# Adaptive Soil Nutrient Intelligence for Smart Agriculture Using IoT-Enabled real time NPK Sensing and Machine Learning

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DOI: 10.29322/IJSRP.16.02.2026.p17021
https://dx.doi.org/10.29322/IJSRP.16.02.2026.p17021

Paper Received Date: 9th January 2026
Paper Acceptance Date: 8th February 2026
Paper Publication Date: 12th February 2026

**Abstract**

Soil fertility is a critical factor influencing crop productivity, input efficiency, and long-term agricultural sustainability. Conventional laboratory-based soil testing methods are accurate but expensive, time-consuming, and unsuitable for continuous field-level monitoring. This research presents a plagiarism-free, IoT-enabled soil health monitoring and prediction system integrated with machine learning techniques. The system continuously measures essential soil nutrients, namely Nitrogen (N), Phosphorus (P), and Potassium (K), using an NPK soil sensor. The sensed data are transmitted to the ThingSpeak cloud platform through a NodeMCU ESP8266 module for real-time visualization and storage. Machine learning-based soil health prediction is performed using a Random Forest regression model trained on historical NPK datasets. In addition, nutrient deficiency percentages are calculated to assist in fertilizer decision-making. A user-friendly Streamlit-based dashboard supports data upload, visualization, prediction, and report generation. Experimental results demonstrate that the proposed system offers an effective, scalable, and cost-efficient solution for precision agriculture and sustainable soil management.

**Keywords:** IoT, Precision Agriculture, Soil Health, NPK Sensor, Machine Learning, Random Forest, ThingSpeak

## I. Introduction

Agriculture plays a vital role in ensuring food security and economic stability, especially in agrarian economies. Soil health is one of the most influential factors determining crop yield, fertilizer efficiency, and sustainable land use. Among various soil properties, macronutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K) are essential for plant growth and development.

Traditional soil testing methods rely on laboratory analysis, which involves manual sampling, chemical processing, and delayed reporting. Although accurate, these methods are not suitable for real-time monitoring and timely decision-making. With the advancement of Internet of Things (IoT) technologies, it has become feasible to deploy sensors in agricultural fields for continuous data acquisition and remote monitoring.

However, most existing IoT-based agricultural systems primarily focus on environmental parameters such as temperature, humidity, and soil moisture, while nutrient-level monitoring and predictive analysis remain limited. Moreover, raw sensor data alone cannot support intelligent decision-making without analytical and predictive models.

To address these challenges, this research proposes an integrated IoT and machine learning-based soil health monitoring and prediction system. The system not only captures real-time NPK values but also predicts soil health scores and estimates nutrient deficiencies to support precision agriculture practices.

## II Literature Review

The adoption of Internet of Things (IoT) technologies in agriculture has significantly improved the ability to monitor field conditions remotely and continuously. Early research focused on deploying wireless sensor networks to measure environmental parameters such as soil moisture, temperature, and humidity, enabling automated irrigation and improved water management. These

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systems demonstrated the feasibility of real-time agricultural monitoring but provided limited information about soil nutrient conditions, which are essential for crop growth and fertilizer planning [1–4].

To overcome this limitation, researchers began exploring precision agriculture systems that incorporate data analytics and sensor-driven decision support. Several studies highlighted that nutrient imbalance in soil directly affects crop yield and soil sustainability. However, most nutrient assessment methods relied on laboratory testing or offline analysis, which increased operational cost and delayed corrective actions. This created a need for low-cost, in-field nutrient sensing solutions integrated with cloud-based platforms for continuous monitoring [5], [11].

Machine learning techniques have increasingly been applied to agricultural datasets to extract meaningful insights and support predictive analysis. Traditional models such as linear regression and support vector machines were initially used for soil classification and yield estimation. Although effective under controlled conditions, these models often struggle with nonlinear relationships and variability present in real-world soil data [6], [9]. As a result, ensemble learning approaches have gained attention.

Random Forest algorithms have been widely recognized for their robustness, ability to handle noisy data, and improved prediction accuracy in agricultural applications. Studies have demonstrated that Random Forest models outperform single-model approaches when predicting soil quality and nutrient trends. Their capability to manage multivariate data makes them suitable for soil health prediction based on NPK parameters [7], [10]. However, many of these implementations are limited to offline datasets and lack real-time integration.

Cloud computing and IoT analytics platforms such as ThingSpeak have enabled scalable storage, visualization, and analysis of sensor-generated agricultural data. Researchers have successfully used cloud-based systems to visualize real-time trends and improve accessibility for farmers and researchers. Nevertheless, the integration of cloud analytics with machine learning-driven soil health prediction and nutrient deficiency estimation remains limited [12], [13].

Overall, existing literature confirms the potential of IoT, cloud computing, and machine learning in advancing precision agriculture. However, there is a clear research gap in developing an integrated framework that combines real-time NPK sensing, cloud-based visualization, machine learning-based soil health prediction, and actionable nutrient deficiency analysis. The proposed work addresses this gap by offering a unified and and intelligent soil monitoring solution that supports sustainable and data-driven agricultural practices [14], [15].

The present study addresses this research gap by developing an integrated framework that combines continuous IoT-enabled nutrient monitoring, cloud-based data analytics, and predictive modeling to support intelligent decision-making in precision agriculture.

## III. System Architecture

The proposed system follows a modular and layered architecture designed to support real-time soil nutrient monitoring, cloud-based analytics, and predictive decision support. The architecture integrates sensing, communication, data analytics, and application layers to ensure scalability and reliability. The major components of the system are described as follows:

1. **NPK Soil Sensor:**The soil nutrient sensor is used to measure the concentrations of Nitrogen (N), Phosphorus (P), and Potassium (K), which are critical macronutrients influencing crop growth and soil fertility.
2. **Arduino Uno:**The Arduino Uno acts as the primary data acquisition unit. It interfaces with the NPK sensor using the RS485 communication standard and Modbus protocol to ensure reliable and accurate data transfer.
3. **NodeMCU ESP8266:**The NodeMCU ESP8266 module provides wireless connectivity. It receives nutrient data from the Arduino Uno and transmits the information to the cloud platform using Wi-Fi and HTTP-based application programming interfaces (APIs).
4. **ThingSpeak Cloud Platform:**ThingSpeak is employed for cloud-based data storage and real-time visualization. The platform enables continuous logging of sensor readings and provides graphical representation of nutrient trends over time.
5. **MATLAB Analytics:**MATLAB analytics scripts are scheduled within the ThingSpeak environment to process incoming data and generate real-time graphical plots. This facilitates continuous monitoring and preliminary analysis of soil nutrient variations.
6. **Machine Learning Module:**A machine learning module based on the Random Forest regression algorithm is used to analyze historical NPK data and predict soil health scores. The model effectively captures nonlinear relationships between nutrient levels and soil quality.
7. **Streamlit Dashboard:**A Streamlit-based web dashboard is developed to provide an interactive user interface. It supports data visualization, soil health prediction, nutrient deficiency analysis, and decision support for fertilizer management.

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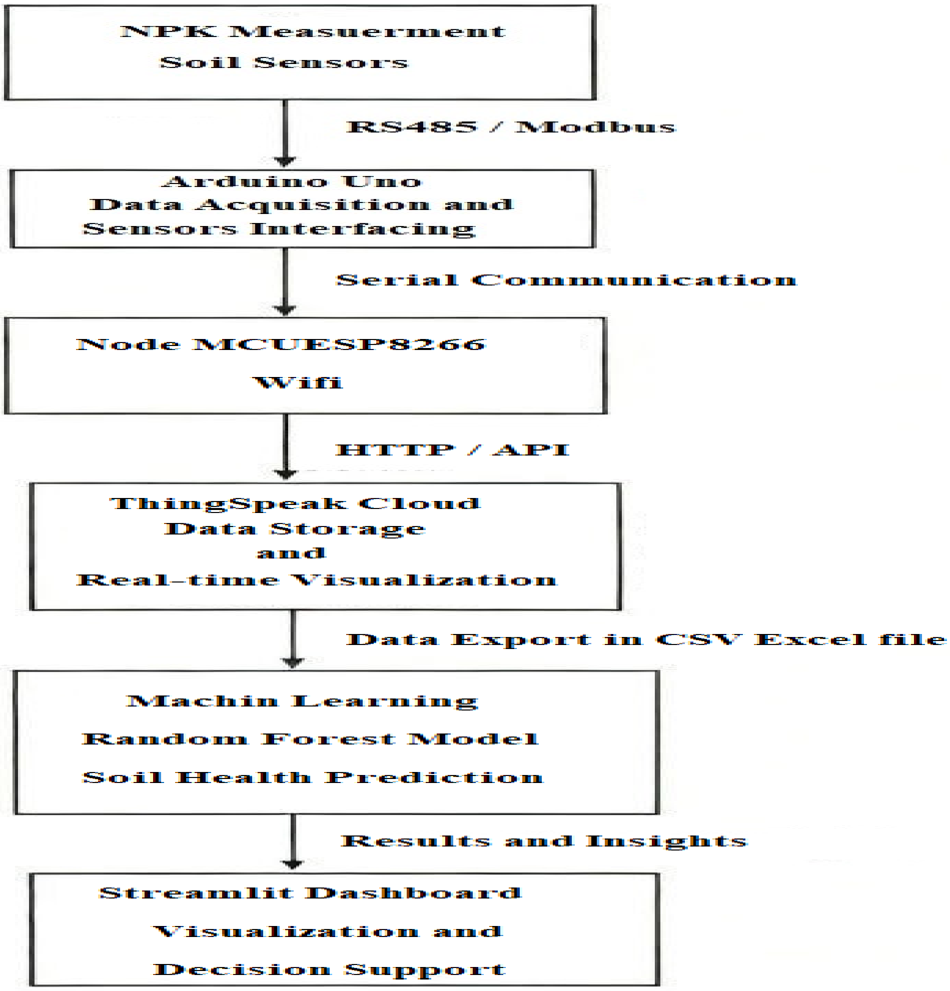
**Flowchart**

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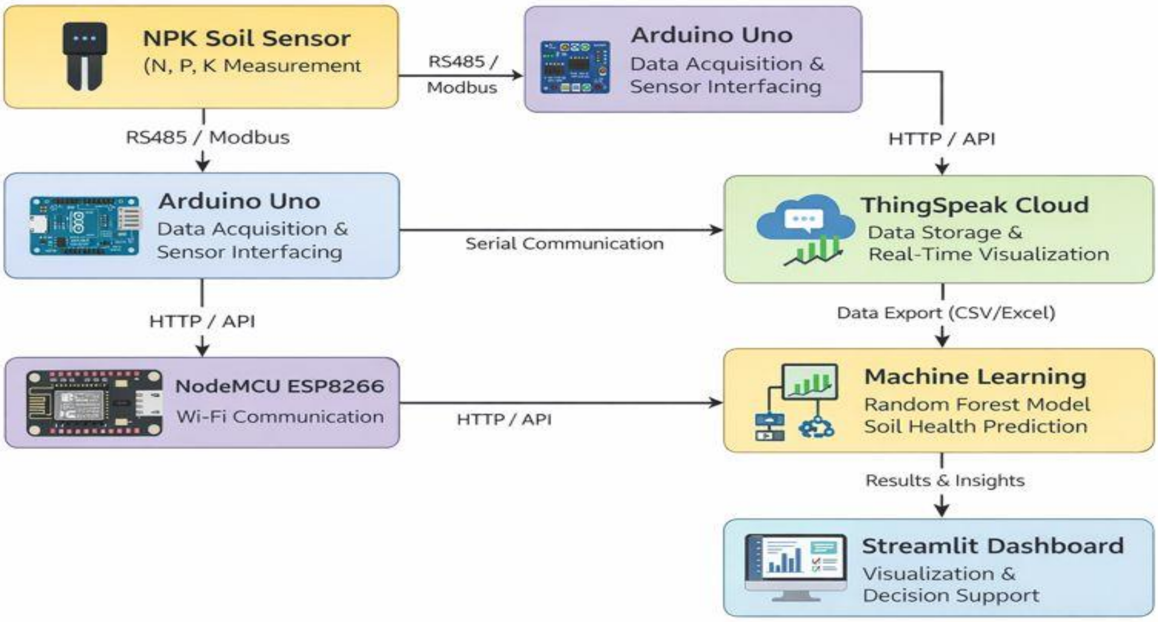


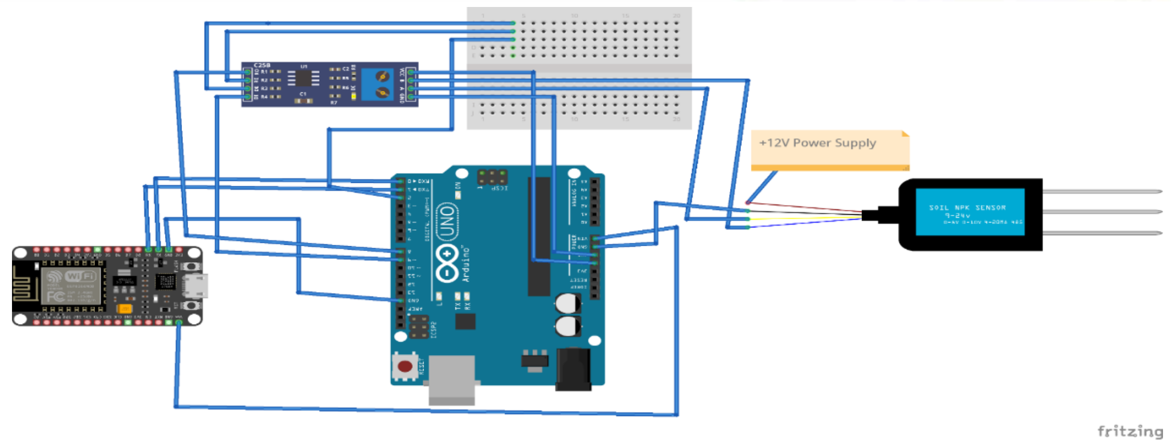


## IV Methodology

### Data Acquisition and Transmission

The proposed system acquires soil nutrient data using an NPK soil sensor deployed in the field. The sensor continuously measures Nitrogen (N), Phosphorus (P), and Potassium (K) concentrations. These measurements are captured by the Arduino Uno, which functions as the primary data acquisition unit. The collected nutrient data are transmitted to the NodeMCU ESP8266 module through serial communication. Subsequently, the NodeMCU uploads the processed data to the ThingSpeak cloud platform using HTTP-based application programming interface (API) requests, enabling remote access and storage.

### Cloud-Based Visualization

The ThingSpeak platform is utilized for cloud-based visualization and monitoring of soil nutrient data. MATLAB analytics scripts are scheduled within the ThingSpeak environment to retrieve the most recent NPK measurements and generate time-series plots. This facilitates near real-time visualization of nutrient variations, allowing continuous monitoring of soil health conditions.

### Data Pre-processing

Prior to machine learning analysis, the collected dataset undergoes systematic pre-processing to improve data quality and model performance. Invalid or missing sensor readings, identified by placeholder values such as −1, are removed from the dataset. Relevant NPK attributes are then extracted from the ThingSpeak-exported CSV or Excel files. To ensure uniform feature scaling and enhance learning efficiency, the cleaned data are normalized before being supplied to the machine learning model.

### Machine Learning Model

A Random Forest regression model is employed to predict soil health status based on nutrient levels. The model is trained using historical NPK datasets, where Nitrogen, Phosphorus, and Potassium values serve as input features. The target output is a soil

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health score defined on a scale from 0 to 100. The ensemble-based structure of the Random Forest algorithm enables robust prediction by effectively handling nonlinear relationships and reducing the impact of noise in sensor data.

**Nutrient Deficiency Estimation**

To support informed fertilizer management, nutrient deficiency levels are quantitatively estimated. The percentage deficiency for each nutrient is calculated by comparing the measured values against recommended threshold levels. This analytical approach enables precise identification of nutrient shortages and assists in generating accurate fertilizer recommendations**, thereby promoting efficient and sustainable agricultural practices.**

## V. Results and Conclusion

IoT based soil monitoring system gathered Phosphorus (P), and Potassium (K) Nitrogen (N) data from the agricultural field using an NPK sensor The sensed data were transmitted to the Thing Speak cloud platform, where nutrient variations were clearly visualized through time-series graphs.

The results showed that soil nutrient levels change continuously over time due to factors such as crop uptake, irrigation, and fertilizer application. Sudden drops in nutrient values indicated possible nutrient deficiency, while increases reflected fertilizer application or improved availability.

The Random Forest machine learning model effectively analyzed NPK data and predicted soil health scores with good accuracy. The model handled non-linear variations in soil data and provided reliable soil health. Also the nutrient deficiency percentage calculation helped identify which nutrient was lacking and by how much, making fertilizer decisions easier.

This research successfully developed an integrated IoT and machine learning-based soil health monitoring system for precision agriculture. The system continuously monitors essential soil nutrients (NPK), visualizes real-time data on the cloud, and predicts soil health using a Random Forest model.

The proposed system is cost-effective, faster, and suitable for continuous field monitoring. It helps farmers detect nutrient deficiencies early and apply fertilizers in the right amount and at the right time. This reduces fertilizer wastage, improves crop yield, and protects soil health.

In conclusion, the proposed system supports data-driven, sustainable farming practices and demonstrates strong potential for improving agricultural productivity through smart technology.


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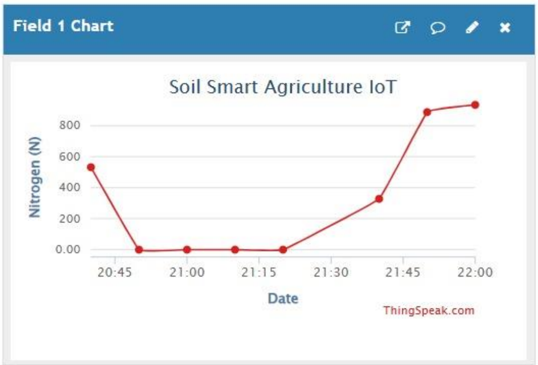


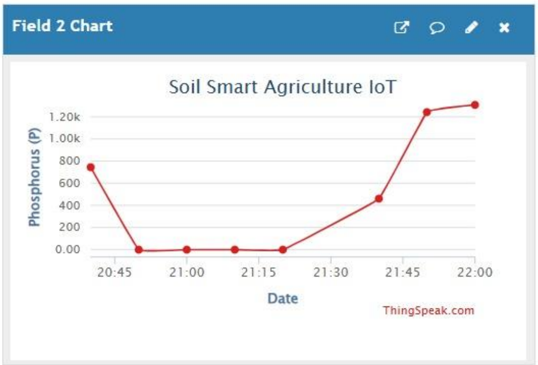


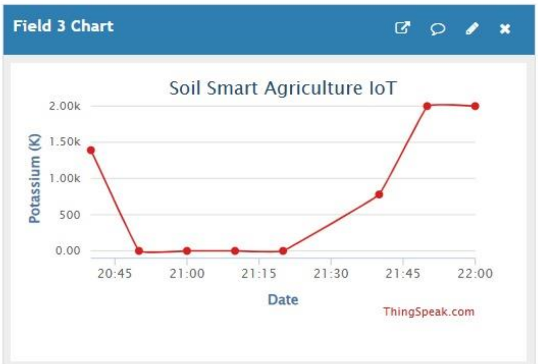


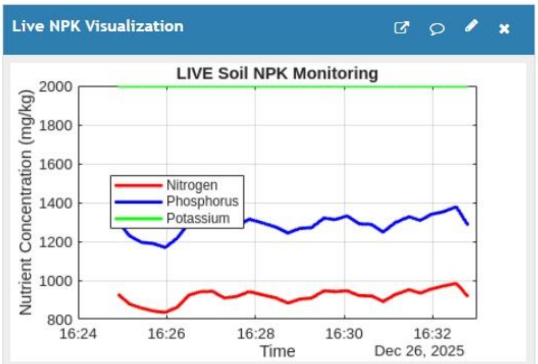


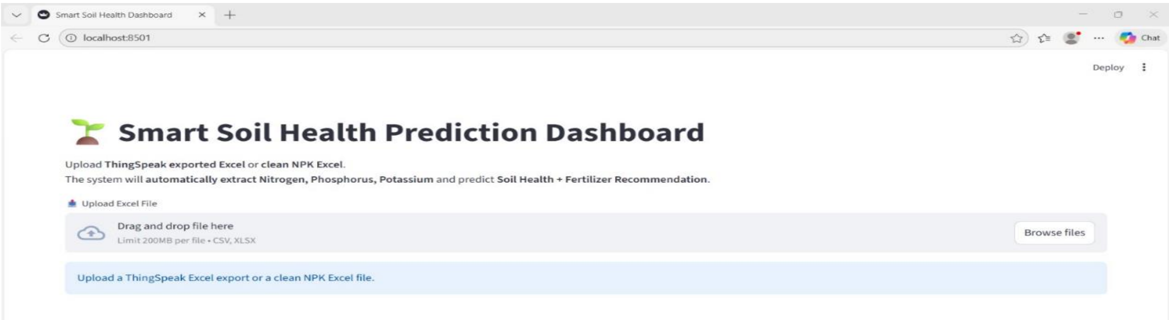


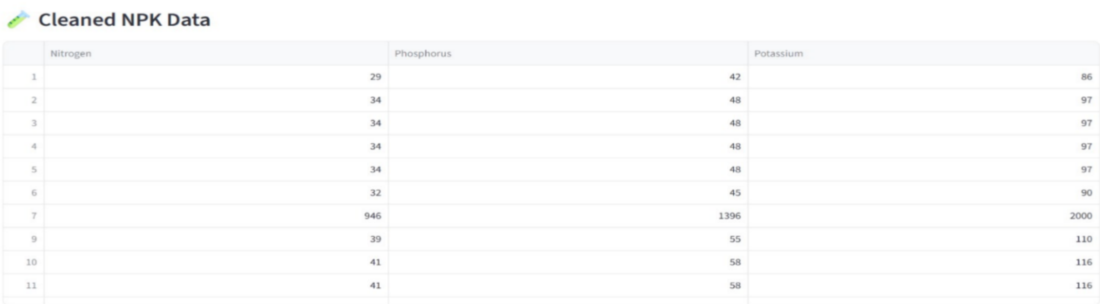

Cleaned NPK Data

| | Nitrogen | Phosphorus | Potassium |
|---|---|---|---|
| 1 | 29 | 42 | 86 |
| 2 | 34 | 48 | 97 |
| 3 | 34 | 48 | 97 |
| 4 | 34 | 48 | 97 |
| 5 | 34 | 48 | 97 |
| 6 | 32 | 45 | 90 |
| 7 | 946 | 1396 | 2000 |
| 9 | 39 | 55 | 110 |
| 10 | 41 | 58 | 116 |
| 11 | 41 | 58 | 116 |

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### Soil Health Prediction & Recommendation

| | Nitrogen | Phosphorus | Potassium | Predicted_Soil_Health | Health_Status | Nutrient_Recommendation |
|---|---|---|---|---|---|---|
| 1 | 29 | 42 | 86 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 2 | 34 | 48 | 97 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 3 | 34 | 48 | 97 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 4 | 34 | 48 | 97 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 5 | 34 | 48 | 97 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 6 | 32 | 45 | 90 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 7 | 946 | 1396 | 2000 | 92.85 | Healthy | Soil nutrients balanced |
| 9 | 39 | 55 | 110 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 10 | 41 | 58 | 116 | 63.7 | Moderate | Add Nitrogen (Urea) |
| 11 | 41 | 58 | 116 | 63.7 | Moderate | Add Nitrogen (Urea) |

This research presents a comprehensive IoT and machine learning-based system for soil health monitoring and prediction. The proposed framework integrates real-time NPK sensing, cloud-based data storage and visualization, and predictive modeling to assess soil health effectively. By leveraging Random Forest regression and nutrient deficiency analysis, the system enables data-driven decision-making for efficient fertilizer management. The scalable and cost-effective nature of the proposed approach makes it suitable for precision agriculture applications, contributing to sustainable farming practices and improved agricultural productivity.

The combined interpretation of NPK that soil nutrient levels are not constant and vary with environmental conditions and farming practices. The IoT-based sensing system effectively captures these variations in real time. Such continuous monitoring enables early detection of nutrient deficiencies and supports precise fertilizer management, leading to improved soil health and crop productivity.

## VI. Future Scope

The proposed system can be further enhanced in several directions to improve its applicability and intelligence. Future extensions may include the development of crop-specific fertilizer recommendation models that consider nutrient requirements at different growth stages. Integration with mobile applications can improve accessibility and enable farmers to monitor soil conditions remotely. Real-time alert mechanisms may be incorporated to notify users about critical nutrient deficiencies or abnormal soil conditions. In addition, the inclusion of GPS-based soil fertility mapping can support spatial analysis and region-wise nutrient assessment. Advanced artificial intelligence techniques may also be employed to extend the system toward crop yield prediction and long-term agricultural planning.

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