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# Application of bidirectional gated recurrent unit algorithm for rainfall prediction

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Abstract

*The management of water resources and various industrial sectors is highly dependent on rainfall. To avoid negative impacts such as floods, droughts and other natural disasters, rainfall forecasts must be accurate and timely.This research aims to find the best algorithm for predicting rainfall. In this study, modeling was carried out using the Bandung city rainfall dataset from 2018 to 2022 using the Bidirectional Gated Recurrent Unit (BiGRU) method. Bidirectional Long Short Term Memory (BiLSTM), Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM) are used to compare the performance of the BiGRU algorithm. The test findings show that, with value Root Mean Squared Error (RMSE) and R2 Score BiGRU gives the best results with the lowest error rate. The algorithm with the biggest error rate is LSTM. This study advances strategies for predicting rainfall that can be applied to managing water resources and responding to natural disasters related to rainfall.*

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## 1. Introduction

Rainfall holds great importance as a meteorological factor in our daily lives, affecting a variety of sectors such as water resource management, agriculture, and hydroelectric power generation In truth, rainfall has a huge influence on how much food poor nations produce. Rainfall during the rainy season accounts for around 65% of developing nations' overall agricultural production [1], [2]. The fundamental factor of hydropower generation globally is rainfall in catchment regions. Rainfall is required to replenish groundwater resources [2], [3]. Furthermore, the intensity and duration of rainfall are strongly associated to major natural catastrophes such as sea-level rise, flood, and drought . It is critical for good water resource management in an area to have rapid and reliable strategies for forecasting the duration and intensity of rainfall [4]. Furthermore, precise and timely rainfall forecasts are useful for planning agricultural activities, particularly during extraordinary rainfall occurrences [2], [4]. Accurate and timely rainfall forecast is also critical for preventing and mitigating the harmful effect of natural disasters is a droughts, landslides, and flood[2], [5]. Rainfall forecasting remains a top priority, attracting the attention of government, risk management groups, scientific community, and corporations. Traditional weather forecasting conjures up images of meteorologists huddled around weather charts, making forecasts based on their knowledge. Years of background knowledge and obeservation on weather theory have contributed to this understanding. Predicting rainfall is especially important in this context since it is intimately related with natural disasters such as mass movements, avalanches, landslides, and flood. These events have long had an influence on society, serving as a primary driving factor behind the development of machine learning techniques and numerical weather prediction [6].

Data mining is required for the process of getting important insights from huge data. Data Mining is the process of studying data in order to reveal hidden information that may be used to make significant decisions in the future. Various Algortim have been used of machine learning to grasp the complexity and nonlinear relationships among distinct components by minimizing errors in forecasts and factual outcomes. Data mining is essential for obtaining useful information from huge databases. It is widely employed in almost every human effort, including engineering, business, and education [7], [8]. Because of recent improvements in data mining methods and information technology, it is now possible to analyze predictive models from a data-driven viewpoint. Studies on short term load forecasting in the literature have used both shallow and deep models in data mining. Shallow models are models that are produced using traditional data mining strategies [9]–[11].

The explanation of prediction is the process of methodically creating forecasts about what could happen in the future based on information from past and present occurrences in order to minimise errors (the difference between what really happens and the predicted outcome). Predictions do not have to be exact, but they should try to identify solutions that are as near to what will actually happen as feasible [12]. The Artificial Neural Network(ANN) is critical for prediction, and the type of data utilized for analysis should be considered while choosing the best neural network model. There are several types of neural network, such asfeed forward neural network, backpropagation neural neural network, recurrent neural networks, and so on, and each model uses a different approach to make predictions within these categories. Because it can handle time series data, Recurrent Neural Network is a great choice for managing rainfall data. Multilayer perceptron, also known as "guerrilla rainstorms" in Japan, may predict even unexpectedly heavy rain [13], [14]. Backpropagation is vital in prediction because neurons create predictions by memorizing the corresponding weights for each input range. Using this scenario, monthly rainfall forecasts for the Kalimantan area of Indonesia were made with the least amount of error using a Back-propagating Neural Network (BPNN) [15].

Memory capacity concerns, possible gradient disappearing in network, increasing prediction errors, and modeling systems that produce accurate rainfall forecasts are some of the issues with prediction methodologies. Various deep learning algorithms are used in this research to decrease prediction mistakes. This study employs the Long Short Term Memory (LSTM) algorithm, Gated Recurrent Unit (GRU), Bidirectional Gated Recurrent Unit(BiGRU) , and Bidirectional Long Short Term Memroy(BiLSTM). Bidirectional techniques are used in BiGRU and BiLSTM because they allow for the capture of semantic information in bothbackward and forward directions. When investigating long-term information dependencies, LSTM is the default behavior. The usage of GRU has the benefit of gathering lengthy sequential data required for Natural Language Processing (NLP) learning. The ultimate findings of these four techniques are projected to provide error levels close to zero [16], [17].

By using its capacity to recall prior information, the Recurrent Neural Network (RNN) confronts hurdles in dealing with consecutive time-series problems. However, due to the vanishing and ballooning gradient difficulties that arise during network training in long-term dependence situations, RNN has limits. These constraints are caused by the single structure and the Back Propagation Through Time-based Parameter Solving methods [18], [19].To address these constraints, two types of RNN-derived models have been developed: LSTM [19], [20] and GRU [19], [21]. Both approaches successfully overcome RNN's difficulties in dealing with long-term dependency. LSTM presents a memory cell and three gates (forget gate, input gate, and output gate) that govern information flow between LSTM cells and determine information input, retention, and output. LSTM and GRU may circumvent RNN's long-term dependence restrictions with more complicated internal structures and gates that govern information flow. Because they maintain pertinent past information, they are a superior alternative for dealing with sequential time-series problems. GRU and LSTM can only extract information in the forward direction and ignore information in the reverse direction. To overcome this issue, the bidirectional idea is developed, in which bidirectional GRU and LSTM may take into account dependencies in both the forward and backward directions. Forward bidirectional data captures past information from input data, and backward bidirectional data captures future information from input data [19].

The research conducted by RF Firdaus and colleagues[22] utilized the LSTM algorithm, which resulted in a relatively low RMSE value of 12.24. The objective of this study was to predict rainfall using a dataset comprising rainfall data from 2017 to 2021 in Bandung City. The findings of this research demonstrate that deep learning algorithms have the potential to accurately predict rainfall with a relatively low margin of error, offering prospects for further advancements in weather and climate prediction.

In this study, the Bidirectional Gated Recurrent Unit (BiGRU) algorithm was chosen for rainfall prediction due to its infrequent utilization in this context. Consequently, this research aims to provide novel insights to other researchers by advocating the adoption of the BiGRU algorithm for predicting various rainfall datasets. The study will compare the performance of the BiGRU algorithm with other deep learning algorithms, such as LSTM, GRU, and BiLSTM, to determine the most optimal algorithm for predicting the given rainfall dataset. Through this comparison, the research seeks to identify the algorithm that yields the most accurate and reliable predictions for rainfall datasets.

## 2. Methods

The strategy employed in this study is to compare the performance of four deep learning systems for forecasting rainfall dataset in Bandung. The study is divided into stages, as shown in Figure 1.

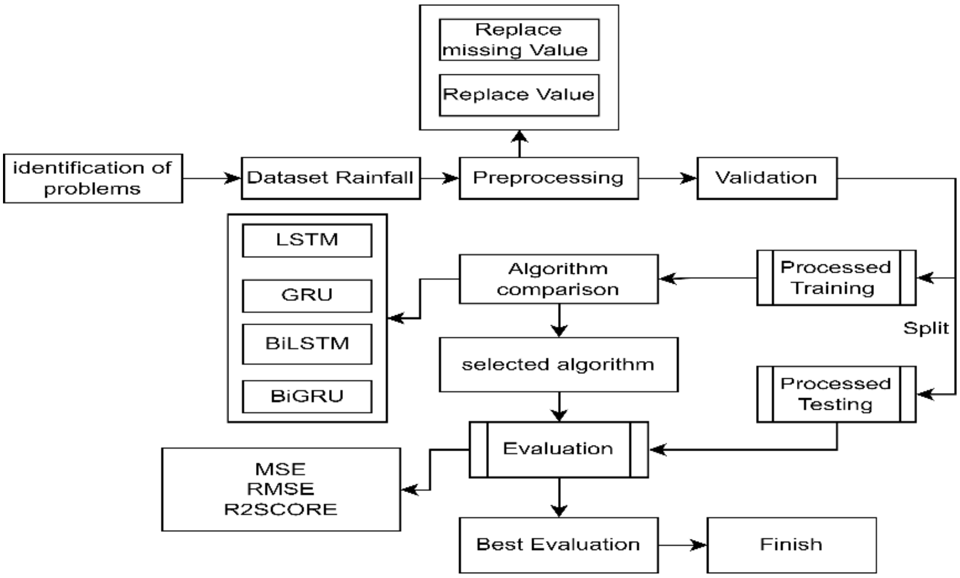


Figure 1. Research Stages

### 2.1. Problem Identification

The goal of this study is to forecast rainfall using deep learning algorithms such as LSTM, GRU, BiGRU, and BiLSTM. The objective is to evaluate the effectiveness of various algorithm in forecasting rainfall and select the most succesfull algorithm specifically in Bandung.

### 2.2. Dataset

A dataset is required as the major input for the algorithm in a research investigation. The rainfall dataset utilized in this study was collected from the BMKG dataonline website. From 2018 to 2022, the collection contains 1878 rainfall data points in the Bandung city region. It comprises crucial rainfall prediction features such as the date and time of rainfall observations, the location in Bandung, and the recorded rainfall levels. The research can use this information to detect patterns and trends in the rainfall data across the time period under consideration.

### 2.3. Pre-Processing

It is not possible to begin processing data immediately in data-driven research since the data may be partial, inconsistent, or redundant. To assess increasing amounts of data obtained, more complicated techniques are necessary. Data pre-processing can help in the processing of impossible data by modifying the data to match the specifications of each data mining method [30]. To get the best results in data processing using the model, data pre-processing is performed in this study to replace empty or missing values in the dataset, as well as to replace the value 8888 in the dataset.

### 2.4. Validation

Split Validation is a validation approach that divides the SampleSet data into training and test data at random [23], [24].The prediction model is trained a set of training data, while the accuracy of model is evaluated by using separateset of test data. This approach is beneficial for determining how well the created model predicts unknown data [25]. During this process, the dataset wil be partitioned into training and test data sets to asses the performance of each model and determine the most accurate prediction result. Initially, the dataset will be split into training and test data sets using predefined ratios. The ratios considered in this study are 0,9, 0,8 , 0,7, 0,6, and 0,5 for training-to-test-data. The training data will be utilized to train the model, whole the test data will be employed to evaluate how well the model performs on unseen data

### 2.5. Algorithm comparison

This is a critical stage in the study since the pre-processed dataset will be processed using four deep learning algorithm models: LSTM, GRU, BiGRU, and BiLSTM. After the training and testing data have been separated, the training phase begins. Each deep learning algorithm model (LSTM, GRU, BiGRU, and BiLSTM) will be trained using the training data. These models will be used to forecast rainfall using test data after the training phase. The prediction outcomes will be assessed using appropriate evaluation metrics such as mean squared error, RMSE, or other metrics appropriate for rainfall prediction issues. This evaluation will give insight into each model's performance and predictive skills in predicting rainfall. By comparing the prediction outcomes and performance assessment of LSTM, GRU, BiGRU, and BiLSTM, the researcher may identify which model delivers the best prediction results for the dataset utilized in this study. The best model will be chosen as an essential component of the research conclusion, and its findings will be beneficial for forecasting future rainfall.

a. Long Short Term Memory
   LSTM is a type.RNNs is a type of neural network that can internally store input memory. As a result, they are appropriate for dealing with situations that need sequential data, such as time series. However, RNNs are frequently afflicted by the vanishing gradient phenomenon, which causes the model's learning to slow down or stop entirely. To address this issue, LSTM was developed in the 1990s. The LSTM has a longer memory and is capable of learning from inputs separated by long time intervals. The LSTM is made up gates of three: an input gate that determines whether or not to receive new data, a forget gate that eliminates unnecessary information, and an output gate that determines whether or not to send data. [26].
b. Gated Recurrent Unit
   GRU is an abbreviation for Gated Recurrent Unit, and it is a variant of the LSTM neural network. It tries to make each recurrent unit capable of recording relationships across several time scales in an adaptable manner. Updates gate and reset gate of GRU are similar to the input gate and forget gate of LSTM. Without the need of a separate cell, these gates alter the flow of information inside the unit [27].
c. Bidirectional Long Short Term Memory
   LSTM frequently ignores future information in time-series processing. dependent on LSTM, BiLSTM processes sequential data in both forward and backward directions, linking the two hidden layers to the same output layer [28], keeping prior and future information dependent on

the present time in time-series data [29]. As a result, theoretical prediction performance is projected to outperform unidirectional LSTM. BiLSTM's hidden layer incorporates activations from both the forward and backward hidden layers [30].

d. Bidirectional Gated Recurrent Unit

The BiGRU model is capable of capturing the bidirectional connections between numerous inputs and outputs and is well suited for examining performance mechanisms using real production data. The input is represented as a dimensional of three tensor. The number of samples is the first dimension; the second is the window size, which is number of time steps used to forecast future time steps; and the third aspect is the number od pertinent features of attributes. The BiGRU layer comes next, which enables the extraction of implicit information from structured input data [19].

### 2.6. Evaluation

In this work, many generally used assessment measures, such as RMSE and R-Squared Score (R2 Score), were utilized to examine the performance of LSTM, GRU, BiGRU, and BiLSTM deep learning models in forecasting rainfall.

a. Root Mean Square Error (RMSE)

RMSE is a measurement statistic that assesses the degree of variance or error between expected and actual values on the same scale.it is determined by taking the square root of the mean squared difference between the expected and actual values. A declining and approaching-zero RMSE indicates that the model is getting better at predicting rainfall.

$$\text{RMSE} = \sqrt{\sum \frac{(y^1 - y)^2}{n}} \quad (1)$$

b. R-Squared Score (R2 Score)

R2 Score is a metric that measures how well a model can explain variance in data. The R2 value goes from 0 to 1, a value of 1 indicates that the model can account for all the variance in the data, while a value of 0 suggests that model is unable to explain aby variation. The model's performance improves as the R2 score rises.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - y_i)^2} \quad (2)$$

These assessment metrics may be derived for each model in this study once the LSTM, GRU, BiGRU, and BiLSTM models have been trained and used to forecast rainfall on test data. The researcher may evaluate the relative effectiveness of these models by comparing their RMSE and R2 Score values and selecting the model that delivers the best prediction results for the rainfall dataset utilized in this study.

## 3. Result and Decission

### 3.1 Dataset

The dataset used in this study consists of rainfall data from the Bandung city region, covering the period from 2018 to 2022. The data was collected from the BMKG online data website and includes important information such as the date and time of rainfall observations, the location in Bandung, and the recorded rainfall levels. The dataset contains a total of 1878 data points.In Figure 2 is the distribution of rainfall data from the Bandung city region can be observed.

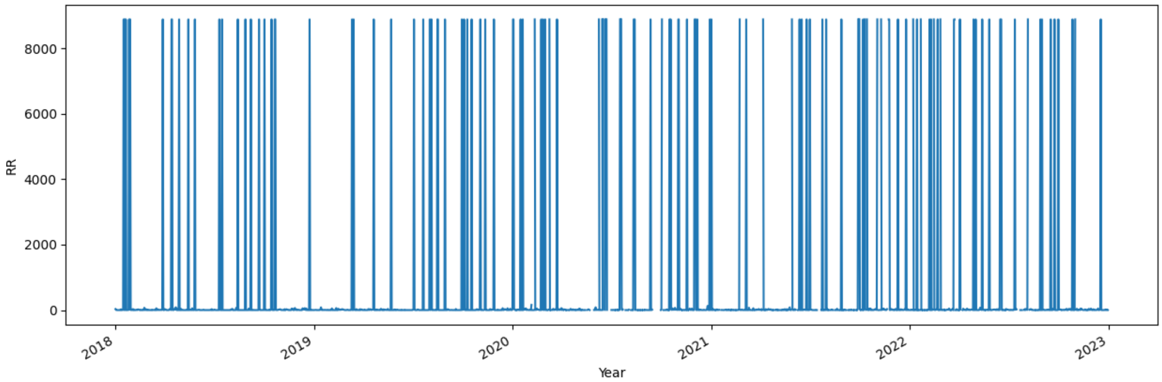


Figure 2. Graph of Bandung city rainfall dataset

### 3.2. Preprocessing Data

Data preprocessing is a crucial step in data-driven research to ensure data integrity and compatibility with the selected deep learning models. In this study, the following preprocessing steps are performed on the rainfall dataset. Handling Missing Values: Missing values in the dataset are replaced with 0 to avoid any disruptions in data processing and handling Inconsistent Data: In some cases, the dataset may include non-standard values, such as 8888. Figure 3 is the data preparation process.

```
df = df.replace(8888, 0)

df = df.fillna(0)
```

Figure 3. Preprocessing Data Process

These inconsistent values are replaced with appropriate values to maintain data consistency.By applying these preprocessing steps, the dataset is prepared and ready for further analysis and model training.In Figure 4, the distribution of rainfall data from the Bandung city region after preprocessing can be observed.

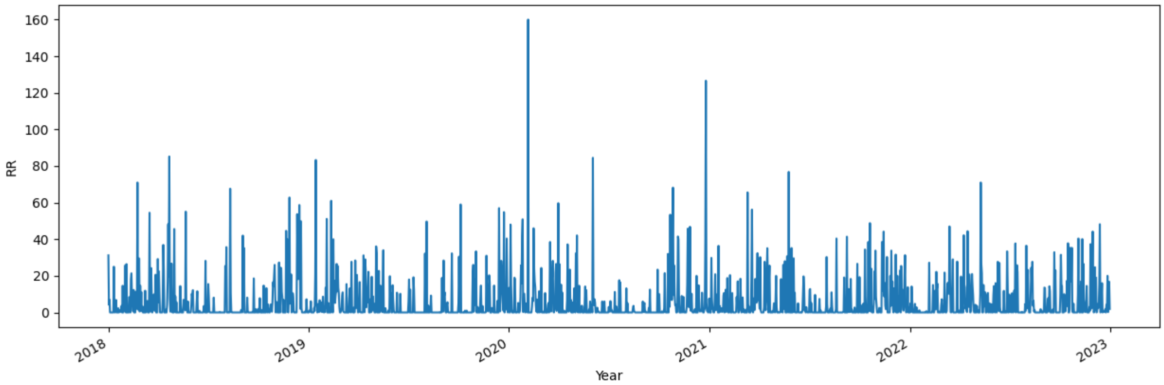


Figure 4. Graph of Bandung City Rainfall Dataset After Preprocessing

### 3.3. Validation

To evaluate the performance of the deep learning algorithms, a split validation approach was employed, dividing the dataset into training and test sets. Five different data ratios (0.9, 0.8, 0.7, 0.6, and 0.5). Figure 5 is the process of dividing data between train and test data.

```
ts_train, ts_test = train_test_split(df, test_size=0.2, shuffle=False)
ts_train.shape, ts_test.shape
train_set = TimeSeriesDataset(ts_train, "RR", seq_len)
```

```
trainloader = DataLoader(train_set, batch_size=bs)

test_set = TimeSeriesDataset(ts_test, "RR", seq_len)
testloader = DataLoader(test_set, batch_size=bs)
```

Figure 5. Data Split

Were used to assess each algorithm's predictive capabilities. The models were trained on the training data and evaluated on the test data. Figure 6 is the data validation process

```
from sklearn.metrics import mean_squared_error, r2_score

# Menghitung prediksi model pada data test
y_pred = []
y_true = []
for feature, target in trainloader:
    feature, target = feature.to(device), target.to(device)
    output, _ = model(feature, None)
    y_pred.append(output.view(-1).cpu().detach().numpy())
    y_true.append(target.view(-1).cpu().detach().numpy())
y_pred = np.concatenate(y_pred)
y_true = np.concatenate(y_true)

# Menghitung nilai RMSE
rmse = np.sqrt(mean_squared_error(y_true, y_pred))
print("RMSE:", rmse)

# Calculate MSE
mse = mean_squared_error(y_true, y_pred)
print("MSE:", mse)

# Calculate R2 Score
r2 = r2_score(y_true, y_pred)
print("R2 Score:", r2)
```

Figure 6. Validation Data

The evaluation was based on metrics like Root Mean Square Error (RMSE) and R2 Score, which are commonly used to measure prediction accuracy. Table 1 presents the results of the validation process for each algorithm.

Table 1.
Algorithm Testing Result

| Algorithm | RMSE Value | | | | | R2Score Value | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | rasio 0.9 | rasio 0.8 | rasio 0.7 | rasio 0.6 | rasio 0.5 | rasio 0.9 | rasio 0.8 | rasio 0.7 | rasio 0.6 | rasio 0.5 |
| LSTM | 11.10 | 10.09 | 10.22 | 10.35 | 11.05 | 0.08 | 0.10 | 0.08 | 0.07 | 0.08 |
| GRU | 11.07 | 10.02 | 10.22 | 10.38 | 10.97 | 0.10 | 0.10 | 0.08 | 0.08 | 11.05 |
| BiLSTM | 5.29 | 4.21 | 5.13 | 4.85 | 6.56 | 0.84 | 0.77 | 0.79 | 0.67 | 11.05 |
| BiGRU | 4.84 | 4.07 | 4.92 | 5.09 | 5.84 | 0.82 | 0.85 | 0.79 | 0.77 | 0.74 |

### 3.4. Algortihm Comparison

A comparison of the performance of deep learning algorithms reveals that the Bidirectional Gated Recurrent Unit (BiGRU) algorithm achieves the best results in predicting rainfall. With an RMSE value of 4.07 and an R2 score of 0.85, the BiGRU algorithm outperforms other models. The Long Short Term Memory (LSTM) algorithm is in second place, with an RMSE value of 4.21 and an R2 score of 0.84. While the Gated Recurrent Unit (GRU) algorithm shows RMSE 10.02 and R2 Score 0.10, and the Bidirectional Long Short Term Memory (BiLSTM) algorithm has RMSE 4.84 and R2 Score 0.79.Table 2 shows a comparison of the performance of each algorithm based on the testing results.

Table 2.
Algorithm comparison

| Algorithm | RMSE | R2Score |
|---|---|---|
| B. LTSM | 4.21 | 0.84 |
| B.Gru | 4.07 | 0.85 |
| LTSM | 10.09 | 0.08 |
| Gru | 10.02 | 0.10 |

### 3.5. Evaluation

The results clearly demonstrate that the BiGRU algorithm is the most accurate and reliable model for rainfall prediction in the Bandung city region. Its lower RMSE and higher R2 Score indicate better performance compared to the other models. Therefore, the BiGRU algorithm can be considered as an excellent choice for predicting rainfall and has the potential to be applied in practical weather forecasting applications.

As mentioned in the introduction, previous research conducted by RF Firdaus and colleagues[22] utilized the LSTM algorithm for rainfall prediction and achieved an RMSE value of 12.24. As a comparison, the BiGRU algorithm in this study outperformed the LSTM algorithm with a much lower RMSE value of 4.07 and R2 Score 0.85 This means that the resulting rainfall prediction results are better. This comparison highlights the advances and advantages of bidirectional architectures such as BiGRU in the task of predicting time series. Figure 7 is a process for displaying a comparison graph between actual data and predicted results.

```
# Menghitung data aktual curah hujan dari ts_train
y_true_actual_train = ts_train["RR"].values

with torch.no_grad():
    # Menghitung prediksi model pada data train
    y_pred_train = []
    for feature, target in trainloader:
        feature, target = feature.to(device), target.to(device)
        output, _ = model(feature, None)
        y_pred_train.append(output.view(-1).cpu().detach().numpy())
    y_pred_train = np.concatenate(y_pred_train)

# Menghitung data aktual curah hujan dari testloader
y_true_actual_test = []
for feature, target in testloader:
    y_true_actual_test.append(target.view(-1).cpu().detach().numpy())
y_true_actual_test = np.concatenate(y_true_actual_test)

with torch.no_grad():
    # Menghitung prediksi model pada data test
    y_pred_test = []
    for feature, target in testloader:
        feature, target = feature.to(device), target.to(device)
        output, _ = model(feature, None)
        y_pred_test.append(output.view(-1).cpu().detach().numpy())
    y_pred_test = np.concatenate(y_pred_test)

# Memotong data test agar memiliki panjang yang sama dengan data
train
y_true_actual_test = y_true_actual_test[:len(y_true_actual_train)]
y_pred_test = y_pred_test[:len(y_true_actual_train)]

# Menampilkan hasil prediksi dan data asli dalam bentuk chart
plt.figure(figsize=(15, 5))
plt.plot(y_true_actual_train, label='Actual (Train)')
plt.plot(y_pred_train, label='Predicted (Train)')
plt.plot(np.arange(len(y_true_actual_train), len(y_true_actual_train) +
len(y_true_actual_test)), y_true_actual_test, label='Actual (Test)')
```

```
            plt.plot(np.arange(len(y_true_actual_train),  len(y_true_actual_train)  +
            len(y_true_actual_test)), y_pred_test, label='Predicted (Test)')
            plt.xlabel('Time')
            plt.ylabel('Rainfall')
            plt.title('Rainfall Prediction')
            plt.legend()
plt.show()
```

Figure 7. Graph Comparison Data process

Figure 8 depicts a graph of the BiGRU algorithm's prediction results vs actual rainfall data. The blue and green lines show the actual data, while the orange and red lines show the predicted results. We can see how well the BiGRU algorithm forecasts rainfall by comparing the two.

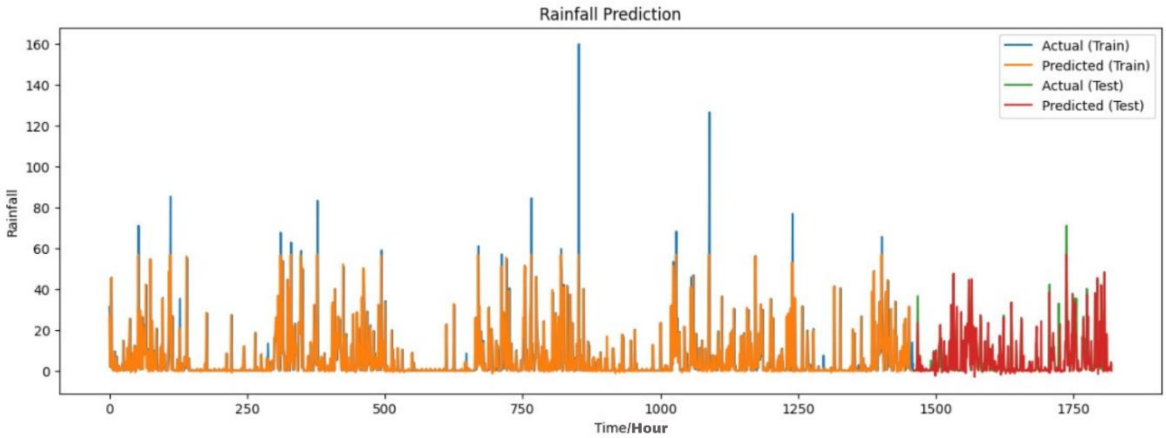


Figure 8. Graph of Comparison of Predicted Results with Actual Data

## 4. Conclusion

This study compared the performance of various deep learning algorithms for predicting rainfall in the city of Bandung. The dataset contains rainfall data from 2018 to 2022, with a total of 1878 data points. Through data pre-processing and validation using different data ratios, the model is evaluated against metrics such as RMSE and R2 Score. The BiGRU algorithm appears as the most effective model for predicting rainfall in the Bandung city area. Its RMSE is lower than 4.07, compared to the LSTM algorithm with an RMSE of 12.24 from previous research by RF Firdaus and colleagues, indicating a significant increase in prediction accuracy. However, it is important to acknowledge the limitations of the study, such as the specific data set and the exclusion of additional meteorological factors. Future research should overcome these limitations and explore the application of the BiGRU algorithm in a broader context to advance the field of weather forecasting. The findings of this study provide valuable insights for meteorologists and computer programmers alike, contributing to the development of more accurate and reliable rainfall prediction systems. Future studies are encouraged to directly apply the findings of this study in practical applications by developing a rainfall prediction system that meteorologists and water resource managers can utilize to enhance their ability to anticipate weather changes effectively.

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