



Predicting coffee productivity using artificial neural networks

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Abstract

Coffee is a leading commodity in Indonesia as a raw material for making food, beverages, and other processed products. The demand for coffee is competitive in the international market as a source of foreign exchange for the country. Uncertain production results greatly affect production costs and impact the economy of farmers. Therefore, it is necessary to make a prediction to determine the likelihood of the development of coffee productivity in the future. This research uses data on coffee production from farmers from 2014 to 2023. The algorithm used in this research is the backpropagation artificial neural network. The backpropagation algorithm is one of the artificial neural networks that uses a systematically working multilayer that is very strong and objective through developed network architecture models so that it can make good predictions. The network architecture model used is 4 input neurons, 2 hidden neurons, and 1 output neuron. The maximum epoch value used is 1000, and the learning rate ranges from 0.1 to 0.9. The training process resulted in the best weights with an MSE value of 0.007703 at a learning rate of 0.2. Based on this research, it is expected to provide benefits for farmers as a solution, reference, and evaluation material to improve coffee productivity and minimize the budget for land and plant processing production costs in the future, as well as provide information on future harvests.

Keywords

Coffee, Productivity, Artificial neural networks

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Coffee is a

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Coffee is a prominent commodity in Indonesia, both in terms of business and its utilization as raw materials for the production of food, beverages, and other products. The demand for coffee usage is competitive in the international market, serving as a vital source of foreign exchange for the country. Rejosari Village, located in Temanggung Regency, is a community where the primary livelihood for most residents revolves around coffee farming. However, the annual productivity of coffee in this village is not consistent; sometimes the yields are favorable, while at other times they are relatively modest, as observed from 2014 to 2023. The fluctuations in productivity

significantly impact production costs for land and crop processing, which remain consistently high each year. Additionally, these fluctuations have broader implications for the economy of individuals dependent on coffee agricultural products [1].

Prediction is the process of systematically estimating something that is most likely to happen in the future based on information from the past and present. This system can be used because it predicts future results using data from the past and present and employs scientific analysis to produce accurate data output for estimating future results [2-3].

Backpropagation is a component of Neural Networks that uses multilayers working systematically, proving to be powerful and objective through developed network architecture models that enable accurate predictions. This method involves supervised training and evaluates the error contribution of each neuron after processing a set of data [4]. Additionally, backpropagation algorithms have advantages in formulating forecasting experiences and knowledge, which can assist in the prediction process [5]. The purpose of employing the Backpropagation method is to minimize errors in the output produced by the network. Furthermore, the output results are highly accurate, making the use of this method expected to yield reliable predictions for the future [6].

Methods

Predictions

Prediction or forecasting is the art and science of predicting future events. This can be done by involving taking data in the past to place it into the future. There are two forecasting models, qualitative and quantitative.

Qualitative is a forecasting that uses the consideration of the opinions of experts or experts in their fields. While quantitative is forecasting based on the availability of raw data accompanied by a series of mathematical rules to predict future results [7].

Neural network

Neural networks are part of artificial intelligence designed to assist in various human tasks using the language of computers. They serve as artificial representations of the human brain, consistently striving to emulate the learning processes occurring in the human brain. The components in an Artificial Neural Network include: (a) Neurons: Nerve cells responsible for transforming received information and transmitting it as output to other neurons. (b) Weights: In Artificial Neural Networks, connections between neurons, referred to as weights, serve to replace synaptic functions [8].

Reverse propagation

Backpropagation is a supervised learning algorithm commonly utilized by perceptron's with multiple layers to adjust the weights associated with neurons in their hidden layers. This method is employed to address complex problems, leveraging training as a key

component of its learning process. Backpropagation involves a process of forward propagation and backward error correction [9].

The training phase utilizing the backpropagation method comprises three stages: forward propagation, reverse propagation phase, and weight change phase. These three phases are iterated continuously until a termination condition is met, often defined by the number of iterations or error targets [10][11]. Figure 1 shows the flowchart of the backpropagation calculation process.

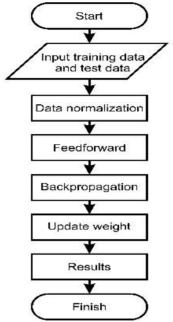


Figure 1. Backpropagation flowchart in the training process

The first step is to input the training data and test data to be used for the calculation process. The second step is to normalize the data to produce input values between 0 and 1. The third step is to perform feedforward calculations to determine the values of each neuron. Next is to perform backpropagation calculations to correct errors at each neuron and then update the resulting best weights. Below are the steps for the backpropagation algorithm [12-14].

Step 1: initialize the initial weight.

Step 2: Set the Maximum Epoch, Error Target, and Learning Rate.

Step 3: Do the following steps during (Epoch < Maximum Epoch) and (MSE > Target Error)

Stage 1: Advanced Propagation

Step 4: Each unit in a hidden layer (Zj, j=1,2, 3..., p) sums the weighted input signals

$$z_{in_{j}} = b1_{j} + \sum_{i=1}^{n} x_{i} v_{ij}$$
 (1)

Step 5: Use the activation function to calculate the output signal.

$$z_j = f(z_{in_j}) \tag{2}$$

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Step 6: Each output unit (Yk, k=1,2, 3..., m) sums the weighted input signals

$$y_{in_{k}} = b2_{k} + \sum_{i=1}^{p} z_{j} w_{jk}$$
 (3)

Step 7: Use the activation function to calculate the output signal

$$y_k = f(y_i n_k) \tag{4}$$

Stage 2: Backward Propagation

Step 8: Each output unit (Yk, k=1,2, 3..., m) receives a pattern target that corresponds to the learning input pattern, calculate the error information

$$\delta 2_k = (t_k - y_k) f'(y_i n_k) \tag{5}$$

Step 9: Calculate weight and bias correction

$$\Delta w_{jk} = \alpha \varphi 2_{jk} \tag{6}$$

$$\Delta b 2_k = \alpha \beta 2_k \tag{7}$$

Step 10: Each unit is hidden (Zj, j=1,2, 3... p) summing its input delta (from different units in its upper layer)

$$\delta_{in_{j}} = \sum_{k=1}^{m} \delta 2_{k} w_{jk} \tag{8}$$

Step 11: Multiply this value by the instance of its activation function to calculate the error information:

$$\delta 1_i = \delta_i n_i f'(z_i n_i) \tag{9}$$

Step 12: Calculate weight and bias correction.

$$\Delta v_{ij} = \alpha \varphi 1_{ij} \tag{10}$$

$$\Delta\beta 1_j = \alpha\beta 1_j \tag{11}$$

Stage 3: Weight Change

Step 13: Each output unit (Yk, k=1,2, 3..., m) corrects its bias and weight (j=0.1, 2..., p)

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$$
(12)
$$b2_k(new) = b2_k(old) + \Delta b2_k$$
(13)

Step 14: Each hidden unit (Zj, j=1,2, 3..., p) corrects its bias and weight (i=0.1, 2..., n)

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$$
(14)

$$b1_j(new) = b1_j(old) + \Delta b1_j$$
(15)

Results and Discussion

Backpropagation testing

The figure below illustrates a graph displaying the results of tests conducted using these parameters. The tests were performed employing a 4-2-1 network architecture, an

epoch value of 1000, and a learning rate ranging from 0.1 to 0.9. Based on the figure, the optimal Mean Squared Error (MSE) value is achieved with a learning rate of 0.2, resulting in an MSE value of 0.007703. Figure 2 shows the parameters with the best values to be implemented into the system. Prediction system application display show in Figure 3.

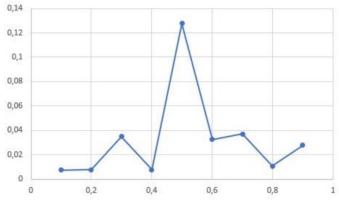


Figure 2. Learning Rate Comparison

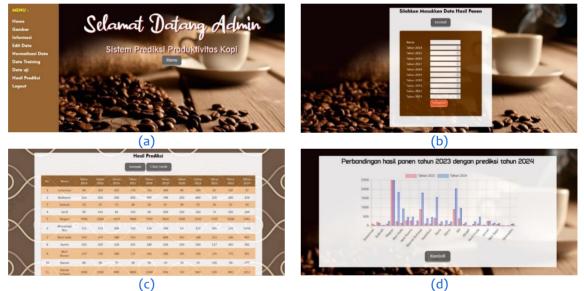


Figure 3. Prediction system application display: (a) Homepage; (b) Add data page; (c) Prediction results page; (d) comparison chart display page

Based on the image Figure 2, the parameter with the best value will be implemented into PHP programming, resulting in a web-based prediction system application. Below is an overview of the created application. Figure 3 is a display of the application that has been created. Figure 3(a) is a display of the dashboard page, on this page there are several menus that can be used to carry out the prediction process. Figure 3(b) is a page display for adding or entering data that will be used for the prediction process, the data used is harvest results for 10 years. Figure 3(c) is a page to display predictions generated for the future as well as previous harvest results. Figure 3(d) is a page that displays a bar chart to compare predicted harvest results with previous harvest results.

Discussion analysis

Many studies have been conducted using the backpropagation method for prediction, one of which was carried out by Anjar Wanto (2019) using the backpropagation method

to predict Indonesian corn productivity for the years 2019-2020. This research resulted in a prediction of corn productivity in Indonesia with an accuracy of 88%, and the best accuracy of the prediction was achieved using a 5-25-1 network architecture, indicating a general increase in corn productivity in Indonesia from 2016 to 2020 [4]. Another study was conducted by Ramadhona Gandi, et al. (2018), using the backpropagation method to predict rice productivity. This research produced a prediction of rice harvest using four tests: learning rate, hidden layer, hidden neurons, and k-fold cross-validation. A small learning rate tended to result in large errors in the prediction, while a large hidden layer tended to produce more uniform prediction values [14]. Furthermore, a study by Willy R.A Situmorang and Miftahul Jannah in 2021 focused on the implementation of backpropagation to predict rice harvests in Pagar Jati Village. This research resulted in a desktop-based system using Visual Studio 2010 as a tool to predict the amount of rice harvest. The testing results of the rice harvest prediction using the Backpropagation Artificial Neural Network successfully addressed the research objective, with a per-rante rice harvest result of 0.17 tons [5].

Based on the relevant research above, this study needs to develop an application that can help farmers to predict coffee productivity for the future. The coffee productivity prediction test was conducted using ten years of harvest data from farmers, which were input into the application. The system will automatically perform the calculation process, starting from data normalization, data training, data testing, to displaying the predicted results from the calculation.

The normalization process is carried out to change raw data into values 0 and 1, this process is carried out to facilitate the training and testing process. After the data is normalized, training is carried out using the back propagation algorithm. This calculation is used to calculate the weight of each neuron used from the input neuron (x), hidden neuron (z), and output (y) then continues to be repeated until there is no change in value, resulting in a weight. best (v).

The best weights produced will be used to carry out tests using test data. This process is carried out to calculate the weight of each neuron from the input neuron (x), hidden neuron (z) so as to produce the best output value (y). The final result in this system is the output from the test which is then denormalized to produce an integer number.

This integer is a prediction of coffee productivity resulting from the calculation stages above. These numbers will be displayed in the form of numbers and bar graphs and will be used to measure comparisons with harvest results in the previous year.

The training was conducted using crop yield data from farmers spanning the years 2014 to 2023. The data was then divided into two parts: data from 2014 to 2018 served as training data, while data from 2019 to 2023 served as test data.

The training utilized a network architecture comprising 4 input layers, 2 hidden layers, and 1 output layer, employing data from 2014 to 2018. Learning rate parameters with a range of 0.1 to 0.9 were applied. From the training, the best score was achieved at a

learning rate of 0.2, resulting in an MSE of 0.007703. The optimal weights obtained from the training were then applied to data from 2019 to 2023.

Conclusion

The prediction system uses Artificial Neural Networks with the Backpropagation method to find out how likely it is that coffee productivity levels will develop successfully. The system has been tested with results that are in accordance with the design so it is hoped that this system can provide benefits for farmers as a solution, reference and evaluation material to be able to increase coffee productivity results and be able to minimize production costs for land and plant processing in the future and can provide information about the upcoming harvest.

Suggestions for future work for further development include the interface still seems simple so a more modern display needs to be created, the min and max values in the programming applied are still done manually so they need to be created automatically. The algorithm used in this application comes from various sources, so it needs to be developed to produce more accurate values.

References

- M. Iqbal Ulumando, "Prediction of Coffee Crop Production in NTT Region Using Backpropagation," JAPPRI: Journal of Agricultural & Agrotechnology Scientific Research Publications, Vol. 4, No. 2, pp. 28–45, 2022.
- [2] A. A. Suryanto and A. Muqtadir, "Application of Linear Regression to Predict Rice Production Needs," Proceedings of the National Seminar on Research Results and Community Service III PGRI Ronggolawe University Tuban, Vol. 3, pp. 331–332, 2018.
- [3] M. Adi DKK., "Application of Backpropagation Algorithm in Predicting Rice Crop Production by District/City in North Sumatera," semantics, Vol. 4, No. 1, pp. 77–86, 2018.
- [4] A. Wanto, "Prediction of Indonesian Corn Productivity in 2019-2020 as an Effort to Anticipate Import Using Backpropagation Artificial Neural Networks," SINTECH Journal | 53 SINTECH JOURNAL, Vol. 1, No. 1, pp. 53–62, 2019, [Online]. Available: http://jurnal.stiki-indonesia.ac.id/index.php/sintechjournal
- [5] W. R. A. Situmorang and M. Jannah, "Implementation of Artificial Neural Network Predicts Rice Yield in Pagar Jati Village by Backpropagation Method," JIKOMSI [Journal of Computer Science and Information Systems], Vol. 3, No. 3, pp. 167–175, 2021.
- [6] C. Oktaviani and Afdal, "Prediction of Monthly Rainfall Using Neural Networks with Multiple Backpropagation Training Functions," Unand Journal of Physics, Vol. 2, No. 4, pp. 228–237, 2013.
- [7] E. P. C. Edi Ismanto, "Neural Network Backpropagation Algorithm in Predicting the Availability of Food Commodities in Riau Province," Rabit: Journal of Technology and Information Systems Univrab, Vol. 2, No. 2, pp. 196–209, August 2017, doi: 10.36341/rabit. v2i2.152.
- [8] M. F. Andrijasa and D. Mistianingsih, "Application of Neural Network to Predict the Number of Unemployed in East Kalimantan Province Using Backpropagation Learning Algorithm," Journal of Informatics Mulawarman, Vol. 5, No. 1, pp. 50–54, 2010.
- [9] R. S. Suhartanto, C. Dewi, and L. Muflikhah, "Implementation of Backpropagation Neural Network to Diagnose Skin Diseases in Children," Journal of Information Technology Development and Computer Science, Vol. 1, No. 7, pp. 555–562, 2017, [brave]. Available: http://j-ptiik.ub.ac.id
- [10] A. Trimulya, F. Agus Setyaningsih, and J. Computer Systems, "Implementation of Neural Networks Backpropagation Method to Predict Stock Prices," Journal of Coding, Untan Computer System, Vol. 03, No. 2, pp. 66–75, 2015.
- [11] W. Santoso and P. Sukmasetya, "Journal of Media Informatics Budidarma Predicting Waste Volume at Banyuurip TPSA Using Backpropagation Neural Network Method," Journal Of Media Informatics Budidarma, Vol. 7, No. 1, pp. 464–472, 2023, doi: 10.30865/mib. v7i1.5499.

- [12] H. I. Fathoni, B. Rahayudi, and D. E. Ratnawati, "Prediction of Vaname Shrimp Harvest using Backpropagation Neural Network Algorithm," Journal of Information Technology Development and Computer Science, Vol. 6, No. 8, pp. 3587–3595, 2022, [Online]. Available: http://j-ptiik.ub.ac.id
- [13] M. Birky Auliya Akbar and A. Afif Supianto, "Optimization of Backpropagation Method Forecasting Using Genetic Algorithm on the Number of Train Passengers in Indonesia," Journal of Information Technology Development and Computer Science, Vol. 3, No. 3, pp. 2533–2541, 2019, [Online]. Available: http://j-ptiik.ub.ac.id.
- [14] G. Ramadhona, B. Darma Setiawan, and F. A. Bachtiar, "Prediction of Rice Productivity Using Backpropagation Neural Network," Journal of Information Technology Development and Computer Science, Vol. 2, No. 12, pp. 6048–6057, 2018, [Online]. Available: http://j-ptiik.ub.ac.id