Monthly Rainfall Prediction Using the Facebook Prophet Model for Flood Mitigation in Central Jakarta

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***Abstract*—Jakarta has been known as the city where floods are prevalent. As the vital region in Jakarta where the center of government and business are located, Central Jakarta is inseparable from the flood when the rainfall is remarkably high. Therefore, the Jakarta Provincial Government need a data-driven policy to facing potential flood that may occur each year to protect the citizen from the threat of flood disaster. Monthly rainfall prediction can be a reference to determine the possibility of considerable loss and damage due to disaster threats. However, at this moment, it is still challenging to find a fitting forecasting model for this context. This paper reports a comparison of three different time series models: Seasonal Autoregressive Integrated Moving Average (SARIMA), Facebook Prophet, and Long Short-Term Memory (LSTM) to forecast monthly rainfall in Central Jakarta for up to two consecutive years. The result indicates that Facebook Prophet, with the lowest Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), is the fittest model to predict the monthly rainfall in Central Jakarta. It shows that a high amount of rainfall will be seen in January and February 2021, which suggests we need to be prepared to anticipate the potential flood. Facebook Prophet shows promising results in supporting data-driven policy for flood mitigation in Jakarta. The development of this model in the future can be used as a baseline study to formulate a data-driven policy for flood mitigation in Jakarta.**

Keywords—Jakarta, rainfall, forecasting, Facebook Prophet, flood mitigation

I. Introduction

Jakarta, the capital city of Indonesia, has been facing regular flood disasters every rainy season. As the capital city, Jakarta is the largest economic centre in Indonesia. Therefore, when floods hit the Jakarta area every time the rainy season arrives, it tarnished Jakarta's image as the nation's capital in the world's eyes and often paralyzed the national economic sector [1].

Jakarta flooding is caused by many factors, such as (1) the geological and geomorphological aspects of the Jakarta region, which are flood basins and floodplains, (2) the morphometry of the 13 river that flows across the Jakarta area, and (3) the infrastructure and social behaviour of its citizens [1]. With Jakarta's geographical condition, which is in a lowland area and is crossed by 13 rivers, the Capital City must be prepared for the risk of flooding, especially during high rainfall season. The high intensity of rain made Jakarta prone to disasters due to the overflow of water from the rivers that passed through it. When the intensity of the precipitation is starting to increase, we must begin to be alert.

Based on the Jakarta flood data report from 2002 to 2020, especially in February 2002, February 2007, January 2013, and February 2015, the iconic Hotel Indonesia (HI) Roundabout to Thamrin, which is a strategic area located in Central Jakarta, was hit by floods due to heavy rainfall [2]. In a separate report, the HI Roundabout was also waterlogged in August 2016, become an anomaly at that time [3]. This is unfortunate because the HI Roundabout location to the Thamrin area is right in the heart of Jakarta Province. Apart from being the center of government, it also functions as a center for business, trade, service activities, and a significant infrastructure development area.

The high risk of floods requires the Jakarta Provincial Government to protect Jakarta citizens from the threat of disaster. Monthly rainfall prediction can be a reference to determine the possibility of considerable loss and damage due to disaster threats. Therefore, the government needs to prepare and produce well-tailored plans to face a high risk of floods.

Many studies have been conducted using statistical models to predict future rainfall. Literature studies have shown several models that are widely used around the globe to forecast rainfall, such as Seasonal Autoregressive Integrated Moving Average (SARIMA) [4][5][6][7] and Long Short-Term Memory (LSTM) [8][9]. The recent model introduced by the nature of time series forecasting at Facebook, the Prophet, which is started to be applied to hydrometeorological time series, has also been used to predict rainfall [10]. However, it is still challenging to find other studies implementing the Prophet for rainfall, especially for Jakarta cases.

This study aims to provide higher accuracy in forecasting the monthly rainfall trend in Jakarta, especially for the Central Jakarta region, through data exploration and a quantitative approach. This approach can be successful by comparing time series forecasting models, such as ARIMA, LSTM, and

Facebook Prophet. The three models can provide decent predictions on monthly rainfall with high accuracy based on the evaluation indicators, such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) [10][11][12].

This study applies three time series methods to forecast monthly rainfall in Central Jakarta by using the accessible datasets from the Meteorological, Climatological, and Geophysical Agency (Indonesian: Badan Meteorologi, Klimatologi, dan Geofisika, abbreviated BMKG), accessible on data.online.bmkg.go.id. The dataset reveals that Facebook Prophet, with the lowest MSE and RMSE, is the most suitable method to predict the upcoming monthly rainfall recorded from Kemayoran Station, Central Jakarta. This paper offers a comprehensible understanding and indication of the predicted monthly rainfall in the next 24 months from September 2020 to August 2022 in the Central Jakarta region. Hence, the Jakarta Provincial Government can prepare and construct policies or strategies that are well-tailored high yielding to tackle floods mainly caused by rainfall in Jakarta.

The writing of this paper is structured as follows. Section 2 explains the materials and methodology for comparing three time-series models. Section 3 describes the findings of the study. Section 4 discusses how the results compare with related work and elaborate on the findings' implication for recommendations. Finally, Section 5 ends with the conclusion and future work.

II. METHODOLOGY

This study aims to conduct rainfall prediction for the next two years, from September 2020 to August 2022, by comparing three time series forecasting models which are frequently applied to forecast seasonal trends. The models used in this study are Seasonal Autoregressive Integrated Moving Average (SARIMA), Facebook Prophet, and Long-Short Term Memory (LSTM) which are evaluated based on Mean Square Error (MSE) and Root Mean Square Error (RMSE) score. MSE and RMSE are the evaluation parameter outcomes to measure the prediction model's fit to the actual data

A. Datasets

The datasets used in the study consist of rainfall time series datasets from January 1st, 2008, to August 31, 2020, recorded daily every 7 am from Kemayoran BMKG Station in Jakarta. These data were collected from http://dataonline.bmkg.go.id/. Table 1 shows the raw dataset of rainfall in millimeter (mm) with the lowest rainfall at "0", which means there is no rain recorded at the moment.

TABLE I. DAILY RAINFALL (MM) RAW DATASET

Date	Rainfall (mm)
01-01-2008	29,4
02-01-2008	1,6
03-01-2008	32,3
04-01-2008	12,5
….	....
30-08-2020	0
31-08-2020	0

B. Data Collection and Analysis

The dataset used in the study contains a daily time series table of rainfall (millimeter, mm) recorded at Kemayoran BMKG Station in Jakarta. Initially, the datasets have been pre-processed for this study to focus on the monthly amount of rainfall by summing up the daily rainfall into monthly rainfall.

In data exploration, we apply data visualization to analyze the rainfall trend and identify the right parameters to answer the problem statement and appropriate approach to conduct time series forecasting. After data pre-processing and data exploration, we split the dataset's rainfall divided into two subsets. The first subset is a training set with time-series data from January 2008 to August 2018 (85% of the data population) to train the models. The second subset is a testing set developed from September 2018 to August 2020 (15% of the data population). SARIMA, Facebook Prophet, and LSTM were selected as models in this study.

1) SARIMA

Box and Jenkins (1970) developed and applied a modeling approach for time series analysis and forecasting to accommodate stationary and seasonality time series data. This modeling approach was also to fit the autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA)[7]. In this study, fine-tuning parameter statsmodels.tsa.statespace.sarimax.SARIMAX in Python for SARIMA parameters (p, q, d)x(P, Q, D) was performed. Stsatsmodels.org provides it to find the model with the lowest Akaike's Information Criterion (AIC). The lower value of AIC (Akaike Information Criterion) indicates the better quality of the statistical model to the fitting [6].

2) Facebook Prophet

A Prophet is developed and introduced by Facebook in 2017, available on Python and R [13][14], to accommodate three main features, namely trend, seasonality, and holidays[15], and the demand for high quality and practical approach to forecasting at scale [16]. Prophet parameters consist of capacities, changepoints, holiday and seasonality, and smoothing parameters that can be interpretably applied to improve the model. In this study, we tune the parameters by imposing assumptions to get the fittest Prophet forecast models, such as choosing classical multiplicative seasonal decomposition and applying hyperparameter tuning using Parameter Grid sklearn.model_selection in Python.

3) LSTM

The Long-Short Term Memory (LSTM) is a form of recurrent neural network that stores past information into its memory cells, and during training, it learns when to use the memory [17]. LSTM parameter consists of the number of hidden layers, the number of hidden units per layer, learning rate of the optimizer, dropout rate, and the number of iterations. Unlike SARIMA and Prophet that use tuning parameters, we will not tune the network parameters with grid search parameters. This study will use multilayer LSTM (three layers) with standard parameters, performed by a little trial and error. The number of epochs was fixed at 50 to get minimal loss.

We apply these three models to analyze and predict the future monthly rainfall recorded. The learning models are then assessed based on important parameters, such as Mean Square Error (MSE) and Root Mean Square Error (RMSE) score

[10][11][12], as described below. Section 3 presents the evaluation indicator outcomes.

1) Mean Squared Error (MSE)

MSE measures the difference between the actual value and the predicted value (residual), which is then squared to get the MSE value. The error is expressed in squared target units by measuring the average squares of the errors, which is the average squared difference between the estimated values and the actual value.

$$MSE(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (1)$$

2) Root Mean Squared Error (RMSE)

RMSE is the square root of MSE. It calculates the prediction model's absolute fit to the data. Therefore, showing how accurate the model's predicted values to the observed data points. It is regularly applied as both an evaluation metric and a loss function.

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (2)$$

After we get the fittest model based on the evaluation parameters, we conduct a 24-months prediction by applying the most suitable model for monthly rainfall in Central Jakarta. Figure 1 shows the proposed approach in the study.

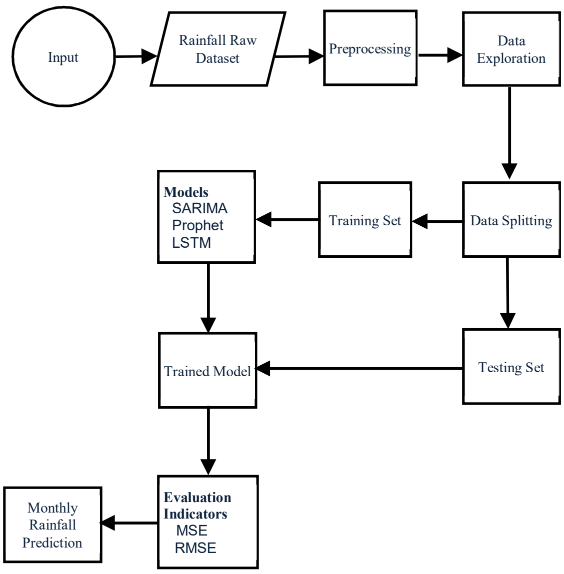

Fig. 1. Workflow Approach

III. Results

This paper presents a system model for forecasting monthly rainfall in Central Jakarta using time series forecasting models. The dataset contains a daily time series table of rainfall (mm) recorded at Kemayoran BMKG Station in Central Jakarta. Data exploration and forecast monthly rainfall in the upcoming 24 months were performed applying three-time series forecasting models frequently used for hydrometeorological analysis. This process was conducted to forecast the forthcoming monthly rainfall as a reference to determine the strategic mitigation and possibility of damage due to flood threat in Central Jakarta.

A. Data Exploration

Data exploration is needed to understand the time series data of monthly rainfall based on trend and seasonality. This is an important step to choose the appropriate variables and the proper approach to conduct time series forecasting. This study uses moving average smoothing analysis and additive decomposition method for data exploration, as shown in Figure 2 and Figure 3, respectively.

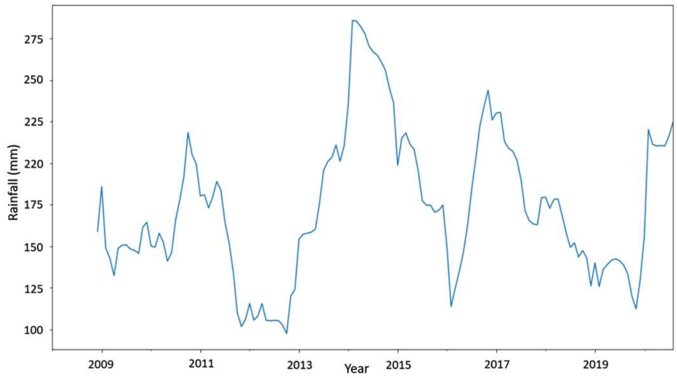

Fig. 2. 12-month Moving Average time-series

At first, an analysis of moving average smoothing was conducted. It is one of effective techniques in time series forecasting. Smoothing is a method used in time series to eliminate the short-term volatility in data to help us better see patterns. We apply the method to reduce noise and to uncover clearer signals in the direction of the rainfall trend. In time series analysis and forecasting, moving average is recognized as a straightforward and usual type of smoothing [18]. Figure 2 illustrates representing the dataset into a moving average with a 12-month window size. It shows a clear pattern appearing when we plot the data. The time-series has a seasonal pattern, which is rainfall is always high every three to four years. This suggests that we may set the yearly seasonal parameters in applying the Prophet and SARIMA models.

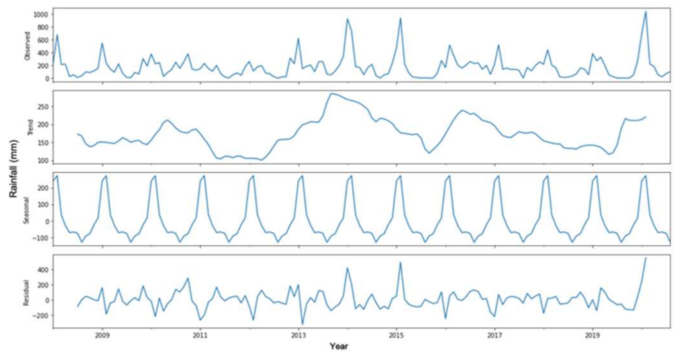

Fig. 3. Additive Decomposition

After analyzing moving average smoothing, we conduct the Time-Series Additive Decomposition method to visualize and decompose the time series into three distinct components: trend, seasonality, and noise. The additive decomposition of the monthly rainfall from September 2008 to August 2020 is shown in Figure 3. The figure reveals no trend detected, and the rainfall is relatively unstable based on the residual curve. However, it is showing seasonality which suits the result of smoothing analysis. It is entirely appropriate to apply SARIMA, Prophet with yearly seasonality, and LSTM with a

12-month batch to predict rainfall for two years ahead from September 2020 to August 2022.

B. *Forecasting Results*

Three favorable time series forecasting models, SARIMA, LSTM, and Prophet methods, have been used to predict the monthly rainfall in the next 24 months from September 2020 to August 2022 recorded at Kemayoran Station. The monthly rainfall dataset is divided into two subsets: a training set (85% of the data population) to train the models and a testing set (15% of the data population). Table 2 and Figure 4 show the validation of the forecasting results of the methods. At first, we evaluate the models using MSE and RMSE, as shown in Table 2. It reveals that Prophet has the lowest MSE (23821,93) and RMSE (154,34), while LSTM (46206,51 and 214,96 respectively) performs poorly. SARIMA has much lower MSE (25006,03) and RMSE (158,13) than LSTM, but it still has a little higher MSE and RMSE than Prophet. This suggests that the fittest model to forecast the monthly rainfall in Central Jakarta is Prophet.

TABLE II. EVALUATION PARAMETERS RESULT

Model Name	**MSE**	**RMSE**
SARIMA	25006,03	158,13
Prophet	23821,93	154,34
LSTM	46206,51	214,96

After evaluating the parameters, as part of the validation test, we also visualize the validation test of SARIMA, LSTM, and Prophet models with the actual rainfall dataset from September 2018 to August 2020, as shown in Figure 4. The figure, including the three models, predicts that the monthly rainfall will probably peak in February both in 2019 and 2020. It also shows that Prophet and SARIMA have an identical curve, and their predictions are closer to the observed monthly rainfall than LSTM. This suits the evaluation parameter result, as previously explained. Based on the evaluation parameter results in Table 2 and supported by Figure 4, we can conclude that the Prophet is the fittest model because it has the lowest score for MSE at 23821,93 and RMSE 154,34, and its value was close to actual rainfall. However, the Prophet prediction still does not fit the actual value by a fairly wide margin from January to February 2020. It may suggest that actual rainfall from January to February 2020 is a rare event.

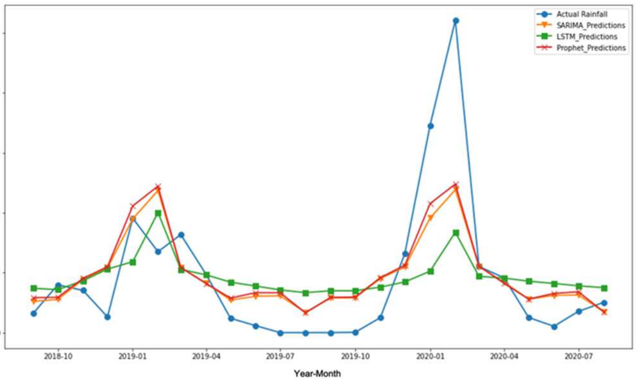

Fig. 4. Time Series Forecasting Models Validation

As we conclude that Prophet is the fittest model to forecast the monthly rainfall based on Table 2 and Figure 4, we then use the Prophet as the chosen model to forecast the monthly rainfall for the next two years from September 2020 to August 2022. The forecasting results are shown in Figure 5, where we also provide the lower and upper values, indicating boundaries for the forecasting. As the lowest value for rainfall is zero, we can change and interpret the negative value for lower rainfall in Figure 5 as zero "0". The result shows that the rainfall fluctuates over this period. In January and February 2021, we will probably see high amounts of rainfall, not as high as or higher than in January and February 2020. This suggests we need to be more prepared to anticipate the flood than before.

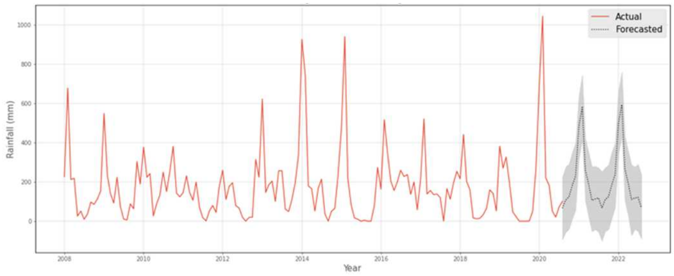

Fig. 5. Monthly Rainfall Prediction using Prophet Model

IV. DISCUSSION

This study aims to monitor and forecast monthly rainfall for the next two years, from September 2020 to August 2022. The dataset used in the study contains a daily time series table of rainfall (mm) from January 1st, 2020 to August 31st, 2022, recorded at Kemayoran BMKG Station in Central Jakarta. The dataset and quantitative analysis can be useful for evaluating rainfall trends in Central Jakarta. Furthermore, it can also present a rainfall trend in the last few years and help government authorities be more proactive by making effective strategies and practical action for mid-term mitigation. Data exploration were applied as opening data analysis to recognize the problem and then to applied appropriate time series forecasting models to predicts the upcoming rainfall situation.

As explained in the Data Exploration part, the monthly rainfall in Central Jakarta keeps fluctuating in the last few years, with the peak in January and February every year. It is an alarming situation. Then we applied time-series forecasting to predict the monthly rainfall for the next two years using SARIMA, Prophet, and LSTM models. Such models can provide us with a decent prediction for time series data.

Table 2 shows that Prophet is the most suitable model for predicting monthly rainfall recorded at Kemayoran Station, Central Jakarta, based on the evaluation indicators with the lowest MSE and RMSE scores. Meanwhile, LSTM, which has the highest MSE and RMSE, is the least accurate for this case, resulting from the lack of high volumes of data that deep-learning algorithms need to thrive. In addition, the SARIMA model accuracy is better than the LSTM model for forecasting monthly rainfall on the evaluation parameters. SARIMA model also has a smaller margin error than Prophet. These results are also supported by their model projection curves in Figure 4, as discussed before.

The use of the Prophet for hydrometeorological time series is still limited. A related study mentioned that the Prophet had not been used to hydrometeorological time series previously[10]. The result of the study of investigating the predictability of monthly temperature and precipitation shows Prophet model is more competitive compared to AutoRegressive Fractionally Integrated Moving Average (ARFIMA), exponential smoothing state-space model with

Box-Cox transformation, ARMA errors, Trend and Seasonal components (BATS), simple exponential smoothing, and Theta. Prophet's superiority over these mentioned models can be seen when combined with externally applied classical seasonal decomposition, as we use classical multiplicative seasonal decomposition for Prophet in this study.

As projected in Figure 10 using the Prophet model, the predicted monthly rainfall for the upcoming months is rising from October 2020 (123,68 mm) to January 2021 (485,41mm) and February 2021 (579,78 mm). The forecasting result also notes that we should be aware of the upper monthly rainfall prediction, which may peak at 742,18 mm in February 2021. As explained in Section 1, the iconic Hotel Indonesia (HI) Roundabout to Thamrin was hit by floods due to rainfall in January 2013, February 2015, and August 2016 [2][3] that has monthly rainfall 621,9 mm, 939,5 mm, and 227,2 mm respectively, shown in Figure 5. From these historic events in Central Jakarta, we will probably see other floods occur in this region if there is no effective mitigation tool.

The Jakarta Provincial Government needs to take more preventive measures and interventions to face the season with increasingly high rainfall in the upcoming months from September 2020 to August 2022. The data-driven policy based on this model, as described above, could help the government in minimizing the impacts of floods. For example, ensuring the water lines and ropes are not clogged. It is essential to maintain the optimum condition of waterways throughout the capital city so that water flow is not obstructed and causes puddles or flooding. In addition, repairing a collapsed dam and normalizing rivers in the entire Jakarta region is necessary. The city co-creator (e.g., citizen and industry) will also decide on this seasonal event. Another key to successful flood management is to involve the community. All parties must possess continuous perception, awareness, and discipline by not littering or throwing garbage into rivers/streams and a culture of protecting the environment.

V. CONCLUSION

To conclude, this paper has presented the trend and forecast of monthly rainfall in Central Jakarta for the next two years. The Prophet has been the most appropriate model in this study compared to SARIMA and LSTM based on the MSE and RMSE scores. The predicted monthly rainfall keeps fluctuating, with the bottom in August and the top in February for each forthcoming year. The result has shown that rainfall will reach the peak from January 2021 (485,41 mm) to February 2021 (579,78 mm), which is alarming.

Some improvements could be added to this proposed model. For example, exploring the prediction methodology using additional historical and updated datasets. Note that it is crucial to optimize the use of LSTM, add more datasets, put historical and updated datasets, and explore different comparison methods. Furthermore, as we can conduct monthly rainfall forecasting for Central Jakarta, we can predict the whole or other regions in Jakarta. Therefore, we also need a historical rainfall dataset representing the other regions in Jakarta. The ultimate goal is to find a more appropriate forecasting model for Jakarta entirely.

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