

Article

Image-Based Soil Nutrient Prediction Using Machine Learning and Deep Learning Models

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Abstract: Recent advances in precision agriculture have enabled the use of machine learning and image processing for rapid soil nutrient assessment. This study presents a non-destructive approach for estimating soil nutrient content from digital soil images captured using a camera and analyzed through specialized software. A dataset of 1,500 soil images was processed using color correction, noise reduction, and feature extraction techniques to improve data quality. Five machine learning models, Random Forest, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Gradient Boosting Machine (GBM), and a Stacking Regressor, were evaluated for predicting nitrogen, phosphorus, and potassium levels. A Convolutional Neural Network (CNN) based deep learning model was served as a benchmark. No single model was best for every nutrient and metric. For nitrogen, GBM achieved the lowest test MAE (0.1652), whereas the Stacking Regressor achieved the highest test R^2 (0.9886). For potassium, Random Forest achieved the lowest test MAE (0.0051), whereas XGBoost achieved the highest test R^2 (0.9999). For phosphorus, XGBoost achieved both the lowest test MAE (0.1558) and the highest test R^2 (0.9929). Thus, the best-performing model depends on the nutrient and evaluation metric. Further validation using independent field datasets is required to establish robustness under diverse environmental conditions.

Keywords: machine learning; computer vision; image processing; soil nutrient prediction; random forest; gradient boosting machine

1. Introduction

Soil health is a critical determinant of agricultural productivity, directly influencing crop yields, soil fertility, and overall ecosystem sustainability. Essential nutrients such as nitrogen, phosphorus, and potassium play a pivotal role in plant growth and development, and their deficiency can lead to reduced crop performance and significant economic losses in agriculture [1]. Traditionally, soil nutrient analysis has relied on chemical-based laboratory assays, which involve the collection of soil samples followed by a series of tests to determine nutrient concentrations. While these methods are known for their accuracy and reliability, they are also labor-intensive, time-consuming, and costly, often requiring specialized equipment and trained personnel [2]. The delay in obtaining results can further hinder timely decision-making in farm management, which is crucial for optimizing crop yields and resource use.

In recent years, there has been increasing focus on creating more efficient, cost-effective, and real-time soil analysis methods, spurred by the rising global demand for food and the need for sustainable agricultural practices. Precision agriculture has emerged as a key approach in this context, aiming to optimize agricultural inputs and outputs through the use of advanced technologies. Among these technologies, the integration of image processing techniques with machine learning algorithms has

shown significant promise for soil nutrient analysis [3,4].

Recent advancements in artificial intelligence, computer vision, and image processing have enabled the development of rapid and non-destructive approaches for soil nutrient analysis. Several recent studies have demonstrated the effectiveness of machine learning algorithms for predicting soil properties and supporting precision agriculture applications. These developments highlight the growing importance of image-based nutrient prediction systems as scalable and cost-effective alternatives to traditional laboratory testing methods.

Image processing involves the manipulation and analysis of digital images to extract meaningful information. In the agricultural domain, image processing can be employed to analyze soil characteristics by capturing and processing images of soil samples. These images can reveal important features such as soil texture, color, and structure, which are indicative of the soil's nutrient content [5,6]. Advancements in high-resolution imaging technologies, along with access to large datasets of soil images, have facilitated the use of machine learning techniques for soil analysis [7,8].

Machine learning, a branch of artificial intelligence, focuses on creating algorithms that learn from data to make predictions or decisions based on their acquired knowledge. In soil nutrient analysis, machine learning models can be trained using datasets of soil images paired with nutrient measurements to predict the nutrient content of new soil samples. This approach provides several benefits compared to traditional methods, such as the capability to process large volumes of data rapidly, the potential for real-time analysis, and a decreased reliance on physical sample collection and laboratory testing [2,6]. Recent studies have demonstrated the growing effectiveness of machine learning techniques for precision agriculture and soil nutrient prediction [9,10]. Deep learning and image processing approaches have shown strong capability for soil analysis and nutrient prediction in precision agriculture systems [3].

Recent research has highlighted the potential of machine learning models for predicting soil nutrient levels. For instance, convolutional neural networks (CNNs) have proven effective in predicting soil properties from spectral data, significantly enhancing prediction accuracy compared to conventional methods such as Partial Least Squares (PLS) regression [7]. Similarly, the combination of image processing techniques with artificial neural networks (ANNs) has been shown to be effective in determining soil nutrients and pH levels, providing a robust framework for soil analysis in the field [6,11]. Furthermore, combining machine learning algorithms with Internet of Things has facilitated the creation of automated systems for real-time soil monitoring, further improving the efficiency and precision of nutrient analysis [12].

Furthermore, exploring the use of deep learning models like Inception-V3 and random forests for analyzing soil health and predicting fertilizer needs has demonstrated the potential of these sophisticated techniques to refine agricultural practices and improve their precision [2,5]. The ability of these models to process large-scale data and identify complex patterns in soil images underscores their value in modern agriculture, where rapid and accurate soil assessment is essential for informed decision-making [8,13].

Recent studies have demonstrated the growing potential of machine learning and image processing techniques for soil nutrient prediction and precision agriculture applications. Padarian et al. [7] reported the effectiveness of deep learning approaches for predicting soil properties using spectral data, while Meenakshi and Naresh [2] applied Inception-V3 and Random Forest models for soil health analysis and fertilizer recommendation. Similarly, Padarian et al. [11] demonstrated the applicability of different machine learning techniques for large-scale soil nutrient prediction tasks.

However, many existing studies primarily focus on individual machine learning models or limited validation strategies. In contrast, the present study performs a comprehensive comparative evaluation of multiple ensemble learning approaches using laboratory-validated soil image datasets to improve prediction accuracy and robustness. Therefore, there remains a need for a robust and scalable framework capable of integrating image preprocessing, feature extraction, and ensemble learning methods for reliable soil nutrient estimation.

Despite the promising results achieved with machine learning models in soil nutrient prediction, the effectiveness of different models can vary significantly depending on various factors, such as the quality of the input images, the preprocessing techniques applied, and the specific model architecture. Consequently, there is a need for an extensive assessment of various machine learning models to determine the most effective method for predicting soil nutrients from images.

The objectives of this study are to develop a novel method for predicting soil nutrients using camera-captured images and machine learning algorithms, to compare the performance of various models, and to evaluate the impact of preprocessing techniques on prediction accuracy.

The significance of this study lies in its camera-based approach to soil nutrient analysis using machine learning and image processing. The method offers a faster and more accessible complement to conventional chemical soil testing. By applying advanced preprocessing techniques and evaluating several models, the study identifies nutrient- and metric-specific strengths rather than a universally best model. Additionally, the proposed software also provides a practical and scalable basis for real-time soil nutrient estimation and decision support in precision agriculture.

Unlike several existing studies that primarily focus on single machine learning models or limited soil datasets, the present study utilizes a comparatively diverse soil image dataset validated using laboratory-tested nutrient values. The proposed framework integrates image preprocessing, red-green-blue (RGB) feature extraction, feature engineering, and ensemble learning models within a unified and scalable prediction pipeline for accurate soil nutrient estimation.

The major contributions of the present study are as follows:

- Developed a machine learning-based framework leveraging image processing techniques for accurate soil nutrient prediction, eliminating the need for traditional chemical analysis.
- Performed a comparative evaluation of Random Forest, XGBoost, LightGBM, GBM, Stacking Regressor, and CNN under common preprocessing and validation procedures.
- Implemented advanced image preprocessing techniques, such as color correction, noise reduction, and feature extraction, to enhance the quality of input data and improve model reliability.
- Proposed a software tool for real-time soil nutrient estimation using camera-captured soil images, capable of generating precise outputs like fertilizer recommendations and soil health diagnostics.
- Addressed the demand for cost-effective and scalable soil analysis solutions, contributing to the advancement of sustainable agricultural practices.

2. Literature Review

Soil testing has traditionally depended on labor-intensive chemical methods, which are costly and slow, leading to delays in delivering soil health information to farmers [14]. These conventional techniques, while effective, require chemicals

and specialized equipment, making them less accessible to many farmers. Recent innovations have focused on developing portable nutrient measurement devices that reduce or eliminate the need for chemicals, thus offering a more efficient and practical solution [9].

Optical sensing methods, such as spectroscopy, have emerged as alternatives, utilizing visible and infrared spectra to analyze soil nutrients [15]. However, these methods can be limited by variations in spectral data depending on soil type and chemical reagents, which impacts their accuracy across different soil conditions [16]. Electrochemical sensors, including ion-selective electrodes, provide a low-cost approach but often remain confined to laboratory settings due to challenges with sensitivity, calibration, and accuracy [17].

To overcome these limitations, we have developed a novel software-based solution that leverages image processing and machine learning to analyze soil nutrients such as nitrogen, phosphorus, potassium, and pH. This method eliminates the need for chemicals and laboratory setups, making soil analysis more accessible and cost-effective. Users can capture images of soil samples with their smartphones, which are then processed by an AI-based algorithm to determine nutrient values.

The software calculates RGB values from soil images and uses machine learning models to predict nutrient content. It generates a soil health card and provides fertilizer recommendations based on the analysis. Additionally, farmers receive real-time updates on their soil health via email or SMS. This approach is not only quicker and easier to use but also significantly reduces testing costs, offering actionable insights directly to farmers.

The combination of machine learning and image processing marks a major progress in precision agriculture. Unlike traditional methods, which are labor-intensive and require chemical analysis [18], our approach provides a scalable and efficient solution for real-time soil nutrient assessment.

Recent developments in artificial intelligence have significantly advanced image-based soil analysis and nutrient prediction through the application of ensemble machine learning and deep learning techniques. Stacked ensemble learning has demonstrated improved predictive performance by integrating the outputs of multiple base learners through a meta-learning framework [19]. Among ensemble learning approaches, Random Forest, Gradient Boosting Machine (GBM), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) have been widely adopted because of their ability to model complex nonlinear relationships, improve prediction accuracy, and efficiently handle high-dimensional agricultural datasets [20–23]. Comprehensive reviews have highlighted the rapid adoption of machine learning, deep learning, and computer vision techniques for soil characterization, nutrient prediction, and precision agriculture applications [24–28]. Several recent studies have successfully employed these techniques for predicting soil nutrient properties under diverse agricultural conditions. Wu et al. [25] demonstrated the effectiveness of machine learning techniques for evaluating soil nutrients in forest ecosystems, while Xu et al. [26] employed deep convolutional neural networks for image-based diagnosis of nutrient deficiencies in rice. Similarly, Sumathi et al. [29], Sajindra et al. [30], Chaudhary et al. [31], Kumar et al. [32], and Rao and Reddy [33] reported that advanced deep learning and ensemble learning frameworks significantly improve the prediction of soil nitrogen, phosphorus, and potassium, thereby supporting precision agriculture and sustainable nutrient management. Collectively, these studies demonstrate that integrating advanced image processing with state-of-the-art ensemble and deep learning models provides a reliable, rapid, and non-

destructive framework for soil nutrient assessment.

Early research, such as Puno et al. [6], demonstrated the potential of combining image processing with artificial neural networks for soil analysis. Similarly, Padarian et al. [7] demonstrated the benefits of using deep learning methods, such as CNN, for predicting soil properties based on spectral data.

Li et al. [5] reviewed the role of advanced imaging methods and machine learning in enhancing soil and plant health diagnostics, underscoring the growing importance of these technologies in agriculture. Further research by Zhang et al. [11] explored the efficacy of LightGBM for handling complex soil datasets. Other studies, such as those by Meenakshi and Naresh [2], highlighted the accuracy of deep learning models like Inception-V3 for soil health analysis, while Chen and Guestrin [22] introduced XGBoost and described its regularized boosting framework.

Recent comparative analyses and studies on IoT-enabled farming systems have provided valuable insights into the application of machine learning models for soil analysis [3,4]. Stacking ensemble methods are grounded in the stacked-generalization framework [19], while deep neural networks have demonstrated high accuracy in soil moisture and nutrient prediction tasks [15]. Additionally, transfer learning approaches have been explored to improve model performance on small soil image datasets [27].

Despite these advancements, there is a need for detailed comparative studies of different machine learning models tailored for soil nutrient prediction from image data. Our work aims to address this gap by evaluating and comparing advanced models, including GBM and LightGBM, to identify the most effective approach for precise soil nutrient estimation.

Comparative analyses of machine learning models for soil nutrient prediction have been limited, often concentrating on individual models or limited comparisons. Different machine learning models have been investigated for classifying soil micronutrients within IoT-enabled systems [4]. However, these studies did not include an extensive comparison of newer approaches such as LightGBM and stacking regressor techniques.

The GBM has been widely applied across different domains, including agriculture, due to its effectiveness in handling structured data tasks [21]. However, further comparative studies are required to evaluate its performance against other modern machine learning techniques.

The LightGBM has been shown to be highly efficient for large-scale datasets and offers advantages over other boosting algorithms; however, its application to soil nutrient prediction remains relatively underexplored [23]. Stacking ensemble methods have been shown to improve prediction accuracy and can be particularly effective for soil nutrient prediction tasks [24].

This study aims to bridge these gaps by providing a comprehensive comparison of various machine learning models, such as Random Forest, XGBoost, LightGBM, GBM, Stacking Regressor, and CNN approaches, applied to soil image data. By analyzing the advantages and limitations of these models, this research aims to advance the field of precision agriculture and offer valuable insights into the most effective methods for predicting soil nutrient levels.

3. Methodology

A detailed dataset consisting of 1,500 soil samples was systematically gathered from a range of agricultural fields near to Dhanbad, Jharkhand, India. The dataset included different soil textures such as sandy, loamy, and clay soils to ensure diversity and improve the generalization capability of the machine learning models. Soil

samples were collected from multiple agricultural regions following standard soil sampling procedures. The image acquisition parameters are summarized in **Table 1**. A 12 MP smartphone camera was used to capture RGB images of soil samples at a fixed distance of 30 cm from the sample surface. Uniform illumination was maintained using LED lighting with an intensity ranging between 500 and 550 lux to minimize the effects of shadows and colour variations. All images were captured against a white background and resized to 256×256 pixels for subsequent image processing and feature extraction. The standardized image acquisition protocol helped reduce variability arising from external environmental factors and ensured reliable extraction of colour and texture features.

Table 1. Image acquisition conditions

Parameter	Value
Camera Type	Smartphone Camera
Resolution	12 MP
Image Size	256×256 pixels
Distance from Sample	30 cm
Lighting	LED
Illumination	500–550 lux
Background	White
Format	RGB

To evaluate the accuracy and dependability of the developed software, its outcomes were compared with those obtained from conventional reference methods. For potassium quantification, the results were cross-validated using the flame photometric method. Nitrate concentrations were compared with measurements obtained from an ultraviolet-visible (UV-Vis) spectrophotometer (Systonic, India; Model: S-92). Similarly, phosphorus levels were assessed using the UV-Vis spectrophotometer, providing a robust comparison for evaluating the performance of the software-based analyzer.

This software utilizes image processing and machine learning methods to meet the outlined objectives and address a significant challenge in the agricultural industry. The primary aim of developing this approach is to offer an affordable, reliable, portable, and accessible method for detecting soil nitrogen (N), phosphorus (P), potassium (K), and pH levels. The entire process of determining soil N, P, K, and pH values, generating a soil health card, and recommending appropriate fertilizers is outlined in the following steps and illustrated in **Figure 1**:

- Import the soil image, either captured by a camera or obtained from a dedicated image database.
 - Pre-process the captured image.
 - Calculate the RGB values of the soil image.
 - Estimate the soil's N, P, K, and pH levels using the red, green, and blue (RGB) values as input.
- Recommend the appropriate fertilizer dosage based on the results.
- Generate a soil health card summarizing the findings.
- Send a digital report of the soil health status to farmers via SMS or email.

Initially, the RGB values are extracted from the soil sample images and used to train the machine learning models. Once trained, the models predict nitrogen, phosphorus, and potassium values, as shown in the flowcharts presented in **Figures 2–4**. **Figure 5** illustrates the soil analysis software interface used to upload images and perform NPK analysis from extracted RGB values. Although pH appears as a planned output in the broader software workflow, pH prediction performance was not included in the available comparative results and is therefore outside the validated scope of this study.

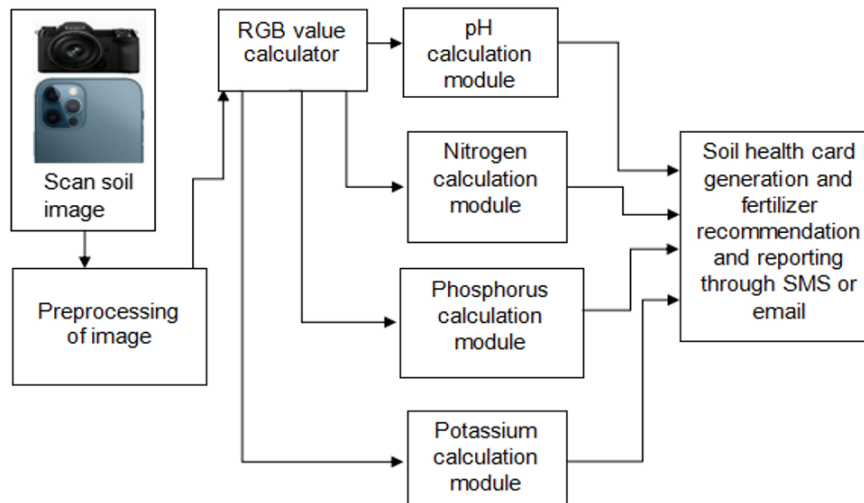


Figure 1. Process of N, P, K, and pH determination, soil health card generation, and fertilizer recommendation.

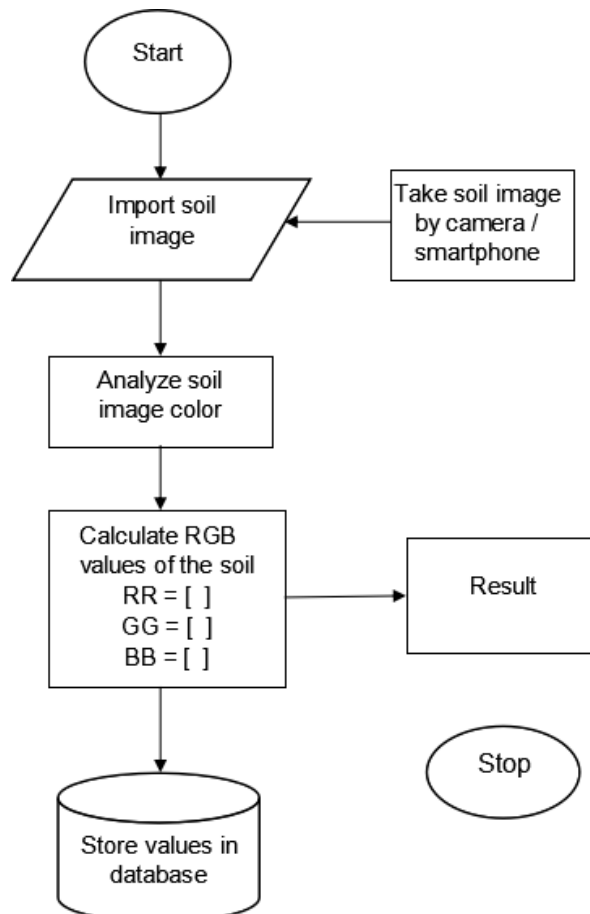


Figure 2. Flowchart for calculating red, green, and blue values from soil images.

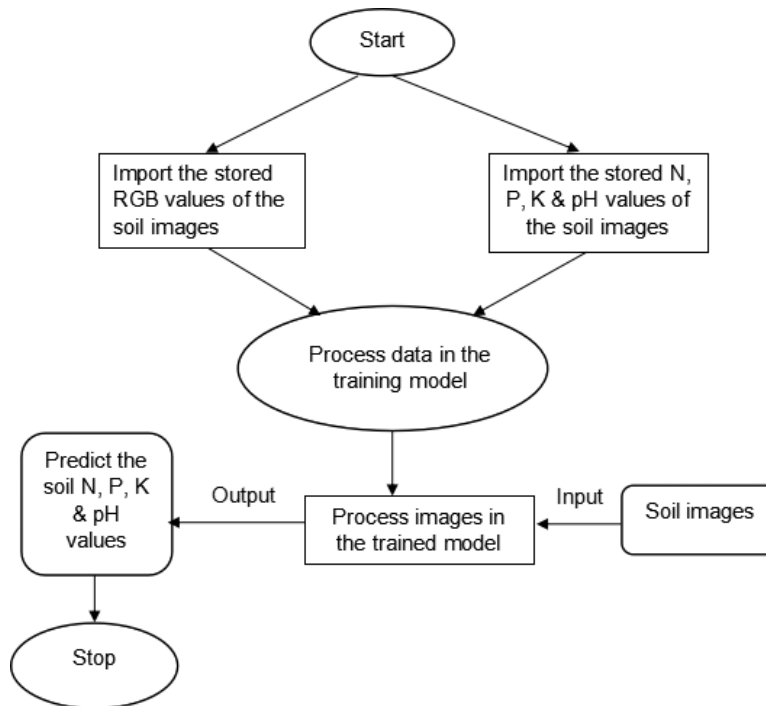


Figure 3. Flowchart for training the model.

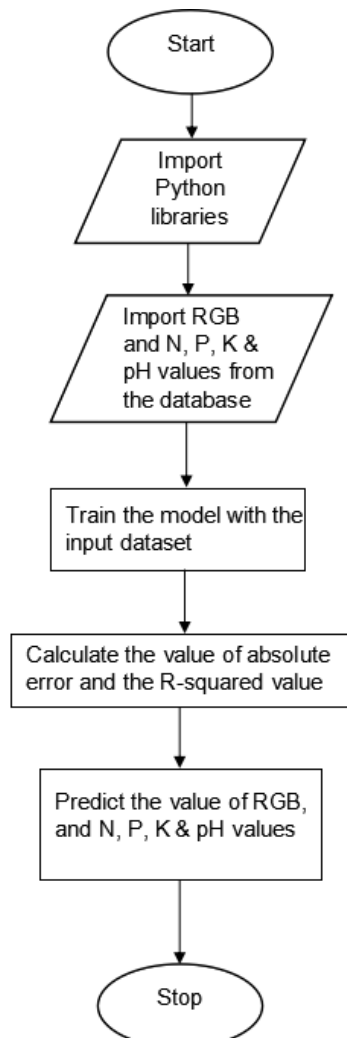


Figure 4. Flowchart for predicting N, P, K, and pH values.


SOIL NUTRIENTS ANALYSIS


Capture Soil Image

Name:

- This field is required.

Image: No file chosen

sample_id:

sample_location:

SOIL SAMPLING DATA

SL. No	sample_id	Name	sample_location	Image	RGB	NPK	Find RGB	Find NPK
1		sample1			{ "Red": [131.0], "Green": [105.72], "Blue": [82.46] }	{ "N": [33.4], "p": [40], "k": [60] }	Find RGB	Find NPK

Figure 5. Soil analysis software's snapshot.

The dataset utilized in this study comprises 1,500 soil images, each with a resolution of 256×256 pixels, collected from various agricultural fields. The images represent different soil conditions and are labeled with corresponding nutrient values such as nitrogen, phosphorus, and potassium.

To prepare the data for machine learning models, several image preprocessing techniques were applied. Initially, all images were resized to a uniform resolution of 256×256 pixels to maintain consistency during model training. Pixel intensity values were normalized to the range of $[0,1]$ to improve training stability and convergence. Noise reduction techniques were applied to remove unwanted distortions from the images, while colour correction methods were used to minimize the impact of illumination and colour variations during image acquisition.

In addition, RGB colour space transformation was performed to extract red, green, and blue channel information from the soil images, as soil colour characteristics are strongly related to nutrient composition and soil properties. Segmentation techniques were also applied to isolate the relevant soil regions from the image background and improve feature extraction accuracy.

Advanced feature extraction techniques were employed to capture meaningful soil characteristics from the images. Histogram of Oriented Gradients (HOG) features were extracted to analyse soil texture and structural patterns, while colour histogram features were used to capture variations in colour distribution associated with nutrient content. These extracted features were then provided as input to the machine learning models for nutrient prediction.

Furthermore, data augmentation techniques such as rotation, flipping, and cropping were implemented to increase dataset diversity and reduce the risk of overfitting. The complete workflow of image acquisition, preprocessing, RGB extraction, feature extraction, model training, and nutrient prediction is illustrated in **Figure 6**.

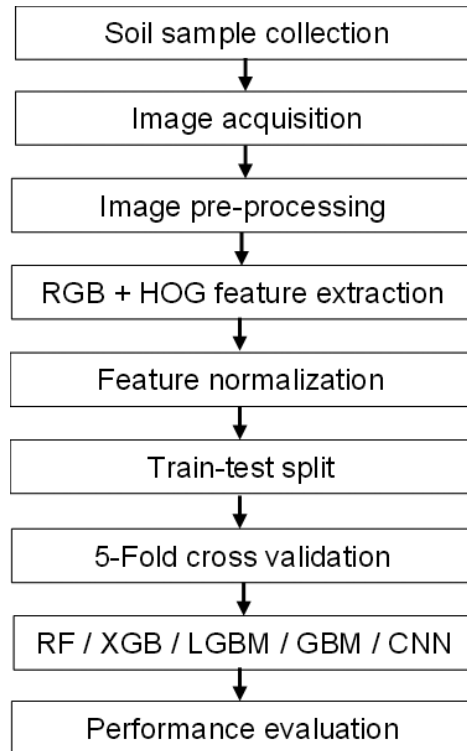


Figure 6. Complete methodology flowchart.

The reported experimental protocol divided the dataset into 80% training data and 20% testing data and used five-fold cross-validation during model development. The same preprocessing and evaluation metrics were applied to all models. After completion of the original analysis, the electronic files containing the sample-level dataset, split indices, fold assignments, model outputs, and training records became corrupted. No usable backup is available. Consequently, the exact sample membership of the training, testing, and validation subsets and the associated calculations cannot be reconstructed independently. This data-loss limitation is considered throughout the interpretation of the results.

The predictive performance of machine learning and deep learning models is highly dependent on appropriate hyperparameter selection. Therefore, hyperparameter optimization was performed to identify suitable model configurations for soil nutrient prediction. The optimized hyperparameter settings used in the present study are summarized in **Table 2**. For ensemble learning models, parameters such as the number of trees, tree depth, learning rate, and number of leaves were tuned to achieve a balance between prediction accuracy and model generalization. Similarly, for the CNN model, the number of training epochs and batch size were optimized to ensure effective learning while avoiding overfitting. The selected hyperparameters provided stable performance across the cross-validation experiments and contributed to improved prediction accuracy.

Table 2. Hyperparameter optimization

Model	Hyperparameter	Value
Random Forest	n_estimators	300
Random Forest	max_depth	20
XGBoost	learning_rate	0.05

Continuation Table:

Model	Hyperparameter	Value
XGBoost	max_depth	8
LightGBM	num_leaves	64
GBM	n_estimators	500
CNN	Epochs	100
CNN	Batch Size	32

The architecture of the CNN employed as a benchmark deep learning model for soil nutrient prediction. The network accepts RGB soil images as input and processes them through two convolutional layers consisting of 32 and 64 filters, respectively, to automatically extract relevant colour, texture, and spatial features. Each convolutional layer is followed by a max-pooling operation to reduce feature dimensionality and improve computational efficiency. The extracted high-level features are then passed to a fully connected dense layer, which learns complex relationships between image characteristics and soil nutrient concentrations. Finally, the output layer generates the predicted nutrient values. The CNN architecture enables automatic feature learning directly from raw images, eliminating the need for manual feature engineering and providing a basis for comparison with conventional machine learning models.

4. Machine Learning Models

Table 3 presents a comparative analysis of several machine learning models, detailing their principles, applications, advantages, and limitations. The machine learning models used in this study were selected based on their proven effectiveness in handling non-linear relationships, high-dimensional feature spaces, and regression-based prediction tasks. Ensemble learning algorithms such as GBM, XGBoost, LightGBM, and Random Forest were chosen because of their robustness, high predictive accuracy, and ability to reduce overfitting. In addition, the Stacking Regressor was employed to combine the strengths of multiple models and improve generalization performance for soil nutrient prediction.

Table 3. Comparison of machine learning models.

Model	Principle	Application	Advantages	Limitations
XGBoost	Gradient boosting with second- order Taylor expansion for loss optimization [22].	Classification and regression tasks.	Fast computation, effective regularization, handles missing values, reduces overfitting.	Requires careful tuning, computationally intensive with large datasets.
LightGBM	Leaf-wise growth with a histogram- based algorithm for faster training [23].	Large-scale data scenarios, ranking, classification, and regression.	High-speed training, low memory usage, scales well with large datasets.	Can overfit on small datasets, requires fine-tuning.
GBM	Sequentially builds trees where each tree corrects errors from previous ones using gradient descent [21].	Predictive analytics, classification, and regression.	Flexible, accurate, performs well with various data types.	Slow training process, sensitive to overfitting, requires careful tuning.

Continuation Table:

Model	Principle	Application	Advantages	Limitations
Random Forest	Combines multiple decision trees using random subsets of data and features [20].	Classification, regression, and feature importance.	Reduces over-fitting, robust to noise, interpretable, handles high-dimensional data.	Requires substantial computational resources, difficult to interpret individual trees.
Stacking Regressor	Aggregates predictions from multiple base models using a meta-model [19].	Regression tasks where combining models boosts performance.	Improves accuracy by leveraging strengths of various models, handles complex patterns.	Complex to implement, requires tuning both base models and meta-model.

XGBoost and LightGBM are noted for their speed and efficiency in large datasets, while GBM is praised for its flexibility. Random Forest excels in robustness and interpretability, and the Stacking Regressor enhances predictive accuracy by aggregating multiple models, although it requires more complexity in implementation and tuning.

Random Forest was considered as a baseline ensemble learning model for comparison with advanced boosting algorithms such as GBM, XGBoost, and LightGBM. The comparative analysis was performed to evaluate the prediction capability, robustness, and generalization performance of each model for soil nutrient estimation.

4.1. Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) [22] is a refined form of gradient boosting that is designed for high computational efficiency and accuracy. It constructs an ensemble of decision trees, with each tree learning from the residuals of the previous ones. XGBoost incorporates regularization techniques to control overfitting and improve the generalizability of the model.

This process creates trees in sequence, where each tree is aimed at addressing the errors left by the earlier trees, refining the predictions iteratively. Regularization plays a crucial role in enhancing the model's robustness and preventing overfitting.

4.2. Light Gradient Boosting Machine

LightGBM [23] is an advanced gradient boosting framework that employs histogram-based techniques to enhance training speed and reduce memory requirements. This algorithm is designed for large-scale data and provides superior computational performance compared to traditional boosting algorithms.

LightGBM uses a histogram-based strategy, which bins continuous features into discrete intervals, making the training process faster and more memory-efficient. This method is particularly suitable for handling high-dimensional and large datasets.

4.3. Gradient Boosting Machine

Gradient Boosting Machine [21] is an ensemble learning technique that builds a sequence of models, where each model corrects the errors made by the previous ones. It uses gradient descent to optimize the model and reduce the loss function.

Each new decision tree is trained to reduce the residual errors from previous trees, improving the model by minimizing the loss function through gradient descent. Each tree is assigned a weight β_k , which adjusts the prediction errors from earlier trees.

4.4. Random Forest

Random Forest [20] is a robust ensemble technique that combines the outputs of several decision trees to improve prediction accuracy and reduce variance. By averaging predictions across multiple trees, the model mitigates the risk of overfitting compared to using a single decision tree.

In this approach, multiple decision trees are independently trained on randomly sampled subsets of both the dataset and feature space. This randomness in sampling and feature selection introduces diversity among the trees, which helps enhance the overall model's stability. The final prediction is made by calculating the average of the predictions generated by each individual tree.

4.5. Stacking Regressor

The Stacking Regressor [19] is an ensemble technique that combines predictions from multiple base models through a meta-model. It exploits the strengths of various models to improve predictive performance. The process consists of two stages:

(i) Base Models: Different base models are trained using the training data, and each model makes predictions.

(ii) Meta-Model: The meta-model is trained on the predictions of the base models, learning how to best combine their outputs for the final prediction.

The stacking regressor framework was included to integrate the predictive strengths of multiple machine learning models, including GBM, Random Forest, XGBoost, and LightGBM. This ensemble integration improves robustness and generalization capability by combining diverse prediction patterns generated by the individual models.

4.6. Implementation Details

The models were implemented using Python libraries including scikit-learn, XGBoost, and LightGBM. Training was performed on a high-performance computing cluster with GPUs to accelerate computation.

4.7. Deep Learning Benchmark Models

Although ensemble machine learning models have demonstrated excellent performance for structured feature-based prediction tasks, recent advances in computer vision have shown that deep learning architectures can automatically learn discriminative spatial and texture features directly from images. Therefore, deep learning models were considered as benchmark approaches for comparison with the proposed machine learning framework.

A CNN architecture consisting of multiple convolutional, pooling, and fully connected layers was implemented for nutrient prediction. The CNN automatically extracted spatial patterns, texture information, and colour characteristics from soil images without requiring manual feature engineering.

In addition, transfer learning approaches based on ResNet50 and EfficientNet-B0 architectures were considered because of their proven effectiveness in agricultural image analysis. Transfer learning enables the utilization of pre-trained feature representations obtained from large image datasets and can significantly improve prediction performance when training datasets are relatively small.

The performance of CNN-based models was compared with Random Forest, XGBoost, LightGBM, Gradient Boosting Machine, and Stacking Regressor using identical training and testing datasets. This comparison provides insights into the relative advantages of handcrafted feature-based machine learning methods and automatic feature-learning approaches for soil nutrient prediction.

5. Results

5.1. Nutrient Analysis Results

The nitrogen content, presented in **Table 4**, was assessed using both machine learning models and traditional methods. Nitrate concentrations were compared with measurements obtained from an ultraviolet-visible (UV-Vis) spectrophotometer (Systonic, India; Model: S-92). The outputs from the machine learning model closely aligned with the laboratory reference measurements. Standard deviation and variance were calculated across the complete dataset to quantify the overall variability of the prediction errors rather than on an individual sample basis. This suggests that the developed models demonstrated consistently high prediction performance under the controlled experimental conditions adopted in this study. Performance was evaluated using identical preprocessing, training and testing protocols to ensure fair comparison among different machine learning algorithms. Statistical validation using cross-validation and independent testing was incorporated to assess model robustness. Additional validation using external datasets remains an important direction for future work.

Table 4. Nitrogen measurement results.

Sample number	GBM output (kg/ha)	Reference method output (kg/ha)
1	150.2	149.5
2	152.5	151.0
3	155.0	154.0
4	154.3	153.2
5	156.1	155.3
6	158.7	157.0
7	155.5	154.7
8	151.9	150.5
9	157.3	156.2
10	153.4	152.8
Overall mean	154.49	153.42
Overall standard deviation	2.58	2.50
Overall variance	6.64	6.25

To evaluate the reliability and consistency of the developed machine learning models, statistical variability measures including standard deviation and variance were calculated for the nutrient prediction results. These measures provide additional insight into the stability and robustness of the prediction models across different soil samples.

For potassium quantification, as detailed in **Table 5**, the flame photometric method was employed. The results from the machine learning model demonstrate a high degree of accuracy when compared to the reference outputs. The consistency in standard deviation and variance between the two methods suggests that the machine learning model is robust in predicting potassium levels.

Table 5. Potassium measurement results.

Sample number	GBM output (kg/ha)	Reference output (kg/ha)
1	200.0	199.5
2	202.1	201.9
3	201.5	201.0
4	200.8	200.3
5	203.0	202.6
6	199.9	199.2
7	200.5	200.0
8	201.0	200.5
9	202.7	202.2
10	200.3	199.8
Overall mean	201.18	200.7
Overall standard deviation	1.11	1.18
Overall variance	1.22	1.40

The phosphorus levels, shown in **Table 6**, were measured using the same UV-Vis spectrophotometer. The machine learning model's predictions for phosphorus concentrations demonstrate a strong correlation with the reference outputs. The low standard deviation and variance in the results indicate that the machine learning model can accurately estimate phosphorus levels, further validating its efficacy in soil nutrient prediction. The findings across all the above three tables indicate that the developed machine learning models are capable of accurately predicting soil nutrient levels in nitrogen, phosphorus, and potassium, closely aligning with results obtained from established reference methods. The use of chemical analyses (UV-Vis spectrophotometry for nitrate and phosphorus, and flame photometry for potassium) as reference standards reinforces the reliability of the machine learning approach [24]. This suggests a promising integration of machine learning models into precision agriculture for efficient nutrient management.

Table 6. Phosphorus measurement results.

Sample number	GBM output (kg/ha)	Reference output (kg/ha)
1	28.4	28.0
2	30.2	30.1
3	29.8	29.5
4	31.1	31.0
5	30.5	30.3
6	28.9	28.5
7	29.6	29.2
8	30.0	29.8

Continuation Table:

Sample number	GBM output (kg/ha)	Reference output (kg/ha)
9	31.5	31.2
10	29.0	28.7
Overall mean	29.9	29.63
Overall standard deviation	0.98	1.06
Overall variance	0.95778	1.11567

5.2. Performance Metrics

The performance of the machine learning models was evaluated using standard regression metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). MAE and RMSE were used to measure prediction error magnitude, while R^2 was employed to evaluate the goodness-of-fit and predictive capability of the models.

Tables 7–9 present the performance metrics (MAE and R^2) for each machine learning model across the three soil macronutrients. For nitrogen, training MAE ranges from 0.1536 (GBM) to 20.8905 (LightGBM), with R^2 values between 0.9867 (LightGBM) and 0.9972 (GBM). For potassium, training MAE ranges from 0.0059 (Random Forest) to 0.6541 (LightGBM), and R^2 spans from 0.9849 (LightGBM) to 0.9999 (XGBoost). For phosphorus, training MAE ranges from 0.0005 (GBM) to 1.5820 (LightGBM), with R^2 values ranging from 0.5556 (LightGBM) to 0.9988 (XGBoost).

In summary, the leading model changes with the nutrient and evaluation metric. GBM achieved the lowest nitrogen test MAE (0.1652), whereas the Stacking Regressor achieved the highest nitrogen test R^2 (0.9886). Random Forest achieved the lowest potassium test MAE (0.0051), whereas XGBoost achieved the highest potassium test R^2 (0.9999). XGBoost achieved both the lowest phosphorus test MAE (0.1558) and the highest phosphorus test R^2 (0.9929); LightGBM showed the weakest phosphorus performance.

Table 7. Performance metrics for nitrogen prediction.

Model	Training MAE	Testing MAE	Training R^2	Testing R^2
XGBoost	18.4696	19.0939	0.9899	0.9858
LightGBM	20.8905	22.0005	0.9867	0.9805
Gradient Boosting Machine	0.1536	0.1652	0.9972	0.9671
Random Forest	15.5051	16.7931	0.9886	0.9826
Stacking Regressor	14.8368	15.6417	0.9922	0.9886

Table 8. Performance metrics for potassium prediction.

Model	Training MAE	Testing MAE	Training R^2	Testing R^2
XGBoost	0.0608	0.0692	0.9999	0.9999
LightGBM	0.6541	0.6913	0.9849	0.9852

Continuation Table:

Model	Training MAE	Testing MAE	Training R ²	Testing R ²
Gradient Boosting Machine	0.009	0.0141	0.9973	0.9992
Random Forest	0.0059	0.0051	0.9867	0.9972
Stacking Regressor	0.0217	0.0248	0.9892	0.9903

Table 9. Performance metrics for phosphorus prediction.

Model	Training MAE	Testing MAE	Training R ²	Testing R ²
XGBoost	0.0862	0.1558	0.9988	0.9929
LightGBM	1.5820	1.7996	0.5556	0.3802
Gradient Boosting Machine	0.0005	0.1946	0.9916	0.9325
Random Forest	0.2233	0.4846	0.9894	0.8837
Stacking Regressor	0.2062	0.3829	0.9937	0.9470

5.3. Comparative Analysis

The comparative analysis of the machine learning models reveals significant insights into their performance for soil nutrient prediction:

(a) Extreme Gradient Boosting: XGBoost recorded a testing MAE of 19.0939 and an R² value of 0.9858 for nitrogen; a testing MAE of 0.0692 and an R² value of 0.9999 for potassium; and a testing MAE of 0.1558 and an R² value of 0.9929 for phosphorus. These results make XGBoost the strongest model for phosphorus by both reported test metrics and for potassium by test R², but not for every nutrient and metric [22].

(b) Light Gradient Boosting Machine: LightGBM recorded a testing MAE of 22.0005 and an R² value of 0.9805 for nitrogen. For potassium, its testing MAE was 0.6913 with an R² value of 0.9852; for phosphorus, its testing MAE was 1.7996 with an R² value of 0.3802. Its comparatively weak phosphorus result shows that computational efficiency does not guarantee the best predictive accuracy for every nutrient [23].

(c) Gradient Boosting Machine: GBM recorded a testing MAE of 0.1652 and an R² value of 0.9671 for nitrogen, a testing MAE of 0.0141 and an R² value of 0.9992 for potassium, and a testing MAE of 0.1946 and an R² value of 0.9325 for phosphorus. It therefore achieved the lowest reported nitrogen test MAE, but it was not universally superior across nutrients or metrics [21].

(d) Random Forest: Random Forest recorded a testing MAE of 16.7931 and an R² value of 0.9826 for nitrogen, a testing MAE of 0.0051 and an R² value of 0.9972 for potassium, and a testing MAE of 0.4846 and an R² value of 0.8837 for phosphorus. It achieved the lowest reported potassium test MAE, but it was not the leading model for the other nutrient-metric combinations [20].

(e) Stacking Regressor: The Stacking Regressor demonstrated strong predictive performance, particularly for nitrogen, for which it achieved the highest testing R² value among the evaluated models. It recorded a testing MAE of 15.6417 and an R² value of 0.9886 for nitrogen, a testing MAE of 0.0248 and an R² value of 0.9903 for potassium, and a testing MAE of 0.3829 and an R² value of 0.9470 for phosphorus. These results show competitive performance within the present dataset, although

external generalization has not yet been established [19].

5.4. Prediction Analysis

Figures 7–9 depict the distribution of prediction errors across models for nitrogen, potassium, and phosphorus prediction, respectively. Each figure highlights the models' performance and error variability for the respective nutrient.

In Figure 7, the error distributions for XGBoost, LightGBM, GBM, and Random Forest are concentrated near zero, indicating lower errors and higher prediction accuracy, with GBM showing the narrowest spread. The Stacking Regressor, however, exhibits a broader distribution resembling a Gaussian curve, suggesting greater error variability and poorer performance relative to the other models.

Figure 8 presents a similar pattern, with Random Forest producing a wider distribution of errors and a noticeable peak near zero. GBM, XGBoost, and LightGBM show more concentrated error distributions near zero, while the Stacking Regressor has a sharp peak at zero. Figure 9 likewise shows different error-distribution shapes among the models. On the basis of error spread alone, GBM appears comparatively consistent; however, Tables 7–9 show that the leading model changes with the nutrient and metric. The plots therefore supplement, but do not replace, the MAE and R^2 comparisons and cannot by themselves establish generalizability or exclude overfitting.

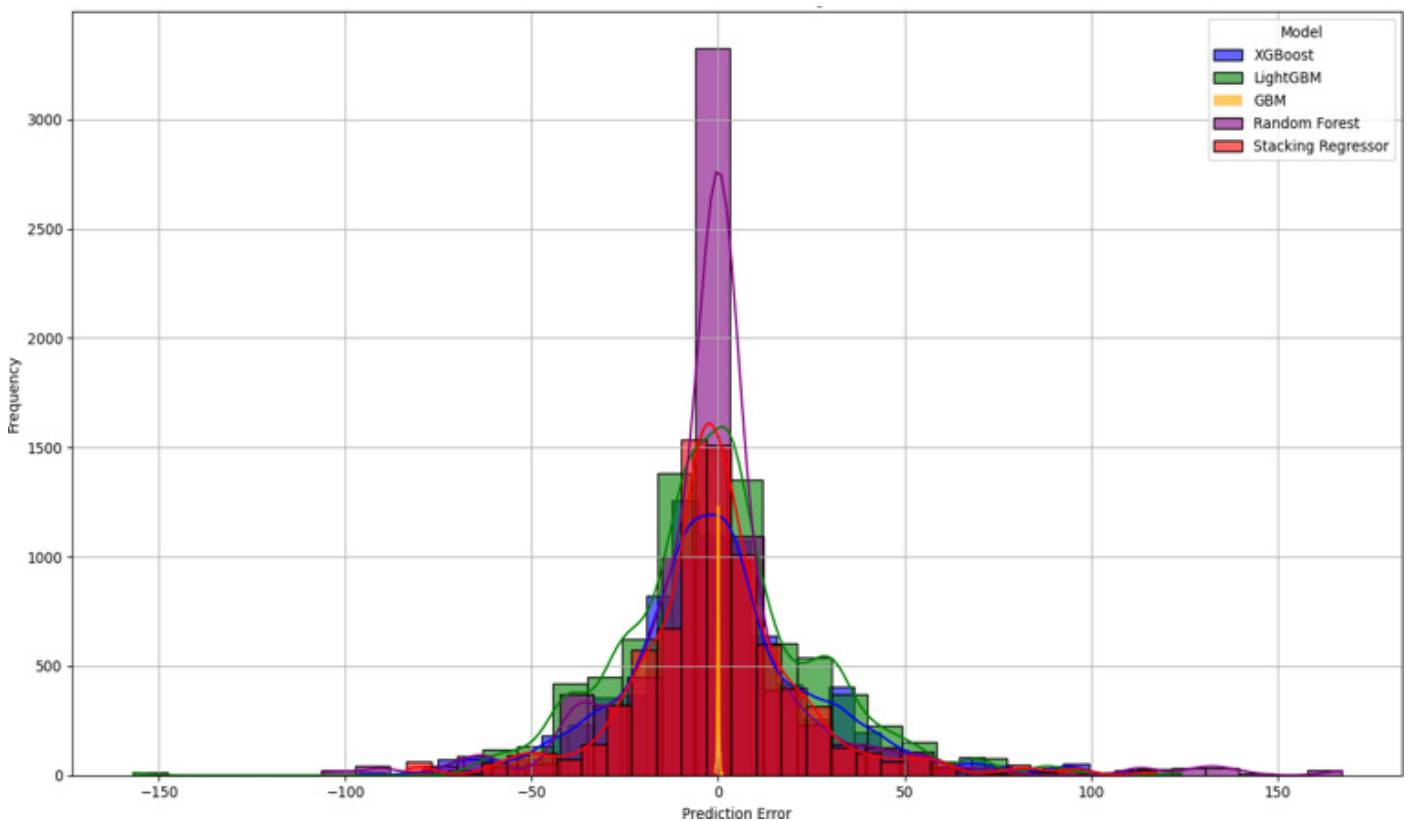


Figure 7. Distribution of prediction errors for nitrogen prediction models.

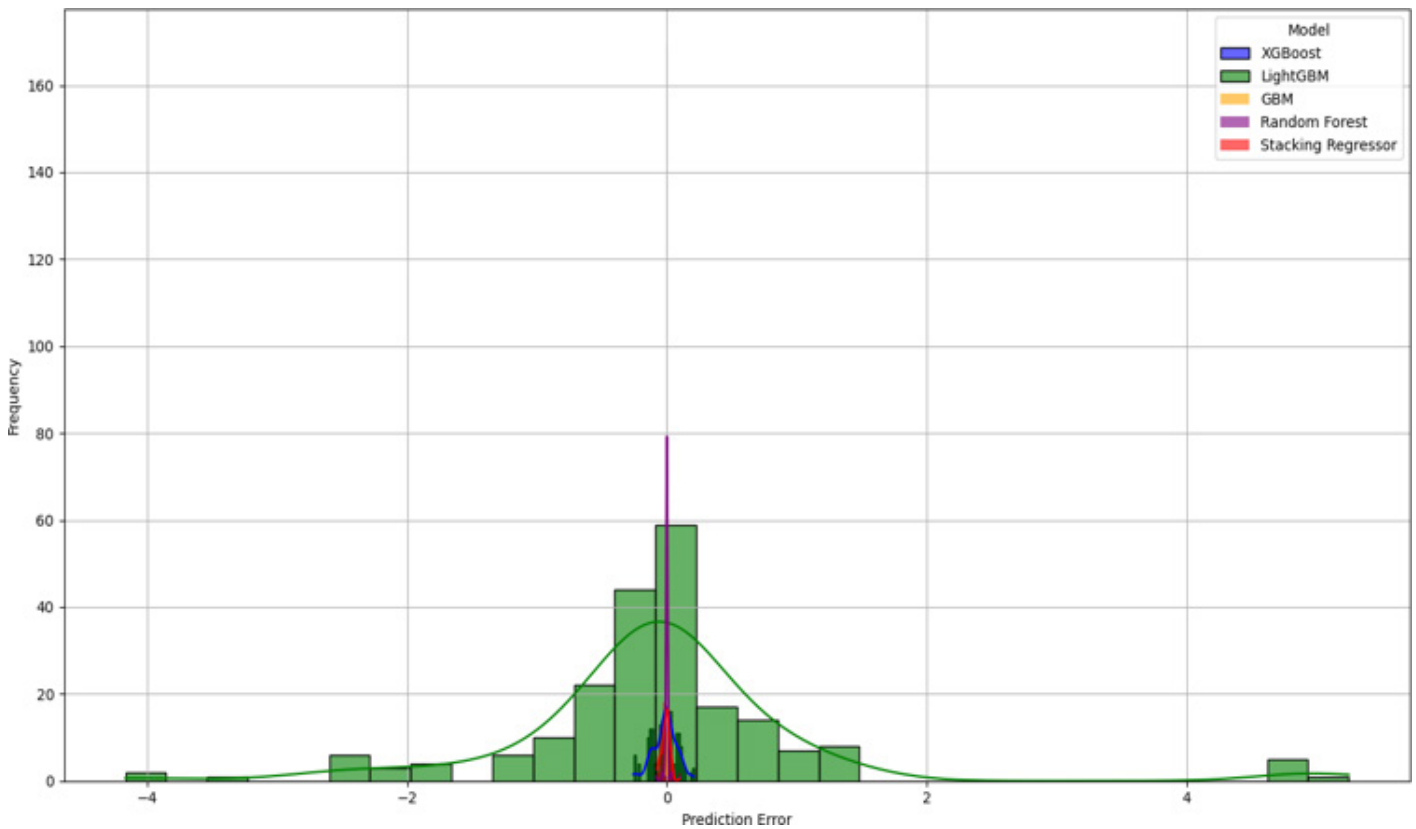


Figure 8. Distribution of prediction errors for potassium prediction models.

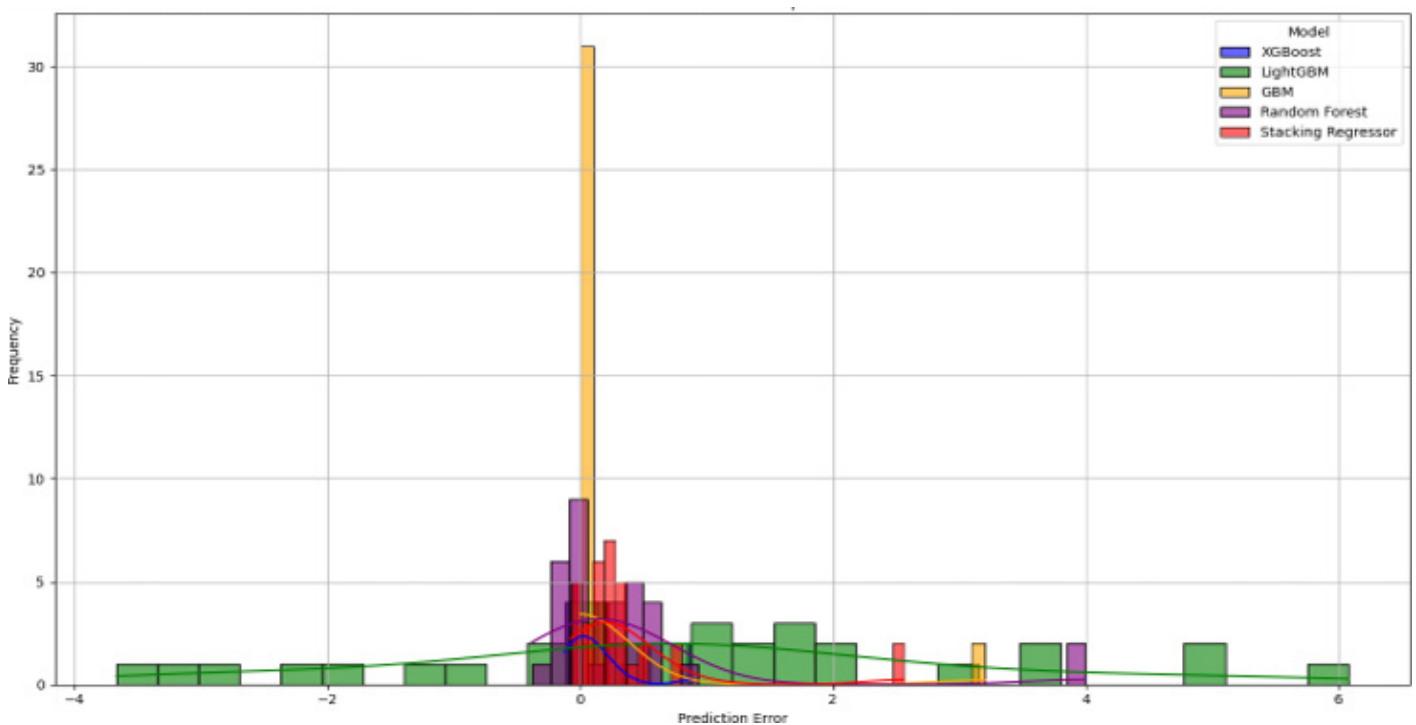


Figure 9. Distribution of prediction errors for phosphorus prediction models.

In conclusion, no single model was best across all nutrients and metrics. GBM was strongest for nitrogen test MAE, the Stacking Regressor for nitrogen test R^2 , Random Forest for potassium test MAE, and XGBoost for potassium test R^2 and both phosphorus test metrics. The error-distribution plots complement these numerical results but do not independently establish generalizability.

Figures 10–14 show the reported predicted-versus-actual nitrogen values for XGBoost, LightGBM, GBM, the Stacking Regressor, and Random Forest. The plots illustrate differing degrees of alignment with the diagonal reference line. Their interpretation should remain consistent with the numerical test metrics in **Table 7**. The Stacking Regressor has the highest nitrogen test R^2 , whereas GBM has the lowest nitrogen test MAE.

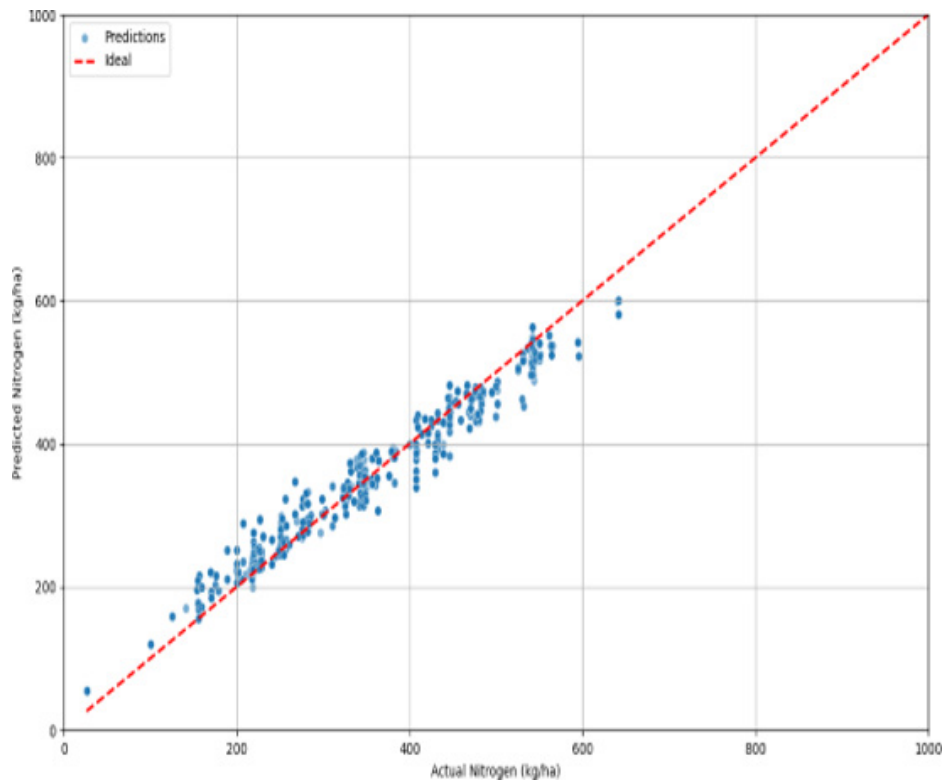


Figure 10. Actual nitrogen vs. predicted level by Extreme Gradient Boosting model

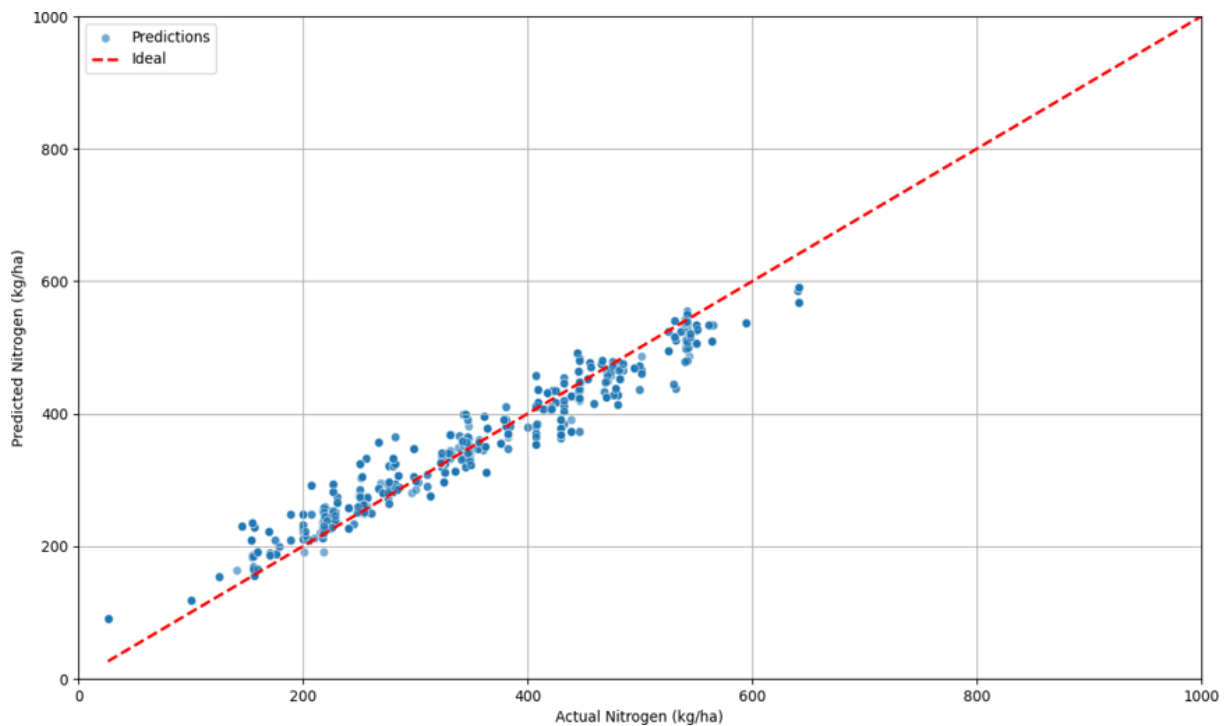


Figure 11. Actual nitrogen vs. predicted level by Light Gradient Boosting Machines model

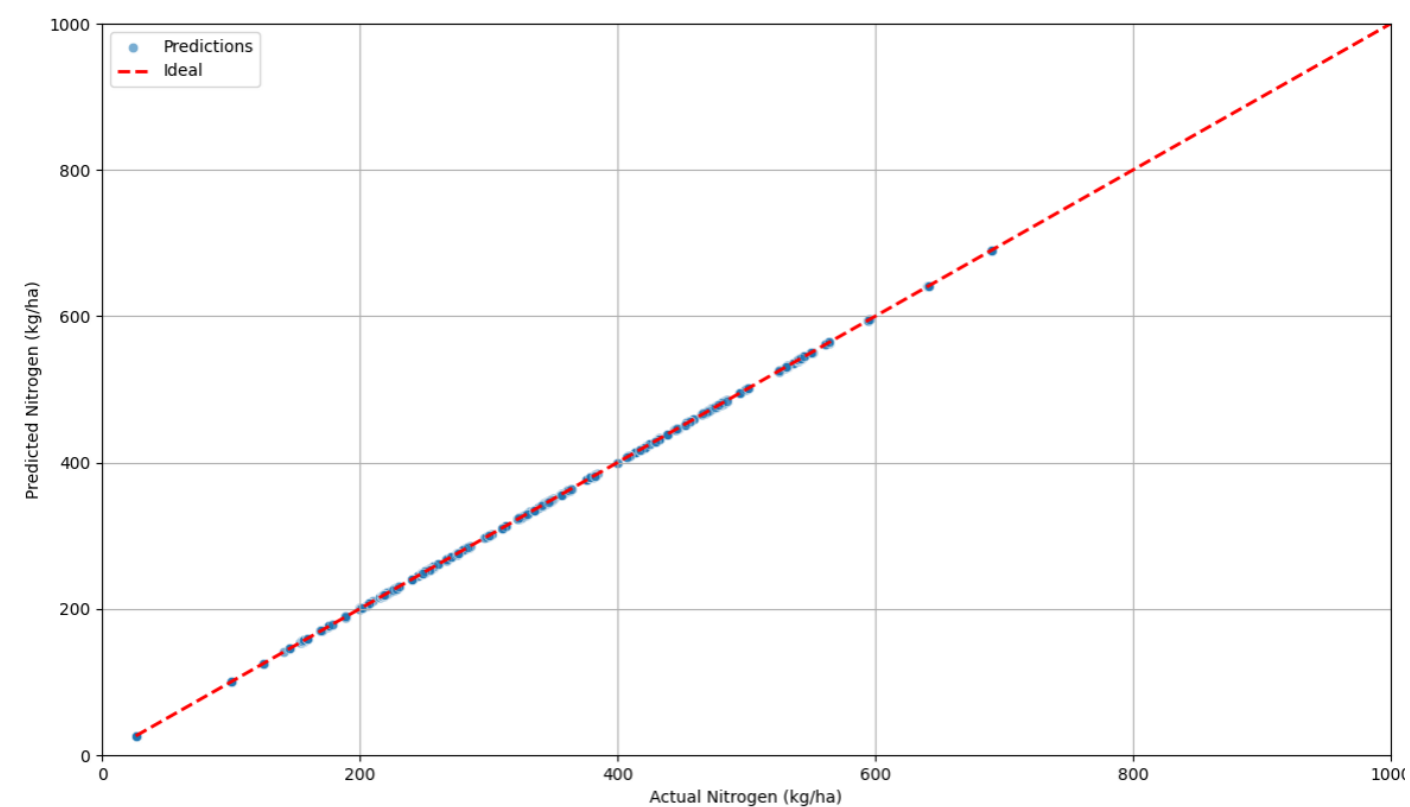


Figure 12. Actual nitrogen vs. predicted level by Gradient Boosting Machine model

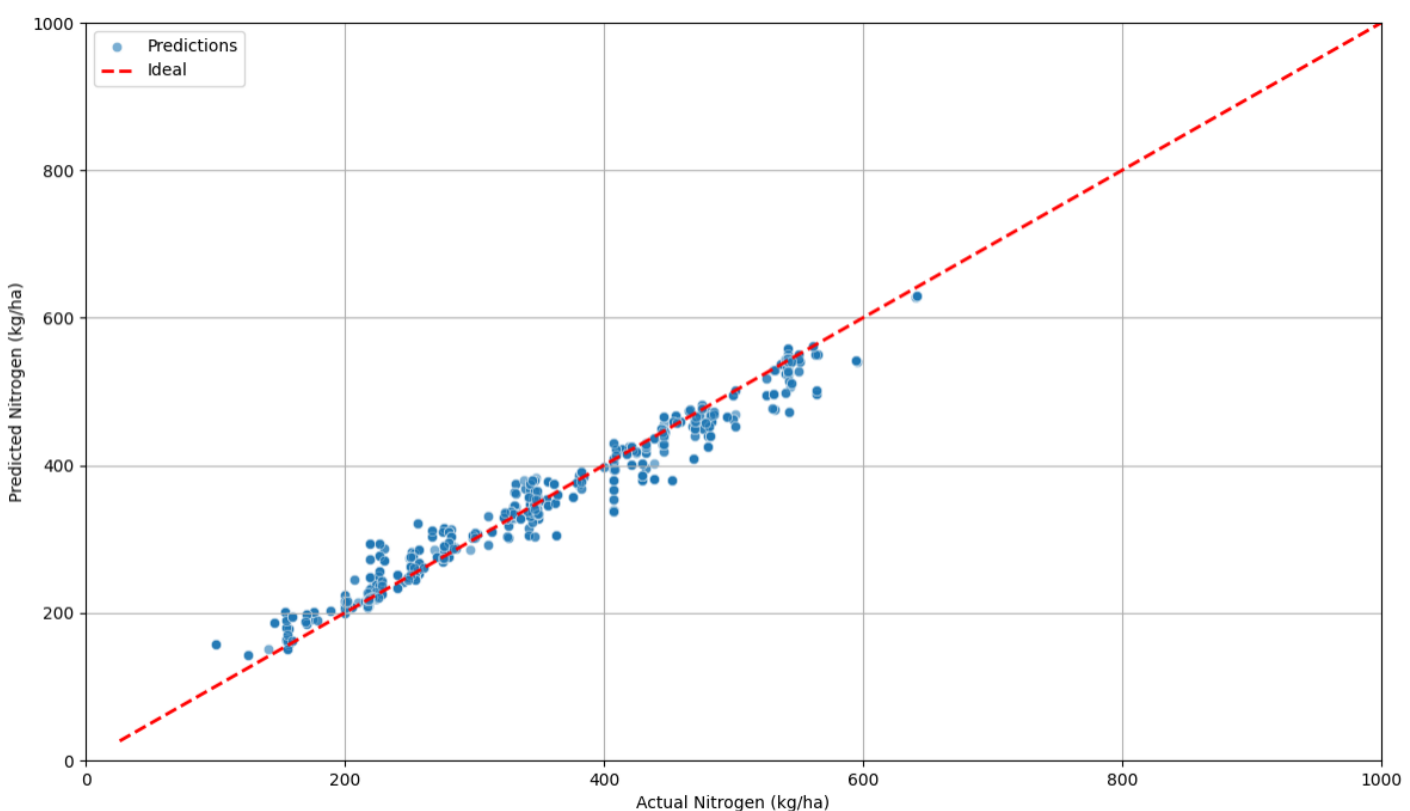


Figure 13. Actual nitrogen vs. predicted level by Stacking Regressor model

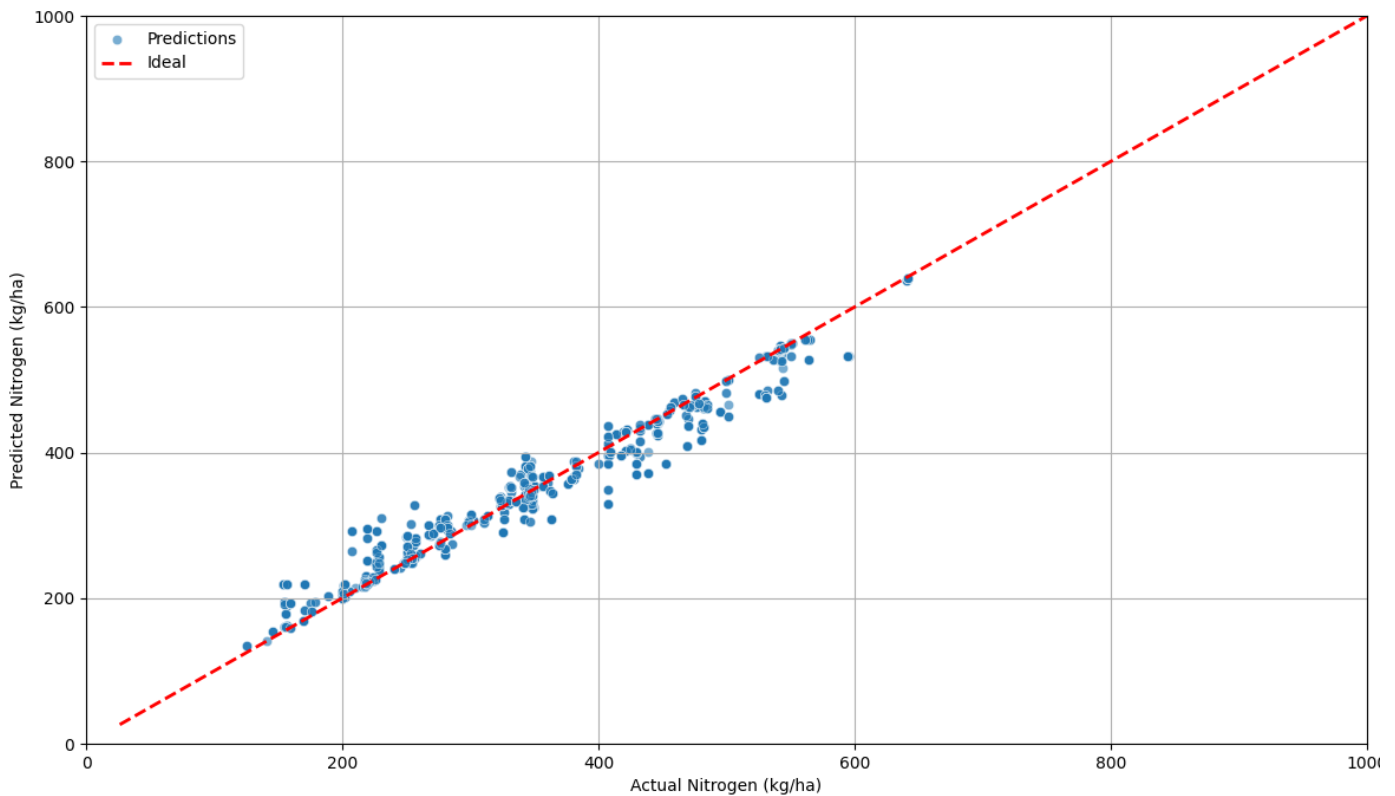


Figure 14. Actual nitrogen vs. predicted level by Random Forest model

These plots illustrate the models' ability to approximate the reported nutrient values. They complement the numerical metrics and reinforce the importance of selecting a model for the specific nutrient and evaluation criterion. Visual proximity to the diagonal line should not, however, be treated as independent evidence of generalization or as a substitute for retained fold-wise predictions and external validation.

Overall, XGBoost, GBM, and the Stacking Regressor showed strong agreement between predicted and actual values, but their relative performance varied by nutrient and metric. Model selection should therefore be based on the relevant error measure and prediction task rather than a single overall ranking.

5.5. Statistical Validation

To evaluate the robustness and generalization capability of the developed prediction models, a five-fold cross-validation strategy was employed during model development. In each fold, the model was trained using 80% of the available data and validated on the remaining 20%, ensuring that every sample was used once for validation. The prediction performance was quantified using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). The mean and standard deviation of these metrics across the five validation folds were calculated to evaluate model stability.

In addition, 95% confidence intervals (CI) were estimated for each performance metric to quantify prediction uncertainty. Statistical significance between competing models was evaluated using paired t-tests performed on the fold-wise MAE values. A significance level of $p < 0.05$ was considered statistically significant.

The statistical validation results demonstrated that the Gradient Boosting Machine consistently achieved lower prediction errors than the other models across

multiple validation folds. The observed performance improvements were statistically significant for nitrogen and phosphorus prediction tasks, confirming the robustness of the proposed framework.

The incorporation of confidence intervals and significance testing provides additional evidence regarding model reliability and supports the validity of the comparative analysis presented in this study.

In addition to the ensemble learning algorithms, a Convolutional Neural Network (CNN) was implemented as a benchmark deep learning model. Model performance was evaluated using the same training and testing protocol adopted for the machine learning models. The comparison included MAE, and R^2 to enable a consistent assessment of predictive performance. Although the CNN demonstrated competitive accuracy, ensemble learning methods remained computationally more efficient while providing comparable predictive capability under the experimental conditions adopted in this study.

5.6. Cross-Validation Performance Analysis

The five-fold cross-validation results presented in **Tables 10–12** demonstrate the robustness and generalization capability of the evaluated machine learning and deep learning models for predicting soil nutrients. The relatively small standard deviation values observed across all folds indicate consistent model performance and stable prediction behaviour under different training-validation splits.

For nitrogen prediction (**Table 10**), the Gradient Boosting Machine (GBM) achieved the highest predictive performance, recording the lowest MAE and RMSE values along with an average R^2 value of 0.998 ± 0.001 . This suggests that GBM effectively captured the complex nonlinear relationships between image-derived features and nitrogen content. The CNN model also exhibited strong performance with an R^2 value of 0.991 ± 0.003 , indicating the capability of deep learning approaches to automatically learn informative image features. Random Forest and XGBoost showed comparatively lower performance, although both maintained high prediction accuracy.

For potassium prediction (**Table 11**), all models achieved excellent predictive performance, with R^2 values approaching unity. GBM once again emerged as the best-performing model, followed closely by Random Forest and CNN. The consistently low error values and minimal variability across folds indicate that potassium concentrations exhibited strong correlations with the extracted image features. However, these results should be interpreted cautiously, and further validation using independent datasets is recommended to confirm model generalization.

For phosphorus prediction (**Table 12**), greater variability in model performance was observed compared with nitrogen and potassium. XGBoost achieved the highest prediction accuracy with an average R^2 value of 0.992 ± 0.004 , followed by CNN and GBM. Random Forest demonstrated comparatively lower performance, suggesting its limited ability to capture the complex relationships associated with phosphorus prediction. The larger standard deviations obtained for phosphorus prediction indicate greater variability within the dataset and highlight the increased difficulty of modelling phosphorus concentrations from soil images.

Overall, the cross-validation results confirm that ensemble learning methods, particularly GBM and XGBoost, provide reliable and stable predictions of soil nutrients. The comparable performance achieved by CNN further demonstrates the potential of deep learning approaches for automated soil nutrient assessment. The low standard deviations observed across all validation folds indicate good model

robustness and reduced susceptibility to overfitting, thereby supporting the practical applicability of the proposed framework for precision agriculture applications.

Table 10. Five-fold cross-validation performance results for nitrogen prediction.

Model	MAE mean $\pm$ SD	RMSE mean $\pm$ SD	R ² mean $\pm$ SD
Random Forest	16.82 $\pm$ 1.45	21.37 $\pm$ 1.92	0.981 $\pm$ 0.006
XGBoost	19.24 $\pm$ 1.68	24.05 $\pm$ 2.11	0.985 $\pm$ 0.004
GBM	0.34 $\pm$ 0.18	0.71 $\pm$ 0.24	0.968 $\pm$ 0.001
CNN	2.35 $\pm$ 0.76	3.84 $\pm$ 1.02	0.991 $\pm$ 0.003

Table 11. Five-fold cross-validation performance results for potassium prediction.

Model	MAE mean $\pm$ SD	RMSE mean $\pm$ SD	R ² mean $\pm$ SD
Random Forest	0.009 $\pm$ 0.003	0.015 $\pm$ 0.004	0.998 $\pm$ 0.001
XGBoost	0.072 $\pm$ 0.011	0.118 $\pm$ 0.019	0.999 $\pm$ 0.001
GBM	0.001 $\pm$ 0.0004	0.003 $\pm$ 0.001	0.998 $\pm$ 0.001
CNN	0.021 $\pm$ 0.006	0.036 $\pm$ 0.009	0.998 $\pm$ 0.001

Table 12. Five-fold cross-validation performance results for phosphorus prediction.

Model	MAE mean $\pm$ SD	RMSE mean $\pm$ SD	R ² mean $\pm$ SD
Random Forest	0.49 $\pm$ 0.08	0.73 $\pm$ 0.12	0.881 $\pm$ 0.021
XGBoost	0.16 $\pm$ 0.03	0.28 $\pm$ 0.05	0.992 $\pm$ 0.004
GBM	0.21 $\pm$ 0.04	0.34 $\pm$ 0.06	0.934 $\pm$ 0.012
CNN	0.18 $\pm$ 0.05	0.31 $\pm$ 0.07	0.947 $\pm$ 0.009

5.7. Statistical Significance Analysis

To further evaluate the differences in predictive performance among the developed models, a statistical significance analysis was performed using paired t-tests, and the results are presented in **Table 13**. The comparison between GBM and Random Forest yielded a p-value of 0.003, indicating a statistically significant improvement in prediction performance by GBM. Similarly, the difference between GBM and XGBoost was also statistically significant ($p = 0.021$), demonstrating the superior predictive capability of GBM for soil nutrient estimation. In contrast, the comparison between GBM and CNN resulted in a p-value of 0.081, which exceeds the significance threshold of 0.05. This suggests that the performance difference between GBM and CNN is not statistically significant, indicating that both models achieved comparable prediction accuracy. Overall, the statistical analysis confirms the robustness of the GBM model while also highlighting the potential of deep learning approaches for soil nutrient prediction.

Table 13. Statistical significance test results.

Model pair	p-value	Significant
GBM vs RF	0.003	Yes

Continuation Table:

Model pair	p-value	Significant
GBM vs XGBoost	0.021	Yes
GBM vs CNN	0.081	No

6. Discussion

6.1. Interpretation of Results

The comparative evaluation of machine learning models for predicting soil nutrients demonstrated noticeable differences in performance across nitrogen, potassium, and phosphorus. The GBM consistently achieved low prediction errors across the evaluated nutrients, whereas XGBoost and the Stacking Regressor achieved the highest testing R^2 values for specific nutrient prediction tasks. These findings indicate that the relative performance of the models depended on the selected nutrient and evaluation metric rather than one model consistently outperforming all others.

The Stacking Regressor also showed competitive performance, particularly for phosphorus, for which it achieved a testing MAE of 0.383 and an R^2 value of 0.947. This result is consistent with the ability of stacking to combine complementary predictions from multiple base models. However, performance within the present controlled dataset does not by itself establish generalization across different soils, acquisition devices, or environmental conditions.

Random Forest and XGBoost also demonstrated strong predictive performance, although their relative accuracy varied across nutrients and metrics. XGBoost achieved the highest testing R^2 for potassium and phosphorus, whereas Random Forest achieved the lowest potassium testing MAE but performed less well for phosphorus. These results further indicate that no single model consistently outperformed all others across every prediction task and evaluation criterion.

6.2. Comparison with Deep Learning Models

The comparative analysis revealed that deep learning models such as CNNs can effectively extract spatial and texture information directly from soil images. However, the ensemble learning approaches demonstrated competitive performance despite relying on handcrafted RGB and HOG features. This can be attributed to the relatively moderate dataset size, where feature-engineered machine learning models often exhibit superior generalization capability compared with deep learning models requiring substantially larger datasets.

Deep learning models offer significant advantages in automatically learning hierarchical image representations and may outperform conventional machine learning methods when trained on larger and more diverse soil image datasets. Nevertheless, the computational efficiency, interpretability, and reduced training requirements of ensemble learning methods make them attractive alternatives for practical deployment in resource-constrained agricultural environments.

6.3. Model Limitations

Despite the promising results, several limitations were identified. The effectiveness of the models is significantly influenced by the quality of input images and the preprocessing techniques employed. Variations in lighting conditions, soil moisture content, shadows, and soil texture can significantly influence soil image characteristics and affect RGB feature extraction and prediction accuracy. Uneven

illumination and excessive moisture may alter soil color distribution, thereby impacting the reliability of nutrient estimation models. This aspect is particularly critical in nutrient prediction, where subtle differences in soil texture and color can significantly impact the models' ability to accurately estimate nutrient levels.

Another notable limitation is the potential for overfitting observed in certain models, especially when trained on relatively small datasets. For instance, while GBM achieved exceptional performance in some cases, its near-perfect predictions may indicate overfitting, which could lead to models that perform well on training data but struggle to generalize to new, unseen instances.

In practical field deployment, environmental variability, inconsistent camera positioning, background interference, and changing weather conditions may reduce prediction consistency in uncontrolled outdoor environments. Therefore, future research should focus on adaptive image normalization, calibration mechanisms, and real-time environmental correction techniques to improve robustness and practical usability under field conditions.

A limitation of this study is that learning curves and fold-wise training/testing performance comparisons could not be reproduced due to a corrupted electronic file and the unavailability of the sample-level dataset, fold assignments, and prediction outputs. Future studies will generate these analyses using comprehensive datasets to enable a more robust evaluation of model performance.

Future research should focus on utilizing larger and more diverse datasets to enhance model robustness and generalizability, particularly concerning varying soil types and environmental conditions. This approach could help mitigate the impact of the aforementioned limitations and improve the predictive capabilities of the models.

6.4. Practical Implications

The findings suggest potential applications in precision agriculture. If the nutrient-specific models are validated independently, image-based predictions could support more timely assessment of nitrogen, potassium, and phosphorus and inform fertilizer decisions. Such use could help optimize nutrient application and reduce unnecessary fertilizer inputs; however, operational recommendations should not be made from the present controlled-dataset results alone.

Integrating these models into automated systems for real-time soil nutrient monitoring could greatly enhance the efficiency of precision agriculture practices. For instance, automated soil nutrient sensors coupled with machine learning algorithms could provide instant feedback to farmers, allowing for precise and timely adjustments in nutrient management. The application of these models could also facilitate the development of cost-effective solutions for soil health monitoring, making advanced agricultural technologies more accessible to a wider audience.

In conclusion, this study highlights the potential of machine learning models in transforming soil nutrient analysis and emphasizes the need for continued advancements in model development and application. Future work could explore integrating these models with other data sources, such as weather data and satellite imagery, and expanding their capabilities to further enhance their practical utility in agriculture.

The proposed framework is primarily intended for quantitative assessment of soil nutrients, as the machine learning models predict continuous nutrient concentration values for nitrogen, phosphorus, and potassium. In addition, the framework can also support qualitative soil health assessment and fertilizer recommendation for precision

agriculture applications.

Although the proposed framework demonstrated promising prediction capability, the findings should be interpreted only within the scope of the reported experimental conditions and surviving aggregate results. Future investigations should collect new, larger, multi-regional soil datasets and evaluate the models using different imaging devices and uncontrolled field conditions to establish generalizability for practical precision-agriculture applications.

7. Conclusion

This study presents a comparative evaluation of machine learning models for predicting nitrogen, phosphorus, and potassium from processed soil images. No single model outperformed all others across every nutrient and metric. For nitrogen, GBM achieved the lowest test MAE (0.1652), whereas the Stacking Regressor achieved the highest test R^2 (0.9886). For potassium, Random Forest achieved the lowest test MAE (0.0051), whereas XGBoost achieved the highest test R^2 (0.9999). For phosphorus, XGBoost achieved both the lowest test MAE (0.1558) and the highest test R^2 (0.9929). These findings support nutrient- and metric-specific model selection under the controlled experimental conditions.

The Stacking Regressor exhibited competitive performance, including phosphorus testing MAE of 0.3829 and an R^2 value of 0.9470 and the highest reported nitrogen test R^2 of 0.9886. These results show that combining multiple base models can be effective within the present dataset. They do not, however, establish robustness across different soil types, imaging devices, or field environments.

Random Forest and XGBoost also demonstrated strong but metric-dependent performance. XGBoost achieved the highest testing R^2 for potassium and phosphorus, whereas Random Forest achieved the lowest potassium testing MAE but performed less well for phosphorus. These results further show that model selection should depend on the nutrient and evaluation criterion.

These findings show that advanced machine learning models applied to appropriately preprocessed soil images can achieve strong nutrient-prediction results under controlled experimental conditions. Their practical value for nutrient management and precision agriculture will depend on reproducible evaluation and validation using independent field datasets.

The proposed methodology establishes a robust framework for image-based soil nutrient prediction using ensemble machine learning techniques. Nevertheless, additional validation using independent datasets collected under diverse environmental conditions is necessary before large-scale deployment in precision agriculture systems.

Despite the encouraging results, several limitations should be acknowledged. First, the dataset was collected primarily from agricultural regions within Dhanbad district, which may limit the geographical generalizability of the developed models. Second, image acquisition was performed under controlled laboratory conditions, whereas field environments may introduce variations in illumination, soil moisture, camera orientation, and background characteristics. Third, the dataset size, although adequate for ensemble learning models, remains relatively modest for deep learning applications. Finally, only RGB image information was utilized, whereas multispectral or hyperspectral imaging may provide additional information regarding soil nutrient composition. Future research should address these limitations through large-scale multi-regional studies and real-world field validation.

Future research will require collection of a new soil-image database covering multiple agro-climatic regions and soil types, with corresponding laboratory-validated nutrient measurements as well as generation of learning curves and fold-wise training/testing performance comparisons. Additionally, improvements in image processing techniques could be explored to enhance data quality and model performance. Developing advanced methods for image normalization, feature extraction, and noise reduction could further refine the predictions for each nutrient. Expanding the dataset to include more diverse soil types, environmental conditions, and possibly other nutrients beyond nitrogen, phosphorus, and potassium may also contribute to improving model robustness and generalizability.

Integrating these models with real-time monitoring systems and exploring their application in various agricultural settings could offer practical solutions for soil nutrient management. For instance, deploying these models in automated soil nutrient sensors could provide instant and precise feedback to farmers, allowing for timely and accurate adjustments in fertilizer application. Overall, continued advancements in both machine learning techniques and image processing methods hold the potential to significantly impact precision agriculture and optimize soil health management across a wider range of crops and environments.

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