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IMPACT OF LARGE SCALE SOCIAL RESTRICTION ON THE COVID-19 CASES IN EAST JAVA

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Abstract: Indonesia is one of the countries affected by COVID-19. The Indonesian government and local governments have issued several guidelines to limit the spread of cases that spread across people in the form of restrictions on physical activity between people. One of the guidelines is large-scale social restrictions (PSBB). PSBB is being implemented in several regions of Indonesia with high COVID-19 cases, including Jakarta, West Java and East Java. Recently, East Java became a province with the highest number of daily new cases, reaching more than 300 reported cases in one day. Some time ago, several regions in Indonesia stopped PSBB policy and took the direction of the New Normal, including East Java. This study suggests machine learning methods that are recognized based on high accuracy, containing Extreme Learning Machines, Multi-Layer Perceptron, and Auto-Regressive Neural Networks to predict the number of daily new, active, confirmed, recovered, and death cases. The MLP (10,10) model was obtained as the best model for predicting the five case variables in East Java for the next 7 days. Based on these results, it can be concluded that the cases in East Java are still increasing. According to this study, the application of the PSBB and the abolition of the PSBB directive, which was replaced by the New Normal directive, had a significant

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impact on the increase in cases in the East Java region. This is in line with the estimation results, which show that cases in East Java tend to increase with fluctuating new daily cases.

Keywords: COVID-19; causal impact analysis; East Java; large scale social restrictions; machine learning.

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1. INTRODUCTION

Since the end of 2019, coronavirus disease 2019 (COVID-19) was spread to a hundred nations and become a global pandemic. Researchers claim that the virus spread rapidly from human to human because by droplets and can spread even in an environment without ventilation with high-grade viral aerosols [1,2]. In order to protect ourselves from this disease, we have to wash our hands with soap and water, keep a distance 1-3 meters away from other people, avoid touching eyes and nose, stay away from the crowd and do quarantine to minimize the spread of the virus [3].

In Indonesia, the first COVID-19 cases were discovered on March 2, 2020, in Depok, West Java. Then, this outbreak spread rapidly to all provinces in Indonesia, with 51.427 positive cases, 21.333 recovered, and 2.683 deaths on June 26, 2020. These numbers are dominated by East Java and DKI Jakarta [4]. Once the confirmed cases increased extensively, the government started to implement a large-scale social restriction also known as PSBB (Pembatasan Sosial Berskala Besar). This restriction means restricting social activities between people, closing schools and workplaces, reducing activities in public places, and restricting transport between regions [5].

By June 26, East Java has reported 10886 confirmed cases with 3619 recovered and 815 deaths. Daily new cases fluctuate, but tend to show an upward trend, with daily cases on May 23, 2020, reaching the highest number at 473 cases [6] then the active cases and confirmed cases getting higher dramatically (Figure 1).

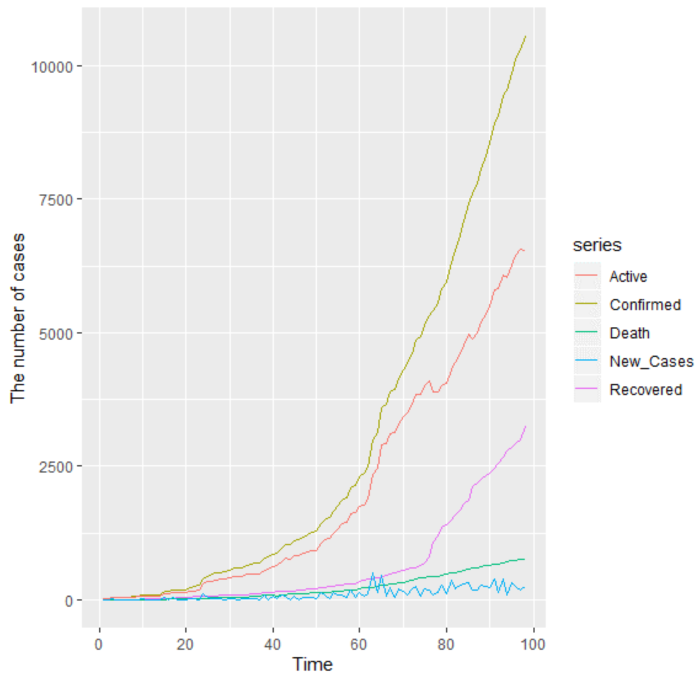

Figure 1. The COVID-19 cases in East Java from March 20, 2020, to June 25, 2020

The governor of East Java, Khofifah, issued the Decree of the Governor of East Java No. 188/202//2020 on the implementation of the PSBB from April 28 to May 11, 2020, in East Java for Greater Surabaya, consist of Surabaya, Gresik, and Sidoarjo [7]. In the first phase of PSBB in the city of Surabaya, the government and police set up 17 checkpoints to restrict drivers entering the city [8]. The number of confirmed cases has actually increased ten days after the PSBB was executed. This is due to the community's poor compliance with health protocols such as physical distancing and masks usage [9]. The PSBB results had not significantly reduced the curve of the new case. Then the governor of East Java decided to run the second phase of the PSBB by May 25, 2020 [10]. FKM UNAIR alumni propose three recommendations for the next PSBB implementation: intensive discipline enforcement, expansion of the PSBB area and monitoring the trend of COVID-19 cases so that the results are optimal [11].

At the end of June, East Java had the highest number of new cases in Indonesia. The worst cases occurred in the city of Surabaya with an average of 100 new cases since the revocation of PSBB. As a result, the city was classified as a "black zone" on June 3, 2020, after the number of confirmed cases rise immediately [12]. Greater Surabaya will go through a transition phase towards "New Normal" from June 8 to June 22. Tri Rismaharini as the mayor of Surabaya City has decided to end the PSBB period in order to restore economic activity. Even though the PSBB period has ended, the government will draft stricter health protocol and ask the police and army for help to ensure that the public adheres to the health protocol [13]. The "New Normal" scenario is being tested for several provinces in Indonesia with the condition of the reproduction number (R_0) <1. For regions with ascending curves, such as East Java, the president urged the army and police to discipline the public to reduce the level of infection [14]. The government regrettably needs to consider the New Normal policy because COVID-19 cases in East Java are increasing day by day. The new normal policy is expected to suppress COVID-19 cases but may also cause an increase in virus transmission if the implementation is incorrect [15].

This study, ergo, aims to predict the number of confirmed cases, recovered cases, death cases, active cases, and the daily new cases in East Java using a simple model using historical data since March 20, 2020, without reckoning with other factors. This means that the results of this prediction will occur unless another government intervention is made, the behaviour of the community does not change, and no more effective treatments are found. Therefore, the analysis for the significance of PSBB and New Normal is also employed. Likewise, modelling by many researchers around the world is used to estimate the number of cases of this outbreak and the peak of this disease. Notwithstanding, due to the lack of past epidemiological information, it is difficult to predict as this pandemic only occurs around the world [16]. In this study, different machine learning methods are employed, taking in extreme Learning Machine, Multilayer Perceptron and Auto-Regressive Neural Network. These methods previously used in South Korea in forecasting the next seven days [17] and in Indonesia to estimate the number of cases after PSBB was implemented [18] both of them achieved good accuracy. Historical data used to predict the number of cases is automatically trained using software by setting and/or optimizing parameters that will be used in the methods previously described.

2. MATERIAL AND METHODS

2.1 Material

The variables that will be used in this study are active cases, confirmed cases, recovered cases, death cases, and daily new cases. Confirmed cases are the cumulative data of the number of infected people from March 2, 2020. Recovered cases are the cumulative data of the number of people who had recovered from the disease. Death cases are the cumulative data of the number of died people because of this pandemic. Active cases are the number of hospitalized patients and self-isolation patients, in other words, the difference between confirmed cases and closed cases, namely recovered and death cases. Daily new cases are the difference of confirmed cases in one day and previous day. The historical data of all the cases caused by COVID-19 in East Java starting March 20, 2020, to June 25, 2020, will be trained using three methods of machine learning and the last two weeks data will be used to verified model performance. From the best model, then, forecasting results will be generated. The dataset was available in Indonesian Task Force of COVID-19 Rapid Response. Furthermore, we will use the dataset in the province of Aceh with the same period for the control variable.

2.2 Extreme Leaning Machine (ELM)

ELM is a rapid learning algorithm for the single hidden layer feed-forward neural networks proposed by Vapnik [19]. Moore-Penrose pseudoinverse [20] is used to determine the output weight under the criterion of the least-squares method [21]. 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 $\widetilde{N}$ hidden nodes and activation function *f(x)* are computationally model as

$$\sum_{i=1}^{\widetilde{N}} \beta_i f_i(x_j) = \sum_{i=1}^{\widetilde{N}} \beta_i f(a_i . x_j + b_i) = t_j \text{ with } j = 1, 2, \dots, N, \quad (1)$$

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

i^{th} hidden and output nodes. The activation function that used commonly is sigmoid, sine, and RBF. Equation 3 also can be written as $H\beta = T$ where:

$$\boldsymbol{H}(a_1, \dots, a_{\tilde{N}}, b_1, \dots, b_{\tilde{N}}, x_1, \dots, x_N) = \begin{bmatrix} f(a_1.x_1 + b_1) & \cdots & f(a_{\tilde{N}}.x_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ f(a_1.x_N + b_1) & \cdots & f(a_{\tilde{N}}.x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}},$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m}, \boldsymbol{T} = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\tilde{N}}^T \end{bmatrix}_{N \times m}.$$

H is the so-called hidden layer output matrix of the network, the i^{th} column of H is the i^{th} hidden node output concerning inputs. Once the input weights and hidden layer biases are stubborn according to the arbitrary allocation, pursuant to the input samples might obtain the hidden layer output matrix. Accordingly, the training process of the ELM is broke down into solving linear equations $H\beta = T$ least-squares solution. The smallest norm least-squares solution of $H\beta = T$ is

$$\widehat{\boldsymbol{\beta}} = \boldsymbol{H}^{\dagger}\boldsymbol{T}. \tag{2}$$

$H^{\dagger}$ means Moore-Penrose pseudoinverse of the H. In general, the optimal solution of $\hat{\beta}$ covers some characteristics. The optimal generalization ability of the minimum model of the output link weights and network. The local optimal solution might prevent to produce due to the exclusive of $\hat{\beta}$.

2.3 Neural Network (NN)

NN is a method of machine learning proposed by McCulloch and Pits [22]. 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 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.

2.4 Multi-Layer Perceptron (MLP)

FFNN has an input layer, an output layer, and one or more hidden layers. SLP or perceptron has no hidden layer and MLP has one or more hidden layers. MLP gives better results once compared with SLP [23]. Each neuron in a hidden layer carries out the computation in Eq. 3 on its inputs and conveys the result (O_c) to the consecutive layer of the neurons.

$$O_c = h_{Hidden}\left(\sum_{p-1}^{P} i_{c,p} w_{c,p} + b_c\right) \text{ wherever } h_{Hidden}(x) = \frac{1}{1+e^{-x}} \tag{3}$$

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 Eq. 3, $h_{Hidden}(x)$ 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. Each neuron in the output layer performs the computation in Eq. 4 on its inputs and transmits the outcome (O_c) to a network output.

$$O_c = h_{Output}\left(\sum_{p-1}^{P} i_{c,p} w_{c,p} + b_c\right) \text{ wherever } h_{Output}(x) = x \tag{4}$$

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. BP algorithm is a generalization of the LMS algorithm or generalized delta rule. It learns a set of weights and biases iteratively. MLP may be elongated to many layers due to the BP algorithm. The execution time of the MLP rise in a row with the increasing of the hidden layer, instead of to improve accuracy.

2.5 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 beginning weights, a sum of revises networks is fitted. Once computing forecasts, at that point, these are found the middle value of. 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 [24].

2.6 Metric Evaluation

After obtaining a model for prediction from the training process, the model is evaluated with testing data to get the predicted accuracy value of the model in every day. The testing data will be evaluated using Absolute Percentage Error in every single day. RMSE, MAE, MASE to evaluate error for the next future values. Root Mean Square Error (RMSE) is widely used when comparing methods with the same unit. For the benchmark, we also carried out Mean Absolute Error (MAE) and Mean Absolute Scaled Error (MASE).

$$APE = \frac{\left|X_t - \hat{X}_t\right|}{X_t} x100\% \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(X_t - \hat{X}_t)^2} \tag{6}$$

$$MAE = \frac{\sum_{t=1}^{n}\left|X_t - \hat{X}_t\right|}{n} \tag{7}$$

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

where n is the number of observations, X_t is the observed value, and $\widehat{X_t}$ is the predicted value. A model can be said to be good if the value of APE is under 20% and the selected model for prediction is the model which has the smallest RMSE, ME, MAE, MAPE, and MASE values.

2.7 Causal Impact Analysis

This analysis is proposed by [25] using a Bayesian structural time series model. The time series model structure is a state-space model for time series data, which is determined as follows:

$$y_t = \boldsymbol{Z_t^T} \alpha_t + \varepsilon_t, \tag{9}$$

$$\alpha_{t+1} = \boldsymbol{T_t} \alpha_t + \boldsymbol{R_t \eta_t}, \tag{10}$$

where $\varepsilon_t \sim N(0, \sigma_t^2)$ and $\eta_t \sim N(0, Q_t)$ are independent of all unknown data. Eq. 9 is an observation equation that combines the y_t observation data with the latent state vector α_t. Eq. 10 is the state equation that is validated by the state of the vector α_t overtime. y_t is the observation value, Z_t is the output vector, T_t t is the transition matrix, R_t is the control matrix, ε_t is the error value of the observation with noise variant, σ_t and η_t is the error value of the system with the diffusion matrix Q_t, where $q \leq d$.

The above model is a generalization of ARIMA and VARIMA. The state-space model can be discussed by considering components of time series, trends, seasonal, regression effects and others. Basic state-space models are basic structured models like the following:

$$\begin{aligned} y_t &= \mu_t + \tau_t + \beta' x_t + \varepsilon_t \\ \mu_{t+1} &= \mu_t + \delta_t + \eta_{\mu,t}, \\ \delta_{t+1} &= \delta_t + \eta_{\delta,t}, \\ \gamma_{t+1} &= -\sum_{s=0}^{S-2} \gamma_{t-s} + \eta_{\gamma,t} \end{aligned} \tag{11}$$

where $\eta_{\mu,t} \sim N\left(0, \sigma_\eta^2\right)$ and $\eta_{\delta,t} \sim N\left(0, \sigma_\delta^2\right)$. The model in Eq. 11 takes into account the trend component (δ_t), the seasonal component (γ_t) and μ_t is the regression coefficient β with intercept.

Bayesian time series or probabilistic time series $y_T = y_1, y_2, \ldots, y_t$ require a common distribution of $p(y_T)$, assuming that y_T is dependent. Modelling independence with likelihood functions in a time series data is more difficult than in cross-sectional data. Time steps have to be developed to include statistical independence in time series data. One of them is the Bayesian concept as follows:

$$p(y_t|y_{T-1}) = \frac{p(y_t, y_{T-1})}{p(y_{T-1})} = \frac{p(y_T)}{p(y_{T-1})} \tag{12}$$

$$p(y_T) = p(y_t|y_{T-1})p(y_{T-1}) \tag{13}$$

$$p(y_T) = \prod_{i=1}^{t} p(y_i|y_{1:i-1}) \tag{14}$$

where $p(y_i|y_{1:i-1}) = p(y_i|y_{t-m:t-1})$ corresponds to the m-order in the Markov model. Bayesian data expansion is the main tool with which simulations can be generated from the posterior distribution of $p(\alpha|y)$. While the parameter model for the posterior distribution state $p(\theta, \alpha|y_T)$ can be interesting in itself, the analysis of the causal impact is related to the posterior incremental.

The evaluation of the post-intervention in a long time after the intervention considering the growth rate in the final stage then rises to zero until the cumulative rate of increase of the total value increases in the counterfactual evaluation period. The average impact will ultimately be zero if the intervals in both cases differ, which lead to conclusions that are increasingly inappropriate in the expected period.

3. RESULTS AND DISCUSSION

This study will forecast the number of confirmed cases, recovered cases, death cases, active cases, and the addition of daily cases in the province of East Java. Variables used for confirmed cases, recovered cases, and death cases are cumulative data from March 20, 2020, to June 25, 2020. While active cases are the difference between confirmed and closed cases, or death and recovered cases. This active case provides information about the number of positive COVID-19 patients in both hospital care and self-isolation. The number of active cases will decrease when this pandemic reach the peaks. However, if the curve still shows an exponential function, the pandemic has not peaked, so the end of the disease is still unpredictable. The last variable is the daily new cases, which is the difference between the cases confirmed today and the previous day. The daily new cases are still varying overtime. This can occur due to various factors, such as PSBB, rapid test, accumulation of untested samples etcetera.

The prediction of the five variables is done using various machine learning methods, namely ELM and NN, including MLP and NNAR, which represent the development of the autoregressive method. The entire method was analyzed using the R software using the nnfor package. In the analysis, there are features of each model through optimization or manual adjustment to attain optimum solution, for example, the number of neurons used.

In the ELM method, the number of hidden nodes to achieve the optimal model which obtained through 20 repetitions are 91 hidden nodes for death cases with univariate lag (1,4), 92 hidden nodes for active cases and confirmed cases with univariate lag (2,3) and 93 hidden nodes for recovered cases and daily new cases with univariate lag (1,2). Initial weights are estimated using the least absolute shrinkage and selection operator method to prevent overfitting. Besides, the MLP method uses the same univariate delay as the ELM method. In the MLP method, regrettably, the number of hidden nodes was predetermined, which is 20 hidden nodes for models with one hidden layer and 10 hidden nodes on each layer for models with two hidden layers. The last method is the NNAR. The output of this method is a linear output that receives the optimal model from an average of 20 networks. For all models with the exception of the number of daily new cases, the network formed is 1-1-1 with the order NNAR (1,1) and 4 weights. A 3-2-1 network with 11 weights is formed for the variable addition of the daily cases.

Before generating a forecast, the methods described above are trained to find the best forecast model, on the other word, the model with the lowest value for metrics evaluation. The model evaluation is carried out using 3 different metrics, i.e. RMSE, MAE and MASE. All three rate differently. RMSE uses the square of errors to evaluate the model, which is then rooted. MAE evaluates the model by the absolute error value and finally, MASE evaluates the model using the scaled error technique. The values of the metrics are shown in Table 1.

Table 1. Metrics evaluation of all the models

Variable	Metrics	RMSE	MAE	MASE
Active	NNAR	88.40944	53.58668	0.709225
	MLP (20)	74.28755	47.52471	0.649397
	ELM	98.50236	72.93889	0.996667
	MLP (10,10)	26.899	17.00585	0.232375
Confirmed	NNAR	78.34542	50.00325	0.460619
	MLP (20)	57.32022	39.08369	0.381524
	ELM	76.65787	56.20979	0.548705
	MLP (10,10)	25.36718	18.26471	0.178295
Recovered	NNAR	37.50509	16.70738	0.500808
	MLP (20)	21.80642	10.53318	0.346802
	ELM	43.65458	26.09565	0.859191
	MLP (10,10)	8.461073	5.293344	0.174282
Death	NNAR	4.714062	3.419347	0.422518
	MLP (20)	3.705056	2.565327	0.328248
	ELM	5.262638	4.258015	0.544836
	MLP (10,10)	2.661569	1.750024	0.223925
Daily New	NNAR	60.01131	41.81858	0.551816
	MLP (20)	57.11647	38.32583	0.503512
	ELM	83.21058	53.117	0.697833
	MLP (10,10)	55.88354	37.29153	0.489924

Based on Table 1 it can be seen that the MLP (10,10) is the best model since the value of the three metrics evaluation is the smallest value in comparison to other models for all variables. The forecast for the five variables, then, is carried out with the MLP model (10,10). The length of the intervals for the forecast is determined based on the performance of the model measured with Absolute Percentage Error (APE) to test the data for the past two weeks from June 12, 2020, to June 25, 2020.

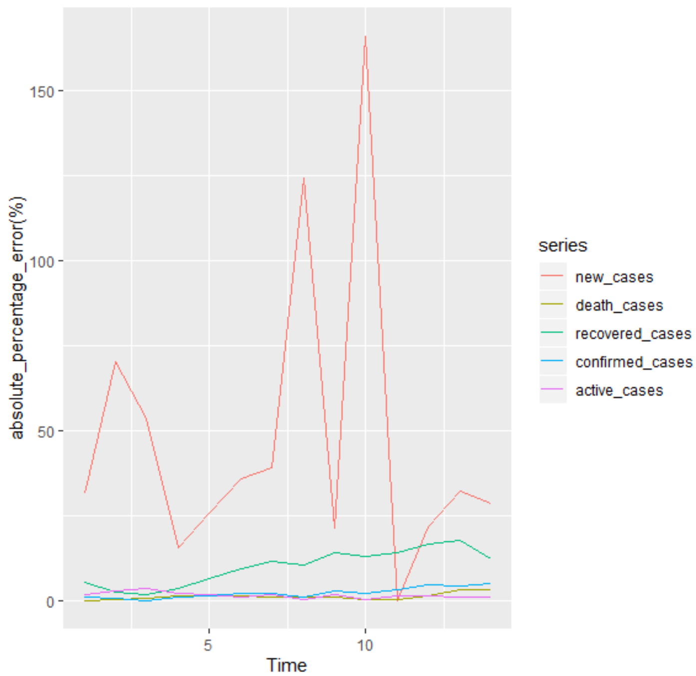

Figure 2. The values of APE in two weeks

In Figure 2 it can be seen that the APE value for daily new cases is very high because the number of daily additions recorded is very volatile. The reason for this was the accumulation of test results from the previous day at ITD Unair, as the deputy governor of East Java, Emil Dardak, reported that there were infected staff so that ITD Unair had limited operations [26]. For death, confirmed, and active cases, the APE is less than 10%, while for recovered cases it is less than 20%. Therefore, a forecast is made for the next 7 days, taking into account that the APE value exceeds 10% for all cases with the exception of the daily new cases after the seventh day. The forecast results with the MLP model (10,10) are shown in Table 2 and the plot is shown in Figure 3.

Table 2. The forecasting results of each case using MLP (10,10) model

Date	Active	Confirmed	Recovered	Death	Daily New
26/06/2020	6600	10764	3310	777	272
27/06/2020	6853	10961	3364	789	191
28/06/2020	6868	11171	3434	808	282
29/06/2020	6996	11384	3499	823	279
30/06/2020	7159	11613	3589	838	208
01/07/2020	7324	11925	3670	853	281
02/07/2020	7535	12193	3880	862	286
03/07/2020	7590	12461	4008	874	218
04/07/2020	7767	12873	4047	887	295
05/07/2020	7896	13056	4153	900	295
06/07/2020	7884	13384	4251	910	231
07/07/2020	8112	13666	4366	922	313
08/07/2020	8139	13957	4404	935	305
09/07/2020	8422	14224	4536	947	241

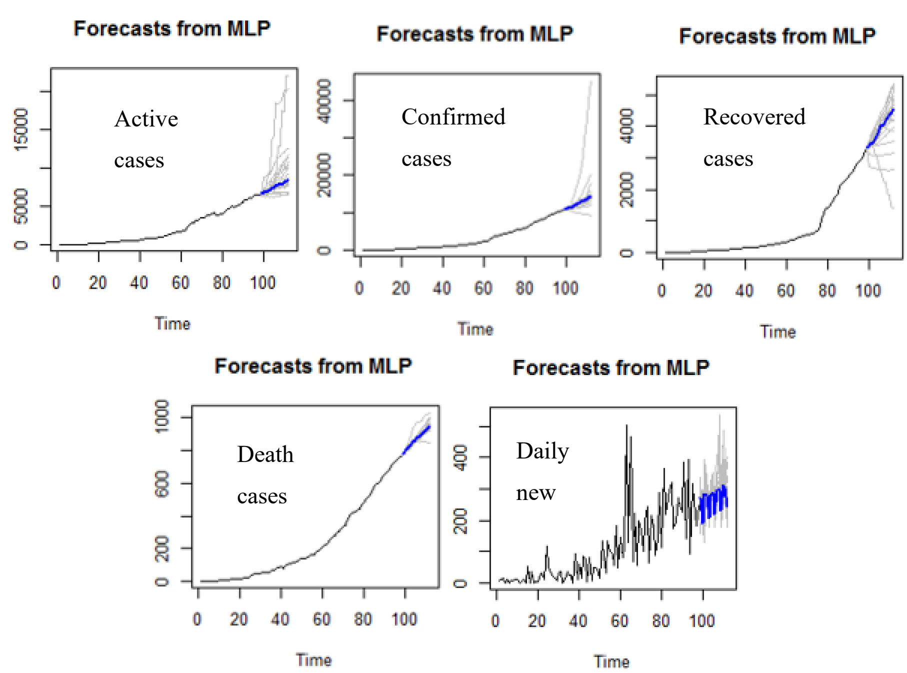

Figure 3. The graph of forecasting results

From the results of the forecast, then the causal impact analysis is performed to find out if there is a difference in the increase in cases in East Java after PSBB and new normal policy was implemented. This analysis was conducted by using the province of Aceh as the control variable since that province did not implement the PSBB. The results of this test are shown in Table 3 and the plot of the daily new cases during, before, and after implementation of the PSBB policy illustrated in Figure 4.

Table 3. The p-value of causal impact analysis

Conditions	Active	Confirmed	Recovered	Death	Daily New
PSBB	0.001	0.001	0.001	0.001	0.001
New normal	0.001	0.002	0.001	0.001	0.001

(a) First intervention: PSBB policy is implemented (April 28 – June 8)
(b) Second intervention: New normal policy is implemented (June 9 – June 25)

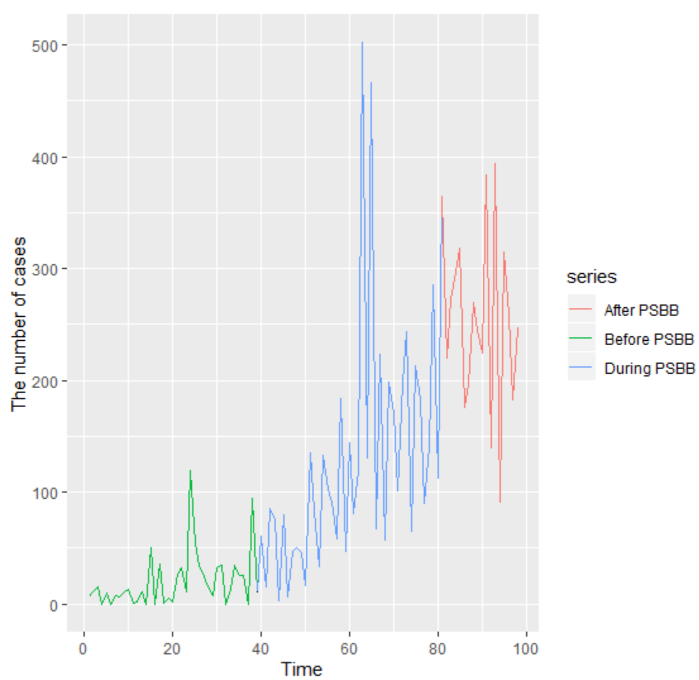

Figure 4. The graph of daily new cases in East Java

Based on the test results in Table 3, it can be concluded that the adoption of the PSBB and the elimination of the PSBB had a significant impact on the COVID-19 case in East Java. In addition, Figure 4 shows that the daily addition of new cases fluctuates greatly and shows an upward trend (positive trend). On the other hand, forecast results from confirmed, recovered, and deaths of COVID-19 in East Java also continue to increase ominously, and forecasting results of active cases have not yet peaked in this case. On the other hand, the forecast results for adding daily new cases still fluctuate as in previous data patterns (Figure 3).

4. CONCLUSIONS

It is known that neural networks, as one of the methods of machine learning, provide good accuracy and can adapt to fluctuations that are not too extreme. Based on tests, we can conclude that the MLP model (10,10) works best in all cases. However, this model can predict in short-term intervals (less than 7 periods).

After the provincial government of East Java announced that it would not extend the PSBB, the forecast value for daily new cases in East Java continued to fluctuate without showing a clear downward trend. In other words, in these cases, the government and community must still be aware of the increasing of this outbreak. Based on the results of the causal impact analysis, we can also conclude that the government intervention known as PSBB has a significant impact on the daily new and active cases. After the adoption of the PSBB was stopped and the new normal system was implemented, thereby, there were also significant differences. Moreover, the forecasting results showed that the COVID-19 case in East Java would still increase drastically. We hence assume that the state intervention, namely PSBB, has been well managed by the community and that the increase in cases after the PSBB deadline has been extended is also still showing a positive trend, which means that the health protocol has not been fully implemented. It can therefore generally be concluded that intervention by the local government to break the COVID-19 transmission chain was considered unsuccessful. Figure 3 shows that the active cases in East Java continue to increase without showing the peak of the pandemic. More importantly, new cases fluctuate daily by showing an upward trend. If this situation continues, obviously, the capacity of the hospital is full, even if patients with mild cases only need to be isolated independently at home.

The best predictive model for each case in East Java only uses daily historical data, which is calculated without considering other factors that affect the number of cases, as this study assumes that all factors that affect each case fit the pattern in historical data follow. Furthermore, the guidelines applied by local governments to reduce the number of COVID-19 cases and the behaviour of the community also affect forecast results. If people do not follow government commendation, forecast results will actually be existing that indicate this increase. The results of this prognosis are expected to be health information to anticipate an increase in patients. This information is also intended to raise government and community awareness. Further investigation is needed to determine which factors affect the estimated value of the number of cases so that the estimation results are more accurate.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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