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Neural Network Analysis With Backpropogation In Predicting Human Development Index (HDI) Component by Regency/City In North Sumatera

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Abstract

Human Development Index (HDI) measures human development outcomes based on a number of basic components of quality of life. As a measure of the quality of life, HDI is built through a basic three-dimensional approach. Data obtained from the Central Bureau of Statistics 2015 for Human Development Index (HDI) by Regency / City in North Sumatera Province consisting of 32 alternatives and with 4 parameters ie life expectancy (year), expectation, school length (%), the average length of school (year) and per capita real expenditure (Rp). By using backpropagation obtained result of 6 testing of architecture pattern that is: 4-5-1, 4-10-1, 4-5-10-1, 4-10-5-1, 4-10-20-1 and 4- 15-20-1 obtained best architectural pattern is 4-10-20-1 with epoch 2126, error 0.0011757393, execution time 00:16 and accuracy 100%.

Keywords: *Prediction, Human Development Index (HDI), Backpropogation, JST*

1. Introduction

Successful development, especially human development can be partially assessed by looking at how much of the most fundamental problems in society can be solved. These problems are poverty, unemployment, illiteracy, food security and democracy enforcement. But the problem is that the achievements of human development are partially varied where some aspects of development are successful and some other aspects of development fail. Quoting the first Human Development Report (HDR) 1990, human development is a process of multiplying human choices. Among the many options, the most important choice is to live long and healthy, to have the knowledgeable knowledge, and to have access to the resources needed to live properly.

Human Development Index (HDI) measures human development outcomes based on a number of basic components of quality of life. As a measure of the quality of life, HDI is built through a basic three-dimensional approach. These dimensions include long and healthy life; knowledge, and decent living. These three dimensions have a very broad sense because it is related to many factors. To measure the health dimension, use life expectancy at birth. Furthermore, to measure the dimensions of knowledge used combined indicators of literacy rates and the average length of school. To measure the living dimension, it is feasible to use the indicator of people's purchasing power to a number of basic needs which are seen from the average of per capita expenditure as income approach which represents the achievement of development for the decent living. To calculate the index of each component of HDI is used maximum and minimum limits which uses the maximum and minimum minimum parameters that are set up as shown in table 1 below:

Table 1. Maximum and Minimum Limits

No	Components of HDI	Maximum	Minimum	Information
1	Angka Harapan Hidup (Tahun)	85	25	Standar UNDP
2	Angka Melek Huruf (Persen)	100	0	Standar UNDP

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No	Components of HDI	Maximum	Minimum	Information
3	Rata-rata Lama Sekolah (Tahun)	15	0	
4	Daya Beli (Rupiah PPP)	732.720	300.000 (1996)	Pengeluaran per Kapita Riil Disesuaikan

Source: Central Bureau of Statistics

This study takes data from the Central Bureau of Statistics 2015 for Human Development Index (HDI) by Regency / City in North Sumatera Province consisting of 32 alternatives and with 4 assessment parameters namely life expectancy (year), expectation, school length (%), average school length (year) and real per capita expenditure (Rp). Increasing HDI is an achievement for the government of a region. Given that HDI is one of the indicators for the allocation of DAU (General Allocation Fund) to an area that has a very positive impact on the allocation of DAU, the higher the HDI than the greater the acquisition of DAU for an area that leads to improving the welfare of Indonesian society. imitations using Backpropagation method that predicts Human Development Index (HDI) based on regencies/cities in North Sumatera. This method is chosen because it is able to form and predict the HDI based on input from the given data. The method is done in two ways, namely training and testing. Data is divided into two parts, first data for the training process and second for testing. The training process aims to identify or search for the best architectural patterns, while the testing process is performed to produce the best accuracy based on the best pattern being treated. After achieving the training objectives based on the best pattern, then tested with new data to see the target accuracy using Matlab 6.1 software.

2. Rudimentary

2.1. Artificial Intelegence

AI is a field of study based on the premise that intelligent thought can be regarded as aform of computation - one that can be formalized and ultimately mechanized. To achievethis, however, two major issues need to be addressed. The first issue is knowledge representation, and the second is knowledge manipulation [1]. The main aim of Artificial Intelligence (AI) is to study how to build artificial systems that perform tasks normallyperformed by human beings. This concept was introduced in 1956 in the Darth mounth conference. From that moment on a lot of effort has been made and many goals have been achieved but unfortunately many failures as well. Today, the AI is a very important discipline and it includes a number of well-recognized and mature areas including Expert Systems [2-4], Fuzzy Logic [5-8], Genetic Algorithms [9-11], Language Processing, Logic Programming, Planning and Scheduling, Neural Networks and Robotics [12]. The general problem of simulating intelligence has been simplified tospecific sub-problems which have certain characteristics or capabilities that an intelligent system should exhibit. The following characteristics have received the most attention:

1. Deduction, reasoning, problem solving (embodied agents, neural networks, statistical approaches to AI);
2. Knowledge representation (ontologies);
3. Planning (multi-agent planning and cooperation);
4. Learning (machine learning);
5. Natural Language Processing (information retrieval – text mining, machine translation);
6. Motion and Manipulation (navigation, localization, mapping, motion planning);
7. Perception (speech recognition, facial, recognition, object recognition);
8. Social Intelligence (empathy simulation);
9. Creativity (artificial intuition, artificial imagination); and
10. General Intelligence (Strong AI).

2.2. Artificial Neural Networks (NN)

Artificial Neural Network (ANN) is a computational model, which is based on Biological Neural Network. Artificial Neural Network is often called as Neural Network(NN) (See Figure 1). From Figure 1, to build artificial neural network, artificial neurons,also called as nodes, are interconnected [13,14]. The architecture of NN is very important forperforming a particular computation. Some neurons arearranged to take inputs fromoutside environment. These neurons are not connected with each other, so the arrangement of these neurons is in a layer, called as Input layer. All the neurons of input layer are producing some output, which is the input to next layer. The architecture of NN can be of single layer or multilayer. In a single layer Neural Network, only one input layer and one output layer is there, while in multilayer neural network, there can be one or more hidden layer.

An artificial neuron is an abstraction of biological neurons and the basic unitin an ANN [15,16]. The Artificial Neuron receives one or more inputs and sums them to produce an output. Usually the sums of each node are weighted, and the sum is passed through a function known as an activation or transfer function. The objective here is todevelop a data classification algorithm that will be used as a general-purpose classifier.To classify any database first, it is required to train the model. The proposed training algorithm used here is aHybrid BP-GA [17,18]. After successful training, user can give unlabeled data to be classified.

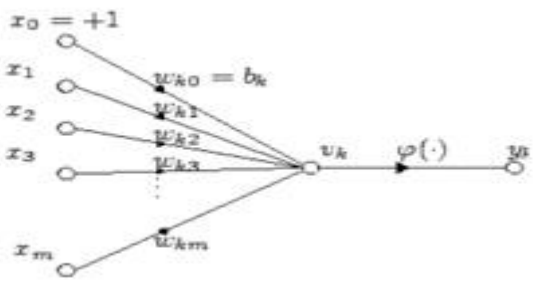

Figure 1. ANN Model

2.3. Architecture of Backpropogation

The back-propagation learning algorithm (BPLA) has become famous learning algorithms among ANNs. In the learning process, to reduce the in accuracy of ANNs, BPLAs use the gradient decent search method to adjust the connection weights. The structure of a back-propagation ANN is shown in Figure 2. The output of each neuron is the aggregation of the numbers of neurons of theprevious level multiplied by its corresponding weights. The input values are converted into output signals with the calculations of activation functions. Backpropagation ANNs have been widely and successfully applied in diverse applications, such as pattern recognition, location selectionand performance evaluations [19].

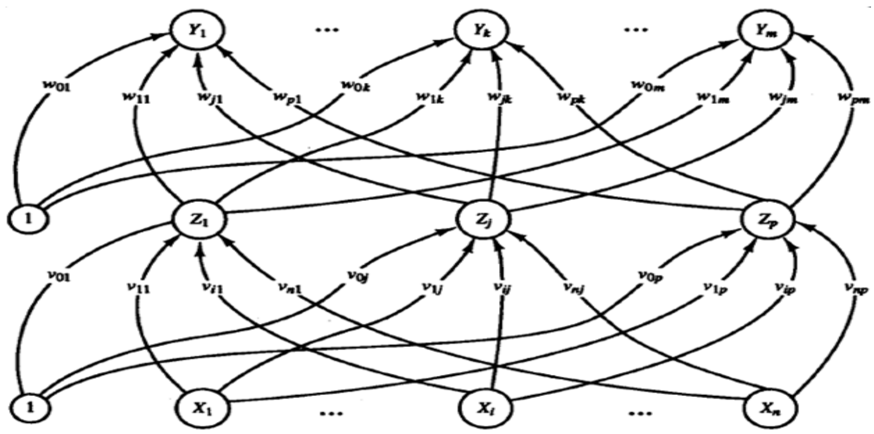

Figure 2. Back-propogation ANN

Each of these layers must be either of the following:
1. Input Layer – This layer holds the input for thenetwork
2. Output Layer – This layer holds the output data, usually an identifier for the input.
3. Hidden Layer – This layer comes between the inputlayer and the output layer. They serve as apropagation point for sending data from the previous layer to the next layer [20].

2.4. Backpropagation Neural Network

Phases in Backpropagation Techniquealgorithm can bedivided into two phases: propagation and weight update.

Phase 1: Propagation
Each propagation involves the following steps:
1. Forward propagation of a training pattern's input is given through the neural network in order to generate the propagation's output activations.
2. Back propagation of the output activations propagation through the neural network using the training pattern's targetin order to generate the deltas of all output and hidden neurons.

Phase 2: Weight Update
For each weight-synapse:
1. Multiply its input activation and output delta to get thegradient of the weight.
2. Bring the weight in the direction of the gradient byadding a ratio of it from the weight.

This ratio impacts on the speed and quality of learning; itis called the learning rate. The sign of the gradient of aweight designates where the error is increasing; this is why the weight must be updated in the opposite direction. The phases 1 and 2 are repeated until the performance of the network is satisfactory [21,22].

3. Research and Methodology

3.1. Research Framework

A framework of research work used in solving this research problem.

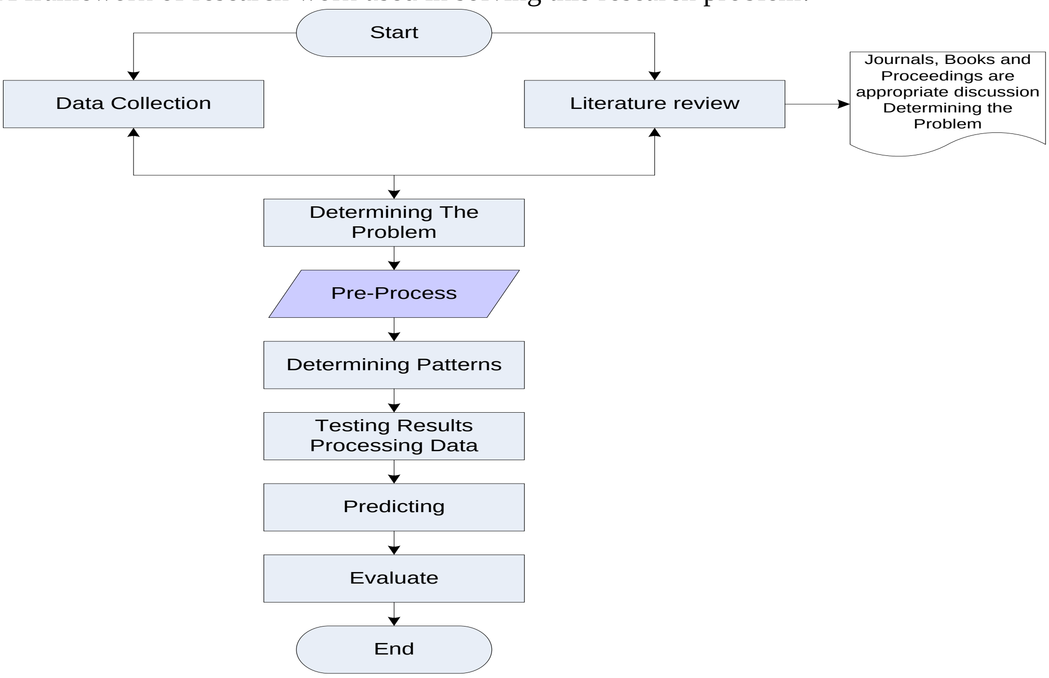

Figure 3. Research Framework

Based on the framework in the picture above, each step can be described as follows :

1. Collecting Data
   At this stage, the data is obtained from the Official Gazette (BRS) which is routinely published monthly by the Central Bureau of Statistics (BPS) Riau.
2. Library Studies
   Literature study is the first step in this research, this literature study was conducted to complement the basic knowledge and theories used in this study.
3. Identifying Problems
   In the identification phase of this problem, done after all the data is met then obtained the appropriate dataset to be done in the process of conversion process data obtained in accordance with the specified weight
4. Preprocess
   Stages done is to make changes to some data types on dataset attributes with the aim to facilitate understanding of the contents of the record, also do the selection by considering the consistency of data, missing value and redundant on the data.
5. Determining the Model
   The results of this stage are some models of artificial neural network with Backpropagation method to determine the pattern
6. Testing Results Data Processing
   After the process of determining the model is completed, then performed the test phase against the results of data processing using Matlab Software R2011b (7.13)
7. Predicting
   Prediction is done to compare the number with Neural Network model with the most accurate Backpropagation method.
8. Evaluate the End
   Evaluate the end done to find out whether the testing of data processing results as expected.

3.2. Data Used

The data used in this research is the Component Data of Human Development Index (HDI) by Regency / City of 2015 which is sourced from BPS-National Socio-Economic Survey 2015 North Sumatera based on new calculation

Table 1. Data Component of Human Development Index (HDI) by Regency / City Year 2015

No	Regency / City	Life expectancy				HDI
		Life Expectancy (year)	Old School Expectations (%)	Average school length (years)	Real per capita expenditure (000 Rp.)	
1	01. N i a s	68,97	11,77	4,76	6 234	58,85
2	02. Mandailing Natal	61,58	12,77	7,63	9 096	63,99
3	03. Tapanuli Selatan	63,74	13,06	8,27	10 623	67,63
4	04. Tapanuli Tengah	66,59	12,40	8,02	9 555	67,06
5	05. Tapanuli Utara	67,55	13,19	9,31	11 079	71,32
6	06. Toba Samosir	69,14	13,18	10,08	11 535	73,40
7	07. Labuhanbatu	69,36	12,57	8,75	10 356	70,23
8	08. A s a h a n	67,37	12,49	8,32	10 067	68,40
9	09. Simalungun	70,34	12,69	8,80	10 728	71,24
10	10. D a i r i	67,78	12,80	8,69	9 708	69,00

No	Regency / City	Life expectancy				HDI
		Life Expectancy (year)	Old School Expectations (%)	Average school length (years)	Real per capita expenditure (000 Rp.)	
11	11. K a r o	70,62	12,22	9,50	11 800	72,69
12	12. Deli Serdang	71,00	12,52	9,48	11 359	72,79
13	13. L a n g k a t	67,63	12,70	7,92	10 364	68,53
14	14. Nias Selatan	67,66	11,96	4,64	6 454	58,74
15	15. Humbang Hasundutan	68,10	13,15	8,90	6 889	66,03
16	16. Pakpak Bharat	64,85	13,80	8,45	7 496	65,53
17	17. Samosir	70,26	13,41	8,84	7 698	68,43
18	18. Serdang Bedagai	67,47	12,31	8,08	10 110	68,01
19	19. Batu Bara	65,80	11,96	7,74	9 692	66,02
20	20. Padang Lawas Utara	66,50	11,87	8,91	9 363	67,35
21	21. Padang Lawas	66,31	12,91	8,40	7 955	65,99
22	22. Labuhanbatu Selatan	68,09	12,73	8,68	10 319	69,67
23	23. Labuhanbatu Utara	68,70	12,12	8,31	11 201	69,69
24	24. Nias Utara	68,59	12,40	6,06	5 627	59,88
25	25. Nias Barat	67,94	12,33	5,74	5 207	58,25
26	71. S i b o l g a	67,70	13,10	9,85	10 765	71,64
27	72. Tanjungbalai	61,90	12,40	9,12	10 326	66,74
28	73. Pematangsiantar	72,29	13,99	10,73	11 388	76,34
29	74. Tebing Tinggi	70,14	12,23	10,06	11 393	72,81
30	75. M e d a n	72,28	13,97	11,00	14 191	78,87
31	76. B i n j a i	71,59	13,56	10,28	10 098	73,81
32	77. Padangsidimpuan	68,32	14,48	10,47	9 668	72,80

Source: BPS-National Socio-Economic Survey, 2015

Keterangan :
From table 1 it is explained that input data (enter) consists of 4 variables, among others :

X_1 = Life expectancy (year)
X_2 = Old school expectations (%)
X_3 = Average school length (years)
X_4 = Real expenditure per capita (000. Rp)
Target = HDI

Data No. 1 through 16 will be used as training data. While data No. 17 to 32 will serve as data testing.

3.3. Data Normalization

Before being processed, the data is normalized first by using the Sigmoid function, represented by the equation (1).

$$x' = \frac{0.8(x-a)}{b-a} + 0.1 \tag{1}$$

3.3.1. Normalization of Data Training

Table 2. Preliminary Training Data Before Normalization

Data	X_1	X_2	X_3	X_4	Target
1	68,97	11,77	4,76	6234,00	58,85
2	61,58	12,77	7,63	9096,00	63,99
3	63,74	13,06	8,27	10623,00	67,63
4	66,59	12,40	8,02	9555,00	67,06
5	67,55	13,19	9,31	11079,00	71,32
6	69,14	13,18	10,08	11535,00	73,40
7	69,36	12,57	8,75	10356,00	70,23
8	67,37	12,49	8,32	10067,00	68,40
9	70,34	12,69	8,80	10728,00	71,24
10	67,78	12,80	8,69	9708,00	69,00
11	70,62	12,22	9,50	11800,00	72,69
12	71,00	12,52	9,48	11359,00	72,79
13	67,63	12,70	7,92	10364,00	68,53
14	67,66	11,96	4,64	6454,00	58,74
15	68,10	13,15	8,90	6889,00	66,03
16	64,85	13,80	8,45	7496,00	65,53

Information :

a. Training data is taken from table 1, ie data number 1 through number 16 based on life expectancy (X1), school life expectancy (X2), average school length (X3) and real expenditure per capita (X4). While Target based on the value of HDI.
b. The maximum value (b) of the table 2 dataset is 11800.00. The minimum value (a) is 4.64.

Table 3. Training Data After Normalization

Data	X1	X2	X3	X4	Target
1	0,104363	0,100484	0,100008	0,522496	0,103677
2	0,103862	0,100551	0,100203	0,716606	0,104025
3	0,104008	0,100571	0,100246	0,820172	0,104272
4	0,104202	0,100526	0,100229	0,747737	0,104234
5	0,104267	0,100580	0,100317	0,851099	0,104522
6	0,104375	0,100579	0,100369	0,882027	0,104664
7	0,104390	0,100538	0,100279	0,802063	0,104449
8	0,104255	0,100532	0,100250	0,782462	0,104324
9	0,104456	0,100546	0,100282	0,827293	0,104517
10	0,104282	0,100553	0,100275	0,758114	0,104365
11	0,104475	0,100514	0,100330	0,900000	0,104615
12	0,104501	0,100534	0,100328	0,870090	0,104622
13	0,104272	0,100547	0,100222	0,802606	0,104333
14	0,104274	0,100496	0,100000	0,537417	0,103669
15	0,104304	0,100577	0,100289	0,566920	0,104164
16	0,104084	0,100621	0,100258	0,608089	0,104130

Information :

a. By using sigmoid function based on table 2, it will get data normalization table 2 as follows :

$$x' = \frac{0{,}8\,(68{,}97 - 4{,}64)}{11800{,}00 - 4{,}64} + 0{,}1 = 0{,}104363$$

b. Then will get result Normalisasi data X_1 = 0,104363. So on for all data, normalized by using the same function.

3.3.2. Normalization of Data Testing

Table 4. Preliminary Testing Data Before Normalization

Data	X_1	X2	X3	X4	Target
17	70,26	13,41	8,84	7698,00	68,43
18	67,47	12,31	8,08	10110,00	68,01
19	65,80	11,96	7,74	9692,00	66,02
20	66,50	11,87	8,91	9363,00	67,35
21	66,31	12,91	8,40	7955,00	65,99
22	68,09	12,73	8,68	10319,00	69,67
23	68,70	12,12	8,31	11201,00	69,69
24	68,59	12,40	6,06	5627,00	59,88
25	67,94	12,33	5,74	5207,00	58,25
26	67,70	13,10	9,85	10765,00	71,64
27	61,90	12,40	9,12	10326,00	66,74
28	72,29	13,99	10,73	11388,00	76,34
29	70,14	12,23	10,06	11393,00	72,81
30	72,28	13,97	11,00	14191,00	78,87
31	71,59	13,56	10,28	10098,00	73,81
32	68,32	14,48	10,47	9668,00	72,80

Information:

a. Data Testing is taken based on table 1, ie data number 17 to number 32 based on life expectancy (X_1), school long expectation (X_2), average school length (X_3) and real expenditure per capita (X_4). While Target based on the value of HDI.

b. The maximum value (b) of the table 2 dataset is 14191.00. The minimum value (a) is 5.74.

Table 5. Data Testing After Normalization

Data	X1	X2	X3	X4	Target
17	0,103639	0,100433	0,100175	0,533817	0,103536
18	0,103481	0,100371	0,100132	0,669846	0,103512
19	0,103387	0,100351	0,100113	0,646272	0,103400
20	0,103427	0,100346	0,100179	0,627717	0,103475
21	0,103416	0,100404	0,100150	0,548311	0,103398
22	0,103516	0,100394	0,100166	0,681632	0,103605
23	0,103551	0,100360	0,100145	0,731374	0,103607
24	0,103545	0,100376	0,100018	0,417020	0,103053
25	0,103508	0,100372	0,100000	0,393333	0,102961

Data	X1	X2	X3	X4	Target
26	0,103494	0,100415	0,100232	0,706785	0,103717
27	0,103167	0,100376	0,100191	0,682027	0,103440
28	0,103753	0,100465	0,100281	0,741920	0,103982
29	0,103632	0,100366	0,100244	0,742202	0,103783
30	0,103753	0,100464	0,100297	0,900000	0,104124
31	0,103714	0,100441	0,100256	0,669169	0,103839
32	0,103529	0,100493	0,100267	0,644918	0,103782

Information:

a. By using sigmoid function based on table 4, it will be obtained data normalization table 2 as follows :

$$x' = \frac{0,8\,(70,26 - 5,74)}{14191,00 - 5,74} + 0,1 = 0,103639$$

b. Then will get result Normalization data X1 0,103639. So on for all data, normalized by using the same function.

4. Results and Discussion

4.1. Analysis

Creating network architecture initialization is the most important thing in programming backpropagation with the Matlab application. The network architecture in this study uses 6 architectural models, among others: 4-5-1 (4 inputs, 5 hidden hidden neurons, 1 output), 4-10-1 (4 inputs, 10 hidden layer neurons, 1 output), 4 -5-10-1 (4 inputs, hidden layer using 5 neurons and 10 neurons, 1 output), 4-10-15-1 (4 inputs, hidden layer using 10 neurons and 15 neurons, 1 output), 4-10 -20-1 (4 inputs, hidden layer using 10 neurons and 20 neurons, 1 output), 4-15-20-1 (4 inputs, hidden layer using 15 neurons and 20 neurons, 1 output). The activation function used is a bipolar sigmoid function (tansig). Minimum error 0.001-0.01 with maximum epoch 10000 and learning rate 0.01.

4.2. Results

Of the 6 models of network architecture used, the best architectural model is 4-10-20-1 with the accuracy rate reaching 100%.

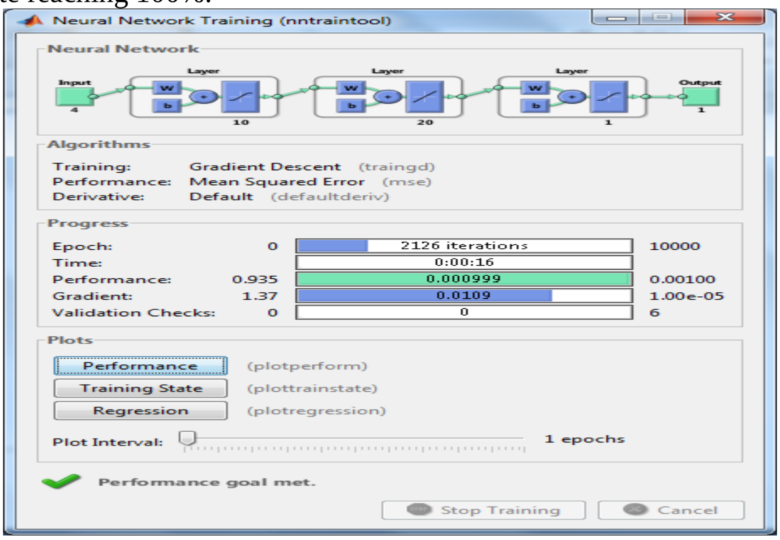

Figure 2. Results of Training Data 4-10-20-1

Information:

Epoch that happened for 2126 iteration with 45 seconds duration.

Table 6. Data Training And Testing Backpropagation

No	Architecture	Training			Testing	
		Epoch	Time	MSE	MSE	Accuracy
1	4-5-1	2440	00:16	0,0010272921	0,2406947561	0%
2	4-10-1	4199	00:26	0,0006399902	0,6233873936	0%
3	4-5-10-1	891	00:06	0,0010891741	0,0112097187	69%
4	4-10-15-1	2330	00:19	0,0011297433	0,0052151298	44%
5	4-10-20-1	2126	00:16	0,0011757393	0,4250456613	100%
6	4-15-20-1	1956	00:16	0,0013123777	0,0752453448	56%

5. Conclution

Based on the description of the previous discussion results can be concluded that the best architectural model used is 4-10-20-1 with 100% accuracy rate. Thus, this model is good enough to be used to predict data.

References

[1] Khalid, Mohd Sazali, *et al*. "Teaching and Learning Using Computers: How Should We Tread on Its' Changing Technology?." *International Journal of Emerging Technologies in Learning* 9.5 (2014).

[2] Chiroma, H., Abdulkareem, S., Abubakar, A.I. and Herawan, T., 2014. Kernel functions for the support vector machine: comparing performances on crude oil price data. In *Recent Advances on Soft Computing and Data Mining* (pp. 273-281). Springer International Publishing.

[3] Hakim, R.F., Sari, E.N. and Herawan, T., 2014. Soft Solution of Soft Set Theory for Recommendation in Decision Making. In *Recent Advances on Soft Computing and Data Mining* (pp. 313-324). Springer International Publishing.

[4] Lasisi, A., Ghazali, R. and Herawan, T., 2014. Comparative performance analysis of negative selection algorithm with immune and classification algorithms. In *Recent Advances on Soft Computing and Data Mining* (pp. 441-452). Springer International Publishing.

[5] Handaga, B., Herawan, T. and Deris, M.M., 2012. FSSC: An Algorithm for Classifying Numerical Data Using Fuzzy Soft Set Theory. *International Journal of Fuzzy System Applications (IJFSA)*, *2*(4), pp.29-46.

[6] Herawan, T., Abdullah, Z., Chiroma, H., Sari, E.N., Ghazali, R. and Nawi, N.M., 2014, September. Cauchy criterion for the Henstock-Kurzweil integrability of fuzzy number-valued functions. In *Advances in Computing, Communications and Informatics (ICACCI, 2014 International Conference on* (pp. 1329-1333). IEEE.

[7] Ma, X., Qin, H., Sulaiman, N., Herawan, T. and Abawajy, J.H., 2014. The parameter reduction of the interval-valued fuzzy soft sets and its related algorithms. *IEEE Transactions on Fuzzy Systems*, *22*(1), pp.57-71.

[8] Yanto, I.T.R., Ismail, M.A. and Herawan, T., 2016. A modified Fuzzy k-Partition based on indiscernibility relation for categorical data clustering. *Engineering Applications of Artificial Intelligence*, *53*, pp.41-52.

[9] Abubakar, A.I., Zeki, A., Chiroma, H. and Herawan, T., 2014. Investigating Rendering Speed and Download Rate of Three-Dimension (3D) Mobile Map Intended for Navigation Aid Using Genetic Algorithm. In *Recent Advances on Soft Computing and Data Mining* (pp. 261-271). Springer International Publishing.

[10] Qin, H., Ma, X., Herawan, T. and Zain, J.M., 2012, May. An improved genetic clustering algorithm for categorical data. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining* (pp. 100-111). Springer Berlin Heidelberg.

[11] Shah, H., Ghazali, R., Nawi, N.M., Deris, M.M. and Herawan, T., 2013. Global artificial bee colony-Levenberq-Marquardt (GABC-LM) algorithm for classification. *International Journal of Applied Evolutionary Computation (IJAEC)*, *4*(3), pp.58-74.

[12] Castaño, B., Moreno, Á., Carbajo, M. and de Pedro, J., 2008. Artificial Intelligence and Bluetooth Techniques in a Multi-user M-learning Domain. *IJCSA*, *5*(1), pp.1-13.

[13] Abubakar, A.I., Khan, A., Nawi, N.M., Rehman, M.Z., Wah, T.Y., Chiroma, H. and Herawan, T., 2016. Studying the Effect of Training Levenberg Marquardt Neural Network by Using Hybrid Meta-Heuristic Algorithms. *Journal of Computational and Theoretical Nanoscience*, *13*(1), pp.450-460.

[14] Chiroma, H., Abdul-kareem, S., Ibrahim, U., Ahmad, I.G., Garba, A., Abubakar, A., Hamza, M.F. and Herawan, T., 2015. Malaria severity classification through Jordan-Elman neural network based on features extracted from thick blood smear. *Neural Network World*, *25*(5), p.565.

[15] Husaini, N.A., Ghazali, R., Nawi, N.M., Ismail, L.H., Deris, M.M. and Herawan, T., 2014. Pi-Sigma Neural Network For A One-Step-Ahead Temperature Forecasting. *International Journal of Computational Intelligence and Applications*, *13*(04), p.1450023.

[16] Nawi, N.M., Rehman, M.Z., Aziz, M.A., Herawan, T. and Abawajy, J.H., 2014, November. Neural network training by hybrid accelerated cuckoo particle swarm optimization algorithm. In *International Conference on Neural Information Processing* (pp. 237-244). Springer International Publishing.

[17] Nawi, N.M., Rehman, M.Z., Aziz, M.A., Herawan, T. and Abawajy, J.H., 2014, November. An Accelerated Particle Swarm Optimization Based Levenberg Marquardt Back Propagation Algorithm. In *International Conference on Neural Information Processing* (pp. 245-253). Springer International Publishing.

[18] Chiroma, H., Abdul-Kareem, S., Muaz, S.A., Khan, A., Sari, E.N. and Herawan, T., 2014, October. Neural Network Intelligent Learning Algorithm for Inter-related Energy Products Applications. In *International Conference in Swarm Intelligence* (pp. 284-293). Springer International Publishing.

[19] Che, Z.G., Chiang, T.A. and Che, Z.H., 2011. Feed-forward neural networks training: A comparison between genetic algorithm and back-propagation learning algorithm. *International Journal of Innovative Computing, Information and Control*, *7*(10), pp.5839-5850.

[20] Choudhary, N.Y., Patil, M.R., Bhadade, U. and Chaudhari, B.M., 2013. Signature Recognition & Verification System Using Back Propagation Neural Network. *International Jorunal of IT, Engineering and Applied Sciences Research (IJIEASR)*, *2*(1), pp.1-8.

[21] Baboo, S.S. and Shereef, I.K., 2010. An efficient weather forecasting system using artificial neural network. *International journal of environmental science and development*, *1*(4), p.321.

[22] Sumijan, A. P. Windarto, A. Muhammad, and Budiharjo, "Implementation of Neural Networks in Predicting the Understanding Level of Students Subject," *Int. J. Softw. Eng. Its Appl.*, vol. 10, no. 10, pp. 189–204, 2016.

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