



## Rainfall Prediction at Ahmad Yani Meteorological Station Using Integration ARIMA and LSTM

Naufal Daffa Pramudya<sup>1\*</sup>, Rahmat Gernowo<sup>2</sup>, Indra Waspada<sup>3</sup>

<sup>1,2,3</sup>Department of Information System, Universitas Diponegoro, Indonesia

### Abstract.

**Purpose:** Predicting rainfall using ARIMA, LSTM, and Hybrid ARIMA-LSTM models to obtain accuracy values on data at the Ahmad Yani Semarang station.

**Methods:** This study implements the ARIMA, LSTM, and hybrid ARIMA-LSTM models to determine which of these models produces the most significant predictions using rainfall data at the Ahmad Yani Meteorological Station in Semarang. This method proves whether using the hybrid ARIMA-LSTM, which is a combination of the two models, is able to provide greater accuracy compared to the ARIMA/LSTM model. The results of these predictions can certainly help relevant stakeholders to improve rainfall accuracy, especially at the Ahmad Yani Meteorological Station.

**Result:** By utilizing the power of statistical models (ARIMA) with deep learning (LSTM), the results of these two models provide higher accuracy compared to each model, as seen from the accuracy of the best ARIMA model using RMSE 15.8 and MAE 8.7, the best LSTM model RMSE 14.65 and MAE 9.06, while in the HYBRID ARIMA-LSTM model the best RMSE is 14.1 and MAE 9.06.

**Novelty:** This research adds to the knowledge regarding the accuracy or combination of ARIMA and LSTM models which are rarely used, especially in the world of meteorology or rainfall. By utilizing the ARIMA model which is able to read linear patterns and the LSTM model which reads non-linear patterns, the accuracy of rainfall increases and can help related stakeholders.

**Keywords:** ARIMA, LSTM, Hybrid-ARIMA-LSTM, Rainfall, Prediction

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### INTRODUCTION

Rainfall modeling and prediction are challenging due to rapidly changing weather conditions, coupled with constant fluctuations in rainfall. Rainfall prediction is also a crucial challenge for meteorologists, as it is vital for monitoring extreme weather events, and rainfall data is fundamental to meteorological systems [1]. Rainfall itself is the precipitation or deposition of air in liquid or solid form originating from the atmosphere [2]. The amount of rainfall is expressed in millimeters (mm), which means rainwater falling on a flat surface of 1 square meter (m<sup>2</sup>) with a height of 1 mm without infiltration, flow, or evaporation for a certain period of time. Accurate information regarding weather conditions makes various parties highly dependent on information. For example, in the agricultural sector, the agricultural sector is one of the sectors that is highly vulnerable to changes in weather, including rainfall, because these changes can affect cropping patterns, planting times, and air quality, causing a decrease in food production and productivity [3]. Another sector that has an impact is the transportation sector. In this sector, changes in the weather can hamper transportation activities, urban transportation is one of the sectors most impacted by extreme rainfall. Flooding caused by high rainfall intensity can disrupt urban mobility and cause significant economic losses [4]. Extreme changes in the weather can cause navigational disruptions and reduced visibility. This can increase delays and the risk of accidents, including train, ship, plane and private vehicle transportation [5]. Anticipating rainfall provides crucial awareness, enabling proactive measures to be taken in advance. Precise estimations of daily rainfall not only enhance agricultural productivity but also play a pivotal role in securing food and water supplies [6]. The uncertainty of the weather or rainfall and sudden changes in the weather recently have hampered several human activities, not only hindering them but the uncertainty of the weather and sudden changes in the weather have also harmed the economy of the country and the nation [7].

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<sup>1\*</sup>Corresponding author.

Email addresses: [naufaldaffapramudya@gmail.com](mailto:naufaldaffapramudya@gmail.com) (Pramudya)

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Time Series or commonly called Time Series is a group of well-defined sequences of data points measured at consistent time intervals over a certain period of time [8]. With this time series, it can be used to predict future needs by studying and seeing how variables can change over time, one of the time series is ARIMA (*Autoregressive Integrated Moving Average*) this model characterized by three parameters, p (autoregressive order), d (difference rate), and q (moving average order) [9]. Another predictive model that can learn patterns from previous historical data is the LSTM, which is a deep learning model. This model uses a gate system to control information that must be stored long-term [10]. Deep learning is designed to automatically learn and represent data by transforming input data through several layers of nonlinear processing units [11]. can detect data to be stored and unused data to be pruned, because LSTM has a layer of neurons commonly called gates to manage memory in each neuron. The main components of the LSTM structure are the forget gate, input gate, cell state, and output gate. Each memory cell has three sigmoid layers and one tanh layer [12]. Meanwhile, the ARIMA-LSTM hybrid model is a model with a combination approach of Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) to increase accuracy in time series prediction. This model combines the strengths of ARIMA in capturing linear patterns and LSTM in understanding non-linear patterns [13]. In the realm of innovative combinations models machine learning, the integration of various deep learning architectures can significantly enhance the performance of rainfall prediction [14].

Previous research on ARIMA and LSTM models have been used in various predictions, such as COVID predictions [15], simulation predictions [16], weather predictions [17], water predictions [18] and various predictions. From the research conducted by Kashif [19] and Feifan Ji [20], both of which combine ARIMA's ability to capture linear patterns in time series data with LSTM's ability to model more complex non-linear patterns. The main similarity of this research with the two journals lies in the use of residual ARIMA prediction results as additional input for LSTM to improve forecasting accuracy. However, this study makes modifications and adjustments according to the context of the data used, namely rainfall data with a dataset division of 80% for training and 20% for testing, this study emphasizes rainfall forecasting as part of meteorological studies and uses MSE and RMSE metric evaluations. From these various studies, the ARIMA model has the advantage of capturing linear patterns, However, statistical models face significant limitations when applied to rainfall forecasting. ARIMA or SARIMA rely heavily on the assumption of linear relationships and stationarity in the data, which often fails to capture the nonlinear and dynamic nature of rainfall patterns [21]. Therefore, it is necessary to LSTM captures non-linear patterns, LSTM has been widely adopted in various fields like agriculture, economics, health science, and climate change [22]. These models are very useful for time series analysis and prediction due to its capability of holding long-term dependencies [23]. With these respective advantages, Hybrid ARIMA-LSTM model was developed that can capture linear and non-linear patterns, The Hybrid ARIMA-LSTM model can improve the accuracy of predictions by capturing the best characteristics of both models in handling linear and nonlinear relationships within patterns [24]. By regularly analyzing historical rainfall patterns and leveraging optimized models, the framework seeks to improve prediction accuracy while also addressing the efficiency limitations of traditional methods [25]. This study aims to determine the performance for accurate rainfall model prediction using ARIMA, LSTM, and Hybrid ARIMA-LSTM models. In addition, this study also aims to find out whether the application of this model can provide better research results. The advantage of this study is by knowing the accuracy of each model so that it can know which model is better from the research and assessing from the ARIMA model that is able to capture linear patterns and LSTM that is able to capture non-linear patterns.

## METHODS

Rainfall prediction research data at Ahmad Yani Station, Semarang was obtained from NOAA (National Oceanic and Atmospheric Administration). This NOAA data was taken from January 2020 to April 2025. The data used were rainfall and the date of data collection with a total of 1949 data, The daily rainfall is considered to be used because it provides better understanding about shape, patterns, and the challenges during a year as compared to the seasonal [26], This information is crucial to describe the rainy season's duration, onset, and the amount of rainfall is vital for decision-makers to improve resource and optimization [27]. This data will then be used as input for the ARIMA, LSTM, and Hybrid ARIMA-LSTM models, then this data will be divided into two as training data and testing data. The comparison ratio of this rainfall data has a variation of 80% training data and 20% testing data. The training data has a total of 1560 data and for testing data has a total of 390 data. Figure 1 is the sequence of stages in the research methodology framework.

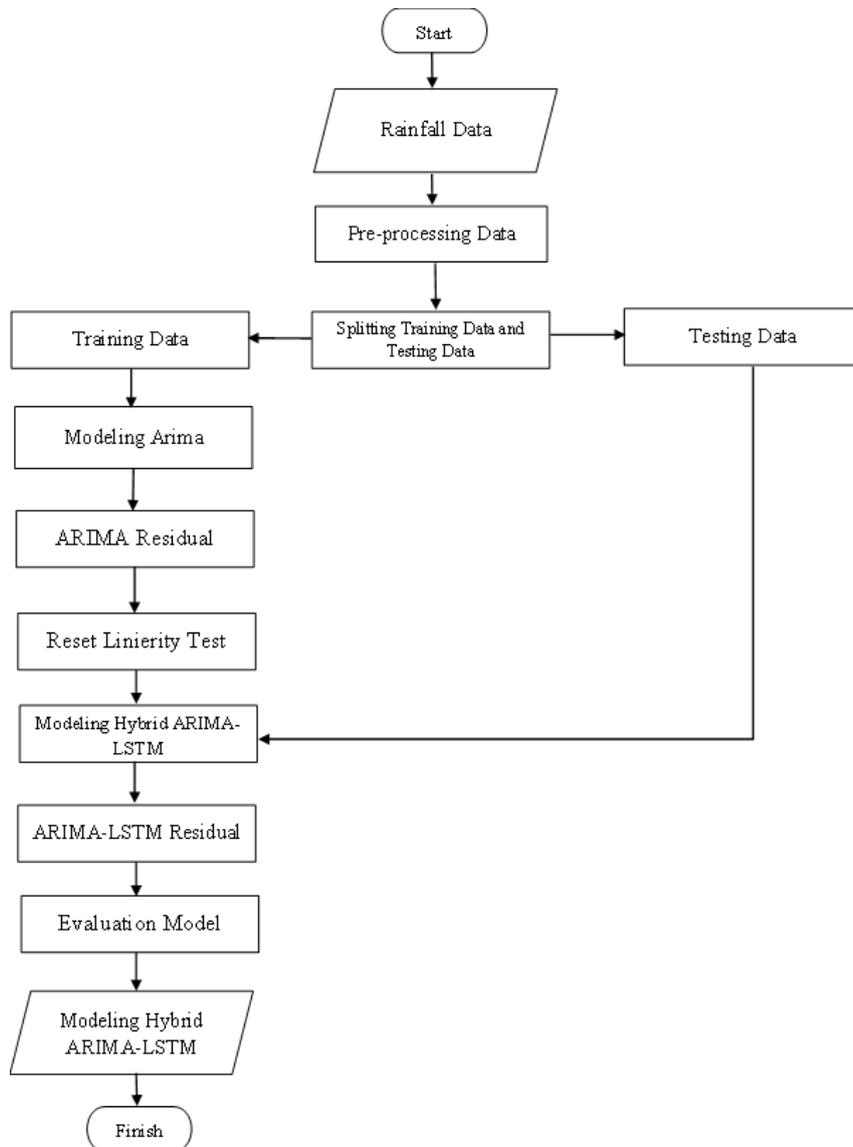


Figure 1. Framework of model

### Pre-Processing Data

Process at preprocessing stage, there is a data cleaning and transformation process, the goal is to ensure the model can run properly without any inconsistent data. In the data cleaning process, data identified as empty or null is filled in and data transformation is carried out to ensure the data to be used is in accordance with the desired format.

### Exploration Data

Before making predictions on the data used, first plot the data to get an idea of the data used. Figure 2 shows the rainfall data plot. The rainfall data plot shows rainfall from January 2020 to April 2025 and plot contains unstable data. Rainfall data from 2020 to 2025 has a value range of 0 to 100.

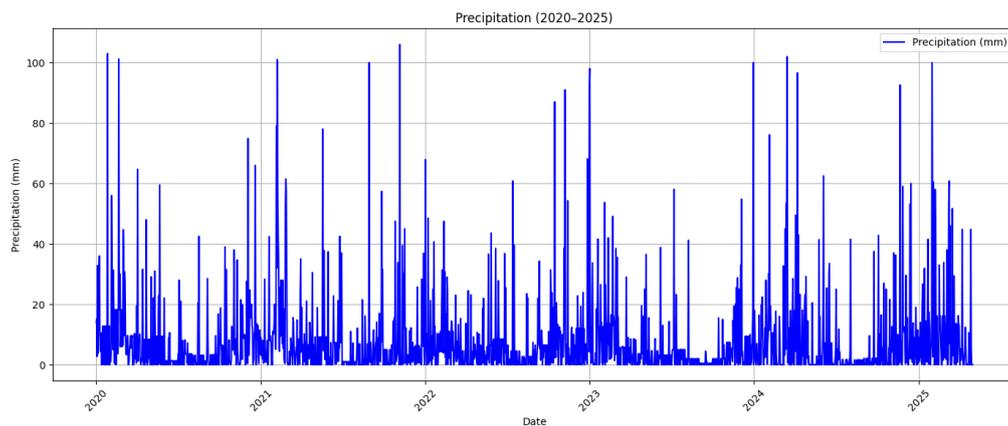


Figure 2. Rainfall plot

### Split Data

In the split stage, the data is divided into two parts: 80% training data and 20% testing data. The purpose of this split is to separate the data into several parts so that the model will not only memorize existing patterns but also be able to generalize from existing data or adapt to new data. The results of the testing data will then reflect the model's response to the data to be predicted.

### Arima Model

The Arima(AutoRegressive Integrated Moving Average) model is a model that works by identifying past patterns in data. The Arima model itself has 3 main parameters, like AR(p), I(d), and MA(q). These parameters have their respective functions [28]. The Arima model procedure consists of identifying data patterns (data stationarity), transformation and differencing, determining parameters (p, d, q), model estimation, model diagnostics and prediction.

### LSTM Model

The LSTM model is a type of artificial neural network from the RNN (recurrent neural network) family. RNN architecture has a loop that allows information to persist, this property allows the RNN to maintain memory of previous inputs [29]. LSTM is a special type of RNN. Its main character is its ability to handle long-term data dependencies and push the outcome to the succeeding node more efficiently. It also addresses the vanishing gradient problem, a known issue with RNN, which is tackled by disregarding nugatory information using its forget gate. LSTM also deals well with long-term dependencies with problems where the output is dependent on the historical input. The main advantage of LSTM is its ability to remember long-term patterns in data and can capture non-linear patterns. In one neuron, the LSTM network has four interacting layers, namely one tanh layer and three sigmoid layers. The sigmoid activation function is a function that returns values in the range of zero and one. While the tanh activation function returns values in the negative range of one to one. LSTM can detect data to be stored and unused data to be pruned, because LSTM has 4 layers of neurons commonly called gates to manage memory in each neuron [30].

### Hybrid Arima-LSTM Model

The ARIMA-LSTM hybrid model is a model that combines the Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) approaches to improve accuracy in time series prediction. This model combines the strengths of ARIMA in capturing linear patterns and LSTM in understanding non-linear patterns. Time series pattern data often contains problems with linear and non-linear time series. By combining these two models, it can be more effective in forecasting time series [31].

### Model Evaluation

Model evaluation is used to measure the accuracy of the applied model's performance. This model evaluation can indicate how well a predictive model captures data. Furthermore, model evaluation is performed after the model has been trained using training data, by testing it on testing data that the model has never seen before. Several metrics are used, such as MAE (Mean Absolute Error) and RMSE (Root Mean Square Error) [32].

### Development Hybrid Arima-LSTM

After the model evaluation is carried out, the model will be embedded into an interface so that readers can see more clearly and well in seeing rainfall conditions, readers and users can see various predictions with several models that have been processed. with this visual interface ensures the accuracy of the model that has been created and displays the prediction results that have been carried out by each model. the application is built using HTML, CSS, and Laravel, while to process the data using numpy, pandas and scikit-learn, as well as the python programming language used in this study.

### RESULTS AND DISCUSSIONS

The rainfall data obtained at the Ahmad Yani Meteorological Station, Semarang, amounted to 1947 data. This data will be divided into 80% training data and 20% testing data, so the total for training data is 1560 data and for testing data is 390 data. We can see in Table 1 for the data that will be used as input for the model to be carried out.

Table 1. Input data

No	Date	Prec
1	2020-01-01	14.0
2	2020-01-02	15.1
3	2020-01-03	2.7
4	2020-01-04	32.8
5	2020-01-05	3.7
...	...	...
...	...	...
...	...	...
1945	2025-04-24	0
1946	2025-04-25	0
1947	2025-04-26	44.8
1948	2025-04-27	5.3
1949	2025-04-28	0
1950	2025-04-29	0
1951	2025-04-30	0

In this study, the ARIMA model was first carried out. In the formation of this ARIMA model, a stationarity test was carried out on the variance data and a stationarity check on the mean. To check the stationarity of the variance, a check was carried out on the data to be used, because the data used has a range of 0 to 100 and if seen on the data it has a value of 0 of 460 so box-cox transformation was used so that the stationarity model on the variance. After that, a stationarity check was carried out on the mean using the ADF test and the results showed a p-value of  $1.43 \times 10^{-5}$ , because the p-value  $< \alpha$  so this indicates that the transformation carried out is stationary on the mean and there is no need to do differencing on the data [33].

After checking for stationarity of the variance and stationarity of the mean, the model identification is continued. Model identification aims to determine the structure of the ARIMA model that best suits the data used. This identification is also useful for determining the order (p, d, q) in ARIMA using ACF and PACF plots [34]. The ACF plot is used to determine the MA(q) component and the PACF plot is used to determine the AR(p) component. If seen from Figure 3, the ACF plot shows many significant lags that are above the blue area, as well as the PACF plot which has quite a lot of significant lags that are above the blue area. However, if all of these lags are taken, the initial model formed will be very complex, while the ARIMA model is a parsimonious model (simple models tend to give better results). Therefore, it is assumed that only the first 5 lags above the blue area are taken. From these first 5 lags, 35 tentative models will be generated.

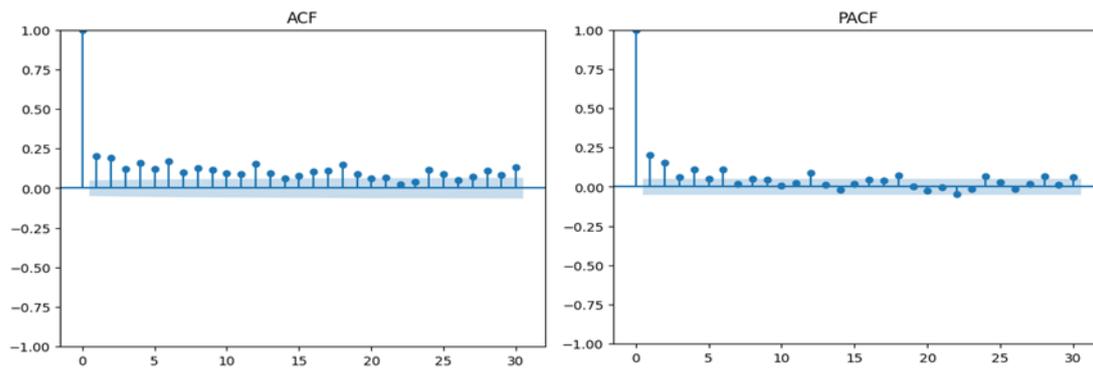


Figure 3. Plot ACF and PACF

Tabel 2. Tentative model

<b>p</b>	<b>d</b>	<b>q</b>
0	0	1
0	0	2
0	0	3
...	...	...
...	...	...
...	...	...
5	0	3
5	0	4
5	0	5

After obtaining a tentative model, parameter estimation is performed on the ARIMA model using the maximum likelihood estimation method. This parameter significance test is useful for determining whether the parameters generated in the ARIMA model are significant or not by considering  $P > |z|$ . Parameters with a P value  $< 0.05$  are considered significant and can be retained in the model. Figure 4 result for significane parameter.

Model ARIMA(0, 0, 1)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3824	0.038	36.282	0.0	1.308	1.457	***
ma.L1	0.1565	0.025	6.172	0.0	0.107	0.206	***
sigma2	1.4547	0.075	19.421	0.0	1.308	1.602	***

Model ARIMA(0, 0, 2)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3826	0.042	32.697	0.0	1.300	1.465	***
ma.L1	0.1645	0.025	6.480	0.0	0.115	0.214	***
ma.L2	0.1411	0.025	5.744	0.0	0.093	0.189	***
sigma2	1.4208	0.072	19.667	0.0	1.279	1.562	***

Model ARIMA(0, 0, 3)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3826	0.044	31.371	0.000	1.296	1.469	***
ma.L1	0.1630	0.026	6.340	0.000	0.113	0.213	***
ma.L2	0.1456	0.025	5.827	0.000	0.097	0.195	***
ma.L3	0.0545	0.025	2.151	0.031	0.005	0.104	*
sigma2	1.4156	0.072	19.698	0.000	1.275	1.557	***

Model ARIMA(0, 0, 4)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3829	0.047	29.559	0.000	1.291	1.475	***
ma.L1	0.1599	0.026	6.267	0.000	0.110	0.210	***
ma.L2	0.1381	0.025	5.554	0.000	0.089	0.187	***
ma.L3	0.0637	0.025	2.501	0.012	0.014	0.114	*
ma.L4	0.0931	0.025	3.772	0.000	0.045	0.142	***
sigma2	1.4024	0.071	19.787	0.000	1.263	1.541	***

Model ARIMA(1, 0, 1)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3971	0.103	13.628	0.0	1.196	1.598	***
ar.L1	0.9597	0.014	70.211	0.0	0.933	0.986	***
ma.L1	-0.8672	0.022	-38.832	0.0	-0.911	-0.823	***
sigma2	1.3573	0.066	20.522	0.0	1.228	1.487	***

Model ARIMA(2, 0, 0)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3829	0.048	28.931	0.0	1.289	1.477	***
ar.L1	0.1724	0.025	6.767	0.0	0.122	0.222	***
ar.L2	0.1551	0.025	6.321	0.0	0.107	0.203	***
sigma2	1.4051	0.071	19.883	0.0	1.267	1.544	***

Model ARIMA(3, 0, 0)							
	coef	std err	z	P> z	[0.025	0.975]	Signif
const	1.3832	0.051	27.253	0.000	1.284	1.483	***
ar.L1	0.1630	0.026	6.334	0.000	0.113	0.213	***
ar.L2	0.1446	0.025	5.856	0.000	0.096	0.193	***
ar.L3	0.0608	0.025	2.400	0.016	0.011	0.110	*
sigma2	1.3999	0.070	19.924	0.000	1.262	1.538	***

Figure 4. Significant parameter of ARIMA model

From the 35 tentative models, parameter significance checks were carried out and those that met the standard significance test were selected. However, of the 35 models tested, only 7 models met the standard, namely a P-value <0.05, indicating that the model could be maintained and passed the significance test. These models consisted of the ARIMA(0,0,1), ARIMA(0,0,2), ARIMA(0,0,3), ARIMA(0,0,4), ARIMA(1,0,1), ARIMA(2,0,0), and ARIMA(3,0,0) models, as shown in Figure 4. There were 7 models that passed the standard significance test.

After obtaining 7 model results, diagnostic checking is then performed to determine which model is suitable for prediction. The main goal is to ensure that the selected ARIMA model truly matches the characteristics of the data so that the forecasting results can be trusted. To determine which model is suitable for use, it can be seen whether the model used is white noise and normally distributed or not. There are several methods in diagnostic checking testing, such as using Ljung-Box and Jarque-Bera [35]. The use of Ljung-Box is used to see whether the model still has remaining autocorrelation, so that no model is white noise. In addition, there is a Jarque-Bera check, this check is used to see whether the model is normally distributed or not.

	Ljung-Box pval	Ljung-Box <sup>2</sup> pval	Jarque-Bera pval
ARIMA(0, 0, 1)	0.0000	0.0003	0.0
ARIMA(0, 0, 2)	0.0000	0.0019	0.0
ARIMA(0, 0, 3)	0.0000	0.0007	0.0
ARIMA(0, 0, 4)	0.0000	0.0024	0.0
ARIMA(1, 0, 1)	0.1326	0.0000	0.0
ARIMA(2, 0, 0)	0.0000	0.0005	0.0
ARIMA(3, 0, 0)	0.0000	0.0002	0.0

Figure 5. Diagnostic checking

From Figure 5, which is the result of diagnostic checking using Ljung-Box and Jarque Bera, it was found that only the ARIMA (1,0,1) model achieved the best results because the model met the white noise test. This is proven by examining the Ljung-Box P-value. Although the Jarque Bera test did not meet the model

assumptions, the model can still be continued, because the most important main requirement in ARIMA is to meet white noise, which means there is no pattern in the data and the autocorrelation has disappeared.

To determine whether a model is good or not, model evaluation is used to determine how well the model works and whether the model is suitable for use for forecasting best model is selected using the RMSE and MAE metrics [36]. Figure 6 shows the results of the RMSE and MAE metrics, with the RMSE being 15.8 and the MAE being 8.13.

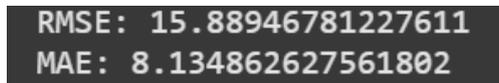


Figure 6. Result ARIMA model for RMSE and MAE

The results of the ARIMA model predictions can be seen in Table 3 a table of actual results and predictions made with the ARIMA model. The model generated from this testing data is capable of being predicted by ARIMA.

**Table 3. Prediction result**

<b>Date</b>	<b>Actual</b>	<b>Forecast</b>
2024-04-06	96.9	4.365318
2024-04-07	0	4.304423
2024-04-08	43	4.246636
2024-04-09	9	4.191772
2024-04-10	0.5	4.139661
...	...	...
2025-04-26	44.8	3.043284
2025-04-27	5.3	3.043284
2025-04-28	0	3.043284
2025-04-29	0	3.043284
2025-04-30	0	3.043284

After obtaining the prediction results from ARIMA, the next step is to form the LSTM model itself. This data is pre-processed, which includes missing values, duplicate data, and formatting the data accordingly. After all of this has been done, data normalization is continued [37]. This is useful for improving data consistency and integrity, reducing data redundancy, and improving data quality. After that, the data is divided into two, namely training data and testing data. The training data is used for the LSTM formation process, while the testing data is used to validate the model that has been created. This data comparison ratio has various variations, such as 80% training data and 20% testing data [38]. In this experiment, several variations of batch size and epoch were used. These variations consist of epochs 50, 100, 200, and 400 and use Adam optimization.

After dividing the data into training data and testing data, the next step is to determine the LSTM parameter initiation to be used. This step consists of defining neurons (hidden layers), defining the number of epochs, and defining the batch size in the LSTM model [39]. The use or trial of several variations of batch size and epoch is important because with several variations carried out, we can determine which model is the best and has accurate predictions. For determining the batch size, there is actually no obligation for how much to use, but it can be used first to determine the optimal results. Once obtained, it is continued with determining the epoch. The size of the epoch that has been set will affect the size of the learning process of a model. In this batch size and epoch variation, the results will be determined. In this study, the number of neurons used was 60, batch sizes were 32, 64, 128, and 256, while the epochs that will be used are 50, 100, 200, 300, and 400 using Adam optimization. To determine which model has the best prediction, a metric evaluation is carried out using MAE and RMSE [40].

Table 4. Result metric evaluation for LSTM model

Batch	Epoch	RMSE	MAE
16	50	14.27	9.7
32	50	14.1	9.3
64	50	14.26	8.98
128	50	14.1	9.09
256	50	14.21	8.94
16	100	14.36	8.93
32	100	14.21	9.38
64	100	14.21	8.84
128	100	14.17	9.01
256	100	14.15	9.06
16	200	16.11	9.99
32	200	15.08	9.8
64	200	14.22	8.95
128	200	14.21	9.09
256	200	14.13	9.06
16	400	17.8	11.42
32	400	16.51	10.9
64	400	16.05	10.14
128	400	14.48	8.77
256	400	14.17	9

Table 4 shows that the model with the lowest RMSE and MSE is the one with a batch size of 128 and epoch 50, with small RMSE and MSE values ranging from 14.65 and 9.06, respectively. This indicates that this model is the best and will be used in the LSTM model. Figure 7 shows the visualization results of the training and validation loss. From the model loss image, it can be seen that the LSTM model with a batch size of 128 and epoch 50 can be said to be good and there are no signs of overfitting.

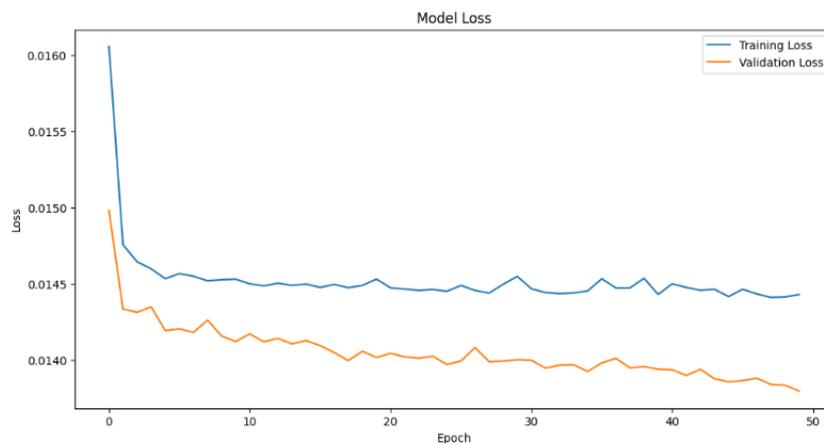


Figure 7. Model loss

After obtaining a model from the training process, the data will be tested using the testing data. To see whether the model is good or not, see Figure 8 Visualization of LSTM Model Predictions, and Table 5 Actual Prediction Results.

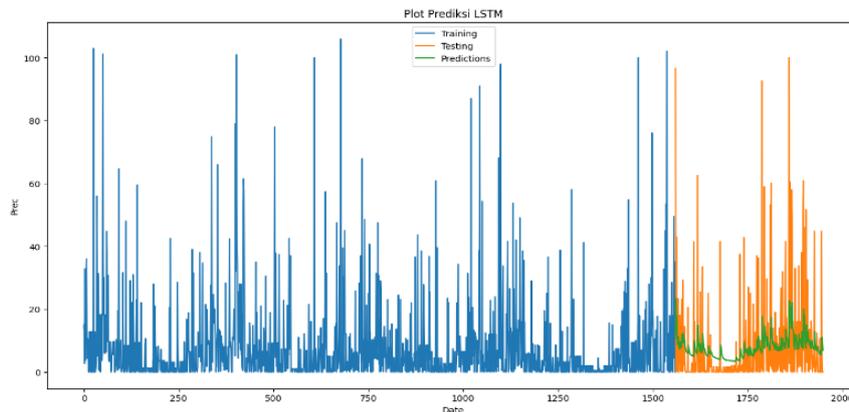


Figure 8. Visualization of LSTM model predictions

Table 5. Result prediction for LSTM model

Date	Actual	Forecast
2024-04-06	96.6	11.55469
2024-04-07	0	22.56018
2024-04-08	43	16.16258
2024-04-09	9	18.64595
2024-04-10	0.5	15.25537
...	...	...
2025-04-26	44.8	4.952577
2025-04-27	5.3	9.67851
2025-04-28	0	8.753676
2025-04-29	0	7.455284
2025-04-30	0	6.499692

After modeling each model, the next step is modeling with Hybrid ARIMA-LSTM. The process is almost the same as the previous model, there is pre-processing. This data pre-processing includes missing values, duplicate data, and formatting the data to make it appropriate. However, in the Hybrid ARIMA-LSTM process, data preprocessing is already done at the beginning of the ARIMA model. After all has been done, it is continued with data normalization, this is useful for improving data consistency and integrity, reducing data redundancy, and improving data

The Hybrid ARIMA-LSTM model is a combination of the ARIMA (Lt) model and the LSTM residual (Nt) model. To proceed to the next step, each model that has been created is first examined using the RMSE and MSE evaluations. After obtaining the model itself, the hybrid model is continued. From this hybrid model, it can be seen whether the Hybrid ARIMA-LSTM method is used. Proof to see which model is the best can be seen from the smallest value of the RMSE and MSE evaluations seen in the testing value.

Table 6. Result metric evaluation for hybrid ARIMA-LSTM model

Batch	Epoch	RMSE	MAE
16	50	14.27	9.7
32	50	14.1	9.3
64	50	14.26	8.98
128	50	14.1	9.1
256	50	14.21	8.94

16	100	14.36	8.93
32	100	14.21	9.38
64	100	14.21	8.84
128	100	14.17	9.01
256	100	14.15	9.06
16	200	16.11	9.99
32	200	15.08	9.8
64	200	14.22	8.95
128	200	14.21	9.09
256	200	14.13	9.06
16	400	17.8	11.42
32	400	16.51	10.9
64	400	16.05	10.14
128	400	14.48	8.77
256	400	14.17	9

Table 6 shows that the model with the lowest RMSE and MAE is the one with a batch size of 128 and epoch 50, with small RMSE and MAE values ranging from 14.1 and 8.99, respectively. This indicates that this model is the best and will be used in the Hybrid ARIMA-LSTM model. Figure 9 shows the visualization results of the training and validation loss. From the model loss image, it can be seen that the Hybrid ARIMA-LSTM model with a batch size of 128 and epoch 50 can be said to be good and there are no signs of overfitting.

After obtaining the model from the training process, the data will be tested using testing data. To see whether the model that has been used is good or not, you can see Figure 10 Visualization of Hybrid ARIMA-LSTM model predictions. From the results of table 6 and figure 10, it can be seen that the hybrid ARIMA-LSTM model provides better results after forecasting on the testing data. It can be seen after evaluation using RMSE and MAE, the results of the Hybrid ARIMA-LSTM modeling produce smaller RMSE and MAE compared to the individual models such as ARIMA and LSTM with an RMSE value of 14.1 and an MAE value of 8.99. This indicates that the hybrid ARIMA-LSTM model is better than the model itself [41].

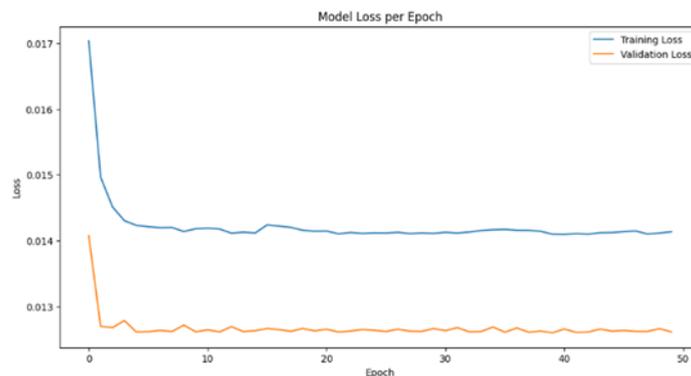


Figure 9. Model loss

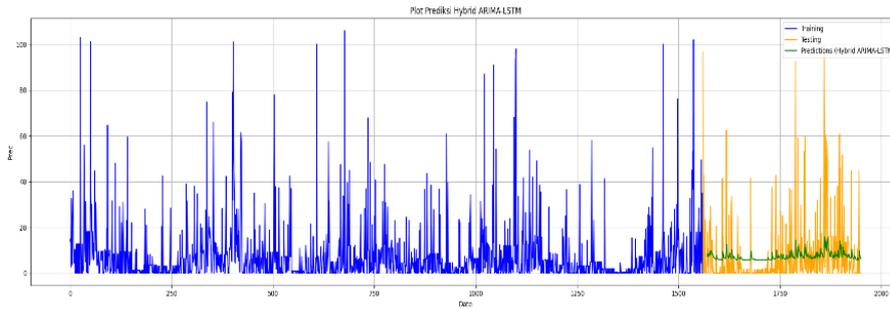


Figure 10. Visualization of hybrid ARIMA-LSTM model predictions

Table 7. Result prediction for hybrid ARIMA-LSTM model

No	Date	Actual	Hybrid_Forecast
0	2024-04-16	4.7	7.062257
1	2024-04-17	18.1	6.994724
2	2024-04-18	3	8.285974
3	2024-04-19	10.7	7.675545
4	2024-04-20	0.1	7.978369
...	...	...	...
375	2025-04-26	44.8	5.804038
376	2025-04-27	5.3	9.683666
377	2025-04-28	0	8.586792
378	2025-04-29	0	7.38614
379	2025-04-30	0	6.625727

In Table 7 Prediction Results, the results of Hybrid ARIMA-LSTM are able to predict actual results better than the ARIMA and LSTM methods. This can also be seen from the evaluation results using RMSE and MSE which show better results.

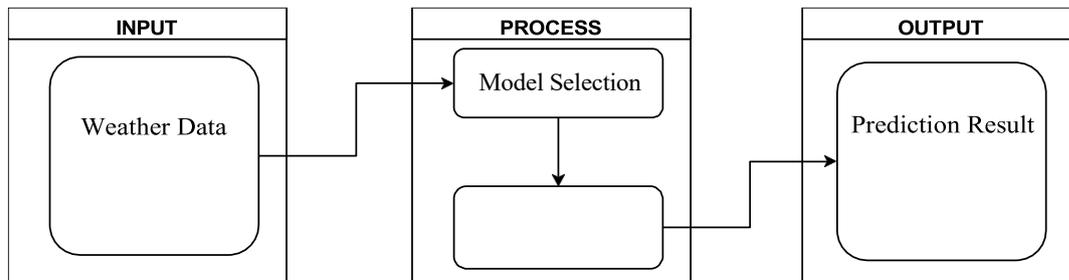


Figure 11. Information system framework

The application of ARIMA, LSTM, and Hybrid ARIMA-LSTM models to predict rainfall involves three stages: input, processing, and output, as shown in Figure 11 of the Information System Framework. The system used in this study is PHP, HTML, JavaScript, and Bootstrap programming. For the system implementation, it consists of an information system framework, database design, system design and system interface. The initial dashboard page to enter the system is as in Figure 12, on this dashboard page there are several menus for selecting models and there are several explanations about the ARIMA, LSTM, and Hybrid ARIMA-LSTM models, on this dashboard page there is also what data is used along with the areas used in this study, and for the result every model and grafik can see in Figure 13.

The input data in this study is automatically usable immediately, as it is embedded within the model. The historical data used consists of temporal data ranging from year, month, day, to rainfall in mm, which has undergone preprocessing. In the rainfall prediction process, the user can select which model to use. In this study, there are three models: ARIMA, LSTM, and Hybrid ARIMA-LSTM. When selecting the ARIMA

model, the data used will be calculated using the ARIMA(1,0,1,) model. When selecting the LSTM model, the data used will calculate the best LSTM model at a batch size of 128, epoch 50, and window 60. When the user selects the Hybrid ARIMA-LSTM model, the data used will calculate the Hybrid ARIMA-LSTM model using the best calculation of that model, namely at a batch size of 128, epoch 50, and window 60. The output results on the prediction page will include evaluation metrics for each model.

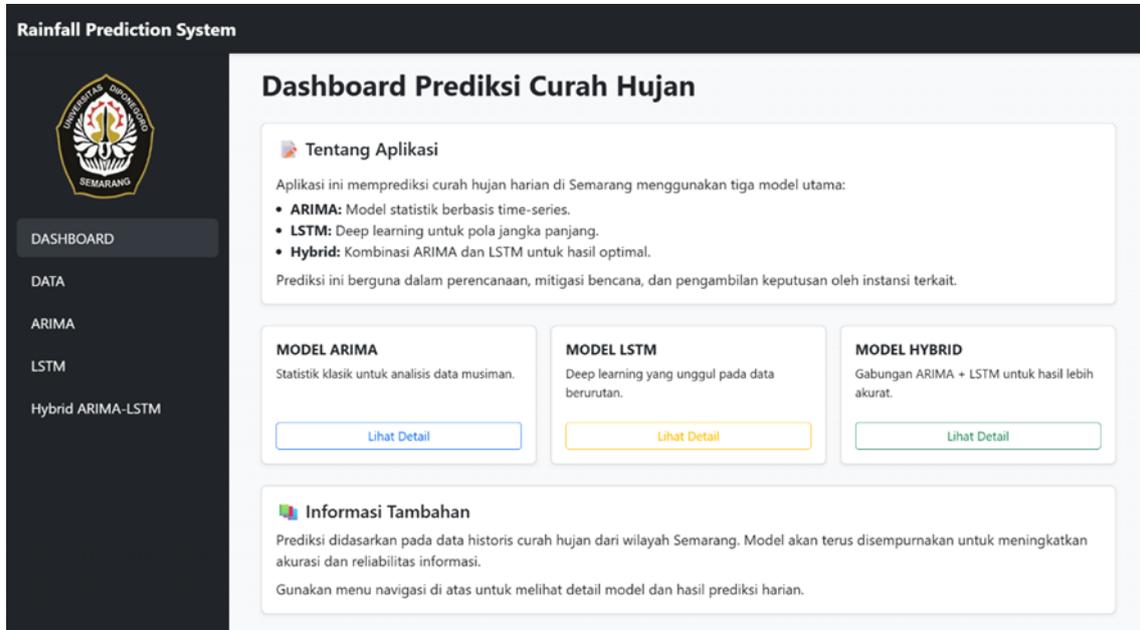
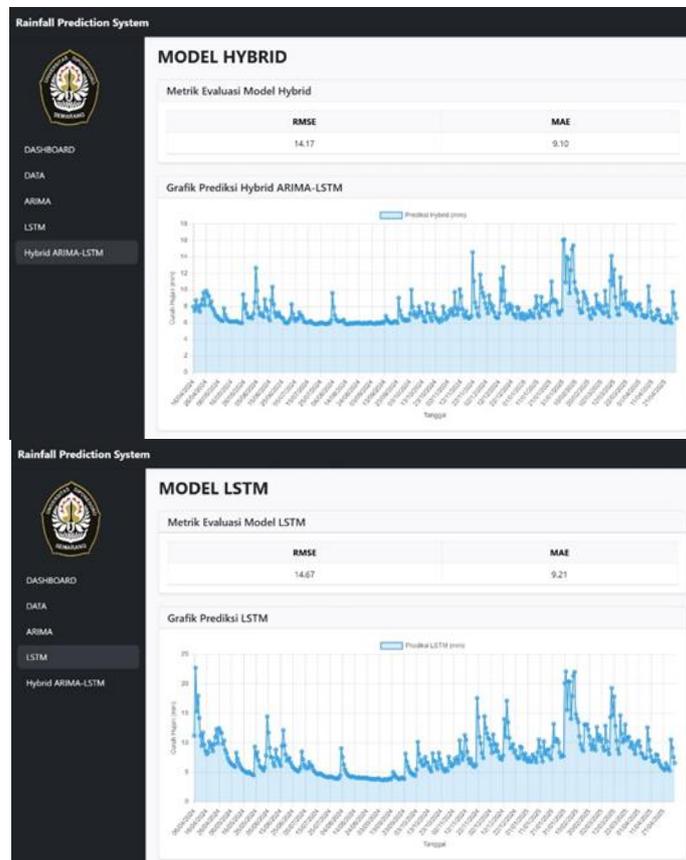


Figure 12. Dashboard



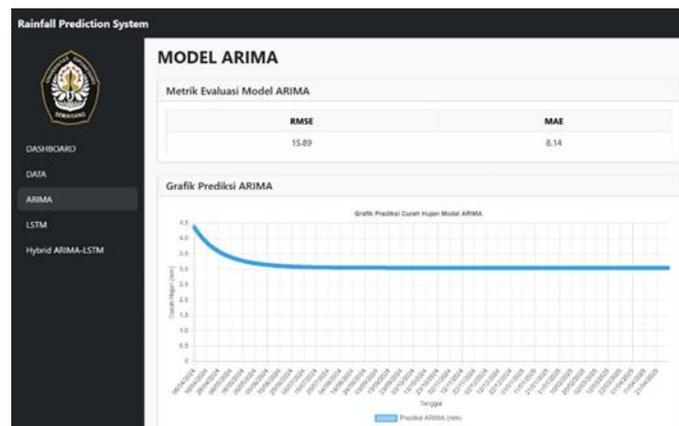


Figure 13. Results and graphs of each model

## CONCLUSION

This study concludes that integrating ARIMA's ability to capture linear temporal structures with LSTM's strength in modeling nonlinear dependencies through a hybrid ARIMA-LSTM approach results in superior rainfall prediction performance compared to the individual models. Based on the evaluation results using rainfall data from the Ahmad Yani Meteorological Station, the best ARIMA model produced RMSE 15.8 and MAE 8.7, while the best LSTM model achieved RMSE 14.65 and MAE 9.06; in contrast, the hybrid ARIMA-LSTM model delivered the most accurate predictions with RMSE 14.1 and MAE 8.89, demonstrating its enhanced capability in representing complex rainfall patterns. Conceptually, these findings highlight the effectiveness of combining statistical and deep learning methods for meteorological forecasting, and the research provides meaningful impact by offering more accurate and reliable rainfall predictions that can support meteorological agencies and stakeholders in improving forecasting precision, early warning systems, and climate-related decision-making.

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