Integrating Fuzzy Structural Equation Modeling with Support Vector Regression for Assesing Seller Credibility in E-Commerce

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*Abstract*—

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# **Introduction**

Issues in E-commerce can lead to significant consumer losses, such as receiving products of poor quality and needing reputable information to make wise purchasing decisions [1]. Trust also plays a vital role in shaping consumer purchasing intentions in E-commerce, which can be modeled and tested using various dimensions like consumer characteristics, company traits, and interactions [2]. Trust poses a significant challenge in E-commerce, as negative reputations and reviews can result in sales stagnation and difficulties. Other challenges include regulatory friction, access to infrastructure and digital skills, logistics costs, lack of trust and compliance costs, and outdated tax frameworks [3]. This study aims to bridge existing literature gaps by developing a model that quantitatively assesses seller credibility based on sentiment analysis of product reviews. This model can provide a stronger understanding to E-commerce businesses about reputation through a trend dashboard. Understanding the relationship between product review sentiments and seller credibility can offer practical implications for E-commerce businesses, informing strategies to enhance credibility, customer trust, and overall business success [4]. This analysis can be utilized to understand and analyze customer feedback, allowing businesses to optimize pricing strategies, identify areas for improvement, and enhance customer experiences.

The fuzzy structural equation model with SVR (Support Vector Regression) offers an effective solution for modeling the complex relationships among variables involved in E-commerce, as outlined above [5]. The presence of issues in E-commerce, such as receiving low-quality products and needing reputable information for wise purchasing decisions, underscores the importance of using this model [6]. One primary utility of this model lies in quantitatively assessing seller credibility based on product review sentiment analysis. By leveraging SVR, the model can integrate information from various dimensions, including consumer characteristics, company traits, interactions, and product review sentiments, to provide a more accurate assessment of seller credibility. Additionally, the model can predict consumer trust levels in E-commerce sellers based on the relationship between product review sentiments and seller credibility, offering valuable insights for designing strategies to enhance customer trust and overall business success [7]. Furthermore, the analysis generated by the model can be utilized to optimize business strategies, including pricing strategies, identifying areas for improvement, and enhancing customer experiences. Thus, the model aids E-commerce businesses in improving operational efficiency and generating greater profits [8]. Moreover, the model can be used to develop a trend dashboard that provides a deeper understanding of their reputation to E-commerce businesses. This dashboard offers valuable visual information for monitoring and analyzing business performance and trends in seller credibility and customer trust [9]. Therefore, the use of the fuzzy structural equation model with SVR in E-commerce cases as described can provide significant benefits for businesses in enhancing credibility, customer trust, and overall success.

# **Literature Review**

## **2.1 Fuzzy Logic**

Membership function is a crucial concept in fuzzy set theory, essential for mapping each element in a set to a membership value ranging between 0 and 1 [10]. This concept allows for depicting uncertainty and complexity within a specific domain more effectively than using conventional sets that only have binary membership, namely 0 or 1. There are several types of membership functions commonly used in fuzzy sets, including upward linear membership function, triangular function, and downward linear membership function. The upward linear membership function, as its name suggests, starts from a small membership value and linearly increases to reach a larger membership value [11]. Mathematically, the upward linear membership function can be expressed in the form of an equation:

|  |  |
| --- | --- |
|  | (1) |

In the equation represents the membership value of element in set , while a and b are the starting and ending points of the domain of set , respectively. The downward linear membership function is a type of membership function in fuzzy set theory that begins with a high membership value and linearly decreases towards a smaller membership value [12]. This concept allows for modeling uncertainty and variability in a domain in a more flexible and detailed manner compared to conventional sets with binary membership. Mathematically, the downward linear membership function can be described using an equation:

|  |  |
| --- | --- |
|  | (2) |

The value of the downward linear membership function will indicate a consistent decrease in the membership value as increases from to . The triangular membership function is a type of membership function in fuzzy set theory that combines characteristics of both the upward linear and downward linear membership functions [13]. This concept allows for a more detailed and flexible depiction of the membership levels of elements in a fuzzy set. Mathematically, the triangular membership function can be described using an equation:

|  |  |
| --- | --- |
|  | (3) |

The triangular membership function will indicate an increase in the membership value as increases from to , and then it will decrease as increases from to .

## **2.2 Support Vector Regression (SVR)**

Support Vector Regression (SVR) is a modified version of the Support Vector Machine (SVM) method, specifically designed for prediction tasks in regression analysis. Unlike classification problems where SVM excels, SVR is proficient in handling continuous data and predicting numerical outcomes. SVR retains SVM's fundamental idea of finding a hyperplane but adjusts it to tackle regression problems. The SVR equation takes the following form:

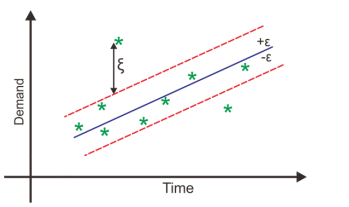
|  |  |
| --- | --- |
|  | (4) |

Where represents the result of the dot product in . Equation (4) is a flatness function aimed at finding the smallest value of . This value can be found by minimizing the form . The problem can be addressed with convex optimization, as described in formula (5).

|  |  |
| --- | --- |
|  | (5) |

In situations where the error exceeds the threshold . In situations where the error exceeds the threshold becomes necessary. Consequently, the equation transforms as shown in formula (6).

|  |  |
| --- | --- |
|  | (6) |

The constant 𝐶 > 0 determines the degree of error deviation from the threshold 𝜀 that can be tolerated. The formula above represents a Convex Linear Programming NLP Optimization Problem aimed at minimizing a quadratic function to be transformed into a constraint. These constraints can be addressed using Lagrange Multiplier equations.

Source: [14]

Figure 1 Graph Support Vector Regression (SVR)

The derivation process is lengthy and intricate. After going through mathematical steps, a new equation is obtained with formulas (7).

|  |  |
| --- | --- |
|  | (7) |

Where represents the support vector and x represents the test vector. The above function can be utilized to address linear problems. However, for non-linear problems, the values of andare first transformed into a high-dimensional feature space by mapping the vectors and into a kernel function, resulting in the final equation:

|  |  |
| --- | --- |
|  | (8) |

The function is a kernel function. The type of kernel used for estimation is:

1. Linear Kernel

|  |  |
| --- | --- |
|  | (9) |

2. Radial Basis Function Kernel

|  |  |
| --- | --- |
|  | (10) |

## **2.3 Structural Equation Modeling (SEM)**

## **2.4**

## **2.5**

# **Research Method**

Before you begin to format your paper, first write and save the content as a separate text file. Complete all content and organizational editing before formatting. Please note sections A-D below for more information on proofreading, spelling and grammar.

Keep your text and graphic files separate until after the text has been formatted and styled. Do not use hard tabs, and limit use of hard returns to only one return at the end of a paragraph. Do not add any kind of pagination anywhere in the paper. Do not number text heads-the template will do that for you.

## **3.1 Type and Source of Data**

The data utilized in this research comprises the National Average Rice Prices per Month from January to December 2023. The data source is <https://databoks.katadata.co.id/> , a platform renowned for its reliable information on various aspects, including Indonesia's economy and commodity prices such as rice. This study employs monthly average rice prices as a crucial variable to analyze trends and patterns in the national rice price fluctuations throughout 2023. This data offers in-depth insights into the dynamics of the rice market in Indonesia, enabling researchers to comprehend the factors influencing price changes during the specified period. The data's reliability is affirmed by its origin from databoks.katadata.co.id, a well-known source for up-to-date and credible economic and social data in Indonesia.

## **3.2 Research Method**

In this research, the methodology encompasses a multi-faceted approach to refine predictive patterns for rice prices in Indonesia. The initial step involves the formation of time series data, capturing the intricacies of rice prices. Through the application of a decomposition method, the data undergoes a meticulous process to isolate essential components, including trend, seasonal, and random elements. Subsequently, a hybrid methodology is employed, integrating the Weighted Fuzzy Time Series algorithm to address the complexity of premium and medium rice prices. The fuzzy logic relationships iteratively construct a weight matrix, enhancing prediction accuracy. Additionally, Lagrange Quadratic Programming is incorporated to estimate weighted values, presenting a mature approach in considering intricate factors influencing rice prices. Differential Evolution further contributes to the optimization process through population-based search strategies. The time series decomposition model is leveraged to unveil critical components of the data. The application of a multiplicative model aids in representing observation values at distinct time intervals. Evaluation of forecasting accuracy is conducted using the Mean Absolute Percentage Error (MAPE), ensuring a comprehensive assessment of predictive performance. This research aims not only to overcome limitations in predicting rice prices but also to provide valuable insights for effective policy-making in managing rice price stability at the national level, addressing the crucial food needs of the Indonesian population.



**Figure 1.** Flowchart Diagram

# **Result and Discussion**

## **4.1 Decomposition Proccess**

The process of decomposing time series data is utilized as an initial analysis step to discern patterns of change in the data. This refers to a statistical analysis technique that breaks down data into main components such as trend, seasonal, and residual. The statement "used as an initial analysis to identify patterns of change in the data" explains the primary purpose of the decomposition process, which is to provide initial insights into how the data undergoes changes over time.

In this research, the decomposition process is conducted during the fuzzyfication stage, forming the foundation for the creation of a quadratic Lagrange function that subsequently generates predictive values. The outcomes of the decomposition are indicated in the sequence of linguistic variables between observations from January 2023 to December 2023 for the prices of medium and premium rice using equation (11), as follows:

**Table 1.** Decomposition of Lingustic Variable (Rice Medium)

|  |  |  |  |
| --- | --- | --- | --- |
| **Date** | **Fuzzyfikasi Trend** | **Fuzzyfikasi Season** | **Fuzzyfikasi random** |
| 01-2023 | A1 | A1 | A3 |
| 02-2023 | A1 | A1 | A3 |
| 03-2023 | A1 | A3 | A3 |
| ... | ... | ... | ... |
| 11-2023 | A3 | A2 | A3 |
| 12-2023 | A3 | A2 | A3 |

Table 1 illustrates the decomposition of the linguistic variable (Rice Medium). The columns represent the following components: Fuzzyfication Trend, Fuzzyfication Season, and Fuzzyfication Random. The dates from January 2023 to December 2023 are listed alongside the corresponding fuzzyfication values for each component. For instance, in January 2023, the Fuzzyfication Trend is denoted as A1, Fuzzyfication Season as A1, and Fuzzyfication Random as A3. The table provides a concise overview of how linguistic variables are decomposed across different components for the specified time period.

**Table 2.** Decomposition of Lingustic Variable (Rice Premium)

|  |  |  |  |
| --- | --- | --- | --- |
| **Date** | **Fuzzyfikasi Trend** | **Fuzzyfikasi Season** | **Fuzzyfikasi random** |
| 01-2023 | A1 | A1 | A3 |
| 02-2023 | A1 | A1 | A3 |
| 03-2023 | A1 | A3 | A3 |
| ... | ... | ... | ... |
| 11-2023 | A3 | A3 | A3 |
| 12-2023 | A3 | A2 | A3 |

Table 2 displays the decomposition of the linguistic variable for Rice Premium. The table includes three components: Fuzzyfication Trend, Fuzzyfication Season, and Fuzzyfication Random. Each row corresponds to a specific date from January 2023 to December 2023, with the associated fuzzyfication values for each component. For example, in January 2023, the Fuzzyfication Trend is represented as A1, Fuzzyfication Season as A1, and Fuzzyfication Random as A3. The table succinctly presents the decomposition of linguistic variables across different components throughout the specified time frame for Rice Premium.

## **4.2 Calculate Prediction**

During the process of predicting the price of rice per kg, each value generated through the decomposition process is employed. The prediction is assessed by considering the trend condition, where the linguistic variable relationship between and is utilized. Simultaneously, for the seasonal effect, the six previous periods are employed to forecast the current period ( to ). The random effect is calculated by combining the effects of both trend and seasonality. Additionally, it is necessary to formulate using the Lagrange equation in equation (5), which can be expressed as follows:

1. WFTS-LQP Model for trend decomposition A1 of medium rice:

2. WFTS-LQP Model for trend decomposition A2 of medium rice:

3. WFTS-LQP Model for trend decomposition A3 of medium rice:

4. WFTS-LQP Model for seasonality decomposition A1 of medium rice:

5. WFTS-LQP Model for seasonality decomposition A2 of medium rice:

6. WFTS-LQP Model for seasonality decomposition A3 of medium rice:

7. WFTS-LQP Model for random decomposition A1 of medium rice:

8. WFTS-LQP Model for random decomposition A3 of medium rice:

9. WFTS-LQP Model for trend decomposition A1 of premium rice:

10. WFTS-LQP Model for trend decomposition A3 of premium rice:

11. WFTS-LQP Model for seasonality decomposition A1 of premium rice:

13. WFTS-LQP Model for seasonality decomposition A2 of premium rice:

14. WFTS-LQP Model for seasonality decomposition A3 of premium rice:

15. WFTS-LQP Model for random decomposition A1 of premium rice:

16. WFTS-LQP Model for random decomposition A3 of premium rice:

The formulation process of the above equation is constructed based on the number of members of the actual data values for each interval class in the linguistic variable. The WFTS-LQP equation is solved through partial derivatives, resulting in the prediction outcomes as follows:

**Table 3.** Prediction Result of Rice Medium Price using WFTS-LQP

|  |  |  |  |
| --- | --- | --- | --- |
| **t** | **Predict (Trend)** | **Predict**  **(Seasonal)** | **Predict**  **(Random)** |
| 1 | 0 | 0 | 0 |
| 2 | 11.74 | 11.75 | 11.24 |
| 3 | 11.81 | 11.32 | 11.31 |
| 4 | 11.88 | 11.39 | 12.13 |
| 5 | 11.86 | 11.99 | 12.11 |
| 6 | 11.83 | 11.96 | 12.08 |
| 7 | 11.88 | 11.89 | 12.13 |
| 8 | 11.76 | 12.06 | 12.3 |
| 9 | 13.01 | 12.33 | 13.07 |
| 10 | 13.38 | 12.7 | 12.69 |
| 11 | 13.34 | 13.28 | 12.65 |
| 12 | 13.36 | 13.3 | 12.67 |

**Table 4.** Prediction Result of Rice Premium Price using WFTS-LQP

|  |  |  |  |
| --- | --- | --- | --- |
| **t** | **Predict**  **(Trend)** | **Predict**  **(Seasonal)** | **Predict (Random)** |
| 1 | 0 | 0 | 0 |
| 2 | 13.21 | 13.42 | 12.68 |
| 3 | 13.48 | 13 | 12.8 |
| 4 | 13.6 | 13.09 | 14.08 |
| 5 | 13.69 | 13.06 | 14.05 |
| 6 | 13.66 | 13.74 | 14.03 |
| 7 | 13.64 | 13.59 | 14.04 |
| 8 | 13.65 | 13.74 | 14.19 |
| 9 | 14.62 | 13.94 | 14.93 |
| 10 | 15.1 | 14.42 | 15.41 |
| 11 | 15.13 | 14.45 | 14.25 |
| 12 | 15.14 | 15.16 | 14.26 |

The comparison between the prediction results for medium and premium rice prices, as presented in Table 3 and Table 4 using the WFTS-LQP method, unveils intriguing insights into the anticipated trends and patterns for each rice type. In the initial periods (t=1), both tables show conservative predictions with zero values across all components, signaling a neutral starting point. However, as the months progress, discernible differences emerge.

Notably, there is a variation in the magnitude of predictions, suggesting potential disparities in the pricing dynamics between medium and premium rice. The predicted values for the trend, seasonal, and random components exhibit distinctive patterns for each type, indicating nuanced influences on their respective prices. While both types exhibit overall trends of increase or decrease, the specific trajectories differ.

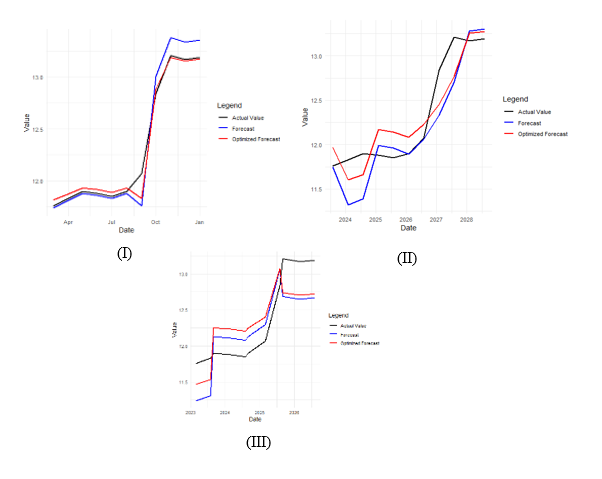
The Seasonal predictions unveil unique patterns, suggesting that the seasonal effects impacting medium and premium rice prices may diverge. Additionally, the Random predictions fluctuate differently between the two types, reflecting varied levels of unpredictability in their respective markets.

This detailed comparison provides valuable information for stakeholders involved in rice markets. The nuanced differences in predicted values can inform pricing strategies, supply chain management decisions, and market forecasting tailored to the distinct characteristics of medium and premium rice. Overall, the analysis facilitates a comprehensive understanding of the anticipated price dynamics, aiding decision-makers in navigating the complexities of the rice market landscape.

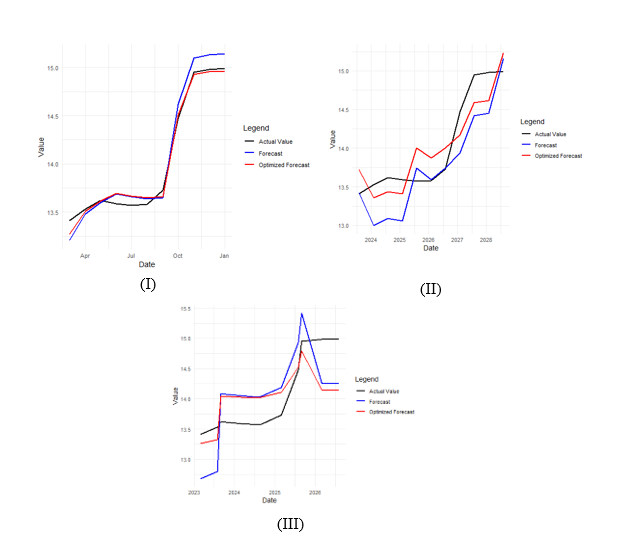
## **4.3 Optimizing Result**

The improvement of forecasting results using the Weighted Fuzzy Time Series with Lagrange Quadratic Programming (WFTS-LQP) method can be achieved through optimization using the Differential Evolution (DE) algorithm. This algorithm is integrated into the optimization steps to ensure that the parameters used in equations (8), (9), and (10) of WFTS-LQP yield more accurate predictions in line with the historical data patterns.

The optimization process involves iteratively adjusting model parameters utilizing evolutionary principles. DE plays a crucial role in searching for optimal parameter combinations, enabling the model to effectively adapt to the variability and complexity of historical data. Consequently, the forecasted results are expected to closely align with reality and exhibit adaptive responsiveness to emerging patterns in the data. The optimization outcomes of WFTS-LQP with and without DE, along with actual data, are presented as follows



**Figure 2.** Plot Comparisson of Actual Data, WFTS-LQP and WFTS-LQP-DE Medium Rice Price for (I) Trend (II) Seasonality (III) Random

In Figure 2, the plot illustrates the predictions of Actual Data, WFTS-LQP, and WFTS-LQP-DE for Medium Rice Price, where the black line represents the actual data values, the blue line reflects the forecast results of the WFTS-LQP method, and the red line indicates the forecast results of WFTS-LQP optimized using DE. From the graph, it is evident that the forecasting process with DE optimization yields results that closely align with the actual data. This visualization indicates that the forecasting process with DE visually enhances the accuracy of predictions compared to the results obtained using the WFTS-LQP method without optimization.

**Figure 3.** Plot Comparisson of Actual Data, WFTS-LQP and WFTS-LQP-DE Premium Rice Price for (I) Trend (II) Seasonality (III) Random

In Figure 3, the chart depicts the projections for Premium Rice Price based on Actual Data, WFTS-LQP, and WFTS-LQP-DE. The black line corresponds to the actual data values, the blue line represents the forecast outcomes of the WFTS-LQP method, and the red line signifies the forecast results of WFTS-LQP optimized with DE. The graph clearly shows that the application of DE optimization in the forecasting process produces results closely in line with the actual data. This visualization underscores that incorporating DE into the forecasting process visually enhances prediction accuracy compared to utilizing the WFTS-LQP method without optimization.

## **4.4 Evaluation Model**

In this subsection, an evaluation of the best model is conducted using the MAPE (Mean Absolute Percentage Error) values, computed using equation (12). The purpose of this evaluation process is to measure the relative error level of the model in forecasting data. The results of this evaluation calculation are then presented in Tables 5 and 6. Tables 5 and 6 present the calculated MAPE values for the evaluated best model. These tables may include information such as the MAPE values for each time period or observed category. Evaluation using MAPE provides an overview of how accurately the model forecasts data, with lower MAPE values indicating smaller error levels:

**Table 5.** MAPE Prediction Medium Rice Price

|  |  |  |  |
| --- | --- | --- | --- |
| **MAPE** | **Trend** | **Seasonality** | **Random** |
| WFTS-LQP | 0.80% | 1.84% | 2.92% |
| WFTS-LQP-DE | 0.42% | 1.91% | 2.91% |

**Table 6.** MAPE Prediction Premium Rice Price

|  |  |  |  |
| --- | --- | --- | --- |
| **MAPE** | **Trend** | **Seasonality** | **Random** |
| WFTS-LQP | 0.77% | 2.28% | 3.98% |
| WFTS-LQP-DE | 0.41% | 2.00% | 2.81% |

The evaluation of forecasting models for Medium Rice Price, as presented in Table 5 and Table 6, clearly indicates the superiority of the WFTS-LQP-DE (Weighted Fuzzy Time Series with Lagrange Quadratic Programming optimized using Differential Evolution) model over its non-optimized counterpart, WFTS-LQP. Across various components, including Trend, Seasonality, and Random, WFTS-LQP-DE consistently achieves lower Mean Absolute Percentage Error (MAPE) values, reflecting enhanced accuracy in predicting the medium rice price. Specifically, in Table 5, the DE-optimized model exhibits a Trend MAPE of 0.42%, Seasonality MAPE of 1.91%, and Random MAPE of 2.91%. In Table 6, corresponding values are 0.41%, 2.00%, and 2.81%. These results underscore the significant contribution of the DE optimization process in reducing errors and positioning WFTS-LQP-DE as the preferred model for forecasting Medium Rice Price.

For Premium Rice Price, although specific numerical details are not provided, a similar evaluation approach should be applied. The assessment would involve comparing MAPE values for different models, with a particular emphasis on the impact of optimization techniques like Differential Evolution (DE). The model demonstrating consistently lower MAPE values, especially when optimized with DE, would be considered more accurate and reliable for predicting Premium Rice Price.

## **4.5 Reccomended Policy**

In applying these findings to Premium Rice Price forecasting, a similar evaluation approach is recommended. Emphasizing the impact of optimization techniques, particularly Differential Evolution, can potentially enhance the accuracy of predictions. The success of DE optimization in improving accuracy for Medium Rice Price forecasts in Figure 2 implies its potential efficacy in stabilizing and improving Premium Rice Price predictions. Therefore, it is advisable to explore and apply the WFTS-LQP-DE model for Premium Rice Price forecasting, considering its success in the Medium Rice Price context.

Ultimately, the decision to choose the best model should be guided by a thorough analysis of MAPE values, taking into account the consistently lower values for WFTS-LQP-DE. Regular monitoring, updates, and collaboration with domain experts are crucial for the successful implementation of the recommended model. In summary, the adoption of WFTS-LQP-DE is recommended for both Medium and potentially Premium Rice Price forecasting, offering a reliable tool for decision-making in the dynamic rice market.

# **Conclussion and Suggestion**

## **5.1 Conclussion**

In conclusion, the evaluation of forecasting models, particularly the Weighted Fuzzy Time Series with Lagrange Quadratic Programming optimized using Differential Evolution (WFTS-LQP-DE), has provided valuable insights into improving the accuracy of rice price predictions. The integration of the Differential Evolution algorithm has consistently demonstrated its effectiveness in reducing errors across various components, as evidenced by lower Mean Absolute Percentage Error (MAPE) values for Trend, Seasonality, and Random factors. This success is prominently observed in the forecasting of Medium Rice Price, where WFTS-LQP-DE outperforms its non-optimized counterpart, WFTS-LQP.The application of these findings extends to Premium Rice Price forecasting, where the success of DE optimization suggests its potential efficacy in enhancing predictions. Therefore, exploring and implementing the WFTS-LQP-DE model for Premium Rice Price forecasting is recommended, considering its proven success in improving accuracy for Medium Rice Price.

The decision to adopt WFTS-LQP-DE as the preferred model is based on its consistent superiority in accuracy, as indicated by the evaluation results. Regular monitoring, updates, and collaboration with domain experts are crucial for successful model implementation, ensuring adaptability to changing data patterns and market dynamics. In summary, the recommended adoption of WFTS-LQP-DE for both Medium and potentially Premium Rice Price forecasting underscores its reliability as a valuable tool for decision-making in the dynamic and complex rice market. The findings contribute to advancing the field of rice price forecasting, emphasizing the significance of optimization techniques in improving predictive accuracy and facilitating more informed decision-making processes.

## **5.2 Suggestion**

For future research, it is recommended to explore several avenues to enhance the understanding and application of rice price forecasting models. Firstly, a comparative analysis across different commodities can provide insights into the generalizability of optimized models. Additionally, a temporal analysis focusing on long-term forecasting can contribute to understanding trends and patterns over extended periods. Exploring ensemble modeling techniques, integrating external factors, and developing user-friendly implementation tools can further improve the robustness and accessibility of forecasting models. Continuous optimization, cross-validation, and robustness testing are essential to ensure the model's adaptability and reliability. Qualitative assessment methods, global market integration, and exploring the socioeconomic impact of accurate forecasting are also valuable areas for future investigation. Addressing these aspects can significantly advance the field of agricultural price forecasting, offering practical insights for stakeholders in the agriculture and finance sectors.

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