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Application of the ANN Algorithm to Predict Access to Drinkable Water in North Sumatra Regency (City)

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Abstract−The increase in population has an impact on increasing the need for drinking water, but this is not in line with the fact that not 100% of the people in Indonesia physically receive or consume safe drinking water. This analysis is based on data from the Central Statistics Agency to look at the social, economic and demographic factors of households regarding the availability of adequate physical quality drinking water. This research aims to predict the percentage of households that have access to adequate drinking water using the Artificial Neural Network (ANN) method. The technique used is Backpropogation. Backrpopagation is a supervised neural network training method, it evaluates the error contribution of each neuron after a set of data has been processed. The goal of backpropagataion is to modify weights to train a neural network to map arbitrary inputs to outputs correctly. Therefore, looking at the above problems, this research aims to determine access to adequate drinking water sources by predicting which households have adequate drinking water so that there is no lack of adequate drinking water sources in the City Regency area. Methods and basic data are needed to make predictions. In this research, data was obtained from BPS which used data from 2014 - 2021, with training data from 2014 - 2020 and testing data from 2015 - 2021. Based on the best architecture produced in this research, namely the 6-17-1 architecture with an accretion of 90%. Thus it can be concluded that the Backpropagation Neural Network can provide good accuracy in carrying out the prediction process.

Keywords: Drinking water; Artificial Neural Networks; Backpropagation; Prediction; Data

1. INTRODUCTION

Clean water is a very important need for human life and is a natural resource with a very important function as well. People use clean water for their daily needs, starting from drinking, bathing, cooking, washing and other purposes. Based on the Regulation of the Minister of Public Works and Public Housing Number 09/PRT/M/2015 concerning the use of water sources, it is stated that water is all water contained in and/or originating from water sources, both above and below the ground surface. Water also plays an important role in efforts to improve the welfare and prosperity of society, as stipulated in article 33 paragraph 3 of the 1945 Constitution which reads: "The earth and water, the natural resources contained therein, are controlled by the state and used for the greatest prosperity of the people"[1], [2].

Water is one of the most needed and important natural elements for all types of human life. Water itself is a resource that is indispensable for all activities and a production factor that determines sustainable development. Unequal access to drinking water means that there are still people in the world who do not have access to safe drinking water, which contributes to the development of water-related chronic diseases [3]. In the household sector, it has an important role in determining the quality of water experienced by individual households because the household is the final point of management before consuming the water [4]. The amount of water consumed and the needs of each person vary according to activities and lifestyle. The water needed by humans must be sufficient for all life needs, especially drinking needs. Water is used by various economic sectors, including households, agriculture, industry and infrastructure[5], [6]. The distribution of water between regions varies, depending on how to distribute water from one water source in an area to the surrounding areas, especially to dry areas that must immediately receive water channels. Adequate drinking water in district/city areas is currently still a serious problem. According to data from the Central Statistics Agency, the amount of drinking water in 2018 decreased. The biggest opportunity to reduce the quality of drinking water so that people use bottled water is changes in land use in urban areas which result in limited open space, resulting in a lack of green space and making it difficult to get drinking water. Apart from river and stream land conversion, water quality also affects the availability of drinking water [7], [8].

Over time, the growth of urban areas has had a significant impact on the needs for facilities and institutions in the area.The government must pay special attention to the correct management of drinking water, considering the importance of water needs for society. Drinking water management obtains correct and healthy water in accordance with healthy water quality standards. The aim of the drinking water system is to produce sufficient water for community needs in accordance with the level of progress and development of the supply area.

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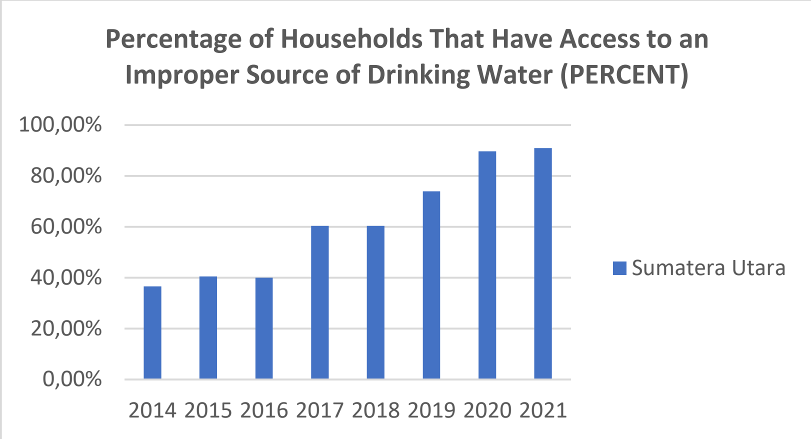

Figure 1. Graph of the Percentage of Households That Have Access to a Source of Adequate Drinking Water in North Sumatra Regency/City

It can be seen in the graph above based on data from the Central Statistics Agency regarding the Percentage of Households that Have Access to a Source of Adequate Drinking Water in the Regency/City of North Sumatra (2014-2021), it is explained that the percentage of households that had access to a source of adequate drinking water in 2014 was 36. 54 percent, in 2015 as much as 40.46 percent, in 2016 as much as 39.98 percent, in 2017 as much as 60.32 percent, in 2018 as much as 60.36 percent, in 2019 as much as 73.90 percent, in 2020 as much as 89.68 percent , in 2021 as much as 90.89 percent [9], [10].

In previous research conducted by [11] entitled "New Method of Artificial Neural Networks (ANN) Based on Back Propagation (BP) and Radial Basis Function (RBF) to Predict the Appearance of Haloketones in Tap Water" the results showed that the overall predictive ability of RBF and BP ANN better than linear/log line models. Although BPANN showed excellent prediction performance in internal validation (N25=98–100%, R2 =0.99–1.00), BPANN could not predict the emergence of HK well in external validation (N25 =62–69%, R2 = 0.202–0.848). The predictive ability of RBF ANN in external validation (N25 = 85%, R2 = 0.692–0.909) is quite good, comparable to internal validation (N25 = 74–88%, R2 = 0.799–0.870). These results demonstrate that RBF ANN can well recognize the complex nonlinear relationship between PA presence and related water quality, and open new avenues for PA prediction and monitoring in practice.

Meanwhile, in the next research conducted by [12] with the title "The Effect of Gradient Descent Using the Backpropagation Momentum Training Function in Detecting Alphabet Letters" the results of the testing process using the Backpropagation algorithm reached 100% with a total of 90 data. The test data test results reached 100% from 90 test data.

Therefore, a problem arises from the large amount of inadequate drinking water in the household. Based on the problems above, the author will create a system to predict the percentage of households that have access to an adequate source of drinking water using the tituan neural network in the backpropagation method therein. The application of the Artificial Neural Network (ANN) algorithm in this research reflects efforts to utilize artificial intelligence (AI) technology in formulating solutions to complex social problems [12], [13]. Through careful analysis using this technique, it is hoped that we can predict and understand household access patterns to safe drinking water with a high degree of accuracy [14]. By using the Backpropagation Artificial Neural Network (ANN) method, it is intended to be able to build a system to predict the value of water distributed in Indonesian provinces. In this study, 5 architectural testing models were used, namely the 6-12-1, 6-15-1, 6-17-1, 6-23-1 and 6-27-1 models and obtained the best architectural model, namely 6-17-1. with 100% accuracy. Through the resulting system, it is hoped that it can help the government predict drinking water needs in districts/cities in North Sumatra province, Indonesia and be able to increase the distribution of adequate drinking water in Indonesia, especially areas that have high population density.

This research is expected to provide significant benefits, including providing a deeper understanding of the factors that influence access to safe drinking water, contributing to scientific literature regarding the application of AI in addressing social problems, and providing guidance to the government and related institutions in planning efficient and sustainable clean water infrastructure [15].

2. RESEARCH METHODOLOGY

2.1 Method of collecting data

The data collection method is collecting and analyzing data to answer certain questions, test hypotheses and assess the results of qualitative and quantitative research using different data collection methods. The method used in this research is Backpropagation Neural Network. The dataset used in the research is the Presentation dataset of

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Households That Have Access to Adequate Drinking Water Sources. The dataset used in this research is sourced from BPS (Central Statistics Agency) with the link https://sumut.bps.go.id/indicator/30/174/1/persentase-rumah-tangga-yang-cepat-akses-terhadap-source -air-minum-layak.html The research has a data set from 2014 - 2021, then the data is normalized using a function, namely the sigmoid function, then carrying out data transformation. Next, a network architecture design will be carried out using a Mathlab application to get the final result. or the conclusion.

2.2 Research Framework

In the picture below you can see that the first process carried out was collecting data from the Central Statistics Agency (BPS) which obtained data from 2014 - 2021, then in this process also collecting references from the internet with various journals and books. artificial neural network. Then, after completing the collection, the process of identifying the research problem is carried out and normalizing the data using the sigmoid function, then determining the division of training data and test data. Next, carry out the process of determining the pattern or architecture that will be tested in the Mathlab application. After determining the pattern, a data testing process will be carried out and make predictions and evaluate the results obtained.

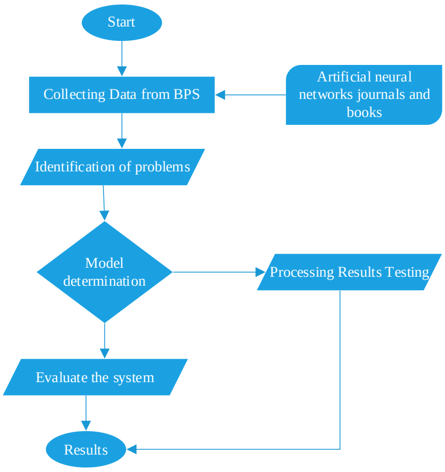

Figure 2. Research Workflow

The research workflow you've provided outlines the process of conducting research using artificial neural networks. Here's a brief explanation of each step:

a. Start: The research process begins with defining the scope, objectives, and research questions. Researchers plan their approach and methodology during this phase.
b. Collecting data from BPS from artificial neural network journals and books: Researchers gather relevant data from various sources such as academic journals, books, and online databases related to artificial neural networks (ANNs) and the Central Statistics Agency (CSA). This step is crucial for building a strong foundation for the research.
c. Identify the problem: Researchers identify a specific problem or challenge within the context of BPS that can be addressed using artificial neural networks. Defining a clear problem statement is essential for guiding the research in the right direction.
d. Model determination: In this step, researchers decide on the type of artificial neural network model that will be used to address the identified problem. This decision is based on the nature of the problem, available data, and the goals of the research.
e. Testing Processing Results: Researchers implement the selected ANN model and conduct experiments using the collected data. They process the data through the model to observe how well the ANN performs in solving the identified problem. This phase involves rigorous testing and analysis of the results obtained.
f. Evaluate the system: After testing, researchers evaluate the performance of the ANN system. They assess the accuracy, efficiency, and effectiveness of the model in addressing the problem. This evaluation helps in understanding the strengths and limitations of the developed system.
g. Results: Researchers analyze the outcomes of the experiments and draw conclusions based on the results obtained. They interpret the findings in the context of the problem identified earlier. The results may also include recommendations for further research or practical applications based on the research findings.

This workflow provides a structured approach to conducting research using artificial neural networks, ensuring that the research process is systematic and methodical from problem identification to result analysis.

2.3 Artificial Neural Network (ANN)

ANN can be used to predict what will happen in the future based on past event data and related factors. Backpropagation is an artificial neural network method that uses multiplayer training which works systematically

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based on very strong and objective mathematical knowledge through developed network architectural models. Artificial Neural Network (ANN) is an information processing system that has characteristics resembling a biological neural network (JSB)[16], [17]. In the learning process, the Backpropagation algorithm is included in the category of supervised learning methods. Backpropagation is a systematic method in artificial neural networks using a supervised learning algorithm and is usually used by perceptrons with many layer screens to change the weights in the hidden layers[18], [19]. According to Haykin (2009) Artificial Neural Network (ANN) is a network designed to resemble the human brain which aims to carry out a certain task. Backpropagation Artificial Neural Network is a branch of artificial intelligence that is used to identify historical data patterns by using training methods[20].

In neural networks, when a process is executed, synaptic weights are used to determine the neural function. Then the neural function determines the network output and the network output determines the network error. One method of training artificial neural networks with supervision is backpropagation. There are several types of layers found in backpropagation including input layers, hidden layers and output layers. The retransmission process consists of two steps. In other words, the process of activating or propagating input values and mapping them to desired output values. In the backpropagation algorithm in solving problems, there are several steps used as follows[10], [21].

Stage 0: Gives the first value to the weight which is done randomly and pays attention to the learning rate.
Stage 1: When the error found has not reached the specified limit, continue with the following steps.
Feedforward stage

a. Input neuron xi with i = 1,2,3…n gets xi and then passes it to each hidden layer neuron.
b. Hidden layer neurons Zi with j = 1,2,3,…p add weighted inputs

$$Z\_in_j = V_{0j} + \sum_i^n = 1\ X_i V_{ij} \tag{1}$$

Calculate the output signal of the hidden layer when using the activation function:

$$Z_j = \frac{1}{1+e-z\_inj} \tag{2}$$

c. The output neuron yk with k=1,2,3,….m sums the weighted inputs:

$$y\_in_k = V_{0k} + \sum_k^p = 1\ Z_j\, W_{jk} \tag{3}$$

use the activation function then calculate the result signal in the result layer with the equation:

$$y_k = \frac{1}{1+e-y\_ink} \tag{4}$$

Backpropagation Algorithm Stage

a. In each output neuron yk with k = 1,2,3,…m, receives a target output pattern that is related to the input and training patterns.
b. In the hidden layer neurons Zj with j = 1,2,3,…p add up the delta factors in the hidden layer
c. In the output neuron yk with k=1,2,3,….m, upgrade the hidden layer weights to the output layer

3. RESULT AND DISCUSSION

3.1 Input Assignment

Determination of input contributions in this research is based on the number of years available at the Central Statistics Agency. Data on the percentage of households that have access to an adequate source of drinking water in this study uses data from 2014-2021. This data is used to guide decision making when making predictions using the backpropagation algorithm. This research has several input numbers which can be seen in table 1 below. Table 1. Explains that the input in this research has 8 variables with variables X1 to variable X8. Each variable has its own criteria.

Table 1. List of Input Data for Households Having Access to Adequate Drinking Water Sources

No	Variable	Criterion Name
1	X1	2014
2	X2	2015
3	X3	2016
4	X4	2017
5	X5	2018
6	X6	2019
7	X7	2020
8	X8	2021

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3.2 Output Determination

The most anticipated step in this research is determining the best value to predict the results of households with an adequate source of drinking water in 2022. In order to get the prediction results, the best architecture is needed by looking at the minimum error value. In this study, a minimum error value of <= 0.05 with a correct value (1) and more than 0.05 with an incorrect value (0) was used. The smaller the minimum error obtained, the better the research.

3.3 Output Determination

Data on the percentage of households that have access to an adequate source of drinking water in 2014-2021 was used for this research. Data obtained from the Central Statistics Agency before implementing the Matlab application was first normalized using the sigmoid function (not reaching 0 or 1) with Excel. In this research, data that has been normalized using the sigmoid function will be divided into two parts, namely training data and test data. In this article the training data starts in 2014-2020 and the test data starts in 2015-2021. Before dividing the training data and test data, the data is normalized first. So data normalization can be represented with the following equation:

$$X^1 = \frac{0.8(x-min)}{max-min} + 0.1$$

Information :
X1 = Normalized Data min = Lowest data of all data 0.8 = Interval
X = Normalized data max = Highest data of all data 0.1 = Interval

Table 2 shows the training data which has been normalized using the sigmoid function. Training data or what is usually called training data is data that will be used in the Mathlab application before carrying out the testing process.

Table 2. Training Data After Normalization

		NORMALISASI							
No	Regency/City	2014	2015	2016	2017	2018	2019	2020	2021
1	Sumatera Utara	0,3689	0,3483	0,4264	0,5326	0,4943	0,6330	0,7578	0,7632
2	Nias	0,1638	0,1000	0,1000	0,1158	0,1000	0,1000	0,1875	0,1000
3	Mandailing Natal	0,1951	0,1354	0,3801	0,2338	0,1870	0,3077	0,4497	0,4999
4	Tapanuli Selatan	0,6141	0,4373	0,3794	0,3916	0,4577	0,4066	0,4516	0,4016
5	Tapanuli Tengah	0,4279	0,2853	0,4624	0,3734	0,2739	0,4525	0,6305	0,4234
..	…..	…..	….	….	….	….	…	….	…..
32	Binjai	0,2556	0,2543	0,3521	0,6042	0,6432	0,7762	0,8911	0,8997
33	Padangsidimpuan	0,2145	0,2307	0,2965	0,2650	0,3267	0,2883	0,1000	0,1976
34	Gunungsitoli	0,1000	0,1510	0,2662	0,4534	0,5742	0,6911	0,6093	0,5050

In table 3 is the data that will be used as test data implemented in Mathlab.

Table 3. Test data after normalization

		NORMALISASI							
No	Regency/City	2014	2015	2016	2017	2018	2019	2020	2020
1	Sumatera Utara	0,3689	0,3483	0,4264	0,5326	0,4943	0,6330	0,7578	0,7578
2	Nias	0,1638	0,1000	0,1000	0,1158	0,1000	0,1000	0,1875	0,1875
3	Mandailing Natal	0,1951	0,1354	0,3801	0,2338	0,1870	0,3077	0,4497	0,4497
4	Tapanuli Selatan	0,6141	0,4373	0,3794	0,3916	0,4577	0,4066	0,4516	0,4516
5	Tapanuli Tengah	0,4279	0,2853	0,4624	0,3734	0,2739	0,4525	0,6305	0,6305
..	…..	…..	….	….	….	….	…	….	…..
32	Binjai	0,2556	0,2543	0,3521	0,6042	0,6432	0,7762	0,8911	0,8911
33	Padangsidimpuan	0,2145	0,2307	0,2965	0,2650	0,3267	0,2883	0,1000	0,1000
34	Gunungsitoli	0,1000	0,1510	0,2662	0,4534	0,5742	0,6911	0,6093	0,6093

From table 3 above it can be seen that it shows test data that has been normalized using the sigmoid function. This data is what will later be used in the data testing process by implementing it into the Mathlab application. In this study, version 7 R2011a was used. Test data in research predicting the results of households with an adequate source of drinking water from the Indonesian Central Bureau of Statistics and the data used in this test is data from 2014-2021. Data for 2021 is used as the target. This test data has data in Percent units.

3.4 Architectural Design and Results

Architectural design using the mathlab application. In this research, an architectural design uses a Mathlab R2011a application. In this research the author uses several network architectures. From the results of the tests that have been carried out, the best architecture with the highest accuracy is obtained, namely architecture 6-17-1 with a

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training MSE of 0.000000124 with an accuracy of 100% and a testing MSE of 0.000000124 with an accuracy of 85% and has an epoch of 1371 iterations. You can see the results of the 6-17-1 architecture in the table below. It can be seen in the table below that the output and errors obtained come from the implementation in the mathlab application, SSE is obtained from the error results and ^2 then the determination of the number of MSE is obtained from the number of sse divided by the number in the data. To get the accuracy value, if the error value is <=0.05, it has a value of 1 (correct), and if it has a value >=0.05, it has a value of 0 or wrong. So the total accuracy truth value is divided by the amount of data processed to obtain how much accuracy the architecture has.

Table 4. Results of the best architecture training data

No	Regency/City	Output	Error	SSE	Results
1	Sumatera Utara	0,8269	-0,0186	0,00034596	1
2	Nias	0,4443	-0,0007	0,00000049	1
3	Mandailing Natal	0,6105	0,0008	0,00000064	1
4	Tapanuli Selatan	0,6127	-0,0001	0,00000001	1
5	Tapanuli Tengah	0,7291	-0,0022	0,00000484	1
..	…………………..	………..	………	……….	..
31	Medan	0,8877	0,0033	0,00001089	0
32	Binjai	0,8925	0,0012	0,00000144	1
33	Padangsidimpuan	0,3874	0,0002	0,00000004	1
34	Gunungsitoli	0,7123	0,0011	0,00000121	1
			Number of SSEs	0,00070703	88%
			MSE	0,00002080	

It can be seen in table 5 that it shows that the 6-17-1 architecture can produce an accuracy of 68% by calculating the correct amount of data based on the predetermined learning rate and dividing by the amount of data then multiplying by 100 to get the accuracy percentage.

Table 5. Best architecture test data results

No	Regency/City	Output	Error	SSE	Results
1	Sumatera Utara	0,9525	-0,1331	0,01771561	1
2	Nias	0,7501	-0,3216	0,10342656	1
3	Mandailing Natal	0,9017	-0,2375	0,05640625	1
4	Tapanuli Selatan	0,8885	-0,2823	0,07969329	1
5	Tapanuli Tengah	0,3533	0,2658	0,07064964	0
..	…………………..	………..	………	……….	..
31	Medan	0,9701	-0,079	0,00624100	1
32	Binjai	0,9859	-0,0861	0,00741321	1
33	Padangsidimpuan	0,4348	0,0512	0,00262144	0
34	Gunungsitoli	0,9321	-0,2649	0,07017201	1
			Number of SSEs	1,26818793	68%
			MSE	0,03729965	

From Figure 3 it is explained that the 6-17-1 architectural model has obtained an Epoch with 1371 iterations in 26 seconds. In this article, it is applied to the mathlab application in designing network architecture using Train Gradient Descent "traingd".

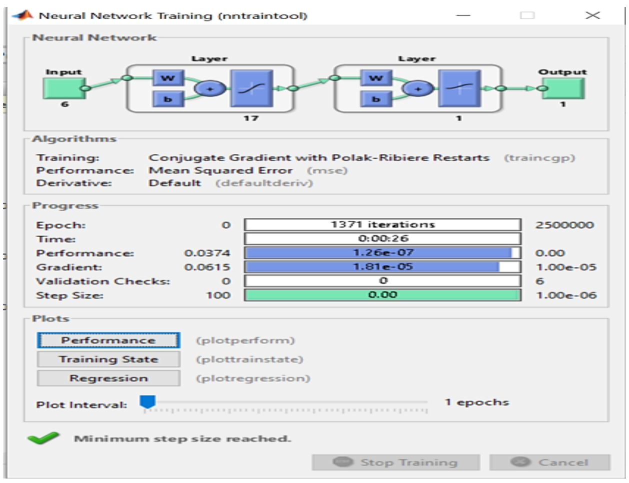

Figure 3. Test Results in Matlab

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Table 6 shows the prediction of the percentage of households that have access to a source of suitable drinking water. It can be seen that the real data is obtained from initial data before being normalized in the last year, the target data is taken from target testing, the predicted target data is taken based on the output obtained from the best architecture. The data in the prediction table below is searched by calculating the prediction target data minus 0.1 (interval) multiplied by the result of the maximum value minus the minimum in real data then dividing by 0.8 (interval) and adding the minimum value in real data so that predicted data is generated. The table below shows interim results for households that have access to an adequate drinking water source in the coming year in order to overcome the above problems.

Table 6. Prediction Results for Households that Have Access to an Improper Drinking Water Source

No	Regency/City	Real Data	Target	Prediction Target	Prediction
1	Sumatera Utara	90,89	0,819365	0,9947	105,93
2	Nias	47,79	0,428435	0,4242	68,86
3	Mandailing Natal	73,78	0,664172	0,8636	97,41
4	Tapanuli Selatan	67,39	0,606213	0,9719	104,45
5	Tapanuli Tengah	68,81	0,619093	0,6372	82,70
..	………..	…….	…….	…….	………..
31	Medan	98,8	0,891111	0,984	105,24
32	Binjai	99,76	0,899819	0,9976	106,12
33	Padangsidimpuan	54,13	0,485941	0,1496	51,01
34	Gunungsitoli	74,11	0,667166	0,9879	105,49

3.5 Discussion

In this research, to get the best results, the author used 5 architectures which were tested using the Mathlab R2011a application. When applying the architectural model the results are different and it can be seen in the previous table that the best architecture is obtained in the 20-15-1 model. Table 7 below shows the architecture that has been tested. It can be seen in table 7 below that training accuracy can be better than testing accuracy.

Table 7. Recapitulation of Architectural Results

Architecture	Epoch	MSE Training	Accuracy	MSE Testing	Accuracy	Time	
6_12_1	1165 Iterations	0,000161129	65%	0,080860939	74%	23 Detik	
6_15_1	1311 Iterations	0,000020795	88%	0,037299645	68%	21 Detik	
6_17_1	1371 Iterations	0,000000124	100%	0,000000124	85%	26 Detik	Best
6_23_1	1667 Iterations	0,000001889	94%	0,089453606	74%	31 Detik	
6_27_1	1278 Iterations	0,000001235	100%	0,044440162	59%	25 Detik	

4. CONCLUSION

Stages of the Artificial Neural Network in the process of predicting the Percentage of Households that Have Access to a Suitable Drinking Water Source using 8 years of data from 2014-2021 obtained from the Central Statistics Agency (BPS). The data prediction process is carried out in 2 stages, namely the Training data stage from 2014-2020 and Testing data from 2015-2021. The prediction system predicts the percentage of households that have access to adequate sources of drinking water using the MATLAB R2011a programming application. The system was built using the stages of the Artificial Neural Network process by implementing the Backpropagation method in the programming script, and the system built can be easily understood by users using the data prediction system by following the interface design that was previously designed. From research on the Backpropagation algorithm in predicting the Percentage of Households that Have Access to a Source of Adequate Drinking Water which has been analyzed and implemented, it was obtained that the 6-17-1 model obtained the best level of accuracy compared to the other 4 architectures with a test accuracy of 85% in 1,371 iterations and an average of The smallest average test error is 0.000000124 at 26 seconds.

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