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Artificial Neural Network Backpropagation Method for Predicting Soil Nutrient Content

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ABSTRACT

Monitoring soil nutrient levels such as nitrogen (N), phosphorus (P), and potassium (K) is essential to support fertilizer efficiency and sustainable agricultural land management. However, commonly used laboratory-based analytical methods are time-consuming and costly. Therefore, alternative approaches that are more practical and efficient are needed. This study aimed to develop an Artificial Neural Network (ANN)-based system for predicting soil nutrient levels using soil physical parameters, namely pH, temperature, moisture content, and electrical resistance, as input variables. Data were collected from red-yellow podzolic soil subjected to different fertilization treatments. After normalization, the data were trained using an ANN model with four input nodes, two hidden layers (each consisting of five nodes), and one output node, employing the backpropagation algorithm and evaluating 27 combinations of activation functions. The training results showed coefficients of determination (R^2) of 0.9642 for nitrogen, 1.0000 for phosphorus, and 0.9996 for potassium, with RMSE values of 0.0107, 10.5386, and 0.016457 and RRMSE values of 8.5048%, 0.79786%, and 1.581111%, respectively. During validation, R^2 values of 0.7218 (nitrogen), 0.6479 (phosphorus), and 0.6137 (potassium) were obtained. Nitrogen prediction exhibited good accuracy (RMSE 0.0222; RRMSE 15.54%), potassium prediction showed moderate accuracy (RMSE 0.2963; RRMSE 28.46%), while phosphorus prediction resulted in relatively high errors (RMSE 1066.77; RRMSE 80.98%), indicating the need for further model development.

1. INTRODUCTION

Agriculture is a key sector in the Indonesian economy, with 27,368,114 farming households recorded in the 2023 Agricultural Census by Statistics Indonesia (BPS). Most are engaged in the food crops, livestock, and plantation subsectors (Badan Pusat Statistik, 2023). One of the crucial processes in agriculture is fertilization, which serves to meet the soil's nutrient needs, particularly macronutrients such as nitrogen (N), phosphorus (P), and potassium (K), which play a role in plant growth, flowering, and yield formation (Triadiawarman *et al*., 2022).

NPK fertilizer is a widely used inorganic fertilizer because it contains three essential macronutrients for plants: nitrogen (N), phosphorus (P), and potassium (K). However, NPK fertilizer application that is not based on actual soil conditions has the potential to cause nutrient imbalances. Overfertilization can lead to the accumulation of certain nutrients, increased soil acidity, decreased microbial activity, and environmental pollution. While nutrient deficiencies can inhibit plant growth and reduce yields (Santhoshkumar *et al*., 2023). Inaccurate fertilizer dosages also increase agricultural production costs due to inefficient fertilizer use without significant yield increases (Hartono *et al*., 2022).

Therefore, predicting soil N, P, and K levels before fertilization is crucial for determining appropriate, efficient, and sustainable fertilizer dosages.

The urgency of soil nutrient prediction is even greater in Red-Yellow Podzolic (PMK) soils, which generally have low fertility, acid soil reaction, low cation exchange capacity, and limited phosphorus availability due to Al and Fe fixation (Amar *et al*., 2022). These conditions cause plant response to fertilizer application to be highly dependent on the accuracy of the dosage and type of fertilizer applied. Therefore, predicting N, P, and K levels in PMK soils is expected to support more precise fertilization, improve cost efficiency, and maintain sustainable soil fertility. Laboratory testing is the primary method for determining nutrient levels, but is considered inefficient in terms of cost, time, and accessibility for farmers (Amri & Sumiharto, 2019). Alternative solutions are needed to provide fast, efficient, and applicable nutrient level prediction methods in the field. One promising technology is artificial neural networks (ANNs), which are capable of modeling nonlinear relationships between soil parameters and nutrient content (López-Aguilar *et al*., 2020; Mohmed *et al*., 2023; Kujawa & Niedbała, 2021). The backpropagation method with added momentum is used to accelerate convergence and improve network training stability (Ampelakiotis *et al*., 2022; Suryadibrata & Chandra, 2019).

Several studies have developed soil nutrient measurement tools using various technological approaches. The magnetic field induction method reportedly still has limited accuracy, especially when measuring low nutrient concentrations (Salsabila *et al*., 2021), while a system based on an analog NPK sensor integrated with a Raspberry Pi can achieve reading accuracy levels above 80% (As'ari *et al*., 2022). In addition to direct measurements, the development of soil nutrient prediction tools also utilizes physical soil parameters that are closely related to nutrient availability. Parameters such as electrical conductivity (resistance), soil moisture, pH, and temperature are known to correlate with nutrient dynamics in the soil. Electrical conductivity reflects the amount of dissolved ions, moisture influences the release and movement of nutrients, while temperature plays a role in increasing ion mobility and the activity of chemical and biological processes in the soil (Sari *et al*., 2019; Salam, 2020).

Based on the description of the limitations of direct soil nutrient measurement methods and the potential use of soil physical parameters as indicators of nutrient availability, this study aims to analyze the relationship between resistance, temperature, pH, and soil moisture on the levels of macronutrients nitrogen (N), phosphorus (P), and potassium (K). In addition, this study aims to evaluate the performance of the artificial neural network model in predicting soil N, P, and K levels based on the coefficient of determination (R^2) values at the training and validation stages, as a basis for developing a more accurate and applicable soil nutrient prediction method.

2. MATERIALS AND METHODS

2.1. Sample Preparation

The soil samples were Red-Yellow Podzolic (PMK) soil from the root layer, which was filtered through a sieving process and placed in transparent plastic containers with a diameter of 10 cm, with each sample weighing 500 g. In this study, the soil samples were subjected to fertilizer treatments to vary the nutrient levels of nitrogen (N), phosphorus (P), and potassium (K). Treatments included the addition of urea (46% N), TSP (44–46% P_2O_5), and KCl (60–62% K_2O) at three fertilizer concentrations: 5 g, 15 g, and 25 g, each dissolved in 200 ml of water. These fertilizer concentrations represented low, medium, and high soil nutrient levels, respectively, and were complemented by a control treatment without fertilizer addition.

Observation parameters included soil resistance, moisture content, pH, and temperature, measured on each sample. N, P, and K contents were obtained through laboratory analysis at the Soil Science Laboratory, Faculty of Agriculture, University of Lampung, and used as observational data for the study. All measurement data was then divided into 80% training data and 20% test (validation) data for the development and evaluation of the artificial neural network model.

2.2. Design of a Nutrient Level Prediction Tool

The designed equipment to predict nutrient level was equipped with four potentiometers (A, B, C, D), each with a specific function as an analog input device. Potentiometer A was used to input soil pH, B for moisture content (KA), C for soil temperature, and D for soil resistance. Each potentiometer was set within a specific range to ensure that the input value does not exceed the limit, which could cause reading errors or unexpected spikes.

Description:
1. Liquid Crystal Display (LCD)
2. Potentiometers
   a) Potentiometer 1 = Soil pH
   b) Potentiometer 2 = Soil Moisture
   c) Potentiometer 3 = Soil Temperature
   d) Potentiometer 4 = Resistance
3. The box contains microcontroller and other supporting components, consisting of an Arduino Uno microcontroller as the main control unit, a ground resistance sensor circuit, an I²C-based LCD display module, and a power supply as the system voltage source.

Figure 1. Design of a soil nutrient level prediction tool model (left) and its detail components (right.

2.3. Artificial Neural Network (ANN) Model Development

The ANN model was designed using an architecture with four input nodes, two hidden layers of five nodes each, and one output layer. Activation functions play a crucial role in the network training process, so simulations were conducted using 27 activation function combinations (Table 1) to determine the best performance.

Table 1. ANN Activation Function Combinations

No	Activation Function	No	Activation Function	No	Activation Function
1	*Logsig-logsig-logsig*	10	*Logsig-logsig-purelin*	19	*Purelin-tansig-logsig*
2	*Logsig-logsig-tansig*	11	*Tansig-logsig-purelin*	20	*Purelin-tansig-tansig*
3	*Logsig-tansig-logsig*	12	*Tansig-tansig-purelin*	21	*Purelin-purelin-purelin*
4	*Logsig-tansig-tansig*	13	*Logsig-purelin-logsig*	22	*Purelin-purelin-tansig*
5	*Tansig-logsig-logsig*	14	*Logsig-purelin-tansig*	23	*Purelin-purelin-logsig*
6	*Tansig-tansig-logsig*	15	*Tansig-purelin-logsig*	24	*Purelin-tansig-purelin*
7	*Tansig-tansig-tansig*	16	*Tansig-purelin-tansig*	25	*Purelin-logsig-purelin*
8	*Tansig-logsig-tansig*	17	*Purelin-logsig-logsig*	26	*Logsig-purelin-purelin*
9	*Logsig-tansig-purelin*	18	*Purelin-logsig-tansig*	27	*Tansig-purelin-purelin*

The best activation function was selected based on the highest coefficient of determination (R^2) and the lowest Root Mean Square Error (RMSE). The combination that produced the R^2 closest to 1 and the smallest RMSE was considered the best configuration. The training process was performed using the backpropagation algorithm with the addition of momentum. The ANN model development process and its network architecture are shown in Figures 2.

2.4. Model Implementation in a Microcontroller

The mathematical model resulting from the ANN training was input into the microcontroller through program syntax. The microcontroller processed the input data from the potentiometer and then displayed the predicted levels of nitrogen (N), phosphorus (P), and potassium (K) on the LCD screen. The reading and prediction process ran repeatedly as long as the system was active.

2.5.1. Data Normalization

The normalization process aims to equalize the scale of each input variable to prevent the dominance of certain variables in the model training process. In this study, data normalization was performed by dividing each input and output value by the maximum value, which was 0.27 for nitrogen (N), 6185.03 for phosphorus (P), and 2.46 for potassium (K). This approach was chosen because the data used was local and limited to the PMK soil type, so the model was developed within the scope of the available experimental data.

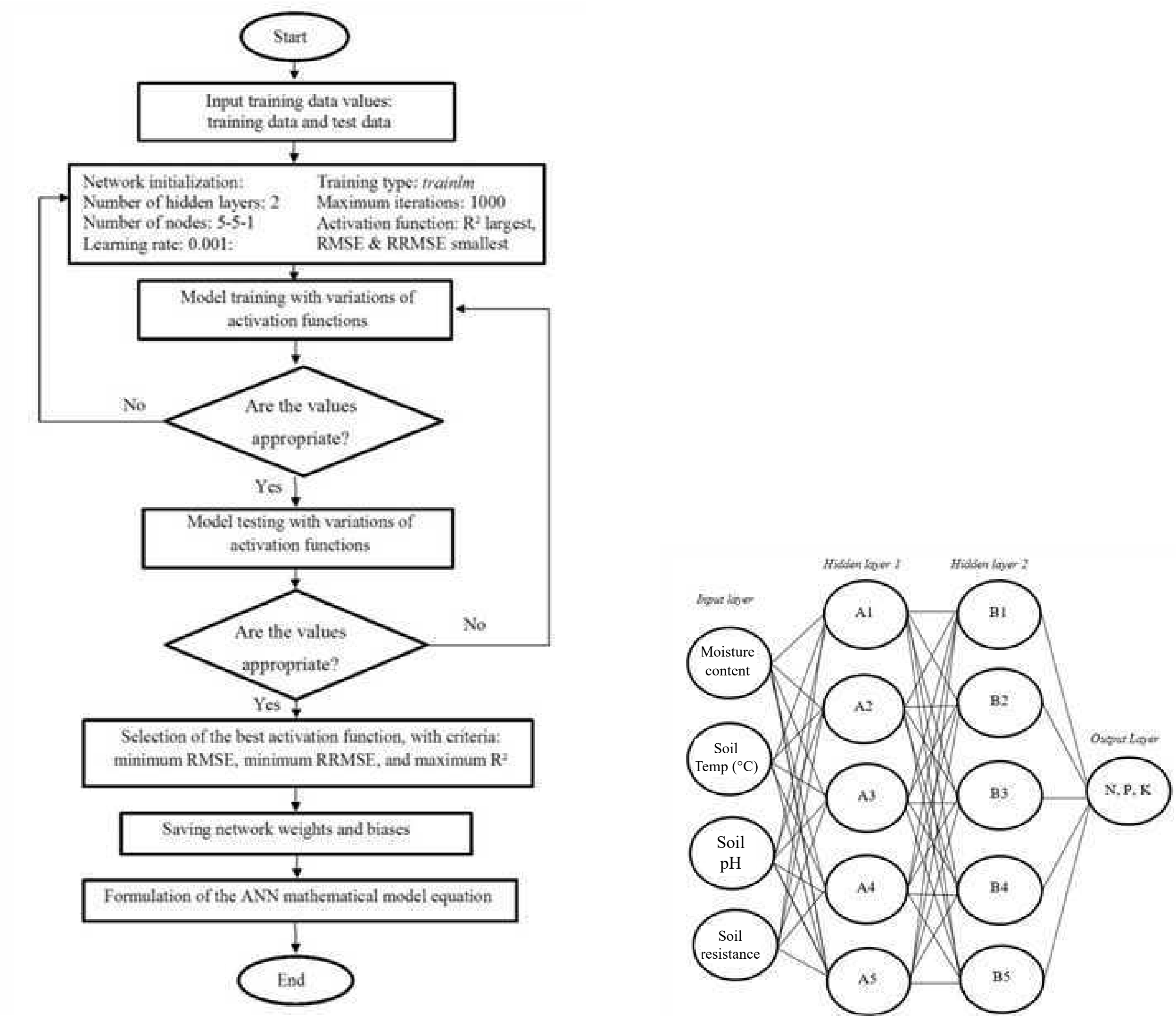

Figure 2. (a) Model development process in ANN, and (b) Artificial neural network architecture

2.5.2. ANN Model Calibration

The calibration of the artificial neural network model was performed by adjusting training parameters, such as the number of neurons in the hidden layer, the number of epochs, and the learning rate. The goal was to obtain the best configuration that produced the lowest possible error. The calibration process was carried out in stages until optimal model performance was achieved on the training data.

2.5.3. Model Validation

Model validation was performed to measure ability of the model to predict new, previously unknown data. The dataset was divided into two parts: 80% training data and 20% testing data. After the model was trained using the training data, its performance is evaluated using the test data. Model performance was evaluated using the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values, which are indicators of prediction accuracy.

The Root Mean Square Error calculation in validation data testing was used to determine the magnitude of the estimation error of the developed rapid measurement tool (Sujon *et al*., 2024). The RMSE was calculated according to the following formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \tag{1}$$

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i}} \times 100\% \tag{2}$$

where n is number of data samples, e_i is error of the i^{th} data, defined as the difference between the predicted value and the actual value, y_i is actual value of the i^{th} data

The coefficient of determination (R^2) calculation was used to measure the contribution of the independent variables to the dependent variables, namely the calibrator data and the rapid measuring instrument data. The coefficient of determination (R^2) was calculated based on the following formula:

$$R^2 = \frac{[n\sum xy - (\sum x)(\sum y)]^2}{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]} \tag{3}$$

where x is predicted value, y is actual value, and n is number of data samples.

3. RESULTS AND DISCUSSION

3.1. Artificial Neural Network Model Training

Prior to developing the artificial neural network (ANN) model, an analysis of the relationships between soil physical parameters as input variables (pH, temperature, moisture, and resistance) and the macronutrient levels of nitrogen (N), phosphorus (P), and potassium (K) as output variables was conducted. This analysis aimed to identify the direction and strength of the relationships between the variables, thus providing a scientific basis for the relationship between the input parameters and changes in soil nutrient levels. The analysis results showed that soil physical parameters had varying degrees of relationships, from weak to quite strong, with N, P, and K levels, which were influenced by soil conditions and fertilizer treatment. These findings support the use of soil physical parameters as inputs in ANN-based nutrient prediction modeling, even though the ANN method does not require an explicit linear mathematical relationship.

Theoretically, changes in soil pH affect nutrient availability through solubility and fixation mechanisms, where nitrogen, phosphorus, and potassium are generally more available at near-neutral pH conditions, while their availability tends to decrease under very alkaline or very acidic conditions (Alwi *et al*., 2023). Soil moisture plays a crucial role in controlling microbial activity and nitrogen mineralization processes, thus increasing N availability under optimal moisture conditions (Xing *et al*., 2019). Soil temperature influences biochemical reaction rates and microbial activity, where increasing temperature within the optimum range can increase nutrient mineralization and mobility (Lisa *et al*., 2022). Meanwhile, soil resistance is closely related to water content and the amount of dissolved ions in the soil, thus reflecting changes in nutrient concentration, particularly in ionic form (Salsabila *et al*., 2021; Salam, 2020). Thus, variations in pH, temperature, moisture, and soil resistance collectively contribute to the dynamics of N, P, and K availability, making them relevant for use as input variables in the development of an ANN-based soil nutrient prediction model.

The results of the analysis of the activation function combination are shown in Table 2 and indicate that the activation function used met the R^2 and RMSE criteria, both during the ANN model training stage. This indicates that the developed model is not only theoretically superior but also stable and accurate in practical applications for predicting soil nutrient levels. Figures 3–5 show the best R^2 graphs for the outputs of Nitrogen, Phosphorus, and Potassium, respectively.

Table 2. Results of training artificial neural network models with variations in activation functions

No	Activation Function	R^2			RMSE			RRMSE (%)		
		N	P	K	N	P	K	N	P	K
1	*Logsig-logsig-logsig*	0.9317	0.9990	0.9910	0.0168	17.3781	0.0926	11.7542	1.3187	7.3202
2	*Logsig-logsig-tansig*	0.9562	0.9879	0.9989	0.0135	241.2877	0.0926	9.4063	18.0058	2.4973
3	*Logsig-tansig-logsig*	0.9506	1.0000	0.9877	0.0148	12.4836	0.0913	10.0416	0.7999	8.7698
4	*Logsig-tansig-tansig*	0.9357	0.9628	0.9587	0.0137	414.4862	0.1389	10.4154	31.4602	13.5388
5	*Tansig-logsig-logsig*	0.9637	1.0000	0.9769	0.0125	12.3189	0.1354	8.5307	0.9350	13.5388
6	*Tansig-tansig-logsig*	0.8749	1.0000	0.9732	0.0127	10.5386	0.1300	15.8984	0.7979	3.9309
7	*Tansig-tansig-tansig*	0.9642	0.9157	0.9973	0.0107	619.1356	0.0328	8.5048	46.9961	3.6633
8	*Tansig-logsig-tansig*	0.9054	0.9894	0.9963	0.0198	221.9805	0.0492	13.8752	16.8855	4.9076
9	*Logsig-tansig-purelin*	0.9060	0.7977	0.9410	0.0197	297.8000	0.2366	13.7827	71.9611	22.7455
10	*Logsig-logsig-purelin*	0.9600	0.9822	0.9967	0.0121	286.9882	0.0457	8.9857	21.7873	3.4918
11	*Tansig-logsig-purelin*	0.8362	0.6996	0.9971	0.0258	1125.9580	0.0374	18.6932	85.4631	41.4996
12	*Tansig-tansig-purelin*	0.8915	0.7146	0.9996	0.0086	1100.7940	0.0165	14.8035	83.5463	1.5811
13	*Logsig-purelin-logsig*	0.5815	0.8521	0.8171	0.0416	858.0531	0.4309	29.0733	65.1668	41.7959
14	*Logsig-purelin-tansig*	0.5392	0.6498	0.6621	0.0331	1203.932	0.5012	30.5116	91.3608	48.1667
15	*Tansig-purelin-logsig*	0.5763	0.8952	0.6741	0.0413	727.3393	0.4880	29.4727	54.8274	46.8855
16	*Tansig-purelin-tansig*	0.5231	0.5474	0.6633	0.0362	1340.9670	0.4602	25.0046	101.7829	44.9479
17	*Purelin-logsig-logsig*	0.6901	0.8810	0.8051	0.0467	741.9108	0.5238	32.6617	31.3297	34.2333
18	*Purelin-logsig-tansig*	0.4719	0.4715	0.6313	0.0467	1425.2070	0.7462	32.6617	108.1770	46.2910
19	*Purelin-tansig-logsig*	0.5790	0.7762	0.6159	0.0420	996.9490	0.4917	29.3649	75.6710	47.2313
20	*Purelin-tansig-tansig*	0.5740	0.6034	0.7591	0.0420	1268.6890	0.3893	29.3649	96.2968	37.3942
21	*Purelin-purelin-purelin*	0.5740	0.0592	0.1321	0.0420	2091.7850	0.7388	29.3649	158.7720	70.9662
22	*Purelin-purelin-tansig*	0.1794	0.0606	0.1333	0.0582	158.6491	0.7382	40.7159	1317.4780	70.9549
23	*Purelin-purelin-logsig*	0.1241	0.0496	0.1310	0.0582	2103.5020	0.7392	40.8920	159.6614	71.0098
24	*Purelin-tansig-purelin*	0.1398	0.5794	0.5444	0.0402	1398.5350	0.5352	28.1749	106.1525	51.4163
25	*Purelin-logsig-purelin*	0.6093	0.6688	0.6234	0.0421	1241.0230	0.4775	29.4491	94.1969	45.8693
26	*Logsig-purelin-purelin*	0.5351	0.7853	0.6247	0.0438	999.1760	0.4883	30.6472	75.8401	46.6663
27	*Tansig-purelin-purelin*	0.5933	0.6147	0.7376	0.0318	1345.1400	0.4041	25.4492	102.2279	39.1949

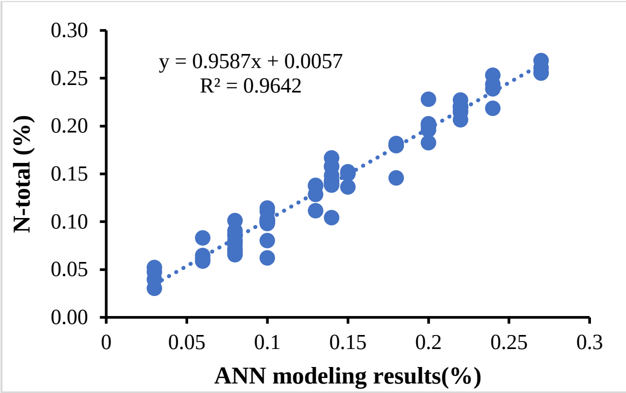

Figure 3. Training graph of the nitrogen output ANN model

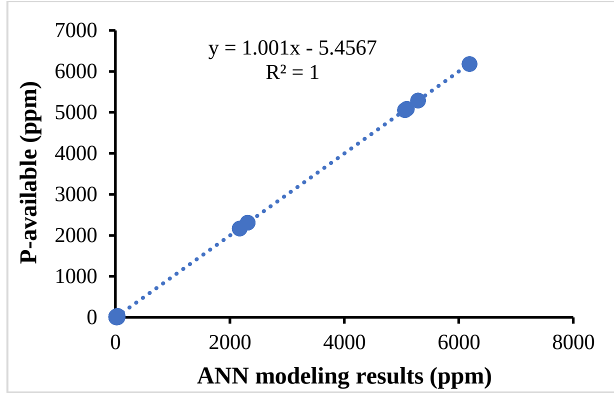

Figure 4. Training graph of the phosporus output ANN model

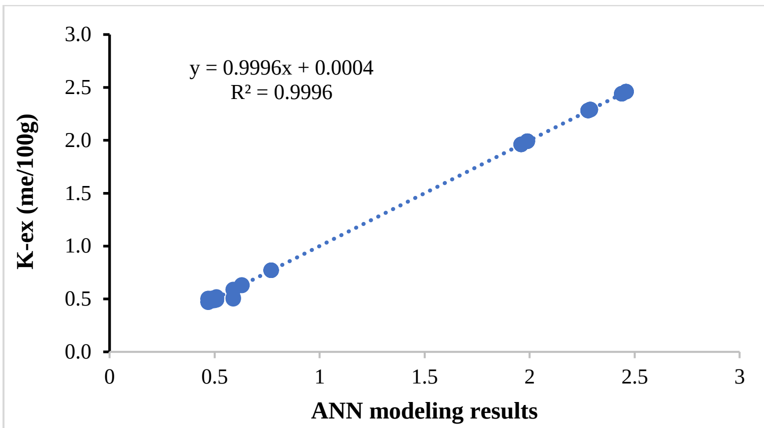

Figure 5. Training graph of the potassium output JST model

This research was evaluated using three main metrics: the coefficient of determination (R^2), root mean square error (RMSE), and relative root mean square error (RRMSE). The RMSE value describes the average prediction error, with lower values indicating better accuracy. The coefficient of determination R^2 indicates how well the model explains the variance of the actual data, with a value range of 0–1 (Normah *et al*., 2022). Based on the R^2 range classification, an R^2 value between 0.8–1.0 is categorized as a very strong relationship (Mostafa & Amano, 2019).

Figure 4 shows the training graph of the ANN model for nitrogen output with the tansig-tansig-tansig activation function configuration, resulting in an R^2 value of 0.9642, an RMSE of 0.0122, and an RRMSE of 8.5048%. A very high R^2 value indicates that the model is able to explain the variability of nitrogen data, while an RRMSE value $<10\%$ indicates very good prediction accuracy (Mostafa & Amano, 2019). Figure 5 displays the results of phosphorus prediction with the tansig-tansig-logsig activation, obtaining an R^2 value of 1.0000, an RMSE of 10.5386, and an RRMSE of 0.7999%. A perfect R^2 indicates that the model correctly explains all data variations, while a very low RRMSE strengthens prediction accuracy of the model (Nurani *et al*., 2023). Figure 6 shows the potassium prediction results using the tansig-tansig-purelin activation function, resulting in an R^2 value of 0.9996, an RMSE of 0.0165, and an RRMSE of 1.5811%. These values indicate that the model has excellent prediction accuracy for potassium, with the RRMSE value remaining in the very good category.

Based on the three training results, all ANN models used were categorized as very good in terms of accuracy. This aligns with the formulation and interpretation of R^2, which states that the smaller the RMSE value and the larger the R^2 value, the better the prediction model is categorized (Normah *et al*., 2022; Mostafa & Amano, 2019).

3.2. Mathematical Equations for Artificial Neural Network Model Development

In this study, the independent variables used as input to the artificial neural network were pH (X_1), soil moisture (X_2), temperature (X_3), and soil resistance (X_4), all of which were normalized to their maximum values. The maximum values used in the output normalization process were 0.27 for nitrogen (N), 6185.03 for phosphorus (P), and 2.46 for potassium (K).

The mathematical equations used were derived from the weights and biases generated by the previously identified best activation function. The weight and bias values recorded during the artificial neural network training process can be converted into mathematical equations. The resulting mathematical equations are:

a. Complete mathematical equation for nitrogen (N) output

$$Y_1 = 55.558503(X_1/9.24) + 24.068107(X_2/56.69) + 42.17181(X_3/31.30) – 4.850174(X_4/31.00) – 115.07083 \quad (4)$$

$$Y_2 = –2.732511(X_1/9.24) + 0.134934(X_2/56.69) + 28.314861(X_3/31.30) + 8.505593(X_4/31.00) – 30.61576 \quad (5)$$

$$Y_3 = 6.074083(X_1/9.24) – 19.29866(X_2/56.69) + 58.254335(X_3/31.30) + 15.512534(X_4/31.00) – 55.581952 \quad (6)$$

$$Y_4 = 0.3306865(X_1/9.24) + 38.41268(X_2/56.69) + 71.398324(X_3/31.30) + 13.262866(X_4/31.00) – 114.29284 \quad (7)$$

$$Y_5 = 23.210712(X_1/9.24) – 7.1043099(X_2/56.69) – 37.74691(X_3/31.30) + 9.5519219(X_4/31.00) + 16.783951 \quad (8)$$

$$Y_6 = 1\ \frac{(1-\exp(-2Y_1))}{(1+\exp(-2Y_1))} \quad (9)$$

$$Y_7 = 1\ \frac{(1-\exp(-2Y_2))}{(1+\exp(-2Y_2))} \quad (10)$$

$$Y_8 = 1\ \frac{(1-\exp(-2Y_3))}{(1+\exp(-2Y_3))} \quad (11)$$

$$Y_9 = 1\ \frac{(1-\exp(-2Y_4))}{(1+\exp(-2Y_4))} \quad (12)$$

$$Y_{10} = 1\ \frac{(1-\exp(-2Y_5))}{(1+\exp(-2Y_5))} \quad (13)$$

$$Y_{11} = –30.4598(Y_6) – 18.146365(Y_7) – 2.6387668(Y_8) + 8.8448447(Y_9) + 63.341346(Y_{10}) + 42.449882 \quad (14)$$

$$Y_{12} = 79.338(Y_6) – 43.342865(Y_7) +67.101086(Y_8) –34.124502(Y_9) –33.897458(Y_{10}) +52.373471 \quad (15)$$

$$Y_{13} = 7.2015703(Y_6) + 10.235603(Y_7) + 23.728956(Y_8) – 10.15598(Y_9) + 23.943019(Y_{10}) – 12.587297 \quad (16)$$

$$Y_{14} = 0.33641252 (Y_6) + 0.40161547(Y_7) + 0.77949492(Y_8) – 0.68902653(Y_9) – 0.27826973(Y_{10}) – 0.18369186 \quad (17)$$

$$Y_{15} = 1.2079812(Y_6) – 7.4009066(Y_7) + 4.7464049(Y_8) + 2.3916046(Y_9) – 0.21416861(Y_{10}) + 1.8553997 \quad (18)$$

$$Y_{16} = 1\ \frac{(1-\exp(-2Y_{11}))}{(1+\exp(-2Y_{11}))} \quad (19)$$

$$Y_{17} = 1\ \frac{(1-\exp(-2Y_{12}))}{(1+\exp(-2Y_{12}))} \quad (20)$$

$$Y_{18} = 1\ \frac{(1-\exp(-2Y_{13}))}{(1+\exp(-2Y_{13}))} \quad (21)$$

$$Y_{19} = 1\ \frac{(1-\exp(-2Y_{14}))}{(1+\exp(-2Y_{14}))} \quad (22)$$

$$Y_{20} = 1\ \frac{(1-\exp(-2Y_{15}))}{(1+\exp(-2Y_{15}))} \quad (23)$$

$$Y_{21} = –1.4667364(Y_{16}) + 1.0272561(Y_{17}) + 0.87802988(Y_{18}) – 2.2419515(Y_{19}) – 0.46389507(Y_{20}) + 2.0065998 \quad (24)$$

$$Y_{22} = 1\ \frac{(1-\exp(-2Y_{21}))}{(1+\exp(-2Y_{21}))} \quad (25)$$

$$Y_{23} = Y_{22} \times 0.27 \quad (26)$$

b. Complete mathematical equation for phosphorus (P) output

$$Y_{24} = 25.622119(X_1/9.24) + 11.844161(X_2/56.69) + 2.6118788(X_3/31.30) - 0.80440503(X_4/31.00) - 34.323175 \qquad (27)$$

$$Y_{25} = -13.85174(X_1/9.24) - 8.7536118(X_2/56.69) + 34.733468(X_3/31.30) + 10.81572(X_4/31.00) - 17.516009 \qquad (28)$$

$$Y_{26} = -3.3570292(X_1/9.24) - 26.444851(X_2/56.69) + 38.96596(X_3/31.30) + 8.2434825(X_4/31.00) - 16.987308 \qquad (39)$$

$$Y_{27} = 3.8207698(X_1/9.24) + 16.419773(X_2/56.69) + 33.194194(X_3/31.30) + 1.2360114(X_4/31.00) - 49.483012 \qquad (30)$$

$$Y_{28} = 10.150082(X_1/9.24) + 4.4279306(X_2/56.69) - 30.954689(X_3/31.30) + 3.4926039(X_4/31.00) + 15.109523 \qquad (31)$$

$$Y_{29} = 1\ \frac{(1-\exp(-2Y_{24}))}{(1+\exp(-2Y_{24}))} \qquad (32)$$

$$Y_{30} = 1\frac{(1-\exp(-2Y_{25}))}{(1+\exp(-2Y_{25}))} \qquad (33)$$

$$Y_{31} = 1\ \frac{(1-\exp(-2Y_{26}))}{(1+\exp(-2Y_{26}))} \qquad (34)$$

$$Y_{32} = 1\ \frac{(1-\exp(-2Y_{27}))}{(1+\exp(-2Y_{27}))} \qquad (35)$$

$$Y_{33} = 1\ \frac{(1-\exp(-2Y_{28}))}{(1+\exp(-2Y_{28}))} \qquad (36)$$

$$Y_{34} = -13.549729(Y_{29}) + 4.018987(Y_{30}) + 6.6299286(Y_{31}) + 2.37409679(Y_{32}) + 8.0787264(Y_{33}) + 9.0968665 \qquad (37)$$

$$Y_{35} = 10.529641(Y_{29}) - 11.18177(Y_{30}) - 9.5026158(Y_{31}) - 7.1212939(Y_{32}) - 10.52775(Y_{33}) + 1.5482697 \qquad (38)$$

$$Y_{36} = 9.3645867(Y_{29}) - 4.8295997(Y_{30}) + 0.091569768(Y_{31}) + 4.2884311(Y_{32}) - 5.5461665(Y_{33}) - 4.8710897 \qquad (39)$$

$$Y_{37} = -9.3645867(Y_{29}) - 4.8295997(Y_{30}) + 0.091569768(Y_{31}) + 4.2884311(Y_{32}) - 5.5461665(Y_{33}) - 4.8710897 \qquad (40)$$

$$Y_{38} = -0.59583357(Y_{29}) - 10.824461(Y_{30}) + 6.0863648(Y_{31}) - 8.735249(Y_{32}) + 5.9550104(Y_{33}) + 2.8382498 \qquad (41)$$

$$Y_{39} = 1\ \frac{(1-\exp(-2Y_{33}))}{(1+\exp(-2Y_{33}))} \qquad (42)$$

$$Y_{40} = 1\ \frac{(1-\exp(-2Y_{34}))}{(1+\exp(-2Y_{34}))} \qquad (43)$$

$$Y_{41} = 1\ \frac{(1-\exp(-2Y_{35}))}{(1+\exp(-2Y_{35}))} \qquad (44)$$

$$Y_{42} = 1\ \frac{(1-\exp(-2Y_{36}))}{(1+\exp(-2Y_{36}))} \qquad (45)$$

$$Y_{43} = 1\ \frac{(1-\exp(-2Y_{37}))}{(1+\exp(-2Y_{37}))} \qquad (46)$$

$$Y_{44} = -17.153885(Y_{39}) - 17.493776(Y_{40}) - 7.544691(Y_{41}) - 7.1198373(Y_{42}) - 6.9536383(Y_{43}) - 13.717326 \qquad (47)$$

$$Y_{45} = \frac{1}{(1+\exp(-Y_{44}))} \qquad (48)$$

$$Y_{46} = Y_{45} \times 6185.03 \qquad (49)$$

c. Complete mathematical equation for potassium (K) output

$$Y_{47} = 21.316504(X_1/9.24) + 12.756581(X_2/56.69) + 20.239099(X_3/31.30) - 0.4094501(X_4/31.00) - 51.707162 \qquad (50)$$

$$Y_{48} = -14.740496(X_1/9.24) - 5.0293409(X_2/56.69) + 32.325374(X_3/31.30) + 6.1513156(X_4/31.00) - 17.15765 \qquad (51)$$

$$Y_{49} = 15.87439(X_1/9.24) - 22.99444(X_2/56.69) + 31.274702(X_3/31.30) + 6.2694253(X_4/31.00) - 26.060498 \qquad (52)$$

$$Y_{50} = 5.2963202(X_1/9.24) + 26.902533(X_2/56.69) + 43.19557(X_3/31.30) - 2.7748419(X_4/31.00) - 67.295972 \qquad (53)$$

$$Y_{51} = 12.084338(X_1/9.24) - 5.0237417(X_2/56.69) - 23.543318(X_3/31.30) + 4.9934595((X_4/31.00) + \qquad (54)$$

14.76452

$$Y_{52} = 1 \frac{(1-\exp(-2Y_{47}))}{(1+\exp(-2Y_{47}))} \tag{55}$$
$$Y_{53} = 1 \frac{(1-\exp(-2Y_{48}))}{(1+\exp(-2Y_{48}))} \tag{56}$$
$$Y_{54} = 1 \frac{(1-\exp(-2Y_{49}))}{(1+\exp(-2Y_{49}))} \tag{57}$$
$$Y_{55} = 1 \frac{(1-\exp(-2Y_{50}))}{(1+\exp(-2Y_{50}))} \tag{58}$$
$$Y_{56} = 1 \frac{(1-\exp(-2Y_{51}))}{(1+\exp(-2Y_{51}))} \tag{59}$$
$$Y_{57} = 24.278767(Y_{52}) + 9.1042515(Y_{53}) - 31.060604(Y_{54}) - 67.983983(Y_{55}) + 31.799568(Y_{56}) + 84.380561 \tag{60}$$
$$Y_{58} = -1.8561997(Y_{52}) - 4.1389079(Y_{53}) - 5.7828181(Y_{54}) - 1.0227185(Y_{55}) + 6.3866275(Y_{56}) + 2.95593 \tag{61}$$
$$Y_{59} = 17.126712(Y_{52}) + 15.088561(Y_{53}) - 9.5451891(Y_{54}) + 6.0240936(Y_{55}) + 15.691524(Y_{56}) + 2.5028356 \tag{62}$$
$$Y_{60} = -17.968137(Y_{52}) - 15.972004(Y_{53}) + 10.255106(Y_{54}) - 6.5273149(Y_{55}) - 16.864093(Y_{56}) - 2.484777 \tag{63}$$
$$Y_{61} = -2.5519067(Y_{52}) - 26.355412(Y_{53}) - 42.192708(Y_{54}) + 11.507524(Y_{55}) + 2.5877625(Y_{56}) + 52.067797 \tag{64}$$
$$Y_{62} = 1 \frac{(1-\exp(-2Y_{57}))}{(1+\exp(-2Y_{57}))} \tag{65}$$
$$Y_{63} = 1 \frac{(1-\exp(-2Y_{58}))}{(1+\exp(-2Y_{58}))} \tag{66}$$
$$Y_{64} = 1 \frac{(1-\exp(-2Y_{59}))}{(1+\exp(-2Y_{59}))} \tag{67}$$
$$Y_{65} = 1 \frac{(1-\exp(-2Y_{60}))}{(1+\exp(-2Y_{60}))} \tag{68}$$
$$Y_{66} = 1 \frac{(1-\exp(-2Y_{61}))}{(1+\exp(-2Y_{61}))} \tag{69}$$
$$Y_{67} = -0.4399902(Y_{62}) + 0.43683859(Y_{63}) - 21.46099(Y_{64}) - 21.462333(Y_{65}) - 0.43440231(Y_{66}) + 0.64037101 \tag{70}$$
$$Y_{68} = Y_{67} \tag{71}$$
$$Y_{69} = Y_{68} \times 2.46 \tag{72}$$

3.3. ANN Model Validation

The designed nutrient level prediction tool is equipped with four potentiometers, each with a specific function as an analog input device. Potentiometer A is used to input soil pH, potentiometer B for moisture content (KA), potentiometer C for soil temperature, and potentiometer D for soil resistance. Each potentiometer is set within a specific range to ensure that input values do not exceed limits that could cause reading errors or unexpected spikes.

The maximum range for each potentiometer is adjusted as follows: the maximum pH value is set to 16, the maximum moisture content to 80, the maximum temperature to 50, and the maximum resistance to 50. These settings ensure that the values read by the system remain within a controlled range and do not produce thousands of digits when converted to digital. Technically, potentiometer A is connected to analog pin A0, potentiometer B to A1, potentiometer C to A2, and potentiometer D to A3 on the microcontroller.

The use of potentiometers in this system is considered effective in simplifying the data input process, particularly during initial testing and tool simulations. Furthermore, this approach provides users with the flexibility to manually adjust input values according to the soil parameters to be tested. The tool validation process is carried out by inputting soil parameter values into each potentiometer based on actual pH, humidity, temperature, and resistance data. The entered values are adjusted to the predetermined ranges for each potentiometer. After these values are processed by the system using an Artificial Neural Network (ANN)-based prediction model, the output, in the form of estimated soil nutrient levels, namely Nitrogen (N), Phosphorus (P), and Potassium (K), is displayed on the LCD screen. The nutrient level prediction tool display is shown in Figure 6.

Figure 6. Display of the NPK content from the designed instrument

The predicted NPK content results are then compared with the NPK content data obtained through laboratory tests as actual reference values to ensure the accuracy of the designed tool. The analysis of the relationship between the predicted and actual results is presented in graphical form. These graphs, shown in Figures 7–9 show the level of agreement between the tool results and the laboratory tests.

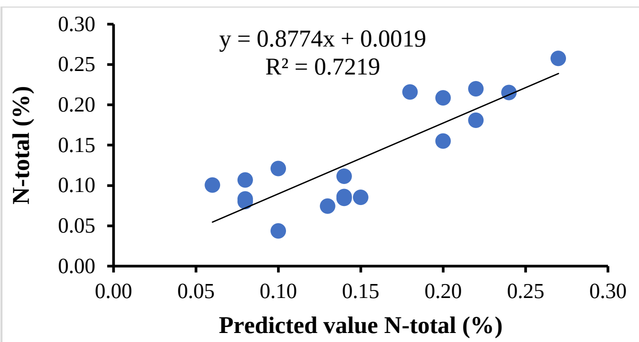

Figure 7. Validation graph of the actual value of the prediction tool test on nitrogen output

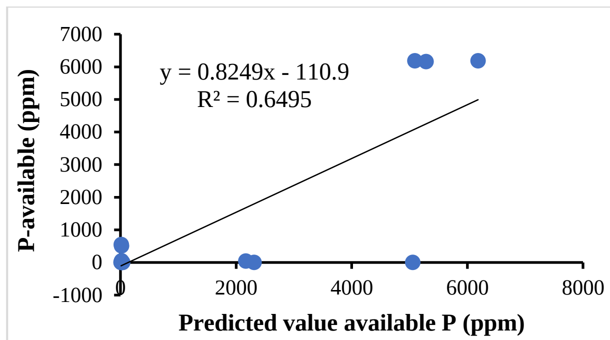

Figure 8. Validation graph of the actual value of the prediction tool test on phosphorus output

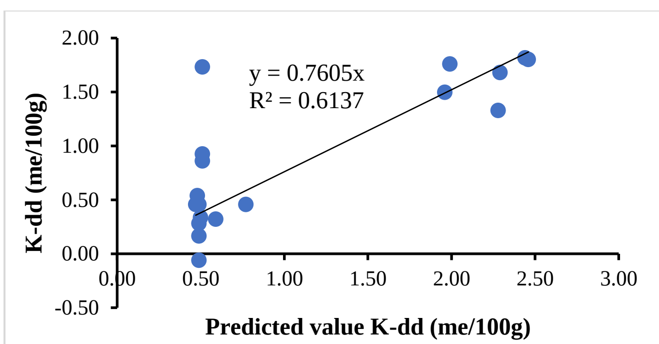

Figure 9. Validation graph of the actual value of the prediction tool test on potassium output

Figure 7 presents a validation graph comparing the total nitrogen (N-total) content based on the tool test results (actual value) with the soil nutrient content values predicted by the system. This graph illustrates the extent to which the predicted results approximate the actual values and can be used to evaluate the system's accuracy in detecting nitrogen content in the soil. The validation results for nitrogen showed a coefficient of determination (R^2) of 0.7218, indicating a fairly strong match between the predicted and actual values. Meanwhile, Figure 8 shows the validation results for phosphorus (P), which also compares the actual test values with the system's predicted values. The coefficient of determination (R^2) for phosphorus is 0.6479, indicating a fairly good correlation between the predicted and actual values. Next, Figure 9 presents the potassium (K) values, using the same approach, comparing the actual and predicted values. The coefficient of determination (R^2) for potassium is 0.6137. This indicates that the tool tends to produce estimates that are close to or slightly exceed the actual values, but still within acceptable tolerances.

A comparison of the predicted and actual values in Tables 3–5 indicate that the model has good ability to represent actual soil conditions. The tendency for predicted values to be slightly higher than actual values is likely related to the characteristics of the training data and the normalization process used. However, this difference is still within acceptable tolerance limits, thus deeming the model suitable for use as a prediction tool. Based on the results of tool testing on actual soil nutrient levels, different RMSE and RRMSE values were obtained for each parameter, nitrogen, phosphorus, and potassium. This difference indicates variations in the tool's accuracy in predicting each nutrient.

Table 3. Comparison of nitrogen (N) content based on prediction using instrument test with actual values

No	Actual Value	Predicted Value	No	Actual Value	Predicted Value	No	Actual Value	Predicted Value	No	Actual Value	Predicted Value
1	0.22	0.22	26	0.20	0.18	51	0.14	0.16	76	0.03	0.05
2	0.22	0.22	27	0.20	0.20	52	0.14	0.17	77	0.08	0.08
3	0.22	0.23	28	0.20	0.20	53	0.14	0.14	78	0.08	0.09
4	0.22	0.22	29	0.08	0.08	54	0.14	0.14	79	0.08	0.07
5	0.18	0.15	30	0.08	0.10	55	0.14	0.14	80	0.08	0.07
6	0.18	0.18	31	0.08	0.08	56	0.14	0.14	81	0.22	0.22
7	0.18	0.18	32	0.08	0.09	57	0.15	0.15	82	0.18	0.22
8	0.18	0.18	33	0.10	0.10	58	0.15	0.14	83	0.27	0.26
9	0.27	0.26	34	0.10	0.10	59	0.15	0.15	84	0.24	0.22
10	0.27	0.26	35	0.10	0.10	60	0.15	0.15	85	0.20	0.16
11	0.27	0.26	36	0.10	0.06	61	0.14	0.14	86	0.22	0.18
12	0.27	0.27	37	0.06	0.06	62	0.14	0.14	87	0.20	0.21
13	0.24	0.25	38	0.06	0.08	63	0.14	0.14	88	0.08	0.11
14	0.24	0.24	39	0.06	0.06	64	0.14	0.10	89	0.10	0.18
15	0.24	0.24	40	0.06	0.06	65	0.10	0.10	90	0.06	0.10
16	0.24	0.22	41	0.10	0.11	66	0.10	0.11	91	0.10	0.04
17	0.20	0.20	42	0.10	0.10	67	0.10	0.10	92	0.08	0.08
18	0.20	0.20	43	0.10	0.10	68	0.10	0.10	93	0.14	0.08
19	0.20	0.20	44	0.10	0.08	69	0.13	0.14	94	0.14	0.09
20	0.20	0.23	45	0.08	0.08	70	0.13	0.13	95	0.15	0.09
21	0.22	0.21	46	0.08	0.07	71	0.13	0.14	96	0.14	0.11
22	0.22	0.22	47	0.08	0.07	72	0.13	0.11	97	0.10	0.12
23	0.22	0.22	48	0.08	0.09	73	0.03	0.03	98	0.13	0.07
24	0.22	0.21	49	0.14	0.15	74	0.03	0.04	99	0.03	0.10
25	0.20	0.20	50	0.14	0.16	75	0.03	0.05	100	0.08	0.08

For nitrogen levels, the RMSE value was 0.0222 and the RRMSE was 15.54%. The RRMSE value, which is below 20%, indicates good nitrogen prediction accuracy. This indicates that the tool is capable of detecting and predicting soil nitrogen levels with relatively small errors compared to actual values. This agreement between predicted and actual values is likely influenced by the relatively narrow nitrogen data range and the sensor's relatively stable response to changes in nitrogen levels. Meanwhile, the phosphorus level test yielded an RMSE of 1066.77 and an RRMSE of 80.98%. The high RRMSE indicates low phosphorus level prediction accuracy. This high error is due to the wide range of phosphorus values, from low to very high, and the presence of several predictions that are zero or significantly different from the actual value. This situation results in a large difference between the actual and predicted values, significantly impacting the RMSE and RRMSE values. This indicates that the tool still requires further development in predicting phosphorus levels, both in terms of the sensor and the prediction model used.

For potassium levels, the RMSE value obtained was 0.2963 with an RRMSE of 28.46%. This value indicates that the accuracy of potassium prediction is in the moderate category. Although most of the data shows a fairly good agreement between actual and predicted values, there are several data points with significant differences that increase the overall error. This indicates that the tool's performance in predicting potassium is quite good, but still needs

Table 4. Comparison of phosphorus (P) content based on prediction using instrument test with actual values

No	Actual Value	Predicted Value	No	Actual Value	Predicted Value	No	Actual Value	Predicted Value	No	Actual Value	Predicted Value
1	16.05	6.55	26	17.87	16.92	51	2166.79	2166.78	76	11.39	8.20
2	16.05	0.07	27	17.87	19.62	52	2166.79	2166.76	77	36.52	0.00
3	16.05	0.00	28	17.87	17.18	53	2310.67	2310.66	78	36.52	36.27
4	16.05	20.71	29	19.29	0.00	54	2310.67	2310.60	79	36.52	36.14
5	35.71	1.10	30	19.29	22.42	55	2310.67	2310.64	80	16.05	0.00
6	35.71	35.64	31	19.29	15.14	56	2310.67	2310.67	81	35.71	0.00
7	35.71	9.80	32	19.29	0.01	57	5286.59	5286.59	82	15.85	0.00
8	35.71	5.28	33	18.68	15.46	58	5286.59	5286.59	83	12.00	16.14
9	15.85	12.56	34	18.68	22.87	59	5286.59	5286.55	84	10.58	6154.96
10	15.85	0.00	35	18.68	21.12	60	5286.59	5286.61	85	9.97	6184.42
11	15.85	3.43	36	18.68	0.00	61	5056.91	5056.91	86	17.87	0.00
12	15.85	4.34	37	12.00	19.43	62	5056.91	5056.90	87	19.29	506.79
13	12.00	0.00	38	12.00	0.00	63	5056.91	5056.91	88	18.68	16.37
14	12.00	15.66	39	12.00	15.88	64	5056.91	5056.93	89	12.00	550.69
15	12.00	11.06	40	12.00	15.70	65	6185.03	6183.23	90	18.28	53.34
16	12.00	14.24	41	18.28	15.25	66	6185.03	6179.58	91	18.68	0.00
17	10.58	7.28	42	18.28	17.68	67	6185.03	6183.40	92	2166.79	44.65
18	10.58	4.72	43	18.28	18.11	68	6185.03	6181.61	93	2310.67	0.00
19	10.58	16.64	44	18.28	24.12	69	5090.69	5090.69	94	5286.59	6163.49
20	10.58	14.93	45	18.68	18.78	70	5090.69	5090.69	95	5056.91	0.00
21	9.97	8.20	46	18.68	4.72	71	5090.69	5090.67	96	6185.03	6185.03
22	9.97	9.81	47	18.68	15.31	72	5090.69	5090.68	97	5090.69	6185.03
23	9.97	19.57	48	18.68	15.18	73	11.39	12.67	98	11.39	0.02
24	9.97	15.83	49	2166.79	2166.80	74	11.39	0.00	99	36.52	0.00
25	17.87	14.07	50	2166.79	2166.50	75	11.39	12.97	100	16.05	0.00

Table 5. Comparison of potassium (K) content based on prediction using instrument test with actual values

No	Actual Value	Predicted Value	No	Actual Value	Predicted Value	No	Actual Value	Predicted Value	No	Actual Value	Predicted Value
1	0.47	0.47	26	1.96	1.96	51	0.77	0.77	76	0.48	0.48
2	0.47	0.47	27	1.96	1.96	52	0.77	0.77	77	0.49	0.50
3	0.47	0.50	28	1.96	1.96	53	0.51	0.51	78	0.49	0.50
4	0.47	0.47	29	1.99	1.99	54	0.51	0.51	79	0.49	0.50
5	0.49	0.50	30	1.99	1.99	55	0.51	0.49	80	0.49	0.50
6	0.49	0.50	31	1.99	1.99	56	0.51	0.50	81	0.47	2.12
7	0.49	0.50	32	1.99	1.99	57	0.51	0.51	82	0.49	-0.06
8	0.49	0.48	33	2.28	2.28	58	0.51	0.49	83	0.49	0.16
9	0.49	0.50	34	2.28	2.28	59	0.51	0.51	84	0.50	0.34
10	0.49	0.50	35	2.28	2.28	60	0.51	0.50	85	0.49	0.28
11	0.49	0.50	36	2.28	2.28	61	0.51	0.51	86	0.47	0.46
12	0.49	0.48	37	2.29	2.29	62	0.51	0.50	87	1.96	1.50
13	0.50	0.48	38	2.29	2.29	63	0.51	0.51	88	1.99	1.76
14	0.50	0.50	39	2.29	2.29	64	0.51	0.52	89	2.28	1.33
15	0.50	0.50	40	2.29	2.29	65	0.59	0.59	90	2.29	1.68
16	0.50	0.50	41	2.44	2.44	66	0.59	0.51	91	2.44	1.82
17	0.49	0.50	42	2.44	2.44	67	0.59	0.50	92	2.46	1.80
18	0.49	0.49	43	2.44	2.44	68	0.59	0.59	93	0.77	0.46
19	0.49	0.49	44	2.44	2.44	69	0.63	0.63	94	0.51	0.86
20	0.49	0.50	45	2.46	2.46	70	0.63	0.63	95	0.51	1.73
21	0.47	0.50	46	2.46	2.46	71	0.63	0.63	96	0.51	0.93
22	0.47	0.50	47	2.46	2.46	72	0.63	0.63	97	0.59	0.32
23	0.47	0.50	48	2.46	2.46	73	0.48	0.48	98	0.63	1.74
24	0.47	0.47	49	0.77	0.77	74	0.48	0.50	99	0.48	0.54
25	1.96	1.96	50	0.77	0.77	75	0.48	0.50	100	0.49	0.46

improvement to match the accuracy of nitrogen predictions. Overall, the test results showed that the tool performed best in predicting nitrogen levels, followed by potassium, while phosphorus predictions still showed a high error rate. Therefore, system improvements are needed, particularly in the measurement and modeling of phosphorus levels, to increase the tool's reliability in soil nutrient analysis applications.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1. Conclusions

This study demonstrates that the Artificial Neural Network (ANN)-based soil nutrient prediction model is capable of providing adequate performance in estimating nitrogen, phosphorus, and potassium levels. The combination of activation functions used produced an R^2 value above 0.96 and an RRMSE below 10% during the training phase, indicating that the model can explain data variability with a low error rate. Mathematical equations for the model have also been formulated for each nutrient element as a reference in the computational process.

The developed prediction tool, with four analog potentiometers as input, has been tested and validated using red-yellow podzolic soil data. The validation results showed R^2 values of 0.7218 for nitrogen, 0.6479 for phosphorus, and 0.6137 for potassium, respectively. This indicates that the tool's estimates have a sufficient level of agreement with laboratory test results, making it suitable for use as an aid in monitoring soil nutrient levels in the field.

4.2. Recommendations

Further research is recommended to use data from a wider range of soil types and environmental conditions, and to apply normalization values based on global ranges to make the model more adaptable and more widely applicable.

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