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Rainfall Prediction from Himawari-8 Data Using the Deep Learning Method

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Abstract

Changes in rainfall affect human activities and can cause natural disasters, such as floods and landslides. This research focuses on changes in extreme rainfall that result in natural disasters. Indonesia, as a country with a tropical climate, certainly has its characteristics regarding rainfall patterns, such as air temperatures that tend to be high, sunlight that occurs throughout the year, and low air pressure. The characteristics of the tropical climate will form patterns and allow natural disasters to occur. Losses due to natural disasters can be minimized if there is thorough preparation in dealing with the possibility of natural disasters. Thorough preparation in facing natural disasters is based on knowledge of predictions of when and where the natural disaster will occur. Changes in rainfall can be predicted based on past rainfall data. These data produce patterns, such as real-time intensity. The data used in this research comes from the himawari-8 satellite using a cloud dataset. The next stage is pre-processing, which is the cleaning and adjustment of data. The deep learning algorithms used in this research are long short-term memory (LSTM) and recurrent neural network (RNN) to manage time series data. In previous research, it has been recommended that LSTM and RNN algorithms be used for rainfall prediction. The system created in this research is a rainfall prediction model using python programming language analysis and system output in the form of software with the accuracy of the LSTM model reaching 92.62% and the RNN model reaching 89.38%.

Keywords: Rainfall, Himawari-8, Long Short-term Memory (LSTM), Recurrent Neural Network (RNN).

1 Introduction

Rainfall is one of our daily lives' most important climate variables (Yang et al., 2020). Rainfall significantly influences several areas, including business, water resources, development, and agriculture. Natural catastrophes like floods and landslides are typically brought on by excessive rain (Hassan et al., 2023). The strongest negative natural catastrophe correlations are found with rainfall (Phadke et al., 2023). However, historical rainfall data has demonstrated that farmers may enhance crop management with rainfall, benefiting the country's economy (Schultz et al., 2021; Ibrahim., 2020). Predicting rainfall is therefore crucial for weather forecasting, alerting farmers to impending natural catastrophes that might harm people or their property, and assisting them in choosing when to plant and harvest their crops. Historical weather and climatic data are gathered and examined to create forecasts (Lagerquist et al., 2021). Rainfall is predicted using temperature, humidity, air pressure, evaporation, sunshine, and rainfall

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levels (Sawada et al., 2019). Much research has been carried out regarding rainfall prediction, such as using observation techniques used to predict rainfall, such as meteorological observations, weather stations, classical radiosondes, aircraft measurements, and remote sensing products (Salehin et al., 2020). Satellite observations are more popularly used as numerical data to make weather predictions, including the himawari-8 satellite (Sharma et al., 2023; Anadel et al., 2022). Several studies have been conducted to detect or predict rainfall in Indonesia, one of which uses data from the himawari-8 satellite. Launched on October 7, 2014, the himawari-8 satellite is the next generation of operational satellites for the Japan meteorological agency/Japan aerospace exploration agency (JMA/JAXA) observation data started to be distributed on July 7, 2015 (Min et al., 2019; Johnson et al., 2021). Research on rainfall prediction, such as numerical data processing with the weather research and forecasting (WRF) model and multicasting techniques, is carried out downscale from the output of the global forecast system (GFS) (Paski, et al., 2017), a deep learning approach to the LSTM algorithm for prediction processing weather (Supriyadi, 2020), and deep learning methods for weather data analysis (Hossain et al., 2020). As a variation of RNNs, LSTM networks are excellent at recognizing order dependencies in sequence prediction tasks, which makes them a good fit for challenging problem areas like voice recognition and machine translation. By including specialized memory cells that can selectively keep or discard information over time, LSTM networks are intended to overcome the problem of disappearing gradients in conventional RNNs (Kothai et al., 2023; Jelena et al., 2023). These memory cells allow LSTMs to capture long-term dependencies in sequential data effectively. With a per-time-step and per-weight computational complexity of 0.1, LSTM networks have comparatively low computational complexity (Srinu et al., 2022; Arora, 2024). Research that has been carried out (Ravi et al., 2022) using the WRF model method and multicasting techniques carried out downscale from the GFS output has the disadvantage that the model results still need to be overestimated compared to observational data The research uses a deep learning approach, namely 3 other algorithms for combining, namely the RNN, generalized regression neural network (GRNN) and extreme learning machine (ELM) algorithms (Rathi et al., 2024; Akila et al., 2023). The LSTM algorithm is suitable for combination with the RNN algorithm, whereas there is still noise for graph results using the GRNN or ELM algorithm (Rayudu et al., 2023). Lastly, the research uses deep learning methods to analyze weather data (Walaa., 2024; Ram et al., 2024). This research uses the LSTM algorithm with the parameters used, namely measuring air temperature, humidity, wind speed, and air pressure measurement. After 1 day of testing, a good root mean square error (RMSE) was obtained based on-air temperature, humidity, wind speed and air pressure parameters. For 3 days, 7 days, and 1 month, only temperature and humidity parameters experienced an increase in RMSE over time. Meanwhile, air pressure and wind speed parameters dropped on the third day and climbed in the subsequent month (Byun et al., 2023; Iman et al., 2023; Kutlu et al., 2021).

In this research, two rainfall prediction models were compared using himawari-8 data with a deep learning approach. The rainfall predictions only focused on heavy rain. The parameters used are cloud datasets in bands 5, 6, 7, 11, 12, and 13. This research uses two algorithms, namely the LSTM algorithm and the RNN algorithm. These two algorithms are then compared to get the best results. The LSTM algorithm and RNN algorithm are superior in processing numerical data and are suitable for use on cloud data in time series and numerical forms.

2 Research Method

This research was carried out with two sub-processes, namely accuracy and data extraction and prediction model training. In the acquisition process, himawari-8 data is stored and collected in NetCDF format. Data information is extracted specifically on bands 5, 6, 7, 11, 12, and 13 which is converted into data in CSV format. Briefly, the dataset collection process is illustrated in Figure 1.

FileZilla client is used to collect NetCDF data. An open-source, cross-platform file transfer program called FileZilla client transfers files from web hosting accounts. A program called FileZilla client may establish a direct connection to JMA/JAXA (Min et al., 2019; Bobir et al., 2024). This research uses FileZilla client version 3.63.2.1. The daily rainfall data in NetCDF format that has been collected is then carried out by the process of reading the data and selecting the data based on the channel used. In this research, the bands used are bands 5, 6, 7, 11, 12, and 13. Band information from each channel was taken in the Java Island area with a longitude of 7.6145° S to 110.7122° E. Next, the data for each band has a 2D array data structure, which needs to be changed to a list data structure. Each data channel has a length of 24 data, with this change in data type intended to simplify the process of converting data from NetCDF to CSV data. Python is the programming language used to extract NetCDF format data into CSV format. The python language used in this research is version 3.9.5. Then, the data for each band will be added into a sequential list data structure based on time so that the process of adding an empty list variable occurs. Data in CSV format is written using a list variable filled with information for each band. After the data in CSV format is obtained, it goes to the data processing to get features for data training, as in Figure 2.

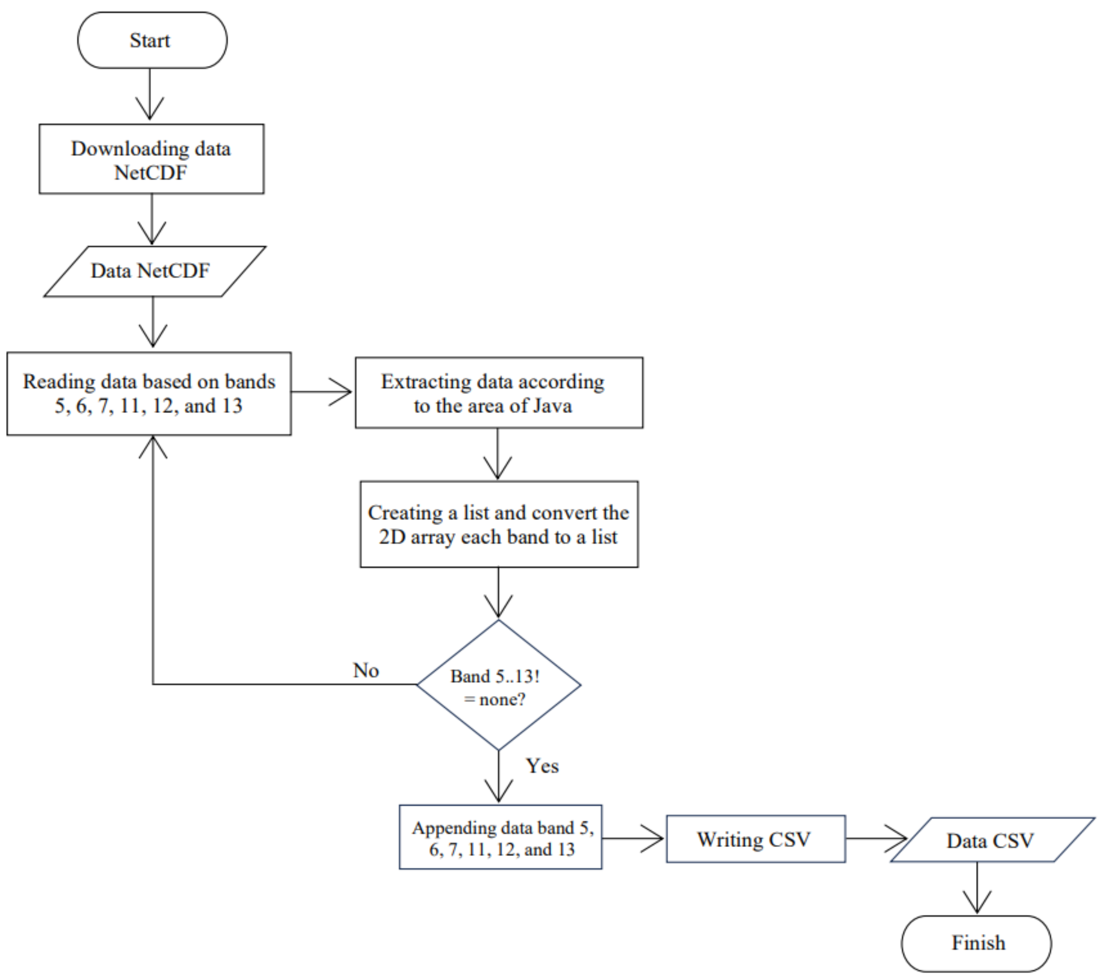


Figure 1: Flowchart Collecting Dataset

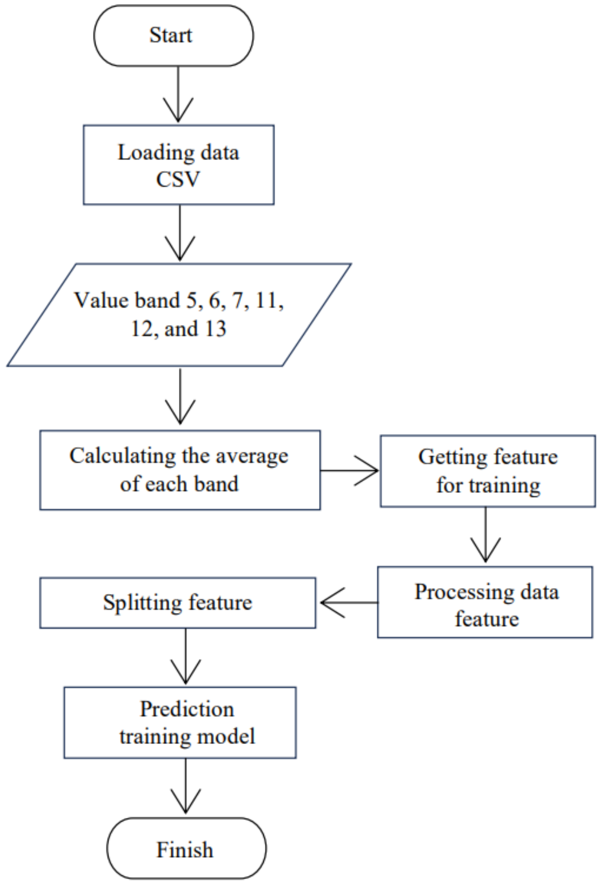


Figure 2: Processing and Training Data

In Figure 2, the process begins with taking CSV data to get the value for each band. Because each band has a data length of 24, a process of averaging the values for each band is carried out. This aims to reduce data features for processing and training processes. After that, the feature value is taken from the average results of each band. After the feature is obtained, it then enters the data processing process. This stage begins with taking 6 or 12 rows of CSV data for one or two-hour predictions. After that, the process continues with mapping labels and grouping data with labels. In this research, the labels from 6 or 12 rows will be averaged, and if almost 50% are heavy rain conditions, then they will be given a label of 1, and if not, they will be given a label of 0. Then, before entering the training process, the feature data will go into the process of splitting features, where 80% is used as training data and 20% as testing data. The final process is to train the model with LSTM and RNN, which will then be evaluated.

Himawari-8 Satellite

The space environment data acquisition (SEDA) monitors onboard the himawari-8 satellite monitors high-energy protons and electrons in orbit. Based on the environmental monitoring unit (EMU) created for the Galileo satellites, SEDA is provided by RUAG Space. The himawari-8 satellite has an advanced himawari imager (AHI) optical sensor that works on the reflective and thermal spectrum. This sensor records data every 10 minutes for maximum area coverage, namely East Asia to the West Pacific, and 2.5 minutes for observations. The himawari-8 satellite has 16 bands of 10 infrared (IR) channels, three visible channels, and three near-infrared (NIR) channels. Information on the 16 bands on the himawari-8 satellite is summarized in Table 1 (Risyanto, 2021; Kavitha., 2020).

Table 1: Himawari-8 Bands

Band		**Spatial Resolution**	**Central Wavelength**	**Physical Properties**
Band 1	Visible Near Infrared	1 km	0.47 µm	Vegetation, aerosol
Band 2			0.51 µm	Vegetation, aerosol
Band 3		0.5 km	0.64 µm	Vegetation, low cloud, fog
Band 4		1 km	0.86 µm	Vegetation, aerosol
Band 5		2 km	1.6 µm	Cloud phase
Band 6			2.3 µm	Particle size
Band 7	Infrared	2 km	3.9 µm	Low cloud, fog, forest fire
Band 8			6.2 µm	Mid and upper-level moisture
Band 9			6.9 µm	Mid-level moisture
Band 10			7.3 µm	Mid and lower-level moisture
Band 11			8.6 µm	Cloud phase, SO2
Band 12			9.6 µm	Ozone content
Band 13			10.4 µm	Cloud imagery, information of cloud top
Band 14			11.2 µm	Cloud imagery, sea surface temperature
Band 15			12.4 µm	Cloud imagery, sea surface temperature
Band 16			13.3 µm	Cloud top height

Himawari-8 image data has several formats, namely himawari standard format (HSF), high-rate information transmission (HRIT), low-rate information transmission (LRIT), portable network graphics (PNG), and network common data format (NetCDF). All satellite images are distributed to the national meteorological and hydrological services (NMHSs) via the Himawari cloud service (Putranto et al., 2023). In this research, NetCDF is used CDF is a conceptual data abstraction that stores, manipulates, and accesses multidimensional data sets. The advantage of this CDF format is that it can be read or written in various programming languages such as Python, C, Fortran, Java, Matlab, etc. CDF has dimensions: time, latitude, and longitude (Min et al., 2019). This research uses bands 5, 6, 7, 11, 12, and 13 because it focuses on cloud data available from the himawari-8 satellite data.

Long Short-Term Memory (LSTM)

LSTM belongs to the RNN class, and the LSTM model is a solution for studying long-term dependencies. An input gate (IG), a forget gate (FG), and an output gate (OG) are three gates that each neuron in an LSTM must regulate the information flow between various time steps, as in Figure 3 (Song et al., 2021).

An FG in the LSTM algorithm determines which data should be ignored or omitted. After reading, this gate produces a value between 0 and 1, the value will bring the existing LSTM unit up to date (Gao et al., 2022). To put it briefly, FG will efficiently store or discard data from the IG and data provided from the prior LSTM unit. FG then feeds behavior recognition with the preexisting frame picture sequence. Equations (1) and (2) formulate the structure of the LSTM (Liu et al., 2022).

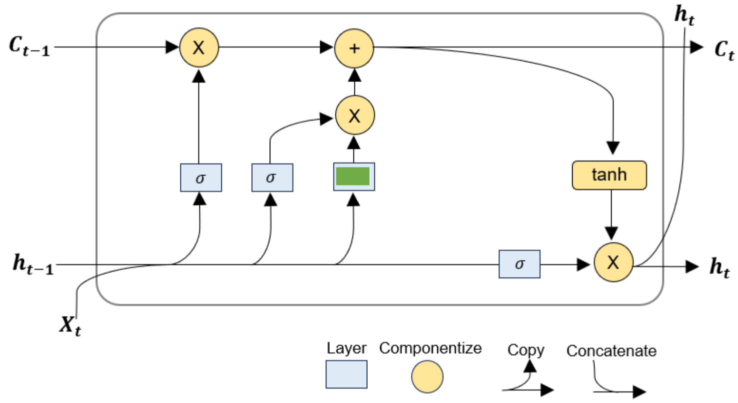


Figure 3: Structure of LSTM Model

$$f_t = \sigma(U_t h_{t-1} + W_f x_t) \tag{1}$$
$$k_t = c_{t-1} f_t \tag{2}$$
$$i_t = \sigma(U_i h_{t-1} + W_i x_t) \tag{3}$$
$$g_t = tanh(U_g h_{t-1} + W_g x_t) \tag{4}$$
$$j_t = g_t i_t \tag{5}$$
$$c_t = j_t + k_t \tag{6}$$
$$o_t = \sigma(U_o h_{t-1} + W_o x_t) \tag{7}$$
$$h_t = tanh(c_t) o_t \tag{8}$$

x_t has cloud feature information, which IG will then forward; The output data from the preceding LSTM cell is included in h_{t-1}; σ represents the sigmoid layer; U_t has data form the FG input coefficient matrix; W_f represents FG's network coefficient matrix; the cell state of the preceding LSTM cell was c_{t-1}; and the output of FG, k_t is utilized to update the current state of the cell (Song et al., 2021).

The IG processes the input data to the current unit after the LSTM unit loses recollection of its current state information. The important thing is to combine h_{t-1} and x_t with a sigmoid layer, which will help ascertain which data in the present unit has to be modified. Furthermore, the tanh activation function helps process h_{t-1} and x_t to obtain information on potential new units as additional information. The formula for this process is stated in Equation (3) to Equation (6) (Liu et al., 2022).

The sigmoid (σ) layer in the OG of the LSTM unit's function is to gather information about the output condition assessment. The inter-decision vector at [−1, 1] is then obtained using the tanh layer. The final LSTM unit results are then obtained by multiplying the resultant vector by the IG results. OG will standardize the final data to forecast significant rain. Equations (7) and (8) provide a mathematical description of this section (Hassan et al., 2023).

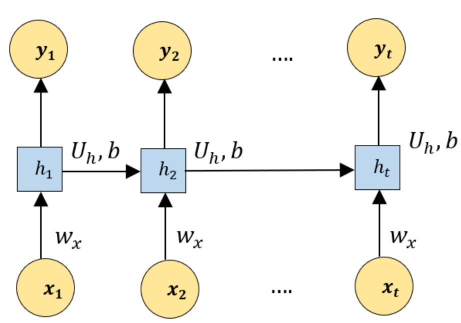


Figure 4: RNN Model Structure

Recurrent Neural Network (RNN)

RNN is an artificial neural networks (ANN) class developed for sequential data processing. Recurrent layers in RNNs are where neurons are linked (Naik et al., 2020). This is because neurons in the same and subsequent layers get information from one another. RNN contains a hidden state to remember specific sequence data, the same as in Figure 4. Recursively applying an active function to the previous state and fresh input allows RNN to calculate a new state. The hidden state value (h_t) at time step t is described in equation (9) (Tran et al., 2021). Where x_t is the input at time t, h_{t-1} is the hidden state from the previous step $(t-1)$, w_x is the input weight, and un is the weight for the previous state value (Tran et al., 2021).

$$h_t = f(w_x x_t + u_h h_{t-1} + b) \tag{9}$$

The RNN algorithm is used to process time series because it can model temporal dynamics in data sequences through feedback connections that send information from the previous input to the following input. However, RNNs have a vanishing gradient problem because RNNs are shallow or straightforward. Therefore, RNN is unsuitable for modelling long-term temporal patterns, weakening the network. In recent years, the problem of gradients often lost in RNNs has been solved by long-term memory neural networks, namely LSTMs, which have more significant computational costs (Tran et al., 2021).

3 Performance Evaluation

Feature of Data Selection

The data collection process is done by reading CSV data and then taking data in bands 5, 6, 7, 11, 12, and 13. This band data aims to form a class of rainfall data that falls to the surface, such as:

- **Band 5 (1.6 µm):** Used to track sea surface temperature and cloud height. Increasing intensity values in this channel may indicate an increase in surface temperature or high clouds with low reflectivity.
- **Band 6 (2.3 µm):** Used to detect the temperature of high clouds and thin clouds. An increase in intensity may indicate the presence of high clouds or clouds with tiny water droplets.
- **Band 7 (3.9 µm):** Used to provide information about sea surface temperatures, clouds, and volcanic debris. Increased values in this channel may indicate higher sea surface temperatures or the presence of clouds with high reflectivity.
- **Band 11 (8.6 µm):** Used to see cloud temperature and identify thicker clouds. An increase in intensity in this channel can indicate the presence of clouds with higher temperatures.
- **Band 12 (9.6 µm):** Used to observe sea surface and cloud temperatures. Increased intensity values may indicate higher sea surface temperatures or the presence of clouds with higher temperatures.
- **Band 13 (10.4 µm):** Provides information about sea surface temperature and clouds. An increase in intensity in this channel could indicate higher sea surface temperatures or the presence of clouds with higher temperatures.

The feature graph for data bands 5, 6, 7, 11, 12, and 13 is as in Figure 5. Apart from the band values, the cloud level (CL) value or initial thickness obtained from subtracting band 7 from band 13 is also taken as in Figure. 6.

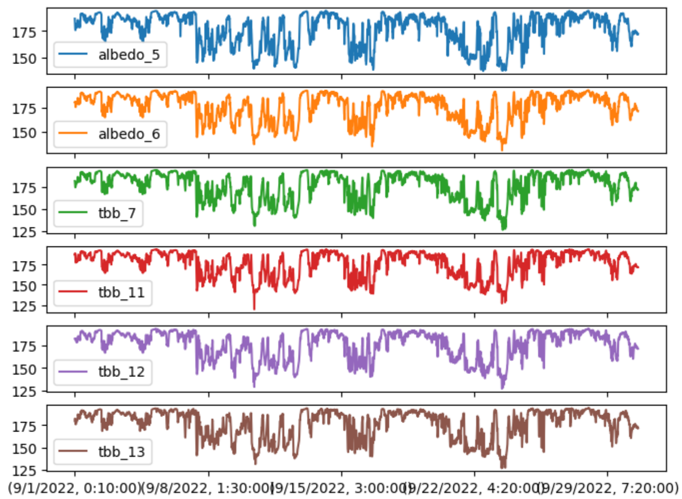


Figure 5: Feature Dataset

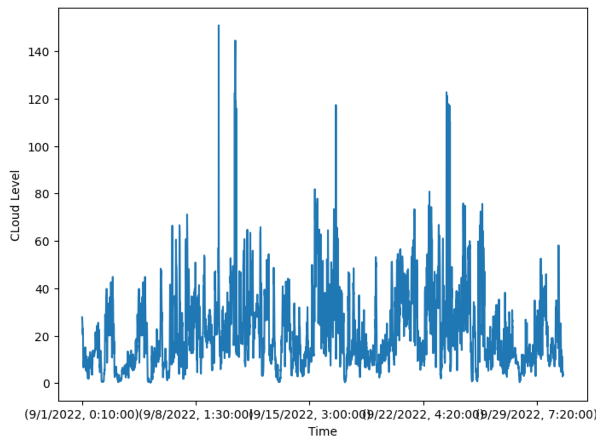


Figure 6: Cloud Level

Feature Selection

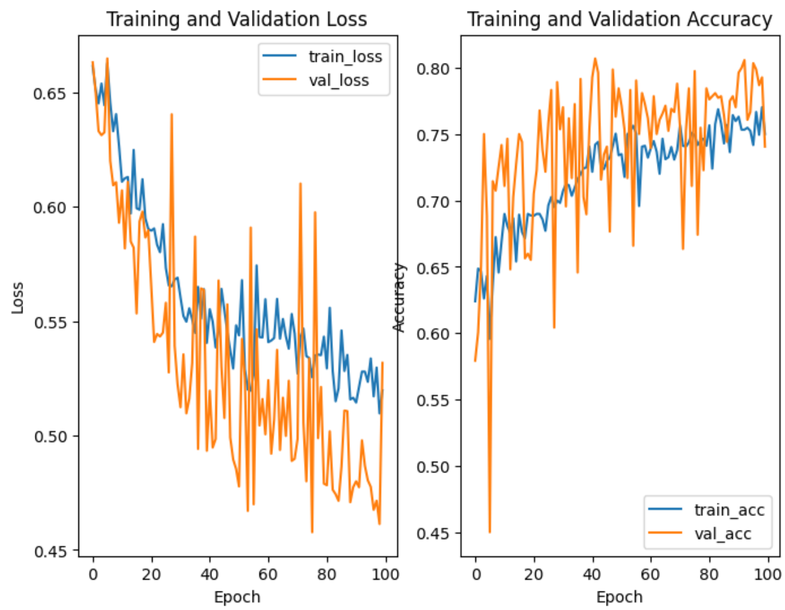
Feature selection is made to prevent multicollinearity or situations in which several independent variables in a model are associated once the characteristics for each data model have been obtained. Consequently, feature selection is required to eliminate redundant and unnecessary variables. Feature selection can decrease the number of variables, lower the amount of data processing and storage resources needed, and improve the interpretability of chosen variables (Verma et al., 2023).

Implementation of the LSTM Method

The LSTM method is an approach in deep learning that is very suitable for processing sequential data, such as rainfall data. Long-term memory is enhanced by LSTM, which can also solve the vanishing gradient issue that plagues many conventional neural network designs.

Albedo data input from bands 5, 6, 7, 11, 12, and 13 is carried out to measure the extent to which the earth's surface reflects sunlight. A higher albedo value indicates a brighter and more reflective surface. Albedo data processing needs to be normalized to have a similar scale while selecting and deleting irrelevant features also needs to be done.

LSTM has an internal memory unit that allows it to remember information from several steps from the previous time. The LSTM architecture comprises several gates, including FG, IG, and OG. FG decides what information will be deleted from internal memory. The IG regulates what information will be entered into memory. The OG produces an output based on internal memory and current input.



(a) (b)

Figure 7: The Result of Training and Validation (a) by Loss (b) by Accuracy on the LSTM Model

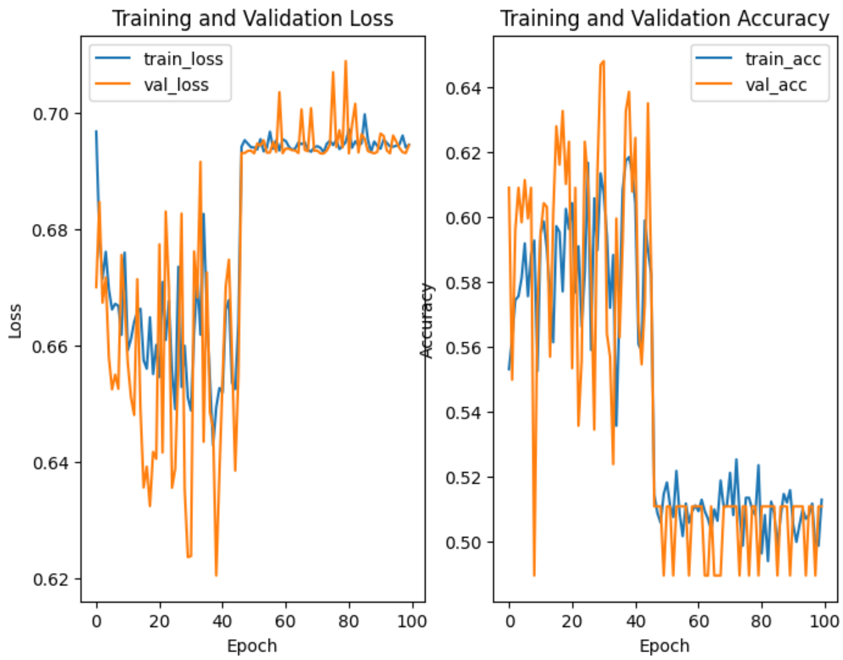
Figure 7 (a) shows the training loss and validation loss values for 100 epochs. Training loss is carried out to measure how well the LSTM method is suitable for predicting rainfall, with the result that the lower the training loss value, the better the model learns data patterns. Validation loss is carried out to measure the performance of the LSTM method in data validation. In this research, validation loss is stable, so the LSTM model does not experience overfitting, (b) test results of training accuracy and validation accuracy for 100 epochs. The test results show that the longer the epoch value, the higher the accuracy of the LSTM method in this research.

Implementation of the RNN Method

RNN is a type of neural network architecture suitable for processing sequential data, such as the range of days used in this study. RNNs have internal memory that allows them to remember information from previous iterations, making them suitable for modeling temporal relationships in weather data.

The RNN method was implemented by collecting data from the Himawari-8 satellite on bands 5, 6, 7, 11, 12, and 13, as well as carrying out data preprocessing. Data preprocessing was carried out for normalization and removal of outliers. The data was divided. The data was divided into training and validation data sets.

Figure 8 (a) shows the training and validation loss results for 100 epochs. Training and validation loss results experienced significant fluctuations at the beginning of the epoch. The training loss and validation loss tests are inversely proportional to the results of the training accuracy and validation accuracy tests in (b), which decreased in the 45 to 100 epochs range. This is influenced by the validating loss process, which experiences overfitting in bands 11 to 13.



(a) (b)

Figure 8: The Result of Training and Validation (a) by Loss (b) by Accuracy on the RNN Model

4 Conclusion and Future Work

In this research, a rainfall prediction system was built using the LSTM and RNN model approaches. LSTM and RNN models work well in modelling data and predicting data. The system model built in this research uses daily rainfall data. Before applying the LSTM and RNN models, data separation and feature selection are carried out as preprocessing techniques. The technique used reduces the potential for multicollinearity while increasing model accuracy. Next, hyperparameter tuning is carried out on the LSTM and RNN models. The research results showed that the accuracy of the LSTM model reached 92.62%, and the RNN model reached 89.38%. The model with the best accuracy of the models used in this research is influenced by experiments carried out, such as selecting features by trying all combinations of available features and then carrying out a data splitting scheme so that many models and sub-models can be created so that the data accuracy of the LSTM model is better than the model RNN. After getting the model accuracy value based on daily data, make predictions and see the distribution of the prediction data. The rainfall predictions carried out in this research are daily based on the best model built. For daily predictions, this research predicts that 7 days from September 1 to September 7, 2022, will not rain.

Author Contribution: Development of ideas and approaches, analysis of research models, and preparation of initial system models. This research contributed to editing and revising written content. The author has reviewed and approved the manuscript for publication.

References

[1] Akila, R., & Revathi, S. (2023). Fine Grained Analysis of Intention for Social Media Reviews Using Distance Measure and Deep Learning Technique. *Journal of Internet Services and Information Security*, *13*(2), 48-64.

[2] Anadel, G., Zahid, B., & Nedim, S. (2022). Correlation And Regression Relationships of Parameters of Rainwater Drainage from Roads. Archives for Technical Sciences, *2*(27), 19-24.

[3] Arora, G. (2024). Desing of VLSI Architecture for a flexible testbed of Artificial Neural Network for training and testing on FPGA. *Journal of VLSI Circuits and Systems*, *6*(1), 30-35.

[4] Bobir, A. O., Askariy, M., Otabek, Y. Y., Nodir, R. K., Rakhima, A., Zukhra, Z. Y., Sherzod, A. A. (2024). Utilizing Deep Learning and the Internet of Things to Monitor the Health of Aquatic Ecosystems to Conserve Biodiversity. *Natural and Engineering Sciences*, *9*(1), 72-83.

[5] Byun, J., Jun, C., Kim, J., Cha, J., & Narimani, R. (2023). Deep Learning-Based Rainfall Prediction Using Cloud Image Analysis. *IEEE Transactions on Geoscience and Remote Sensing*, *61*, 1-11.

[6] Gao, Y., & Li, Y. (2022). Prediction of rainfall-type debris flow in Jiangjiagou based on LSTM-Attention. *In IEEE 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA)*, 1-6.

[7] Hassan, M. M., Hassan, M. M., Yasmin, F., Khan, M. A. R., Zaman, S., Islam, K. K., & Bairagi, A. K. (2023). A comparative assessment of machine learning algorithms with the Least Absolute Shrinkage and Selection Operator for breast cancer detection and prediction. *Decision Analytics Journal*, *7*, 100245. https://doi.org/10.1016/j.dajour.2023.100245

[8] Hassan, M. M., Rony, M. A. T., Khan, M. A. R., Hassan, M. M., Yasmin, F., Nag, A., & El-Shafai, W. (2023). Machine learning-based rainfall prediction: Unveiling insights and forecasting for improved preparedness. *IEEE Access*, *11*, 132196-132222.

[9] He, Z. (2021). Rain prediction in Australia with active learning algorithm. *In IEEE International Conference on Computers and Automation (CompAuto)*, 14-18.

[10] Ibrahim, R. (2020). Workstation Cluster's Hadoop Distributed File System Simulation and Modeling. *International Journal of Communication and Computer Technologies (IJCCTS)*, *8*(1), 1-4.

[11] Iman, M. B., Qusay, A. A., Inass, S. H., & Refed, A. J. (2023). Mobile-computer Vision Model with Deep Learning for Testing Classification and Status of Flowers Images by using IoTs Devices. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *14*(1), 82-94.

[12] Jelena, T., & Srđan, K. (2023). Smart Mining: Joint Model for Parametrization of Coal Excavation Process Based on Artificial Neural Networks. *Archives for Technical Sciences*, *2*(29), 11-22.

[13] Johnson, C., Khadka, B., Ruiz, E., Halladay, J., Doleck, T., & Basnet, R. B. (2021). Application of deep learning on the characterization of tor traffic using time based features. *Journal of Internet Services and Information Security*, *11*(1), 44-63.

[14] Kavitha, M. (2020). A ku Band Circular Polarized Compact Antenna for Satellite Communications. *National Journal of Antennas and Propagation (NJAP)*, *2*(2), 15-20.

[15] Kothai, G., Sushmitha, Y., Saranya, K. L., Sri, P. N. R., & Amulya, P. (2023). Rainfall Prediction Using Deep Learning and Machine Learning Techniques. *In IEEE International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, 1-7.

[16] Kutlu, Y., & Camgözlü, Y. (2021). Detection of coronavirus disease (COVID-19) from X-ray images using deep convolutional neural networks. *Natural and Engineering Sciences*, *6*(1), 60-74.

[17] Lagerquist, R., Stewart, J.Q., Ebert-Uphoff, I., & Kumler, C. (2021). Using deep learning to nowcast the spatial coverage of convection from Himawari-8 satellite data. *Monthly Weather Review*, *149*(12), 3897–3921.

[18] Liu, W., Liu, X., Hu, Y., Shi, J., Chen, X., Zhao, J., & Hu, Q. (2022). Fall detection for shipboard seafarers based on optimized BlazePose and LSTM. *Sensors*, *22*(14), 5449. https://doi.org/10.3390/s22145449

[19] Min, M., Bai, C., Guo, J., Sun, F., Liu, C., Wang, F., Xu, H., Tang, S., Li, B., Di, D., Dong, L., & Li, J. (2019). Estimating Summertime Precipitation from Himawari-8 and Global Forecast System Based on Machine Learning. *IEEE Transactions on Geoscience and Remote Sensing, 57*(5), 2557–2570.

[20] Naik, A. R., Deorankar, A. V., & Ambhore, P. B. (2020). Rainfall prediction based on deep neural network: a review. *In IEEE 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*, 98-101.

[21] Paski, J. A. (2018). Pengaruh asimilasi data penginderaan jauh (radar dan satelit) pada prediksi cuaca numerik untuk estimasi curah hujan (Impact of remote sensing data assimilation (radar and satellite) on numerical weather prediction for rainfall estimation). *Jurnal Penginderaan Jauh dan Pengolahan Data Citra Digital*, *14*(2), 79-88.

[22] Phadke, R., Ramadan, G. M., Reddy, R. A., Pani, A. K., & Al-Jawahry, H. M. (2023). Prediction of Rainfall Using Seasonal Auto Regressive Integrated Moving Average and Transductive Long Short-Term Model. *In IEEE International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE)*, 1-5.

[23] Putranto, M. F., & Munir, R. (2023). Deep Learning Approach for Heavy Rainfall Prediction Using Himawari-8 And RDCA Data. *In IEEE International Conference on Computer, Control, Informatics and its Applications (IC3INA)*, 424-429.

[24] Ram, A., & Chakraborty, S. K. (2024). Analysis of Software-Defined Networking (SDN) Performance in Wired and Wireless Networks Across Various Topologies, Including Single, Linear, and Tree Structures. *Indian Journal of Information Sources and Services, 14*(1), 39–50.

[25] Rathi, S., Mirajkar, O., Shukla, S., Deshmukh, L., & Dangare, L. (2024). Advancing Crack Detection Using Deep Learning Solutions for Automated Inspection of Metallic Surfaces. *Indian Journal of Information Sources and Services, 14*(1), 93–100.

[26] Ravi, S. S., & Sai, R. G. K. (2022). Design of Deep Learning Model for Predicting Rainfall. *In IEEE 8th International Conference on Advanced Computing and Communication Systems (ICACCS), 1*, 1343-1347.

[27] Rayudu, D. V., & Roseline, J. F. (2023). Accurate Weather Forecasting for Rainfall Prediction Using Artificial Neural Network Compared with Deep Learning Neural Network. *In IEEE International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF)*, 1-6.

[28] Risyanto. (2021). Pengolahan Data Satelit Himawari-8. *Knowledge Sharing: Pengolahan Data Atmosfer Menggunakan Python*.

[29] Salehin, I., Talha, I. M., Hasan, M. M., Dip, S. T., Saifuzzaman, M., & Moon, N. N. (2020). An Artificial intelligence-based rainfall prediction using LSTM and neural network. *In IEEE international women in engineering (WIE) conference on electrical and computer engineering (WIECON-ECE)*, 5-8.

[30] Sawada, Y., Okamoto, K., Kunii, M., & Miyoshi, T. (2019). Assimilating every- 10-minute Himawari-8 infrared radiances to improve convective predictability. *Journal of Geophysical Research: Atmospheres, 124*, 2546–2561.

[31] Schultz, M. G., Betancourt, C., Gong, B., Kleinert, F., Langguth, M., Leufen, L. H., & Stadtler, S. (2021). Can deep learning beat numerical weather prediction? *Philosophical Transactions of the Royal Society A*, *379*(2194), 20200097. https://doi.org/10.1098/rsta.2020.0097

[32] Sharma, O., Trivedi, D., Pattnaik, S., Hazra, V., & Puhan, N. B. (2023). Improvement in District Scale Heavy Rainfall Prediction Over Complex Terrain of North East India Using Deep Learning. *IEEE Transactions on Geoscience and Remote Sensing*. https://doi.org/10.1109/TGRS.2023.3322676

[33] Song, L., Yu, G., Yuan, J., & Liu, Z. (2021). Human pose estimation and its application to action recognition: A survey. *Journal of Visual Communication and Image Representation*, *76*, 103055. https://doi.org/10.1016/j.jvcir.2021.103055

[34] Srinu, N., & Bindu, B. H. (2022). A Review on Machine Learning and Deep Learning based Rainfall Prediction Methods. *In IEEE International Conference on Power, Energy, Control and Transmission Systems (ICPECTS)*, 1-4.

[35] Supriyadi, E. (2021). Prediksi Parameter Cuaca Menggunakan Deep Learning Long-Short Term Memory (LSTM). *Jurnal Meteorologi dan Geofisika*, *21*(2), 55-67.

[36] Sutikno, S., Amalia, I. R., Sandhyavitri, A., Syahza, A., Widodo, H., & Seto, T. H. (2020). Application of weather modification technology for peatlands fires mitigation in Riau, Indonesia. *In AIP Conference Proceedings*, 2227*(1)*. AIP Publishing.

[37] Tran, T. T. K., Bateni, S. M., Ki, S. J., & Vosoughifar, H. (2021). A review of neural networks for air temperature forecasting. *Water*, *13*(9), 1294.

[38] Verma, V. K., Janagama, H. S., & Patil, N. (2023). An Efficient Rainfall Prediction Model Using Deep Learning Method. *In IEEE Third International Conference on Secure Cyber Computing and Communication (ICSCCC)*, 566-572.

[39] Walaa, S. I. (2024). Emotion Detection in Text: Advances in Sentiment Analysis Using Deep Learning. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA)*, *15*(1), 17-26.

[40] Yang, S. C., Huang, Z. M., Huang, C. Y., Tsai, C. C., & Yeh, T. K. (2020). A case study on the impact of ensemble data assimilation with GNSS-zenith total delay and radar data on heavy rainfall prediction. *Monthly Weather Review*, *148*(3), 1075-1098.

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