

# Artificial Neural Network Backpropagation Method to Predict Tuberculosis Cases

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**Abstract:** Artificial neural networks are information processing systems that have certain performance characteristics in common with biological neural networks. Backpropagation is a method in artificial neural networks that uses supervised learning. Backpropagation has a weakness in reaching the convergence level. The convergence rate is the difference from the mean square error value. The mean square error is the difference between the target value and the actual value. One way to increase the convergence rate is to provide input values. In this study using the Nguyen Widrow backpropagation method. The network will predict Tuberculosis cases. Data sourced from the North Sumatra Provincial Health Office from 2019 to 2021. Architectural testing with a learning rate ranging from -0.5 to 0.5 and momentum ranging from 0 to 1 obtained a learning rate of 0.5, the epoch process stops at the 172nd iteration with an achievement gradient of 0.0001598 and the R value for training data is 0.99841 which means it is very good because it is close to 1 with an accuracy rate of 81.82%.

**Keywords:** Artificial Neural Network; Backpropagation; Mean Square Error; Nguyen Widrow; Rate Convergence

## INTRODUCTION

Artificial neural network is an information processing system that has characteristic capabilities that are generally similar to biological neural networks [1]. Artificial neural networks can be applied as a diagnostic tool for TB prediction and support in expanding the role of computer technology in diagnostics for rapid TB management [2]. Medical diagnosis using artificial neural networks is a very active area of research in medicine and it is believed that it will be used more and more in biomedical systems in the coming years. With the development of neural network technology, the use of artificial neural networks is becoming increasingly widespread, and their application fields are also expanding. The main characteristic of ANN is self-learning without prior knowledge of the complex non-linear relationships that exist between input and output variables [3].

According to WHO (2018) tuberculosis cases in Indonesia have never decreased. Many cases of tuberculosis have not been reached and detected, even though they have been detected and treated but have not been reported [4]. Indonesia ranks third highest for tuberculosis cases after India and China with 700 thousand cases. Seeing this case is certainly a challenge for health service facilities, especially at first-level health care facilities, namely the health center, to treat and treat tuberculosis patients in order to reduce mortality and minimize someone from getting tuberculosis [5]. Tuberculosis case finding is one of the Directly Observed Treatment Short-course (DOTS) strategies in tuberculosis control that aims to find sufferers. Tuberculosis (TB) is an infectious disease caused by *Mycobacterium tuberculosis* (M.tb), causing the highest number of deaths globally for all bacterial diseases that require new diagnoses and treatment strategies. Diagnostic methods that are slow and insensitive can hinder global control of tuberculosis, and scientists are seeking strategies for early and

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accurate detection, which remain the foundation of tuberculosis control [6]. Diagnostic inaccuracies can allow the emergence of new cases through transmission, causing high drug resistance in countries with a high TB burden, so a model is needed that assists medical personnel in making an accurate diagnosis of Tuberculosis.[7]

According to research [8] that the backpropagation neural network predicts tuberculosis incidents in the Southeast Province of China, which shows better performance than the Autoregressive Integrated Moving Average (ARIMA) model, which obtains a minimum MSE value of 0.00190. According to research [9] prediction of TB incidence in Kashgar using the single Box-Jenkins method and the Box-Jenkins and Elman neural network (ElmanNN) The Box-Jenkins method has good predictive performance and high prediction accuracy and the Elman Neural network can capture nonlinear information from time series data very well, thus the Box-Jenkins and ElmanNN hybrid method can be highlighted in predicting the temporal trends of TB incidence in Indonesia Kashgar, which can act as potential far-reaching implications for TB prevention and control.

## LITERATURE REVIEW

### *Backpropagation Algorithm*

Backpropagation is a multi-layer Artificial Neural Network. Backpropagation is a method that is quite good at making predictions (forecasting) [10]. The BP algorithm is a generalization of the delta rule (Widrow-Hoff), which applies the gradient descent method to minimize the total squared error of the output calculated by the network. In the neural network training process, each input value and expected output value are required, and the whole algorithm repeats a two-stage loop: forward propagation and weight update[11].

### *Mean Square Error*

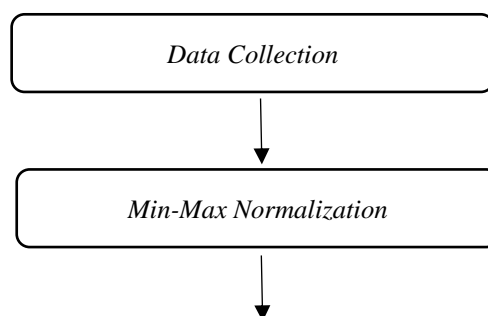
*Mean Square Error* can be used to calculate the error values for all normalized output layers. The error value indicates the error value of the predicted results obtained [12]. This method is effective in calculating the error value regardless of whether the actual value is below or above the ideal result. Mean Square Error is used as a parameter for the accuracy of the output target value . The smaller the mean square error does not guarantee the higher the accuracy [13].

### *Nguyen Widrow*

*Nguyen widrow* is a weight initialization method developed by Derrick Nguyen and Bernard Widrow to increase learning speed. This algorithm uses a number of small random values assigned to initialize the weights. In weight initialization, a number of values are randomized to set the backpropagation network weights [14]. If the initial weight is too large the input signal to each hidden or output unit will fall to the saturation point where the derivative of the sigmoid has a very small value ( $f(\text{net}) = 0$ ). If the weights are too small, the net input to the hidden unit or output unit will be close to zero, resulting in very low learning. To get the best weight and bias results set to random numbers between -0.5 and +0.5 or -1 and +1. Thus the initial weights and biases can be carried out randomly and on the basis of using this concept the weight initialization method is improved [15].

## METHOD

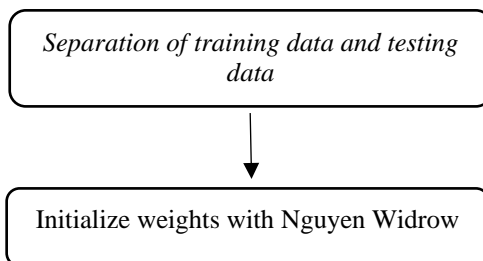
### Research Framework



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### Data Collection

The data collection technique in this study was the technique of collecting documentation at the Health Service, namely studying documents related to all the data needed in the research. In this study, secondary datasets were used which were obtained from the Disease Prevention and Control Division of the North Sumatra Provincial Health Office. Data is taken from 2019 – 2021.

### Min-Max Normalization

The TB disease dataset from the North Sumatra Provincial Health Office has been normalized beforehand using the Normalization Formula:

$$v'(i) = (v(i) - \min(v(i))) / (\max(v(i)) - \min(v(i)))$$

Min-Max Normalization was chosen because the error rate for classification is lower than Z-Score Normalization

### Separation of Training and Testing Data

At this stage, the data is divided into 2 groups, namely data for the training process on artificial neural networks and data for testing. In the training section, the dataset has been trained to make predictions from a machine learning algorithm. The system is trained to recognize input patterns in order to produce output that matches certain targets. We provide clues through our algorithms so that the machine we are training can either look for correlations on its own or learn from patterns that have been given. In the testing section, the dataset is tested to see its accuracy, or in other words to see its performance. This network has only one hidden layer. The weight value will continue to be modified until it finds a convergent final value. In this study, one training session is defined as one epoch.

### Initialize the weights with Nguyen Widrow

After the node weights in the input layer are normalized, the next step is to initialize the weights from the input layer to the hidden layer. For the weight initialization step using Nguyen Widrow.

### Training with Backpropagation

After the process of normalization and initialization of weights is complete, the testing phase is carried out on the results of data processing using Matlab R2013a Software.

### Data Used

The data used in this study are Notification Rate data for all Case Notification Rate (CNR) treated and reported among 100,000 residents in the Province of North Sumatra. The benefit of knowing the number of TB cases is to find out the pattern of the spread of tuberculosis so as to reduce the death rate and minimize a person's exposure to tuberculosis. Therefore, this study will discuss the prediction of the number of TB cases based on CNR Health Office data for all cases treated and reported from 2019-2021.

**Table 1. Normalization Data Training**

Pola	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>4</sub>	X <sub>5</sub>	X <sub>6</sub>	X <sub>7</sub>	Target
1	0,019	0,428	0,019	0,011	0,018	0,019	0,021	0,020
2	0,118	0,593	0,119	0,069	0,119	0,119	0,119	0,119
3	0,041	0,313	0,041	0,024	0,041	0,041	0,041	0,042
4	0,093	0,564	0,094	0,054	0,096	0,094	0,095	0,094

\*name of corresponding author



5	0,022	0,105	0,022	0,013	0,023	0,022	0,025	0,022
6	0,027	0,394	0,028	0,016	0,027	0,028	0,029	0,028
7	0,082	0,312	0,083	0,048	0,082	0,082	0,082	0,083
8	0,116	0,271	0,117	0,061	0,119	0,117	0,119	0,118
9	0,171	0,368	0,173	0,090	0,174	0,173	0,173	0,173
10	0,051	0,407	0,052	0,030	0,050	0,052	0,053	0,052
11	0,056	0,243	0,057	0,033	0,055	0,057	0,058	0,057
12	0,399	0,302	0,405	0,211	0,406	0,405	0,403	0,406
13	0,127	0,155	0,129	0,067	0,128	0,129	0,132	0,129
14	0,025	0,113	0,026	0,015	0,027	0,025	0,025	0,026
15	0,014	0,179	0,014	0,008	0,014	0,014	0,016	0,014
16	0,000	0,525	0,000	0,000	0,000	0,000	0,000	0,000
17	0,021	0,540	0,022	0,012	0,023	0,022	0,021	0,022
18	0,078	0,191	0,079	0,041	0,078	0,079	0,078	0,079
19	0,049	0,194	0,050	0,029	0,050	0,050	0,049	0,050
20	0,036	0,282	0,037	0,021	0,037	0,037	0,037	0,037
21	0,056	0,465	0,057	0,033	0,055	0,057	0,058	0,057
22	0,012	0,000	0,012	0,007	0,014	0,012	0,012	0,012
23	0,037	0,166	0,038	0,043	0,037	0,038	0,037	0,038
24	0,003	0,109	0,003	0,002	0,005	0,003	0,004	0,003
25	0,001	0,221	0,001	0,000	0,000	0,001	0,000	0,001
26	0,023	0,930	0,023	0,013	0,023	0,023	0,025	0,023
27	0,022	0,333	0,022	0,013	0,023	0,022	0,025	0,022
28	0,067	0,649	0,068	0,039	0,068	0,068	0,070	0,068
29	0,015	0,264	0,016	0,009	0,014	0,016	0,016	0,016
30	0,987	1,000	1,000	1,000	1,000	1,000	1,000	1,000
31	0,044	0,358	0,045	0,026	0,046	0,045	0,045	0,045
32	0,055	0,634	0,056	0,032	0,055	0,056	0,058	0,056
33	0,001	0,056	0,001	0,001	0,000	0,001	0,000	0,001

**Table 2. Normalization Data Testing**

<b>Pola</b>	<b>X<sub>1</sub></b>	<b>X<sub>2</sub></b>	<b>X<sub>3</sub></b>	<b>X<sub>4</sub></b>	<b>X<sub>5</sub></b>	<b>X<sub>6</sub></b>	<b>X<sub>7</sub></b>	<b>Target</b>
1	0,019	0,428	0,019	0,011	0,018	0,019	0,021	0,023
2	0,118	0,593	0,119	0,069	0,119	0,119	0,119	0,144
3	0,041	0,313	0,041	0,024	0,041	0,041	0,041	0,050
4	0,093	0,564	0,094	0,054	0,096	0,094	0,095	0,114
5	0,022	0,105	0,022	0,013	0,023	0,022	0,025	0,026
6	0,027	0,394	0,028	0,016	0,027	0,028	0,029	0,033
7	0,082	0,312	0,083	0,048	0,082	0,082	0,082	0,100
8	0,116	0,271	0,117	0,061	0,119	0,117	0,119	0,142
9	0,171	0,368	0,173	0,090	0,174	0,173	0,173	0,209
10	0,051	0,407	0,052	0,030	0,050	0,052	0,053	0,062
11	0,056	0,243	0,057	0,033	0,055	0,057	0,058	0,068
12	0,399	0,302	0,405	0,211	0,406	0,405	0,403	0,491
13	0,127	0,155	0,129	0,067	0,128	0,129	0,132	0,156
14	0,025	0,113	0,026	0,015	0,027	0,025	0,025	0,030
15	0,014	0,179	0,014	0,008	0,014	0,014	0,016	0,017
16	0,000	0,525	0,000	0,000	0,000	0,000	0,000	0,007
17	0,021	0,540	0,022	0,012	0,023	0,022	0,021	0,025
18	0,078	0,191	0,079	0,041	0,078	0,079	0,078	0,095
19	0,049	0,194	0,050	0,029	0,050	0,050	0,049	0,060

\*name of corresponding author



20	0,036	0,282	0,037	0,021	0,037	0,037	0,037	0,044
21	0,056	0,465	0,057	0,033	0,055	0,057	0,058	0,068
22	0,012	0,000	0,012	0,007	0,014	0,012	0,012	0,014
23	0,037	0,166	0,038	0,043	0,037	0,038	0,037	0,045
24	0,003	0,109	0,003	0,002	0,005	0,003	0,004	0,003
25	0,001	0,221	0,001	0,000	0,000	0,001	0,000	0,000
26	0,023	0,930	0,023	0,013	0,023	0,023	0,025	0,028
27	0,022	0,333	0,022	0,013	0,023	0,022	0,025	0,026
28	0,067	0,649	0,068	0,039	0,068	0,068	0,070	0,081
29	0,015	0,264	0,016	0,009	0,014	0,016	0,016	0,018
30	0,987	1,000	1,000	1,000	1,000	1,000	1,000	1,214
31	0,044	0,358	0,045	0,026	0,046	0,045	0,045	0,054
32	0,055	0,634	0,056	0,032	0,055	0,056	0,058	0,067
33	0,001	0,056	0,001	0,001	0,000	0,001	0,000	0,008

**a. Input definition**

Input Data Variables are attributes that become a reference in making decisions on research using an Artificial Neural Network. The input data for predicting the number of TB sufferers is based on data from the North Sumatra Provincial Health Office:

No	Variable Name	Criteria
1	X <sub>1</sub>	Treatment coverage of all treated TB cases (Case Detection Rate/CDR).
2	X <sub>2</sub>	Case Notification Rate/CNR per 100,000 residents
3	X <sub>3</sub>	TB treatment success rate for all cases
4	X <sub>4</sub>	Coverage of drug-resistant TB case finding (cases)
5	X <sub>5</sub>	Treatment success rate for drug-resistant TB patients
6	X <sub>6</sub>	Coverage of TB case detection knowing HIV status
7	X <sub>7</sub>	Number of drug-resistant TB cases starting second-line treatment (Enrollment)

**b. Defining Input and Target**

Data on the number of TB suspects found based on data from the North Sumatra Provincial Health Office will be processed using the Backpropagation Artificial Neural Network method. In order for the data to be recognized and read by the Artificial Neural Network, the data must be transformed into a numeric form between 0 and 1.

**c. Defining Targets**

The target data in this study is TB case data based on the North Sumatra Provincial Health Office in 2021.

**d. Output definition**

The expected results at this stage are pattern detection to determine the best architecture for predicting the number of TB cases based on TB data from the North Sumatra Provincial Health Office. The test results are as follows:

1. To find out the prediction results for the number of TB cases in North Sumatra Province by looking at the minimum error.
2. Categories of training output (train) and test (test) are determined by the minimum error rate of the target. With category restrictions in the following table:

\*name of corresponding author



No	Description	Minimum Error	
1	0	False	>0.01
2	1	True	<=0.01

**e. Neural Network Model Determination**

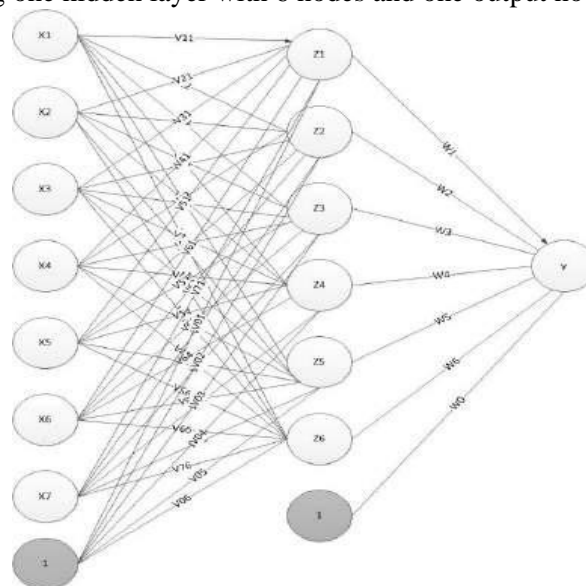
In this study using a feed-forward backpropagation neural network, where the information signal exists from two directions (from the input layer to the output layer and vice versa) iteratively until an equilibrium is reached, with an appropriate bias level and noise to minimize the error value (Mean Squared Error).

**f. Input Layer Determination**

The information used as input data is the information needed to determine the TB case threshold value. Treatment coverage of all treated TB cases (Case Detection Rate/CDR), Case Notification Rate/CNR per 100,000 population, Treatment success rate for drug-resistant TB patients, Coverage of TB case detection knowing HIV status, Number of resistant TB cases (Enrollment). Therefore, there are approximately 7 (seven) variable nodes in the input layer of this study.

**g. Perancangan Arsitektur Jaringan Syaraf Tiruan**

At the architectural design stage is designing the Backpropagation ANN architecture. In this case, 7 input nodes were tested, using one hidden layer with 6 nodes and one output node.



**RESULTS AND DISCUSSION**

**Data Testing Using Matlab R2013a**

The training of the backpropagation neural network model is carried out by combining the training function and the number of hidden layer neurons to train the data set with the following criteria:

1. The number of hidden nodes tested is 6 nodes
2. The learning rate is -0.5 to 0.5
3. Momentum is 0 to 1
4. Bias on the input layer and hidden layer = 1

Table 1 below shows the results of the training data set which shows the relationship between the learning rate and momentum on the Mean Square Error (MSE) when data training is carried out.

\*name of corresponding author



**Table 3 Results of Nguyen Widrow's Backpropagation Training with bias**

Laju Pembelajaran/ Learning Rate	Momentum	Epoch	Time	MSE	Gradient	Regression
-0.5	0	16	0:00:14	0.90427	0.096621	0.90427
-0.4	0	123	0:02:00	0.0038129	0.0017823	0.97532
-0.3	0	105	0:01:41	0.00025513	0.010009	0.943
-0.2	0	58	0:00:54	0.0014714	0.056653	0.67002
-0.1	0	181	0:04:12	0.0032891	0.0023965	0.92576
0.1	0	35	0:00:00	0.043565	0.021961	0.95556
0.2	0	87	0:03:59	0.00094153	0.0016922	0.9786
0.3	0	9	0:00:08	0.0017692	0.0401	0.98357
0.4	0	118	0:01:44	0.0018803	0.0011415	0.9958
0.5	0	109	0:01:36	0.0020609	0.001468	0.99087
-0.5	0.1	164	0:02:17	0.003647	0.0020485	0.9513
-0.4	0.1	74	0:01:07	0.0050306	0.077359	0.87444
-0.3	0.1	50	0:00:44	0.0017629	0.06175	0.984
-0.2	0.1	58	0:00:56	0.0014714	0.056653	0.67002
-0.1	0.1	85	0:00:00	0.043264	0.019982	0.966
0.1	0.1	19	0:00:17	0.0025919	0.032513	0.4071
0.2	0.1	129	0:01:57	0.00034561	0.0073537	0.9919
0.3	0.1	112	0:01:41	0.001192	0.0014588	0.9949
0.4	0.1	79	0:01:12	0.0030239	0.0041298	0.93939
0.5	0.1	120	0:01:48	0.003832	0.00056845	0.94111
-0.5	0.2	164	0:02:17	0.0024204	0.024586	0.96306
-0.4	0.2	74	0:01:07	0.026885	0.026678	0.98044
-0.3	0.2	50	0:00:44	0.0038129	0.0017823	0.97532
-0.2	0.2	58	0:00:56	0.00034094	0.013459	0.91749
-0.1	0.2	85	0:00:00	0.043264	0.019982	0.966
0.1	0.2	19	0:00:17	0.020639	0.0004997	0.99915
0.2	0.2	129	0:01:57	0.00062651	0.00057452	0.99505
0.3	0.2	112	0:01:41	0.00036585	0.0016659	0.99342
0.4	0.2	79	0:01:12	0.00030309	0.0020023	0.99408
0.5	0.2	120	0:01:48	0.0029641	0.0091591	0.98758
-0.5	0.3	77	0:01:08	0.00061148	0.0053555	0.96525
-0.4	0.3	77	0:01:09	0.0024857	0.043597	0.97268
-0.3	0.3	64	0:00:54	0.0049765	0.059039	0.85845
-0.2	0.3	106	0:01:33	0.028527	0.012173	0.95978
-0.1	0.3	85	0:01:00	0.043264	0.019982	0.966
0.1	0.3	72	0:01:05	0.014699	0.0099205	0.96343
0.2	0.3	45	0:00:41	0.0052824	0.010696	0.97696
0.3	0.3	44	0:00:38	0.0023084	0.0034733	0.97811
0.4	0.3	64	0:00:57	2.0326	0.0030812	0.83959
0.5	0.3	50	0:00:46	0.0051426	0.0061385	0.98063
-0.5	0.4	89	0:01:03	0.00040881	0.003139	0.99236
-0.4	0.4	129	0:01:52	0.00091126	0.0026156	0.98891
-0.3	0.4	124	0:01:51	0.0013647	0.0031762	0.97351
-0.2	0.4	128	0:01:51	0.0036001	0.0063126	0.94811
-0.1	0.4	93	0:00:00	0.0045231	0.010154	0.98586
0.1	0.4	21	0:00:18	0.0035123	0.012929	0.97805
0.2	0.4	144	0:02:37	0.00038969	0.0086824	0.99012
0.3	0.4	156	0:02:14	0.028605	0.00046484	0.98657

\*name of corresponding author



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0.4	0.4	16	0:00:14	0.0015422	0.012009	0.96606
0.5	0.4	24	0:00:22	0.031974	0.010185	0.97362
-0.5	0.5	177	0:02:32	0.0055414	0.0015892	0.94109
-0.4	0.5	171	0:02:32	0.22287	0.0012251	0.91236
-0.3	0.5	96	0:01:22	0.0016237	0.0039916	0.93945
-0.2	0.5	272	0:04:33	0.0046366	0.0011129	0.97848
-0.1	0.5	38	0:00:00	0.0026436	0.081257	0.85358
0.1	0.5	91	0:01:17	0.0035745	0.0015901	0.9502
0.2	0.5	137	0:02:02	0.00020615	0.0007197	0.99703
0.3	0.5	16	0:00:14	0.0017084	0.016716	0.92621
0.4	0.5	147	0:02:07	0.00012387	0.0010225	0.98995
0.5	0.5	177	0:02:42	0.0033162	0.00045192	0.97073
-0.5	0.6	98	0:01:24	0.0079274	0.010605	0.90993
-0.4	0.6	194	0:02:40	0.0019116	0.00092415	0.97101
-0.3	0.6	122	0:01:47	0.003011	0.0078341	0.97827
-0.2	0.6	105	0:01:30	0.0049723	0.010311	0.97708
-0.1	0.6	205	0:02:27	0.0042279	0.0062283	0.89942
0.1	0.6	175	0:02:31	0.00067833	0.00033304	0.99491
0.2	0.6	16	0:00:14	0.0052471	0.070417	0.9441
0.3	0.6	24	0:00:21	0.0003344	0.0039075	0.91426
0.4	0.6	89	0:01:18	0.0013111	0.00057997	0.95653
0.5	0.6	172	0:02:29	0.00013193	0.0001598	0.99841
-0.5	0.7	225	0:03:16	0.00017885	0.00027531	0.99734
-0.4	0.7	77	0:01:09	0.006779	0.082291	0.88946
-0.3	0.7	143	0:02:09	0.00019938	0.0019046	0.98395
-0.2	0.7	236	0:03:33	0.00017445	0.00057329	0.99873
-0.1	0.7	85	0:00:00	0.043264	0.019982	0.966
0.1	0.7	47	0:00:44	0.0045901	0.076815	0.95994
0.2	0.7	59	0:00:54	0.001142	0.0054449	0.97935
0.3	0.7	12	0:00:11	0.0046337	0.064165	0.91693
0.4	0.7	47	0:00:43	0.041594	0.0062826	0.97537
0.5	0.7	133	0:01:57	0.00063122	0.0010824	0.95024
-0.5	0.8	86	0:01:44	0.0070585	0.049283	0.81287
-0.4	0.8	233	0:03:20	0.00030819	0.0011481	0.99841
-0.3	0.8	144	0:02:06	0.0060625	0.0083901	0.92303
-0.2	0.8	144	0:02:10	0.0023997	0.0012669	0.99274
-0.1	0.8	205	0:02:24	0.0042279	0.0062283	0.89942
0.1	0.8	27	0:00:37	0.0025618	0.008281	0.9191
0.2	0.8	97	0:02:04	0.16189	0.0018397	0.92045
0.3	0.8	146	0:02:13	0.00073059	0.0013317	0.9951
0.4	0.8	14	0:00:13	0.0066203	0.062375	0.92459
0.5	0.8	8	0:00:07	0.034908	0.006706	0.86975
-0.5	0.9	118	0:01:50	0.0021515	0.0051707	0.919
-0.4	0.9	112	0:01:37	0.00058136	0.0074991	0.87053
-0.3	0.9	90	0:01:19	0.0053953	0.021861	0.88295
-0.2	0.9	106	0:01:35	0.028527	0.012173	0.95978
-0.1	0.9	85	0:00:00	0.043264	0.019982	0.966
0.1	0.9	50	0:00:47	0.0041446	0.010287	0.98555
0.2	0.9	69	0:01:01	0.0012453	0.0094784	0.83941
0.3	0.9	13	0:00:12	0.0056531	0.056241	0.92802
0.4	0.9	28	0:00:26	0.0052217	0.0078369	0.97511
0.5	0.9	15	0:00:14	0.0005281	0.013658	0.97991

\*name of corresponding author

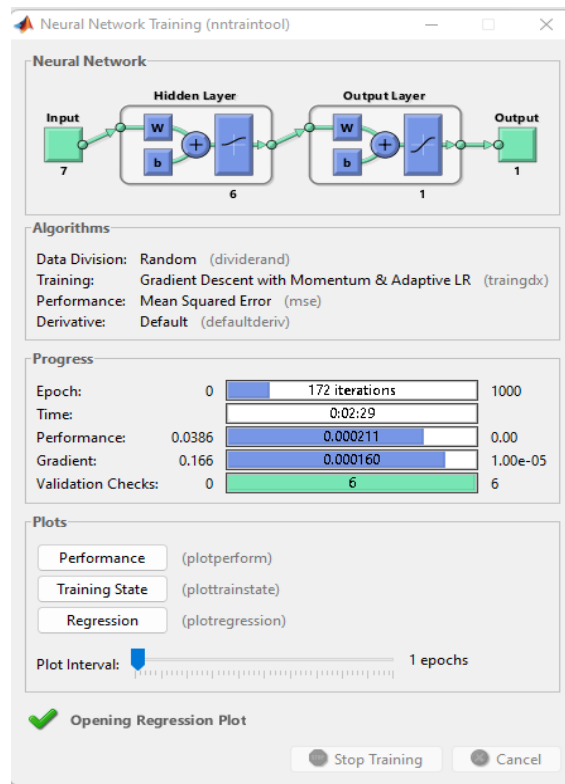


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-0.5	1	144	0:02:10	0.0060625	0.0083901	0.92303
-0.4	1	182	0:02:47	0.003291	0.00054758	0.9891
-0.3	1	81	0:01:15	0.00086228	0.061298	0.71166
-0.2	1	106	0:01:37	0.028527	0.012173	0.95978
-0.1	1	88	0:01:07	0.040866	0.93811	0.96031
0.1	1	34	0:00:30	0.0083608	0.092267	0.84423
0.2	1	14	0:00:12	0.0010843	0.003158	0.85624
0.3	1	24	0:00:22	0.00077826	0.019825	0.92788
0.4	1	40	0:00:38	0.0043729	0.029982	0.96755
0.5	1	18	0:00:17	0.0052931	0.0085473	0.97143

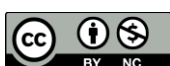
The model with 7 input nodes and 1 output node is the most optimal to achieve the desired result. This can be done using one hidden layer with six nodes. The activation function used in the hidden layer and the output of each layer is logsig. The training and learning functions (trainingdx and learningdx) can help algorithms learn faster. The model has been able to achieve balance in the 172nd epoch with an MSE value of 0.00013193. The model is very accurate in predicting the target value.

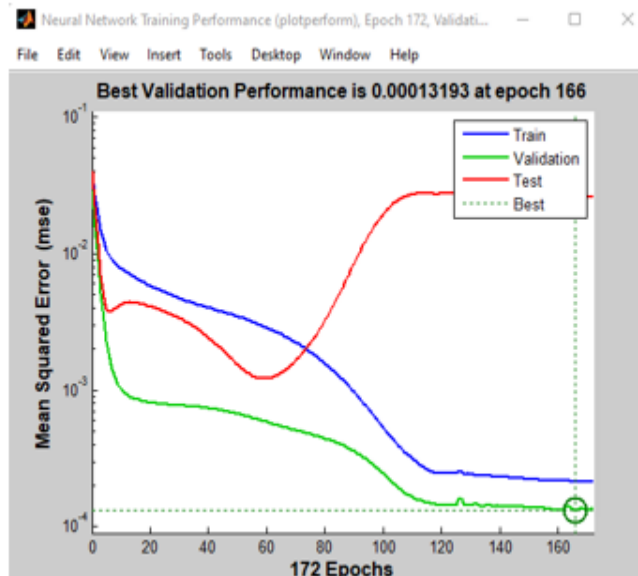


**Judul Gambar**

Increasing the number of epochs during the training process until the training process stops has no effect on the Mean Square Error (MSE). From these graphs it can be estimated that there will be no overfitting in the training and testing process. This shows that the resulting model will produce good performance for training data only, but the performance will be different when tested with data outside the training data. The training data is more accurate than the testing data as indicated by the higher MSE value in the training data.

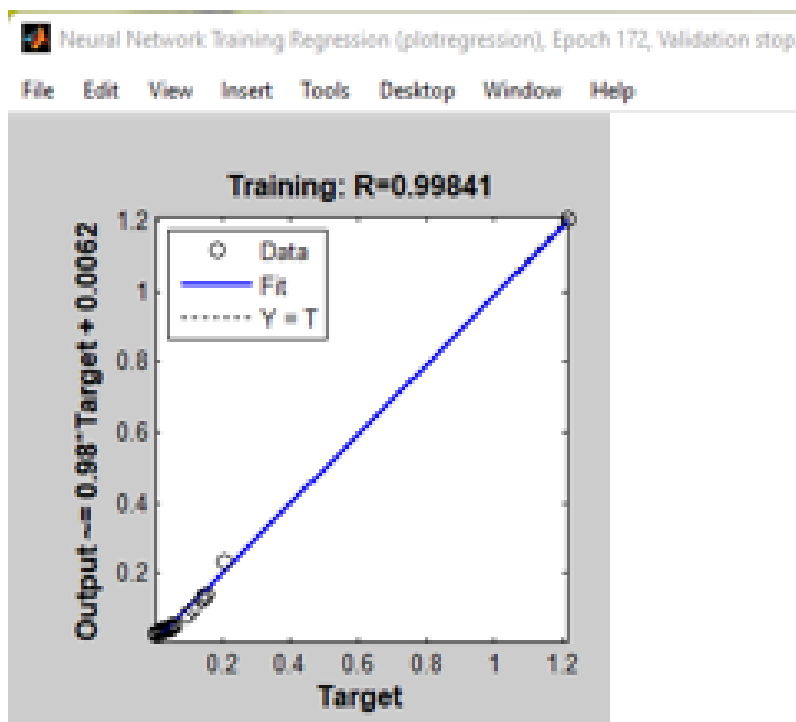
\*name of corresponding author





**Judul Gambar**

Based on the results of training using the Matlab 2013a combination of learning rate and momentum, the smallest MSE is obtained at the training learning rate of 0.5 and momentum of 0.6, so that in the testing process a correlation coefficient of 0.99841 is produced.



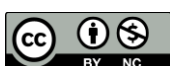
**Judul Gambar**

Table 3 shows a comparison of training data with a combination of learning rates -0.1 to -0.5 and 0.1 to 0.5 and momentum from 0-1. The epoch level and time were obtained using Matlab Application 2013a, while the accuracy of each architectural model was obtained using calculations in Microsoft Excel.

**Table 4 Best architecture with Backpropagation**

Pola	Target	Output	Error	SSE	Result
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\*name of corresponding author



1	0.02283	0.03661	-0.01361	0.000185309	1
2	0.14403	0.13598	0.00802	6.4389E-05	1
3	0.04957	0.04771	0.00229	5.24554E-06	1
4	0.11373	0.09903	0.01497	0.000224248	0
5	0.02649	0.03719	-0.01119	0.00012518	1
6	0.03298	0.04052	-0.00752	5.64932E-05	1
7	0.09951	0.08082	0.01918	0.000367721	0
8	0.14183	0.12559	0.01641	0.000269395	0
9	0.20903	0.23486	-0.02586	0.000668723	1
10	0.06193	0.05499	0.00701	4.91377E-05	1
11	0.06836	0.05749	0.01051	0.00011041	0
12	0.49077	0.85333	-0.36233	0.131285969	1
13	0.15593	0.14138	0.01462	0.000213871	0
14	0.03027	0.03862	-0.00862	7.43211E-05	1
15	0.01667	0.03358	-0.01658	0.000274743	1
16	0.00705	0.02931	-0.02231	0.000497748	1
17	0.02548	0.03853	-0.01353	0.000183098	1
18	0.09533	0.07664	0.01836	0.000336932	0
19	0.05950	0.05254	0.00746	5.56701E-05	1
20	0.04370	0.04496	-0.00096	9.27125E-07	1
21	0.06830	0.05920	0.00880	7.74761E-05	1
22	0.01402	0.03264	-0.01864	0.000347366	1
23	0.04528	0.04299	0.00201	4.05201E-06	1
24	0.00319	0.02948	-0.02648	0.00070142	1
25	-0.00003	0.02876	-0.02876	0.000827062	1
26	0.02762	0.04256	-0.01456	0.000212098	1
27	0.02599	0.03758	-0.01158	0.000134111	1
28	0.08128	0.07160	0.00940	8.83614E-05	1
29	0.01825	0.03437	-0.01637	0.000268102	1
30	1.21370	1.20801	0.00599	3.5912E-05	1
31	0.05380	0.05031	0.00369	1.36479E-05	1
32	0.06689	0.06067	0.00633	4.00482E-05	1
33	0.00762	0.02846	-0.02046	0.000418643	1
Total				0.13821783	27
<b>Accuracy</b>				<b>81.82%</b>	

Based on the results of training using the Matlab 2013a combination of learning rate and momentum, the smallest MSE is obtained at the training learning rate of 0.5 and momentum of 0.6, so that in the testing process a correlation coefficient of 0.99841 is produced. The Mean Square Error (MSE) graph shows that the learning rate and momentum greatly affect the convergence achieved. The training with the lowest MSE score in the prediction model is at a learning rate of 0.5, momentum is 0.6, the maximum epoch is 1000, the length of time the training requires duration 149 seconds. The resulting training MSE is 0.00013193 with an accuracy of the resulting prediction model of 81.82%.

## CONCLUSION

The learning rate has an influence on the Mean Square Error value. The greater the value of the learning rate / learning rate in data training can achieve convergence when given a value range between 0.1 to 0.5. The Momentum value influences the Mean Square Error value, the greater the momentum value during training, the smaller the Mean Square Error value. In this research, the data training reaches convergence when the momentum value is 0.6 The existence of bias when conducting training is to accelerate to get the desired output value. The Mean Square Error (MSE) graph shows that the learning rate and momentum greatly affect the convergence achieved. The training with the lowest MSE value in the prediction model is at a learning rate of 0.5, momentum of 0.6, maximum

\*name of corresponding author



epoch 1000, length of training time takes 149 seconds duration. The resulting training MSE is 0.00013193 with an accuracy of the resulting prediction model of 81.82%.

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