LSTM and ARIMA for Forecasting COVID-19 Positive and Mortality Cases in DKI Jakarta and West Java

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***Abstract*—The spread of COVID-19 in Indonesia is still classified as a pandemic until October 31, 2022. Even though the endemic has been enforced in several nations worldwide. However, the fact that people's mobility is increasing means that this condition can increase the number of new cases of COVID-19. The Indonesian government remains vigilant about any decisions that will be taken to maintain the stability of the country's health sector, economy, and population mobility. First, The purpose of this our research is to forecast of daily positive confirmed and daily mortality for the next 13 days using COVID-19 epidemiological data in Indonesia, i.e. DKI Jakarta and West Java. Second, the forecasting model uses a deep learning approach, i.e. LSTM and ARIMA. furthermore, The LSTM method and ARIMA modeling results are compared based on their respective to regions. Finally, The LSTM method has good model performance and the ability to forecast COVID-19 cases based on RMSE and MAPE.**

Keywords—Forecasting, LSTM, ARIMA, DKI Jakarta, West Java, Indonesia

I. Introduction

Aksoy et al. [1] The worldwide consequence of the emergence of COVID-19 is of grave concern. Hanifah et al. [2] Although some nations have adopted endemic, there are still numerous developing nations, such as Indonesia, who are not persuaded to do so. Because, Roziqin et al. [3] The Indonesian government is still executing the PPKM policy for COVID-19 control (Enforcement of Community Restrictions). Gautama et al. [4] The policy seeks to preserve an optimal situation, which comprises the health sector, the economy, and population mobility.

Petropoulos et al. [5] The efforts to deal with COVID-19 based on previous studies conducted a comprehensive analysis by predicting a positive confirmed case based on historical data with the characteristics of the timeseries data for policy intervention. This was done to determine whether or not an intervention should be implemented. Sardar et al. [6] After that, the model is assessed using statistical criteria, specifically RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and R-Square.

Several studies that have used LSTM and ARIMA to forecast COVID-19 cases, including RMSE and MSE. Adiga et al. [7] found that the best model results were obtained by employing ARIMA (Autoregressive Integrated Moving Average) with MAPE=999.1. The predicted positive confirmed cases were found in four separate regions in the United States: Maricopa, Los Angeles, San Bernardino, and Kings. Arora et al. [8] The stacked LSTM (Long Short-Term-Memory) model and the bidirectional LSTM model are used in India, and the outcomes of these models are RMSE=3.22 and MAPE = 3.22 respectively. Chatterjee et al. [9] Forecasting daily positive cases in 17 countries using Bidirectional LSTM with findings of RMSE=8649,154, MAE=7130.149, and R-Square=1. Furthermore, Chaurasia et al. [10] for the whole world using the ARIMA model yields MAE=0.1517, MAPE=0.12044, and R-Square=0.0091.

However, because of the dynamic characteristics of the COVID-19 data, it is surely difficult to produce correct predictions. As a result, we want intelligent computing that is able to assess the timeseries data, as stated by Dash et al. [11]. In the earlier studies, Machine Learning was successful in making accurate forecasts of the development and trend data of COVID-19. According to what is said in Chandra et al. [12], The use of deep learning to the problem of predicting cases, i.e., LSTM, demonstrates both the ability to predict properly and high performance. The primary objective of this study is to predict daily positive confirmed cases and daily mortality using historical data in a different region of Indonesia, specifically DKI Jakarta and West Java based on the characteristics of the timeseries data. This will be accomplished by comparing the data from the two regions to one another and comparing the results. LSTM and ARIMA are the two approaches of forecasting that are suggested to be employed in this research. To the best of our ability, LSTM and ARIMA are frequently used forecasting models; however, in Indonesia, they are not yet accessible in these two region;DKI Jakarta and West Java.

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Consequently, our research contributes as follows:

1) Using the LSTM and ARIMA method, we forecast daily positive confirmed cases and daily mortality cases.
2) Using statistical measurements like RMSE, MAE, MAPE, and R-Square, we will compare how well the LSTM and ARIMA method work in each region.

The following are the systematics for writing the remainder of this paper: Section II discusses papers related to this research. Section III shows our study's design and the method we propose. Section IV presents the results of our research. Finally, Section V highlights the results of our research

II. Related Works

It is difficult to forecast the rise of COVID-19 instances, such as confirmed positives and mortality, based on the characteristics of COVID-19 data; thus, a computational technique, such as the deep learning approach, is required to solve these difficulties, according to Mohan et al. [13]. Forecasting is often used to forecast future events based on historical data, according to Touga et al. [14]. In deep learning, several forecasting models exist. Several models are used to anticipate future occurrences using forecasting techniques according to Ali et al. [15]. Using intelligent computing techniques, you can predict, forecast, and sort a problem quickly [16].

Several studies that have used LSTM and ARIMA to forecast COVID-19 cases. Alassafi et al. [17], the accuracy of the LSTM model in forecasting of positive cases and mortality for the following seven days using a deep learning technique, i.e., RNN and LSTM, was 98.58%, whereas the accuracy of the RNN model was 93.45%. Using the LSTM model and CNN, figure out how many people got sick, got better, and died in Egypt. According to Marzouk et al. [18], Using RMSE, the LSTM model did the best job of predicting the total number of infections for one week and one month from now. [18]. Ganiny et al. [19] used the ARIMA approach to predict cases of COVID-19 in India. RMSE=457.61, MAE=330.79, and MAPE=2,471. R-Square=0.99. Hridoy et al. [20] Using the LSTM Method with success in Bangladesh RMSE=593764, MAPE=0.0176, R-Square=0.95. Perone et al. [21] Using the ARIMA approach with the model evaluation results for Italy (RMSE=412.79, MAE=283.49, MAPE=13.039, R-Square =0.95), then for the United States (RMSE=606.66, MAE=430.83, MAPE=11.39, R-Square=0.98) and Russia (RMSE=430.83, MAE=1,631.3, MAPE=5.95, R-Square=0.95).

III. Research Design

Fig. 1 shows the steps of this research. First, collect the COVID-19 dataset, which contains two variables of interest: daily confirmed positives and daily mortality. The information is derived from two different Indonesian regions, i.e. DKI Jakarta and West Java. The second step is pre-processing, which involves identifying missing data if a linear interpolation technique exists. Next, do split data training and testing to develop a reliable model. The third step of modeling uses LSTM and ARIMA for each region; the model findings are then examined according to the model used. The model is evaluated using RMSE and MAPE.

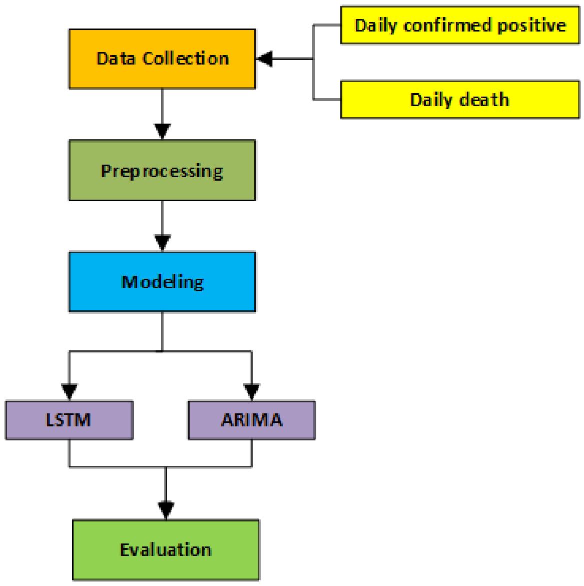

Fig. 1: The proposed research methodology.

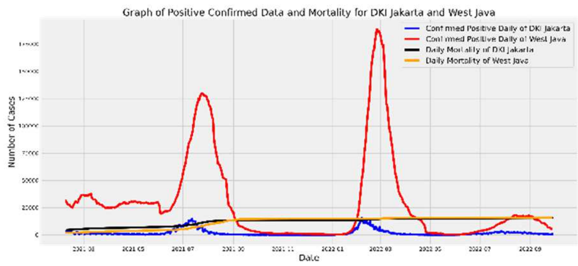

Fig. 2: Graph of Positive Confirmed Data and mortality for DKI Jakarta and West Java.

A. Data Collection

This research utilizes the COVID-19 epidemiological dataset from DKI Jakarta and West Java, Indonesia, between 1 March 2020 and 28 September 2022. The number of datasets is 968 for 3 years. Daily confirmed positive cases are utilized as the dependent variable, and daily mortality cases may be observed in Fig. 2

B. Preprocessing

At this step, a check for missing data values is performed; if there are any, the data are filled in using linear interpolation state the units for each quantity that you use in an equation.

According to Siregar et al. [22], Interpolation is a technique for calculating the value of a linear equation function using the law of proportionality. The formula for interpolation is as follows:

$$l = \frac{r - t_{\text{value}}}{r - d.f} x(d.f - \text{lowest}.d.f) \tag{1}$$

Based on the equation formula (1), explain that l is the interpolation value while r-t_{value} equals the range of t_{value} between two closest $d.f$.

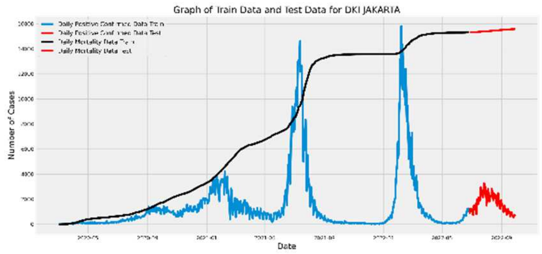

Fig. 3: Graph of Train Data and Test Data for DKI Jakarta

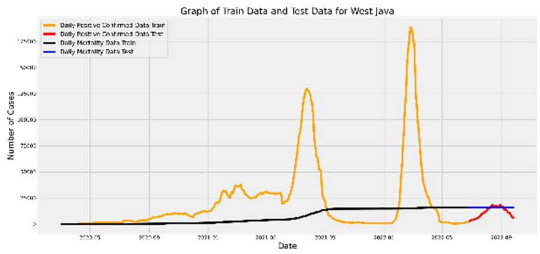

Fig. 4: Graph of Train Data and Test Data for West Java

In the previous study, Acording to Chimmula et al. [23] interpolation was also utilized to fill in missing data values in the prior research. After the preprocessing stage, according to Siami-Namini et al. [24], Following the preparation step, a data split was conducted to partition the dataset into training and testing data. The training data is used to train the algorithm to find the best model, whilst the testing data is used to assess the model's performance. Fig. 3 show is a visual representation of training and testing data for daily positive confirmed variables and daily mortality in the DKI Jakarta region, whereas Fig. 4 for the West Java region.

C. Modeling

LSTM is a neural network having four gates: the input gate, the cell gate, the forget gate, and the output gate. With a high number of gates, LSTM is able to filter data containing redundant information, Acording to Siami-Namini et al. [25]. The Formula is as follows:

$$k_t = \sigma_g(W_z X_t + U_z h_{t-1} + b_z) \quad (2)$$

$$l_t = \sigma_g(W_z X_t + U_r h_{t-1} + b_r) \quad (3)$$

$$\hat{s}_t = y_h(W_h X_t + U_h(l_t \odot h_{t-1}) + b_r) \quad (4)$$

$$u_t = k_t \odot \hat{u}_t + (1 - k_t) \odot h_{t-1} \quad (5)$$

The weights by W and U, the bias by b, the sigmoid function by sigma, the ReLU function by y_h, the input vector by x_t, the candidate activation vector by $\hat{s}_t$, and the output vector by ht are all represented by $\hat{s}_t$. Additionally, $\odot$ stands for the Hadamard outcome. Fig. 5 The input gate is represented by k_t, the previous cell memory by C_{t-1}, the previous Cell output by A_{t-1}, the current cell memory by Y_t, the current cell output by h_t, the forget gate by S_t, the intermediate cell state by $\bar{y}_t$, the input gate by U_t, the output gate by P_t.

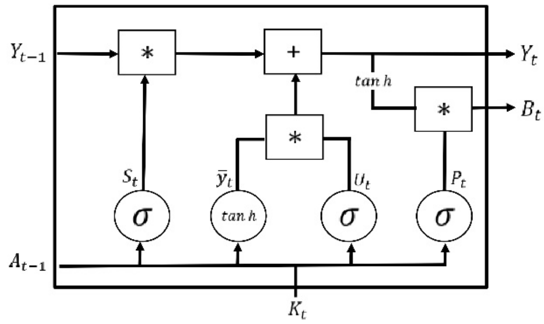

Fig. 5: LSTM Cell

Furthermore, the second model used in this study is ARIMA. Acording to Putri et al [26] ARIMA is a forecasting model that fully disregards independent variables. Acording to Usher et al. [27] ARIMA leverages past and current dependent variable values to provide accurate short-term predictions. ARIMA is appropriate if the data in a time series are statistically connected (dependent). The formula for ARIMA is as follows:

$$S_t = \mu' + \emptyset_1 S_{t-1} + \emptyset_2 S_{t-2} + \cdots + \emptyset_p S_{t-p} + e_t[0] \quad (6)$$

Based on the equation formula (6), explains that S_t is forcast point at time t. μ' is a constant. $\emptyset_p$ is the autoregressive parameter for *p*. *et* denotes the error value returned by *t*.

$$S_t = \mu' + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-k} \quad (7)$$

Based on the equation formula (7), explains that S_t is forcast point at time t. μ' is a constant. θ_l to θ_q is the parameter-parameter MA. e_{t-k} is the error value when *t*.

$$S_t = \mu' + \emptyset_1 S_{t-1} + e_t - \theta_1 e_{t-1} \quad (8)$$

or

$$\underset{\text{AR(1)}}{(1 - \emptyset_1 T)S_t} = \underset{\text{MA(1)}}{\mu' + (1 - \theta_1 T)e_t} \quad (9)$$

$$\underset{\text{AR(1)}}{(1 - T)(1 - \emptyset_1 T)X_t} = \mu' + \underset{\text{MA(1)}}{(1 - \theta_1 T)e_t} \quad (10)$$

ARIMA is a stationary model. AR(p) is Autoregression, I(d) Integration and MA(q) is Moving Average. According to Shrestha et al. [28] Differentiation is required to transform nonstationary data to stationary data. Acording to Schaffer et al. [29] Differencing is the process of calculating the difference or change in the value of an observation. The resulting difference value is rechecked to see whether it is stationary or not. If it is not stationary, differencing is repeated. If the variance is not stationary, then a logarithmic transformation is performed. Acording to Chimmula et al. [23] The p-value is used to determine whether the data is stationary or non-stationary using the Augmented Dickey-Fuller (ADF) test. If the ADF *p*-value is between 0.05 and 0.01 it is considered stationary; alternatively, if *p* is more than 0.05, it is considered non-stationary.

D. Model Evaluation

The final stage of this research, the method used are based on standard statistical evaluations [30][31], i.e. RMSE, MAPE. Acording to Ganiny et al. [19] The evaluations used to determine the performance of the model in predicting cases of COVID-9 are RMSE and MAPE. RMSE to evaluate the performance of the model while MAE to evaluate the forecasting ability of the model. The following is the formulation of the evaluation model used in this study:

$$RMSE = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^{n} (y_i - x_i)^2} \quad (11)$$

Based on the equation formula (11), explains that y_i is predicted value. x_i is true value. n is amount of data.

$$MAPE = \sum_{t=1}^{n} \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right| \times 100 \quad (12)$$

Based on the equation formula (12), explains that y_i is predicted value. $\hat{y_i}$ is true value. n is amount of data.

IV. Result and Discussion

A. Result

First, We build the LSTM to forecast positive confirmed cases and mortality in DKI Jakarta and West Java. The parameter used by LSTM is the optimizer using adam, epochs=5, batchsize=100, loss=mean squared error. Acording to Utama et al. [32] Optimizer functions to maintain the learning rate, backsize is the number of sample data, epoch functions to optimize training data efficiency. The results of forecasting with LSTM are as follows, Fig. 6 and Fig. 7 explain the forecasting of daily positive confirmed in DKI Jakarta and West Java. Figure 8 and Fig. 9 explain the forecasting of daily mortality in the DKI Jakarta and West Java.

The next step, We build the ARIMA model for the same case was then compared with the LSTM model in each region. First, the ADF test will examine the daily positive confirmed data and daily mortality in the DKI Jakarta and West Java regions, whether stationary or non-stationary. As a result, the daily positive confirmed variable in DKI Jakarta produces a p-value of 0.000227, meaning stationary data, and West Java, with a p-value of 0.016147, meaning stationary data. Furthermore, the daily mortality data in the DKI Jakarta Region produces a p-value of 0.781775, meaning non-stationary data, and West Java, with a p-value of 0.645635 meaning non- stationary. Fig. 12 and Fig. 13 explains that differencing was used on the non-stationary data using ACF (Autocorrelation Function) twice. Furthermore, Fig. 14 and Fig. 15 explains that differencing was used on the non-stationary data using PCF (Partial Autocorrelation Function) once with the result lag=1. So, the order values for p=1, d=2 and q=1. The value (p,q,r) is used to observe the performance of the ARIMA model when predicting positive confirmed cases and mortality in each region. Finally, we try to evaluate the performance of the LSTM and ARIMA method in each region; DKI Jakarta and West Java with RMSE and MAPE. The LSTM model for daily positive confirmed cases in DKI Jakarta with a value of RMSE=0.23 and MAPE=0.15. Meanwhile, West Java with a value of RMSE=0.20 and MAPE=2.46. Furthermore, daily death cases in DKI Jakarta with a value of RMSE=0.095 and MAPE=0.09. Meanwhile, West Java with a value of RMSE=0.08 and MAPE=0.05. The ARIMA model for daily positive confirmed cases in the DKI Jakarta with a value of RMSE=904.22 and MAPE= 0.64. Meanwhile, West Java with a value of RMSE=7589.65 and MAPE=1.11. Furthermore, daily death cases in DKI Jakarta with a value of RMSE=314.96 and MAPE= 0.02. Meanwhile, West Java with a value of RMSE= 721.0 and MAPE=0.04.Forecasting visualization on ARIMA model can be seen in Fig. 10 and Fig. 11

B. Discussion

The LSTM method performed better than ARIMA in our experiment based on the RMSE and MAPE evaluations in forecasting COVID-19 cases, i.e., daily positive confirmations and daily mortality in Indonesia Jakarta and West Java. According to Marzouk et al. [18] The LSTM model did the best job of forecasting the number of infections over a week and a month. Table I shows the results of our method are better than previous paper, including Arora et al. [8] RMSE=3.22 and MAPE=3.22, Hridoy et al. [20] RMSE=593764 and MAPE=0.0176, Ganiny et al. [19] RMSE=457.6 and MAPE=2,471. The contribution of our research is confirming that LSTM is a good method of forecasting COVID-19 cases for the next 13 days, from September 29, 2022, to October 12,2022 based on two different regions in Indonesia. The dataset we use starts from the early 2020 of COVID-19 until 2022.

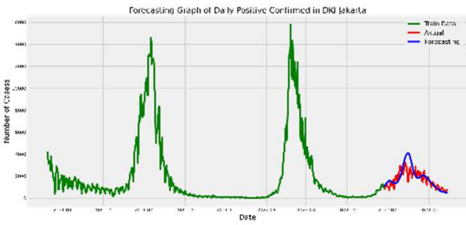

Fig.6: Daily Positive Visualization of DKI Jakarta with LSTM

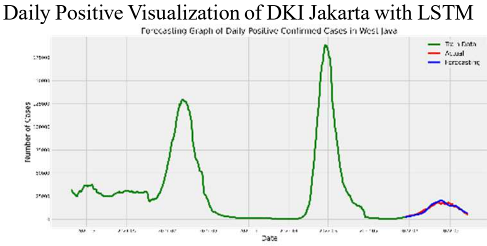

Fig.7: Daily Positive Visualization of West Java with LSTM

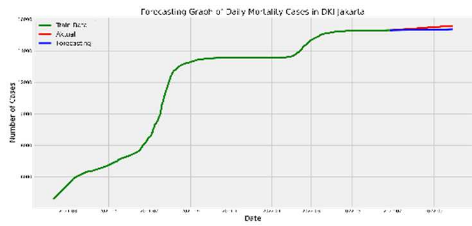

Fig. 8: Daily Mortality Visualization in DKI Jakarta with LSTM

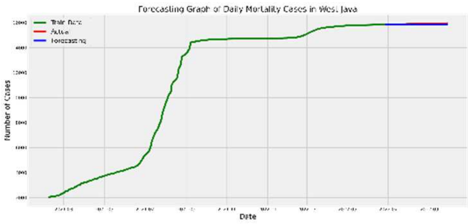

Fig.9: Daily Mortality Visualization in West Java with LSTM

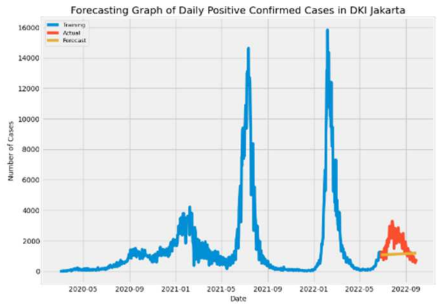

Fig.10: Daily Positive Visualization of West Java with ARIMA

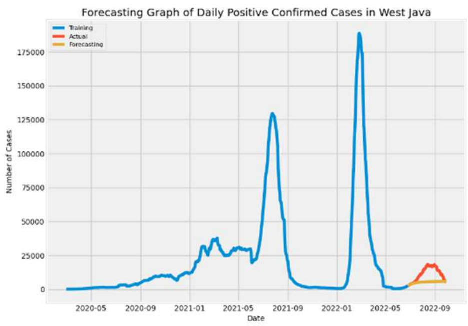

Fig.11: Daily Positive Visualization of West Java with ARIMA

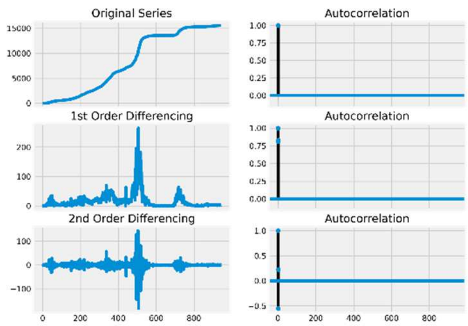

Fig.12: ACF Daily Mortality Visualization in DKI Jakarta with ARIMA

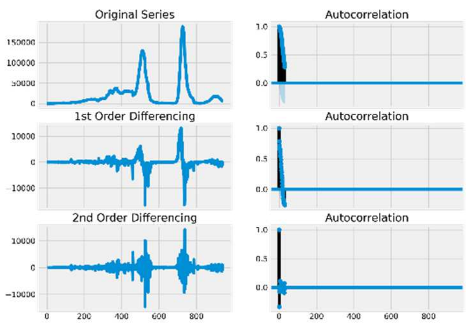

Fig.13: ACF Daily Mortality Visualization in West Java with ARIMA

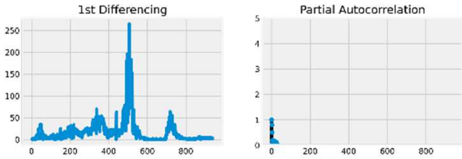

Fig.14: PACF Daily Mortality Visualization in DKI Jakarta with ARIMA

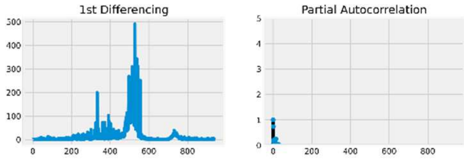

Fig.15: PACF Daily mortality Visualization in West Java with ARIMA

V. Conclusion

This research effectively used two LSTM and ARIMA method to forcasting daily positive confirmed and mortality in DKI Jakarta and West Java. Table I explains the results of our research, the LSTM method has the best performance in forecasting daily positive confirmation cases and daily deaths in DKI Jakarta and West Java. LSTM for forecasting results for the next 13 days, from September 29, 2022, to October 12, 2022. DKI Jakarta shows new cases to be confirmed positive. However, the number of mortalities has decreased. Meanwhile, West Java showed new cases to be confirmed positive. However, the number of mortalities has decreased. The future work: first, The model that is built needs to settle concentration to other factors such as mobility and economic growth as a recommendation to make optimal policies for handling the pandemic in Indonesia. Second, try to change existing models like LSTM and ARIMA so that they can be compared and give better model performance.

TABLE I. Model Evaluation

Model	Region	Params	Model Evaluation	
			MAPE	RMSE
LSTM	Greater Jakarta	Daily positive confirme	0.15	0.23
ARIM	Greater Jakarta		0.64	904.22
LSTM	Greater Jakarta	Daily mortality	0.009	0.095
ARIM	Greater Jakarta		0.02	314.96
LSTM	West Java	Daily positive confirme	2.46	0.20
ARIM	West Java		1.11	7589.65
LSTM	West Java	Daily mortality	0.05	0.08
ARIM	West Java		0.04	721.0

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