Forecasting model of COVID-19 pandemic in Malaysia: An application of time series approach using neural network

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C H R O N I C L E	A B S T R A C T
	COVID-19 has spread to more than a hundred countries worldwide since the first case reported in late 2019 in Wuhan, China. As one of the countries affected by the spread of COVID-19 cases, the local government of Malaysia has issued several policies to reduce the spread of this outbreak. One of the measures taken by the Malaysian government, namely the Movement Control Order, has been carried out since March 18, 2020. In order to provide precise information to the government so that it can take the appropriate measures, many researchers have attempted to predict and create the model for these cases to identify the number of cases each day and the peak of this pandemic. Therefore, hospitals and health workers can anticipate a surge in COVID-19 patients. In this research, confirmed, recovered, and death cases prediction was performed using the neural network as one of the machine learning methods with high accuracy. The neural network model used is the Multi-Layer Perceptron, Neural Network Auto-Regressive, and Extreme Learning Machine. The three models calculated the average percentage error (APE) values for 7 days and obtained APE values for most cases less than 10%; only 1 case in the last day of one method had an APE value of approximately 11%. Furthermore, based on the best model, then the forecast is made for the next 7 days. In conclusion, this study identified that the MLP model is the best model for 7-step ahead forecasting for confirmed, recovered, and death cases in Malaysia. However, according to the result of testing data, the ELM performs better than the MLP model.

1. Introduction

The COVID-19 disease started in Wuhan, China, as of the end of December 2020. On June 15, 2020, this outbreak spread to 215 countries and territories, also affecting 8,128,490 people, with 439,421 deaths (Worldometer, 2020). Due to the severity of the virus, on January 30, 2020, the World Health Organization (WHO) declared that the COVID-19 epidemic had become a global health emergency of international concern. In Malaysia, the first case of COVID-19 was confirmed on January 25, 2020, involving three Chinese citizens who entered Johor Bharu, Malaysia, via Singapore on January 23, 2020 (Foo *et al.,* 2020). Out of 32 million total population, Malaysia has reported 8,494 confirmed cases of COVID. -19 cases with 121 deaths in mid-June 2020. COVID-19 spread through direct or indirect contact, droplet spray for short-range transmission, and aerosol for long-distance transmission (Moriyama *et al.,* 2020). In order to support the belief that the virus spreads between people in close contact with each other through respiratory droplets that arise when an infected person coughs, sneezes, or speaks, possibly from people through contact with contaminated surfaces or objects (CDC, 2019). COVID-19, thus, can also be spread by people

who show no symptoms (Rettner, 2020). However, person-to-person transmission is an essential factor in the spread of this outbreak through any activity related to physical interactions (Dalton *et al.,* 2020). As the number of deaths from global transmission through the community has increased, governments in several countries have put a barrier to control this pandemic, namely lockdown. The UK government estimates that mortality rates can increase rapidly and prevent social distance from being maintained (Mahase, 2020). Physical and social distance measurements aim to reduce the spread of disease by disrupting the chain of COVID-19 transmission and preventing the emergence of new ones. The initiative guarantees a physical distance between people (at least one meter) and minimizes face-to-face interaction while promoting and maintaining virtual social relationships within families and communities (WHO, 2020). However, government measures might overcome the other problems, such as mental health conditions, especially for the children (Pontoh *et al.,* 2021a), economic stability in a country (Pontoh *et al.,* 2021b).

To fully contain the virus, the Malaysian Prime Minister announced the four phases of the Movement Control Order (MCO) because they guessed that the number of COVID-19 cases would continue to increase (PMO, 2020) from March 18 to prevent widespread use (Arumugam, 2020). Figure 1 shows that the number of confirmed cases significantly increased day by day since early March. The ban during the MCO will continue to put pressure on the Malaysian tourism industry, and therefore effective measures to support industry players are crucial (Foo *et al.*, 2020). The Malaysian government has also announced that it will avoid unnecessary public gatherings, including sporting, social, cultural, and religious events, and maintain social distance from others (Haque *et al.,* 2020). The main focus of social distance is the physical distance to others, where public places such as supermarkets, bazaars, and shopping centers are to be avoided (FMT, 2020). Social alignment is a public health technique that people can use to slow the spread and spread of infectious diseases such as coronaviruses. These local measures had been done in Indonesia and worked effectively to control the pandemic's spread (Pontoh *et al.,* 2020a).

Although the number of deaths reported in the country on the hyperbolic curve is not increasing (Fig. 1), there is an urgent need to be well prepared to deal with the deaths from this epidemic. It is important not only for health professionals but especially for first aiders. The positive COVID-19 cases active in Malaysia have continued to increase since March 2020. The National Institute of Forensic Medicine (IPFN) in Malaysia has to look to the worst-case scenario of a sudden increase in the number of deaths due to COVID-19 to prepare, which can exceed the capacity of forensic services (Khoo *et al.,* 2020) because the number of confirmed cases is dramatically rising. Due to the intervention announced by the government, the number of death cases keeps steadily increasing to 100 cases (see Fig. 1). As of May 13, 2020, the number of deaths in Malaysia had only increased by 9. Besides that, the cure rate of COVID-19 patients in Malaysia is quite high, i.e., 86% as of June 13, 2020.
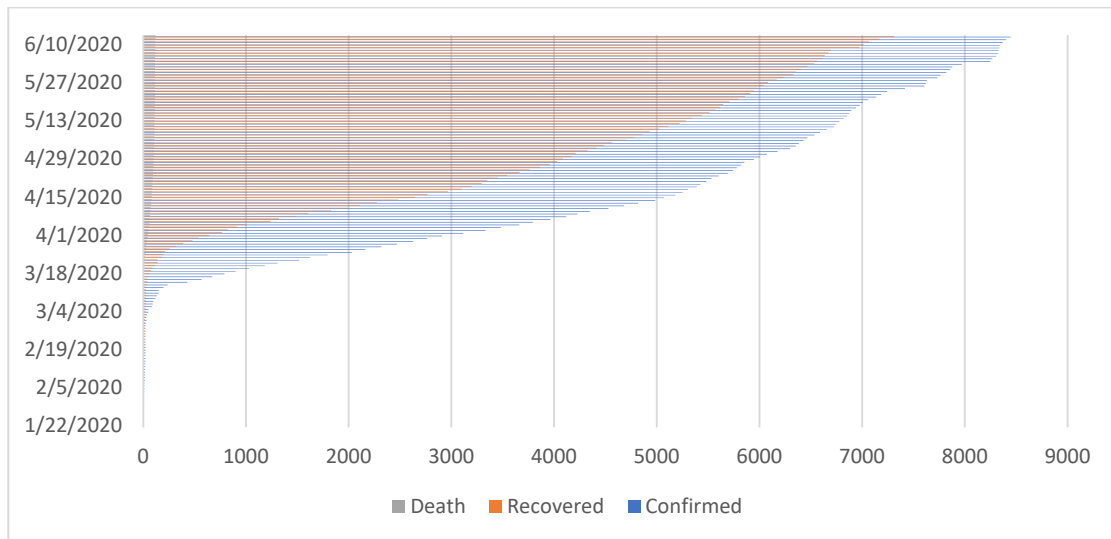

Fig. 1. The confirmed, recovered, and death cases in Malaysia
Note: January 22, 2020, to June 13, 2020

Many researchers worldwide tried to perform modeling also forecasting the number of this outbreak's cases and the peak of this disease. However, forecasting is more difficult due to the lack of past epidemiological information (Huang *et al.,* 2020). In addition, interventions by the current government are varying the results of forecasting uncontrollably. This research aims to find the most appropriate model to predict the number of confirmed, recovered, and death cases in Malaysia. All models used in this study are simple models that do not consider other factors that can affect the development of these cases. In this study, we created a representation model for the number of COVID-19 cases using different neural network models, specifically Neural Network Auto-Regressive, Multi-Layer Perceptron, and Extreme Learning Machine. These models were used previously in South Korea and obtained good accuracy for seven-step ahead forecasting (Pontoh *et al.,* 2020b).

2. Materials and Methods

The historical data of the number of confirmed, recovered, and death cases of the COVID-19 pandemic in Malaysia would separate into training and testing. The training data are starting January 22, 2020, to June 6, 2020, and testing data starting June 7, 2020, to June 13, 2020. From the best model, then, forecasting results are generated for the next seven-day. The datasheet was available in Novel Coronavirus (COVID-19) Cases Data provided by Humanitarian Data Exchange.

2.1 Artificial Neural Network (ANN)

ANN, first introduced by McCulloch and Pits in 1943 (McCulloh and Pits, 1943), is an associate science system that is believed to be highly accurate (Fausset, 1994). ANN has three types of layers: the input layer, output layer, and hidden layer. ANN is divided into two types, Feed Forward Neural Network (FFNN) and Recurrent Neural Network (RNN). FFNN is a network where connections between neurons in a layer do not form cycles as the RNN performed, which means that the input only propagates forward from the input level to the output level (Toharudin *et al.,* 2021).

2.2 Multi-Layer Perceptron (MLP)

The machinability in perceptron for single-layer feed-forward networks is targeted by (Rosenblatt 1962). FFNN is the foremost well-known neural network model for applications of time series prediction. It considers a single hidden layer with many neurons. A total of rehashes systems are fitted, each with random beginning weights that arrive at the midpoint of once processing forecasts.

Two types of FFNN are Single-Layer Perceptron (SLP) with no hidden layer and Multi-Layer Perceptron (MLP) with one or more hidden layers. From a statistical point of view, MLP's universal approximation ability arises from the nonlinearities used in the neurons (Du and Swamy, 2013). Every single connection between the input to neuron and neuron to the neuron is adjusted by weight. Also, every single neuron has an additional input, namely bias, that a persistent value of one is assumed (Plummer, 2000). Once the network is running, each neuron in a hidden layer carries out the computation on its inputs and conveys the result (O_c) to the consecutive layer of the neurons.

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

Eq. (1) is an activation function of a neuron in a hidden layer. Where O_c is that the output of the existing hidden layer neuron c, P is the number of neurons among the earlier hidden layer or the network input, $i_{c,p}$ is input to neuron c of the earlier hidden layer neuron p, $w_{c,p}$ is the weight that modifies the link from neuron p to neuron c, and b_c is the bias. In Eq. (1), $h_{Hidden}(x)$ is the sigmoid activation function of the neuron. Hence, the data should be scaled to avoid the network being more durable during the training process. In the same way, to fittingly scaled data before training, the weights and biases are initialized. Each neuron in the output layer carries out the subsequent computation equation on its inputs and transmits the outcome (O_c) to a network output.

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

Eq. (2) is the activation function of associate neurons in the output layer. Where O_c is the output of the existing output layer neuron c, P is the number of neurons among the earlier hidden layer, $i_{c,p}$ is the input to neuron c from the earlier hidden layer neuron p, $w_{c,p}$ is the weight that modifies the link from neuron p to neuron c, and b_c is the bias. Activation function will be used for $h_{Output}(x)$ is a linear activation function.

2.3 Neural Network Auto Regression Model (NNAR)

A feed-forward neural network is fitted with slacked estimations of y as inputs and a single hidden layer with extent neurons. The inputs are for lags 1 to p, and lags m to MP where $m = freq(y)$. On the off chance that x_{reg} is given, its columns are additionally utilized as inputs. However, if there are missing values in y or x_{reg} the relating rows are discarded from the fit. A sum of rehashes networks is fitted, each with irregular beginning weights. Once computing forecasts, at that point, these are found the middle value. The network processes multi-step predictions, although one-step predictions are prepared. The fitted model for data with a non-seasonal pattern is NNAR (p,k), where k is the number of hidden neurons. It is practically equivalent to an AR(p) with non-linear functions. However, while linear AR can model cyclicity, the modeled cycles are always symmetric. In contrast, the cyclicity in the NNAR model has been modeled well and captured the asymmetry of the cycles. It is the one difference between AR and NNAR (Hyndmann & Athanasopoulos, 2018).

2.4 Extreme Learning Machine (ELM)

ELM was proposed by Huang *et al.* (2004). ELM is a rapid learning algorithm for the single hidden layer feed-forward neural networks, overcomes the debility of the previous neural network in the process of learning speed because ELM could be reducing the training time and improving the generalization performance (Wang *et al.,* 2014; Huang *et al.,* 2006*)*. The weights

and biases of the hidden neurons are set randomly. Moreover, Moore-Penrose pseudoinverse (Liang and Huang, 2006) is used to determine the output weight under the criterion of the least-squares method (Xiao *et al.*, 2017). For N random definite samples (x_i, t_i), wherever $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2}, \ldots, t_{in}]^T \in R^m$, more, $(x_i, t_i) \in R^n x R^m$ and $i = 1, 2, \ldots, N$. Standard ELM with $\widetilde{N}$ hidden neurons and activation function $f(x)$ are computationally model as

$$\sum_{i=1}^{\widetilde{N}} \beta_i f_i(x_j) = \sum_{i=1}^{\widetilde{N}} \beta_i f(a_i . x_j + b_i) = t_j \text{ with } j = 1, 2, \ldots, N, \tag{3}$$

where $a_i = [a_{i1}, a_{i2}, \ldots, a_{in}]^T$ is the weight vector that linking the ith hidden and input neurons, bi is the threshold of the ith hidden neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ is the weight vector linking the ith hidden and output neurons. The activation function that used commonly is sigmoid, sine, and RBF. Equation 3 also can be written as $H\beta = T$ where:

$$H(a_1, \ldots, a_{\widetilde{N}}, b_1, \ldots, b_{\widetilde{N}}, x_1, \ldots, x_N) = \begin{bmatrix} f(a_1 . x_1 + b_1) & \cdots & f(a_{\widetilde{N}} . x_1 + b_{\widetilde{N}}) \\ \vdots & \ddots & \vdots \\ f(a_1 . x_N + b_1) & \cdots & f(a_{\widetilde{N}} . x_N + b_{\widetilde{N}}) \end{bmatrix}_{N \times \widetilde{N}}, \beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\widetilde{N}}^T \end{bmatrix}_{\widetilde{N} \times m}, T = \begin{bmatrix} t_1^T \\ \vdots \\ t_{\widetilde{N}}^T \end{bmatrix}_{N \times m}.$$

H is the so-called hidden layer output matrix of the network, the ith column of H is the ith hidden neuron output concerning inputs. ELM allocates to the input link weights a and hidden layer neuron biases b arbitrarily when the training starts. While the training process is unvaried, it could approach any continuous function. As a means to gain better generalization performance, take $\widetilde{N}"N$. The input samples might obtain the hidden layer output matrix once the input weights and hidden layer biases are stubborn according to the arbitrary allocation. Accordingly, the training process of the ELM is broken down into solving linear equations $H\beta = T$ least-squares solution. The smallest norm least-squares solution of $H\beta = T$ is

$$\hat{\beta} = H^\dagger T. \tag{4}$$

$H^\dagger$ means Moore-Penrose pseudoinverse of the H. Generally, 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 optimal local solution might prevent to produce due to the exclusive of $\hat{\beta}$.

2.5 Model 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 every day. The testing data will be evaluated using Absolute Percentage Error every single day. Root Mean Square Error (RMSE) is widely used to assess error for the next seven-day when comparing methods with the same unit. Also, Mean Absolute Error (MAE) is used for the benchmark.

$$APE = \frac{|X_t - \hat{X}_t|}{X_t} \times 100\% \tag{5}$$

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

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

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 10%, and the selected model for prediction is the model which has the smallest RMSE and MAE values.

4. Results And Discussion

The training data are starting January 22, 2020, to June 6, 2020, and testing data starting June 7, 2020, to June 13, 2020. First, the three methods explained before are used to train the data. Then, with the testing data, those models are generated and evaluate the values of APE every single day from June 7, 2020, to June 13, 2020. The APE values for each model are presented in Table 1.

Table 1
The percentage value of APE tested by using NNAR, ELM, and MLP models

Date	NNAR (1,1)			ELM			MLP (5)			MLP (10,5)		
	C	R	D	C	R	D	C	R	D	C	R	D
07 June 2020	0.90	0.96	0.85	1.05	0.16	0.85	0.83	0.03	0.85	0.49	0.12	1.71
08 June 2020	1.57	1.57	0.85	1.84	0.45	1.71	1.80	0.24	1.71	1.27	0.45	3.42
09 June 2020	2.17	5.79	1.71	2.53	2.88	1.71	2.86	3.23	2.56	2.20	2.88	4.27
10 June 2020	2.65	6.56	2.54	3.45	2.81	1.69	4.16	3.17	3.39	3.17	2.69	5.08
11 June 2020	3.41	7.43	2.54	3.98	2.82	2.54	5.23	3.23	4.24	3.85	2.63	5.93
12 June 2020	4.14	8.93	4.20	4.43	3.54	2.52	6.33	3.98	4.20	5.61	3.22	6.72
13 June 2020	4.94	10.86	5.00	4.77	4.75	2.50	7.42	5.21	4.17	6.23	4.34	6.67

From the three models in Table 1, forecasting is performed. Then, the evaluation of the model is carried out for the forecasting for 7-step ahead. The value of metric evaluation for each case that contains RMSE and MAE is shown in Table 2.

Table 2
The value of metric evaluation using the NNAR, ELM, and MLP models

	Confirmed		Recovered		Death	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
NNAR	60.91	48.81	50.64	34.97	1.17	0.74
ELM	40.50	28.80	38.46	27.51	1.14	0.80
MLP (5)	**34.52**	**21.51**	25.60	13.44	0.80	0.46
MLP (10,5)	**34.52**	**21.51**	**7.98**	**4.60**	**0.66**	**0.32**

Table 2 shows the forecasting will be conducted using MLP (10,5) for all the cases because this model has the lowest value of RMSE and MAE, even though MLP (5) and MLP (10,5) have the same values for the confirmed cases. However, as mentioned in Table 1, the minimum APE is produced by the ELM model. Therefore, we will forecast with both models, ELM and MLP (10,5). The interval forecasting results for the next 7-day, in other words, from June 14, 2020, to June 20, 2020, with a 5% error from the point forecast, are mentioned in Table 3, and the plot of forecasting results can be seen in Fig. 2.

Table 3
The forecasting results of ELM and MLP models

|	ELM			MLP (10,5)		
	Confirmed	Recovered	Death	Confirmed	Recovered	Death
14 June 2020	8069-8919	7008-7746	115-127	8070-8920	7004-7742	115-127
15 June 2020	8121-8975	7076-7820	116-128	8123-8979	7092-7838	116-128
16 June 2020	8175-9035	7148-7900	117-129	8177-9037	7194-7952	117-129
17 June 2020	8233-9099	7225-7985	117-129	8237-9104	7299-8067	118-130
18 June 2020	8294-9167	7286-8052	118-130	8297-9171	7353-8127	119-131
19 June 2020	8357-9237	7348-8122	119-131	8358-9238	7498-8288	120-132
20 June 2020	8423-9309	7409-8189	120-132	8418-9304	7617-8419	122-134
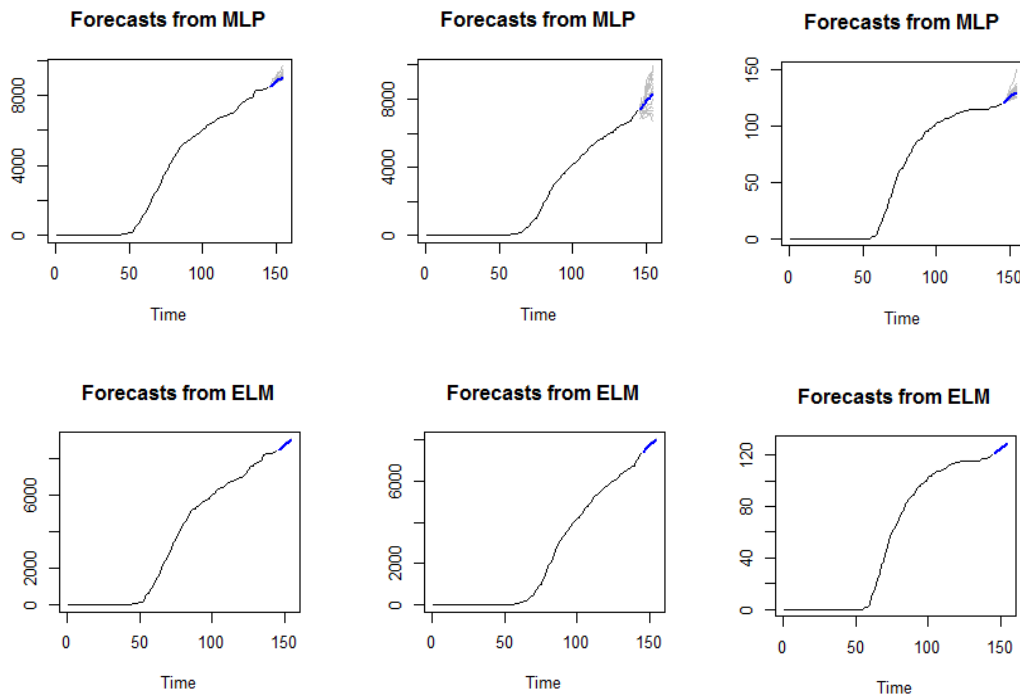
Fig. 2. Results of forecasting using ELM and MLP models
Note: Left to right: confirmed, recovered, deaths with y-axis is the number of cases, and the x-axis is the time period.

The percentage value of APE was tested using NNAR, ELM, and MLP models that showed good accuracy. However, the APE values for all models are below 10%. Only the NNAR model for recovered cases has a value above 10% on the seventh day. Additionally, all models will also be looking for the value of metric evaluation from the combined training and testing data for further prediction in seven days. The best model, then, forecasting results will be generated for the next seven-day. Before that, the characteristics of each model will be explained.

The NNAR method obtained a 1-1-1 network with 4 weights for confirmed, recovered, and death cases. First, it means that the order for both AR and NN is 1 with a difference. Secondly, the ELM method fitted 100 hidden neurons for all the cases with output weight using the lasso and combined the median operator. Lastly, the MLP has two models. On the one hand, MLP has a hidden layer fitted with 5 hidden neurons. Next, MLP with two hidden layers uses 10 hidden neurons in the first hidden layer and 5 hidden neurons in the second hidden layer. The number of hidden neurons is determined earlier. The ELM and MLP reached the optimum model after 20 repetitions with different univariate lags in each case. For the confirmed cases, the univariate lags are (1,3). Univariate lags for the recovered cases are (1,2,3,4) and the death cases, using univariate lags of (2,3,4).

The lag values in the time series can be used as input for an artificial neural network.NNAR uses a single hidden layer for forecasting univariate time series data. Each hidden layer node performs a single sigmoid transformation of its input. The NNAR function produced a good model by averaging the results of 20 networks with linear output units, but it was not the best. A trial-and-error mechanism will produce a better model than the function automatically selected model (Toharudin et al., 2021). Based on Table 2, the forecasting will be conducted using MLP (10,5) for all the cases because this model has the lowest value of RMSE and MAE, even though MLP (5) and MLP (10,5) have the same values for the confirmed cases. However, as mentioned in Table 1, the minimum APE is produced by the ELM model. Therefore, to facilitate it, we will forecast with both models, ELM and MLP (10,5). The interval forecasting results for the next 7-day, in other words, from June 14, 2020, to June 20, 2020, with a 5% error from the point forecast.

5. Conclusion

In conclusion, this study identified that the MLP model is the best model for 7-step ahead forecasting for confirmed, recovered, and death cases in Malaysia. However, according to the result of testing data, the ELM performs better than the MLP model. It is possible that the evaluation of the model was carried out with different metrics. Nevertheless, the interval predictions are not significantly different between the two models. Also, the forecast results for confirmed cases in Malaysia did not increase substantially, or the curves tended to be sloping. It can, therefore, be concluded that the Malaysian government's interventions to manage COVID-19 have been fairly successful. It is certainly also influenced by the community's behavior, which carries out the government interventions well. Modeling the cases in Malaysia used in this study is a simple model without considering other factors that affect the number of these cases. The other factors are assumed to follow the existing pattern. In addition, the policy addition that was implemented by the local government to reduce the number of infected cases with COVID-19 also affected the outcome of the forecasts. Since forecasting the cases becomes hard, further research is needed to find out which factors influence the forecast value of the number of cases so that the forecast results might use another approach obtained more accurately.

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