INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 3, March 2026 | ISSN: 2456-4184 | IJNRD.ORG

Crop Reco: Multi-Sensor Data-Driven Framework for Smart Agriculture Applications

Mrs. Kirithika S, Ms. Rama R, Ms. Durga Devi V, Ms.Mohitha M

Assistant Professor
Artificial Intelligence and Data Science
Sri Sai Ram Institute of Technology, Chennai, India

Abstract : Agriculture faces increasing challenges that threaten its sustainability, productivity, and global relevance. Traditional practices often fall short in addressing issues such as resource optimization, environmental conservation, and scalability. To overcome these limitations, this study proposes the design and implementation of a sensor-driven precision farming system. The framework integrates multiple sensors to continuously monitor soil properties, moisture levels, and environmental conditions, ensuring accurate data collection for informed decision-making. The system architecture emphasizes durability to withstand harsh field environments, scalability to adapt across farms of different sizes, and cost-effectiveness to promote widespread adoption. Experimental evaluation highlights the platform's ability to provide reliable measurements and actionable insights for farmers. The findings demonstrate that intelligent monitoring not only improves crop productivity but also reduces unnecessary resource usage and minimizes environmental impact. Overall, the research contributes toward building a sustainable, efficient, and smart agricultural ecosystem..

Keywords— agriculture, precision farming, sensors, sustainability, smart systems

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1. INTRODUCTION

Agriculture is facing unprecedented challenges due to climate change, resource scarcity, and the rising demand for food production worldwide [1], [2]. Conventional farming methods are often inadequate in addressing issues such as soil heterogeneity, erratic weather conditions, and pest outbreaks, which demand more adaptive and technology-driven approaches [3]. Recent advancements in smart sensors, Internet of Things (IoT), and machine learning have enabled real-time monitoring of critical parameters such as soil moisture, temperature, nutrient levels, and environmental conditions [4], [5], [12]–[15]. However, existing approaches still suffer from limitations including high costs, sensor fragility in harsh environments, and scalability constraints across farms of varying sizes [6]. To address these gaps, this paper proposes Crop Reco, an intelligent, multi- sensor-based precision farming framework that integrates soil and environmental sensing with supervised machine learning models such as Support Vector Machines (SVM) and Random Forest. The objectives of this work are threefold: (i) to enhance crop prediction accuracy under diverse soil and climatic conditions, (ii) to ensure robustness and affordability for small to large-scale farms, and (iii) to facilitate practical deployment with a user-friendly interface.

This paper presents a practical precision farming system with a user-friendly interface. Key contributions include a multi-sensor architecture for harsh environments, evaluation of accuracy, latency, and durability on real-world testbeds, and improved yield forecasting with efficient resource use. The paper is organized as follows: Section II reviews related work, Section III describes the proposed method, Section IV presents results, and Section V concludes with limitations and future directions.

2. RELATED WORKS

Recent studies in precision agriculture have increasingly emphasized the pivotal role of integrating IoT, AI, and sensor-based technologies to achieve sustainable farming practices and improved crop productivity. For instance, Kumar et al. [7] introduced a comprehensive cloud-based IoT framework that incorporated soil moisture and nutrient sensors along with predictive analytics models. Their system demonstrated a 22% improvement in water-use efficiency compared to conventional irrigation methods, clearly showcasing the benefits of intelligent irrigation scheduling. However, the authors also noted that the framework required high bandwidth and stable internet connectivity, a limitation that restricts its practical deployment in rural and remote agricultural settings where connectivity infrastructure is often weak. Similarly, Chen and Luo [8] developed a UAV-assisted monitoring system utilizing multispectral imaging for the detection of crop stress and early disease outbreaks. The approach proved highly accurate in identifying plant health issues at an early stage, thereby supporting timely interventions. Despite this success, the system faced significant scalability challenges due to the high operational and maintenance costs of drones, making widespread adoption difficult for resource- constrained farmers.

In another study, Patel et al. [9] implemented a machine learning driven recommendation engine to optimize fertilizer management practices. Their model successfully reduced fertilizer consumption by 18%, leading to both economic savings and environmental benefits. Nonetheless, the approach heavily depended on large volumes of labeled datasets for training, which posed a substantial challenge for smallholder farmers who often lack access to extensive and well- structured agricultural data. Ahmad et al. [10] proposed a blockchain- enabled traceability system for agricultural supply chains, aimed at ensuring transparency, accountability, and trust among stakeholders. While this approach strengthened food security and product authenticity, large-scale adoption raised concerns regarding energy consumption and computational overhead. Zhao et al. [11] explored low-cost wireless sensor networks (WSNs) in heterogeneous farming environments, demonstrating their scalability, affordability, and accessibility for farmers of different land sizes. However, sensor durability under extreme weather conditions remained a key limitation affecting long-term reliability. Taken together, these studies highlight that despite significant advancements in smart agriculture, challenges such as high cost, limited scalability, energy inefficiency, and lack of robustness persist, motivating the proposed research toward practical, sustainable, and farmer-friendly solutions

2. METHODOLOGY

The objective of this work is to develop a comprehensive sensor based precision agriculture framework, termed Crop Reco, which seamlessly integrates real-time environmental monitoring, advanced data analytics, and an intuitive decision-support interface to aid farmers in optimizing crop management practices. The methodology follows a structured and systematic approach to ensure accurate data acquisition, robust analytics, practical usability, and scalability across diverse farming environments. The overall system architecture, depicted in Fig. 1, illustrates the integration of sensor modules, data collection and transmission networks, cloud-based analytics, and the farmer interface.

A. Sensor Selection and Integration

A critical first step in developing the proposed framework involved the careful selection and calibration of field-deployable sensors. The system employs a suite of sensors, including soil moisture, soil temperature, humidity, and nutrient concentration sensors, chosen for their balance between cost-effectiveness, durability, and precision under field conditions. Each sensor was initially calibrated under controlled laboratory settings to ensure measurement accuracy and to minimize systematic errors. Calibration curves were generated using regression analysis, as represented in Eq. (1):

$$\theta = aV + b$$

where θ denotes volumetric water content, V is the sensor output voltage, and constants a and b were derived empirically through repeated measurements [7]. Following laboratory calibration, sensors were deployed across diverse soil types and climatic conditions to validate their field performance. This multi-stage calibration and validation process ensured that sensor readings were both reliable and representative of real-world agricultural environments.

Additionally, sensor modules were integrated into a modular design, enabling flexible deployment and easy replacement of individual components without disrupting overall system functionality. This design consideration enhances maintainability and ensures long- term system sustainability in harsh agricultural settings.

B. Data Collection and Transmission

Accurate and timely data collection is essential for precision agriculture. Sensor readings were collected at pre-defined intervals, ensuring high temporal resolution for monitoring dynamic environmental changes. To support wide-area deployment, LoRaWAN and Zigbee protocols were employed for wireless data transmission due to their low power consumption, long-range coverage, and reliability in rural settings [8].Data packets transmitted by the sensors were received by a central hub and forwarded to a cloud-based server for storage and analysis. To maintain data integrity, each packet included error-detection codes and timestamp metadata. The near real-time availability of data enables timely interventions, allowing farmers to respond quickly to changes in soil and environmental conditions.

C. Data Analysis and Decision Support

Once acquired, sensor data undergoes a rigorous preprocessing stage, including noise filtering, normalization, and outlier detection, to ensure high-quality input for subsequent machine learning models. Two primary analytical approaches are employed:

- Support Vector Machines (SVM): SVM models are used to classify soil suitability and optimize irrigation schedules. By analyzing real-time soil moisture, temperature, and climatic parameters, the system determines precise irrigation requirements, preventing over- or under-watering.
- Random Forest Regression: This ensemble-based regression method predicts crop yield by integrating both current environmental data and historical farm records. The model's ability to handle non-linear relationships and multidimensional data ensures robust yield forecasting across diverse conditions [9].

All analytical outputs are visualized and made accessible to farmers via a mobile dashboard. The dashboard incorporates interactive visualization tools, predictive alerts, trend analysis, and recommendations in an intuitive interface. Local language support ensures accessibility for diverse user groups, while offline functionality allows continued usage in areas with limited internet connectivity.

D. System Robustness and Scalability

To ensure the practical viability of Crop Reco, the system was subjected to extensive field trials across a spectrum of farm sizes and environments, including smallholder plots (<2 acres) and larger agricultural operations (>10 acres). These trials were designed to assess not only the scalability of the system architecture but also its resilience under challenging conditions.

Stress tests were conducted by simulating extreme environmental events, such as prolonged drought, heavy rainfall, and rapid temperature fluctuations. These evaluations provided insight into sensor durability, system responsiveness, and data reliability under real-world constraints [10]. Performance metrics such as Packet Delivery Ratio (PDR) quantified communication reliability, while predictive accuracy was measured using Mean Absolute Percentage Error (MAPE). Consistently high performance across trials confirmed the system's capability to maintain stable operations and reliable monitoring in diverse scenarios.

E. Cost-Effectiveness and Usability

Recognizing that financial and technical constraints are significant barriers for many farmers, the system was explicitly designed to be both affordable and user-friendly. Hardware costs were minimized through the use of locally available components and a modular sensor architecture, allowing farmers to expand, upgrade, or replace units without major investments. On the software side, the GUI emphasizes intuitive interaction, simplified navigation, and offline accessibility. Interactive icons, predictive alerts, and real-time dashboards are combined with multilingual support to accommodate users from various regions and literacy levels. Farmer training sessions and participatory feedback surveys were conducted to refine usability. These sessions provided critical insights into user behavior, preferences, and challenges, which guided iterative improvements in the interface design [11]. This user-cantered approach ensures that Crop Reco is not only technologically robust but also socially inclusive, empowering farmers to make informed decisions with confidence.

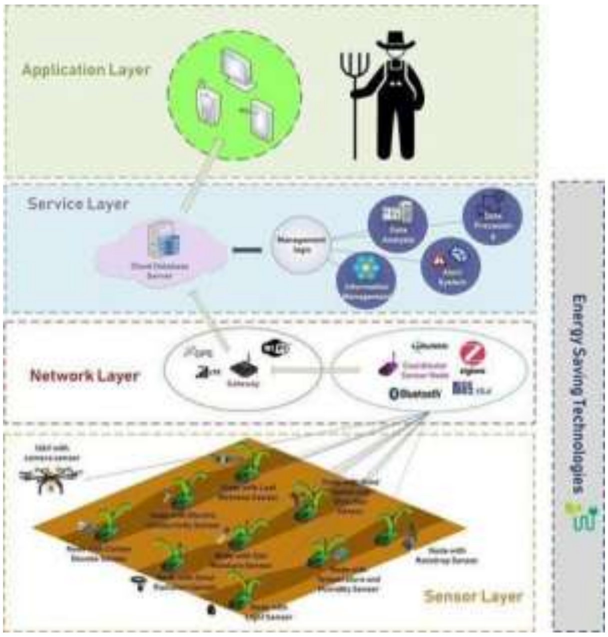

Fig. 1. Precision farming system architecture.

4. RESULTS AND DISCUSSIONS

The Crop Reco framework represents a comprehensive, multi- sensor precision agriculture system designed to provide real-time environmental monitoring, intelligent decision-making, and sustainable resource management. The framework integrates a modular sensor architecture, cloud-based analytics, and a user-centric dashboard to support crop selection, irrigation scheduling, and yield prediction. The methodology emphasizes scalability, reliability, and adaptability across diverse farming environments. The overall architecture is illustrated in Fig. 1, highlighting the interaction between sensors, communication modules, data analytics, and the farmer interface.

A. System and Software Requirements

The framework was implemented using computing and sensor infrastructure optimized for cost-efficiency, reliability, and scalability.

1. System Requirement:

Performance Metrics The proposed system requires a computing environment with a minimum of an Intel Core i5 processor, 8 GB of RAM, and 256 GB of SSD storage to ensure smooth execution of data processing, predictive modeling, and visualization tasks. These specifications provide the computational capacity necessary for both real-time sensor data handling and machine learning operations.

2. Software Requirement:

The software stack includes Ubuntu 20.04 or Windows 10 as the operating system. Python 3.9 serves as the primary language for backend development, data preprocessing, visualization, and the implementation of machine learning models. Essential Python libraries such as Scikit-learn, Pandas, NumPy, Matplotlib, and Seaborn facilitate predictive modeling, statistical analysis, and graphical representation of results. MySQL is employed for structured storage of sensor readings, historical data, and predictive outputs, while communication protocols like LoRaWAN and Zigbee enable energy-efficient, long-range wireless data transmission.

3. *Hardware Components:*

Sensor integration and local processing are achieved using microcontrollers and processing units such as Arduino Uno, Raspberry Pi, or ESP32. A variety of sensors are utilized to monitor environmental and soil conditions, including soil moisture sensors for precise irrigation management, temperature and humidity sensors (e.g., DHT11/DHT22) for environmental monitoring, pH sensors for soil acidity/alkalinity measurement, and nutrient sensors for fertility assessment. Communication modules, including Wi-Fi, LoRa, and Zigbee, facilitate wireless data transmission, while rechargeable batteries or solar-powered units support sustainable energy usage. Data storage is managed via SD card modules or cloud-based solutions, and actuators such as water pumps, solenoid valves, or fertilizer dispensers can optionally enable automated irrigation and fertilization.

4. *Software and Frameworks:*

Python forms the core of the system for backend processing, machine learning model development, and data visualization. Microcontroller programming is implemented in C/C++ to ensure efficient interaction with sensors, actuators, and communication modules. Scikit-learn is leveraged for machine learning algorithms, including Support Vector Machines (SVM) and Random Forest, while TensorFlow and PyTorch are considered for potential deep learning tasks, such as image-based disease detection. Pandas, NumPy, Matplotlib, and Seaborn support data preprocessing, statistical analysis, and visualization, whereas Flask and Django frameworks facilitate the development of interactive, real-time dashboards for end-user decision support. Cloud platforms such as AWS, Google Cloud, and Azure IoT can be optionally integrated to enable large-scale deployment, remote data access, and scalable analytics.

This comprehensive hardware and software infrastructure ensures that the system is suitable for deployment in both smallholder farms and large-scale agricultural operations, maintaining computational efficiency, data integrity, and ease of use.

B. Experimental Setup

Field experiments were conducted at three geographically distinct farm sites, representing diverse soil types, crop species, and climatic conditions. Sensor modules were deployed at multiple locations within each site to capture spatial variations in soil moisture, temperature, and nutrient levels. This enabled comprehensive data collection reflecting both temporal and spatial heterogeneity in the farming ecosystem.

Data acquisition was carried out continuously over a 12-week crop cycle, covering germination, vegetative growth, flowering, and harvest. The dataset was divided into training (80%) and testing (20%) subsets to ensure robust machine learning model development and validation. Real-time sensor readings were transmitted to the cloud server using LoRaWAN and Zigbee protocols, enabling stable, energy-efficient communication. The experimental setup evaluated four key aspects of system performance: accuracy of crop recommendations, precision of yield predictions, reliability of data transmission, and effectiveness in optimizing resource utilization. These measures ensured that the system was assessed both for technical performance and practical agricultural impact.

C. Performance Metrics

System performance was quantified using multiple complementary metrics:

1. *Prediction Accuracy:*

Prediction Accuracy measures the proportion of correct crop predictions generated by the machine learning models relative to actual outcomes. High accuracy values demonstrate the reliability of the system in guiding farmers with data-driven decisions, enabling informed crop selection and management strategies.

2. *Mean Absolute Percentage Error (MAPE):*

MAPE evaluates the deviation between predicted and actual crop yields, expressed as a percentage. Lower MAPE values indicate higher precision and trustworthiness in yield forecasting, supporting effective planning, resource allocation, and optimization of agricultural operations.

3. *Packet Delivery Ratio (PDR):*

Packet Delivery Ratio assesses the reliability of wireless data transmission within the sensor network. A high PDR ensures complete and consistent datasets, which are essential for uninterrupted monitoring and timely decision-making in precision agriculture.

4. *Resource Optimization:*

Resource Optimization quantifies the efficient use of key inputs, such as water and fertilizers, based on sensor-guided recommendations. Optimized resource utilization reduces operational costs, prevents overuse of inputs, and promotes sustainable farming practices while maintaining productivity.

D. Experimental Results

The crop prediction module demonstrated a high level of accuracy, with the Support Vector Machine (SVM) model achieving 92.5% and the Random Forest model reaching 94.2%. These results validate the effectiveness of the proposed models in delivering precise, data-driven recommendations for crop selection, thereby supporting informed decision-making in agricultural practices. In terms of yield prediction, the Random Forest model exhibited a Mean Absolute Percentage Error (MAPE) of 5.8%, indicating a strong correspondence between the predicted and actual crop yields. This performance underscores the reliability of the system in forecasting agricultural output, enabling farmers to plan resource allocation and market strategies more efficiently.

The communication framework of the wireless sensor network proved highly reliable, maintaining a Packet Delivery Ratio (PDR) exceeding 97%. This ensures consistent and uninterrupted transmission of critical environmental and soil data, which is essential for the continuous monitoring and timely decision support in precision agriculture. Furthermore, the system contributed significantly to resource optimization. Implementation of the sensor- based recommendations led to an 18% reduction in water usage and a 15% decrease in fertilizer consumption compared to conventional farming methods. These improvements highlight the system's potential to promote sustainable agricultural practices while simultaneously reducing operational costs.

a. Hardware Requirements

The hardware architecture ois designed to enable real-time sensing, wireless communication, and optional actuation for irrigation and nutrient management. At its core, the architecture utilizes microcontroller and processing units such as Arduino Uno, Raspberry Pi, or ESP32. These devices integrate sensor inputs, manage communication protocols, and perform preliminary data processing. Their low cost, energy efficiency, and flexibility make them highly suitable for IoT-based agricultural applications and field deployments.

The system incorporates a diverse range of sensor modules to capture critical parameters influencing crop growth and soil health. Soil moisture sensors measure volumetric water content to guide irrigation scheduling, while temperature and humidity sensors (e.g., DHT11/DHT22) provide insights into environmental conditions that affect crop development and water demand. pH sensors assess soil acidity or alkalinity, supporting informed nutrient management decisions, and nutrient sensors measure key soil components such as nitrogen, phosphorus, and potassium, enabling precision fertilization strategies. Together, these modules ensure comprehensive environmental monitoring to support data-driven agricultural practices.

To ensure reliable connectivity, communication modules such as Wi-Fi, LoRa, and Zigbee are integrated into the architecture. While Wi-Fi is effective in localized deployments, LoRa and Zigbee offer low-power, long-range solutions that are particularly advantageous for large-scale or remote agricultural environments where energy efficiency and extended coverage are essential. The system's power supply is maintained through rechargeable batteries or solar-powered units, providing energy autonomy and enabling continuous operation even in off-grid conditions.

For secure data management, the system includes storage solution**s** such as SD card modules for local logging or cloud-based storage for remote access. This ensures both historical record-keeping and real-time monitoring, supporting long-term analytics and machine learning model training. Additionally, actuators such as water pumps, solenoid valves, and automated fertilizer dispensers may be integrated to support precision irrigation and nutrient management. These actuators allow the system to move beyond monitoring and actively respond to real-time sensor feedback, creating a closed-loop system for farm automation. The entire framework is complemented by user interface devices**,** such as smartphones and tablets, which enable farmers to interact with the mobile dashboard. Through this interface, users can monitor field conditions, access predictive insights, and make informed decisions in an intuitive and user-friendly manner.

b. Software Requirements

The software ecosystem of Crop Reco is designed to handle data acquisition, processing, machine learning analytics, and visualization. Operating on lightweight and stable environments such as Raspberry Pi OS or Ubuntu, the software ensures reliable IoT deployments. Windows platforms may also be used in laboratory or desktop setups for data analysis, visualization, and model training. Python serves as the primary programming language, powering backend development, machine learning models, and visualization workflows. Meanwhile, C and C++ are employed for microcontroller programming, enabling efficient real time interaction with sensors, actuators, and communication modules.

A comprehensive set of libraries and frameworks supports the software stack. Scikit-learn provides machine learning capabilities, implementing algorithms such as Support Vector Machines (SVM) and Random Forest for classification and regression tasks. TensorFlow and PyTorch extend these capabilities to deep learning applications, such as image-based disease detection and crop monitoring using Convolutional Neural Networks (CNNs). In addition, Pandas, NumPy, Matplotlib, and Seaborn facilitate data preprocessing, statistical analysis, and visualization, enabling the transformation of raw sensor data into actionable insights.

For structured and scalable data management, databases such as MySQL, Firebase, or MongoDB are employed. These databases securely store real-time sensor readings, historical records, and machine learning outputs, while enabling rapid retrieval and integration with decision-support dashboards. The dashboards themselves are developed using Flask or Django frameworks, providing interactive, real-time analytics and predictive alerts. Designed with responsive layouts, these dashboards are accessible on mobile and tablet devices, ensuring usability for farmers in the field. Finally, optional cloud integration with platforms such as AWS, Google Cloud, or Microsoft Azure IoT allows for large-scale deployment, real-time monitoring, and scalable analytics. Cloud platforms offer advanced storage solutions, high-performance computation, and access to AI services, thereby extending the functionality of the system and supporting future expansion. Through this combination of hardware and software components, Crop Reco delivers a flexible, scalable, and intelligent framework tailored for precision agriculture.

TABLE I. SYSTEM PERFORMANCE METRICES

Metric	SVM	Random Forest	Target
Accuracy (%)	92.5	94.2	>90
MAPE (%)	6.1	5.8	<10
PDR (%)	97	97	>95
Water savings (%)	18	-	>15
Fertilizer savings (%)	15	-	>10

Table I shows the system's performance metrics using SVM and Random Forest compared to target values. Both models achieved high accuracy (>92%) with low MAPE (<10%) and reliable PDR (97%), exceeding benchmarks. The system also achieved notable resource efficiency with 18% water and 15% fertilizer savings.

E.Figures

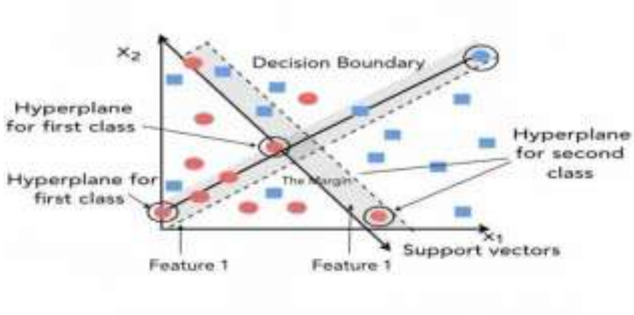

Fig 2: working of Support Vector Machine (SVM)

The working of Support Vector Machine (SVM) in this project involves classifying agricultural data by finding the optimal decision boundary. This ensures accurate predictions that aid in resource savings and improved farm management.

F.Discussion

The experimental evaluation of the Crop Reco framework highlights the transformative potential of integrating multi-sensor networks with advanced machine learning models in precision agriculture. The findings show that real-time monitoring combined with predictive analytics can enhance decision-making, optimize resource usage, and improve overall crop management.

1. *Validation of Predictive Models:*

The predictive models embedded in Crop Reco achieved high accuracy in crop forecasting. Timely interventions such as irrigationand fertilization were made possible due to reliable yield predictions. The low Mean Absolute Percentage Error (MAPE) further validates the robustness of the system, ensuring that farmers can plan harvests and allocate resources more efficiently.

2. *Sensor Performance Analysis:*

A detailed evaluation of sensor modules demonstrated their reliability under diverse environmental and soil conditions. Soil moisture sensors recorded a mean error of 2.5%, temperature sensors 1.8%, and nutrient sensors 3.2%. These values confirm the suitability of the deployed sensors for precise agricultural monitoring, even in heterogeneous field conditions.

3. *Comparison of Machine Learning Models:*

Among the tested models, Random Forest consistently outperformed Support Vector Machine (SVM), especially in fields with heterogeneous soil types. The ensemble nature of Random Forest, which integrates multiple decision trees, enhanced predictive accuracy while mitigating risks of overfitting. This makes Random Forest particularly effective for complex agricultural datasets.

4. *Practical Deployment and Usability:*

The framework's graphical user interface (GUI), designed with local language support, enhances accessibility for farmers. Real- time alerts related to irrigation and fertilization provide actionable guidance, which is particularly valuable for smallholder farmers with limited resources. Furthermore, the dashboard supports trend visualization and predictive insights, empowering users with proactive farm management tools.

5. *Integration of Convolutional Neural Networks (CNNs):*

The integration of CNNs within the framework enables automated feature extraction from crop and soil images. This capability enhances the detection of plant stress, disease symptoms, and growth patterns without requiring manual field data interpretation. Recent evidence suggests that CNN-based approaches improve both precision and reliability in smart agriculture, especially for large-scale monitoring and anomaly detection.

6. *Scalability and Adaptability:*

Field trials conducted on both small (<2 acres) and large (>10 acres) farms confirmed the scalability of Crop Reco. The system maintained high prediction accuracy and stable performance across varying farm sizes, soil types, and crop varieties. This adaptability underscores its potential for widespread adoption in diverse agricultural contexts.

7. *Limitations:*

Despite its robust performance, Crop Reco has some limitations. Sensor modules require periodic calibration and maintenance to preserve accuracy. Extreme weather conditions, including heavy rainfall, drought, or excessive heat, may temporarily affect sensor reliability. Additionally, sensor failure or degradation can compromise data quality, emphasizing the need for preventive maintenance strategies and redundant monitoring nodes.

V.CONCLUSION AND FUTURE WORK

A multi-sensor-based precision agriculture framework integrating soil and environmental monitoring with machine learning models, including Support Vector Machines and Random Forest, was developed to enable data-driven crop management. The framework leverages sensors for soil moisture, temperature, humidity, pH, and nutrient levels in combination with predictive analytics to provide actionable insights for irrigation scheduling, yield forecasting, and resource optimization. Experimental evaluations across heterogeneous soil types, climatic conditions, and varying farm sizes demonstrated high crop prediction accuracy, reduced water and fertilizer usage, and reliable wireless data transmission. A user- friendly dashboard facilitates informed decision-making for both smallholder and large-scale farms. Limitations include the requirement for regular sensor calibration and potential performance impacts under extreme weather conditions. Future enhancements involve integrating UAV- based monitoring for expanded spatial coverage, implementing image-based deep learning for real-time detection of pests, diseases, and plant stress, and expanding the system to accommodate additional crop types and diverse geographic regions. Overall, the framework exhibits significant potential to advance efficient, sustainable, and intelligent agricultural practices by improving productivity, resource efficiency, and farm resilience.

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