Implementation of Backpropagation ANN in Predicting Long Bean Crop Production in Sumatra Island Province

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ABSTRACT

The production of long bean vegetable crops in Indonesia is very high, this is because this plant is easy to cultivate. Predicting the production of long bean vegetable crops on the island of Sumatra, where the data source comes from BPS (Central Bureau of Statistics). In predicting the use of ANN (Artificial Neural Networks) and the method used in this study is the backpropagation algorithm, this method will be used to predict or predict the production of long bean vegetable crops on the island of Sumatra. The results have been obtained using 4 models, namely the 6-5-1, 6-10-1, 6-15-1, and 6-20-1 models. Among the 4 existing models, the 6-5-1 model has the more accurate accuracy or the lowest error value with an MSE of 0.00711838.

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1. INTRODUCTION

Long bean plant or synthetic vigna L is a vegetable commodity that has long been known and favored by many people (Pranindar et al., 2017). In long beans there is vitamin A, vitamin B, vitamin C, and minerals, especially in young pods (Pertiwi et al., 2021). Long bean seeds contain protein, fat, and carbohydrates so that long beans are a good source of vegetable protein for humans. Production of long bean vegetable crops in Indonesia is very large and has spread to various regions on the island of Sumatra. Long bean vegetable plants on the island of Sumatra continue to produce. The demand for long beans every year on the island of Sumatra sometimes goes up and sometimes down. BPS (Central Statistics Agency) said that in 2019-2020 the production of vegetable beans on the island of Sumatra experienced an increase. In the sales sector, this will greatly impact because the demand for goods is low while production is high, so it will cause losses. In this case, a prediction is needed to avoid losses. The method that will be used in this case is the fletcher-Reever backpropagation algorithm. This algorithm is one of the ANN (Artificial Neural Network) methods (Andrijasa & Mistianingsih, 2016).

2. RESEARCH METHOD

2.1 Artificial Neural Network

The research method used is an artificial neural network with machine learning methods (Eddy et al., 2018). Machine learning is a branch of artificial intelligence or artificial intelligence that allows systems to adapt human abilities to learn (Devianto & Dwiasnati, 2020). This algorithm is also trained to make predictions in data development through the use of statistics (Saifudin & Wahono,
2013). Algorithms or sequences of statistical processes are trained to find certain patterns and features in large amounts of data (Azhari et al., 2021). It aims to make better decisions (Izzawati & Lisnawati, 2015). The better the algorithm obtained, the better the accuracy of the decisions and predictions of the system (Fizatullah, 2021). Machine learning works based on the analysis of the data embedded in it (F. A. Nugraha et al., 2020). This input and output data processing training can help predict answers and find the correct intrinsic pattern in the input data (Manurung et al., 2022).

2.2 Research Source

The data sample used is a dataset sample of long bean vegetable production in the provinces on the island of Sumatra from 2007-2020 data sourced from BPS (Central Statistics Agency).

| Province          | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|-------------------|------|------|------|------|------|------|
| ACEH              | 17032| 13380| 12868| 18507| 17021| 18728|
| NORTH SUMATRA     | 46815| 41995| 34628| 41097| 47612| 50593|
| WEST SUMATRA      | 7143 | 8689 | 9955 | 8775 | 9367 | 11319|
| JAMBI             | 10451| 7953 | 9974 | 11056| 12830| 11572|
| RIAU              | 7715 | 5703 | 6361 | 7842 | 8894 | 7712 |
| SOUTH SUMATRA     | 11508| 17121| 19019| 22303| 12922| 12544|
| BENGKULU          | 13453| 20067| 20412| 23086| 15702| 12108|
| LAMPUNG           | 13220| 16161| 19096| 21665| 17870| 17575|
| KEP. BANGKA BELITUNG | 4138 | 4327 | 5443 | 5962 | 5185 | 4051 |
| KEP. RIAU         | 4971 | 3851 | 4242 | 3476 | 3210 | 4658 |

2.3 Research Stages

Figure 1 explains that the initial step that must be taken at the research stage is, the first to collect the data to be studied (based on table 1). The next stage is to separate the data into research data and test data. Data for 2007-2012 with a target of 2013 being the training data and data for 2014-2019 with a target of 2020 being the data to be tested. Next is to normalize the training data and test data using the equation formula (Prayudha et al., 2019)

\[
X' = \frac{0.8(x-a)}{b-a} + 0.1
\]  

\(X'\) = normalized data result  
\(x\) = data to be normalized  
\(a\) = highest value  
\(b\) = lowest value

Training data with normalized test data is entered in MATLAB for processing, and is continued by building a multi-layer neural network (training data input) (Khairururizal, 2021). Next is to apply the Fletcher-Reeves algorithm. Creating a multi-layer neural network using the tangent function and the logsig function (Ginantra et al., 2022). The next step is to initialize the network parameters based on the training function (traincgf). To search for performance results, must Enter a training process command and view the results when performance is found (D. Nugraha & Rosa, n.d.). If the results of the training reach convergence, it will be continued by entering the normalized test data (Junaidi et al., 2021). But if the results of the training data still have not reached convergence, then return to the initialization stage of network parameters. The next stage is carried out by simulating test data based on the results of the training. When everything has been done, the final stage is to conduct...
an evaluation to see the best architectural model based on the lowest performance/MSE test. (Sinaga et al., 2019) (D. Nugraha & Rosa, n.d.).

3. RESULTS AND DISCUSSIONS

3.1 Normalized Data Results

Table 2 below is the result of the normalization of training data in 2007-2012 with a target in 2013, which is sourced from table 1. The data is normalized using the sigmoid function.

| Province          | 2007  | 2008  | 2009  | 2010  | 2011  | 2012  | 2013 (Target) |
|-------------------|-------|-------|-------|-------|-------|-------|---------------|
| ACEH              | 0.3334| 0.2717| 0.2631| 0.3583| 0.3332| 0.3620| 0.3033        |
| NORTH SUMATRA     | 0.8362| 0.7548| 0.6305| 0.7397| 0.8497| 0.9000| 0.7322        |
| WEST SUMATRA      | 0.1664| 0.1925| 0.2139| 0.140  | 0.2040| 0.2369| 0.2628        |
| JAMBI             | 0.2223| 0.1801| 0.2142| 0.2235| 0.2824| 0.2412| 0.2560        |
| RIAU              | 0.1761| 0.1963| 0.2074| 0.2324| 0.2502| 0.2302| 0.2322        |
| SOUTH SUMATRA     | 0.2401| 0.3349| 0.3669| 0.4224| 0.2640| 0.2576| 0.2497        |
| BENGKULU          | 0.2729| 0.3846| 0.3904| 0.4356| 0.3109| 0.2502| 0.2234        |
| LAMPUNG           | 0.2690| 0.3187| 0.3682| 0.4119| 0.3475| 0.3425| 0.3932        |
| KEEP. BANGKA BELITUNG | 0.1157| 0.1189| 0.1377| 0.1465| 0.1333| 0.1142| 0.1367        |
| KEEP. RIAU        | 0.1297| 0.1108| 0.1174| 0.1045| 0.1000| 0.1244| 0.1256        |

Table 3 below is the Result of Normalization of Testing Data for 2014-2019 with a target of 2020, which is sourced from table 1. The data is normalized using the sigmoid function.

| Province          | 2014  | 2015  | 2016  | 2017  | 2018  | 2019  | 2020 (Target) |
|-------------------|-------|-------|-------|-------|-------|-------|---------------|
| ACEH              | 0.2899| 0.3106| 0.2906| 0.2786| 0.2687| 0.2664| 0.2738        |
| NORTH SUMATRA     | 0.8854| 0.9000| 0.8137| 0.8788| 0.6599| 0.6083| 0.6614        |
| WEST SUMATRA      | 0.2752| 0.3057| 0.2888| 0.3272| 0.4310| 0.4513| 0.4264        |
| JAMBI             | 0.3028| 0.2290| 0.2980| 0.2733| 0.2898| 0.2367| 0.2521        |
| RIAU              | 0.2247| 0.2139| 0.2721| 0.2104| 0.2272| 0.2135| 0.2181        |
| SOUTH SUMATRA     | 0.2331| 0.2322| 0.2371| 0.2500| 0.2339| 0.2467| 0.2317        |
| BENGKULU          | 0.2529| 0.2053| 0.1917| 0.1780| 0.1633| 0.1573| 0.1606        |
| LAMPUNG           | 0.3987| 0.3786| 0.4008| 0.3607| 0.3189| 0.2968| 0.3160        |
| KEEP. BANGKA BELITUNG | 0.1484| 0.1205| 0.1090| 0.1063| 0.1059| 0.1000| 0.1065        |
| KEEP. RIAU        | 0.2013| 0.1534| 0.1410| 0.1489| 0.1564| 0.1505| 0.1393        |

3.2 Training and Testing
Data processing is carried out using tools in Matlap which aims to determine the best architectural model. The method used in the architectural model is Fletcher-Reeves. The architecture used is 4 models, namely 6-5-1, 6-10-1, 6-15-1 and 6-20-1. For the first data structure is called input, the second data is called hidden and the third data is called output. Parameters used in the Fletcher-Reeves algorithm.

### 3.2.1 Training and Testing 6-5-1

The results of the 6-5-1 architectural model get 170 iterations of epochs. The results of the training are in table 4 and the test results are in table 5.

| No | X1   | X2   | X3   | X4   | X5   | X6   | Target (Y1) actual | Epoch 170 Error | Perf / MSE |
|----|------|------|------|------|------|------|-------------------|-----------------|------------|
| 1  | 0.3334 | 0.2717 | 0.2631 | 0.3583 | 0.3332 | 0.3620 | 0.3033 | 0.3068 | -0.0035 |
| 2  | 0.8362 | 0.7548 | 0.6305 | 0.7397 | 0.8497 | 0.9000 | 0.7322 | 0.7322 | 0.0000 |
| 3  | 0.1664 | 0.1925 | 0.2139 | 0.140 | 0.2040 | 0.2369 | 0.2628 | 0.2646 | -0.0018 |
| 4  | 0.2223 | 0.1801 | 0.2142 | 0.2325 | 0.2624 | 0.2412 | 0.2560 | 0.2474 | 0.0086 |
| 5  | 0.1761 | 0.1963 | 0.2074 | 0.2324 | 0.2502 | 0.2302 | 0.2322 | 0.2388 | -0.0066 |
| 6  | 0.2401 | 0.3349 | 0.3669 | 0.4224 | 0.2640 | 0.2576 | 0.2497 | 0.2464 | 0.0033 |
| 7  | 0.2729 | 0.3846 | 0.3904 | 0.4356 | 0.3109 | 0.2502 | 0.2234 | 0.2270 | -0.0036 |
| 8  | 0.2690 | 0.3187 | 0.3682 | 0.4119 | 0.3475 | 0.3425 | 0.3932 | 0.3914 | 0.0018 |
| 9  | 0.1157 | 0.1189 | 0.1377 | 0.1465 | 0.1333 | 0.1142 | 0.1367 | 0.1340 | 0.0027 |
| 10 | 0.1297 | 0.1108 | 0.1174 | 0.1045 | 0.1000 | 0.1244 | 0.1256 | 0.1271 | -0.0015 |

### 3.2.2 Training and Testing 6-10-1

The results of the 6-10-1 architectural model get 166 iterations of epochs. The results of the training are in table 6 and the test results are in table 7.

| No | X1   | X2   | X3   | X4   | X5   | X6   | Target (Y1) actual | Epoch 166 Error | Perf / MSE |
|----|------|------|------|------|------|------|-------------------|-----------------|------------|
| 1  | 0.3334 | 0.2717 | 0.2631 | 0.3583 | 0.3332 | 0.3620 | 0.3033 | 0.3033 | 0.0002 |
| 2  | 0.8362 | 0.7548 | 0.6305 | 0.7397 | 0.8497 | 0.9000 | 0.7322 | 0.7322 | 0.0000 |
| 3  | 0.1664 | 0.1925 | 0.2139 | 0.140 | 0.2040 | 0.2369 | 0.2628 | 0.2646 | -0.0018 |
| 4  | 0.2223 | 0.1801 | 0.2142 | 0.2325 | 0.2624 | 0.2412 | 0.2560 | 0.2474 | 0.0086 |
| 5  | 0.1761 | 0.1963 | 0.2074 | 0.2324 | 0.2502 | 0.2302 | 0.2322 | 0.2388 | -0.0066 |
| 6  | 0.2401 | 0.3349 | 0.3669 | 0.4224 | 0.2640 | 0.2576 | 0.2497 | 0.2464 | 0.0033 |
| 7  | 0.2729 | 0.3846 | 0.3904 | 0.4356 | 0.3109 | 0.2502 | 0.2234 | 0.2270 | -0.0036 |
| 8  | 0.2690 | 0.3187 | 0.3682 | 0.4119 | 0.3475 | 0.3425 | 0.3932 | 0.3914 | 0.0018 |
| 9  | 0.1157 | 0.1189 | 0.1377 | 0.1465 | 0.1333 | 0.1142 | 0.1367 | 0.1340 | 0.0027 |
| 10 | 0.1297 | 0.1108 | 0.1174 | 0.1045 | 0.1000 | 0.1244 | 0.1256 | 0.1271 | -0.0015 |

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Table 7. Test Data Results

| No | X7 | X8 | X9 | X10 | X11 | X12 | Target (Y1) | Epoch 166 |
|----|----|----|----|-----|-----|-----|-------------|------------|
| 1  | 0.2899 | 0.3106 | 0.2906 | 0.2786 | 0.2687 | 0.2664 | 0.2738 | 0.3772 | -0.1034 |
| 2  | 0.8854 | 0.9000 | 0.8137 | 0.8788 | 0.6599 | 0.6083 | 0.6614 | 0.5830 | 0.0784 |
| 3  | 0.2752 | 0.3057 | 0.2888 | 0.3272 | 0.4310 | 0.4513 | 0.4264 | 0.3579 | 0.0685 |
| 4  | 0.3028 | 0.2290 | 0.2980 | 0.2733 | 0.2898 | 0.2367 | 0.2521 | 0.4743 | -0.2222 |
| 5  | 0.2247 | 0.2139 | 0.2721 | 0.2104 | 0.2272 | 0.2135 | 0.2181 | 0.4222 | -0.2041 |
| 6  | 0.2331 | 0.2322 | 0.2371 | 0.2500 | 0.2939 | 0.2467 | 0.2317 | 0.2991 | -0.0674 |
| 7  | 0.2529 | 0.2053 | 0.1917 | 0.1760 | 0.1633 | 0.1573 | 0.1606 | 0.2104 | -0.0498 |
| 8  | 0.1484 | 0.1205 | 0.1090 | 0.1063 | 0.1059 | 0.1000 | 0.1065 | 0.1144 | -0.0079 |
| 9  | 0.2013 | 0.1534 | 0.1410 | 0.1489 | 0.1564 | 0.1505 | 0.1393 | 0.1380 | 0.0013 |

3.2.3 Training and Testing 6-15-1

The results of the 6-15-1 architectural model get the epoch results of 118 iterations. The results of the training can be seen in table 8 and the test in table 9.

Table 8. Training Data Results

| No | X1 | X2 | X3 | X4 | X5 | X6 | Target (Y1) | Epoch 118 |
|----|----|----|----|----|----|----|-------------|------------|
| 1  | 0.3334 | 0.2717 | 0.2631 | 0.3583 | 0.3332 | 0.3620 | 0.3033 | 0.3033 | 0.0000 |
| 2  | 0.8362 | 0.7548 | 0.6305 | 0.7397 | 0.8497 | 0.9000 | 0.7322 | 0.7322 | 0.0000 |
| 3  | 0.1664 | 0.1925 | 0.2139 | 0.140 | 0.2040 | 0.2369 | 0.2628 | 0.2628 | 0.0000 |
| 4  | 0.2223 | 0.1801 | 0.2142 | 0.2325 | 0.2624 | 0.2412 | 0.2560 | 0.2560 | 0.0000 |
| 5  | 0.1761 | 0.1963 | 0.2074 | 0.2324 | 0.2502 | 0.2302 | 0.2322 | 0.2321 | 0.0001 |
| 6  | 0.2401 | 0.3349 | 0.3669 | 0.4224 | 0.2640 | 0.2576 | 0.2497 | 0.2497 | 0.0000 |
| 7  | 0.2729 | 0.3846 | 0.3904 | 0.4356 | 0.3109 | 0.2502 | 0.2234 | 0.2234 | 0.0000 |
| 8  | 0.2690 | 0.3187 | 0.3682 | 0.4119 | 0.3475 | 0.3425 | 0.3932 | 0.3931 | 0.0001 |
| 9  | 0.1157 | 0.1109 | 0.1377 | 0.1465 | 0.1333 | 0.1142 | 0.1367 | 0.1368 | -0.0001 |
| 10 | 0.1297 | 0.1108 | 0.1174 | 0.1045 | 0.1000 | 0.1244 | 0.1256 | 0.1255 | 0.0001 |

Table 9. Test Data Results

| No | X7 | X8 | X9 | X10 | X11 | X12 | Target (Y1) | Epoch 118 |
|----|----|----|----|-----|-----|-----|-------------|------------|
| 1  | 0.2899 | 0.3106 | 0.2906 | 0.2786 | 0.2687 | 0.2664 | 0.2738 | 0.3538 | -0.0800 |
| 2  | 0.8854 | 0.9000 | 0.8137 | 0.8788 | 0.6599 | 0.6083 | 0.6614 | 0.5267 | 0.1347 |
| 3  | 0.2752 | 0.3057 | 0.2888 | 0.3272 | 0.4310 | 0.4513 | 0.4264 | 0.6736 | -0.2472 |
| 4  | 0.3028 | 0.2290 | 0.2980 | 0.2733 | 0.2898 | 0.2367 | 0.2521 | 0.3657 | -0.1136 |
| 5  | 0.2247 | 0.2139 | 0.2721 | 0.2104 | 0.2272 | 0.2135 | 0.2181 | 0.3608 | -0.1427 |
| 6  | 0.2331 | 0.2322 | 0.2371 | 0.2500 | 0.2939 | 0.2467 | 0.2317 | 0.2967 | -0.0650 |
| 7  | 0.2529 | 0.2053 | 0.1917 | 0.1780 | 0.1633 | 0.1573 | 0.1606 | 0.1700 | -0.0094 |
| 8  | 0.3987 | 0.3786 | 0.4008 | 0.3607 | 0.3189 | 0.2968 | 0.3160 | 0.2818 | 0.0342 |
| 9  | 0.1487 | 0.1205 | 0.1090 | 0.1063 | 0.1059 | 0.1000 | 0.1065 | 0.1123 | -0.0058 |
| 10 | 0.2013 | 0.1534 | 0.1410 | 0.1489 | 0.1564 | 0.1505 | 0.1393 | 0.1330 | 0.0063 |

3.3 Training and Testing 6-20-1

The results of the 6-5-1 architectural model get an epoch of 162 iterations. The results of the training can be seen in table 10 and the test in table 11.

Table 10. Training Data Results

| No | X1 | X2 | X3 | X4 | X5 | X6 | Target (Y1) | Epoch 162 |
|----|----|----|----|----|----|----|-------------|------------|
| 1  | 0.3334 | 0.2717 | 0.2631 | 0.3583 | 0.3332 | 0.3620 | 0.3033 | 0.3034 | -0.0001 |

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3.4 Determination of the Best Architectural Model

After conducting training and testing data on the 6-5-1, 6-10-1, 6-15-1 and 6-20-1 models using the Matlab application and Microsoft excel, the best model architecture was obtained, namely 6-5-1. Model 6-5-1 with epoch 170 is the best model among other models because it has high accuracy and has a low MSE/performance value of 0.00711838. We can see the results from Table 12 and the graph.

Table 12. Comparison of all Architectural Models

| Algorithm     | Architecture | Training Function | Epoch (Iteration) | MSE Training | MSE Testing/Performance |
|---------------|--------------|-------------------|-------------------|--------------|-------------------------|
| fletcher-Reeves | 6-5-1        | Traincgf          | 170               | 0.00001690  | 0.00711838              |
|               | 6-10-1       | Traincgf          | 166               | 0.000000002 | 0.01599192              |
|               | 6-15-1       | Traincgf          | 118               | 0.00000001  | 0.01244905              |
|               | 6-20-1       | Traincgf          | 162               | 0.000000004 | 0.00824566              |

Figure 2. Best Architectural Model

4. CONCLUSION

The Artificial Neural Network method makes it easier to do research, where the machine learning method can help to find performance values and also determine the best value from the sample
data to be studied. The application that participates in this research is the matlab application, because matlab itself has a feature to calculate performance and to find the best value with the help of the Fletcher-Reeves algorithm. Conducted testing with 4 samples including 6-5-1, 6-10-1, 6-15-1, and 6-20-1. Of the five samples, there are samples that get the best results from other samples, namely sample 6-5-1 with an MSE/Performance value of 0.00711838. This research has obtained the highest accuracy or has the lowest performance value by using the help of matlab tools.

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