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Prediction of Air Temperature on Runway 10 Juanda Airport Using Hybrid LSTM

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Abstract – Global climate change increases the frequency of extreme weather, impacting various sectors, including aviation. Accurate weather prediction becomes crucial to ensure the safety of human activities, including aviation operations. This study aims to predict air temperature variables on Runway 10 at Juanda Airport using a Long Short Term Memory (LSTM) architecture stacked with a Gated Recurrent Unit (GRU) architecture, named Hybrid LSTM. The data used in this study is air temperature (per minute) obtained from the Automatic Weather Observing System (AWOS) in (.csv) format. Testing was conducted for short-term predictions and comparisons were made between Hybrid and non-Hybrid models. The test results show that the LSTM-GRU architecture produced the lowest evaluation values for predicting temperature with an MSE of 0.0181, MAE of 0.0814, RMSE of 0.1345, and MAPE of 0.29% using a batch size of 64 and 20 epochs. This indicates that the developed model is suitable for predicting the next short-term period (5 minutes). For future research, model development is needed by adding features or adjusting hyperparameters to accurately predict the long term.

Keywords: Predict, Air Temperature, Automatic Weather Observing System (AWOS), LSTM, GRU

I. INTRODUCTION

Global climate change has increased the intensity of extreme weather, significantly impacting various sectors such as energy, agriculture, transportation, aviation, and the environment. Weather conditions can change rapidly, particularly due to variations in temperature and humidity in different locations. Accurate weather forecasting has become crucial for efficiency and safety in various human activities [1].

Weather forecasting utilizes scientific knowledge and technology to anticipate atmospheric conditions in specific areas[2]. In recent decades, deep learning techniques and the availability of weather observation data have enabled further research into accurate weather predictions. One important source of weather data is the Automatic Weather Observing System (AWOS) from BMKG, which provides real-time data on temperature, humidity, wind speed, and air pressure[3].

A runway is an essential facility at an airport for aircraft landing and takeoff [4]. Juanda Airport has two runways, runway 10 and runway 28. This research focuses on runway 10 in the northern part of Juanda Airport.

Traditional weather forecasting by BMKG involves various processes such as geographical observation, meteorological variable conditions, atmospheric disturbances, and numerical weather modeling. This process is considered time-consuming and complex for real-time predictions.

CNNs, RNNs, LSTMs, and Gated Recurrent Units (GRUs) are commonly used deep learning models for time series prediction[5]. Research conducted by Jingyang Wang compared three methods for making predictions, stating that the RNN method is the most independent artificial neural network, but it faces challenges with long-term data processing, causing issues during data training. The LSTM method can handle long-term data processing and manage irrelevant data, but it has a drawback of using many parameters, which leads to long training times [6] . The GRU method can reduce long training times by reducing the number of parameters [7]. Supriyadi's research on predicting weather parameters with LSTM achieved RMSE values of 0.576 for temperature, 2.8687 for humidity, 2.1963 for wind speed, and 1.0647 for air pressure[8] .

This research combines the LSTM method with GRU, referred to as Hybrid-LSTM, to evaluate its effectiveness in predicting air temperature. It is hoped that this method can improve prediction accuracy and help society in coping with extreme weather changes.

II. LITERATURE

Air Temperature

Air temperature is the measure of the average kinetic energy of the movement of molecules or the degree of heat from molecular activity in the atmosphere[1]. Changes in air temperature from one place to another depend on altitude and astronomical location (latitude)[2]. The distribution of temperature in the atmosphere is highly dependent on solar radiation, which causes air temperature to constantly change. The surface air temperature of the earth is one of the important elements observed by weather observers (Meteorological Station and Climatological Station)[3]. Temperature changes due to differences in altitude occur much faster than changes due to differences in latitude. Typically, temperature changes about 0.6 degrees Celsius for every 100 meters increase in altitude. The instrument used to measure temperature is the thermometer.

Prediction or Forecasting

Forecasting is an important tool for effective and efficient planning. Forecasting is the prediction, projection, or estimation of uncertain future events. It is the process of utilizing data to estimate future occurrences so that preventive measures can be taken by performing objective calculations using appropriate data, both past and present, to determine future outcomes[4]. The future is often influenced by the past.

AWOS (Automatic Weather Observing System)

The Automated Weather Observing System (AWOS) is an automated weather observation system installed at airports to measure, analyze, and present weather data automatically[5]. AWOS measures key weather variables such as wind direction and speed, pressure, temperature, humidity, precipitation, clouds, and visibility using attached sensors. In Indonesia, AWOS Category I is also equipped with precipitation sensors and solar radiation sensors. These sensors send their measurements to the Data Collections Platform (DCP), which is then processed by the Central Data Processor (CDP) to store and present observation data to pilots and ATC through VHF radio communication, NAVAID, or ATIS[6].

LSTM (Long Short Term Memory)

LSTM (Long Short Term Memory), introduced by Hochreiter and Schmidhuber in 1997, is a type of Recurrent Neural Network (RNN) architecture frequently employed in deep learning applications[7][8]. LSTM consists of recurrent layers that include various calculations such as addition, multiplication, and mathematical functions (tanh and sigmoid).

LSTM was created to improve RNNs by adding a cell state and three main gates: the input gate, the output gate, and the forget gate[9]. The input gate controls how much new information is added to the cell, the forget gate decides how much of the existing information is kept, and the output gate regulates how much of the cell's information is used for the output.

LSTM is especially effective for tasks involving classification, processing, and predicting outcomes using time series data, due to its ability to handle variable time intervals between important events within a sequence[10].

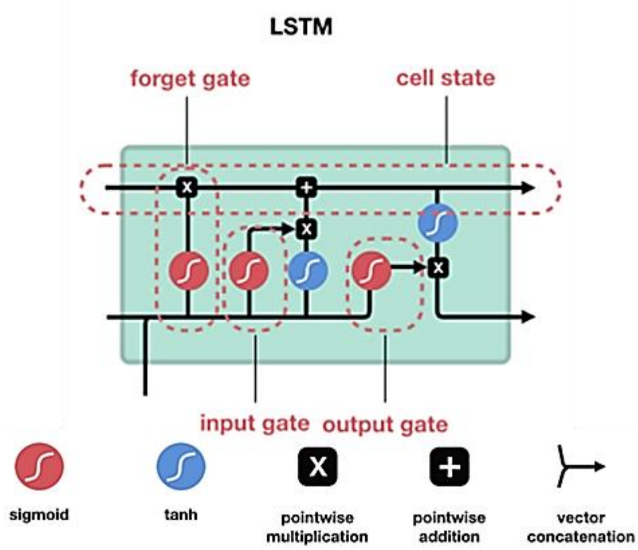

Figure 1 LSTM Architecture

From figure 1 the way the gates work in LSTM is as follows:

1. Forget Gate

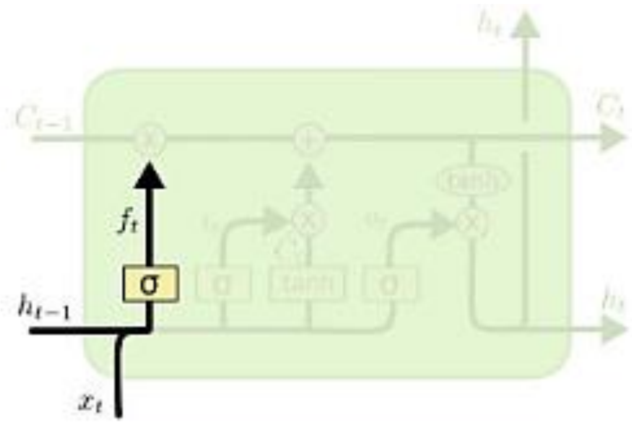

Figure 2 Forget Gate

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (1)$$

In Figure 2 Forget Gate, the value of each input data is processed and selected to determine which data will be stored or discarded in the memory cells.

2. Input Gate

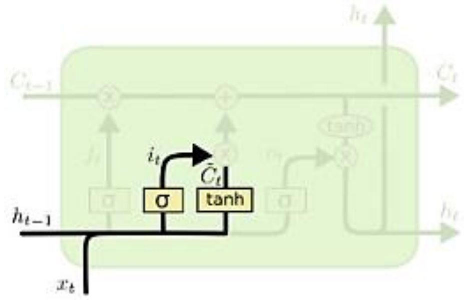

Figure 3 Input Gate

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (2)$$

$$\hat{c}_t = tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (3)$$

In Figure 3, the Input Gate performs two operations. First, data is assessed using the sigmoid activation function to decide which values will be updated. Then, the tanh activation function creates new values that will be utilized and stored in the memory cell.

3. Memory Update (cell state)

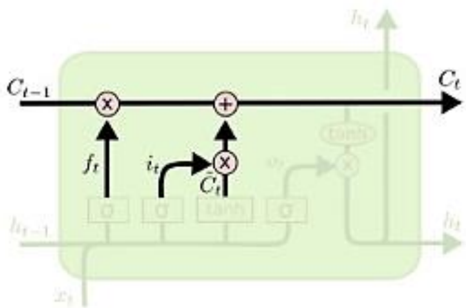

Figure 4 Cell State

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \hat{c}_t \quad (4)$$

In Figure 4, the Cell State or memory update gate replaces the old memory cell value with a new one. This new memory cell value is obtained by combining the values from the forget gate and the input gate.

4. Output Gate

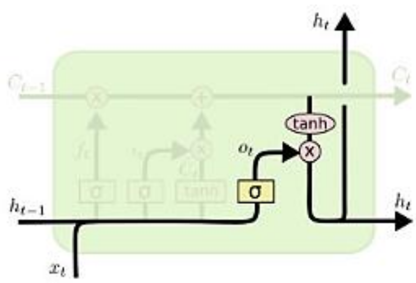

Figure 5 Output Gate

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (5)$$

$$h_t = o_t tanh \otimes c_t \quad (6)$$

In Figure 5, the Output Gate of the LSTM performs two operations. First, the sigmoid activation function determines the value to be output from the memory cell. Then, the tanh activation function processes the data within the memory cell. These two values are then multiplied element-wise to generate the final output value.

The notation used is as follows:

σ : logistic sigmoid function

⊗ : element-wise multiplication of two vectors

tanh : hyperbolic tangent function

x_t : input vector

$\hat{c}_t$: cell input activation vector

h_{t-1} : hidden state vector

W_{xi}, W_{hi}, W_{xf}, W_{hf}, W_{xo}, W_{ho}, W_{xc} ,W_{hc} : network weight matrices.

b_i, b_f, b_o,b_c : bias vectors

f_t, i_t, o_t : vectors for the activation values of the forget gate

GRU (Gated recurrent unit)

GRU (Gated Recurrent Unit) is an architecture created by Kyunghyun Cho in 2014 to address the vanishing gradient problem in RNNs[11]. GRU is a simplified version of LSTM and uses two gates: Update Gate and Reset Gate. GRU does not have a cell state[12]; instead, it uses a hidden state to store information. The Reset Gate determines whether new information should be forgotten, while the Update Gate manages which information needs to be remembered. Due to its simpler architecture, GRU can be trained faster than LSTM, although its performance depends on the specific case being addressed.

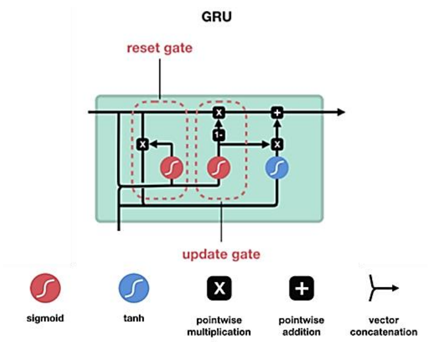

Figure 6 GRU Architecture

In Figure 6 the structure of a GRU cell, the equations are calculated as follows:

1. Reset Gate

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \quad (7)$$

The reset gate determines how to combine the new input information with past information.

2. Update Gate

$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \quad (8)$$

The update gate decides how much of the past information should be retained. Then, the candidate hidden state at the current time step and past information are calculated using the tanh activation function with the following equation:

$$\hat{c}_t = tanh(W_{xc}x_t + W_{hc}(r_t \otimes h_{t-1}) + b_c) \quad (9)$$

$$c_t = (1 - z_t) \otimes c_{t-1} + z_t \otimes \hat{c}_t \quad (10)$$

$$h_t = c_t \quad (11)$$

The notation used is as follows:

σ : logistic sigmoid function

⊗ : element-wise multiplication of two vectors

tanh : hyperbolic tangent function

x_t : input vector

$\hat{c}_t$: cell input activation vector

h_{t-1} : hidden state vector

W_{xr}, W_{hr}, W_{xz}, W_{hz} : network weight matrices.

b_r, b_z : bias vectors

r_t, z_t : Vectors for the activation values of the reset gate and update gate.

III. RESEARCH METHODS

Data

The dataset used in this research is sourced from the output data of AWOS, accessible through a specific file-sharing platform provided by the equipment and technique unit of BMKG Juanda. The dataset used is the AWOS runway 10 data. The dataset to be processed consists of AWOS timeseries data for 3 months (per minute) in .csv format. This dataset will be used for preprocessing, model prediction creation, training, validation, and testing stages. The division of training, validation, and testing data is done with a ratio of 70% for training data, 15% for validation data, and 15% for testing data. Details of the contents of the AWOS dataset are as follows:

a. Data Period Used: 3 months (from December 1, 2022, at 07:00 AM WIB to February 28, 2023, at 06:59 AM WIB), per minute.

b. Number of Data Used: 1 variables, 129,600 rows.

System Flowchart

The flow of the overall system to be implemented is as follows :

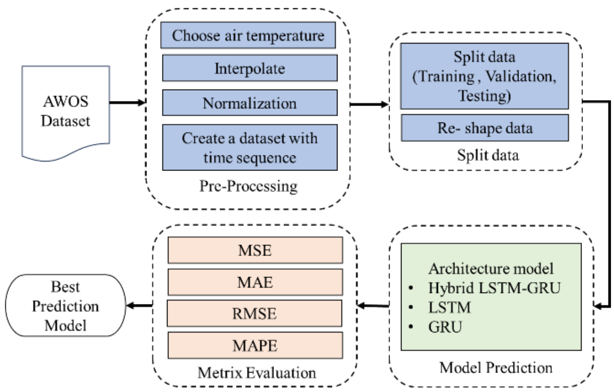

Figure 7 System design of research

1. Pre-processing

Data pre-processing is carried out to enhance the quality of raw data, making it ready for processing in the prediction program. The stages of pre-processing include variable selection, interpolation of missing values, data normalization, creating time-sequenced datasets, splitting the data into training and testing sets, and reshaping the data. Interpolation: Filling in missing data based on existing data, converting all non-numeric data (except for column headers) to zero. Normalization: Using MinMaxScaler to standardize the range of the variables, facilitating statistical analysis. Creating time-sequenced datasets: Using the create_dataset function to prepare the time series data, determining the look_back and look_forward periods.

2. Data splitting

The data is divided into training, validation, and testing sets as follows: 70% of the total data (90,720 rows) is allocated for training, 15% (19,440 rows) for validation, and another 15% (19,440 rows) for testing. Since this research utilizes the Hybrid LSTM model, the data arrays are reshaped into appropriate dimensions, specifically into three-dimensional arrays at this stage.

3. Build Prediction Model

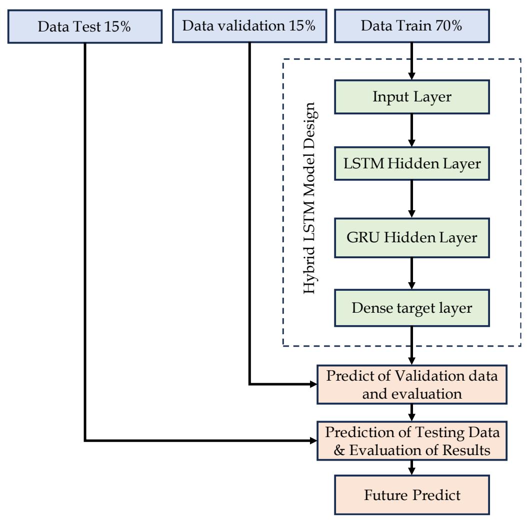

Figure 8 Hybrid Prediction Model

Figure 8 the architecture of the Hybrid LSTM model, which comprises four layers: the input layer, the LSTM layer, the Hybrid (GRU) layer, and the Dense layer as the output layer. Hyperparameters, including ReLU as the activation function for the LSTM and Hybrid layers, and linear as the activation function for the Dense layer, are incorporated. During this phase, hyperparameter tuning is conducted, adjusting the Batch

Size to 32 and 64, and setting the number of epochs to 10, 20, and 50 for each architecture, using ADAM as the optimizer.

4. Evaluation metrix

To evaluate the model's performance and identify the prediction/forecast errors in this study, Mean Square Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) are employed.

a. Mean Square Error (MSE)

Mean Square Error (MSE) is utilized to measure accuracy by averaging the squares of the differences between the predicted and actual values[13]. The formula is:

$$\mathrm{MSE} = \frac{1}{2}\sum_{i=1}^{n}(f_i - y_i)^2 \tag{12}$$

Description :

n : the number of data points

fi: the predicted value from the model.

yi: the actual value for data point i.

b. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) quantifies the average of the absolute differences between the predicted and actual values[14]. The formula is:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|f_i - y_i| \tag{13}$$

Where :

n : the number of data points tested

fi: the predicted value at time t (t=1,...,n),

yi: the actual value at time t (t=1,...,n),

c. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is the square root of the Mean Square Error (MSE) and measures the average magnitude of the errors[15][16] . It provides an indication of the size of the prediction errors. The formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(f_i - y_i)^2} \tag{14}$$

Where :

n : the number of data points tested

fi: the predicted value for data point i. (t=1,...,n),

yi: the actual value for data point i. (t=1,...,n),

i : Sequence of data in the database

d. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) measures the average percentage difference between the predicted and actual values[17][18]. The formula is:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{f_i - y_i}{f_i}\right| \times 100\% \tag{15}$$

Where :

n : the number of data points.

yi : the actual value at time t.

fi : the predicted value at time t.

Table 1 MAPE Accuracy Levels

MAPE Value	Prediction Accuracy
MAPE < 10%	Very high prediction accuracy.
MAPE 10%-20%	Good prediction accuracy
MAPE 20%-50%	Reasonable prediction accuracy.
MAPE > 50%	Poor prediction accuracy.

IV. RESULT AND DISCUSSION

System Testing

Based on the research conducted by eko supriyadi in 2019, an lstm architecture was used to predict weather parameters with a dataset from synoptic observations at the tanjung priok maritime meteorological station. The research by david and chairani in 2023 compared the lstm and gru architectures to predict rainfall using a dataset from the iris application, which is a database of the lampung utara geophysical station. Finally, the research by yuslena et al. In 2022 used a hybrid gru-lstm architecture to predict temperature using online daily average temperature data from the syamsudin noor meteorological station.

In this research, a combination of the LSTM architecture with another architecture (GRU), called Hybrid LSTM, was used. Experiments were conducted using the selected variable, air temperature, with epochs of 10, 20, and 50, and batch sizes of 32 and 64, to predict short-term (5 minute) air temperature. This research also compared the results between the Hybrid architecture and the non-Hybrid architecture. Based on the experiments conducted, the analysis results of this research are as follows.

Table 2 Comparison Performances Model

Model	Batch Size	Epoch	Metrix Evaluation			
			MSE	MAE	RMSE	MAPE
LSTM-GRU	32	10	0.0183	0.0835	0.1355	0.30%
		20	0.0183	0.0834	0.1356	0.30%
		50	0.0185	0.0849	0.1360	0.31%
	64	10	0.0198	0.0841	0.1406	0.30%
		20	0.0181	0.0814	0.1345	0.29%
		50	0.0189	0.0841	0.1377	0.30%
LSTM	32	10	0.0184	0.0813	0.1359	0.29%
		20	0.0196	0.0834	0.1402	0.30%
		50	0.0182	0.0810	0.1349	0.29%
	64	10	0.0354	0.1215	0.1881	0.44%
		20	0.0211	0.0899	0.1452	0.33%
		50	0.0185	0.0813	0.1363	0.29%
GRU	32	10	0.0195	0.0849	0.1399	0.31%
		20	0.0191	0.0835	0.1384	0.30%
		50	0.0182	0.0806	0.1349	0.29%
	64	10	0.0218	0.0925	0.1476	0.34%
		20	0.0199	0.0878	0.141	0.32%
		50	0.0186	0.0841	0.1366	0.30%

Based on the results in table 2, the best model for prediction is the hybrid lstm-gru with a batch size of 64 and 20 epochs. This model has the best evaluation metrics with an MSE of 0.0181, an MAE of 0.0814, an RMSE of 0.1345, and a MAPE of 0.29%. These results can also be displayed in a graph showing the model's performance in making predictions on the test data.

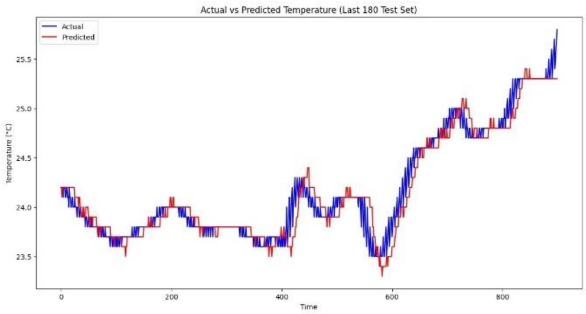

Figure 9 graph of prediction results with testing data

Figure 9 presents a comparison graph that illustrates the actual data (depicted by the blue line) alongside the prediction results (represented by the red line) on the test dataset. Table 3 provides a numerical comparison between the actual values and the predicted values.

Table 3 comparison of actual and predicted data

Data	Actual	Predicted
1	24.4	24.4
2	24.3	24.4
3	24.3	24.4
4	24.3	24.4
5	24.3	24.4
6	24.3	24.4
7	24.3	24.4
8	24.3	24.4
9	24.3	24.4
10	24.3	24.4
...	...	...
97066	25.8	25.3

The LSTM architecture is excellent at capturing long-term patterns in time series data , enabling LSTM to recognize broader patterns relevant for short-term predictions. It is then hybridized with the GRU architecture, which is similar to LSTM but has a simpler structure . This simplicity allows GRU to be trained faster and aids in adapting to rapid changes.

After determining the optimal architecture for the temperature variable and the desired output, the next step is to use this architecture to predict future temperature values. In this study, the prediction is focused on the short-term, specifically the next 5 minutes. To make predictions, the study utilizes the most recent observation data from the dataset, corresponding to the 'look_back' length or the number of previous time steps used by the model to make predictions. With the last observations in hand, the trained architecture is employed to forecast the temperature variable for the upcoming time point.

Once the prediction for the next time step is obtained, the last actual data point is combined with the predicted data. The predicted value for the next time step is rounded for easier interpretation. Based on the architectural comparison conducted, this study uses the LSTM-GRU architecture to predict the temperature variable for the next 5 minutes, as it yielded the best evaluation results during the testing process.

```
predicted temperatures for the next 5
minutes are : [25.283474 25.29093  25.29459
25.325108 25.335697]
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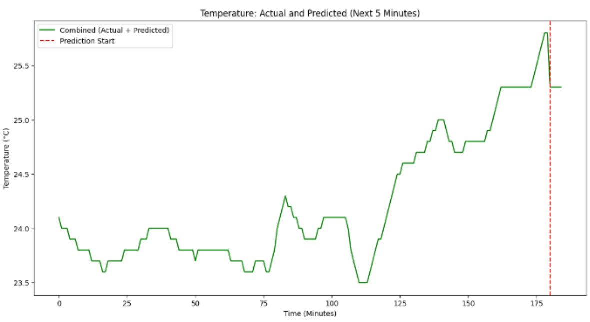

Figure 10 graph of prediction results for the next 5 minutes

Figure 10 displays the predicted temperatures for the next 5 minutes using the best-performing model, LSTM-GRU. In the figure, the red line indicates the starting point of the predictions. Since there are no actual data points for these future predictions, model evaluation for this prediction period cannot be performed.

V. CONCLUSION AND SUGGESTION

Conclusion

The implementation of the Hybrid LSTM-GRU architecture model for predicting air temperature has proven to be quite effective. With an LSTM layer consisting of 40 units and ReLU activation, a GRU layer with 40 units and ReLU activation, and ADAM as the optimizer, this model achieved the lowest evaluation metrics: an MSE of 0.0181, an MAE of 0.0814, an RMSE of 0.1345, and a MAPE of 0.29% using a batch size of 64 and 20 epochs. The trained model is also capable of predicting future temperatures. Therefore, the Hybrid LSTM-GRU architecture model is optimal for short-term air temperature prediction.

Suggestion

Based on the conducted research, the recommendations for future studies using the Hybrid LSTM architecture include using datasets with other weather-determining variables, better hyperparameter tuning, and adding regularization techniques to enhance the model's prediction accuracy. Additionally, the model should aim to predict over longer time horizons.

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