Epoch Analysis and Accuracy 3 ANN Algorithm using Consumer Price Index Data in Indonesia

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Abstract: This research uses Backpropagation Algorithm, Conjugate Gradient Fletcher-Reeves (CGFR) and Resilient. The purpose of this research is to see how much iteration and accuracy using this method compared with the level of iteration and accuracy in previous research using only backpropagation algorithm with Conjugate Gradient Fletcher-Reeves (CGFR) only in measuring consumer price index level. The data used as an example in this study is the Consumer Price Index (CPI) data based on foodstuffs sourced from the Central Statistics Agency Pematangsiantar Indonesia. There are 5 similar network architectures used in previous research and in this study for more objective results, including 12-6-1, 12-15-1, 12-24-1, 12-33-1 and 12- 34-1. In the previous study, the best architecture was 12-15-1, with epoch level when using backpropagation algorithm of 821 iterations with 75% accuracy and Gradient fletcher reeves of 2 iterations with 67% accuracy. While the results of this study using the same architecture will be obtained epoch of 19 iterations with an accuracy of 50%. So it can be concluded that the use of backpropagation algorithm and gradient fletcher reeves to produce iteration and accuracy level better when compared with Resilient Algorithm.

1 INTRODUCTION

The theory of ANN is inspired by the animal brain neuron structure and its ability to deal with huge information. This network achieves the purpose of processing information by adjusting the relationship between a large number of nodes connected to each other, and it has the ability of self-learning and is adaptive (Wang et al. 2017). Artificial Neural Network is one of the artificial representations of the human brain that always tries to simulate the learning process in the human brain (Wanto, Windarto, et al. 2017). ANN approach can imitate any complex and non-linear relationship through non-linear units (neurons) and has been widely used in the forecasting area (Wang et al. 2016) (Huang and Wu 2017) (Wanto, Zarlis, et al. 2017).

Prediction (forecasting) is basically a presumption about the occurrence of an event or event in the future. Prediction (forecasting) is very helpful in planning and decisionmaking activities of a policy. There are several Artificial Neural Network Algorithms that are often used for forecasting, among others: Backpropagation Algorithm, Conjugate Gradient Fletcher-Reeves (CGFR) And Resilient. It's just between these 3 algorithms need to be tested again the level of accuracy and speed in terms of forecasting. Therefore the author will analyze the epoch and accuracy of the 3 algorithms to obtain the best results.

The data used to test the 3 algorithms is taken from the Consumer Price Index data sourced from the Central Statistics Agency Pematangsiantar-Indonesia. Consumer Price Index (CPI) is one of the important economic indicators that can provide information about the price development of goods/services paid by consumers in a region. The calculation of the CPI is aimed at knowing the price

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changes of a fixed group of goods/services commonly consumed by the local community. The Consumer Price Index (CPI) measures the average change in the price paid by consumers for consumer goods and services (Yaziz, Mohd, and Mohamed 2017). Inflation is defined as a situation where generally the price of goods has increased continuously. In order to measure inflation, Statistics of Indonesia (BPS) use the Consumer Price Index (CPI) (Bonar, Ruchjana, and Darmawan 2017). Therefore predict the Consumer Price Index is very important to do. This research is expected to be widely used, both for local government and for academics as study material/research especially related to the economic field and public policy.

In previous research, (Wanto, Zarlis, et al. 2017) Conducting research to predict the Consumer Price Index (CPI) of foodstuffs group using artificial neural network backpropagation and Conjugate Gradient Fletcher-Reeves. The research resulted in an accuracy of 75% when using backpropagation method, the best architecture used 12-15-1. While using the method Fletcher-Reeves produce the level of 67% drain which also use architectural model 12-15-1. The drawback of this research is the result of less accurate accuracy as it decreases, which is probably caused by the inappropriate selection of network architecture.

2 RUDIMENTARY

2.1 Algoritma Backpropagation

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) (Sumijan et al. 2016). 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 (Putra Siregar and Wanto 2017). 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).

2.2 Algoritma Fletcher Reeves

The conjugate gradient method (CGM) is particularly effcient and simple approaches with low storage, good numerical performances and global convergent properties for solving unconstrained optimization problems (Keshtegar 2016). Conjugate gradient method, as an efficient method, is used to solve unconstrained optimization problems (Li, Zhang, and Dong 2016). The conjugate gradient (CG) method can be considered as an instance of the heavy ball method with adaptive step size (Yao and Ning 2017).

In the above types, the weights update, for each iteration, is made by the step size in the negative gradient direction by learning rate. In the conjugate gradient algorithms, this step size is modified by a search function at every iteration such that the goal is reached as early as possible within a few iterations Fletcher-Reeves update (cgf) is much faster than variable learning rate algorithms & resilient backpropagation but requires a little more storage as computations are more but suffers from the fact that the results may vary from one problem to another (Madhavan 2017).

2.3 Algoritma Resilient

The concept of resilient propagation was floated by Riedmiller in 1993 (Riedmiller and Braun 1993), which had been exploited in single (Igel and Husken 2003) and two dimension (Tripathi and Kalra 2011) (Kantsila, Lehtokangas, and Saarinen 2004) problems, where it proved its momentousness. This paper proposes a quaternionic domain resilient propagation algorithm (RPROP) for multilayered feed-forward networks in quaternionic domain and presents its exhaustive analysis through a wide spectrum of benchmark problems containing three or four dimension information and motion interpretation in space.

The propagation of this procedure is based on the sign of partial derivatives of error function instead of its value as in back-propagation algorithm. The basic idea of the proposed algorithm is to modify the components of quaternionic weights by an amount Δ (update value) with a view to decrease the overall error and the sign of gradient of error function indicates the direction of weight update. Without increasing the complexity of algorithm, the proposed RPROP algorithm is boosted by error-ependent weight backtracking step, which accelerates the training speed appreciably and provides better approximation accuracy. The neural network (ARENA et al. 1996) (Minemoto et al. 2016) and backpropagation algorithm in quaternionic domain (BP) (Cui, Takahashi, and Hashimoto 2013) has been widely applied in problems dealing with three and four dimensional information; recently its comparison with quaternionic scaled conjugate gradient (SCG) learning scheme is presented in (Popa 2016). This paper proposes an RPROP algorithm and compare with BP and SCG algorithms through application in 3D imaging and chaotic time series predictions. Though, BP and SCG learning algorithms can solve the typical class of 3D and 4D dimensional problems, but the proposed ℍ-RPROP algorithm has demonstrated its superiority over BP and SCG in all respects, which is reported by different statistical parameters (Kumar and Tripathi 2018).

3 RESEARCH METHODS

3.1 Research Framework

The research methodology can be seen in Figure 1. The literature study used to collect data or sources related to the topic raised was obtained from various sources, journals, documentation books, and internet. Then the sampling of data from the Central Bureau of Statistics (BPS) -Indonesia, which will be processed by using ANN (Backpropagation, Conjugate Gradient Fletcher-Reeves and Resilient).

System design means designing inputs, file structures, programs, procedures necessary to support information systems. Implementation is an action or implementation plan that has been prepared based on system design. System testing is the evaluation phase of the system architecture that has been built. System Evaluation includes a review of the performance results of the system.

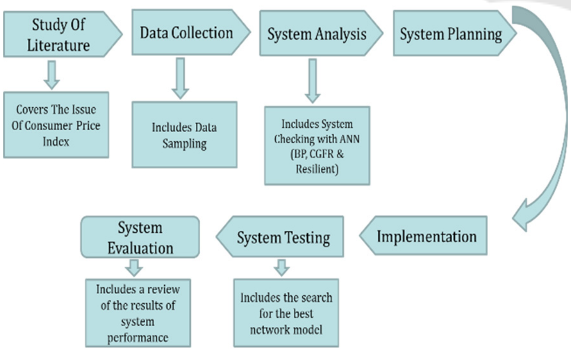

Figure 1: Research Framework

3.2 Data Used

The data used in this paper is the Consumer Price Index (CPI) data based on the Foodstuffs of Pematangsiantar-Indonesia from 2014 to 2016 January to December.

Table 1: Data Used

Consumer Price Index 2014-2016 Sector: Foodstuff					
Year	Month				
	Jan	Feb	...	Nov	Dec
2014	116,22	116,03	...	126,17	127,07
2015	125,95	119,60	...	123,72	128,40
2016	130,65	128,53	...	141.85	144,06

Based on table 1. It can be explained that, the Consumer Price Index (CPI) dataset based on Foodstuff Sector on 2014-2015 is used as training with target 2015, while dataset on 2015-2016 is used as testing with target 2016.

3.3 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

Data	Input					Target
	Jan	Feb	...	Nov	Dec	
1	0,2285	0,2180	...	0,7771	0,8267	0,7649
2	0,2180	0,3012	...	0,8267	0,7649	0,4148
3	0,3012	0,1000	...	0,7649	0,4148	0,3470
4	0,1000	0,4435	...	0,4148	0,3470	0,3216
5	0,4435	0,4253	...	0,3470	0,3216	0,5560
6	0,4253	0,4396	...	0,3216	0,5560	0,8250
7	0,4396	0,3939	...	0,5560	0,8250	0,7418
8	0,3939	0,4358	...	0,8250	0,7418	0,6657
9	0,4358	0,6315	...	0,7418	0,6657	0,5565
10	0,6315	0,7771	...	0,6657	0,5565	0,5940
11	0,7771	0,8267	...	0,5565	0,5940	0,6420
12	0,8267	0,7649	...	0,5940	0,6420	0,9000

Table 3: Normalization of testing data

Data	Input					Target
	Jan	Feb	...	Nov	Dec	
1	0,3460	0,1517	...	0,2777	0,4209	0,4898
2	0,1517	0,1141	...	0,4209	0,4898	0,4249
3	0,1141	0,1000	...	0,4898	0,4249	0,4913
4	0,1000	0,2300	...	0,4249	0,4913	0,4179
5	0,2300	0,3793	...	0,4913	0,4179	0,4953
6	0,3793	0,3331	...	0,4179	0,4953	0,5207
7	0,3331	0,2909	...	0,4953	0,5207	0,5280

Data	Input					Target
	Jan	Feb	...	Nov	Dec	
8	0,2909	0,2303	...	0,5207	0,5280	0,5925
9	0,2303	0,2511	...	0,5280	0,5925	0,6433
10	0,2511	0,2777	...	0,5925	0,6433	0,7146
11	0,2777	0,4209	...	0,6433	0,7146	0,8324
12	0,4209	0,4898	...	0,7146	0,8324	0,9000

3.4 Analysis and Results

3.4.1 Analysis

This study uses 5 architectural models, among others: 12-6-1, 12-15-1, 12-24-1, 12-33-1 and 12-34-1. This training and testing parameter uses Target Minimum Error = 0.001 - 0.01, Maximum Epoch = 10000 and Learning Rate = 0, 01 when using backpropagation algorithm. Whereas in conjugate gradient fletcher reeves and resilient do not use learning rate. For more details about the parameters used for the 3 algorithms can be seen in the following description:

a. Backpropagation

```
>>
net=newff(minmax(P),[Hidden,Target],{'tansig','logsig'},'traingd');
>> net.IW{1,1};
>> net.b{1};
>> net.LW{2,1};
>> net.b{2};
>> net.trainparam.epochs=10000;
>> net.trainparam.Lr=0.01;
>> net.trainParam.goal = 0.001;
>> net.trainParam.show = 1000;
>> net=train(net,P,T);
```

b. Conjugate Gradient Fletcher Reeves

```
>>
net=newff(minmax(P),[Hidden,Target],{'tansig','logsig'},'traincgf');
>> net.IW{1,1}
>> net.b{1}
>> net.LW{2,1}
>> net.b{2}
>> net.trainParam.epochs=10000;
>> net.trainParam.goal = 0.001;
>> net=train(net,P,T)
```

c. Resilient

```
>>
net=newff(minmax(P),[15,1],{'tansig','logsig'},'trainrp');
>> net.IW{1,1};
>> net.b{1};
>> net.LW{2,1};
>> net.b{2};
>> net.trainParam.epochs=10000;
>>net.trainParam.goal = 0.001;
>>net=train(net,P,T)
```

3.4.2 Results

Overall, the best results of 5 models of network architecture using Backpropagation Algorithm, Conjugate Gradient Fletcher-Reeves and Resilient are 12-15-1, with 75% accuracy when backpropagation, 67% using conjugate gradient Fletcher-Reeves and 50% when using resilient. While the epoch on the backpropagation method of 821 iterations, conjugate gradient fletcher reeves of 2 iterations and 19 iterations resilient

For more details can be seen in the following picture:

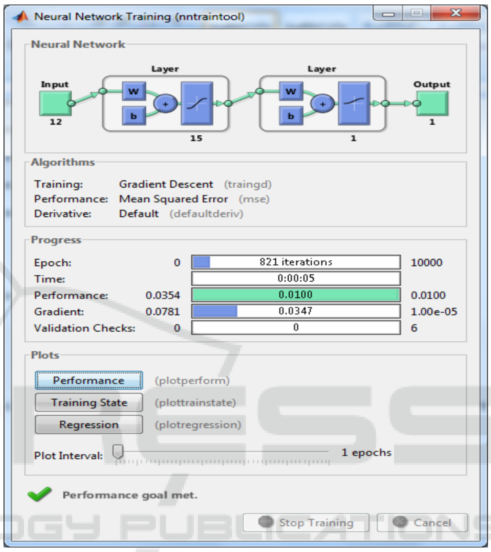

Figure 2: Training with Algorithm Backpropagation

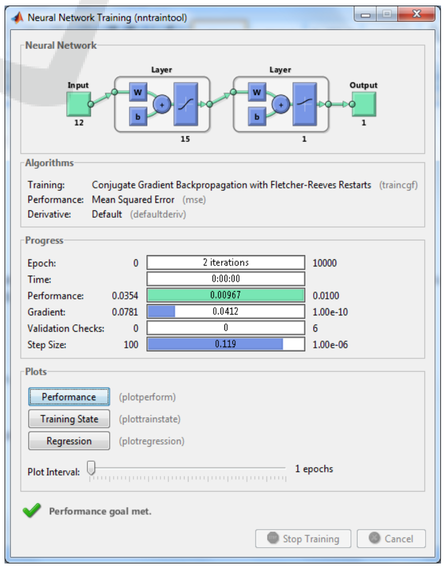

Figure 3: Training with Algorithm CGFR

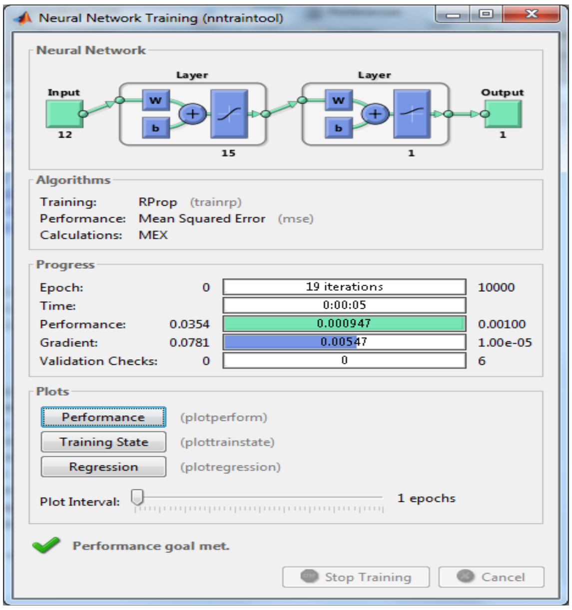

Figure 4: Training with Algorithm Resilient

As for the comparison of Epoch and accuracy of the 3 algorithms can be seen in the following table:

Table 4: Epoch Comparison

Architecture	Epoch (Iterations)		
	Backpropagation	CGFR	Resilient
12-6-1	5308	6	48
12-15-1	**821**	**2**	**19**
12-24-1	4999	15	29
12-33-1	961	16	16
12-34-1	1491	149	34

Table 5: Comparison of Accuracy

Architecture	Accurate		
	Backpropagation	CGFR	Resilient
12-6-1	50%	58%	42%
12-15-1	**75%**	**67%**	**50%**
12-24-1	58%	50%	50%
12-33-1	25%	42%	42%
12-34-1	25%	33%	50%

From table 4 and 5 it can be explained that the best architectural model of 5 architectural models used is 12-15-1. The testing results of the 3 algorithms with architectural model 12-15-1 can be seen in the following table:

Table 6: Results of Testing Backpropagation Algorithm

Pattern	Target	Output	Error	SSE	Results
Pattern 1	0,4898	0,4070	0,0828	0,0068477998	True
Pattern 2	0,4249	0,4827	-0,0578	0,0033414368	True
Pattern 3	0,4913	0,4482	0,0431	0,0018559787	True
Pattern 4	0,4179	0,1914	0,2265	0,0512834561	False
Pattern 5	0,4953	0,5469	-0,0516	0,0026668831	True
Pattern 6	0,5207	0,4776	0,0431	0,0018533107	True
Pattern 7	0,5280	0,5700	-0,0420	0,0017646425	True
Pattern 8	0,5925	0,4542	0,1383	0,0191387915	False
Pattern 9	0,6433	0,3757	0,2676	0,0716241896	False
Pattern 10	0,7146	0,6659	0,0487	0,0023724722	True
Pattern 11	0,8324	0,7609	0,0715	0,0051108283	True
Pattern 12	0,9000	0,8408	0,0592	0,0035046400	True
				0,1713644294	**75%**
			MSE	**0,0142803691**	

Table 7: Results of CGFR Testing Algorithm

Pattern	Target	Output	Error	SSE	Results
Pattern 1	0,4898	0,4246	0,0652	0,0042447094	True
Pattern 2	0,4249	0,5277	-0,1028	0,0105689014	False
Pattern 3	0,4913	0,4969	-0,0056	0,0000315724	True
Pattern 4	0,4179	0,2228	0,1951	0,0380478218	False
Pattern 5	0,4953	0,5439	-0,0486	0,0023660319	True
Pattern 6	0,5207	0,4983	0,0224	0,0004995268	True
Pattern 7	0,5280	0,5951	-0,0671	0,0045034364	True
Pattern 8	0,5925	0,4892	0,1033	0,0106797800	False
Pattern 9	0,6433	0,4546	0,1887	0,0356178654	False
Pattern 10	0,7146	0,7284	-0,0138	0,0001902184	True
Pattern 11	0,8324	0,8018	0,0306	0,0009357516	True
Pattern 12	0,9000	0,8787	0,0213	0,0004536900	True
				0,1081393054	**67%**
			MSE	**0,0090116088**	

Table 8: Results Testing Algoritma Resilient

Pattern	Target	Output	Error	SSE	Results
Pattern 1	0,4898	0,5622	-0,0724	0,0052487947	True
Pattern 2	0,4249	0,6476	-0,2227	0,0495975894	False
Pattern 3	0,4913	0,5967	-0,1054	0,0111131506	False
Pattern 4	0,4179	0,3279	0,0900	0,0080925333	True
Pattern 5	0,4953	0,6973	-0,2020	0,0408209188	False
Pattern 6	0,5207	0,7009	-0,1802	0,0324900280	False
Pattern 7	0,5280	0,7581	-0,2301	0,0529495298	False
Pattern 8	0,5925	0,6464	-0,0539	0,0029005742	True
Pattern 9	0,6433	0,5372	0,1061	0,0112629316	False
Pattern 10	0,7146	0,7823	-0,0677	0,0045822027	True
Pattern 11	0,8324	0,8127	0,0197	0,0003876984	True
Pattern 12	0,9000	0,8738	0,0262	0,0006864400	True
				0,2201323915	**50%**
			MSE	**0,0183443660**	

The Epoch comparison graph and the accuracy of the 3 algorithms can be seen in the following figure:

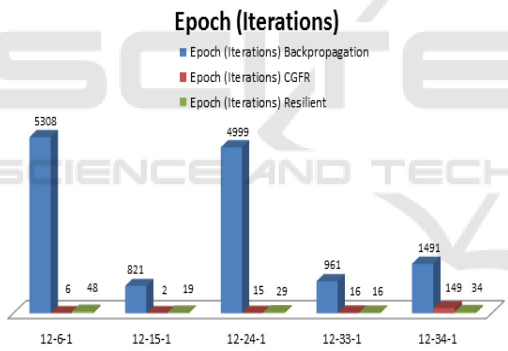

Figure 5: Graphic Level Epoch 3 Algorithm

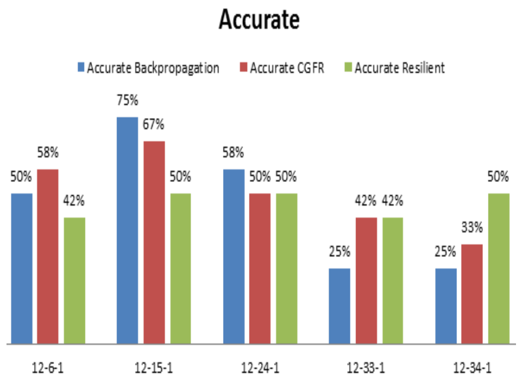

Figure 6: Graphic Level Accuracy 3 Algorithm

4 CONCLUSIONS

The conclusions that can be drawn from this research are as follows:

1. The accuracy of the Backpropagation Algorithm is the best compared to CGFR and Resilient. However, his training time is relatively long. While CGFR algorithm can accelerate the training, but the accuracy level is still lower than backpropagation.
2. Network Architecture model used greatly affect the level of training and testing.
3. By viewing Results test, it can be concluded that the speed and Results accuracy varied on 5 experiments in each test performed.

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