

# Estimations of Indonesian poor people as poverty reduction efforts facing industrial revolution 4.0

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**Abstract.** Indonesia is one of the developing countries that have serious problems with poverty. The still many poor people in Indonesia encourage the government to make and determine the right policies so that the problem of poverty can be overcome and not drag on. Therefore, the authors conducted this study to try to help the government conduct an analysis in predicting the level of development of the poor in Indonesia. The prediction method used is the Bayesian Regulation artificial neural network. This method is a development of the backpropagation method that is often used to predict data. The data used are data on poor people in Indonesia in 2012-2018, which are sourced from the Indonesian Central Bureau of Statistics. Based on this data a network architecture model will be formed and determined using the Bayesian Regulation method, including 10-5-10-2, 10-10-10-2, 10-10-15-2, 10-10-20-2, 10-15-10-2, 10-15-15-2, 10-15-20-2, 10-20-20-2, 10-25-25-2 and 10-30-30-2. From these 10 models after training and testing, the results show that the best architectural model is 10-25-25-2. The accuracy of the architectural models is 94.1% and 61.8% with MSE values of 0,00013571 and 0,00005189. The results of this study are the prediction of the poor for the next 5 years.

## 1. Introducing

Poverty is one of the fundamental global problems that need serious attention from the government, especially in developing countries[1]. Especially in the current 4.0 industrial revolution, not only middle and upper economic communities are invited to progress and prepare to follow that era. But the middle and lower classes of society must also be a concern, especially their welfare because Indonesia is one of the countries with a high poverty rate. If not noticed, the poor will be crushed by the industrial revolution 4.0. Moreover, poverty is one of the phenomenal and serious problems faced by almost all countries, including Indonesia. Economic growth that is not spread evenly in Indonesia's territory is one of the factors developing poverty. Broad poverty coverage also means there is no access to employment or education and does not get the proper respect as citizens. So that the impact of poverty directly or indirectly can affect people's thinking and behavior[2]. In some developing countries, poverty is a fairly complex problem even though some countries have succeeded in reducing poverty by implementing development in the fields of national production and income[3]. Therefore, one indicator in overcoming the problem of poverty is by increasing economic growth, where economic growth is a concept of economic development and national income[4], [5].

In recent decades, according to the Indonesian Central Bureau of Statistics, the number of poor people in Indonesia shows a gradual decline, but the uncertain economic climate in this country has the potential to re-grow the poverty rate. As in Semester 1 (March) in 2018 in the

province of East Java, there are  $\pm 4$  million 332 thousand poor people or the highest in Indonesia. Whereas in Semester 2 (September) in 2018, the number of poor people fell to  $\pm 4$  million 292 thousand poor people, or down by around 40 thousand residents[6].

Therefore, it is necessary to predict to get the estimation of the number of poor people in Indonesia for the following years, this is done so that the government has references and considerations in determining policies and in making the right steps to overcome this poverty. Measuring poverty is important to target efforts in places that most need help and evaluate the effectiveness of government programs. But in making predictions it is not easy, requires the right data, methods, and stages. One of the appropriate methods used is the Bayesian regulation method, this method is a development of the Backpropagation method that is able to predict data based on previous data so that the estimation results are obtained after learning and training based on data that has already occurred[7]–[10]. Many previous studies discussed the problem of poverty, including: Predicting Poverty in a Region from Satellite Images using CNN (Convolutional Neural Network)[11]. Predict poverty and wealth using mobile metadata[3], to combine satellite imagery and machine learning to predict poverty[12].

## 2. Methodology

### 2.1. Research Methods

The research method used was Artificial Neural Networks with the Bayesian regulation backpropagation method. This method is able to make predictions based on past data. Bayesian Regularization (BR) is an artificial neural network training algorithm that improves weight and bias values based on Levenberg-Marquardt optimization. This algorithm minimizes the combination of squared errors and weights, then determines the correct combination to produce a good network[13]. This process is called Bayesian regularization. BR neural networks introduce network weights into objective training functions. The training objective function is denoted as follows[14].

$$F(\omega) = \alpha E_{\omega} + \beta E_D \quad (1)$$

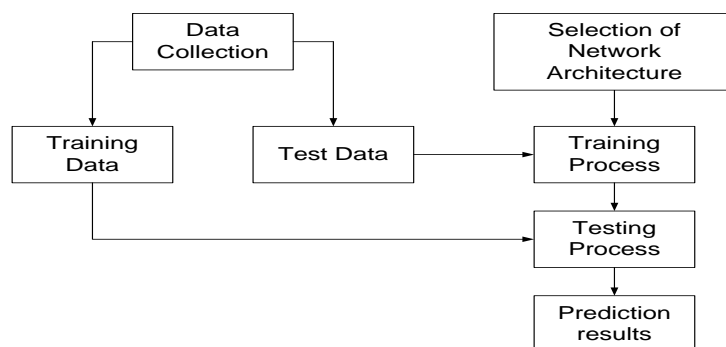
$E_{\omega}$  is the sum of squares of network weights and  $E_D$  number of squares of network errors. Value  $\alpha$  and  $\beta$  is a parameter of objective function.

### 2.2. Data Source

The dataset used in this study is a dataset of the Number of Poor Population in Indonesia based on the Province of 2012-2018, which is sourced from the website of the Indonesian Statistics Agency[6].

### 2.3. Research Flow

Broadly speaking, the flowchart of research in this study can be described as follows:



**Figure 1.** Research Flow

In Figure 1 it can be explained that the first thing to do is to collect datasets. The dataset used is data on the number of poor Indonesians. Next is the preprocessing stage and dividing the data into several parts, namely the data used for training and the data used for testing. Then determine the network architecture model that will be used for the training process and the testing process. Furthermore, the best chosen architectural models are used. After all, is done, predictions will be obtained based on the architectural model used.

#### 2.4. Research Variable

The research variables used in this article are 2 parts, namely input variables, and output variables. There are 10 input variables, namely the number of poor people in semester 1 (March) and Semester 2 (September) based on the year from training and testing input data. While the output variable is 2, namely the number of poor people in semester 1 (March) and Semester 2 (September) who are the targets of training and testing input data. While the criteria used there are 34, namely data for each province in Indonesia starting from the Province of Aceh to Papua.

#### 2.5. Normalization

The data is first divided into 2 parts, namely training data and test data. Data for 2012-2016 with 2017 targets are used as training data, while data for 2013-2017 with the 2018 target are used as testing data. Then the data that has been divided into two is normalized using the equation (2)[15]–[18].

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

Explanation:  $x'$  is the result of normalization,  $x$  is data that will be normalized,  $a$  is the lowest data and  $b$  is the highest data from the dataset.

### 3. Results and Discussion

#### 3.1. Results and Discussion

The following table 1 is the result of the normalization of training data used in each semester of 2012-2016 with 2017 as the target. Whereas Table 2 is the result of normalization of test data used in each semester of 2013-2017 with a target in 2018. This data is normalized using functions as written in the equation (2).

**Table 1.** Normalization of training data Table

Data	Poor Population (Thousand Souls)			Target			
	2012			2017			
	Mar	Sep	...	Mar	Sep	Mar	Sep
1	0,24341	0,23829	...	0,23385	0,23273	0,23766	0,23091
2	0,32201	0,31746	...	0,32969	0,32915	0,32936	0,30928
3	0,16385	0,16277	...	0,15862	0,15940	0,15751	0,15679
4	0,17621	0,17593	...	0,18131	0,17913	0,18119	0,17831
5	0,14286	0,14261	...	0,14572	0,14588	0,14521	0,14395
6	0,26676	0,26439	...	0,27372	0,27298	0,27147	0,27145
7	0,14917	0,14898	...	0,15184	0,15137	0,15001	0,14774
8	0,29780	0,29231	...	0,28452	0,27981	0,27854	0,27097
9	0,11126	0,11108	...	0,11148	0,11121	0,11169	0,11202
10	0,12070	0,12070	...	0,11900	0,11880	0,11978	0,12026
11	0,15730	0,15786	...	0,16063	0,16087	0,16148	0,16202
12	0,80638	0,79753	...	0,76643	0,75756	0,75761	0,69545
13	0,88523	0,86725	...	0,81101	0,80894	0,80215	0,76220
14	0,18919	0,18868	...	0,17808	0,17712	0,17707	0,17357
15	0,90000	0,88258	...	0,84199	0,83178	0,82838	0,79498
16	0,20299	0,20227	...	0,20382	0,20377	0,20649	0,21041

Data	Poor Population (Thousand Souls)				Target		
	2012		...	2016		2017	
	Mar	Sep	...	Mar	Sep	Mar	Sep
17	0,12663	0,12539	...	0,12811	0,12760	0,12842	0,12784
18	0,23451	0,23068	...	0,22691	0,22409	0,22523	0,21802
19	0,25974	0,25781	...	0,28141	0,28144	0,28155	0,27902
20	0,15732	0,15612	...	0,16016	0,16158	0,16112	0,16134
21	0,12336	0,12239	...	0,12264	0,12169	0,12195	0,12175
22	0,12996	0,12985	...	0,13087	0,12905	0,13059	0,13069
23	0,13997	0,13883	...	0,13359	0,13333	0,13473	0,13450
24	0,10000	0,10000	...	0,10649	0,10742	0,10780	0,10766
25	0,12984	0,12801	...	0,13200	0,13161	0,13138	0,13074
26	0,16604	0,16462	...	0,16634	0,16518	0,16592	0,16678
27	0,23028	0,22714	...	0,22732	0,22571	0,22827	0,23031
28	0,14990	0,14800	...	0,15157	0,15163	0,15233	0,14940
29	0,12949	0,12962	...	0,13206	0,13213	0,13240	0,13170
30	0,12531	0,12533	...	0,12409	0,12318	0,12363	0,12358
31	0,15525	0,15346	...	0,15170	0,15234	0,15056	0,15055
32	0,11448	0,11393	...	0,11178	0,11205	0,11206	0,11235
33	0,13628	0,13522	...	0,13562	0,13528	0,13603	0,13358
34	0,25249	0,25403	...	0,24377	0,24433	0,24162	0,24363

**Table 2.** Normalization of test data

Data	Poor Population (Thousand Souls)					Target	
	2013		...	2017		2018	
	Mar	Sep	...	Mar	Sep	Mar	Sep
1	0,23822	0,24069	...	0,24347	0,23643	0,23802	0,23671
2	0,32017	0,32866	...	0,33903	0,31810	0,31784	0,31242
3	0,16699	0,16258	...	0,15993	0,15919	0,15872	0,15808
4	0,17716	0,18591	...	0,18461	0,18161	0,18228	0,18126
5	0,14376	0,14629	...	0,14711	0,14581	0,14631	0,14628
6	0,28256	0,28220	...	0,27870	0,27868	0,27564	0,27697
7	0,15382	0,15268	...	0,15212	0,14975	0,14962	0,14991
8	0,29122	0,28649	...	0,28607	0,27818	0,28037	0,27947
9	0,11138	0,11166	...	0,11218	0,11253	0,11254	0,11150
10	0,12082	0,12055	...	0,12061	0,12112	0,12165	0,12061
11	0,15823	0,16177	...	0,16407	0,16464	0,16135	0,16120
12	0,80649	0,82056	...	0,78534	0,72056	0,69448	0,68192
13	0,87815	0,87354	...	0,83175	0,79012	0,74075	0,73585
14	0,19046	0,18799	...	0,18032	0,17667	0,17565	0,17403
15	0,88445	0,90000	...	0,85909	0,82428	0,81233	0,80568
16	0,20790	0,21225	...	0,21098	0,21506	0,20874	0,20995
17	0,12672	0,13067	...	0,12962	0,12902	0,12824	0,12768
18	0,23660	0,23193	...	0,23051	0,22300	0,22125	0,22094
19	0,26335	0,26592	...	0,28920	0,28657	0,28779	0,28646
20	0,16067	0,16481	...	0,16370	0,16393	0,16364	0,16079
21	0,12252	0,12390	...	0,12288	0,12267	0,12251	0,12243
22	0,12988	0,13013	...	0,13188	0,13199	0,13108	0,13206
23	0,13912	0,14207	...	0,13620	0,13595	0,13599	0,13656
24	0,10000	0,10000	...	0,10813	0,10798	0,10828	0,10815
25	0,13032	0,13291	...	0,13270	0,13204	0,13178	0,13108
26	0,16666	0,16578	...	0,16870	0,16959	0,16909	0,16798
27	0,22950	0,24098	...	0,23368	0,23580	0,23032	0,22818
28	0,14960	0,15372	...	0,15454	0,15149	0,15049	0,14963
29	0,13166	0,13304	...	0,13377	0,13303	0,13264	0,13096
30	0,12532	0,12535	...	0,12462	0,12457	0,12495	0,12513
31	0,15291	0,15302	...	0,15270	0,15268	0,15263	0,15226
32	0,11372	0,11411	...	0,11257	0,11287	0,11339	0,11347
33	0,13687	0,13851	...	0,13755	0,13500	0,13526	0,13513
34	0,26727	0,27394	...	0,24759	0,24968	0,25087	0,25047

### 3.2. Best Model Training and Testing

Of the 10 architectural models used in this study, the 10-25-25-2 architectural model is the best model.

**Table 3 .Model training data 10-25-25-2**

No	Target		Output		Error		SSE	
	Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep
1	0,2377	0,2309	0,2349	0,2309	0,0028	0,0000	0,00000764	0,00000000
2	0,3294	0,3093	0,3279	0,3107	0,0015	-0,0014	0,00000214	0,00000202
3	0,1575	0,1568	0,1568	0,1566	0,0007	0,0002	0,00000050	0,00000004
4	0,1812	0,1783	0,1820	0,1818	-0,0008	-0,0035	0,00000066	0,00001218
5	0,1452	0,1440	0,1454	0,1448	-0,0002	-0,0008	0,00000004	0,00000072
6	0,2715	0,2714	0,2723	0,2700	-0,0008	0,0014	0,00000068	0,00000210
7	0,1500	0,1477	0,1499	0,1501	0,0001	-0,0024	0,00000001	0,00000556
8	0,2785	0,2710	0,2801	0,2698	-0,0016	0,0012	0,00000243	0,00000137
9	0,1117	0,1120	0,1128	0,1119	-0,0011	0,0001	0,00000124	0,00000001
10	0,1198	0,1203	0,1195	0,1184	0,0003	0,0019	0,00000008	0,00000346
11	0,1615	0,1620	0,1610	0,1623	0,0005	-0,0003	0,00000023	0,00000008
12	0,7576	0,6955	0,7577	0,6954	-0,0001	0,0001	0,00000001	0,00000000
13	0,8021	0,7622	0,8019	0,7624	0,0002	-0,0002	0,00000006	0,00000004
14	0,1771	0,1736	0,1779	0,1764	-0,0008	-0,0028	0,00000069	0,00000802
15	0,8284	0,7950	0,8286	0,7948	-0,0002	0,0002	0,00000005	0,00000003
16	0,2065	0,2104	0,2061	0,2060	0,0004	0,0044	0,00000016	0,00001941
17	0,1284	0,1278	0,1291	0,1277	-0,0007	0,0001	0,00000047	0,00000002
18	0,2252	0,2180	0,2252	0,2209	0,0000	-0,0029	0,00000000	0,00000827
19	0,2815	0,2790	0,2828	0,2790	-0,0013	0,0000	0,00000156	0,00000000
20	0,1611	0,1613	0,1604	0,1614	0,0007	-0,0001	0,00000052	0,00000000
21	0,1220	0,1218	0,1230	0,1218	-0,0010	0,0000	0,00000109	0,00000000
22	0,1306	0,1307	0,1297	0,1286	0,0009	0,0021	0,00000080	0,00000438
23	0,1347	0,1345	0,1343	0,1337	0,0004	0,0008	0,00000019	0,00000064
24	0,1078	0,1077	0,1083	0,1075	-0,0005	0,0002	0,00000025	0,00000003
25	0,1314	0,1307	0,1319	0,1315	-0,0005	-0,0008	0,00000028	0,00000058
26	0,1659	0,1668	0,1644	0,1643	0,0015	0,0025	0,00000232	0,00000613
27	0,2283	0,2303	0,2296	0,2281	-0,0013	0,0022	0,00000177	0,00000486
28	0,1523	0,1494	0,1510	0,1512	0,0013	-0,0018	0,00000177	0,00000322
29	0,1324	0,1317	0,1316	0,1314	0,0008	0,0003	0,00000064	0,00000009
30	0,1236	0,1236	0,1240	0,1227	-0,0004	0,0009	0,00000014	0,00000078
31	0,1506	0,1505	0,1510	0,1501	-0,0004	0,0004	0,00000019	0,00000020
32	0,1121	0,1123	0,1138	0,1126	-0,0017	-0,0003	0,00000301	0,00000006
33	0,1360	0,1336	0,1352	0,1348	0,0008	-0,0012	0,00000069	0,00000149
34	0,2416	0,2436	0,2420	0,2444	-0,0004	-0,0008	0,00000014	0,00000060
SumSSE							0,00003242	0,00008638
MSE							<b>0,00000095</b>	<b>0,00000254</b>

**Table 4. Model testing data 10-25-25-2**

Target		Output		Error		SSE	Results	
Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep	Mar Sep
0,2380	0,2367	0,2361	0,2322	0,0019	0,0045	0,00000370	0,00002033	1 0
0,3178	0,3124	0,3258	0,3044	-0,0080	0,0080	0,00006332	0,00006430	1 0
0,1587	0,1581	0,1579	0,1555	0,0008	0,0026	0,00000067	0,00000664	1 0
0,1823	0,1813	0,1815	0,1805	0,0008	0,0008	0,00000061	0,00000058	1 1
0,1463	0,1463	0,1460	0,1454	0,0003	0,0009	0,00000010	0,00000077	1 1
0,2756	0,2770	0,2754	0,2666	0,0002	0,0104	0,00000006	0,00010760	1 0
0,1496	0,1499	0,1500	0,1486	-0,0004	0,0013	0,00000014	0,00000171	1 1
0,2804	0,2795	0,2791	0,2692	0,0013	0,0103	0,00000161	0,00010552	1 0
0,1125	0,1115	0,1133	0,1122	-0,0008	-0,0007	0,00000058	0,00000049	1 1
0,1216	0,1206	0,1208	0,1200	0,0008	0,0006	0,00000072	0,00000037	1 1
0,1613	0,1612	0,1625	0,1647	-0,0012	-0,0035	0,00000133	0,00001222	1 1
0,6945	0,6819	0,7454	0,6739	-0,0509	0,0080	0,00259286	0,00006433	1 0

**Table 4.** Model testing data 10-25-25-2

Target		Output		Error		SSE	Results		
Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep
0,7407	0,7359	0,7822	0,7192	-0,0415	0,0167	0,00171834	0,00027725	1	0
0,1756	0,1740	0,1770	0,1754	-0,0014	-0,0014	0,00000183	0,00000189	1	1
0,8123	0,8057	0,8228	0,7835	-0,0105	0,0222	0,00010961	0,00049203	1	0
0,2087	0,2099	0,2141	0,2149	-0,0054	-0,0050	0,00002878	0,00002451	1	1
0,1282	0,1277	0,1291	0,1287	-0,0009	-0,0010	0,00000074	0,00000105	1	1
0,2212	0,2209	0,2271	0,2241	-0,0059	-0,0032	0,00003425	0,00000995	1	1
0,2878	0,2865	0,2880	0,2816	-0,0002	0,0049	0,00000005	0,00002363	1	0
0,1636	0,1608	0,1611	0,1600	0,0025	0,0008	0,00000645	0,00000062	0	1
0,1225	0,1224	0,1230	0,1222	-0,0005	0,0002	0,00000024	0,00000005	1	1
0,1311	0,1321	0,1314	0,1314	-0,0003	0,0007	0,00000010	0,00000044	1	1
0,1360	0,1366	0,1348	0,1341	0,0012	0,0025	0,00000142	0,00000607	1	0
0,1083	0,1082	0,1092	0,1084	-0,0009	-0,0002	0,00000085	0,00000006	1	1
0,1318	0,1311	0,1312	0,1301	0,0006	0,0010	0,00000034	0,00000096	1	1
0,1691	0,1680	0,1677	0,1676	0,0014	0,0004	0,00000193	0,00000015	1	1
0,2303	0,2282	0,2300	0,2259	0,0003	0,0023	0,00000010	0,00000521	1	0
0,1505	0,1496	0,1500	0,1484	0,0005	0,0012	0,00000024	0,00000151	1	1
0,1326	0,1310	0,1325	0,1315	0,0001	-0,0005	0,00000002	0,00000029	1	1
0,1250	0,1251	0,1246	0,1238	0,0004	0,0013	0,00000013	0,00000176	1	1
0,1526	0,1523	0,1512	0,1497	0,0014	0,0026	0,00000203	0,00000654	1	0
0,1134	0,1135	0,1140	0,1128	-0,0006	0,0007	0,00000037	0,00000045	1	1
0,1353	0,1351	0,1351	0,1338	0,0002	0,0013	0,00000003	0,00000177	1	1
0,2509	0,2505	0,2445	0,2276	0,0064	0,0229	0,00004057	0,00052319	0	0
SumSSE						0,00461410	0,00176425	94,1 61,8	
MSE						0,00013571	0,00005189		

### 3.3. Prediction results

In table 5 below, we will see a comparison of the 10 architectural models.

**Table 5.** Comparison of Architectural Models

No	Architectural Model	Time	MSE		Accuracy	
			Mar	Sep	Mar	Sep
1	10-5-10-2	00:04	0,00012437	0,00010828	79,4%	44,1%
2	10-10-10-2	00:04	0,00012720	0,00006593	67,6%	44,1%
3	10-10-15-2	00:04	0,00010894	0,00009123	79,4%	41,2%
4	10-10-20-2	00:06	0,00010166	0,00006463	88,2%	55,9%
5	10-15-10-2	00:08	0,00013210	0,00006715	67,6%	44,1%
6	10-15-15-2	00:08	0,00011641	0,00005717	91,2%	61,8%
7	10-15-20-2	00:12	0,00014373	0,00006799	67,6%	44,1%
8	10-20-20-2	00:19	0,00010098	0,00005980	85,3%	61,8%
9	10-25-25-2	00:52	0,00013571	0,00005189	94,1%	61,8%
10	10-30-30-2	01:46	0,00014419	0,00008901	76,5%	44,1%

Next, you will predict 10-25-25-2 using a formula that returns a value:  $x_n = \frac{(x-0,1) \cdot (b-a)}{0,8} + a$

**Table 6.** Poor Year Prediction Results for 2019-2023 (Thousand Souls)

No	2019		2020		2021		2022		2023	
	Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep
1	777,8	767,6	708,5	686,3	588,9	553,3	472,8	429,7	410,9	368,9
2	1214,6	1179,2	1043,6	999,9	794,6	740,0	552,2	497,1	423,0	378,0
3	364,0	359,3	381,3	369,8	387,2	364,9	395,1	361,5	399,1	359,8
4	482,3	472,3	479,0	464,1	446,8	420,0	417,8	381,5	402,5	362,4
5	293,4	286,6	330,5	319,0	355,4	334,1	382,7	350,5	397,2	358,4

No	2019		2020		2021		2022		2023	
	Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep	Mar	Sep
6	987,6	972,9	872,5	842,0	689,4	646,0	511,5	463,2	416,8	373,3
7	318,5	313,2	346,9	335,6	365,7	344,0	386,7	354,1	397,8	358,8
8	1015,5	1002,6	890,9	860,0	700,7	656,6	516,0	467,0	417,5	373,8
9	122,1	119,1	194,2	185,5	271,8	254,6	350,6	321,7	392,3	354,6
10	161,7	157,8	227,5	218,3	292,2	274,4	358,4	328,9	393,5	355,5
11	384,4	378,4	396,8	384,6	396,0	373,0	398,4	364,7	399,7	360,2
12	3232,1	3136,1	2609,6	2495,8	1758,5	1630,7	924,0	818,9	479,2	420,9
13	3482,6	3420,8	2814,1	2706,9	1884,2	1756,2	972,6	864,2	486,8	426,8
14	458,2	451,6	454,6	440,5	432,2	407,0	412,2	376,7	401,7	361,8
15	3861,0	3792,6	3099,9	2996,6	2060,0	1928,8	1040,3	926,5	497,3	434,9
16	644,0	634,0	597,5	579,6	520,2	489,7	446,1	406,8	407,0	365,7
17	202,9	197,0	258,6	248,3	311,6	292,0	365,6	335,2	394,6	356,3
18	708,7	698,7	649,7	629,0	551,7	518,3	458,5	417,1	408,8	367,1
19	1059,4	1039,2	923,3	890,9	720,1	674,3	523,4	473,3	418,7	374,7
20	381,2	374,1	397,7	385,1	396,7	373,4	398,7	364,7	399,7	360,2
21	173,5	168,9	235,5	225,7	297,0	278,6	360,2	330,6	393,8	355,7
22	216,8	212,4	269,8	259,9	318,5	299,5	368,5	337,9	395,1	356,7
23	237,2	233,1	287,7	277,9	329,1	309,4	372,6	341,7	395,8	357,1
24	100,1	96,8	176,8	167,9	261,5	244,7	346,5	318,1	391,7	354,1
25	221,1	216,1	271,3	261,3	319,6	300,2	369,0	338,1	395,2	356,7
26	412,7	406,5	422,6	410,0	412,1	388,2	404,7	370,1	400,6	360,9
27	752,6	740,6	682,1	660,9	572,5	538,1	466,6	424,2	410,0	368,1
28	324,9	318,5	348,8	337,0	367,5	345,8	387,4	354,8	397,9	358,9
29	225,9	220,9	273,6	263,6	321,1	301,6	369,4	338,8	395,2	356,8
30	181,5	177,4	243,5	234,0	302,1	283,6	362,2	332,2	394,1	355,9
31	328,2	322,2	355,4	343,9	371,1	349,3	388,8	356,0	398,2	359,0
32	124,2	121,2	197,9	189,2	274,0	256,7	351,2	322,6	392,5	354,6
33	240,4	235,7	285,8	275,6	328,4	308,7	372,4	341,3	395,7	357,1
34	857,6	849,3	766,3	742,6	624,0	586,6	486,3	441,7	413,0	370,5

#### 4. Conclusion

Bayesian backpropagation regulation algorithm can be used to predict the number of poor people in each province in Indonesia as one of the efforts to assist the government in reducing poverty in the future. Based on the 10 architectural models used in this study (10-5-10-2, 10-10-10-2, 10-10-15-2, 10-10-20-2, 10-15-10-2, 10-15-15-2, 10-15-20-2, 10-20-20-2, 10-25-25-2 and 10-30-30-2), obtained the best architectural model 10-25-25 -2 with predictive accuracy of 94.1% and 61.8%. The training MSE for the prediction of Semester 1 is 0.00000095 and MSE is testing 0.00013571. Whereas the training MSE for the prediction of Semester 2 is 0.00000254 and MSE is testing 0.00005189.

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