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Application of the Attention-Based LSTM Method for Rainfall Prediction in East Java

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***Abstract*— *This research aims to measure the performance of the Attention-Based Long Short-Term Memory (LSTM) predictive model in rainfall prediction analysis in East Java, with a focus on including the application of the model in predicting complex time-series data. The main objective of this study is to create an efficient and accurate model and to emit the performance of the Attention-Based LSTM algorithm compared to conventional methods. The methodology used includes rainfall data collection, data preprocessing, Attention-Based LSTM model design, training models, and testing to assess accuracy. The results of the study indicate that the Attention-Based LSTM model is able to improve rainfall prediction compared to conventional methods, with the Root Mean Squared Error (RMSE) evaluation metrics with a value of 0.00807 and Mean Squared Error (MSE) with a value of 0.08987 which shows better results, so this model can be relied on for real-world applications.*

Keywords *: Attention-Based Long Short-Term Memory, Rainfall, Mean Squared Error, Root Mean Squared Error.*

I. INTRODUCTION

Rainfall is one of the environmental factors that significantly affect daily life [1], especially in regions that rely on agriculture, such as East Java. In this area, high rainfall can lead to various negative impacts, including infrastructure damage, transportation disruptions, and significant social and economic consequences. East Java, as the largest rice producer in Indonesia, contributes approximately 17.89% of the total national rice production in 2023 [2]. Therefore, it is crucial to pay serious attention to rainfall prediction to minimize the adverse effects of extreme weather events [3]. By understanding rainfall patterns, we can reduce damage caused by climate change and improve marine health evaluations and weather forecasting [4].

Although rainfall cannot be predicted with absolute certainty, its intensity can be estimated using historical data. Advances in technology and the development of sophisticated computer models have enabled researchers to predict rainfall patterns more accurately and in a timely manner. Various methods have been developed for this purpose, including artificial neural networks (Backpropagation) [5], regression [6], Support Vector Machine, Random Forest, and Linear Regression[7]. The artificial neural network with the Backpropagation algorithm [8], for example, offers advantages in recognizing complex patterns [9], although it has weaknesses such as slow convergence and the need for large training data [10], [11], [12]. This indicates that despite advancements in prediction technology, challenges remain in improving the accuracy of rainfall forecasts.

Most existing studies currently use rainfall data from relatively short periods, such as a few years or decades. However, to obtain a more accurate picture of rainfall patterns, data from longer periods are needed. Long-term data can provide insights into climate fluctuations that may not be visible in short-term data. Therefore, this research focuses on developing the Attention-based LSTM method, which is designed to highlight important features in time-series data processing. This method is expected to bridge existing gaps in accurate and dynamic rainfall prediction [13] and provide a better understanding of rainfall patterns in East Java.

In this study, the Attention-based LSTM method will be applied by processing rainfall data from 2000 to 2023 in East Java. The primary goal of this research is to build an adaptive and comprehensive rainfall prediction model that can significantly contribute to disaster resilience and sustainable development in the region. By utilizing broader historical data and more advanced methods, the findings of this research are expected to provide meaningful contributions to efforts in mitigating the negative impacts of high rainfall. Additionally, this study also aims to support the development of better policies for managing natural resources and agriculture in East Java.

The Attention-based LSTM method has several advantages that make it an ideal choice for this research. First, this method can capture long-term relationships in time-series data, which is crucial for predicting rainfall influenced by various climate factors. Second, the attention mechanism in this model allows the system to focus on the most relevant parts of the data, thereby improving prediction accuracy by reducing noise from irrelevant data. Third, the Attention-based LSTM can overcome the vanishing gradient problem often encountered in traditional LSTM models, making it more efficient in training and faster in convergence. With these advantages, using the Attention-based LSTM method is expected to yield more accurate and reliable rainfall predictions while providing deeper insights into rainfall patterns in East Java.

A study conducted by [14] used the Long Short-Term Memory (LSTM) method, which is an architecture of the Recurrent Neural Network (RNN). LSTM can process sequential data and retain long-term information, making it suitable for predicting time-series weather data. The data used in this study consisted of rainfall and temperature data in Surabaya, Indonesia. The training data covered the period from 2013 to 2020, while the test data was from 2021. The data processing involved data collection, preprocessing, normalization, and data splitting. The study results showed that the LSTM model with 100 epochs and a batch size of 50 provided the best RMSE and MAPE values for rainfall and temperature predictions. The best RMSE and MAPE values obtained were 1.7444 and 1.9499%, respectively. The prediction model offers recommendations for implementing an effective weather prediction model using the LSTM method.

A similar study conducted by [15] aimed to predict monthly rainfall in Sorong City using the Multiple Linear Regression method. The data used were obtained from BMKG DEO Sorong, covering the period from 2017 to 2021, with parameters including monthly average air humidity, monthly average air temperature, and total monthly rainfall. The research methodology involved data collection and preprocessing, the use of multiple linear regression to develop a regression equation, and model evaluation using Root Mean Square Error (RMSE) and Correlation Coefficient. The study results showed a correlation coefficient value of 0.8175, a Mean Absolute Error (MAE) of 78.8695, and an RMSE of 95.1982. The study stated that temperature and air humidity significantly influence rainfall prediction in Sorong City, with an influence of 81.75%. Although the RMSE value indicates a relatively large deviation, the strong correlation suggests a fairly good prediction.

A study conducted by [16] investigated rainfall forecasting in Aceh Province. The primary objective of this study was to predict monthly rainfall in Aceh Province for 2022 and 2023. The data used consisted of monthly rainfall data from 2014 to 2021. The method applied was the Box-Jenkins approach, specifically the Autoregressive Moving Average (ARMA) model. After undergoing several steps, such as splitting the data into training and testing sets, square root transformation for variance stationarity, and ADF tests for mean stationarity, the study results showed that the best model for forecasting rainfall in Aceh Province was the ARMA (8,6) model, with a Mean Absolute Error (MAE) of 175.372 and a Root Mean Square Error (RMSE) of 246.647 on the test data. The forecasting results using this model indicated that rainfall in Aceh Province in 2022 and 2023 was expected to be high in March, April, May, September, October, and November.

II. RESEARCH METHODS

This research consists of several stages that are systematically arranged to achieve the research objectives. Each stage is designed to ensure that the research proceeds in a structured and methodological manner, resulting in valid and useful findings. These stages can be seen in Figure 1.

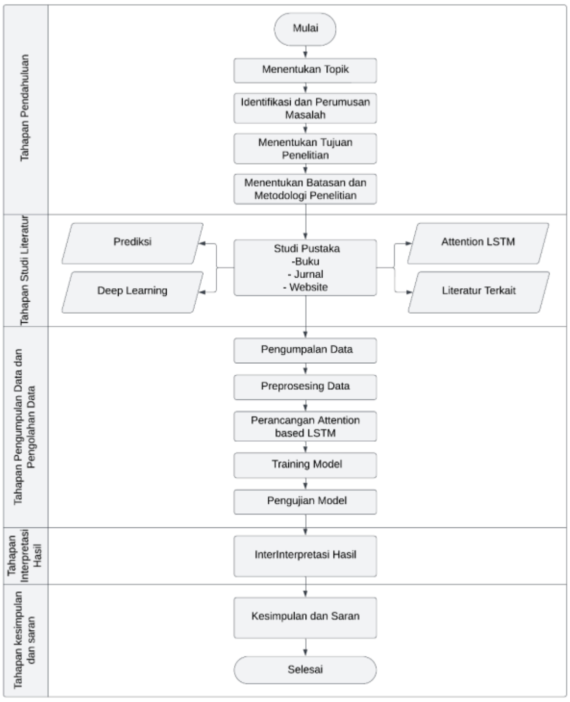

Figure 1. Research Stages

The figure illustrates the research stages that are systematically arranged to achieve the research objectives. The process begins with determining the topic, followed by identifying and formulating the problem, as well as establishing research objectives and methodological constraints. Next, during the literature review stage, researchers make predictions by utilizing sources such as books, journals, and websites, and studying the Attention-based LSTM method. After that, data is collected and processed through the preprocessing stage, where the Attention-based LSTM model is designed. The model is then trained and tested to ensure its performance. The results of these tests will be interpreted, concluding with findings and recommendations before the research is considered complete. Each stage is designed to ensure that the

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research proceeds in a structured and methodological manner, resulting in valid and useful findings.

The data used in this research is secondary data obtained from the official website dataonline.bmkg.go.id/data_iklim, provided by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). A total of 8,765 rainfall data points were collected from the years 2000 to 2023. All collected data will be validated for further analysis and to determine the next steps in data handling and processing. The obtained data includes information on average temperature (Tavg), average relative humidity (RH_avg), rainfall (RR), sunshine duration (ss), and average wind speed (ff_avg).

The data preprocessing process in this study includes date format conversion, handling missing data, identifying and replacing outliers, feature selection, data normalization, data reshaping, and, finally, data splitting.

After the preprocessing process, the next stage is to develop the Attention-based LSTM model using the prepared data. The dataset is divided using an 80:10:10 ratio, with 80% used for training, 10% for validation, and 10% for testing. After splitting the data, the Attention-based LSTM model is created using the training and validation data. Once the model is successfully developed, the final stage is testing the model with the testing data to determine the MSE (Mean Squared Error) and RMSE (Root Mean Squared Error) of the obtained predictions. The smaller the MSE and RMSE values, the better the prediction results, which will then be used to draw conclusions from the conducted research.

III. RESULT AND ANALYSIS

3.1 Data Collection

A total of 8,764 rainfall data points were collected from the years 2000 to 2023. The obtained data includes information on average temperature (Tavg), average relative humidity (RH_avg), rainfall (RR), sunshine duration (ss), and average wind speed (ff_avg). A sample of the rainfall data can be seen in Table 1.

Table 1. Sample of Rainfall Dataset

Date	Tavg (°C)	RH avg (%)	RR (mm)	ss (jam)	ff_avg(m/s)
2000/01/01	24.1	69.0	82.0	5.4	2.0
2000/01/02	22.9	77.0	0.0	null	4.0
2000/01/03	23.8	78.0	14.0	4.1	null
2000/01/04	24.2	77.0	10.0	1.3	2.0
.....	.....	.....	.....	.....	.....
2023/12/31	26.6	81.0	null	4.0	2.0

3.2 Data Preprocessing

The data preprocessing process is carried out in several stages, including date format conversion, handling missing data, identifying and replacing outliers, feature selection, data normalization, data reshaping, and finally, data splitting.

The date format conversion process ensures that the dates used follow the day/month/year format. Once the date format conversion is completed, the next step is to identify missing data. The number of missing data points that need to be replaced with a value of 0 can be seen in Table 2.

Table 2. Number of Missing Data

Variabel	Jumlah
Tanggal	0
Tavg (°C)	33
RH avg (%)	36
RR (mm)	217
ss (jam)	53
ff_avg (m/s)	237

After identifying the number of missing data points, the next step is to replace/fill in the missing data with a value of 0 to ensure that the data can be processed properly. A sample of the preprocessed data, including date format conversion and filling in missing values with 0, can be seen in Table 3.

Table 3. Sample Dataset After Date Conversion and Missing Data Filling

Date	Tavg (°C)	RH avg (%)	RR (mm)	ss (jam)	ff_avg(m/s)
01/01/2000	24.1	69.0	82.0	5.4	2.0
02/01/2000	22.9	77.0	0.0	0.0	4.0
03/01/2000	23.8	78.0	14.0	4.1	0.0
04/01/2000	24.2	77.0	10.0	1.3	2.0
.....	.....	.....	.....	.....	.....
31/12/2023	26.6	81.0	0.0	4.0	2.0

After completing the previous steps, the next stage of preprocessing is handling outlier values. Outliers are values that deviate significantly from the normal range within a dataset. These values can affect statistical analysis and the performance of predictive models, making it crucial to identify and address them appropriately.

Once this step is completed, the next stage involves selecting the features to be used by analyzing the correlation between each variable. The independent variables (X) include Tavg (°C), RH_avg (%), ss (hours), and ff_avg (m/s), while the dependent variable

(Y) is RR (mm). The results of the feature selection process can be seen in Table 4.

Table 4. Feature Selection Results (Correlation)

Variabel	Correlation Values
RH avg (%) vs RR (mm)	0.326558
Tavg (°C) vs RR (mm)	0.040954
ss (jam) vs RR (mm)	-0.257047
ff avg (m/s) vs RR (mm)	-0.181402

Based on the analysis of the four variables, relative humidity (RH_avg) has the strongest correlation with rainfall, followed by average temperature (Tavg). The other variables show weaker correlations. Therefore, the selected features are relative humidity (RH_avg) and average temperature (Tavg).

Next, columns that are considered to have low correlation, namely 'Date', 'ss (hours)', and 'ff_avg (m/s)', are removed from the dataset.

The next step is to normalize the data from the selected features. This is done to ensure that all features have the same scale, specifically within the range of [0:1]. This process is carried out using MinMaxScaler. A sample of the normalized data can be seen in Table 5.

Table 5. Sample of Normalized Data

Tavg (°C)	RH_avg (%)	RR (mm)
0.557143	0.325581	0.565517
0.385714	0.511628	0.000000
0.514286	0.534884	0.096552
0.571429	0.511628	0.068966
0.457143	0.534884	0.000000

After the data has been normalized, the next step is the reshaping process. This process is used to modify the structure or format of the dataset to facilitate analysis and modeling.

3.3 Data Splitting

The dataset in this study is split using an 80:10:10 ratio, where 80% of the data is used for training, 10% for validation, and 10% for testing. This distribution ensures an optimal balance for model training and evaluation. The details of the dataset split can be seen in Table 6 below.

Table 6. Data Splitting

Description	Total Amount
Training (80%)	7013
Validation (10%)	876
Testing (10%)	876
Total	8765

3.4 Model Development

In the model development stage, several parameters need to be configured to ensure optimal predictive performance for the Attention-based LSTM algorithm. Various parameter trials were conducted to fine-tune the model. The tested parameters for the Attention-based LSTM algorithm are as follows:

Hidden layer	:	7013
Neuron hidden	:	128
Batch size	:	4, 16, 32, 64, 128
Epoch	:	100
Optimizer	:	Adam
Fungsi aktivasi	:	tanh

Several parameter values from the above trials were used to determine the optimal parameters for rainfall prediction in this study. Based on the results of testing the training and validation data using different parameter configurations, the outcomes are presented in Table 7

Table 7. Training and Validation Data Testing Results

Batch	Epoch	Training MSE	Training RMSE	Validation MSE	Validation RMSE
4	10	0.006500	0.080624	0.007491	0.086552
4	20	0.006253	0.079081	0.007338	0.085662
4	50	0.006028	0.077645	0.007181	0.084742
4	100	0.005905	0.076845	0.007165	0.084648
16	10	0.006545	0.080903	0.007590	0.087124
16	20	0.006189	0.078674	0.007339	0.085673
16	50	0.006018	0.077578	0.007185	0.084766
16	100	0.005845	0.076455	0.007038	0.083893
32	10	0.006482	0.080516	0.007526	0.086754
32	20	0.006367	0.079794	0.007470	0.086429
32	50	0.005998	0.077447	0.007146	0.084537
32	100	0.005888	0.076734	0.007089	0.084198
64	10	0.006526	0.080787	0.007528	0.086768
64	20	0.006452	0.080328	0.007472	0.086441
64	50	0.006068	0.077900	0.007214	0.084940
64	100	0.005951	0.077144	0.007110	0.084322
128	10	0.006520	0.080746	0.007508	0.086649
128	20	0.006468	0.080429	0.0075777	0.087049
128	50	0.006039	0.0777161	0.0071652	0.084647
128	100	0.005922	0.0769579	0.0070545	0.083991

The visualization of some of the best results based on Table 7 can be seen in Figure 2 below.

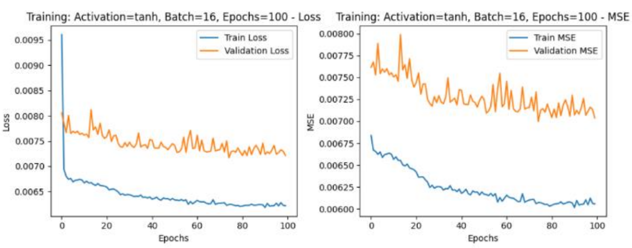

Figure 2. Training Model Performance Graph

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Based on Table 7 and Figure 2, the results can be explained as follows:

a. At a batch size of 4, the training loss consistently decreases from 10 to 100 epochs, indicating that the model is learning well. At 10 epochs, the validation loss stabilizes after an initial decline, showing no early overfitting. The validation loss starts to fluctuate at 50 and 100 epochs, indicating a risk of overfitting at higher epochs. Overall, increasing the number of epochs helps reduce errors, although there is a risk of overfitting.
b. At a batch size of 16, the training loss steadily decreases from 10 to 100 epochs. The validation loss tends to remain stable and decrease, indicating the model's ability to validate without significant overfitting. The model with a batch size of 16 and 100 epochs shows the best performance, with the lowest MSE and RMSE values on the validation data, signifying good generalization ability.
c. The training loss at a batch size of 32 steadily decreases from 10 to 100 epochs. The validation loss shows minor fluctuations but remains generally stable, indicating that the model remains stable without significant overfitting. Increasing the number of epochs helps reduce errors in both training and validation data, despite some fluctuations in validation loss.
d. At a batch size of 64, the training loss steadily decreases from 10 to 100 epochs. The validation loss is fluctuating but remains stable, indicating that the model does not experience significant overfitting. Increasing the number of epochs helps reduce errors in both training and validation data, with only minor fluctuations in validation loss.
e. The training loss at a batch size of 128 steadily decreases from 10 to 100 epochs. The validation loss fluctuates but remains generally stable, indicating that the model remains stable without significant overfitting. Increasing the number of epochs helps reduce errors in both training and validation data, with only minor fluctuations in validation loss.

Increasing the number of epochs generally reduces training loss, indicating continuous learning. However, it can also lead to overfitting, where the model loses its ability to generalize to validation data. Fluctuations in validation loss after a certain point signal signs of overfitting.

Meanwhile, smaller batch sizes (4 and 16) exhibit less fluctuation in validation loss and more consistent reductions in training loss compared to larger batch sizes (64 and 128). Smaller batch sizes provide more frequent and smaller updates, aiding better convergence, although they require longer training times. In contrast, larger batch sizes speed up training but increase the risk of overfitting.

As a result, the model with a batch size of 16 and 100 epochs was found to deliver the best generalization, showing the lowest MSE and RMSE values.

3.5 Model Testing

At this testing stage, the study uses a separate X_test dataset to evaluate the model's performance in predicting rainfall. The trained model is used to predict rainfall values based on input from X_test, and these predictions are compared with the actual values from Y_test. The evaluation is conducted by calculating the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which are 0.008076804690063 and 0.0898710447811919, respectively.

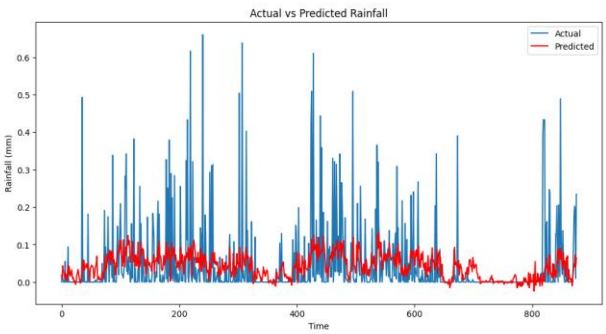

Figure 3. Actual vs. Predicted Graph

The visualization of the prediction results in Figure 3 shows that the prediction line closely follows the pattern of the actual value line, although there are some points of deviation indicating that the model's predictions are not always perfectly accurate

3.6 Results Interpretation

A low MSE indicates that the average squared difference between predicted and actual values is relatively small, suggesting that the model has a good ability to predict rainfall. A low RMSE shows that the average square root of the differences between predictions and actual values is not too large, indicating that the model is fairly accurate in its estimations. The test RMSE of 0.089871 is slightly higher than the validation RMSE. This is expected and indicates that the model's performance on completely unseen data is slightly worse but still within an acceptable range.

The visualization graph demonstrates that the predicted pattern aligns well with the actual values, although there are some points where predictions are not entirely accurate. This could be due to the complex variability of rainfall data. Prediction errors may arise from the complexity of the data that the model does not fully capture or the model's limitations in identifying all patterns and anomalies within the data.

Nevertheless, these test results suggest that the trained LSTM model performs well in predicting rainfall, although further refinements may be necessary to improve its accuracy and reliability. The following is a comparison of the model's performance in this study with relevant research.

Table 8. Comparison of Research Results

Description	**Method**	**Result**
Luttifia, (Lattifia et al., 2022)	*Long Short Term Memory* (LSTM)	RMSE:1.7444 MAPE: 1.9499%
Yusuf M, (Yusuf et al., 2022)	*Multiple Linear Regression*	MAE:78.8695 RMSE: 95.1982
Patriardian, (Patriardian et al., n.d. 2023)	*Autoregressive Moving Average (ARMA)*	MAE:175.372 RMSE: 246.647
Purposed Method	***Attention Based* LSTM**	**MSE:0.00807 RMSE: 0.08987**

Table 8 above shows that the LSTM and Attention-Based LSTM methods provide better metric results compared to Multiple Linear Regression and ARMA methods. This study employs the Attention-Based LSTM method, yielding an MSE of 0.0081 and an RMSE of 0.0899, indicating more accurate predictions and smaller deviations. This proves that Attention-Based LSTM is a more effective method for rainfall prediction in East Java.

VI. CONCLUSION

Based on the analysis of daily rainfall data collected from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) during the period from January 1, 2000, to December 30, 2023, this study finds that the Attention-Based LSTM model demonstrates strong performance in predicting rainfall in East Java. This is evidenced by the low MSE and RMSE values, indicating a small difference between predictions and actual values. The test RMSE of 0.089871 is slightly higher than the validation RMSE but remains within an acceptable range.

The graph visualization shows that the predicted pattern aligns well with the actual values, although some inaccuracies are present due to the complexity of rainfall data. Additionally, the integration of training with the Streamlit application enhances usability, making the training process more accessible. Overall, this model holds great potential for practical applications in rainfall prediction, although further refinements may be necessary to enhance its accuracy and reliability.

Several suggestions can be considered for future research. To improve the model's accuracy, it is recommended to consider additional weather variables such as wind direction and atmospheric pressure, which can provide deeper insights and enhance prediction accuracy. Developing a hybrid model by combining LSTM with other predictive models such as ARIMA or ensemble-based models can also explore potential improvements in predictive performance. Implementing this model in a real-time weather monitoring system will assist in decision-making and early warnings for extreme weather conditions. Additionally, further studies on outlier handling by applying advanced techniques can help address more complex anomalies in weather data.

REFERENCES

[1] T.-T. Le, B. T. Pham, H.-B. Ly, A. Shirzadi, and L. M. Le, “Development of 48-hour precipitation forecasting model using nonlinear autoregressive neural network,” presented at the CIGOS 2019, innovation for sustainable infrastructure: Proceedings of the 5th international conference on geotechnics, civil engineering works and structures, Springer, 2020, pp. 1191–1196.

[2] Zulkipli, “Produksi Padi Jawa Timur pada 2023 sekitar 9,59 juta ton gabah kering giling (GKG),” Oktober 2023. [Online]. Available: Https://Jatim.Bps.Go.Id/Pressrelease/2023/10/16/1385/Pada-2023--Luas-Panen- Padi.

[3] M. A. R. Suleman and S. Shridevi, “Short-term weather forecasting using spatial feature attention based LSTM model,” *IEEE Access*, vol. 10, pp. 82456–82468, 2022.

[4] W. Setiawan and A. Barokah, “Rainfall Prediction Using Backpropagation with Parameter Tuning,” presented at the MATEC Web of Conferences, EDP Sciences, 2022, p. 07003.

[5] S. Sunardi, A. Yudhana, and G. Z. Muflih, “Sistem prediksi curah hujan bulanan menggunakan jaringan saraf tiruan backpropagation,” *Jurnal Sistem Informasi Bisnis*, vol. 10, no. 2, pp. 155–162, 2020.

[6] G. U. Auliarahman, “Prediksi Curah Hujan Menggunakan Metode Regresi Bayesian di Kota Bandung pada Tahun 2022,” presented at the Bandung Conference Series: Statistics, 2023, pp. 265–272.

[7] M. Jalgaonkar and D. Kulkarni, “Rainfall prediction using regression and multiple algorithms,” *International Research Journal of Computer Science (IRJCS)*, vol. 8, no. 4, 2021.

[8] C. Sekhar and P. S. Meghana, “A study on backpropagation in artificial neural networks,” *Asia-Pacific Journal of Neural Networks and Its Applications*, vol. 4, no. 1, pp. 21–28, 2020.

[9] I. Budiman, A. Mubarak, S. Kapita, S. D. Abdullah, and M. Salmin, “Implementation of Backpropagation Artificial Network Methods for Early Children’s Intelligence Prediction,”

presented at the E3S Web of Conferences, EDP Sciences, 2021, p. 04033.

[10] V. Lestari, H. Mawengkang, and Z. Situmorang, “Artificial Neural Network Backpropagation Method to Predict Tuberculosis Cases,” *Sinkron: jurnal dan penelitian teknik informatika*, vol. 7, no. 1, pp. 35–47, 2023.

[11] M. Wahyudi and L. Pujiastuti, “Application of Neural Network Variations for Determining the Best Architecture for Data Prediction,” *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 5, pp. 742–748, 2022.

[12] M. Falah, D. P. Rini, and I. Pahendra, “Kombinasi Algoritma Backpropagation Neural Network dengan Gravitational Search Algorithm Dalam Meningkatkan Akurasi”.

[13] Y. Shali, B. Brahma, R. Wadhvani, and M. Gyanchandani, “Attention LSTM for Time Series Forecasting of Financial Time Series Data,” presented at the International Conference on Internet of Things and Connected Technologies, Springer, 2020, pp. 74–84.

[14] T. Lattifia, P. W. Buana, and N. K. D. Rusjayanthi, “Model Prediksi Cuaca Menggunakan Metode LSTM,” *JITTER J. Ilm. Teknol. dan Komput*, vol. 3, no. 1, pp. 994–1000, 2022.

[15] M. Yusuf, A. Setyanto, and K. Aryasa, “Analisis Prediksi Curah Hujan Bulanan Wilayah Kota Sorong Menggunakan Metode Multiple Regression,” *J-SAKTI (Jurnal Sains Komputer dan Informatika)*, vol. 6, no. 1, pp. 405–417, 2022.

[16] F. Patriardian, A. Hidayati, R. Rahil Alzahira, D. Jhuandra Tasyant, and S. Anwar, “Peramalan curah hujan di Provinsi Aceh menggunakan metode Box-Jenkins (Rainfall forecasting in Aceh Province using Box-Jenkins methods),” *Majalah Ilmiah Matematika dan Statistika*, vol. 23, no. 1, 2022.