Indonesia in Facing New Normal: An Evidence Hybrid Forecasting of COVID-19 Cases Using MLP, NNAR and ELM

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***Abstract*— Since COVID-19 spread to hundreds of countries, it has become a global pandemic. This pandemic is spreading rapidly through the human transmission. To reduce the spread of COVID-19, the government has issued various guidelines regarding restrictions on human activity. Jakarta and West Java are two provinces that had a fairly high rate of spread when COVID-19 began to appear. To reduce the rate of spread, local governments in each province have issued a Large Scale Social Restriction (PSBB) policy. After the implementation of this policy, there was a significant decrease in the addition of new cases in the two provinces. Therefore, the government replaced this policy with a new normal policy as well as to address economic problems in society. This new normal policy actually led to the emergence of new cases as a result of failure to follow government-set health protocols. This study examines whether there are significant differences in the movement of COVID-19 cases across the two provinces. In addition, this study examines how the incidence rate of COVID-19 will move in the future using various NN (Neural Network) methods such as MPL, NNAR and ELM. The results show that there was a significant decrease in the Jakarta region before and after the implementation of the PSBB, but it did not occur in West Java province. Another finding is that this study shows that the new normal has resulted in a significant increase in COVID-19 cases in both provinces and is expected to increase further if the community fails to follow to the government-established health protocol.**

***Index Terms*— COVID-19; Extreme Learning Machine, Indonesia, Neural Network**

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I. Introduction

CORONAVIRUSES are non-segmented sensory RNA viruses that belong to the Coronaviridae family and the Nidovirales sequence. This virus commonly found in humans and mammals [1]. COVID-19 can be transmitted through droplets, contacts, and can also spread in an environment without ventilation with high levels of viral aerosols [2]. On top of that, researchers claim that the virus spread rapidly from human to human [3]. In order to minimize the spread of the virus, therefore we have to wash our hands with a hand-sanitizer or wash it with soap and water, keep a distance of 1-3 meters from other people, avoid touching eyes and nose, stay away from the crowd and do self-quarantine [4]. In Indonesia, the COVID-19 case was first discovered on March 2, 2020, in Depok, West Java. This outbreak then spread quickly to all provinces in Indonesia with an accumulation of 36.406 positive cases, 13.213 recovered, and 2.048 deaths on June 12, 2020 [5]. Moreover, investigations revealed that both first patients had previously interacted with Japanese citizens who were infected with COVID-19 [6]. Since the virus spread rapidly to several regions, the government started to implement a large-scale social restriction or PSBB (Pembatasan Sosial Berskala Besar) [7].

PSBB was intended to limit activities in provinces that have been infected with COVID-19 [8] in line with the social distancing policy that being implemented around the world to prevent further spread [9]. This restriction means restricting social activities between people, closing schools and workplaces, reducing activities in public places, and restricting transport between regions [10].

COVID-19 cases were dominated by DKI Jakarta and West Java province, although in a few days later East Java province surpassed the province of West Java [11]. The daily new cases in Jakarta and West Java from March 2, 2020, to August 31, 2020, are presented in Fig. 1. This consists of the implementation of PSBB in Jakarta on April 10, 2020, implementation of PSBB in West Java on April 15, 2020, and announced of the New Normal on May 25, 2020.

From Fig. 1, both provinces show an upward trend. In Jakarta, the trend has been increasing quite extremely since day 100, reaching 1000 new cases by the end of August. In West Java, daily new cases had increased since June 28, 2020, and fluctuate tremendously This indicates that the policies issued by the government have not resolved the COVID-19 problem.

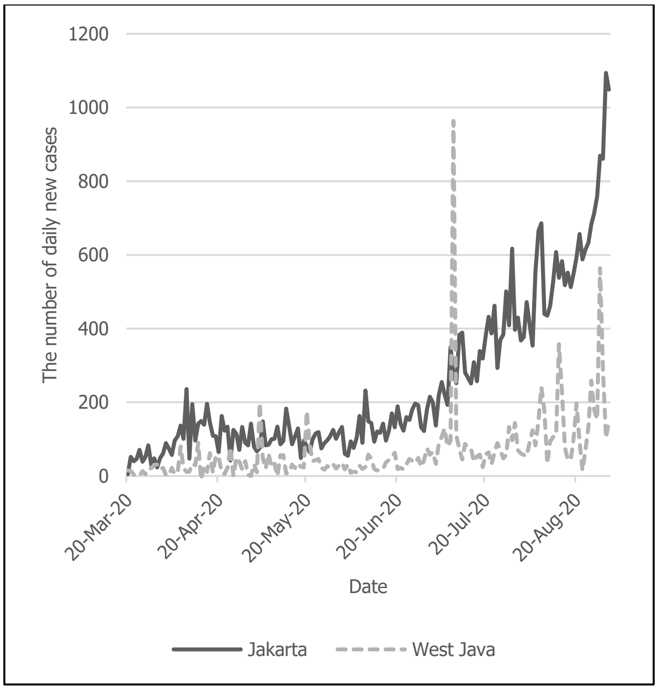

Fig. 1. The daily new cases in three provinces from March 20, 2020, to August 31, 2020.

A. Jakarta

Jakarta as the largest contributor to COVID-19 cases become the first province that introduces a PSBB policy since April 7, 2020. Furthermore, on April 11, 2020, the government enforced the Health Minister's Decree No. HK.01.07/MENKES/248/2020 on PSBB in several key areas in West Java Province (Bogor City, Depok City, Bekasi City) to reduce the spread of the virus [12].

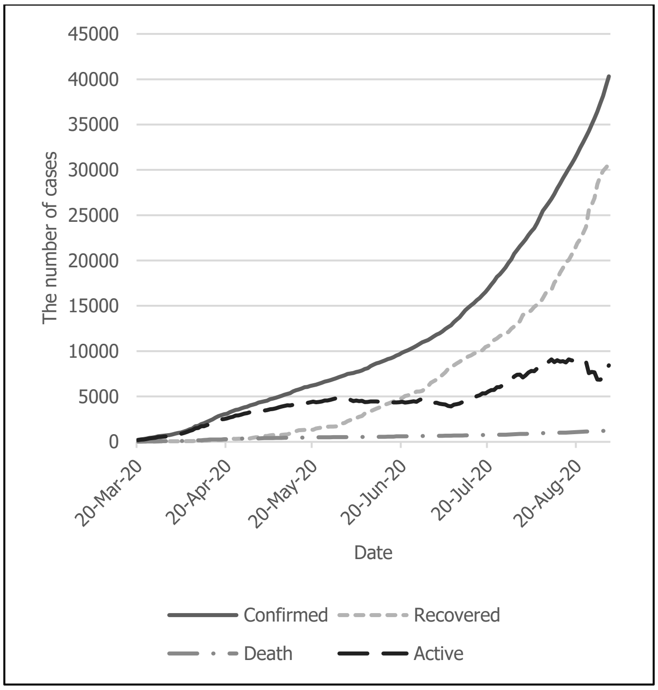

Fig. 2. The cases in Jakarta from March 20, 2020, to August 31, 2020.

In addition, Jakarta has reported 8,968 confirmed cases, 4,198 recovered, and 580 died on June 15, 2020. The distribution of daily case data appears to be volatile, with daily cases reaching the highest numbers on April 9, 2020, and June 9, 2020 [13]. The high number of cases in this province is due to Jakarta as the capital of Indonesia has a high social movement. However, However, the people in this province have low awareness of implementing government policies to reduce the rate of spread of Covid 19.[14], [15]. During the PSBB, the government of Jakarta, with the support of the police and the army, set up 11 checkpoints at Jakarta’s border, 13 checkpoints at the train stations included bus stations, 5 checkpoints at the entrance to the toll booth and 4 checkpoints in the city. Moreover, the Governor of DKI Jakarta, Anies Baswedan, urged residents to carry out physical distancing and have to wear masks when leaving the house. [16].

Jakarta implemented the first 14 days of the PSBB by closing schools, offices and places of worship and entering a normal transition phase (PSBB transition) at the beginning of June 2020 by gradually opening public spaces such as offices, restaurants, places of worship, parks and zoos. Since the implementation of the PSBB transition, there has been another increase in COVID-19 cases. The first peak occurred on June 9, 2020, with 1,043 new cases in Indonesia [17]. The presentation of historical data for each case in Jakarta is shown in Fig. 2. This graph shows that the number of cases recovered increased as the number of confirmed active cases increased. The cumulative deaths remained stable and showed an increase after the end-June 2020. However, the active cases still fluctuate until August 31, 2020.

Based on previous information, it appears that COVID-19 cases in Jakarta continue to increase despite the implementation of the PSBB in DKI Jakarta. However, the increase tended to decrease. This suggests that PSBB has not been effective in suppressing the spread of COVID-19 as many people fail to comply with government regulations [18]. Besides, the DKI Jakarta government announced an economic slowdown, followed by a 45% drop in tax revenues. In line with the decline in cases and the handling of economic problems in the municipality, Governor Anies Baswedan issued Governor Regulation No. 51/2020 on the implementation of the "PSBB Transition" on June 4, 2020. DKI Jakarta was the first province to implement the PSBB policy towards the "new normal" [19]. The Governor of DKI Jakarta was gradually opening public facilities, although it was still limited to only 50% of total capacity. However, these regulations did not apply to areas in the red zone (areas with high prevalence) [20].

B. West Java

At the beginning of the emergence of the COVID-19 case in Indonesia, West Java was in second place after Jakarta as a contributor to the COVID-19 case. There were no new cases reported in this province on May 10, 2020, which resulted in East Java Province replacing West Java. On June 15, 2020, West Java announced 2,623 confirmed active cases, 1,142 recovered cases, and 162 deaths. In the following days, there was still an increase in confirmed active cases during the PSBB, although it was small, accompanied by an increase in recovered cases [5]. On June 14, 2020, the Ministry of Health announced 857 new cases of COVID-19 in Indonesia and only 17 new cases in West Java. At the same time, there were 117 new cases in Jakarta [21]. To reduce the number of active cases, the Governor of West Java asked the public to properly register all guests from other areas to receive special treatment [22]. After the first phase of the PSBB was completed on 29 May 2020, the West Java Provincial Government extended the PSBB in Bogor, Depok and Bekasi until 2 July 2020 due to a relatively high increase in cases. Then, the Governor of West Java assigned all regents and mayors in the West Java region to formulate a plan for implementing the New Normal strategy [23].

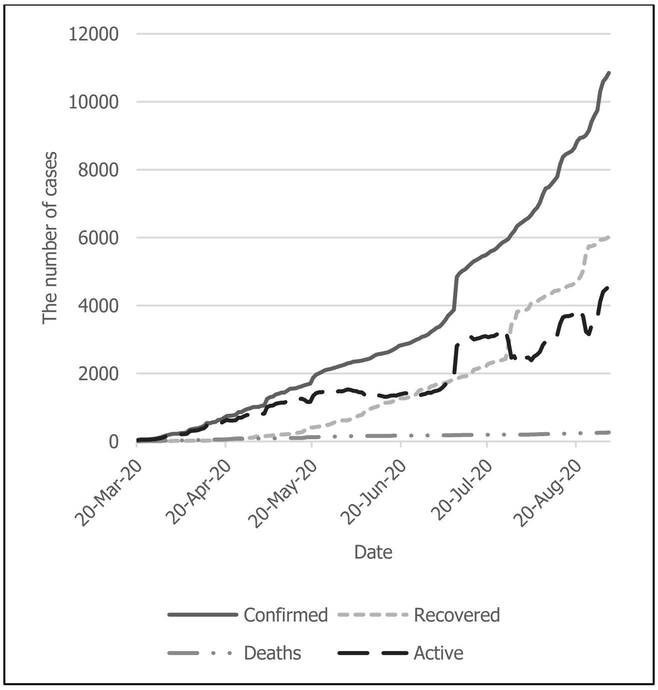

Fig. 3. The cases in West Java from March 20, 2020, to June 13, 2020.

The graphical representation of historical data of confirmed cases and deaths in West Java which is mentioned in Fig. 3 shows that the number of recovered cases increases dramatically according to the growth of confirmed cases and the graphical deaths remain stable. As well as the active cases in Jakarta, active cases in West Java are also fluctuating although based on the graphic shows an unexpected pattern. The central government has actually developed a New Normal concept to change lifestyles and encourage citizens to adopt a healthy lifestyle to prevent the spread of COVID-19 [24], [25]. At the same time, residents can carry out activities as usual in a New Normal era and be productive during the COVID-19 outbreak but they must still obey health protocols, such as wearing masks, keeping a distance from other people, washing hands and avoiding the crowd [26]. Due to the high COVID-19 infection level in vulnerable population groups, the calculation of the basic reproduction number (R_0) is very important in order to implement preventive measures and guidelines. Basic reproductive numbers are used to estimate the severity level of the pandemic and to control the spread of the virus [27], [28]. According to the WHO, Indonesia can implement new normal if a region has a moderate status and R_0<1 [29], but then again, Indonesia still implement the "new normal" while the estimated value of R_0 is between 2.24 and 3.58 [30] and has an average positivity rate of 14%, which is still well above the WHO standard for entering the "new normal" [31].

After the regional government of West Java introduced the new normal, the incidence rate of COVID-19 continued to rise [32]. This is due to excessive euphoria and a lack of public awareness of the implementation of government-required health protocols.

Initially, it was hoped that implementing the new normal would improve people's economies while suppressing the spread of COVID-19 cases. In reality, the prevalence is increasing [33]. Indonesia's gross domestic product fell by 5.32% in the second quarter. This suggests that PSBB regulations like closing businesses and factories and encouraging people to stay home are affecting a large part of economic activity. The government decided in early June to restore economic activity [34].

In anticipation of the economic crisis and recession, the Ministry of Finance revised the national budget to prevent negative growth [35]. Because of these circumstances, the government must find strategic solutions to overcome the problem, as it seems impossible to stop the new normal while economic conditions are not improving.

The aim of this study is to find out whether the actions taken by the government regarding PSBB and the new normal related to the COVID-19 incident in DKI Jakarta and West Java are having a significant impact on the change in the number of COVID-19 in both regions. Furthermore, this study also aims to predict what the possibility of this COVID-19 case developing in the future after the new normal is introduced in both regions.

Some simple models that only included the number of active, confirmed, recovered, died and daily COVID-19 cases in Jakarta and West Java are applied due to data limitations. In this study, we will build a model that represents the number of COVID-19 cases using different machine learning models, namely Neural Network Auto-Regressive, Multi-Layer Perceptron and Extreme Learning Machine. Confirmed cases can only be part of the total number of people infected. For this reason, there may be unreported cases. We have used a time series, which is a time-oriented or chronological sequence of observations of the observed variables [36]. The evaluation of this simple model [37] is used to find suitable data patterns to describe the development of COVID-19 DKI Jakarta and West Java. Moreover, the results can later be used as basic public information on future conditions. Additionally, this study is a continuation of previous studies [38].

II. Materials and Methods

A. Description of the Data Collection and Study Area

The data used in this study are historical data of confirmed cases, recovered cases, and death cases of COVID-19 in two provinces in Indonesia, Jakarta and West Java. The analysis is performed using 5 variables, specifically confirmed cases, recovered cases, death cases, daily new cases or the difference between confirmed cases in the present day and the previous day, and active case or the difference between the confirmed case and closed case, which included cases of recovery and death. The forecast was determined using a machine learning approach, specifically MLP, NNAR, and ELM. The historical data used are from March 20, 2020, to August 31, 2020. The dataset was collected by the Task Force formed by the Indonesian government to accelerate the handling of COVID-19.

B. Artificial Neural Network (ANN)

ANN is a method of machine learning proposed by McCulloch and Pits [39]. ANN widely used for forecasting models due to its ability to adapt a system that changes continuously [40], [41]. Three layers in ANN are the input layer, output layer, and hidden layer. There are activation functions in the output and hidden layer. Sigmoid and tangent hyperbolic is the most common activation function. Two types of ANN are Feed-Forward Neural Network (FFNN) and Recurrent Neural Network (RNN). FFNN is a network where the input only propagates forward from the input level to the output level. Instead, the RNN network forms a cycle [42], [43].

C. Multi-Layer Perceptron (MLP)

FFNN has an input layer, an output layer, and one or more hidden layers. Perceptron has no hidden layer and MLP has one or more hidden layers. MLP gives better results when compared with perceptron [44]. Each neuron in a hidden layer carries out the computation in (1) on its inputs and conveys the result (O_c) to the consecutive layer of the neurons.

$$O_c = h_{Hidden}\left(\sum_{p-1}^{P} i_{c,p} w_{c,p} + b_c\right);\ h_{Hidden}(x) = \frac{1}{1+e^{-x}} \quad (1)$$

O_c is the output of the current hidden layer of neuron c, P is the number of neurons among the previous network input, $i_{c,p}$ is input to neuron c of the previously hidden layer neuron p, $w_{c,p}$ is the weight that modifies the association from neuron p to neuron c, and b_c is the bias. In (1), $h_{Hidden}(x)$ is the sigmoid activation function. In order to avoid saturation of the activation function, the data should be scaled before training the weights and biases are initialized [45]. Each neuron in the output layer performs the computation in (2) on its inputs and transmits the outcome (O_c) to a network output.

$$O_c = h_{Output}\left(\sum_{p-1}^{P} i_{c,p} w_{c,p} + b_c\right);\ h_{Output}(x) = x \quad (2)$$

O_c is the output of the current output layer of neuron c. Activation function will be used for $h_{Output}(x)$ is a linear activation function. Backpropagation (BP) is one of the most used algorithms for the training dataset by determining hyperparameters manually [46], [47]. BP algorithm is a generalized delta rule. It learns a set of weights and biases iteratively.

D. Neural Network Auto-Regressive (NNAR)

A feed-forward neural network is fitted with estimations of y as inputs and a single hidden layer with neurons. The inputs for lags 1 to p and lags m to MP where $m = freq(y)$. Its columns are additionally utilized as inputs if x_{reg} is given. Though, if there are missing values in y or x_{reg} the involving rows are rejected from the fit. With irregular initial weights, a total of revises networks is fitted. Recursively, multi-step predictions are processed, although the network is prepared for a one-step prediction.

The fitted model for data with a non-seasonal pattern is inevitable as NNAR (p,k), where k is the number of hidden neurons. This is corresponding to an AR(p) with non-linear functions. For data with seasonal pattern, the fitted model is indicated as NNAR (p,P,k)[m], which is similar to ARIMA (p,0,0)(P,0,0)[m] with non-linear functions. The modelled cycles are always symmetric in AR. Nonetheless, the cyclic model in the NNAR has been modelled well to facilitate the irregularity of the cycles. This is the one difference between AR and NNAR [48].

E. Extreme Learning Machine (ELM)

ELM which proposed by Vapnik [49] is a rapid learning algorithm for the feed-forward neural networks with a hidden layer. This method overcomes the hindrance of the previous neural network in the process of learning speed because ELM could be reducing the training time and enhancing the performance of an overview [50], [51]. Moore-Penrose pseudoinverse [52] is employed to determine the output weight under the criterion of the least-squares method.

The ELM network includes n neurons in the input layer, h neurons in the hidden layer, and m neurons in the output layer. For N random definite samples (x_i, t_i), wherever $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, \dots, t_{in}]^T \in R^m$, more, $(x_i, t_i) \in R^n x R^m$ and $i = 1, 2, \dots, N$. Standard ELM with $\tilde{N}$ hidden neurons and activation function $f(x)$ are computationally model as (3).

$$\sum_{i=1}^{\tilde{N}} \beta_i f_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i f(a_i . x_j + b_i) = t_j \quad (3)$$

where $a_i = [a_{i1}, a_{i2}, \dots, a_{in}]^T$ is the weight vector that connecting the i^{th} hidden and input neurons, bi is the threshold of the i^{th} hidden neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]^T$ is the weight vector connecting the i^{th} hidden and output neurons.

The activation function that used ordinarily is sigmoid, sine, and RBF. Equation (3) can be written as $H\beta = T$ where $\boldsymbol{H} = [f(a_1.x_1 + b_1) \cdots f(a_{\tilde{N}}.x_1 + b_{\tilde{N}}) \ \vdots \ddots \vdots \ f(a_1.x_N + b_1) \cdots f(a_{\tilde{N}}.x_N + b_{\tilde{N}})\ ]_{N \times \tilde{N}}$, $\boldsymbol{\beta} = \left[\beta_1^T \ \vdots \ \beta_{\tilde{N}}^T\ \right]_{\tilde{N} \times m}$, $T = \left[t_1^T \ \vdots \ t_{\tilde{N}}^T\ \right]_{N \times m}$.

H is the so-called hidden layer output matrix of the network, the i^{th} column of H is the i^{th} hidden neuron output relating to inputs. ELM distributes the input connecting weights and hidden layer neuron biases b. Once the hidden layer biases and input weights are persistent, the input might acquire the hidden layer output matrix. Accordingly, the training process of the ELM is mentioned on (4).

$$\|H(a_1, \dots, a_{\tilde{N}}, b_1, \dots, b_{\tilde{N}}, x_1, \dots, x_N)\hat{\beta} - T\| = \|H(a_1, \dots, a_{\tilde{N}}, b_1, \dots, b_{\tilde{N}}, x_1, \dots, x_N)\hat{\beta} - T\| \quad (4)$$

The smallest norm least-squares solution of (4) is in (5).

$$\widehat{\boldsymbol{\beta}} = \boldsymbol{H}^{\dagger}\boldsymbol{T} \quad (5)$$

$H^{\dagger}$ is the Moore-Penrose pseudoinverse of the H. The optimal generalization ability of the model minimizes output weights. Because of $\hat{\beta}$ is sole, the local optimal solution might prevent to produce.

F. Metrics Evaluation

The most common selection criteria are the Mean Absolute Percentage Error (MAPE) because the value is in the form of a percentage then it is appropriate to measure the accuracy of a model [53], [54], [55]. Since the data contained zero values, the Mean Absolute Error (MAE) (6), Root Mean Square Error (RMSE) (7), and Mean Absolute Scaled Error (MASE) (8) will be utilized. Metrics evaluation will be conducted for multi-step ahead although it is better to use for one-step prediction [56]. A model becomes the best model if it has the smallest metrics evaluation.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|X_t - \widehat{X_t}\right| \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(X_t - \widehat{X_t}\right)^2} \quad (7)$$

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_t - \widehat{X_t}}{\frac{1}{T-1}\sum_{t=2}^{T}|X_t - X_{t-1}|}\right| \quad (8)$$

where n is the number of observations, X_t is the observed value, $\bar{X}_t$ is the mean of the observed value, and $\widehat{X_t}$ is the predicted value.

G. Welch t-test

The t-test is a type of statistical hypothesis test used to determine a significant difference between the average of two groups. Once the number of members of the two groups is different, an independent t-test is used instead of a paired t-test. This is the test where you do not assume that the variance of the two groups is the same, which outcomes in the partial degrees of freedom (9) [57].

$$t = \frac{m_A - m_B}{\sqrt{\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}}} \quad (9)$$

where m_i is the average of each group, s_i^2 is the variance of each group, and n_i is the number of observations in each group. Moreover, the degree of freedom of the Welch t-test is estimated as.

$$df = \left(\frac{s_A^2}{n_A} + \frac{s_B^2}{n_B}\right)^2 / \left(\frac{s_A^4}{n_A^2(n_A-1)} + \frac{s_B^4}{n_B^2(n_B-1)}\right) \quad (10)$$

III. Results and Discussions

All analyzes were performed in open-source R with the nnfor package. The artificial neural network is a method that does not require assumptions so that general model identification is not carried out including transformation and stationary checking. The methods used in this study were NNAR, MLP, and ELM. The selection of the model that best fits the existing data patterns is seen from the RMSE, MAE, and MASE values which have the smallest values. Furthermore, the selected model was used to predict the next ten days of daily new cases, active cases, confirmed cases, recovered cases, and death cases.

In this study, no data was lost so that all datasets would be processed into a training process. All parameters, such as weight, input delay, and so on, are acquired automatically during the training process.

A. NNAR

The NNAR method is run automatically using nnar function to find the best order for both NN and AR. Consequently, NNAR produced the best model for all the cases, except daily new cases from averages 20 networks and each network that has 4 weights is a 1-1-1 network, means the model is a network with last one observations used as input and with one neuron in the hidden layer. The output from this method is a linear output unit with σ^2 estimated as 32077, 13958, 10875, 8419, 26489, 5198, 40.25, 5.838 for active cases, confirmed cases, recovered cases, and death cases in Jakarta and West Java, respectively.

For daily new cases in Jakarta, the network is 2-2-1 which means there are two input lags with two hidden neurons with nine weights and σ^2 estimated as 3329 while daily new cases in West Java has 3-2-1 network means there are three input lags with two hidden neurons and 11 weights and σ^2 estimated as 3810.

B. MLP

Then, the MLP model with two hidden layers with 10 neurons in each hidden layer is applied. These series modelled in differencing with 20 repetitions. During the training process, Mean Squared Error is obtained for the training process. Lag 1 is always included hence the selection algorithm decides that nothing stays in the network. The Mean Square Error (MSE) for each case in Jakarta and West Java obtained with different univariate lags using the median as the best operator. The MSE value and univariate lags for each case are presented in Table 1.

TABLE I
MSE VALUES AND UNIVARIATE LAGS OF MLP MODELS

Variable	MSE	Lags
Jakarta_A	12680.93	(1, 4)
Jakarta_N	140.948	(1, 2, 3)
Jakarta_C	2532.864	(1, 2, 4)
Jakarta_R	4408.432	(1, 2, 3, 4)
Jakarta_D	1.435	(1, 2, 3, 4)
West Java_A	11871.087	(-1)
West Java_N	1472.262	(1, 3)
West Java_C	1565.267	(1, 3)
West Java_R	3269.197	(-1)
West Java_D	4.719	(-1)

A: active cases, N: daily new cases, C: confirmed cases, R: recovered cases, and D: death cases.

C. ELM

This method fits with 20 repetitions and one differencing as well as the MLP model with the same univariate lags, except the death cases in Jakarta (using univariate lags of (1, 2, 3)). With different hidden neurons, then, MSE value was acquired for each case. For all the cases in both provinces, operated 100 hidden neurons with MSE value of 34392.827, 13983.986, 4386.771, 9759.104, 3847.020, 9797.969, 42.532, 5.269, 42445.419, 6028.479 with the order of active cases, daily new cases, confirmed cases, death cases, and recovered cases in Jakarta follow by the cases in West Java.

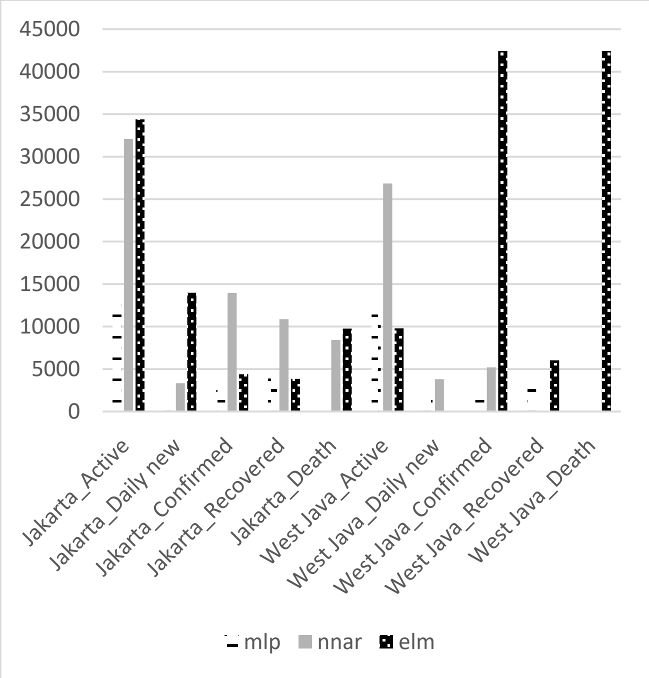

Fig. 4. The MSE value of each model for all cases.

In short, it can be said that the MSE value of the MLP model in the training process has the lowest value compared with other models (Fig. 4). In the previous study [58], the ELM model has several advantages over MLP, namely better accuracy and shorter time in both the training and the testing process. In this study, however, the MLP model was able to perform better than ELM because the data set used had extreme values and MLP was able to overcome this better [59], although the training process took longer. This is in line with another research [60].

D. Welch t-test

Before predicting using the best model of the above three methods, based on historical data, a t-test is performed using the Welch t-test. This test is carried out to test whether the data groups used differ significantly. Instead of all variables, we only test the active cases and daily new cases because other variables are cumulative values. This test is done to compare whether before and after PSBB differ significantly and to determine if the new normal and PSBB periods differ significantly. The PSBB period will take place in Jakarta from April 10, while PSBB for West Java firstly introduced in several cities consists of Bogor, Depok, and Bekasi on April 15. Moreover, the new normal was implemented since May 25, 2020.

TABLE II
P-VALUES OF EACH CASE

Variable	Active cases	Daily new cases
PSBB_Jakarta	1.829e-10	1.406e-4
New normal_Jakarta	1.346e-27	6.765e-12
PSBB_West Java	1.611e-13	0.129
New Normal_West Java	7.104e-45	6.896e-4

Based on the p-value in Table 2 with the assumption α = 5%, the application of the PSBB and the application of new norms had a significant impact on active cases in both provinces, DKI Jakarta and West Java. On the other hand, for new daily cases, the implementation of the PSBB only had a significant impact in DKI Jakarta. The implementation of the PSBB in West Java for new cases every day did not show a significant effect.

Thus, this information shows that the implementation of the PSBB in DKI Jakarta has significantly reduced the number of COVID-19 cases in the region. However, after the local government imposed the new normal, the number of cases in DKI Jakarta began to increase significantly.

This is different from West Java, where the PSBB did not have a significant impact on reducing COVID-19 cases in the region. This is not too surprising because the number of cases in West Java actually decreased before the implementation of the PSBB. However, similar to DKI Jakarta, there has been a significant increase in cases in the region since the new normal was introduced.

This happened because the people in these two provinces did not follow the health protocols implemented by the government. People tend to ignore the existence of COVID-19 and even think that the people around them are unlikely to catch the disease.

E. Forecasting

Concerning future case prediction, the three NN models used, NNAR, MPL, and ELM, are evaluated to obtain the model that best fits the existing data patterns. Here we are using three different methods as they also use different metrics. MAE uses the mean of the absolute error values, RMSE uses the square root of the mean square error, and MASE uses the mean of the scaled errors.

Based on Table 3, we can see that the difference between the NNAR and ELM model is not too far. However, the MAE, RMSE, and MASE values of the MLP model are far below the other two models. The ELM model used in this study whereas is a further development of the MLP model, both of them use a single feed-forward neural network, but with a shorter training time.

Between the ELM and NNAR models, not every case has the same best model, in other words, not all cases have NNAR error values that are smaller than the ELM model or vice versa. However, the metric evaluation of MLP has the smallest values.

Moreover, Table 3 explains that the model with the smallest MAE, RMSE, and MASE values is MLP, corresponding to the previous result of the training process. Therefore, this model is used to predict the evolution of COVID 19 cases in the two provinces.

The error measures are obtained by testing the data for multi-step prediction with 10 periods of time because if we make a forecast over too long, the results will be less accurate. The more prediction steps are performed, the greater the error will be obtained.

TABLE III
METRICS EVALUATION OF THE MODELS

Variable	Method	MAE	RMSE	MASE
Jakarta_A	NNAR	107.887	179.101	0.914
Jakarta_N	NNAR	42.466	57.699	0.910
Jakarta_C	NNAR	71.989	104.284	0.297
Jakarta_R	NNAR	101.343	162.754	0.545
Jakarta_D	NNAR	4.399	6.344	0.622
West Java_A	NNAR	52.940	118.143	0.887
West Java_N	NNAR	33.325	61.727	0.721
West Java_C	NNAR	41.868	91.757	0.632
West Java_R	NNAR	35.754	72.100	15.285
West Java_D	NNAR	1.712	2.416	1.071
Jakarta_A	MLP	72.125	112.609	0.676
Jakarta_N	MLP	7.408	11.872	0.163
Jakarta_C	MLP	37.307	50.327	0.169
Jakarta_R	MLP	43.852	66.396	0.261
Jakarta_D	MLP	0.717	1.197	0.104
West Java_A	MLP	52.924	108.954	0.891
West Java_N	MLP	25.059	38.370	0.570
West Java_C	MLP	25.788	39.563	0.422
West Java_R	MLP	28.356	57.176	0.758
West Java_D	MLP	1.577	2.172	1.005
Jakarta_A	ELM	105.488	185.453	0.990
Jakarta_N	ELM	47.120	66.232	1.038
Jakarta_C	ELM	46.058	62.241	0.209
Jakarta_R	ELM	127.947	206.022	0.761
Jakarta_D	ELM	4.905	6.521	0.708
West Java_A	ELM	54.174	118.253	0.912
West Java_N	ELM	50.732	98.788	1.154
West Java_C	ELM	50.828	98.984	0.833
West Java_R	ELM	37.651	77.643	1.006
West Java_D	ELM	1.653	2.295	1.054

A: active cases, N: daily new cases, C: confirmed cases, R: recovered cases, and D: death cases.

Multi-step ahead prediction is used to create the model. Fig. 5 through Fig. 9 (x-axis is the number of cases and y-axis is the day from March 20 to September 10) illustrates the future forecast of active cases, daily new cases, confirmed cases, recovered cases, and death cases while the Table 4 and Table 5 is the forecasting results of the MLP model as the best model to predict each case in Jakarta and West Java.

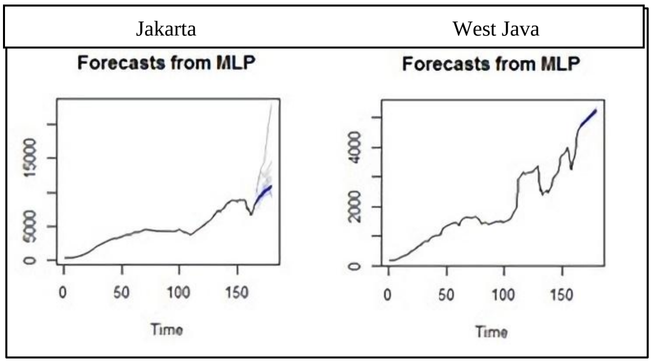

Fig. 5. The forecasting results of active cases.

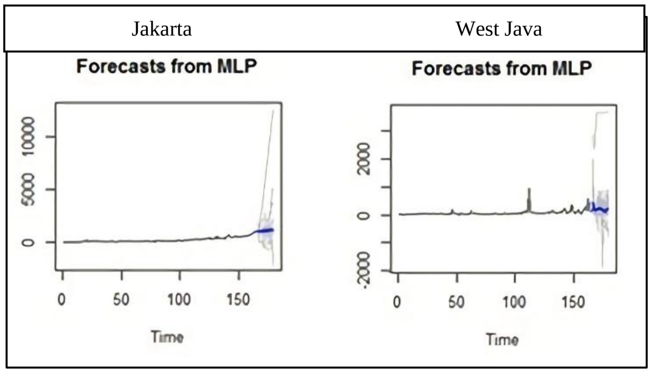

Fig. 6. The forecasting results of daily new cases.

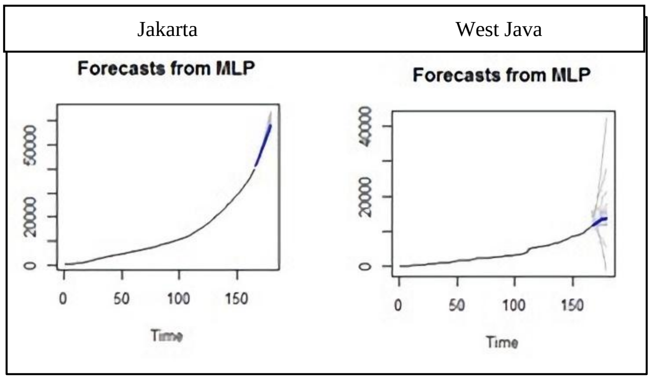

Fig. 7. The forecasting results of confirmed cases.

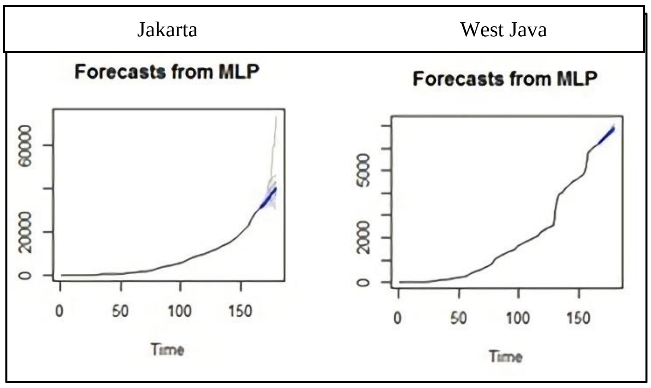

Fig. 8. The forecasting results of recovered cases.

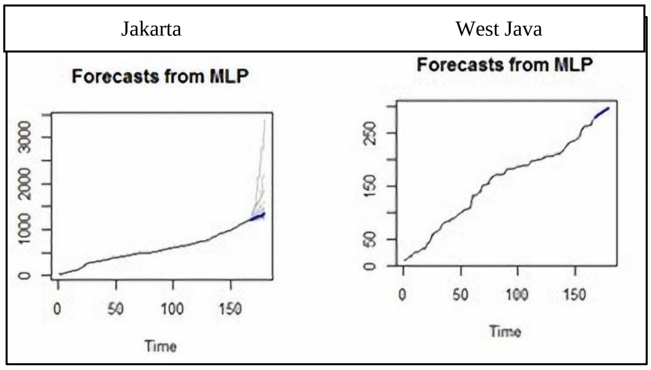

Fig. 9. The forecasting results of death cases.

Figure 5, which is clarified by the results in Table 4 and Table 5, explains that the number of active cases in both areas, DKI Jakarta and West Java, will continue to increase after implementing the new normal in both provinces. This would worsen if the strict health protocols were not followed by the public.

However, it appears that the number of people recovering from this disease has also increased significantly, as shown in Fig. 8. The addition of new recovered cases is predicted increasing by 100 in Jakarta and by about 50 cases in West Java. This informs that the ability of health workers to treat patients with COVID-19 in both provinces and people's awareness of enhancing the body's immunity is also improving.

TABLE IV
FORECASTING RESULTS OF THE BEST MODEL FOR JAKARTA

Date	A	N	C	R	D
September 1, 2020	8522	1074	41266	31354	1198
September 2, 2020	8687	970	42456	31936	1211
September 3, 2020	9117	1044	43706	32361	1216
September 4, 2020	9357	1053	44937	32803	1228
September 5, 2020	9499	1048	46231	33524	1232
September 6, 2020	9630	1092	47541	34261	1245
September 7, 2020	9936	1059	48861	35037	1257
September 8, 2020	10118	1113	50184	35662	1268
September 9, 2020	10246	1053	51511	36425	1271
September 10, 2020	10314	1096	52839	37262	1277

A: active cases, N: daily new cases, C: confirmed cases, R: recovered cases, and D: death cases.

TABLE V
FORECASTING RESULTS OF THE BEST MODEL FOR WEST JAVA

Date	A	N	C	R	D
September 1, 2020	4705	445	11517	6206	278
September 2, 2020	4760	192	11708	6260	279
September 3, 2020	4808	136	11947	6314	281
September 4, 2020	4851	193	12117	6367	282
September 5, 2020	4891	194	12295	6421	284
September 6, 2020	4931	202	12538	6474	285
September 7, 2020	4969	243	12738	6526	287
September 8, 2020	5009	204	12967	6579	288
September 9, 2020	5048	190	13253	6632	289
September 10, 2020	5088	148	13328	6684	291

A: active cases, N: daily new cases, C: confirmed cases, R: recovered cases, and D: death cases.

According to Fig. 6, the forecast results of daily new cases in both provinces still in wide interval due to its previous patterns that show rapid fluctuation. Also, based on Table 4, the daily new cases in Jakarta is about 1000 cases and between 100 to 400 cases in West Java, as well as Table 5 mentioned.

Regarding death cases, based on Fig. 9 and Table 4, the addition of death cases in Jakarta is predicted that it will be lower in the future. This prediction is also similar to West Java, as shown in Table 5.

IV. CONCLUSION

The government's policy of replacing the PSBB with a new normal cannot be avoided as economic conditions in Indonesia are gradually weakening. Obviously, the lessening of policies which was not accompanied by public awareness of compliance with government-implemented health protocols resulted in the number of COVID-19 cases in Indonesia continuing to rise. This is supported by the results of this study using the NN method which is known for its high accuracy. From data processing performed with MLP (10,10) as the best model, it appears that the incidence of daily new cases of COVID 19 continues to occur and worsen if health protocols are not followed by the public. However, the number of recovered patients also increased significantly, and the increase in mortality was not as huge. This shows that the role of the medical staff is very large and the public awareness of strengthening the body's immunity is getting better. DKI Jakarta as the capital of Indonesia cannot avoid the daily density of economic activity. It is therefore not surprising that COVID 19 cases are expected to continue to rise unless central and regional governments immediately seek strategic solutions to mitigate the effects of this spread. This situation cannot be denied either the province of West Java is also part of the country and also almost all areas have very popular tourist areas.

Based on the results of the analysis using the Welch t-test, it can be seen that the implementation of PSBB has a significant effect on reducing the incidence of COVID 19 in DKI Jakarta although this is not happening in West Java. This is in line with the fact that applying new normal based on this analysis has had a significant impact on the increase in COVID 19 cases. The government is expected to be able to better educate the public in order to stay alert to the dangers of disease through the implementation of various policies implemented during the PSBB period, such as the burden of restriction and sanctions for violators.

Other than that, the prediction model for each case in Jakarta and West Java uses only historical data calculated without considering other factors that affect the number of cases due to the lack of the data. In this study, it is assumed that all factors that influence each case follow the pattern previously shown in the historical data. The guidelines applied by local governments to reduce the number of COVID-19 cases and behavior of the community in new normal and PSBB transitions also affect estimated results. Therefore, further study is needed to determine which factors influence the estimated value of the number of cases therefore the estimated results are more accurate.

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