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Analysis of Interrelationships between Weather Parameters in North Jakarta and Central Jakarta Based on Predictions Using LSTM and GRU

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Abstract. This study analyzes the interrelationships between weather parameters, including average temperature (Tavg), relative humidity (RH_avg), rainfall (RR), and average wind speed (ff_avg) in North Jakarta and Central Jakarta, and compares the performance of Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models in predicting these parameters. Data was collected from Tanjung Priok Maritime Meteorological Station in North Jakarta and Kemayoran Meteorological Station in Central Jakarta from December 2021 to December 2024. The results show that GRU performs better in North Jakarta, with RMSE of 9,02, MSE of 81,28, and MAE of 4,21 at 75 epochs, while LSTM yields RMSE of 10,02, MSE of 100,34, and MAE of 4,62 at 50 epochs. Conversely, LSTM outperforms GRU in Central Jakarta, with RMSE of 8,96, MSE of 80,22, and MAE of 4,65 at 100 epochs, while GRU produces RMSE of 9,53, MSE of 90,78, and MAE of 4,85 at 75 epochs. GRU is more effective in capturing extreme fluctuations, while LSTM excels in predicting interrelationships between parameters. This study provides insights into selecting the appropriate weather prediction model based on the priority of prediction accuracy or the ability to capture extreme fluctuations.

Keywords: LSTM, GRU, Weather Prediction, Weather Parameters, Prediction Accuracy

1 Introduction

Weather is an atmospheric phenomenon that greatly influences human life, especially in tropical countries such as Indonesia. Located on the equator, Indonesia experiences dynamic weather variations, ranging from clear skies to heavy rainfall. Jakarta, although located in a lowland area, frequently experiences extreme weather events such as heavy rainfall and heatwaves, which can disrupt various sectors, including agriculture, fisheries, transportation, and tourism. Weather is defined as the atmospheric condition measured comprehensively by considering the changes and developments of air phenomena [1].

As one of the largest metropolitan areas in Indonesia, Jakarta experiences highly dynamic and frequently changing weather. Sudden heavy rain can cause flooding, while long dry periods often trigger heatwaves. Rapid urban development, environmental degradation, and global climate change contribute to significant weather fluctuations in Jakarta. Changes in rainfall patterns, temperature, and humidity due to climate change can increase the risk of flooding and pose a threat to the agricultural sector [2].

The use of machine learning in weather prediction is not limited to rainfall but also includes other weather parameters that are time series data [3]. Deep learning, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), is widely used to accurately predict weather parameters. While LSTM is effective in handling complex time series data and requires greater computational resources, GRU is more efficient for smaller datasets [4]. Both methods address the vanishing gradient problem in Recurrent Neural Networks (RNN) and can process long-term temporal relationships between weather parameters.

Although BMKG has developed weather prediction models, the accuracy of predictions remains a significant challenge. Experts at BMKG believe that the accuracy of weather predictions is still insufficient, which is why ongoing research is being conducted to select methods that can improve accuracy [5]. Research conducted in Bandung City showed that LSTM produced good accuracy in predicting rainfall, with an RMSE value of 12,24 for training data and 8,86 for test data [6].

Similar research was conducted in Malang Regency using LSTM, showing promising results with an RMSE value of 10,16 [7]. In Pekanbaru City, a study also used LSTM and reported an RMSE of 21,328 for training data and 454,901 for test data [8]. Meanwhile, in Surabaya City, a study compared the performance of LSTM, GRU, and RNN, with LSTM showing the best performance with an MSE value of 0,489 [9]. Humidity is

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influenced by temperature, air pressure, and wind movement, highlighting the importance of considering the interrelationship between weather parameters in the development of predictive models [10].

This research contributes to the development of weather prediction technology by analyzing the relationships between various weather parameters and comparing the effectiveness of LSTM and GRU models in different urban contexts. The findings of this study are expected to help develop more accurate and adaptive weather prediction systems, benefiting various sectors that rely on weather information for their operations.

2 Methodology

This study follows a systematic approach, starting with dataset collection and input, followed by data preprocessing to prepare the data for modeling. The research implements LSTM and GRU models for analysis, followed by a denormalization process to bring the results back to their original scale. Evaluation testing is then performed to assess the performance of the models. Finally, the interrelationship between weather parameters is analyzed. Figure 1 provides a clear picture of the flow of the research process.

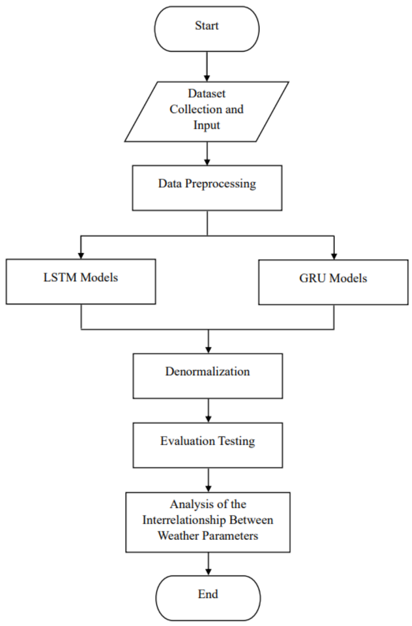

Figure 1. Research Methodology Flowchart

2.1 Dataset Collection and Input

The dataset for this study was sourced from two meteorological stations in Jakarta: Tanjung Priok Maritime Meteorological Station in North Jakarta and Kemayoran Meteorological Station in Central Jakarta, covering the period from December 2021 to December 2024. Time series data collected in continuous time sequence is one of the statistical methods that can be used to predict the probability structure of future situations [11].
Key weather parameters considered include:

a. Average temperature (Tavg): Air temperature in an area can be measured based on two conditions: minimum and maximum air temperature [12].
b. Average relative humidity (RH_avg): Relative humidity is defined as the ratio of measured water vapor pressure to the maximum water vapor pressure that can be achieved at a given temperature and pressure [13].
c. Rainfall (RR): Rainfall is a key weather parameter that can cause changes in weather conditions in an area and plays a critical role in understanding atmospheric dynamics [14].
d. Average wind speed (ff_avg): Wind speed is a critical weather parameter that influences atmospheric dynamics through its interactions with temperature and humidity [15].

Parameters such as temperature, wind speed, and humidity were selected because they significantly influence rainfall, which is crucial for meteorological prediction [16].

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The data was obtained from the online database of the Indonesian Agency for Meteorological, Climatological and Geophysics (Badan Meteorologi, Klimatologi, dan Geofisika or simply BMKG), specifically from the official website at https://dataonline.bmkg.go.id/data-harian. BMKG provides comprehensive daily weather data for various regions in Indonesia, ensuring the reliability and accuracy of the dataset used in this study.

2.2 Data Preprocessing

Data preprocessing is a critical step to ensure the quality and integrity of the dataset before applying machine learning models. LSTM is designed to handle data with long-term temporal dependencies, making proper preprocessing essential [17]. The following steps were taken:

a. Data Cleaning
   Duplicate and irrelevant data were removed. Missing values, indicated by placeholders such as "-" or "8888", were handled using imputation techniques.
b. Handling Missing Data
   Missing values were imputed using the mean of the respective parameter over a specified period, as this approach is effective for datasets with normal distributions.
c. Data Splitting
   The dataset was split into training (80%), validation (10%), and test (10%) sets to train and evaluate the models.
d. Normalization
   Data normalization was performed using Min-Max scaling to ensure all weather parameters were within a comparable range of 0 to 1. The normalization formula is as follows:

$$X' = \frac{(x - Xmin)}{(Xmax - Xmin)} \quad (1)$$

Explanation:

X	= Original data.
$Xmin\ Xmax$	= Minimum and maximum values of the parameter.
X'	= Normalized value.

2.3 Implementation of LSTM and GRU Models

LSTM and GRU models were implemented for weather prediction, leveraging their ability to handle time series data and capture temporal dependencies. LSTM is designed to address the vanishing gradient problem in RNN by introducing memory cells and gate mechanisms (gates), such as forget gate, input gate, and output gate [18]. The LSTM approach enables complex modeling of meteorological parameters, allowing for more nuanced prediction of interrelated weather variables such as rainfall, humidity, and temperature [19].

a. LSTM Gates: Forget Gate, Input Gate, Candidate Cell State, Output Gate, Update Cell State, Hidden State.
b. GRU Gates: Reset Gate, Update Gate, Candidate Hidden State, Current Hidden State.
   The models were trained and evaluated through the following steps:
   1. Model Architecture: Both LSTM and GRU architectures were chosen to handle time series data for weather prediction. LSTM was selected for capturing long-term dependencies, while GRU was chosen for its computational efficiency, especially for smaller datasets. Both models utilize hidden layers to learn relationships between relevant weather parameters.
   2. Training: The models were trained on pre-processed weather data for different epochs:
      a) LSTM North Jakarta: 50 epochs.
      b) LSTM Central Jakarta: 100 epochs.
      c) GRU North Jakarta: 75 epochs.
      d) GRU Central Jakarta: 75 epochs.

Adam optimizer was used to maximize accuracy and minimize error. Validation data helped monitor performance and detect overfitting. If validation loss stopped improving, early stopping was applied. Final evaluation was done on test data to assess the models' generalization ability.

a. Model Storage: After training, the best-performing models from both LSTM and GRU were saved for future use, ensuring faster predictions in subsequent implementations.

2.3.1 LSTM Gates and States Calculations

LSTM uses three main gates: Forget Gate, Input Gate, and Output Gate. In addition, the LSTM process also involves calculating Candidate Cell State, Update Cell State, and Hidden State. The order of the operations is as follows:

a. Forget Gate: The forget gate determines which information from the previous time step will be discarded from the cell state.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

b. Input Gate: The input gate controls how much new information will be added to the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

c. Candidate Cell State: The candidate cell state represents the potential new information to be added to the memory.

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{4}$$

d. Output Gate: The output gate determines which part of the cell state will be output as the hidden state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t]) + b_o \tag{5}$$

e. Update Cell State and Hidden State: The cell state is updated by combining the previous state with the new candidate cell state, weighted by the forget and input gates.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

$$h_t = o_t * \tanh(C_t) \tag{7}$$

The final Hidden State h_t is generated after applying the output gate to the updated cell state C_t.

Explanation:

x_t	= Input data at time step t.
h_{t-1}	= Hidden state from the previous time step.
C_{t-1}	= Cell state from the previous time step.
W_f, W_i, W_C, W_o	= Weight matrices for each gate.
b_f, b_i, b_C, b_o	= Bias terms for each gate.
σ	= Sigmoid activation function.
tanh	= Hyperbolic tangent activation function.

2.3.2 GRU Gates and States Calculations

GRU uses two main gates: Reset Gate and Update Gate. It combines the memory updating process into one hidden state. The GRU also includes the Candidate Hidden State and Current Hidden State. The operations are as follows:

a. Reset Gate: The reset gate determines how much of the previous hidden state should be forgotten.

$$r_t = \sigma(W_r \cdot x_t + U_r \cdot h_{t-1} + b_r) \tag{8}$$

b. Update Gate: The update gate controls how much of the new information should be added to the hidden state.

$$z_t = \sigma(W_z \cdot x_t + U_z \cdot h_{t-1} + b_z) \tag{9}$$

c. Candidate Hidden State: The candidate hidden state represents the new information to be added to the hidden state.

$$\tilde{h}_t = \tanh(W_h \cdot x_t + U_h \cdot (r_t * h_{t-1}) + b_h) \tag{10}$$

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d. Current Hidden State: The current hidden state is the weighted combination of the previous hidden state and the new candidate hidden state.

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (11)$$

Explanation:

x_t	= Input data at time step t.
h_{t-1}	= Hidden state from the previous time step.
W_r, W_z, W_h	= Weight matrices that connect x_t to the gates.
U_r, U_z, U_h	= Weight matrices that connect h_{t-1} to the gates.
b_r, b_z, b_h	= Bias terms for each gate.
σ	= Sigmoid activation function.
tanh	= Hyperbolic tangent activation function.

2.4 Denormalization

After predictions were made, denormalization was performed to return the data to its original scale using the inverse of the Min-Max scaling formula:

$$d = d'(max - mix) + min \quad (12)$$

Explanation:

d'	= Predicted normalized value.
$min\ max$	= Minimum and maximum values of the respective parameter.
d	= Denormalized value.

2.5 Evaluation Testing

LSTM and GRU models was conducted using three key metrics: Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE). MSE and RMSE are used to reflect overall model errors [20], while MSE provides an overview of overall error distribution and is also sensitive to large errors, making it suitable for measuring average error [21]. Furthermore, the smaller the RMSE and MAE values, the better the model in predicting data with a low error rate [22].

a. Root Mean Square Error (RMSE): RMSE measures the square root of the average squared differences between predicted and actual values. It penalizes larger errors more than smaller ones, making it sensitive to outliers.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2} \quad (13)$$

A lower RMSE indicates better model performance, as it implies that the predictions are closer to the actual values.

b. Mean Square Error (MSE): MSE is calculated by averaging the squared differences between predicted and actual values. It is more sensitive to larger errors than MAE, which makes it useful for identifying larger discrepancies in the model's predictions.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2 \quad (14)$$

Where the terms are defined as above. Like RMSE, a lower MSE indicates better performance. MSE is particularly useful when you want to give higher importance to larger errors.

c. Mean Absolute Error (MAE): MAE calculates the average of the absolute differences between the predicted and actual values. It is less sensitive to outliers than RMSE and MSE, making it a straightforward and easy-to-interpret metric.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{y}i| \quad (15)$$

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A lower MAE indicates that the predictions are, on average, closer to the actual values, with less emphasis on large deviations. MAE is particularly useful when a straightforward understanding of average prediction error is needed.

Explanation:
yi = Actual value of the weather parameter.
$\hat{y}i$ = Predicted value of the weather parameter.
n = Number of days in the evaluated data.

These metrics were selected due to their wide acceptance in the literature and their flexibility in handling various types of data without introducing significant bias. The comprehensive use of these three metrics helps to evaluate the model's performance across multiple aspects, offering insights into how well the model can predict weather parameters, including temperature, humidity, rainfall, and wind speed.

2.6 Analysis of the Interrelationship Between Weather Parameters

The analysis of interrelationships between weather parameters is conducted through three comprehensive approaches. Each approach provides unique insights into how weather parameters interact and how well the models capture these relationships.

First, the Evaluation Metrics Analysis employs three key statistical measures: RMSE, MSE, and MAE. These metrics are used to quantitatively assess the prediction accuracy of both LSTM and GRU models in North Jakarta and Central Jakarta. The comparative analysis of these metrics provides a statistical foundation for understanding how well each model performs in different regions and for different weather parameters.

Second, the Visualization Analysis focuses on comparing prediction graphs with actual data to understand how well the models capture weather patterns. This analysis examines the models' capabilities in handling various aspects of weather data, including regular weather patterns, extreme fluctuations, parameter interdependencies, and temporal variations. Through visual analysis, it is possible to assess how effectively each model adapts to different weather conditions and identify patterns in the data.

Third, the Direct Prediction Model Analysis evaluates the models' accuracy in predicting specific weather parameters: average temperature (Tavg), relative humidity (RH_avg), rainfall (RR), and average wind speed (ff_avg). This analysis includes a comparative assessment of model performance between the two regions and examines how different parameters influence each other based on prediction results. This direct approach helps understand the practical applicability and reliability of each model in real-world weather prediction scenarios.

The combined insights from these three analytical approaches provide a comprehensive understanding of the models' capabilities and limitations in predicting weather parameters and their interrelationships. This understanding is crucial for determining which model is more suitable for specific prediction tasks and environmental conditions.

3 Results and Discussion

This section presents the results from the application of LSTM and GRU models, followed by an evaluation of the interrelationship between weather parameters.

3.1 Dataset Collection and Input

The dataset used for this study spans from December 1, 2021, to December 31, 2024, and was collected from the Tanjung Priok and Kemayoran Meteorological Stations in Central Jakarta. A sample dataset from December 2021 was used for training and testing, including key weather parameters such as temperature (Tavg), relative humidity (RH_avg), rainfall (RR), and wind speed (ff_avg), all obtained from BMKG's database. Table 1 below shows a sample of the raw data from December 1 to December 10, 2021, collected from the Kemayoran Meteorological Station in Central Jakarta.

Table 1. Raw Dataset Sample

Date	Tavg	RH_avg	RR	ff_avg
01-12-2021	29,9	63	-	2
02-12-2021	30,7	66	0	3
03-12-2021	29,6	71	-	2
04-12-2021	-	85	0	1

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05-12-2021	26,2	85	2,5	0
06-12-2021	26,8	84	11,9	1
07-12-2021	26,8	86	65,6	1
08-12-2021	28,1	81	1,5	1
09-12-2021	28	84	30,5	2
10-12-2021	28,1	82	0,6	2

3.2 Data Preprocessing

Data preprocessing involved several essential steps: data cleaning, handling missing values, and normalizing the data. First, duplicate entries and irrelevant data were removed to ensure data quality. Missing values were addressed using mean imputation, and normalization was performed using Min-Max Scaling to bring all parameters to a uniform scale between 0 and 1. This step ensured that the dataset was well-prepared for modeling with LSTM and GRU. Table 2 below shows a sample of the cleaned data, and Table 3 displays the normalized data.

Table 2. Dataset Sample After Data Cleaning

Date	Tavg	RH_avg	RR	ff_avg
01-12-2021	29,9	63	8,54	2
02-12-2021	30,7	66	0	3
03-12-2021	29,6	71	8,54	2
04-12-2021	28,2	85	0	1
05-12-2021	26,2	85	2,5	0
06-12-2021	26,8	84	11,9	1
07-12-2021	26,8	86	65,6	1
08-12-2021	28,1	81	1,5	1
09-12-2021	28	84	30,5	2
10-12-2021	28,1	82	0,6	2

Table 3. Dataset Sample After Normalization

Date	Tavg	RH_avg	RR	ff_avg
01-12-2021	0,822	0	0,130	0,667
02-12-2021	1	0,12	0	1
03-12-2021	0,756	0,32	0,130	0,667
04-12-2021	0,451	0,88	0	0,333
05-12-2021	0	0,88	0,038	0
06-12-2021	0,133	0,84	0,181	0,333
07-12-2021	0,133	0,92	1	0,333
08-12-2021	0,422	0,72	0,023	0,333
09-12-2021	0,400	0,84	0,465	0,667
10-12-2021	0,422	0,76	0,009	0,667

3.3 Implementation of LSTM and GRU Models

Both the LSTM and GRU models were used to predict the weather parameters. LSTM, with its forget, input, and output gates, captured long-term dependencies in the time series data, while GRU, using reset and update gates, was tested for comparison. Both models processed the dataset and were evaluated on their ability to predict weather data accurately. Tables 4 and 5 below display the results from the manual calculations for the LSTM and GRU models, respectively, using the sample data.

Table 4. Manual LSTM Calculation Results from the Dataset Sample

Date	*Forget Gate* (f_t)	*Input Gate* (i_t)	*Candidate Cell State* ($\tilde{C}_t$)	*Output Gate* (o_t)	*Cell State* (C_t)	*Hidden State* (h_t)
01-12-2021	0,638	0,608	0,155	0,584	0,0944	0,055
02-12-2021	0,668	0,694	0,0295	0,709	0,0835	0,059

03-12-2021	0,612	0,672	0,443	0,590	0,3482	0,197
04-12-2021	0,5546	0,566	0,521	0,5115	0,4883	0,2319
05-12-2021	0,4963	0,5037	0,3504	0,4736	0,4187	0,1875
06-12-2021	0,5019	0,5159	0,2338	0,4957	0,3305	0,1581
07-12-2021	0,6113	0,5467	0,0262	0,5410	0,2162	0,1153
08-12-2021	0,5300	0,5227	0,2581	0,5171	0,2494	0,1263
09-12-2021	0,5619	0,5368	0,2199	0,5393	0,2582	0,1362
10-12-2021	0,5417	0,5237	0,2801	0,5220	0,2865	0,1456

Table 5. Manual GRU Calculation Results from the Dataset Sample

Date	***Reset Gate*** (r_t)	***Update Gate*** (z_t)	***Candidate Hidden State*** $(\tilde{h}_t)$	***Current Hidden State*** (h_t)
01-12-2021	0,708	0,632	0,794	0,502
02-12-2021	0,735	0,678	0,853	0,739
03-12-2021	0,749	0,688	0,785	0,770
04-12-2021	0,733	0,706	0,667	0,698
05-12-2021	0,693	0,666	0,417	0,511
06-12-2021	0,705	0,678	0,620	0,583
07-12-2021	0,776	0,723	0,811	0,746
08-12-2021	0,713	0,682	0,694	0,710
09-12-2021	0,748	0,719	0,779	0,759
10-12-2021	0,734	0,662	0,844	0,814

3.4 Denormalization

After generating predictions with the models, the results were still in their normalized form. Denormalization was applied to return the predictions to their original scale, allowing for direct comparison with actual weather data. This process ensures that the predicted values are in the correct unit scale, making the evaluation meaningful. Table 6 below shows the sample data that has been denormalized back to its original scale.

Table 6. Dataset Sample After Denormalization

Date	Tavg LSTM	Tavg GRU	RH_avg LSTM	RH_avg GRU	RR LSTM	RR GRU	ff_avg LSTM	ff_avg GRU
01-12-2021	26,45	28,46	64,38	75,55	3,61	32,93	0,17	1,51
02-12-2021	26,47	29,53	64,48	81,48	3,87	48,51	0,18	2,22
03-12-2021	27,09	29,67	67,93	82,25	12,92	50,55	0,59	2,31
04-12-2021	27,24	29,34	68,80	80,45	15,21	45,75	0,70	2,09
05-12-2021	27,04	28,50	67,69	75,78	12,30	33,47	0,56	1,53
06-12-2021	26,91	28,82	66,95	77,58	10,37	38,23	0,47	1,75
07-12-2021	26,72	29,56	65,88	81,65	7,56	48,94	0,35	2,24
08-12-2021	26,77	29,40	66,16	80,75	8,29	46,50	0,38	2,13
09-12-2021	26,81	29,62	66,41	81,98	8,95	49,79	0,41	2,28
10-12-2021	26,86	29,86	66,64	83,35	9,55	53,39	0,44	2,44

3.5 Evaluation Testing

The performance of the LSTM and GRU models was evaluated using three main metrics: RMSE, MSE, and MAE. These metrics were used to measure the prediction error in comparison to the actual weather data.

Table 7 below presents an example of the calculated differences ($yi - \hat{y}i$) for the sample data on temperature (Tavg) in the LSTM method. It is important to note that yi represents the actual value of the weather parameter (Tavg) from the dataset, and $\hat{y}i$ represents the predicted value of the weather parameter (Tavg) from the model's output.

yi = Actual value of the weather parameter (Tavg).

$\hat{y}i$ = Predicted value of the weather parameter (Tavg).

n = Number of days in the evaluated data (10 days, corresponding to the sample from December 1 to December 10, 2021).

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This calculation is done for each day in the dataset. Table 7 provides a sample calculation of the difference between the actual and predicted values for the Tavg parameter.

Table 7. Calculation of the Difference Between the Actual Value and the Predicted Value (Tavg LSTM)

Day	yi	$\hat{y}i$	Difference $(yi - \hat{y}i)$	Squared Difference $(yi - \hat{y}i)^2$
1	29,9	26,45	3,45	11,9025
2	30,7	26,47	4,23	17,8929
3	29,6	27,09	2,51	6,3001
4	28,2	27,24	0,96	0,9216
5	26,2	27,04	-0,84	0,7056
6	26,8	26,91	-0,11	0,0121
7	26,8	26,72	0,08	0,0064
8	28,1	26,77	1,33	1,7689
9	28,0	26,81	1,19	1,4161
10	28,1	26,86	1,24	1,5376
	Total		14,04	42,4638

Following this, the evaluation metrics for the Tavg parameter were computed to assess the accuracy of the models.

a. Calculate RMSE using the total squared differences

$$RMSE = \sqrt{\frac{42{,}4638}{10}} \approx \sqrt{4{,}24638} \approx 2{,}06$$

b. Calculate RMSE using the total squared differences

$$MSE = \frac{42{,}4638}{10} \approx 4{,}2464$$

c. Calculate MAE using the total differences

$$MAE = \frac{14{,}04}{10} \approx 1{,}404$$

Following the manual calculation of RMSE, MSE, and MAE for the Tavg parameter, Table 8 presents the evaluation results for all parameters, including temperature (Tavg), relative humidity (RH_avg), rainfall (RR), and wind speed (ff_avg), based on the predictions from the LSTM and GRU models.

Table 8. Evaluation Test Results from the Dataset Sample

Parameters and Methods	RMSE	MSE	MAE
Tavg LSTM	2,06	4,25	1,40
Tavg GRU	1,71	2,91	1,56
RH_avg LSTM	14,27	203,68	12,44
RH_avg GRU	8,34	69,55	6,74
RR LSTM	20,85	434,74	13,51
RR GRU	37,31	1391,98	35,17
ff_avg LSTM	1,41	1,97	1,19
ff_avg GRU	0,90	0,81	0,80

3.6 Analysis of the Interrelationship Between Weather Parameters

This section presents the analysis of the relationship between weather parameters, including insights based on evaluation metrics, visualizations, and direct model prediction results.

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3.6.1 Based on Evaluation Metrics

Table 9 below presents the evaluation results from the full dataset, highlighting the best-performing models based on their evaluation metrics (RMSE, MSE, and MAE). The table emphasizes the performance of the LSTM and GRU models across different epochs and regions (North Jakarta and Central Jakarta).

Table 9. Evaluation Test Results from the Dataset

Model	Epochs	Region	Train RMSE	Test RMSE	Train MSE	Test MSE	Train MAE	Test MAE
LSTM	25	North Jakarta	10,18	11,17	103,68	124,88	3,84	5,36
LSTM	50	North Jakarta	10,15	10,02	103,03	100,34	4,01	4,62
LSTM	75	North Jakarta	10,41	10,25	108,33	105,09	4,24	4,96
LSTM	100	North Jakarta	9,90	11,03	98,09	121,60	3,59	5,27
LSTM	25	Central Jakarta	7,48	9,62	55,90	92,51	3,13	4,90
LSTM	50	Central Jakarta	7,71	10,11	59,38	102,19	3,13	5,25
LSTM	75	Central Jakarta	7,12	9,40	50,69	88,29	3,07	4,81
LSTM	100	Central Jakarta	7,25	8,96	52,50	80,22	3,19	4,65
GRU	25	North Jakarta	10,20	11,32	104,09	128,09	3,88	5,34
GRU	50	North Jakarta	10,00	10,83	100,09	117,36	3,60	5,04
GRU	75	North Jakarta	9,86	9,02	97,25	81,28	3,71	4,21
GRU	100	North Jakarta	9,49	9,64	90,02	92,83	3,46	4,43
GRU	25	Central Jakarta	7,57	9,95	57,34	99,10	3,10	5,07
GRU	50	Central Jakarta	7,32	9,90	53,64	97,98	3,12	4,99
GRU	75	Central Jakarta	7,37	9,53	54,38	90,78	3,04	4,85
GRU	100	Central Jakarta	7,88	10,70	62,08	114,54	3,14	5,43

a. Best Results Based on Model and Region
   1. LSTM
      a) North Jakarta: 50 epoch (Test RMSE: 10,02, Test MSE: 100,34, Test MAE: 4,62)
      b) Central Jakarta: 100 epoch (Test RMSE: 8,96, Test MSE: 80,22, Test MAE: 4,65)
   2. GRU
      a) North Jakarta: 75 epoch (Test RMSE: 9,02, Test MSE: 81,28, Test MAE: 4,21)
      b) Central Jakarta: 75 epoch (Test RMSE: 9,53, Test MSE: 90,78, Test MAE: 4,85)

b. Best Overall Results
   1. North Jakarta: GRU 75 epoch (Test RMSE: 9,02, Test MSE: 81,28, Test MAE: 4,21)
   2. Central Jakarta: LSTM 100 epoch (Test RMSE: 8,96, Test MSE: 80,22, Test MAE: 4,65)

c. Conclusion Based on Evaluation Metrics
   The evaluation results show that:
   1. In North Jakarta, GRU (75 epochs) outperforms LSTM (50 epochs) across all metrics: RMSE, MSE, and MAE.
   2. In Central Jakarta, LSTM (100 epochs) outperforms GRU (75 epochs) across all metrics: RMSE, MSE, and MAE.

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In summary, GRU is more effective for weather prediction in North Jakarta, while LSTM performs better in Central Jakarta based on the evaluation metrics. However, the accuracy based on visualization and model prediction results will be analyzed further.

3.6.2 Based on Visualization

The following visualizations (Figures 2 to 5) provide insights into how well the models (LSTM and GRU) captured the weather patterns across different parameters.

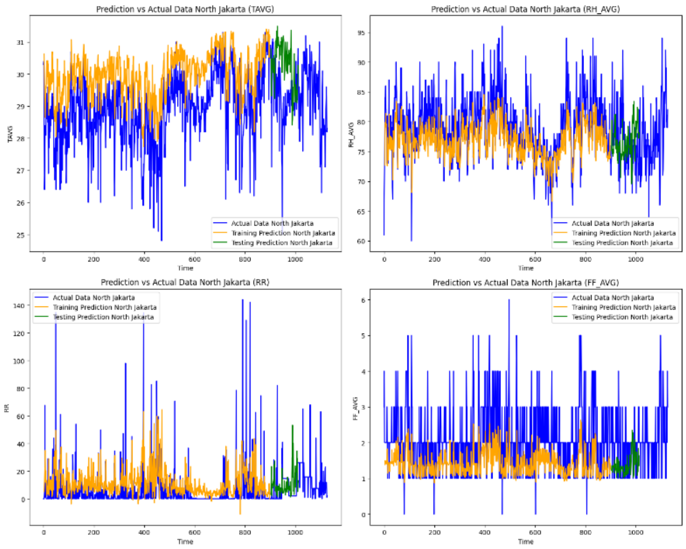

Figure 2. LSTM Prediction vs Actual Data Chart for North Jakarta

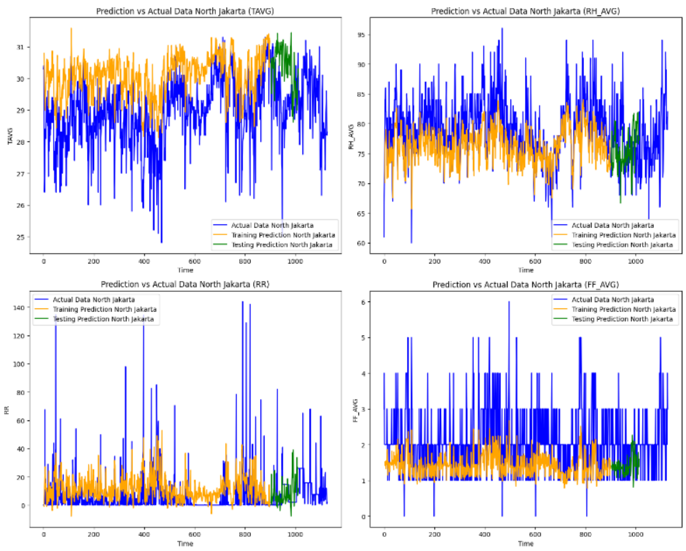

Figure 3. GRU Prediction vs Actual Data Chart for North Jakarta

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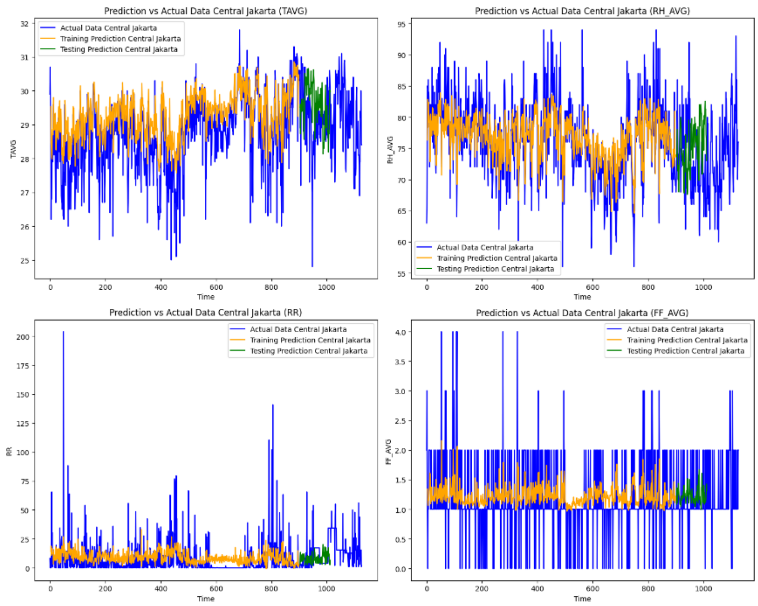

Figure 4. LSTM Prediction vs Actual Data Chart for Central Jakarta

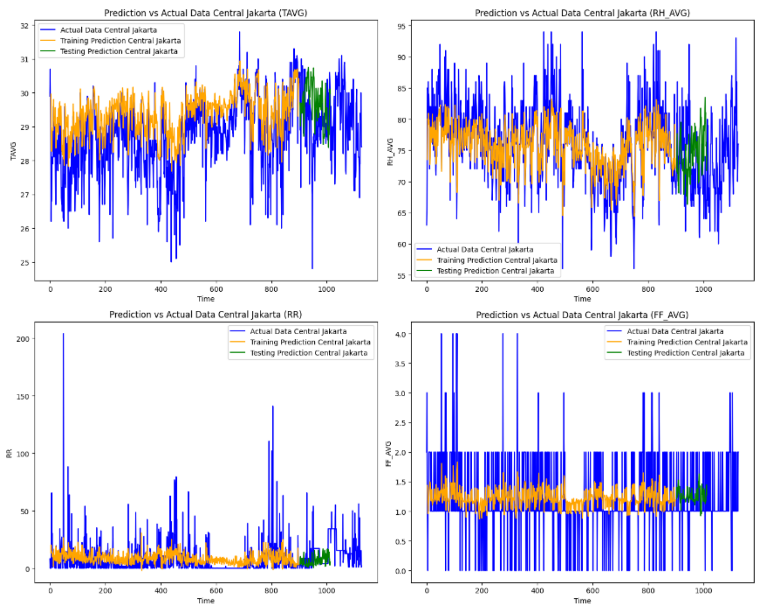

Figure 5. GRU Prediction vs Actual Data Chart for Central Jakarta

a. Data Source: The blue line represents actual weather data, while the orange and green lines represent predictions from the training and testing data, respectively.
b. LSTM Model Analysis (North Jakarta):
   1. Tavg (Temperature Average): LSTM captures the general temperature trend but is less responsive to rapid fluctuations. Predictions are smoother compared to actual data.
   2. RH_avg (Relative Humidity Average): LSTM performs reasonably well in tracking humidity patterns, though some small deviations are observed in peak values.
   3. RR (Rainfall): LSTM struggles with capturing extreme values of rainfall, leading to smoother predictions that fail to capture spikes in rainfall.
   4. ff_avg (Wind Speed Average): LSTM captures the general wind speed trends but is less accurate in predicting extreme values.
c. GRU Model Analysis (North Jakarta):
   1. Tavg (Temperature Average): GRU is more responsive to smaller fluctuations, better capturing seasonal patterns compared to LSTM.
   2. RH_avg (Relative Humidity Average): GRU captures humidity changes more effectively than LSTM.

3. RR (Rainfall): GRU handles rainfall spikes better, providing more accurate predictions of fluctuating rainfall.
4. ff_avg (Wind Speed Average): GRU performs better in predicting wind speed extremes.

d. LSTM Model Analysis (Central Jakarta):
1. Tavg (Temperature Average): LSTM captures the overall temperature trend well but tends to smooth out rapid changes. The predictions are close to actual values for most of the time, though LSTM sometimes struggles with sudden temperature shifts.
2. RH_avg (Relative Humidity Average): Similar to North Jakarta, LSTM tracks humidity well but has some difficulties in capturing sharp changes in humidity.
3. RR (Rainfall): Like North Jakarta, LSTM struggles to predict extreme fluctuations in rainfall. The model fails to capture the intensity of rainfall peaks.
4. ff_avg (Wind Speed Average): LSTM performs reasonably well for general wind speed trends but doesn't accurately predict the extremes in wind speed.

e. GRU Model Analysis (Central Jakarta):
1. Tavg (Temperature Average): GRU captures the seasonal trends in temperature more effectively than LSTM, especially with sudden temperature shifts.
2. RH_avg (Relative Humidity Average): GRU follows changes in humidity more accurately than LSTM, making it more reliable for this parameter.
3. RR (Rainfall): GRU performs better than LSTM in predicting fluctuating rainfall values, particularly when there are sharp increases or decreases in rainfall.
4. ff_avg (Wind Speed Average): GRU excels at predicting wind speed fluctuations and extreme values, outperforming LSTM in this aspect.

f. Conclusion Based on Visualization
Based on the visual analysis, the GRU model outperforms LSTM in capturing trends and fluctuations in weather parameters, especially in handling sudden changes in the test data. While LSTM performs reasonably well in recognizing general patterns for temperature (Tavg) and humidity (RH_avg), it struggles with predicting extreme changes. Both models face challenges in predicting rainfall (RR) and wind speed (ff_avg) due to their high variability, but GRU remains more stable and accurate in capturing spikes and trend changes. This makes GRU the superior model for weather prediction analysis in both North Jakarta and Central Jakarta.

3.6.3 Based on Direct Model Prediction Results

Table 10 and Table 11 below compare the predicted values from LSTM and GRU against the actual values for North Jakarta (July 6, 2024) and Central Jakarta (July 6, 2024), respectively.

a. North Jakarta (July 6, 2024):
LSTM outperforms GRU as it produces predictions closer to the actual values for all parameters (Tavg, RH_avg, RR, and ff_avg).

b. Central Jakarta (July 6, 2024):
LSTM performs better for 2 out of 4 parameters: RH_avg and ff_avg. However, GRU performs better for 2 out of 4 parameters: Tavg and RR.

Table 10. Comparison of Prediction Results and Actual Values for North Jakarta (July 6, 2024)

Parameter	Actual Value	LSTM Prediction	GRU Prediction	Best Model
Tavg	25	27,29	21,19	LSTM
RH_avg	92	65,98	60,94	LSTM
RR	25	15,63	11,33	LSTM
ff_avg	1	1,46	0,12	LSTM

Table 11. Comparison of Prediction Results and Actual Values for Central Jakarta (July 6, 2024)

Parameter	Actual Value	LSTM Prediction	GRU Prediction	Best Model
Tavg	24,8	27,22	26,40	GRU
RH_avg	92	51,67	50,13	LSTM
RR	15,3	41,44	18,32	GRU
ff_avg	0	0,79	1,40	LSTM

c. Conclusion Based on Direct Model Prediction Results
In North Jakarta, LSTM provides more accurate predictions for all weather parameters. In Central Jakarta, LSTM is more accurate for two parameters (RH_avg and ff_avg), while GRU performs better for two parameters (Tavg and RR). Overall, LSTM is the more reliable model for North Jakarta, while both LSTM and GRU perform better in certain aspects of Central Jakarta's weather predictions.

3.6.4 Conclusion of Results and Discussion

Based on the analyses conducted in the previous sections, the following conclusions can be drawn:

a. Based on Evaluation Metrics
In section 3.6.1, the evaluation of the models was performed using three primary metrics: RMSE, MSE, and MAE. The results show:
   1. In North Jakarta, the GRU model outperforms LSTM with lower test RMSE, MSE, and MAE values, indicating that GRU is more effective in predicting weather parameters in this region.
   2. In Central Jakarta, the LSTM model outperforms GRU with lower test RMSE, MSE, and MAE values, suggesting that LSTM is more effective in predicting weather parameters in this region.

b. Based on Visualization
In section 3.6.2, the visual analysis compared the predicted values with the actual data and examined how the models captured fluctuations in the weather data. The results indicate:
   1. LSTM performs reasonably well in capturing the general trends for temperature (Tavg) and relative humidity (RH_avg). However, it struggles to capture high fluctuations and extreme values in rainfall (RR) and wind speed (ff_avg). This suggests that LSTM is less effective in capturing extreme patterns that occur frequently in these parameters.
   2. GRU shows more consistent performance across all four parameters (Tavg, RH_avg, RR, and ff_avg). It is better at capturing fluctuations and extreme values, especially in RR and ff_avg, where LSTM tends to fail to predict accurately.

c. Based on Direct Model Prediction Results
In section 3.6.3, the models were tested for direct predictions based on manual input provided by the user. The results show:
   1. In North Jakarta, LSTM performs better, as its predictions are closer to the actual values for all four weather parameters (Tavg, RH_avg, RR, and ff_avg).
   2. In Central Jakarta, LSTM is superior for two parameters (RH_avg and ff_avg), while GRU performs better for two parameters (Tavg and RR).

d. Final Conclusion
Based on the findings from the evaluation metrics, visualizations, and direct model predictions, the following conclusions can be made:
   1. If focusing on evaluation metrics:
   GRU outperforms LSTM in North Jakarta due to better performance across all evaluation metrics (RMSE, MSE, MAE). In contrast, LSTM performs better in Central Jakarta, excelling in all evaluation metrics compared to GRU.
   2. If focusing on visualization:
   GRU demonstrates superior consistency in capturing fluctuations and extreme values in both regions (North Jakarta and Central Jakarta), especially for challenging parameters like RR (rainfall) and ff_avg (wind speed), making it more reliable in dealing with unpredictable weather patterns.
   3. If focusing on direct model predictions:
   LSTM excels in North Jakarta, providing more accurate predictions for all four weather parameters. In Central Jakarta, LSTM predicts two weather parameters more accurately than GRU, which only outperforms LSTM in predicting Tavg and RR (wind speed, ff_avg).

In conclusion, LSTM proves to be more accurate for direct weather parameter predictions, especially in North Jakarta, where it successfully predicts all four parameters with greater accuracy. However, GRU excels in capturing extreme patterns, particularly for Tavg and RR, making it more reliable in handling fluctuating weather conditions. Therefore, the choice between LSTM and GRU should depend on the user's specific needs: whether they prioritize statistical accuracy, the ability to capture extreme fluctuations, or the accuracy of direct predictions.

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4 Conclusion

Based on the evaluation of the models, the prediction accuracy of weather parameters such as average temperature (Tavg), relative humidity (RH_avg), rainfall (RR), and average wind speed (ff_avg) in both North Jakarta and Central Jakarta has been influenced by the interrelationships between these parameters.

In terms of evaluation metrics, the GRU model demonstrated superior performance in North Jakarta, achieving a Test RMSE of 9,02, Test MSE of 81,28, and Test MAE of 4,21 at 75 epochs. In contrast, LSTM yielded a Test RMSE of 10,02, Test MSE of 100,34, and Test MAE of 4,62 at 50 epochs. However, in Central Jakarta, LSTM outperformed GRU with a Test RMSE of 8,96, Test MSE of 80,22, and Test MAE of 4,65 at 100 epochs, whereas GRU produced a Test RMSE of 9,53, Test MSE of 90,78, and Test MAE of 4,85 at 75 epochs. In the challenging environment of North Jakarta, where fluctuations are more pronounced, GRU proved more effective in capturing extreme variations in parameters like rainfall (RR) and wind speed (ff_avg), as observed in the visual analysis. On the other hand, in Central Jakarta, where interparameter relationships play a more significant role, LSTM excelled in predicting the general trends, particularly for temperature (Tavg) and relative humidity (RH_avg), as shown in the visual comparison. Direct predictions based on the models showed that LSTM outperformed GRU in North Jakarta, providing predictions that were closer to actual values for all four parameters. In Central Jakarta, LSTM was more accurate for two parameters (RH_avg and ff_avg), whereas GRU performed better for two parameters (Tavg and RR).

Overall, the results suggest that the choice of model for weather prediction depends on the user's priorities: if the goal is to capture accurate relationships between parameters, LSTM is the preferable choice, especially in Central Jakarta. However, for scenarios requiring the ability to handle extreme weather fluctuations, particularly in rainfall and wind speed, GRU proves more effective, especially in North Jakarta. Therefore, the selection of either LSTM or GRU should be made based on the specific needs of weather prediction and the characteristics of the region under study.

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