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## SHORT TERM PREDICTION OF COVID-19 CASES BY USING VARIOUS TYPES OF NEURAL NETWORK MODEL

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**Abstract:** Coronavirus disease 2019 (Covid-19) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The increasing number of positive cases caused by this virus in an area or country is suspected to form a certain pattern. The pattern of growth is thought to follow certain statistical distributions or model. In this research, the three types of neural network model are used to predict the number of Covid-19 cases in Indonesia. The types are Feed Forward Neural Network (FFNN), Cascade Forward Neural Network (CFNN), General Regression Neural Network (GRNN) and Recurrent Neural Network (RNN). The pattern of adding cases which always increases continuously makes the data pattern not easy to predict in the long term. In this study, repeated short-term predictions were carried out. In-sample predictions are repeated after new data are obtained, and so are out-sample predictions. The results show that the out-sample predictions of the three types of neural network are always under the actual value for each repetition. This condition is of course very worrying because the cases have a high possibility to increase more sharply than expected. However, the CFNN as the only type which giving a positive and negative variations of Mean Percentage Error (MPE), is the best model with the smallest error.

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## 1. INTRODUCTION

Coronavirus disease 2019 (Covid-19) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Since a while ago, Covid-19 has been declared a pandemic by World Health Organization because its spread has spread globally to almost all countries. The number of patients who tested positive for the virus continues to increase from day to day. Its growth increased rapidly in just a few days. In Indonesia, the number of cases has also continued to increase rapidly. The increasing number of positive patients, the number of patients treated, the number of people suspected, and the number of deaths caused by this virus in an area or country is suspected to form a certain pattern. The pattern of growth is thought to follow certain statistical distributions or models. The problem is that in almost each country, the actual number of Covid-19 cases are likely much higher than that reported to date due to the reporting delays. Some researchers have tried several deterministic and stochastic models to predict the growth pattern. However, the correctness of the prediction model used will be tested when the outbreak is over. Therefore, a breakthrough is needed to find alternative models that can overcome this problem.

Based on the background, it can be formulated problem that is how to build prediction of Covid-19 confirmed as time series data based on stochastic process with a high level of accuracy. This research will try to do a stochastic modeling approach to predict the number of Covid-19 sufferers in Indonesia. The scope of this research is the use of four types of neural network models to predict the number of Covid-19 sufferers as time series data. Through these modeling, it is hoped that the input-output relationship pattern becomes more perfect and can produce more accurate predictions. For near-term benefit, the sort term prediction models can be used for selecting the best predictions model. This study is expected to answer the problems that have been described previously and specifically.

## 2. PRELIMINARIES

Forecasting technologies through a stochastic approach such as time series and regression models have grown quite rapidly, as the circulation models are drawn up by the laws of physics and expressed in terms of mathematical equations that identify relationships between various variables. The development of stochastic models has been carried out both on parametric and nonparametric models. Predictive models based on statistical approaches are continuously developed to obtain model specifications appropriate to the research location. Modelling time series data relating to epidemiology and environmental health has also been done in depth, also both in parametric and nonparametric models. Bhaskaran [1] has used time series regression to control for seasonality and long-term trends of the daily levels of environmental variables and daily number of deaths and explore shortterm associations between them. Zhang et al [2] have used four time series methods, namely, two decomposition methods (regression and exponential smoothing), autoregressive integrated moving average (ARIMA) and support vector machine (SVM) for predicting the epidemiological surveillance data. Tian et al. [3] have also used time-series modelling and forecasting of hand, foot and mouth disease cases in China by using SARIMA model. Kalligeris et al. [4] have developed a modeling of influenza-like syndrome morbidity by utilizing periodic auto-regressive moving average (PARMA) models. In this research, climatological and meteorological covariates associated with influenza-like syndrome were also incorporated into the model structure.

The development of nonparametric time series modeling in the fields of epidemiology and environmental health has also been carried out. Wu et al. [5] have made an analysis of human brucellosis in mainland China by using Elman and Jordan recurrent neural networks. Wu et al. [6] have developed a deep learning framework to predict epidemiology profiles in the time-series perspective. Recurrent Neural Networks (RNNs) has been adopted to capture the long-term correlation in the data whereas Convolutional Neural Networks (CNNs) has been used to fuse information from data of different sources. Wang et al. [7] have made a research that focused on short-term but high resolution forecasting and propose DEFSI (Deep Learning Based Epidemic Forecasting with Synthetic Information), an epidemic forecasting framework that integrates the strengths of artificial neural networks and causal methods.

Regarding predictions of the growth modelling, Loibel et al. [8] have used Richards growth model

and viability indicators for populations subject to interventions whereas Moroianu & Moroianu [9] have applied Cobb Douglass model for economic growth. In the case of the growth of infectious diseases, Viboud et al. [10] have developed a generalized-growth model to characterize the early ascending phase of infectious disease outbreaks. The using of time series regression model for infectious disease and weather has also been carried out by Imai et al. [11], which was used ARIMA and wavelet models. Modifications proposed to standard time series regression practice include using sums of past cases as proxies for the immune population, and using the logarithm of lagged disease counts to control autocorrelation due to true contagion, both of which are motivated from Susceptible-Infectious-Recovered” (SIR) models. The using of SIR model has also discussed by Wakefield et al [12] whereas the using of ARIMA has carried out by Zhang et al. [13] in the case of temporal and long-term trend analysis of class C notifiable diseases in China. Nonparametric approaches to predicting infectious diseases have been carried out, including by Chae et al. [14] by using Deep Learning and Big Data. Venna et al [15] have applied a novel data-driven model for real-time influenza forecasting whereas Wang et al. [16] have developed a deep learning approach for modeling seasonality and trends in hand-foot-mouth disease incidence in mainland China. Deep Transformer Models also has been used for time series forecasting by Wu et al. [17] in the case of influenza prevalence.

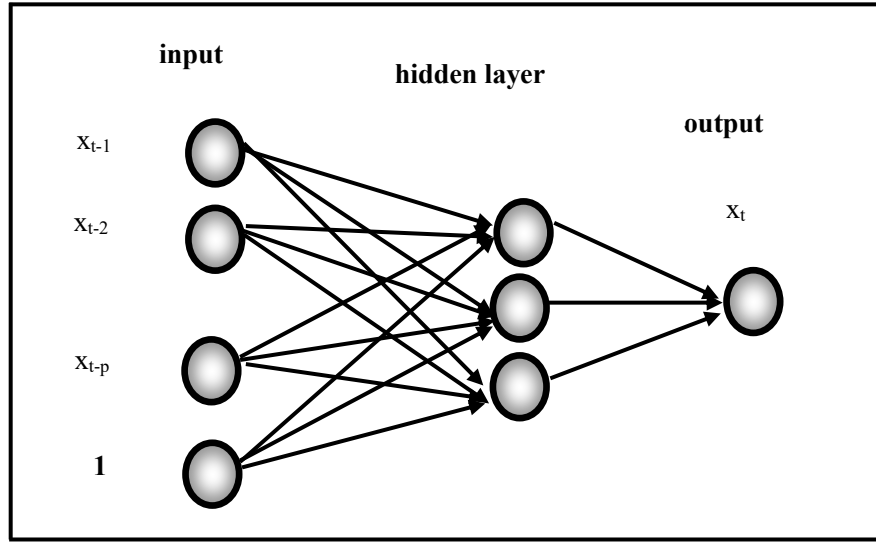
In the research related to the prediction and analysis of coronavirus disease, Jia et al. [18] has adopted three kinds of mathematical models, i.e., Logistic model, Bertalanffy model and Gompertz model for predicting the total number of people expected to be infected in China. Lin et al. [19] has used Susceptible-Exposed-Infectious-Recovered (SEIR) as a conceptual predictive model for the case in Wuhan. Hao [20] has modeled the number of Covid-19 suspected with the integration of the Eyring rate process theory and free volume concept. The using of neural network model for predicting Covid-19 also have been developed, as in China and India [21-24]. In this research, statistical models for predicting the number of Covid-19 confirmed will be developed. The main focus is on the modeling procedure for short term prediction and obtaining the most appropriate model for the case in Indonesia. Various Neural Network models are used for experiments, they are Feed Forward Neural Network (FFNN), Cascade Forward Neural Network (CFNN), General Regression Neural Network (GRNN) and Recurrent Neural Network (RNN).

### 3. MATERIAL AND METHODS

#### 3.1 Feed Forward Neural Network

Feed Forward Neural Network (FFNN), the main class of neural network model, is used in this research. This contains three layers processing, i.e. input layer, hidden layer and output layer. In neural network for time series modeling, the input contains lagged time from past series [25]. The weighted sum of the input is then sent to the hidden layer. A nonlinear activation function in the hidden layer processes the incoming signal from the input. The network then carries out the weighted sum of the signals coming out from the hidden layer. A linear activation function at the output layer then works to produce an output, which is expected to be as close as possible to the intended target. Connection weights between layers in the neural network should be estimated to get the output as expected. Network architecture as described can be seen in Fig. 1.

FIGURE 1. Neural network architecture for predicting time series



Mathematical model of the architecture can be seen in eq. (1).

$$x_t = f^o(w^b + \sum_{j=1}^k w_j^o f^h(w_j^b + \sum_{i=1}^p w_{ji}^h x_{t-1})) \quad (1)$$

The symbols  $w^b, w_j^o, w_j^b, w_{ji}^h$  represent the weights from bias to output, the weights from hidden unit  $j$  to output, the weights from bias to hidden unit  $j$  and the weights from input  $i$  to hidden unit  $j$ , respectively. The numbers of hidden unit  $k$  and lags  $p$  are specified by using a certain technique. The activation function in hidden layer is symbolized by  $f^h$  and in this case the sigmoid logistic is chosen. Whereas, the linear activation function in output layer is symbolized by  $f^o$ . The weights

vector  $w = (w^b, w_j^o, w_j^b, w_{ji}^h)$  could be estimated by using gradient based optimization method.

### 3.2 Cascade Forward Neural Network

Cascade Forward Neural Network (CFNN) model is rather similar with FFNN. There also three layers in the architecture that are input layer, hidden layer and output layer. The most different thing between CFNN and FFNN is the direct and the number of connection weights. Unlike the FFNN, there are connection weights as direct link between the input layer and the output [26]. This connection is the completeness of the indirect link through the hidden layer. The form of direct connection can be flexibly selected, either a linear or nonlinear function. Therefore, the formula that applies to the CFNN model is an extension of the FFNN model as in (1). As a consequence, the number of weights estimated becomes more. The general form of the CFNN model for time series model is written in eq. 2.

$$x_t = \sum_{i=1}^p f^i w_i^i x_{t-i} + f^o (w^b + \sum_{j=1}^k w_j^o f^h (w_j^b + \sum_{i=1}^p w_{ji}^h x_{t-i})) \quad (2)$$

where  $w_i^i$  is the direct connection weight between input  $i$  to output and  $f^i$  is the activation function from input  $i$  to output. Architecture of CFNN can be seen in Fig. 2.

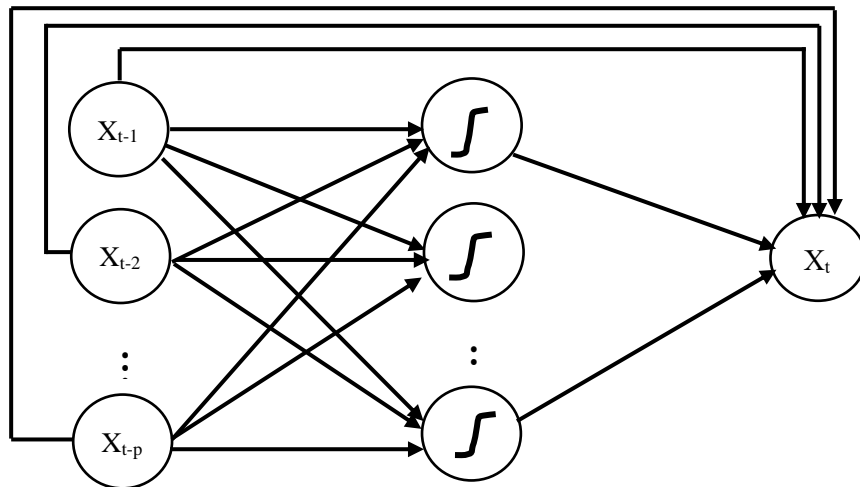


FIGURE 2. Architecture of CFNN for time series prediction

### 3.3 General Regression Neural Network

GRNN construction consists of four layers of processing units, namely input, pattern, summation and output neurons [27]. The input layer accepts an  $X$  input vector and distributes the data to the pattern layer. Each neuron in the pattern layer then builds the output  $\theta$  and sends the results to the

summation layer. The numerator and denominator neurons from the summation layer compute a simple, weighted arithmetic sum based on the values of  $\theta$  and  $w_{ij}$  obtained through training with supervision. The neurons in the output layer then divide the sum that has been calculated by the neurons in the summation layer. Figure 2 illustrates the schematic of the GRNN design for a time series.

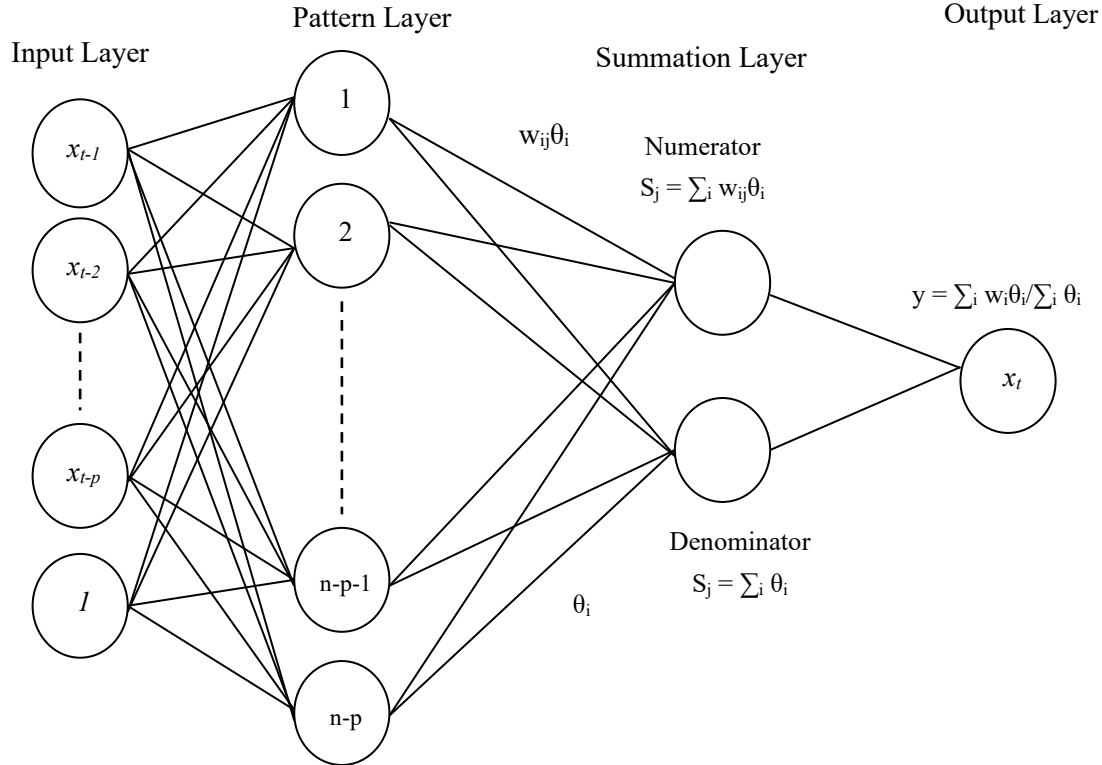


FIGURE 4. Architecture of GRNN for time series

### 3.4 Recurrent Neural Network

Recurrent Neural Network (RNN) is a part of the neural network model that has feedback from the hidden layer output to the input layer. It has a more complex structure and training algorithm than FFNN. In RNN, output from the network is reused as a network input. In this network, the outputs of the hidden layer are allowed to feedback onto themselves through a buffer layer, called the recurrent layer [28]. Therefore, the recurrent layer is virtually a copy of the previously hidden layer state. As the consequent, the number of recurrent neurons is the same with the number of unit in hidden layer. In this research, Elman Recurrent Neural Network, a simplest class of RNN, was used. Architecture of RNN for time series is described in Figure 3 and the formula is presented in

equation (3).

$$x_t = f^o(w^b + \sum_{j=1}^k w_j^o f^h(w_j^b + \sum_{i=1}^p w_{ji}^h x_{t-i} + \sum_{j=1}^k c_j u_j)) \quad (3)$$

where  $c_j$  is connection weight from recurrent layer  $j$  to hidden unit  $j$ . As in FFNN, all of the weights in the RNN could also be estimated by using a certain gradient based optimization.

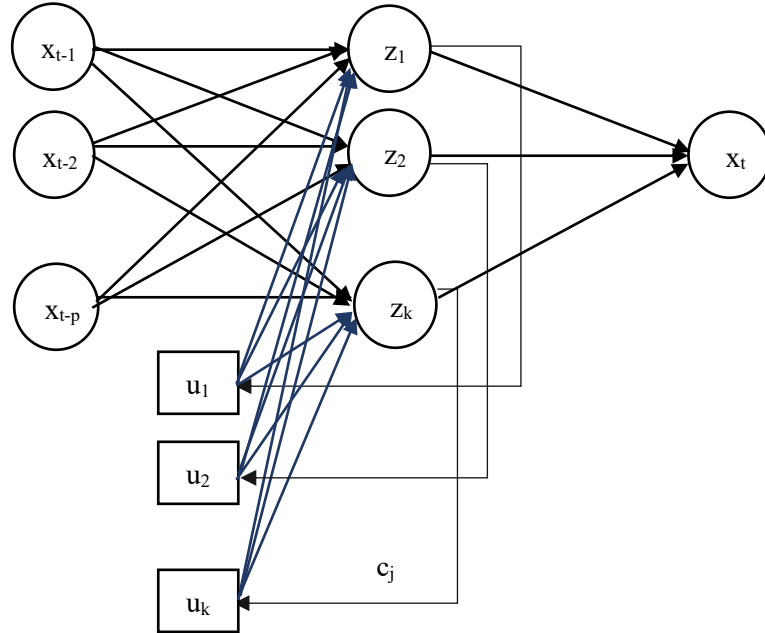


FIGURE 3. Recurrent Neural Network Architecture for Time Series

### 3.5 Data and Accuracy

The data used in this research is the total Covid-19 cases in Indonesia from 3 March to 22 September 2020. By this period, we have 205 data. We tried to make a short term prediction for several times by using in-sample and out-sample data. For the first time, the first 184 data was used as training and the next 7 data as testing. Furthermore, the first 191 data was used as training and the next 7 data as testing. The latter, the first 198 data was used as training and the 7 remaining data as testing. Normalization was used as pre-processing and after processing stage, the denormalization was done to return the data to its original form. The architecture of neural networks consist of lagged time variables as input layer, hidden layer and output layer as prediction. Input and output variables of each type of neural network are same, whereas the hidden layer is depend on the modeling type. The model accuracy was determined by using Mean Percentage Error (MPE) of training and testing data. The formula of MPE is:



$$\text{MPE} = \frac{100\%}{n} \sum_{t=1}^n \frac{x_t - \hat{x}_t}{x_t} \quad (4)$$

where  $x_t$  is the actual value of the quantity being predict,  $\hat{x}_t$  is the prediction and  $n$  is the number of different times for which the variable is predict. Besides, the Mean Square Error (MSE) is also counted because of the risk function, corresponding to the expected value of the squared error loss. The formula is:

$$\text{MSE} = \frac{1}{n} \sum_{t=1}^n (x_t - \hat{x}_t)^2 \quad (5)$$

#### 4. MAIN RESULTS

In determining neural networks model for time series, the input should be determined first. In this case, the plot of Partial Autocorrelation Function (PACF) is used as a tool to determine the lagged time. The PACF plot is shown in Figure 5. The ACF plot in Figure 5 provides a clue that the variables at lagged times 1-3 are far out of the tolerance line. Thus, these variables can be used as model inputs. For equivalence, the number of units in the hidden layer is also determined to be the same as the input unit, which is three. Now, we have a 3-3-1 FFNN, CFNN and RNN architectures for making the short time predictions. Whereas, the the number of hidden layer in GRNN was determined according to the input. The results of the experiments from the four types of neural network model are shown in Table 1.

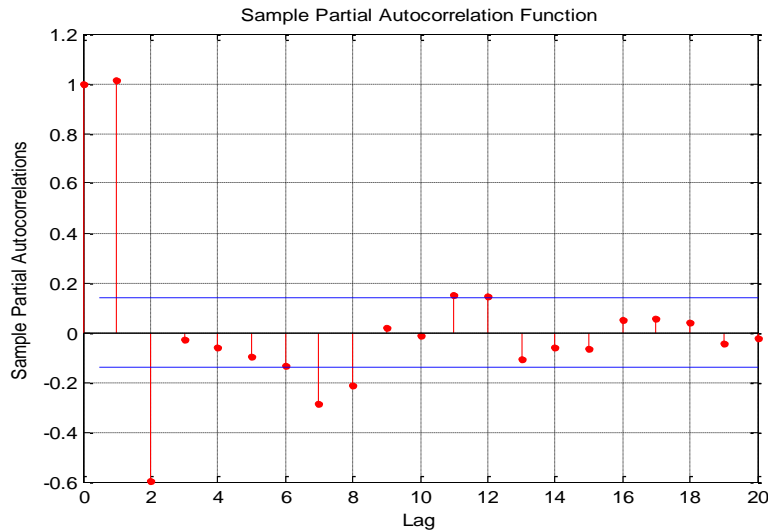


FIGURE 5. Plot of Partial Autocorrelation Function

TABLE 1. Result of the short term prediction for three experiments

Model	Time step of testing data	Training		Testing	
		MSE ( $\times 10^4$ )	MPE (%)	MSE ( $\times 10^5$ )	MPE (%)
FFNN	1 <sup>st</sup> seven days	4.8462	-1.0851	6.3749	0.4023
	2 <sup>nd</sup> seven days	3.3822	-0.6831	3.7718	0.3235
	3 <sup>rd</sup> seven days	4.5104	-1.4337	1.6832	0.1833
CFNN	1 <sup>st</sup> seven days	3.6707	-0.7167	1.1623	0.0147
	2 <sup>nd</sup> seven days	4.0181	-0.6225	1.3972	-0.0677
	3 <sup>rd</sup> seven days	4.2979	0.9769	-0.5605	-0.1119
GRNN	1 <sup>st</sup> seven days	25.8456	-7.9749	21.1982	6.7650
	2 <sup>nd</sup> seven days	30.5982	-8.4942	26.0836	6.6534
	3 <sup>rd</sup> seven days	36.5875	-9.0981	31.2641	6.4639
RNN	1 <sup>st</sup> seven days	67.0376	-19.9118	121.2957	5.6799
	2 <sup>nd</sup> seven days	60.9906	-61.0288	141.5018	17.1817
	3 <sup>rd</sup> seven days	37.4396	-12.0873	15.0860	4.5880

Table 1 shows that MPE at both training and testing data of the FFNN and CFNN given very good results. The mean of error percentage are less than 2%, even for testing it does not reach 1%. Whereas, the results from GRNN and RNN given more diverge results in the both in-sample and out-sample predictions. These results are in line with [29] which has obtained that the Covid-19 prediction for total cases with 14 days evaluation period of the FFNN model is better than the RNN. Meanwhile, the results presented by Lee et al. [30] show that RNN is better than FFNN and logistic regression for the prediction of Covid-19 cases on classification problems, instead of time series. The cases observed were severity prediction for COVID-19 patients, not the number of confirmed cases as in this study. Furthermore, Pal et al. [31] applied LSTM which is a variation of RNN and has obtained more accurate prediction results than some other classical and combination models. This is an interesting finding where RNN classmates can provide different predictive

results. It is also interesting to study further the comparison between LSTM and Elman, which are both variations of RNN. The results in Table 1 also indicate that the GRNN model is worse than FFNN and CFNN. This is in line with [32], which compared GRNN with other Statistical Neural Network (SNN) models and their hybrid version for COVID-19 mortality prediction in Indian populations. In fact, the prediction accuracy of the GRNN model was still under the results of Probabilistic Neural Network model. In this case, it can be stated that GRNN is not the best prediction model for cases of Covid-19 confirmed, although with different comparisons.

So far, there is no use of CFNN to predict the Covid-19 cases and the comparison with other models or other class of neural network. However, the comparison with FFNN showed the superiority of CFNN have been found in [33,34] for the other case. This also strengthens the selection of the CFNN model as the best. The CFNN have a consistency in the three experiments. It delivers good results not only from MPE but also MSE, which is consistently of low values in both training and testing data. Now, attention is paid to the numeric sign. The MPE value of the training data always produces a negative value. On the contrary, the MPE of the testing data from the three types are always positive. The phenomenon of the results mean that the in-sample prediction is always over-estimation however however, the out-sample prediction is always under-estimation. This of course is a very worrying matter. The possibility of increasing the number of cases is very large, greater than the results of the model estimates. Luckily, these results were obtained from the two type of models with less accuracy and from one model whose accuracy was good bur not the best. The CFNN as the best model with the smallest error has given a positive and negative variation of MPE in both in-sample and out-sample predictions. It means that sometimes the forecast were overfits and in the other times were underfits. Base on the results, it makes perfect sense to choose the CFNN as the best short term prediction model for patients of Covid-19 confirmed in Indonesia. The following figures present plots of actual training data versus in-sample prediction and testing data versus the out-sample prediction.

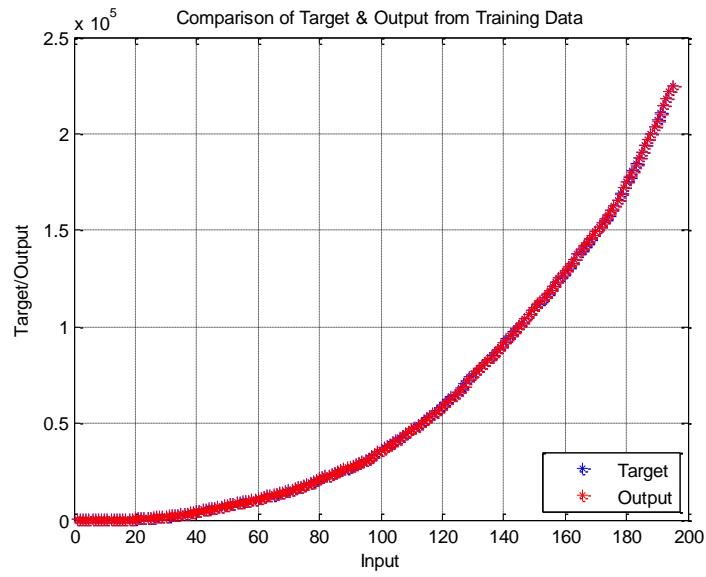


FIGURE 6. Comparison of target and output of in-sample prediction

In the two plots, the blue line showed the actual whereas, the red line was the in-sample and out-sample predictions. In the training data, we can see that the predicted model were succesfull of approaching the actual in both in-sample and out-sample predictions.

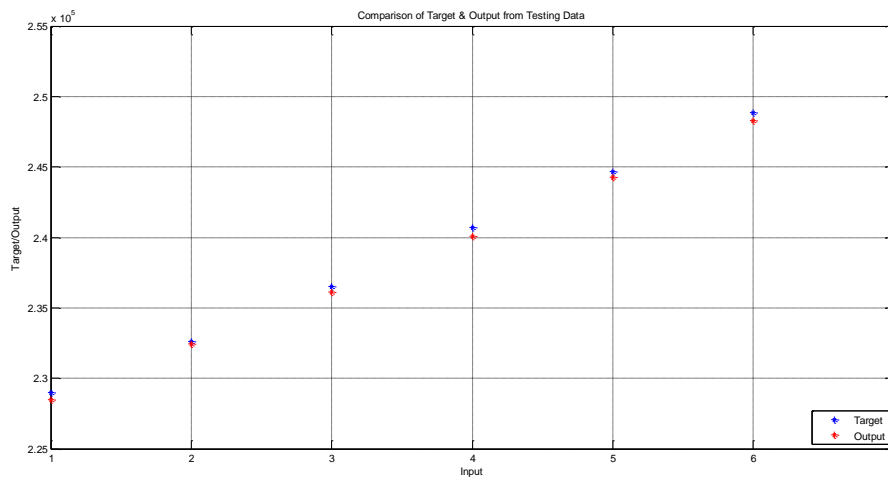


Figure 7 Comparison of target and output of out-sample prediction

The short term predictions of the total number of Covid-19 cases have been built by using four class of neural network models. Cascade Forward Neural Network model has been recommended to be selected as the best

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model. The accuracy of the CFNN model is the highest with varying MPE values, between positive and negative. This implies that the prediction results do not always under-estimated or over-estimated as in the three other models whose predictions are always under the actual value. In the modeling aspect, further studies of an accurate long term prediction are needed so that anticipatory can be taken. It can also be built by using the short term prediction results. The model developed should use time as independent variable. The using of Cascade Forward Neural Network and the comparison with other types like Generalized Exponential or Richards model for long term prediction of Coronavirus cases will be carried out at the future work. Therefore, prediction of the peak period and the end of the pandemic can also be done accurately.

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**CONFLICT OF INTERESTS**

The authors declare that there is no conflict of interests.

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