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Time Series Modelling For Weather Forecasting Using The Long Short Term Memory Method (Case Study: Lampung Climatology Station)

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ABSTRACT

Weather significantly influences human activities, including environmental management, health, agriculture, and urban planning. Accurate temperature prediction is essential for managing energy consumption, public health, and agriculture. This study employs Long Short Term Memory (LSTM) networks for weather fore-casting at the Lampung Climatology Station, focusing on minimum, maximum, and average temperatures. LSTM networks, capable of learning long-term de-pendencies in data, have proven effective in various forecasting applications. The research aims to identify the optimal LSTM model for temperature forecasting us-ing time series data from the Lampung Climatology Station. Different LSTM model parameters, such as hidden neurons, batch size, and epochs, were tested to find the best configuration with the smallest Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) values. The results indicate that the optimal LSTM model for forecasting minimum air temperature (X1) includes 100 hidden neurons, a batch size of 4, and 50 epochs, achieving an RMSE of 0.59 and a MAPE of 1.90%. For maximum air temperature (X2), the best model uses 5 hidden neurons, a batch size of 4, and 50 epochs, with an RMSE of 1.22 and a MAPE of 3.15%. The optimal model for average air temperature (X3) comprises 5 hidden neurons, a batch size of 4, and 150 epochs, achieving an RMSE of 0.73 and a MAPE of 2.10%. These findings demonstrate the effective-ness of LSTM models in accurately forecasting air temperatures, providing valu-able insights for applications ranging from agricultural planning to disaster pre-paredness.

1. INTRODUCTION

Weather plays a crucial role in human life, both directly and indirectly, influencing a wide range of areas, including environmental issues, health, agriculture, and urban planning. For instance, farmers rely heavily on weather patterns to determine the best times for planting and harvesting crops, while urban planners use weather data to design infrastructure that can withstand extreme weather conditions. Moreover, weather conditions can significantly impact public health, as seen in cases of heat-waves or cold snaps, which can lead to increased mortality and morbidity.

One of the key elements of weather that significantly impacts our daily lives is temperature. Accurate temperature prediction is essential for energy consumption management, public health, and the spread of diseases.

Temperature variations dic-tate heating and cooling demands, influence agricultural cycles, and affect human comfort and health. The need for reliable weather forecasting methods has thus be-come paramount, driving the development of advanced predictive models. Although rainfall is important, it is not the focus of this study.

In recent years, Long Short Term Memory (LSTM) networks, a type of recurrent neural network, have shown great promise in various forecasting applications, includ-ing weather prediction. LSTM networks are particularly suited for time series forecast-ing due to their ability to learn and remember long-term dependencies in data, which is a common challenge in weather prediction. By capturing patterns in historical weather data, LSTM models can provide more accurate forecasts, helping communi-ties and industries make better-informed decisions.

Previous studies have successfully applied LSTM models to diverse domains. For example, LSTM networks have been used for rainfall prediction in Malang, showing significant improvements over traditional methods (Rizki et al, 2020). In commerce, LSTM has demonstrated effectiveness in product sales forecasting, highlighting its versatility and robustness (Wiranda and Sadikin, 2019). Similarly, LSTM models have been used in analyzing COVID-19 cases (Qori et al, 2022), predicting cargo revenue (Aprian et al, 2020), and forecasting Bitcoin prices (Aldi and & Adit- sania, 2018). Notably, LSTM has also been effective in predicting air quality and temperature in Bandung, achieving RMSE values of 1.85 for air quality and 3.15 for temperature (Khumaidi et al, 2020).

Building on this body of work, the current study aims to apply LSTM networks for weather forecasting at the Lampung Climatology Station. The focus will be on three key variables: minimum temperature (X1), maximum temperature (X2), and average temperature (X3). By experimenting with different LSTM model parameters, such as the number of hidden neurons, batch size, and epochs, this study seeks to identify the optimal model configuration that yields the smallest Mean Absolute Percentage Error (MAPE) and RMSE values. The objectives of this research are multifaceted: to de-termine the optimal LSTM model for temperature forecasting, evaluate the perfor-mance of the LSTM method, and generate accurate temperature forecasts using the best model, offering valuable information for various applications, from agricultural planning to disaster preparedness.

2. METHOD

Long Short Term Memory (LSTM)

Long Short Term Memory (LSTM) is an advanced form of Recurrent Neural Net-work (RNN) introduced by Hochreiter and Schmidhuber in 1997. LSTM was devel-oped to address the limitations of traditional RNNs, particularly their inability to maintain long-term memory due to the vanishing gradient problem. This issue causes older information to become less relevant over time, reducing prediction accuracy (Zhao et al, 2017). Unlike RNNs, LSTM networks utilize memory cells and gate units—input, forget, and output gates—to manage information flow and maintain long-term dependencies. This architecture allows LSTM to handle large sequential data effectively, making it suitable for applications like speech recognition and fore-casting. The ability of LSTM to remember and recall information over long periods addresses the shortcomings of RNNs, enabling more accurate predictions.

The LSTM architecture features three primary gates: the input gate, forget gate, and output gate. These gates control the flow of information into and out of the memory cells. The input gate determines what information is added to the memory cell, the forget gate decides what information is discarded, and the output gate regu-lates what information is used for the current output and passed to the next time step. This gating mechanism ensures efficient information management, allowing LSTM networks to read, store, and update information dynamically. As a result, LSTM networks can effectively handle both short-term and long-term memory, making them powerful tools for various sequential data tasks. The robust architecture of LSTM networks, characterized by these memory cells and gate units, has led to sig-nificant advancements in fields such as speech recognition and time series forecast-ing (Hochreiter and Schmidhuber, 1997). The ability of LSTM to track long-term dependencies in data has been further highlighted in various applications (Karpathy et al, 2015). The architecture of LSTM can be seen in Figure 1.

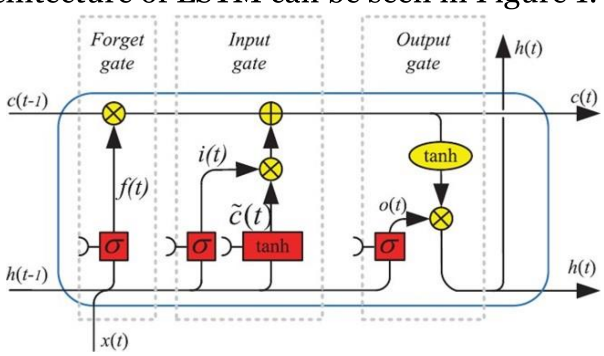

Fig. 1. Long Short Term Memory (LSTM) Architecture.

Denormalization

Denormalization is the process of converting forecast results from normalized data back to their original form. This step is essential to compare the predicted data with actual values and assess the model's performance. When normalization was initially performed within the interval [0,1], denormalization is expressed by the equation (Wiranda and Sadikin, 2019):

xt=x'(Xmax-Xmin)+Xmin (1).

where xt is the denormalized weather data value, x' is the normalized weather data, Xmin is the minimum value of the weather data, and Xmax is the maximum value of the weather data.

Model Validation

Validation is the process of testing the accuracy of a model's performance in predict-ing data to assess its effectiveness. Validation can be done using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for model evaluation (Wiranda and Sadikin, 2019). RMSE measures the accuracy of a model by calculat-ing the square root of the average squared differences between actual and predicted temperature data over multiple forecasting periods. It is formulated as:

RMSE=t=1nYi-Yi2n (2)

where Yi denotes the actual temperature at period t, Yi represents the predicted temperature, and n is the number of data points. On the other hand, MAPE quantifies the absolute percentage error between actual and predicted values, providing insight into the model's accuracy relative to the actual data. It is formulated as:

MAPE=t=1nYi-YiYin×100 (3)

where Yi and Yi represent actual and predicted temperature values respectively, and n is the total number of data points.

A smaller MAPE value indicates that the LSTM model's predictions are closer to the actual values, making it a better model for weather forecasting. The range of MAPE values for evaluating an LSTM model's accuracy is shown in Table 1 (Hayuningtyas, 2017).

Table 1. Range Category of MAPE Value.

MAPE Range	Category
< 10 %	Excellent forecasting model capability
10–20 %	Good forecasting model capability
20 –50 %	Viable forecasting model capability
>50 %	Poor forecasting model capability

Dataset

The data used in this study are secondary data obtained from Lampung Climatology Station in the form of daily data from January 01, 2021 to April 30, 2024. The data measured includes minimum air temperature data, maximum air temperature, and average air temperature. Because the data used is based on a certain period of time, this air temperature data is classified as time series data.

Research Methodology

The LSTM model is built by initializing several parameters that will be used during testing. These parameters include the number of hidden neurons, batch size, and epochs. The hidden neurons are set at 5, 25, 50, and 100, while the batch sizes are 4, 16, 32, 64, and 128. The number of epochs is set at 50, 100, 150, and 200. Flowchart of the research methodology can be seen in the Figure 2.

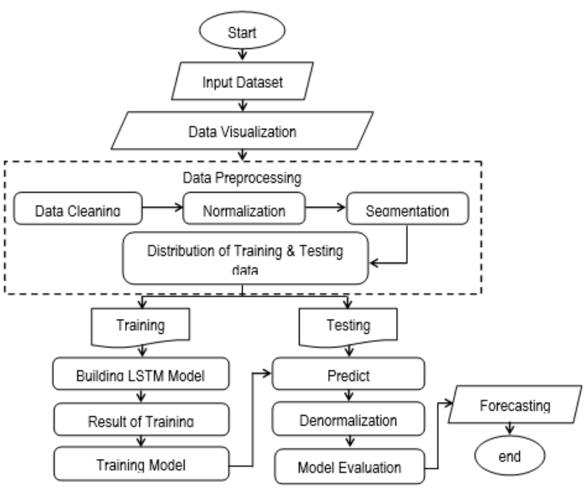

Fig. 2. Flowchart of Research Methodology.

3. RESULT AND DISCUSSION

The formation of the LSTM model is formed from various compositions of the divi-sion of training data and testing data. Then determine the most optimal hidden neu-ron, batch size and epoch parameters from the various parameter values given.

Table 2. LSTM model accuracy value based on the number of hidden neurons.

Neuron	Batch Size	Epoch	RMSE X1	RMSE X2	RMSE X3	MAPE X1	MAPE X2	MAPE X3
5	4	50	0,76	1,40	0,82	2,44 %	3,51 %	2,29 %
25	4	50	0,69	1,45	0,82	2,26 %	3,62 %	2,32 %
50	4	50	0,70	1,48	0,82	2,26 %	3,67 %	2,34 %
100	4	50	0,69	1,64	0,92	2,25 %	4,11 %	2,68 %

Based on Table 2, the LSTM model at minimum air temperature (X1) with hidden neuron parameters of 100 hidden neurons has the smallest RMSE and MAPE values, which are 0.69 and 2.25%. While the maximum air temperature (X2) and average air temperature have the smallest RMSE and MAPE values in the LSTM model formed from 5 hidden neurons. The smallest RMSE and MAPE values at maximum air temperature are 1.40 and 3.51%, while the smallest RMSE and MAPE values at av-erage air temperature are 0.82 and 2.29%.

Table 3. LSTM model accuracy value based on the number of batch sizes.

Batch Size	Epoch	RMSE X1	RMSE X2	RMSE X3	MAPE X1	MAPE X2	MAPE X3
4	50	0,69	1,40	0,82	2,25 %	3,51 %	2,29 %
16	50	0,70	1,53	0,86	2,29 %	3,82 %	2,40 %
32	50	0,71	1,59	0,91	2,35 %	3,98 %	2,56 %
64	50	0,73	2,10	0,96	2,40 %	5,07 %	2,71%
128	50	0,74	1,95	0,98	2,41 %	4,79 %	2,76 %

Based on Table 3, the LSTM model on each variable has the smallest RMSE and MAPE values at the number of batch sizes of 4 batch sizes. The smallest RMSE and MAPE values for minimum air temperature (X1) are 0.69 and 2.25%. The smallest RMSE and MAPE values at maximum air temperature (X2) were 1.40 and 3.51%, while the smallest RMSE and MAPE values at average air temperature (X3) were 0.82 and 2.29%.

Table 4. LSTM model accuracy value based on the number of epochs

Batch Size	Epoch	RMSE			MAPE		
		X1	X2	X3	X1	X2	X3
4	50	0,69	1,40	0,82	2,25 %	3,51 %	2,29 %
4	100	0,87	1,50	0,81	2,74 %	3,75 %	2,30 %
4	150	0,86	1,53	0,77	2,87 %	3,75 %	2,16 %
4	200	0,90	1,54	0,80	2,96 %	3,77 %	2,21 %

Based on Table 4, the LSTM model on the minimum air temperature (X1) and max-imum air temperature (X2) variables has the smallest RMSE and MAPE values at the number of epochs of 50 epochs. The smallest RMSE and MAPE values for mini-mum air temperature (X1) are 0.69 and 2.25%, for maximum air temperature (X2) are 1.40 and 3.51%. Meanwhile, the average air temperature variable (X3) has the smallest RMSE and MAPE values at the number of epochs of 150 epochs with RMSE and MAPE values of 0.77 and 2.16%.

Table 5. LSTM model accuracy value based on the training and testing data split

Training / Testing	RMSE			MAPE		
	X1	X2	X3	X1	X2	X3
50% / 50 %	0,79	1,64	0,78	2,66%	3,93%	2,29 %
60% / 40%	0,80	1,55	0,82	2,69%	3,87%	2,45%
70% / 30%	0,76	1,36	0,76	2,53%	3,35%	2,11 %
80% / 20%	0,69	1,40	0,77	2,25%	3,51%	2,16%
90% / 10%	0,59	1,22	0,73	1,90 %	3,15%	2,10 %

Based on Table 5, testing the LSTM model on each variable based on the composi-tion of this dataset has the smallest RMSE and MAPE values, namely the model with the division of training data by 90% and testing data by 10%. The smallest RMSE and MAPE values for minimum air temperature (X1) are 0.59 and 1.90%. The smallest RMSE and MAPE values for maximum air temperature (X2) are 1.22 and 3.15%, while for average air temperature (X3) are 0.73 and 2.10%.

Thus, the best LSTM model for forecasting minimum air temperature (X1) is built with 100 hidden neurons, a batch size of 4, 50 epochs, and a data split of 90% for training and 10% for testing. Similarly, the optimal LSTM model for maximum air temperature (X2) utilizes 5 hidden neurons, a batch size of 4, 50 epochs, and the same 90%/10% data split. For average air temperature (X3), the most effective LSTM model incorporates 5 hidden neurons, a batch size of 4, 150 epochs, and fol-lows the 90%/10% data partitioning scheme. These configurations are tailored to maximize the accuracy of weather predictions based on historical data.

Forecasting on air temperature data which includes Minimum Air Temperature (X1), Maximum Air Temperature (X2) and Average Air Temperature (X3) based on the best Long Short Term Memory (LSTM) model can be seen in the following figure.

Fig. 3. Minimum air temperature forecasting results (X1).

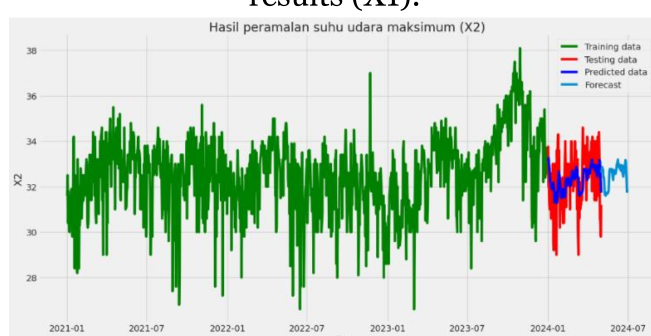

Fig. 4. Maximum air temperature forecasting results (X2).

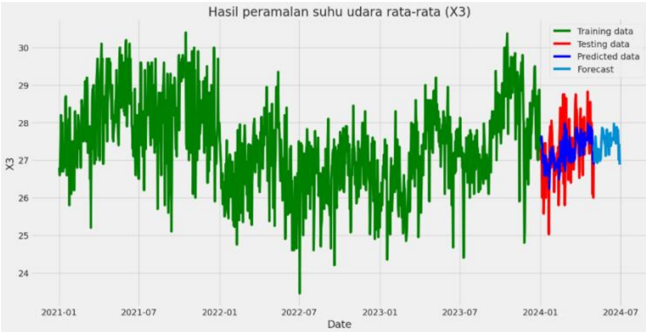

Fig. 5. Average air temperature forecasting results (X3).

4. CONCLUSION

Based on the discussion, the conclusions of this research are as follows: The best LSTM model for air temperature forecasting is determined by a dataset division of 90% for training and 10% for testing. This specific composition of the dataset divi-sion has proven to be the most effective in training the LSTM model for accurate air temperature prediction.

For forecasting minimum air temperature (X1), the optimal LSTM model configu-ration includes 100 hidden neurons, a batch size of 4, and 50 epochs. In contrast, the best LSTM model for forecasting maximum air temperature (X2) utilizes 5 hidden neurons, a batch size of 4, and 50 epochs. For average air temperature (X3), the ideal model configuration consists of 5 hidden neurons, a batch size of 4, and 150 epochs. These specific configurations have been identified as the most effective for predicting each respective temperature variable.

The performance of these LSTM models is evaluated using Root Mean Square Er-ror (RMSE) and Mean Absolute Percentage Error (MAPE) values. The RMSE and MAPE for the best LSTM model predicting minimum air temperature (X1) are 0.59 and 1.90%, respectively. For maximum air temperature (X2), the RMSE is 1.22 and the MAPE is 3.15%. For average air temperature (X3), the RMSE is 0.73 and the MAPE is 2.10%. Given that all MAPE values are below 10%, these LSTM models are highly effective for forecasting air temperature at the Lampung Climatology Station..

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