Rainfall Nowcasting based on Satellite Images using Convolutional Long-Short Term Memory

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Abstract— **Rain that falls at a small and moderate rate is a blessing but incessant rainfall can bring many adverse effects such as loss of life, and destruction of property, crops and fields. One of the ways that can reduce the negative effects of natural disasters like this is to study trends and make predictions about what will happen. The predictive system, e.g. a nowcasting model can play an important role in dealing with rain issues, especially being able to provide early warning before bad weather occurs and this to some extent can help save lives and property. However, the determination of predictive models is a technically challenging task because rainfall is a non-linear phenomenon. In this research, a combination of a deep learning model called Convolutional Long-Short Term Memory (ConvLSTM) assisted by digital image processing is applied to real-time radar time series and satellite images. The goal is to predict the next event in a sequence of images with different timestamps i.e., 10-minutes, 30-minutes, and 60-minutes. Experimental results were evaluated with performance metrics using the Structural Similarity Index Measure (SSIM).**

Keywords—Rainfall forecasting, image processing, ConvLSTM

I. Introduction

Rain is a common natural phenomenon in our daily life, but incessant rain can be a major cause of flooding. The effects of flooding can affect the social, economic, and agricultural sectors. The coast of Peninsular Malaysia is particularly vulnerable to flooding during the northeast monsoon season from October to March. Selangor and Kuala Lumpur experienced the heaviest rain during the December 2021 event. There are 8 districts in the state of Selangor that experienced 4 consecutive days of rain. However, a day before the warning, flooding had already occurred in Sepang, Hulu Langat and Klang. 39 people were killed in the flood. On December 20th, the city of Taman Muda in Shah Alam was hit by floods and devastated. During the night, the main station at Glenmarie exploded causing power outages in several parts of Shah Alam.

Weather and rain information is important to the needs and daily life of today's society because it can help us, both in terms of benefits and avoiding harm. Attention to this aspect has been given in most modern cities for event planning or environmental monitoring as well as for preparing for natural hazards. In addition, rain forecast is also important for the needs of solar farms, because rain will affect the rate of electricity generation.

A deep learning model requires massive amounts of satellite imagery data to create the algorithm for a computer to understand. The more satellite imagery data available, the better. Since this deep learning is built on a large amount of data, the predictions made are more accurate. However, satellite imagery data without present rainfall information can lead to incorrect results. Currently, there is a limit to the amount of satellite imagery and sequence datasets available for machine learning models. Furthermore, relying on raw satellite imagery data from open sources is not enough for deep learning algorithms to produce accurate rainfall forecasts.

Accurate forecasting is very important to correctly determine the rainfall conditions in a particular area. Due to cloud changes in the atmosphere, it is quite difficult to make accurate predictions. The use of LSTM architecture to solve problems in this context was also found to be insufficient by previous researchers. To achieve good results in any situation, the most suitable parameters must be selected. So, one of the main focuses of this research is to figure out how to improve the model so that it can achieve maximum accuracy. The time series model used to predict rainfall in the near future is the most important component of deep learning algorithms for rainfall forecasting systems. Although more satellite imagery data are needed to train the ConvLSTM model, the effectiveness of rain forecasting using deep learning is still uncertain. As a result, the performance of the ConvLSTM model remains unclear. The ConvLSTM model will be able to predict future events once the deep learning algorithm has been trained.

The main idea proposed in this study is to integrate two prediction models namely Convolutional Networks and LSTM especially to make predictions based on images in time series. This combines the pattern recognition of CovNets and the memory properties of pure LSTM networks. Therefore, the algorithm is expected to find patterns in the radar image sequence and then predict the next expected rainfall pattern.

II. Related Works

This section will feature some publications related to this research. Among the areas of focus are weather forecasting based on ConvLSTM networks and image processing.

A. Digital Image Processing

Cloud detection is an important task in remote sensing image processing. To detect cloud patterns and colors from remote sensing devices, the OpenCV library in the Python environment was used. Chenwei Deng et al have proposed a remote sensing application driven by image processing [1]. They applied image segmentation techniques based on color similarity and proximity in images to segment potential clouds including small clouds. In another study, [2] used the FastICA algorithm to detect large-scale thick clouds and thin clouds at the same time. Thick clouds can be detected based on spectral differences, then the thick cloud mask can be optimized by the connected domain analysis method and the region growth algorithm method.

Based on these related studies, methods involving image processing are recommended because they are found to improve the quality of data and in turn can be used to perform significant feature extraction and classification.

B. LSTM and ConvLSTM Networks

In previous studies, RNN (Recurrent Neural Network) was used to process data and predict the next scenario such as [3][4][5] and [6]. However, RNN has some problems, such as vanishing gradient and exploding gradient in processing historical information over a long period, which will weaken its learning effect [7]. To overcome this problem, a new version of RNN, LSTM (Long-short Term Memory) was introduced.

LSTM has achieved great success in processing sequential multimedia data and producing results in speech recognition, digital signal processing, video processing and text data analysis. For example, the LSTM network has been used to predict depression trends from EEG signals based on extracted features [8]. Xi Juan Song et al [9] proposed the LSTM network integrated with an adaptive Kalman filter, to predict the air quality of time series. This study can show that time series processing is required by using the LSTM model to get the next prediction. Another RNN approach with the LSTM method was proposed by Dires Negash Fente et al [10] to develop a weather forecast model. Based on these references, the LSTM network is found to be very suitable for classification, processing and prediction based on time series data. LSTM can handle noise, distributed representation and continuous values. Therefore, the model is believed to be more efficient and faster to fit than traditional time series models.

Many studies in the last five years have shown that ConvLSTM has been used for precipitation nowcasting. Recently, Ma Bo [11] and Haruki Takehana [12] applied the ConvLSTM network for rainfall nowcasting based on time series. Another approach developed by [13], uses IoT sensors integrated with ConvLSTM to recognize corrupted data streams combined with autonomous vehicle navigation and powertrain data. From the referred studies, the existing ConvLSTM architecture has been designed to be suitable for sequencing prediction problems with spatial input.

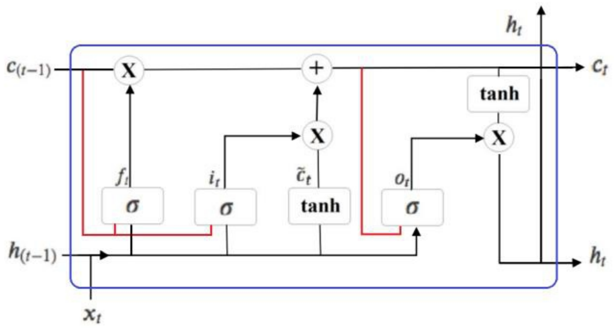

Fig. 1. The architecture of ConvLSTM Network

Fig. 1 shows the construction details of the hybrid ConvLSTM network. . With such an approach, our rainfall nowcasting system can be adapted to such a hybrid model through image processing based on time series. The ConvLSTM network can be formulated as:

$$i_t = \sigma\left(W_{xi} * X_t + W_{hi} * H_{t-1} + W_{ci} \circ C_{t-1} + b_i\right) \quad (1)$$

$$f_t = \sigma\left(W_{xf} * X_t + W_{hf} * H_{t-1} + W_{cf} \circ C_{t-1} + b_f\right) \quad (2)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \quad (3)$$

$$o_t = \sigma\left(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o\right) \quad (4)$$

$$H_t = o_t \circ \tanh(C_t) \quad (5)$$

Where

i_t = represents input gate.

f_t = represents forget gate.

o_t = represents output gate.

σ = represents the sigmoid function.

W_x = weight for the respective gate neurons.

$h_{(t-1)}$ = output of the previous LSTM block

x_t = input at current timestamp.

b_x = biases for the respective gates.

III. Methodology

The overall methodology of this research will be presented in this section, starting with an overview of this project, followed by a more detailed explanation of the research activities to be conducted. The whole system consists of three main components responsible for the process of i) data collection, ii) data preparation, and iii) model construction.

A. Data Collection

The activity flow begins with the collection of satellite imagery data extracted from the Himawari Real-Time Images site from the meteorological satellite center (MSC) of the Japan Meteorological Agency (JMA) [14]. Successfully extracted imagery data will be stored in a local folder. To enable such an extraction process, a local server, i.e., WampServer allows some PHP programs to run on it. The data will be collected every 10 minutes. The longer the program is run, the more images will be extracted and collected. However, some images were found to be missing during the extraction process due to intermittent internet connection.

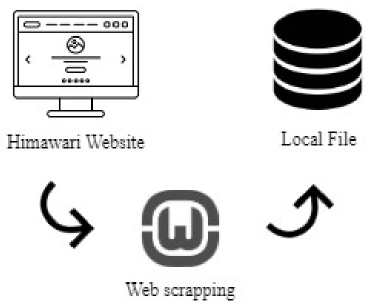

Fig. 2. Web scrapping activity

B. Data Preparation

Before designing the model, some pre-processing needs to be carried out on the image data.

1) Data Processing: This study uses image processing to enhance images and extract useful information from image datasets. Fig. 3 shows the flow of image processing activities before the model training process.

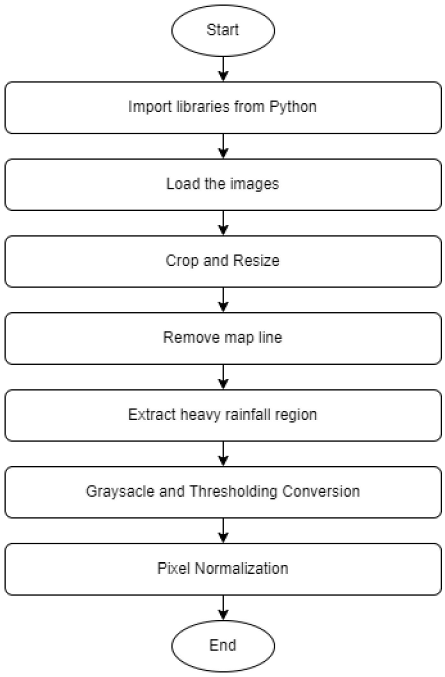

Fig. 3. Image processing flow activity

The amount of data successfully collected is 39 343, which was from May 2021 to December 2021. However, during this period, some data were lost due to intermittent connectivity issues. Table 1 shows the total dataset for different time intervals.

TABLE I. TOTAL DATASETS ACCORDING TO DIFFERENT TIME INTERVALS

Time interval	*Total dataset*
10-minute	39 343
30-minute	13 362
60-minute	6 687

The raw image size was 901x1501 pixels. All raw image sizes were then cropped to 115x85 pixels within the Peninsular Malaysia region. Since the size of cropped images was too large to train the deep learning model, the images' size was halved to 57x42 pixels. Since OpenCV uses BGR images by default, each image was converted from BGR to RGB. Next, the map line was removed by using image inpainting. In addition, the detection of heavy rain information (magenta region) requires color detection and image patching. All images were converted to grayscale, with threshold and pixel values normalized between 0 and 1.

2) Data monitoring learning: After image processing is complete, all sequential data must be split in the form of (samples, timestep, row, column, channel) and (samples, row, column, channel). After that, the dataset is divided into the correct form by generating the array of output and input arrays as shown in Table 2. Practically, the timestep is the number of occurrences in each sample, so in this case timestep=5. So, given a time series of five images, the model will forecast the next occurrence.

TABLE II. SPLIT DATA INTO SUPERVISED LEARNING

Input	*Output*
x1, x2, x3, x4, x5	x6
x2, x3, x4, x5, x6	x7
x3, x4, x5, x6, x7	x8

The output images were generated in grayscale form, so the parameter channel was set to 1. Then about 80% of the sequential dataset was selected as the training set, 10% was selected as the validation set, and the remaining 10% is the test set. The steps are repeated with different timestamps; i.e. 10-minute, 30-minute and 60-minute intervals.

C. Construction of ConvLSTM

This research will explore how to use image sequences as input to the neural network model in forecasting problems using ConvLSTM. Before setting the parameters for the model, several combinations were tested to have acceptable results that could be improved later. Therefore, for the ConvLSTM model, only three ConvLSTM layers have been stacked, associated with the Batch Normalization and Dropout layers to normalize values coming from the previous layer and respectively avoid the phenomenon of overfitting. Since the images are non-linear objects, the Rectifier Linear Unit, RELU is always used as an activator in the ConvLSTM layers. In the third layer of ConvLSTM, the sigmoid function is selected as an activator used to add non-linearity in ConvLSTM to predict the probability as an output.

During training, the Adaptive Moment optimization (ADAM) optimizer helps the process to obtain small training loss values. So, the ADAM optimizer which is defined by equations (6) to (9), has been adopted for the rest of the work.

$$v_t = \beta_1 * v_{t-1} - (1 - \beta_1) * g_t \tag{6}$$

$$s_t = \beta_2 * s_{t-1} - (1 - \beta_2) * g_t^2 \tag{7}$$

$$\Delta w_t - \eta \frac{v_t}{\sqrt{s_t + \epsilon}} * g_t \tag{8}$$

$$w_{t+1} = w_t + \Delta w_t \tag{9}$$

The following functions have been used as loss functions; i.e. the Mean Squared-Error (MSE) given by equations (10).

$$MSE = \frac{1}{n} \Sigma \left(y - \hat{y} \right)^2 \tag{10}$$

The epoch is set to 100 and 10% of the original training data to be used as validation data. The model will set apart this fraction of the training data, will not train on it, and will evaluate the loss and metrics on this data at the end of the epoch.

IV. Result and Discussion

This section presents the implementation of the system, the undertaken analysis, and the findings. Some conclusions on the result are also discussed. Since both Convolutional Network and LSTM models are combined and trained together at the beginning of the study, the model will be tested by evaluating the accuracy values achieved. This assessment is required before proceeding to the next step. If the accuracy values obtained are not sufficient, then more data and training are needed to produce a better output.

A. Results

Fig.4, Fig. 5, and Fig. 6 depict the prediction results generated based on three different timestamps using the ConvLSTM model. The figures present the input sequence, actual output, ground truth and predicted output respectively by the ConvLSTM model.

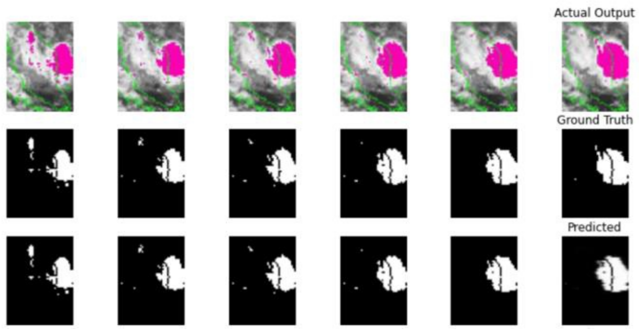

Fig. 4. Prediction result for timestamp = 10-minute

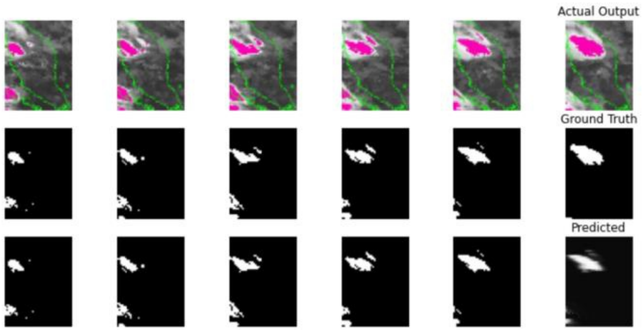

Fig. 5. Prediction result for timestamp = 30-minute

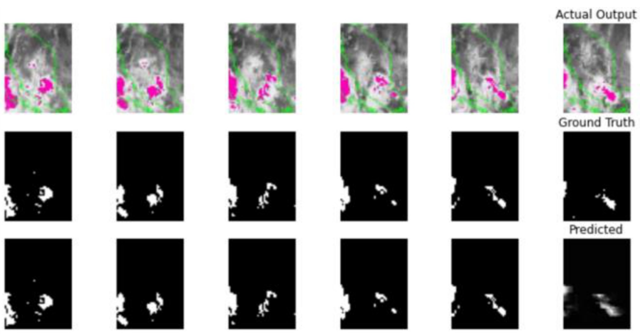

Fig. 6. Prediction result for timestamp = 60-minute

B. Discussion

Deep learning's primary objective is to find similarities between pixels in the actual and predicted images. Low training loss values generally show that the model is picking up new information well. A model with low values does not necessarily imply that it is effective, though. Additionally, values that are too close to zero can sometimes be a sign that a model is over-fitting and will not perform well on new data. For a better evaluation, this study must consider additional factors like validation loss, training time, and the Structural Similarity Index Measure (SSIM). SSIM values that are close to 1 show that similarities are generally good. SSIM values are generated according to the following equation (11).

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{11}$$

Where,

μ_x = pixel sample mean of x;

μ_y = pixel sample mean of y;

σ_x^2 = variance of x;

σ_y^2 = variance of y;

σ_{xy} = covariance of x and y;

c_x = stabilize the division with a weak denominator.

TABLE III. Average Evaluation Metrics on Different Timestamps

Timestamp (0-1 hour)	ConvLSTM Model		
	SSIM	*MSE*	*Accuracy*
10	0.96274	0.00059	0.9907
30	0.94063	0.00103	0.9717
60	0.64179	0.00375	0.9201

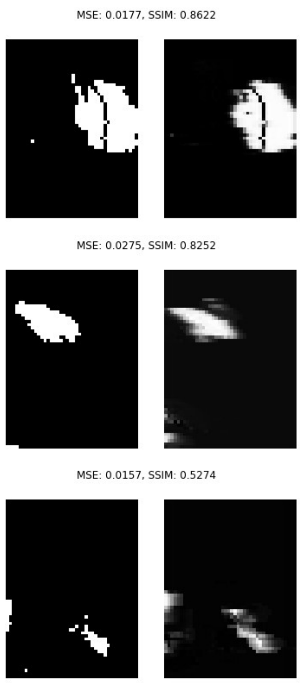

Fig. 7. Comparison between the actual and predicted image

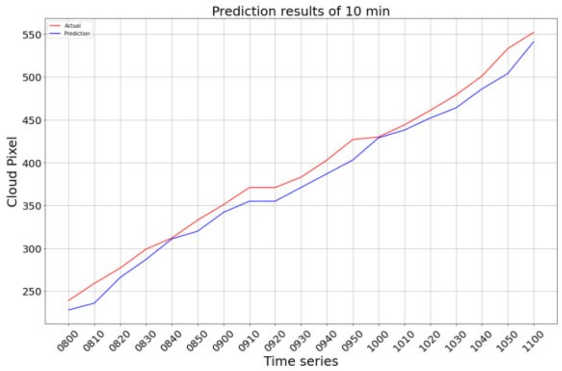

Fig. 8. Actual vs predicted rainfall nowcasting for timestamp = 10-minute

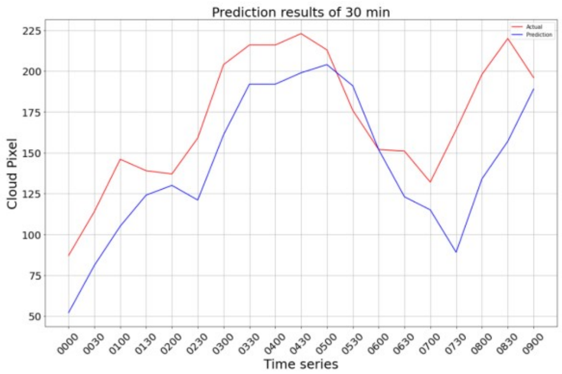

Fig. 9. Actual vs predicted rainfall nowcasting for timestamp = 30-minute

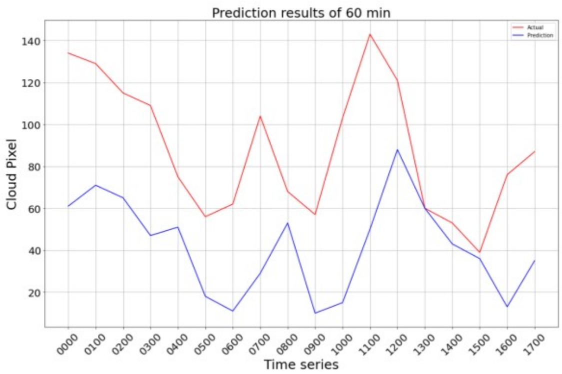

Fig. 10. Actual vs predicted rainfall nowcasting for timestamp = 60-minute

Based on Fig. 8, Fig. 9, and Fig. 10, the closest between the actual image and the predicted image for the rainfall nowcasting system is the 10-minute timestamp. On the other hand, the farthest between the actual image and the predicted image for the rainfall nowcasting system is the 60-minute timestamp. With the ConvLSTM model, the shorter the period, the better the accuracy of the rainfall nowcasting system as shown in Table 3. It is then deduced that the use of ConvLSTM for a long period is not recommended.

V. Conclusion

In this paper, satellite imagery was used to train the ConvLSTM model in predicting rainfall. Several parameters were chosen to determine the suitable interval or timestamp for the prediction problem in remote sensing images based on time series. Based on the analyzed results, it was confirmed that the shorter period or interval will produce better nowcasting accuracy.

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