



A Smart Decision-Support System for Soil Analysis, Irrigation Scheduling, and Crop-Specific Fertilizer Recommendation Using AI

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Abstract: Agriculture requires effective decisions related to soil, crops, irrigation, fertilizers, diseases, yield, weather, and market conditions. This paper presents an AI-driven Smart Agriculture System that integrates machine learning, IoT, weather services, and web technologies into a unified platform. The system provides soil analysis, crop recommendation, fertilizer recommendation, irrigation prediction, crop yield prediction, plant disease detection, weather monitoring, and market-price analysis. Random Forest, Linear Regression, and MobileNetV3-Small models are used for different agricultural tasks. The system is implemented using React, FastAPI, Python, SQLite, and ESP32-S3-based sensing. Experimental results achieved approximately 92.34% crop accuracy, 95.79% soil accuracy, $R^2 \approx 0.642$ for irrigation, $R^2 \approx 0.971$ for yield prediction, and 91.32% validation accuracy for disease detection. The proposed system demonstrates the integration of AI and IoT for data-driven agricultural decision support.

Keywords: Artificial Intelligence, Smart Agriculture, Machine Learning, Random Forest, IoT, Soil Analysis, Crop Recommendation, Irrigation, Plant Disease Detection.

I. INTRODUCTION

Agriculture plays a vital role in India's economy and provides livelihood and food security to a large population. Farmers make several important decisions throughout the cultivation process, such as selecting suitable crops, monitoring soil conditions, managing irrigation, applying fertilizers, identifying plant diseases, and understanding market conditions. Traditionally, many of these decisions depend on farmers' experience, manual observation, and conventional farming practices. Although such knowledge is valuable, the absence of timely and data-driven information can sometimes make agricultural decision-making difficult. With the advancement of **Artificial Intelligence (AI)**, **Machine Learning (ML)**, and **Internet of Things (IoT)**, modern technologies can be used to support farmers in making more informed decisions.

This paper presents an **integrated Smart Agriculture System** that brings multiple agricultural services together on a single platform. Instead of requiring separate applications for different farming activities, the proposed system combines machine learning models, IoT-based sensing, weather information, agricultural market data, and a web-based interface. The system is designed to collect relevant agricultural information, process the available data, and provide useful recommendations to farmers through an easy-to-use platform. The proposed system includes major modules such as **soil health analysis, crop recommendation, fertilizer recommendation, irrigation prediction, weather monitoring, and crop yield prediction**. These modules are designed to assist farmers in understanding field conditions and selecting appropriate actions based on the available agricultural parameters. The system also incorporates **plant disease detection**, which helps in identifying possible crop diseases from plant images and can support early intervention.

In addition to the machine learning modules, the system includes **IoT-based soil and environmental monitoring** using sensors connected to an **ESP32 microcontroller**. The IoT layer collects real-time parameters such as soil moisture and other environmental conditions, which are transmitted to the backend for processing and visualization. This connects actual field conditions with the digital decision-support system. The platform also provides **market-price analysis** and an **AI-based agricultural assistant** for agriculture-related queries. By combining these services, the proposed system provides a centralized platform for accessing agricultural information and recommendations. Overall, the system aims to reduce dependence on manual observation, improve resource utilization, support timely decisions, and assist farmers in efficient cultivation. The integration of **AI, ML, IoT, weather data, market information, and an interactive web platform** provides a practical approach toward smarter and more sustainable agriculture.

II. LITERATURE REVIEW

A. AI-Based Smart Agriculture

Artificial Intelligence and machine learning are increasingly being used to solve different agricultural problems. These techniques can be used to analyze soil conditions, recommend suitable crops, estimate irrigation requirements, predict crop yield, and identify plant diseases. However, many existing systems concentrate on only one agricultural problem. For example, a system may be developed specifically for crop recommendation, while another may focus only on disease detection or yield prediction.

B. IoT-Based Agriculture

IoT technology allows information from agricultural fields to be collected using sensors. Parameters such as soil moisture, temperature, humidity, and other environmental conditions can be monitored and used for decision-making. Real-time sensor information can help reduce dependence on manual monitoring and provide farmers with timely information about field conditions.

C. Machine Learning in Agriculture

Different machine learning algorithms can be selected depending on the type of agricultural problem. Classification algorithms can be used to classify soil conditions or recommend crops, while regression algorithms can be used to predict irrigation requirements and crop yield. Deep-learning models can be used for image-based plant disease detection.

D. Research Gap

Although several systems have been developed for individual agricultural tasks, farmers may still have to depend on multiple applications or information sources. There is a need for a system that combines different agricultural services in one platform. The proposed work attempts to address this gap by bringing together machine learning, IoT monitoring, weather information, market-price data, and an AI-based assistant within a single agricultural platform.

III. EXISTING SYSTEM

In conventional agricultural systems, individual activities such as soil testing, crop selection, irrigation planning, disease identification and market-price checking are generally performed separately. Most existing approaches focus on a single agricultural problem. For example, one system may only recommend crops, while another may focus on plant disease detection. This requires farmers to use multiple applications or sources of information. Such systems may also have limited integration between machine learning predictions, real-time sensor information, weather data and market information.

IV. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

Farmers often need to collect agricultural information from different sources. Soil analysis, crop selection, fertilizer selection, irrigation, disease identification, yield estimation, and market-price checking are usually handled separately.

These challenges can lead to difficulty in accessing agricultural information through a single platform, increased dependence on manual assessment, improper irrigation practices, incorrect fertilizer usage, delayed identification of plant diseases, difficulties in accurately estimating crop yield, and limited awareness of prevailing market prices. Therefore, an integrated system is developed to provide these services through a single platform.

B. Objectives

Here are the objectives consolidated into **four clear and research-oriented points**:

- 1. To develop an AI-based agricultural decision-support platform** for providing intelligent and data-driven recommendations to farmers.
- 2. To analyze soil and environmental parameters** for recommending suitable crops and fertilizers, and for estimating irrigation requirements based on crop and environmental conditions.
- 3. To develop AI-based modules for crop yield prediction and plant disease detection**, along with integrated weather and market-price information to support effective farm management.
- 4. To integrate IoT-based real-time soil monitoring and multilingual conversational assistance** to provide farmers with timely, accessible, and user-friendly agricultural support.

V. PROPOSED SYSTEM

The system follows a web-based architecture in which the farmer interacts with the React frontend. The frontend communicates with the **FastAPI backend**, which processes user inputs and connects them with machine learning models, weather services, market data, and IoT sensor information.

The main modules of the proposed system include soil health analysis, crop recommendation, fertilizer recommendation, irrigation prediction, and crop yield prediction to support effective and data-driven crop management. The system also incorporates plant disease detection, weather monitoring, and market-price analysis to help farmers make informed decisions throughout the crop production cycle. Furthermore, IoT-based soil-moisture monitoring enables real-time monitoring of soil conditions, while the **AI-based agricultural assistant** provides intelligent, interactive, and farmer-friendly guidance.

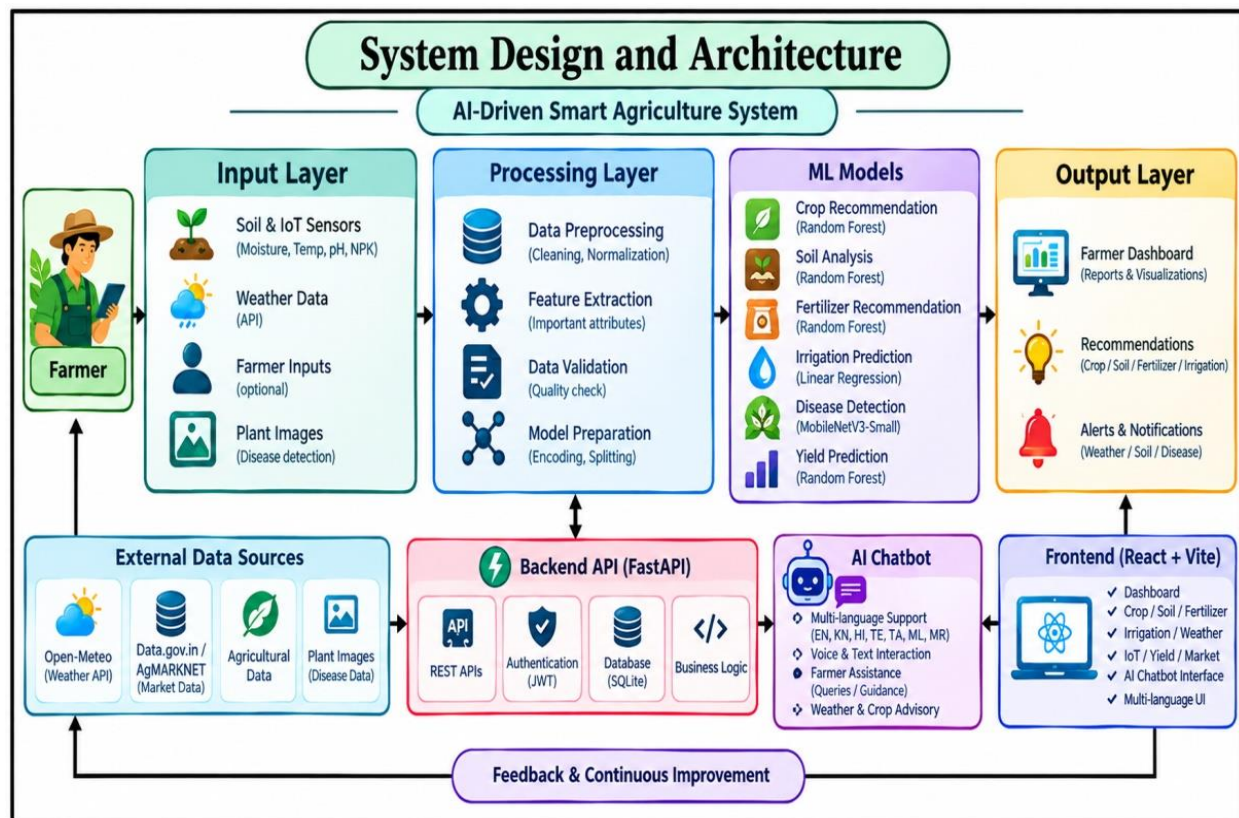


Fig-5.1: Architecture AI –Driven Smart Agriculture System

VI. METHODOLOGY

The proposed system follows a systematic approach involving data collection, preprocessing, machine learning model development, evaluation, and web application integration. Different techniques are used for crop recommendation, soil analysis, irrigation prediction, fertilizer recommendation, yield prediction, and plant disease detection.

A. Data Collection

Datasets containing agricultural parameters such as nitrogen, phosphorus, potassium, temperature, humidity, pH, rainfall, crop information, and yield-related attributes were collected and prepared for model training. Image data was used for plant disease detection.

B. Data Preprocessing

The collected data was cleaned and converted into a suitable format for machine learning. Numerical features were prepared for model training, while categorical features were encoded where required. For disease detection, images were resized and normalized before training.

C. Model Development

Different machine learning models were selected based on the requirements of each module. Random Forest is used for crop recommendation and soil health analysis, Linear Regression is used for

irrigation prediction, and Random Forest Regressor is used for yield prediction. MobileNetV3-Small is used for plant disease detection.

Table-1: The major machine learning models are:

Module	Algorithm
Crop Recommendation	Random Forest Classifier
Soil Analysis	Random Forest Classifier
Fertilizer Recommendation	Random Forest Classifier
Irrigation	Linear Regression
Yield Prediction	Random Forest Regressor
Disease Detection	MobileNetV3-Small

D. Model Evaluation

The trained models were evaluated using suitable performance measures. Classification models were evaluated using accuracy and prediction confidence, while regression models were evaluated using metrics such as R^2 and MAE. The crop recommendation model achieved approximately 92.34% accuracy and the soil health model achieved approximately 95.79% accuracy.

E. System Integration

The trained models are integrated with a FastAPI backend and connected to the React-based frontend. The system also integrates weather information, IoT sensor data, market information, authentication, and database services to provide a unified agricultural platform

VII. MODULE IMPLEMENTATION

A. CROP RECOMMENDATION

A **Random Forest Classifier** is used to recommend suitable crops based on nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall. The dataset contains **50,000 records and 22 crop classes**. The model achieved approximately **92.34% accuracy** on the project's test data.



Fig-7.1: System Flow for Crop Recommendation Module

B. SOIL ANALYSIS

The soil module classifies soil into three categories: Healthy, Moderate, Poor. A **Random Forest Classifier** is used for classification. The current model achieved approximately **95.79% accuracy**.

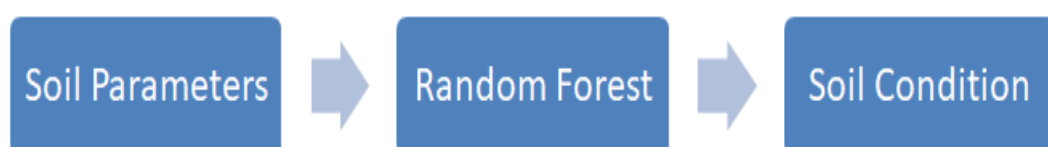


Fig-7.2: System Flow for Soil Analysis Module

C. FERTILIZER RECOMMENDATION

The fertilizer module recommends an appropriate fertilizer based on agricultural and soil-related inputs. The planned approach uses machine learning classification to map input conditions to suitable fertilizer recommendations. The final experimental accuracy should be reported after completing and evaluating the final model.



Fig-7.3: System Flow for Fertilizer recommendation Module

D. IRRIGATION PREDICTION

Linear Regression is used to estimate irrigation requirements. The model considers crop, soil, weather, and environmental parameters. Crop-specific water requirements are also considered.

The current model achieved an **R² value of approximately 0.642**.

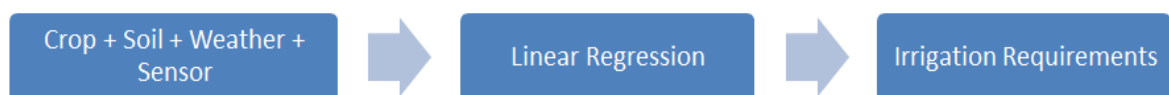


Fig-7.4: System Flow for Irrigation Prediction Module

E. CROP YIELD PREDICTION

Crop yield prediction is performed using a **Random Forest Regressor**, which uses various agricultural and environmental parameters as input features. These include the **year, state, crop type, season, cultivated area, annual rainfall, fertilizer usage, and pesticide usage**. By analyzing these factors, the model estimates the expected crop yield and supports farmers in making informed decisions related to crop planning and management.

The dataset contains **17,400 records**. Production was excluded from the input features to avoid target leakage. The model achieved approximately **R² = 0.971** on the project's test split.

F. PLANT DISEASE DETECTION

Plant disease detection is performed using **MobileNetV3-Small**, a lightweight deep-learning model suitable for resource-constrained environments.

The image processing pipeline is:

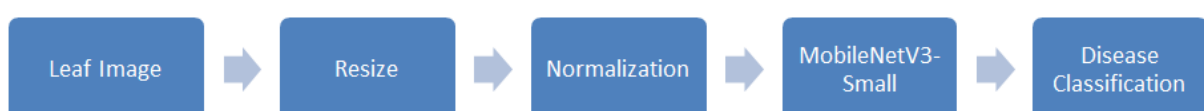


Fig-7.5: System Flow for Plant Disease Detection Module

The model was trained using **5,700 images covering 38 classes** and achieved approximately **91.32% validation accuracy**. The trained model was converted to **ONNX format** and integrated using ONNX Runtime to reduce the computational overhead during deployment.

VIII. INTEGRATED SERVICES

A. IOT-BASED SOIL MONITORING

IoT is used in the system to monitor agricultural field conditions through an ESP32-based controller. Sensor information can be collected and made available to the application for further analysis. This approach helps reduce the need for continuous manual observation and provides a way to use real-time field information for agricultural decision-making.

B. WEATHER MONITORING

Weather information is useful when making decisions related to irrigation and crop management. The system uses Open-Meteo to obtain location-based weather information. Farmers can use this information to monitor weather conditions, rainfall, and other environmental factors that may affect agricultural activities.

C. MARKET PRICE ANALYSIS

The Market Price Analysis module provides information about agricultural commodity prices using Data.gov.in/AGMARKNET. The available information includes the state, district, market, commodity, variety, grade, arrival date, minimum price, maximum price, and modal price. Providing this information within the same platform allows farmers to check market conditions without depending on a separate source.

D. AI AGRICULTURAL ASSISTANT

The system also includes an AI-based agricultural assistant. Farmers can interact with the assistant using natural-language questions and obtain information related to different agricultural activities. The assistant can provide guidance related to crop selection, soil conditions, irrigation, fertilizer usage, plant diseases, market information, and crop yield prediction. The application is designed to support **English, Kannada, Hindi, Telugu, Tamil, Malayalam, and Marathi**. Voice-based interaction can be added as a future extension to make the system more convenient for farmers.

IX. SYSTEM IMPLEMENTATION

The proposed AI-driven IoT-based Smart Agriculture Decision Support System is implemented as an integrated web-based platform that combines machine learning models, IoT sensing, agricultural data services, and an AI-based assistant. The system follows a client-server architecture in which the frontend provides the user interface, while the backend manages data processing, machine learning models, APIs, authentication, and communication with IoT devices.

A. FRONTEND

The frontend of the system is developed using **React with Vite**. It provides a user-friendly interface through which farmers can access different agricultural services. The dashboard provides separate modules for soil analysis, crop recommendation, fertilizer recommendation, irrigation prediction,

crop yield prediction, plant disease detection, weather monitoring, market-price analysis, and the AI agricultural assistant.

The frontend communicates with the backend through REST APIs and displays the processed results and recommendations to the user. The responsive interface enables users to access the system and interact with the agricultural modules through a unified platform.

B.BACKEND

The backend is developed using **Python and FastAPI**. It provides RESTful APIs for communication between the frontend, machine learning models, database, IoT devices, and external services.

The backend manages user authentication, sensor-data processing, agricultural predictions, weather information, market information, notifications, and AI-assisted agricultural queries. The machine learning models are integrated into the backend so that input data can be processed and predictions can be returned to the frontend. The backend also provides separate API endpoints for the major agricultural modules, allowing the system to process soil and environmental parameters and generate appropriate recommendations.

C. DATABASE

SQLite is used as the database for storing application-related information. The database manages user information, authentication-related data, agricultural records, and system information required by the application. The backend communicates with the database through the application layer, allowing data to be securely stored and retrieved when required. The database also supports the integration of sensor and agricultural information with the web application.

D. IoT HARDWARE

The IoT layer enables the system to acquire agricultural parameters from physical sensors. An **ESP32 microcontroller** is used as the primary IoT device for collecting and transmitting sensor data. The IoT system can acquire parameters such as soil moisture, temperature, humidity, pH, and nutrient values depending on the connected sensors. The collected sensor data is transmitted to the backend through the IoT communication layer. The backend processes the received data and makes the latest values available to the corresponding agricultural modules.

a. ESP32 – S3 Dev Module

The ESP32 acts as the central controller of the IoT system. It collects data from the connected sensors and transmits the readings to the backend system.

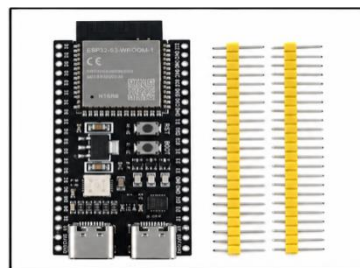


Fig-9.1: ESP32 – S3 Dev Module.

b. HW-080 Soil Moisture Sensor and DHT11 Temperature & Humidity Sensor

HW-080 Soil Moisture Sensor: The soil moisture sensor measures the moisture content of the soil. The obtained value can be used to monitor soil conditions and support irrigation-related decisions.

DHT11 Temperature & Humidity Sensor: This measures the surrounding temperature and humidity. These values help monitor environmental conditions and support irrigation and crop-management decisions.

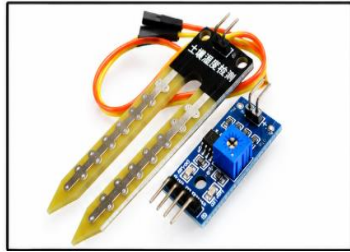


Fig-9.2: HW-080 Soil Moisture Sensor.

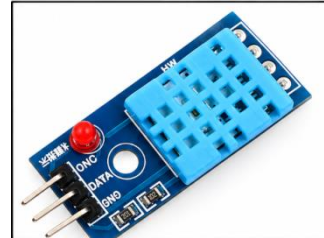


Fig-9.3: DHT11 Temperature & Humidity Sensor

c. NPK Soil Sensor & Rain drop Sensor

NPK Soil Sensor Measures the Nitrogen (N), Phosphorus (P), and Potassium (K) levels in the soil. This information helps determine the nutrient condition of the soil and supports fertilizer recommendations. **Rain drop Sensor** Detects the presence and intensity of rainfall. It helps the system avoid unnecessary irrigation when sufficient rain is detected.



Fig-9.4: NPK Soil Sensor



Fig-9.5: Rain Drop Sensor

E. Technology Stack

Table 2: Technology Stack

Technology	Purpose
React + Vite	Frontend
FastAPI	Backend API
Python	Machine Learning and backend
Scikit-learn, Python	Machine Learning
SQLite	Database
JWT	Authentication
Open-Meteo	Weather data
Data.gov.in/AGMARKNET	Market data
Vercel + Railway	Application Deployment

X. RESULTS AND DISCUSSIONS

Table-3: The current experimental results are summarized below:

Module	Model	Dataset	Result
Crop Recommendation	Random Forest	50,000 Records	92.34%
Soil Analysis	Random Forest	50,000 Records	95.79%
Fertilizer Recommendation	Random Forest Classifier	50,000 Records	91.86%
Irrigation	Linear Regression	50,000 Records	R² = 0.642
Crop Yield	Random Forest Regressor	17,400 Records	R² = 0.971
Disease Detection	MobileNetV3-Small	5,700 images	91.32%

The above table summarizes the **machine learning models, datasets, and performance results** obtained for the major modules of the proposed agricultural system. The results can be explained as follows:

- 1. Crop Recommendation:** The Crop Recommendation module uses a **Random Forest** classification model trained on **50,000 records**. The model achieved an accuracy of **92.34%**, indicating its ability to recommend suitable crops based on the input agricultural parameters.
- 2. Soil Analysis:** The Soil Analysis module employs a **Random Forest** model using **50,000 records**. It achieved an accuracy of **95.79%**, demonstrating effective analysis and classification of soil-related conditions.
- 3. Fertilizer Recommendation:** The Fertilizer Recommendation module uses a **Random Forest Classifier** trained on **50,000 records**. The model achieved an accuracy of **91.86%**, demonstrating its ability to recommend suitable fertilizer based on the provided soil and agricultural parameters.
- 4. Irrigation Prediction:** The Irrigation module uses **Linear Regression** trained on **50,000 records**. The model achieved an **R² value of 0.642**, indicating a moderate level of capability in predicting irrigation requirements based on the available input parameters.
- 5. Crop Yield Prediction:** The Crop Yield Prediction module uses a **Random Forest Regressor** trained on **17,400 records**. It achieved an **R² value of 0.971**, indicating a strong relationship between the input agricultural parameters and the predicted crop yield.
- 6. Disease Detection:** The Plant Disease Detection module uses the **MobileNetV3-Small** deep-learning architecture and a dataset containing **5,700 images**. The model achieved an accuracy of **91.32%**, demonstrating its capability to identify plant diseases from crop images.

Overall, the results show that machine learning can be combined with other technologies to build a practical agricultural decision-support platform. At the same time, the performance of these models depends on the quality and representativeness of the training data, and the results may vary when the system is used under different real-world field conditions.

XI. ADVANTAGES

The main advantage of the proposed system is that several agricultural services are available through one platform instead of requiring separate applications.

The system provides: Soil condition analysis, Crop recommendation, Irrigation prediction, Crop yield estimation, Plant disease detection, Weather information, Market-price information, IoT-based monitoring and Multilingual agricultural assistance

CONCLUSION

This paper presents an AI-driven Smart Agriculture System that brings machine learning, IoT, weather information, market data, and web technologies together in a single platform. The system provides several services, including soil analysis, crop recommendation, fertilizer recommendation, irrigation prediction, crop yield prediction, plant disease detection, weather monitoring, and market-price analysis. The developed models achieved 92.34% accuracy for crop recommendation, 95.79% accuracy for soil analysis, an R^2 value of 0.642 for irrigation prediction, an R^2 value of 0.971 for crop yield prediction, and 91.32% validation accuracy for plant disease detection. By combining these services in one application, the system provides farmers with an easier way to access agricultural information and use data to support their decisions.

FUTURE WORK

The system can be further improved by completing and evaluating the fertilizer recommendation model and by expanding the use of IoT sensors for field-level monitoring. Future work can also include automated irrigation, larger and more diverse agricultural datasets, improved disease detection, and better irrigation prediction using additional sensor and environmental data. Voice-based interaction can also be extended to provide a more convenient way for farmers to interact with the system in different languages.

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