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ENHANCE METHOD OF PREDICTION OF A DOMESTIC PASSENGERS AIRPLANE DURING COVID-19 BASED ON RESILIENT BACKPROPAGATION METHOD

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ABSTRACT

The troublesome administration makes passengers discouraged from traveling using Air transportation. In 2022, the world health organization provided recommendations for lifting or easing international traffic bans. In early 2022, international airplane passengers experienced an increase, even in May 2022, exceeding May 2019. Since the COVID-19 pandemic, the number of passengers both domestically and internationally has decreased. National and international restrictions caused a decrease in the number of passengers. This study predicts the number of international airplane passengers during the COVID-19 recovery period with the Resilient Backpropagation algorithm at Indonesia's main airport, Kuala Namu airport, Sukarno. Hatta, Juanda, Ngurah Rai and Hasanuddin. This method is expected to improve the performance of the Backpropagation algorithm so that the prediction results are more accurate. The results of this study are the best model of the Resilient Backpropagation algorithm with a test performance of 0.0040, namely the 5-3-1 model. This model can be used to predict the number of international airplane passengers during the COVID-19 pandemic recovery period as information for airport managers to determine transportation business management.

Keywords: *Resilient Backpropagation, Transportation Business Management, Prediction, Performance.*

INTRODUCTION

The COVID-19 pandemic involves a novel coronavirus characterized by respiratory illness resulting from severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection.(Matias, Dominski, & Marks, 2020).

The COVID-19 pandemic has brought the most significant global challenge in a generation. The ultimate impact of this pandemic is on global health, the world, the economy, social cohesion, and everyday life. The unpredictable nature of the spread of this virus has brought great uncertainty to society(Gavin, Lyne, & McNicholas, 2020).

We are in the global Covid-19 pandemic, causing two types of shocks in countries: health and economic. Given the highly contagious nature of the disease, ways to contain its spread include policy measures such as the implementation of social distancing, self-isolation at home, closure of institutions and public facilities, restrictions on mobility, and even lockdowns throughout the country.(Mahendra Dev & Sengupta, 2020).

Restrictions on mobility and even lockdowns of entire countries have resulted in declining international airline passengers. However, during the Covid-19 recovery period, with recommendations for lifting or easing international traffic restrictions, the number of airplane passengers in 2022 began to increase again. The graph of the number of international airline passengers in 2019-2022 can be seen in Figure 1.

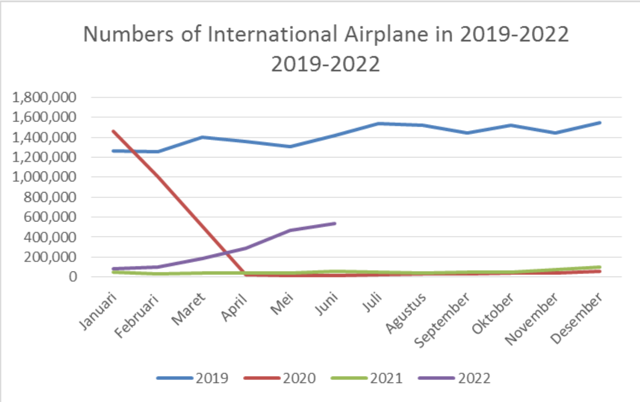

Figure 1. Number of International Airplane Passengers in 2019-2022

Based on the description above, it is necessary to conduct an in-depth study to predict the number of international airline passengers during the recovery period of the COVID-19 pandemic. The algorithm used is Resilient Backpropagation with several architectural models to produce the best architectural model by looking for the best performance/MSE, which can later be used to predict the number of international airplane passengers during the recovery period of the Covid-19 pandemic.
Resilient backpropagation (Rprop) is considered the best algorithm, measured in terms of convergence speed, accuracy, and robustness concerning training parameters(Riedmiller & Braun, 1993).

METHOD.

2.1 Research Method

The method used in this study is a Resilient Backpropagation Artificial Neural Network to predict the number of international airplane passengers according to major airports in Indonesia. The data used in this study is data on the number of international aircraft passengers at Indonesia's main airports during the recovery period for the COVID-19 pandemic in 2022, sourced from the website of the Indonesian Central Statistics Agency.

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Table 1. Number of International Airplane Passengers (Source: Indonesian Central Statistics Agency)

Bandara Utama	Januari	Februari	Maret	April	Mei	Juni
Kuala Namu	15	15	26	1,994	16,793	23,176
Soekarno Hatta	82,944	100,774	173,978	226,526	307,859	301,659
Juanda	108	8	2,376	14,791	31,804	43,037
Ngurah Rai	518	1,028	11,453	47,923	110,403	170,325
Hasanudin	0	0	0	0	0	0
Total	83,585	101,825	187,833	291,234	466,859	538,197

2.2 Research Framework

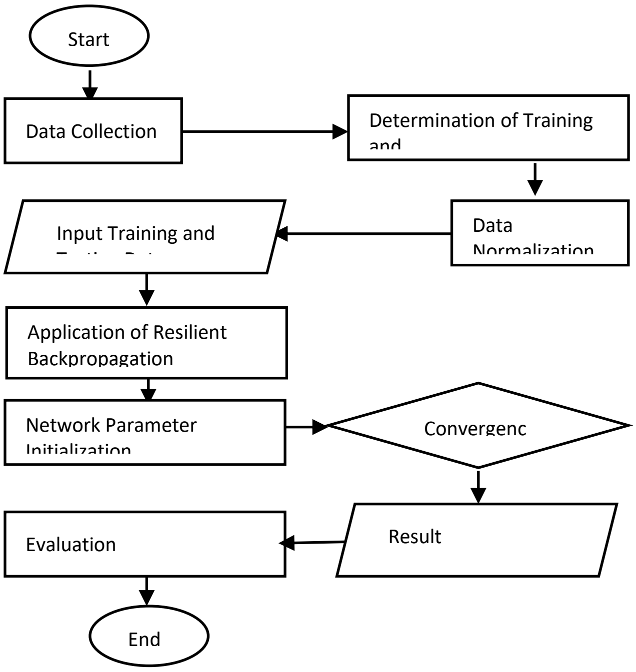

Figure 2. Flow Chart Research.

Prior to data processing, the data were normalized with the following equation:

$$x' = \frac{0.8(x-a)}{b-a} + 0.1$$

Information :
x' = Normalization result
x = Data to be normalized
a = smallest data from dataset
b = The largest data from the dataset

2.3. Backpropagation.

2.3.1. AlgorithmBackpropagation

Backpropagation (BP) algorithm was used to develop the ANN model. The typical topology of BPANN (Backpropagation Artificial Neural Network) involves three layers: input layer, where the data are introduced to the network; hidden layer, where the data are processed; and output layer, where the results of the given input are produced(Solikhun, Wahyudi, Safii, & Zarlis, 2020),(Wahyudi, Safii, & Zarlis, 2020).

2.3.2. Resistant Backpropagation

Resilient Backpropagation has the same steps as Backpropagation, the difference is that the backward time is in the updateweight section. For To update the weight, selection must be made based on the resulting error gradient, then determine the learning rate used to update the weight.

FeedForward

Feedforward training on the Resilient algorithmBackpropagationthe same as feedforward training on the Backpropagation algorithm, which differs when updating weight with learningrate in backward training(Riedmiller & Braun, 1993).

RESULTS

3.1. *Normalization Results*

The table below is the result of normalization of international passenger data for 2022 from January to June. The training input data is international passenger data for 2022 from January to April with target data for May. While the test input data is international passenger data for 2022 from February to May with target data for June.

Table 2. Results of Training Normalization Data

AIRPORT	Januari	Februari	Maret	April	Mei
Kualan Namu	0.1000	0.1000	0.1001	0.1052	0.1436
Soekarno Hatta	0.3155	0.3619	0.5521	0.6886	0.9000
Juanda	0.1003	0.1000	0.1062	0.1384	0.1826
Ngurah Rai	0.1013	0.1027	0.1298	0.2245	0.3869
Hasanudin	0.1000	0.1000	0.1000	0.1000	0.1000

AIRPORT	Februari	Maret	April	Mei	Juni
Kualan Namu	0.1000	0.1001	0.1052	0.1436	0.1602
Soekarno Hatta	0.3619	0.5521	0.6886	0.9000	0.8839
Juanda	0.1000	0.1062	0.1384	0.1826	0.2118
Ngurah Rai	0.1027	0.1298	0.2245	0.3869	0.5426
Hasanudin	0.1000	0.1000	0.1000	0.1000	0.1000

The data were processed using Matlab 2011a tools. To find the best architectural model, the author uses several models. The best architectural model is the architecture that has the smallest performance/MSE.

3. 2. Training and Testing with Model 4-2-1

The results of the training using the 4-2-1 architectural model with the Resilient Backpropagation method can be seen in Figure 3 below.

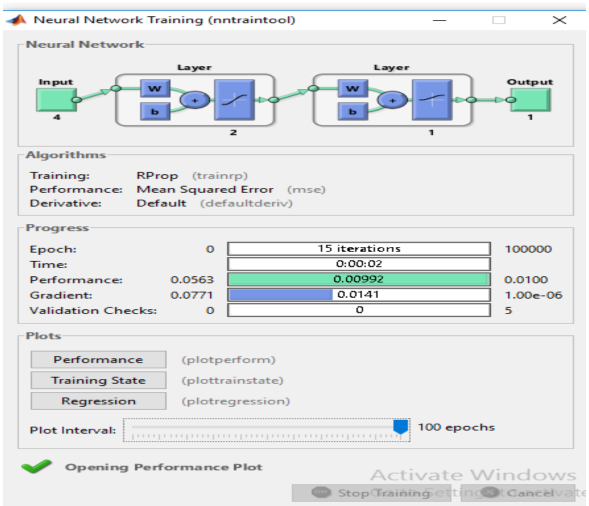

Figure 3. Training and Testing Model 4-2-1

The results of the 4-2-1 model training show that there are 15 iterations of epochs, performance = 0.00992 and time = 00:00:02. While the test performance = 0.0320.

3.3. Training and Testing with the 4-3-1. Model

The results of the training using the 4-3-1 architectural model with the Resilient Backpropagation method can be seen in Figure 4 below.

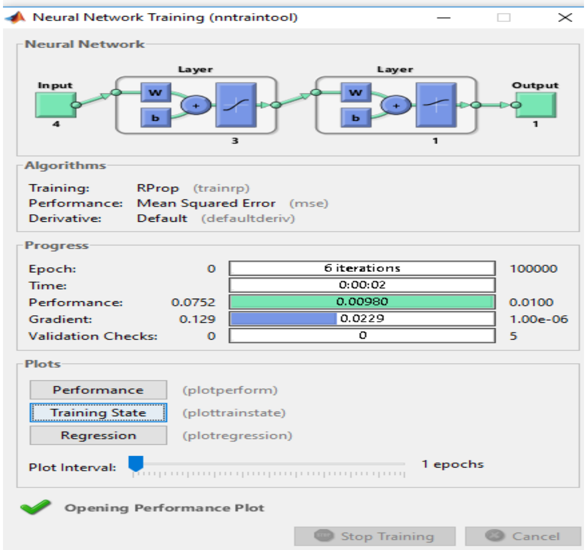

Figure 4. Training and Testing Model 4-3-1

The results of the 4-3-1 model training show that there are 6 iterations of epochs, performance = 0.00980 and time = 00:00:02. While the test performance = 0.0128. When viewed from the epoch, the training and testing performance of the 4-3-1 model is better than the 4-2-1 model.

3.4. Training and Testing with Model 4-4-1

The results of the training using the 4-4-1 architectural model with the Resilient Backpropagation method can be seen in Figure 5 below.

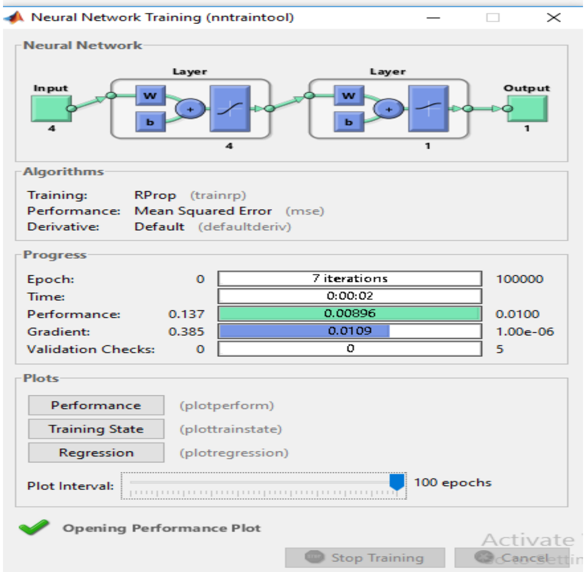

Figure 5. Training and Testing Model 4-4-1

The results of the 4-4-1 model training show that there are 7 iterations of epochs, performance = 0.00896 and time = 00:00:02. While the test performance = 0.0074. When viewed from the epoch, the training and testing performance of the 4-4-1 model is better than the 4-3-1 model.

Table 3. Comparison of Models with 4 Inputs

No	Model	Perf. Training	Perf. Testing
1	4-2-1	0.00992	0.0320
2	4-3-1	0.00980	0.0128
3	4-4-1	0.00896	0.0074

Comparison of training and testing performance of several models can be seen in Figure 6 below.

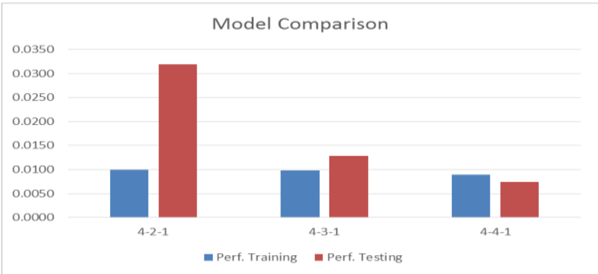

Figure 6. Performance Comparison Graph with 4 Inputs

3.5. Training and Testing with Model 5-2-1

The input data for training and testing is international passenger data for 2022 from January to May, with target data for June.

The results of training and testing using the 5-2-1 architectural model with the Resilient Backpropagation method can be seen in Figure 7 below

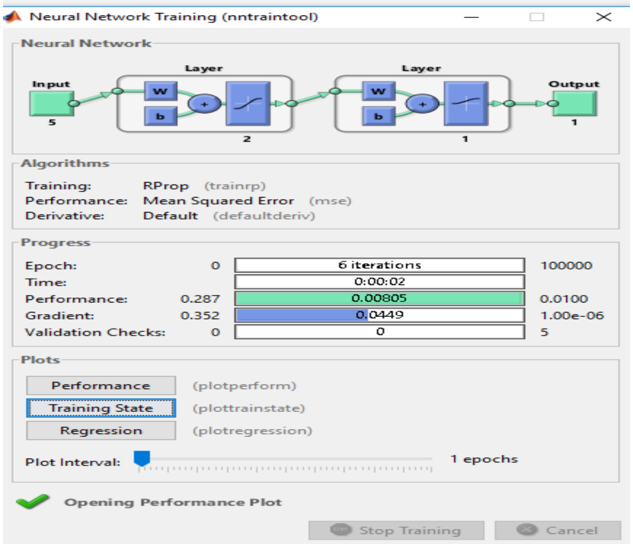

Figure 7. Training and Testing Model 4-5-1

The results of the 5-2-1 model training show that there are six iterations of epochs, performance = 0.00805 and time = 00:00:02. While the test performance = 0.0081.

3.6. Training and Testing with the 5-3-1. Model

The results of training and testing using the 5-3-1 architectural model with the Resilient Backpropagation method can be seen in Figure 8 below.

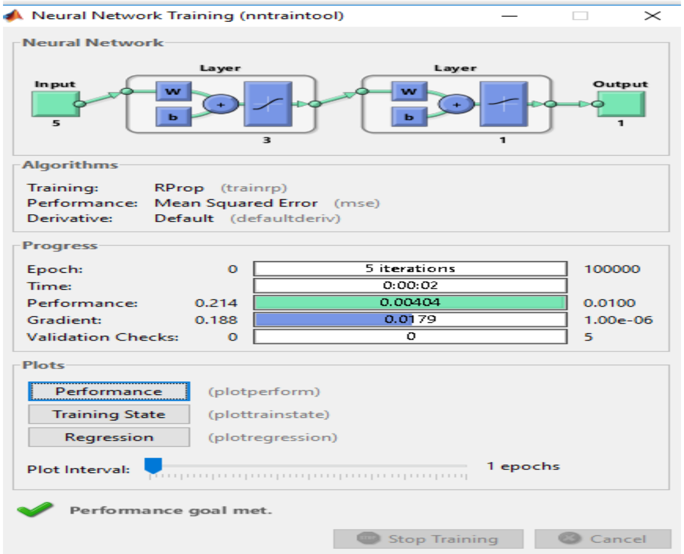

Figure 8. Training and Testing Model 5-3-1

The results of the 5-3-1 model training show that there are 5 iterations of epochs, performance = 0.00404 and time = 00:00:02. While the test performance = 0.0040.

Table 4. Comparison of Models with 5Input

No	Model	Perf. Training	Perf. Testing
1	5-2-1	0.00992	0.0081
2	5-3-1	0.00404	0.0040

Comparison of training and testing performance of several models can be seen in Figure 9 below.

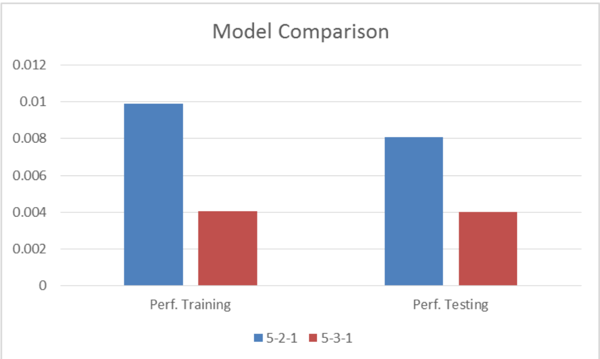

Figure 9. Performance Comparison Graph with 5 Inputs

The comparison graph of training and testing performance can be seen in Figure 10 as shown below

CONCLUSION

From the discussion and the results of the above description, it can be concluded that the best architectural model to predict the number of international aircraft passengers during the pandemic recovery period is the 5-3-1 architectural model with a performance testing of 0.0040. The data used is data on the number of international airline passengers in 2022 from January to June obtained from the Indonesian Central Statistics Agency.

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