OPTIMIZATION FORECASTING USING BACK-PROPAGATION ALGORITHM

Budi Raharjo1, Nurul Farida2, Purwo Subekti3, Rima Herlina S Siburian4, Putu Doddy Heka Ardana5, Robbi Rahim6,*

1Universitas STEKOM, Department of Information System, Semarang, Indonesia
2Universitas Islam Balitar, Department of Management, Blitar, Indonesia
3Universitas Pasir Pengaraian, Department of Mechanical Engineering, Riau, Indonesia
4Universitas Papua, Department of Forestry, Papua Barat, Indonesia
5Universitas Ngurah Rai, Department of Civil Engineering, Denpasar, Indonesia
6Sekolah 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 dataset 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 )
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.

**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 | 0.15368 |
| 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 | 0.10377 | 0.10197 |
| Maluku               | 0.10016 | 0.10023 | 0.10064 |
| North Maluku         | 0.10009 | 0.10007 | 0.10022 |
| West Papua           | 0.10503 | 0.10058 | 0.10068 |
| Papua                | 0.10702 | 0.10776 | 0.10640 |

**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 Rapid Miner 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...
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 +/- 0.000         | 0.996       | 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         | 0.996       | 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         | 0.996       | 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         | 0.996       | 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| 0.18692    | 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 | 0.0001401| TRUE   |
| Riau                  | 0.19805 | 0.15517    | 0.04288 | 0.00189884| 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       | 0.14564 | 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| 0.00090663| 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
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.

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