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Application of the Fletcher-Reeves Algorithm to Predict Spinach Vegetable Production in Sumatra

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ABSTRACT

Determination of spinach plant predictions is one of the most critical decision-making processes. In predicting spinach plants in each period, it depends on each period, both the previous and subsequent periods. The production of spinach plants that change every period causes uncertainty in predicting. The method used to indicate the data is the Fletcher-Reeves algorithm, it is an appropriate development technique compared to the backpropagation strategy because this strategy can speed up the preparation time to arrive at the minimum convergence value. This paper does not discuss the prediction results. Still, it discusses the ability of the Fletcher-Reeves algorithm to make predictions based on the spinach production dataset obtained from the Central Statistics Agency. The purpose of this research is to see the accuracy and performance measurement of the algorithm in the search for the best results to solve the prediction of spinach plants in Sumatra. The research data used are spinach vegetable production data in North Sumatra. Based on this data, a network architecture model will be formed and determined, including 2-20-1, 2-30-1, 2-35-1, 2-45-1, and 2-50-1. After training and testing, these five models show that the best architectural model is 2-20-1 with an MSE value of 0.00608399, the lowest among the other four models. So the model can be used to predict spinach plants in Sumatra.A well-prepared abstract enables the reader to identify the basic content of a document quickly and accurately, to determine its relevance to their interests, and thus to decide whether to read the document in its entirety.

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1. INTRODUCTION

Indonesian people who live in rural areas work by farming. This shows that agricultural areas have a massive commitment to the course of monetary improvement in rural areas. The decreasing agricultural land and the low quality of spinach produced by farmers are examples of problems encountered in spinach cultivation activities. Horticulture is also the largest area in the economy of any non-industrialized country [1, 2]. This area provides food for most of the population, employment for almost the entire workforce, and produces natural, raw, or auxiliary materials for the trade industry [3, 4]. Vitamins from plants are a source of nutrients and minerals that are key to the well-being of the human body. Spinach is the most crucial leaf vegetable. In 100 grams of edible spinach, there is about 2.9 mg of iron (Fe) small [5, 6].

From previous studies, this study will analyze the performance of the Fletcher-Reeves algorithm to solve the problem of predicting spinach in Sumatra [7, 8]. This dataset is only used to assist in the proof and process of measuring the algorithm's performance. The purpose of this research is to see the accuracy and performance measurement of the algorithm in the search for the best results to solve the prediction of spinach plants in Sumatra.

2. RESEARCH METHOD

2.1. Data Collection

In the analysis process, this study uses a production dataset of spinach (Tons) on the island of Sumatra for six years (2015 - 2020). The data were obtained from the Indonesian Statistics Center (BPS) [9, 10] (Table 1).

Table 1. Spinach Production in Sumatra

PROVINCE	Year					
	2015	2016	2017	2018	2019	2020
ACEH	5973	4367	3541	3427	3914	3838
NORTH SUMATRA	19891	20924	20435	20244	16610	12786
WEST SUMATRA	4528	3271	3398	4028	4434	5173
RIAU	7258	8734	9125	11183	8554	8860
JAMBI	2958	3609	3603	4644	3834	2861
SOUTH SUMATRA	3149	3563	2888	4271	3627	4387
BENGKULU	1904	1808	1235	756	670	870
LAMPUNG	5923	7357	6494	6933	7489	7225
KEP. BANGKA BELITUNG	1005	730	1011	1287	1225	1755
KEP. RIAU	6052	6246	5467	4618	4198	3378

2.2. Research Stages

The stages carried out in this research can be seen in the Figure 1.

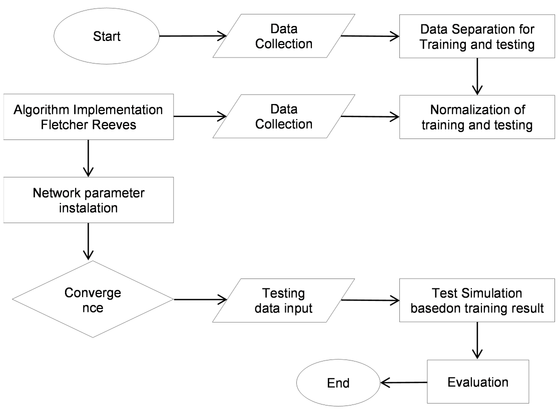

Figure 1. Preprocessing Data Scheme

Scheme Preprocessing Data explains that the first step is to collect data. The data used is export value data by the produce spinach plants. Then the data is divided into two (training data and testing data). Next, determine the architectural model and the method used for the training and testing process. Finally, after obtaining results based on the methods and models used, select the best model.

2.3. Data Processing

The sample data was used to produce spinach plants in Sumatra from 2015 to 2020. This data will later be transformed before being tested for training and testing using an artificial neural network using the following formula (1).

$$x' = \frac{0,8(x-a)}{(b-a)} + 0,1 \tag{1}$$

x' is results of data that have been normalized, x is data to be normalized, a is lowest data, and n is highest data.

3. RESULT AND ANALYSIS

3.1. Separation of Training and Testing Data

The production data of spinach plants on the island of Sumatra (Table 1) were normalized using the above formula and then divided into two groups, namely the training dataset and the test dataset [11, 12]. The training dataset is from 2015-2016 (X1-X2), and the target year is 2017 (Y1) (Table 2).

Table 2. Normalization of Training Data

No	X1	X2	Target (Y1)
1	0,3077	0,2441	0,2114
2	0,8591	0,9000	0,8806
3	0,2505	0,2007	0,2057
4	0,3586	0,4171	0,4326
5	0,1883	0,2141	0,2138
6	0,1958	0,2122	0,1855
7	0,1465	0,1427	0,1200
8	0,3057	0,3625	0,3283
9	0,1109	0,1000	0,1111
10	0,3108	0,3185	0,2877

The test data is from 2018-2019 (X3-X4), and the target is 2020 (Y2) (Table 3).

Table 3. Normalization of Examiner Data

No	X1	X2	Target (Y2)
1	0,2127	0,2326	0,2295
2	0,9000	0,7515	0,5952
3	0,2372	0,2538	0,2840
4	0,5297	0,4222	0,4347
5	0,2624	0,2293	0,1895
6	0,2472	0,2209	0,2519
7	0,1035	0,1000	0,1082
8	0,3560	0,3787	0,3679
9	0,1252	0,1227	0,1443
10	0,2614	0,2442	0,2107

3.2. Training and Testing Result

Simulation and testing were carried out using the MatLab 2011b software with 5 network models, namely: 2-20-1n (inputm2, hidden layer 20, outputn1), 2-30-1 (input 2, hidden layer 30, outputn1), and 2-35-1 (inputn2, hidden layer 35, output 1), 2-45-1 (input

2, hidden layer 45, output 1), 2-50-1 (input 2, hidden layer 50, output 1) [13–15].
Training and testing using the standard Backpropagation method.

a. Model Network Architecture 2-20-1.

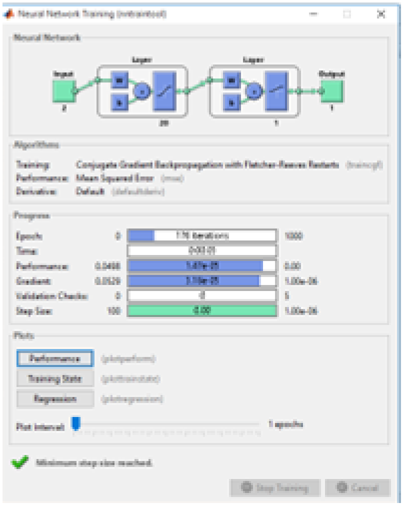

Figure 2. Training Model 2-20-1

Results of training with traincgf function model 2-20-1,nepoch = 176 iterations, training time = 3 seconds. The Table 4 (Training Results) and Table 5 (Testing Results).

Table 4. Results Training Model 2-20-1

No	X1	X2	Target (Y1)	Epoch 176		
				actual	eror	Perf
1	0,3077	0,2441	0,2114	0,2117	-0,0003	
2	0,8591	0,9000	0,8806	0,8807	-0,0001	
3	0,2505	0,2007	0,2057	0,2050	0,0007	
4	0,3586	0,4171	0,4326	0,4325	0,0001	
5	0,1883	0,2141	0,2138	0,2072	0,0066	0,00001482
6	0,1958	0,2122	0,1855	0,1934	-0,0079	
7	0,1465	0,1427	0,1200	0,1242	-0,0042	
8	0,3057	0,3625	0,3283	0,3286	-0,0003	
9	0,1109	0,1000	0,1111	0,1063	0,0048	
10	0,3108	0,3185	0,2877	0,2872	0,0005	

Table 5. ResultsiTesters Model 2-20-1

No	X1	X2	Target (Y2)	Epoch		
				actual	eror	Perf
1	0,2127	0,2326	0,2295	0,2132	0,0163	
2	0,9000	0,7515	0,5952	0,7636	-0,1684	
3	0,2372	0,2538	0,2840	0,2091	0,0749	
4	0,5297	0,4222	0,4347	0,5509	-0,1162	
5	0,2624	0,2293	0,1895	0,1892	0,0003	0,0061
6	0,2472	0,2209	0,2519	0,1856	0,0663	
7	0,1035	0,1000	0,1082	0,1068	0,0014	
8	0,3560	0,3787	0,3679	0,4517	-0,0838	
9	0,1252	0,1227	0,1443	0,1144	0,0299	
10	0,2614	0,2442	0,2107	0,1827	0,0280	

Based on the results of training and testing using Matlab 2011b and then comparing it using Ms. Excel, then the Value Actual, Value Error, and value MSE/Performances(Perf) values are appropriate (Valid) [16, 17].

b. Model Network Architecture 2-30-1.

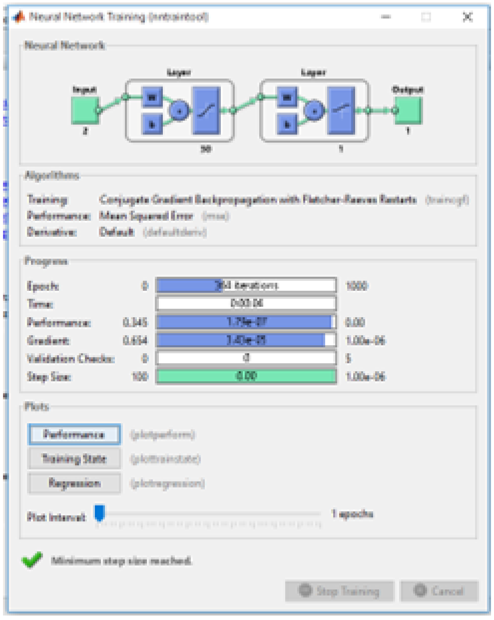

Figure 3. Training Model 2-3-1

Results of training with traincgf function model 2-3-1,nepoch = 364 iterations,itraining time = 3 seconds. The Table 6 (Training Results) and Table 7 (Testing Results).

Table 6. Training Results Model 2-30-1

No	X1	X2	Target (Y1)	Epoch 364		
				actual	error	Perf
1	0,3077	0,2441	0,2114	0,2114	0,0000	
2	0,8591	0,9000	0,8806	0,8807	-0,0001	
3	0,2505	0,2007	0,2057	0,2057	0,0000	
4	0,3586	0,4171	0,4326	0,4326	0,0000	
5	0,1883	0,2141	0,2138	0,2128	0,0010	0,00000019
6	0,1958	0,2122	0,1855	0,1864	-0,0009	
7	0,1465	0,1427	0,1200	0,1201	-0,0001	
8	0,3057	0,3625	0,3283	0,3284	-0,0001	
9	0,1109	0,1000	0,1111	0,1112	-0,0001	
10	0,3108	0,3185	0,2877	0,2875	0,0002	

Table 7. Results Testers Model 2-3-1

No	X1	X2	Target (Y2)	Epoch		
				actual	eror	Perf
1	0,2127	0,2326	0,2295	0,1545	0,0750	
2	0,9000	0,7515	0,5952	0,9425	-0,3473	
3	0,2372	0,2538	0,2840	0,1178	0,1662	
4	0,5297	0,4222	0,4347	0,916	-0,4813	
5	0,2624	0,2293	0,1895	0,1823	0,0072	0,0399
6	0,2472	0,2209	0,2519	0,1771	0,0748	
7	0,1035	0,1000	0,1082	0,1222	-0,0140	

No	X1	X2	Target (Y2)	Epoch		
				actual	eror	Perf
8	0,3560	0,3787	0,3679	0,4349	-0,0670	
9	0,1252	0,1227	0,1443	0,1218	0,0225	
10	0,2614	0,2442	0,2107	0,1559	0,0548	

Based on the results of training and testing using Matlab 2011b and then comparing it using Ms. Excel, then the ValueiActual, ValuenError, and value MSE/Performances(Perf) values are appropriate (Valid).

c. Model Network Architecture 2-35-1.

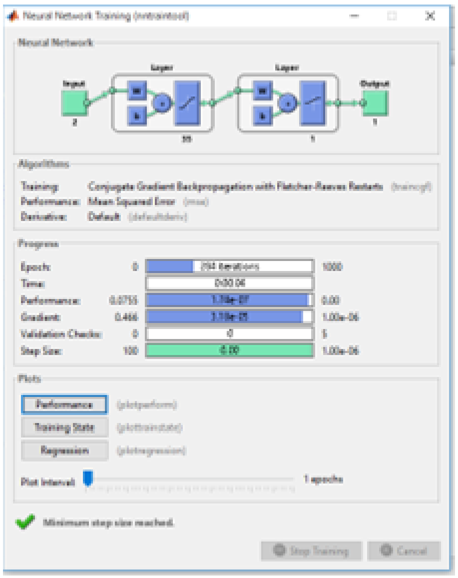

Figure 4. Training Model 2-35-1

Results from training with the traincgf function model 2-35-1, epoch = 284 iterations, training time = 3 seconds. The Table 7 (Training Results) and Table 9 (Testing Results).

Table 8. Results Training Model 2-35-1

No	X1	X2	Target (Y1)	Epoch 284		
				actual	error	Perf
1	0,3077	0,2441	0,2114	0,2114	0,0000	0,00000027
2	0,8591	0,9000	0,8806	0,8806	0,0000	
3	0,2505	0,2007	0,2057	0,2056	0,0001	
4	0,3586	0,4171	0,4326	0,4326	0,0000	
5	0,1883	0,2141	0,2138	0,2132	0,0006	
6	0,1958	0,2122	0,1855	0,1865	-0,0010	
7	0,1465	0,1427	0,1200	0,1195	0,0005	
8	0,3057	0,3625	0,3283	0,3293	-0,0010	
9	0,1109	0,1000	0,1111	0,1115	-0,0004	
10	0,3108	0,3185	0,2877	0,2877	0,0000	

Table 9. Results Testers Model 2-35-1

No	X1	X2	Target (Y2)	Epoch		
				actual	eror	Perf
1	0,2127	0,2326	0,2295	0,1998	0,0297	
2	0,9000	0,7515	0,5952	0,5229	0,0723	
3	0,2372	0,2538	0,2840	0,1878	0,0962	
4	0,5297	0,4222	0,4347	0,1019	0,3328	
5	0,2624	0,2293	0,1895	0,1888	0,0007	0,0134
6	0,2472	0,2209	0,2519	0,1775	0,0744	
7	0,1035	0,1000	0,1082	0,1263	-0,0181	
8	0,3560	0,3787	0,3679	0,3625	0,0054	
9	0,1252	0,1227	0,1443	0,123	0,0213	
10	0,2614	0,2442	0,2107	0,1772	0,0335	

Based on the results of training and testing using Matlab 2011b and then comparing it using Ms. Excel, then the ValueiActual, ValuenError, and value MSE/Performances(Perf) values are appropriate (Valid).

d. Network Architecture Model 2-45-1.

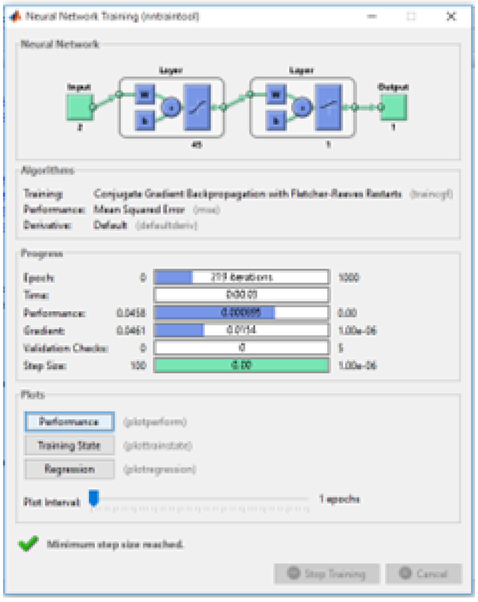

Figure 5. Training Model 2-45-1

Results of training with the traincgf function model 2-45-1, epoch = 219 iterations, training time = 3 seconds. The Table 10 (Training Results) and Table 11 (Testing Results)

Table 10. Results Training Model 2-45-1

No	X1	X2	Target (Y1)	Epoch 219		
				actual	error	Perf
1	0,3077	0,2441	0,2114	0,2821	-0,0707	
2	0,8591	0,9000	0,8806	0,9086	-0,0280	
3	0,2505	0,2007	0,2057	0,2054	0,0003	
4	0,3586	0,4171	0,4326	0,3913	0,0413	
5	0,1883	0,2141	0,2138	0,2002	0,0136	0,000894
6	0,1958	0,2122	0,1855	0,1886	-0,0031	
7	0,1465	0,1427	0,1200	0,1398	-0,0198	
8	0,3057	0,3625	0,3283	0,3502	-0,0219	

No	X1	X2	Target (Y1)	Epoch 219		
				actual	error	Perf
9	0,1109	0,1000	0,1111	0,1292	-0,0181	
10	0,3108	0,3185	0,2877	0,2798	0,0079	

Table 11. Results of Model 2-45-1 Testers

No	X1	X2	Target (Y2)	Epoch		
				actual	error	perf
1	0,2127	0,2326	0,2295	0,2327	-0,0032	0,0181
2	0,9000	0,7515	0,5952	0,1891	0,4061	
3	0,2372	0,2538	0,2840	0,2845	-0,0005	
4	0,5297	0,4222	0,4347	0,5009	-0,0662	
5	0,2624	0,2293	0,1895	0,2423	-0,0528	
6	0,2472	0,2209	0,2519	0,2160	0,0359	
7	0,1035	0,1000	0,1082	0,1308	-0,0226	
8	0,3560	0,3787	0,3679	0,3020	0,0659	
9	0,1252	0,1227	0,1443	0,1368	0,0075	
10	0,2614	0,2442	0,2107	0,2595	-0,0488	

Based on the results of training and testing using Matlab 2011b and then comparing it using Ms. Excel, then the ValueiActual, ValueiError, and value MSE/Performances(Perf) values are appropriate (Valid).

e. Network Architecture Model 2-50-1.

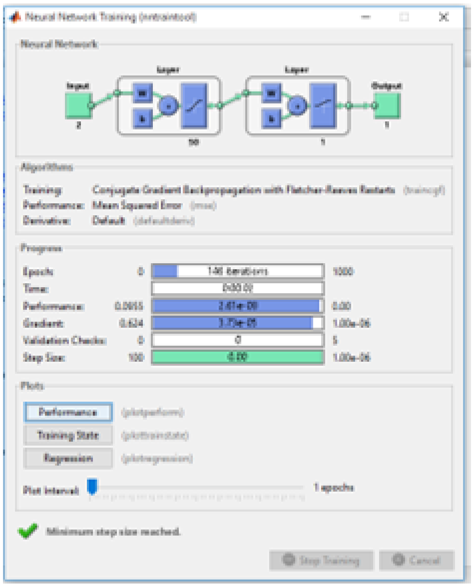

Figure 6. Training Model 2-50-1

The result of training with the function traincgf model 2-50-1, epoch = 146 iterations, training time = 3 seconds. The Table 12 (Training Results) and Table 13 (Testing Results).

Table 12. Training Results Model 2-50-1

No	X1	X2	Target (Y2)	Epoch 146		
				actual	error	perf
1	0,3077	0,2441	0,2114	0,2114	0,0000	0,00000002
2	0,8591	0,9000	0,8806	0,8807	-0,0001	
3	0,2505	0,2007	0,2057	0,2056	0,0001	

No	X1	X2	Target (Y2)	Epoch 146		
				actual	error	perf
4	0,3586	0,4171	0,4326	0,4323	0,0003	
5	0,1883	0,2141	0,2138	0,2139	-0,0001	
6	0,1958	0,2122	0,1855	0,1856	-0,0001	
7	0,1465	0,1427	0,1200	0,1199	0,0001	
8	0,3057	0,3625	0,3283	0,3286	-0,0003	
9	0,1109	0,1000	0,1111	0,1111	0,0000	
10	0,3108	0,3185	0,2877	0,2876	0,0001	

Table 13. Test Results Model 2-50-1

No	X1	X2	Target (Y2)	Epoch		
				actual	error	perf
1	0,2127	0,2326	0,2295	0,2005	0,0290	0,0105
2	0,9000	0,7515	0,5952	0,8382	-0,2430	
3	0,2372	0,2538	0,2840	0,2236	0,0604	
4	0,5297	0,4222	0,4347	0,6266	-0,1919	
5	0,2624	0,2293	0,1895	0,2278	-0,0383	
6	0,2472	0,2209	0,2519	0,2074	0,0445	
7	0,1035	0,1000	0,1082	0,1341	-0,0259	
8	0,3560	0,3787	0,3679	0,3770	-0,0091	
9	0,1252	0,1227	0,1443	0,1255	0,0188	
10	0,2614	0,2442	0,2107	0,2278	-0,0171	

Based on the results of training and testing using Matlab 2011b and then comparing it using Ms. Excel, then the ValuenActual, ValuenError, and value MSE/Performances(Perf) values are appropriate (Valid).

3.3. Result Analysis and Evaluation

Based on the results of the training and testing carried out using the Matlab 2011b and MS applications. Excel continued by analyzing and evaluating the results of the network architecture model (Table 14) and the best training functions [18, 19].

Table 14. Results of Training Function Analysis

Model	**Algorithm**	**Function Activation**	**Function Training**	**Epoch (Iteration)**	**MSE Training**	**MSE Testing/Performance**
2-20-1	Fletcher-Reeves	'tansig','logsig'	Traincgf	176	0,00001482	0,00608399
2-30-1		'tansig','logsig'	Traincgf	364	0,00000019	0,03993481
2-35-1		'tansig','logsig'	Traincgf	284	0,00000027	0,01336164
2-45-1		'tansig','logsig'	Traincgf	219	0,00089430	0,01806651
2-50-1		'tansig','logsig'	Traincgf	146	0,00000002	0,01052101

It can be seen from the comparison of each training function method used. After training and data testing on architectural models 2-20-1, 2-30-1, 2-35-1, 2-45-1, and 2-50-1 utilizing the help of Matlab 2011b and Microsoft Excel software, the best architectural model was obtained 2-20-1 with MSE Testing values (Figure 7). The lowest performance is 0.00608399 with 176 epochs (Figure 8) [20, 21].

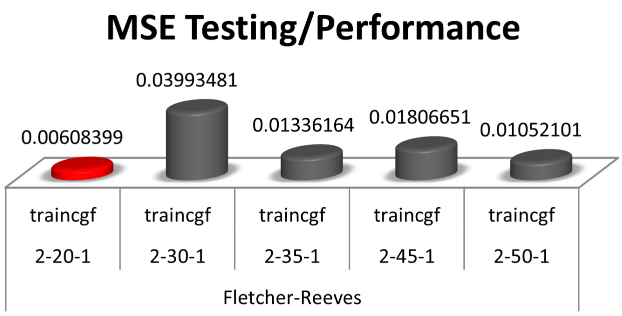

Figure 7. Comparison of MSE Testing/Performance

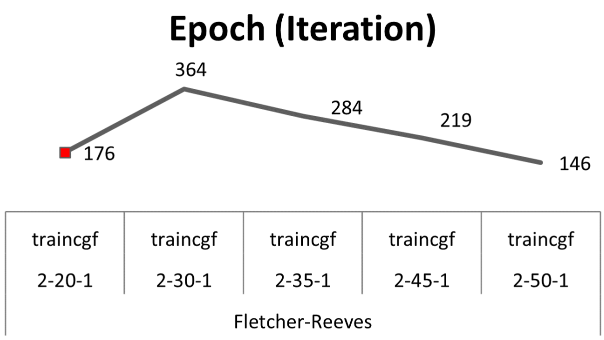

Figure 8. Comparison Epoch

The results above show the comparison of each algorithm and architectural model used. From the picture, it can be concluded that the Conjugate Gradient Fletcher-Reeves Algorithm with an architectural model of 2-20-1 is the best result [22, 23].

4. CONCLUSION

Based on the results and discussion above, the Fletcher-Reeves Conjugate Gradient Algorithm with the 2-20-1 architectural model can be used to predict the production of spinach vegetables in Sumatra in 2015-2020 because the training time for achieving convergence is not too long. The resulting performance is quite good compared to the other four architectural models. Overall, the Fletcher-Reeves algorithm (traincgf) can produce a reasonable level, which results in the lowest Performance/MSEn test scores, time to achieve relative convergence, and iteration.

5. DECLARATIONS

AUTHOR CONTIBUTION

All authors contributed to the writing of this article.

FUNDING STATEMENT

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COMPETING INTEREST

The authors declare no conflict of interest in this article.

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