Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

Application Of Support Vector Regression Method In Predicting Rice Prices In Langkat Regency

Anisa Ratuliza[1], Dahlan Abdullah[2*], Defry Hamdhana[3]
[1,2,3]Informatics Engineering, Faculty of Technic, Malikussaleh University, Indonesia
[1]anisa.200170118@mhs.unimal.ac.id, [2*]dahlan.abdullah@unimal.ac.id, [3]defry.hamdhana@unimal.ac.id

***Corresponding Author**

Article History:
Submitted: 13-08-2026
Accepted: 05-09-2026
Published: 01-11-2026

Keywords:
Support Vector Regression; RBF Kernel; Rice Price Prediction; Time Series; Food Commodities.

Brilliance: Research of Artificial Intelligence is licensed under a Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0).

ABSTRACT

This study aims to predict rice prices in Langkat Regency using Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel. Historical price data from 2020–2024 covering six rice categories in time series format were utilized. The research stages include data preprocessing, time-based feature engineering, chronological data splitting with an 80:20 ratio, SVR model training, and performance evaluation using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results demonstrate that SVR with RBF kernel achieves Very Good prediction accuracy across all categories, with MAPE values ranging from 5.07% to 7.01%, an average MAPE of 5.66%, MAE of IDR 779, and RMSE of IDR 834. The best performance was achieved by Medium Quality II rice (MAPE 5.07%), while Low Quality I rice exhibited the highest prediction error due to greater price fluctuations. Weather factor analysis revealed that daily temperature has a positive and statistically significant correlation with prediction error ($r = +0.416$ to $+0.710$, $p < 0.001$), where high temperatures consistently increased prediction deviation. Furthermore, feature engineering incorporating time-based features, lag features, and rolling mean proved effective in capturing price change patterns. The model was implemented into a web-based prediction system presenting performance visualization, weather analysis, and interactive prediction results, serving as a decision support tool for price control and food commodity planning in Langkat Regency.

INTRODUCTION

Food price stability is a crucial element in maintaining food security and public economic stability. For agricultural regions like Langkat Regency, fluctuating food prices often pose a serious problem that affects public purchasing power and the sustainability of local farming operations (Tanjung et al., 2021). This condition not only impacts farmers' income but also poses a risk of food sector inflation, which has the potential to worsen poverty levels and social welfare. High price instability is often driven by various factors such as erratic weather conditions, dependence on harvest seasons, supply chain disruptions, and policy changes in the food trade and distribution sectors (Hidayat et al., 2021).

Along with population growth and increasing food demands, the challenge of maintaining food price stability has become increasingly urgent. Sudden food price fluctuations make it difficult for various stakeholders—including the government, producers, and consumers—to make accurate economic plans and manage budgets effectively. This situation highlights the need for a mechanism or method capable of predicting food prices more accurately, enabling market actors to better prepare for potential price changes (Putri Dewita Sari & Faiz Ahyaningsih, 2024).

Rice, as the primary staple food of Indonesian society, holds a strategic position in the national food structure. In Langkat Regency, rice is a highly essential commodity as it is consumed by almost all segments of society and contributes significantly to the consumer price index. Fluctuations in rice prices are extremely sensitive and can trigger socioeconomic instability, particularly for low-income communities that allocate a large portion of their income to purchasing rice. The focus of this research on rice is based on the consideration that this commodity exhibits a stable consumption pattern, relatively complete historical data, and a direct impact on household economic stability as well as regional food security.

Langkat Regency is one of the regions in North Sumatra Province characterized by its agrarian nature and relatively high rice production potential. Several sub-districts, such as Stabat, Secanggang, and Tanjung Pura, are known for their dominant agricultural activities. Consequently, rice prices in Langkat Regency are heavily influenced by agricultural production and distribution factors. Therefore, a system capable of predicting rice prices more accurately is required as a proactive measure against potential price instability.

Several previous studies have examined food price prediction using various machine learning methods. A study by Saadah et al. (2021) utilized the Support Vector Regression (SVR) method with a Radial Basis Function (RBF) kernel to predict palm oil prices and the EUR/USD exchange rate, achieving an accuracy of 99.97% (MAPE) for forex

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

and 98% (MSE) for CPO prices. Suyono et al. (2022) applied SVR to predict the Consumer Price Index of food commodities in Surabaya, obtaining the best results using the Polynomial kernel (MAPE 4.31%). Meanwhile, Adam et al. (2024) implemented SVR to forecast financial patterns in the Indonesian Stock Exchange, achieving optimal performance with the RBF kernel (MAPE 6.04%).

In prior literature, the Support Vector Regression method with a Radial Basis Function kernel has proven effective across various time-series forecasting applications (Fevrierdo Nathaniel Shanahan Putra Mawan Pradana & Frederik Samuel Papilaya, 2023). The RBF kernel was selected for its capability to handle complex non-linear relationships by mapping data from a lower-dimensional space to a higher-dimensional space without explicitly defining the mapping function. Optimizing hyperparameter values—such as C (regularization parameter), γ (gamma), and ε (epsilon)—is crucial to obtaining an optimal SVR model.

Based on the review of previous studies, a research gap was identified: no study has specifically applied the Support Vector Regression method integrated with weather data to predict rice prices in Langkat Regency. Most existing research relies solely on historical price data as the predictor variable, neglecting external factors such as weather conditions, which are highly relevant to agricultural productivity. In reality, weather factors like temperature and rainfall significantly influence the rice production cycle, ultimately impacting local rice price fluctuations.

Therefore, this study applies the Support Vector Regression method with a Radial Basis Function kernel by integrating weather variables (temperature and rainfall)—retrieved via the Historical Weather API—as additional features in the rice price prediction model for Langkat Regency. This research is expected to benefit various stakeholders: helping farmers determine optimal crop sale timing, assisting traders in inventory management, and serving as a basis for the government in formulating price stabilization policies.

LITERATURE REVIEW

Food products refer to anything edible and drinkable by humans, whether processed or unprocessed, intended for human consumption. Food products include all items derived from biological sources—such as agricultural, plantation, forestry, fishery, livestock, and aquatic products—as well as non-biological sources that can be processed into food or beverages. This definition also encompasses food additives, raw food materials, and other ingredients used in the preparation, processing, and manufacturing of food or drinks (Rudika Harminingtyas & Ria Noviana, 2021).

Fundamentally, food products serve as raw materials containing one or more nutritional components essential for the human body's growth, maintenance, and daily activities. These nutritional components include carbohydrates, proteins, fats, vitamins, minerals, and water, all of which function to maintain health and human survival. Food products can exist as raw materials requiring further processing, semi-processed goods, or ready-to-consume food for consumers (Rahmalia et al., 2022).

Rice is the seed of the paddy plant that has been separated from the husk and serves as the primary staple food for the majority of the population in Indonesia and Asia (Ghulam et al., 2022). It is the product of processed paddy grain that has undergone a milling process to remove the outer skin (husk) and the aleurone layer, producing white rice grains ready to be cooked into steamed rice. As one of the strategic food commodities, rice plays a vital role in national food security, serving as the main carbohydrate source consumed by more than 95% of the Indonesian population (Arinal & Azhari, 2023).

In terms of nutritional content, rice primarily consists of carbohydrates, which function as the main energy source, alongside significant amounts of protein, B-complex vitamins, and minerals (Yanti, 2023). Rice comes in various types and quality grades, ranging from premium and medium to lower grades, each possessing distinct characteristics in taste, aroma, and texture. Due to its massive consumption and inelastic demand in Indonesia, the price of rice frequently serves as a key indicator of economic stability and public welfare (Ghulam et al., 2022).

Data Mining is the process of discovering hidden knowledge within databases by utilizing statistical, mathematical, artificial intelligence, and machine learning techniques (Musa et al., 2024). Its primary goal is to extract useful information and contextual knowledge from various large databases. Although Data Mining is often associated with Knowledge Discovery in Databases (KDD), these two concepts differ despite being interrelated (Qamal & Zura Izmi Parapat, 2023). Data Mining is the core component of the KDD process, serving as the method to discover previously unknown information or knowledge within a database. By combining disciplines such as statistics, artificial intelligence, and machine learning, Data Mining becomes a highly useful tool for analyzing data and deriving valuable insights from large datasets (Yani et al., 2023).

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

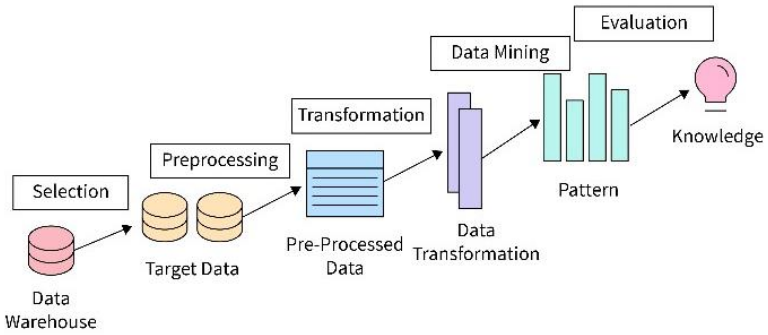


Figure 1. KDD Process

The figure illustrates the sequential stages of the Knowledge Discovery in Databases (KDD) process, which systematically transforms raw data into actionable knowledge through five interconnected phases. The process commences with the selection stage, wherein relevant data are extracted from a data warehouse to construct a target dataset aligned with the analytical objectives (Almufqi & Voutama, 2023). This is followed by the preprocessing stage, which aims to enhance data quality by handling missing values, eliminating noise, and resolving inconsistencies, thereby yielding a clean and reliable pre-processed dataset (Dona Ariyatma & Fahmi, 2023). The subsequent transformation stage standardizes and restructures the data into a format suitable for analysis, producing transformed data that are ready for modeling. In the data mining stage, appropriate algorithms are then applied to the transformed data in order to extract latent patterns and underlying relationships. Finally, the evaluation stage interprets and assesses the discovered patterns in terms of their validity, usefulness, and relevance, ultimately culminating in knowledge that can support decision-making processes. Collectively, this pipeline demonstrates that knowledge is not derived directly from raw data, but rather emerges through a systematic and progressive sequence of selection, preprocessing, transformation, mining, and evaluation.

Forecasting is a method used to predict what is likely to occur in the future, based on current situations and conditions as well as historical data. Approaches to forecasting vary depending on the perspective of the scientific method employed for decision-making. This forecasting technique generates estimates for the future, which then serve as the foundation for smarter business planning and decision-making. Given that every organization must face future uncertainty, the need for accurate predictions is essential (Puspaning Ramadhan et al., 2022).

Support Vector Regression (SVR) is a machine learning method developed from the concepts of Support Vector Machine (SVM) to solve regression and prediction problems. SVR was first introduced by Vapnik in 1995 as an extension of SVM, which was originally used for classification tasks. Unlike conventional regression methods that aim to minimize the error between predicted and actual values, SVR seeks to find a function that has at most an ε (epsilon) deviation from the actual target, while keeping the model as flat as possible (Malem Ginting et al., 2021).

The fundamental principle of SVR is to find the optimal hyperplane that represents the data within a specified tolerance margin. In SVR, the training data is mapped into a higher-dimensional feature space using a kernel function, allowing non-linear relationships in the original input space to be transformed into linear relationships within the feature space (Khasanah & Purwadi, 2022). The SVR prediction function is mathematically expressed as:

$$f(x) = w^T \phi(x) + b \qquad (1)$$

Where:

a) w : Weight vector indicating the contribution of each feature to the model.
b) $\phi(x)$: Transformation function mapping the input data x into a higher-dimensional feature space.
c) b : Bias term that shifts the hyperplane position.
d) $f(x)$: Predicted output of the model.

During the optimization process, SVR utilizes an ε-insensitive loss function that ignores minor errors falling below the tolerance threshold ε.

METHOD

The scheme for the food price prediction system in Langkat Regency using the Support Vector Regression method is as follows:

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence
E-ISSN : 2807-9035
Volume 6, Number 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

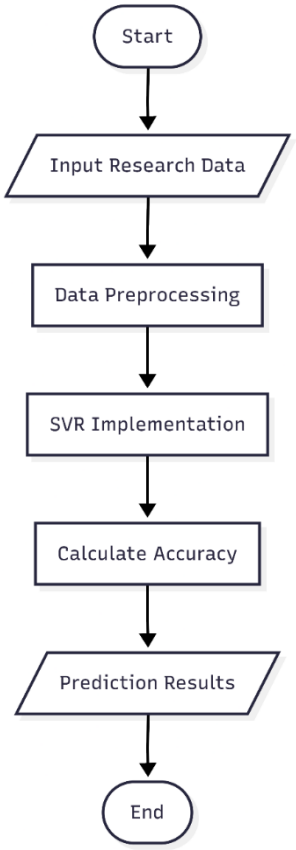


Figure 2. System Schema

The flowchart scheme begins with the initialization phase to build the food price prediction system using Support Vector Regression (SVR). The research dataset integrates two primary sources: daily rice price data (2020–2024) across six categories in Langkat Regency sourced from the National PIHPS, and historical weather data—specifically daily temperature and rainfall—retrieved via the Open-Meteo Historical Weather API for Langkat's coordinates (3.5° N, 98.3° E). Integrating weather features serves as a unique aspect of this study, considering climatic influences on distribution and price fluctuations. Subsequently, the data preprocessing phase involves merging price and weather data by date, aggregating hourly weather API metrics into daily averages to match the price granularity, handling missing values, and generating derived climate features—such as 7-day and 30-day rolling averages—to better capture short- and medium-term climate trends.In the model implementation phase, SVR with a Radial Basis Function (RBF) kernel is configured using parameters $C = 100$, $\varepsilon = 0.1$, and $\gamma = \text{scale}$. The model incorporates 49 total features, combining weather metrics with temporal variables (year, month, day, quarter) and historical price lags/rolling averages to capture complex price patterns. Model training is executed on 982 training samples (80%), followed by performance evaluation on 246 testing samples (20%) using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The evaluation yielded highly accurate predictions across all six rice categories, achieving an average MAPE of 5.66%, MAE of IDR 779, and RMSE of IDR 834, categorized as "Very Good." Finally, these prediction results are deployed via an interactive web-based system for visualization and analysis, concluding the algorithm process to support decision-making and food price policy planning in Langkat Regency.

RESULT

Referring to the problem statement outlined previously, this study aims to apply the Support Vector Regression (SVR) method to predict rice prices in Langkat Regency based on historical price data. The developed system is machine learning-based, employing a supervised learning approach in which the SVR model utilizes a Radial Basis Function (RBF) kernel to capture non-linear relationship patterns within food price data. Prior to modeling, the data undergoes data cleaning and preprocessing phases to enhance data quality and consistency, making it suitable for model training and testing.

The modeling results demonstrate that the Support Vector Regression method with an RBF kernel effectively learns the patterns of rice price fluctuations. Model performance evaluation was conducted using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) metrics to measure

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

prediction errors between actual and predicted values. These evaluation metric values provide insights into the accuracy and reliability of the model in predicting rice prices in Langkat Regency, allowing the findings of this research to serve as a foundational consideration for planning and decision-making regarding food price stability.

Problem Analysis

Predicting rice prices in Langkat Regency is a complex problem as it is influenced by various factors such as seasonality, supply availability, demand, distribution, and weather conditions. These factors cause price change patterns to be dynamic and inherently non-linear, making them difficult to predict using conventional approaches such as moving averages or simple trend analysis. Inaccuracies in rice price predictions can lead to market instability and complicate decision-making for the government, traders, and farmers regarding distribution, price control, and food stock planning.

To address this issue, this study applies the Support Vector Regression (SVR) method with a Radial Basis Function (RBF) kernel. The SVR method was selected for its capability to model non-linear relationships in time-series data, thereby effectively capturing complex rice price patterns based on historical data. Through the application of the Support Vector Regression method, the developed model is expected to generate more accurate rice price predictions that can serve as decision support for maintaining rice price stability in Langkat Regency.

Data Description Analysis

10 Data PERTAMA:

	Tahun	Tanggal	Beras Kualitas Bawah I	Beras Kualitas Bawah II	Beras Kualitas Medium I	Beras Kualitas Medium II	Beras Kualitas Super I	Beras Kualitas Super II
0	2020	2020-01-02	9700	9950	11150	11200	12100	12000
1	2020	2020-01-03	9700	9950	11150	11200	12100	12000
2	2020	2020-01-06	9700	9950	11150	11200	12100	12000
3	2020	2020-01-07	9700	9950	11150	11200	12100	12000
4	2020	2020-01-08	9700	9950	11150	11150	12100	12000
5	2020	2020-01-09	9700	9950	11150	11200	12100	12000
6	2020	2020-01-10	9700	9950	11150	11200	12100	12000
7	2020	2020-01-13	9700	9950	11150	11200	12100	12000
8	2020	2020-01-14	9700	9950	11150	11200	12100	12000
9	2020	2020-01-15	9700	9950	11150	11150	12100	12000

Figure 3. 10 First Line Data

The research dataset used in this analysis consists of historical rice price data in Langkat Regency. The dataset comprises 1,258 observations across 8 variables, which include temporal variables and the prices of various rice types. The variables used encompass the year, recording date, and rice prices categorized by quality grade—namely Lower Quality I, Lower Quality II, Medium Quality I, Medium Quality II, Super Quality I, and Super Quality II Rice. This dataset provides a comprehensive overview of rice price movements over time across different quality variations.
Descriptively, the rice price data exhibits a relatively stable fluctuation pattern during certain periods, yet continually shifts over time. The price disparities among different quality grades reflect market segmentation, where higher-quality rice generally commands a higher price compared to other categories. The time-series characteristics and non-linear patterns of this dataset form the fundamental rationale for selecting the Support Vector Regression method with a Radial Basis Function kernel, as this method effectively and accurately captures complex price change dynamics.

System Implementation

This subsection focuses on the implementation details of the food price prediction system developed to present prediction analysis results using the Support Vector Regression method. The primary goal of this system's implementation is to interactively visualize and communicate the outcomes of historical food price data processing in a user-friendly manner for stakeholders, including researchers, policy makers, and relevant entities in food price management. The system functions as a decision support system that delivers food price forecasts based on historical data, accompanied by model performance analyses and price trend visualizations to support more accurate decision-making.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

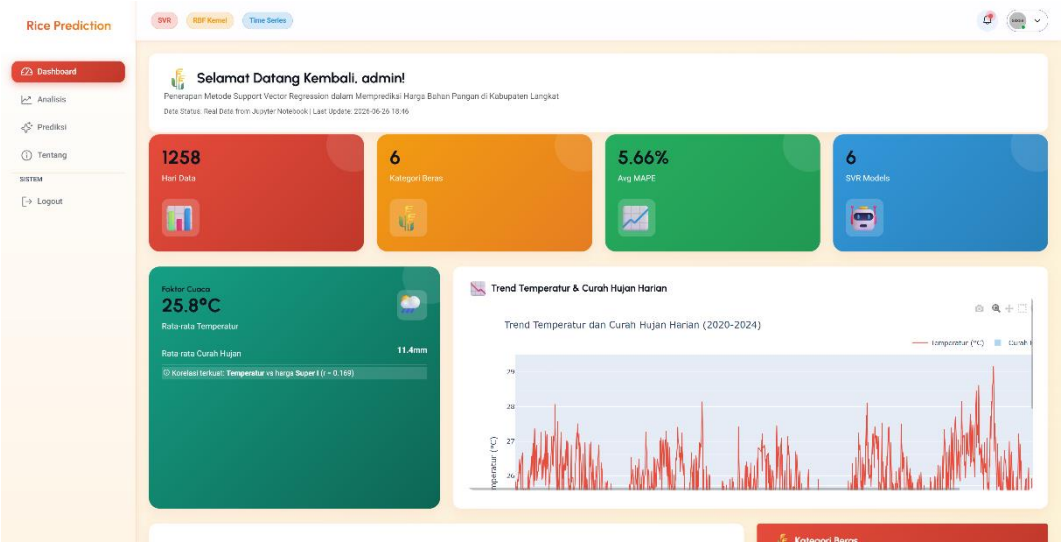


Figure 4. Dashboard Page

The dashboard page of the rice price prediction system presents a comprehensive summary of key information regarding the data, model, and prediction performance following successful user authentication. The dashboard features four primary statistical cards: a total dataset size of 1,258 daily records, 6 predicted rice categories, an average MAPE of 5.66%, and 6 trained Support Vector Regression models. Alongside the model statistics, this page includes a weather factor panel displaying an average temperature of 25.8°C and an average rainfall of 11.4 mm, complete with details on the strongest correlation—observed between temperature and Super Quality I rice prices with a value of $r = 0.169$. Positioned to the right of the weather panel, line charts illustrate daily temperature and rainfall trends from 2020 to 2024, offering insights into the climate data patterns used as features in the prediction process. Overall, the dashboard page serves as a centralized hub for information and system performance monitoring, enabling users to easily interpret food price predictions and evaluate the reliability of the applied SVR method with an RBF kernel.

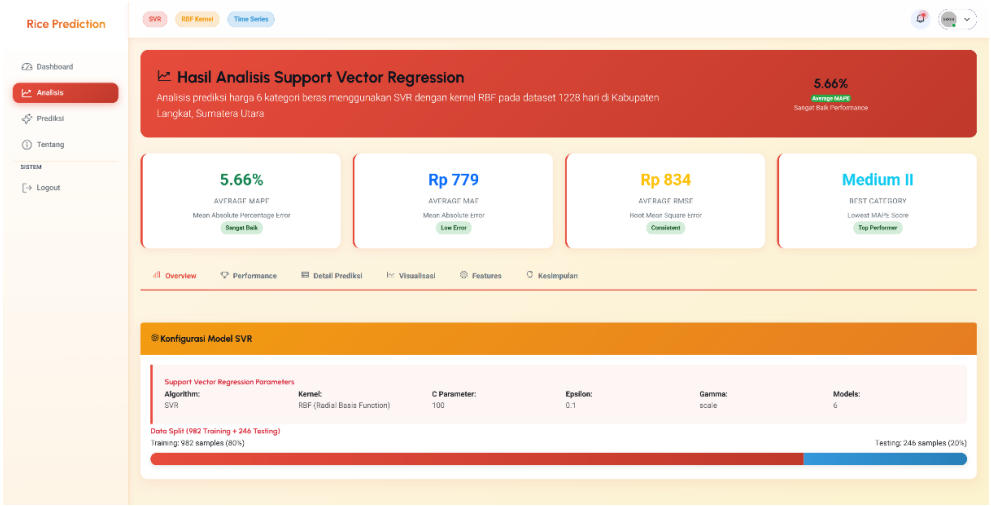


Figure 5. Result Analysis Page

The analysis page of the system presents the results of the food price prediction analysis using the Support Vector Regression method with a Radial Basis Function kernel in a structured and informative manner. This page displays a model performance summary highlighting an average MAPE of 5.66%, an average MAE of IDR 779, and an RMSE of IDR 834, which reflects the accuracy and stability of the model in predicting rice prices in Langkat Regency. Furthermore, the page highlights the best-performing rice category, Medium Quality II, which achieved the lowest MAPE value, alongside the utilized SVR model configuration—including an RBF kernel type, a C parameter value of 100, an ε (epsilon) of 0.1, and a γ (gamma) set to "scale", with a dataset split proportion of 80% training data (982 samples) and 20% testing data (246 samples). This presentation of information aims to provide a comprehensive overview of the analytical process, model configurations, and obtained evaluation results, thereby enabling users to transparently and thoroughly understand model performance within the context of machine learning-based food price

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence
E-ISSN : 2807-9035
Volume 6, Number 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

forecasting.

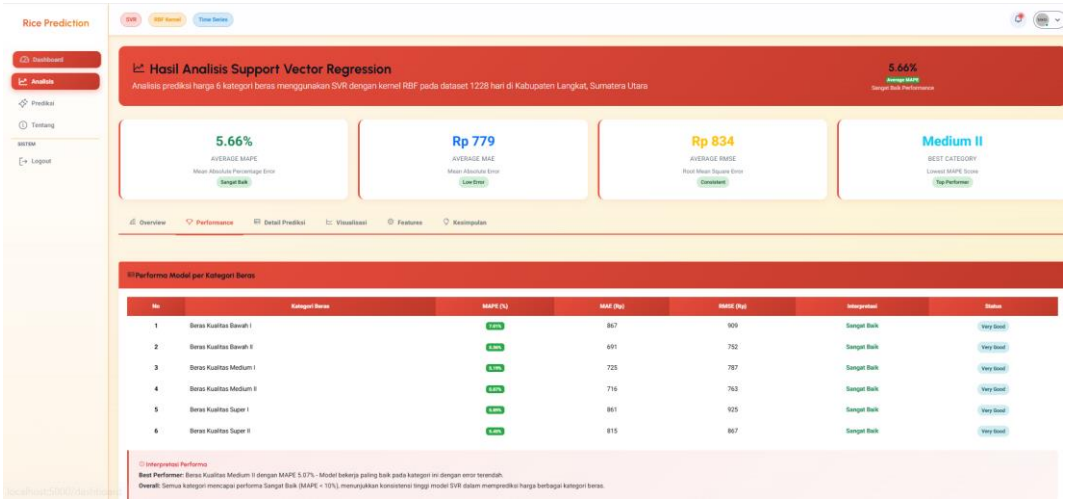


Figure 6. Model Performance

The Performance page under the Analysis menu displays a detailed performance table of the Support Vector Regression model for each predicted rice category. Based on the evaluation results, all six rice categories achieved a "Very Good" rating with MAPE values below 10%, demonstrating high model consistency in predicting food prices. In order, the MAPE values obtained for each category are 7.01% for Lower Quality I Rice (MAE IDR 867, RMSE IDR 909), 5.36% for Lower Quality II Rice (MAE IDR 691, RMSE IDR 752), 5.19% for Medium Quality I Rice (MAE IDR 725, RMSE IDR 787), 5.07% for Medium Quality II Rice (MAE IDR 716, RMSE IDR 763), 5.89% for Super Quality I Rice (MAE IDR 861, RMSE IDR 925), and 5.45% for Super Quality II Rice (MAE IDR 815, RMSE IDR 867). The Medium Quality II Rice category emerged as the best performer with the lowest MAPE value of 5.07%, while the overall model average yielded a MAPE of 5.66%, MAE of IDR 779, and RMSE of IDR 834, indicating that the Support Vector Regression method with an RBF kernel effectively predicts rice prices in Langkat Regency with high accuracy and consistency across all categories.

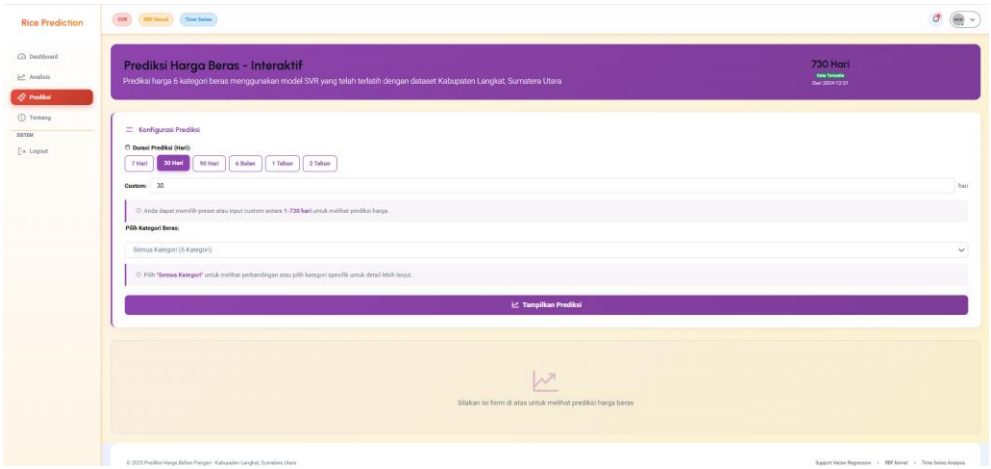


Figure 7. Prediction Page

The prediction page is designed as an interactive interface that allows users to perform rice price forecasting based on the Support Vector Regression model trained on historical data from Langkat Regency. On this page, users can flexibly adjust the prediction horizon—ranging from short-term to long-term—either through preset options or custom input for the number of days. Additionally, users can select the target rice category for prediction, choosing either a single specific category or all categories for comparative analysis. Once the configurations are specified, the system displays the price forecasts corresponding to the selected parameters. This interface is structured to facilitate intuitive exploration of prediction results, enabling users to gain insights into future rice price projections and utilize this information as decision support for food price planning and control.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

Brilliance
Research of Artificial Intelligence

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

DISCUSSION

In this section, a comprehensive discussion is provided regarding the empirical results obtained from predicting rice prices across six categories in Langkat Regency using Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel. The findings are evaluated from both theoretical machine learning and practical agricultural economic perspectives.

Model Validation and Performance across Categories

The implementation of SVR with an RBF kernel ($C = 100$, $\varepsilon = 0.1$, $\gamma =$ scale) yielded high predictive accuracy across all six rice quality categories on the testing dataset (2024 period, $n = 246$), achieving a overall average Mean Absolute Percentage Error (MAPE) of 5.66%, Mean Absolute Error (MAE) of IDR 779, and Root Mean Squared Error (RMSE) of IDR 834. All evaluated categories fell well within the "Very Good" predictive rating (MAPE $< 10\%$).

A granular comparison across commodities highlights the influence of historical price stability on predictive performance:

a) **Best Performer**: *Medium Quality II Rice* achieved the lowest error rates (MAPE = 5.07%, MAE = IDR 716, RMSE = IDR 763). The stability of price changes in medium-grade commodities allowed the RBF kernel to effectively map decision boundaries with minimal variance.
b) **Highest Fluctuation**: *Lower Quality I Rice* exhibited the highest prediction error (MAPE = 7.01%, MAE = IDR 867, RMSE = IDR 909). This higher deviance is attributed to greater dynamic price volatility in lower-grade markets driven by irregular local supply shifts.
c) **Manual Verification**: The manual calculation performed on *Medium Quality I Rice* validated the exactness of the SVR formulation ($f(x) = \sum(\alpha_i - \alpha_i^*) K(x_i, x) + b$). Out of 10 training samples, 5 support vectors were identified. Notably, an anomaly data point (e.g., price spike to IDR 15,800) generated the maximum dual coefficient ($\alpha_2 = 100.0$), demonstrating how SVR strategically relies on boundary instances to shape non-linear decision spaces.

Impact of Feature Engineering and External Climate Factors

A key innovation of this research lies in integrating temporal, lag, rolling mean, and exogenous climate variables (daily temperature and rainfall from Open-Meteo API) into a 49-column feature space.

a) **Exogenous Weather Influence**: Although direct Pearson correlation between weather parameters and actual rice prices was weak ($r < 0.20$), correlation analysis against model prediction errors (Absolute Percentage Error / APE) revealed significant insights. Daily temperature showed a strong, statistically significant positive correlation with prediction error across all categories ($r = +0.416$ to $+0.710, p < 0.001$).
b) **High-Temperature Sensitivity**: On high-temperature days (> 27°C), the average APE increased by 2.37% to 3.31% compared to normal temperature conditions. Furthermore, all six rice categories reached their peak prediction error on the exact same date—July 26, 2024 (APE 12.04% − 13.90%, temperature 29.1°C, rainfall 0.5 mm). This systemic spike demonstrates that extreme heat-dry events induce unpatterned market shocks that strictly historical time-series approaches struggle to anticipate fully.

Practical Implications and Decision Support

The trained SVR models were successfully deployed into a web-based interactive interface that allows stakeholders to simulate flexible forecast horizons (from 7 days up to 2 years). By translating complex machine learning outputs into intuitive visual trends, performance cards, and climate correlations, the system serves as a functional Decision Support System (DSS). Local government agencies, traders, and agricultural planners in Langkat Regency can leverage these insights to anticipate supply imbalances, mitigate food inflation, and formulate proactive price control policies.

CONCLUSION

Based on the results of predicting rice prices in Langkat Regency using the Support Vector Regression (SVR) method with a Radial Basis Function (RBF) kernel, the model demonstrated excellent performance across all rice categories—achieving an overall average MAPE of 5.66%, MAE of IDR 779, and RMSE of IDR 834, with Medium II Quality Rice emerging as the best performer (MAPE 5.07%). The preprocessing stages, optimal hyperparameter tuning ($C = 100$, $\varepsilon = 0.1$, $\gamma =$ scale), and an 80:20 chronological data split effectively captured price patterns without significant overfitting, although categories with higher price fluctuations naturally yielded slightly larger errors. Furthermore, Pearson correlation analysis revealed that daily temperature positively and significantly correlated with prediction errors ($r = +0.416$ to $+0.710$, $p < 0.001$), identifying extreme hot and dry conditions as the primary limitation of historical pattern-based forecasting. Ultimately, the successful deployment of this SVR model into an interactive web-based prediction system confirms its feasibility as a decision support tool for food price control in Langkat Regency, while offering clear potential for future development through the integration of

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

E-ISSN : 2807-9035
Volume 6, **Number** 4, November 2026
https://doi.org/10.47709/brilliance.v6i4.9527

weather variables as exogenous features.

REFERENCES

Almufqi, F. M., & Voutama, A. (2023). PERBANDINGAN METODE DATA MINING UNTUK MEMPREDIKSI PRESTASI AKADEMIK SISWA. *Jurnal Teknika*, *15*(1), 61–66. https://doi.org/10.30736/jt.v15i1.929

Arinal, V., & Azhari, M. (2023). Penerapan Regresi Linear Untuk Prediksi Harga Beras Di Indonesia. *Jurnal Sains Dan Teknologi*, *5*(1), |pp. https://doi.org/10.55338/saintek.v5i1.1417

Dona Ariyatma, R., & Fahmi, S. (2023). Data Mining Menggunakan Multiple Regression untuk Prediksi Harga Saham Netflix. *Jurnal SAINTEKOM*, *13*(2), 184–192. https://doi.org/10.33020/saintekom.v13i2.419

Fevrierdo Nathaniel Shanahan Putra Mawan Pradana, & Frederik Samuel Papilaya. (2023). Analisa Prediksi Harga Emas Dengan Kemungkinan Terjadinya Resesi Menggunakan Metode Svr. *SINTECH JOURNAL*, *6*(1). https://doi.org/10.31598

Ghulam, B., Shidiq, A., Furqon, M. T., & Muflikhah, L. (2022). *Prediksi Harga Beras menggunakan Metode Least Square* (Vol. 6, Number 3). http://j-ptiik.ub.ac.id

Hidayat, S., Girsang, M. A., Tobing, S. P., Khairiah, K., Haloho, L., & Nainggolan, P. (2021). Potensi Pengembangan Komoditas Unggulan Tanaman Pangan Berdasarkan Analisis Location Quotient (LQ) di Kabupaten Langkat. *Proceedings Series on Physical & Formal Sciences*, *2*, 356–361. https://doi.org/10.30595/pspfs.v2i.211

Musa, D. M., Sakti, D., Shantiony, K. A., Zega, S. K. P., Hamzah, S., Zega, Y. J., & Lubis, B. O. (2024). Penerapan Data Mining Untuk Klasifikasi Data Penjualan Pakan Ternak Terlaris Dengan Algoritma C4.5. *Jurnal Teknologi Informatika Dan Komputer*, *10*(1), 168–182. https://doi.org/10.37012/jtik.v10i1.1985

Puspaning Ramadhan, V., Yulian Pamuji, F., & History, A. (2022). *Jurnal Teknologi dan Manajemen Informatika Analisis Perbandingan Algoritma Forecasting dalam Prediksi Harga Saham LQ45 PT Bank Mandiri Sekuritas (BMRI) Article Info ABSTRACT*. *8*, 39–45. http://http://jurnal.unmer.ac.id/index.php/jtmi

Putri Dewita Sari, & Faiz Ahyaningsih. (2024). Jaringan Saraf Tiruan Backpropagation untuk Prediksi Harga Bahan Pangan di Wilayah Kabupaten Deli Serdang. *Algoritma : Jurnal Matematika, Ilmu Pengetahuan Alam, Kebumian Dan Angkasa*, *2*(6), 105–117. https://doi.org/10.62383/algoritma.v2i6.287

Qamal, M., & Zura Izmi Parapat, A. (2023). *Implementasi Data Mining Untuk Rekomendasi Paket Menu Makanan Menggunakan Algoritma Apriori Implentasi Data Mining Untuk Rekomendasi Paket Menu Makanan Menggunakan Algoritma Apriori*.

Rahmalia, D., Sari, I. R. M., Kasymir, E., & Tantriadisti, S. (2022). Keputusan Pembelian Bahan Pangan Online oleh Konsumen Rumah Tangga di Kota Bandar Lampung, Indonesia. *Agro Bali : Agricultural Journal*, *5*(2), 384–391. https://doi.org/10.37637/ab.v5i2.942

Rudika Harminingtyas, & Ria Noviana. (2021). Pengaruh Sertifikasi Halal, Kesadaran Halal, dan Bahan Makanan Terhadap Minat Beli Produk Makanan Halal di Semarang. *Jurnal Ekonomika Dan Bisnis*, *8*, 103–112.

Tanjung, A. F., Salsabila, S., & Siregar, A. F. (2021). ANALISIS FORECASTING KOMODITI STRATEGIS DAERAH SERTA KETAHANAN PANGAN YANG BERKELANJUTAN. *JURNAL AGRICA*, *14*(1), 71–79. https://doi.org/10.31289/agrica.v14i1.4042

Yani, A., Azmi, Z., Suherdi, D., Informasi, S., & Triguna Dharma, S. (2023). Implementasi Data Mining Menganalisa Data Penjualan Menggunakan Algoritma K-Means Clustering. *JURNAL SISTEM INFORMASI TGD*, *2*(2), 315–323. https://ojs.trigunadharma.ac.id/index.php/jsi

Yanti, D. (2023). Prediksi Harga Beras Belida Di Kota Pekanbaru Menggunakan Metode Fuzzy Time Series Cheng. *Jurnal Teknologi Dan Manajemen Industri Terapan (JTMIT)*, *2*(3), 234–241.

This is an Creative Commons License This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.