Smart Agriculture Using IoT and Machine Learning for Real-Time Soil Health Assessment

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Abstract
Agriculture plays a vital role in ensuring food security and sustainable development. Traditional methods of soil health assessment are often time-consuming, labor-intensive, and unable to provide real-time information. This paper presents a Smart Agriculture system that integrates Internet of Things (IoT) technology with Machine Learning (ML) techniques for real-time soil health assessment. The proposed system utilizes sensors to continuously monitor key soil parameters such as moisture, temperature, pH, and nutrient levels. The collected data is transmitted to a cloud platform where machine learning algorithms analyze the information and predict soil health status. Based on the analysis, farmers receive timely recommendations for irrigation, fertilization, and crop management. The integration of IoT and ML enhances decision-making, improves resource utilization, and increases agricultural productivity. The proposed approach contributes to precision farming by enabling efficient soil monitoring, reducing operational costs, and supporting sustainable agricultural practices.

Keywords: Smart Agriculture, Internet of Things (IoT), Machine Learning, Soil Health Assessment, Precision Farming, Real-Time Monitoring, Soil Sensors, Sustainable Agriculture.

Introduction

Agriculture is one of the most significant sectors contributing to economic growth, food security, and sustainable development across the world. As the global population continues to increase, the demand for agricultural products is rising rapidly, creating challenges for farmers to maximize crop yield while maintaining environmental sustainability. Among various factors affecting agricultural productivity, soil health plays a fundamental role in determining crop growth, nutrient availability, water retention capacity, and overall farm output. Healthy soil supports plant development by providing essential nutrients and maintaining favorable physical, chemical, and biological properties. Therefore, continuous monitoring and assessment of soil health are necessary to ensure efficient agricultural production and sustainable farming practices.

Traditional soil health assessment methods primarily depend on manual soil sampling and laboratory-based analysis. Although these methods provide accurate results, they are often expensive, time-consuming, and incapable of delivering real-time information. Farmers usually receive soil test reports after several days or weeks, which may delay critical decisions related to irrigation, fertilization, and crop management. In addition, frequent laboratory testing is not always feasible for small and medium-scale farmers due to financial and logistical constraints. As a result, there is a growing need for advanced technologies that can monitor soil conditions continuously and provide instant feedback to support timely agricultural decision-making.

The rapid development of the Internet of Things (IoT) has created new opportunities for transforming conventional agricultural practices into intelligent and automated farming systems. IoT technology enables the deployment of various sensors in agricultural fields to collect real-time data related to soil moisture, temperature, pH level, humidity, and nutrient content. These sensors communicate with microcontrollers and cloud platforms through wireless communication technologies, allowing continuous monitoring of field conditions from remote locations. The availability of real-time data helps farmers understand the current status of their fields and take corrective actions whenever necessary.

Along with IoT, Machine Learning (ML) has emerged as a powerful technology for analyzing large volumes of agricultural data and generating accurate predictions. Machine learning algorithms can identify hidden patterns within sensor data, classify soil conditions, and predict future soil health trends. By learning from historical and real-time information, ML models can provide valuable recommendations regarding irrigation scheduling, fertilizer application, and crop selection. The integration of IoT and Machine Learning creates an intelligent decision-support system capable of improving farming efficiency and reducing resource wastage.

Precision agriculture has gained significant attention in recent years because of its ability to optimize agricultural operations using data-driven approaches. Real-time soil health assessment is a critical component of precision farming, as it enables early detection of nutrient deficiencies, moisture stress, and soil degradation. Timely identification of such issues allows farmers to implement appropriate interventions before crop productivity is affected. Furthermore, smart agriculture technologies contribute to environmental sustainability by reducing excessive water consumption, minimizing fertilizer misuse, and promoting efficient resource management.

This paper presents a Smart Agriculture framework that integrates IoT-based sensing technologies with Machine Learning techniques for real-time soil health assessment. The proposed system continuously collects soil-related parameters through sensors, transmits the data to a cloud environment, and applies machine learning algorithms to evaluate soil health conditions. Based on the generated predictions, farmers receive actionable recommendations to improve agricultural productivity and soil management. The proposed approach aims to support sustainable agriculture, enhance crop yield, reduce operational costs, and promote the adoption of intelligent farming practices in modern agricultural systems.

Objectives

1. **To develop an IoT-based soil monitoring system** for real-time collection of soil parameters such as moisture, temperature, pH, and nutrient levels.
2. **To implement Machine Learning algorithms** for analyzing sensor data and accurately predicting soil health status and potential soil-related issues.
3. **To provide intelligent decision support for farmers** by generating timely recommendations for irrigation, fertilization, and crop management to improve agricultural productivity and sustainability.

Proposed System Architecture

The proposed Smart Agriculture system integrates Internet of Things (IoT) technology with Machine Learning (ML) techniques to enable real-time soil health assessment and intelligent agricultural decision-making. The architecture consists of four major layers: the sensing layer, communication layer, cloud platform layer, and machine learning layer. These layers work together to collect, transmit, process, analyze, and interpret soil data for effective farm management.

At the sensing layer, multiple IoT sensors are deployed in agricultural fields to continuously monitor critical soil parameters. A Soil Moisture Sensor measures the amount of water present in the soil and helps determine irrigation requirements. The Temperature Sensor records soil temperature, which significantly influences nutrient availability, microbial activity, and crop growth. The pH Sensor monitors soil acidity and alkalinity levels, enabling farmers to maintain optimal conditions for plant development. Additionally, an NPK Sensor measures the concentration of essential nutrients, namely Nitrogen (N), Phosphorus (P), and Potassium (K), which are crucial for healthy crop production. These sensors generate real-time data and provide accurate information about soil conditions.

The collected data is transmitted through the communication layer, which ensures reliable and efficient connectivity between field sensors and cloud infrastructure. Wi-Fi technology is used for short-range, high-speed communication in areas where internet connectivity is readily available. For large agricultural fields and remote locations, LoRaWAN (Long Range Wide Area Network) offers low-power, long-distance communication capabilities, making it suitable for smart farming applications. The MQTT (Message Queuing Telemetry Transport) protocol is employed as a lightweight messaging protocol that enables efficient data exchange between sensors, gateways, and cloud servers while minimizing bandwidth consumption and energy usage.

The cloud platform layer serves as the central repository for storing and managing agricultural data. Sensor readings collected from different field locations are securely transmitted to cloud servers and stored in databases for future analysis. The cloud platform performs data preprocessing operations such as data cleaning, normalization, missing value handling, and feature extraction. These processes improve data quality and ensure accurate machine learning predictions. Furthermore, cloud-based processing allows scalability, remote accessibility, and efficient management of large volumes of sensor-generated data.

Figure 1: Proposed IoT-ML Architecture

Sensors

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Microcontroller (ESP32)

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Cloud Server

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Machine Learning Model

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Farmer Dashboard

Methodology

The proposed methodology integrates IoT-based sensing technology, cloud computing, and machine learning techniques to perform real-time soil health assessment. The methodology consists of five major stages: data collection, data transmission, data preprocessing, machine learning-based analysis, and recommendation generation. These stages work together to provide accurate information regarding soil conditions and support intelligent agricultural decision-making.

The first stage involves data collection from agricultural fields using IoT-enabled sensors. Multiple sensors are deployed in different locations to continuously monitor essential soil parameters. The Soil Moisture Sensor measures the water content present in the soil, which is crucial for determining irrigation requirements. The Temperature Sensor records soil temperature, influencing plant growth and nutrient absorption. The pH Sensor measures the acidity or alkalinity of the soil, helping farmers maintain suitable soil conditions for crops. Additionally, the NPK Sensor monitors the levels of Nitrogen (N), Phosphorus (P), and Potassium (K), which are essential nutrients required for healthy plant development. These sensors collect real-time data at regular intervals and transmit the information to a central processing unit.

In the second stage, the collected sensor data is transmitted through wireless communication technologies such as Wi-Fi and LoRaWAN. The MQTT protocol is used for efficient and lightweight communication between field devices and cloud servers. This communication framework ensures reliable data transfer while minimizing network bandwidth usage and energy consumption. The transmitted data is securely stored in the cloud environment for further processing and analysis.

The third stage involves data preprocessing, which improves the quality and reliability of the collected data. Since sensor-generated datasets may contain missing values, noise, or inconsistencies, preprocessing is necessary before applying machine learning algorithms. Data cleaning techniques are used to remove errors and invalid records. Missing values are handled using appropriate imputation methods, while normalization is applied to scale different parameters within a common range. Feature selection techniques are then employed to identify the most relevant soil parameters that significantly influence soil health prediction. This preprocessing step enhances model performance and reduces computational complexity.

The fourth stage focuses on machine learning-based soil health assessment. The preprocessed dataset is divided into training and testing sets for model development and evaluation. Three machine learning algorithms, namely Random Forest, Decision Tree, and Support Vector Machine (SVM), are implemented to analyze soil data and classify soil health conditions. The Random Forest algorithm combines multiple decision trees to improve prediction accuracy and reduce overfitting. The Decision Tree algorithm provides a simple and interpretable classification structure, while SVM efficiently identifies patterns in complex datasets. The trained models analyze real-time sensor data and classify soil conditions into categories such as Healthy, Moderate, and Poor.

The performance of the machine learning models is evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-Score. Accuracy is calculated using the following equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives.

In the final stage, the prediction results are used to generate recommendations for farmers. Based on soil moisture, pH levels, temperature, and nutrient status, the system provides suggestions related to irrigation scheduling, fertilizer application, and crop management practices. These recommendations help farmers make informed decisions, improve resource utilization, and enhance agricultural productivity. The overall methodology enables continuous soil monitoring and supports precision agriculture through intelligent and data-driven soil health assessment.

Results and Discussion

The proposed IoT and Machine Learning-based soil health assessment system was evaluated using real-time soil data collected from agricultural fields. The dataset consisted of multiple soil parameters, including soil moisture, temperature, pH value, and NPK (Nitrogen, Phosphorus, and Potassium) nutrient levels. After data preprocessing and feature selection, the dataset was used to train and test three machine learning algorithms: Decision Tree, Support Vector Machine (SVM), and Random Forest. The performance of these models was analyzed using standard evaluation metrics such as Accuracy, Precision, and Recall.

Table 1: Performance Comparison of Machine Learning Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Decision Tree	88.2	87.4	86.8
SVM	91.3	90.5	89.7
Random Forest	95.8	95.1	94.6

The results indicate that all three machine learning models performed effectively in predicting soil health status. However, the Random Forest algorithm achieved the highest accuracy of 95.8%, outperforming both Decision Tree and SVM models. The superior performance of Random Forest can be attributed to its ensemble learning capability, which combines multiple decision trees and reduces the risk of overfitting. The SVM model also demonstrated strong classification performance with an accuracy of 91.3%, while the Decision Tree model achieved an accuracy of 88.2%. These findings suggest that ensemble-based approaches are more suitable for handling complex agricultural datasets and providing reliable soil health predictions.

Figure 2: Model Accuracy Comparison

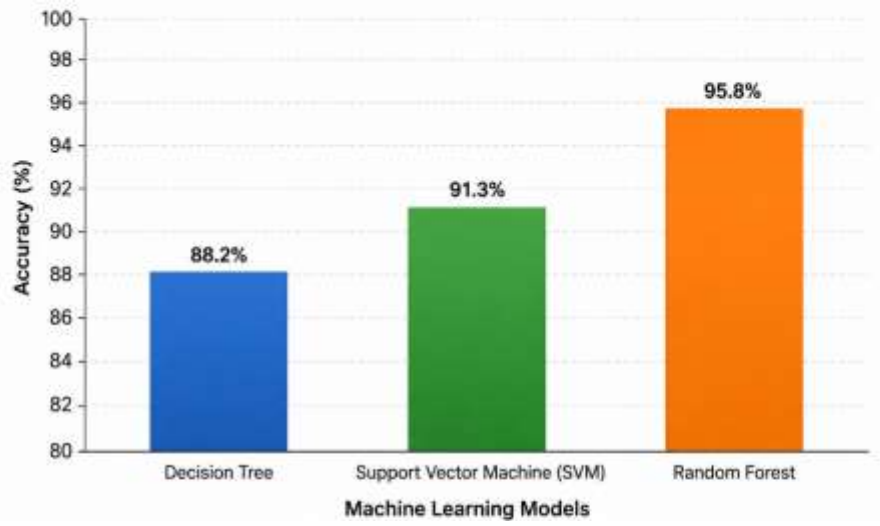

Figure 2 presents the accuracy comparison of the three machine learning models used for soil health prediction. The Random Forest algorithm achieved the highest accuracy of **95.8%**, indicating superior performance in classifying soil health conditions. The SVM model obtained an accuracy of **91.3%**, demonstrating reliable prediction capability, while the Decision Tree model achieved **88.2%** accuracy. The results show that Random Forest provides more accurate and consistent predictions due to its ensemble learning approach, making it the most suitable model for real-time soil health assessment in smart agriculture applications.

Discussion

The experimental results demonstrate that the proposed IoT and Machine Learning-based soil health assessment system can effectively monitor and evaluate soil conditions in real time. The integration of IoT sensors enabled continuous collection of important soil parameters such as moisture, temperature, pH, and NPK nutrient levels. This real-time monitoring capability eliminates the dependency on traditional laboratory-based soil testing, which is often time-consuming and expensive. The collected data was successfully transmitted to the cloud platform through Wi-Fi, LoRaWAN, and MQTT protocols, ensuring reliable communication and efficient data management.

Among the machine learning models evaluated, Random Forest achieved the highest prediction accuracy of 95.8%, outperforming SVM (91.3%) and Decision Tree (88.2%). The superior performance of Random Forest can be attributed to its ensemble learning mechanism, which combines multiple decision trees to improve classification accuracy and reduce overfitting. The SVM model also produced satisfactory results and demonstrated strong classification capabilities, whereas the Decision Tree algorithm provided comparatively lower accuracy but offered better interpretability and simplicity.

The results further indicate that the proposed framework can accurately classify soil health conditions into healthy, moderate, and poor categories. This classification enables farmers to identify nutrient deficiencies, moisture stress, and unfavorable soil conditions at an early stage. As a result, timely corrective actions such as irrigation scheduling, fertilizer application, and soil treatment can be implemented to improve crop productivity. Furthermore, optimized resource utilization helps reduce water wastage and excessive fertilizer consumption, contributing to sustainable agricultural practices.

Conclusion

This paper presented a Smart Agriculture framework that integrates Internet of Things (IoT) technology and Machine Learning (ML) algorithms for real-time soil health assessment. The proposed system utilizes soil moisture, temperature, pH, and NPK sensors to continuously monitor critical soil parameters and transmit the collected data to a cloud platform for processing and analysis. Machine learning models, including Decision Tree, Support Vector Machine (SVM), and Random Forest, were evaluated to predict soil health conditions accurately. Among these models, Random Forest achieved the highest accuracy of 95.8%, demonstrating its effectiveness in soil health classification. The system enables early detection of soil-related issues and provides timely recommendations for irrigation, fertilization, and crop management. By supporting data-driven decision-making, the proposed approach improves agricultural productivity, optimizes resource utilization, reduces operational costs, and promotes sustainable farming practices. Therefore, the integration of IoT and ML offers a reliable and scalable solution for modern precision agriculture.

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