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Application of Neural Network Variations for Determining the Best Architecture for Data Prediction

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Abstract

This study focuses on the application and comparison of the epoch, time, performance/MSE training, and performance/MSE testing of variations of the Backpropagation algorithm. The main problem in this study is that the Backpropagation algorithm tends to be slow to reach convergence in obtaining optimum accuracy, requires extensive training data, and the optimization used is less efficient and has performance/MSE which can still be improved to produce better performance/MSE in this research—data prediction process. Determination of the best model for data prediction is seen from the performance/MSE test. This data prediction uses five variations of the Backpropagation algorithm: standard Backpropagation, Resistant Backpropagation, Conjugate Gradient, Fletcher Reeves, and Powell Beale. The research stage begins with processing the avocado production dataset in Indonesia by province from 2016 to 2021. The dataset is first normalized to a value between 0 to 1. The test in this study was carried out using Matlab 2011a. The dataset is divided into two, namely training data and test data. This research's benefit is producing the best model of the Backpropagation algorithm in predicting data with five methods in the Backpropagation algorithm. The test results show that the Resilient Backpropagation method is the best model with a test performance of 0.00543829, training epochs of 1000, training time of 12 seconds, and training performance of 0.00012667.

Keywords: *Data Prediction, Backpropagation, Resilent Backpropagation, Conjugate Gradient, Fletcher Reeves, Powell Beal.*

1. Introduction

Backpropagation is an algorithm of an Artificial Neural Network (ANN). The advantages of the Backpropagation algorithm are in terms of convergence, and its minimum local location, which is very sensitive to the selection of initial initialization, and weighting improvements can be continued until the result value is almost the same as the target where the resulting error is close to zero [1][2][3]. The backpropagation algorithm can solve the problem of data prediction. Research [4], the results of this study are the value of stock price movements with an error rate based on the MSE value of 11.85. This study provides information in the form of useful knowledge for making a decision. Research [5] the result of this research is the prediction of the price of a coffee with the Backpropagation Neural Network with the 3-9-1 model yielding an accuracy of 88.2%. To optimize the backpropagation algorithm, which is often referred to as Garident Descent, it can be done using several methods such as Resilient Backpropagation [6][7][6], Conjugate Gradient [8][9], Fletcher Reeves [10][11][12] and Powell Beale [13][14][15]. In a previous study [16], a comparison of the Backpropagation (BP) algorithm with Resilient Backpropagation (Rprop) was carried out. The result of this research is experimental results show that the Rprop algorithm avoids some of the problems of the standard BP algorithm, such as local minima and simple classification problems. Rprop is short in time compared to standard BP batch mode, but by increasing the complexity issue in experiment 2, standard BP in pattern mode gives the best results in accuracy and time. Research [12], experimental results show that the Backpropagation ANN Fletcher–Reeves method performs better than the Standard BP ANN with the Gradient Descent method. The MSE value is smaller than the MSE in standard BP with the Gradient Descent method. Research [17], the results of this study indicate the MSE value of the Conjugate Gradient is smaller than the Standard BP, which is 0.0198012, while the Standard BP is 1.02159. Research [15], the accuracy

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results using Standard BP after optimization using Conjugate Gradient Beale-Powell Restarts produce the same accuracy value.
The main problem in this study is that the Backpropagation algorithm tends to be slow to reach convergence in obtaining optimum accuracy [18], requires large training data and the optimization used is less efficient [19], and has performance/MSE that can still be improved to produce performance. Better /MSE in the data prediction process.

The purpose of this research is to optimize Standard BP and compare it with Resilient Backpropagation, Conjugate Gradient, Fletcher Reeves, and Powell Beale to determine the best model for data prediction. The benefit of this research is to produce the best model by comparing several methods of the Backpropagation algorithm. The best model is the model that has the smallest performance/MSE test. The best model can be used to predict data

2. Research Methods

2.1 Research data

There is no perpendicular line in the table. This research data uses a dataset of avocado production in Indonesia by province from 2016 to 2021[20]. The data is taken rom the Central Statistics Agency of Indonesia.

Table 1. Avocado Production Data for 2016-2018 (Data Source: https://www.bps.go.id/)

Province	2016	2017	2018
Aceh	5,026	8,427	8,844
Sumut	14,104	15,123	15,863
Sumbar	44,457	50,247	48,513
Riau	585	653	789
Jambi	1,623	2,186	3,236
Sumsel	15,603	35,178	28,902
Bengkulu	4,904	5,066	6,490
Lampung	11,652	13,569	13,676
Bangka			
Belitung Islands	338	333	468
Riau Islands	80	79	81
Jakarta	512	469	96
West Java	63,509	82,663	91,383
Central Java	33,123	36,528	44,522
Yogyakarta	6,047	3,777	3,149
East Java	72,502	78,067	108,381
Banten	689	1,349	1,926
ali	2,205	2,261	2,242
NTB	2,352	4,467	2,984
NTT	10,178	9,639	12,189
Kalbar	349	289	292
Kalteng	142.00	6	115
Kalsel	64	59	31
Kaltim	586	1,207	1,017
Kalut	39	32	65
Sulut	2,828	2,105	2,760
Sulteng	3,239	2,284	1,949
Sulsel	5,426	4,325	7,272
Sulteng	690	515	643
..	..	..	..
..	..	..	..
West Papus	70	102	45
Papua	218	193	394

Table 2. Avocado Production Data for 2019-2021 (Data Source: https://www.bps.go.id/)

Province	2019	2020	2021
Aceh	5,026	8,427	8,844
Sumut	11,576	20,609	44,484
Sumbar	18,525	32,012	35,378
Riau	54,204	69,787	84,083
Jambi	965	1,179	1,714
Sumsel	4,892	9,817	10,489
Bengkulu	38,266	36,343	15,927
Lampung	6,470	6,282	6,877
Bangka	18,502	17,304	24,008
Belitung Islands			
Riau Islands	491	839	1,509
Jakarta	114	230	93
West Java	998	1,491	1,698
Central Java	104,084	104,665	110,046
Yogyakarta	60,145	73,933	75,707
East Java	2,385	2,304	10,931
Banten	101,310	175,735	158,581
Bali	2,047	2,019	1,444
NTB	2,452	2,815	5,123
NTT	4,189	19,260	8,889
Kalbar	11,682	13,870	34,638
Kalteng	504	687	1,667
Kalsel	194	176	895
Kaltim	42	29	58
Kalut	1,719	1,148	674
Sulut	105	119	85.00
Sulteng	4,017	3,317	8,697
Sulsel	2,945	2,131	10,478
Sulteng	5,159	6,795	8,972
..	..	..	..
..	..	..	..
West Papua	931	878	1,061
Papua	339	400	575

2.2 Research Framework

In achieving the research objectives, it has been determined the stages in the research, from the preparation of the dataset to the evaluation of the model or comparison between the existing methods from BP Standard, Resilient Backpropagation, Conjugate Gradient, Fletcher Reeves, and Powell Beale. The data is divided into 2, namely training data and testing data. The Standard BP algorithm is optimized with existing methods from Standard BP, Resilient Backpropagation, Conjugate Gradient, Fletcher Reeves, and Powell beale. The test results are evaluated based on performance/MSE.

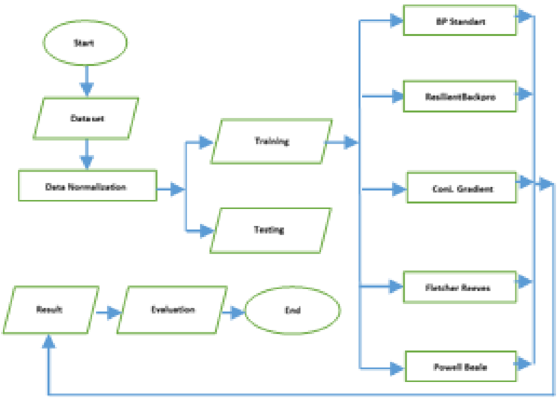

Figure 1. Database Mirroring Architecture

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It is recommended to use Mendeley/Zotero tools for Information:

1. Dataset: This stage is the stage of preparing research data.
2. Data Normalization: The researcher converts the data into 0 and 1 forms.
3. Training Data: Data used for training data on the model created.
4. Test Data: The data used for testing data on the model created.
5. Training and testing with Standard Backpropagation, Resilient Backpropagation, Conjugate Gradient, Fletcher Reeves, and Powell Beale.
6. Test results with Standard Backpropagation, Resilient Backpropagation, Conjugate Gradient, Fletcher Reeves, and Powell Beale.
7. Evaluation: The stage of evaluating the five proposed methods to produce the best model.

2.3. Normalization Data

The research data were normalized by the formula:

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

Information : x' = Normalization result, x = Data to be normalized, a = smallest data from dataset, b = The largest data from the dataset

The results of data normalization are divided into 2, namely normalization of training data and normalization of test data. The results of data normalization can be seen in table 3 and table 4.

Table 3. Normalization of Training Data

Province	2016	2017	2018	2019	2020 (Target)
Aceh	0.1228	0.1383	0.1402	0.1526	0.1938
Sumut	0.1642	0.1688	0.1722	0.1843	0.2457
Sumbar	0.3023	0.3287	0.3208	0.3467	0.4177
Riau	0.1026	0.1029	0.1035	0.1043	0.1053
Jambi	0.1073	0.1099	0.1147	0.1222	0.1446
Sumsel	0.1710	0.2601	0.2315	0.2742	0.2654
Bengkulu	0.1223	0.1230	0.1295	0.1294	0.1285
Lampung	0.1530	0.1617	0.1622	0.1842	0.1787
Bangka Belitung Islands	0.1015	0.1015	0.1021	0.1022	0.1038
Riau Islands	0.1003	0.1003	0.1003	0.1005	0.1010
Jakarta	0.1023	0.1021	0.1004	0.1045	0.1067
West Java	0.3891	0.4763	0.5160	0.5738	0.5764
Central Java	0.2507	0.2662	0.3026	0.3738	0.4365
Yogyakarta	0.1275	0.1171	0.1143	0.1108	0.1104
East Java	0.4300	0.4554	0.5934	0.5612	0.9000
Banten	0.1031	0.1061	0.1087	0.1093	0.1091
Bali	0.1100	0.1102	0.1102	0.1111	0.1128
NTB	0.1107	0.1203	0.1135	0.1190	0.1876
NTT	0.1463	0.1438	0.1554	0.1531	0.1631
...	...	...	...	...	...
...	...	...	...	...	...
West Papua	0.1003	0.1004	0.1002	0.1015	0.1018
Papua	0.1009	0.1008	0.1017	0.1006	0.1006

Table 4. Normalization of Testing Data

Propinsi	2017	2018	2019	2020	2021 (Target)
Aceh	0.1383	0.1402	0.1526	0.1937	0.3024
Sumut	0.1688	0.1721	0.1842	0.2457	0.2610
Sumbar	0.3287	0.3208	0.3467	0.4176	0.4827
Riau	0.1029	0.1035	0.1043	0.1053	0.1077
Jambi	0.1099	0.1146	0.1222	0.1446	0.1477
Sumsel	0.2601	0.2315	0.2741	0.2654	0.1724
Bengkulu	0.1230	0.1295	0.1294	0.1285	0.1312
Lampung	0.1617	0.1622	0.1841	0.1787	0.2092
Bangka Belitung Islands	0.1014	0.1020	0.1021	0.1037	0.1068
Riau Islands	0.1003	0.1003	0.1004	0.1010	0.1003
Jakarta	0.1020	0.1003	0.1044	0.1067	0.1076
Wes Java	0.4763	0.5160	0.5738	0.5764	0.6009
Central Java	0.2662	0.3026	0.3737	0.4365	0.4446
Yogyakarta	0.1171	0.1142	0.1108	0.1104	0.1497
East Java	0.4553	0.5933	0.5612	0.9000	0.8219
Banten	0.1060	0.1087	0.1092	0.1091	0.1065
Bali	0.1102	0.1101	0.1111	0.1127	0.1232
NTB	0.1202	0.1135	0.1190	0.1876	0.1404
NTT	0.1438	0.1554	0.1531	0.1631	0.2576
Kalbar	0.1012	0.1012	0.1022	0.1030	0.1075
Kalteng	0.1002	0.1004	0.1008	0.1007	0.1040
Kalsel	0.1002	0.1000	0.1001	0.1000	0.1002
Kaltim	0.1054	0.1045	0.1077	0.1051	0.1030
...	...	...	...	...	...
...	...	...	...	...	...
Papua Barat	0.1004	0.1001	0.1014	0.1017	0.1025
Papua	0.1008	0.1017	0.1005	0.1005	0.1040

2.4. Architectural Design

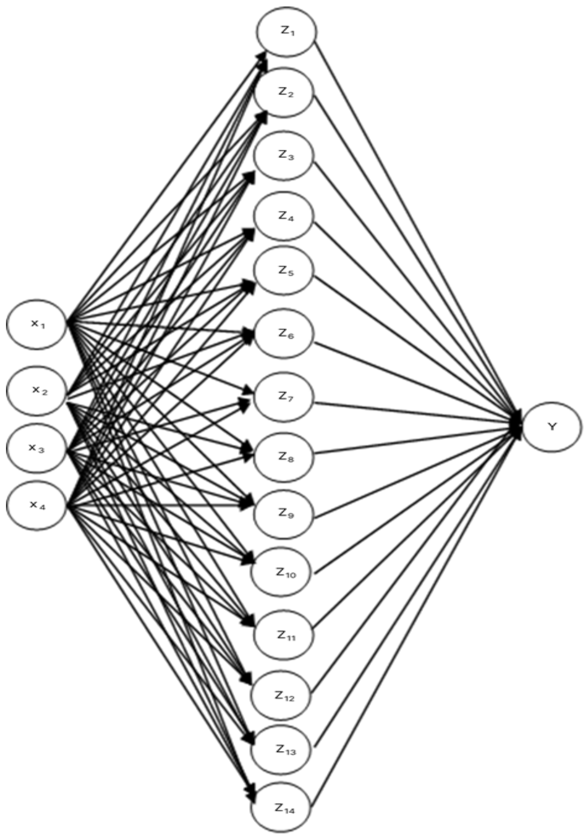

Figure 2. Architectural Design

The architecture used is the 4-14-1 architecture, consisting of 4 data input layers, 14 hidden layers, and one output layer. The input layer training consists of 2016, 2017, 2018, and 2019 with a target of 2020, while the input layer testing consists of 2017, 2018, 2019, and 2020 with a target of 2021. The architectural design can be seen in Figure 2.

3. Results and Discussion

3.1. Training And Testing with BP

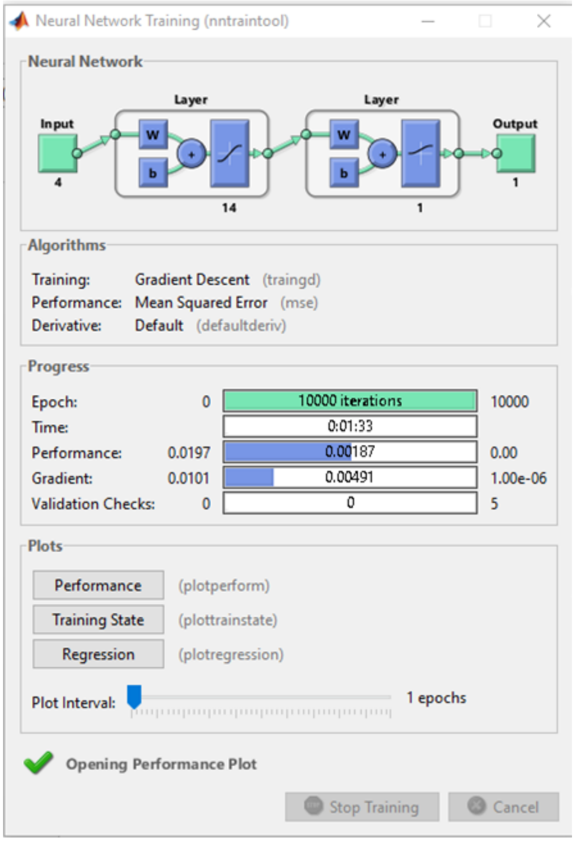

Figure 3. Training Model 4-14-1 Standard BP Method

The results of the training using the 4-14-1 architecture model with the Standard BP method produced epochs of 10000, performance (MSE) 0.00186570, time 00:01:33 and performance (MSE) in the test of 0.02045534. The results of the training and testing of the Standard BP method can be seen in Figures 3 and 4.

3.2. Training and Testing with Resilient Backpropagation

The results of the training using the 4-14-1 architectural model with the Resilient Backpropagation method resulted in 1000 epochs, 0.00012667 performance(MSE), 00:00:12 time and 0.00543829 performance (MSE). The results of the training and testing of the Resilient Backpropagation method can be seen in Figures 5 and 6.

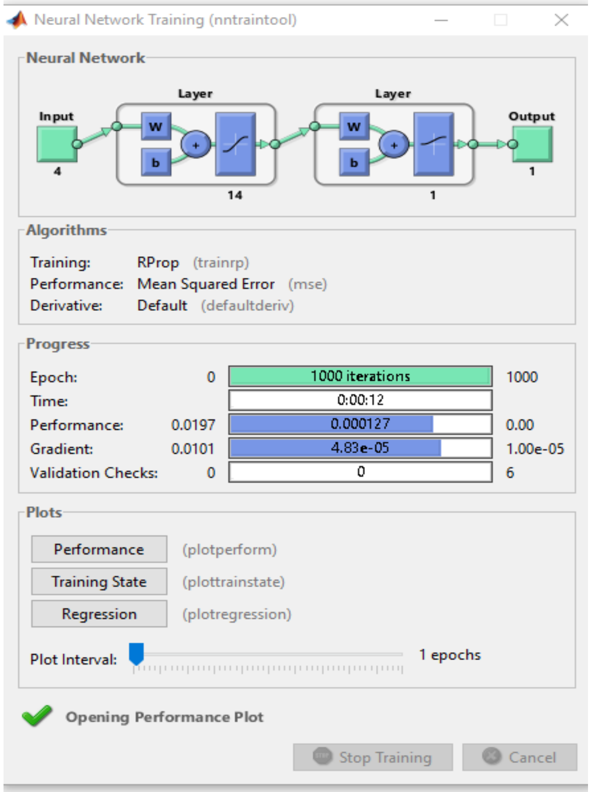

Figure 4. Performance and Epoch Model 4-14-1

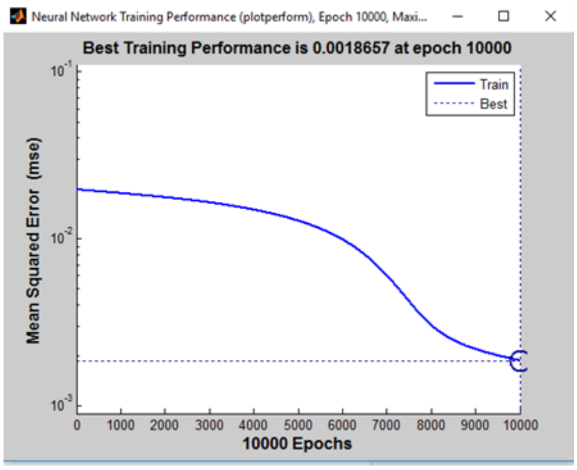

Figure 5. Training Model 4-14-1 Resilient Backpropagation Method

3.3. Training And Testing with Conjugate Gradient

The results of the training using the 4-14-1 architectural model with the Conjugate Gradient method yielded epochs of 1000, performance (MSE) 0.00003422, time 00:00:17 and performance (MSE) in the test of 0.03318314. The results of the training and testing of the Conjugate Gradient method can be seen in Figures 7 and 8.

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3.4. Training And Testing with Fletcher Reeves

The results of the training using the 4-14-1 architectural model with the Fletcher Reeves method produced epochs of 608, performace(MSE) 0.00003637, time 00:00:19 and performance (MSE) in the test of 0.02503777. The results of the training and testing of the Fletcher Reeves method can be seen in Figures 9 and 10.

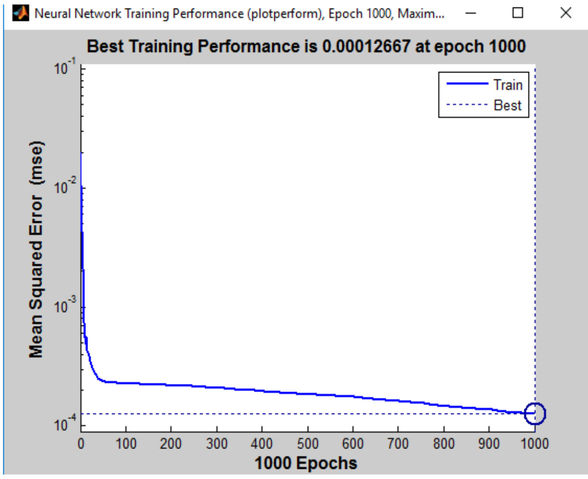

Figure 6. Performance and Epoch Model 4-14-1 Resilient Bacpropagation Method

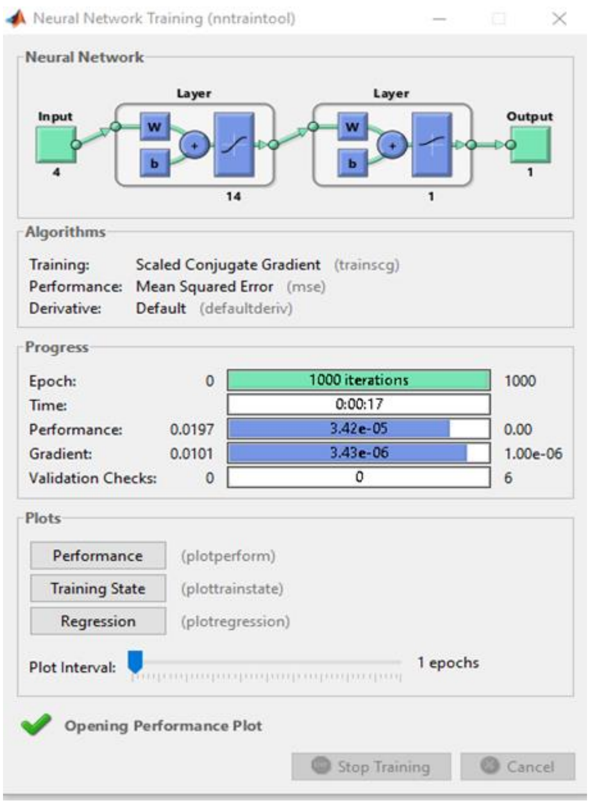

Figure 7. Training Model 4-14-1 Conjugate Gradient Method

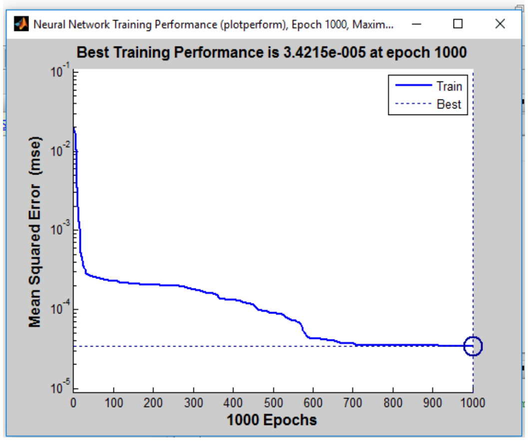

Figure 8. Performance and Epoch Model 4-14-1 Conjugate Gradient Method

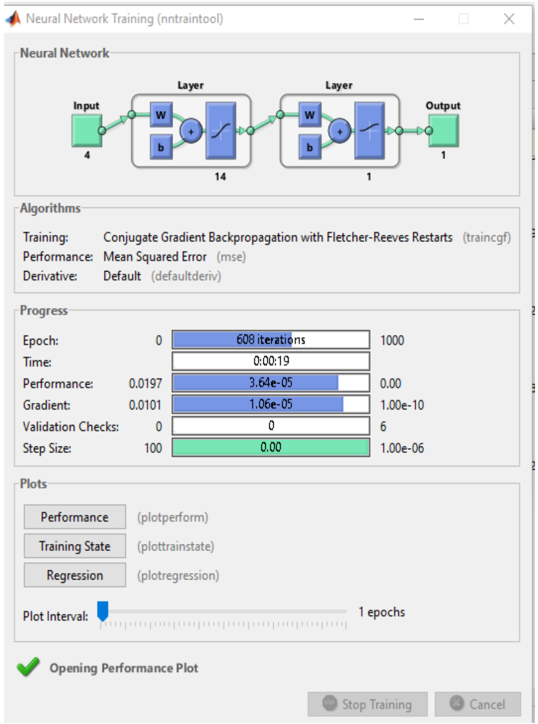

Figure 9. Training Model 4-14-1 Fletcher Reeves Method

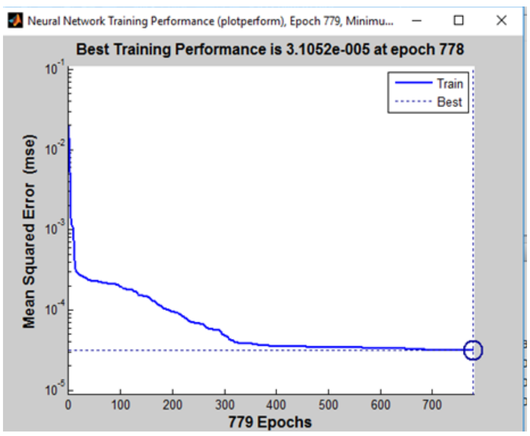

Figure 10. Performance and Epoch Model 4-14-1 Fletcher Reeves

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3.5. Training And Testing with Powell Beale Method

The results of the training using the architectural model 4-14-1 with the Powell Beale method produced epoch 778, performace(MSE) 0.000031052, time 00:00:24 and performance (MSE0 in the test was 0.03763985. The results of training and testing of the Powell Beale method can be seen in Figures 11 and 12.

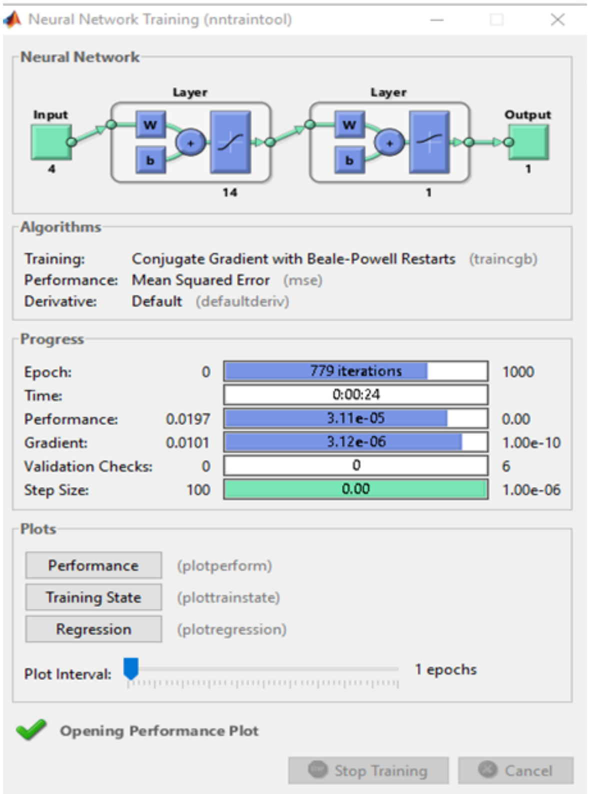

Figure 11. Training Model 4-14-1 Powell Beale Metode Method

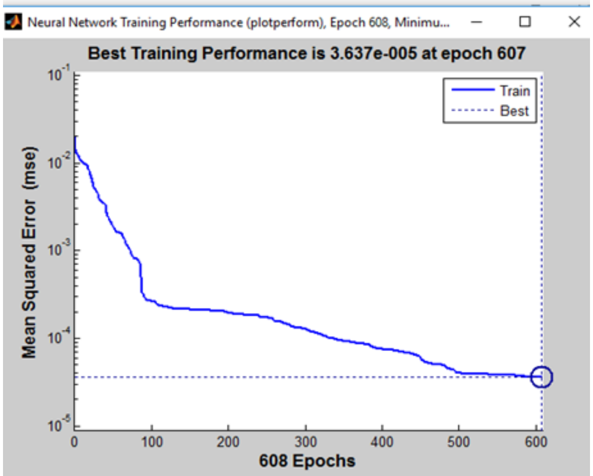

Figure 12. Performance and Epoch Model 4-14-1 Powell Beale Method

3.6. Result Analysis and Model Evaluation

The results of the evaluation of the application of variations in the Backpropagation algorithm to determine the best model for data prediction can be seen in Table 5 and Figures 13 to 16.

Table 5. Results of Evaluation of Backpropagation Variations

No	Metode	*Epoch*	Time	*Perf.* Training	*Perf.* Tseting
1	BP Standard	10000	00:01:33	0,00186570	0,02045534
2	*Resilient Backpropagation*	1000	00:00:12	0,00012667	0,00543829
3	*Conjugate Gradient*	1000	00:00:17	0,00003422	0,03318314
4	*Fletcher Reeves*	608	00:00:19	0,00003637	0,02503777
5	*Powell Beale*	778	00:00:24	0,00003105	0,03763985

The results of the application of the Backpropgation variation obtained that the lowest epoch was the Fletcher Reeves method, which was 608. The smallest time was Resilient Backpropagation, which was 00:00:12. The smallest training performance (MSE) is the Powell Beale method, which is 0.000003105. The smallest Performance (MSE) in the test is the Resilient Backpropagation method. From the results of the comparison of methods on performance (MSE) at the time of testing, the Resilient Backpropagation method is the best method with the smallest performance (MSE) which is 0.03763985

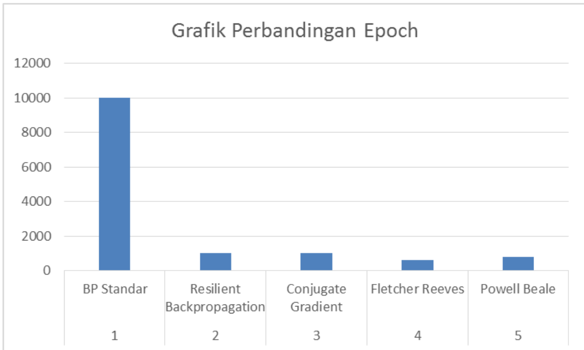

Figure 13. Epoch Comparison Graph

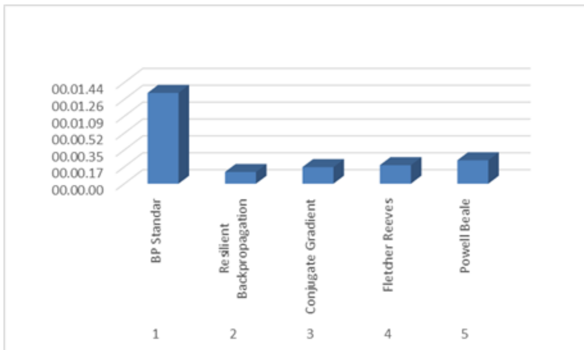

Figure 14. Time Comparison Chart

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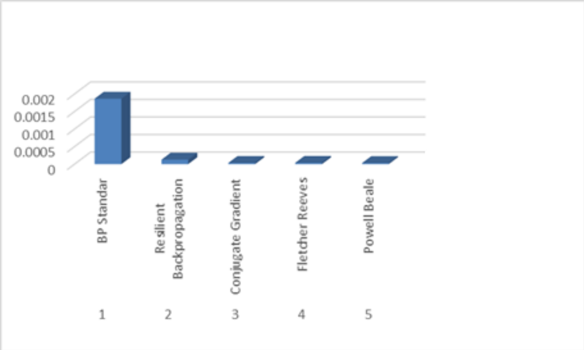

Figure 15. Comparative Graph of Training Performance(MSE)

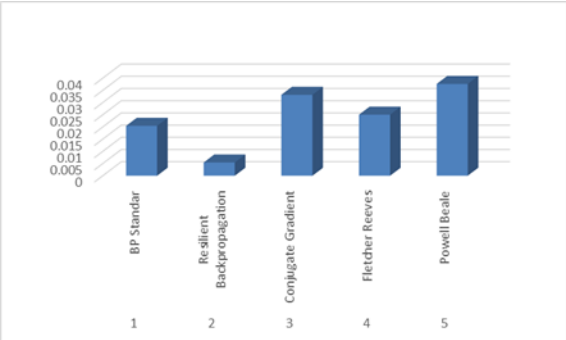

Figure 16. Comparison Graph of Testing Performance (MSE)

4. Conclussion

Based on the results of the application of backpropagation variations to determine the best model for data prediction using 5 methods, the best model is the Resilient Backpropagation method with a performance/MSE value of 0.00543829 which is the smallest test performance/MSE. For further researchers to add several other methods to get the best model on data prediction.

Reference

[1] R. Sistem and M. P. Matematika, “Implementasi Algoritma Backpropagation Prediksi Kegagalan Siswa Pada,” vol. 2, no. 3, pp. 753–759, 2018.

[2] D. Monika, A. Ahmad, S. Wardani, and Solikhun, “Model Jaringan Syaraf Tiruan Dalam Memprediksi Ketersediaan Cabai Berdasarkan Provinsi,” Teknika, vol. 8, no. 1, pp. 17–24, 2019.

[3] B. Yang, M. Pajak, D. Kabupaten, E. Rumapea, and M. R. Lubis, “Penerapan Jaringan Syaraf Tiruan Dalam Memprediksi Jumlah Kendaraan,” pp. 245–248, 2020.

[4] R. Sistem, “Jurnal resti,” vol. 1, no. 10, pp. 1–2, 2021.

[5] I. System, S. Dian, and C. Cendikai, “th,” no. December 2003, pp. 153–163.

[6] C. Florescu and C. Igel, “R Esilient B Ackpropagation (R Prop) Learning In T Ensor F Low For B Atch -,” no. 1997, pp. 1–5, 2018.

[7] M. Ayoub and M. Ayoub, “Application of Resilient Back-Propagation Neural Networks for Generating a Universal Pressure Drop Model in Pipe ...”

[8] Y. Sari and U. L. Mangkurat, “Prediksi Harga Emas Menggunakan Metode Neural Network Backropagation Algoritma Conjugate Gradient,” no. January 2018, 2022.

[9] S. S. S, S. Defit, and M. Ramadhan, “Analisis Optimasi Fungsi Pelatihan Machine Learning Neural Network dalam Peramalan,” vol. 7, no. 3, pp. 359–369, 2021.

[10] S. Anam, T. Adriyanto, and M. K. Wuryansari, “Diagnosis Diabetes Mellitus Menggunakan Algoritma Jaringan Syaraf Tiruan Backpropagation dengan Metode Conjugate Gradient Fletcher-Reeves Adaptive Gain,” pp. 47–52, 2017.

[11] S. R. Rusamsi, A. A. Rohmawati, F. Informatika, U. Telkom, and W. Haar, “Deteksi Kanker Berdasarkan Klasifikasi Microarray Data Menggunakan Wavelet Transform dan Backpropagation Termodifikasi dengan Conjugate Gradient Flechter,” vol. 5, no. 1, pp. 1772–1779, 2018.

[12] S. Anam et al., “Predicting the Number of COVID-19 Sufferers in Malang City Using the Backpropagation Neural Network with the Fletcher – Reeves Method,” vol. 2021, 2021.

[13] P. Anggara, “Perbandingan Model Jaringan Syaraf Tiruan Dengan Algoritma Levenberg-Marquadt Dan Powell-Beale Conjugate Gradient Pada Kecepatan Angin Rata-Rata Di Kota Semarang,” vol. 8, no. 2, 2020.

[14] I. L. Sirait, J. M. Gultom, J. Tindaon, R. J. Tampubolon, and W. J. Mawaddah, “Peramalan tingkat produktivitas kedelai di indonesia menggunakan algoritma,” vol. 4, no. 2, pp. 183–192, 2018.

[15] J. Nasional, S. Informasi, and A. Wanto, “Optimasi Prediksi Dengan Algoritma Backpropagation Dan Conjugate Gradient Beale-Powell Restarts,” vol. 03, no. 2017, pp. 370–380, 2018.

[16] H. M. Mushgil, H. A. Alani, and L. E. George, “Comparison between Resilient and Standard Back Propagation Algorithms Efficiency in Pattern Recognition,” no. March 2015, pp. 4–10, 2019.

[17] H. Y. Sari and A. Pendahuluan, “Optimasi Conjugate Gradient Pada Algoritma Backpropagation Neural Network Untuk Prediksi Kurs Time Series,” vol. 5, no. 1, pp. 86–90, 2016.

[18] Riska Yanu Fa’arifah and Z. Busrah, “Backpropagation Neural Network untuk Optimasi Akurasi pada Prediksi Financial Distress Perusahaan,” J. Inf. Sains dan Teknol., vol. 2, no. April, pp. 101–110, 2017.

[19] D. N. I. Muzakkir Irvan, Syukur Abdul, “Backpropagation Dengan Seleksi Fitur Particle Swarm Optimization Dalam Prediksi Pelanggan Telekomunikasi,” J. Pseudocode, vol. 1, no. 1 ISSN 2355 – 5920 PENINGKATAN, pp. 1–10, 2014.

[20] https://www.bps.go.id/

DOI: https://doi.org/10.29207/resti.v6i5.4356