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Original Article

Soil Testing Using Image Processing

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Abstract *- Precision agriculture is a globally growing practice that requires accurate soil health assessment. The health of the soil is characterized by parameters such as pH and nutrients like NPK. Soil testing is very important to predict crop yield and manage fertilizers and pesticides. Traditionally, soil testing methods were time and resource-intensive, often leading to delays. This discouraged farmers from conducting regular soil tests. We propose a machine learning-based application for rapid soil analysis. We have utilized 7000 soil images paired with their corresponding laboratory-tested results. These samples were used to train our CNN (Convolutional Neural Network) model to identify soil properties from images. The machine learning model ensures accuracy and robustness as it has been trained under various lighting conditions. Preliminary evaluations indicate an average prediction variance of 0.02 pH units, 1.5 kg/ha for N, 0.8 kg/ha for P, and 1.2kg/ha for K measured as the Mean Squared Error normalized by the range of actual nutrient values. This innovation aims to contribute to sustainable agricultural practices by making soil testing in real-time possible without the need for any extra equipment or expertise.*

Keywords *- Feature extraction, Image processing, Pattern recognition, Remote sensing, Segmentation.*

1. Introduction

In Permanent farmland, soil nutrients deplete gradually due to continuous cropping. One approach to restoring the soil nutrients is to leave the soil fallow, allowing organic matter from previous harvests to decompose and naturally replenish nutrient levels. However, this method is time-consuming and impractical for modern agricultural systems, which demand higher productivity. A more commonly practised approach is the application of fertilizers, and with the increasing demand for higher crop yields and declining soil quality, fertilization has become widespread. [1] Applying the correct amount of fertilizer is crucial for crop yield, and evaluating what fertilizer needs to be applied and what amount of soil fertility must be thoroughly checked. [2, 3] Excessive or improper use can lead to soil toxicity, reduced fertility, and environmental pollution [4]. Historically, farmers relied on traditional knowledge passed down through generations, but scientific advancements have revolutionized soil management. Nowadays, various methods for soil testing are available, one of which is a Soil Testing Kit (STK), which is easily available in the market or can be purchased online. This approach relies on color matching after the chemical treatment of soil to identify soil pH and macronutrients (NPK). The accuracy of the result depends on the user's ability to interpret the color change in such cases [5]. Other methods for soil testing involve optical sensing and electrochemical sensing. Optical methods measure reflected wavelengths after light is reflected from the soil. The electrochemical method uses changes in electrical signals by ion concentrations in the soil to measure soil properties [6]. Near Infrared Spectroscopy, Diffuse Reflectance Spectroscopy and Attenuated Total Reflectance Spectroscopy are some spectroscopy techniques utilized for soil nutrient detection [7-9]. Electrochemical spectroscopy, on the other hand, uses ion-selective field effect transistors or ion-selective electrodes [10-12]. Soil testing has become an essential tool for assessing soil health.

To address the need for even quicker and more accessible soil testing, we propose a technology-driven solution using image processing and machine learning. This method offers a free, accurate, and user-friendly approach that delivers real-time results [13]. Such solutions can motivate farmers to test their soil before applying fertilizers, saving time and reducing costs while minimizing environmental impact.

Key nutrients to test include pH and NPK (Nitrogen, Phosphorus, and Potassium). Soil pH measures the hydrogen ion concentration and determines the acidity, alkalinity or neutrality of soil. It is crucial for soil health, as the availability of essential nutrients depends on pH [14]. A pH range of 6.5 to 7.5 is considered neutral, ideal for most crops. Values above 7.5 indicate alkalinity, while values below 6.5 indicate acidity. When soil is too acidic, the availability of nutrients like Phosphorus (P) decreases, while toxic elements such as Aluminum (Al) and Manganese (Mn) increase, adversely affecting plant growth. Similarly, nutrients become less available in highly alkaline soils, impacting crop yields. Thus, maintaining a neutral pH is critical for optimal plant growth and nutrient uptake [15].

1.1. Literature Review

To address the challenges of soil testing in 2020, Rahman et al. used various IoT sensors to read moisture, water levels, pH, temperature, and humidity. They display this information on a cloud-based dashboard that the farmer can use to make decisions related to farming. They additionally provided security by using a laser shield on the farm [16]. However, the system is effective, but it does not provide macro nutrient information. Integrating Convolutional Neural Networks (CNNs) in soil testing has significantly advanced the precision and efficiency of soil property analysis. Fernandez et al. also conducted a study to improve farming in 2020, wherein they developed a system to conserve water. The system developed was an energy-efficient system that used low-power sensors and solar energy to supply only the needed amount of water [17]. This system also does not provide soil testing results required to decide optimal crop and fertilizer requirements.

In 2021, Montanez et al. developed a prototype for soil testing that provided NPK results. They also provided crop and fertilizer recommendations based on results [13]. The system we have proposed, however, reduces the need for any soil testing device and makes soil testing even more convenient. Other studies conducted in the field of smart farming were related to optimizing irrigation using big data analytics, remote sensing and neural networks, like work done by Rabhi et al. in 2021 [18]. Varsitha et al. also conducted a study emphasizing the need to provide farmers with Artificial Intelligence powered solutions. Using IoT and deep learning, they predicted soil fertility based on features like NPK, pH, organic carbon, and moisture. They further suggested crops and nutrients based on the analysis done. They also compared the accuracy of various machine learning classifiers [19]. In 2022, Varshitha et al. further improved their work using bootstrap aggregation regression and ensemble machine learning techniques to check soil fertility [20]. The study also compared various regression methods that could be useful to future researchers. In 2023, Shanmugan et al. used historical information to forecast yield using LSTM time series analysis. To make predictions, they analyzed a large dataset comprising weather data, soil nutrient information, and season and past yield information [21]. Later, in 2023, Karthikeyan et al. proposed a system to monitor soil pH and irrigation by combining drones with multispectral imaging and IoT sensors. They also integrated a triboelectric nanogenerator for a sustainable energy source [22]. Rahim et al. 2023 proposed a system for soil monitoring and automated irrigation using IoT, and their proposed system effectively reduces 35% water need [23]. Rumiche-Cardenas et al. 2025 used IoT to monitor the weather for small to medium-scale farms. It was a very efficient system that provided alerts to farmers depending on the weather to optimize farming [24]. According to the literature, previous studies require expensive equipment, focus on specific soil properties, and do not provide image-based soil analysis. Our approach reduces the need for costly equipment and makes it likely to be adopted by farmers.

Our paper is divided into an introduction, which discusses the background of the research. The research gap and section cover the methodology, which discusses our research method, results, and discussion. Lastly, a conclusion that discusses the limitations and future scope in this field of research is presented.

2. Methodology

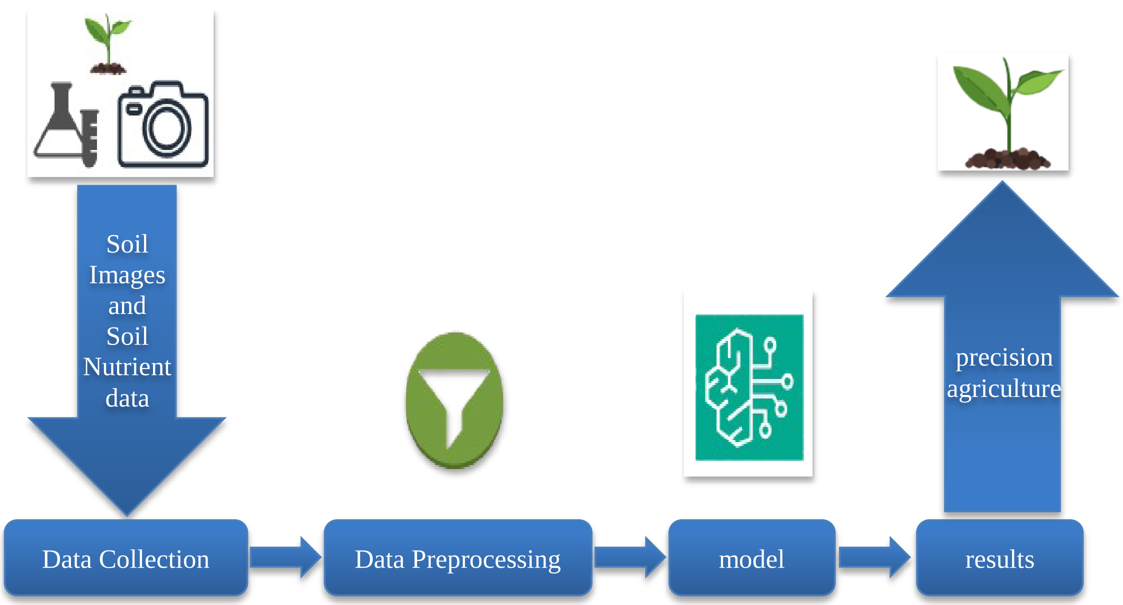

Fig. 1 Workflow of image processing model

2.1. Data Collection

The data collection was done in two parts: firstly, we collected soil samples; secondly, we collected soil images and soil test results (NPK and pH) from the laboratory. Below is a detailed description of both.

2.1.1. Soil Sampling

Table 1. Soil sampling locations of Dehradun Uttarakhand and area type

Area type	Location
Agricultural land	Doiwala, Rishikesh outskirts, Vikasnagar, Harrawala, Sahaspur.
Forest areas	Rajaji National Park, Mussoorie forest division, Lachhiwala Nature Park.
Urban and semi-urban areas	Dehradun city (Race Course, Rajpur Road), FRI campus and local parks like Gandhi Park.
Hilly and sloped regions	Mussoorie, Maldevta, and Chakrata region.
Riverbanks and floodplains	Banks of River Ganga, Song River, Tons River.
Industrial zones	Selaqui industrial area, Bhagwanpur.
Degraded and barren lands	Areas near Raipur and regions affected by deforestation or mining.

Different soil locations were gathered to ensure a comprehensive analysis of soil conditions across the Dehradun region in Uttarakhand, India. It is a state situated near the Himalayas. We collected samples from these locations, including agricultural lands, particularly farms growing common crops such as wheat, rice, and sugarcane, to study cultivated soil characteristics.

Samples from forest areas were included to analyze natural, undisturbed soil conditions, providing a baseline for comparison. Samples were collected from urban and semi-urban areas to understand the impact of urbanization. Soil from hilly and sloped terrains and high altitudes were sampled to examine erosion and nutrient leaching.

Sampling near rivers provided insights into nutrient deposition and sedimentation processes. Soil from industrial zones was collected to assess the influence of industrial activities, while barren lands were sampled to evaluate soil restoration needs.

All samples were collected following the sampling guidelines provided by the Indian Agricultural Research Institute. Each soil sample was labelled with a unique number, including details of the location of the collection site and date. The labelled samples were securely packed and transported to the soil testing laboratory for further analysis.

Fig. 2 Collection of soil samples and testing in the lab

2.1.2. Images and Soil Test Results

The dataset for image processing was created to enable the identification of soil macronutrients and pH using image processing. High-resolution images of the prepared soil samples were captured using a digital camera under controlled lighting conditions to maintain uniformity. Consistent lighting and background settings are critical for reducing noise in image-based data collection. The images were taken against a neutral background to minimize interference, and multiple angles were captured for each sample to account for texture variability, as suggested in a similar study on soil texture analysis. Each image was assigned a unique identification number. We created a CSV to store the location, unique identification number, and corresponding pH and NPK values obtained from laboratory analysis of the soil sample. This mapping ensures a clear association between the visual data and the chemical properties of the soil. The labelled dataset was organized systematically, with directories categorizing the images based on soil type, nutrient levels, and pH values. This comprehensive dataset, containing unique image identifiers and corresponding laboratory-tested values, serves as the foundation for training, validating, and testing machine learning models designed for soil nutrient and pH prediction.

2.2. Data Preprocessing

2.2.1. Image Data Preprocessing

To standardize the input size for the model, pictures were resized to a dimension of 224 x 224 pixels. Pixels were scaled to a range of [0, 1] by dividing each value by 255 for normalizing. This normalization improved training efficiency. Data was augmented using random rotations (e.g., ±20 degrees), horizontal and vertical flips, random zoom-in and zoom-out and adjustments in brightness and contrast.

2.2.2. CSV Dataset Preprocessing

The CSV dataset contained structured data, including soil properties and labels. The preprocessing involved handling missing values, data cleaning and feature scaling. Handling missing values for numerical values (e.g., NPK levels and pH) was done by imputing using mean or median values; for categorical labels (e.g., soil type), imputing using the mode was done. For data cleaning, duplicates were removed to ensure each sample was represented only once. After that, outliers in continuous variables (NPK levels, pH) were handled using statistical methods like z-score or IQR (interquartile range). For feature scaling, continuous features (NPK and pH values) were scaled using z-score normalization:

$$z = \frac{x - mean}{standard\ deviation}$$

This ensured all features were on a comparable scale, improving model performance; for label encoding, Soil type labels were encoded as integers for classification models (e.g., 0 for alluvial, 1 for black, etc.). For multiclass classification, one-hot encoding was applied to generate binary vectors for each class. For feature engineering additional features, such as categorical labels for nutrient levels (e.g., "low," "medium," "high"), were derived from the continuous NPK values using predefined thresholds. The dataset was divided into three sets, 70%, 15%, and 15%, in train test and validate subsets while ensuring a balanced distribution of labels. For the integration of image and CSV data, the processed images and pre-processed CSV data were merged into a unified dataset using the unique sample identifiers as keys. This integration enabled machine learning models to leverage both structured (NPK, pH) and unstructured (image features) data.

Table 2. The final dataset ready for training, consisted of the following

Image Features	Representing visual patterns in soil samples.
Structured Features	Scaled NPK and pH values, along with encoded categorical labels.
Target Labels	Soil classification labels for supervised learning.

This preprocessing cleaned the data and made it consistent and suitable for soil classification and nutrient prediction.

2.2.3. Machine Learning Algorithm

A CNN-based machine learning model was designed to predict the four target variables (pH, N, P, K). CNNs are suitable for image-based learning as they are good at extracting hierarchical spatial features efficiently. The architecture comprised:

1. Three convolutional layers with ReLU activation and batch normalization to extract spatial features from soil images.
2. MaxPooling layers to reduce the spatial dimensions and prevent overfitting.
3. Dropout layers for regularization, ensuring better generalization.
4. A GlobalAveragePooling2D layer to reduce parameters before the fully connected layer.
5. Dense layers for prediction, with the final output layer designed for four continuous variables (N, P, K, and pH).

2.2.4. Model Training and Validation

After the model training was done, the model was evaluated based on the mean squared error loss function and mean absolute error metric. Model optimization using Adam optimizer. For validation we have compared the results of pH and NPK obtained by our model with those that came from the laboratory. The average difference between both was minimal, indicating high model accuracy. For pH, the average difference was approximately 0.02 units, with a predicted range of 6.40–7.20 compared to the laboratory range of 6.42–7.22. Similarly, the average deviation for Nitrogen (N) was 1.5 kg/ha, with predicted values ranging from 140–150 kg/ha compared to laboratory values of 141.5–151.5 kg/ha. For Phosphorus (P), the average deviation was 0.8 kg/ha, and for Potassium (K), it was 1.2 kg/ha. The model generates accurate predictions that are close to laboratory findings as per the results.

3. Results and Discussion

3.1. Comparison with Existing Methods

The performance of the CNN model was compared against other machine learning approaches, including Linear Regression, which is a baseline model to establish simple relationships between image-derived features and nutrient values, Support Vector Regression (SVR), which is used for its ability to model complex relationships with kernel-based transformations, Random Forest Regressor which does not rely on specific parameters ensemble method that is capable of managing complex non-linear relationships, Gradient Boosting Machines (GBM) which is an advanced ensemble method known for its predictive accuracy and lastly Convolutional Neural Network (CNN) which outperformed all other tested approaches. The results in Table 2 demonstrate CNN's superior capability in leveraging spatial features from soil images.

Table 3. Model comparison

1. MODEL	2. MSE	3. R^2
4. Linear Regression	5. 7.45	6. 0.72
7. Support Vector Regression (SVR)	8. 6.20	9. 0.78
10. Random Forest Regressor	11. 5.12	12. 0.85
13. Gradient Boosting Machines (GBM)	14. 5.34	15. 0.83
16. Convolutional Neural Network (CNN)	17. 4.67	18. 0.89

3.2. Model Performance

Each model was assessed using MSE, which determines the average squared values among predicted and actual values, and (R^2) Score, which determines how well the model accounts for variability in the target data.

The CNN model outperformed all the other tested approaches, achieving the lowest Mean Squared Error and the highest R squared value. This demonstrates the effectiveness of CNNs in leveraging information from soil images for accurate nutrient prediction. Ensemble methods like Random

Forest and GBM showed competitive performance but were less effective in capturing intricate patterns compared to CNN.

The relationships between the features and soil nutrient levels are analyzed through correlation analysis. Figure 3 displays the heatmap as evidence of strong or weak correlations. Correlation heatmaps highlight any surprising insights or confirmatory findings.

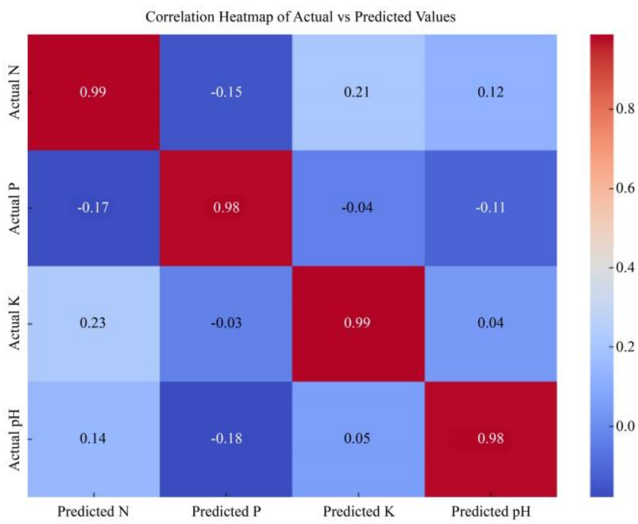

Fig. 3 Correlation heatmap for soil features and nutrients

The heatmap in Figure 1 to visualize how strongly the actual and predicted values are related for each parameter (N, P, K, and pH). The heatmap shows a high correlation (values close to 1), indicating that the model predictions are closely aligned with actual values. This demonstrates the model's effectiveness in capturing the patterns in data.

Figure 4 presents the scatter plot to show the relationship between actual and predicted values. It mentions how well the forecasts match with the ground truth for N, P, K, and pH. It also discusses R^2 values for each nutrient and the model's overall accuracy.

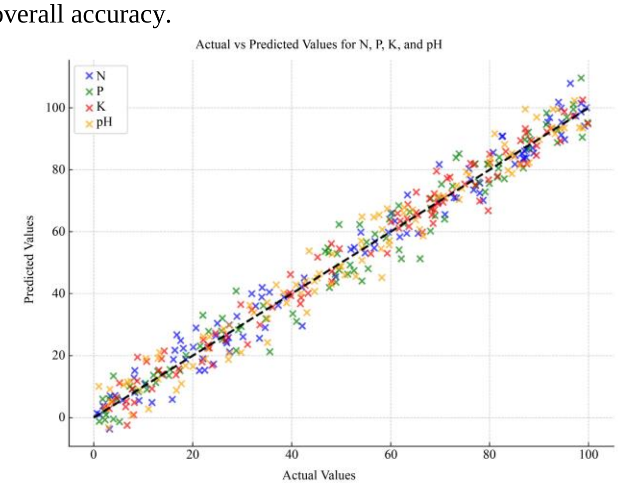

Fig. 4 Scatter plot of actual vs Predicted values for soil nutrients

The purpose of this scatter plot in Figure 4 is to compare actual values with predicted values. Accurate predictions are indicated by data points near the diagonal line y=x. Each parameter (N, P, K, pH) is represented by a distinct color, and the tight clustering of points around the line confirms high prediction accuracy.

Figure 5 uses the residual distribution to discuss the error distribution and how closely the actual values match the predicted values. It emphasizes minimal residuals, if applicable, indicating high performance.

The purpose of Figure 5 is to analyze the error (residuals) between actual and predicted values. A residual cantered around zero with minimal spread indicates that the model has minimal bias and low prediction errors. The smooth, narrow distribution confirms good model calibration.

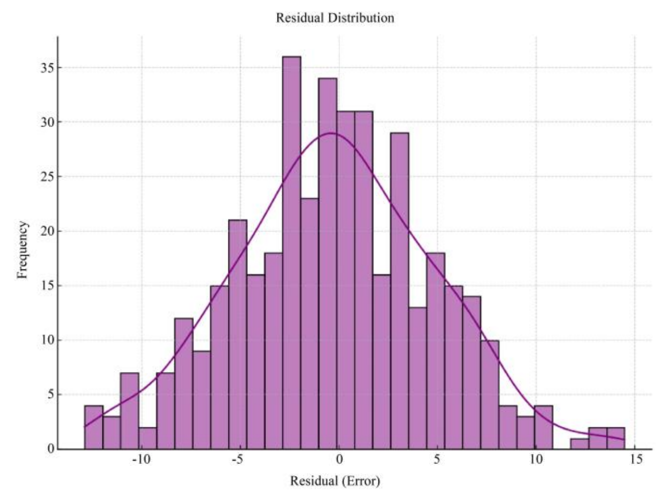

Fig. 5 Residual distribution of model predictions

Figure 6 summarizes the model's performance using the bar chart. It discusses each nutrient's metrics, such as MSE, MAE, and R^2. It also highlights the model's strengths in nutrient prediction.

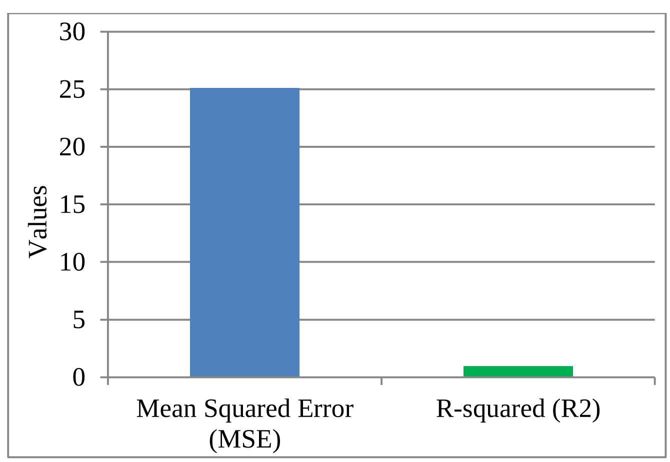

Fig. 6 Performance metrics for soil nutrient prediction model

The purpose of Figure 6 is to summarize model assessment criteria. For MSE, a low value (25.10) shows that the mean squared error between predicted and actual values is small. For R squared, a high value (0.97) signifies that the model explains 97% of the variance in the target variables (N, P, K, pH), demonstrating strong predictive power.

This research demonstrates the feasibility of using image processing and CNN models for accurate soil nutrient and pH detection, enabling precision agriculture practices.

4. Conclusion

As a result of our study, we have created a machine learning model that can test soil in real time. Our model was compared with various other models to check its performance. This model offers real-time soil testing results for practical applications. Our model is evaluated against two studies, and the results show that the ML method used can deliver a better accuracy from 2.88 to 12.67 %.

Even though we ran a number of tests, there is still an opportunity for more research and development using a variety of deep learning models. We will also work with datasets from other cities and states in the future to expand our research.

The study was limited to the soil of Dehradun Uttarakhand, but we can expand our research to other areas; we can also add more features to our model like prediction of other soil macro and micronutrients along with fertilizer recommendation, crop recommendation, irrigation-related information and much more.

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