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Fletcher-reeves algorithm for predicting the quantity of production tomato plants in indonesia

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ABSTRACT

The growth of Indonesia's tomato plants continues to increase, and this increase needs to be balanced, according to data from 2015 to 2020. Tomatoes should be used all the time, even in Indonesia. Tomatoes are not only edible but also good for your health and appearance. For the government and various conferences to include this as a point of view in dealing with this problem, it is important to look at the amount of tomato production in Indonesia. Data from the Central Statistics Agency was used to obtain statistics on tomato plant cultivation in Indonesia from 2015 to 2020. This data is solved using the Fletcher-Reeves algorithm using architectural models 2-10-1, 2-20-1, 2-30-1, and 2-35-1. Model 2-10-1 is the best architectural model to predict the amount of tomato production compared to other models, according to the training and testing results of the four models. Model 2-10-1 is used to measure the accuracy of the Fletcher-Reeves method, with MSE Training set at 0.00008463 and MSE Testing at 0.0006094.

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1. INTRODUCTION

Tomato, scientifically known as Lycopersicum esculentum Mill., is a food plant with a distinctive taste that combines sweet and sour flavors (Halid, 2021). There are many ways to enjoy tomatoes. For vegetables, juices, or spice mixes, fresh tomatoes are used. In addition, it is also used as an industrial raw material. For example, raw tomatoes are processed to make sauces, cosmetics, and medicines. According to legend, the vitamin content of tomatoes can treat several diseases. Regular consumption of tomatoes can help prevent cancer, especially prostate cancer. (Andriani et al., 2018) (Agriculture & Samarinda, 2015) (Novaldy & Iyos, 2016). One of the fruits and vegetables with high economic value and potential for agribusiness growth is tomato. It contains vitamins, minerals, proteins, carbohydrates, lipids, and vitamin C (St. Sabahannur & Herawati, 2017) (Abadi et al., 2022) (Wijaya et al., 2015) (Tomato et al., 2019). One of the most expensive horticultural commodities today is tomatoes(Tursilawati et al., 2016). To increase yield and fruit quality, this must be taken very seriously. Compared with Taiwan, Saudi Arabia, and India, whose average production is 21 tons/hectare, 13.4 tons/hectare, and 9.5 tons/hectare, it is clear that Indonesia's tomato production is still low at 6.3 tons. /hectare(Wasonowati, 2010).

According to data from the Central Statistics Agency, tomato output in Indonesia has increased every year for the last six years, from 2015 to 2020. Indonesia produced 87,801 tomatoes in 2015, rising to 1,084,995 tons in 2020. In the six years from 2015 to 2020, the increase was 207,194. Production increases yearly, which benefits tomato cultivation and needs to be maintained.

For the government to take the necessary actions to address the problem of tomato production in Indonesia, this study was conducted to estimate the production of tomato plants next year. The decline in tomato production is not a significant and consistent problem yearly. The Fletcher-Reeves algorithm is one of the better methods.

Some literature claims that compared to the backpropagation method, the Fletcher-Reeves algorithm is a good optimization technique. With this approach, the training time is reduced, and the minimum convergence value is achieved (Mahmudi, 2020). In general, the Conjugate gradient algorithm is available in three ways, namely Fletcher-Reeves (GCF) (Wanto et al., 2017), Polak-Ribiere (CGP) (Tinambunan et al., 2020), dan FletcherReeves Restarts (CGB) (Wanto, 2018). Several studies have been conducted to use backpropagation and the Fletcher-Reeves algorithm to solve CPI prediction problems, such as the research of Wanto et al., 2017. While the Fletcher-Reeves method excels in performance, MSE, and speed, the backpropagation approach excels in prediction accuracy, scoring 75 percent versus 67 percent. Discovered Fletcher-Reeves algorithm and demonstrates a new non-linear architecture that uses leaf gradients to predict blast-induced air explosions as research by Keshtegar et al., 2018.

So that the government can refer to, review, and implement the necessary steps to overcome the problem of import/export of tomatoes, it is essential to forecast Indonesian tomato plants for the coming years.

2. RESEARCH METHOD

2.1. Data

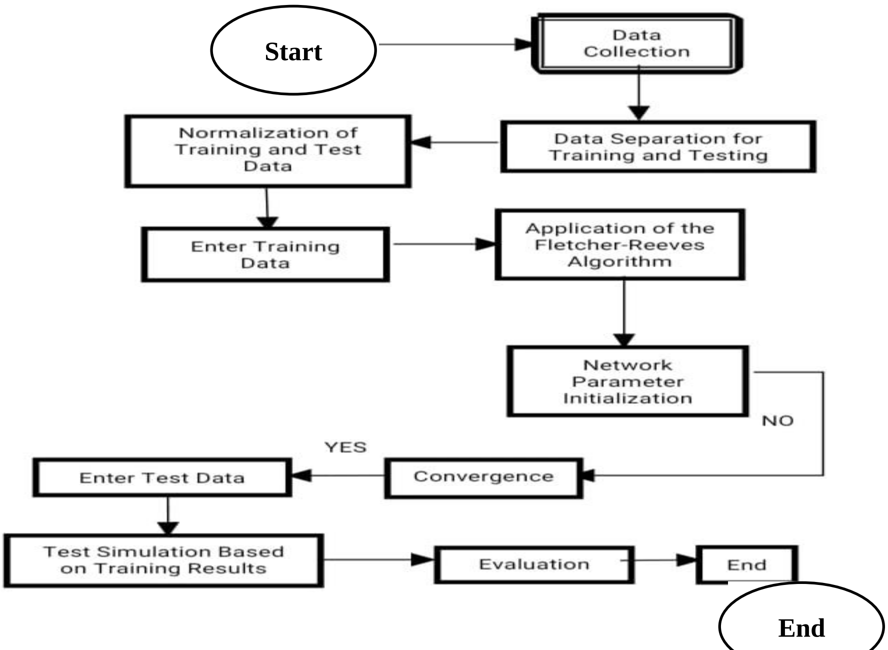
This census information was taken from the website of the Central Statistics Agency and relates to tomato production in Indonesia from 2015 to 2020 (Table 1) (BPS, n.d.).

Table 1. Tomato Plant Production

No	Provinsi	2015	2016	2017	2018	2019	2020
1	Aceh	21093	25647	26136	19682	20821	20781
2	Sumatera Utara	114652	99884	97358	103650	118583	162744
3	Sumatera Barat	88669	93487	101292	131819	146829	113491
4	Riau	127	204	293	241	117	158
5	Jambi	8408	9255	24450	11621	12348	19652
6	Sumatera Selatan	7140	11355	13559	14050	12487	10620
7	Bengkulu	21084	22459	18545	18284	18485	23033
8	Lampung	24491	23638	25432	19604	18669	19096
9	Kep. Bangka Belitung	410	555	704	685	473	536
10	Kep. Riau	52	4	2	6	285	235
11	Jawa Barat	296217	278394	295321	268448	284948	299267
12	Jawa Tengah	62405	61587	71772	90404	81710	79832
13	DI Yogyakarta	1243	1134	871	821	1372	1531
14	Jawa Timur	59180	60719	66758	65585	74558	83920
15	Banten	1052	1680	1017	784	830	1894
16	Bali	16716	24806	24520	25602	15171	13811
17	Nusa Tenggara Barat	25700	25218	22970	20871	29215	28609
18	Nusa Tenggara Timur	4442	4876	6716	5466	9950	9907
19	Kalimantan Barat	2006	3766	1805	1128	2088	1857
20	Kalimantan Tengah	1933	1867	1909	1831	2410	4352
21	Kalimantan Selatan	4915	4782	9153	7813	7399	7409
22	Kalimantan Timur	8049	5291	6429	7151	7430	8210
23	Kalimantan Utara	2666	3724	2754	2843	2688	2367
24	Sulawesi Utara	25118	24258	30276	53075	42392	57331
25	Sulawesi Tengah	12439	18134	22490	16163	16516	26706
26	Sulawesi Selatan	47598	49291	64917	67373	58513	60435
27	Sulawesi Tenggara	5399	6796	3464	3792	5608	4720
28	Gorontalo	1165	1235	2574	3148	3543	2721
29	Sulawesi Barat	777	1914	1924	1378	1662	760
30	Maluku	2810	2458	2761	3549	3324	4110
31	Maluku Utara	5222	3984	1834	877	7548	6785
32	Papua Barat	631	2501	525	826	2511	1311

33	Papua	3992	8339	12314	8220	9850	6804

2.2. Research Steps



Picture 1. Research Steps

Figure 1 illustrates that dataset collection should come first. The information used is related to the growth of tomato plants in Indonesia. Next, we must separate the data into training and testing sections. First, choose an architectural model, then decide how to use it for training and testing. The techniques and models used are what determine the results. Then select the top model.

2.3. Data Normalization

We will use 2017 adjusted data for 2015–2016 as training data and 2018–2019 adjusted for 2018–2019 as test data according to Table 1. Next, normalize the data values when divided by 2 using Equation 1 (Purba et al., 2019), (Wanto, Ginantra, et al., 2019), (Siregar et al., 2019), (Zamzamy Sormin et al., 2019), (Wanto, Parulian, et al., 2019), (Andriani et al., 2018), (Saputra et al., 2019), (N. Ginantra et al., 2021), (Purba et al., 2019), (Julham et al., 2019), (Zola, 2018), (Suheri, 2012)

$$\boldsymbol{x}' = \frac{\mathbf{0.8}\,(\boldsymbol{x} - \boldsymbol{a})}{\boldsymbol{b} - \boldsymbol{a}} + \mathbf{0.1}$$

Which one :

x'	=	Data normalization results,
x	=	Data to be normalized,
a	=	The smallest data from the dataset
b	=	The largest data from the dataset

2.4. Research Variable

We will use 2017 adjusted data for 2015–2016 as training data and 2018–2019 adjusted for 2018–2019 as test data according to Table 1. Next, normalize the data values when divided by 2 using Equation 1.

3. RESULTS AND DISCUSSION

3.1. Data Normalization Results

The results of the normalization of the training data used between 2015 and 2016 with the 2017 target are shown in Table 2. The information collected is based on Table 1. The sigmoid function of the equation is used to standardize this data (1).

Table 2. Results of Normalization of Training Data

2015	2016	2017
0.1570	0.1693	0.1706
0.4096	0.3698	0.3629
0.3395	0.3525	0.3736
0.1003	0.1005	0.1008
0.1227	0.1250	0.1660
0.1193	0.1307	0.1366
0.1569	0.1607	0.1501
0.1661	0.1638	0.1687
0.1011	0.1015	0.1019
0.1001	0.1000	0.1000
0.9000	0.8519	0.8976
0.2685	0.2663	0.2938
0.1034	0.1031	0.1023
0.2598	0.2640	0.2803
0.1028	0.1045	0.1027
0.1451	0.1670	0.1662
0.1694	0.1681	0.1620
0.1120	0.1132	0.1181
0.1054	0.1102	0.1049
0.1052	0.1050	0.1052
0.1133	0.1129	0.1247
0.1217	0.1143	0.1174
0.1072	0.1101	0.1074
0.1678	0.1655	0.1818
0.1336	0.1490	0.1607
0.2285	0.2331	0.2753
0.1146	0.1183	0.1093
0.1031	0.1033	0.1069
0.1021	0.1052	0.1052
0.1076	0.1066	0.1075
0.1141	0.1108	0.1049
0.1017	0.1067	0.1014
0.1108	0.1225	0.1333

The findings of the normalization test data used from 2018 to 2019 with a 2020 target are presented in Table 3 below. The information collected is based on Table 1. The sigmoid function equation was used to standardize these data (1).

Table 3. Testing Data Normalization Results

2018	2019	2020 (Target)
0,1526	0,1556	0,1555
0.3771	0.4170	0.5350
0.4524	0.4925	0.4034
0.1006	0.1003	0.1004
0.1310	0.1330	0.1525
0.1375	0.1334	0.1284
0.1489	0.1494	0.1616
0.1524	0.1499	0.1510
0.1018	0.1012	0.1014
0.1000	0.1007	0.1006
0.8176	0.8617	0.9000
0.3417	0.3184	0.3134
0.1022	0.1037	0.1041
0.2753	0.2993	0.3243
0.1021	0.1022	0.1050
0.1684	0.1405	0.1369

0.1558	0.1781	0.1765
0.1146	0.1266	0.1265
0.1030	0.1056	0.1049
0.1049	0.1064	0.1116
0.1209	0.1198	0.1198
0.1191	0.1198	0.1219
0.1076	0.1072	0.1063
0.2419	0.2133	0.2532
0.1432	0.1441	0.1714
0.2801	0.2564	0.2615
0.1101	0.1150	0.1126
0.1084	0.1095	0.1073
0.1037	0.1044	0.1020
0.1095	0.1089	0.1110
0.1023	0.1202	0.1181
0.1022	0.1067	0.1035
0.1220	0.1263	0.1182

3.2. Training and Testing

Matlab 2011b is supported by Tables 2 and 3 for data processing(N. L. W. S. R. Ginantra et al., 2022). Use the Fletcher-Leaves algorithm to define and train architectural models. This model uses four architectural models: 2-10-1, 2-20-1, 2-30-1, and 2-35-1. The Fletcher-Reeves algorithm determines the optimal architectural model by determining the minimum error from the training and testing process.

a. 2-10-1 Model (Training Function : Traincgf)

Table 4. Training Results with 2-1-1 Model

2015	2016	2017 (Target)	Epoch 616		
			Actual	Error	Perfect
0.1570	0.1693	0.1706	0.1739	-0.0033	
0.4096	0.3698	0.3629	0.3634	-0.0005	
0.3395	0.3525	0.3736	0.3731	0.0005	
0.1003	0.1005	0.1008	0.1003	0.0005	
0.1227	0.1250	0.1660	0.1302	0.0358	
0.1193	0.1307	0.1366	0.1343	0.0023	
0.1569	0.1607	0.1501	0.1656	-0.0155	
0.1661	0.1638	0.1687	0.1691	-0.0004	
0.1011	0.1015	0.1019	0.1016	0.0003	
0.1001	0.1000	0.1000	0.0997	0.0003	
0.9000	0.8519	0.8976	0.8972	0.0004	
0.2685	0.2663	0.2938	0.2921	0.0017	
0.1034	0.1031	0.1023	0.1042	-0.0019	
0.2598	0.2640	0.2803	0.2924	-0.0121	
0.1028	0.1045	0.1027	0.1052	-0.0025	
0.1451	0.1670	0.1662	0.1701	-0.0039	0.000084626
0.1694	0.1681	0.1620	0.1738	-0.0118	
0.1120	0.1132	0.1181	0.1169	0.0012	
0.1054	0.1102	0.1049	0.1116	-0.0067	
0.1052	0.1050	0.1052	0.1068	-0.0016	
0.1133	0.1129	0.1247	0.1170	0.0077	
0.1217	0.1143	0.1174	0.1206	-0.0032	
0.1072	0.1101	0.1074	0.1123	-0.0049	
0.1678	0.1655	0.1818	0.1710	0.0108	
0.1336	0.1490	0.1607	0.1527	0.0080	
0.2285	0.2331	0.2753	0.2603	0.0150	
0.1146	0.1183	0.1093	0.1223	-0.0130	
0.1031	0.1033	0.1069	0.1042	0.0027	
0.1021	0.1052	0.1052	0.1055	-0.0003	
0.1076	0.1066	0.1075	0.1092	-0.0017	
0.1141	0.1108	0.1049	0.1154	-0.0105	
0.1017	0.1067	0.1014	0.1067	-0.0053	
0.1108	0.1225	0.1333	0.1247	0.0086	

Table 5. Test Results with 2-10-1 Model

2018	2019	2020 (Target)	Epoch		
			Actual	Error	Perfect
0.1526	0.1556	0.1555	0.1594	-0.0039	
0.3771	0.4170	0.5350	0.4213	0.1137	
0.4524	0.4925	0.4034	0.4736	-0.0702	
0.1006	0.1003	0.1004	0.1012	-0.0008	
0.1310	0.1330	0.1525	0.1364	0.0161	
0.1375	0.1334	0.1284	0.1364	-0.0080	
0.1489	0.1494	0.1616	0.1527	0.0089	
0.1524	0.1499	0.1510	0.1529	-0.0019	
0.1018	0.1012	0.1014	0.1023	-0.0009	
0.1000	0.1007	0.1006	0.1015	-0.0009	
0.8176	0.8617	0.9000	0.8988	0.0012	
0.3417	0.3184	0.3134	0.3284	-0.0150	
0.1022	0.1037	0.1041	0.1049	-0.0008	
0.2753	0.2993	0.3243	0.3248	-0.0005	
0.1021	0.1022	0.1050	0.1034	0.0016	
0.1684	0.1405	0.1369	0.1388	-0.0019	
0.1558	0.1781	0.1765	0.1856	-0.0091	0.00060963
0.1146	0.1266	0.1265	0.1296	-0.0031	
0.1030	0.1056	0.1049	0.1070	-0.0021	
0.1049	0.1064	0.1116	0.1081	0.0035	
0.1209	0.1198	0.1198	0.1230	-0.0032	
0.1191	0.1198	0.1219	0.1229	-0.0010	
0.1076	0.1072	0.1063	0.1093	-0.0030	
0.2419	0.2133	0.2532	0.2277	0.0255	
0.1432	0.1441	0.1714	0.1474	0.0240	
0.2801	0.2564	0.2615	0.2736	-0.0121	
0.1101	0.1150	0.1126	0.1175	-0.0049	
0.1084	0.1095	0.1073	0.1117	-0.0044	
0.1037	0.1044	0.1020	0.1059	-0.0039	
0.1095	0.1089	0.1110	0.1112	-0.0002	
0.1023	0.1202	0.1181	0.1215	-0.0034	
0.1022	0.1067	0.1035	0.1079	-0.0044	
0.1220	0.1263	0.1182	0.1296	-0.0114	

Based on Tables 4 and 5, the training results with the 2-10-1 model resulted in 616 iteration epochs.

b. 2-20-1 Model (Training Function : Traincgf)

Table 6. Training Results with 2-20-1 Model

2015	2016	2017 (Target)	Epoch 247		
			Actual	Error	Perfect
0.1570	0.1693	0.1706	0.1722	-0.0016	
0.4096	0.3698	0.3629	0.3636	-0.0007	
0.3395	0.3525	0.3736	0.3723	0.0013	
0.1003	0.1005	0.1008	0.0975	0.0033	
0.1227	0.1250	0.1660	0.1345	0.0315	
0.1193	0.1307	0.1366	0.1404	-0.0038	
0.1569	0.1607	0.1501	0.1654	-0.0153	
0.1661	0.1638	0.1687	0.1673	0.0014	
0.1011	0.1015	0.1019	0.0991	0.0028	
0.1001	0.1000	0.1000	0.0967	0.0033	0,00008153
0.9000	0.8519	0.8976	0.8976	0.0000	
0.2685	0.2663	0.2938	0.2941	-0.0003	
0.1034	0.1031	0.1023	0.1020	0.0003	
0.2598	0.2640	0.2803	0.2946	-0.0143	
0.1028	0.1045	0.1027	0.1038	-0.0011	
0.1451	0.1670	0.1662	0.1682	-0.0020	
0.1694	0.1681	0.1620	0.1713	-0.0093	
0.1120	0.1132	0.1181	0.1182	-0.0001	
0.1054	0.1102	0.1049	0.1126	-0.0077	
0.1052	0.1050	0.1052	0.1052	0.0000	

0.1133	0.1129	0.1247	0.1180	0.0067	
0.1217	0.1143	0.1174	0.1208	-0.0034	
0.1072	0.1101	0.1074	0.1129	-0.0055	
0.1678	0.1655	0.1818	0.1688	0.0130	
0.1336	0.1490	0.1607	0.1565	0.0042	
0.2285	0.2331	0.2753	0.2564	0.0189	
0.1146	0.1183	0.1093	0.1254	-0.0161	
0.1031	0.1033	0.1069	0.1022	0.0047	
0.1021	0.1052	0.1052	0.1047	0.0005	
0.1076	0.1066	0.1075	0.1080	-0.0005	
0.1141	0.1108	0.1049	0.1152	-0.0103	
0.1017	0.1067	0.1014	0.1067	-0.0053	
0.1108	0.1225	0.1333	0.1299	0.0034	

Table 7 Test Result with 2-20-1 Model

2018	2019	2020 (Target)	Actual	Epoch Error	Perfect
0.1526	0.1556	0 .1555	0.1615	-0.0060	
0.3771	0.4170	0.5350	0.454	0.0810	
0.4524	0.4925	0.4034	0.5004	-0.0970	
0.1006	0.1003	0.1004	0.0973	0.0031	
0.1310	0.1330	0.1525	0.1434	0.0091	
0.1375	0.1334	0.1284	0.1431	-0.0147	
0.1489	0.1494	0.1616	0.1566	0.0050	
0.1524	0.1499	0.1510	0.1564	-0.0054	
0.1018	0.1012	0.1014	0.0989	0.0025	
0.1000	0.1007	0.1006	0.0977	0.0029	
0.8176	0.8617	0.9000	0.9624	-0.0624	
0.3417	0.3184	0.3134	0.3267	-0.0133	
0.1022	0.1037	0.1041	0.1025	0.0016	
0.2753	0.2993	0.3243	0.3439	-0.0196	
0.1021	0.1022	0.1050	0.1004	0.0046	
0.1684	0.1405	0.1369	0.1369	0.0000	
0.1558	0.1781	0.1765	0.1777	-0.0012	0,00070297
0.1146	0.1266	0.1265	0.1354	-0.0089	
0.1030	0.1056	0.1049	0.1055	-0.0006	
0.1049	0.1064	0.1116	0.1071	0.0045	
0.1209	0.1198	0.1198	0.1281	-0.0083	
0.1191	0.1198	0.1219	0.1279	-0.0060	
0.1076	0.1072	0.1063	0.1089	-0.0026	
0.2419	0.2133	0.2532	0.2198	0.0334	
0.1432	0.1441	0.1714	0.1527	0.0187	
0.2801	0.2564	0.2615	0.2749	-0.0134	
0.1101	0.1150	0.1126	0.1202	-0.0076	
0.1084	0.1095	0.1073	0.1123	-0.0050	
0.1037	0.1044	0.1020	0.1039	-0.0019	
0.1095	0.1089	0.1110	0.1117	-0.0007	
0.1023	0.1202	0.1181	0.1252	-0.0071	
0.1022	0.1067	0.1035	0.1068	-0.0033	
0.1220	0.1263	0.1182	0.136	-0.0178	

Based on Tables 6 and 7, the results of the training with the 2-20-1 model resulted in 247 iteration epochs.

c. 2-30-1 Model (Training Function : Traincgf)

Table 8. Training Results with 2-30-1 Model

2015	2016	2017 (Target)	Actual	Epoch 2 Error	Perfet
0.1570	0.1693	0.1706	0.9096	-0.7390	
0.4096	0.3698	0.3629	0.814	-0.4511	
0.3395	0.3525	0.3736	0.7207	-0.3471	0,56367805
0.1003	0.1005	0.1008	0.9413	-0.8405	
0.1227	0.1250	0.1660	0.9276	-0.7616	
0.1193	0.1307	0.1366	0.9229	-0.7863	

0.1569	0.1607	0.1501	0.9097	-0.7596	
0.1661	0.1638	0.1687	0.9045	-0.7358	
0.1011	0.1015	0.1019	0.9406	-0.8387	
0.1001	0.1000	0.1000	0.9417	-0.8417	
0.9000	0.8519	0.8976	0.4437	0.4539	
0.2685	0.2663	0.2938	0.7266	-0.4328	
0.1034	0.1031	0.1023	0.9401	-0.8378	
0.2598	0.2640	0.2803	0.7312	-0.4509	
0.1028	0.1045	0.1027	0.9385	-0.8358	
0.1451	0.1670	0.1662	0.914	-0.7478	
0.1694	0.1681	0.1620	0.9019	-0.7399	
0.1120	0.1132	0.1181	0.934	-0.8159	
0.1054	0.1102	0.1049	0.9343	-0.8294	
0.1052	0.1050	0.1052	0.939	-0.8338	
0.1133	0.1129	0.1247	0.9347	-0.8100	
0.1217	0.1143	0.1174	0.9359	-0.8185	
0.1072	0.1101	0.1074	0.935	-0.8276	
0.1678	0.1655	0.1818	0.9032	-0.7214	
0.1336	0.1490	0.1607	0.9166	-0.7559	
0.2285	0.2331	0.2753	0.7979	-0.5226	
0.1146	0.1183	0.1093	0.9306	-0.8213	
0.1031	0.1033	0.1069	0.9397	-0.8328	
0.1021	0.1052	0.1052	0.9375	-0.8323	
0.1076	0.1066	0.1075	0.9384	-0.8309	
0.1141	0.1108	0.1049	0.9368	-0.8319	
0.1017	0.1067	0.1014	0.9359	-0.8345	
0.1108	0.1225	0.1333	0.926	-0.7927	

Table 9. Test Results with 2-30-1 Model

2018	2019	2020 (Target)	Epoch		
			Actual	Error	Perfect
0.1526	0.1556	0.1555	0.9121	-0.7566	
0.3771	0.4170	0.5350	0.6347	-0.0997	
0.4524	0.4925	0.4034	0.599	-0.1956	
0.1006	0.1003	0.1004	0.9416	-0.8412	
0.1310	0.1330	0.1525	0.9236	-0.7711	
0.1375	0.1334	0.1284	0.9238	-0.7954	
0.1489	0.1494	0.1616	0.9149	-0.7533	
0.1524	0.1499	0.1510	0.9139	-0.7629	
0.1018	0.1012	0.1014	0.9412	-0.8398	
0.1000	0.1007	0.1006	0.9409	-0.8403	
0.8176	0.8617	0.9000	0.3227	0.5773	
0.3417	0.3184	0.3134	0.7783	-0.4649	
0.1022	0.1037	0.1041	0.939	-0.8349	
0.2753	0.2993	0.3243	0.7165	-0.3922	
0.1021	0.1022	0.1050	0.9404	-0.8354	
0.1684	0.1405	0.1369	0.9125	-0.7756	
0.1558	0.1781	0.1765	0.9121	-0.7356	
0.1146	0.1266	0.1265	0.9243	-0.7978	
0.1030	0.1056	0.1049	0.9375	-0.8326	
0.1049	0.1064	0.1116	0.9375	-0.8259	
0.1209	0.1198	0.1198	0.9312	-0.8114	
0.1191	0.1198	0.1219	0.9307	-0.8088	
0.1076	0.1072	0.1063	0.9378	-0.8315	0,55017894
0.2419	0.2133	0.2532	0.7713	-0.5181	
0.1432	0.1441	0.1714	0.9178	-0.7464	
0.2801	0.2564	0.2615	0.7304	-0.4689	
0.1101	0.1150	0.1126	0.9318	-0.8192	
0.1084	0.1095	0.1073	0.936	-0.8287	
0.1037	0.1044	0.1020	0.9389	-0.8369	
0.1095	0.1089	0.1110	0.937	-0.8260	
0.1023	0.1202	0.1181	0.9246	-0.8065	
0.1022	0.1067	0.1035	0.9362	-0.8327	
0.1220	0.1263	0.1182	0.9265	-0.8083	

Based on Tables 8 and 9, the results of the 2-30-1 model training resulted in 2 iteration epochs.

d. 2-35-1 Model (Training Function : Traincgf)

Table 10. Training Results with 2-35-1 Model

2015	2016	2017 (Target)	Epoch 497		
			Actual	Error	Perfect
0.1570	0.1693	0.1706	0.1688	0.0018	
0.4096	0.3698	0.3629	0.3629	0.0000	
0.3395	0.3525	0.3736	0.3736	0.0000	
0.1003	0.1005	0.1008	0.0964	0.0044	
0.1227	0.1250	0.1660	0.1356	0.0304	
0.1193	0.1307	0.1366	0.1407	-0.0041	
0.1569	0.1607	0.1501	0.165	-0.0149	
0.1661	0.1638	0.1687	0.1673	0.0014	
0.1011	0.1015	0.1019	0.0983	0.0036	
0.1001	0.1000	0.1000	0.0956	0.0044	
0.9000	0.8519	0.8976	0.8976	0.0000	
0.2685	0.2663	0.2938	0.2932	0.0006	
0.1034	0.1031	0.1023	0.1017	0.0006	
0.2598	0.2640	0.2803	0.2809	-0.0006	
0.1028	0.1045	0.1027	0.1033	-0.0006	
0.1451	0.1670	0.1662	0.1662	0.0000	
0.1694	0.1681	0.1620	0.1701	-0.0081	0,0000632
0.1120	0.1132	0.1181	0.1189	-0.0008	
0.1054	0.1102	0.1049	0.1122	-0.0073	
0.1052	0.1050	0.1052	0.1052	0.0000	
0.1133	0.1129	0.1247	0.1189	0.0058	
0.1217	0.1143	0.1174	0.1219	-0.0045	
0.1072	0.1101	0.1074	0.113	-0.0056	
0.1678	0.1655	0.1818	0.1685	0.0133	
0.1336	0.1490	0.1607	0.1574	0.0033	
0.2285	0.2331	0.2753	0.2753	0.0000	
0.1146	0.1183	0.1093	0.1261	-0.0168	
0.1031	0.1033	0.1069	0.1018	0.0051	
0.1021	0.1052	0.1052	0.1039	0.0013	
0.1076	0.1066	0.1075	0.1084	-0.0009	
0.1141	0.1108	0.1049	0.1162	-0.0113	
0.1017	0.1067	0.1014	0.1056	-0.0042	
0.1108	0.1225	0.1333	0.1291	0.0042	

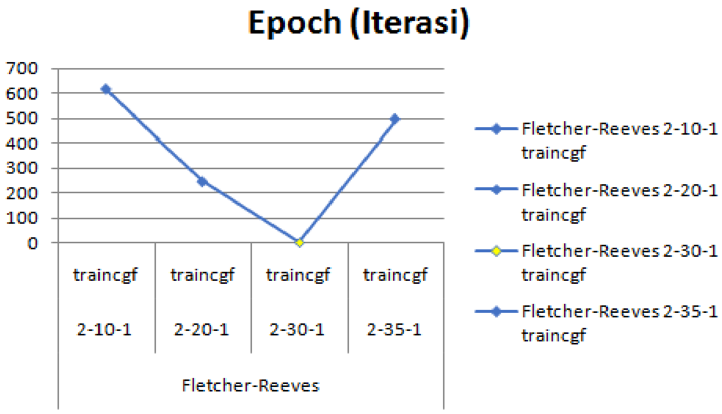
Based on Tables 10, the results of the 2-35-1 training model with 497 iteration epochs.

3.2 Evaluation

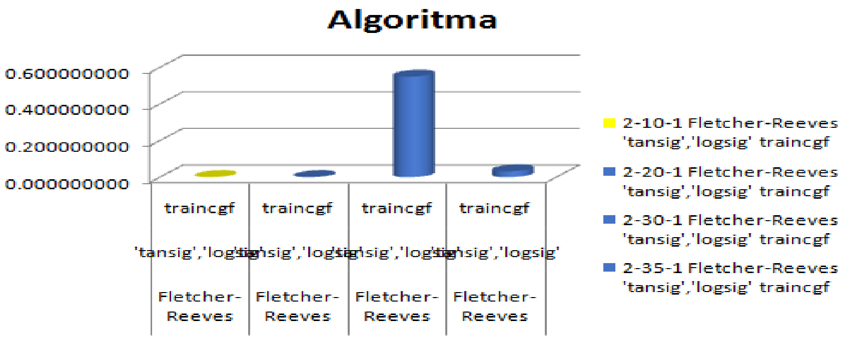
2-10-1, which is more accurate than the other models, is the best architectural model built using the traincgf approach. Look at table 12 below.

Table 12. Comparative Analysis of All Model Results

Arsitektur	Algoritma	Fungsi Training	Epoch (Iterasi)	MSE Training	MSE Testing/ Performance
2-10-1	Fletcher-Reeves	Traincgf	616	0.00008463	0.00060964
2-20-1	Fletcher-Reeves	Traincgf	249	0.00008153	0.000702929
2-30-1	Fletcher-Reeves	Traincgf	2	0.56367805	0.55017894
2-35-1	Fletcher-Reeves	Traincgf	497	0.00006322	0.032003798



Picture 2. Epoch Comparison Graph (Iteration)



Picture 3. Comparison Graph of MSE Testing/MSE Performance

4. CONCLUSION

We can draw the following conclusions from the findings and considerations of this study: Indonesian tomato yields can be predicted using the Fletcher-Reeves algorithm as the first step in a determined effort to continue to increase tomato yields in the future. Information based on the Indonesian Central Statistics Agency website covers the years 2015 to 2020 for Indonesian tomato production. One approach is to use the Fletcher-Leaves method and the best architectural model 2-10-1 at MSE 0.00060964 to forecast Indonesian tomato production for the coming year.

REFERENCE

Abadi, A. F. S., Purwanti, E. W., & Muditha, I. G. N. (2022). Response of Tomato Growth and Productivity to Various MOL Doses of Fruit Waste. *Indonesian Journal of Agricultural Sciences*, *27*(1), 103–108. https://doi.org/10.18343/jipi.27.1.103

Andriani, Y., Silitonga, H., & Wanto, A. (2018). Artificial neural network analysis predicts the volume of oil and gas exports and imports in Indonesia. *Register: Scientific Journal of Information Systems Technology, 4*(1), 30–40. https://doi.org/10.26594/register.v4i1.1157

BPS. (n.d.). *Production of Vegetable Crops 2015-2020*. Www.Bps.Go.Id. Retrieved June 16, 2022, from https://www.bps.go.id/indicator/55/61/7/hasil-tanaman-vegetable.html

Ginantra, N., Bhawika, G., Daengs, G. S., Panjaitan, P., Arifin, M. A., Wanto, A., Amin, M., Okprana, H., Syafii, A., & Anwar, U. (2021). Performance One-step secant Training Method for Forecasting Cases. *Journal of Physics: Conference Series*, *1933*, 12032. https://doi.org/10.1088/1742-6596/1933/1/012032

Ginantra, N. L. W. S. R., GS, A. D., Andini, S., & Wanto, A. (2022). Utilization of the Fletcher-Reeves Algorithm for Determining Export Value Price Prediction Models by SITC Group. *Building of Informatics, Technology and Science (BITS), 3*(4), 679–685. https://doi.org/10.47065/bits.v3i4.1449

Halid, E. (2021). GROWTH AND PRODUCTION OF TOMATO PLANTS (Lycopersicum esculentum Mill) ON VARIOUS DOSAGES OF EGG SHELL POWDER. *Agroplantae: Scientific Journal of Applied Cultivation and Management of Agricultural and Plantation Crops, 10*(1), 59–66. https://doi.org/10.51978/agro.v10i1.250

Julham, M., Sumarno, S., Anggraini, F., Wanto, A., & Solikhun, S. (2019). Application of Artificial Neural Networks in Predicting Crime Rates in Simalungun Regency Using the Backpropagation Algorithm. *BRAHMANA: Journal of Application of Artificial Intelligence, 1*(1), 64–73. https://doi.org/10.30645/brahmana.v1i1.9

Keshtegar, B., Hasanipanah, M., Bakhshayeshi, I., & Esfandi Sarafraz, M. (2018). A novel nonlinear modeling for the prediction of blast-induced airblast using a modified conjugate FR method. *Measurement*, *131*. https://doi.org/10.1016/j.measurement.2018.08.052

Mahmudi, A. A. (2020). Conjugate Gradient Optimization in Backpropagation Neural Network for Predicting Fishing Results. *Saintekbu, 12*(2), 29–39. https://doi.org/10.32764/saintekbu.v12i2.1031

Novaldy, R., & Iyos, R. N. (2016). Effect of Tomato (Solanum Lycopersicum) in Reducing the Risk of Prostate Carcinoma Influence of Tomato (Solanum Lycopersicum) in Reducing the Risk of CA Prostate. *A majority, 5*(5), 9–13.

Agriculture, F., & Samarinda, U. A. (2015). *GROWTH AND PRODUCTION OF TOMATO (Lycopersicum esculentum Mill) PERMATA VARIETY Tomato (Lycopersicum manure (compost) will significantly increase the type of macro fertilizer. Research conducted: "The Effect of Organic Fertilizer Type and Fertilizer Dosage. XIV* (February 2013), 87–94.

Purba, N. Z., Wanto, A., & Kirana, I. O. (2019). Implementation of ANN for Prediction of Unemployment Rate Based on Urban Village in 3 Sub-Districts of Pematangsiantar. *International Journal of Information System & Technology*, *3*(1), 107–116.

Saputra, W., Hardinata, J., & Wanto, A. (2019). Implementation of Resilient Methods to Predict Open Unemployment in Indonesia According to Higher Education Completed. *JOURNAL OF INFORMATICS AND TELECOMMUNICATION ENGINEERING*, *3*, 163. https://doi.org/10.31289/jite.v3i1.2704

Siregar, E., Mawengkang, H., Nababan, E., & Wanto, A. (2019). Analysis of Backpropagation Method with Sigmoid Bipolar and Linear Function in Prediction of Population Growth. *Journal of Physics: Conference Series*, *1255*, 12023. https://doi.org/10.1088/1742-6596/1255/1/012023

St. Sabahannur, S. S., & Herawati, L. (2017). GROWTH AND PRODUCTION OF TOMATO PLANTS (Lycopersicon esculentum Mill) AT VARIOUS PLANTING DISTANCES AND Pruning. *AGROTECH: Scientific Journal of Agricultural Sciences, 1*(2), 32–42. https://doi.org/10.33096/agrotek.v1i2.35

Suheri, Edi. (2012). UNIVERSITY OF NORTH SUMATRA Polyclinic UNIVERSITY OF NORTH SUMATRA. *Journal of Urban & Regional Development, 1*(3), 82–91.

Tinambunan, M. H., Nababan, E. B., & Nasution, B. B. (2020). Conjugate Gradient Polak Ribiere in Improving Performance in Predicting Population Backpropagation. *IOP Conference Series: Materials Science and Engineering*, *835*(1). https://doi.org/10.1088/1757-899X/835/1/012055

Tomato, E., Esculentum, L., Kadar, M., Blood, G., & Wistar, T. (2019). Tomato Extract (Lycopersicon Esculentum Mill.) Lowers Blood Glutathione Levels of Hyperuricemic Wistar Mice. *Diponegoro Medical Journal (Diponegoro Medical Journal), 8*(2), 758–767.

Tursilawati, S., Damanhuri, & Purnamaningsih, S. L. (2016). THE YIELD POTENTIAL TRIALS OF ORGANIC TOMATO (Lycopersicum esculentum Mill.). *Journal of Crop Production, 4*(4), 283–290.

Wanto, A. (2018). Prediction Optimization With Backpropagation Algorithm And Conjugate Gradient Beale-Powell Restarts. *Journal of Technology and Information Systems, 3*, 370. https://doi.org/10.25077/TEKNOSI.v3i3.2017.370-380

Wanto, A., Ginantra, N. L. W. S. R., Nurmawati, N., Bhawika, G., Daengs, G. S., Purwantoro, P., Abdussakir, A., & T., T. (2019). Analysis of the Backpropagation Algorithm in Viewing Import Value Development Levels Based on Main Country of Origin. *Journal of Physics: Conference Series*, *1255*, 12013. https://doi.org/10.1088/1742-6596/1255/1/012013

Wanto, A., Parulian, P., Siahaan, H., Windarto, A., Afriliansyah, T., Saputra, W., Parlina, I., Lubis, M., & Damanik, I. (2019). Analysis of the Accuracy Batch Training Method in Viewing Indonesian Fisheries Cultivation Company Development. *Journal of Physics: Conference Series*, *1255*, 12003. https://doi.org/10.1088/1742-6596/1255/1/012003

Wanto, A., Zarlis, M., Sawaluddin, & Hartama, D. (2017). Analysis of Artificial Neural Network Backpropagation Using Conjugate Gradient Fletcher Reeves in the Predicting Process. *Journal of Physics: Conference Series*, *930*(1). https://doi.org/10.1088/1742-6596/930/1/012018

Wasonowati, C. (2010). I am increasing the Production and Quality of Tomato (Lycopersicon esculentum) with a Hydroponic Cultivation System. *Engineering, 3*(2), 83–89. https://www.pertanian.go.id/home/index.php?show=repo&fileNum=292

Wijaya, A. S., Sangadji, M. N., & Muhardi. (2015). Production and quality of tomato fruit production given

various concentrations of liquid organic fertilizer. *Agrotechnics, 3*(6), 689–696.
Zamzamy Sormin, M. K., Sihombing, P., Amalia, A., Wanto, A., Hartama, D., & Chan, D. M. (2019). Predictions of World Population Life Expectancy Using Cyclical Order Weight / Bias. *Journal of Physics: Conference Series*, *1255*(1). https://doi.org/10.1088/1742-6596/1255/1/012017
Zola, F. (2018). Artificial Neural Network Using Backpropagation Algorithm To Predict Student Achievement. *Journal of Technology And Open Source, 1*(1), 58–72. https://doi.org/10.36378/jtos.v1i1.12