Forecasting Covid-19 Time Series Data using the Long Short-Term Memory (LSTM)

Harun Mukhtar[1], Reny Medikawati Taufiq[2], Ilham Herwinanda[3], Doni Winarso[4], Regiolina Hayami[5]
Informatics engineering department, Faculty of Computer Science, Universitas Muhammadiyah Riau, Pekanbaru, Indonesia[1, 2, 3, 5]
Information system department, Faculty of Computer Science, Universitas Muhammadiyah Riau, Pekanbaru, Indonesia[4]

***Abstract*—Confirmed statistical data of Covid-19 cases that have accumulated sourced from (https://corona.riau.go.id/data-statistik/) in Riau Province on June 7, 2021, there were 63441 cases, on June 14, 2021, it increased to 65883 cases, on June 21, 2021, it increased to 67910, and on June 28, 2021, it increased to 69830 cases. Since the beginning of this pandemic outbreak, it has been observed that the case data continues to increase every week until this July. This study predicts cases of Covid-19 time series data in Riau Province using the LSTM algorithm, with a dataset of 64 lines. Long-Short Term Memory has the ability to store memory information for patterns in the data for a long time at the same time. Tests predicting historical data for Covid-19 cases in Riau Province resulted in the lowest RMSE value in the training data, which was 8.87, and the test data, which was 13.00, in the death column. The evaluation of the best MAPE value in the training data, which is 0.23%, is in the recovered column, and the evaluation of the best MAPE value in the test data, which is 0.27%, in the positive_number column. In the test to predict the next 30 days using the LSTM model that has been trained, it was found that the performance evaluation of the prediction results for the positive_number column and the death column was very good, the recovery column was categorized as good, the independent_isolation column and the care_rs column were categorized as poor.**

Keywords—Time series prediction; forecasting; recurrent neural network; long short-term memory

I. Introduction

Indonesia is one of the countries hit by the Covid-19 pandemic which continues to increase every day. Covid-19 outbreak due to the coronavirus began to appear in mid-December 2019 in China, precisely in the city of Wuhan, and has spread to several countries worldwide. The World Health Organization (WHO) had declared January 30, 2020, a public health emergency. The Covid-19 pandemic entered Indonesia on March 2, 2020, it is known from existing information that there have been Indonesian citizens who have been infected. The two 64-year-old women, and their 31-year-old daughter were declared positive for Covid-19 after having contact with a Japanese citizen [1], [2].

The Riau Provincial Government made various efforts to suppress the transmission of the coronavirus, namely by providing health protocol directions, including washing hands, maintaining a distance of two meters, avoiding crowds, avoiding touching your face with your hands, and maintaining a healthy diet. This is in the spotlight with the aim of suppressing the addition of new cases and reducing the death rate. Confirmed statistical data for the accumulation of the Covid-19 cases sourced from (https://corona.riau.go.id/data-statistik/), in Riau Province on June 7, 2021, as many as 63441 cases; on June 14, 2021 it increased to 65883 cases, on June 21, 2021 it increased to 67910, on June 28, 2021 it increased to 69830 cases, and so on. Since the beginning of the outbreak of this pandemic outbreak, it has been observed that case data continues to grow every week until this August [3]. Riau Province is one of the areas in Indonesia which is included in the dangerous zone.

A method is needed to estimate the number of Covid-19 cases every day with data in Riau Province. Forecasting is a technique for predicting conditions that will occur in the future based on data from the past. Predicting the Covid-19 phenomenon based on incident data with sequential time series can be done using the Machine Learning approach [4]. The predicted data in this study are classified as time series. Time series data is a series of observed data based on a certain time interval. The time-series approach explains that the model is influenced by data that occurred in the past [5]. This study makes predictions using the Long Short-Term Memory (LSTM) algorithm. LSTM can store memory information for patterns in the data for a long time simultaneously. LSTM is used for data processing, one of which is time-series data, including that carried out in research by [6] using the LSTM machine learning method, to predict the spread of Covid-19 cases in India based on the realization of prevention that have been implemented such as social restrictions and lockdowns. Then research [7] also uses the LSTM architecture, in forecasting time series data in predicting the development of Covid-19 transmission in Canada.

Based on the previous description, this study aims to predict cases of Covid-19 time series data in Riau Province, using the LSTM algorithm, by achieving the maximum level of accuracy and producing the slightest difference in values between the actual data and prediction [8]. The data sample used was obtained from public data which amounted to 64 lines of accumulated data on Covid-19 cases in Riau Province, starting from June 7, 2021, to August 9, 2021. Referring to the reference, the attributes used as input data are positive numbers, self-isolation, hospitalization, recovery, and death.

II. Literature Review

Forecasting is a challenging part of time series data analysis. The dominant factors that affect the performance and accuracy of time series data analysis and the forecasting techniques used are based on the type of data and its context. Several problem domains that have dependent variables such as seasons, economic shocks, unexpected events, and internal organizational changes that produce data also affect predictions [9]. Another review by the same author points out evaluation, and dynamic modeling is exciting fields of study with a wide variety of packages in business, economics, finance, and computer science. The reason for evaluating the collection time is to look at the observations of the time collection path and build a mode to explain the shape of the information and then predict the value of gathering time density. Due to the importance of time collection forecasting in many branches of implemented science, it is important to build robust modes with the aim of increasing forecasting accuracy [10].

Forecasting techniques are used in various case studies, such as in predicting the future affordability of Covid-2019 throughout countries by utilizing real-time information from the Johns Hopkins dashboard [11]. Indicates the accuracy of the flow of foreign tourist arrivals in the Intelligent Tourism System (ITS), using the Long Short Term Memory Neural Network (LSTM) method [12]. Forecasts the arrival of foreign tourists in the Covid-19 pandemic situation, using the LSTM artificial neural network approach [13]. Conducted a study predicting the value of financial market assets in the future with higher accuracy [14].

LSTM is a variation of RNN and has been proven to carry out proper time collection mastering due to the fact that LSTM can preserve contextual data in addition to conducting primarily based totally on sure time-collection events [15]. LSTM is a form of iterative community which has been tested to be very successful on several problems, given its capacity to differentiate between maximum current and initial instance through assigning extraordinary weights to each at the same time as forgetting reminiscences deemed imprecise to predict subsequent outputs [16]. Siami-Namini *et al.* [10], compared Deep Learning algorithms such as LSTM and traditional algorithms such as ARIMA to estimate time series data. They got the result that LSTM is better than ARIMA. More specifically, the average reduction in the error rate obtained by LSTM is between 84 - 87 percent compared to ARIMA. Dutta *et al.* [17] use machine learning to help doctors verify and predict disease growth shortly. The result of their research is that the combination of machine learning models (CNN–LSTM) outperforms other models.

By evaluating the prediction outcomes of the LSTM and AT-LSTM fashions, it may be visible that the AT-LSTM overall performance is higher due to the fact the smallest MAPE cost is obtained. MAPE is a degree of the predictive accuracy of forecasting strategies in data and is greater persuasive whilst evaluating the overall performance of fashions on one-of-a-kind facts sets, as it is now no longer most effective considering the deviation among the expected cost and the authentic cost; however additionally considers the ratio among them [18].

Comparing the LSTM and BI-LSTM forecasting models, where the BI-LSTM combines the LSTM in the incoming collection school system instead of using a single LSTM and ends up with a decreased RMSE compared to the LSTM version. The BI-LSTM version plays higher than the LSTM version due to the fact that the BI-LSTM version has backward propagation at every time the school expects data. Therefore, the prediction version proposed using the BI-LSTM can be utilized by the public and companies for forecasting the inventory market [19]. To test the performance of the prediction engine, Root Mean Square Error (RMSE) was used. The error or difference between the objective and the obtained output price is minimized by using the RMSE price. RMSE is the rectangular root of the implication/rectangular implication of all errors. The use of RMSE may be very unusual and lead to first-degree forecasting errors of metrics for the prediction of numerical data [20].

III. Research Methodology

The study predicts Covid-19 cases in Riau Province using the Long Short-Term Memory algorithm, carried out with data mining flow steps for forecasting as shown in Fig. 1.

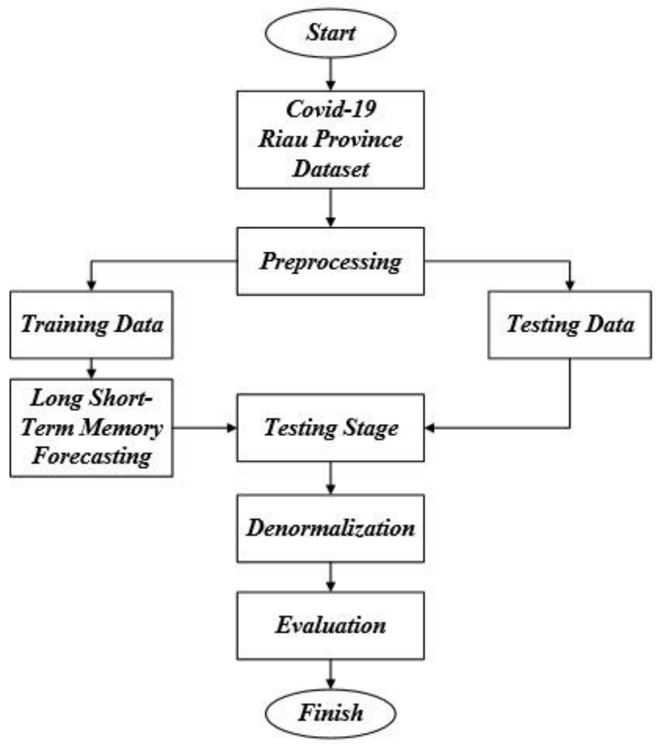

Fig. 1. Forecasting Workflow.

A. Dataset

The dataset being searched comes from public data obtained from the official website https://corona.riau.go.id/data-statistik/. This dataset is a time-series data type, containing information on Covid-19 cases in Riau Province, which is visualized in the form of a bar graph. Data collection starts from June 7, 2021, to August 9, 2021. The dataset consists of 64 rows of data manually entered in a Microsoft Excel spreadsheet and saved in .csv file format and named the file dataset_covid19_riau. Table I is a representation of time series data that has been accumulated, from Covid-19 cases that have occurred in Riau Province.

TABLE I. COVID-19 RIAU PROVINCE DATASET

date	total_ positive	self_ isolation	hospital_ care	recover	decease
6/7/2021	63441	4335	867	56546	1693
6/8/2021	63786	4060	837	57183	1706
6/9/2021	64188	3836	806	57827	1719
6/10/2021	64626	3836	762	58297	1731
6/11/2021	65010	3808	715	58744	1743
...	...	...	...	...	...
8/5/2021	102926	12365	1392	86375	2794
8/6/2021	105125	13416	1374	87486	2849
8/7/2021	106376	13574	1376	88526	2900
8/8/2021	107532	12783	1356	90466	2927
8/9/2021	108316	12012	1362	91963	2979

B. Preprocessing

This time-series data processing leads to one sample of attribute data as input and output data for the future, and determines how many prediction outputs are generated. Processing of data categorized as numerical data is carried out by normalizing the min-max scale. The min-max normalization preprocessing stage is the stage of changing the value of the actual numeric data (units, tens, hundreds, thousands, and so on) to a scaled value between 0 (as the minimum value) to 1 (as the maximum value) [3]. The data normalization process for all columns is intended as data input into the LSTM forecasting engine, which accepts input values with a distance between 0 to 1. For example, the smallest value in the positive_number column, which is 63441, is changed to 0, then the largest value 108316 is changed to 1. The other data values are converted to decimal numbers between 0 and 1. Table II is the result of normalization data in the positive_number column.

TABLE II. DATA NORMALIZATION RESULTS

date	positive_number	data normalization
6/7/2021	63441	0
6/8/2021	63786	0.007688022
6/9/2021	64188	0.01664624
6/10/2021	64626	0.026406685
6/11/2021	65010	0.034963788
...	...	...
8/5/2021	102926	0.879888579
8/6/2021	105125	0.928891365
8/7/2021	106376	0.956768802
8/8/2021	107532	0.982529248
8/9/2021	108316	1

C. Composition of Training Data and Test Data

The dataset is divided into two, namely training data and test data. The proportion of distribution for training data is more than for test data. The training data is intended to build a forecasting learning machine with the Long Short-Term Memory (LSTM) algorithm, and the test data is intended for testing in predicting Covid-19 cases in Riau Province. The separation process of training data and test data is carried out with a division ratio of 85:15. As much as 85% of the total dataset, namely 54 data lines, starting from June 7, 2021, to July 30, 2021, is used for training data in order to build a forecasting engine with the LSTM algorithm. As much as 15% of the total dataset, which is 10 data lines, starting from July 31, 2021, to August 9, 2021, is used for test data in predicting the next accumulated cases of Covid-19 in Riau Province.

D. Long Short-Term-Memory Forecasting

Build an LSTM forecasting architecture using the python hard module, then import the sequential model, LSTM layer, and dense layer. A sequential model is a model that has one input layer, several hidden layers, and one output layer. By creating a new variable, namely the model, the architecture that is built is composed of one hidden LSTM layer with 50 units of neurons or nerves that function to process input data, which in the LSTM layer also becomes an input layer with shape parameters that have been made in the previous program code. It also uses the sigmoid activation function parameter. Dense layer functions as an output that receives the input information that has been processed in the hidden layer. After that call the compile() function to configure the data training process, with adam optimization and perform a loss percentage calculation with the mean squared error, to review the information on the predicted error rate that is targeted to a minimum. The LSTM forecasting architecture can be seen in Fig. 2.

```
Model: "sequential_17"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_17 (LSTM)               (None, 50)                10200
_________________________________________________________________
dense_16 (Dense)             (None, 1)                 51
=================================================================
Total params: 10,251
Trainable params: 10,251
Non-trainable params: 0
_________________________________________________________________
```

Fig. 2. LSTM Forecasting Architecture.

E. Testing Predictions of Covid-19 Cases in Riau Province

The tests carried out were comparing and calculating the difference between the results of the actual test case data values and the test data values for the predicted accumulated Covid-19 cases. The prediction testing process is carried out with training data that has gone through the training stage. Furthermore, predictions of positive cases of Covid-19 are carried out on training data, starting from June 8, 2021, to July 29, 2021, and test data starting from August 1, 2021, until August 8, 2021.

F. Denormalization of Actual Data and Predicted Data

After the test is complete, the prediction results on the two data are data that are still normalized. The normalized values in the training data, test data, training data prediction results, and test data prediction results are converted into actual values by a denormalization process and then display the overall results of these actual values. The results of denormalization can be seen in Table III and Table IV.

G. *Evaluation of Test Results*

In proving the accuracy and performance of the LSTM forecasting engine, it is necessary to calculate the difference between the predicted data value and the actual data value, based on the results of the Covid-19 prediction test in Riau Province. First measured by calculating the level of accuracy using the calculation of Root Mean Square Error (RMSE) to find the smallest error, which can be seen in the following equation (1).

$$RMSE = \frac{\sqrt{\sum_{i=1}^{N}(y-\hat{y})^2}}{N} \quad (1)$$

Where N is the number of observed data, $y_1, y_2, y_3, \ldots.. y_n$ is the observed value, while $\hat{y}_1, \hat{y}_2, \hat{y}_3, \ldots, \hat{y}_n$ Is the predicted value.

The higher the resulting RMSE value, the lower the level of accuracy, and the lower the resulting RMSE value, the higher the level of accuracy [5]. The second measure is the Mean Absolute Percentage Error (MAPE) calculation, to determine LSTM performance evaluation in forecasting (forecasting), which can be seen in the following equation (2).

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\frac{|yi-y|}{yi} \quad (2)$$

TABLE III. EXAMPLE OF TRAINING DATA DENORMALIZATION RESULTS

No	Training Data	Practice Prediction Results	Difference
0	63786.0	63429.894531	356.105469
1	64188.0	63789.914062	398.085937
2	64626.0	64209.484375	416.515625
3	65010.0	64666.703125	343.296875
4	65398.0	65067.613281	330.386719
5	65720.0	65472.753906	247.246094
...	...	...	...
47	88019.0	87932.093750	86.906250
48	89115.0	88988.500000	126.500000
49	90582.0	90112.601562	469.398438
50	91857.0	91613.523438	243.476562
51	93913.0	92914.335938	998.664063

TABLE IV. EXAMPLES OF TEST DATA DENORMALIZATION RESULTS

No	Testing Data	Practice Prediction Results	Difference
0	98310.0	98246.726562	63.273438
1	99380.0	99438.843750	-58.843750
2	100623.0	100510.085938	112.914062
3	102086.0	101750.359375	335.640625
4	102926.0	103204.218750	-278.218750
5	105125.0	104035.960938	1089.039062
6	106376.0	106202.570312	173.429688
7	107532.0	107427.906250	104.093750

The use of MAPE in the evaluation of the prediction results can calculate the measurement accuracy of the actual value and the predicted value. MAPE calculates the error from the observation and prediction data, that is expressed in percent value [18]. The MAPE value criteria are shown in Table V.

TABLE V. MAPE QUALITATIVE CRITERIA [21]

MAPE Value	Interpretation
<10%	Evaluation of forecasting model capability is very good
10% - 20%	Evaluation of forecasting model capability is good
20% - 50%	Evaluation of forecasting model capability is sufficient
>50%	Evaluation of forecasting model capability is poor

Evaluation of predictions on statistics of COVID-19 instances is performed in five columns, specifically, positive_number, independent_isolation, hospitalization_rs, recovered, and died. Information on the assessment effects in every column, in predicting the dataset of showed Covid-19 instances that befell in Riau Province, is offered in Table VI.

Fig. 3 shows the positive case prediction test results, the yellow line shows the actual value of the training data, which coincides with the red dotted line, which is the predicted value of the training data, with an evaluation of RMSE 246.92 and MAPE 0.24%. Then the black line shows the actual value of the test data, which coincides with the green dotted line which is the predicted value of the test data, with an evaluation of RMSE 423.85 and MAPE 0.27%.

Fig. 4 shows the results of the self-isolation case prediction test, the yellow line shows the actual value of the training data, which coincides with the red dotted line, which is the predicted value of the training data, with an evaluation of RMSE 236.41 and MAPE 4.39%. Then the black line shows the actual value of the test data, which coincides with the green dotted line which is the predicted value of the test data, with an evaluation of RMSE 815.17 and MAPE 5.36%.

Fig. 5 shows the results of the prediction test for hospitalization cases, the yellow line show the actual value of the training data, which coincides with the red dotted line which is the predicted value of the training data, with an evaluation of RMSE 33.21 and MAPE 3.61%. Then the black line shows the actual value of the test data, which coincides with the green dotted line which is the predicted value of the test data, with an evaluation of RMSE 33.03 and MAPE 2.00%.

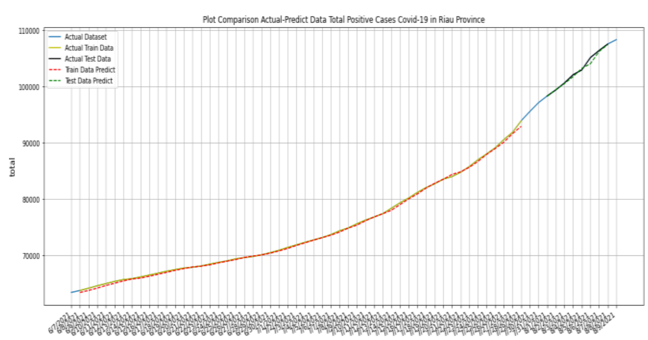

Fig. 3. Prediction Result of Positive Number.

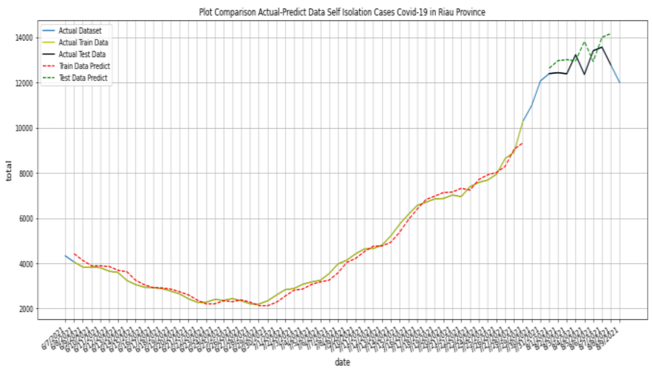

Fig. 4. Prediction Results of Isolation Cases.

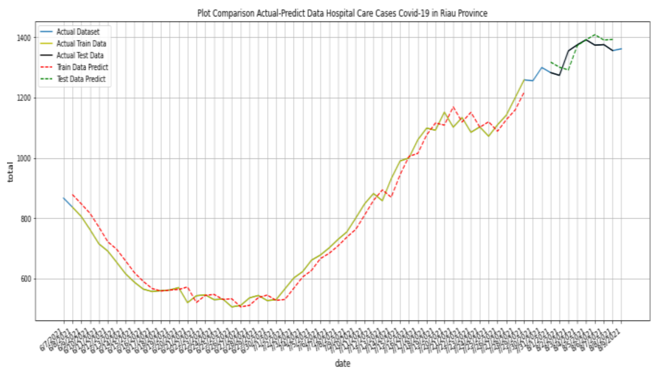

Fig. 5. Prediction Results of Hospitalization Cases.

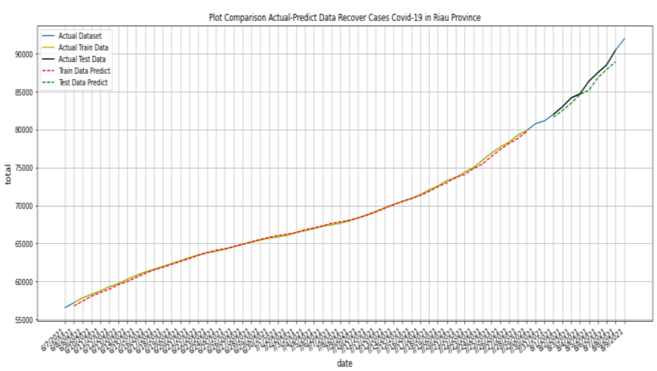

Fig. 6. Prediction Results of Healed Cases.

Fig. 6 shows the results of the prediction test for cured cases, the yellow line, show the actual value of the training data, which coincides with the red dotted line which is the predicted value of the training data, with RMSE 201.34 and MAPE 0.23% evaluation results. Then the black line shows the actual value of the test data, which coincides with the green dotted line which is the predicted value of the test data, with an evaluation of RMSE 827.57 and MAPE 0.81%.

Fig. 7 shows the death case prediction test results, the yellow line, show the actual value of the training data, which coincides with the red dotted line, which is the predicted value of the training data, with an evaluation of RMSE 7.51 and MAPE 0.32%. Then the black line shows the actual value of the test data, which coincides with the green dotted line which is the predicted value of the test data, with an evaluation of RMSE 17.85 and MAPE 0.54%.

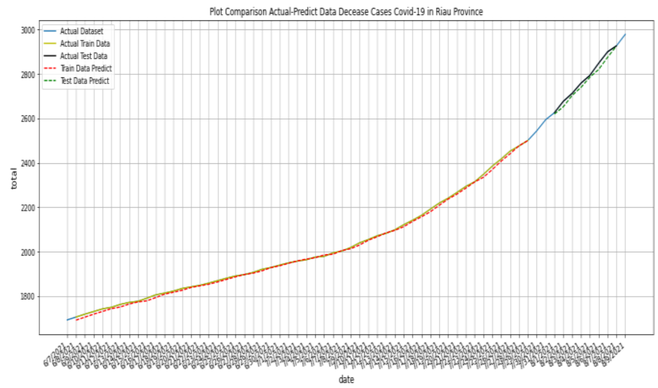

Fig. 7. Prediction Results of Death Cases.

In the graph above, it can be explained that the blue line is the overall data or dataset of Covid-19 cases that have accumulated in Riau Province. The yellow line shows the actual value of the training data, which coincides with the red dotted line which is the predicted value of the training data. Then the black line shows the actual value of the test data, which coincides with the green dotted line which is the predicted value of the test data.

TABLE VI. CONCLUSION OF EVALUATION OF HISTORICAL DATA PREDICTION TEST

No	Column Name	RMSE		MAPE		MAPE Criteria
		Actual & Prediction Training Data	**Actual & Prediction Testing Data**	**Actual & Prediction Training Data**	**Actual & Prediction Testing Data**	
1.	total_positive	246.92	423.85	0.24%	0.27%	Very Good
2.	self_isolation	236.41	815.17	4.39%	5.36%	Very Good
3.	hospital_care	33.21	33.03	3.61%	2.00%	Very Good
4.	recover	201.34	827.57	0.23%	0.81%	Very Good
5.	decease	7.51	17.85	0.32%	0.54%	Very Good

From Table VI, it can be seen that the column that has the lowest evaluation of the RMSE value in the training data is 7.51 and the test data is 17.85 in the death column, meaning that the actual data and the predicted data have the smallest difference in values. Then the evaluation of the best MAPE value in the training data, which is 0.23%, is in the recovered column, and the evaluation of the best MAPE value in the test data, which is 0.27%, in the positive_number column. The MAPE value in the table above is the average MAPE value of all existing data. Overall, the implementation of the Long Short-Term Memory (LSTM) algorithm, in predicting each column of Covid-19 cases in Riau Province, resulted in excellent forecasting machine learning capabilities.

H. Future Covid-19 Predictions

With a dataset of 64 data lines, predictions of Covid-19 cases are made for the next 30 days, using LSTM forecasting. The predicted value data obtained are then combined in tabular form with the initial dataset, and make a line graph comparing the actual data (blue line) and predictive data for 30 days in the future (red line). A composite graph between the initial dataset and the predicted results for each column.

Fig. 8 shows dataset on the number of positive cases with a blue line graph. In this case, where data is showing the number 108316, it is predicted that the number of positive cases in the next 30 days with a red line graph will be an increase which accumulated as many as 14939 cases.

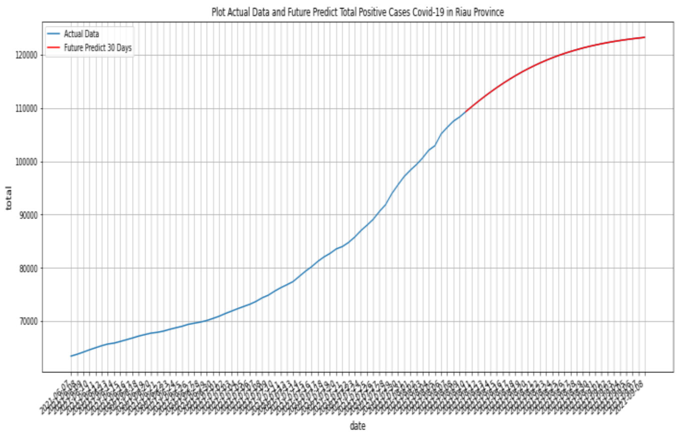

Fig. 8. 30 Days Prediction of Positive Number.

Fig. 9 shows dataset on the number of positive cases with a blue line graph. In this case, where data is showing the number 12012, it is predicted that the number of positive cases in the next 30 days with a red line graph will be an increase which accumulated as many as 11200 cases.

Fig. 10 shows dataset on the number of positive cases with a blue line graph. In this case, where data is showing the number 1362, it is predicted that the number of positive cases in the next 30 days with a red line graph will be an increase which accumulated as many as 336 cases.

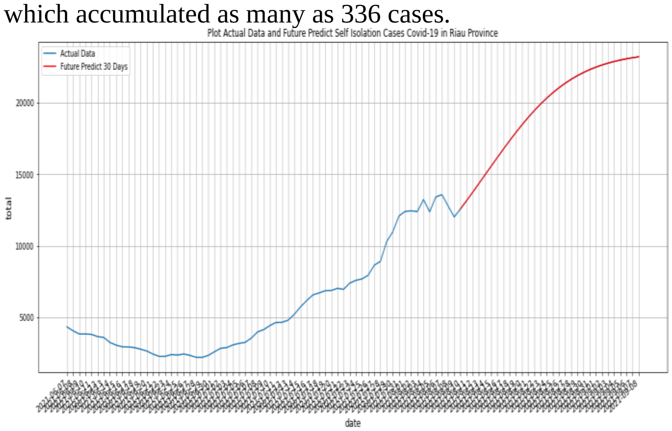

Fig. 9. 30 Days Prediction of Independent Isolation Cases.

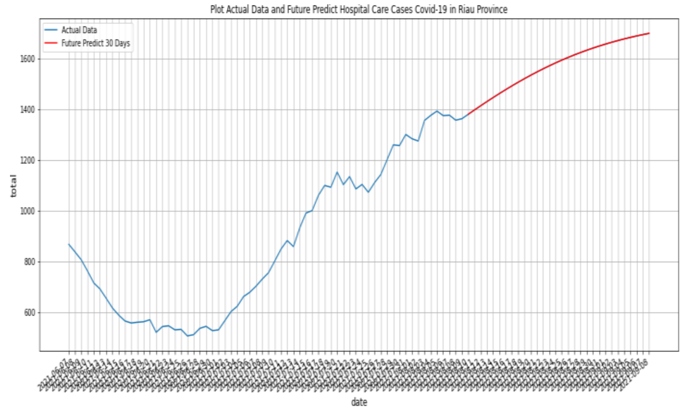

Fig. 10. Prediction of 30 Days of Hospitalization Cases.

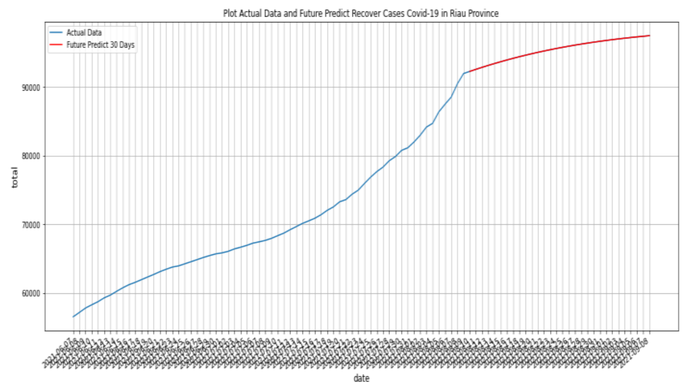

Fig. 11. Prediction of 30 Days of Cure Cases.

Fig. 11 shows dataset on the number of positive cases with a blue line graph. In this case, where data is showing the number 91963, it is predicted that the number of positive cases in the next 30 days with a red line graph will be an increase which accumulated as many as 5512 cases.

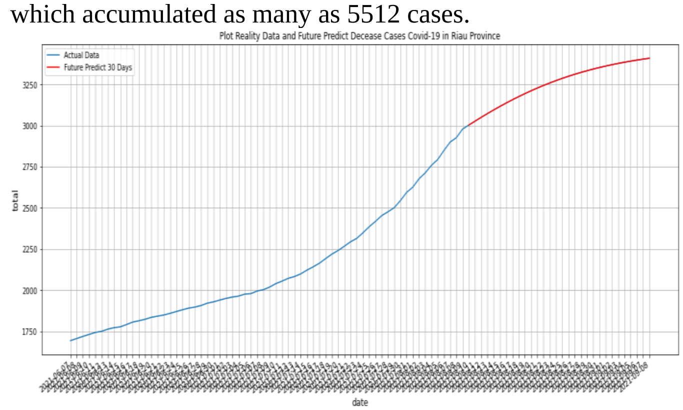

Fig. 12. Prediction of 30 Days of Death Cases.

Fig. 12 shows dataset on the number of positive cases with a blue line graph. In this case, where data is showing the number 2979, it is predicted that the number of positive cases in the next 30 days with a red line graph will be an increase which accumulated as many as 430 cases.

TABLE VII. CONCLUSION OF FUTURE PREDICTION TEST EVALUATION

No	Column Name	RMSE	MAPE	MAPE Criteria
		Reality Data & Future Predict 30 Days	Reality Data & Future Predict 30 Days	
1.	total_positive	1148.67	0.86%	Very Good
2.	self_isolation	13775.46	257.89%	Poor
3.	hospital_care	795.79	107.84%	Poor
4.	recover	13833.96	11.10%	Good
5.	decease	294.68	7.24%	Very Good

Table VII is the evaluation of the LSTM model for testing the prediction results for the next 30 days, with the real data that has been running from the initial data acquisition. The positive_number column obtained an RMSE value of 1148.67 and a MAPE value of 0.86%, then the death column with an RMSE value of 294.68 and a MAPE value of 7.24%. LSTM's prediction performance on the two columns is categorized as very good. The cured column has a good predictive performance with an RMSE value of 13833.96 and a MAPE value of 11.10%. This column of positive_number, recovered, and dead obtains the difference between each value in the data row and the difference in the average value which is not far away. The last two columns, namely isolation_mandiri and care_rs, obtained prediction performance that was categorized as poor because the MAPE value was above 50% and the RMSE value was very far, as seen from the difference in comparison between the real data values and the predicted results.

IV. CONCLUSION

From the results of research on forecasting that have been carried out, several conclusions can be drawn including (1) the application of the Long Short Term-Memory algorithm can be used to predict cases of time series data that have accumulated from Covid-19 in Riau Province which has occurred within a day; (2) prediction testing on a dataset consisting of 64 data lines, produces the lowest RMSE value in the training data, which is 8.87 and the test data, which is 13.00, in the death column. The evaluation of the best MAPE value in the training data, which is 0.23%, is in the recovered column, and the evaluation of the best MAPE value in the test data, which is 0.27%, is in the positive_number column; (3) evaluation of the Long Short Term-Memory algorithm in predicting historical data on Covid-19 cases that have accumulated in Riau Province, resulting in excellent forecasting machine learning capabilities, with the MAPE value criteria below 10% in both training data and test data; in the column of positive_number, independent_isolation, care_rs, recovered, and died; (4) in the test to predict the next 30 days using the LSTM model that has been trained, it was found that the performance evaluation of the prediction results for the positive_number column and the death column was very good, the recovery column was categorized as good, the independent_isolation column and the care_rs column were categorized as poor.

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