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Neural Network Model for COVID-19 Pandemic Prediction

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Abstract. Predictive model of the spread of COVID-19 play an important role in epidemiological study and government effort to deal with this pandemic. However, some COVID-19 prediction models are dominated by constant model parameters so they cannot reflect the actual situation of the spread of COVID-19. This study presents a method for dynamic prediction of the spread of COVID-19 by considering time-dependent model parameters. Neural Network is a computer technique that produce predictive models with a simpler and more flexible form. This is because the resulting model from this method is shaped by many processing units and the flexibility comes from iterating between units. One of the applications of Neural Networks is for time series data prediction algorithms. In this study, the Neural Network was applied to predict the number of deaths caused by the COVID-19 pandemic. From the results obtained, it can be concluded that the prediction model for cases of death due to COVID-19 has been successfully created in its entirety with the best architecture obtained is (12, 10, 3) from the test set between testing and trending data. In addition, the architectural model has a Mean Squared Error (MSE) of 0.286.

INTRODUCTION

The COVID-19 pandemic presents new challenges for researchers around the world, especially in building predictive models for infectious diseases. Building a predictive model is very important, considering the increasing number of infected cases and deaths caused by this pandemic has been worrying all over the world, including Indonesia. Based on the results of the COVID-19 Task Force report that there was a spike in cases in various provinces of more than 100%. This addition caused the total number of COVID-19 cases now reach 1,739,750 people, as of the announcement of the first patient on March 2, 2020. Meanwhile, the national death rate rose from 2.74 percent to 2.76 percent [1, 2].

In addition, build a prediction model is an effort to deal with this pandemic, whether to take steps to prevent it, allocate limited resources or treat it. Since the beginning of this pandemic, many prediction models for COVID-19 cases have been built using classical methods and time series-based methods [3 - 7]. However, the formation of the constructed models varies substantially in the construction method and the prediction results. Building a predictive model with both classical and time series methods requires many assumptions that must be met when interpreting the predictive model. One of the most basic factors to consider when designing a COVID-19 prediction model is the occurrence of extreme data fluctuations due to the fast, massive nature of its transmission and its spread influenced by environmental and social factors [8, 9]. This factor may be difficult to accommodate by classical and time series methods. Therefore we need a method that produces a robust predictive model and can capture also represent complex Input-Output relationships. In addition, it must also have high flexibility, be fast in execution, be consistent, and initialize complex systems.

In this research, we use a neural network method with a backpropagation algorithm which is expected to provide another alternative in predicting the number of deaths caused by the COVID-19 pandemic in Indonesia. Neural Network is an information processing method that is inspired by the human nervous system [10 - 13]. This method consists of several neurons, and between these neurons there is a relationship that is used to study data patterns that adjust the weights between the input layer, hidden layer and output layer [14, 15]. These neurons will transform the information received through the output connection to other neurons. So that it can capture extreme data fluctuations

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and represent complex Input-Output relationships [16]. This makes the prediction model generated from the neural network method consistent because it is flexible and robust [17]. The following figure shows the structure of the neural network activity.

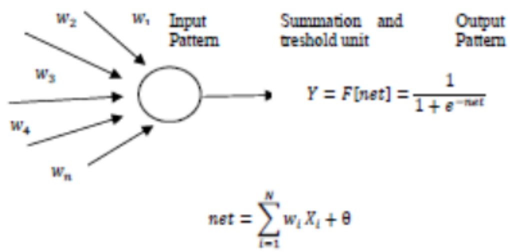

FIGURE 1. Simple Neural Network Architecture.

METHODS

The data used in this research is monthly data on the number of death cases caused by the COVID-19 pandemic. The data comes from the "Daily Technical Report" issued by the Ministry of Health of the Republic of Indonesia (https://covid19.go.id) (https://covid19.kemkes.go.id/) [1, 2]. The data is divided into two parts, the in sample data from April 1, 2020 to March 31, 2021, while the out sample data is from April 1, 2021 to June 30, 2021.

The method to build the prediction model used in this research is the backpropagation neural network method. In the input layer, there are 12 input values, referring to the number of months in a year (12 months), in the output layer, the number of neuron is set at 3, referring to the forecast time for the next three months and for the hidden layer of the number of neuron used will be determined based on the best error results.. The activation function used in the hidden layer is a binary sigmoid function. The activation function in the output layer follows the activation function in the previous layer. The best architecture is chosen based on the smallest mean square error (MSE) from the trending data results. The architecture with the best performance will then be used for forecasting.There are 3 phases in BPNN training, the forward phase (feed forward), the backward phase (back propagation), and the weight modification phase. In the feed forward phase, the input pattern is calculated forward starting from the input layer to the output layer. In the back propagation phase, each output unit receives a target pattern that corresponds to the input pattern to calculate the error value. The error will propagate backwards. While the weight modification phase aims to reduce error that occur. The three phases are repeated continuously until the termination condition is met.

The following are the steps in building an architectural model:

Step 1: Set the initial weight (initial weight is taken randomly with a value between -0.5 to 0.5)

Step 2: Determine the maximum iterations, (Epoch < Maximum Epoch) and (error > target error) with the value of Epoh = 0, MSE = 1.

Phase I : Feed Forward

Step 3: Sum up all the signals coming into the unit layer

$$X\_net_j = \sum_{i=1}^{N} w_i X_{ij} + \theta_{0j} \quad (1)$$

With : i=1, 2, 3,…n

j= 1, 2, 3, …p

The input signal is propagated to the hidden layer using the specified activity function. The output of each neuron in the hidden layer is then propagated forward to the next hidden layer using a predetermined activity function until it produces a network output.

$$X_j = F[X\_net_j] \quad (2)$$

Step 4: Sum all the incoming signals to the Output layer

$$Y\_net_k = \sum_{i=1}^{N} v_i Y_{ij} + \emptyset_{0j} \quad (3)$$

With : i=1, 2, 3,…n

k= 1, 2, 3.

calculate output of all j unit layer in hidden layer based on activation function

$$Y_j = F[Y\_net_k] \quad (4)$$

Phase II: Back Propagation

Step 5: Calculate the error value, weight correlation and bias correlation of each output unit that receive the target pattern associated with the training input pattern

With:

Error value $\lambda_k = (t_k - y_k)f'(y\_net_k)$

Weight correlation $\Lambda v_{jk} = \alpha\lambda_k x_j)$

Correlation bias $\Lambda v_{0k} = \alpha\lambda_k$

Step 6: Calculate the error value, weight correlation and bias correlation in the hidden layer by adding up the input delta of the unit in the layer above it

With:

Number of errors $\lambda\_net_j = \sum_{n=1}^{m} \lambda_k\, v_{jk}$

Number of errors $\lambda_j = \lambda\_net_j f'[X\_net_j]$

Weight correlation $\Lambda w_{ji} = \alpha\lambda_j x_i$

Correlation bias $\Lambda w_{0j} = \alpha\lambda_j$

Phase II: Weight modification

Correction of the bias of each output unit

$$v_{jk(new)} = v_{jk}(old) + \Lambda v_{jk} \quad (5)$$

Correction of bias for each weight

$$w_{ij(new)} = w_{ij}(old) + \Lambda w_{ij} \quad (6)$$

RESULT AND DISCUSSION

Determining the number of hidden layer

Using a neural network architecture consisting of 12 data input values, namely the number of months in each year, 10 neurons in one hidden layer, and 3 output values of death cases data in the following month of the year is the best architecture. After some experimenting one and two hidden layers . shown in table 1.

TABLE 1. Comparison Result of Forecasting the Number of Covid-19 Death Cases Based on the Number of Hidden Layer in the Network Training Process.

Period	Number of Death Cases	Neural Network			
		1 Hidden Layer (12,1,3)		2 Hidden Layers (12,1,1,3)	
		Number of Death Cases	Error (%)	Number of Death Cases	Error (%)
App-20	373	249.91	33	249.91	33
May-20	399	299.25	25	299.25	25
Jun-20	459	413.1	10	504.9	10
	.	.	.	.	.
	.	.	.	.	.
	.	.	.	.	.
Jan-21	45949	44570.53	3	44570.53	3
Feb-21	46137	39677.82	14	39677.82	14
Mar-21	46349	46812.49	1	45885.51	1
Average	18729.07	18729.07		18729.07	
Correlation coefficient	…	0.57		0.57	

Table 1 shows the network training process, these results are used to determine the number of hidden layers that are effectively used as a neural network model for prediction. The average error for each hidden layer has the same value. The correlation between actual data and forecasting data for 1 hidden layer and 2 hidden layer does not have a significant difference. Therefore, taking into account the efficiency of the process, 1 hidden layer was selected to be used.

Determination Of The Number Of Neuron In The Hidden Layer

After selecting the number of hidden layer, by comparing the results of the number of hidden layers, then testing to carry out to get the best number of neuron in the hidden layer. There will be several selection of the number of neuron to be tested, that is 1 to 12 neurons. The results are shown in table 2.

TABLE 2. Comparison Result of Forecasting the Number of Covid-19 Death Cases Based on the Number of Neuron in the Hidden Layer in the Network Training Process.

Period	Neural Network					
	(12,1,3) Error (%)	**(12,2,3) Error (%)**	**(12,3,3) Error (%)**	**(12,4,3) Error (%)**	**(12.5,3) Error (%)**	**(12,6,3) Error (%)**
Apl-20	33	33	88	43	81	76
May-20	25	25	87	20	48	61
Jun-20	10	10	84	54	48	54
	.	.	.	.	.	.
	.	.	.	.	.	.
	.	.	.	.	.	.
Jan-21	3	3	13	12	9	7
Feb-21	14	14	6	12	15	8
Mar-21	1	1	15	8	15	14
Correlation coefficient	0.57	0.66	0.67	0.59	0.71	0.85
Period	**Neural Network**					
	(12,7,3) Error (%)	**(12.8,3) Error (%)**	**(12,9,3) Error (%)**	**(12,10,3) Error (%)**	**(12,11,3) Error(%)**	**(12,12,3) Error (%)**
Apl-20	40	48	73	20	77	85
May-20	81	57	37	13	35	25
Jun-20	77	60	68	5	39	14
	.	.	.	.	.	.
	.	.	.	.	.	.
	.	.	.	.	.	.
Jan-21	8	8	4	2	19	11
Feb-21	6	7	4	0	15	11
Mar-21	4	10	11	1	11	10
Correlation coefficient	0.63	0.75	0.84	0.89	0.50	0.52

Table 2 shows the result on the training process of the hidden layer 1 network model with different neuron. From the table, it can be seen the correlation value between the actual data with the predicted data and data from each trained model. The architectural model with 6, 9, and 10 neurons on the hidden layer has a very high correlation value, which is above 80%, with architectural models (12, 6, 3), (12, 9, 3) and (12, 10, 3) . The selected architectural model will be tested for the best model, which will later be used in predictions.

Model Testing

From the results of the training, several network architecture models with optimal performance were obtained, (12,6.3), (12, 9, 3) and (12,10, 3). Furthermore, the network architecture models will be tested using test data that have never been trained before. The test results for the network architecture models are shown in the following table.

TABLE 3. Comparison Result of Forecasting the Number of Covid-19 Death Cases Based on the Number of Neurons in the Hidden Layer in the Network Training Process.

Period	Number of Death Cases	Neural Network Architecture		
		(12,6,3) Error (%)	(12,9,3) Error (%)	(12,10,3) Error (%)
Apl-21	49771	46287.03	47780.16	48775.58
May-21	49907	45914.44	47910.72	49907
Jun-21	50100	57114	55611	50601
Correlation coefficient		0.85	0.84	0.89
MSE		0.66	0.627	0.286

Table 3 shows the results of the network architecture model tested. From the three network architecture models tested, it was found that the architectural model (12,10,3) has the highest correlation value and the smallest RMSE value compared to the other 2 network architecture models. Thus the architectural model (12,10,3) was chosen as the best model.

Prediction

After getting the best method, with architectural model (12, 10, 3), then the prediction are made for the number of COVID-19 deaths. The prediction results are presented in the following figure.

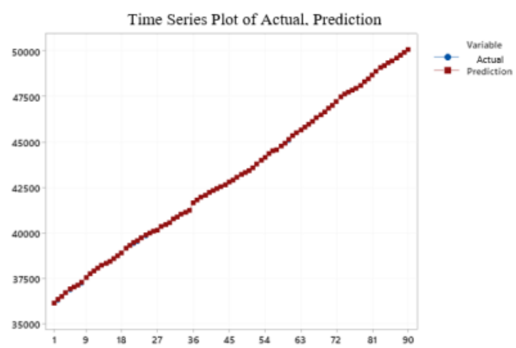

FIGURE 2. Prediction Results.

Fig. 2. shows that the difference between the actual data and the predicted data is very small. This provides information that the neural network architecture model built (12, 10, 3) in predicting the number of COVID-19 deaths has high accuracy and flexibility. In addition, from Fig. 2. it can also be seen that the data on the number of deaths continue to increase, this indicates that the COVID-19 pandemic will continue to occur even though the possibility of deaths will decrease.

CONCLUSION

From this research, it can be concluded that the more number of hidden layer in the artificial network, it does not guarantee that it will give the best prediction results. Test with 1 hidden layer layer have the same correlation coefficient if using 2 hidden layers, but because 1 hidden layer is more efficient, in this case 1 hidden layer is used. Similarly, determining the number of neuron in the hidden layer, does not guarantee that the more neurons used, the better the architectural model formed. It can be seen that for 10 neurons in the hidden layer, the best results compared to 11 or 12 hidden layers are reflected in the correlation coefficient and the resulting MSE. In addition, different number of hidden layers will result in different number of iterations, a larger number of hidden layers does not always lead to increased iterations, an increase in network performance by increasing training data and changing parameters that affect performance, such as the number of epochs, error goal and network architecture. The prediction results obtained for the number of cases of death, the increase in numbers is increasing. increasing even though the difference from day to day is decreasing. This can be used as a reference for policy makers in their efforts to deal with the COVID-19 pandemic.

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