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Analysis of the Resilient Method in Training and Accuracy in the Backpropagation Method

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Abstract−Artificial Neural Network (ANN) is one of the clusters of computer science that leads to artificial intelligence, there are several methods in ANN, one of which is the backpropagation method. This method is used in the prediction process. In some cases the backpropagation method can help in problems solving, especially predictions. However, the backpropagation method has weaknesses. The results of the backpropagation method are very influenced by the determination of the parameters so that the convergence becomes very slow. So needed an optimization method to optimize the performance of the bakpropagation method. The resilient backpropgation method is one solution, this method can change the weight and bias of the network with a direct adaptation process of weighting based on local gradient information from learning iterations so that it can provide optimal results. The data used is the Higher Education Gross Enrollment Rate in Indonesia from 2015-2020 by province. The results were obtained from several data testing with architectural experiments 3-5-1, 3-20-1, 3-37-1, 3-19-1, 3-26-4 and 3-4-1 from backpropagation and resilient testing, shows that the data training process can be optimized significantly, but the accuracy is not evenly optimal.

Keywords: Backpropagation; Resilient; Training; Accuracy; Higher Education Gross Enrollment Rate

1. INTRODUCTION

Artificial Intelligence (AI) is a part of computer science that studies how machines or computers can perform activities like humans do, even better than humans can do. There are many existing methods in AI, one of which is Artificial Neural Network Backpropagation. Artificial Neural Network backpropagation is a science that is used to solve problems, especially in the data prediction process. Based on previous data, this method can carry out trainings so that it can provide accurate prediction results. However, the backpropagation method has weaknesses such as it is often trapped in a local minimum [1]. The parameter setting is very specific to the results. The convergence speed of the backpropagation method is very slow, convergence depends on the initial parameters such as the number of hidden notes, input, output, learning rate and weight in the network. So needed a method to optimize training on backpropagation. The resilient backpropagation method is a development of the backpropagation method. This method can cover the weaknesses that occur in backpropagation.

Resilient method is a neural network algorithm that is supervised and adaptive learning. In the resilient backpropagation parameter has been set so it does not require a learning rate determination [2]. The training process in the relisient backpropagation method is the same as in the backpropagation method, the resilient method changes the weight with the learning rate in the training process so that the resilient method can optimize training on backpropagation [2]. The data used to test the optimization of the resilient backpropagation method is data on the Higher Education Gross Enrollment Rate (APKPT) in Indonesia from Aceh to Papua provinces. APKPT data used from 2015 to 2020 in each province. Data obtained from www.bps.go.id.

2. RESEARCH METHODOLOGY

To get the results of the training and the accuracy of the prediction the method used is part of Artificial Intelligence (AI), namely Artificial Neural Network (ANN) backpropagation with the optimization method, namely resilient backpropagation. The data used is the Higher Education Gross Enrollment Rate (APKPT) data based on the provinces in Indonesia from 2015 to 2020 as many as 34 provinces.

2.1 Reserch Methods

2.1.1 Artificial Neural Network

Artificial Neural Network (ANN) is an intelligent computation method that quantitatively analyzes information by learning and practicing, such as intelligence in humans [3]. There are several methods available in ANN such as backpropagation, perceptron and others. each existing method what ANN has its own characteristics.

2.1.1 Backpropagation

Backpropagation method is one of the existing methods in ANN, this method is a method that is widely used in the case of data prediction. There are 3 stages of Backpropagation Training, namely the advanced stage where the Input and output layers can be calculated forward by being determined through the activation function. The second is the backward stage, which is a condition when the desired output target has a difference with the output network, an error occurs. So that the error is propagated backwards, starting from the output layer on the corresponding line units. The third stage is to change the weight value in order to minimize errors that occur [2]. The three stages will continue until certain conditions are reached. The backpropagation method has been applied widely and successfully in various applications, such as pattern recognition, site selection, and performance evaluation [4]. Backpropagation consists of several layers including input layer, hidden layer and output layer.

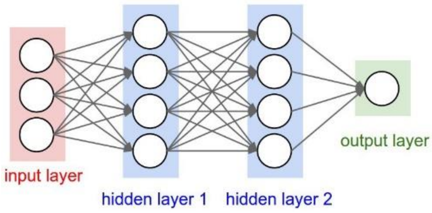

Figure 1. Backpropagation Artificial Neural Network

From figure 1:

a) Input layer : this layer stores input to the network
b) Output layer : this layer stores the output data, usually an input identifier
c) Hidden layer : this layer is in the input and output layers as a point of backpropagation to send data from the previous report to the next layer.

2.1.3 Resilient Backpropagation

The resilient backpropagation method is a development of the backpropagation method. The change in Backpropagation weight is influenced by the learning rate and depends on the slope of the error curve (∂E/∂Wij) [5]. If the learning rate used is getting smaller, the learning will take longer. The greater the level of learning, the weighting value will be far from the minimum weight. Resilient methods are used and developed to overcome these problems [5]. The resilient method can change the weight and bias of the network with a direct adaptation process of weighting based on the local gradient information from the learning iterations, so the number of iterations is needed to reach the target [6]. then the measure of change in the weight given is the value of Δjk. This value adjusts the development during the local vision-based learning process to the error function with the following learning rules:

$$\Delta jk(m) = \Delta jk\ (m-1) * \eta^{+},\ \text{if}\ \frac{\partial E}{\partial wjk}(m)\ x\ \frac{\partial E}{\partial wjk}\ (m-1) > 0$$
$$\Delta jk(m) = \Delta jk\ (m-1) * \eta^{-},\ \text{if}\ \frac{\partial E}{\partial wjk}(m)\ x\ \frac{\partial E}{\partial wjk}\ (m-1) > 0$$
$\Delta jk(m) = \Delta jk\ (m-1)$, for more
Where $0 < \eta^{-} < 1 < \eta^{+}$

The working rule of adaptation is each partial derivative of weight and bias on two different iterations in a row to show that the increase in the last value is too large and the algorithm must skip the local minimum, the correction value Δjk derived by a factor η−. If in two iterations the derivative is constant, the correction value is increased by a factor η+ to accelerate convergence in the surface fault area. If the child is zero, then the renewal value remains the same. Each time a repair is made, the weight oscillation decreases. If we change the weight in the same direction for several iterations, the resulting change in weight increases [6].

2.2 Data Source

The data used is the Higher Education Rough Partition Rate (APKPT) data based on the provinces in Indonesia from 2015 to 2020 as many as 34 provinces. Data obtained from the website of the Badan Pusat Statistik (www.bps.go.id). Sustainable Development Goal's (SDG's) is a movement to reduce poverty, inequality, and protect the environment which contains 17 goals with 169 targets agreed upon by world leaders, including Indonesia. This action is planned to be achieved in 2030. One of the objectives is to ensure that education is equitable and comprehensive, with the same quality of learning opportunities for all levels of society. One of the indicators of the target is the Higher Education Gross Enrollment Rate (APKPT) [7]. The Gross Enrollment Rate (APK) is the ratio between students at a certain level of education and the population of school age and expressed as a percentage. APK is a statistical indicator used to determine the level of education participation in a region. One GER that is of concern is the Higher Education APK which is used to see the active participation of those aged (19-23 years) who are studying in higher education. [8]. The data can be seen in table 1.

Table 1. Higher Education Gross Enrollment Rate Data (APKPT) 2015-2020

No	Provinsi	Tahun					
		2015	**2016**	**2017**	**2018**	**2019**	**2020**
1	Aceh	41.67	42.06	45.73	43.86	44.51	44.58
2	Sumatera Utara	25.89	28.93	30.71	31.11	30.82	31.14
3	Sumatera Barat	38.51	40.54	43.53	44.19	42.18	43.09

No	Provinsi	Tahun					
		2015	2016	2017	2018	2019	2020
4	Riau	30	29.81	33.37	34.15	33.93	35.07
5	Jambi	26.33	26.98	32.27	33.78	30.71	31.42
6	Sumatera Selatan	18.6	21.64	23.77	26.23	25.59	26.41
…	…..	…..	…..	…..	…..	…..	…..
29	Gorontalo	30.35	32.23	37.88	35.23	36.71	37.74
30	Sulawesi Barat	25.51	27.54	29.72	28.9	30.85	29.44
31	Maluku	44.46	46.38	47.39	48.42	47.65	48.62
32	Maluku Utara	33.72	40.87	45.01	42.68	44.02	43.97
33	Papua Barat	32.83	32.37	36.32	35.97	34.83	35.3
34	Papua	16.01	20.44	20.37	19.03	21.08	21.87

Source:https://www.bps.go.id/indicator/28/1443/1/angka-partisipasi-kasar-apk-perguruan-tinggi-pt-menurut-provinsi.html

3. RESULT AND DISCUSSION

To perform data processing, the MATLAB 2011b application is used. The architecture used to test the data is as in table 2:

Table 2. Architecture Backpropagation

Characteristics	Specification
Architecture	1 hidden layer
Neuron input	3
Neuron Hidden	10
Activation Function	Logsig, tansig
Initialize weights	Random
Target *Error*	>= -0.05 - < = 0.05
Maximum *Epoch*	100000
Learning Rate	0.01

From the data used, it can be adjusted to the network architecture where the input is 3 and neiron hidden is 10. The activation functions used are logsig and tansig where the initialization random weight and target error are greater than equal to -0.05 to less than 0.05. The maximum number of iterations is 100 000 and the learning rate is 0.01.

3.1 Result of Normalization Data

The data will be divided into 2 parts, namely training data and testing data where training data consisting of 2015 - 2017 and 2018 is the target. For testing data consisting of 2017 - 2019 and 2020, it is the target. After the training and testing data have been determined, the data will be normalized.
formula for normalization :

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

Normalization of shared testing and training data can be seen in Table 3.

Table 3. Normalization of training data

X1	X2	X3	T
0.51083	0.51608	0.56544	0.54029
0.29855	0.33945	0.36339	0.36877
0.46832	0.49563	0.53585	0.54473
0.35384	0.35129	0.39918	0.40967
0.30447	0.31322	0.38438	0.40469
0.20049	0.24138	0.27004	0.30313
0.44168	0.50182	0.50881	0.46563
0.11789	0.16618	0.20372	0.23708
0.10000	0.14506	0.15219	0.12785
…..	…..	…..	…..
0.49428	0.49845	0.52872	0.50491
0.51944	0.56033	0.58226	0.57473
0.35855	0.38384	0.45985	0.42420
0.29344	0.32075	0.35008	0.33904
0.54836	0.57419	0.58778	0.60163
0.40388	0.50007	0.55576	0.52442
0.39191	0.38572	0.43886	0.43415
0.16565	0.22524	0.22430	0.20627

Table 4. Normalization of testing data

X1	X2	X3	T
0.52322	0.49889	0.50735	0.50826
0.32781	0.33301	0.32924	0.33340
0.49460	0.50319	0.47704	0.48888
0.36242	0.37256	0.36970	0.38453
0.34811	0.36775	0.32781	0.33705
0.23752	0.26952	0.26120	0.27187
0.46845	0.42669	0.41784	0.42773
0.17338	0.20564	0.21423	0.22854
0.12355	0.10000	0.11392	0.11991
…..	…..	…..	…..

0.48771	0.46468	0.48406	0.48367
0.53949	0.53220	0.54703	0.54495
0.42109	0.38662	0.40587	0.41927
0.31493	0.30426	0.32963	0.31129

0.54482	0.55822	0.54820	0.56082
0.51386	0.48354	0.50098	0.50033
0.40080	0.39624	0.38141	0.38753
0.19328	0.17585	0.20252	0.21280

Tables 3 and 4 can be seen from normalized training and testing data. The data will be processed using a network architecture which can be seen in table 2. The data will be tested with different patterns.

3.2 Model Arsitektur Training dan Testing

There are 6 architectures used, namely 3-5-1, 3-20-1, 3-37-1, 3-19-1, 3-26-4 and 3-4-1. Each architecture is applied to backpropagation and resilent to see the training process and the accuracy obtained. Each architecture gets different results, from each architecture tested from the backpropagation standard and resilient shows an increase in the speed of training data, but not all architectures can improve accuracy. Comparison of standard backpropagation with resilient can be seen in table 5 and table 6.

Table 5. Results of Training and Testing Bacpropagation

No	Method	Architecture	Epoch	Times	Accuracy (%)
1	Backpropagation Standart	3-5-1	2744	00.11	**11.76**
2		3-20-1	1427	00.06	**52.94**
3		3-37-1	1152	00.05	**32.35**
4		3-19-1	2481	00.11	**11.76**
5		3-26-1	1528	00.07	**2.94**
6		3-4-1	1265	00.05	**20.59**

Table 6. Results of Training and Testing Resilient Bacpropagation

No	Metode	Architecture	Epoch	Times	Accuracy (%)
1	Resilient Backpropagation	3-5-1	18	00.00	**23.53**
2		3-20-1	7	00.00	**38.24**
3		3-37-1	10	00.00	**26.47**
4		3-19-1	21	00.00	**14.71**
5		3-26-1	15	00.00	**2.94**
6		3-4-1	15	00.00	**55.88**

It can be seen from table 5 that the epoch value on architecture 3-5-1 reaches 2744 and a time of 11 seconds with a test accuracy of 11.76% while in table 6 Epoch on architecture 3-5-1 is only 18 and a time of 0 seconds with an accuracy of 23.53%. This shows that the process of training data, time and accuracy produced by the resilient method is faster and increases compared to standard backpropagation, as well as the 3-4-1 architecture in the resilient epoch method, time and accuracy are improved well. However, it is different from the 3-20-1, 3-37-1, 3-19-1 and 3-26-1 architectures in the resilient, even though the epoch and time obtained give an increase but the accuracy decreases, for example in the 3-20-1 architecture, the accuracy in standard backpropagation is 52.94%, while in the resilient the accuracy obtained decreases, namely 38.24%.

4. CONCLUSION

The following conclusions can be given in the analysis of the resilient method of backpropagation training and accuracy, the resilient backpropagation method is able to increase the speed of training in backpropagation, it can be seen from the test results that the epoch and time values generated in the resilient method are better. Determination of parameters is very influential on the results so that in the process of looking for good results the determination of parameters must be considered and adjusted to the needs. From the test results, it can be concluded that the resilient bacpropagation method can improve the learning process and time, it's just not always to improve accuracy.

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