OPTIMIZATION FORECASTING USING BACK-PROPAGATION ALGORITHM

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Budi Raharjo
Universitas STEKOM, Semarang, Indonesia

Nurul Farida
Universitas Islam Balitar, Blitar, Indonesia

Purwo Subekt
Mechanical Engineering Universitas Pasir Pengaraian, Riau, Indonesia

Rima Herlina S Siburian
Universitas Papua, Papua Barat, Indonesia

Putu Doddy Heka Ardana
Universitas Ngurah Rai, Denpasar, Indonesia

Robbi Rahim
Sekolah Tinggi Ilmu Manajemen Sukma, Medan, Indonesia

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OPTIMIZATION FORECASTING USING BACK-PROPAGATION ALGORITHM

Budi Raharjo[1], Nurul Farida[2], Purwo Subekti[3], Rima Herlina S Siburian[4], Putu Doddy Heka Ardana[5], Robbi Rahim[6,*]

[1]Universitas STEKOM, Department of Information System, Semarang, Indonesia
[2]Universitas Islam Balitar, Department of Management, Blitar, Indonesia
[3]Universitas Pasir Pengaraian, Department of Mechanical Engineering, Riau , Indonesia
[4]Universitas Papua, Department of Forestry, Papua Barat, Indonesia
[5]Universitas Ngurah Rai, Department of Civil Engineering, Denpasar, Indonesia
[6]Sekolah Tinggi Ilmu Manajemen Sukma, Medan, Indonesia

The purpose of this study was to evaluate the back-propagation model by optimizing the parameters for the prediction of broiler chicken populations by provinces in Indonesia. Parameter optimization is changing the learning rate (lr) of the backpropagation prediction model. Data sourced from the Directorate General of Animal Husbandry and Animal Health processed by the Central Statistics Agency (BPS). Data is the population of Broiler Chickens from 2017 to 2019 (34 records). The analysis process uses the help of RapidMiner software. Data is divided into 2 parts, namely training data (2017-2018) and testing data (2018-2019). The backpropagation model used is 1-2-1; 1-25-1 and 1-45-1 with a learning rate (0.1; 0.01; 0.001; 0.2; 0.02; 0.002; 0.3; 0.03; 0.003). From the three models tested, the 1-45-1 model (lr = 0.3) is the best model with Root Mean Squared Error = 0.028 in the training data. With this model, the prediction results obtained with an accuracy value of 91% and Root Mean Squared Error = 0.00555 in the testing data.

Key words: optimization, back-propagation, parameter, Indonesia

INTRODUCTION

Back-propagation is a method that has the ability to adapt to network conditions through an excellent learning process[1][2][3][4]. Apart from the advantages of back-propagation, this method also has a weakness in terms of time when carrying out the learning process. So, to overcome these weaknesses, many studies have been carried out on artificial neural networks[5]. Such as research conducted [6] on back-propagation optimization with memetic algorithms and genetic algorithms. The paper proposes an efficient method for selecting parameters (weights and thresholds). Weights and threshold parameters are optimized with memetic and genetic algorithms. The dataset used is a diagnosis of Wisconsin breast cancer from the UCI Machine Learning Repository. The results show that the proposed method has better accuracy than the previous one.

Furthermore, research conducted [7] on Feedforward Neural Network Optimization on back-propagation. This paper proposes an optimization of the activation function and the sigmoid function with three parameters. this is done because this parameter affects the speed of learning. the results of the study have the advantage of convergence speed and generalizability.

Furthermore, research conducted nikentari[8] on optimization of back-propagation by adding the Particle Swarm Optimization method to tide predictions. This method uses Particle Swarm Optimization to optimize the prediction from back propagation. The test results show that the prediction accuracy has increased to 91.56% by using 90 swarms, learning rate 0.9 and iterating 20 times.

Increased optimization[9] can be done at the adaptive learning rate. In some cases the adaptive learning rate can minimize the error value and in some other cases the adaptive learning rate also does not have a significant role in improving learning[10][11][12]. Based on this, an evaluation of the performance of the improvised results was carried out using the adaptive learning rate in the case of the prediction of the broiler chicken population by province in Indonesia so that the research results are expected to provide another alternative in improving the performance in the field of prediction using the back-propagation network.

METHODOLOGY

Dataset

The information provided for the study included broiler population data by province in Indonesia from the General Directorate for Animal Husbandry and Animal Health processed by the Central Bureau of Statistics (abbreviated as BPS). The data are 34 records for the entire griller chicken's population from 2017 to 2019. You may use https://osf.io/hbe2z to access a dataset. This data set is used for the back-propagation network optimization. After the dataset has been normalized, the data set is divided into 2 parts, i.e., the training data set (https://osf.io/mwgk6)

*usurobbi85@zoho.com

Table 1: Dataset of conversion result of broiler chicken population by province

Province	2017	2018	2019
Aceh	0.11390	0.11680	0.13658
North Sumatra	0.28401	0.27435	0.24013
West Sumatra	0.16227	0.16547	0.15365
Riau	0.18667	0.18375	0.19805
Jambi	0.14085	0.15263	0.13171
South Sumatra	0.19098	0.20543	0.17581
Bengkulu	0.10526	0.10651	0.10750
Lampung	0.18669	0.18022	0.18562
Kep. Bangka Belitung	0.11911	0.12155	0.12325
Kep. Riau	0.11776	0.11899	0.12338
DKI Jakarta	0.10744	0.10667	0.11789
West Java	0.72813	0.85954	0.90000
Central Java	0.55949	0.60096	0.69958
In Yogyakarta	0.11286	0.12436	0.15093
East Java	0.53492	0.54250	0.56055
Banten	0.36198	0.36261	0.30136
Bali	0.20065	0.20161	0.17067
West Nusa Tenggara	0.12956	0.12712	0.13727
East Nusa Tenggara	0.11190	0.11093	0.11775
West Kalimantan	0.16238	0.15720	0.15070
Central Kalimantan	0.12621	0.12546	0.12294
South Borneo	0.18276	0.18342	0.18547
East Kalimantan	0.16145	0.16677	0.14964
North Kalimantan	0.10006	0.10088	0.10461
North Sulawesi	0.11268	0.11208	0.10913
Central Sulawesi	0.10791	0.10802	0.10511
South Sulawesi	0.19800	0.20207	0.17533
Southeast Sulawesi	0.10296	0.10415	0.10409
Gorontalo	0.10228	0.10263	0.10314
West Sulawesi	0.10142	0.10677	0.10197
Maluku	0.10016	0.10023	0.10064
North Maluku	0.10000	0.10007	0.10022
West Papua	0.10503	0.10058	0.10068
Papua	0.10702	0.10776	0.10640
source: ***Processed Personal data***			

and the testing dataset (https://osf.io/rknz5). Training data for 2017 and 2018 are the total broiler population. Where input is in 2017 and output is in 2018 (target). In 2018 and 2019, while the test data set is the number of broilers. Where 2018 is the start and where 2019 is the end (target). Each architectural background propagation model is tested with the test data set. A number of tests are performed to show the best architectural model from several parameters. The architectural model for back-propagation tested in this study consists of 1-2-1 models, 1-25-1 models of architecture, 1-45-1 models of architecture. In the case of the back propagation of architectural models, the optimization rate of learning (lr) is 0.1; 0.01; 0.001; 0.2; 0.02; 0.002; 0.3; 0.03; 0.003. Optimization of the learning rate (lr) value used in the study was carried out randomly. Where lr is a constant (usually between 0-1) that determines how fast the model learning process is carried out. The testing process uses software Rapid Miner.

Table 1 shows the normalized dataset results obtained by using the Rapid Miner software during the analysis process. The dataset is normalized because it employs an activation function (logsig) with input and output values ranging from 0 to 1 [13]. The dataset below contains conversion results for the broiler chicken population by province.

Flowchart of back-propagation ANN Optimization

The following is a research design of the back-propagation method parameter optimization in predicting broiler chicken populations according to provinces in Indonesia as in Figure 1 below.

RESULTS AND DISCUSSION

The analysis process uses the he–lp of RapidMiner software. Before the data is processed, the dataset is divided into sections, namely training data and testing data. Training data consists of data for 2017 and 2018. Where 2017 data becomes input (X1) and data for 2018 becomes output (Y). Meanwhile, testing data consists of data for 2018 and 2019. Where 2018 data becomes

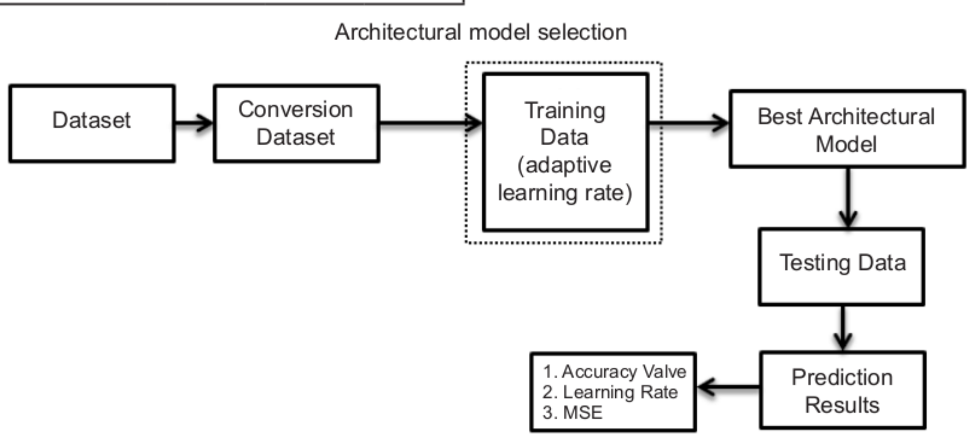

Figure 1: Back-propagation flow

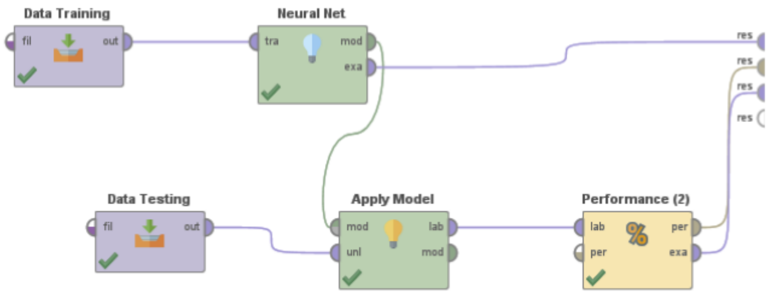

Figure 2: The back-propagation model using Rapid Miner

input (X1) and data for 2019 becomes output (Y). The following is a design drawing of the back-propagation model using Rapid Miner as shown in Figure 2 above.

Based on Figure 2, the architectural model to be trained is 1-2-1; 1-25-1 and 1-45-1. Meanwhile, the learning rate used to optimize the architectural model is (0.1; 0.01; 0.001; 0.2; 0.02; 0.002; 0.3; 0.03; 0.003). The results of the calculation of RMSE ≤ 1 where RMSE calculations if the RMSE value is getting smaller, the accuracy is getting better [14]. The following is the recapitulation of training data using Rapid Miner software as shown in Table 2 below.

Table 2: Recapitulation of training data for all architectural models

Model	*Learning rate*	*Root Mean Squared Error*	*correlation*	*Squared correlation*
1-2-1	0.1	0.163 +/- 0.000	0.996	0.027 +/- 0.072
1-2-1	0.01	0.228 +/- 0.000	0.996	0.052 +/- 0.040
1-2-1	0.001	0.315 +/- 0.000	0.996	0.099 +/- 0.037
1-2-1	0.2	0.164 +/- 0.000	0.996	0.027 +/- 0.067
1-2-1	0.02	0.184 +/- 0.000	0.996	0.034 +/- 0.055
1-2-1	0.002	0.302 +/- 0.000	0.996	0.091 +/- 0.036
1-2-1	0.3	0.161 +/- 0.000	0.996	0.026 +/- 0.069
1-2-1	0.03	0.169 +/- 0.000	0.996	0.029 +/- 0.066
1-2-1	0.003	0.290 +/- 0.000	0.996	0.084 +/- 0.034
1-25-1	0.1	0.284 +/- 0.000	0.996	0.081 +/- 0.034
1-25-1	0.01	0.169 +/- 0.000	0.996	0.028 +/- 0.068
1-25-1	0.001	0.305 +/- 0.00	0	0.093 +/- 0.036
1-25-1	0.2	0.530 +/- 0.000	0.996	0.281 +/- 0.098
1-25-1	0.02	0.170 +/- 0.000	0.996	0.029 +/- 0.066
1-25-1	0.002	0.256 +/- 0.000	0	0.066 +/- 0.035
1-25-1	0.3	0.860 +/- 0.000	0.996	0.739 +/- 0.185
1-25-1	0.03	0.178 +/- 0.000	0.996	0.032 +/- 0.06
1-25-1	0.003	0.223 +/- 0.000	0	0.050 +/- 0.041
1-45-1	0.1	0.163 +/- 0.000	0.996	0.027 +/- 0.085
1-45-1	0.01	0.166 +/- 0.000	0.996	0.028 +/- 0.090
1-45-1	0.001	0.245 +/- 0.000	0.996	0.060 +/- 0.036
1-45-1	0.2	0.176 +/- 0.000	0	0.031 +/- 0.091
1-45-1	0.02	0.168 +/- 0.000	0.996	0.028 +/- 0.093
1-45-1	0.002	0.196 +/- 0.000	0.996	0.039 +/- 0.050
1-45-1	0.3	0.028 +/- 0.000	0.986	0.001 +/- 0.001
1-45-1	0.03	0.168 +/- 0.000	0.996	0.028 +/- 0.093
1-45-1	0.003	0.174 +/- 0.000	0.996	0.030 +/- 0.062

Based on table 2, each architectural model has different results if given a different learning rate. Based on the 3 architectural models being trained, architectural models 1-45-1 (lr = 0.3) are the best with root mean squared error = 0.028; correlation = 0.986 and squared correlation = 0.001 +/- 0.001. The following is the complete calculation result of the best architectural model (1-45-1) as shown in Table 3 below.

Table 3. The results of the calculation of the best architectural model (1-45-1 and lr = 0.3)

Province	Target	prediction	error	SE	Result
Aceh	0.11680	0.13564	-0.01884	0.00035	TRUE
North Sumatra	0.27435	0.22528	0.04907	0.00241	TRUE
West Sumatra	0.16547	0.15529	0.01018	0.00010	TRUE
Riau	0.18375	0.16677	0.01698	0.00029	TRUE
Jambi	0.15263	0.14611	0.00652	0.00004	TRUE
South Sumatra	0.20543	0.16892	0.03651	0.00133	TRUE
Bengkulu	0.10651	0.13252	-0.02601	0.00068	TRUE
Lampung	0.18022	0.16678	0.01344	0.00018	TRUE
Kep. Bangka Belitung	0.12155	0.13757	-0.01603	0.00026	TRUE
Kep. Riau	0.11899	0.13707	-0.01807	0.00033	TRUE
DKI Jakarta	0.10667	0.13329	-0.02663	0.00071	TRUE
West Java	0.85954	0.88815	-0.02861	0.00082	TRUE
Central Java	0.60096	0.55053	0.05043	0.00254	FALSE
In Yogyakarta	0.12436	0.13526	-0.01090	0.00012	TRUE
East Java	0.54250	0.50982	0.03269	0.00107	TRUE
Banten	0.36261	0.29022	0.07238	0.00524	FALSE
Bali	0.20161	0.17387	0.02774	0.00077	TRUE
West Nusa Tenggara	0.12712	0.14158	-0.01446	0.00021	TRUE
East Nusa Tenggara	0.11093	0.13491	-0.02398	0.00058	TRUE
West Kalimantan	0.15720	0.15534	0.00186	0.00000	TRUE
Central Kalimantan	0.12546	0.14028	-0.01481	0.00022	TRUE
South Borneo	0.18342	0.16485	0.01857	0.00034	TRUE
East Kalimantan	0.16677	0.15492	0.01185	0.00014	TRUE
North Kalimantan	0.10088	0.13069	-0.02982	0.00089	TRUE
North Sulawesi	0.11208	0.13519	-0.02312	0.00053	TRUE
Central Sulawesi	0.10802	0.13346	-0.02545	0.00065	TRUE
South Sulawesi	0.20207	0.17249	0.02958	0.00087	TRUE
Southeast Sulawesi	0.10415	0.13171	-0.02756	0.00076	TRUE
Gorontalo	0.10263	0.13147	-0.02884	0.00083	TRUE
West Sulawesi	0.10677	0.13117	-0.02440	0.00060	TRUE
Maluku	0.10023	0.13073	-0.03050	0.00093	TRUE
North Maluku	0.10007	0.13068	-0.03060	0.00094	TRUE
West Papua	0.10058	0.13244	-0.03185	0.00101	TRUE
Papua	0.10776	0.13315	-0.02538	0.00064	TRUE
			MSE	0.00081	94
			SSE	0.02739	

Based on table 3 it can be explained that the truth accuracy value is 94%. This result is obtained by looking at the difference in error between the target and the predicted results. In this case the prediction is correct if the error value is less than 0.04 and the prediction is wrong if the error value is greater than 0.04. The error value is determined based on the needs of the study. The smaller the error value, the better the prediction results. The best architectural models (1-45-1 and lr = 0.3) are then tested using testing data so that the results of testing with testing data can be seen in table 4 below.

Table 4: Test results with the test dataset (1-45-1 and lr = 0.3)

Province	Target	prediction	error	SE	Result
Aceh	0.13658	0.13740	-0.00081	0.00000066	TRUE
North Sumatra	0.24013	0.18661	0.05352	0.00286472	FALSE
West Sumatra	0.15365	0.14991	0.00374	0.00001401	TRUE
Riau	0.19805	0.15517	0.04288	0.00183884	TRUE
Jambi	0.13171	0.14640	-0.01469	0.00021587	TRUE
South Sumatra	0.17581	0.16186	0.01396	0.00019484	TRUE
Bengkulu	0.10750	0.13501	-0.02750	0.00075652	TRUE
Lampung	0.18562	0.15413	0.03149	0.00099160	TRUE
Kep. Bangka Belitung	0.12325	0.13852	-0.01527	0.00023323	TRUE
Kep. Riau	0.12338	0.13791	-0.01453	0.00021115	TRUE
DKI Jakarta	0.11789	0.13505	-0.01715	0.00029420	TRUE
West Java	0.90000	0.71755	0.18245	0.03328906	FALSE
Central Java	0.69958	0.40502	0.29456	0.08676813	FALSE
In Yogyakarta	0.15093	0.13920	0.01173	0.00013761	TRUE
East Java	0.56055	0.35119	0.20936	0.04383097	FALSE
Banten	0.30136	0.22743	0.07393	0.00546528	TRUE
Bali	0.17067	0.16064	0.01003	0.00010051	TRUE
West Nusa Tenggara	0.13727	0.13987	-0.00260	0.00000678	TRUE
East Nusa Tenggara	0.11775	0.13602	-0.01827	0.00033395	TRUE
West Kalimantan	0.15070	0.14763	0.00307	0.00000941	TRUE
Central Kalimantan	0.12294	0.13947	-0.01653	0.00027338	TRUE
South Borneo	0.18547	0.15507	0.03039	0.00092368	TRUE
East Kalimantan	0.14964	0.15027	-0.00063	0.00000040	TRUE
North Kalimantan	0.10461	0.13374	-0.02913	0.00084833	TRUE
North Sulawesi	0.10913	0.13629	-0.02716	0.00073782	TRUE
Central Sulawesi	0.10511	0.13535	-0.03024	0.00091462	TRUE
South Sulawesi	0.17533	0.16079	0.01454	0.00021154	TRUE
Southeast Sulawesi	0.10409	0.13447	-0.03038	0.00092307	TRUE
Gorontalo	0.10314	0.13413	-0.03099	0.00096063	TRUE
West Sulawesi	0.10197	0.13507	-0.03310	0.00109559	TRUE
Maluku	0.10064	0.13359	-0.03295	0.00108583	TRUE
North Maluku	0.10022	0.13356	-0.03334	0.00111165	TRUE
West Papua	0.10068	0.13367	-0.03299	0.00108855	TRUE
Papua	0.10640	0.13530	-0.02889	0.00083491	TRUE
			MSE	0.00555	91
			SSE	0.18857	

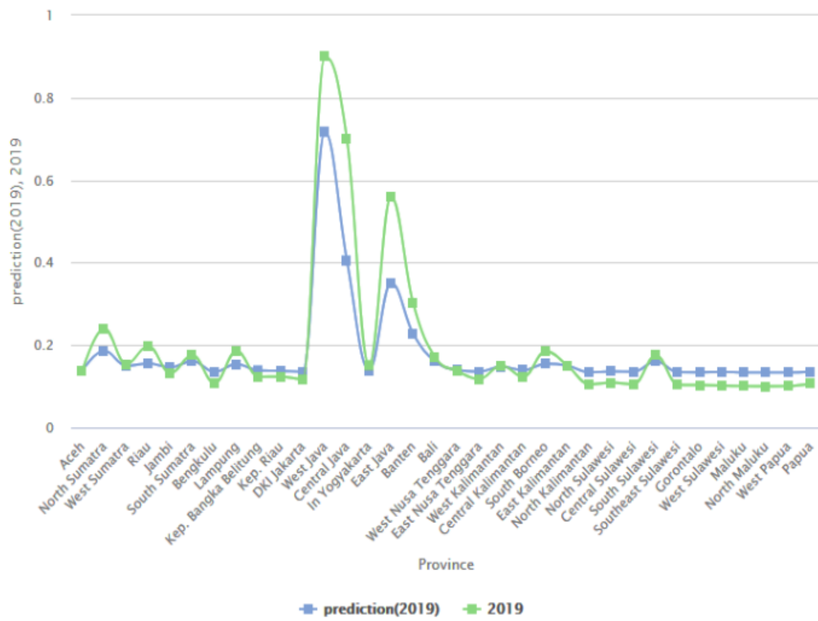

Figure 3: Comparison of the predicted results with the target

Based on table 4 it can be explained that the truth accuracy value reaches 91%. The following is a visualization of the prediction comparison chart with the target based on the input testing dataset as in the figure 3.

Based on Figure 3, the comparison of the target and prediction has a small error value (smaller than 0.04). This explains that learning rate optimization has an impact on the prediction of broiler chicken population by province in Indonesia. The results show that the learning rate can produce the best architectural model seen from the root mean squared error; correlation and squared correlation.

CONCLUSION

Based on the research results, it can be explained that the application of the learning rate can improve learning outcomes in the back-propagation architectural model in the case of broiler chicken populations according to provinces in Indonesia. From the three architectural models (1-2-1; 1-25-1 and 1-45-1) and the learning rate (0.1; 0.01; 0.001; 0.2; 0.02; 0.002; 0.3; 0.03; 0.003), the model 1-45 is obtained. -1 (lr = 0.3) is the best model with Root Mean Squared Error = 0.028 in the training data. With this model, the prediction results obtained with an accuracy value of 91% and Root Mean Squared Error = 0.00555 in the testing data.

REFERENCES

1. Karimi, H., Yousefi, F., 2012. Application of artificial neural network-genetic algorithm (ANN-GA) to correlation of density in nanofluids. Fluid Phase Equilibria 336: 79–83, Doi: 10.1016/j.fluid.2012.08.019.
2. Rahim, R., 2020. Educational Data Mining (EDM) on the use of the internet in the world of Indonesian education. TEM Journal, Doi: 10.18421/TEM93-39.
3. Šlibar, B., 2019. Predicting the number of downloads of open datasets by naive bayes classifier. TEM Journal 8(4): 1331–8, Doi: 10.18421/TEM84-33.
4. Rozaq, I., Satriyanto, E., 2018. Wireless Sensor Network (WSN) application for Monitoring the River Water Level. Proceedings of the The 1st International Conference on Computer Science and Engineering Technology Universitas Muria Kudus, EAI.
5. Wu, Y.K., Hong, J.S., 2007. A literature review of wind forecasting technology in the world. 2007 IEEE Lausanne POWERTECH, Proceedings, p. 504–9.
6. Li, Q., Zhang, X., Rigat, A., Li, Y., 2016. Parameters optimization of back propagation neural network based on memetic algorithm coupled with genetic algorithm. Proceedings - 2015 IEEE 12th International Conference on Ubiquitous Intelligence and Computing, 2015 IEEE 12th International Conference on Advanced and Trusted Computing, 2015 IEEE 15th International Conference on Scalable Computing and Communications, 20: 1359–64, Doi: 10.1109/UIC-ATC-ScalCom-CBDCom-IoP.2015.245.
7. Han, J.U.N., Sinne, S., 1996. Contributed Paper Optimization of Feedforward Neural Networks. Engineering Applications of Artificial Intelligence 9(2): 109–19.

8. Nikentari, N., Kurniawan, H., Ritha, N., Kurniawan, D., Maritim, U., Ali, R., 2018. Particle Swarm Optimization Untuk Prediksi Pasang Surut Air Optimization of Backpropagation Artificial Neural Network With Particle Swarm Optimization To Predict Tide Level. Jurnal Teknologi Informasi Dan Ilmu Komputer 5(5): 605–12, Doi: 10.25126/jtiik2018551055.
9. Rahman, W., Nguyen, P.T., Rusliyadi, M., Laxmi Lydia, E., Shankar, K., 2019. Network monitoring tools and techniques uses in the network traffic management system. International Journal of Recent Technology and Engineering 8(2 Special Issue 11): 4182–8, Doi: 10.35940/ijrte.B1603.0982S1119.
10. Moreira, M., Fiesler, E., 1995. Neural Networks with Adaptive Learning Rate and Momentum Terms. Technique Report 95 4: 1–29.
11. Susanto, E., Novitasari, Y., Rahman, W., Amane, A.P.O., 2019. Designing Software to Introduce the Musical Instruments. Journal of Physics: Conference Series, vol. 1364. Institute of Physics Publishing.
12. Elgimati, Y., 2020. Weighted Bagging in Decision Trees: Data Mining. JINAV: Journal of Information and Visualization, Doi: 10.35877/454ri.jinav149.
13. Sudirman., Windarto, A.P., Wanto, A., 2018. Data mining tools | rapidminer: K-means method on clustering of rice crops by province as efforts to stabilize food crops in Indonesia. IOP Conference Series: Materials Science and Engineering 420: 012089, Doi: 10.1088/1757-899X/420/1/012089.
14. Hizham, F.A., Nurdiansyah, Y., Firmansyah, D.M., 2018. Implementasi Metode Backpropagation Neural Network (BNN) dalam Sistem Klasifikasi Ketepatan Waktu Kelulusan Mahasiswa (Studi Kasus: Program Studi Sistem Informasi Universitas Jember). Berkala Sainstek 6(2): 97, Doi: 10.19184/bst.v6i2.9254.

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