Vol. 15, No. 2 (2026): 732 - 742 http://dx.doi.org/10.23960/jtepl.v15i2.732-742

JURNAL TEKNIK PERTANIAN LAMPUNG

ISSN 2302-559X (print) / 2549-0818 (online)
Journal homepage : https://jurnal.fp.unila.ac.id/index.php/JTP

Design and Implementation of an Artificial Neural Network Model for Soil Nitrogen Prediction

Rita Anggraini[1], Sri Ratna Sulistiyanti[1,✉], Helmy Fitriawan[1], Fx Arinto Setyawan[1], Mareli Telaumbanua[2], Witaningsih[1]

[1] Master of Electrical Engineering, Faculty of Engineering, Universitas Lampung, Bandar Lampung, INDONESIA.
[2] Department of Agricultural Engineering, Faculty of Agriculture, Universitas Lampung, Bandar Lampung, INDONESIA.

Article History:

Received : 20 October 2025
Revised : 15 January 2026
Accepted : 12 February 2026

Keywords:

Artificial Neural Network,
Backpropagation,
GUI,
Soil Nitrogen,
trainbr.

Corresponding Author:
✉ sr_sulistiyanti@eng.unila.ac.id
(Sri Ratna Sulistiyanti)

ABSTRACT

The availability of nitrogen in soil is a crucial factor determining crop productivity. However, the measurement of total nitrogen (N-total) content requires considerable time and cost. Therefore, a fast, accurate, and easy prediction method is needed to support the agricultural development. This study aims to develop an Artificial Neural Network (ANN) model based on the backpropagation algorithm to identify soil N-total content using soil pH, moisture content, and soil resistance as input parameters. The model was trained using the trainbr training function with variations of logsig and tansig activation functions and hidden layer structures of 5–5, 8–8, and 12–12 to obtain the best configuration. The training results indicate that the tansig–tansig combination with 8–8 hidden layer structure achieved the highest performance, with a R^2 training of 0.953 and a R^2 testing of 0.911. The model was implemented in the form of a Graphical User Interface (GUI) application to facilitate field-level prediction. Validation using 40 testing data samples showed a classification accuracy of 70% and an R^2 value of 0.932 for nitrogen prediction. The model correctly classified 28 data samples out of the total 40 tested data. These results indicate that the proposed model is capable of predicting soil nitrogen content accurately and reliably.

1. INTRODUCTION

Soil nutrients are a fundamental component of agricultural systems because they play a direct role in supporting plant growth and productivity. The availability of balanced nutrients in the soil significantly determines the success of agricultural cultivation and the efficiency of land management. In practice, soil fertility is often uncertain without adequate measurements, leading farmers to fertilize based on estimates. This situation has the potential to lead to inaccurate fertilizer dosages, reduced crop yields, and negative impacts on the environment. Therefore, efforts are needed to understand and predict soil nutrient content more accurately and sustainably.

Macro and micronutrients play a vital role in plant growth. One essential macronutrient is nitrogen (N), which functions in tissue formation, metabolism, and vegetative growth (Kumar *et al*., 2021). Nitrogen deficiency can inhibit growth, cause yellowing of leaves, and reduce yields (Agustina, 2022). Improper management of marginal land often leads to crop failure due to a lack of knowledge about soil characteristics and nutrient content (Indraningsih, 2016). Soil nutrient testing is rarely performed by traditional farmers due to limited funds and knowledge of land management (Kamau *et al*, 2024). Measuring or identifying these nutrient levels can be done using technology such as intelligent systems. The use of intelligent systems can shorten the time and cost of identifying soil nutrients.

Nitrogen measurement methods are generally conducted in laboratories, which are time-consuming, expensive, and labor-intensive, making them less efficient for farmers and other agricultural practitioners. While other soil parameters, such as pH, water content, and resistance, can now be measured quickly using portable tools like pH meters, soil detectors, and digital multimeters, nitrogen measurement still requires a more practical approach.

The application of modern technology is needed to predict soil nitrogen levels quickly, accurately, and efficiently. One potential approach is artificial neural networks (ANNs), which can analyze nonlinear relationships between soil parameters, such as pH, water content, and resistance, and can be used with portable tools in the field (Elakiya & Keerthana, 2024). The parameters pH, water content, and soil resistance are used as input because pH affects microbial activity and nitrification and denitrification processes. Water content plays a role in nitrogen mobility and soil biological activity. While soil resistance is related to water content and dissolved ion content, reflecting soil chemical properties. This method has been successfully applied in other agricultural sciences, for example, predicting organic matter levels in soil (Hermantoro, 2011), combining ANN with NIR spectroscopy to determine macronutrient content such as nitrogen (N), phosphorus (P), and potassium (K) in rice paddy soil (Devianti *et al*., 2024).

This research focuses on the design and implementation of an artificial neural network (ANN) model to predict soil nitrogen levels based on pH, water content, and resistance parameters, as a first step towards an intelligent system that can help farmers optimize fertilization and agricultural productivity. The purpose of this study is to develop an ANN model that is able to predict and classify total nitrogen (N total) levels in marginal soil based on soil characteristic data, to design a user interface application that can be used practically to predict nitrogen levels directly in the field, and to determine the level of accuracy of the system validation results to assess the model's ability to predict soil N-total (%) levels accurately and reliably.

2. MATERIALS AND METHODS

2.1. Research Location and Tools

This research was conducted at the Department of Electrical Engineering, Faculty of Engineering, University of Lampung. The software tools used in this study included Microsoft Office Word, Microsoft Office Excel, and MATLAB.

The variables used as training and testing data in the Artificial Neural Network (ANN) model included soil pH, soil water content, and soil resistance. Soil pH was measured using a pH meter, soil water content was determined using the gravimetric method, and soil resistance was measured using an analog multimeter. Analysis of nitrogen and soil water content was conducted at the Bandar Lampung Center for Standardization and Industrial Services (BSPJI) using the Kjeldahl method.

2.2. Soil Sampling and Data Preparation

The data used in this study were obtained from soil sampling conducted at five different locations, namely:

- T1: Unproductive oil palm plantation soil located in Natar District, South Lampung Regency
- T2: Ultisol soil located in Natar District, South Lampung Regency
- T3: Coastal soil located in Teluk District, Bandar Lampung City
- T4: Tin post-mining soil (tailings soil) located in Sungai Liat District, Bangka Regency
- T5: Red-yellow podzolic soil located in Rajabasa District, Bandar Lampung City

Initially, 100 soil samples were collected from different treatments. These samples were sorted from the smallest to the largest values and then divided into four nitrogen classes. From the divided data, 25 data sets belonged to the deficient class, 24 data sets to the suboptimal class, 27 data sets to the optimal class, and 24 data sets to the excessive class. Because Artificial Neural Network (ANN) models require balanced training data to avoid bias during training, an undersampling approach was applied. Therefore, the number of data points in each class was equalized to the smallest available number, resulting in 24 data points per class.

2.3. Soil Conditioning and Nitrogen Classification

The soil samples were varied by adding urea fertilizer at specific doses and undergoing conditioning processes, including homogenization and incubation, prior to measurement. The addition of urea fertilizer was intended to vary nitrogen content so that the training data covered a wider range of nitrogen values. The nitrogen values used in this study were the actual measured values obtained after the conditioning process. A total of 96 data sets were used as training data, while 40 data sets were used as testing data. The nitrogen classification was based on total nitrogen (N-total) content in the soil, divided into four categories:

- Deficient: 0.001–0.149%
- Suboptimal: 0.15–0.249%
- Optimal: 0.25–0.49%
- Excessive: ⩾ 0.5%

Soil with total nitrogen content below 0.15% is categorized as deficient, indicating that nitrogen availability is insufficient to support plant growth. Low nitrogen availability reduces plant biomass production because nitrogen plays a critical role in protein, chlorophyll, and amino acid formation. Nitrogen deficiency also decreases microbial activity in the soil, slowing the mineralization of organic matter.

In the suboptimal class, nitrogen is available in moderate amounts, which may support the growth of certain crops but is not ideal for achieving maximum yield. Soil nitrogen levels between 0.25% and less than 0.5% are categorized as optimal, where nitrogen availability supports balanced vegetative and generative plant growth. Excessive nitrogen levels (>0.5%) may lead to nutrient imbalance and plant physiological disorders due to the accumulation of toxic compounds such as nitrite.

2.4. Artificial Neural Network Model Development

This study used the trainbr (Bayesian Regularization) training function in the Backpropagation Neural Network algorithm. This training method was selected because it provides better generalization performance and reduces the risk of overfitting, especially when working with relatively small datasets. To obtain the optimal model configuration, controlled hyperparameter exploration was performed on the Artificial Neural Network. The exploration focused on the activation function and the number of neurons in the hidden layer, as these parameters significantly influence the network's ability to model nonlinear relationships. The activation function combinations used in this study included: *logsig–logsig, logsig–tansig, tansig–logsig, tansig–tansig*. Meanwhile, the number of neurons in the two hidden layers was varied as follows: 5–5 neurons, 8–8 neurons, 12–12 neurons.

The purpose of these variations was to determine the best combination of activation functions and neuron numbers that produces optimal performance during both training and testing stages. The selected model was then implemented into a Graphical User Interface (GUI) application for predicting soil nitrogen content.

2.5. Backpropagation Neural Network Architecture

The architecture of the Artificial Neural Network used in this study is illustrated in Figure 1.

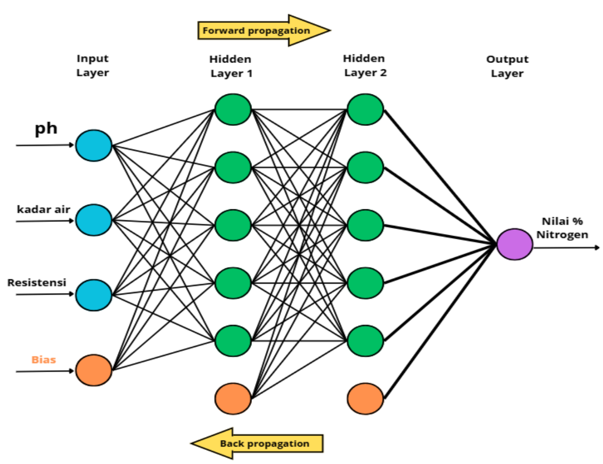

Figure 1. Backpropagation neural network architecture

Figure 1 shows the structure of the Backpropagation Neural Network consisting of an input layer, two hidden layers, and an output layer. The input layer receives three input variables, namely soil pH, soil water content, and soil resistance. These inputs are processed through two hidden layers with varying numbers of neurons, depending on the tested configuration. The output layer produces the predicted soil nitrogen class based on the trained model. This architecture enables the network to model nonlinear relationships between soil parameters and nitrogen content.

2.6. Model Evaluation Parameters

The output of the training and testing process includes training accuracy, testing accuracy, Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). The Mean Squared Error (MSE) measures the average squared difference between the actual and predicted values. Smaller MSE values indicate better model performance. The Coefficient of Determination (R^2) indicates how well the model explains the variability of the actual data, where values closer to 1 indicate excellent predictive performance. The GUI application developed in this study was validated using the same 40 testing data sets to ensure accurate and reliable output.

2.7. Classification Performance Evaluation

The nitrogen classification results produced by the ANN model and displayed in the GUI were evaluated using a confusion matrix. Model performance was assessed using three main parameters: precision, recall, and F1-score. Precision measures the accuracy of predicted classes, while recall indicates the model's ability to correctly identify actual data for each class. The F1-score represents the harmonic balance between precision and recall. These parameters were used to evaluate the reliability of the classification model. The class accuracy is calculated using Equation (1):

$$Class\ accuracy\ = \frac{TP + TN}{Total\ data} \times 100\% \tag{1}$$

$$Precision\ per\ class = \frac{TP}{TP + FP} \tag{2}$$

$$Recall\ per\ class = \frac{TP}{TP + FN} \tag{3}$$

$$Class\ F1\ score = \frac{2(precision\ \times\ recall)}{(precision +\ recall)} \tag{4}$$

where TP (true positive) represents the number of matching positive data, TN (true negative) represents the number of matching negative data, FP (false positive) represents the number of non-matching positive data, and FN (false negative) represents the number of non-matching negative data.

2.8. Error Analysis

To evaluate the prediction accuracy of the model, Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Relative Root Mean Square Error (RRMSE) were calculated using the following equations:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \quad (y_i - \hat{y}_i)^2 \tag{5}$$

$$RMSE\ = \sqrt{MSE} \tag{6}$$

$$\text{RRMSE}=\frac{RMSE}{\bar{y}}100\% \tag{7}$$

where n: Total number of data points., y_i: Actual soil nitrogen value., $\hat{y}_i$: Predicted soil nitrogen value., $\bar{y}$: Mean of actual soil nitrogen values.

3. RESULTS AND DISCUSSION

3.1. Relationship between Nitrogen and pH, Water Content, and Resistance

The prepared soil samples were tested for pH, water content, and resistance, which will be used as training data for the ANN. These values were graphed to demonstrate the linearity of pH, water content, and resistance to nitrogen. The following graph shows the relationship between pH, water content, and resistance to nitrogen.

Figure 2 shows a graph of the position of nitrogen in relation to soil pH in each soil sample from T1 to T5. Each soil sample, differentiated by its shape, shows its own distribution of nitrogen and pH. In soil samples T1, T2, T3, and T5, the increase in soil nitrogen levels is consistent with the increase in soil pH. However, in soil sample T4, the increase in soil pH occurs, but the nitrogen levels tend to remain low. In soil sample T4, a post-tin mining tailings soil with a sandy texture, the pH increase occurred due to the addition of urea fertilizer, but was not accompanied by a significant increase in nitrogen.

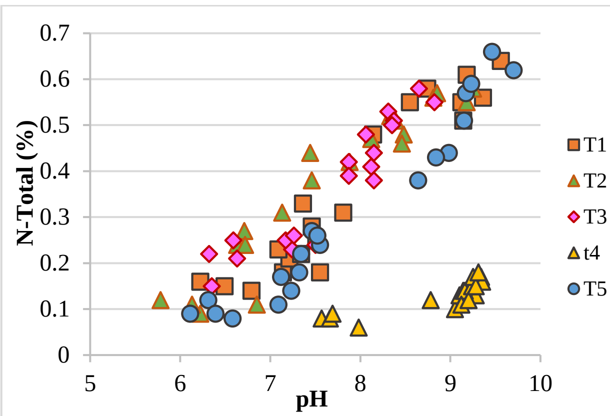

Figure 2. Graph of pH distribution in each soil sample

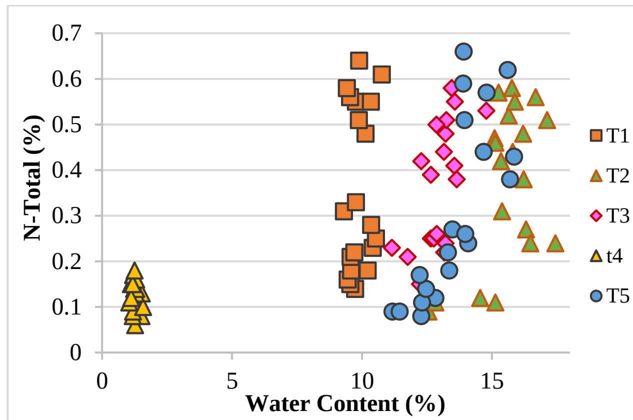

Figure 3. Graph of water content distribution in each soil sample

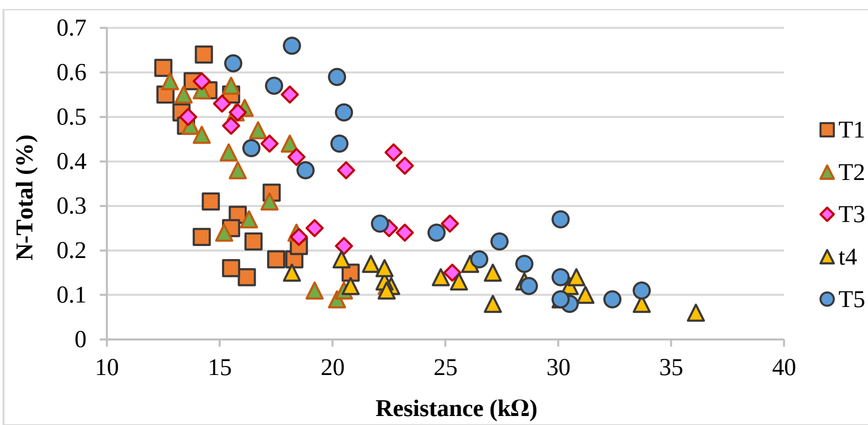

Figure 4. Graph of resistance distribution for each soil sample

Figure 3 shows that each soil sample has a fairly regular distribution, with the highest water content in soil sample T2 and the lowest water content in soil sample T4. This is influenced by the soil texture of each sample. Soil T2 is an ultisol with a silty clay loam texture that is able to retain water better than soil sample T4, which has a sandy texture. The distribution of each soil water content did not follow a significant increase in nitrogen content, especially in soil sample T4, which had a very low content.

Research by Wang *et al*. (2018) explains that nitrogen uptake and utilization by plants is partly influenced by the soil's ability to provide nitrogen. Plant-available nitrogen is produced through the mineralization of soil organic nitrogen, a process influenced by temperature and soil water content. At an optimum water content (neither too dry nor too saturated), microbial activity increases, resulting in more intensive decomposition of organic matter and release of mineral nitrogen. At excessively high water content, the nitrification process decreases due to limited oxygen in the soil, which can reduce the availability of nitrogen in a form that can be absorbed by plants (Norton & Ouyang, 2019).

Figure 4 shows the distribution of each value in each soil sample compared to the other samples. Nitrogen values show a decrease with increasing resistance values. However, in soil sample T4, the nitrogen value does not follow the downward trend like the other soil samples. In soil sample T4, the nitrogen value (%) only ranges from 0.05% to 0.2%. Soil resistance values increase with increasing density. The amount of dissolved water in the soil also influences the decrease in soil resistance. Water in soil pores carries dissolved ions, providing a pathway for electrical conduction. The greater the water content (humidity/volumetric water content), the greater the number of conductive pathways, resulting in a decrease in resistivity (Sangprasat *et al*, 2025; Acosta *et al*., 2022). Therefore, soil resistance can be used as an indirect indicator to estimate available nitrogen content in the soil, especially under adequate water content. Given that this model only has three input parameters: water content, pH, and resistance, significant differences in each soil sample will impact the model's bias weight calculation and the accuracy of the resulting output. If possible, soil type or texture composition can be incorporated into the model's input parameters for greater accuracy.

3.2. Training and Testing Results of the ANN Model

The training results using 96 training data sets and 40 testing data sets, using the previously created ANN model, are shown in Tables 1, 2, 3 and 4. It can be seen that the combination of the *tansig-tansig* activation function with 8–8 neurons provided the most optimal results, with a training accuracy of 71%, a testing accuracy of 73.38%, an MSE of 0.00152, and a coefficient of determination (R^2) of 0.953. These values indicate that the model is capable of representing nonlinear relationships between soil parameters with a low error rate and a strong correlation between predicted and actual values.

The best model was selected based on the highest accuracy value, also considering the gap between training and testing accuracy. A model with a small difference between these two values indicates a good level of generalization and indicates the model is not experiencing overfitting. This is crucial for the system's stability when applied to new data in the field. The best ANN model was then implemented into a MATLAB-based Graphical User Interface (GUI) application to make it easier for users to predict soil nitrogen levels.

Table 1. System accuracy results using *trainbr* function and *logsig–logsig* activation function

No	Function	Number of Neurons	Value Accuracy			Accuracy (%)	Number of Training Data		
			MSE	MAE	R^2		Total Data	Matched	Not Matched
1		5-5	0.00282	0.0404	0.911	69.00%	96	67	29
2	Training	8-8	0.00279	0.0405	0.912	71.00%	96	69	27
3		12-12	0.00259	0.0393	0.919	70.00%	96	68	28
4		5-5	0.000115	0.0302	0.952	72.86%	40	33	7
5	Testing	8-8	0.00115	0.0303	0.952	72.59%	40	28	12
6		12-12	0.00159	0.0306	0.951	72.59%	40	28	12

Table 2. System accuracy results using *trainbr* function and *logsig–tansig* activation function

No	Function	Number of Neurons	Value Accuracy			Accuracy (%)	Number of Training Data		
			MSE	MAE	R^2		Total Data	Matched	Not Matched
1		5-5	0.00262	0.0395	0.918	70.00%	96	68	28
2	Training	8-8	0.00312	0.0430	0.900	66.00%	96	64	32
3		12-12	0.00287	0.0406	0.909	71.00%	96	69	27
4		5-5	0.00162	0.0310	0.950	71.80%	40	28	12
5	Testing	8-8	0.00126	0.0269	0.958	76.79%	40	28	12
6		12-12	0.00159	0.0306	0.951	74.16%	40	28	12

Table 3. System accuracy results using *trainbr* function and *tansig–logsig* activation function

No	Function	Number of Neurons	Value Accuracy			Accuracy (%)	Number of Training Data		
			MSE	MAE	R^2		Total Data	Matched	Not Matched
1	Training	5-5	0.00353	0.0453	0.880	63.00%	96	61	35
2		8-8	0.00330	0.0424	0.885	67.50%	96	65	31
3		12-12	0.00242	0.0380	0.923	69.50%	96	67	29
4	Testing	5-5	0.00092	0.0229	0.969	80.45%	40	29	11
5		8-8	0.00104	0.0244	0.964	76.97%	40	32	8
6		12-12	0.00137	0.0281	0.957	74.86%	40	29	11

Table 4. System accuracy results using *trainbr* function and *tansig–tansig* activation function

No	Function	Number of Neurons	Value Accuracy			Accuracy (%)	Number of Training Data		
			MSE	MAE	R^2		Total Data	Matched	Not Matched
1	Training	5-5	0.00281	0.0411	0.911	70.00%	96	68	28
2		8-8	0.00283	0.0408	0.911	71.00%	96	69	27
3		12-12	0.00281	0.0411	0.911	70.00%	96	68	28
4	Testing	5-5	0.00151	0.0300	0.953	73.89%	40	28	12
5		8-8	0.00152	0.0299	0.953	73.38%	40	28	12
6		12-12	0.00151	0.0300	0.953	73.64%	40	28	12

3.3. GUI System Design and Implementation Results

The soil nitrogen content identification application system in this study was designed by defining application functions, user navigation flows, and designing a graphical user interface. The application was designed to accept soil parameter inputs in the form of pH, water content, and soil resistance, process the data using an ANN model, and display predicted soil nitrogen content results. This system has two main interfaces: the home page and the identification page. The application logo or splash screen is shown in Figure 5, the home page interface design is shown in Figure 6, and the identification page interface design is shown in Figure 7.

Figure 5. GUI application logo and splash screen

Figure 6. Interface display of the home page

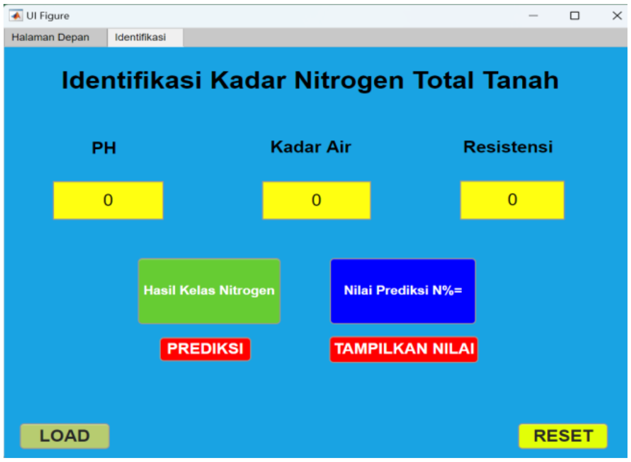

Figure 7. Interface display of the identification page

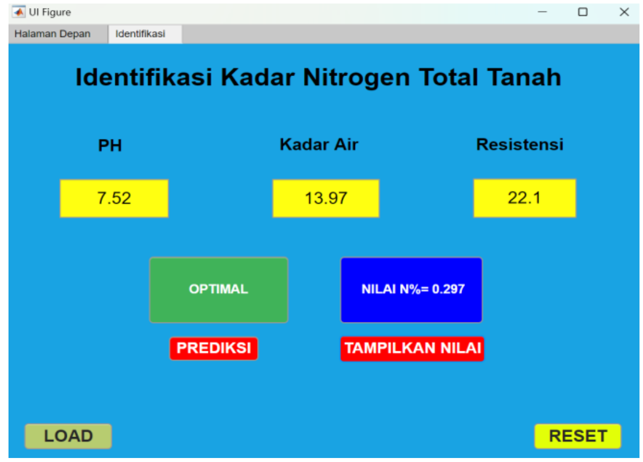

Figure 8. Identification page interface after the N value appears

In the illustrated design of the home page interface, there is 1 axis and 3 static text components. In the interface design for the Total Soil Nitrogen Content Identification page, there are 2 static text components, 3 edit text fields (pH, moisture content, and resistance), and 4 push buttons: predict, display value, load, and reset. In the nitrogen value display text box shown in Figure 7, there are 4 different colors that change according to the class being displayed. The color changes in the display following the class prediction results are intended to make it easier for users to distinguish between each class.

1. Deficient class with a red background ➜
2. Suboptimal class with a yellow background ➜
3. Optimal class with a green background ➜
4. Excessive class with a purple background ➜

Figure 8 displays the soil nitrogen content identification page, which displays the soil's class classification and total N (%) value. These results are displayed after entering the pH, water content, and resistance values.

3.4. ANN Model Validation

In the developed GUI application, the interface section was tested using 40 available testing datasets. This analysis was conducted to validate the output values generated by the GUI application. The soil nitrogen prediction GUI provides two types of predictions: nitrogen class identification (which assigns values to specific classes) and the predicted numerical value.

From the 40 testing datasets, two types of comparisons were performed: Actual Classification – Predicted Classification and Actual Value – Predicted Value. The actual classification/value represents the true value, while the predicted classification/value is the result displayed on the identification page of the GUI application. The comparison between actual and predicted values is shown in Figure 9. The class prediction results in the GUI application are presented using a Confusion Matrix graph (Figure 10). The Confusion Matrix graph is used to evaluate the performance of classification models, particularly in machine learning.

Figure 9 illustrates the scatter plot of actual versus predicted soil nitrogen values. Within a 15% tolerance threshold, 62.5% of the data points fall within the acceptable accuracy range. The model's performance is further validated by low error metrics, yielding an RMSE of 0.0476 and an MAE of 0.00227. These results indicate that the model exhibits high precision and reliable predictive capability. Figure 10 shows a class accuracy of 70%, as 28 data points were correctly classified and 12 were misclassified out of the total 40 tested datasets.

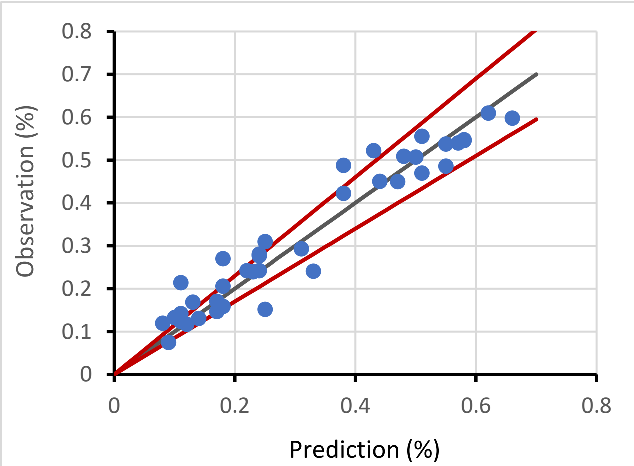

Figure 9. Graph of actual and predicted soil nitrogen values in the GUI application with red line is ±15% tolerance.

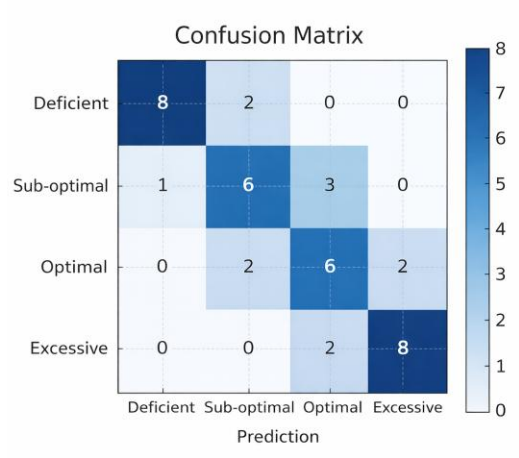

Figure 10. Confusion matrix graph for nitrogen class identification by the GUI

Table 9. Validation of Nitrogen Values Based on Class

Class	Precision	Recall	F1-Score
Deficient	0.89	0.8	0.84
Sub-optimal	0.6	0.6	0.6
Optimal	0.55	0.6	0.57
Excessive	0.8	0.8	0.8
Average	**0.71**	**0.7**	**0.7**

Table 9 presents the performance evaluation results of the Backpropagation Artificial Neural Network (ANN) model across four nitrogen content classes: Deficient, Sub-optimal, Optimal, and Excessive. The evaluation was conducted using three main parameters: precision, recall, and F1-score, which measure the accuracy and reliability of the model in performing classification. Based on Figure 10, the Deficient class achieved the highest precision value of 0.89 and a recall of 0.80, with an F1-score of 0.84. This indicates that the model is highly capable and consistent in identifying nitrogen deficiency conditions. The Excessive class also shows strong performance, with both precision and recall values of 0.80, resulting in F1-score 0.80. This demonstrates the model's stable ability to identify excessive nitrogen conditions.

In contrast, the model performance for the Sub-optimal and Optimal classes is relatively lower, with F1-scores of 0.60 and 0.57, respectively. Based on the analysis of nitrogen data distribution, these two classes exhibit overlapping distribution patterns within certain value ranges. In Figure 10, the nitrogen distribution for the Sub-optimal and Optimal classes shows overlapping interquartile ranges and closely positioned distribution peaks (modes), resulting in no clear numerical separation between the classes.

This condition makes it difficult for the model to distinguish samples located in the overlapping region, even though a nonlinear network architecture was used. Therefore, the lower F1-scores in these two classes are primarily caused by the intrinsic characteristics of the data, which are not fully statistically separable, rather than solely by limitations of the model's classification capability. Overall, the average precision of 0.71, recall of 0.70, and F1-score of 0.70 indicate that the Backpropagation ANN model has fairly good and balanced classification performance across classes. These results suggest that the model can be used to identify nitrogen levels with adequate reliability, particularly under extreme conditions (deficient and excessive).

The research results show that the Artificial Neural Network (ANN) model developed using soil pH, moisture content, and resistance as input parameters is capable of predicting soil nitrogen content with good performance. Based on testing results, the model produced an RMSE value of 0.0476 and a coefficient of determination (R^2) of 0.9324. These values indicate that the ANN model effectively captures the nonlinear relationship between soil physical properties and nitrogen content. Compared with previous research by Liu *et al.* (2024), which proposed a total soil nitrogen prediction method based on a convolutional noise reduction autoencoder (CDAE), whale optimization algorithm (WOA), and deep residual shrinkage network (DSRN), their testing results showed that the CAE–WOA–DSRN model achieved an R^2 value of 0.968, significantly higher than traditional algorithms (R^2 = 0.873) and a simple backpropagation neural network (R^2 = 0.877). Thus, it can be concluded that the ANN model developed in this study demonstrates good accuracy and remains agronomically relevant, as it can be practically implemented through a field-usable application.

4. CONCLUSIONS

Based on the research results, it can be concluded that this study successfully developed an Artificial Neural Network This research successfully developed an Artificial Neural Network (ANN) model based on the Backpropagation algorithm to predict and classify total nitrogen (N-total) levels in marginal soils using pH, moisture content, and soil resistance as input parameters. The optimal model was obtained using the *trainbr* training function with an 8–8 hidden layer architecture and *tansig–tansig* activation functions, which was subsequently integrated into a Graphical User Interface (GUI) application for practical field monitoring. The model's performance demonstrated high stability without indications of overfitting, yielding a training R^2 of 0.953 and a testing R^2 of 0.911. Validation using 40 independent datasets achieved a nitrogen classification accuracy of 70% (28 out of 40 data points correctly classified) and an overall coefficient of determination $R^2$of 0.932. Other statistical results showed low error rates, with an RMSE of 0.0476 and an MAE of 0.00227, proving that the developed ANN model is reliable and efficient for rapid soil nitrogen assessment.

For future research, it is recommended to expand the scope of input parameters—such as soil texture and electrical conductivity (EC)—and increase the volume of the training dataset to improve model generalization. Additionally, exploring alternative machine learning algorithms is suggested to evaluate the potential for increasing classification accuracy beyond the 70% threshold.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to the Directorate of Research, Technology, and Community Service (DRTPM) of the Directorate General of Higher Education (Dikti) for the financial support provided for the implementation and publication of this research, in accordance with Decree Number 0459/E5/PG.02.00/2024 and Contract Agreement Number 057/E5/PG.02.00.PL/2024.

AUTHOR CONTRIBUTION STATEMENT

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
RA	✓							✓	✓	✓				✓
SRS	✓	✓							✓			✓		✓
HF		✓		✓										
FAS		✓		✓								✓		
MT	✓		✓									✓		✓
Wit						✓	✓		✓	✓	✓			

C: Conceptualization	Fo: Formal Analysis	O: Writing - Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing - Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

REFERENCES

Acosta, J.A., Gabarrón, M., Martínez-Segura, M., Martínez-Martínez, S., Faz, Á., Pérez-Pastor, A., Gómez-López, M.D., & Zornoza, R. (2022). Soil water content prediction using electrical resistivity tomography (ERT) in Mediterranean Tree Orchard Soils. *Sensors*, ***22***(4), 1365. https://doi.org/10.3390/s22041365

Agustina, R.M. (2022). Kajian Unsur Hara Makro dan Mikro Pada Pertumbuhan Tanaman. [*Undergraduated Thesis*]. UIN Raden Intan Lampung.

Chicco, D., Warrens, M.J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, *7*, e623. https://doi.org/10.7717/peerj-cs.623

Devianti, Sufardi, Bulan, R., & Sitorus, A. (2022). Vis-NIR spectra combined with machine learning for predicting soil nutrients in cropland from Aceh Province, Indonesia. *Case Studies in Chemical and Environmental Engineering*, ***6***, 100268. https://doi.org/10.1016/j.cscee.2022.100268

Ding, C., Lv, C., Chen, H., Zhou, J., & Ren, H. (2024). Evaluation of soil total nitrogen as an indicator of soil bacterial community response to biochar and plant growth-promoting rhizobacteria applications. *Agronomy*, ***14***(3), 428. https://doi.org/10.3390/agronomy14030428

Elakiya, N., & Keerthana, G. (2024). Application of artificial neural networks in soil science research. *Archives of Current Research International*, ***24***(5), 1–15. https://doi.org/10.9734/ACRI/2024/v24i5674

Hermantoro. (2011). Aplikasi pengolahan citra digital dan jaringan syaraf tiruan untuk memprediksi kadar bahan organik dalam tanah. *Jurnal Keteknikan Pertanian*, ***25***(1), 1–8.

Indraningsih, K.S. (2016). Faktor-faktor yang memengaruhi kinerja usahatani petani sebagai representasi strategi penyuluhan pertanian berkelanjutan di lahan marjinal. *Jurnal Agro Ekonomi*, ***31***(1), 71–95.

Kamau, P., Ndirangu, I., Richardson, S., Pamme, N., & Gitaka, J. (2024). Gendered farmer perceptions towards soil nutrition and willingness to pay for a cafetière-style filter system for in-situ soil testing: Evidence from Central Kenya. *Heliyon*, ***10***(18), e37568. https://doi.org/10.1016/j.heliyon.2024.e37568

Kumar, S., Kumar, S., & Mohapatra, T. (2021). Interaction between macro- and micro-nutrients in plants. *Frontiers in Plant Science*, ***12***, 665583. https://doi.org/10.3389/fpls.2021.665583

Kuusemets, L., Mander, Ü., Escuer-Gatius, J., Astover, A., Kauer, K., Soosaar, K., & Espenberg, M. (2025). Interactions of fertilisation and crop productivity in soil nitrogen cycle microbiome and gas emissions. *SOIL*, ***11***, 1–15. https://doi.org/10.5194/soil-11-1-2025

Lai, H., Gao, F., Su, H., Zheng, P., Li, Y., & Yao, H. (2022). Nitrogen distribution and soil microbial community characteristics in a legume–cereal intercropping system: A review. *Agronomy*, ***12***(8), 1900. https://doi.org/10.3390/agronomy12081900

Li, M., Han, X., & Li, L.-J. (2022). Total nitrogen stock in soil profile affected by land use and soil type in three counties of Mollisols. *Frontiers in Environmental Science*, ***10***. https://doi.org/10.3389/fenvs.2022.945305

Liu, H., Wang, J., Liu, S., Hu, Q., & Huang, D. (2024). Study on soil total nitrogen content prediction method based on synthetic neural network model. *Sustainability*, ***16***(8), 3195. https://doi.org/10.3390/su16083195

Liu, J., Cai, H., Chen, S., Pi, J., & Zhao, L. (2023). A review on soil nitrogen sensing technologies: Challenges, progress and perspectives. *Agriculture*, ***13***(4), 743. https://doi.org/10.3390/agriculture13040743

Norton, J., & Ouyang, Y. (2019). Controls and adaptive management of nitrification in agricultural soils. Frontiers in Microbiology, 10, 1931. https://doi.org/10.3389/fmicb.2019.01931

Sangprasat, K., Puttiwongrak, A., & Inazumi, S. (2025). Review of correlations between soil electrical resistivity and geotechnical properties. *Geosciences*, ***15***(5), 166. https://doi.org/10.3390/geosciences15050166

Troiano, M., Nobile, E., Mangini, F., Mastrogiuseppe, M., Conati Barbaro, C., & Frezza, F. (2024). A comparative analysis of the Bayesian Regularization and Levenberg–Marquardt training algorithms in neural networks for small datasets: A metrics prediction of neolithic laminar artefacts. *Information*, ***15***(5), 270. https://doi.org/10.3390/info15050270

Wang, X.-W., Xu, J.-C., Long, C.-Z., Zhu, S.-W., Lu, M.-J., & Yang, W.-T. (2018). Effect of nitrogen rates and soil water contents on soil nitrogen mineralization under ryegrass returning into red soil. *Journal of Plant Nutrition and Fertilizers*, ***24***(2), 365–374. https://doi.org/10.11674/zwyf.17373

Zhai, J., Zhang, Y., Zhang, G., Xu, W., Xie, R., Ming, B., Hou, P., Wang, K., Xue, J., & Li, S. (2022). Nitrogen application and dense planting to obtain high yields from maize. *Agronomy*, ***12***(6), 1308. https://doi.org/10.3390/agronomy12061308