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ANN: Model of Back-Propagation Architecture on the Logs Production by Type of Wood

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Abstract

Indonesia is rich in forest products. The production forest is a forest area that can be utilized for the community, such as logs, rattan, and some forest plants that have high economic value. This research aims to make the best architectural model by using artificial neural network. The method used is backpropagation algorithm. With this model it will continue to predict the output of logs. Data are sourced from BPS-Statistics Indonesia. Based on the results of research results of logs production using backpropogation method, obtained the result of 3 model architecture (18-18-1, 18-25-1 and 18-18-25- 1) that model of architecture 18- 25-1 is the best model with 72% accuracy, MSE: 0.0221670942 and epochs: 660.

Keywords: *ANN, Logs production, Backpropagation, JST, Prediction*

1. Introduction

Indonesia is rich in forest products, but not all forests can be harnessed and produced. For forest utilization, the government has established certain forest areas designated as Production Forest. The production forest is a forest area whose results can be utilized for the community, such as logs, rattan, and some forest plants that have high economic value. Logs that are cut or harvested can be used as raw materials for upstream wood processing production. This production of logs is produced from natural forests through the activities of forest concession companies. Forest Concessionaire Enterprises is a business / legal entity engaged in the field of harvesting of forest products. Based on the source of Indonesia's Forestry Statistics Book, the data of log production in Indonesia for the last 10 years has increased by 314.64% In 2001 Indonesia's log production amounted to 11,432,501 m3 and in 2011 amounted to 47,429,335 m3.

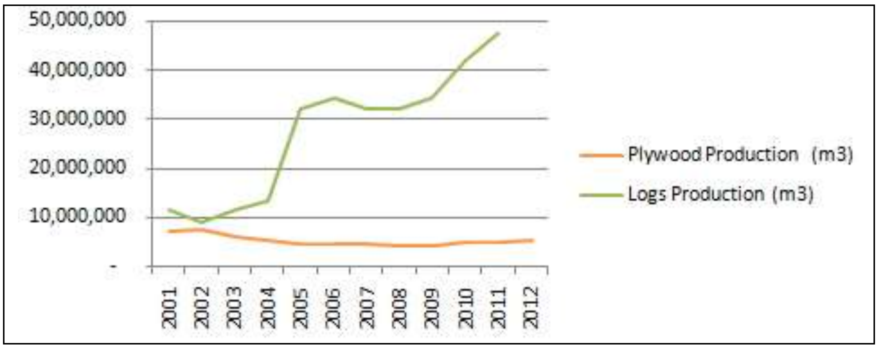

Figure 1. Logs Production in Indonesia
(Source : Indonesia Forest Statistics Book)

Increased production of logs gives some negative impacts. One of them is the destruction of natural ecosystems that encourage the emergence of concerns shortage of industrial raw materials in the future. This study aims to create a prediction model of the total prediction of logs in Indonesia using artificial intelligence. This model can then be used to predict long-term log production so that the government can anticipate and provide solutions to the negative impacts resulting from the production of logs in Indonesia. One

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branch of computer science related to prediction is artificial intelligence. There is a lot of artificial intelligence that deals with predictions.

The Artificial Neural Network is one of the branches of artificial intelligence [1]. Today, the AI is a very important discipline and it includes a number of well-recognized and mature areas including Expert Systems [2-4], Fuzzy Logic [5-8], Genetic Algorithms [9-11], Language Processing, Logic Programming, Planning and Scheduling, Neural Networks and Robotics [12]. There are many techniques that can be used for the implementation of the Neural Network Tirua one of the methods used is Backpropagation [2-6]. Backpropogation is one of the artificial neural network algorithms that is often used to solve complex problems related to input identification, prediction, pattern recognition, and so on. Repeated training will result in a network that responds correctly to all its inputs.

2. Rudimentary

2.1. Artificial Intelegence

AI is a field of study based on the premise that intelligent thought can be regarded as aform of computation - one that can be formalized and ultimately mechanized. To achievethis, however, two major issues need to be addressed. The first issue is knowledge representation, and the second is knowledge manipulation [1].

2.2. Artificial Neural Networks (NN)

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) (See Figure 1). From Figure 1, to build artificial neural network, artificial neurons, also called as nodes, are interconnected [13,14]. An artificial neuron is an abstraction of biological neurons and the basic unitin an ANN [15,16]. The Artificial Neuron receives one or more inputs and sums them to produce an output[17,18]. After successful training, user can give unlabeled data to be classified.

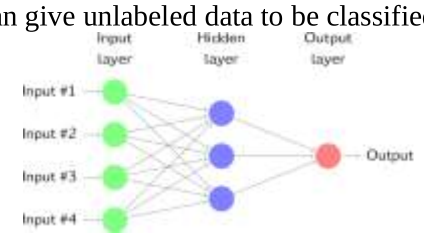

Figure 1. Artificial Neural Network Model

2.3. Architecture of Backpropogation

The back-propagation learning algorithm (BPLA) has become famous learning algorithms among ANNs. In the learning process, to reduce the in accuracy of ANNs, BPLAs use the gradient decent search method to adjust the connection weights. The structure of a back-propagation ANN is shown in Figure 2[19]. Each of these layers must be either of the following:

1. Input Layer – This layer holds the input for thenetwork
2. Output Layer – This layer holds the output data, usually an identifier for the input.
3. Hidden Layer – This layer comes between the inputlayer and the output layer[20].

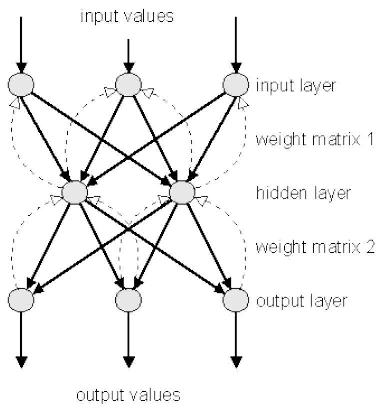

Figure 2. Back-propogation ANN

2.4. Backpropagation Neural Network

Phases in Backpropagation Techniquealgorithm can bedivided into two phases: propagation and weight update.

Phase 1: Propagation Each propagation involves the following steps: 1. Forward propagation of a training pattern's input is given through the neural network in order to generate the propagation's output activations. 2. Back propagation of the output activations propagation through the neural network using the training pattern's targetin order to generate the deltas of all output and hidden neurons. Phase 2: Weight Update For each weight-synapse: 1. Multiply its input activation and output delta to get thegradient of the weight. 2. Bring the weight in the direction of the gradient byadding a ratio of it from the weight. [21,22].

3. Research and Methodology

3.1. Research Framework

A framework of research work used in solving this research problem.

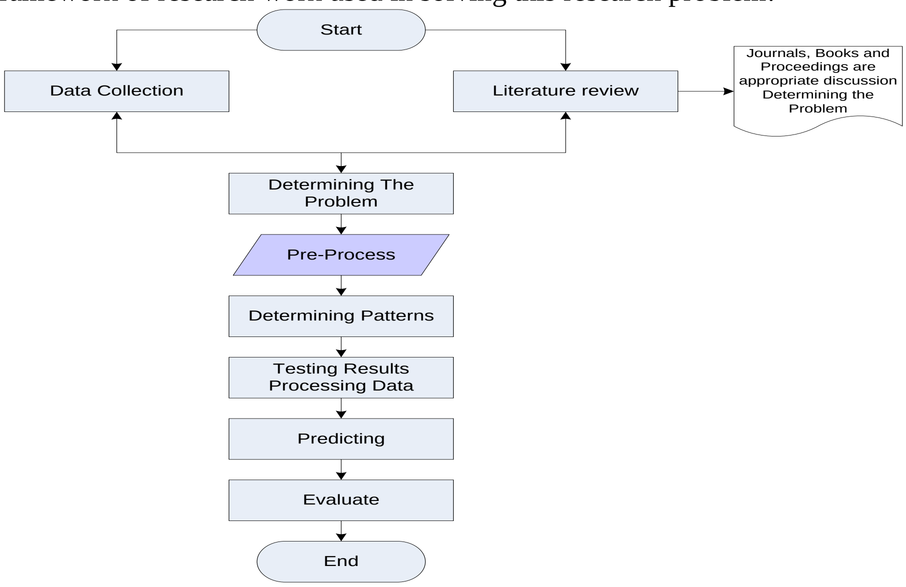

Figure 3. Research Framework

Based on the framework in the picture above, each step can be described as follows :
1. Collecting Data
2. Library Studies
3. Identifying Problems
4. Preprocess
5. Determining the Model
6. Testing Results Data Processing
7. Predicting
8. Evaluate the End

3.2. Input Data

The data used in this research is round wood production data by type obtained from BPS Statistic Indonesia (2004-2015). Log production data can be seen in the following table:

Table 1. Logs Production by Type of Wood (M3)

Type of Logs	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Agathis	32134	29888	1612	26132	18121	6034	5853	6380	4707	453	453	2173
Bakau	290475	213291	155582	52913	55558	110205	160989	0	0	139521	110144	14165
Bangkirai	48776	64733	66136	73207	77127	77818	82063	99244	112141	44244	71864	112541
Benuang	14861	8029	6655	9549	39945	36450	36109	0	5122	6098	18223	15145
Damar	2777	3543	1625	3830	2409	1491	525	0	0	0	0	0
Duabanga	32393	0	0	0	0	0	0	0	30	14	14	35
Indah	72980	57799	45209	108083	85434	59699	45307	48094	41466	17959	23307	34300
Jelutung	22226	1201	18580	24539	24813	17431	21340	0	16	70	471	777
Kapur	307602	323635	390958	261523	281591	268621	250500	209827	233432	31878	22486	78972
Kruing	242706	372573	308901	375459	372044	369933	342897	168467	255099	272201	262685	327803
Meranti	4135592	5049694	4377991	4460637	4231197	4062671	4385510	4091990	3160592	3082766	3742865	4169157
Mersawa	20103	14957	12675	22761	106304	105334	100886	3657	6675	5659	9775	11238
Nyatoh	31434	26345	23587	53551	41595	39141	35449	22337	18460	8904	10566	16272
Palapi	17598	15176	20522	54185	35767	15756	7222	0	802	292	2585	5159
Ramin	81127	65393	81587	92965	92425	67707	31583	35256	28400	0	0	0
Resak	3703	6045	4548	8411	7458	6756	4822	246	2197	2019	1317	3324
Lainnya	1117565	945863	909309	1061444	1040050	1237864	960548	948357	849772	753926	651929	513774
Rimba Campuran	1684351	1571497	1475917	1813744	1546896	1249338	869666	739554	623201	486877	518357	574545

Source: BPS-Statistic Indonesia

In table 1, it can be explained that, the input value consists of 18 variables and 1 target value. The input value consists of log type (X1-X18) and the target value consists of the total number of logs production. In the process of selecting the best architectural model using backpropagation, the data is normalized first using the formula :

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

After the data is normalized, the process of selecting the best architecture model with backpropogation is divided into 2 parts, namely: data traning and data testing. The results of normalization of data can be seen in the following table:

Table 2. DataTraining After Normalization

Types of logs	2004	2005	2006	2007	2008	2009
Agathis	0,1051	0,1047	0,1003	0,1041	0,1029	0,1010
Bakau	0,1460	0,1338	0,1246	0,1084	0,1088	0,1175
Bangkirai	0,1077	0,1103	0,1105	0,1116	0,1122	0,1123
Benuang	0,1024	0,1013	0,1011	0,1015	0,1063	0,1058
Damar	0,1004	0,1006	0,1003	0,1006	0,1004	0,1002
Duabanga	0,1051	0,1000	0,1000	0,1000	0,1000	0,1000
Indah	0,1116	0,1092	0,1072	0,1171	0,1135	0,1095
Jelutung	0,1035	0,1002	0,1029	0,1039	0,1039	0,1028

Kapur	0,1487	0,1513	0,1619	0,1414	0,1446	0,1426
Kruing	0,1385	0,1590	0,1489	0,1595	0,1589	0,1586
Meranti	0,7552	0,9000	0,7936	0,8067	0,7703	0,7436
Mersawa	0,1032	0,1024	0,1020	0,1036	0,1168	0,1167
Nyatoh	0,1050	0,1042	0,1037	0,1085	0,1066	0,1062
Palapi	0,1028	0,1024	0,1033	0,1086	0,1057	0,1025
Ramin	0,1129	0,1104	0,1129	0,1147	0,1146	0,1107
Resak	0,1006	0,1010	0,1007	0,1013	0,1012	0,1011
Lainnya	0,2771	0,2498	0,2441	0,2682	0,2648	0,2961
Rimba Campuran	0,3668	0,3490	0,3338	0,3873	0,3451	0,2979

In table 2, input data is log production (2004-2009) where the input value (X1-X18) and target value (logs production in 2009)

Table 3. Data Testing After Normalization

types of logs	2010	2011	2012	2013	2014	2015
Agathis	0,1011	0,1012	0,1009	0,1001	0,1001	0,1004
Bakau	0,1294	0,1000	0,1000	0,1255	0,1201	0,1026
Bangkirai	0,1150	0,1181	0,1205	0,1081	0,1131	0,1205
Benuang	0,1066	0,1000	0,1009	0,1011	0,1033	0,1028
Damar	0,1001	0,1000	0,1000	0,1000	0,1000	0,1000
Duabanga	0,1000	0,1000	0,1000	0,1000	0,1000	0,1000
Indah	0,1083	0,1088	0,1076	0,1033	0,1043	0,1063
Jelutung	0,1039	0,1000	0,1000	0,1000	0,1001	0,1001
Kapur	0,1457	0,1383	0,1426	0,1058	0,1041	0,1144
Kruing	0,1626	0,1307	0,1465	0,1497	0,1479	0,1598
Meranti	0,9000	0,8465	0,6766	0,6624	0,7828	0,8605
Mersawa	0,1184	0,1007	0,1012	0,1010	0,1018	0,1021
Nyatoh	0,1065	0,1041	0,1034	0,1016	0,1019	0,1030
Palapi	0,1013	0,1000	0,1001	0,1001	0,1005	0,1009
Ramin	0,1058	0,1064	0,1052	0,1000	0,1000	0,1000
Resak	0,1009	0,1000	0,1004	0,1004	0,1002	0,1006
Lainnya	0,2752	0,2730	0,2550	0,2375	0,2189	0,1937
Rimba Campuran	0,2586	0,2349	0,2137	0,1888	0,1946	0,2048

In table 3, input data is log production (2010-2015) where the input value (X1-X8) and target value (logs production in 2015)

3.3. Output Data

The expected result is the selection of an arsitertur model to predict the results of the Logs Production by Type of Wood. The best architectural model is seen from the smallest minimum error rate. In this study, the minimum error used is: (0,001-0,009 or (-0,001)- (-0,009): True) and (>0,009: False).

4. Results and Discussion

4.1. Model Arsitektur 18-18-1

Here are the results of architectural model calculations 18-18-1 (18 inputs, 18 hidden hidden neurons, 1 output) using matlab software.

Table 4. Data Training Backpropagation (18-18-1)

No	types of logs	Target	ANN 18-18-1		
			Output	Error	SSE
1	Agathis	0,1010	0,1206	-0,020	0,0003858891
2	Bakau	0,1175	0,1431	-0,026	0,0006574467
3	Bangkirai	0,1123	0,1176	-0,005	0,0000277903

4	Benuang	0,1058	0,1204	-0,015	0,0002139021
5	Damar	0,1002	0,1191	-0,019	0,0003558425
6	Duabanga	0,1000	0,1239	-0,024	0,0005712100
7	Indah	0,1095	0,1204	-0,011	0,0001197309
8	Jelutung	0,1028	0,1209	-0,018	0,0003290047
9	Kapur	0,1426	0,1248	0,018	0,0003152898
10	Kruing	0,1586	0,1138	0,045	0,0020076492
11	Meranti	0,7436	0,7703	-0,027	0,0007112651
12	Mersawa	0,1167	0,1202	-0,004	0,0000123371
13	Nyatoh	0,1062	0,1192	-0,013	0,0001689758
14	Palapi	0,1025	0,1179	-0,015	0,0002372786
15	Ramin	0,1107	0,1211	-0,010	0,0001076093
16	Resak	0,1011	0,1189	-0,018	0,0003178974
17	Lainnya	0,2961	0,1892	0,107	0,0114295664
18	Rimba Campuran	0,2979	0,2939	0,004	0,0000162161
				Total	0,0057073574
				MSE	0,0004756131

Table 5. Data Testing Backpropagation (18-18-1)

No	types of logs	Target	ANN 18-18-1			Result
			Output	Error	SSE	
1	Agathis	0,1004	0,1196	-0,019	0,0003687784	FALSE
2	Bakau	0,1026	0,1414	-0,039	0,0015066847	FALSE
3	Bangkirai	0,1205	0,1206	0,000	0,0000000050	TRUE
4	Benuang	0,1028	0,1249	-0,022	0,0004900585	FALSE
5	Damar	0,1000	0,1193	-0,019	0,0003724900	FALSE
6	Duabanga	0,1000	0,1192	-0,019	0,0003683949	FALSE
7	Indah	0,1063	0,1212	-0,015	0,0002232942	FALSE
8	Jelutung	0,1001	0,1228	-0,023	0,0005133968	FALSE
9	Kapur	0,1144	0,1385	-0,024	0,0005805215	FALSE
10	Kruing	0,1598	0,1492	0,011	0,0001123064	FALSE
11	Meranti	0,8605	0,6976	0,163	0,0265472014	FALSE
12	Mersawa	0,1021	0,1362	-0,034	0,0011662209	FALSE
13	Nyatoh	0,1030	0,1225	-0,020	0,0003814865	FALSE
14	Palapi	0,1009	0,1204	-0,019	0,0003786488	FALSE
15	Ramin	0,1000	0,1212	-0,021	0,0004494400	FALSE
16	Resak	0,1006	0,1199	-0,019	0,0003722445	FALSE
17	Lainnya	0,1937	0,1719	0,022	0,0004762040	FALSE
18	Rimba Campuran	0,2048	0,1898	0,015	0,0002252364	FALSE
				Total	0,0322493524	6%
				MSE	0,0026874460	

In Table 5, the back-propagation architectural model 18-18-1 has an accuracy of 6% with MSE: 0.0026874460 and epochs: 3797

4.2. Model Arsitektur 18-25-1

Here are the results of architectural model calculations 18-25-1 (18 inputs, 25 hidden hidden neurons, 1 output) using matlab software.

Table 6. Data Training Backpropagation (18-25-1)

No	types of logs	Target	ANN 18-25-1		
			Output	Error	SSE
1	Agathis	0,1010	0,1072	-0,006	0,0000389883
2	Bakau	0,1175	0,1229	-0,005	0,0000296015
3	Bangkirai	0,1123	0,1055	0,007	0,0000466264

4	Benuang	0,1058	0,1042	0,002	0,0000024794
5	Damar	0,1002	0,1044	-0,004	0,0000173371
6	Duabanga	0,1000	0,1062	-0,006	0,0000384400
7	Indah	0,1095	0,1085	0,001	0,0000009175
8	Jelutung	0,1028	0,1046	-0,002	0,0000033800
9	Kapur	0,1426	0,1133	0,029	0,0008559370
10	Kruing	0,1586	0,1160	0,043	0,0018153393
11	Meranti	0,7436	0,7300	0,014	0,0001857891
12	Mersawa	0,1167	0,1030	0,014	0,0001873500
13	Nyatoh	0,1062	0,1059	0,000	0,0000000906
14	Palapi	0,1025	0,105	-0,003	0,0000062693
15	Ramin	0,1107	0,1068	0,004	0,0000154175
16	Resak	0,1011	0,1044	-0,003	0,0000110868
17	Lainnya	0,2961	0,1935	0,103	0,0105286377
18	Rimba Campuran	0,2979	0,2331	0,065	0,0042025301
				Total	0,0032221855
				MSE	0,0002685155

Table 7. Data Testing Backpropagation (18-25-1)

No	types of logs	Target	ANN 18-25-1			Result
			Output	Error	SSE	
1	Agathis	0,1004	0,1046	-0,004	0,0000176703	TRUE
2	Bakau	0,1026	0,1160	-0,013	0,0001799900	FALSE
3	Bangkirai	0,1205	0,1062	0,014	0,0002053377	FALSE
4	Benuang	0,1028	0,1061	-0,003	0,0000111373	TRUE
5	Damar	0,1000	0,1043	-0,004	0,0000184900	TRUE
6	Duabanga	0,1000	0,1042	-0,004	0,0000175864	TRUE
7	Indah	0,1063	0,1066	0,000	0,0000001177	TRUE
8	Jelutung	0,1001	0,1057	-0,006	0,0000308943	TRUE
9	Kapur	0,1144	0,1187	-0,004	0,0000184385	TRUE
10	Kruing	0,1598	0,1185	0,041	0,0017054810	FALSE
11	Meranti	0,8605	0,3470	0,514	0,2637162646	FALSE
12	Mersawa	0,1021	0,1112	-0,009	0,0000837221	TRUE
13	Nyatoh	0,1030	0,1064	-0,003	0,0000117764	TRUE
14	Palapi	0,1009	0,1046	-0,004	0,0000133876	TRUE
15	Ramin	0,1000	0,1062	-0,006	0,0000384400	TRUE
16	Resak	0,1006	0,1045	-0,004	0,0000151604	TRUE
17	Lainnya	0,1937	0,1932	0,001	0,0000002726	TRUE
18	Rimba Campuran	0,2048	0,1752	0,030	0,0008766265	FALSE
				Total	0,2660051298	72%
				MSE	0,0221670942	

In Table 7, the back-propagation architectural model 18-25-1 has an accuracy of 72% with MSE: 0.0221670942 and epochs: 660

4.3. Model Arsitektur 18-18-25-1

Here are the results of architectural model calculations 18-18-25-1 (18 inputs, hidden layer using 18 neurons and 25 neurons, 1 output) using matlab software.

Table 8. Data Training Backpropagation (18-18-25-1)

types of logs	Target	ANN 18-18-25-1		
		Output	Error	SSE
Agathis	0,1010	0,1179	-0,017	0,0002871012
Bakau	0,1175	0,1220	-0,005	0,0000206182
Bangkirai	0,1123	0,1180	-0,006	0,0000321676

Benuang	0,1058	0,1181	-0,012	0,0001519153
Damar	0,1002	0,1173	-0,017	0,0002911728
Duabanga	0,1000	0,1171	-0,017	0,0002924100
Indah	0,1095	0,1169	-0,007	0,0000553857
Jelutung	0,1028	0,1166	-0,014	0,0001915037
Kapur	0,1426	0,1262	0,016	0,0002675318
Kruing	0,1586	0,1314	0,027	0,0007402099
Meranti	0,7436	0,7430	0,001	0,0000003975
Mersawa	0,1167	0,1197	-0,003	0,0000090746
Nyatoh	0,1062	0,117	-0,011	0,0001166199
Palapi	0,1025	0,1164	-0,014	0,0001933170
Ramin	0,1107	0,1172	-0,006	0,0000419061
Resak	0,1011	0,1173	-0,016	0,0002634024
Lainnya	0,2961	0,1816	0,115	0,0131123455
Rimba Campuran	0,2979	0,3418	-0,044	0,0019248468
			Total	0,0023394884
			MSE	0,0001949574

Table 9. Data Training Backpropagation (18-18-25-1)

No	types of logs	Target	ANN 18-18-25-1			Result
			Output	Error	SSE	
1	Agathis	0,1004	0,1174	-0,017	0,0002891225	FALSE
2	Bakau	0,1026	0,1139	-0,011	0,0001280527	FALSE
3	Bangkirai	0,1205	0,1196	0,001	0,0000008642	TRUE
4	Benuang	0,1028	0,1173	-0,015	0,0002113321	FALSE
5	Damar	0,1000	0,1172	-0,017	0,0002958400	FALSE
6	Duabanga	0,1000	0,1173	-0,017	0,0002990691	FALSE
7	Indah	0,1063	0,1183	-0,012	0,0001450346	FALSE
8	Jelutung	0,1001	0,1171	-0,017	0,0002875826	FALSE
9	Kapur	0,1144	0,1206	-0,006	0,0000383658	TRUE
10	Kruing	0,1598	0,1167	0,043	0,0018573919	FALSE
11	Meranti	0,8605	0,8003	0,060	0,0036280287	FALSE
12	Mersawa	0,1021	0,1170	-0,015	0,0002235018	FALSE
13	Nyatoh	0,1030	0,1176	-0,015	0,0002140860	FALSE
14	Palapi	0,1009	0,1173	-0,016	0,0002676136	FALSE
15	Ramin	0,1000	0,118	-0,018	0,0003240000	FALSE
16	Resak	0,1006	0,1171	-0,016	0,0002720401	FALSE
17	Lainnya	0,1937	0,2022	-0,008	0,0000718748	TRUE
18	Rimba Campuran	0,2048	0,1607	0,044	0,0019455050	FALSE
				Total	0,0074041859	17%
				MSE	0,0006170155	

In Table 9, the back-propagation architectural model 18-18-25-1 has an accuracy of 17% with MSE: 0.0006170155 and epochs: 11442.

4.4. Results

By using the same parameters on each activation function, namely: sigmoid bipolar (tansig) with net.trainparam.epochs = 1500000 net.trainparam.LR = 0.1; net.trainParam.goal = 0.001; net.trainParam.show = 1000; Minimum error of 0.001-0.009 obtained result backpropagation architecture model 18-25-1 is the best with the accuracy of 72%. Here is the comparison of 3 architectural models and the performance of each architecture model

Table 10. Data Training And Testing Backpropagation

No	Architecture	Training	Testing

		Epoch	Time	MSE	MSE	Accuracy
1	18-18-1	3797	00:10	0,0004756131	0,0026874460	6%
2	18-25-1	660	00:07	0,0002685155	0,0221670942	72%
3	18-18-25-1	11442	00:15	0,0001949574	0,0006170155	17%

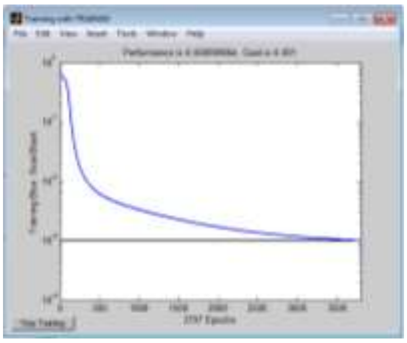

Figure 4. Performance of architecture model 18-18-1

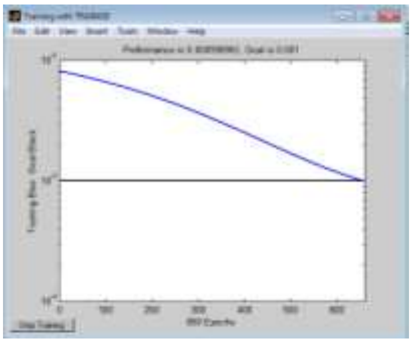

Figure 5. Performance of architecture model 18-25-1

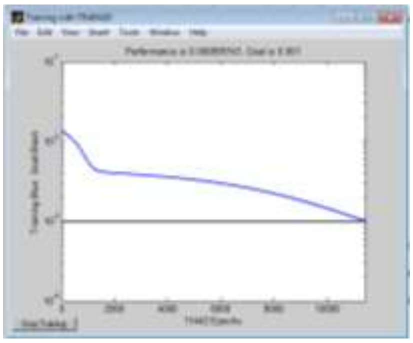

Figure 6. Performance of architecture model 18-18-25-1

5. Conclution

Based on the results of research in determining the architecture model on the prediction of the result of logs production using backpropogation method, obtained the result of 3 model architecture (18-18-1, 18-25-1 and 18-18-25-1) that model of architecture 18- 25-1 is the best model with 72% accuracy.

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