

Jakarta Pandemic to Endemic Transition: Forecasting COVID-19 Using NNAR and LSTM

Resa Septiani Pontoh ^{1,*} , Toni Toharudin ¹ , Budi Nurani Ruchjana ² , Farhat Gumelar ¹,
Fariza Alamanda Putri ¹ , Muhammad Naufal Agisya ¹ and Rezzy Eko Caraka ^{1,3} 

- ¹ Department of Statistics, Padjadjaran University, Bandung 45363, Indonesia; toni.toharudin@unpad.ac.id (T.T.); farhat20001@mail.unpad.ac.id (F.G.); fariza20001@mail.unpad.ac.id (F.A.P.); muhammad20089@mail.unpad.ac.id (M.N.A.); rezzy.eko.caraka@brin.go.id (R.E.C.)
² Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Sumedang 45363, Indonesia; budi.nurani@unpad.ac.id
³ Research Center for Data and Information Sciences, Research Organization for Electronics and Informatics, National Research and Innovation Agency (BRIN), Bandung 40135, Indonesia
* Correspondence: resa.septiani@unpad.ac.id

Abstract: In December 2021, the latest COVID-19 variant, Omicron, was confirmed in Indonesia. Unlike the Delta variant, the number of deaths in the Omicron type did not increase significantly and remained constant, even though the cases increased significantly. It is hoped that Indonesia will declare COVID-19 endemic. Jakarta is the capital of Indonesia and the first city where the new COVID-19 virus emerged. Therefore, we are trying to model COVID-19 cases in Jakarta and predict future cases to see if endemic conditions are identified. We applied Neural Network Auto-Regressive (NNAR) and Long Short-Term Memory (LSTM) methods. It is found that the NNAR forecast better for positive confirmed cases with an R-squared 0.939 and the LSTM forecast better for cases of death with an R-squared 0.9337. The forecasting results for the next 7 days reveal that positive confirmed cases of COVID-19 in Jakarta will increase slightly. In addition, the death cases experienced a very small increase, only one new case. According to the results of this study, it can be concluded that COVID-19 in Jakarta will enter an endemic phase in Jakarta, with no substantial increase in cases and a low mortality rate.

Keywords: COVID-19; endemic; pandemic; neural network; machine learning; forecasting



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1. Introduction

In December 2019, the first mysterious case of pneumonia was discovered in the city of Wuhan, Hubei Province, China [1]. There have been 41 cases of this mysterious pneumonia, identified with symptoms of a dry cough, fever, and fatigue that began at the city's seafood and wet animal market. On 30 January 2020, the World Health Organization (WHO) issued a public health emergency of international concern (PHEIC) alert [2]. This mysterious pneumonia was later discovered to be an infection from the Coronavirus.

Coronavirus is one of the pathogens that attacks the respiratory system [3]. This virus can be spread person-to-person through direct contact or droplets spread by coughing or sneezing from an infected person [3]. Consequently, some precautions that can be taken to avoid coronavirus transmission are diligently washing hands, maintaining cleanliness, and keeping a distance from other people. The scale and spread of outbreaks were one of the most crucial challenges in outbreaks [4]. The World Health Organization (WHO) declared COVID-19 a pandemic on 11 March 2020 [5]. A pandemic is defined as a disease that spreads over a whole country or the world [6].

The first COVID-19 case in Indonesia was detected on 2 March 2020, in Depok, West Java. Afterward, many cities and provinces in Indonesia were attacked by this virus. According to the data from the Coronavirus COVID-19 Global Cases by the Center for

Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), as of 1 April 2022, a total of 6,015,748 confirmed cases with 155,164 deaths were documented [7]. In addition, Jakarta is one of the most impacted provinces in Indonesia, with 20% positive cases and 9% death nationwide. Jakarta, Indonesia's capital city, is one of the provinces with the highest degree of community transmission, indicating a high risk of COVID-19 infection for the general population [8]. The daily new COVID-19 cases in Jakarta from 2 March 2020 to 3 April 2022, are shown in Figure 1. This consists of the implementation of some stringent quarantine protocols in place.

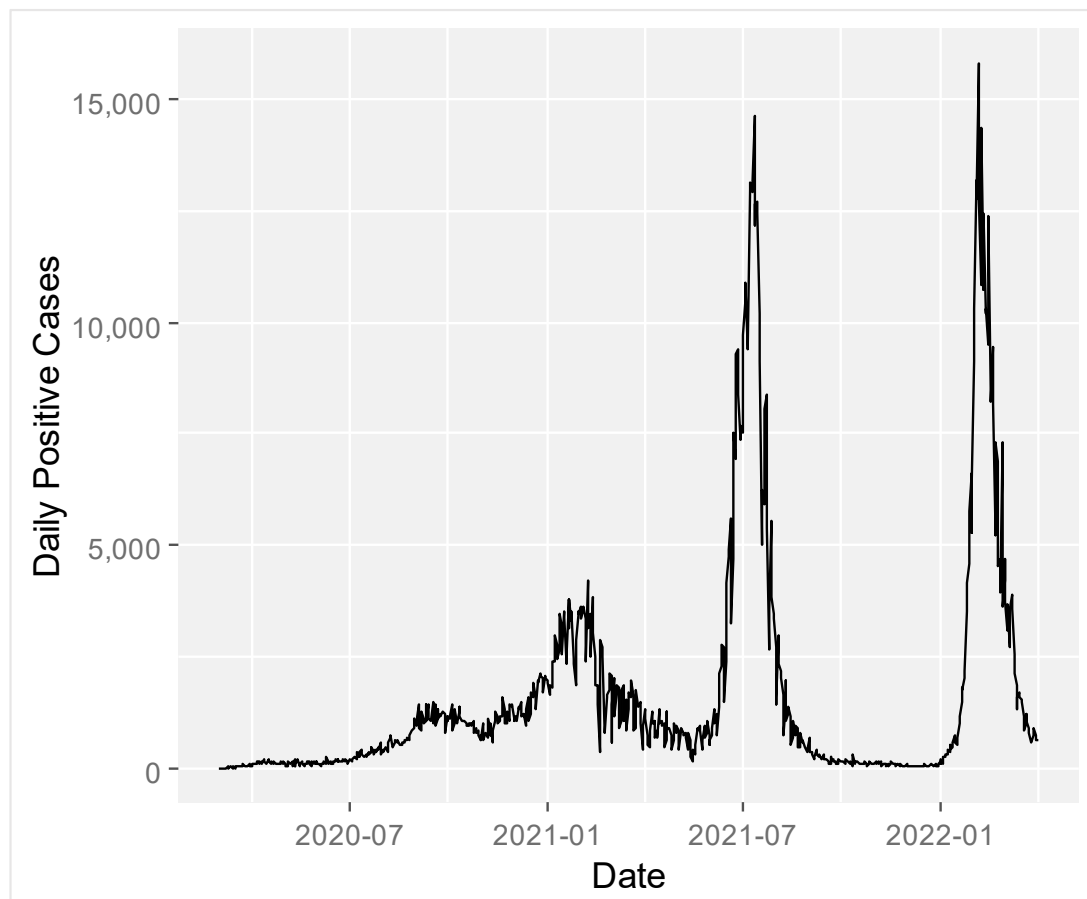


Figure 1. The daily new cases from 2 March 2020 to 3 April 2022, in Jakarta.

From Figure 1, COVID-19 cases in Jakarta appear to fluctuate. Many COVID-19 cases in this province are related to Jakarta's high social movement as Indonesia's capital city [9]. COVID-19 cases in Jakarta increased significantly on 12 July 2021, reaching 14,619 new cases. This lousy condition is related to the entry of the Delta variant into Indonesia. According to the Ministry of Health of Indonesia, the Delta variant was discovered in April 2021, and it is more transmissible and causes severe symptoms [10]. The delta variant of COVID-19 is causing an expanding crisis. This significant increase in positive cases has driven the demand for health services to increase sharply. The bed occupancy rate (BOR) in hospitals was high. Based on the data released by The Ministry of Health of Indonesia on 5 July 2021, Jakarta had a hospital BOR of 88% [11]. This high demand for health services caused a high mortality rate.

Since this Delta variant spreads quickly, the government of Indonesia started to implement a movement restriction policy known as Indonesia Officially Imposes Restrictions Towards Community Activities (PPKM DARURAT) on 1 July 2021 [12]. Implementing this PPKM Darurat cannot instantly reduce positive cases of COVID-19. As seen in Figure 1, despite PPKM being implemented on 1 July 2021, positive cases still increased significantly.

Some of the internal factors that caused the increase in COVID-19 cases were the community's increased domestic mobility and social activities that coincided with the Eid al-Fitr homecoming period [13]. At the end of July 2021, COVID-19 cases began to decline.

COVID-19 cases started to increase again in early 2022. The highest number of new cases in Jakarta was confirmed on 6 February 2022, reaching 15,825 new cases. This increase in positive cases was caused by the entry of the Omicron variant into Indonesia. On 15 December 2021, the Indonesian Ministry of Health found the first confirmed Omicron case in a patient [14]. Concerning the invasion of Omicron, the government of Indonesia implemented PPKM Level 3 in several provinces in Indonesia, including Jakarta [15].

The death cases in Jakarta due to COVID-19 can be seen in Figure 2. The death cases of COVID-19 in Jakarta tend to be sloping. Since the first 100 days of COVID-19 attacking Indonesia, death cases in Jakarta have increased. In addition, the death cases in Jakarta increased significantly in July 2021, with the highest confirmed death cases being 265 deaths on 20 July 2021. This high number of deaths due to COVID-19 is caused by the Delta variant that has entered Indonesia since April 2021. A study conducted by the Faculty of Medicine Universitas Indonesia (FKUI) and the government of Jakarta showed that old age, pneumonia, shortness of breath, and hypertension were predictors of death in patients with confirmed COVID-19 [16].

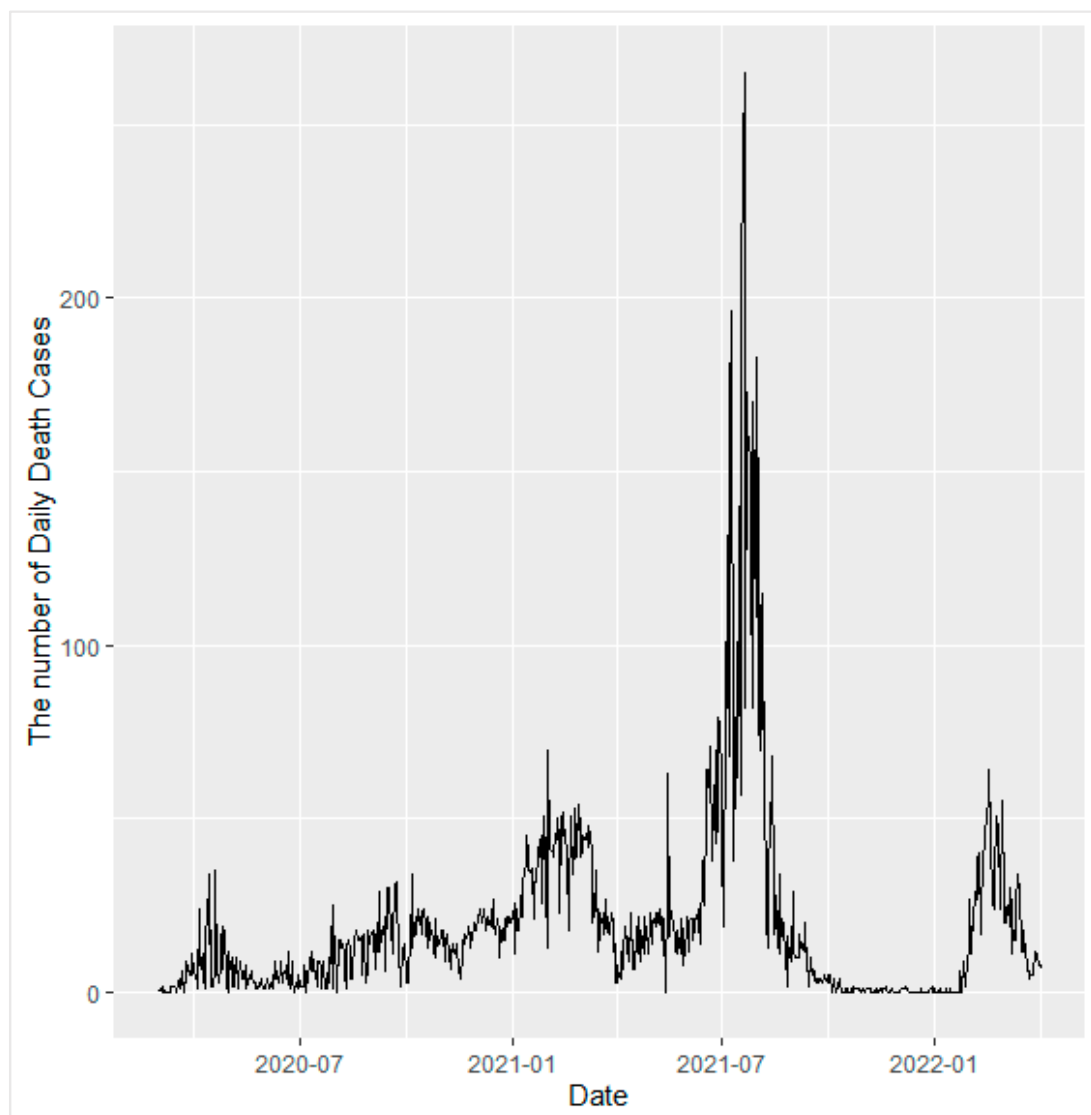


Figure 2. The daily death cases from 2 March 2020 to 3 April 2022, in Jakarta.

The death cases decreased until the end of 2021, then increased again in February 2022, related to the entry of the Omicron variant to Indonesia. According to the government, even though the Omicron variant has a high transmission rate, the effect on the hospital's BOR and the death rate is relatively small [15]. This is caused by vaccinations that have reached almost the entire population. Until 3 April 2022, Jakarta's COVID-19 vaccination has reached 123.7% for the first dose and 104.9% for the second dose from the number of vaccination targets [17]. Therefore, individuals who have been fully vaccinated and have received booster vaccines are permitted to engage in normal activities while wearing facial masks and cleaning their hands properly [15].

Treating COVID-19 as an endemic disease after two years into the pandemic is one of the goals of every country. Endemic disease refers to the constant presence of a disease or infectious agent within a given geographic area or population group. It may also refer to the usual prevalence of a given disease within such an area or group [18]. In other words, a disease will be endemic if its presence becomes stable in a particular area. This increase in positive cases was caused by the entry of the Omicron variant into Indonesia. On 15 December 2021, the Indonesian Ministry of Health found the first confirmed Omicron case in a patient [14]. Concerning the invasion of Omicron, the government of Indonesia implemented PPKM Level 3 in several provinces in Indonesia, including Jakarta [15].

According to Dr. Elisabetta Groppelli, a virologist at St George's, endemicity was written into the coronavirus [19]. This was the unavoidable result of a virus that spreads through the air for many. Others are using endemic to indicate COVID-19 is still around, but we no longer need to restrict our lives, according to Prof Azra Ghani, an epidemiologist at Imperial College London [19]. According to Prof Julian Hiscox, the end of the COVID-19 pandemic is just around the corner in the UK [19]. Therefore, the same possibility could also happen in Jakarta, Indonesia.

The restrictions on activities carried out to reduce contact to reduce the spread of COVID-19 also impact the economic sector [20]. The Gross Domestic Regional Product (GDRP) of Jakarta in 2020 decreased by 2.4% from 2019 [21]. Nationwide, the Indonesian economy grew by minus 2.1 percent in 2020 while severely hampered by the COVID-19 pandemic [22]. Thus, appropriate policies are needed to improve economic conditions that have declined since the COVID-19 pandemic.

Many countries are already moving to the endemic phase of COVID-19. Malaysia, one of the countries in the region of Indonesia, began treating COVID-19 as an endemic disease around the end of October 2021 [23]. Not only that, some countries no longer require people to wear masks. The Nordic countries (Denmark, Iceland, Finland, Norway, and Sweden), Eastern European countries (Bulgaria, Hungary, Poland, Romania, and Slovenia), Croatia, Czech Republic, Estonia, Ireland, the Netherlands, and the United Kingdom are all mask-free [24].

Treating COVID-19 as an endemic disease can be achieved when herd immunity has been formed in the population. Herd immunity refers to the indirect protection from infection offered to vulnerable individuals when a sufficiently significant number of immune individuals are present in a population [25]. Thus, efforts need to be made to create herd immunity related to COVID-19. Herd immunity will be achieved through vaccination or immunity gained from past infection [26]. When these conditions are achieved, even though COVID-19 persists and becomes endemic, the death rate caused by COVID-19 will decrease. As shown in Figure 2, the daily death cases caused by COVID-19 in early 2022 are not as high as death cases in 2021, even though the Omicron variant has entered Indonesia with very high positive cases.

This study is conducted to forecast the COVID-19 condition in the future in Jakarta according to daily positive cases and deaths caused by COVID-19. Since hospital capacity is limited and there are limited health workers and vaccines in pandemic situations, governments should make plans based on predicted case numbers. Additionally, this study is also conducted to know whether COVID-19 in Jakarta, the capital city of Indonesia, can be

said to have become endemic or not by looking at the pattern of daily positive cases, death cases, and forecasts for the next period.

In this study, we will use machine learning models called Neural Network Auto-Regressive (NNAR) and Long Short-Term Memory (LSTM) to create a forecast model representing the number of COVID-19 positive and death cases in Jakarta. A time series, a chronological or time-oriented sequence of observations on a variable of interest [27], is used in this study. Furthermore, the findings of this study can be used as basic public information on prospective conditions in the future.

2. Materials and Methods

2.1. Description of the Data Collection and Study Area

The data used in this study are time-series data of the number of confirmed cases and death cases of COVID-19 in Jakarta, the capital city of Indonesia. The time-series data used are from 1 March 2020 to 3 April 2022. The dataset was gathered by the Indonesian government's Task Force, which was designed to accelerate the treatment of COVID-19. The analysis is performed using two variables, specifically the daily new cases obtained from the confirmed cases in the present day and the previous day and daily death cases of COVID-19 in Jakarta. Forecasting was carried out using the machine learning approach, namely Neural Network Auto-Regressive (NNAR).

2.2. Artificial Neural Network (ANN)

ANN is a computer system developed as part of artificial intelligence research [28]. Warren McCulloch and Walter Pitts proposed a simple neuron model in 1940 as the basis of artificial neural networks [29]. ANN comprises an input layer, hidden layer, and output layer [29]. A neuron, the basic building of an ANN [28], uses an activation function in the output and hidden layer. The most common activation functions are sigmoid and hyperbolic tangent [9]. Artificial neural networks (ANN) have some advantages in time series forecasting. ANNs are highly flexible, as they don't require a formal model specification [30]. There are two types of ANN, Recurrent Neural Network (RNN) and Feed Forward Neural Network (FFNN). The recurrent layer of RNNs has feedback loops [31]. Moreover, the input of an FFNN network only propagates forward from the input level to the output level [32].

2.3. Neural Network Auto-Regressive (NNAR)

The Neural Network Auto-Regressive (NNAR) model is a feed-forward neural network with a single variable input, and lag 1, lag 2, etc., until lag to p ; hence, it is called Neural Network Auto-Regressive (NNAR) [33]. This model is only for a feed-forward neural network with estimations of y and a single hidden layer with neurons and is denoted by NNAR(p, k), where k is the number of nodes in the hidden layer and p denotes lag- p as input [34]. The fitted model for data with a seasonal pattern is denoted as NNAR(p, P, k)_m model, where P is the seasonal lags and m is the seasonal period's length. NNAR fitted model for seasonal data is similar to ARIMA ($p, 0, 0$)($P, 0, 0$)_m. NNAR does not restrict on its parameters to achieve stationarity [35]. The mathematical representation of the relationship between the model output and the input is as follows:

$$y_t = w_0 + \sum_{j=1}^h w_j \cdot g(w_{0j} + \sum_{i=1}^n w_{ij} \cdot y_{t-1}) + \varepsilon_t, \quad (1)$$

where y_t is the output, $y_{t-1}; \dots; y_{t-p}$ are the inputs, w_j ($j = 0, 1, \dots, h$), and w_{ij} ($i = 0, 1, \dots, n; j = 1, 2, \dots, h$) are connection weights or parameters of the model, h is the number of nodes in the hidden layer, and n is the number of the input nodes. NNAR scales well to large p -orders, allowing long-range dependencies to be estimated (important in high-resolution monitoring applications) [36].

2.4. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a development of RNN that can solve vanishing gradient or exploding gradient problems [37]. The LSTM method solves the problem of RNN by adding a cell state or memory cell with a constant error to allow errors to reproduce without vanishing or exploding gradients occurring. The gate serves to regulate whether the information is forwarded or stopped. Each gate has parameters, namely, weight and bias. There are three gates in the LSTM: input gate, forget gate, and output gate. The forget gate regulates how much information must be removed, the input gate regulates how many cells the input gates must store states, and the output gate regulates how many cell output gates must send states to the next cell.

2.5. Metrics Evaluation

A common approach is to use percentage errors based on measures to be scale-independent, for example, using Mean Absolute Percentage Error (MAPE) [38]. Since the observation value contained zero, the Mean Absolute Error (MAE) (2) and Root Mean Square Error (RMSE) (3) will be used. MAE is obtained by calculating the arithmetic mean of absolute errors. On the other hand, RMSE is the square root of the residual variance. A model can be concluded as the best model if it has the smallest metrics evaluation.

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n |X_t - \hat{X}_t|, \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (X_t - \hat{X}_t)^2} \quad (3)$$

where n is the number of observations, X_t is the observations at time t , and $\hat{X}_t$ is the predicted value of X_t .

3. Results

The open-source R software performed the data analysis of confirmed positive and death cases due to COVID-19. Moreover, the method used in this study was the NNAR or Neural Network Auto-Regressive method. This method does not require assumptions, so no transformation and data stationarity is checked in this analysis. In addition, the selection of the best model was based on RMSE, MAE, and R Square. The model chosen was the model with the smallest value of RMSE and MAE. Meanwhile, the selection based on R-squared was conducted by selecting the model with the most considerable R-square value. The model chosen will predict daily positive and death cases caused by COVID-19 in Jakarta for the next seven days.

3.1. NNAR

Neural Network Auto-Regressive (NNAR) consists of three layers. There is one input layer, one output layer, and one hidden layer. The number of neurons in this input layer is determined by the PACF plot at significant values.

In the autoregressive process, the input or predictor used is historical data. The number of predictors is selected by looking at the significant lag in the ACF plot. A significant lag indicates an autocorrelation or relationship between the data and over time. Figure 3 shows a significant lag in the 1st, 2nd, 3rd, 5th, 6th, 8th, 9th, 11th, 12th, 13th, 15th, 18th, 20th, 24th, and 27th lags. As input neurons, as many as 27 lags will be used in this analysis. In addition, the number of neurons in the hidden layer is determined by trial and error. The number of neurons analyzed starts from 5 to 31 neurons with a learning rate of 0.01 and a step max of 100,000. The analysis of the number of hidden layer neurons shows that 28 neurons for the hidden layer produce the smallest MSE, which is 0.00318.

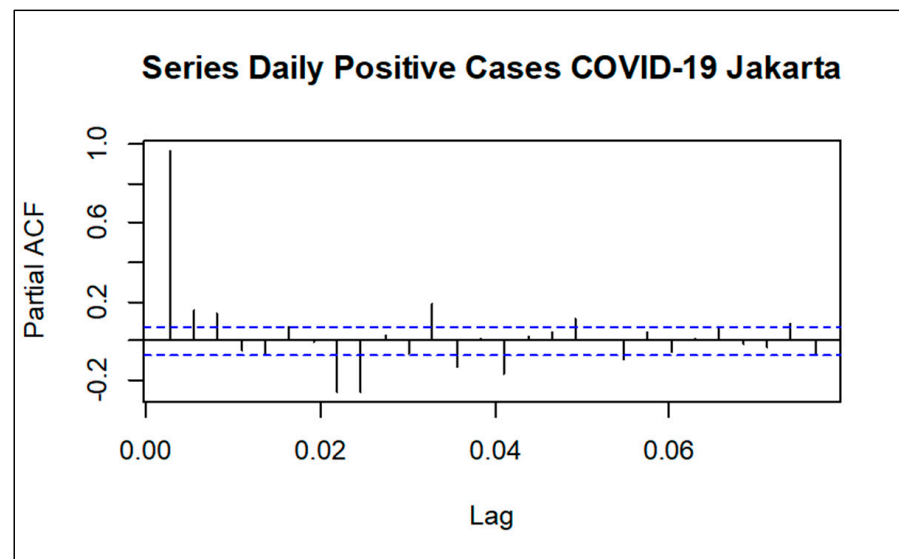


Figure 3. PACF Plot for Daily Confirmed Positive Cases of COVID-19 Data in Jakarta.

Moreover, the learning rate was also determined by trial and error, starting from a learning rate of 0.001 to 0.2 with 28 hidden neurons. The results show that a learning rate of 0.01 produces the smallest MSE value, which is 0.00318. Thus, the best model for confirmed positive cases of COVID-19 is NNAR (27,28,1) with a learning rate of 0.01, 100,000 step max, and ten repetitions.

Figure 4 shows the plot of actual data layered by predicted data obtained using the NNAR model (27,28,1). Furthermore, the plot indicates that the predicted data almost follows the actual data. It means that the prediction model can predict the confirmed positive cases of COVID-19 in the future. Additionally, it is supported by the MAE value of 298.142, RMSE of 453.75, and the R Square value of 0.939.

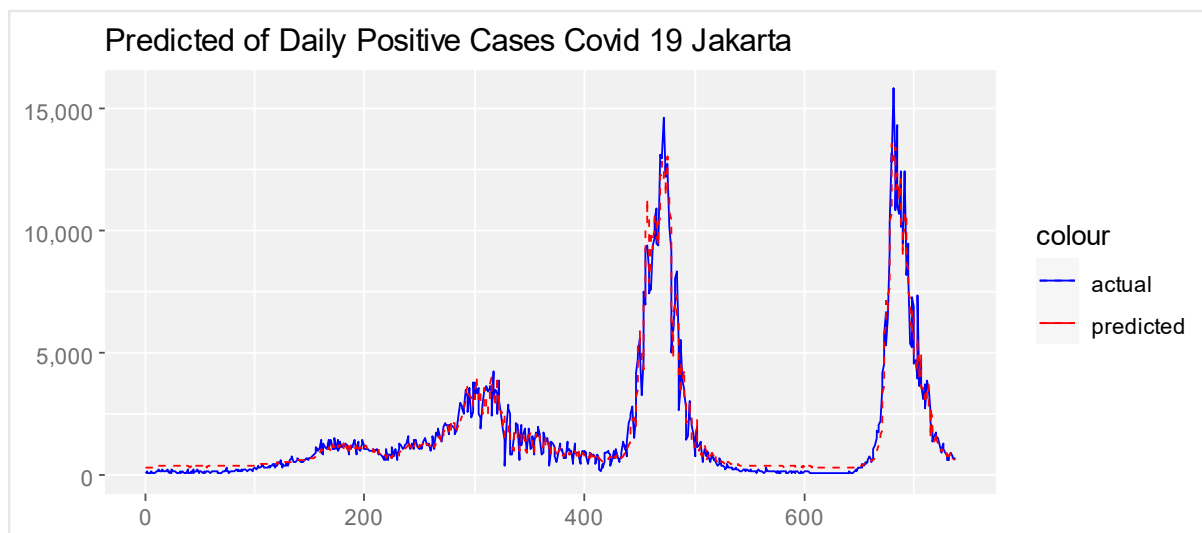


Figure 4. A plot of actual data and predicted data for daily confirmed positive cases of COVID-19 in Jakarta.

The same as the network in the confirmed positive cases of COVID-19, the network architecture in the analysis using the neural network method in the case of death due to COVID-19 also consists of three layers (one input layer, one output layer, and one hidden layer). Figure 5 shows the number of neurons in this input layer is determined by the PACF plot at significant values.

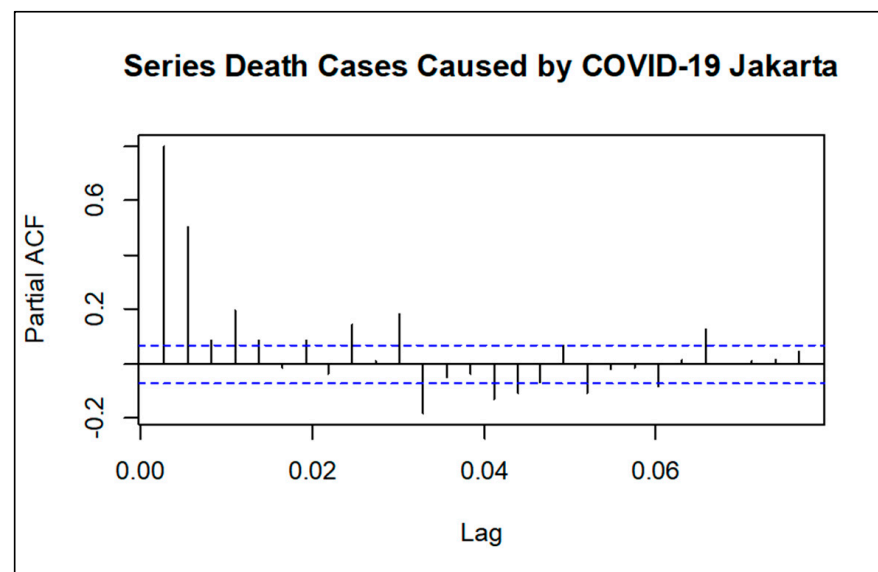


Figure 5. PACF plot for death cases caused by COVID-19 in Jakarta.

Figure 5 shows that there is a significant lag in the 1st, 2nd, 3rd, 4th, 5th, 7th, 9th, 11th, 12th, 15th, 16th, 17th, 18th, 19th, 22nd, and 24th lags. In this analysis, 24 lags will be used as input neurons.

Moreover, the number of neurons in the hidden layer and the learning rate are determined by a trial-and-error process. The number of neurons in the hidden layer will be analyzed starting from 5 to 28 neurons, while the learning rate will be analyzed starting from a learning rate of 0.001 to 0.2. The results show that a network with 24 neurons in the input layer, nine neurons in the hidden layer, and a learning rate of 0.01 produces the smallest MSE value, which is 0.001019. Thus, Figure 6 shows the best model results for death cases caused by COVID-19 are NNAR (24,9,1) with a learning rate of 0.01, 100,000 step max, and two repetitions.

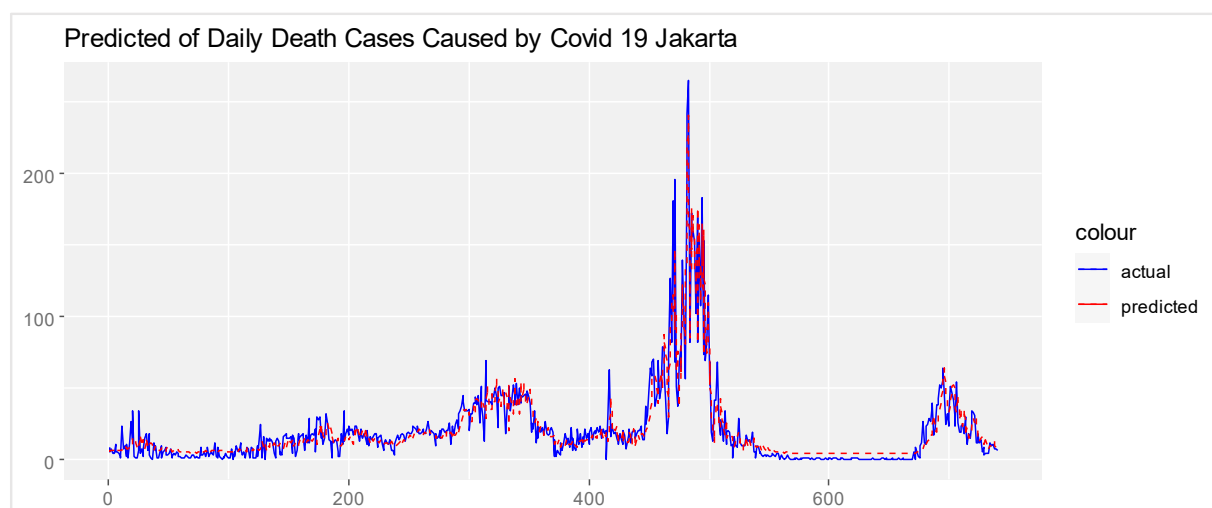


Figure 6. A plot of actual data and predicted data on death cases due to COVID-19 in Jakarta.

Figure 6 shows the actual data plot and the predicted data using the NNAR model (24,9,1). The plot indicates that the predicted data are almost in accordance with the actual data. It means that the prediction model can be used to forecast the death cases due to COVID-19 in Jakarta in the future. In addition, it is supported by the MAE of 6.41, RMSE of 9.41, and the R Square value of 0.8417.

3.2. LSTM

LSTM uses supervised learning so that the target will be set first. The predictor data are first converted into a three-dimensional form, consisting of samples, timesteps, and features. Furthermore, the training data that have been converted into a three-dimensional form is used for LSTM modeling. Samples are the length of the data, timesteps are the number of lags, and features are the number of predictions. Meanwhile, the target data are converted into a two-dimensional form consisting of samples and timesteps.

In this study, the data used are daily data of 764 datapoints divided into two parts; 80% for training data, or 611 datapoints, and 20% for testing data or as many as 153 datapoints. Subsequently, modeling using LSTM is carried out with optimizer Adam parameters, 100 batch size (mini-batch gradient descent), one hidden layer, 100 epochs, and ten neurons in the hidden layer. Based on these characteristics, a decrease in loss function can be seen until it reaches the local minimum in Figure 7.

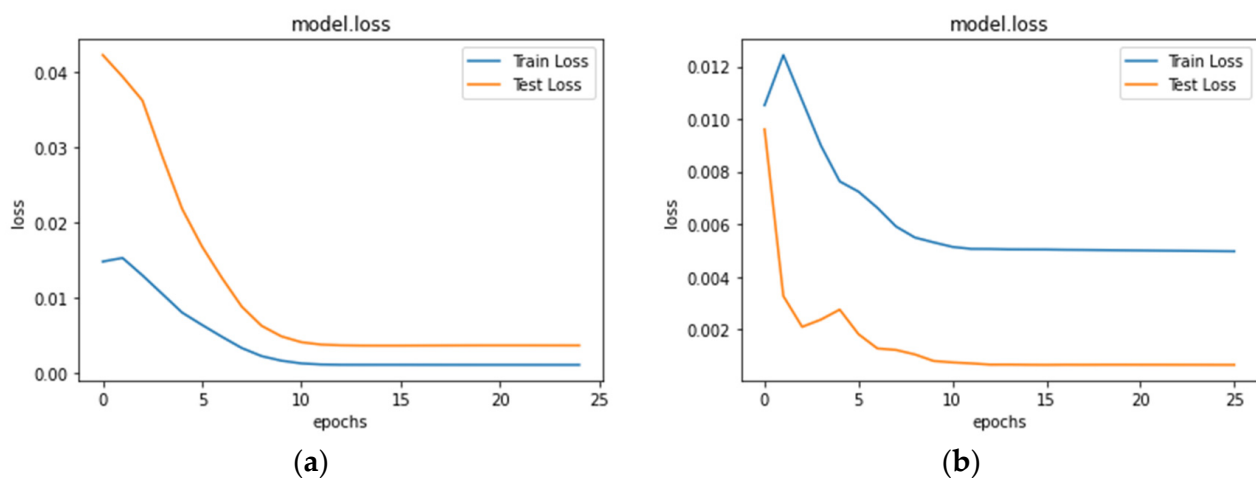


Figure 7. (a) Graph of loss function derivation for positive cases; and (b) graph of loss function derivation for death cases.

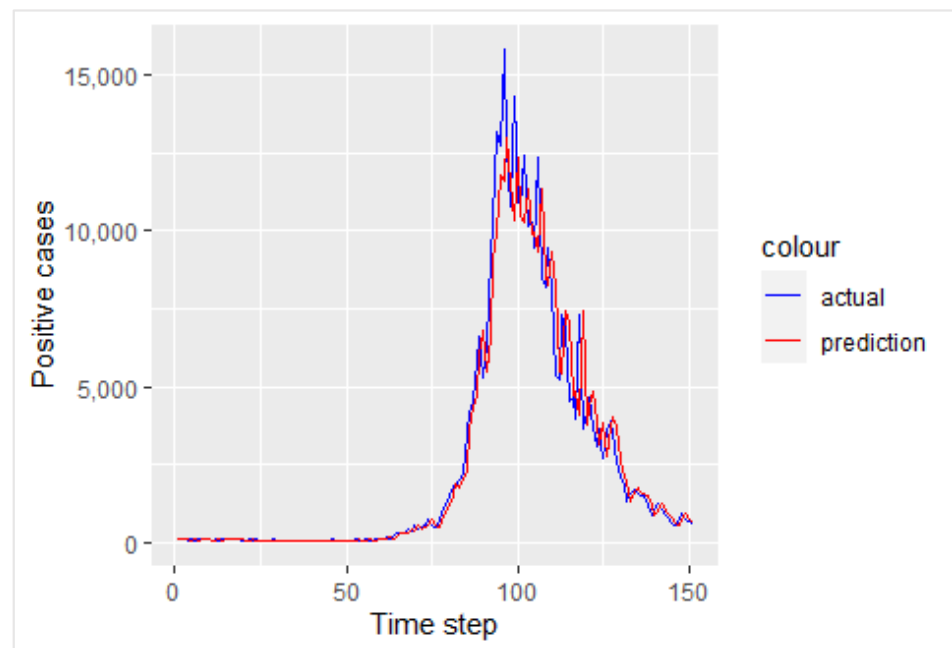
From Figure 7, it can be seen that in the case of the positive cases, the decrease in loss function becomes constant after five epochs and stops at 24 epochs, while for the death cases, the decrease in loss function becomes constant after ten epochs and stops at 25 epochs. After determining the parameters to be initialized to get the best model, we can see the plot between the actual data and the predicted data from the best model for the test data in Figure 8.

Based on Figure 8, the predictions generated through the best model on the LSTM can follow the actual data pattern. Hence, it can be concluded that the best model of the LSTM produces a good prediction.

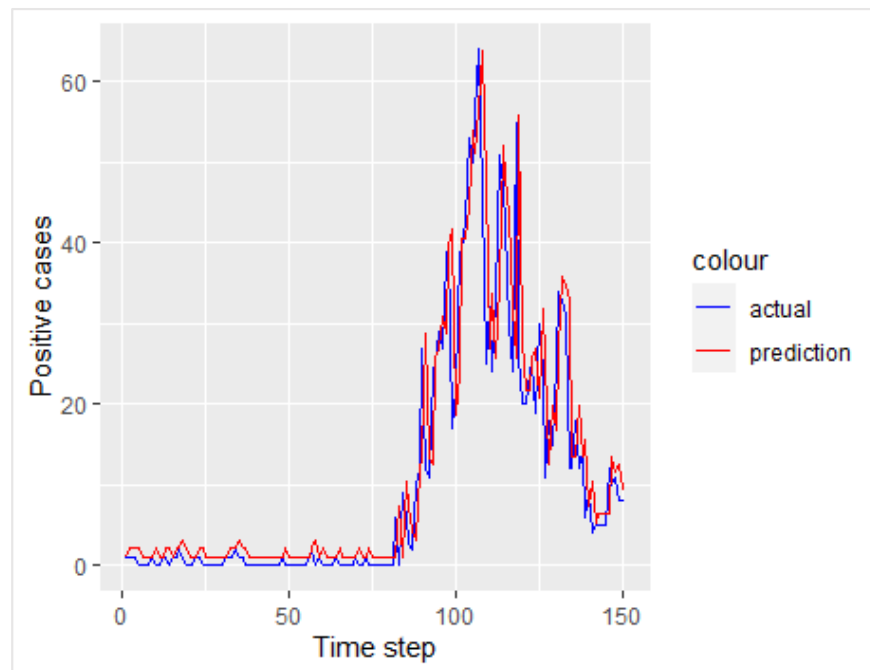
3.3. Forecasting

Regarding future positive cases and deaths due to COVID-19 prediction, the two NN models utilized, NNAR and LSTM, are compared to see which one best matches the existing data patterns. Here we use two different metrics, namely MAE and RMSE. MAE is the mean of the absolute error, and RMSE is the square root of the mean square error. The error measures are obtained by testing the data for multi-step prediction with seven periods.

According to Table 1, we can see the difference in the metrics evaluation values between the NNAR and LSTM models. In the daily positive case, the MAE and RMSE of the NNAR model are far below the LSTM model. However, MAE and RMSE in the death cases due to COVID-19 between the NNAR and LSTM models are not much different. This time, the MAE and RMSE of the LSTM model are slightly lower than the NNAR model. Thus, the NNAR model will be used to forecast daily COVID-19 cases, and the LSTM model will be used to forecast daily death cases due to COVID-19 in Jakarta.



(a)



(b)

Figure 8. (a) Plot of actual data and predicted data for positive cases; and (b) plot of actual data and predicted data for death cases due to COVID-19.

The results of forecasting confirmed positive cases of COVID-19 using the NNAR model (27,28,1) are shown in Table 2 below.

The forecast results can be shown in Table 2. It shows that in the seven periods after 3 April 2022, starting from 4 April 2022 to 10 April 2022, daily confirmed positive cases of COVID-19 will increase, and there is a significant increase. Figure 9a shows the confirmed number of COVID-19, which tends to increase day by day from 4 April to 8 April. Moreover, Figure 9b shows the confirmed positive cases of COVID-19 are predicted to experience declines from 9 April.

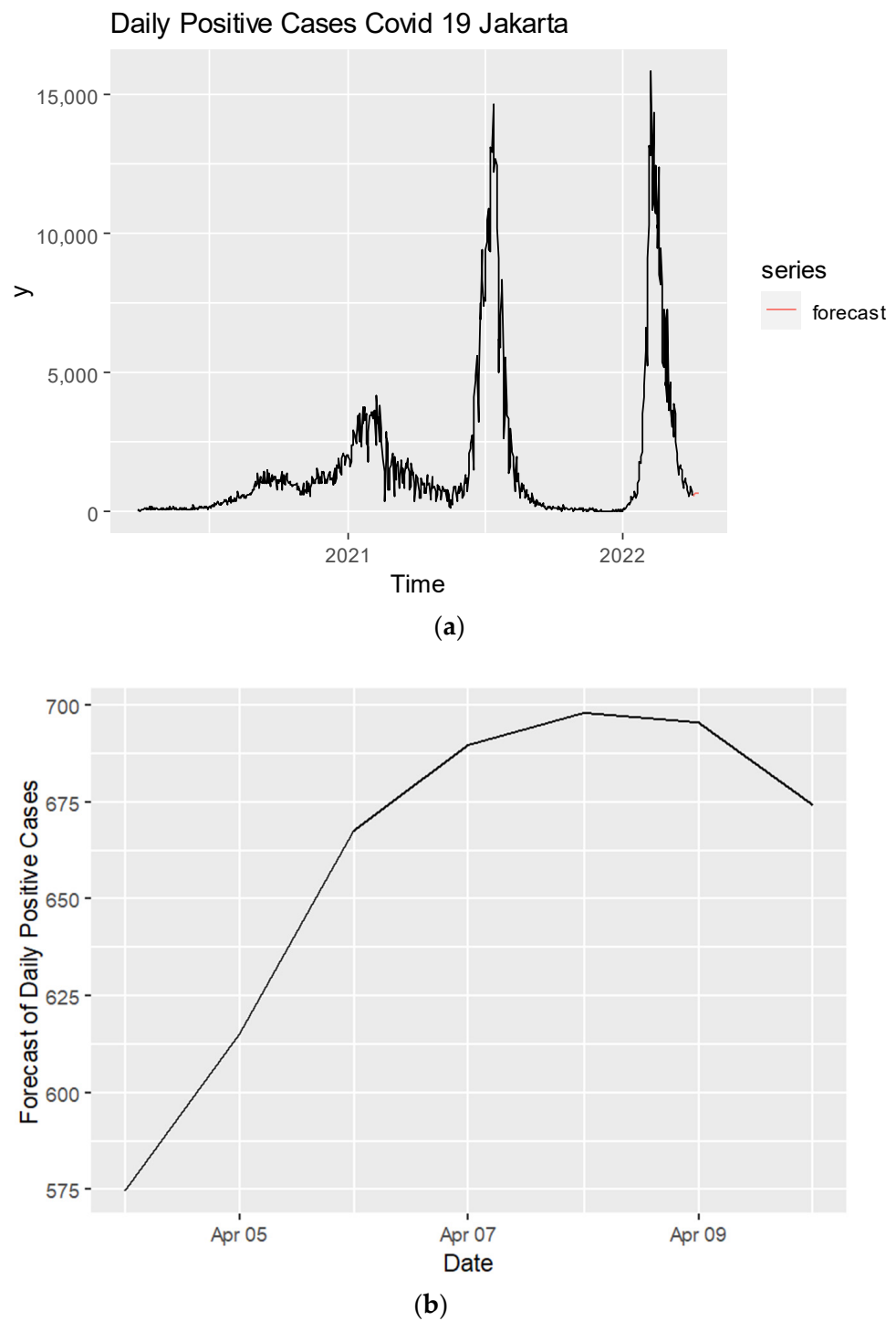


Figure 9. (a) Daily confirmed positive cases of COVID-19 in Jakarta and prediction for the next seven periods; and (b) forecast plot of daily confirmed positive cases of COVID-19 in Jakarta.

Table 1. Models Evaluation.

Variable	Method	RMSE	MAE	R-Square
Positive Cases	NNAR	458.51	302.02	0.941
Death Cases	NNAR	9.41	6.41	0.8417
Positive Cases	LSTM	964.63	462.43	0.9337
Death Cases	LSTM	6.72	4.64	0.8068

Table 2. Forecasting Results of Daily Confirmation Positive Cases using NNAR (27,28,1).

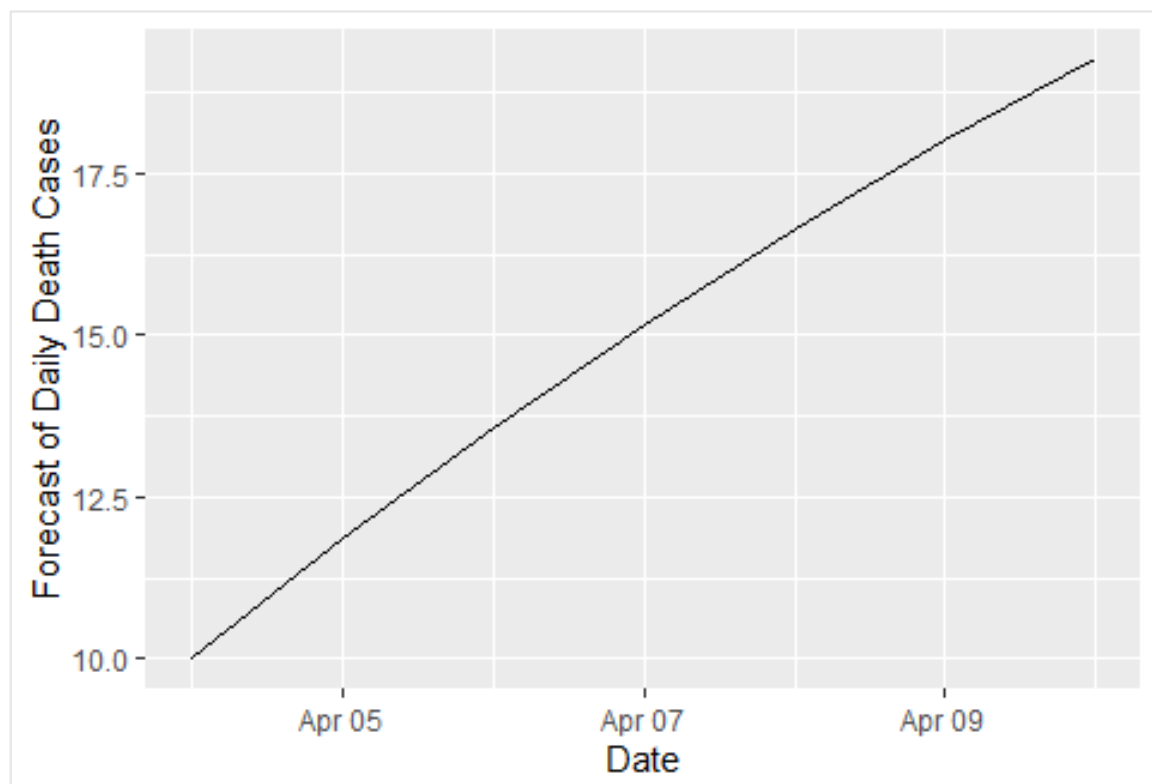
Date	Forecast
4 April 2022	575
5 April 2022	615
6 April 2022	668
7 April 2022	690
8 April 2022	698
9 April 2022	696
10 April 2022	674

The results of forecasting death cases caused by COVID-19 using LSTM are shown in Table 3 below.

Table 3. Forecasting daily death cases caused by COVID-19 using LSTM.

Date	Forecast
4 April 2022	10
5 April 2022	12
6 April 2022	14
7 April 2022	16
8 April 2022	17
9 April 2022	18
10 April 2022	20

Table 3 shows the multi-step forecast of daily death cases caused by COVID-19 for the following 7 periods from 4 April 2022 to 10 April 2022. The results show that the death cases caused by COVID-19 in Jakarta will experience a small increase, with only one or two death cases each day. Additionally, the increase in the number of death cases is not significant, as shown in Figure 10.

**Figure 10.** Forecast plot of death cases caused by COVID-19 in Jakarta.

4. Discussion

By the end of 2021, the second vaccination dosage in the Jakarta region had reached 92.2% of the vaccination target set by the government. This number shows that almost all people in DKI Jakarta have acquired additional immunity against COVID-19. By the end of 2021, vaccination in Jakarta had reached 92.2% of the target. This made a significant difference in the mortality rate due to the Omicron variant of COVID-19. Compared to the highest number of deaths from the delta variant in 2021, the highest number of deaths from the omicron variant did not reach half of the highest death rate from the delta variant. The highest cases of COVID-19 in Jakarta occurred in the first quarter of 2022. At that time, out of 15,825 daily positive cases, 495 were Omicron variants. With a high number of COVID-19 positive cases and a low mortality rate, it can be said that the Omicron variant has a lower death risk than the Delta variant.

Endemic refers to diseases that are consistently present in a particular geographic location without causing changes to the pattern of people's daily lives. An outbreak is said to change its status from a pandemic to an endemic if there is a decrease in the number of deaths caused by it and if the number of cases is constant or increases in specific periods (a seasonal pattern occurs). In other words, the transition from a pandemic to an endemic period is indicated by a decrease in the fatality rate.

Based on the statement above, predictions are made for COVID-19 positive cases and death cases caused by COVID-19 in Jakarta for the next seven days. Forecasting of positive instances of COVID-19 was performed using the NNAR or Neural Network Autoregressive method with 27 neurons in the input layer, 28 neurons in the hidden layer, and one neuron in the output layer. The results of the prediction are shown in Table 2. As shown in Table 2, forecasting daily positive cases using NNAR shows that the positive cases from 4 April to 8 April will significantly increase. Within seven days, from 4 to 10 April, the highest cases will occur on 8 April, as many as 698 cases. However, on 9 and 10 April, positive cases of COVID-19 in Jakarta are predicted to decrease. Compared to 8 April, cases on 9 April are predicted to be lower by two instances. On 10 April, the difference in daily positive cases is expected to be more significant because the forecast results show a decrease to as many as 22 cases.

Meanwhile, the results of forecasting the number of deaths caused by COVID 19 in Jakarta using the LSTM method are shown in Table 3. It shows the multi-step forecast of daily death cases caused by COVID-19 for the following seven periods after 3 April 2022, from 4 April 2022 to 10 April 2022. The results show that the death cases caused by COVID-19 in Jakarta tend to increase from the beginning to mid-April and then remain constant until June. Nevertheless, the increase in the number of death cases is not significant.

These results show that although the number of positive cases of COVID-19 is high, the mortality rate is low. As already mentioned, it can be concluded that the fatality rate from COVID-19 is not very high at the moment. Thus, this forecasting showed that Jakarta had entered an endemic phase. In Jakarta, the transition from the pandemic phase to the endemic phase will prompt the government to end the policy of enforcing community emergency restrictions (PPKM) and return community activities to normal. Activities in schools and offices can continue as usual (work from the office), although health protocols, such as wearing masks and regular hand washing, still need to be implemented. The results of this study are supported by the decision of President Joko Widodo on 17 May 2022, which allows the public to no longer wear masks in outdoor areas.

The predictions made regarding the number of confirmed positives and the number of deaths from COVID-19 are based only on historical data without considering other factors affecting them. In this study, the other influencing factors were deemed to be constant. Therefore, further research needs to include the factors that influence the model's positive rate and death cases to make more suitable predictions.

5. Conclusions

The government has made some efforts of Jakarta to control COVID-19 cases, such as appeals for quarantine and vaccination. This effort is carried out to reduce the number of cases of COVID-19 and the number of deaths caused by COVID-19. Therefore, it is necessary to forecast daily positive cases and deaths caused by COVID-19 in Jakarta for the future. Based on the findings obtained from this study, daily positive and death cases of COVID-19 are predicted to increase from 4 April 2022 to 10 April 2022, but it is not significant.

After more than two years of a worldwide COVID-19 pandemic, it is hoped that COVID-19 will become an endemic disease. The forecast results of this study show that it is very likely that COVID-19 is no longer a pandemic but has transformed into an endemic in Jakarta. The results of modeling support this carried out using NNAR (24,9,1), which shows that COVID-19 cases are predicted to increase, but it tends to be sloping. Other than that, forecasting results for the death cases due to COVID-19 using LSTM are expected to experience a very small increase, only one or two death cases each day.

This condition can be achieved with cooperation between the government and the community in dealing with COVID-19, specifically in implementing social restrictions policy (PPKM) and vaccination. Therefore, the government and the community must continue to collaborate to reduce the spread of COVID-19.

Moreover, further study is needed to get a better accuracy of the estimation results.

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