



Rainfall Prediction Using Gate Recurrent Unit (Gru) for The Mataram City Area

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Abstract: Rainfall prediction is crucial for urban planning, agriculture, and disaster mitigation. This study predicts rainfall intensity in Mataram City using the Gated Recurrent Unit (GRU), a variant of Recurrent Neural Networks (RNN) optimized for sequential data. The dataset consists of hourly rainfall data from NASA's MERRA Power (2010–2021). Data preprocessing includes normalization, feature engineering, and dataset splitting. The GRU model architecture comprises input, GRU, and dense layers. Model performance is evaluated using Root Mean Squared Error (RMSE), yielding 67, 112, 69, and 109 for Ampenan, Cakranegara, Majeluk, and Selaparang, respectively. Results show that the GRU model captures rainfall trends but has limitations in predicting extreme values. This study demonstrates GRU's potential for improving rainfall forecasting while highlighting the need for further optimization to enhance accuracy.

Keywords: GRU; Rainfall; RMSE.

Introduction

Rainfall is a critical meteorological phenomenon that affects agriculture, urban management, and water resource planning. Accurate rainfall prediction is essential for mitigating floods, optimizing agricultural practices, and enhancing disaster preparedness (Mohr et al., 2022). However, rainfall forecasting remains challenging due to its stochastic nature, seasonal variations, and dependence on multiple atmospheric factors (Avalon Cullen & Al Suhili, 2023). Traditional statistical models often struggle to capture these complexities, leading to inaccurate predictions, especially in extreme weather conditions.

The rapid development of technology has led to progress in the field of data processing, one of which is Artificial Neural Network (ANN). Artificial Neural Network is an artificial neural network that imitates the working principle of the human brain. One type of ANN is Recurrent Neural Network (RNN). RNN is a type of

ANN that has advantages in processing data in the form of time series.

RNN has a suitability in processing time-series data because there is a lot of data with a fairly large amount and requires quite complex computation. RNN has high accuracy in processing time-series data. RNN has several methods, namely LSTM (Long Short Term Memory) and GRU (Gate Recurrent Unit).

LSTM is a form of development of RNN with the addition of memory cells. The addition of memory cells helps improve computing which causes accuracy to increase. However, LSTM has a weakness where high computing causes computer performance to be heavy, thus increasing training time. For that, GRU is here to overcome this deficiency.

GRU is a form of development of LSTM Arifah et al. (2022) which replaces memory cells with system gates. There are two gates in GRU, namely update gate and reset gate (Zhijian et al., 2022). This system gate makes computer performance lighter, thereby reducing

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training time and also increasing accuracy. The results of Zakiyah et al. (2024) research, showed that GRU gave results that were 10% better than RMSE.

Root Mean Square Error (RMSE) is a standard metric used to evaluate the performance of a model (Hodson, 2022). The value of RMSE reflects the performance of a model. The use of RMSE is common in evaluating modeling results because RMSE provides a value in the form of whole numbers that clearly describe the error of a model. Where the smaller the number given by RMSE, it can be said that the model is closer to the truth (Lim et al., 2024; Setiawan, 2021).

This research focuses on developing a GRU-based rainfall prediction model for Mataram City using hourly data from NASA's MERRA Power. While previous studies have applied GRU in various forecasting tasks, its application in high-resolution rainfall prediction remains limited (Xiong et al., 2022). By evaluating the model's performance using the Root Mean Squared Error (RMSE), this study seeks to provide a more reliable and computationally efficient approach for rainfall forecasting (Leite-Filho et al., 2021). The findings are expected to enhance urban planning, agricultural decision-making, and disaster risk reduction in Mataram City.

Method

This study utilizes the Gated Recurrent Unit (GRU) model to predict rainfall in Mataram City using historical hourly rainfall data from NASA's MERRA Power for the period of 2010–2021.

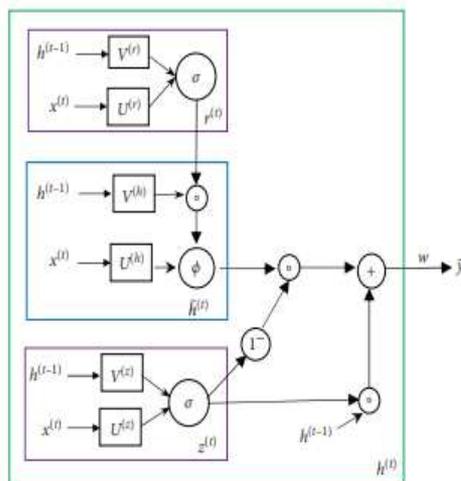


Figure 1. Structure of GRU (Hong & Zhang, 2020)

The research methodology includes data preprocessing, model architecture design, and model evaluation.

Data Collection and Pre processing

Hourly rainfall data from four regions in Mataram (Ampenan, Cakranegara, Majeluk, and Selaparang) were collected, amounting to 122,712 data points per region. The preprocessing steps included normalizing the data using the MinMaxScaler to scale values between 0 and 1, creating sequential data windows, and splitting the dataset into training (80%) and testing (20%) sets. These steps are aimed at preparing the data for efficient and accurate learning using the GRU model (Abeltino et al., 2022; Tomazzoli et al., 2024).

GRU Model Architecture

The GRU model was constructed using a sequential architecture with the following components: input layer: configured for time-series data with a window size of 5; GRU layer: a hidden layer consisting of 64 units, optimized to learn sequential patterns; dense layers: a dense layer with 8 neurons and relu activation function, followed by a final dense layer with linear activation for numerical output; and the model was compiled using the adam optimizer and the mean squared error (MSE) loss function, with root mean squared error (RMSE) as the evaluation metric (Bi et al., 2023).

Model Training and Evaluation

The model was trained over 100 epochs. Evaluation was performed using RMSE to quantify the deviation between predicted and actual rainfall values. The final model performance was analyzed across the four regions to determine its effectiveness in capturing rainfall trends and addressing extreme values (Berndt et al., 2020).

Result and Discussion

The results of this study present the performance of the GRU model in predicting rainfall for four regions in Mataram: Ampenan, Cakranegara, Majeluk, and Selaparang. The model was evaluated using RMSE to measure prediction accuracy and visualized through graphs comparing predicted rainfall against BMKG observation data.

Model Performance Evaluation

The GRU model achieved RMSE values of 67, 112, 69, and 109 for Ampenan, Cakranegara, Majeluk, and Selaparang, respectively. These results indicate that the model effectively captures rainfall trends, with Ampenan and Majeluk showing better predictive accuracy. However, higher RMSE in Cakranegara and Selaparang suggests limited accuracy in extreme rainfall conditions.

Visualization of Rainfall Trends

Graphs comparing predicted and observed rainfall highlight the model's ability to follow seasonal patterns. For instance, in Ampenan, the predicted data closely matched BMKG trends, particularly during peak rainfall periods. However, deviations were noted in extreme cases, such as significant rainfall spikes and rapid changes in patterns.

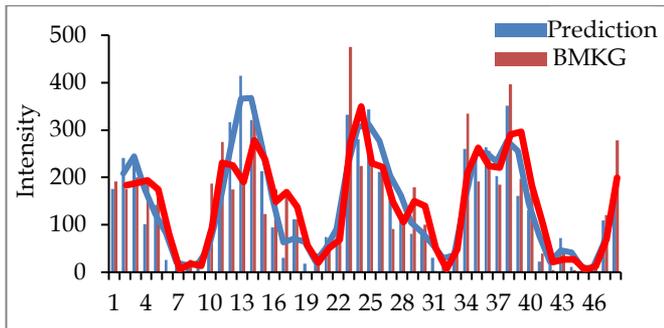


Figure 2. Comparison Predicted Results vs BMKG

The graph compares the predicted rainfall intensity generated by the GRU model with the observed data from BMKG for the Ampenan region between 2020 and 2023. Overall, the predictions successfully followed the patterns observed in the BMKG data, although there were some notable discrepancies at specific points (Ji et al., 2021).

For instance, during peak rainfall periods, such as November 2021 and February 2023, the GRU model tended to overestimate rainfall, producing values slightly higher than BMKG observations. Similarly, during low rainfall periods, such as August 2022, the model occasionally underestimated the intensity. These discrepancies suggest that while the GRU model is effective in capturing general trends, its sensitivity to extreme changes, such as sudden increases or decreases in rainfall, requires improvement. Enhancements in model architecture or data preprocessing could further optimize prediction accuracy and reduce these deviations (Giordani et al., 2023).

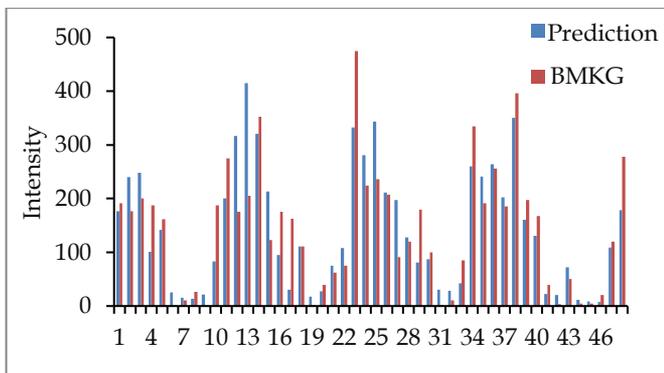


Figure 3. Annual trends predictions and BMKG

The predicted rainfall closely follows the seasonal trends observed in the BMKG data, indicating that the GRU model effectively captures the general pattern of rainfall fluctuations. Notable peaks in rainfall, such as in November 2021 and February 2023, are observed in both the predicted and observed datasets, showing that the model is able to identify these significant wet periods (Bochenek & Ustrnul, 2022).

However, some discrepancies are evident, particularly during the dry months, where the predicted rainfall slightly diverges from BMKG data. For example, in August 2022, the GRU model slightly underestimated the rainfall intensity. Despite these minor differences, the model effectively mirrors the broader trends in the BMKG data, though further refinement is needed for more accurate predictions during extreme conditions.

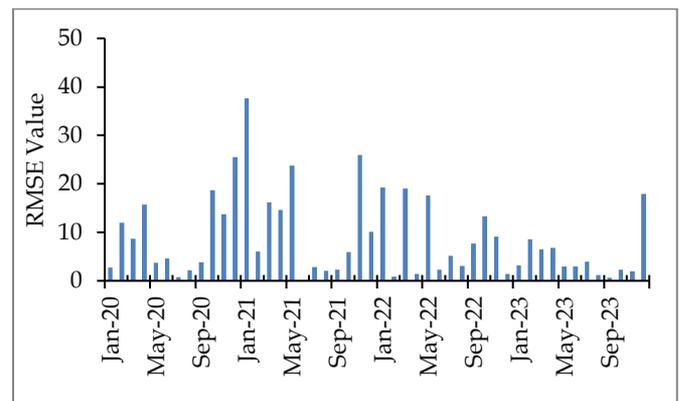


Figure 4. RMSE graphics

This figure presents the Root Mean Squared Error (RMSE) values for the GRU model's rainfall predictions in Ampenan compared to BMKG observations from 2020 to 2023. The RMSE values measure the accuracy of the model, with lower values indicating better alignment with the actual data. Ampenan exhibited the lowest RMSE among the four regions studied, highlighting the GRU model's effectiveness in predicting rainfall trends in this area (Kalu & Madueme, 2018; Zhang et al., 2023). The low RMSE values suggest that the model successfully captured the general seasonal patterns and intensity of rainfall, even during peak wet months such as November 2021 and February 2023.

Although the model demonstrated strong performance, minor discrepancies were still observed during periods of rapid rainfall fluctuations. For example, during certain dry months, slight overestimations occurred, which contributed to small increases in the RMSE. Overall, the low RMSE values for Ampenan underscore the GRU model's capability to accurately predict rainfall in areas with relatively stable meteorological patterns. Further refinement of the model could potentially reduce the small deviations

observed in extreme or transitional periods (Clarke et al., 2022; Praveen et al., 2020).

The results obtained are better compared to the results obtained in research conducted by Aprianto et al. (2024) who tried to analyze the pattern of the rainy and dry seasons based on rainfall data for 2024 using ANN, where the general error in the RMSE score was 3.3, as well as the research results obtained by Diandra et al. (2022) who used LSTM to predict climate in Indonesia, where the error results obtained with an RMSE score was 3.7. The error results obtained in this study were better with an RMSE score of 2. This could happen because the model used in the two previous studies was LSTM, whereas in this study used GRU, which is a development and refinement of the LSTM model (Li & Qian, 2022).

Similar research results were also obtained by Kumar (2024) who made predictions of the number of solar sunspots using GRU, which resulted in an error of 2.7. This shows that using GRU provides better and more accurate prediction results compared to using LSTM (Lesik et al., 2020).

Conclusion

This study demonstrates the effectiveness of the Gated Recurrent Unit (GRU) model in predicting rainfall in Mataram City using hourly data from NASA's MERRA Power. The model successfully captures general seasonal rainfall trends across four regions: Ampenan, Cakranegara, Majeluk, and Selaparang. The evaluation results, based on Root Mean Squared Error (RMSE), indicate that the GRU model provides reasonable accuracy, with lower errors in Ampenan and Majeluk, while Cakranegara and Selaparang show higher RMSE values, suggesting challenges in predicting extreme rainfall events. Compared to traditional statistical models, GRU exhibits superior performance in processing sequential meteorological data. However, its limitations in handling extreme weather conditions highlight the need for further improvements, such as incorporating additional climate variables, optimizing model architecture, and utilizing hybrid deep learning approaches. The findings of this study have significant practical implications. More accurate rainfall predictions can support urban flood mitigation strategies, optimize agricultural planning, and improve early warning systems for disaster preparedness. Future research should explore integrating real-time weather station data and satellite imagery to enhance the model's predictive capability and robustness in different climatic conditions.

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Author Contributions

This article was written by Galih Dimas Aryoso as the creator and Mrs. Bulkis Kanata and Mr. Made Sutha Yadnya as the supervisor.

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Conflicts of Interest

The authors declare no conflict of interest.

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