Analysis of Standard Gradient Descent with GD Momentum and Adaptive LR for SPR Prediction

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Keywords: Analysis, ANN, GD, GDMALR, SPR.

Abstract: Gradient Descent (GD) is used to find the local minimum value, its purpose is to find variables on the error function so that a function can model the data with minimum error. Therefore, the purpose of this research is to see how much iteration is needed and how big is the accuracy level in predicting the data when using Gradient Descent (GD) Standard and GD With Momentum and Adaptive Learning Rate (GDMALR) functions. In this study, the data to be processed using the gradient descent function is the data of School Participation Rate (SPR) in Indonesia aged 19-24 years, which began in 2011 to 2017. The reason for selection This age range is one of the factors that determine success education in a country, especially Indonesia. SPR is known as one of the indicators of successful development of education services in an area of either Province, Regency or City in Indonesia. The higher the value of SPR, then the area is considered successful in providing access to education services. SPR data are taken from Indonesian Central Bureau of Statistics. This study uses 3 models of network architecture, namely: 5-5-1, 5-15-1 and 5-25-1. From 3 models, the best model is 5-5-1 with epoch 6202 iteration, 94% accuracy and MSE 0.0008658637. This model is then used to predict SPR in Indonesia for the next 3 years (2018-2020). These results will be expected to help the Indonesian government to further improve the scholarship and improve the quality of education in the future.

1 INTRODUCTION

School Participation Rate (SPR) is the proportion of all school-aged children in a certain age group of people with appropriate age groups. SPR is known as one of the indicators of successful development of education services in an area of either Province, Regency or City in Indonesia. The higher the value of APS, then the area is considered successful in providing access to education services. A high APS indicates greater opportunities for access to education in general. In the age group where these opportunities occur can be seen from the magnitude of SPR in each age group. School Participation Rate is a measure of the absorptive capacity of educational institutions towards school-age population. SPR is a basic indicator used to view

population access to educational facilities, especially for school-aged residents in a region. The higher the School Participation Rate the greater the number of people who have the opportunity to receive education.

Therefore, predicting the value of RPS for subsequent years is very important to do, as a barometer of the government in determining related policies in the field of education. One way to measure the value of RPS with the Neural Network using Gradient Descent function. Gradient Descent is usually used to find the local minimum value that can be generated from a parametric function, the purpose is to find variables on the error function so that a function can model the data with minimum error. The gradient descent has a linear complexity with respect to data expansion and is also easy to compute in parallel (using GPUs). This

characteristic allows a model of a large enough neural network to be trained with millions of training data. However, the use of standard gradient descent functions in processing the data to be predicted sometimes takes a long time. So it takes another faster function to process the data, without reducing the quality of the results to be determined. The function is Gradient Descent With Momentum & Adaptive Learning Rate (GDMALR). This function is able to speed prediction without unduly affecting the quality of the results when using a standard gradient descent.

In the previous study, Friedman proposed a gradient descent (GD) algorithm (Friedman, Hastie, et al. 2000) (Friedman. 2001) in which each calculation reduces the residual of the last model base, and a new ensemble model is established in the direction of the reduced residual. This ultimately produces a forward distribution additive model by continuous iteration, which can optimize the minimization of the loss function. A series of efficient algorithms have been obtained (Friedman, et al. 2004) (Rosset, et al. 2004) (Friedman. 2002) (Zhang, et al. 2011) (Zhang, Liu, et al. 2013).

The contribution of this research are:

- As an input for academics to use the gradient descent With Momentum & Adaptive Learning Rate (GDMALR) training function to predict because training with this method is proven to be fast without unduly influencing the quality of the results obtained.
- As an input for the government to be able to make appropriate policies to advance education by pressing the numbers of people who do not go to school or drop out of school.

2 RUDIMENTARY

2.1 Artificial Intelligence

Artificial Intelligence is one area that is quite reliable in solving problems such as prediction (forecasting) (Wanto, Zarlis, et al. 2017). AI is a very important discipline and it includes a number of well recognized and mature areas including Neural Network (Chiroma, et al. 2014) (Hakim, et al. 2014) (Lasisi, et al. 2014). Artificial Intelligence (AI) is a general term that implies the use of a computer to model intelligent behavior with minimal human intervention. AI is generally accepted as having started with the invention of robots. The term derives from the Czech word *robota*, meaning biosynthetic machines used as forced labor (Hamet

and Tremblay. 2017). AI is a field of study based on the premise that intelligent thought can be regarded as a form of computation - one that can be formalized and ultimately mechanized. To achieve this, however, two major issues need to be addressed. The first issue is knowledge representation, and the second is knowledge manipulation (Sumijan, et al. 2016).

2.2 Artificial Neural Networks (NN)

Artificial Neural Network (ANN) is one of the studies of Artificial Intelligence and is a new computing technology in the field of computer science study. Neural networks mostly used for problem-solving in pattern recognition, data analysis, control and clustering (J. Adnan et al. 2017). Initially ANN were developed in the field of artificial intelligence and were first introduced for image recognition. The central concept was inspired by knowledge of the nervous system, especially the human brain with its closely connected neurons (Ehret, et al. 2015). Artificial neural network (ANN) is one of the methods that is suitable to deal with the internal relations of complex model because of its highly nonlinear, large amounts of data parallel processing, high robustness, and fault tolerance (Wang, et al. 2017) (Wanto, et al. 2017).

Figure 1: Artificial Neural Networks

The schematic representation of artificial neural network. It consists of: (1) input layer (independent variables), (2) hidden layers and, (3) the output layer (dependent variable) (Parveen and Danish. 2017) (Siregar and Wanto. 2017)

2.3 Architecture of Backpropagation

The back-propagation learning algorithm (BPLA) has become famous learning algorithms among ANNs. In the learning process, to reduce the inaccuracy 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 the

previous 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 selection and performance evaluations (Che, et al. 2011).

Figure 2: Back-propagation ANN

There are several algorithms that can be used to create an artificial neural network, but the Back propagation was chosen because it is probably the easiest to implement, while preserving efficiency of the network. Backward Propagation Artificial Neural Network (ANN) use more than one input layers (usually 3). Each of these layers must be either of the following:

- Input Layer : This layer holds the input for the network.
- Output Layer : This layer holds the output data, usually an identifier for the input.
- Hidden Layer : This layer comes between the input layer and the output layer. They serve as a propagation point for sending data from the previous layer to the next layer (Choudhary, et al. 2013).

2.4 Backpropagation Neural Network

Backpropagation (BP) algorithm was used to develop the ANN model (Antwi, et al. 2017). The typical topology of BPANN (Backpropagation Artificial Neural Network) 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 (Huang and Wu. 2017). A back-propagation algorithm was used for training. It is a convenient and simple iterative algorithm that usually performs well, even with complex data. Unlike other learning algorithms (like Bayesian learning) it has good computational properties when dealing with largescale data (Ehret, et al. 2015). Backpropagation training method involves feedforward of the input training pattern, calculation

and backpropagation of error, and adjustment of the weights in synapses (Tarigan, et al. 2017).

2.5 Descent Gradient

Descent gradient methods are the most frequently used algorithms for computing regularizers of inverse problems. They are either directly applied to the discrepancy term, which measures the difference between operator evaluation and data or to a regularized version incorporating suitable penalty terms. In its basic form, gradient descent methods converge slowly (Muoi, et al. 2015). Despite its simplicity, gradient descent algorithm suffers from variety of drawbacks. One of the main problem relates to the learning rate parameter: if it is chosen to be too big the estimate will dangle around the optimal point, not approaching it. On the other hand, if it is too small, convergence might take vast amount of iterations and we won't approach optimum for iterations (Senov and Granichin 2017).

Gradient descent backpropagation artificial neural network has been successively used for prediction of school enrollment rates by considerable number of researchers. Its performance can be improved by using variable learning rate during the training process i.e instead of using constant learning rate; adaptive learning rate can be employed. The affect of using variable learning rate will be larger step size and stable learning. In this study Gradient Descent With Momentum & Adaptive LR is used for prediction of school participation rate. The result is compared with standard gradient descent algorithm, Gradient Descent With Momentum & Adaptive LR is better (Singh, Verma, and Thoke 2015)..

3 RESULT AND DISCUSSION

3.1 Data Used

The data used in this study is data on School Participation Rate by province in Indonesia aged 19-24 years. Sources of data were taken from Indonesian Central Bureau of Statistics in 2011-2017.

Table 1: Dataset School Participation Rate in Indonesia

School Participation Rate (aged 19-24 years)					
Province	Year (In Tens of Thousands)				
	2011	2012	...	2016	2017

School Participation Rate (aged 19-24 years)					
Province	Year (In Tens of Thousands)				
	2011	2012	...	2016	2017
Aceh	27,68	28,55	...	33,94	34,28
Sumatera Utara	16,94	17,27	...	26,62	26,80
Sumatera Barat	23,95	27,55	...	34,71	35,45
Riau	15,34	15,81	...	26,18	27,28
Jambi	15,64	15,22	...	23,86	24,12
Sumatera Selatan	12,75	13,91	...	18,07	19,17
Bengkulu	17,02	19,64	...	28,93	29,90
Lampung	10,39	11,90	...	19,72	20,96
Kep. Bangka Belitung	8,63	9,30	...	13,81	14,99
Kep. Riau	9,67	10,14	...	18,58	19,13
DKI Jakarta	17,83	18,02	...	23,06	24,60
Jawa Barat	11,15	12,25	...	20,37	21,50
Jawa Tengah	11,51	11,83	...	21,59	22,13
DI Yogyakarta	44,17	44,69	...	49,95	51,33
Jawa Timur	12,69	14,59	...	22,67	23,34
Banten	13,56	15,97	...	20,74	21,33
Bali	18,93	18,99	...	25,36	26,56
NTB	16,99	17,82	...	27,79	28,52
NTT	17,40	17,92	...	26,75	27,80
Kalimantan Barat	11,94	14,17	...	24,75	25,80
Kalimantan Tengah	13,05	14,04	...	22,72	24,15
Kalimantan Selatan	13,62	16,48	...	21,89	23,53
Kalimantan Timur	16,92	20,33	...	28,88	30,04
Kalimantan Utara	0,00	0,00	...	19,07	20,72
Sulawesi Utara	15,16	16,12	...	22,82	24,22
Sulawesi Tengah	16,72	16,74	...	25,57	26,31
Sulawesi Selatan	21,46	23,17	...	31,48	32,16
Sulawesi Tenggara	21,48	23,62	...	29,31	30,03
Gorontalo	19,85	20,46	...	28,98	29,21
Sulawesi Barat	13,03	14,65	...	22,36	23,49
Maluku	26,71	28,98	...	37,51	38,20
Maluku Utara	19,33	21,79	...	31,75	32,10
Papua Barat	16,46	20,03	...	31,45	31,92
Papua	12,81	13,86	...	23,75	24,57
Indonesia	14,82	16,05	...	23,93	24,77

Based on table 1. It can be pointed out that the 2011-2015 School Participation Figures dataset is used for

training with targets for 2016, while the 2012-2016 dataset is used for testing targeted by 2017.

3.2 Normalization Data

The data will be normalized using the following formula.

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

Table 2: Normalization of training data

Province	Years				
	2011	2012	...	2015	Target
Aceh	0,5433	0,5573	...	0,6296	0,6436
Sumatera Utara	0,3713	0,3766	...	0,5030	0,5263
Sumatera Barat	0,4836	0,5412	...	0,6306	0,6559
Riau	0,3457	0,3532	...	0,4980	0,5193
Jambi	0,3505	0,3438	...	0,4559	0,4821
Sumatera Selatan	0,3042	0,3228	...	0,3723	0,3894
Bengkulu	0,3726	0,4146	...	0,5544	0,5633
Lampung	0,2664	0,2906	...	0,4013	0,4158
Kep. Bangka Belitung	0,2382	0,2489	...	0,3039	0,3212
Kep. Riau	0,2549	0,2624	...	0,3833	0,3976
DKI Jakarta	0,3856	0,3886	...	0,4637	0,4693
Jawa Barat	0,2786	0,2962	...	0,4107	0,4262
Jawa Tengah	0,2843	0,2895	...	0,4294	0,4458
DI Yogyakarta	0,8074	0,8158	...	0,8875	0,9000
Jawa Timur	0,3032	0,3337	...	0,4516	0,4631
Banten	0,3172	0,3558	...	0,4152	0,4322
Bali	0,4032	0,4041	...	0,4804	0,5062
NTB	0,3721	0,3854	...	0,5299	0,5451
NTT	0,3787	0,3870	...	0,5251	0,5284
Kalimantan Barat	0,2912	0,3269	...	0,4735	0,4964
Kalimantan Tengah	0,3090	0,3249	...	0,4599	0,4639
Kalimantan Selatan	0,3181	0,3639	...	0,4288	0,4506
Kalimantan Timur	0,3710	0,4256	...	0,5412	0,5625
Kalimantan Utara	0,1000	0,1000	...	0,3862	0,4054
Sulawesi Utara	0,3428	0,3582	...	0,4413	0,4655
Sulawesi Tengah	0,3678	0,3681	...	0,5025	0,5095
Sulawesi Selatan	0,4437	0,4711	...	0,5907	0,6042
Sulawesi Tenggara	0,4440	0,4783	...	0,5627	0,5694
Gorontalo	0,4179	0,4277	...	0,5545	0,5641

Province	Years				
	2011	2012	...	2015	Target
Sulawesi Barat	0,3087	0,3346	...	0,4519	0,4581
Maluku	0,5278	0,5641	...	0,6862	0,7008
Maluku Utara	0,4096	0,4490	...	0,6005	0,6085
Papua Barat	0,3636	0,4208	...	0,5798	0,6037
Papua	0,3052	0,3220	...	0,4612	0,4804
Indonesia	0,3374	0,3571	...	0,4676	0,4833

Table 3: Normalization of testing data

Province	Years				
	2012	2013	...	2016	Target
Aceh	0,5450	0,5548	...	0,6290	0,6343
Sumatera Utara	0,3692	0,4399	...	0,5149	0,5177
Sumatera Barat	0,5294	0,5778	...	0,6410	0,6525
Riau	0,3464	0,4435	...	0,5080	0,5252
Jambi	0,3372	0,4156	...	0,4719	0,4759
Sumatera Selatan	0,3168	0,3194	...	0,3816	0,3988
Bengkulu	0,4061	0,4759	...	0,5509	0,5660
Lampung	0,2855	0,3523	...	0,4073	0,4267
Kep. Bangka Belitung	0,2449	0,2474	...	0,3152	0,3336
Kep. Riau	0,2580	0,3314	...	0,3896	0,3981
DKI Jakarta	0,3808	0,4063	...	0,4594	0,4834
Jawa Barat	0,2909	0,3703	...	0,4175	0,4351
Jawa Tengah	0,2844	0,3715	...	0,4365	0,4449
DI Yogyakarta	0,7965	0,8147	...	0,8785	0,9000
Jawa Timur	0,3274	0,4038	...	0,4533	0,4638
Banten	0,3489	0,3818	...	0,4232	0,4324
Bali	0,3960	0,4092	...	0,4952	0,5139
NTB	0,3777	0,4529	...	0,5331	0,5445
NTT	0,3793	0,4566	...	0,5169	0,5333
Kalimantan Barat	0,3208	0,4003	...	0,4857	0,5021
Kalimantan Tengah	0,3188	0,4100	...	0,4541	0,4764
Kalimantan Selatan	0,3568	0,3642	...	0,4412	0,4667
Kalimantan Timur	0,4169	0,4903	...	0,5501	0,5682
Kalimantan Utara	0,1000	0,1000	...	0,3972	0,4229
Sulawesi Utara	0,3512	0,3550	...	0,4557	0,4775
Sulawesi Tengah	0,3609	0,4391	...	0,4985	0,5101
Sulawesi Selatan	0,4611	0,5333	...	0,5906	0,6012
Sulawesi Tenggara	0,4681	0,4741	...	0,5568	0,5680

Province	Years				
	2012	2013	...	2016	Target
Gorontalo	0,4189	0,4627	...	0,5517	0,5553
Sulawesi Barat	0,3283	0,3812	...	0,4485	0,4661
Maluku	0,5517	0,6268	...	0,6846	0,6954
Maluku Utara	0,4396	0,5118	...	0,5948	0,6003
Papua Barat	0,4122	0,4756	...	0,5902	0,5975
Papua	0,3160	0,3727	...	0,4702	0,4829
Indonesia	0,3501	0,4139	...	0,4730	0,4861

3.4 Analysis And Results

3.4.1 Analysis

This study uses 3 architectural models, among others: 5-5-1, 5-15-1, 5-25-1. The training and test parameters use Target Minimum Error = 0.001 - 0.05, Maximum Epoch = 15000 and Learning Rate = 0.01. The standard gradient descent and gradient descent with Momentum and adaptive LR functions will use the same architectural and parameter model in system processing.

a. Gradient Descent Standard

```
>>
net=newff(minmax(P),[Hidden,Target],{'tansig','purelin'},'traingd');
>> net.IW{1,1};
>> net.b{1};
>> net.LW{2,1};
>> net.b{2};
>> net.trainparam.epochs=15000;
>> net.trainparam.Lr=0.01;
>> net.trainParam.goal = 0.001;
>> net.trainParam.show = 1000;
>> net=train(net,P,T);
```

b. Gradient Descent with Momentum and Adaptive LR

```
>>
net=newff(minmax(P),[Hidden,Target],{'tansig','purelin'},'traingdx');
>> net.IW{1,1};
>> net.b{1};
>> net.LW{2,1};
>> net.b{2};
>> net.trainParam.epochs=15000;
>> net.trainParam.goal = 0.001;

>> net=train(net,P,T)
```

3.4.2 Results

Overall, the best results of the 3 network architecture models used are 5-5-1, with the same accuracy 94% when using standard gradient descent training functions as well as gradient descent with

momentum and adaptive LR. The difference lies in the iteration that occurs. Iterations on the standard gradient descent of 6202 and 130 on the gradient descent with momentum and adaptive LR.

For more details can be seen in the following picture:

Figure 3: Training with Standard Gradient Descent

Figure 4: Training with Momentum and Adaptive LR

Comparison of standard gradient descent training functions with gradient descent with momentum and adaptive LR can be seen in the following table:

Table 4: Results with Gradient Descent

Arsitektur	Gradient Descent Standard		
	Iterasi	MSE	Accuracy
5-5-1	6202	0,0008658637	94%

5-15-1	10633	0,0008604072	58%
5-25-1	1407	0,0006577640	89%

Table 5: Results with GD Momentum and Adaptive LR

Arsitektur	With Momentum & Adaptive LR		
	Iterasi	MSE	Accuracy
5-5-1	130	0,0008708473	94%
5-15-1	322	0,0008283832	58%
5-25-1	96	0,0006339944	89%

From table 4 and 5 it can be explained that the best architectural model of 3 architecture model used is 5-5-1. Test results from the 2 training functions with architectural model 5-5-1 can be seen in the following table:

Table 6: Results of Testing Standard Gradient Descent

Pattern	Target	Output	Error	SSE	Results
Pat 1	0,63427	0,72350	-0,08923	0,0079622679	1
Pat 2	0,51769	0,55390	-0,03621	0,0013112032	1
Pat 3	0,65250	0,70430	-0,05180	0,0026828868	1
Pat 4	0,52517	0,53880	-0,01363	0,0001857642	1
Pat 5	0,47592	0,48840	-0,01248	0,0001557376	1
Pat 6	0,39877	0,43960	-0,04083	0,0016668727	1
Pat 7	0,56600	0,62660	-0,06060	0,0036718406	1
Pat 8	0,42667	0,41940	0,00727	0,0000528611	1
Pat 9	0,33363	0,43370	-0,10007	0,0100148935	1
Pat 10	0,39815	0,40090	-0,00275	0,0000075667	1
Pat 11	0,48340	0,52360	-0,04020	0,0001037687	1
Pat 12	0,43509	0,42490	0,01019	0,0000656993	1
Pat 13	0,44491	0,43680	0,00811	0,0049561600	1
Pat 14	0,90000	0,82960	0,07040	0,0002668688	0
Pat 15	0,46376	0,48010	-0,01634	0,0009836270	1
Pat 16	0,43244	0,46380	-0,03136	0,0009828879	1
Pat 17	0,51395	0,54530	-0,03135	0,0023720411	1
Pat 18	0,54450	0,59320	-0,04870	0,0027588874	1
Pat 19	0,53327	0,58580	-0,05253	0,0000000384	1
Pat 20	0,50210	0,50230	-0,00020	0,0000625985	1
Pat 21	0,47639	0,48430	-0,00791	0,0001556228	1
Pat 22	0,46673	0,47920	-0,01247	0,0017651555	1
Pat 23	0,56819	0,61020	-0,04201	0,0070107230	1
Pat 24	0,42293	0,33920	0,08373	0,0000350576	0

Pattern	Target	Output	Error	SSE	Results
Pat 25	0,47748	0,48340	-0,00592	0,0021019840	1
Pat 26	0,51005	0,55590	-0,04585	0,0038903472	1
Pat 27	0,60123	0,66360	-0,06237	0,0085136806	1
Pat 28	0,56803	0,66030	-0,09227	0,0055427517	1
Pat 29	0,55525	0,62970	-0,07445	0,0001562076	1
Pat 30	0,46610	0,47860	-0,01250	0,0016270465	1
Pat 31	0,69536	0,73570	-0,04034	0,0052284141	1
Pat 32	0,60029	0,67260	-0,07231	0,0027053678	1
Pat 33	0,59749	0,64950	-0,05201	0,0000173559	1
Pat 34	0,48293	0,48710	-0,00417	0,0005220749	1
Pat 35	0,48605	0,50890	-0,02285	0,0000000000	1
MSE				0,0303052303 0,0008658637	94%

Explanation : 1 = True 0 = False

Table 7: Results of Testing Momentum and Adaptive LR

Pattern	Target	Output	Error	SSE	Hasil
Pat 1	0,63427	0,72650	-0,09223	0,0085066572	1
Pat 2	0,51769	0,55030	-0,03261	0,0010634473	1
Pat 3	0,65250	0,70750	-0,05500	0,0030246250	1
Pat 4	0,52517	0,53620	-0,01103	0,0001216506	1
Pat 5	0,47592	0,48480	-0,00888	0,0000788453	1
Pat 6	0,39877	0,44280	-0,04403	0,0019384078	1
Pat 7	0,56600	0,62580	-0,05980	0,0035755274	1
Pat 8	0,42667	0,42340	0,00327	0,0000106966	1
Pat 9	0,33363	0,43940	-0,10577	0,0111882321	1
Pat 10	0,39815	0,40740	-0,00925	0,0000855767	1
Pat 11	0,48340	0,51790	-0,03450	0,0000606326	1
Pat 12	0,43509	0,42730	0,00779	0,0000212108	1
Pat 13	0,44491	0,44030	0,00461	0,0034456900	1
Pat 14	0,90000	0,84130	0,05870	0,0002142160	0
Pat 15	0,46376	0,47840	-0,01464	0,0007931449	1
Pat 16	0,43244	0,46060	-0,02816	0,0006275547	1
Pat 17	0,51395	0,53900	-0,02505	0,0022376310	1
Pat 18	0,54450	0,59180	-0,04730	0,0025225619	1
Pat 19	0,53327	0,58350	-0,05023	0,0000000092	1
Pat 20	0,50210	0,50220	-0,00010	0,0000520118	1
Pat 21	0,47639	0,48360	-0,00721	0,0000897735	1
Pat 22	0,46673	0,47620	-0,00947	0,0015220730	1

Pattern	Target	Output	Error	SSE	Hasil
Pat 23	0,56819	0,60720	-0,03901	0,0071622471	1
Pat 24	0,42293	0,33830	0,08463	0,0000153738	0
Pat 25	0,47748	0,48140	-0,00392	0,0018789970	1
Pat 26	0,51005	0,55340	-0,04335	0,0039655543	1
Pat 27	0,60123	0,66420	-0,06297	0,0080945304	1
Pat 28	0,56803	0,65800	-0,08997	0,0053508726	1
Pat 29	0,55525	0,62840	-0,07315	0,0001463690	1
Pat 30	0,46610	0,47820	-0,01210	0,0022030505	1
Pat 31	0,69536	0,74230	-0,04694	0,0055514083	1
Pat 32	0,60029	0,67480	-0,07451	0,0028851025	1
Pat 33	0,59749	0,65120	-0,05371	0,0000332473	1
Pat 34	0,48293	0,48870	-0,00577	0,0003705224	1
Pat 35	0,48605	0,50530	-0,01925	0,0000000000	1
MSE				0,0304796543 0,0008708473	94%

Comparison of Gradient Descent Standard With Gradient Descent With Momentum & Adaptive LR can be seen in the following figure:

Figure 5: Graph of GD with GDMALR comparison

Comparison of prediction results using standard gradient descent and gradient descent with momentum and adaptive LR for 2018, 2019, 2020 in predicting school enrollment rates by the province in Indonesia can be seen in the following table:

Table 8: Predicted Results Using Gradient Descent

Gradient Descent			GD WMALR		
2018	2019	2020	2018	2019	2020
40,87	43,10	42,36	40,94	43,50	42,73
33,90	40,88	42,07	33,72	40,97	42,31
40,85	43,10	42,33	41,02	43,52	42,69

33,39	41,05	41,97	33,34	41,14	42,21
31,41	39,68	41,90	31,31	39,78	42,19
30,17	39,11	42,18	30,13	39,57	42,52
36,93	42,30	42,56	36,88	42,51	42,86
29,20	38,88	42,27	29,45	39,23	42,61
30,15	40,11	42,06	30,11	40,68	42,42
28,77	39,03	42,38	29,09	39,47	42,72
32,31	39,51	41,90	31,93	39,62	42,18
29,30	39,05	42,24	29,54	39,34	42,57
29,50	38,51	42,20	29,86	38,75	42,52
46,75	42,84	42,25	47,04	43,52	42,66
30,88	39,29	42,00	30,91	39,43	42,31
30,69	39,17	42,11	30,48	39,44	42,45
33,33	39,85	41,87	32,86	39,93	42,12
35,49	41,60	42,42	35,44	41,75	42,67
34,97	41,63	42,34	34,85	41,74	42,59
31,80	39,41	41,83	31,95	39,50	42,09
30,90	39,61	41,95	31,03	39,72	42,25
31,17	38,51	41,91	30,93	38,72	42,23
36,24	42,55	42,48	36,04	42,75	42,76
28,35	38,78	41,35	28,48	39,40	41,74
31,27	37,99	41,83	31,12	38,18	42,14
33,66	40,82	42,13	33,56	40,90	42,37
38,84	43,26	42,55	38,87	43,57	42,88
37,50	42,30	42,60	37,19	42,52	42,91
36,87	42,00	42,56	36,75	42,19	42,85
30,79	38,61	41,96	30,86	38,77	42,27
43,23	43,04	42,04	43,56	43,55	42,43
39,57	42,89	42,50	39,72	43,21	42,84
38,67	42,14	42,54	38,82	42,44	42,86
31,11	38,30	41,90	31,33	38,43	42,19
31,95	39,70	41,89	31,80	39,79	42,17

4 CONCLUSIONS

Based on the previous description, the following conclusions are drawn:

1. Gradient descent With Momentum & Adaptive Learning Rate (GDMALR) training function proved faster and better used to predict than standard gradient descent,

without unduly affecting the quality of the results obtained.

2. Ability Neural Networks can be applied to shape the relationship between the function of the free variables on the dependent variable although the relationship is not well known or difficult to detect.
3. Determination of the parameters of optimum network can only be done based on the learning process and the determination of the error so that the length of study time can't be determined with certainty.
4. The number of iterations can't be determined by the size of the desired pattern recognition accuracy but is determined by the parameters of the network used, the initial conditions of the network and the characteristics of the input data.
5. Speed to get the pattern of training results are not determined by the speed of computing, but is determined by the network parameters and space solutions sought.

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