

FORECASTING CLIMATE CHANGE IMPACTS ON RED ONION YIELD IN BREBES REGENCY

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Introduction

Red onion is one of the flagship commodities in the horticultural sector in Indonesia, with Brebes Regency standing out as the country's largest producing area. However, challenges such as floods and droughts frequently cause crop failures, impacting supply. Additionally, crop failures lead to price surges in several regions, which severely impact underprivileged communities in Indonesia who still rely on imports.

In December 2023, drought affected 930 hectares of red onion fields, while floods in February-March 2024 impacted 547 hectares of land. Consequently, in April 2024, the price of red onions in several regions of Indonesia increased by up to 55.8% compared to the previous month (National Food Agency, 2024). Therefore, an early warning system is crucial to mitigate the risk of climate change on crop yields in vulnerable areas.

To address this issue, we focus on leveraging machine learning to accurately predict the effects of climate change on red onion production in Brebes Regency. By analyzing synoptic data, particularly rainfall and maximum temperature, we trained various machine learning models, including Support Vector Regression (SVR), Neural Network (NN), Recurrent Neural Network (RNN), and Long Short-Term Memory Network (LSTM).

Methodology

We focused on Brebes Regency, Indonesia. This location was chosen because Brebes is geographically the largest red onion-producing region in Indonesia, currently facing environmental challenges such as floods and droughts that impact crop yields.

Historical weather data was obtained from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). The observed variables include daily rainfall and maximum temperature in Brebes Regency, with a sample size of 3,377 observations from January 1, 2015, to April 30, 2024. Numerical tests were conducted using Python and executed on a macOS with a 2.3 GHz Dual-Core i5 processor and 8 GB 2133 MHz LPDDR3 memory. Readers are encouraged to review models SVR, NN, RNN, and LSTM from sources [1,2,3], as we adopted the theory of these models from the cited works.

Figure 1 shows the proposed model framework used for forecasting. The integrated system consists of three main parts: (1) data preprocessing, (2) model building, and (3) model selection and forecasting. We evaluated the model performance using accuracy metrics such as MSE, MAE, and RMSE.

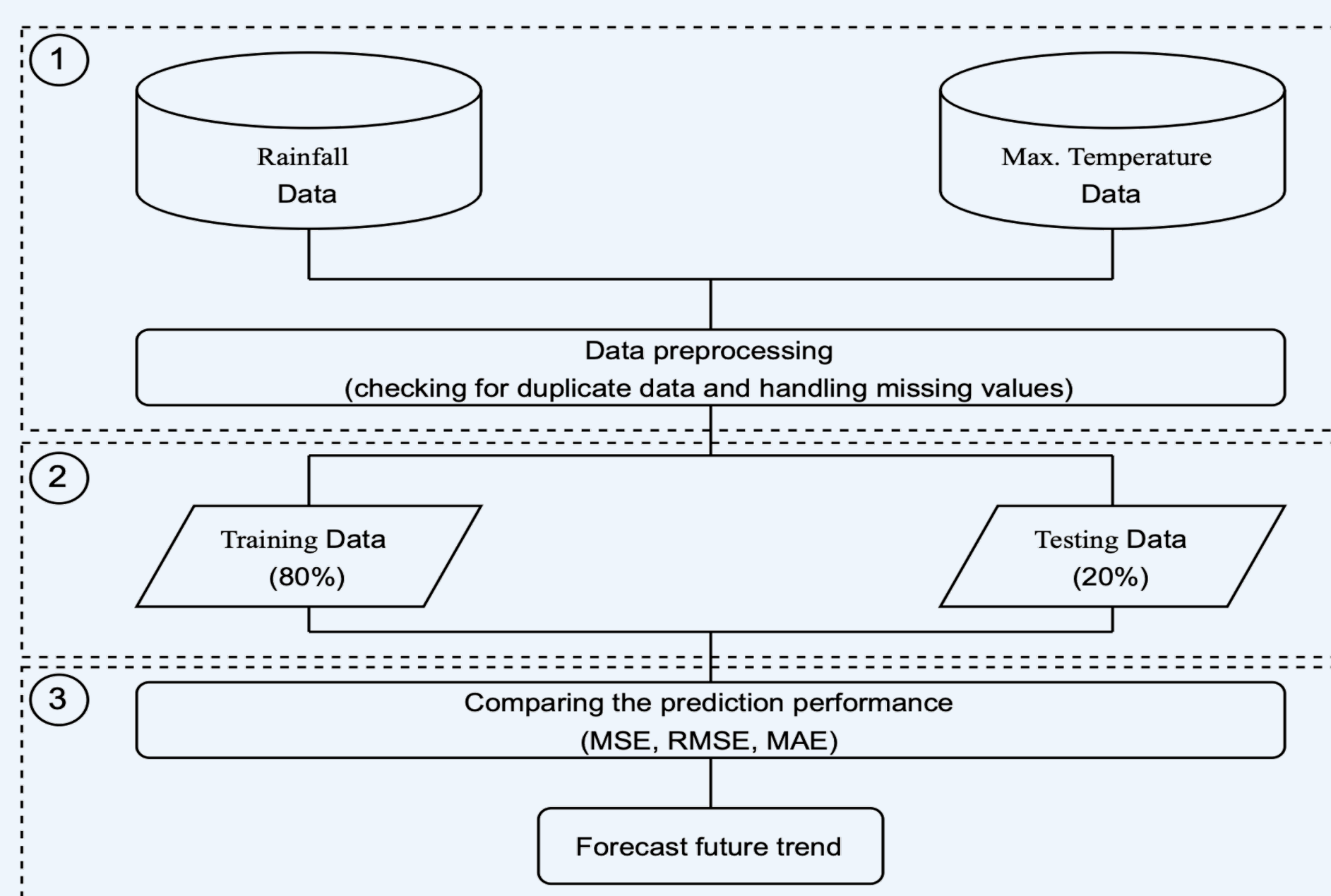


Figure 1. Flow chart of the analytical framework

Results

We evaluated the model performance using the MSE, MAE, and RMSE accuracy metrics. The results show that the Neural Network offers the most accurate predictions for rainfall, with an MSE \approx 136.662, MAE \approx 8.458, and RMSE \approx 11.690, respectively, compared to an MSE \approx 406.911, MAE \approx 18.632, and RMSE \approx 20.172 from SVR; MSE \approx 440.067, MAE \approx 15.986, and RMSE \approx 20.977 from LSTM; and MSE \approx 464.575, MAE \approx 12.909, and RMSE \approx 21.554 from RNN.

Moreover, the results show that the Recurrent Neural Network offers the most accurate predictions for temperature, with an MSE \approx 0.893, MAE \approx 0.695, and RMSE \approx 0.945, respectively, compared to an MSE \approx 2.189, MAE \approx 1.199, and RMSE \approx 1.479 from SVR; MSE \approx 1.609, MAE \approx 0.952, and RMSE \approx 1.268 from LSTM; and MSE \approx 2.205, MAE \approx 1.179, and RMSE \approx 1.485 from NN. Figures 2 and 3 show the predicted rainfall and maximum temperature until April 2026.

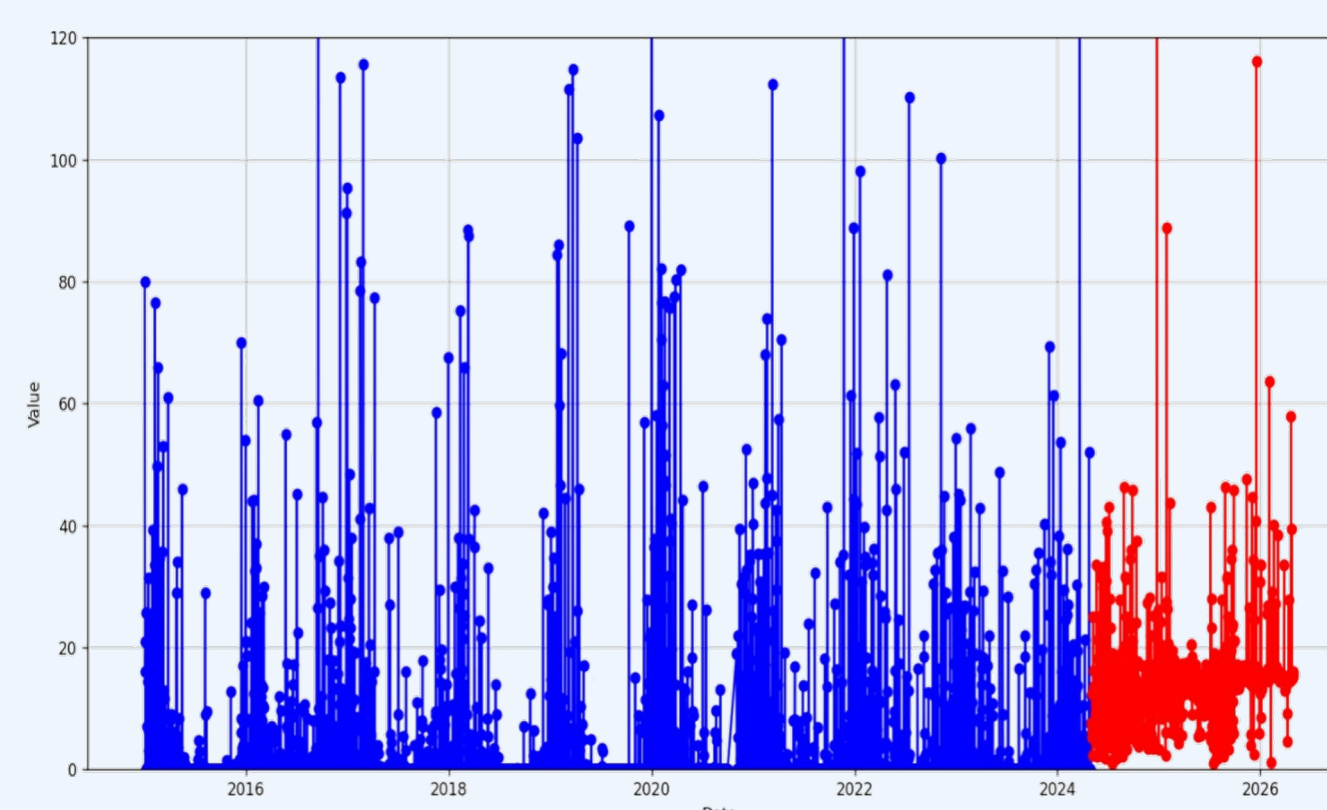


Figure 2. Actual vs Predicted Rainfall Data

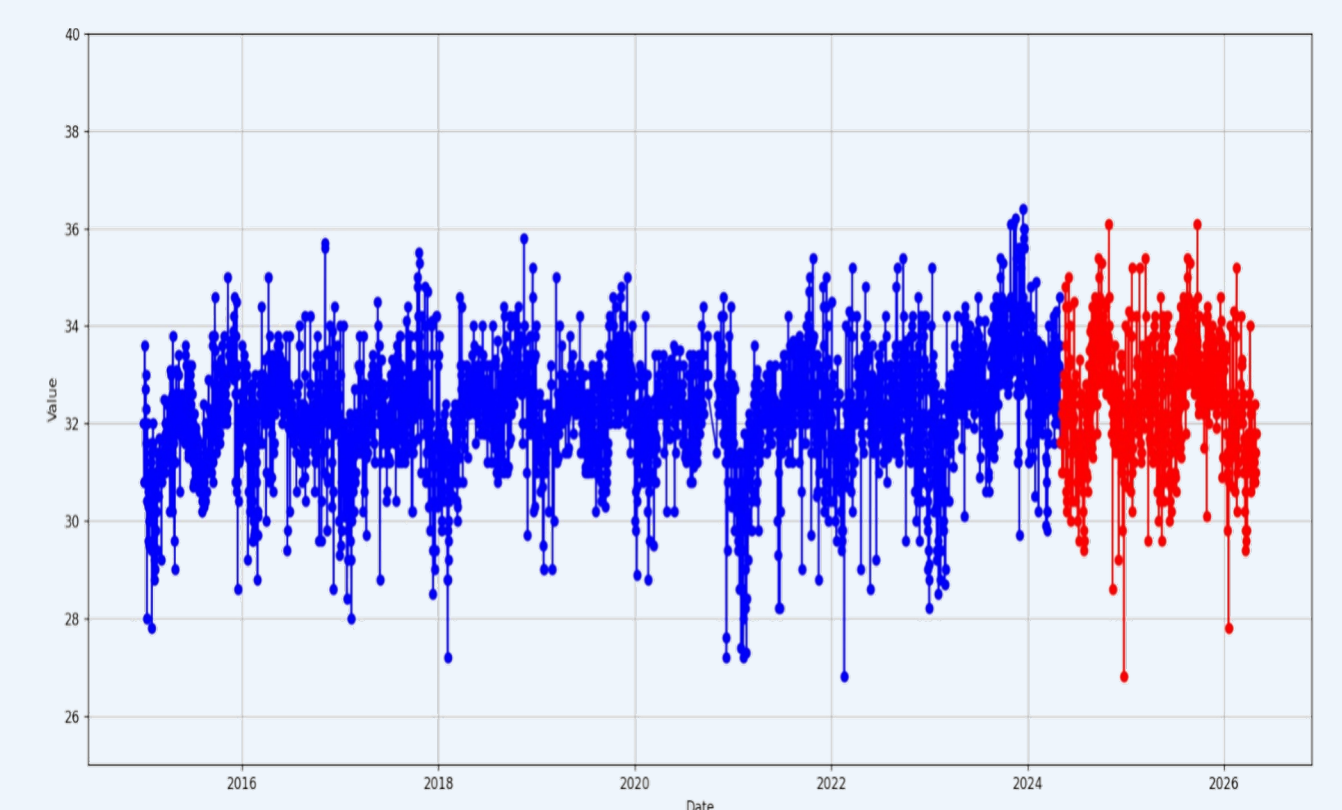


Figure 3. Actual vs Predicted Max. Temperature Data

The results suggest that Brebes Regency is likely to reach its maximum temperature in October 2024 and September 2025, with increased rainfall expected from December 2024 to February 2025. Another rise in rainfall is predicted for late December 2025, fluctuating until April 2026. This pattern indicates the potential for high rainfall following prolonged dry seasons. The findings obtained in this study can serve as a reference for the government of Brebes Regency in proactively managing weather-related risks, thereby reducing the negative impact on red onion cultivation.

Conclusion

The Neural Network algorithm indicates a potential hydrometeorological disaster in Brebes Regency in February 2025, predicting flooding following a prolonged drought. To mitigate the impact of this potential disaster, local governments can proactively implement disaster mitigation measures by constructing dams and irrigation systems and conducting regular climate change awareness campaigns for affected communities.

Additionally, the central government can initiate targeted policies to maintain economic stability, such as preventing inflation due to red onion scarcity, opening new agricultural land for red onion cultivation in other regions, market operations (subsidy programs for crop failure), and developing agricultural infrastructure.

The study also predicts a drought in August 2025. One form of mitigation that can be undertaken is the optimization of weather modification technology operations.

“DO NOT BLAME NATURE FOR THE MISTAKES MADE BY HUMANS”

Reference/Footnotes

- ¹Poornima, S., & Pushpalatha, M. (2019). Prediction of rainfall using intensified LSTM-based recurrent neural network with weighted linear units. *Atmosphere*, 10(11), 668.
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Acknowledgments

I would like to express my sincere gratitude to Professor Ravinesh Deo and Dr. Thong Nguyen-Huy from the University of Southern Queensland for their invaluable guidance, constructive feedback, and encouragement throughout this research project.