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Analysis of Forecasting Methods on Rice Price Data at Milling Level According to Quality

Indira Dhekawanti Aulia✉, Irfan Pratama

Department of Information Systems, Faculty of Information Technology, Universitas Mercu Buana Yogyakarta, Indonesia

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Abstract

Rice is a primary source of carbohydrates for many Indonesians, and its prices often surge due to uncontrolled demand. Therefore, the government is crucial in monitoring rice prices to maintain stability. Information technology, particularly data mining such as forecasting, is essential for providing accurate information on future rice prices. It will assist various stakeholders in making informed pricing policy decisions. This study employs Random Forest Regression and Gradient Boosting Regressor methods to predict rice prices using a dataset that includes monthly average rice prices at milling levels, categorized by quality (Premium and Medium), spanning from January 2013 to April 2024. The dataset consists of 136 rows, each representing a unique combination of year, month, and quality, and is stored in CSV format. Methodological steps include data collection, preprocessing, modeling, and model evaluation using monthly average rice prices at milling levels based on quality, including premium and medium grades. The results from Random Forest Regression indicate Root Mean Square Error (RMSE) values of 24.90 for premium rice and 25.47 for medium rice. The study reveals that Random Forest Regression outperforms Gradient Boosting Regressor in this context. Future research should explore additional prediction methods and consider other variables influencing rice prices to enhance model accuracy.

✉ Correspondence address:
Fakultas Teknologi Informasi, Universitas Mercu Buana Yogyakarta, Gg. Jemb. Merah No.84C, Condongcatur, Yogyakarta, 55281, Indonesia
E-mail: indiraaulia1708@gmail.com

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INTRODUCTION

Rice is one of the agricultural products and a staple food for a significant portion of the Indonesian population. As Indonesia is an agricultural country, with nearly 90% of its people consuming rice as their primary carbohydrate source, rice plays a crucial role in economic and political stability. The price of rice commodities is continuously monitored and intervened by the government. It was because rice prices contribute to food security, poverty alleviation, macroeconomic stability, and the country's economic growth (Jiuhardi, 2023).

Information technology plays a pivotal role in monitoring and predicting rice prices at the milling level based on quality. Artificial intelligence in the food sector is an innovative technology that supports the management of staple foods, such as price prediction, food quality determination, and demand mapping (Putra & Sinaga, 2022). These technologies offer innovative solutions that enhance the management of staple foods like rice, ensuring that supply and demand dynamics are efficiently addressed.

Data mining is a discipline that studies methods for extracting knowledge or discovering patterns from large datasets (Sumarni & Rustam, 2020). The government also plays a crucial role in ensuring price regulation to prevent drastic fluctuations. Such fluctuations usually occur during major holidays, caused by increased goods such as food, particularly rice, leading to a rise in prices. Fluctuations are changes in certain variables that generally occur due to market mechanisms (R. Amalia et al., 2023).

Therefore, it is necessary to monitor and predict rice prices to maintain stability and prevent burdening disadvantaged community groups, which can be achieved by applying data mining techniques. In this context, data mining is used in the form of forecasting. According to (Yudianto et al., 2023), forecasting methods are divided into quantitative and qualitative categories. Qualitative methods are based on opinions and descriptive analysis, while quantitative methods rely on mathematical calculations.

Forecasting methods have been widely applied in various aspects, particularly in pricing. Research on price prediction has been conducted by several researchers, such as Putra and Sinaga (2022), Mukhlisin, Imrona, and Murdiansyah (2019), Saadah and Salsabila (2021), and Amalia et al. (2022). However, existing studies have yet to focus on simultaneously predicting rice prices based on different types, such as premium or medium.

The previous research titled 'Estimation of Premium Rice Prices in DKI Jakarta using Linear Regression' aimed to predict the prices of premium rice in DKI Jakarta, resulting in a Mean Absolute Error (MAE) of 275.55 and a Mean Squared Error (MSE) of 103169.10. When the MSE was squarely rooted, the result was an RMSE (Root Mean Squared Error) of approximately 321.199 (Putra & Sinaga, 2022).

Previous research was also conducted by (Adjie Setyadj et al., 2023) with the titled "Forecasting Rice Commodity Prices in East Kalimantan Using Neural Network Algorithm." This study used daily premium rice price data obtained from the community in East Kalimantan. ThThistudy yielded a Root Mean Square Error (RMSE) value of 52.846 for premium rice.

Similar research was also conducted previously by (Mukhlisin et al., 2019) titled 'Prediction of Premium Rice Prices using the K-Nearest Neighbor Algorithm' using data from the Central Statistics Agency of Bandung and weather data from BMKG Bandung. The study resulted in an RMSE of 352.450 for non-normalized data and an RMSE of 174.38 for normalized data.

Another research study is titled 'Bitcoin Price Prediction Using Random Forest Method.' The research utilizes several attributes: low, high, and price. The Random Forest Regression method produces a MAPE value of 1.50% or achieves an accuracy of around 98% using random data. The data used in this study had high fluctuation characteristics, so the Random Forest Regression method could provide fittings that match the actual data (Saadah & Salsabila, 2021).

Similarly, research conducted by (A. Amalia et al., 2022) with the title 'Car Price Prediction using Regression Algorithm with Hyper-Parameter Tuning.' This study developed three regression models: Linear Regression, Random Forest Regression, and Gradient Boosting Regression. Hyperparameter tuning was applied to enhance the accuracy of the models. Parameters added included an intercept for Linear Regression, 'sqrt' for max features, 'gini' for criterion in Random Forest, and 'sqrt' for max features, and 'friedman_mse' for criterion in Gradient Boosting. The results of this study showed that Gradient Boosting Regression achieved the highest model accuracy, with a training accuracy of 99.58% and a testing accuracy of 96.75%.

Based on the previous explanation, the Random Forest Regression and Gradient Boosting Regression methods have shown promising results. This study aims to test these models on a rice price dataset, comparing them with other methods from previous research to evaluate their effectiveness. The results from evaluating the best model can then be used to predict rice prices at the milling level based on quality.

RESEARCH METHODS

The research materials used in this study are monthly average rice prices at the Milling Level according to quality sourced from the Central Bureau of Statistics of Indonesia from 2013 to 2024. This research is conducted using a quantitative method. Quantitative research is a process of discovering knowledge using numerical data as a tool to analyze information about what is sought (Wantari, 2021). The research flowchart can be seen in Figure 1.

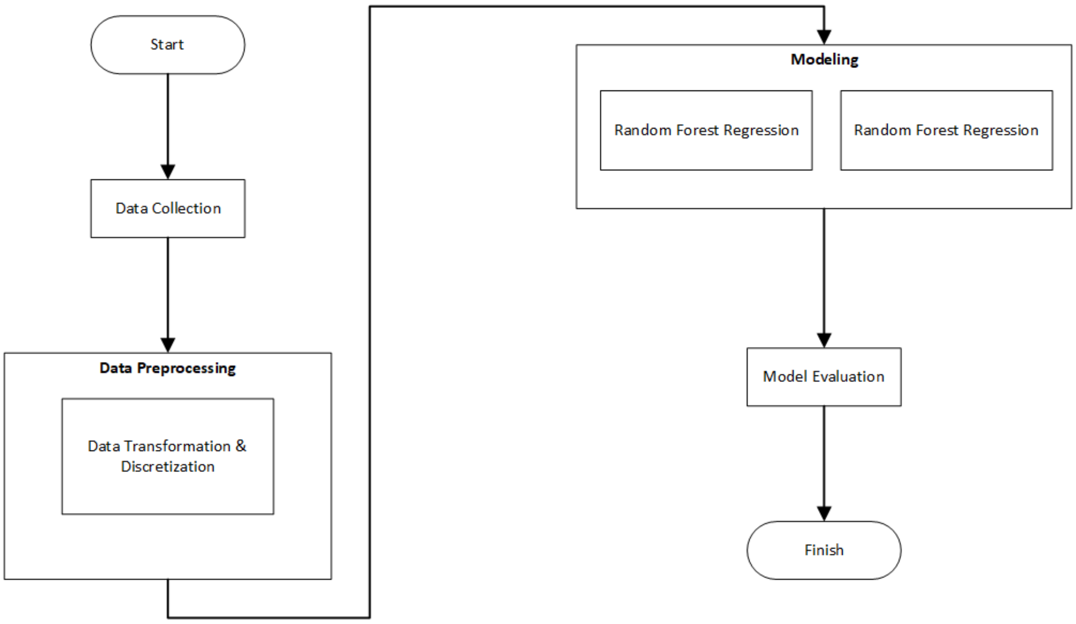

Figure 1. Research flowchart

Based on Figure 1 above, the research flow/path can be explained as follows:

A. Dataset Collection

The data collection in this study involves obtaining data from the Central Bureau of Statistics of Indonesia, which can be accessed at https://www.bps.go.id/id/statistics-table/2/NTAwIzI=/rata-rata-harga-beras-bulanan-di-tingkat-penggilingan-menurut-kualitas.html. The dataset includes monthly average rice prices at the Milling Level, categorized by quality (Premium and Medium), spanning from January 2013 to April 2024. It consists of 136 rows, each representing a unique combination of year, month, and quality (Premium and Medium), and is stored in CSV format. The data is utilized to analyze rice prices at the Milling Level according to quality, aiming to assist in building a rice price prediction system. The data format is in the form of a time series. The example dataset used is shown in Table 1.

Table 1. Sample Data of Rice Prices at the Milling Level According to Quality in 2013

Bulan	Tahun	Premium	Medium
1	2013	7797.3	7697.37
2	2013	7773.26	7645.05
3	2013	7576.27	7503.27
4	2013	7420.72	7290.96
5	2013	7545.5	7261.71
6	2013	7548.22	7419.63
7	2013	7823.68	7553.54
8	2013	7761.29	7524.03
9	2013	7746.17	7652.87
10	2013	7846.05	7702.05
11	2013	7919.98	7732.05
12	2013	7976.72	7871.21

Source: https://www.bps.go.id/id/statistics-table/2/NTAwIzI=/rata-rata-harga-beras-bulanan-di-tingkat-penggilingan-menurut-kualitas.html

B. Data Preprocessing

In the data preprocessing stage, the data obtained from the Central Bureau of Statistics of Indonesia, which consists of monthly average rice prices at the Milling Level according to quality, undergoes several steps. The preprocessing steps applied to this research data include Data Transformation and Discretization.

Data Transformation is a preprocessing stage where data is modified or combined into a suitable data format for processing in Data Mining (Rayuwati et al., 2022). Meanwhile, Discretization is a technique in transformation aimed at converting numerical attributes into categorical attributes, thereby creating several levels or hierarchies (Alghifari & Juardi, 2021).

The data used can improve the model further through this data preprocessing stage. In this stage, what needs to be done is adjusting the delimiter in each data field, converting the month format into numbers, and combining the month and year columns into a date format to form the Year-Month-Date, which is stored in the date column. Next, the premium and medium data are divided into training and testing data using time series splitting.

C. Modeling

This stage begins by determining the prediction method suitable for predicting rice prices at the mill level according to quality. The methods or models used to evaluate this study's best models are Random Forest Regression and Gradient Boosting Regressor.

Random Forest Regression is a supervised machine learning algorithm that repeatedly builds decision trees, thus forming a forest (Saadah & Salsabila, 2021). Random Forest is a classification consisting of several decision trees, each constructed using a random vector (Mambang & Byna, 2017).

Gradient Boosting Regressor is a machine learning model that can be used for regression and classification, and it generates a predictive model consisting of an ensemble of weak prediction models on decision trees that result in shallow prediction errors when using the median as the prediction method (Riyadi et al., 2023).

The selection of these two models is because each model has its advantages. For instance, the Random Forest Regression method has several strengths, such as its ability to improve accuracy when dealing with incomplete data and its robustness against extreme data variations. Therefore, Random Forest Regression can effectively handle large datasets with complex parameters (Mardiyanti Elsa Nurul & Dewi Tresna, 2021).

Furthermore, the Gradient Boosting Regressor is a decision tree classification algorithm for addressing prediction and classification issues. This algorithm is also tree-based, which helps avoid overfitting (Kraugusteeliana et al., 2023). Those advantages are among the reasons for selecting the Random Forest Regression and Gradient Boosting Regressor methods for modeling rice prices at the Milling Level according to quality.

D. Model Evaluation

The evaluation stage is the most crucial as it aims to assess how well the prediction model performs. The steps in evaluating the model here involve comparing the best models to determine which will be used to predict rice prices at the Milling Level according to quality.

In this evaluation, a loop is used to repeat the training and model evaluation process 30 times, which is used to calculate the average of MAPE and MAE. Thus, in this evaluation stage, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) are generated.

Root Mean Square Error (RMSE) is the square root of the Mean Square Error (MSE) value obtained from the calculation of a method (Syakir et al., 2022). A high RMSE score means low forecasting accuracy. On the other hand, a low RMSE score means high forecasting accuracy (Sabar Sautomo & Hilman Ferdinandus Pardede, 2021). The formula for calculating RMSE can be seen in Equation (1).

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

Where:
$\hat{y}_i$ = forecasted value
y_i = observed value at i-th observation
n = number of data points

Mean Absolute Percentage Error (MAPE) is the average percentage error value obtained from the sum of each % error value divided by the number of periods in the data (Alfarisi, 2017). The Equation of MAPE can be seen in eq (2).

$$MAPE = \frac{100\%}{n}\sum\left|\frac{y - \hat{y}_i}{y_i}\right| \tag{2}$$

Where:
$\hat{y}_i$ = forecasted value
y_i = observed value at i-th observation
n = number of data points

Mean Absolute Error (MAE) is one method used to measure a model's accuracy by intuitively calculating the average error with equal weighting given to all data (Suryanto, 2019). The formula for calculating MAE is here, as seen in Equation (3).

$$MAE = \frac{1}{n}\sum|f_i - y_i| \qquad (3)$$

Where:
f_i = forecasted value
y_i = observed value at i-th observation
n = number of data points

From the evaluation results, we can see which method performs better while comparing the evaluation outcomes from previous studies as a reference for selecting the best model.

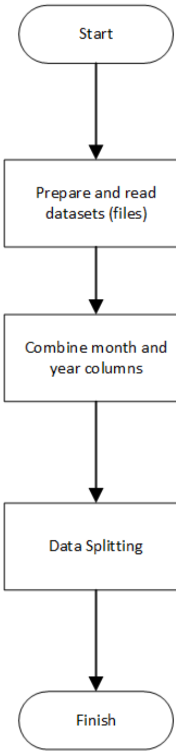

Figure 2. The flowchart of data preprocessing

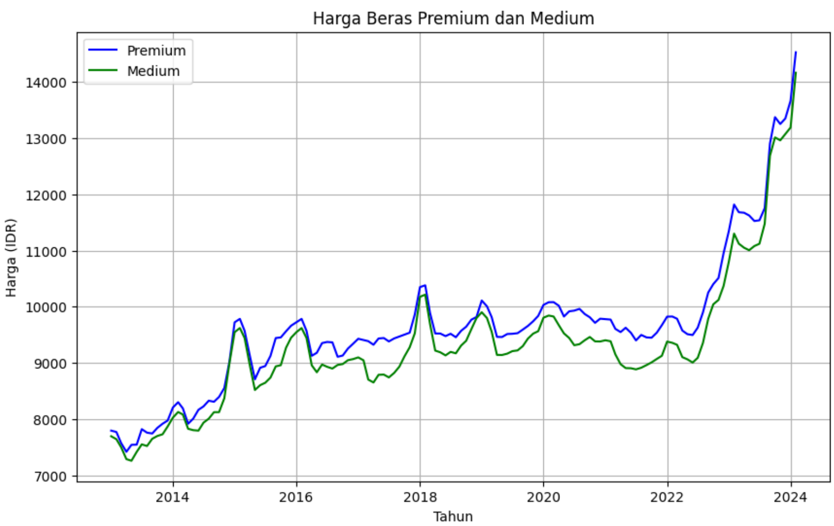

Figure 3. Visualization of actual prices of premium and medium rice

RESULT AND DISCUSSION

In this research, the accuracy results of the models or methods used will be obtained, along with comparisons with previous research that has been conducted. The findings and discussion of this study are as follows:

A. Data Preprocessing

The stages of data preprocessing in this research are crucial as they aim to prepare raw data in a suitable format for further analysis or modeling. The following is the data preprocessing workflow, as depicted in Figure 2.

In Figure 2, the first stage of this data preprocessing involves preparing and reading the dataset. The data obtained from the Central Bureau of Statistics of Indonesia, consisting of monthly average rice prices at the Milling Level according to quality, undergoes this initial phase. In this stage, delimiter=';' is also used, which serves as a separator between values in each column, ensuring that the data system can be interpreted correctly and the columns read accurately. Below is the visualization of actual premium and medium rice prices, as depicted in Figure 3.

Next, the stage involves combining the month and year columns. This combination transforms the 'Bulan' (Month) and 'Tahun' (Year) columns into a DateTime object unified in a single column named 'Tanggal' (Date). Subsequently, the 'Tanggal' column is set as the primary index of the 'data' data frame. The format of the combined 'Bulan' and 'Tahun' data can be seen in Table 2 and Table 3.

Table 2. Sample Data of Month and Year Before Combination

Month	Year
1	2013
2	2013
3	2013
4	2013
5	2013
6	2013
7	2013
8	2013
9	2013
10	2013
11	2013
12	2013

Table 2 presents the sample data of 'Bulan' (Month) and 'Tahun' (Year) before the combination process. The data is in its original form and does not yet reflect the unified 'Tanggal' (Date) column resulting from the combination of month and year.

Table 3. Sample Data Resulting from Month and Year Columns After Combination

Date	Month	Year
2013-01-01	1	2013
2013-02-01	2	2013
2013-03-01	3	2013
2013-04-01	4	2013
2013-05-01	5	2013
2013-06-01	6	2013
2013-07-01	7	2013
2013-08-01	8	2013
2013-09-01	9	2013
2013-10-01	10	2013
2013-11-01	11	2013
2013-12-01	12	2013

Table 3 shows the sample data after combining the 'Bulan' (Month) and 'Tahun' (Year) columns into a single 'Tanggal' (Date) column. The 'Tanggal' column is created by merging the month and year into a DateTime format. For example, January 2013 is represented as '2013-01-01' in the 'Tanggal' column. This table illustrates the resulting unified date format for the year 2013.

Next, the final stage in this data preprocessing involves data splitting. In this study, data splitting utilizes the technique of time series split, dividing the data into five parts. Each iteration provides index sets within the for loop for training and testing data based on the previously performed time series split. Below are sample training and testing data, as shown in Table 4, Table 5, Table 6, and Table 7.

Table 4. Sample Data for 'y_train_premium'

Date	y_train_premium
2021-12-01	9672.54
2022-01-01	9824.23
2022-02-01	9826.88
2022-03-01	9786.63
2022-04-01	9576.75

Table 5. Sample Data for 'y_test_premium'

Date	y_test_premium
2022-05-01	9512.63
2022-06-01	9497.40
2022-07-01	9628.57
2022-08-01	9901.15
2022-09-01	10252.31

Table 4 and Table 5 represent examples of sample training and testing data from the premium dataset. In contrast, Table 6 and Table 7 illustrate examples of some sample training and testing data from the medium dataset.

Table 6. Sample Data for 'y_train_medium'

Date	y_train_medium
2021-12-01	9128.44
2022-01-01	9381.24
2022-02-01	9358.61
2022-03-01	9323.35
2022-04-01	9104.35

Table 7. Sample Data for 'y_test_medium'

Date	y_test_medium
2022-05-01	9065.18
2022-06-01	9007.86
2022-07-01	9091.92
2022-08-01	9358.34
2022-09-01	9785.04

B. Modeling

In the modeling stage of this research, two methods or models were chosen to predict rice prices at the milling level according to quality: random forest regression and gradient boosting regression.

In the modeling process, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) are calculated. The parameter `n_estimators` in the chosen methods or models, Random Forest Regression and Gradient Boosting Regressor is not explicitly specified, so the default value of 100 will be used for `n_estimators` parameter settings.

Additionally, the data is divided, where the targets used are premium and medium rice prices. The variables used to store these prediction targets are 'y_premium' and 'y_medium.' The model is trained using different training and testing data in each iteration. In the final iteration, the training data consists of 114 records, and the testing data consists of 22.

Thus, the training data encompasses approximately 83.21% of the total data, while the testing data comprises about 13.25%. The modeling outcomes will yield RMSE, MAPE, and MAE values for each tested model.

C. Model Evaluation

In the model evaluation stage, the data is split using the time series splitting technique. The `cross_val_score` function is used to calculate the RMSE. The `scoring` parameter used is `neg_root_mean_square_error`, which results in negative RMSE values. The negative values are converted to positive using the function `np.sqrt(-cross_val_score(...))` to address this. The calculation of RMSE is performed five times, corresponding to the number of splits in the time series splitting (`n_splits=5`), and the results are then averaged to obtain the RMSE value used for model evaluation.

Additionally, a loop is employed to obtain MAPE and MAE results, indicating that the model evaluation process is repeated 30 times to measure these metrics. MAPE and MAE are calculated in each iteration, stored in a list, and then averaged to obtain the final values. This iterative approach ensures a robust assessment of model performance across different data splits.

The model evaluation results, consisting of RMSE, MAPE, and MAE, were obtained using the mentioned technique. The library used for model evaluation was sklearn. The model testing results for predicting rice prices at the milling level according to quality, including premium and medium rice, can be seen in Table 8.

Table 8. Model Evaluation Results

Testing Results	Random Forest Regression	Gradient Boosting Regressor
	Premium	**Premium**
RMSE	**24.90**	25.48
MAPE	18.88%	18.95%
MAE	2390.67	2398.03
	Medium	**Medium**
RMSE	**25.47**	26.24
MAPE	19.57%	19.40%
MAE	2392.18	2371.62

Table 9. Previous Research Results

Testing Results	K-Nearest Neighbor (Mukhlisin et al., 2019)		Linear Regression (Putra & Sinaga, 2022)	Neural Network (Adjie Setyadj et al., 2023)
	Non-Normalization	Denormalized		
	Premium	**Premium**	**Premium**	**Premium**
RMSE	352,450	174,38	321,199	52,846
MAPE	-	-	-	-
MAE	-	-	275,55	-

Table 9 highlights the RMSE results from previous research studies, focusing solely on the performance of different prediction models used in those studies. The comparison is limited to RMSE values without accounting for factors such as the volume of data used, data sources, or other evaluation metrics. Concentrating on RMSE, this comparison provides a snapshot of the accuracy of various models employed in past research to predict rice prices.

From Table 8, it can be observed that the Random Forest Regression method has the lowest RMSE compared to Gradient Boosting Regression and other techniques used in previous studies, with RMSE values of 24.90 for the Premium Rice dataset and 25.47 for the Medium Rice dataset. Therefore, in general, the Random Forest Regressor method applied without changing hyperparameter values is quite effective compared to similar methods for rice price data.

Based on the testing results in Table 8, here are visualizations of the actual prices of premium and medium rice with the tested models, as shown in Figure 4 and Figure 5.

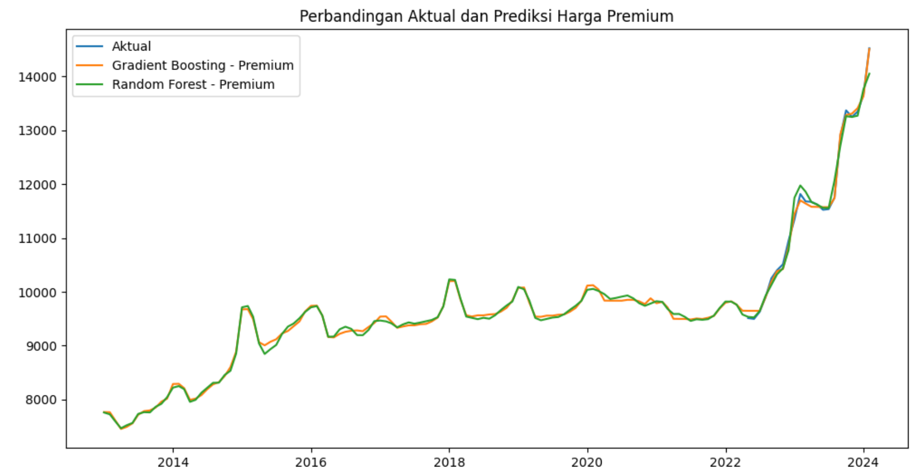

Figure 4. Visualization of Model and Actual Prices of Premium Rice

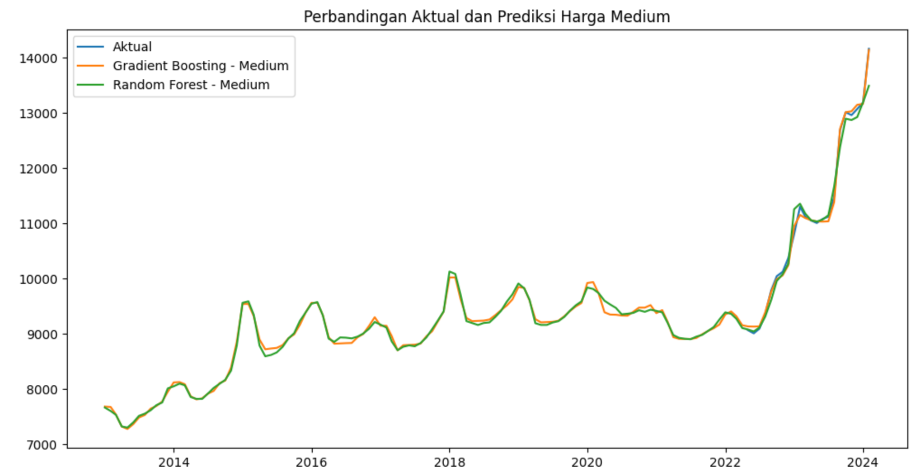

Figure 5. Visualization of Model and Actual Prices of Medium Rice

From the visualizations shown in Figure 4 and Figure 5, the results from the Random Forest Regression model align well with the actual data of both premium rice and medium rice prices. The price movement graphs in these visualizations use data from 2013 – 2024. In 2022, there is a significant increase in both premium and medium rice prices compared to previous years, indicating a drastic upward trend.

The results of this study provide new insights by showing that the Random Forest Regression method for predicting rice prices at the milling level, according to quality, yields lower RMSE values compared to previous research.

CONCLUSION

From the results of this research, it can be concluded that the Random Forest Regression model demonstrates good performance when implemented on monthly average rice prices at the Milling Level according to quality from 2013 – 2024 data obtained from the Central Bureau of Statistics of Indonesia website.

Data splitting using Time Series Splitting significantly impacts model evaluation. The use of 'cross_val_score' in this study is employed to calculate the RMSE, which is tailored to time series data format utilizing Time Series Splitting for data splitting.

In this research, model testing involved experimenting with two models: Random Forest Regression and Gradient Boosting Regressor. From the model testing results, the Random Forest Regression method produced the smallest Root Mean Square Error (RMSE), with values of 24.90 for premium rice and 25.47 for medium rice. The MAPE was 18.88% for premium rice and 19.57% for medium rice, while the MAE was 2397.67 for premium rice and 2392.18 for medium rice.

The results of this research are expected to be further developed to enhance the prediction of rice prices at the Milling Level according to quality, using either the same method or different methods to achieve optimal performance. Future research should consider expanding the dataset by integrating additional sources such as regional price variations, production data, and economic indicators to address the limitation of the current dataset size. Additionally, extending the period or incorporating more granular data could provide a more comprehensive view and improve the model's accuracy.

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