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Prediction of Soil Nutrients from Different Soil Textures using Portable Spectrometer and Machine Learning

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Abstract. Soil nutrients, such as nitrogen, phosphorus, and potassium, are essential for plant growth and agricultural productivity. Conventional laboratory methods for measuring these nutrients are accurate, but often time-consuming, expensive, and harmful to the environment. This study explores the potential of portable visible-near infrared (Vis-NIR) spectrometers combined with machine learning algorithms as a fast, cost-effective, and environmentally friendly alternative for soil nutrient analysis. The soil samples used consisted of clay, sandy clay, and loamy clay. The machine learning model used was artificial neural network (ANN). The ANN model was developed using the H2O library with the AutoML feature as a hyperparameter tuner to improve accuracy and cross-validation to reduce overfitting. A total of 81 reflectance spectrum data from each soil type were obtained using the AS7265x sensor and processed to develop a predictive model of nutrient content. The ANN model demonstrated high accuracy, with R^2 values exceeding 0.8 for each soil texture type. This study highlights the potential of integrating portable Vis-NIR spectrometers and machine learning to revolutionize soil nutrient analysis, offering significant improvements in agricultural efficiency and sustainability.

Keywords: artificial neural network, machine learning, portable vis-nir spectrometer, soil nutrient prediction, spectral analysis

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1. Introduction

The availability of soil nutrients such as nitrogen (AN), phosphorus (AP), and potassium (AK) is crucial for supporting plant growth and directly impacts agricultural productivity [1].A deficiency in one or more of these essential nutrients can hinder plant growth, cause nutrient deficiencies, and ultimately reduce crop yields [2]. Therefore, monitoring and measuring soil nutrient levels is vital to ensure agricultural sustainability and optimize harvest outcomes.

Amid the growing global food demand and food security issues, precision fertilizer management is becoming increasingly urgent. Excessive fertilizer use not only leads to resource wastage but also negatively impacts the environment, such as water pollution, eutrophication, and increased greenhouse gas emissions. In this context, accurate soil nutrient assessment is essential to optimize fertilizer usage and minimize ecological impacts [3]. Conventional methods such as Kjeldahl testing for nitrogen, Bray testing for phosphorus, and HCl extraction for potassium are still widely used [4]. However, these methods have several limitations, including long processing times, high costs, potential environmental harm from chemical use, and heavy reliance on personnel expertise. Variability in procedures often affects the consistency of results, ultimately limiting efficiency and sustainability.

As a more efficient and environmentally friendly alternative, visible-near infrared spectroscopy (Vis-NIR) has gained attention in soil nutrient analysis. This method utilizes light spectra and mathematical models to estimate nutrient content. The main advantages of Vis-NIR lie in its non-destructive, rapid, and chemical-free nature, allowing large-scale monitoring with low costs and providing timely information in agricultural contexts.

To improve the accuracy of Vis-NIR measurements, machine learning-based prediction models, such as Artificial Neural Networks (ANN), have been adopted. ANN is selected for its ability to handle both linear and non-linear complex data, as well as high variability in soil samples [5]. Compared to other machine learning algorithms, ANN offers the advantage of creating more robust predictive models, thereby enhancing prediction accuracy [6]. A key advantage of portable spectrometers is their ability to deliver immediate results in the field, unlike conventional methods, which tend to be more expensive and require larger equipment. Portable spectrometers enable farmers to easily access soil nutrient analysis data, leading to faster, data-driven decision-making.

Several studies have demonstrated the potential of Vis-NIR spectroscopy for this purpose. Jiang et al. [7] successfully used NIR spectroscopy to predict various soil parameters, including TN, TP2O5, and TK2O, with improved accuracy through the application of machine learning. Similarly, Saidi et al. [8] demonstrated the reliability of this method in predicting phosphorus adsorption at the watershed scale. Furthermore, Metzger et al. [9] confirmed its effectiveness in detecting organic carbon soil and nitrogen content. Meanwhile, Devianti et al. [10] demonstrated its accuracy in tropical agricultural land with the help of machine learning, highlighting the great potential of Vis-NIR to support precision agriculture.

In this study, three types of soil texture were selected, namely clay, sandy clay, and loamy clay. The selection of these three soil textures was based on the types of soil commonly used in agriculture. These three types of soil represent the characteristics of soil commonly found in various agricultural areas, with significant differences in terms of structure, texture, and water retention capacity. Therefore, this study has great potential to provide practical and applicable solutions that can be used by farmers on various types of land. Vis-NIR spectroscopy is a promising approach for measuring soil nutrients, offering several advantages over conventional methods. Its application can help farmers optimize fertilization, improve agricultural production efficiency, and minimize negative environmental impacts. However, this technology still requires further research to enhance accuracy and field application, as well as address challenges related to calibration and soil sample variability. The use of Vis-NIR for soil nutrient measurement could be a strategic step toward more sustainable and environmentally friendly agriculture.

2. **Methods**

2.1. Sample preparation

Soil samples were collected from three areas: clay soil from UB Forest, clay loam soil from UB experimental land (Jatimulyo, Malang), and sandy clay soil from Sirah Kencong tea plantation (Blitar). Soil samples were taken from a 2 x 2 m area at a depth of 0–30 cm, amounting to 50 kg. Furthermore, these samples were analyzed in a laboratory to determine pH, organic carbon content (C-Organic, %), available nitrogen (%), available phosphorus (mg/kg), and available potassium (me/100g). Soil samples were mixed with distilled water and a 1 N KCl solution at a 1:1 ratio to measure pH. Organic carbon content was measured using the Walkey and Black method, nitrogen was measured using the Kjeldahl method, phosphorus was measured using the Bray I method, and potassium was measured using the ammonium acetate (NH_4OAc) extraction method. The laboratory results are presented in Table 1.

Table 1. Research on weather/rain prediction

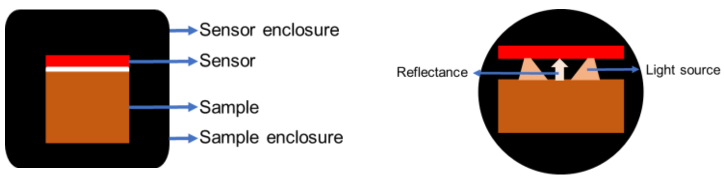
Soil texture	Result						
	pH 1:1		C-Organic (%)	Nitrogen (%)	C/N ratio	Phosphorus (mg/Kg)	Potassium (me/100g)
	H_2O	KCl 1 N					
Clay	5.6	5.5	3.53	0.23	15	19.91	1.10
Loam clay	6.4	5.7	1,25	0,13	10	23,51	0,51
Sandy clay	5,6	4,8	2,79	0,32	9	22,71	0,21

Next, nitrogen, phosphorus, and potassium levels were varied by adding single fertilizers, namely Urea (46%), TSP (46%), and KCl (60%). Calculations were made for the addition of each single fertilizer to determine the increase in nitrogen (%), phosphorus (mg/100g), and potassium (mg/100g). Furthermore, nutrient levels were categorized into three groups: low (<20 mg/100g), medium (20–40 mg/100g), and high (>40 mg/100g) [11]. Based on these categories, 27 combinations of nitrogen, phosphorus, and potassium levels were obtained. Three values were selected for each category of each nutrient, resulting in 81 samples. The pre-calculated mass of fertilizer was dissolved in distilled water and homogenized with 300g of soil sample, then dried without heat treatment. The dried samples were then ground to a fine powder and sieved with a 2 mm sieve.

2.2. Reflectance Spectrum Measurement and Data Acquisition

The reflectance spectrum measurement system consists of two parts: The sensor casing with dimensions of 60.2 x 60.2 x 34 mm and the sample casing with dimensions of 60.2 x 60.2 x 19.5 mm (Figure 1). The AS7265X sensor (SparkFun) covers the Vis-NIR wavelength range of 410-940 nm with 18 channels. This sensor is integrated with a Wemos Lolin ESP32 microcontroller and programmed in C++ language to transmit data via Bluetooth. In addition, a 3.7V Li-Po battery serves as the power source. A sample cage was used to house the sample container during spectral data acquisition. Data was collected from three points per sample, each point was scanned five times and averaged per point, resulting in 81 sets of spectrum data. After collecting spectrum data from each soil sample, the soil samples were analyzed in the laboratory to determine the content of nitrogen, phosphorus, and potassium.

(a)



(b)

Figure 1. Research Methodology

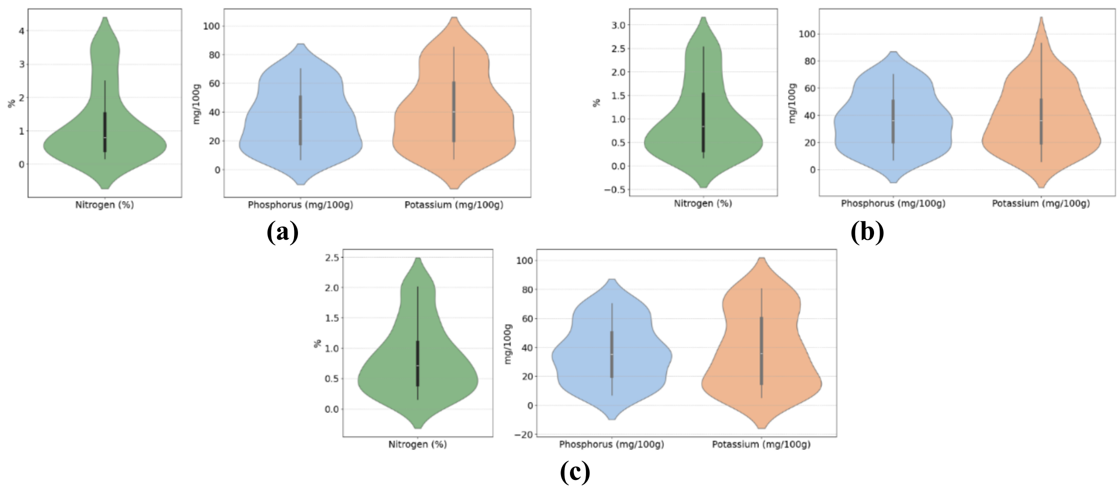
Before acquisition the spectral data, reference data from a white card and dark spectrum (non-active LED sensor) were collected. These reference values were used to normalize the sample spectrum data. The white card reference is defined as I_{white}, the dark spectrum reference is defined as I_{dark}, and the reflectance spectrum of the sample is defined as I_{sample}. The sample spectrum values were normalized using the following formula (1):

$$I_{sample} = \frac{I_{sample} - I_{dark}}{I_{white} - I_{dark}} \tag{1}$$

2.3. Classification and Prediction Model Development
The classification and prediction model for soil nitrogen, phosphorus, and potassium levels was developed using ANN algorithm on the Google Colab platform with python programming language. A total of 81 datasets were used, split into 90% for model development (with an internal 90:10 split for training and validation) and 10% for testing. The data preprocessing technique of normalization is used to reduce data noise, thereby improving the sensitivity of the built model. Additionally, feature selection is performed using Principal Component Analysis (PCA) to extract the most important information. Feature selection is based on loading scores, with the highest correlated scores being selected. Spectral data served as predictors, while nutrient levels were the targets. Artificial neural networks (ANN) were implemented using the H_2O library with AutoML. This approach uses machine learning to automatically build the optimal model by selecting parameters such as the number of hidden layers and neurons. Cross-validation techniques were used to reduce overfitting [10]. During the AutoML process, several ANN configurations were trained and evaluated based on validation metrics to identify the model with the best performance. The final model selection is based on achieving the highest coefficient of determination (R^2) and the lowest root mean square error (RMSE). With this approach, ANN AutoML helps reduce the time and effort required to build effective ANN models, as well as making machine learning technology more accessible to users without in-depth experience in the field.

3. **Results and Discussion**
3.1. Nitrogen, Phosphorus, and Potassium Levels
Figure 2 presents violin plots of soil nutrient data, nitrogen, phosphorus, and potassium, showing data distribution through median, interquartile range, outliers, and density estimation. Phosphorus and potassium display a relatively normal distribution, indicated by their balanced density curves. In contrast, nitrogen exhibits a narrower distribution due to differing measurement units. Despite this, nitrogen values remain representative across low, medium, and high categories.

Nitrogen, phosphorus, and potassium are critical macronutrients for plant growth. Nitrogen supports protein, enzyme, and chlorophyll synthesis, essential for photosynthesis. Deficiency may cause stunted growth, chlorosis, and yield loss, while excess can lead to excessive vegetative growth at the expense of reproductive parts [12]. Phosphorus promotes root development, flowering, and seed production, with deficiency symptoms including stunted roots and leaf purpling [13]. Potassium strengthens stress resistance to drought, disease, and temperature extremes, where deficiency results in necrotic leaf edges, weak stems, and reduced quality of fruits and seeds [14].



(a) (b) (c)

Figure 2. Violin plots of nutrients of soil (a) clay, (b) sandy loam, and (c) loam clay

3.2. Characteristics of the soil spectrum

Figure 3 displays the reflectance spectra of clay, loam clay, and sandy clay soils in the 410–940 nm range, showing distinct patterns influenced by texture, mineral composition, and moisture content [15]. Absorption in the 400–1000 nm range is mainly due to iron oxides like hematite and goethite, along with organic matter [16], while absorption beyond 1000 nm relates to overtone and combination vibrations of organic and inorganic functional groups [17]. Clay soils exhibit low reflectance in the visible range (410–700 nm) with a sharp increase after 700 nm, influenced by kaolinite and montmorillonite minerals that absorb visible light and reflect more in the NIR region [18]. Loam clay soils follow a similar pattern but with slightly higher visible reflectance due to enhanced light scattering from higher clay content. This indicates that clay plays a key role in modulating light absorption by soil minerals [16]. Sandy clay soils show the highest reflectance, particularly in the NIR range, attributed to larger sand particles that scatter light more effectively and retain less water. This aligns with Rossel & Webster [16], who found that sand content increases reflectance in the NIR spectrum.

Overall, reflectance spectra reveal distinct optical behaviors: clay exhibits stronger absorption, loam clay combines absorption and scattering, while sandy clay emphasizes scattering. These observations support the application of Vis-NIR spectroscopy in distinguishing soil properties, as demonstrated by Barman & Choudhury [19].

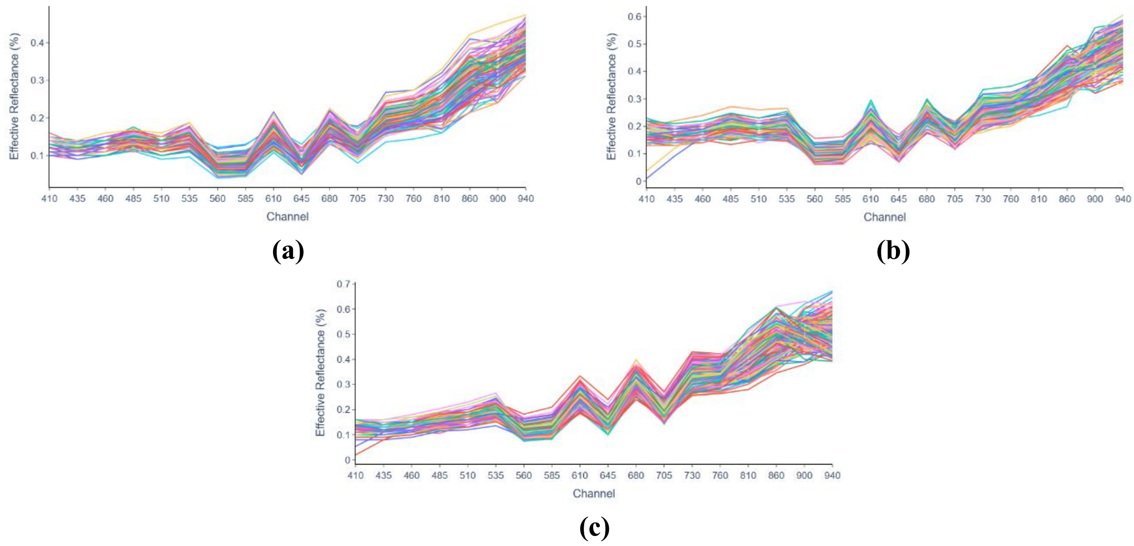


Figure 3. Spectrum of (a) Clay soil, (b) Loam clay soil, and (c) Sandy clay soil

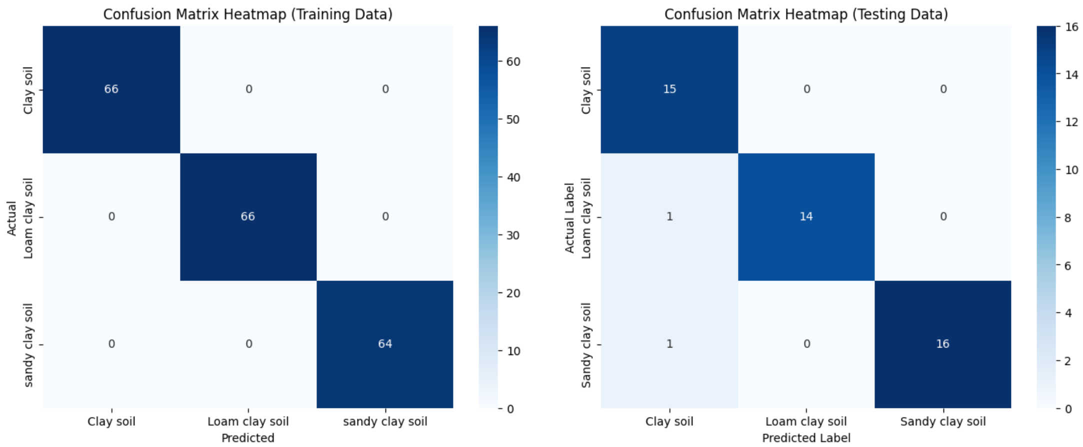
3.3. Classification model based on soil texture and soil nutrient categories

The classification model for soil texture was developed using ANN with both full and selected reflectance spectral features. Based on Table 2, the model using all spectral features yielded the highest performance, with 100% training accuracy and 96% testing accuracy. This model used three hidden layers with ten nodes each. These results affirm that Vis-NIR reflectance can effectively distinguish soil texture types by capturing spectral differences associated with soil profile characteristics [17,20]. Each soil type exhibits distinct spectral patterns due to differences in particle composition: clay soil contains balanced sand, silt, and clay; loam clay has a higher clay fraction, while sandy clay has dominant sand content [19].

Table 2. Categories classification model of soil texture

Dataset	ANN structure	Accuracy training	Accuracy testing
All feature	10-10-10	100%	96%
Selected feature	100-100	99%	95%

Figure 4 shows the confusion matrix results of the training and testing data. The training model was performed with 100% accuracy (Figure 4a), where all samples were classified correctly. The 66 clay soil samples, 66 loam clay soil samples, and 64 sandy clay soil samples are all on the main diagonal, indicating no misclassification. This result indicates that the model has learned the patterns from the training data very well. Then, regarding the testing data, the model still performed very well, with an accuracy of about 96% (Figure 4b), although there were a few misclassifications. 15 of 16 Clay soil samples were correctly classified, while one was incorrectly classified as Sandy clay soil. For the Loam clay soil category, 14 out of 15 samples were correctly classified, with 1 sample incorrectly classified as Clay soil. As for Sandy clay soil, 16 of 17 samples were correctly classified, with 1 sample incorrectly classified as Clay soil. This misclassification occurred between Clay soil and Sandy clay soil, most likely due to the similarity in physical characteristics between the two soil types, such as higher sand content than Loam clay soil.



(a) **(b)**

Figure 4. Confusion matrix for soil texture classification (a) Training, (b) Testing

In addition to the classification model based on soil texture, a classification model based on the categories of nitrogen, phosphorus, and potassium nutrients from each type of soil texture was also produced. The dataset used includes all and selected features from the reflectance spectrum. The classification model based on nutrient categories is presented in Table 3.

Table 3. Categories classification model of nitrogen, phosphorus, and potassium of each soil type

Soil texture	Soil nutrients	Dataset	ANN structure	Accuracy training	MSE
Clay soil	Nitrogen (%)	All feature	100	0.97	0.015
		Selected feature	100-100	0.80	0.168
	P_2O_5 (mg/100g)	All feature	100-100-100	1.00	0.013
		Selected feature	100-100	0.91	0.072
	K_2O	All feature	20-20	0.97	0.016

	(mg/100g)	Selected feature	10-10-10	0.44	0.412
Loam clay soil	Nitrogen (%)	All feature	100-100-100	0.98	0.018
		Selected feature	100-100	0.96	0.013
	P_2O_5 (mg/100g)	All feature	100	0.95	0.052
		Selected feature	100	0.96	0.033
	K_2O (mg/100g)	All feature	20-20	1.00	0.001
		Selected feature	100	0.93	0.072
Sandy lay soil	Nitrogen (%)	All feature	100-100-100	0.90	0.084
		Selected feature	100-100-100	0.88	0.084
	P_2O_5 (mg/100g)	All feature	100-100	1.00	0.007
		Selected feature	100-100	069	0.238
	K_2O (mg/100g)	All feature	100	1.00	0.031
		Selected feature	100-100	0.74	0.197

3.4. Prediction model for nitrogen, phosphorus, and potassium

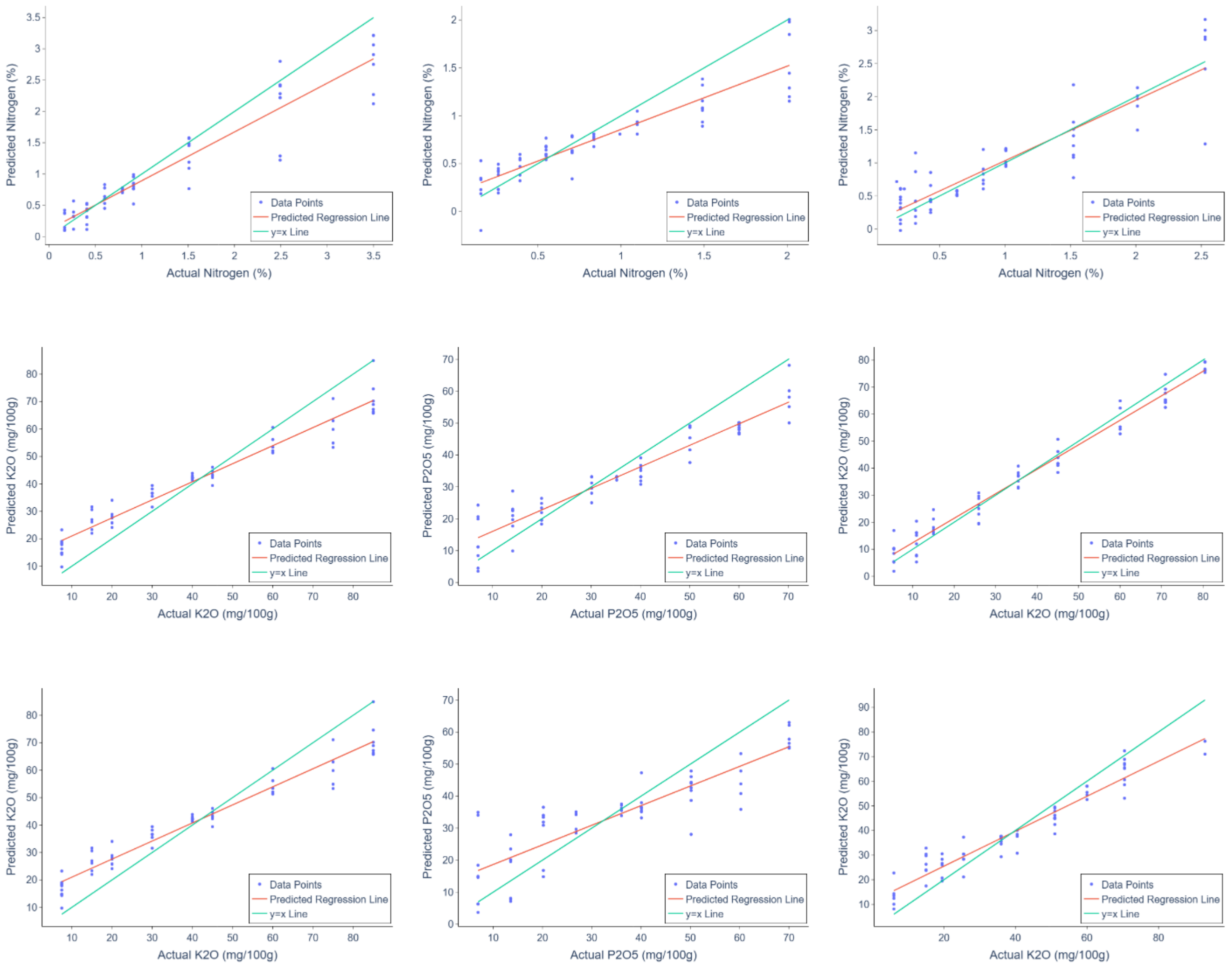
In this study, the best prediction models were selected based on the coefficient of determination (R^2), where values closer to 1 indicate a higher proportion of variability in nutrient content explained by the soil reflectance spectra [10]. As shown in Table 4, the optimal models were developed using the full set of spectral features. The highest R^2 value for nitrogen prediction ($R^2 = 0.88$) was achieved in clay soil using a three-layer ANN with 20 nodes per layer (20-20-20). For loam clay soil, the best phosphorus (P_2O_5) prediction model yielded an R^2 of 0.81 using a two-layer ANN with 50 nodes per layer. The most accurate potassium prediction ($R^2 = 0.97$) was also obtained in loam clay soil using a three-layer ANN with 20 nodes per layer. ANNs demonstrated strong performance for both linear and non-linear relationships. These findings are consistent with Daniel et al. [21], who achieved an R^2 of 0.8 for macronutrient estimation using Vis-NIR spectra (400–1100 nm). In contrast, Devianti et al. [10] reported overfitting when using a broader spectral range (400–2500 nm) due to noise in spectral acquisition. In this study, consistent spectral trends contributed to reliable and implementable models. Other studies employing partial least squares regression (PLSR) reported R^2 values of 0.82 for soil organic carbon and 0.71 for phosphorus [22].

The application of portable Vis-NIR spectrometer combined with a machine learning model (ANN) enables faster, more economical, and environmentally friendly measurement of soil nutrient content. In addition, these portable spectrometers can be used directly in the field, providing instant results and facilitating faster decision-making for farmers. With lower costs and ease of operation, this method offers better scalability, allowing its application to various types of land with higher cos efficiency [23]. However, it is important to note that the accuracy of the model can be affected by varying soil conditions. Factors such as moisture content, temperature, and soil pH can be affects spectral response, which in turn affects the model's prediction of nutrient content. Soils with high moisture content tend to exhibit different spectral behavior compared to dry soils, which can affect light absorption and reflection in the Vis-NIR spectrum [24]. In addition, differences in soil pH can alter the interaction between light and soil particles, which may impact the model's accuracy in measuring nutrient levels. Therefore, further research is needed to evaluate the robustness of this model under various soil conditions and to optimize the calibration process in order to handle these variations more effectively.

Table 4. Prediction models of nitrogen, phosphorus, and potassium from each soil type

Soil texture	Soil nutrients	Dataset	ANN structure	R^2 Training	R^2 Testing	RMSE Training	RMSE Testing
Clay soil	Nitrogen (%)	All feature	20-20-20	0.88	0.95	0.38	0.25
		Selected feature	20-20	0.82	0.91	0.46	0.32
	P_2O_5 (mg/100g)	All feature	100	0.67	0.93	11.88	5.73
		Selected feature	100	0.37	0.65	15.91	12.75
	K_2O (mg/100g)	All feature	100-100	0.85	0.83	9.72	11.10
		Selected feature	100-100	0.85	0.71	9.46	14.35
Loam clay soil	Nitrogen (%)	All feature	50-50	0.79	0.53	0.27	0.35
		Selected feature	50-50	0.71	0.78	0.30	0.23
	P_2O_5 (mg/100g)	All feature	50-50	0.82	0.84	8.64	5.14
		Selected feature	100	0.50	0.35	14.72	10.21
	K_2O (mg/100g)	All feature	20-20-20	0.97	0.96	4.46	4.01
		Selected feature	50-50	0.76	0.67	12.69	12.38
Sandy clay soil	Nitrogen (%)	All feature	100-100-100	0.83	0.72	0.31	0.37
		Selected feature	20-20	0.72	0.77	0.40	0.33
	P_2O_5 (mg/100g)	All feature	50-50-50	0.72	0.64	10.58	11.82
		Selected feature	100-100-100	0.46	0.05	14.82	20.37
	K_2O (mg/100g)	All feature	100-100	0.85	0.91	8.83	4.24
		Selected feature	50-50-50	0.54	0.24	16.36	12.32

A more complex network structure is required to improve the phosphorus prediction model, especially for soil types that exhibit low performance. This can involve increasing the number of layers or neurons in the model [6]. The scatter plot of training data can be seen in Figure 5. The scatter plot shows that the predicted results closely align with a linear line, indicating minimal error values. Based on the prediction model generated, it has great potential to be used as an approach for measuring soil nutrient content, replacing laboratory testing. By understanding the availability of soil nutrients through this model, farmers can determine the precise fertilizer dosage according to crop needs, thereby avoiding over-fertilization or under-fertilization [25]. Moreover, it can assist in determining the optimal timing for fertilization based on plant growth stages and the availability of soil nutrients, ensuring optimal nutrient uptake by plants and reducing nutrient losses due to leaching. This approach minimizes negative environmental impacts, such as groundwater contamination by nitrates or phosphates caused by over-fertilization, making agricultural systems more sustainable [26].



(a) Clay soil **(b) Loam clay soil** **(c) Sandy clay soil**

Figure 5. Plot scatter of training data from each soil texture

4. Conclusion

This study confirms that the integration of Vis-NIR spectroscopy and ANN algorithms is a viable and efficient method for soil nutrient analysis. By leveraging spectral data and advanced machine learning techniques, the proposed approach delivers accurate predictions for nitrogen, phosphorus, and potassium content across different soil textures. ANN models, with their capability to handle non-linear and complex relationships, enhanced the predictive accuracy, achieving R^2 values above 0.8 in each type soil texture. The results demonstrate that this method can effectively replace traditional laboratory methods, reducing costs, environmental impact, and time requirements. Furthermore, the application of these models in agricultural practices has the potential to optimize fertilizer application, minimize environmental harm, and support sustainable farming systems. Further research needs to focus on improving the ANN model architecture to increase accuracy and robustness in the field, as well as addressing soil sample variability so that the model is more robust in diverse conditions. The integration of this model into real-time agricultural practices also needs to be considered in order to increase its applicability and reliability on a large scale, thereby realizing more efficient, environmentally friendly, and sustainable agricultural solutions.

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