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Price Forecasting of West Java Rice using Multivariate Decomposition SARIMAX-Gated Recurrent Unit Combination

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Abstract: In countries like Indonesia, rice prices significantly influence economic and social dynamics. The prices are subject to fluctuations driven by seasonal changes, market demand, and production levels, making accurate forecasting crucial. This study proposes a novel forecasting approach called Multivariate Decomposition Combination (MDC) for forecasting rice prices in West Java. This approach deconstructs a dataset into trend, seasonal, and residual components, applying multiple forecasting models. The final forecasts integrate the best-performing models for each component, enhancing overall forecasting accuracy. This study resulted in a method combination of Seasonal Autoregressive Integrated Moving Average with Exogenous Variable (SARIMAX) excelling in seasonal prediction and Gated Recurrent Unit (GRU) proficient in handling residuals and trend prediction. The combined model performs on a multivariate non-linear dataset of West Java's rice economy, achieving a Mean Squared Error (MSE) of 276,695.7, Mean Absolute Error (MAE) of 439.0, and Root Mean Squared Error (RMSE) of 526.0, outperforming deep learning individual forecasting approaches.

Keywords: Rice price forecasting, Multivariate decomposition combination, SARIMAX, GRU, Time series analysis.

Notation list

T_t = Trend component
$\widehat{T}_t$ = Forecasted trend component
S_t = Seasonal component
$\widehat{S}_t$ = Forecasted seasonal component
R_t = Residual component
$\widehat{R_t}$ = Forecasted residual component
Y_t = Original time series value
$\widehat{Y}_t$ = Final forecasted value
y_t = Time series value
t = Time
y_i = Actual value
$\hat{y}_i$ = Predicted value
$f(t)$ = Function of time
m = Length of seasonality period
T = Number of trees
$h_t(x)$ = Prediction of the t-th tree for input x
l = Loss function
Ω = LightGBM regularization term
$||w||^2$ = SVR regularization term
C = Penalty parameter
f_k = k-th tree
L_ϵ = ϵ-insensitive loss function
$f(x_i)$ = Predicted values
σ = Sigmoid function
$tanh$ = Hyperbolic tangent function
W = Weight matrices
b = Bias vectors
h_t = Hidden state at time
x_t = Input at time
C_t = Cell state at time
f_t = Forget gate
i_t = Input gate
o_t = Output gate
z_t = Update gate
r_t = Reset gate
$\widetilde{h}_t$ = Candidate activation
h_t = New hidden state
c = Constant
$\emptyset_i$ = Autoregressive (AR) coefficients
θ_i = Moving Average (MA) coefficient
Φ_i = Seasonal AR coefficients

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Θ_i = Seasonal MA coefficients
$\in_t$ = Error term at time
s = Length of the seasonal cycle
X_t = Exogenous variables
β = Coefficients for the exogenous variables

1. Introduction

For more than half of the world's population, rice is a primary food staple that supports important economic and social aspects. Accurate forecasting of rice prices is crucial for decision-making in agricultural economics, impacting stakeholders across the supply chain, including farmers, traders, and policymakers [1-2]. As one of the largest rice producers globally [3], Indonesia experiences significant price fluctuations due to various factors such as seasonal changes, market demand, and production levels [2]. West Java, a central rice-producing province [4], provides a pertinent case study for exploring effective forecasting methodologies.

Numerous approaches can be used for price forecasting. Xu et al. [5] explored corn price forecasting using Neural Network models, with 20 hidden neurons and two delays, achieving high performance. However, previous study does not delve deeply into the economic implications of these forecasts for different stakeholders in the market. Hoque et al. [6] investigated several machine learning models, such as Decision Tree, Support Vector Regression (SVR), and K-Nearest Neighbor (KNN), in multiple datasets, resulting in SVR as the lowest error metrics with specific hyperparameters. Abunofal et al. [7] compared ARIMA, SARIMA, SARIMAX, and multiple linear regression to forecast future electricity prices. SARIMAX performed the best due to its ability to incorporate the exogenous variables. The accuracy of SARIMAX model could potentially be further enhanced if it were hybridized with another method. Nunna et al. [8] compared ARIMA, Facebook Prophet, machine learning, and deep learning models to forecast U.S. Housing Price Index (HPI). The hybrid model of XGBoost and LSTM showed superior performance compared to the other models by integrating macroeconomic indicators into forecasting models. Sun et al. [9] developed a SARIMA-LSTM model that utilized keyword search data to forecast electric vehicle volumes in China, enhancing accuracy through linear and non-linear data patterns. Hybrid models work by taking outputs from the SARIMA model and further processed by the LSTM network. Jisha et al. [10] assembled a hybrid forecasting model combining ARIMA and SARIMA with LSTM or GRU to enhance stock price predictions by effectively managing linear and seasonal trends. Initial stock price predictions are made using ARIMA and SARIMA, after which residuals are processed and refined by LSTM or GRU networks to enhance overall forecast accuracy.

Traditional forecasting methods often rely on univariate time series models [5, 8], considering historical prices to predict future trends. However, these models can fall short of capturing the complex, multifactorial influences on data [8-9]. This study employs a multivariate framework, incorporating multiple variables that can be regulated within the supply chain management entities. Factors such as rice harvest area, prices of harvested and milled dry grain, daily rice production, employee salaries, and transportation costs interplay in dynamic ways that a univariate approach may not adequately address.

To address these limitations, this study proposes a Multivariate Decomposition Combination (MDC) approach. The MDC approach uses decomposition techniques to separate time series data into trend, seasonal, and residual components for rice price prediction. The detailed analysis allows for selecting the best-performing model for each component, thereby enhancing forecast accuracy and reliability. The MDC flexibility allows it to adapt to different datasets and conditions, incorporating various data sources like economic indicators.

The findings of this study are expected to contribute to developing more robust and accurate forecasting combination models for rice prices using MDC. This study addresses the limitations of existing models and explores innovative combinations of statistical, ML, and DL techniques.

This paper consists of several sections. The proposed system is discussed in section 2. Analysis of the findings is discussed in section 3. Section 4 ends with a conclusion.

2. Methodology

The methodology discusses the experimental setup for this study, which involves a series of steps designed to systematically evaluate the performance of various forecasting models on rice price data from West Java. Fig. 1 shows the general proposed method in this study. This section provides a detailed explanation of each stage and the specific configurations used.

2.1 Data collection

The collected data for forecasting rice retail prices in West Java used in this study is available at

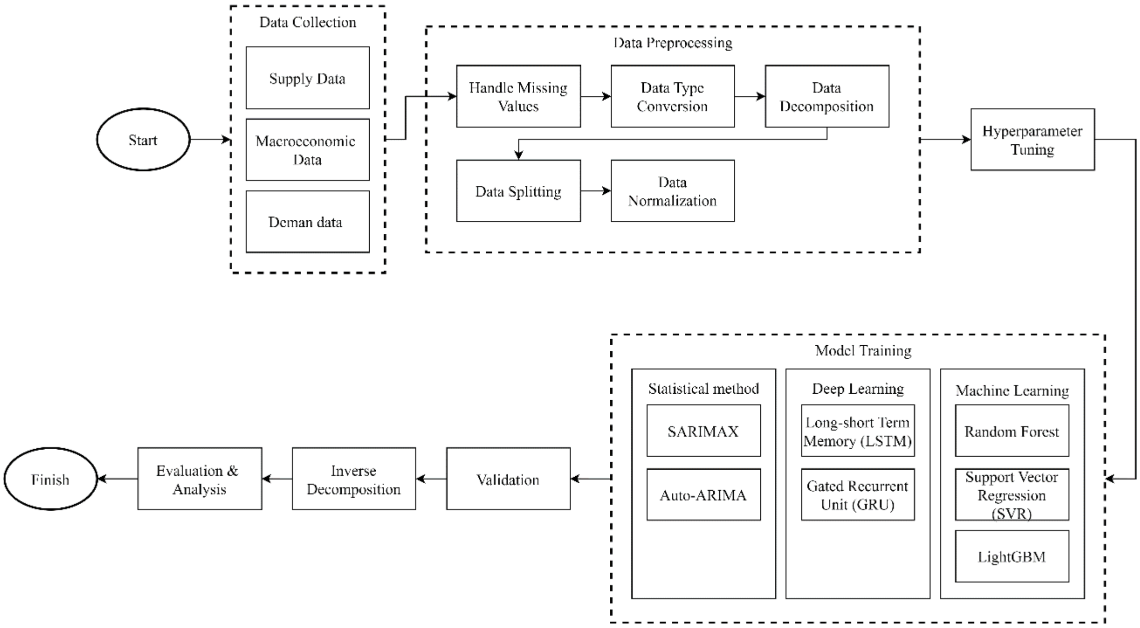

Figure. 1 Proposed method

https://github.com/Danazzz/JabarSupplyChainDataset.git. The data range from 2021-2023, focused on daily records of rice production and distribution factors. The dataset aimed to capture influences on rice prices at producer and retail levels, as shown in Table 1. The dataset was collected from three key sources: BPN (Badan Pangan Nasional) provided data on rice production and availability, BI PIHPS (Bank Indonesia) offered insights into strategic food prices, and BPS (Badan Pusat Statistik) contributed macroeconomic indicators and regional agricultural outputs. These features were selected for their relevance to supply chain stakeholders, allowing producers, distributors, millers, and retailers to adjust strategies based on actionable data.

2.2 Data pre-processing

This step aims to clean, transform, and prepare the dataset to ensure high-quality input for the forecasting models. Detailed data pre-processing steps include handling missing values, data type conversion, normalization, data splitting, and dataset decomposition.

Missing values can significantly impact the performance of forecasting models [11]. The dataset is first examined for missing values. Rows containing missing values are removed to ensure data integrity. Converting data types ensures that all values are in a format suitable for analysis. For the dataset, all values are converted to integer data types. Normalization scales the data to a specific range, usually between 0 and 1, which is essential to bring all features to a consistent and comparable scale [12]. The Min-Max normalization technique is used in this study. The transformation ensures that all features contribute equally to the model's training process. The dataset is split into training and testing subsets using an 80:20 ratio. 80% of the data is used for training the models, and 20% is reserved for testing their performance. Let X be the dataset Y be the target variable (rice price).

2.3 Data decomposition

Dataset decomposition involves breaking down data into trend, seasonal, and residual components [13].

2.3.1 Trend component

The trend component (T_t) captures the long-term progression of the time series, captured by the equation Eq. (4),

$$T_t = f(t) \tag{4}$$

where $f(t)$ underlying shifts over time, independent of seasonal or irregular changes.

2.3.2 Seasonal component

The seasonal component (S_t) represents repeating short-term cycles in the time series, described by Eq. (5),

$$S_t = S(t + m) \tag{5}$$

where m defined to capture regular fluctuations at consistent intervals.

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Table 1. Dataset Description

Name	Description	Code
Supply data		
Harvest area	Rice paddy field area, percentage (%) of rice harvest area	a
Price of harvested dry grain, Farmer-level	Price of harvested dry grain at the farmer level. (Rp/Kg)	b
Price of harvested dry grain, Milling-level	Price of harvested dry unhusked rice at the milling level. (Rp/Kg)	c
Price of dry milled grain, Milling-level	Price of milled dry unhusked rice at the milling level. (Rp/Kg)	d
Milled Rice Price	The average of the price of medium and premium milled rice. (Rp/Kg)	e
Rice Production Level	Rice production in west java 2021-2023. (unit tons)	f
Macroeconomic data		
Rice Price	The average rice price of lower quality rice I & II, medium quality rice I & II, super quality rice I & II at traditional market level. (Rp/Kg)	g
Provincial Minimum Wage	Regional Minimum Wage in West Java from 2021-2023 (Represents labor cost)	h
Solar Fuel Price	Solar price from 2021-2023 (Representing distributor entities)	i
Demand data		
Rice Consumption Level	The level of rice consumption in West Java 2021-2023. (unit tons)	j

2.3.3 Residual component

The residual component (R_t) captures random variations in a time series once trend and seasonal components are removed, as shown in Eq. (6),

$$R_t = Y_t - T_t - S_t \tag{6}$$

where Y_t captures the entirety of the data's variations at that specific point. This includes irregular fluctuations that are not explained by the trend or seasonal components identified in the model.

2.4 Multivariate Decomposition Combination Method (MDC)

The proposed method mainly used Seasonal and Trend decomposition using Loess (STL) decomposition to estimate future value in multivariate data. STL uses Locally Weighted Scatterplot Smoothing (LOESS) to estimate the trend and seasonal components [14-16]. This method involves an inner loop for seasonal and trend smoothing and an outer loop to extract residual series [14]. Eq. (7) represents the STL decomposition.

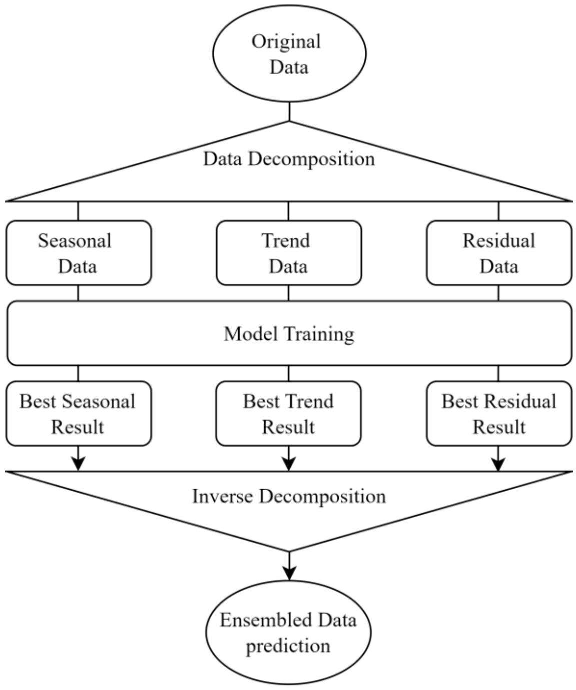

Figure. 2 MDC method

$$Y_t = T_t - S_t - R_t \tag{7}$$

The separation allows for tailored modeling and forecasting of each component. After decomposition, each component is modeled and forecasted separately using forecasting methods. Eq. (8) illustrates the final forecast obtained by combining the forecasts of each component. Fig. 2 illustrates the MDC flow.

$$\widehat{Y_t} = \widehat{T_t} + \widehat{S_t} + \widehat{R_t} \tag{8}$$

2.5 Forecasting methods

This study employs various statistical, machine learning (ML), and deep learning (DL) models to predict rice prices. Each model is selected based on its unique capabilities to handle different aspects of time series data. The following sections provide an in-depth explanation of each forecasting method.

2.5.1 Random Forest (RF)

Random Forest is a machine learning method that constructs multiple decision trees to make predictions.

Random Forest excels at handling complex, non-linear relationships among features in multivariate datasets but struggles with temporal dependencies critical in time series forecasting [15]. For regression tasks, the predicted value is the average output of the trees, represented by Eq. (9).

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \tag{9}$$

2.5.2 Light Gradient Boosting Machine (LightGBM)

This method is a gradient-boosting framework that improves XGBoost by requiring less memory and supporting parallel computing. Like Random Forest, this decision tree-based learning algorithm is excellent for capturing non-linear relationships and interactions between variables but does not inherently account for the order of data, which is crucial in time series analysis [16]. Eq. (10) depicts the objective function for LightGBM.

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{10}$$

2.5.3 Support Vector Regression (SVR)

SVR is a type of supervised learning developed from SVM used primarily for regression tasks. This method is adept at managing high-dimensional space and can model complex, non-linear relationships efficiently through the use of different kernel functions [17], and the method lacks native support for multivariate time series data. This method aims to find a function that minimally deviates from observed values by a predefined margin. Eq. (11) presents the objective function of SVR.

$$min \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} L_\epsilon(y_i, f(x_i)) \tag{11}$$

$L_\epsilon(y_i, f(x_i))$ is the ϵ-insensitive loss function. The ϵ-insensitive loss function is defined in Eq. (12),

$$L_\epsilon\big(y_i, f(x_i)\big) = \max\,(0, |y_i - f(x_i)| - \epsilon) \tag{12}$$

where ϵ is the margin within which no penalty is assigned.

2.5.4 Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network designed for sequence prediction, utilizing memory cells to retain information over extended periods. This deep learning method is particularly effective in capturing the long-term dependencies in multivariate non-linear datasets, enabling more accurate prediction of complex, time-dependent patterns [18]. While LSTM excels in handling sequences, LSTM can overfit smaller or noisier datasets, especially when the relationships between variables are highly complex [19]. The key components of an LSTM cell include:

a) Forget Gate: Decides what information to discard from the cell state, as shown in Eq. (12).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{12}$$

b) Input Gate: Determines the updates to the cell state, illustrated in Eq. (13).

$$\begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \widetilde{C_t} &= \tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C) \end{aligned} \tag{13}$$

c) Cell State Update: Modifies the cell state with new inputs, as per Eq. (14).

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \tag{14}$$

d) Output Gate: Controls the output from the cell state, represented in Eq. (15).

$$\begin{aligned} o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t &= o_t \cdot \tanh\,(C_t) \end{aligned} \tag{15}$$

2.5.5 Gated Recurrent Unit (GRU)

GRU is a streamlined version of RNN, like LSTM, but with fewer gates. This method might perform comparably or sometimes even better than LSTM on tasks with shorter sequences or where the training data is limited due to a more straightforward and more efficient structure [20]. The GRU architecture includes:

a) Update Gate: Merges the functions of forget and input gates, shown in Eq. (16).

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{16}$$

b) Reset Gate: Determines how much past information to discard, as per Eq. (17).

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{17}$$

The new memory content and the final output are computed as Eq. (18).

$$(\widetilde{h_t}) = \tanh(W \cdot [r_t \cdot h_{t-1}, x_t] + b) \tag{18}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t \cdot \widetilde{h_t}$$

2.5.6 AutoRegressive Integrated Moving Average (ARIMA)

ARIMA is a statistical model for analyzing and forecasting time series data. This statistical technique struggles with multivariate, non-linear datasets due to linear assumptions and univariate design. However, ARIMA can still provide effective short-term forecasts in stable scenarios with consistent, linear relationships [21]. ARIMA combines autoregression (AR), differencing for stationarity (I), and moving average (MA) components. The model is described by three parameters: p for the number of lag observations, d for the degree of differencing, and q for the number of lagged forecast errors. The ARIMA equation is as Eq. (19).

$$\begin{aligned} y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} \\ + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots \\ + \theta_q \epsilon_{t-q} + \epsilon_t \end{aligned} \tag{19}$$

2.5.7 Seasonal Auto-Regressive Integrated Moving Average (SARIMAX)

$$\begin{aligned} y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots \\ + \emptyset_p y_{t-p} + \theta_1 \epsilon_{t-1} \\ + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} \\ + \Phi_1 Y_{t-s} + \Phi_2 Y_{t-2s} \\ + \cdots + \Phi_P Y_{t-Ps} \\ + \Theta_1 \varepsilon_{t-s} + \Theta_2 \varepsilon_{t-2s} \\ + \cdots + \Theta_Q \varepsilon_{t-Qs} + \beta X_t \\ + \epsilon_t \end{aligned} \tag{20}$$

SARIMAX extends the ARIMA model by incorporating seasonal effects and exogenous variables, making it suitable for time series data with seasonal patterns and external factors [22]. The SARIMAX model is defined as Eq. (20).

2.6 Hyperparameter tuning

This step uses several hyperparameter tuning techniques to find the optimal parameters: GridSearchCV, Adam Optimizer, and Auto-ARIMA. The GridSearchCV systematically searches through a predefined parameter grid using cross-validation, evaluates each combination, and identifies the best parameters based on the outcomes.

The Adam Optimizer is a first-order gradient-based optimization algorithm for deep learning models, utilizing adaptive estimates of lower-order moments and key parameters like learning rate, β_1, β_2, and ϵ to optimize performance. The Auto-ARIMA automatically selects the optimal ARIMA model using AIC/BIC criteria by testing various AR, MA, and differencing parameter combinations. SARIMAX extends this by tuning seasonal parameters and incorporating exogenous variables.

2.7 Evaluation

The models are evaluated on testing data using Mean Squared Error (MSE) as Eq. (24), Root Mean Squared Error (RMSE) as Eq. (25), and Mean Absolute Error (MAE) as Eq. (26),

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{24}$$

$$RMSE = \sqrt{MSE} \tag{25}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{26}$$

where n is the number of observations.

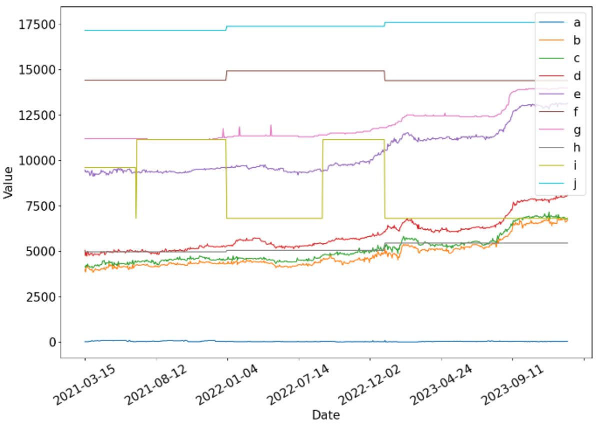

Figure. 3 Dataset Visualization

3. Result and Discussion

This section explained the experimental results and analyzed the performance result of each model using decomposition and non-decomposition, as well as the MDC result.

3.1 Dataset analysis

The dataset used in this study consists of 678 rows and 10 columns. Fig. 3 displays a dataset with multiple and complex time series, each representing different variables within the rice commodity's supply chain management in West Java. Each colored line represents a variable or a set of related metrics, illustrating trends from May 2021 to January 2024. Some variables shown here are based on assumptions (the flat lines), which are common when actual data are hard to obtain or estimate. These include

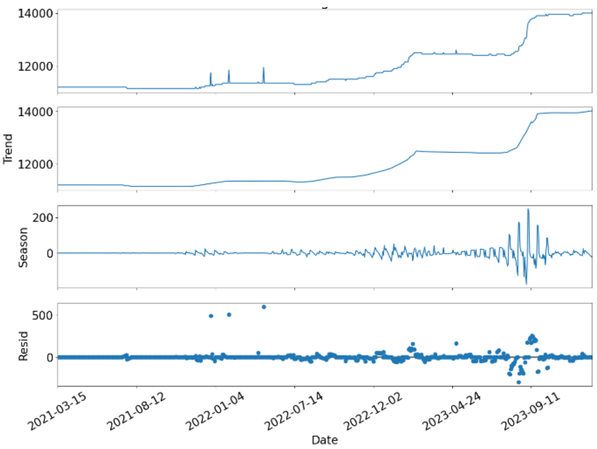

Figure. 4 Rice Price Decomposition

estimated rice consumption levels or projected production outputs.

Characteristics of rice prices in West Java, shown in Fig. 4, display decomposition with four graphs. The "Original" graph shows the raw data, which exhibits an increasing trend over time with some notable spikes. The "Trend" graph reveals a noticeable acceleration in the upward trend of rice prices around mid-2023. The "Seasonal" plot displays clear and consistent patterns, which repeat annually. Finally, the "Residuals" graph, which is mostly stable with a few spikes, shows the deviations from the modeled trend and seasonality, capturing the unpredicted or random fluctuations in the dataset.

3.2 Model performance comparison

Table 2 showcases the performance metrics of various forecasting models applied to the dataset, which has been decomposed into seasonal, trend, and residual components. The models have been evaluated based on three error metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE).

SARIMAX performs exceptionally well in handling the seasonal component of the data. Table 2 shows the lowest RMSE, MAE, and MSE with other models. The SARIMAX effectively captures the seasonal fluctuations in rice prices.

Deep learning models demonstrate strong performance across trend and residual components. GRU shows powerful results in the trend decomposition, suggesting its ability to capture long-term dependencies and trends in the dataset. Random Forest and GBM (Gradient Boosting Machine) show higher error rates across all components, indicating that these machine learning models may struggle with the non-linear and complex nature of the time series data. The GRU outperforms other models by considering the total error across all decomposed components. The GRU is better at capturing both the nonlinearities and complex patterns in the complete dataset.

The models without the MDC method exhibit higher error metrics than those using the MDC method, as shown in Table 3. Decomposing the data into trend, seasonal, and residual components generally results in better model performance by simplifying the patterns each model needs to capture. The analysis revealed that the trend metrics were high across all models, mainly because the training dataset did not include the significant price increase observed in mid-2023. This price spike, which did not follow previous patterns, led to the inability of the model to predict similar trends in the test data.

3.3 Multivariate decomposition combination performance

The best performance model on each decomposed component is integrated into optimizing rice price forecasting. Seasonal components produced the best performance using the SARIMAX model because it can handle seasonal variations. The selected GRU model on Trend component because of its ability to capture and forecast the trend effectively. The residual component uses GRU as the selected model because of the ability to learn the residuals with random fluctuations not accounted for by the trend or seasonal.

The specific capabilities of SARIMAX and GRU to address different aspects of the time series decomposition explain the varied performance across the seasonal, trend, and residual components of the rice price dataset. While SARIMAX effectively handles the seasonal patterns due to its structural advantages, GRU excels in managing the residuals and remaining variability due to its gating mechanisms and adaptability. Combining these models based on their strengths improves accuracy and robustness in forecasting complex time series data like rice prices.

This methodological approach, known as model stacking or ensemble learning, leverages the strengths of different models to improve the overall forecasting accuracy. Each model deals with a specific aspect of the data's structure, allowing for a more nuanced and comprehensive approach to forecasting. The final combined model, SARIMAX-GRU, compared by performance with statistical, machine learning, and deep learning methods without MDC, is seen in Table 3. The final combined results demonstrate a significant improvement in error

Table 3. Model Comparison Performance MDC-SARIMAX-GRU and Without MDC Method

Error Metrics	Statistical		Machine Learning			Deep Learning		SARIMAX-GRU
	SARIMAX	ARIMA	SVR	RF	GBM	LSTM	GRU	
RMSE	800.2	1171.1	1982.4	1176.8	1111.0	683.2	653.7	**470.6**
MAE	650.6	970.0	1720.0	958.9	903.2	557.0	530.6	**388.1**
MSE	640399.9	1371699.2	3930195.9	1384875.0	1234342.7	466792.7	427425.4	**221468.2**

Table 2. Model Performance Comparison using MDC Method

Decomposition	Error Metrics	Statistical		Machine Learning			Deep Learning	
		SARIMAX	ARIMA	SVR	RF	GBM	LSTM	GRU
Seasonal	RMSE	**48.1**	52.8	55.4	64.1	54.5	51.4	51.2
	MAE	**28.9**	29.4	30.7	41.3	30.4	30.1	30.4
	MSE	**2318.4**	2797.2	3076.4	4118.4	2978.0	2644.3	2626.8
Trend	RMSE	611.6	782.5	1892.4	2086.7	1163.4	529.2	**522.3**
	MAE	494.0	649.3	1649.7	1987.6	969.7	438.9	**432.4**
	MSE	374082.6	612329.4	3581408.7	4354342.3	1353591.2	280097.9	**272860.0**
Residual	RMSE	82.4	81.8	76.9	81.1	79.6	67.5	**66.2**
	MAE	47.6	46.6	46.7	47.2	46.4	38.1	**37.1**
	MSE	6801.9	6695.5	5924.3	6580.6	6339.5	4568.2	**4387.8**
Total	RMSE	615.2	790.9	1896.8	2108.1	1165.0	532.4	**525.5**
	MAE	502.4	647.0	1648.0	2004.7	967.4	446.0	**440.0**
	MSE	378562.7	625619.2	3598018.9	4444374.7	1357398.9	283542.2	**276177.1**

metrics, showcasing the efficacy of this hybrid modeling approach. This combination reduces the forecast error and enhances the model's robustness by integrating diverse modeling strengths.

4. Conclusion

The staple commodity price forecasting, such as rice, needs accurate results because of the complexities in agricultural forecasting. This study proposed that the Multivariate Decomposition Combination (MDC) can leverage the unique strengths of different model combinations to enhance predictive accuracy. The combination of SARIMAX and GRU using the MDC method has outperformed the overall result, showing a 470.6 RMSE score compared to the best total decomposition and non-decomposition score with GRU. Another challenge of this study was trend prediction, particularly during the significant price spike in mid-2023, which did not exist in the training data. Making some models resulted in deficient performance due to its inability to extrapolate.

Future research should enhance the dataset with recent and real-time data, including significant price spikes not previously captured, to improve model responsiveness to market changes. Exploring hybrid modeling techniques that combine statistical, machine learning, and deep learning approaches could further refine predictive accuracy.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

This study can run well and successfully because of the following research contributions: Conceptualization by Prof. Riyanarto Sarno and Agus Tri Haryono; methodology by Agus Tri Haryono, I Nyoman Gde Artadana Mahaputra Wardhiana, and Muhammad Zakky Ghufron; software by Muhammad Zakky Ghufron and I Nyoman Gde Artadana Mahaputra Wardhiana; validation and formal analysis by Prof. Riyanarto Sarno, Agus Tri Haryono, I Nyoman Gde Artadana Mahaputra Wardhiana, and Muhammad Zakky Ghufron; data, visualization, and editing by I Nyoman Gde Artadana Mahaputra Wardhiana and Muhammad Zakky Ghufron; preparation of the original draft by I Nyoman Gde Artadana Mahaputra Wardhiana and Muhammad Zakky Ghufron; supervision by Prof. Riyanarto Sarno.

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