs for their life. However, of the many human needs, in principle, three basic needs rank at the top of the demand to fulfil people's needs: food, clothing, and shelter [1]. Of the three basic human needs, food is fundamental for humans to survive. Food has an essential role in human life, one of which is as a source of energy and nutrition. One of the most significant sectors in the economic sector is the food sector. This sector involves the agricultural, distribution, processing, and retail sectors [2]. The food sector creates jobs in various industries and contributes to economic growth. Food is the central pillar of a country's food security. Providing and distributing adequate and equitable food are essential for social and financial stability. Sustainable food production and consumption help preserve the environment and natural resources for future generations [3]. Increasing food security through government policy is very important because food security impacts the availability of supplies for people's basic needs and affects economic, social, and environmental stability [4].

Chili is an essential ingredient in various foods and is the leading food, as stated in Presidential Regulation (PERPRES) Number 71 the Year 2015 [5]. Based on Indonesian Horticultural Agriculture Statistics data, chili production in Indonesia annually reaches an average of 15,544,984 quintals, and more than 70% of chili is sold [6]. This data shows a considerable production amount. As an agricultural commodity, chili has high price volatility due to seasonal factors, limited supply, and fluctuating demand. Chili also has a limited shelf life and is susceptible to quality degradation. The vulnerability of chili causes farmers to try to sell chili as quickly as possible so that the quality does not decrease. Farmers' rush to sell chili caused prices to drop sharply when the harvest was abundant. Chili price instability can be detrimental to consumers and producers [7]. As a necessary commodity in many countries, fluctuations in chili prices affect people's purchasing power. The low purchasing power of society is the government's focus when determining policies related to chili because sharp chili price volatility can trigger inflation and disrupt economic stability. From a macro perspective, this situation can cause inflation and losses for the country and society [8].

A nation whose people are highly dependent on chili as a staple food, such as Indonesia and Malaysia, requires chili price forecasting for various economic, social, and policy reasons. Chili price forecasting can help consumers and producers plan their budgets. Chili price forecasting also helps farmers determine harvest and distribution times. Accurate price forecasting allows the government to design more effective policies, such as managing chili stocks, providing subsidies to chili farmers, or regulating imports and exports to stabilize market prices for chili. Chili price forecasting can also help farmers plan strategies for storing chili from their harvest, diversifying crop yields, or adjusting planting patterns to mitigate the risk of losses. This chili price forecasting can support the supply chain planning process from production to distribution. This mechanism can help the government ensure that the supply and price of chili remain stable [8], [9], [10], [11], [12], [13]. Forecasting commodity prices, such as chili on the market, is also a critical fiscal issue for traders and investors [14].

Research on chili price forecasting encourages applying technology such as machine learning and big data analytics to increase forecasting accuracy and opens up opportunities for innovation in the agricultural sector. There are algorithms for forecasting, both with traditional statistical approaches such as ARIMA (Autoregressive Integrated Moving Average), SARIMA (Seasonal ARIMA), and Exponential Smoothing (ETS), and Supervised Machine Learning approaches such as Linear Regression, Decision Tree, Random Forest algorithms, and Gradient Boosting Algorithms. Apart from that, forecasting can also utilize Deep Learning algorithms such as Recurrent Neural Networks (RNN), Temporal Convolutional Networks (TCN), and Multi-layer Perceptron (MLP).

A study uses a Neural Network algorithm to predict the price of red chili. This research uses a backpropagation neural network architecture with two inputs, one hidden layer, and nine neurons. The accuracy of the test data shows an RMSE value of 2555.593 and an MAPE of 4.531. These results show that the accuracy of NN in forecasting chili prices is entirely accurate [15]. Basnayake et al. also strengthened the performance of the NN algorithm to predict chili prices with the same level of accuracy in the sufficient category [16]. Besides NN, chili price forecasting can also use the Multi-layer Perceptron (MLP) algorithm. The research results show that the MLP method shows a high level of accuracy, with an MAPE smaller than 10% [5].

Chili price predictions can also use the Long Short-Term Memory Method. The accuracy of this algorithm in forecasting chili prices shows root mean square error values on test data of 2.11% and 2.17%. This value shows an accuracy value close to 98% [13]. Other research also uses the ARIMA statistics-based method to predict national prices of essential commodities in the short term, 1 to 30 days. The test results show ARIMA's performance in forecasting prices of essential commodities with an average error rate of 2.22% [17]. Another method for predicting chili prices is the Support Vector Regression (SVR) algorithm. The experimental results of testing chili price forecasting data with SVR have an average R2 score of 0.94. This result shows that the accuracy level of SVR for forecasting chili prices is 94% [18]. Even though it shows a high level of accuracy, this algorithm has shortcomings. NN has some disadvantages, such as it requires extensive data, it is prone to overfitting, it is challenging to interpret, and it is slow to train. Meanwhile, MLP is unsuitable for time series because it makes it difficult to capture seasonal patterns, it is susceptible to noise, and it is highly complex. SVM has the weakness of being less efficient for large datasets, being sensitive to noise, and having difficulty capturing time series/seasonal patterns.

One algorithm that is effective for forecasting conditions with nonlinear variables and for the short term is the Radial Basis Function Neural Network (RBFNN). Many forecasting studies have utilized the RBFNN algorithm, one of which is to predict water flow in rivers. This research shows that the

RBFNN model is superior to the feed-forward NN (FFNN) forecasting model. RBFNN shows high accuracy and reliability for daily river flow forecasting [19]. RBFNN can also predict the price of electrical equipment whose prices fluctuate following the dollar's value. Based on research results, this algorithm is effective for forecasting the cost of electrical equipment in real-time [20]. The RBFNN method can also potentially solve the Hamilton – Jacobi – Bellman (HJB) equation for nonlinear control systems. Based on the HJB equation, with a limited number of neurons, RBFNN shows good performance on microcontroller hardware [21]. Combining the Levenberg-Marquardt training function, gradient descent with momentum and adaptive learning rate, and the Bayesian regulator are the essential functions of the RBFNN algorithm. These functions can produce the best model [22], [23].

Based on the capabilities and advantages of RBFNN, this research offers a method for forecasting chili prices, such as commodities with a high economic value, using RBFNN to overcome the volatility of chili prices. The RBFNN is a forecasting method developed in the NN algorithm [24], [25]. RBFNN produces a more compact topological structure than other NN-based algorithms [26]. RBFNN has advantages that make it suitable for prediction problems because it can handle data with nonlinear patterns and support time series prediction, classification, and system control [27]. Factors that influence chili prices are weather, distribution, demand, and seasonal patterns. These factors are nonlinear. RBFNN can model these nonlinear relationships well using radial basis functions (e.g., Gaussian) as activation units [28]. RBFNN can also utilize radial basis functions that work locally around a particular data center. This capability of RBFNN allows the model to capture local changes in data, such as sudden price movements due to distribution disruptions or supply drops. In forecasting chili prices, many influencing variables exist (for example, rainfall, fuel prices, and market demand). RBFNN can accommodate multivariable input and capture complex relationships between variables. RBFNN is robust against noisy data, such as irregular price fluctuations due to expectations or external factors [29], [30]. RBFNN can also predict chili prices in the short term, starting from daily price forecasts and going up to the next seven days [20], [31].

Based on the explanation above, this research aims to develop a chili price forecasting model using the RBFNN method. This research also tests the reliability and accuracy of the RBFNN algorithm as a price forecasting algorithm for chili variants. Factors influencing chili prices have a nonlinear relationship, requiring accurate data modeling to predict chili prices. For this reason, this research offers a forecasting model for variables that have nonlinear data to predict chili prices. Utilizing the RBFNN algorithm, capable of handling data with high variability, such as chili prices, can also produce a more robust model with predictive accuracy using traditional basis functions according to historical data patterns. The RBFNN method tends to work well on test data, so the results of this research provide a significant contribution to forecasting systems on nonlinear data such as chili prices.

## 2 METHOD

This research aims to develop a chili price forecasting model using RBFNN. RBFNN is appropriate for forecasting chili prices because it can handle nonlinear and dynamic data, such as patterns of changes in chili prices, where many factors influence chili prices, such as weather, season, market demand, and distribution. This research takes data from the Special Capital Region of Jakarta Province (DKI Jakarta) in Indonesia because Jakarta is the capital of the Republic of Indonesia, making it the center of government and a barometer of economic activity in Indonesia [32], [33]. The steps for forecasting chili prices using the RBFNN method in research go through the following stages. Fig. 1 shows the stages in designing a chili price forecasting model using RBFNN.

### *2.1 Data Preparation*

The initial stage of data preparation is to collect historical data on chili and related variables, such as daily chili prices, weather factors (rainfall, temperature), production volume, and demand. The chili data collection in this research used time series data on chili commodities from September 2018 to June 2022. The data consists of three variants: red chili, curly red chili, and cayenne peppers. This research collects historical data on Chili via the website http://www.infopangan.jakarta.go.id by taking market locations at the Kramat Jati market, DKI Jakarta [34]. Kramat Jati Market is the leading market that connects markets in the DKI Jakarta area: Jatinegara Market, Minggu Market, Tanah Abang Market, Grogol Market, and Koja Baru Market. All food commodity distribution in DKI Jakarta Province goes through the Kramat Jati Main Market first, so all commodity prices throughout DKI Jakarta Province follow commodity prices at the Kramat Jati Main Market, including the cost of Chili [35]. In forecasting chili prices, observations in this study used weekly chili price data because Chili is a commodity with a fluctuating price. Stock and demand for chilies are factors that influence chili price fluctuations. Weekly data also makes identifying seasonal patterns and more accurate price forecasts easier [36], [37], [38]. Apart from this, chili commodity prices are very volatile in the short term. By selecting seven days, this research can capture significant price fluctuations and is helpful for market participants [39].

### *2.2 Data Pre-processing*

After the data collection stage, this research carried out data preprocessing. Raw Data is often not ideal because it can contain noise, missing data, or inconsistent formatting [40]. Data preprocessing ensures that the data used in training or analysis is high quality, representative, relevant to modeling goals, and suitable for studying or training machine learning models, including RBFNN. By preprocessing data, the RBFNN algorithm can provide more accurate, efficient, and reliable results [41]. Data preprocessing in this research uses three processing stages: Data Cleaning, Data Normalization, and Data Split.

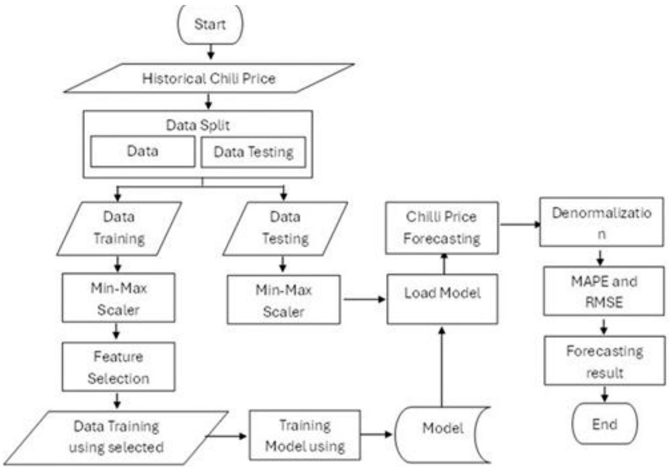


Figure 1. The Flow of the proposed study

*2.2.1* *Data Cleaning:* Data cleaning is vital to ensure data quality before use in RBFNN training. Clean data can improve prediction accuracy and model stability. Data cleaning in this research involves handling missing data due to incomplete recording or technical problems. The handling of missing data in this study used linear interpolation. Linear interpolation is a method for guessing missing values utilizing a dataset's previous and next values. Linear interpolation to overcome missing data in this study uses (1) [42].

$$y = y_1 + (x - x_1) \cdot \frac{y_2 - y_1}{x_2 - x_1} \tag{1}$$

Where $y_1$ and $y_2$ are the values before and after the data is lost, $x_1$ and $x_2$ are the time indices before and after the data is lost, and y is the result of calculating the missing values. Based on (1), to overcome missing data in the data cleaning process, this research identifies missing data to find the position of missing data in the Dataset. After finding the position of missing data in the Dataset, this research takes the two closest values before and after the missing data and calculates the missing data value.

*2.2.2* *Data Normalization:* Data normalization in RBFNN aims to improve the model's performance, efficiency, and accuracy during training and prediction. Normalization changes data values to a uniform scale. Data normalization in RBFNN aims to improve model performance, efficiency, and accuracy during the training and prediction process. This research normalizes data by changing values from 0 to 1. This research uses the MinMax Scaler to scale data so all feature values are in the range [0, 1]. The intervals 0 and 1 are the most precise range of floating-point values [43]. Eq. (2) is this study's equation for normalizing data using the MinMax Scaler Method [44].

$$X_{new} = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{2}$$

$X_{new}$ is a normalized value, **min**($X$) is the minimum value in the Dataset, **max**($X$) is the maximum value in the dataset, and $X$ is the original value.

*2.2.3* *Data Split:* Data split in RBFNN is the process of dividing the Dataset into training and test data. This process aims to ensure that the model can learn well from the data without losing generalization capabilities. This research divides the Dataset with a ratio of training data to test data of 75:25. From the division of the ratio, in each group of training datasets, this research divides the Dataset into two groups of datasets with a ratio of 80:20. 80% of the data is for training the model, and 20% is for testing the trained model. This ratio shows that this research uses 75%-80% of the Dataset as training data for training and 25%-20% of the Dataset as test data for model testing. Splitting data by ratios of 75:25 and 80:20 is a common practice in machine learning, including using RBFNN. This ratio was chosen based on scientific considerations to balance the need to train the model with sufficient data and ensure that the model performance evaluation on unknown data remains accurate [45]. The RBFNN learning model requires a lot of data to learn data patterns in the Dataset. A ratio of 75%-80% indicates that this research uses a large portion of the Dataset to train the model, thereby reducing the possibility of the model missing patterns.

### *2.3 RBFNN Initialization*

Initializing RBFNN in chili price forecasting aims to determine optimal initial parameters. This stage helps the network learn data patterns efficiently and produce accurate chili price predictions. The RBFNN initialization process in this research is through 3 stages: building the network structure, determining the activation function, and clustering using K-Nearest Neighbor (KNN).

The RBFNN architecture design in this study aims to build the network structure. This step goes through 3 systematic steps: building the input, hidden, and output layers. The input layer in RBFNN for forecasting chili prices is an input layer that receives feature data to predict chili prices. Each neuron in this layer represents one feature. This research uses the Lag Features feature extraction method to forecast chili prices based on weekly daily prices. Lag Features is the proper feature extraction method for time series data such as chili prices, which are the input for this study. The lag feature is a technique of extracting features in time series data analysis using data values from the previous time (lag) to predict future values. In forecasting chili prices, this research uses daily chili prices for a week as input to predict chili prices on the $8^{th}$ day. This research adds new features: the weekly average price of chili peppers, daily price changes and the average chili price each week. Based on the input data, the input layer in this study uses seven neurons. The construction of the input layer in this research consists of signal input nodes $z = [z_1, z_2, \dots, z_n]^T$.

After the feature extraction process, RBFNN will store the new values from the input layer into the input of the hidden layer to map the input into the new feature space using a radial basis function. The number of neurons in the hidden layer in this study adjusts the number of neurons in the input layer, which is 16 neurons. This research uses the Gaussian Radial Basis function. Gaussian has the flexibility to cope with chili price data with nonlinear pattern characteristics and temporal fluctuations. Eq. (3) is the formula for the Gaussian function [46], [47].

$$\varphi(z) = \exp\left(-\frac{\|z-c\|^2}{\sigma^2}\right) \tag{3}$$

With $Z$ as input data, $c$ is the center of the radial basis function, and $\sigma$ is a spread parameter that determines the width of the radial basis function.

This research uses the K-Nearest Neighbors (KNN) algorithm to determine the center of the radial basis function. Using the KNN algorithm in chili price forecasting is vital because chili prices are dynamic, and price patterns have significant local variations [48], [49]. In RBFNN, each neuron has a $C_i$ as the center of the hidden layer. Determination of the $C_i$ on each neuron in the hidden layer by determining the value of $k$. $K$ is a parameter that determines how many nearest neighbors each neuron has. This research considers the value of $k$ when calculating chili price prediction. The value of $k$ in chili price forecasting can affect the performance and accuracy of the model. A value of $k$ that is too small can cause the model to be too sensitive to noise in the data(overfitting), while a value of $k$ that is too large can cause the model to be so general that it cannot capture local patterns(underfitting). This research uses the Elbow method to determine the value of $k$. This method can find the point where the decrease in error or accuracy starts to slow down, indicating that the model considers the optimal $k$ value. The $k$ value at that point provides the best balance between bias and variance [50].

After determining the value of $k$, the next step is to determine the nearest neighbor by calculating the distance between the input and the nearest neighbor. In this research, the distance calculation uses the Euclidean Distance. If there are two points in the $n$-dimensional feature space, namely point $A = (a_1, a_2, \dots, a_n)$ and point $B = (b_1, b_2, \dots, b_n)$, then calculate the Euclidean distance between point $A$ and point $B$ using (4) [51].

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(a_i - b_i)^2} \tag{4}$$

Where $A = (a_1, a_2, \dots, a_n)$ is the coordinate of the first point, $B = (b_1, b_2, \dots, b_n)$ is the coordinate of the second point, and $n$ is the number of dimensions or features in the data. After calculating the input distance to the nearest neighbor, the last step is to calculate the input distance to the neuron's center using the Gaussian function and combine all the values generated from each neuron to produce an output on the output layer as a chili price prediction. Fig. 2 shows the RBFNN architecture of the proposed research model.

### 2.4 *RBFNN Model Testing and Evaluation*

During training, the RBFNN model adjusts the weights and biases for the prediction error between the predicted and actual chili prices. The training process in this study is optimized using the least squares method to find weights that can minimize prediction errors. This research calculates weights and biases using (5) [52].

$$W = (\Phi^{\mathrm{T}}.\Phi)^{-1}\Phi^{\mathrm{T}}y \tag{5}$$

Where $\Phi$ is the activation matrix of the hidden layer, $y$ is the actual chili price, and $W$ is the weight vector calculated for the output layer.

After training the model, this research evaluates its performance. This testing process involves test data that the model has never seen during training. Prediction evaluation in the study was carried out by calculating metrics with the MAPE and RMSE approaches. MAPE calculates the average absolute percentage error between predicted and actual values. Meanwhile, RMSE measures the average squared error between the expected and actual values. To calculate MAPE and RMSE, use (6) and (7) [53].

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right|}{n} \tag{6}$$

Note:

$n$ = amount of data

$Y_t$ = actual index value in period/day $t$

$F_t$ = value of forecasting data in period/day $t$

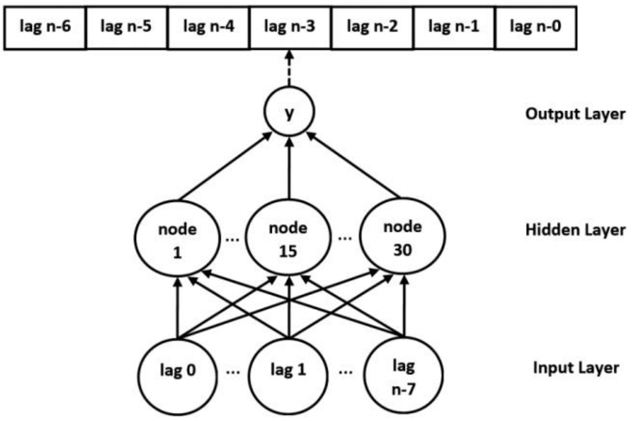


Figure 2. The architecture of our RBFNN model

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \quad (7)$$

Note:

$S_i$ = actual index value in period/day $i$

$O_i$ = value of forecasting data in period/day $i$

Where $S_i$ is the actual value, $O_i$ is the predicted value, and $n$ is the number of data. Generalization of the MAPE calculation results in this study uses the criteria described in Table 1. The RMSE should be < 10 of the average actual value [54].

## 3 RESULT AND DISCUSSION

### 3.1 Data Description

This study uses input data in the form of chili prices collected weekly. This research takes chili price data from September 2018 to June 2022. This study obtained as much chili price data based on field data as 1398. This data represents weekly chili prices for three variants: Large Red Chili, Curly Red Chili, and Cayenne pepper. Table 2 shows a sample of weekly chili prices in 3 variants of chili types [34].

This research is data from 3 types of chili variants, where each chili variant has 466. This research divides the dataset for each chili variant into two groups of datasets, namely 75%-25%. This ratio shows that from the data collected, this research divides the Dataset as much as 75% of the data for training and 25% for testing on each chili variant. After splitting into two groups of datasets, in each dataset, this research divides the training dataset into two more groups with a ratio of 80%-20%. Table 3 shows the data on each chili pepper variety for each group of datasets.

From September 2018 to December 2022, the price of chili peppers in DKI Jakarta experienced significant fluctuations. Seasonal factors, supply availability, and market demand greatly influence the fluctuation of chili prices. Field data shows that chili prices often increase sharply ahead of religious holidays and decrease during the harvest season. Field data also indicates that the price of red cayenne pepper and curly red chili frequently spikes due to weather disturbances that can affect chili production and distribution. Fig. 3 shows the fluctuation of chili prices during December 1-7, 2021.

### 3.2 Feature Selection

This study's input data in chili price forecasting is the historical chili price. This research uses a lag variable feature, namely the price of chili in the previous time, and an additional feature in the form of an average weekly chili price to describe temporal patterns and trends. In this research, if missing values are in the Dataset, handling missing values using the interpolation method is described in Table 4. If, during the data collection process in the field, the Dataset has missing data on day 3, where the chili price data on the previous day was 30,000 and 32,000, the missing value on day 3 using the Interpolation method is as follows.

if

$y_1$ = 30,000
$y_2$ = 32,000
$x$ = 2
$x_1$ = 1
$x_2$ = 3

then

$$y = 30{,}000 + \frac{(2-1)}{(3-1)}\, x\, (32{,}000 - 30{,}000) = 31{,}000$$

The second step in feature selection is scaling/Normalization. In this study, data normalization standardizes the data to prevent certain features from dominating the model. Data normalization uses the MinMax Scaler Method. Table 5 shows the results of data normalization using the MinMax Scaler Method. The normalization process results in the selected feature becoming the hidden layer's input.

### 3.3 Model Training

Model testing on RBFNN in this study ensures that the model can predict accurately and has optimal performance. Model testing in this study begins with cross-validation. Cross-validation in research using RBFNN to evaluate model performance and ensure that the model does not overfit training data. This study conducted cross-validation on normalized data using the Hold-Out Validation technique by dividing the dataset into two subsets: training data and test data, with 75% as training data and 25% as testing data. The data is further divided into two dataset groups in the training dataset group, 80% for training and 20% for testing data.

Table 1. Generalization of the MAPE [55], [56]

| Range of MAPE | Result Interpretation |
|---|---|
| < 10% | Very Accurate |
| 10% ≤ MAPE < 20% | Accurate |
| 20% ≤ MAPE < 50% | Reasonable |
| ≥ 50% | Poor |

Table 2. Sample Data from Chili Variant Commodities (December 1-5, 2021)

| Date | Curly Red Chilies (IDR) | Large Red Chilies (IDR) | Cayenne pepper (IDR) |
|---|---|---|---|
| 12/01/2021 | 30,000 | 35,000 | 39,000 |
| 12/02/2021 | 32,000 | 34,000 | 41,000 |
| 12/03/2021 | 31,000 | 38,000 | 44,000 |
| 12/04/2021 | 30,000 | 40,000 | 50,000 |
| 12/05/2021 | 30,000 | 38,000 | 48,000 |
| 12/06/2021 | 33,000 | 40,000 | 46,000 |
| 12/07/2021 | 29,000 | 35,000 | 48,000 |

Table 3. Research Dataset Splitting

| Chili Variant | Data Training | | | Data Testing |
|---|---|---|---|---|
| | Total Data | Data Training | Data Testing | |
| Curly Red Chilies | 350 | 280 | 70 | 116 |
| Large Red Chilies | 350 | 280 | 70 | 116 |
| Cayenne pepper | 350 | 280 | 70 | 166 |

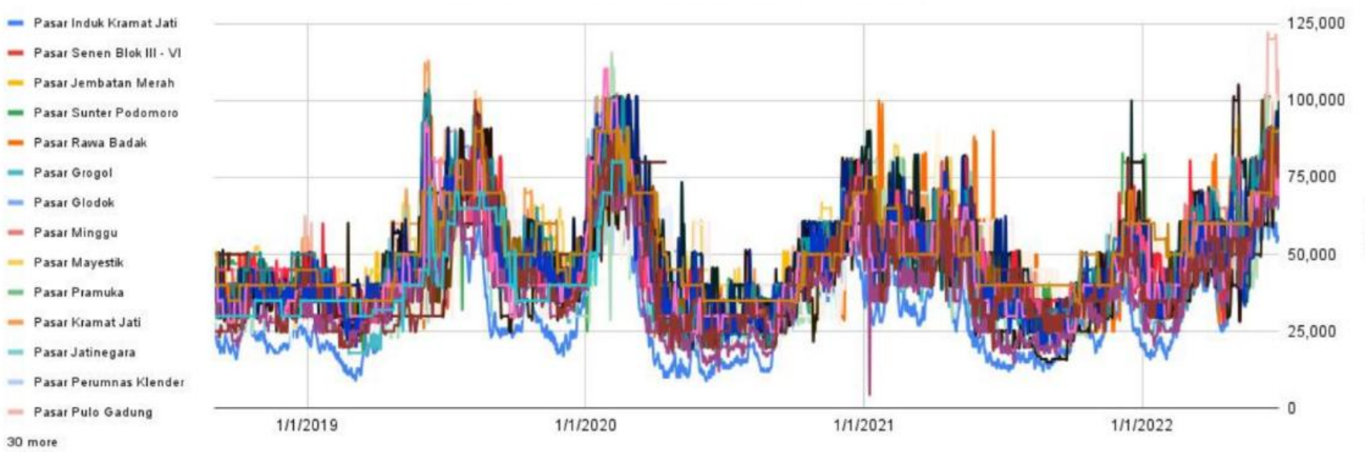


Figure 3. The fluctuation of chili prices from December 1-7, 2021, in the DKI Jakarta area.

Table 4. Missing Value Handling

| Date | Curly Red Chilies (IDR) |
|---|---|
| 12/01/2021 | 30,000 |
| 12/02/2021 | 32,000 |
| 12/03/2021 | Missing Value |
| 12/04/2021 | 30,000 |
| 12/05/2021 | 30,000 |
| 12/06/2021 | 33,000 |
| 12/07/2021 | 29,000 |

Testing goes through two stages. The first stage is testing in the training dataset, where 20% of the data in the training dataset will become test data. After testing the system's performance in predicting data on the training dataset, this study conducts stage 2 testing using the test dataset, where the system has not recognized the dataset. The training process using the cross-validation technique will dynamically change the data weights in the hidden layer.

This research performs the data training process iteratively. One complete iteration where the neural network uses the entire training dataset to train the neural network is called an epoch. The epoch function in RFNN adjusts the Radial Basis Function Center, improves the weights in the hidden layer, and reduces the model error to achieve optimal convergence. By running multiple epochs, the model can learn to capture deeper patterns without overfitting as long as regularization or early stopping is applied. For this reason, this study conducted experiments to determine the number of epochs that can improve the convergence of the model. Fig. 4 shows the RMSE value of each epoch of the significant red chili variant in the experimentation process. Curly chili and cayenne pepper variants in the experimental method also showed the same performance: stagnation occurred after the number of epochs 200. Thus, this study uses the number of epochs 200 in the training process.

This research uses two stages of training: training using the training dataset and training using the test dataset. This research conducts an experimental process to calculate the period that can produce optimal convergence. Period is the total iterations of all training stages, while epoch refers only to the iterations in one stage. Fig. 5, 6, and 7 are the experiment results to determine the number of periods for the three chili variants.

Based on the experiment, as shown in Fig. 5, the most optimal period with a 75:25 dataset split in the experiment on the big red chili price data was reached in period 6. Period 6 showed the smallest MAPE and RMSE values; subsequent periods did not show a downward trend in the data. Meanwhile, in the curly red chili and cayenne paper, optimal convergence on the 75:25 split dataset can be achieved in period 4 and period 8, as shown in Fig. 6 and 7.

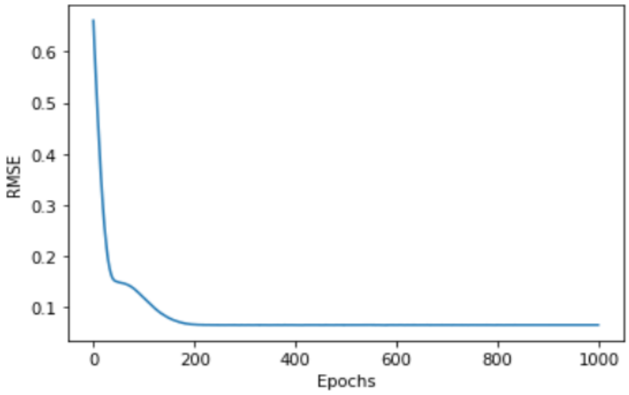


Figure 4. RMSE values of every epoch

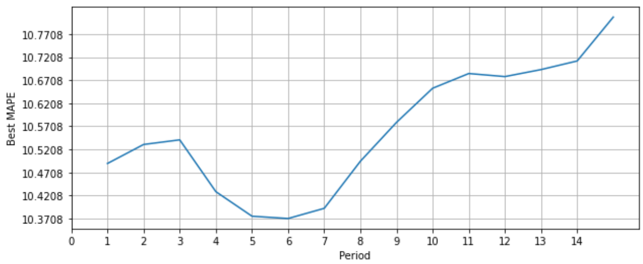


Figure 5. Graph of the period for Large Red chili

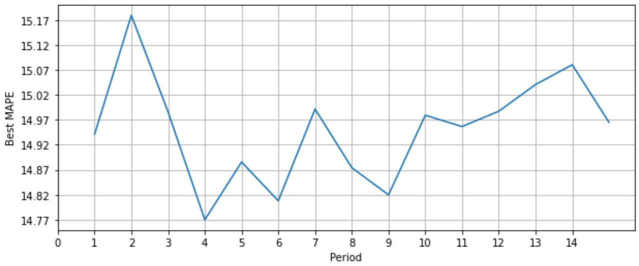


Figure 6. Graph of the period for Curly Red Chili

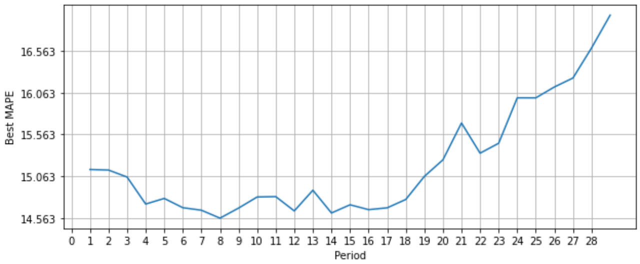


Figure 7. Graph of the period for Cayenne Pepper

### 3.4 *Forecasting Result*

This study evaluates the price forecasting model for chili variant commodities. It aims to forecast the price of chili in one week from July 1-7, 2022. Table 9 shows the results of predicting the price of three chili variants in that period. Figs. 8, 9, and 10 compare the forecast and actual prices of the three chili variants.

### 3.5 *Discussion*

Forecasting the price of strategic food commodities, such as Chili, is crucial in supporting economic stability and decision-making in the agribusiness sector. Kramat Jati Market is one of the leading food distribution centers in DKI Jakarta. This market has chili price dynamics influenced by various factors, including supply, demand, and weather. This research develops a model to predict chili prices based on the Radial Basis Function Neural Network (RBFNN) artificial neural network model. The purpose of developing this model is to improve prediction accuracy to support more effective supply planning and management.

To evaluate the ability of the RBFNN model to predict chili prices, we have conducted tests using historical chili price data collected from September 2021 to June 2022. The test to predict chili prices for 1-7 July 1-7 2022, to measure the accuracy and reliability of the model in providing predictions based on past data patterns and trends. The test results, as shown in Table 9, are as follows.

3.5.1 *Large Red Chili:* This study predicted the price of large red chili for July 1-7, 2022, as shown in Table 9. On July 1, 2022, the forecasted price was higher than the actual price by IDR 492. In contrast, from July 2-7, 2022, the forecasted prices were lower than the actual prices, with differences ranging from IDR 1,014 to IDR 2,583. Despite these differences, the overall discrepancy between forecasted and actual prices remained minimal, as illustrated in Fig. 8. The model's accuracy was further validated by the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values, which provided additional confirmation of its performance. For the training dataset, the MAPE was 10.95% and RMSE was 5.08052, while for the testing dataset, the MAPE was 10.56% and RMSE was 4.62316 (Table 6). Given that the MAPE values fell between 10% and 20% and the RMSE values were below 10, these results indicate a high level of accuracy in forecasting prices for large red chilies, categorizing the model as accurate according to the criteria in Table 1.

*3.5.2* *Curly Red Chili:* In contrast with forecasting the price of large red chili peppers, which predicts ups and downs in the price of chili peppers, forecasting the price of curly red chili peppers shows a tendency for prices to continue to rise. On July 1-7, 2022, as shown in Table 9, the model predicts the price of curly red Chili successively. This price is higher than the actual price of curly red chili in the period 1-7 July 2022. The range of actual price differences with predicted prices on curly red chili shows a reasonably high difference from IDR 6,901 to IDR 10,918. Fig. 9 corroborates the test data, where the graph seen in Fig. 9 shows a very high spike starting in March 2022. The high demand for this commodity is due to a seasonal increase in demand ahead of the Eid al-Fitr holiday. Demand for curly chili is higher than for large red chili ahead of Eid due to their flexibility of use, distinctively spicy flavor, consumer preference for traditional cooking, and their essential role in typical Eid dishes. These conditions result in a seasonal spike in demand ahead of Eid for the chili variant of curly red chili. The test results of the accuracy level of the RBFNN model for forecasting the price of chili pepper variants of crab red chili show the MAPE value in testing using the training dataset, as shown in Table 7 shows a MAPE value of 15.15% and an RMSE of 6.31884. While testing, the test dataset showed a MAPE value of 14.94% and an RMSE of 5.79159. This range shows the ability of RBFNN to predict curly red chili prices at a high level of accuracy, according to Table 1.

*3.5.3* *Cayenne Pepper:* Cayenne pepper stands out as the chili variant with the highest selling price, primarily due to its longer harvest period and the need for intensive pest and disease management. As illustrated in Fig. 10, the price of cayenne pepper experienced significant fluctuations from September 2021 to June 2022, with sharp increases and dramatic drops. According to Table 9, the price trend from July 1-7, 2022, shows that the RBFNN model's predictions were consistently lower than the actual prices, with differences ranging from IDR 5,142 to IDR 10,181. Despite the challenges posed by the more volatile price patterns of cayenne pepper compared to large red or curly chilies, the RBFNN model demonstrated a high level of accuracy. As shown in Table 8, the MAPE for the training dataset was 14.70% with an RMSE of 7.21210, while the testing dataset yielded an MAPE of 14.80% and an RMSE of 6.84619, indicating reliable predictive performance.

The results show that our experiments are accurate with less than 20% of MAPE values. These results are the price prediction of chili for seven days. Other research, such as in [13], they obtained the smallest RMSE on the price of red chili and curly red chili in the traditional market, which are 2.57% and 2.07%, as compared to 2.11% and 2.07% in the modern market. Those RMSEs are better than ours, and our result for the lowest RMSE is 44.8%. Furthermore, if we compare with other research, such as in [12], their MAPE is lower than ours. Despite the comparisons, our study is still reasonable and promising with less than 20% of MAPE.

The results of testing the chili price forecasting model using RBFNN based on historical data show that RBFNN can identify price patterns accurately despite significant price fluctuations. This finding indicates that RBFNN has the potential to be a reliable prediction model to support decision-making in supply management and chili price stabilization. However, further research must improve the model's performance by integrating external factors such as weather, distribution, and seasonal demand to optimize the prediction results.

# 4 CONCLUSION

This study demonstrates that the Radial Basis Function Neural Network (RBFNN) model, utilizing radial basis functions as activation functions, achieves high accuracy in forecasting chili prices. The model's performance, evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE), shows MAPE values below 20%, indicating good accuracy. The combination of K-Means clustering with RBFNN proves effective, allowing the model to adaptively calculate weights and integrate real-time price updates. Future research directions include incorporating external factors such as weather, seasonal demand, and distribution dynamics to further optimize the model's performance. Additionally, automating the determination of the k-value in K-Means using Genetic Algorithms (GA) or other optimization techniques could enhance the model's efficiency and accuracy, supporting better decision-making in the agribusiness sector.

# AUTHOR'S CONTRIBUTION

All authors contributed equally to this research.

Table 5. Minmax Scaler Normalization Results

| Date | Curly Red Chilies | Large Red Chilies | Cayenne pepper |
|---|---|---|---|
| 12/01/2021 | 0.369231 | 0.382353 | 0.323232 |
| 12/02/2021 | 0.400000 | 0.367647 | 0.343434 |
| 12/03/2021 | 0.415385 | 0.426471 | 0.373737 |
| 12/04/2021 | 0.369231 | 0.455882 | 0.434343 |
| 12/05/2021 | 0.369231 | 0.426471 | 0.414141 |
| 12/06/2021 | 0.415385 | 0.455882 | 0.393939 |
| 12/07/2021 | 0.353846 | 0.382353 | 0.414141 |

Table 6. Accuracy of Price Forecasting on Large Red Chilli RBFNN Model

| Date | RATIO | | | | | |
|---|---|---|---|---|---|---|
| | 75:25 | | | 80:20 | | |
| | MAPE | Sum of Node | RMSE | MAPE | Sum of Node | RMSE |
| 1 | 10.49% | 3 | 4.59529 | 10.79% | 2 | 5.06717 |
| 2 | 10.53% | 25 | 4.61520 | 10.81% | 10 | 5.05296 |
| 3 | 10.54% | 9 | 4.61018 | 10.75% | 13 | 4.99340 |
| 4 | 10.43% | 9 | 4.50819 | 10.73% | 26 | 4.94126 |
| 5 | 10.38% | 4 | 4.48187 | 10.67% | 17 | 4.94306 |
| 6 | 10.37% | 3 | 4.48400 | 10.71% | 15 | 4.92733 |
| 7 | 10.39% | 5 | 4.53207 | 10.85% | 13 | 4.98379 |
| 8 | 10.49% | 4 | 4.57305 | 10.93% | 8 | 5.03680 |
| 9 | 10.58% | 5 | 4.58307 | 10.97% | 21 | 5.13594 |
| 10 | 10.65% | 19 | 4.73273 | 11.14% | 20 | 5.19223 |
| 11 | 10.69% | 9 | 4.83331 | 11.25% | 13 | 5.15299 |
| 12 | 10.68% | 4 | 4.69764 | 11.25% | 14 | 5.15182 |
| 13 | 10.69% | 1 | 4.69035 | 11.09% | 9 | 5.16229 |
| 14 | 10.71% | 7 | 4.70328 | 11.11% | 13 | 5.14503 |
| 15 | 10.81% | 6 | 4.70726 | 11.25% | 9 | 5.32181 |
| Average | 10.56% | | 4.62316 | 10.95% | | 5.08052 |

Table 7. Accuracy of Price Forecasting on Curly Red Chilli RBFNN Model

| Date | MAPE | Sum of Node | RMSE | MAPE | Sum of Node | RMSE |
|---|---|---|---|---|---|---|
| 1 | 14.94% | 8 | 5.72404 | 15.07% | 4 | 6.19067 |
| 2 | 15.18% | 18 | 5.96621 | 15.29% | 5 | 6.40341 |
| 3 | 14.99% | 20 | 5.71889 | 15.13% | 17 | 6.12772 |
| 4 | 14.77% | 10 | 5.59016 | 14.99% | 13 | 6.13906 |
| 5 | 14.89% | 7 | 5.67686 | 15.08% | 10 | 6.18468 |
| 6 | 14.81% | 2 | 5.63617 | 15.20% | 18 | 6.25684 |
| 7 | 14.99% | 14 | 5.88824 | 15.20% | 8 | 6.38128 |
| 8 | 14.87% | 4 | 5.78448 | 15.10% | 12 | 6.34495 |
| 9 | 14.82% | 30 | 5.70712 | 15.21% | 10 | 6.37659 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 10 | 14.98% | 1 | 5.88373 | 15.00% | 27 | 6.28244 |
| 11 | 14.96% | 6 | 5.83650 | 14.92% | 26 | 6.28846 |
| 12 | 14.99% | 2 | 5.81049 | 15.01% | 28 | 6.23501 |
| 13 | 15.04% | 25 | 5.77255 | 15.36% | 15 | 6.59188 |
| 14 | 15.08% | 8 | 5.89310 | 15.26% | 10 | 6.28896 |
| 15 | 14.97% | 21 | 6.09247 | 15.50% | 11 | 6.64713 |
| Average | 14,94% | | 5.79159 | 15,15% | | 6.31884 |

Table 8. Accuracy of Price Forecasting on Cayenne Pepper RBFNN Model

| Date | 75:25 | | | 80:20 | | |
|---|---|---|---|---|---|---|
| | MAPE | Sum of Node | RMSE | MAPE | Sum of Node | RMSE |
| 1 | 15.14% | 10 | 7.16207 | 15.10% | 3 | 7.54732 |
| 2 | 15.14% | 9 | 7.18267 | 15.11% | 14 | 7.78347 |
| 3 | 15.05% | 13 | 7.07555 | 14.93% | 21 | 7.40051 |
| 4 | 14.73% | 20 | 7.03720 | 14.82% | 21 | 7.29430 |
| 5 | 14.80% | 6 | 7.04199 | 14.71% | 14 | 7.19645 |
| 6 | 14.69% | 10 | 6.97155 | 14.57% | 7 | 7.25234 |
| 7 | 14.66% | 12 | 6.85950 | 14.55% | 16 | 7.10423 |
| 8 | 14.56% | 6 | 6.84692 | 14.52% | 10 | 7.12231 |
| 9 | 14.68% | 5 | 6.83636 | 14.59% | 16 | 7.07957 |
| 10 | 14.82% | 9 | 6.78435 | 14.63% | 4 | 7.00910 |
| 11 | 14.82% | 28 | 6.91592 | 14.68% | 8 | 7.05925 |
| 12 | 14.65% | 25 | 6.92550 | 14.59% | 6 | 7.10545 |
| 13 | 14.90% | 8 | 6.63971 | 14.54% | 26 | 7.08807 |
| 14 | 14.62% | 14 | 6.74835 | 14.67% | 11 | 7.18848 |
| 15 | 14.72% | 25 | 6.93327 | 14.42% | 2 | 6.95079 |
| Average | 14.80% | | 6.84614 | 14.70% | | 7,21210 |

Table 9. Prices Forecasting Result of Three Chilli Variants from July 1-7, 2022

| Days to | Large Red Chili (IDR) | | Curly Red Chili (IDR) | | Cayenne Pepper (IDR) | |
|---|---|---|---|---|---|---|
| | Forecasting Price | Actual Price | Forecasting Price | Actual Price | Forecasting Price | Actual Price |
| 1 | 55,578 | 55,086 | 61,121 | 51,567 | 80,871 | 87,301 |
| 2 | 54,195 | 55,209 | 58,166 | 50,718 | 80,729 | 87,963 |
| 3 | 52,874 | 54,783 | 56,892 | 47,991 | 80,491 | 87,848 |
| 4 | 52,809 | 53,980 | 54,672 | 43,754 | 81,751 | 86,893 |
| 5 | 52,097 | 54,635 | 54,637 | 47,728 | 81,302 | 87,017 |
| 6 | 51,218 | 53,067 | 50,369 | 43,151 | 80,466 | 88,744 |
| 7 | 49,721 | 51,640 | 49,516 | 42,615 | 79,671 | 89,852 |

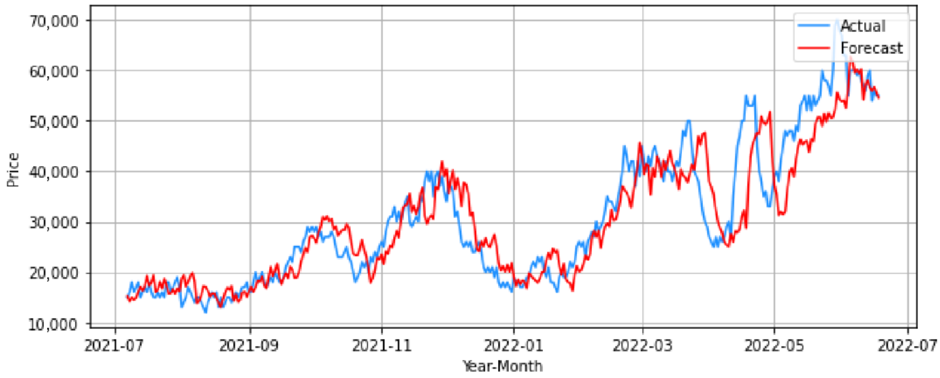


Figure 8. Comparison graph of actual prices and forecasted prices for Large Red Chili.

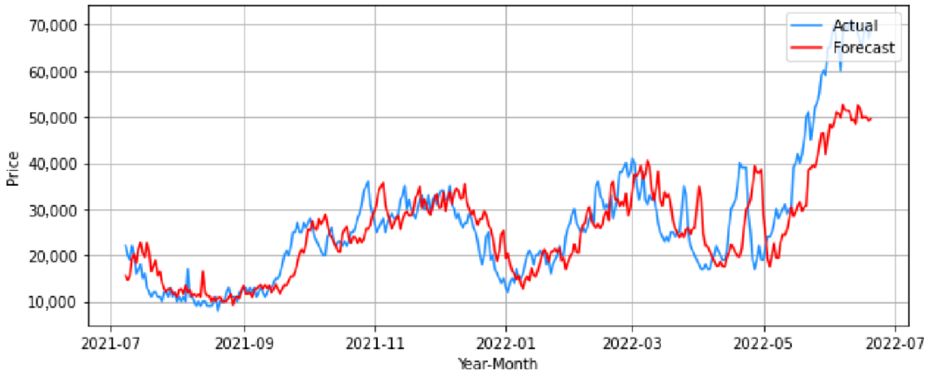


Figure 9. Comparison graph of actual prices and forecasted prices for Curly Red Chili

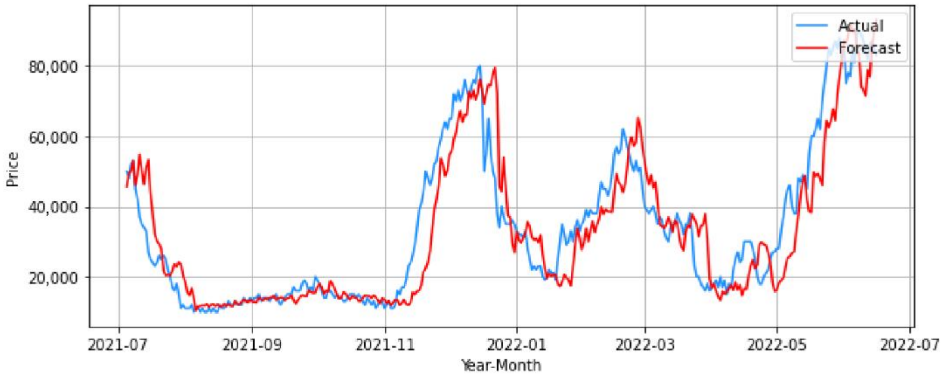


Figure 10. Comparison graph of actual prices and forecasted prices for Cayenne Pepper

## COMPETING INTERESTS

The authors declare no conflict of interest.

## ACKNOWLEDGMENT

The data in this study can be accessed through open source provided by the DKI Jakarta Government.

## REFERENCES

[1] M. F. Rohmah, K. G. D. Putra, R. S. Hartati, and L. Ardiantoro, "Minimum wage correlation with consumer price index predictions using support vector regression," International Journal of Scientific and Technology Research, vol. 9, no. 3, pp. 4596–4602, 2020.

[2] N. G. Society, "Food." [Online]. Available: https://education.nationalgeographic.org/resource/food/

[3] C. Chauhan, A. Dhir, M. U. Akram, and J. Salo, "Food loss and waste in food supply chains. A systematic literature review and

framework development approach," J Clean Prod, vol. 295, p. 126438, 2021, doi: 10.1016/j.jclepro.2021.126438.

[4] W. Hidayat, M. Ardiansyah, and K. Kusrini, "Decision support system for selection of staples food and food commodity price prediction post-COVID-19 using simple additive weighting and multiple linear regression methods," 2020 3rd International Conference on Information and Communications Technology, ICOIACT 2020, pp. 45–50, 2020, doi: 10.1109/ICOIACT50329.2020.9332095.

[5] M. C. Zamzami and Nucke Widowati Kusumo Projo, "Nowcasting of Chili Pepper (Capsicum frutescens L.) Prices in East Java Province Using Multi-Layer Perceptron Method," Proceedings of The International Conference on Data Science and Official Statistics, vol. 2023, no. 1 SE-Data Science, pp. 2–12, Dec. 2023, doi: 10.34123/icdsos.v2023i1.274.

[6] International Center for Applied Finance and Economics (InterCAFE) IPB University, "Market Study on Food Sector in Indonesia," 2018.

[7] M. Rachmaniah, A. I. Suroso, M. Syukur, and I. Hermadi, "Strategic Food Risks – Chili'S Agrosystem Perspective," Jurnal Manajemen dan Agribisnis, vol. 18, no. 1, p. 19, 2021, doi: 10.17358/jma.18.1.19.

[8] U. S. Nurainun, S. Dur, R. Widyasari, U. Islam, N. Sumatera, and A. Info, "Predict the Price of Curly Red Chili in North Sumatra Using the Holt Winters Additive Method," Journal of Mathematics and Scientific Computing With Applications, vol. 2, no. October 2020, pp. 55–60, 2021.

[9] I. M. Wirawan, I. A. E. Zaeni, U. A. Mujaddid, and A. S. B. M. Jaya, "Fuzzy Time Series Method Comparison of Chen and Cheng Models to Predict Chili Prices," in 2021 7th International Conference on Electrical, Electronics and Information Engineering (ICEEIE), 2021, pp. 541–546. doi: 10.1109/ICEEIE52663.2021.9616907.

[10] G. Hegde, V. R. Hulipalled, and J. B. Simha, "A study on agriculture commodities price prediction and forecasting," Proceedings of the International Conference on Smart Technologies in Computing, Electrical and Electronics, ICSTCEE 2020, pp. 316–321, 2020, doi: 10.1109/ICSTCEE49637.2020.9277401.

[11] K. Prasetyo, D. D. Putri, I. Kartika Eka Wijayanti, and L. Zulkifli, "Forecasting of Red Chilli Prices in Banyumas Regency: The ARIMA Approach," E3S Web of Conferences, vol. 444, 2023, doi: 10.1051/e3sconf/202344402017.

[12] D. Sepri and A. Fauzi, "Prediksi Harga Cabai Merah Menggunakan Support Vector Regression," Computer Based Information System Journal, vol. 8, no. 2, pp. 1–5, 2020, doi: 10.33884/cbis.v8i2.1921.

[13] R. A. Falah and M. Rachmaniah, "Price Prediction Model for Red and Curly Red Chilies using Long Short Term Memory Method," Indonesian Journal of Statistics and Its Applications, vol. 6, no. 1, pp. 143–160, May 2022, doi: 10.29244/ijsa.v6i1p143-160.

[14] K. C. S, "Hybrid models for intraday stock price forecasting based on artificial neural networks and metaheuristic algorithms," Pattern Recognit Lett, vol. 147, pp. 124–133, 2021, doi: 10.1016/j.patrec.2021.03.030.

[15] A. Dani, F. B. Putra, and Q. Q. A'yun, "Red Chili Price Forecasting in Indonesia Based on Data from the Strategic Food Price Information Center Using the Neural Network," SSRN Electronic Journal, vol. 10, no. 3, pp. 14–20, 2023, doi: 10.2139/ssrn.4497728.

[16] B. R. P. M. Basnayake, K. D. Kaushalya, R. H. M. Wickaramarathne, M. A. K. Kushan, and N. V. Chandrasekara, "An Approach for Prediction of Weekly Prices of Green Chili in Sri Lanka: Application of Artificial Neural Network Techniques," Journal of Agricultural Sciences - Sri Lanka, vol. 17, no. 2, pp. 333–349, 2022, doi: 10.4038/jas.v17i2.9746.

[17] M. A. Rasyidi, "Prediksi Harga Bahan Pokok Nasional Jangka Pendek Menggunakan ARIMA," Journal of Information Systems Engineering and Business Intelligence, vol. 3, no. 2, p. 107, Oct. 2017, doi: 10.20473/jisebi.3.2.107-112.

[18] T. Handhayani, I. Lewenusa, and M. Y. R. Arpipi, "Forecasting Volatile Fresh Chili Prices In Indonesia Using Support Vector Regression," Proceeding - 2024 International Conference on Information Technology Research and Innovation, ICITRI 2024, pp. 281–286, 2024, doi: 10.1109/ICITRI62858.2024.10699118.

[19] Z. M. Yaseen, A. El-Shafie, H. A. Afan, M. Hameed, W. H. M. W. Mohtar, and A. Hussain, "RBFNN versus FFNN for daily river flow forecasting at Johor River, Malaysia," Neural Comput Appl, vol. 27, no. 6, pp. 1533–1542, 2016, doi: 10.1007/s00521-015-1952-6.

[20] Z. Yun, Z. Quan, S. Caixin, L. Shaolan, L. Yuming, and S. Yang, "RBF Neural Network and ANFIS-Based Short-Term Load Forecasting Approach in Real-Time Price Environment," IEEE Transactions on Power Systems, vol. 23, no. 3, pp. 853–858, 2008, doi: 10.1109/TPWRS.2008.922249.

[21] I. Ambarwati, "Metode Radial Basis Function Neural Network (RBFNN) untuk Peramalan Kunjungan Wisatawan dengan Perbandingan Kombinasi Fungsi Pelatihan," in PRISMA, 2023, pp. 687–693.

[22] M. Yanis, A. Y. Budiman, A. S. Mohruni, S. Sharif, M. A. Suhaimi, and H. Dwipayana, "Levenberg-Marquardt, Bayesian-regularization, and scaled conjugate gradient algorithms for predicting surface roughness accuracy on side milling AISI 1045," AIP Conf Proc, vol. 2544, no. 1, p. 20013, Apr. 2023, doi: 10.1063/5.0117323.

[23] U. A. Dodo et al., "Comparative study of different training algorithms in backpropagation neural networks for generalized biomass higher heating value prediction," Green Energy and Resources, vol. 2, no. 1, p. 100060, 2024, doi: https://doi.org/10.1016/j.gerr.2024.100060.

[24] X. Yin, Q. Zhang, H. Wang, and Z. Ding, "RBFNN-Based Minimum Entropy Filtering for a Class of Stochastic Nonlinear Systems," IEEE Trans Automat Contr, vol. 65, no. 1, pp. 376–381, 2020, doi: 10.1109/TAC.2019.2914257.

[25] Q. Jiang, L. Zhu, C. Shu, and V. Sekar, "An efficient multilayer RBF neural network and its application to regression problems," Neural Comput Appl, vol. 34, no. 6, pp. 4133–4150, 2022, doi: 10.1007/s00521-021-06373-0.

[26] Y. Zhang, Z. Luo, Q. Li, D. Cheng, and W. Tan, "Using the Radial Basis Function with the Novel Optimization Algorithms to Appraise the Pile Settlement Rates," vol. 28, no. 3, pp. 489–499, 2024.

[27] C. Yang, J. Luo, and N. Wang, "Chapter Three - Uncertainties compensation-based teleoperation control," C. Yang, J. Luo, and N. B. T.-H.-I. L. and C. for R. T. Wang, Eds., Academic Press, 2023, pp. 39–71. doi: https://doi.org/10.1016/B978-0-32-395143-2.00007-3.

[28] H. Hong et al., "Radial basis function artificial neural network (RBF ANN) as well as the hybrid method of RBF ANN and grey relational analysis able to well predict trihalomethanes levels in tap water," J Hydrol (Amst), vol. 591, no. April, p. 125574, 2020, doi: 10.1016/j.jhydrol.2020.125574.

[29] S. Panda and G. Panda, "On the Development and Performance Evaluation of Improved Radial Basis Function Neural Networks," IEEE Trans Syst Man Cybern Syst, vol. 52, no. 6, pp. 3873–3884, 2022, doi: 10.1109/TSMC.2021.3076747.

[30] A. Zhao, A. Toudeshki, R. Ehsani, J. H. Viers, and J. Q. Sun, "Robustness improvement of optimal control in terms of RBFNN with empirical model reduction and transfer learning," Int J Control, 2024, doi: 10.1080/00207179.2024.2328687.

[31] H. Haviluddin and A. Jawahir, "Comparing of ARIMA and RBFNN for short-term forecasting," International Journal of Advances in Intelligent Informatics; Vol 1, No 1 (2015): March 2015, 2015, doi: 10.26555/ijain.v1i1.10.

[32] U. Salam, S. Lee, V. Fullerton, Y. Yusuf, S. Krantz, and M. Henstridge, "Indonesia case study: Rapid technological change–challenges and opportunities," Pathways for Prosperity Commission Background Paper Series, 2018.

[33] F. Novitasari, N. C. Drestalita, and S. Maryati, "The impacts of infrastructure development on economic growth (case study: DKI Jakarta, Banten Province and West Java Province)," in IOP Conference Series: Earth and Environmental Science, IOP Publishing, 2020, p. 12017.

[34] PD. P. Jaya, "Informasi Pangan Jakarta." [Online]. Available: https://infopangan.jakarta.go.id/commodity

[35] A. Yuditya, A. Hardjanto, and U. Sehabudin, “Fluktuasi Harga dan Integrasi Pasar Cabai Merah Besar (Studi Kasus: Pasar Induk kramat Jati dan Pasar Eceran di DKI Jakarta),” Indonesian Journal of Agriculture Resource and Environmental Economics, vol. 2, no. 1, pp. 1–13, 2023, doi: 10.29244/ijaree.v2i1.50669.

[36] D. M. C. Dos Santos, B. K. Dos Santos, and C. G. Dos Santos, “Implementation of a standard work routine using Lean Manufacturing tools: A case Study,” Gestao e Producao, vol. 28, no. 1, 2021, doi: 10.1590/0104-530X4823-20.

[37] D. Egger et al., “Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries,” Sci Adv, vol. 7, no. 6, p. eabe0997, Jan. 2025, doi: 10.1126/sciadv.abe0997.

[38] O. Haroon and S. A. R. Rizvi, “Flatten the Curve and Stock Market Liquidity – An Inquiry into Emerging Economies,” Emerging Markets Finance and Trade, vol. 56, no. 10, pp. 2151–2161, Aug. 2020, doi: 10.1080/1540496X.2020.1784716.

[39] D. McMillan, A. Speight, and O. Apgwilym, “Forecasting UK stock market volatility,” Applied Financial Economics, vol. 10, no. 4, pp. 435–448, 2000, doi: 10.1080/09603100050031561.

[40] A. Ambarwari, Q. J. Adrian, and Y. Herdiyeni, “Analisis Pengaruh Data Scaling Terhadap Performa Algoritme Machine Learning untuk Identifikasi Tanaman,” RESTI, vol. 4, no. 1, pp. 117–122, 2020, doi: https://doi.org/10.29207/resti.v4i1.1517.

[41] S. Uyun, S. Rahardyan, and M. Anshari, “Skew Correction and Image Cleaning Handwriting Recognition Using a Convolutional Neural Network,” International Journal on Informatics Visualization, vol. 7, no. 3, pp. 681–687, 2023, doi: 10.30630/joiv.7.3.1712.

[42] T. Blu, P. Thevenaz, and M. Unser, “Linear interpolation revitalized,” IEEE Transactions on Image Processing, vol. 13, no. 5, pp. 710–719, 2004, doi: 10.1109/TIP.2004.826093.

[43] M. R. Islam, M. N. Akhtar, and M. Begum, “Long short-term memory (LSTM) networks based software fault prediction using data transformation methods,” in 2022 International Conference on Advancement in Electrical and Electronic Engineering (ICAEEE), 2022, pp. 1–6. doi: 10.1109/ICAEEE54957.2022.9836388.

[44] R. D. Martin, V. J. Yohai, and R. H. Zamar, “Min-Max Bias Robust Regression,” The Annals of Statistics, vol. 17, no. 4, pp. 1608–1630, Dec. 1989, doi: 10.1214/aos/1176347384.

[45] L. A. Badulescu, “Experiments for a better Gini index splitting criterion for data mining decision trees algorithms,” 2020 24th International Conference on System Theory, Control and Computing, ICSTCC 2020 - Proceedings, pp. 208–212, 2020, doi: 10.1109/ICSTCC50638.2020.9259691.

[46] N. Karimi, S. Kazem, D. Ahmadian, H. Adibi, and L. V Ballestra, “On a generalized Gaussian radial basis function: Analysis and applications,” Eng Anal Bound Elem, vol. 112, pp. 46–57, 2020, doi: https://doi.org/10.1016/j.enganabound.2019.11.011.

[47] F. Fernández-Navarro, C. Hervás-Martínez, and P. A. Gutierrez, “Generalised Gaussian radial basis function neural networks,” Soft comput, vol. 17, no. 3, pp. 519–533, 2013, doi: 10.1007/s00500-012-0923-4.

[48] M. D. R. Wahyudi, “Evaluation of TF-IDF Algorithm Weighting Scheme in The Qur’an Translation Clustering with K-Means Algorithm,” The Journal of Information Technology and Computer Science (JITeCS), vol. 6, no. 2, pp. 117–129, 2021, doi: https://doi.org/10.25126/jitecs.202162295.

[49] Qomariyah and M. U. Siregar, “Comparative Study of K-Means Clustering Algorithm and K-Medoids Clustering in Student Data Clustering,” JISKA (Jurnal Informatika Sunan Kalijaga), vol. 7, no. 2, pp. 91–99, May 2022, doi: 10.14421/jiska.2022.7.2.91-99.

[50] P. Dangeti, Statistical for Machine Learning. Packt Publishing, 2017.

[51] R. Suwanda, Z. Syahputra, and E. M. Zamzami, “Analysis of Euclidean Distance and Manhattan Distance in the K-Means Algorithm for Variations Number of Centroid K,” J Phys Conf Ser, vol. 1566, no. 1, p. 12058, 2020, doi: 10.1088/1742-6596/1566/1/012058.

[52] J. Ferreirós, “Gauss and the Mathematical Background to Standardisation,” HoST - Journal of History of Science and Technology, vol. 14, no. 1, pp. 32–51, 2020, doi: 10.2478/host-2020-0003.

[53] D. Chicco, M. J. Warrens, and G. Jurman, “The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation,” PeerJ Comput Sci, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.623.

[54] H. Yao, Y. Wang, L. Zhang, J. Zou, and C. Finn, “C-Mixup: Improving Generalization in Regression,” in 36th Conference on Neural Information Processing Systems (NeurIPS 2022), 2022.

[55] D. A. Swanson, “On the Relationship among Values of the Same Summary Measure of Error when it is used across Multiple Characteristics at the Same Point in Time: An Examination of MALPE and MAPE,” Review of Economics and Finance, vol. 5, no. 1, pp. 1–14, 2015, [Online]. Available: https://escholarship.org/uc/item/1f71t3x9

[56] E. Vivas, H. Allende-Cid, and R. Salas, “A Systematic Review of Statistical and Machine Learning Methods for Electrical Power Forecasting with Reported MAPE Score,” 2020. doi: 10.3390/e22121412.