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Application of Learning Rate in Artificial Neural Networks to Increase Prediction Accuracy on Rubber Tree Maintenance Costs

Erene Gernaria Sihombing[1], Ester Aristawati[2], Rinawati[3], Frisma Handayanna[4], Linda Sari Dewi[5]*
[1,2,3,5]Universitas Bina Sarana Informatika, Indonesia
[4]Universitas Nusa Mandiri, Jakarta, Indonesia
E-mail: erene.egs@bsi.ac.id[1], ester.err@bsi.ac.id[2], rinawati.riw@bsi.ac.id[3], frisma.fha@nusamandiri.ac.id[4], linda.lrw@bsi.ac.id[5]

Abstract

This research aims to explore the impact of various learning rate values in artificial neural networks (ANN) in increasing the accuracy of predicting rubber tree maintenance costs. Using a dataset that includes factors such as tree age, soil conditions, weather, and maintenance methods, an ANN model is built and tested with various learning rate values to find optimal parameters. The research results show that the influence of various learning rate values on the performance of artificial neural networks (ANN) in predicting rubber tree maintenance costs varies significantly. From the training and testing results, learning rate 0.1 shows the best results with MSE 0.00995387 and 75% accuracy on training data, and MSE 0.00976614 and 83% accuracy on testing data. This conclusion emphasizes the importance of choosing the right learning rate value in applying ANN to predict rubber tree maintenance costs, which is expected to help plantation managers improve operational efficiency and cost management.

Keywords: *Artificial Neural Networks, Learning Rate, Cost Prediction, Rubber Tree Care, Prediction Accuracy*

1. Introduction

Rubber plantations are one of the important agricultural sectors in various countries, including Indonesia [1]. Rubber produced from the Hevea brasiliensis tree has high economic value and is used in various industries, from automotive to consumer goods manufacturing [2]. However, to ensure high rubber productivity and quality, rubber tree care requires special attention [3]. This maintenance process includes fertilization, pest control, watering, and pruning, all of which require quite a bit of money [4]. Therefore, the ability to predict is very necessary. Prediction is a crucial aspect in business and agricultural management, including rubber plantation management [5], [6], [7]. The ability to accurately predict rubber tree maintenance costs has a variety of significant benefits, both from an operational and strategic perspective. Especially accurate maintenance cost predictions to assist in budget planning. By knowing the estimated costs required for various maintenance activities such as fertilizing, watering, pest control and pruning, plantation managers can plan their budget more precisely and avoid waste. This is important to maintain the company's financial stability, especially in cyclical industries such as rubber plantations [8], [9], [10].

Several prediction algorithms are often used in data science and machine learning to capture patterns in data and predict future events [11], [12], [13]. These algorithms include linear regression and logistic regression for linear and binary relationships, as well as neural networks which are capable of handling complex and non-linear patterns [14], [15], [16]. Other algorithms such as support vector machines (SVM) search for the best hyperplane for classification [11], [17] [18], [19], K-nearest neighbors (KNN) classify based on nearest neighbors [20], [21][17], [22], and naive Bayes which uses probability even with the assumption of feature independence. In addition, Long Short-Term Memory networks (LSTM) specifically handle sequential and time series data with sophisticated

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memory mechanisms. The selection of an appropriate algorithm depends on the characteristics of the data and the problem at hand, and often a combination of several algorithms is used to increase prediction accuracy [23].

Previous research conducted by Indra Ranggadara et al [24] produced accurate predictions with a MAPE of 3%, this article shows that the prediction model used has a high level of accuracy, which shows that the method chosen is effective for research purposes. However, it has the weakness that this article does not provide information about model validation with data not used in training, which is important for measuring model performance in the real world. Meanwhile, in other research conducted by Xiao-Yu Huang et al [25] in this article developed an artificial neural network (ANN) model based on the ASAPSO optimization algorithm to predict the strength of rubber concrete. This model successfully achieves higher accuracy than conventional ANN models and ANN models optimized by a single algorithm under large datasets. However, this article also lacks discussion of potential limitations or weaknesses of the developed model, such as how this model can react to unexpected data or outliers.

Based on the literature studies that have been described, in this digital era, artificial intelligence (AI) and machine learning technology have made significant contributions in various fields, including agriculture [2], [6], [26]. Artificial neural networks (ANN) are a machine learning method that has been proven effective in predicting and processing complex data. In the context of predicting rubber tree maintenance costs, ANN can be used to analyze various factors that influence these costs and provide more accurate predictions than traditional methods.

One of the important parameters in ANN training is the learning rate, which determines how much adjustment the model makes in each learning iteration. Choosing the right learning rate value is very crucial because it can affect model convergence and prediction accuracy. A learning rate that is too high can cause the model to fail to achieve convergence, while a learning rate that is too low can make the training process very slow and less efficient [24], [26] [11], [27]. Therefore, this research is focused on exploring various learning rate values to find optimal parameters that can increase the accuracy of predicting rubber tree maintenance costs.

With the increasing complexity and volume of available data, the application of ANN technology with optimized parameters becomes increasingly relevant. This research not only aims to improve prediction accuracy, but also to provide insight into the importance of parameter settings in applying ANN. It is hoped that the results of this research can help rubber plantation managers make more precise and efficient decisions regarding rubber tree care, as well as optimizing their operational costs. Thus, this research has the potential to make a significant contribution to increasing the productivity and profitability of the rubber plantation industry.

2. Research Methodology

2.1. Research Design

This research uses a quantitative approach with experimental methods to explore the influence of various learning rate values on artificial neural networks (ANN) in predicting rubber tree maintenance costs. This experimental design was chosen to test the hypothesis that there is an optimal learning rate value that can increase the accuracy of ANN predictions.

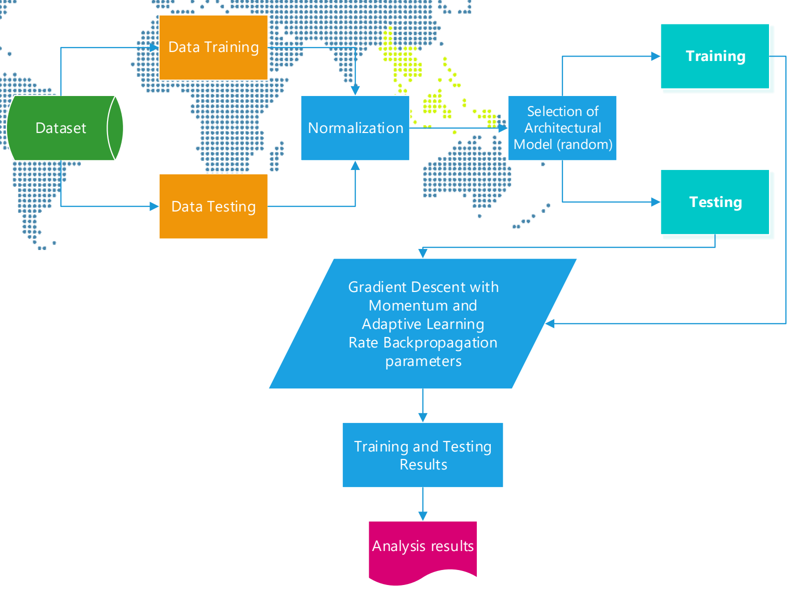


Figure 1. Research Design

Figure 1 explains that this research was designed to optimize the backpropagation algorithm with various activation functions in predicting the level of rubber tree maintenance costs. The following flow diagram explains the main steps in the research process:

1. Dataset: The first step is to collect the dataset that will be used in the research. This dataset contains historical data on the level of rubber tree maintenance costs which will be divided into two parts: training data and testing data.
2. Data Division: The dataset is divided into two parts: training data and testing data. Training data is used to train the neural network model, while testing data is used to test the performance of the trained model.
3. Normalization: Data that has been divided is then normalized. Normalization is the process of scaling data so that it falls within a certain range, usually between 0 and 1. This is important to ensure that the neural network model can learn effectively from the data.
4. Architectural Model Selection: After the data is normalized, the neural network architectural model is randomly selected. This includes selecting the number of hidden layers, the number of neurons in each layer, and other parameters to be used in the model.
5. Training: The selected neural network model is then trained using the training data. The training process uses a backpropagation algorithm with momentum-enhanced gradient descent and adaptive learning rate. Different learning rates are also applied in each experiment to see their effect on model performance.
6. Testing: After training, the model is tested using test data. This test aims to evaluate the model's performance in predicting the level of rubber tree maintenance costs based on data that has never been seen before.
7. Evaluation of Training and Testing Results: The results of training and testing are analyzed to measure prediction accuracy. Evaluation metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used to determine how well the model predicts the level of rubber tree maintenance costs.
8. Results Analysis: The results of the model evaluation are then analyzed to understand the influence of the various activation functions and backpropagation parameters used. This analysis helps determine the most

optimal model configuration in predicting the level of rubber tree maintenance costs.

The diagram as a whole depicts the process flow from the beginning of data collection to the analysis of the final results, ensuring that each step is taken to optimize the prediction of rubber tree care costs using artificial neural networks.

2.2. Data collection

The data used in this research is historical data on rubber tree maintenance costs obtained from rubber plantations in Indonesia at PT Bridgestone Sumatra Rubber Estate. This dataset includes various rubber tree care variables such as tree age, soil condition, rainfall, temperature, type of fertilizer, and pruning frequency which are summarized in the form of monthly maintenance costs. Data were collected over a recent eight-year period to ensure sufficient variation in observations.

Table 1. Sampel Dataset

Month / Year	2015	2016	2017	2018	2019	2020	2021	2022
January	Rp11.280.000	Rp10.560.000	Rp10.920.000	Rp10.800.000	Rp10.920.000	Rp10.800.000	Rp11.280.000	Rp11.005.000
February	Rp11.040.000	Rp10.800.000	Rp10.200.000	Rp10.680.000	Rp11.160.000	Rp11.040.000	Rp11.400.000	Rp11.262.000
March	Rp10.920.000	Rp10.200.000	Rp9.960.000	Rp10.680.000	Rp11.160.000	Rp11.040.000	Rp11.400.000	Rp11.382.000
April	Rp11.040.000	Rp10.560.000	Rp10.080.000	Rp10.560.000	Rp11.040.000	Rp11.280.000	Rp11.280.000	Rp11.280.000
May	Rp11.400.000	Rp10.560.000	Rp10.440.000	Rp10.080.000	Rp10.800.000	Rp11.400.000	Rp11.160.000	Rp11.022.000
June	Rp10.920.000	Rp11.400.000	Rp10.680.000	Rp10.680.000	Rp10.800.000	Rp11.400.000	Rp11.280.000	Rp11.194.000
July	Rp10.920.000	Rp10.440.000	Rp10.800.000	Rp10.560.000	Rp10.560.000	Rp11.280.000	Rp11.280.000	Rp11.194.000
August	Rp11.160.000	Rp10.800.000	Rp10.560.000	Rp10.800.000	Rp10.560.000	Rp10.800.000	Rp11.160.000	Rp10.834.000
September	Rp11.280.000	Rp10.560.000	Rp10.560.000	Rp10.800.000	Rp10.800.000	Rp11.400.000	Rp11.160.000	Rp11.160.000
October	Rp11.400.000	Rp10.800.000	Rp10.680.000	Rp10.080.000	Rp10.800.000	Rp11.400.000	Rp11.400.000	Rp11.125.000
November	Rp11.400.000	Rp11.040.000	Rp10.800.000	Rp9.720.000	Rp10.920.000	Rp11.400.000	Rp11.400.000	Rp11.074.000
December	Rp10.920.000	Rp11.040.000	Rp10.560.000	Rp9.360.000	Rp11.400.000	Rp11.400.000	Rp11.400.000	Rp11.297.000

2.3. Research procedure

This research was carried out through a series of systematic steps to ensure the accuracy and reliability of the results obtained. It can be seen in Figure 2 below:

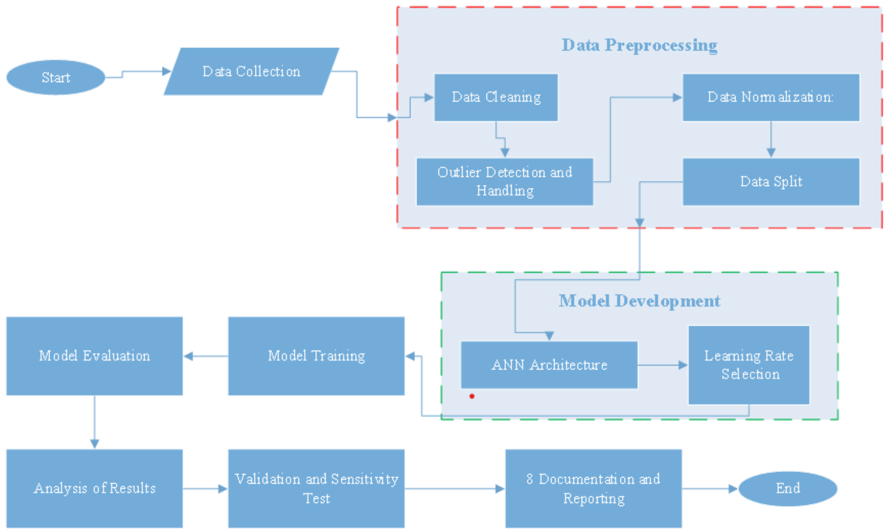


Figure 2. Research Procedure

Figure 2 shows the research procedure including the following steps:

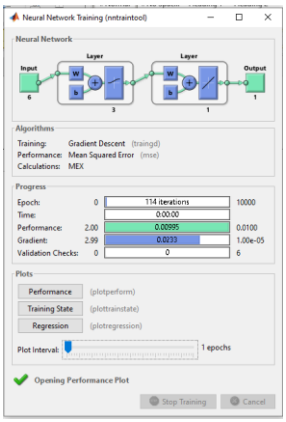
1. Data collection by identifying data sources collected from historical records of rubber plantations in Indonesia which includes information on maintenance costs, environmental conditions and other agronomic factors. And data capture: collecting data in digital format and integrating it into one coherent dataset.

2. Data preprocessing, starting from data cleaning by deleting or imputing missing values using appropriate methods, such as mean imputation or model-based imputation. Identify and handle significant outliers using statistical methods such as z-score or iqr (interquartile range). Uses min-max scaling to normalize all features into the range [0, 1]. And divide the dataset into training data (50%) and testing data (50%) randomly.
3. Development of an jst architectural model by designing a neural network architecture with one input layer, two hidden layers, and one output layer. The number of neurons in each hidden layer is set based on initial experiments. And learning rate selection: determines a series of learning rate values to be tested: 0.001, 0.01, 0.1, 0.2, and 0.5.
4. Training the jst model by training the jst model for each learning rate value determined using the backpropagation algorithm and adam optimizer. Carry out training for 100,000 epochs for each experiment, but use the early stopping technique to avoid overfitting. Measures model performance during training using the mean squared error (mse) metric.
5. Evaluation of model performance after training, evaluate the model on test data for each learning rate value using mse and r-squared (r^2) metrics. Comparing model performance results to determine the optimal learning rate value.
6. Analyze the results by analyzing the mse and r^2 results to understand the impact of various learning rate values on prediction accuracy. Create graphs and tables to visualize differences in model performance with various learning rates.
7. Validate and test sensitivity by carrying out cross-validation with k-fold (k=5) to ensure the reliability of the model. Test the sensitivity of the model to changes in other parameters such as the number of neurons in the hidden layer and the number of layers to ensure the results do not depend on certain settings alone.
8. Documentation and reporting by documenting each research step in detail for transparency and replication. Prepare research reports that include methodology, results, analysis and conclusions.

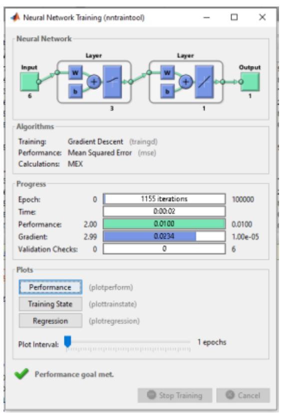
3. Results and Discussion

3.1. Results

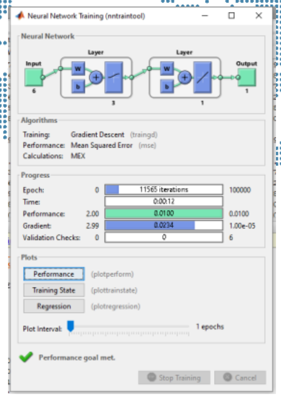
This study tested five different learning rate values: 0.001, 0.01, 0.1, 0.2, and 0.5. Each ANN model is trained for 1000000 epochs, but uses an early stopping technique to avoid overfitting. And the training results are evaluated using Mean Squared Error (MSE). The following Figure 3 is the result of each learning rate value:



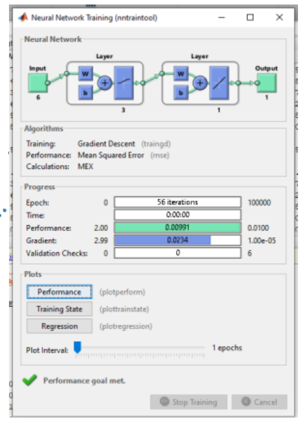
a) Lr 0.1



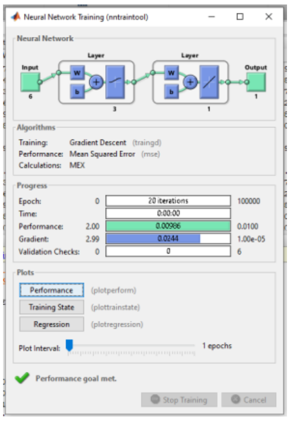
b) Lr 0.01



c) Lr 0.001



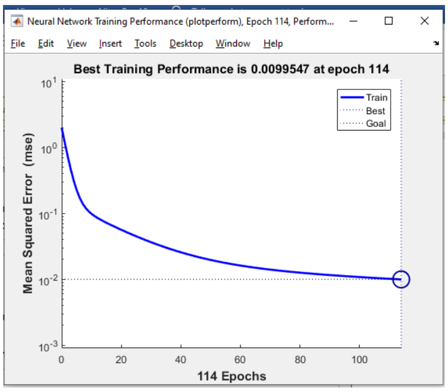
d) Lr 0.2



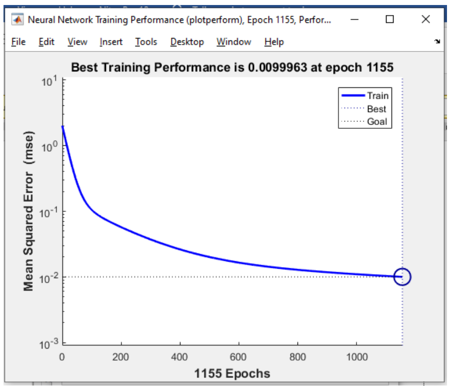
e) Lr 0.5

Figure 3. The following is the architecture of the five learning rate values a) 0.1, b) 0.01, c) 0.001, d) 0.2, and e) 0.5.

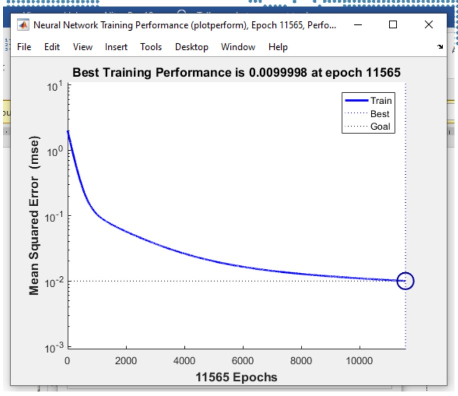
Figure 3 below shows the architecture with five different learning rates, so that in the picture you can see the epoch, times. Performance gradient and validation that work with each training. Meanwhile, in Figure 4, the curve is:



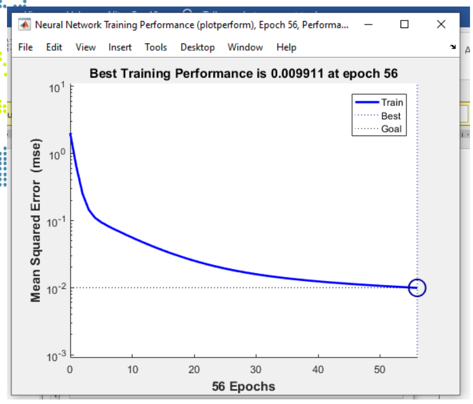
a) Lr 0.1



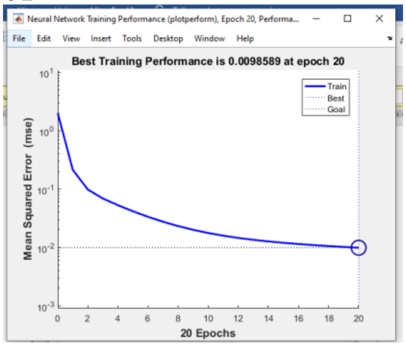
b) Lr 0.01



c) Lr 0.001



d) Lr 0.2



e) Lr 0.5

Figure 4. Draw the Curves of five different Learning rate Models

In Figure 4, it can be seen that the overall movement of the model training curve is very good without visible overweighting of the values obtained. The artificial neural network model was trained using the backpropagation algorithm with five different learning rate values: 0.001, 0.01, 0.1, 0.2, and 0.5. Results The evaluation metrics used include prediction accuracy, Mean Squared Error (MSE). The following is table 2 as an explanation of the values.

Table 2. Recap of Research Results

Architecture	Learning rate	*Training*			*Testing*		
		Epoch	MSE	Accuracy	Epoch	MSE	Accuracy
6-3-1	0.1	114	0,00995387	75	29	0,00976614	83
	0.01	1155	0,00999544	75	900	0,10010781	42
	0.001	11565	0,00999897	75	23747	0,10906233	50
	0.2	56	0,00991016	75	44	0,10005462	42
	0.5	20	0,00082585	75	16	0,09604643	42

In table 2 you can see the research results showing that the influence of various learning rate values on the performance of artificial neural networks (ANN) in predicting rubber tree maintenance costs varies significantly. The ANN architecture used was 6-3-1, and five different learning rate values were tested: 0.1, 0.01, 0.001, 0.2, and 0.5. From the training and testing results, learning rate 0.1 shows the best results with MSE 0.00995387 and 75% accuracy on training data, and MSE 0.00976614 and 83% accuracy on testing data. This shows that a learning rate of 0.1 allows the model to achieve an optimal balance between convergence speed and prediction accuracy, compared to other learning rate values that show higher MSE and lower accuracy on test data.

3.2. Discussion

3.2.1. Model Analysis of the Effect of Learning Rate on Model Performance

The research results show that the learning rate value has a significant influence on the performance of ANN in predicting rubber tree maintenance costs. A learning rate of 0.1

provides the best performance, indicating that this value allows the model to learn quickly and efficiently without overfitting or underfitting. A learning rate that is too low (0.001) causes the model to learn too slowly, while a learning rate that is too high (0.5) causes the model to fail to achieve good convergence, resulting in less accurate predictions.

3.2.2. Practical Implications

These findings have practical implications for rubber plantation managers and agricultural practitioners. By optimizing the learning rate in ANN, predictions of rubber tree maintenance costs can be improved, enabling more accurate and efficient budget planning. This can help plantation managers allocate resources more effectively and reduce waste.

3.2.3. Recommendations for Further Research

Further research could explore the use of more complex ANN architectures or ensemble methods to further improve prediction accuracy. Additionally, the application of adaptive learning rate optimization techniques, such as learning rate annealing or the use of other optimizers such as RMSprop or Nadam, can provide further insight into the influence of learning rate on ANN performance.

4. Conclusion

This research shows that choosing the right learning rate value is very important in increasing the accuracy of artificial neural network (ANN) predictions for rubber tree maintenance costs. Of the various learning rate values tested, learning rate 0.1 provides the best performance with the lowest MSE of 0.00976614 and the highest accuracy of 83% on test data. This confirms that a learning rate of 0.1 allows the model to achieve an optimal balance between convergence speed and prediction accuracy. Other learning rate values, such as 0.01, 0.001, 0.2, and 0.5, indicate higher MSE and lower accuracy, indicating that too low or too high a learning rate can hinder the model's ability to learn effectively. Thus, learning rate optimization is the key to improving ANN performance in agricultural cost prediction applications, providing practical implications for rubber plantation management in planning and managing costs more efficiently.

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