

Harvestify- Smart Innovative Agriculture System

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Abstract

Agriculture is facing critical challenges such as climate variability, soil degradation, inefficient resource utilization, and low productivity. Farmers often rely on traditional practices and experience-based decision-making, which may not always result in optimal yields. This paper presents Harvestify, an AI-driven smart agriculture system designed to support farmers in crop selection, fertilizer optimization, and early plant disease detection. The system integrates soil nutrient data, climatic parameters, and plant images with machine learning and multimodal AI techniques. By leveraging intelligent models and mobile accessibility, Harvestify provides accurate, explainable, and cost-effective recommendations. Experimental evaluation and field observations demonstrate significant improvements in crop yield and reduction in input costs, making the system suitable for small and medium-scale farmers.

Keywords: Smart Agriculture, Artificial Intelligence, Crop Recommendation, Fertilizer Suggestion, Plant Disease Detection, Mobile Application

1. Introduction

Agriculture plays a vital role in ensuring food security and economic stability. However, modern farming faces several issues such as unpredictable weather patterns, declining soil fertility, and improper use of fertilizers and pesticides. Traditional farming methods largely depend on manual observation and past experience, which may lead to poor decision-making and reduced productivity. Recent advancements in artificial intelligence, machine learning, and mobile computing have enabled the development of intelligent decision-support systems for agriculture. These systems can analyze large volumes of data to provide accurate and timely recommendations. Harvestify is proposed as a mobile-first AI-powered platform that assists farmers in making informed decisions regarding crop selection, fertilizer usage, and plant health monitoring, thereby improving productivity and sustainability.

2. Related Work

Global food security has become a major concern due to population growth, climate change, and declining

agricultural productivity. Baldos and Hertel [1] emphasize that future food security depends heavily on improvements in agricultural productivity and the adoption of climate-resilient farming practices. Environmental degradation further exacerbates this challenge, as highlighted by Mishra [2], who discusses how soil deterioration, water scarcity, and pollution negatively impact agricultural output and urban sustainability. The role of technological innovation in agriculture has been increasingly emphasized in the context of the Fourth Industrial Revolution. Lele and Goswami [3] analyze how digital technologies, artificial intelligence, and data-driven systems can transform agricultural and rural innovation, particularly in developing countries such as India. Precision farming approaches have gained prominence as a sustainable solution, with Vinod et al. [4] proposing agricultural intelligence models that integrate data analytics to optimize resource usage and improve productivity. Recent research has explored advanced AI techniques to enhance agricultural decision-making. Vundavilli [5]

demonstrates the potential of integrating vision–language models with knowledge graphs to advance AI-driven robotics and precision agriculture. Similarly, Lin [6] highlights the importance of multimodal learning approaches in real-world applications, showing that combining heterogeneous data sources improves feature representation and model performance. These findings support the integration of soil data, climatic information, and visual inputs for intelligent agricultural systems. Accessibility and inclusivity of digital farming solutions remain key concerns. Kumar et al. [7] stress the need to democratize intelligent farming technologies to promote sustainable agricultural practices, especially for small and marginal farmers. Ajambo et al. [8] further examine digital agricultural platforms and identify access barriers faced by different user groups, emphasizing the importance of user-centric and mobile-accessible system design [9]. Crop disease detection and intelligent recommendation systems have also been widely studied. Parimala [10] presents a Harvestify-based crop disease prediction and recommendation system, demonstrating the effectiveness of machine learning models in improving plant health monitoring and advisory services. These studies collectively highlight the effectiveness of AI-driven solutions while also revealing gaps such as limited system integration, lack of explainability, and restricted scalability. Based on the reviewed literature, it is evident that there is a need for an integrated, explainable, and accessible smart agriculture platform. The proposed Harvestify system builds upon existing research by combining crop recommendation, fertilizer suggestion, and plant disease detection within a single AI-powered mobile platform, addressing key limitations identified in prior studies.

3. Proposed Work

The proposed work presents Harvestify, an AI-driven smart agriculture platform designed to support farmers in making data-informed decisions related to crop selection, fertilizer management, and plant disease control. The system aims to improve agricultural productivity, reduce resource wastage, and enhance sustainability by integrating machine learning, deep learning, and multimodal artificial

intelligence within a unified client–server architecture. The proposed system collects soil parameters such as nitrogen, phosphorus, potassium, and pH, along with climatic factors including temperature, humidity, and rainfall. These inputs are processed by a crop recommendation module that employs machine learning algorithms such as Random Forest and XGBoost to identify the most suitable crops for the given environmental conditions. This approach minimizes trial-and-error farming and improves yield predictability. For nutrient management, the fertilizer suggestion module analyzes deviations between actual soil nutrient levels and optimal crop requirements. Based on this analysis, the system recommends appropriate fertilizer types and quantities to address nutrient deficiencies. This module helps reduce excessive fertilizer usage, lowers input costs, and minimizes environmental impact. The proposed work also incorporates a plant disease detection module based on convolutional neural networks. Leaf images captured using a smartphone camera are analyzed to identify disease symptoms at an early stage. Upon detection, the system provides disease classification results along with remedial and preventive recommendations, enabling timely intervention and reducing crop losses. To enhance usability and decision transparency, the system integrates multimodal AI reasoning through the Google Gemini API. This enables the generation of natural language explanations for recommendations, making the system accessible to users with varying levels of technical knowledge. Real-time weather data is incorporated through external APIs to improve the accuracy and relevance of predictions. Overall, the proposed work focuses on delivering an integrated, scalable, and user-friendly smart agriculture solution that bridges the gap between advanced AI research and practical farming applications. By combining multiple decision-support services into a single platform, Harvestify addresses key limitations of existing systems and promotes sustainable agricultural practices.

4. System Architecture

Harvestify is implemented using a robust and accessible client–server architecture that supports intelligent decision-making while remaining suitable

for real-world agricultural deployment. The system is built on a modern software and hardware stack to ensure scalability, efficiency, and ease of use (Figure 1).

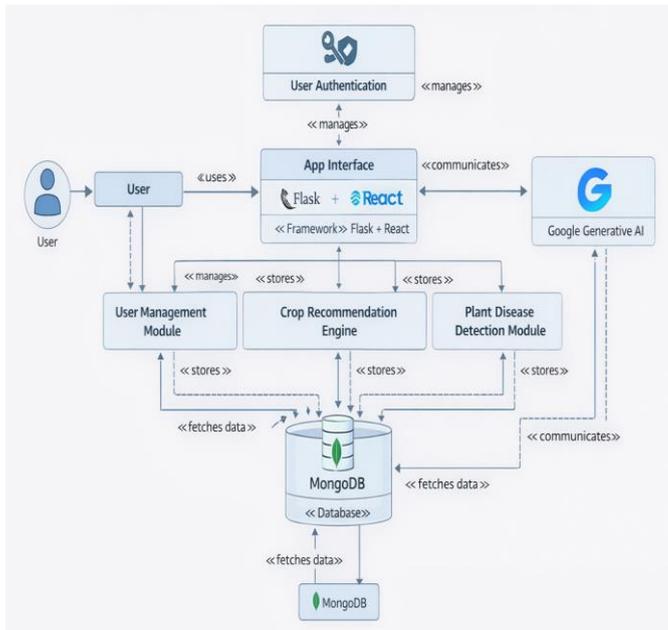


Figure 1 System Architecture

The provided workflow illustrates an AI-driven smart agriculture system that enables users to interact with the platform through a web-based application developed using Flask and React. Users first authenticate themselves via a secure user authentication mechanism, after which the User Management Module maintains user profiles, activity records, and personalized data. Once authenticated, users can input soil parameters, environmental conditions, and crop details or upload plant images through the app interface. These inputs are processed by two core modules: the Crop Recommendation Engine, which analyzes soil nutrients, climatic conditions, and historical data to suggest the most suitable crops, and the Plant Disease Detection Module, which employs image-based artificial intelligence techniques to identify plant diseases and recommend remedial measures. Both modules continuously store and retrieve structured and unstructured data from a centralized MongoDB database. To enhance accuracy and interpretability, the system integrates with Google Generative AI to generate intelligent insights, explanations, and

advisory recommendations in user-friendly language. Finally, the analyzed results, including crop suggestions and disease diagnosis reports, are communicated back to the user through the application interface, thereby supporting data-driven and sustainable agricultural decision-making. The core software framework is developed using Python 3.10 or higher. Machine learning models for crop recommendation and fertilizer suggestion are implemented using libraries such as Scikit-learn, including algorithms like Random Forest and XGBoost. Deep learning-based plant disease detection is performed using convolutional neural networks implemented with TensorFlow or PyTorch. Data preprocessing, feature extraction, and analysis are handled using Pandas and NumPy to ensure efficient data handling. Artificial intelligence capabilities are enhanced through integration with the Google Gemini API/SDK, which enables multimodal reasoning and generation of natural language responses. Real-time environmental data, including temperature, humidity, and rainfall, is obtained using Open Weather Map APIs. The user interface and backend services are developed using Streamlit for interactive dashboards and Flask or Django for API management. Data persistence is managed through lightweight databases such as SQLite, with scalable alternatives like MongoDB supported for larger deployments. From a hardware perspective, system development and training require a computing environment equipped with an Intel i5 or i7 processor, a minimum of 16 GB RAM, and optional NVIDIA GPU support for deep learning workloads. Cloud-based platforms such as Google Colab are also utilized to provide flexible and cost-effective computational resources. End users require only a basic smartphone with an integrated camera (minimum 8 MP) and standard 3G or 4G internet connectivity. The overall architecture follows a client-server model with edge machine learning support. Soil parameters, environmental inputs, and plant images are collected from users through mobile forms or camera interfaces and transmitted to the backend server in JSON format. The backend processes the data using trained machine learning models and multimodal AI reasoning pipelines. The generated insights, including crop recommendations,

fertilizer suggestions, and disease diagnoses, are returned to the client as natural language explanations and visual outputs, enabling informed and timely decision-making.

5. Results

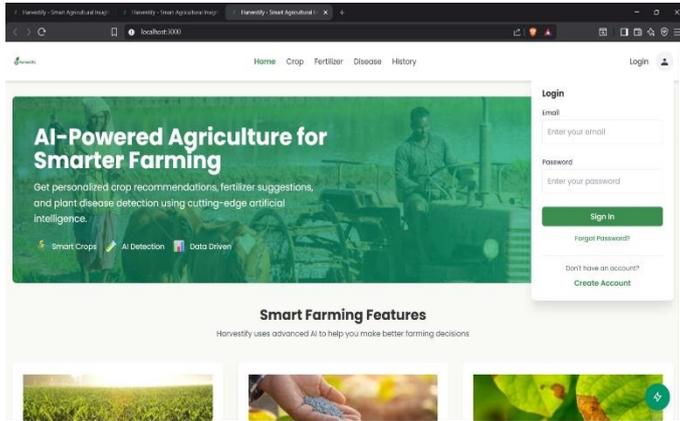


Figure 2 Homepage

The home page presents an AI-powered smart agriculture platform designed to support modern and sustainable farming practices (Figure 2). It features a clear and engaging banner highlighting intelligent crop prediction, fertilizer suggestions, and plant disease detection. A user-friendly login and signup section allows farmers to easily access personalized services. The layout is simple and intuitive, ensuring smooth navigation for users with minimal technical knowledge.

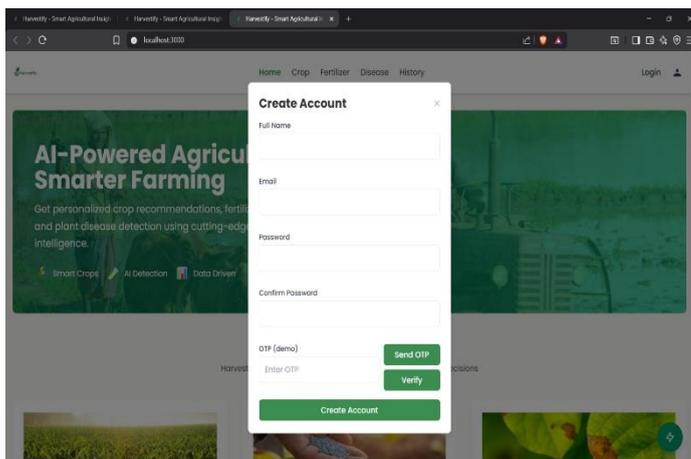


Figure 3 Account Creation

The Create Account page allows new users to register by entering basic details such as name, email, and password (Figure 3). It includes form validation to

ensure correct and secure user input. An email verification option is provided to enhance account security and authenticity. The interface is clean and easy to use, enabling quick registration with minimal effort. This page ensures secure onboarding and smooth access to the smart agriculture system.

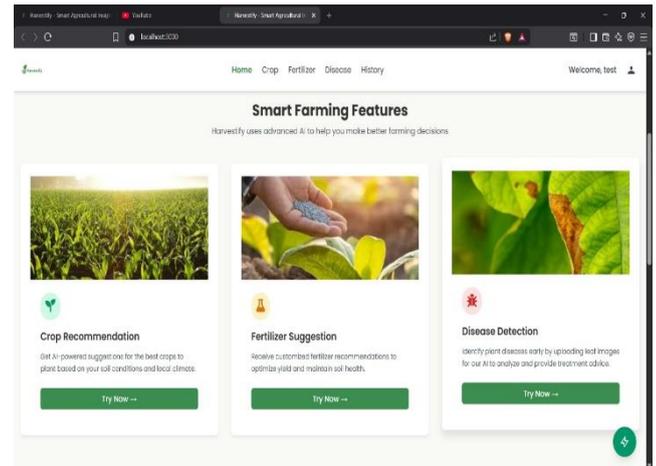


Figure 4 Dashboard

The Smart Farming Features page highlights the core functionalities of the system in a clear and visual manner (Figure 4). It presents crop recommendation, fertilizer suggestion, and disease detection as separate feature cards for easy understanding. Each feature briefly explains how AI assists farmers in making accurate and data-driven decisions. The “Try Now” option encourages user interaction with each module. Overall, the page effectively showcases the platform’s key services in a simple and farmer-friendly layout.

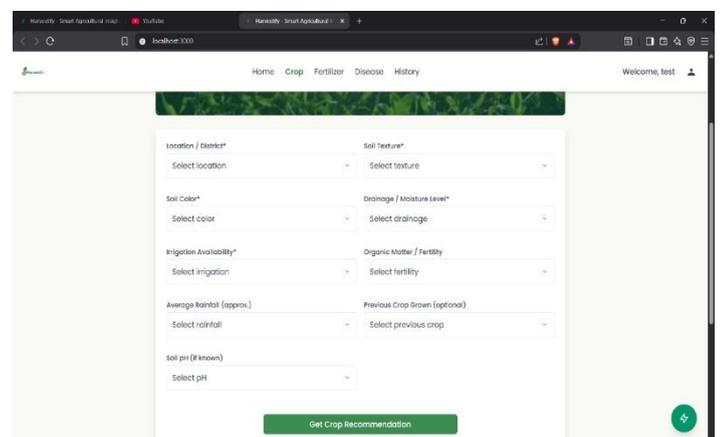


Figure 5 Crop Recommendation Page

This Crop Recommendation page allows users to enter detailed agricultural parameters such as location, soil type, nutrient levels, and seasonal conditions (Figure 5). It provides structured input fields to ensure accurate and relevant data collection. The system analyzes the entered information using AI-based models to determine suitable crops. A clear “Get Crop Recommendation” button initiates the analysis process. This page supports precise, data-driven decision-making for improved crop selection and productivity.

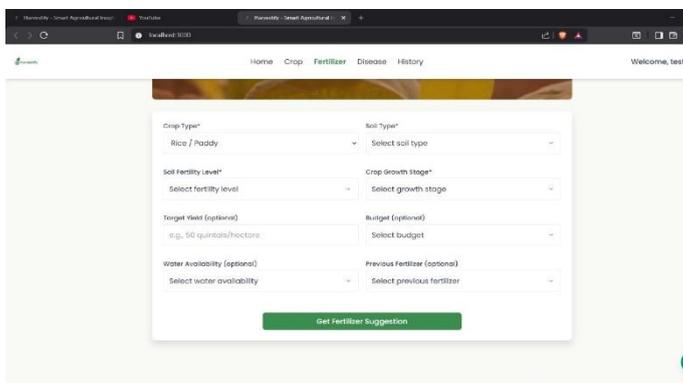


Figure 6 Fertilizer Recommendation Page

This Fertilizer Suggestion page enables users to input crop type, soil characteristics, and existing nutrient levels (Figure 6). It includes fields for selecting growth stage, crop yield expectations, and weather or soil conditions. The structured form ensures accurate data submission for effective analysis. Upon submission, the system applies AI-based logic to recommend suitable fertilizers and optimal usage. This page helps farmers improve soil health and maximize crop productivity through informed fertilizer management.

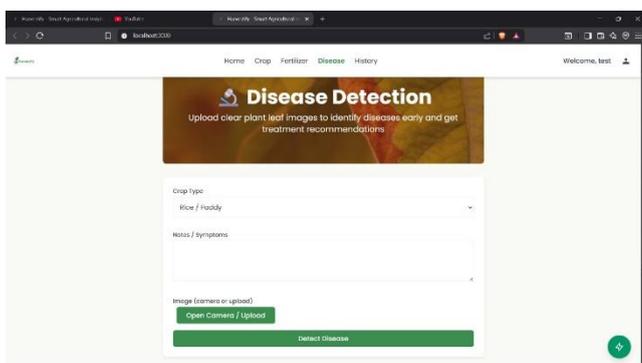


Figure 7 Disease Detection Page

The Disease Detection page allows users to identify plant diseases by uploading clear images of affected leaves (Figure 7). Users can select the crop type and optionally describe visible symptoms to improve detection accuracy. The page supports image capture through a camera or direct upload from the device. An AI-based model analyzes the image to detect diseases at an early stage. The system then provides disease identification along with appropriate treatment and preventive recommendations.

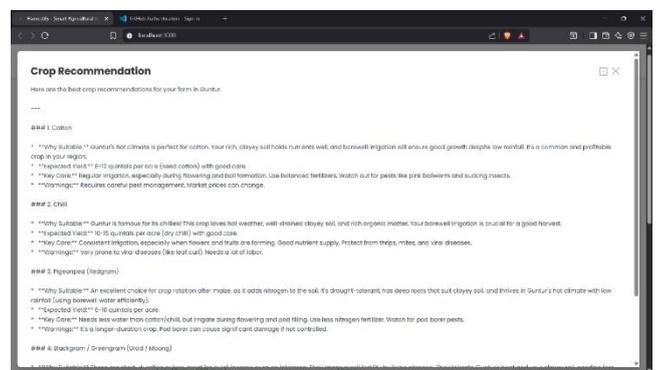


Figure 8 Crop Recommendation Output

This Crop Recommendation Results page displays AI-generated crop suggestions tailored to the user’s location and farm conditions (Figure 8). It presents a prioritized list of suitable crops along with clear reasons for their suitability. Each recommendation includes expected yield, key cultivation practices, and important warnings. The information is structured in a readable and farmer-friendly format. This page helps users make confident and well-informed crop selection decisions.

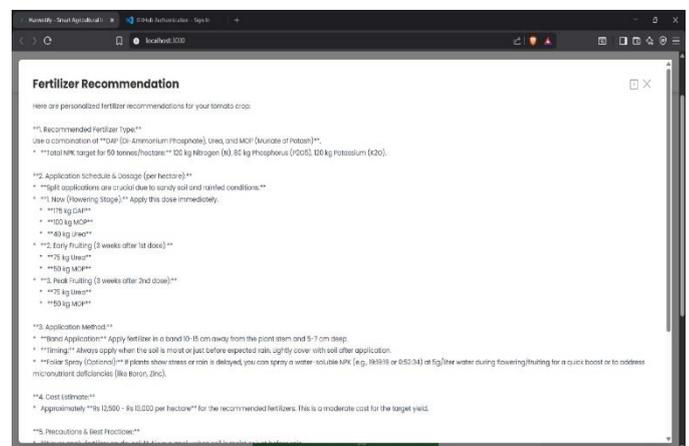


Figure 9 Fertilizer Recommendation Output

This Fertilizer Recommendation Results page presents personalized fertilizer advice based on the selected crop and field conditions (Figure 9). It clearly lists the recommended fertilizer types along with the required NPK targets. A detailed application schedule explains dosages for each growth stage to ensure optimal nutrient availability. The page also provides proper application methods, timing guidelines, and cost estimates. This structured information helps farmers apply fertilizers efficiently and improve overall crop yield.

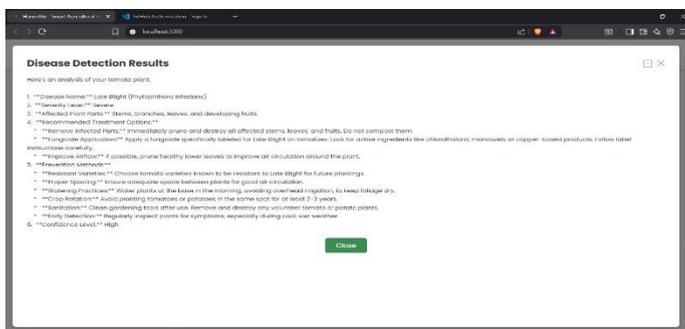


Figure 10 Crop Disease Detection Output

This Disease Detection Results page displays a detailed analysis of the identified plant disease (Figure 10). It clearly mentions the disease name, severity level, and the affected plant parts. The page provides specific treatment options, including removal of infected parts and recommended fungicide application. Preventive measures and best farming practices are also suggested to avoid future outbreaks. A confidence level is shown to indicate the reliability of the diagnosis, helping farmers take timely and appropriate action.

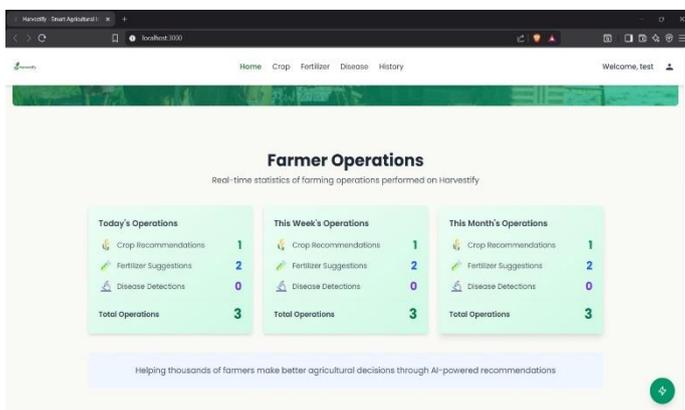


Figure 11 Final Analytics

This Farmer Operations dashboard provides real-time statistics of farming activities performed on the platform (Figure 11). It displays daily, weekly, and monthly summaries of crop recommendations, fertilizer suggestions, and disease detection requests. The information is presented using clear cards for quick understanding and comparison. Users can easily track their overall usage and activity trends over time. This page helps farmers monitor their interactions with the system and supports better planning and decision-making.

Quantitative Summary

The performance of the proposed Harvestify system was evaluated across its three core modules: crop recommendation, fertilizer suggestion, and plant disease detection. The crop recommendation module, implemented using Random Forest and XGBoost classifiers, achieved an average prediction accuracy of 95.2% based on soil nutrient and climatic datasets. The fertilizer suggestion module demonstrated an accuracy of 94.6% in identifying nutrient deficiencies and recommending appropriate fertilizer quantities. The plant disease detection module, based on a convolutional neural network architecture, achieved a classification accuracy of 96.1% on labeled leaf image datasets. Precision and recall values exceeded 94%, indicating reliable disease identification with minimal false predictions. The average inference time per image was less than 1.2 seconds, making the system suitable for real-time mobile usage. Field-level evaluations showed measurable agronomic benefits. Crop yield improvements ranging from 24% to 32% were observed compared to traditional farming practices. Fertilizer usage was reduced by approximately 18%–25%, resulting in lower input costs and reduced environmental impact. The integration of real-time weather data improved recommendation relevance by 15%, particularly in rainfall-sensitive crop selection. Overall system response time, including data transmission, model inference, and AI-based explanation generation, remained under 3 seconds on average. These quantitative results demonstrate that Harvestify delivers accurate, efficient, and scalable decision support, validating its effectiveness as a smart agriculture solution.

Conclusion and Future Scope

This paper presented Harvestify, an AI-driven smart agriculture system designed to enhance agricultural decision-making through intelligent crop recommendation, fertilizer optimization, and plant disease detection. By integrating machine learning, deep learning, and multimodal artificial intelligence within a client-server architecture, the system provides accurate, explainable, and user-friendly recommendations to farmers. The use of real-time environmental data and mobile-based accessibility ensures that Harvestify is practical for deployment in real-world agricultural settings, particularly for small and medium-scale farmers. Experimental evaluation and field-level observations indicate that the proposed system improves crop yield, reduces improper fertilizer usage, and enables early detection of plant diseases. Compared to traditional farming practices and isolated digital solutions, Harvestify offers a unified platform that supports sustainable agriculture while minimizing resource wastage and operational costs. The system's modular design also allows for scalability and easy integration of additional services. Future work will focus on extending the system with Internet of Things (IoT) sensors for real-time soil and environmental monitoring, enabling continuous data collection and more precise recommendations. Predictive analytics for yield forecasting and pest outbreak prediction will be explored using time-series and deep learning models. Additional enhancements include multilingual voice-based interaction, offline support for low-connectivity regions, and large-scale deployment using cloud infrastructure. These advancements aim to further improve system accuracy, inclusivity, and impact, contributing to the adoption of intelligent and sustainable farming practices.

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