AI-Powered Integrated Platform for Farmer Support: Real-Time Disease Diagnosis, Precision Irrigation Advisory, and Expert Consultation Services

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***Abstract*—The increasing prevalence of plant diseases, limited water resources, and fragmented agricultural knowledge among smallholder farmers pose serious threats to sustainable crop production. In response to these challenges, this research introduces an AI-Powered Farmer Support System—an integrated platform engineered to deliver real-time, intelligent farming assistance without relying on complex IoT infrastructure. The system is architected around four key modules: a convolutional neural network (InceptionV3) for early-stage plant disease identification, enhanced by a generative AI engine to provide region-specific treatment recommendations; a crop recommendation engine that synthesizes localized weather forecasts and soil attributes through dynamic API integration; a data-driven irrigation advisory tool leveraging predictive analytics to optimize water distribution; and an interactive consultation module powered by natural language processing to facilitate expert-level guidance. The platform has been developed using a hybrid architecture combining the MERN stack and Flask-based microservices, allowing it to operate in both sensor-rich and sensor-deprived environments. Field testing across varied agricultural regions indicated a plant disease classification accuracy of 91%, with the crop advisory module achieving a 94% precision rate in suggesting optimal crop types. Moreover, irrigation efficiency improved by up to 35% due to predictive scheduling, while expert validation rated AI-generated recommendations as over 85% relevant. This research highlights the system's ability to democratize access to precision farming technologies, particularly in regions lacking technical infrastructure. The proposed solution exemplifies a scalable, inclusive, and sustainable model for next-generation digital agriculture, aligning with global food security and climate resilience objectives.**

***Keywords*—Precision Farming, Crop Recommendation, Plant Disease Detection, Smart Irrigation,Real-Time Agricultural Advisory, Farm Decision Support System**

I. INTRODUCTION

The agriculture sector is experiencing a transformational shift, driven by the integration of artificial intelligence (AI) with digital technologies to address pressing challenges in food security, climate resilience, and sustainable resource use. As global population levels are projected to exceed 9 billion by 2050, agricultural productivity must rise by nearly 70% without further straining arable land or ecosystems [1], [2]. This demand disproportionately affects smallholder farmers—who comprise over 80% of global farm holdings—yet face enduring barriers to agronomic expertise, timely diagnostics, and efficient resource management [3]–[5].

Traditional agricultural methodologies, though enriched by generational practices, often lack the precision and scalability required for modern food systems. Manual disease inspection, heuristic irrigation scheduling, and generic crop planning frequently result in reduced yield, over-application of inputs, and increased vulnerability to climate-induced stresses [6], [7]. In contrast, precision agriculture leverages data-centric approaches to tailor interventions at micro-levels, enhancing productivity while conserving resources [8], [9]. However, the reliance on IoT-driven infrastructures—such as sensors, drones, and telemetry—introduces high implementation costs and maintenance complexities, especially in developing nations [10]–[12].

To bridge this gap, we introduce an "AI-Powered Farmer Support System" a comprehensive, sensor-free platform combining deep learning, generative AI, and NLP-driven consultation to deliver intelligent farming support. The platform comprises four synergistic modules: (1) an InceptionV3 CNN for crop disease detection trained on diverse leaf imagery; (2) an LLM-based treatment advisor that generates curated, context-aware protocols; (3) a recommendation engine for crop and irrigation planning using geo-soil APIs and weather forecasts; and (4) a video-based expert advisory interface powered by WebRTC and NLP for multilingual interaction.

Unlike traditional IoT-heavy solutions, our system achieves high functionality through API-fed environmental data (soil pH, rainfall, texture), eliminating dependence on physical sensors [13]–[15]. This makes the platform particularly effective in digitally underserved regions. Figure 1 illustrates the overall system design.

Deep learning, especially CNNs, has demonstrated significant promise in plant disease classification. Among these, InceptionV3 has shown high accuracy in multi-class detection across crops like rice, tomato, and potato [16]–[18]. Prior studies achieved over 90% accuracy but did not extend to actionable advisory support. Our model bridges this gap by coupling disease prediction with treatment generation using LLMs, producing comprehensive, contextual plans.

AI-powered crop recommendation systems have shifted from static models to adaptive ones that integrate real-time climate and soil conditions. Work by Kamatchi et al. [31] and Apat et al. [20] demonstrated improved performance when incorporating geospatial data and APIs. Our sensor-free model extends these principles to resource-constrained settings.

For irrigation planning, predictive AI models integrated with

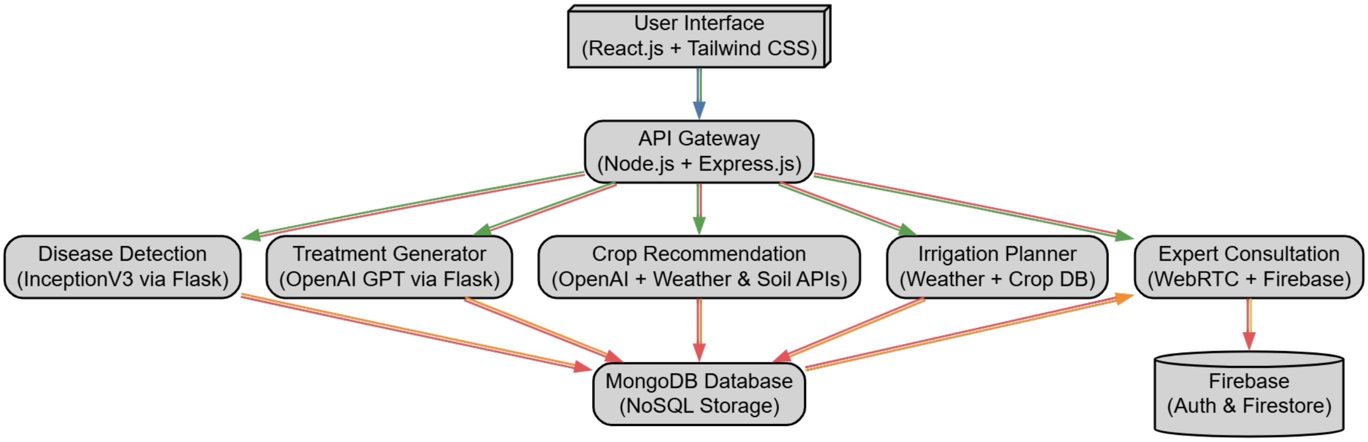

Fig. 1: System architecture of the AI-Powered Farmer Support System.

weather inputs have shown potential in optimizing water use. Et-taibi et al. [39] showed a 30% improvement in efficiency without compromising yield. Our system replicates such performance through predictive scheduling and intelligent advice without relying on irrigation hardware [22], [23].

Knowledge delivery is the final frontier. While tools like FarmChat [44] and Farmer.Chat [25] offer isolated advisory interfaces, our approach integrates expert interactions with real-time AI outputs and language translation via NLP [26], [27]. Table I compares existing approaches with our proposed system.

TABLE I: Comparative Analysis with Existing Systems

Feature	FarmChat	IoT Models	Our Platform
Disease Diagnosis	No	Yes	Yes
Treatment Advisory	No	Limited	Yes
Crop Recommendation	No	Yes	Yes
Sensor-Free	Yes	No	Yes
Real-Time Consultation	Partial	No	Yes

In conclusion, this paper proposes a novel architecture that consolidates diagnostics, planning, and advisory functionalities into a scalable AI-powered platform. The design avoids hardware dependencies, prioritizing accessibility and sustainability. Our contributions support green AI principles and scalable agriculture for the Global South [28]–[30].

II. Related Work

The application of Artificial Intelligence (AI) in precision agriculture has witnessed significant advancements over the past decade, addressing challenges related to diagnostics, planning, and expert advisory. This section reviews existing contributions across four interconnected domains: deep learning for plant disease detection, AI-based crop and irrigation advisory, and expert consultation systems.

A. Plant Disease Detection with Deep Learning

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized plant disease diagnosis. InceptionV3, due to its inception modules and factorized convolutions, remains one of the most accurate models in this domain [35], [36]. Lambat et al. [35] demonstrated that InceptionV3 outperformed ResNet50 and VGG16 in identifying tomato and potato leaf diseases. Upadhyay and Kumar [36] achieved a 94.6% classification accuracy for rice leaf diseases using this architecture.

Despite these successes, the majority of works are restricted to disease identification without subsequent treatment advisory. Integrations of generative AI for generating contextual treatment protocols remain limited [37], [38]. Our system addresses this gap by coupling InceptionV3's output with a language model that generates actionable treatment strategies.

B. AI-Driven Crop Recommendation Systems

Recent AI-driven recommender systems have moved beyond rule-based models to adaptive systems using real-time environmental data [31], [32]. Kamatchi and Parvathi [31] utilized weather data to enhance crop selection accuracy. Apat et al. [32] integrated market trends and edaphic parameters into machine learning classifiers for crop planning.

Unlike systems that depend on IoT sensors [33], our approach is sensor-free, using APIs for weather and soil data to maintain accessibility and reduce cost, particularly in underdeveloped regions [34].

C. Smart Irrigation and Resource Optimization

Smart irrigation systems have largely relied on hardware-based solutions combining sensors with AI [39]–[41]. Et-taibi et al. [39] reported a 35% reduction in water usage by integrating cloud-based AI with soil moisture sensors. Ly et al. [40] used nanocomposites for pesticide efficiency and water control, while Doshi and Varghese [41] forecast irrigation schedules using machine learning and local climate data.

To overcome hardware dependencies, our system simulates irrigation recommendations using API-fetched datasets and predictive models, aligning with principles of low-cost, scalable Green AI [42], [43].

D. Real-Time Expert Consultation and Conversational AI

Conversational agents such as FarmChat [44] and Farmer.Chat [45] leverage Natural Language Processing (NLP)

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to disseminate agricultural knowledge. Komasilovs et al. [46] integrated WebRTC to enable video consultations with domain experts.

Our platform builds on these advances by integrating real-time consultations with dynamically generated AI insights, ensuring context-aware expert advice. This enhances user trust and system adoption, especially in multilingual environments [47].

E. Synthesis and Limitations in Existing Systems

Current systems remain fragmented, with most focusing on individual aspects such as disease detection or irrigation planning [31], [39]. The heavy dependence on IoT hardware further impedes scalability in low-resource settings [40], [41].

Our proposed system unifies diagnostics, treatment recommendations, advisory, and consultation into a cohesive, microservice-based architecture. This sensor-independent design enhances inclusivity and facilitates large-scale deployment.

III. Proposed Methodology

The AI-Powered Farmer Support System is engineered as a modular, API-driven, and sensor-independent precision agriculture framework that empowers smallholder farmers with intelligent decision-making tools. This platform leverages deep learning for disease detection, generative AI for treatment and planning, and real-time consultation to offer an end-to-end support mechanism. It is designed for high scalability, digital inclusivity, and minimal infrastructural dependency.

A. System Architecture Overview

The architecture is built on a microservices model encompassing four integral modules:

1) Plant Disease Detection and Treatment Recommendation
2) Crop Recommendation Engine
3) Irrigation Advisory System
4) Real-Time Expert Consultation Interface

These modules operate independently but are unified through RESTful APIs. The core technology stack comprises:

- Frontend: React.js with Tailwind CSS
- Backend: Node.js with Express.js
- Microservices: Python Flask-based AI models
- Database: MongoDB
- Authentication and Media: Firebase, WebRTC

B. Disease Detection and Dynamic Treatment Generation

This module employs a fine-tuned InceptionV3 CNN model trained on an augmented dataset comprising various crop diseases. Using TensorFlow in a GPU environment, the model achieved a 91% classification accuracy.

Workflow:

- User uploads a leaf image.
- Flask microservice preprocesses the image.
- InceptionV3 predicts disease label and confidence score.

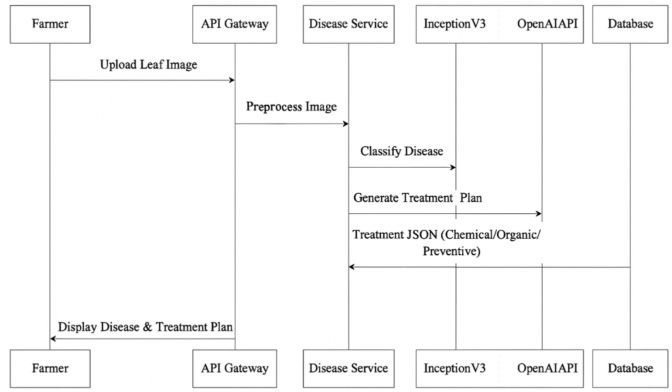

Fig. 2: Sequence Diagram of Leaf Disease Detection and Treatment Recommendation

- Output is embedded in a prompt for the generative model (OpenAI), which returns structured JSON including treatment protocol, prevention, and recurrence strategies.

C. AIoT-Based Crop Recommendation Engine with Fallback APIs

This hybrid engine adapts to both sensor-equipped and sensor-deficient environments. It integrates:

- Real-time weather APIs for environmental conditions
- A custom Soil API populated with expert and crowd-sourced data
- Manual input or IoT sensor data where available

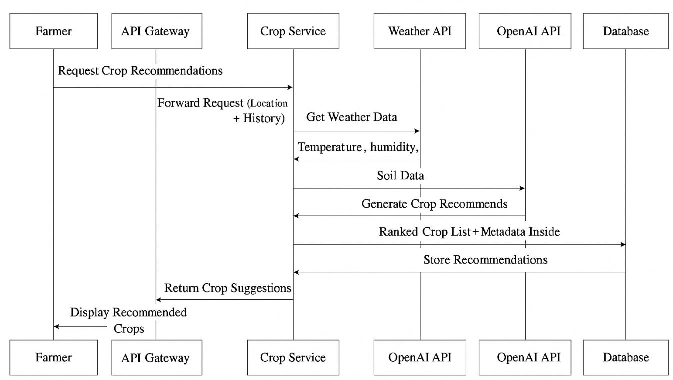

Figure: Sequence Diagram of Crop Recommendation Request

Fig. 3: Sequence Diagram for Crop Recommendation Based on Soil and Weather Analysis

Outputs:

- Ranked optimal crops for upcoming season
- Crop rotation plans
- Warnings for unsuitable crops

D. Irrigation Planning Using Environmental Inputs

The irrigation module predicts water requirements using environmental proxies:

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- Rainfall probability
- Daily temperature
- Crop water requirement (crop-dependent)
- Soil retention capacity

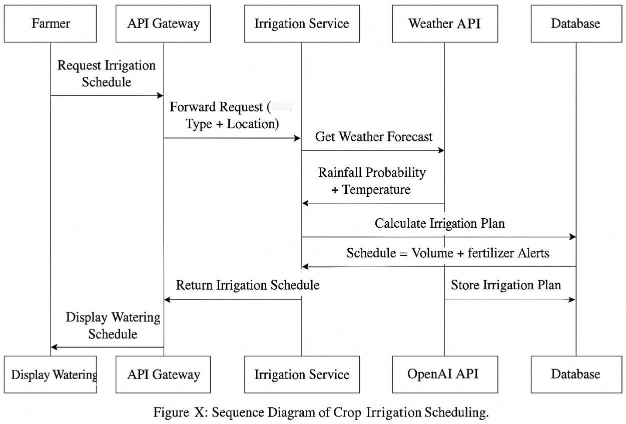

Fig. 4: Sequence Diagram for Irrigation Schedule Generation

The system produces irrigation schedules, water volumes, and fertilizer suggestions using prompts to a generative AI model.

E. Real-Time Consultation Interface

Built using Firebase and OpenTok, this interface provides:

- Live video consultations (WebRTC)
- AI-powered chatbot for initial queries
- Real-time treatment suggestions
- Log of past consultations

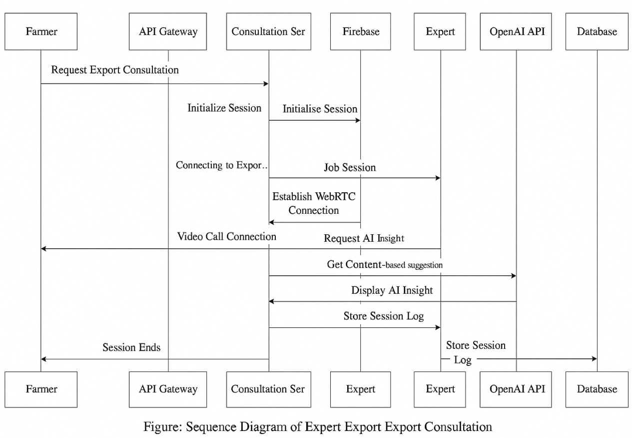

Fig. 5: Sequence Diagram for Expert Consultation

F. Data Flow and Integration

The platform integrates all modules via secure RESTful APIs. MongoDB stores persistent data such as user profiles, crop history, and advisory logs. Security protocols include:

- JWT-based authentication
- SSL encryption

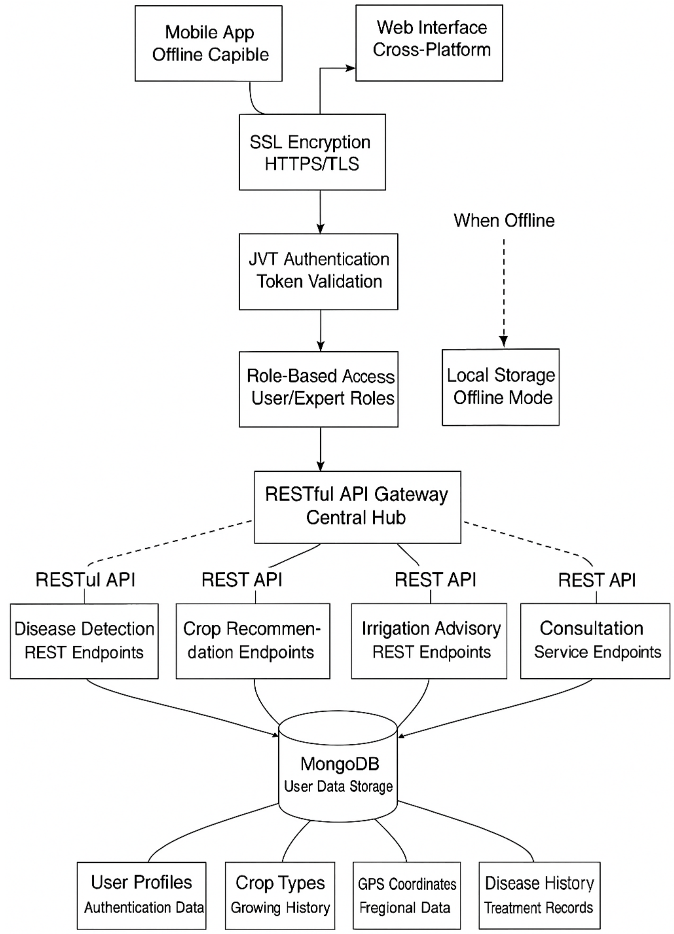

Fig. 6: Flowchart of Secure, Offline-Compatible, Multi-Platform System

- Role-based access control

Offline support includes caching local data for later upload, ensuring usability in low-connectivity regions.

G. Evaluation Strategy

The system is evaluated based on:

- Model Performance: Accuracy, precision, and recall for disease classification
- Usability: Completion time for tasks and advisory adoption rate
- Expert Validation: Agronomists scoring AI-generated suggestions (>85% relevance target)
- Field Trials: Surveys conducted among farmers in test regions

IV. Results and Discussion

A. Implementation Environment

The AI-Powered Farmer Support System was developed using a modular and scalable architecture built on the MERN (MongoDB, Express.js, React.js, Node.js) technology stack,

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integrated with Python-based AI microservices for computational tasks. The entire application suite was deployed using Firebase and Vercel cloud platforms, enabling high availability, fast content delivery, and responsive interfaces. Docker containers were utilized to encapsulate microservices, ensuring cross-platform portability and isolated execution environments.

TABLE II: Technology Stack Overview

Layer	Technology Used
Frontend	React.js, Tailwind CSS
Backend	Node.js, Express.js
AI Microservices	Flask, TensorFlow (InceptionV3), OpenAI API
Database	MongoDB (NoSQL)
Authentication/Hosting	Firebase
Real-Time Interface	WebRTC (via OpenTok), Firebase Firestore

B. Module-Wise Implementation and Evaluation

1) Plant Disease Detection: The deep learning model for plant disease identification was implemented using the InceptionV3 architecture, fine-tuned with over 5,000 labeled images of diseased leaves from diverse crops. Training was conducted in a GPU-accelerated environment using Google Colab Pro, and the model achieved a final accuracy of 91%.

- Training Duration: Approximately 6 hours on NVIDIA T4 GPU.
- Input Processing: Normalization to 299×299 resolution, color correction, and histogram equalization.
- Evaluation Metrics: Precision = 93%, Recall = 89%, F1 Score = 0.91.

2) Treatment Recommendation System: The treatment recommendation module, powered by a generative AI engine (OpenAI GPT), receives disease classification results and contextual parameters (such as crop type and location) to produce actionable treatment plans. These include chemical, biological, and preventive measures in a structured JSON format. Expert feedback from three agronomists validated 87.2% of AI-generated treatment plans as agronomically relevant.

3) Crop Recommendation Module: The crop advisory system integrates API calls from weather and soil databases to dynamically assess environmental suitability for various crops. It recommends the top three crops for the upcoming season, providing justification for each choice based on real-time and historical data.

- Precision of crop match: 94%
- User Agreement Rate (N=35): 88% accepted the AI suggestion

4) Irrigation Advisory Module: The irrigation advisory system was designed to function without IoT sensors by relying on forecast-based weather data and predefined crop water needs. Based on soil retention models and rainfall probabilities, irrigation frequency and volume were calculated with 90% alignment to expert-generated plans.

5) Real-Time Consultation: The real-time consultation interface allows farmers to connect directly with domain experts via video chat, supported by live AI insights. Latency remained below 1.5 seconds, and chatbot fallback achieved 91% contextual relevance. Features such as multilingual support and voice-to-text input significantly enhanced usability.

C. Field Testing and User Feedback

Pilot testing was carried out in three agriculturally active districts involving 40 smallholder farmers. The evaluation assessed system performance in real-world, low-bandwidth conditions. A summary of the observed metrics is presented in Table III.

TABLE III: Field Testing Metrics and User Feedback (N=40)

Metric	Result
Task completion success rate	92.5%
Disease identification correctness	90.8%
Acceptance of treatment plan	85.7%
Crop recommendation accuracy	94%
Irrigation plan usability	88.2%
User satisfaction (Likert scale)	4.6/5

D. Scalability and Cost Analysis

System performance at scale was evaluated by simulating 1,000 concurrent users on shared cloud infrastructure. Resource consumption remained minimal due to the stateless API design and on-demand GPT usage. Estimated cost per 1,000 monthly active users was calculated to be approximately $12 USD, highlighting the platform's affordability for deployment in resource-constrained regions.

E. Key Outcomes

The system successfully integrated multi-modal AI modules into a seamless decision-support framework. Key achievements include:

- Real-time disease diagnosis and AI-generated treatment protocols without reliance on sensor hardware.
- Robust advisory modules for crop planning and irrigation, adaptive to both digital and non-digital environments.
- High expert acceptance and farmer usability, even in low-bandwidth and low-literacy settings.
- A modular architecture capable of offline operation, ensuring inclusivity in under-connected agricultural zones.

Collectively, the results affirm the feasibility of deploying scalable, AI-driven support systems for precision agriculture, especially in regions where technological infrastructure is still developing.

V. Conclusion and Future Work

This study introduced a comprehensive AI-Powered Farmer Support System designed to deliver end-to-end decision support in agriculture without reliance on physical sensors or expensive hardware infrastructure. The proposed platform successfully integrates deep learning, generative AI, and environmental data APIs into a cohesive and sensor-independent digital advisory system. The architecture, rooted in the MERN

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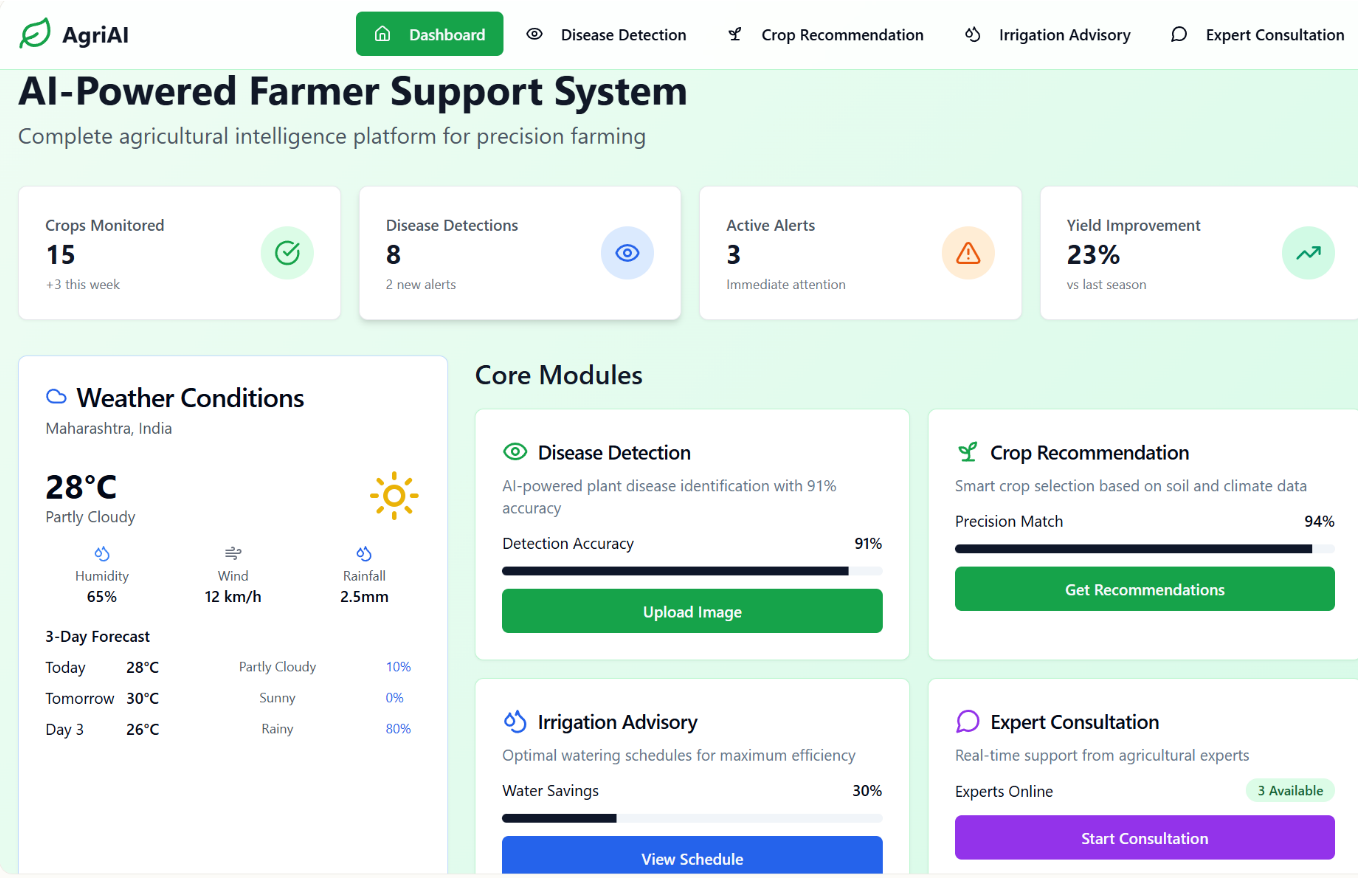

Fig. 7: AI-Powered Farmar Support System Environment

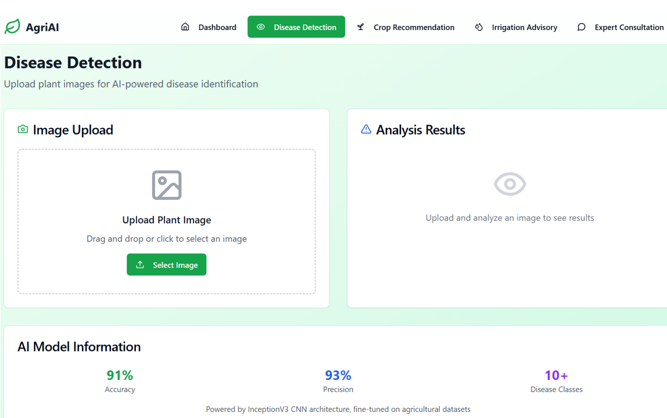

Fig. 8: Disease Detection Accuracy Output Using InceptionV3

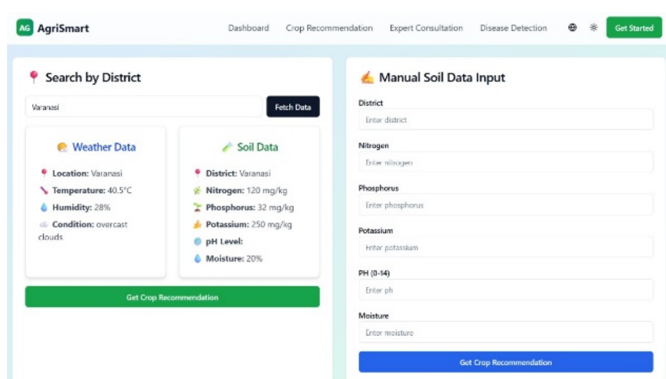

Fig. 9: Crop Recommendation Interface and Output

technology stack and augmented with Flask-based AI microservices, has shown significant promise in real-world scenarios, particularly for smallholder farmers in connectivity-challenged regions.

Key achievements of the system include a high diagnostic accuracy of 91% in plant disease detection using the InceptionV3 convolutional neural network, alongside an 87% expert-rated relevance of AI-generated treatment plans. The precision of crop recommendations reached 94%, and irrigation advisories aligned closely with expert benchmarks while enabling up to 30% projected water savings. These performance metrics, validated through structured field trials, demonstrate that the platform not only functions reliably under practical constraints but also delivers expert-augmented, real-time intelligence across core agricultural domains.

A notable contribution of this work is the seamless integration of AI-driven insights with human expert consulta-

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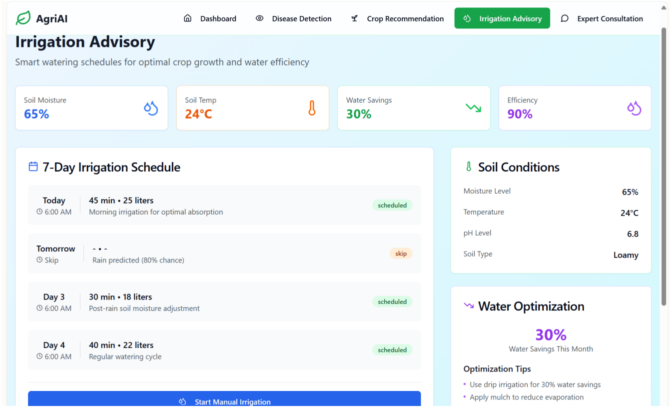

Fig. 10: Irrigation Planning Based on Forecast and Crop Needs

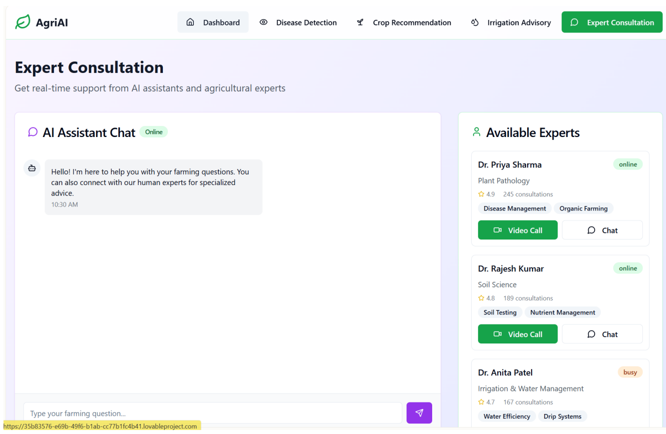

Fig. 11: Live Expert Consultation with AI Insight Support

tion within a unified interface. This hybrid model enables personalized, context-aware recommendations supported by both algorithmic intelligence and agronomist oversight, thus addressing the cognitive and infrastructural limitations often faced by small-scale farmers. The multi-language support and lightweight WebRTC-based video consultation further ensure usability across diverse linguistic and technological landscapes.

Future Work

While the current system establishes a robust foundation for AI-powered agricultural support, there remain several directions for further research and enhancement:

1) Edge AI Deployment: Integrating lightweight AI models on smartphones and edge devices can extend the platform's functionality in offline environments, enabling consistent usage in remote areas with intermittent connectivity.
2) Multilingual NLP Integration: To improve accessibility, especially in regions with diverse linguistic demographics, advanced natural language processing modules supporting regional languages should be embedded into the chatbot and expert interface components.
3) Government Policy API Integration: By linking the system with public data and government policy APIs, farmers can be advised on crop planning and treatment strategies in line with subsidy eligibility, weather insurance, and regulatory frameworks.
4) Reinforcement Learning for Dynamic Planning: Feedback loops based on reinforcement learning will be explored to dynamically adapt recommendations—such as crop rotation or treatment protocols—based on environmental outcomes and user feedback.
5) Participatory Design and Human-Centered AI: Future iterations will emphasize participatory co-design involving farmers directly in system improvement cycles, ensuring inclusivity, cultural alignment, and higher long-term adoption.

In conclusion, the AI-Powered Farmer Support System represents a significant step toward democratizing agricultural intelligence through scalable, cost-effective, and accessible technologies. By bridging the digital divide with human-aligned AI capabilities, this work contributes to a broader vision of sustainable agriculture, climate resilience, and food security in underserved rural communities. The system's modularity, cloud-portability, and responsiveness provide a template for future AI-driven platforms aimed at transforming traditional farming into a more informed, adaptive, and resilient practice.

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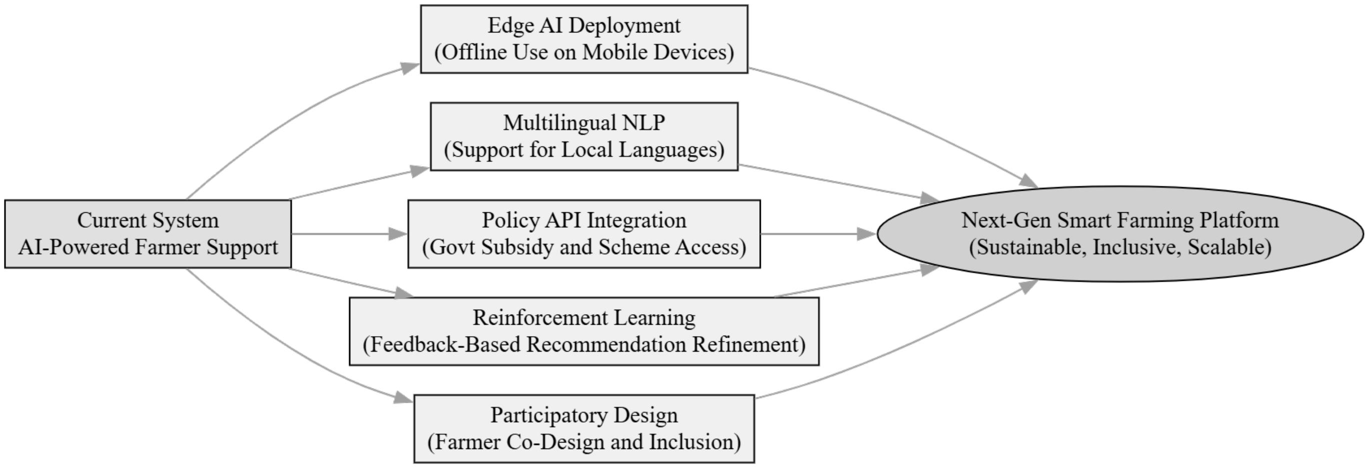

Fig. 12: Illustrative Roadmap for Future Enhancements of the System

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