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Survey on Soil Micro-Nutrients Analysis and Crop Recommendation System in Smart Agriculture

P. Abinaya[1], A. Faaiza[2], S. Tharshni[3], G. Vishali[4], M. Aravindan[5], Dr. G. Santhi[6]*
[1]PHD Information Technology, Puducherry Technological University, Puducherry, India.
[2, 3, 4, 5]UG Information Technology, Puducherry Technological University, Puducherry, India.
[6]Professor, Information Technology, Puducherry Technological University, Puducherry, India.
Emails: *abinayap286@gmail.com[1], faaiza.a@pec.edu[2], tharshni.s@pec.edu[3], vishal.g@pec.edu[4], aravindan.m@pec.edu[5]*
****Corresponding Author Orcid ID:*** *https://orcid.org/0009-0002-3087-2961*

Abstract
Healthy and sufficient crop and food production are very much essential for everyone as the population is increasing globally. At present, many advancements have been made in recent times, mainly, the roles of the data analysis and machine learning tools help a farmer to analyze and make better decisions in each stage of cultivation. Once suitable crop seeds are chosen, the farmer shall proceed with seeding, monitoring crop growth, disease detection, finding the ripening stage and then crop cutting. The main objective is to provide a continuous support system to a farmer so that he can obtain regular inputs about his field and crop. This survey thoroughly analyzes different soil micro nutrients such as nitrogen, boron, potassium and sulphur to improve Crop Recommendation Systems. It explores soil analysis components, various algorithms, and datasets used in precision agriculture.

Keywords: *Smart agriculture, Machine learning, Micronutrients, Soil analysis*

1. Introduction
Smart farming for soil nutrient analysis refers to the application of advanced technologies and data-driven techniques to assess and manage soil health more efficiently and accurately [2]. By utilizing tools such as remote sensing, sensor networks, and data analytics, farmers can gather real-time data on soil conditions, including nutrient levels, moisture content, and pH levels. This data allows them to make informed decisions about fertilization, irrigation, and crop selection, ultimately optimizing yield while minimizing environmental impact. Smart farming for soil nutrient analysis plays a crucial role in sustainable agriculture by helping farmers enhance productivity and reduce resource wastage, leading to more resilient and environmentally-friendly farming practices

1.1 Components of Smart Agriculture
Smart farming for soil nutrient analysis relies on a variety of technologies and tools to assess soil health and nutrient content accurately [5]. Some of the components used in this field:

Soil Sensors: The devices measure the moisture content of the soil, helping farmers optimize irrigation and prevent overwatering or under watering. PH sensors determine the acidity or alkalinity of the soil, which is crucial for nutrient availability and crop growth.

Nutrient Sensors: These sensors detect the levels of nitrogen compounds in the soil, allowing farmers to adjust nitrogen fertilization as needed. These sensors measure the levels of essential macronutrients in the soil.

Remote Sensing: Satellite imagery and drones equipped with multispectral or hyperspectral cameras can provide real-time data on crop health, soil moisture, and nutrient levels across large areas.

Data Analytics and Machine Learning: Advanced data analytics and machine learning algorithms can process and interpret the data

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collected from. Components of Smart Agriculture shown in Figure 1. Various sensors and sources to provide actionable insights for farmers.

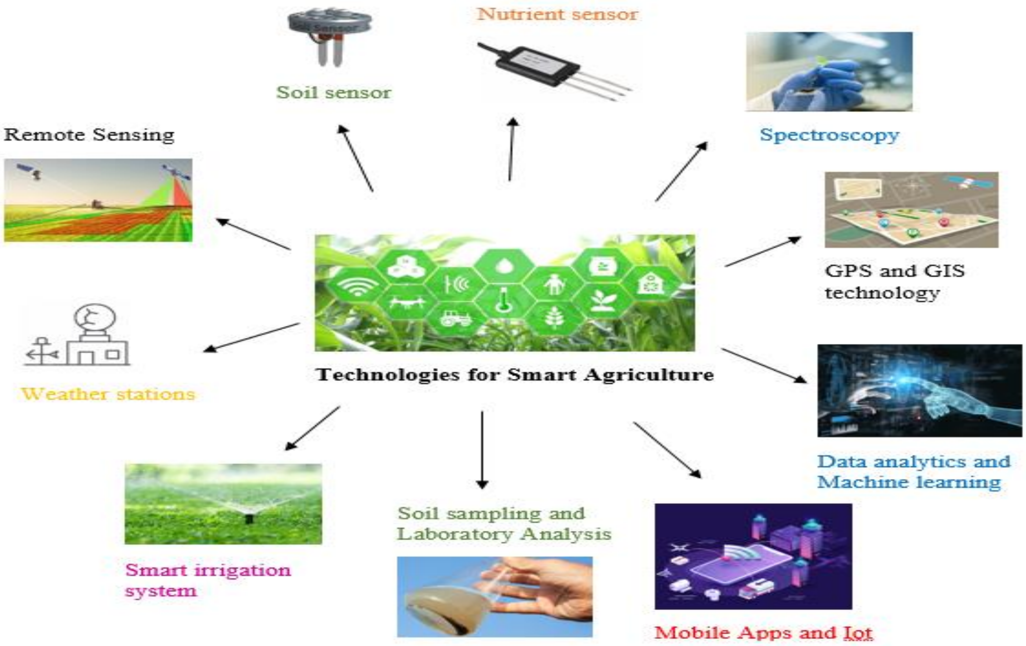

Figure 1 **Components of Smart Agriculture**

By combining these technologies, farmers can adopt data-driven approaches to soil nutrient management, improving crop yields, reducing input costs, and promoting sustainable agriculture practices. The specific technologies used may vary depending on the farm's size, budget, and goals [3].

1.2 Micronutrients

Micronutrients refer to essential elements that are required by plants in small quantities for their growth. These micronutrients include elements such as iron (Fe), manganese (Mn), and zinc (Zn), copper (Cu), molybdenum (Mo), boron (B), and chlorine (Cl) [5]. Soil analysis involves assessing the levels of these micronutrients in the soil to ensure that they are present in adequate amounts for plant growth.

Organic Matter: Organic matter plays a crucial role in soil health by influencing nutrient availability and microbial activity. The presence of organic matter helps stabilize soil pH in micronutrients. Organic matter even helps balance the soil's acidity, making sure micronutrients are available to plants [9].

Soil Texture: Soil texture is defined by the relative proportions of sand and clay, is a key factor guiding fertilizer recommendations. A comprehensive understanding of soil texture is essential for optimizing nutrient availability, ultimately contributing to enhanced agricultural productivity [12].

Soil pH: Soil pH measurement, indicating soil acidity or alkalinity, has a direct impact on plant health. Its crucial role extends to effective fertilizer action, providing an assessment of overall soil health and influencing microbial activity.

Climate and Spatial Variability: Considering dynamic factors such as climate, including temperature and precipitation patterns, and spatial variability, which acknowledges soil differences due to topography, is essential in soil analysis. [10]

2. Soil Analysis in Smart Agriculture

Smart agriculture for soil nutrient analysis encompasses various components that work together to optimize soil health and crop production [1]. These components include in Table 1.

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Table 1 Components of Soil Analysis

COMPONENT	SIGNIFICANCE	DESCRIPTION
Soil texture	Determines the relative amounts of sand, silt, and clay.	Soil texture influences water drainage, aeration, and nutrient availability. Sandy soils drain quickly but may lack nutrients, while clayey soils retain water but can be poorly aerated. Silt represents a balance between the two.
pH Level [1]	Measures the acidity or alkalinity of the soil.	PH affects nutrient availability to plants. Most crops thrive in slightly acidic to neutral soils (pH 6-7). Acidic soils may require lime to raise pH, while alkaline soils may need amendments to lower ph.
Organic Matter Content	Assesses the amount of decomposed plant and animal material.	Organic matter improves soil structure, water retention, and nutrient content. It enhances microbial activity, contributing to nutrient cycling and overall soil health.
Nitrogen [1]	Key for plant growth and protein synthesis.	Nitrogen is a crucial component of amino acids, proteins, and chlorophyll. Deficiencies lead to stunted growth, yellowing of leaves, and reduced yields. Soil testing helps optimize nitrogen application.
Phosphorus [1]	Essential for energy transfer in plants.	Phosphorus is vital for root development, energy transfer, and flower and fruit formation. Adequate phosphorus promotes early plant growth and flowering, impacting overall yield.
Potassium [1]	Important for plant water regulation and photosynthesis.	Potassium regulates water uptake, enzyme activation, and photosynthesis. It enhances drought tolerance, disease resistance, and overall plant vigour.
Calcium [1]	Supports cell structure and nutrient uptake	Calcium is essential for cell wall structure, root development, and nutrient transport within plants. It neutralizes soil acidity and improves soil stability.
Magnesium	Vital for chlorophyll formation and photosynthesis.	Magnesium is a central component of chlorophyll, essential for photosynthesis and energy transfer. Deficiencies manifest as yellowing between leaf veins.
Sulphur	Important for amino acid and protein production.	Sulphur is critical for amino acid and protein synthesis. It contributes to the formation of vitamins and enzymes, impacting overall plant health and vigour.
Soil Moisture Content	Measures the amount of water present in the soil.	Soil moisture affects plant water uptake and growth. Understanding moisture content helps optimize irrigation practices and prevent issues like waterlogging or drought stress.

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By integrating these components, smart agriculture for soil nutrient analysis empowers farmers with comprehensive tools and insights to make precise, sustainable, and economically sound decisions about nutrient management, ultimately improving crop yields. [11]

3. Machine Learning in Soil Analysis

Decision Trees, Random Forests, and Support Vector Machines (SVM) are versatile machine-learning algorithms used in soil analysis [4]. Decision Trees make decisions based on input features, Random Forests enhance accuracy through ensembles, and SVM excels in classifying and predicting soil types by finding optimal hyperplanes. Together, they contribute to precise soil characterization and management. [14] Machine Learning Algorithms for Soil Analysis are shown in Table 2.

Table 2 Machine Learning Algorithms for Soil Analysis

ALGORITHM	FEATURES	RESULT	LIMITATIONS
Random Forest [4]	Ensemble learning with multiple decision trees focusing on soil features: pH, texture, organic content. Random feature selection provides diverse perspectives.	Aggregation of votes for predictions, providing robust and accurate outcomes.	Computational complexity increases with the number of trees. May be challenging to interpret due to ensemble nature
Support Vector Machine (SVM) [4]	Classification and regression using optimal hyperplanes. Utilizes various soil features: texture, pH, organic content.	Finds optimal decision boundaries effectively, especially in handling non-linear relationships.	Sensitivity to the choice of kernel function. Computationally intensive for large datasets
Decision Tree [4]	Decision-making through recursive partitioning based on soil attributes: pH, texture, etc.	Interpretable tree-like structure, offering insights into decision-making.	Prone to overfitting, especially with deep trees. Limited expressiveness for capturing complex relationships.
K-Nearest Neighbours (KNN)	Considers proximity of k-nearest neighbours based on soil characteristics.	Simple and intuitive classification. Effective for local patterns in data.	Sensitive to irrelevant features or outliers. Computationally expensive for large datasets.
K-Means Clustering	Unsupervised learning for grouping similar soil samples.	Identifies natural clusters within the data.	Requires the choice of the number of clusters (k). Sensitive to initial cluster centroids.

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4. Available Datasets for Soil Analysis

In the extensive repository of datasets accessible on Kaggle, a diverse array of information is encapsulated, encompassing crucial parameters such as the concentrations of zinc, iron, copper, manganese, carbon, silicon, nitrogen, phosphorus, And potassium within soil matrices [4]. Additionally, this repository comprises data about environmental variables, including temperature, humidity, pH levels, and rainfall patterns. [15] The datasets that are available for soil analysis are shown in Table 3.

Table 3 Dataset that are Available for Soil Analysis

SOURCE	DESCRIPTION	URL
National Bureau of Soil Survey and Land Use Planning (NBSS&LUP)	Conducts soil surveys and research in India. Soil composition, properties, mapping	https://nbsslup.icar.gov.in/
National Remote Sensing Centre (NRSC)	Under ISRO, NRSC may provide remote sensing data related to soil and land use in India.	https://www.nrsc.gov.in/
Open Government Data (OGD) Platform India	Platform providing access to diverse soil datasets released by the Indian government,	https://data.gov.in/sector/Biotechnology
National Spatial Data Infrastructure (NSDI) India	May provide access to geospatial data, including soil-related information in India.	https://dst.gov.in/national-spatial-data-infrastructure
State Agricultural Universities and Departments	Local agricultural universities and departments often conduct region specific soil research.	https://tnau.ac.in/

The objective is to leverage this wealth of information for data-driven recommendations. These recommendations aim to optimize nutrient compositions and environmental conditions to facilitate the augmentation of crop yields. By delving into the intricacies of these datasets, researchers can uncover insights that contribute to the advancement of agricultural practices and the sustainable enhancement of crop productivity. [13]

5. Challenges of Soil Micro Nutrient Analysis in Smart Agriculture

The field of smart agriculture and soil micronutrient analysis faces several challenges. These include:

- **Sensor Integration and Accuracy:** Integrating sensors for real-time micronutrient analysis involves overcoming technical hurdles to ensure the accuracy, reliability, and compatibility of various sensor technologies. Calibration and standardization across different sensor types remain significant challenges. [6]
- **Cost-Effective Technology:** Developing cost-effective technologies for soil micronutrient analysis is critical, especially for small-scale farmers with limited resources. Reducing the overall cost of technology implementation while maintaining accuracy poses a significant challenge. [7]
- **Predictive Modeling Accuracy:** Improving the accuracy of predictive models, especially

in diverse soil types and under varying environmental conditions, requires continuous refinement. Adapting machine learning algorithms to account for complex interactions affecting micronutrient levels poses a significant challenge [8].

- **Remote Sensing Challenges:** Leveraging remote sensing technologies for large-scale soil analysis faces challenges related to spatial and spectral resolution, coverage, and the ability to accurately capture micronutrient variations across diverse landscapes.
- **Climate Variability Impact:** Addressing the impact of climate variability on soil micronutrient levels involves unraveling complex interactions between changing climate patterns and soil nutrient dynamics. Developing adaptive soil management strategies that consider climate variations is a continual challenge.

Conclusion

In conclusion, the soil micronutrient analysis and crop recommendation survey emphasize the crucial role of accurate soil assessments in optimizing agricultural practices. The findings underscore the intricate relationship between soil attributes, particularly micronutrient levels, and crop performance. Understanding these dynamics is vital for precise crop recommendations by enhancing nutrient efficiency and promoting sustainability in farming. The survey underscores the significance of advanced techniques like Random Forest, Support Vector Machines, and Decision Trees in deciphering complex soil patterns. Going forward, integrating these insights into precision agriculture strategies can inform decision-making, ensuring optimal crop selection and nutrient management for resilient and productive agricultural systems.

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