

Implementation of ANN for Prediction of Unemployment Rate Based on Urban Village in 3 Sub-Districts of Pematangsiantar

Nuraysah Zamil Purba¹, Anjar Wanto², Ika Okta Kirana³

^{1,2,3} STIKOM Tunas Bangsa Pematangsiantar

¹ nuraysah7388@gmail.com, ² anjarwanto@amiktunasbangsa.ac.id,

³ ikaoktakirana@stikomtb.ac.id

Abstract

Unemployment is a serious social and economic problem faced by the Pematangsiantar City government, high unemployment is also caused by the low education and skills of the workforce. To be able to reduce the number of unemployed, especially in the city of Pematangsiantar, it is necessary to predict the unemployment rate based on urban villages in the three sub-districts of the city of Pematangsiantar, so that the government has a policy so that it can tackle the number of unemployed. The data used in this study are unemployment data based on 19 urban areas from 2013-2017 in 3 districts in Pematangsiantar City. Data sources were obtained from the Pematangsiantar 03 / SS Koramil Office. The research method used is Backpropagation Artificial Neural Network. Data analysis was performed with backpropagation algorithm using Matlab. There are 5 network architecture used, namely 2-35-1, 2-38-1, 2-41-1, 2-43-1, 2-46-1 with the best model is 2-38-1 which produces accuracy by 79%. Thus this model is good enough to be used to predict the unemployment rate based on wards in 3 sub-districts in the city of Pematangsiantar.

Keywords: ANN, Unemployment, Urban Village, Sub-Districts, Pematangsiantar

1. Introduction

Artificial Neural Network (ANN) is one of the artificial representations of the human brain that always tries to simulate the learning process in the human brain. Artificial Neural Network will serve as a substitute for the nerves and brain, which at the time will relate to the outside world, the ability to learn and generalization quickly and easily in the recognition of a character pattern and easy to implement. An example of using Artificial Neural Networks is in the case of forecasting. Frequently used methods for forecasting (prediction) include Backpropagation Neural Network Algorithm [1]–[3].

Unemployment is termed for people who do not work at all, are looking for work, work no more than 2 days a week, or someone who is trying to get a decent job [4]. The cause of unemployment is generally because job seekers or the number of workforces is not comparable with the number of jobs available. Many factors influence the unemployment rate, one of which is inflation, the financial crisis to the low level of public education. Unemployment is often a problem in the economy because, with unemployment, people's productivity and income will decrease so that it can cause poverty and other social problems [5]. Unemployment in the city of Pematangsiantar is increasing every year because there are few jobs available. Moreover, Pematangsiantar is the second largest city in North Sumatra Province after Medan. This problem should be the main concern for the Pematangsiantar city government, in this case a high unemployment rate also affects economic growth in the Pematangsiantar city. The things that should be done by the Pematangsiantar city government is how to prevent unemployment from increasing.

Quite a large number of residents in each urban village in the sub-districts in the city of Pematangsiantar increasingly make the difficulties of the Pematangsiantar city government in overcoming this problem of unemployment. This is what caused the authors to conduct research to predict unemployment rates in each urban village in the

three sub-districts of Pematangsiantar, to be more effective and efficient. With the hope that the unemployment rate in these three districts will get more priority from the city government. The three sub-districts include: Siantar Marihat District, Marimbun District and Siantar Selatan District. The method used in this research is Backpropagation. This is because this algorithm is often used by researchers to make predictions or forecasting related to times series data, including this unemployment problem. Previously there has been research that discusses the prediction of the unemployment rate, namely unemployment in Indonesia based on the level of education completed. It's just the method using the resilient method. This research resulted in an accuracy rate of 75%, with an error rate of 0.02-0001 and the best architectural model 12-18-2 [6]. Therefore, the authors conducted this research which in turn will produce a higher level of accuracy.

2. Research Methodology

2.1. Data Source

The data used in this study are unemployment data based on urban villages from 2013-2017 in three sub-districts in Pematangsiantar City. Data sources were obtained from the Pematangsiantar 03 / SS Koramil Office.

Table 1. Unemployment Data Based on Urban villages in 3 Districts

No	Urban village	Years				
		2013	2014	2015	2016	2017
1	Suka Maju	20	15	18	21	23
2	Suka Makmur	22	14	20	33	33
3	Pardamean	15	22	32	23	24
4	Parhorasan Nauli	32	19	17	33	27
5	Bp Nauli	17	31	21	29	30
6	Mekar Nauli	23	22	33	28	22
7	Suka Raja	28	17	27	24	30
8	Simarimbun	19	27	22	29	27
9	Tong Marimbun	25	24	26	30	26
10	Nagahuta Timur	17	18	25	32	30
11	Pematang Marihat	21	25	35	28	29
12	Marihat Jaya	28	23	33	25	22
13	Simalungun	33	29	28	30	31
14	Karo	17	16	25	33	30
15	Toba	11	20	30	27	25
16	Kristen	27	33	27	22	32
17	Martimbang	19	26	22	19	21
18	Aek Nauli	21	13	20	21	23
19	Nagahuta	33	20	17	20	28

Source: Koramil Office 03/SS Pematangsiantar

2.2. Backpropagation

The back-propagation learning algorithm (BPLA) has become famous learning algorithms among ANNs. Backpropagation ANNs have been widely and successfully applied in diverse applications, such as pattern recognition, location selection and performance evaluations [7]. BPANN is the most extensively used ANN model. The typical topology of BPANN 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 [8]. Backpropagation training method involves feedforward of the input training pattern, calculation and backpropagation of error, and adjustment of the weights in synapses [9].

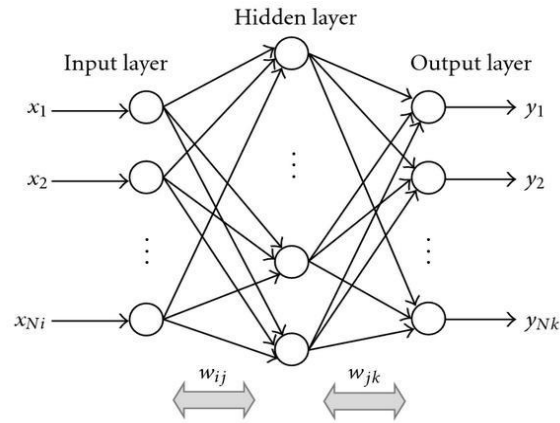


Figure 1. Schematic diagram of a general back-propagation neural network

2.3. Research Flow

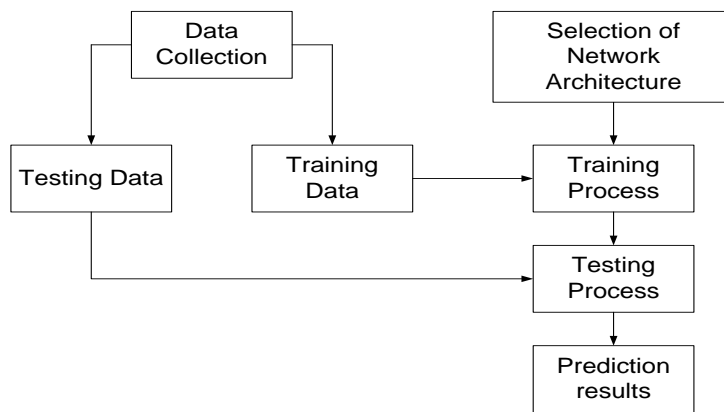


Figure 2. Research Flow

In figure 2 it can be explained that the first thing to do is to collect the dataset. The dataset used is unemployment data in 19 urban villages in 3 sub-districts in Pematangsiantar. Then preprocessing and dividing the data are done into several parts, namely the data used for training and the data used for testing. Then determine the network architecture model that will be used for the training process and the testing process, after all is done will be obtained based on the architectural model used. Furthermore, from the several architectural models used, the best is chosen. After that a prediction will be made using the best architectural model that has been selected.

2.4. Normalization Formula

The data in table 1 will be normalized using the following formula [10]–[22]:

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

Explanation : x' is the result of normalization, x is data that will be normalized, a is the lowest data and b is the highest data from the dataset.

3. Results and Discussion

3.1. Normalized Result Data

Research data in table 1 will be divided into 2 parts, namely training data and testing data. The training data used is the 2013-2014 data with the 2015 target. While the test data is taken from the Years 2015-2016 with the 2017 target. For the Normalization results of the training data can be seen in table 2 below.

Table 2. Normalization of Training Data

No	Urban village	2013	2014	Target (2015)
1	Suka Maju	0,40000	0,23333	0,33333
2	Suka Makmur	0,46667	0,20000	0,40000
3	Pardamean	0,23333	0,46667	0,80000
4	Parhorasan Nauli	0,80000	0,36667	0,30000
5	Bp Nauli	0,30000	0,76667	0,43333
6	Mekar Nauli	0,50000	0,46667	0,83333
7	Suka Raja	0,66667	0,30000	0,63333
8	Simarimbun	0,36667	0,63333	0,46667
9	Tong Marimbun	0,56667	0,53333	0,60000
10	Nagahuta Timur	0,30000	0,33333	0,56667
11	Pematang Marihat	0,43333	0,56667	0,90000
12	Marihat Jaya	0,66667	0,50000	0,83333
13	Simalungun	0,83333	0,70000	0,66667
14	Karo	0,30000	0,26667	0,56667
15	Toba	0,10000	0,40000	0,73333
16	Kristen	0,63333	0,83333	0,63333
17	Martimbang	0,36667	0,60000	0,46667
18	Aek Nauli	0,43333	0,16667	0,40000
19	Nagahuta	0,83333	0,40000	0,30000

As for the results of Normalization of test data can be seen in table 3 below.

Table 3. Normalization of Testing Data

No	Urban village	2013	2014	Target (2015)
1	Suka Maju	0,14444	0,27778	0,36667
2	Suka Makmur	0,23333	0,81111	0,81111
3	Pardamean	0,76667	0,36667	0,41111
4	Parhorasan Nauli	0,10000	0,81111	0,54444
5	Bp Nauli	0,27778	0,63333	0,67778
6	Mekar Nauli	0,81111	0,58889	0,32222
7	Suka Raja	0,54444	0,41111	0,67778
8	Simarimbun	0,32222	0,63333	0,54444
9	Tong Marimbun	0,50000	0,67778	0,50000
10	Nagahuta Timur	0,45556	0,76667	0,67778
11	Pematang Marihat	0,90000	0,58889	0,63333
12	Marihat Jaya	0,81111	0,45556	0,32222
13	Simalungun	0,58889	0,67778	0,72222
14	Karo	0,45556	0,81111	0,67778
15	Toba	0,67778	0,54444	0,45556
16	Kristen	0,54444	0,32222	0,76667
17	Martimbang	0,32222	0,18889	0,27778
18	Aek Nauli	0,23333	0,27778	0,36667
19	Nagahuta	0,10000	0,23333	0,58889

In this study data processing was assisted with the 2011b matlab tools in determining the best architectural model with Backpropagation. The architecture is used as many as 5 models, namely: namely 2-35-1, 2-38-1, 2-41-1, 2-43-1 and 2-46-1. How to determine the

best architectural model with the Backpropagation method is to determine the minimum error of the training and testing process carried out. The error rate used is 0.05-0001. In this study, the code parameters used were analyzed using the Matlab 2011b application which can be seen in the following table 4.

Table 4. Program Parameters and Codes

Training Code	Testing Code
<pre>>> net=newff(minmax(P),[hidden layer,outputlayer],{'tansig','logsig'},'traingd'); >> net.IW{1,1}; >> net.b{1}; >> net.LW{2,1}; >> net.b{2}; >> net.trainParam.epochs=10000; >> net.trainParam.goal = 0,001; >> net.trainParam.lr=0.01; >> net.trainParam.show = 1000; >> net=train(net,P,T) [a,Pf,Af,e,Perf]=sim(net,P,[],[],T)</pre>	<pre>>> PP=[input data pengujian] >> TT=[output pengujian] [a,Pf,Af,e,Perf]=sim(net,PP,[],[],TT)</pre>

3.2. Training and Testing

There are 5 training results and 5 test results using each architectural model, namely 2-35-1, 2-38-1, 2-41-1, 2-43-1 and 2-46-1. However, the writer will only write and explain the best architectural model, 2-38-1. For the results of training using architectural models 2-38-1 can be seen in the following figure.

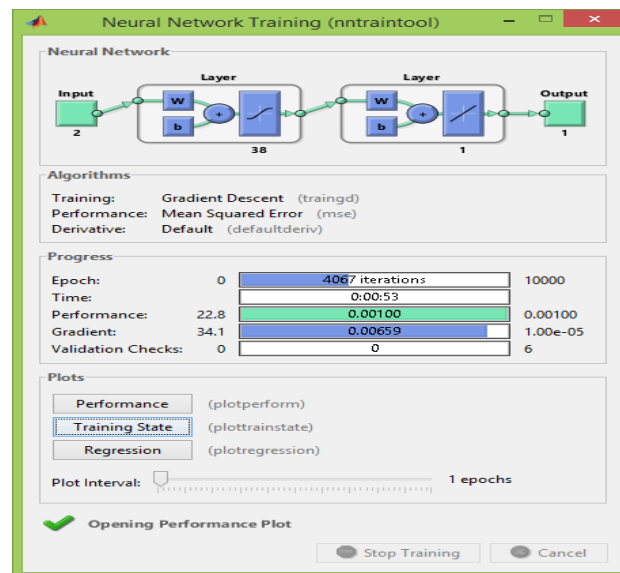


Figure 3. Training Results with Architectural Models 2-38-1

Based on figure 3 it can be explained that the results of the training using models 2-38-1 produce an epoch of 4067 iterations with 53 seconds, and this model is the best architecture compared to the other 4 models. For training and testing tables can be seen in table 5 and table 6 below.

Table 5. Training with Models 2-38-1

No	Urban village	Target	Output	Error	SSE
1	Suka Maju	0,33333	0,32950	0,00383	0,00001
2	Suka Makmur	0,40000	0,39300	0,00700	0,00005
3	Pardamean	0,80000	0,78530	0,01470	0,00022
4	Parhorasan Nauli	0,30000	0,35650	-0,05650	0,00319
5	Bp Nauli	0,43333	0,42530	0,00803	0,00006
6	Mekar Nauli	0,83333	0,86410	-0,03077	0,00095
7	Suka Raja	0,63333	0,61700	0,01633	0,00027
8	Simarimbun	0,46667	0,53500	-0,06833	0,00467

No	Urban village	Target	Output	Error	SSE
9	Tong Marimbun	0,60000	0,60330	-0,00330	0,00001
10	Nagahuta Timur	0,56667	0,61010	-0,04343	0,00189
11	Pematang Marihat	0,90000	0,85870	0,04130	0,00171
12	Marihat Jaya	0,83333	0,83920	-0,00587	0,00003
13	Simalungun	0,66667	0,68030	-0,01363	0,00019
14	Karo	0,56667	0,54510	0,02157	0,00047
15	Toba	0,73333	0,73000	0,00333	0,00001
16	Kristen	0,63333	0,61510	0,01823	0,00033
17	Martimbang	0,46667	0,42920	0,03747	0,00140
18	Aek Nauli	0,40000	0,40090	-0,00090	0,00000
19	Nagahuta	0,30000	0,24050	0,05950	0,00354
Total SSE					0,01900
MSE					0,00100

Table 6. Testing with Models 2-38-1

No	Urban village	Target	Output	Error	SSE	Results
1	Suka Maju	0,36667	1,60380	-1,23713	1,53050	1
2	Suka Makmur	0,81111	0,13440	0,67671	0,45794	0
3	Pardamean	0,41111	0,58340	-0,17229	0,02968	1
4	Parhorasan Nauli	0,54444	1,41350	-0,86906	0,75526	1
5	Bp Nauli	0,67778	0,72380	-0,04602	0,00212	1
6	Mekar Nauli	0,32222	1,07630	-0,75408	0,56863	1
7	Suka Raja	0,67778	0,99120	-0,31342	0,09823	1
8	Simarimbun	0,54444	0,28090	0,26354	0,06946	0
9	Tong Marimbun	0,50000	0,52550	-0,02550	0,00065	1
10	Nagahuta Timur	0,67778	0,68900	-0,01122	0,00013	1
11	Pematang Marihat	0,63333	0,27030	0,36303	0,13179	0
12	Marihat Jaya	0,32222	0,72070	-0,39848	0,15878	1
13	Simalungun	0,72222	0,63990	0,08232	0,00678	0
14	Karo	0,67778	0,82480	-0,14702	0,02162	1
15	Toba	0,45556	0,82650	-0,37094	0,13760	1
16	Kristen	0,76667	1,22770	-0,46103	0,21255	1
17	Martimbang	0,27778	0,86340	-0,58562	0,34295	1
18	Aek Nauli	0,36667	0,75750	-0,39083	0,15275	1
19	Nagahuta	0,58889	1,93630	-1,34741	1,81552	1
Total SSE					6,49294	79%
MSE					0,34173	

3.3. Determination of the Best Architectural Model

After training and testing data on models 2-35-1, 2-38-1, 2-41-1, 2-43-1 and 2-46-1 using the help of Matlab and Microsoft Excel tools, the best architectural model is obtained 2-38-1 with an accuracy level of 79% or the highest accuracy compared to the other 4 models. The overall results of the 5 architectural models used can be seen in table 7 below.

Table 7. Comparison of Overall Results of the Architectural Model Used

No	Model	Training			Testing	
		Epoch	Time	MSE	MSE	Accuracy
1	2-35-1	2013	00.25	0,0009998570	0,3018341070	63%
2	2-38-1	4067	00.53	0,0009997998	0,3417335287	79%

No	Model	Training			Testing	
		Epoch	Time	MSE	MSE	Accuracy
3	2-41-1	2965	00.36	0,0009992319	1,1213037726	32%
4	2-43-1	1743	00.21	0,0010002460	0,9093120739	58%
5	2-46-1	2423	00.29	0,0010004404	1,1571583800	53%

3.4. Prediction Results

Furthermore, predictions will be made with models 2-38-1 using the formula returns the value:

$$x_n = \frac{(x - 0,1) * (b - a)}{0,8} + a \quad (2)$$

The formula description can be seen in equation (1).

For the next 3 Years prediction results (2018-2020) can be seen in the following table 8.

Table 8. Prediction Results

No	Urban village	Years							
		2013	2014	2015	2016	2017	2018	2019	2020
1	Suka Maju	20	15	18	21	23	26	26	27
2	Suka Makmur	22	14	20	33	33	32	31	29
3	Pardamean	15	22	32	23	24	26	26	26
4	Parhorasan Nauli	32	19	17	33	27	28	28	27
5	Bp Nauli	17	31	21	29	30	29	29	28
6	Mekar Nauli	23	22	33	28	22	21	23	25
7	Suka Raja	28	17	27	24	30	30	29	28
8	Simarimbun	19	27	22	29	27	28	28	28
9	Tong Marimbun	25	24	26	30	26	27	27	27
10	Nagahuta Timur	17	18	25	32	30	29	30	28
11	Pematang Marihat	21	25	35	28	29	29	29	28
12	Marihat Jaya	28	23	33	25	22	24	25	26
13	Simalungun	33	29	28	30	31	30	30	28
14	Karo	17	16	25	33	30	30	29	28
15	Toba	11	20	30	27	25	26	27	27
16	Kristen	27	33	27	22	32	31	30	29
17	Martimbang	19	26	22	19	21	24	25	25
18	Aek Nauli	21	13	20	21	23	24	26	26
19	Nagahuta	33	20	17	20	28	27	28	27
Amount		33	33	35	33	33	32	32	31

4. Conclusion

- Architecture Model 2-38-1 can predict unemployment rate with 79% accuracy.
- Based on the prediction results it can be seen that the unemployment rate in 19 urban villages in 3 sub-districts in Pematangsiantar is relatively stable, there is no significant increase and decrease in the unemployment rate.

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Authors



1st Author

Nuraysah Zamil Purba

Student of STIKOM Tunas Bangsa Pematangsiantar
nuraysah7388@gmail.com



2nd Author

Anjar Wanto

Lecturer of STIKOM Tunas Bangsa Pematangsiantar
anjarwanto@amiktunasbangsa.ac.id



3rd Author

Ika Okta Kirana

Lecturer of STIKOM Tunas Bangsa Pematangsiantar
ikaoktakirana@stikomtb.ac.id