

DEEP LEARNING-BASED PLANT HEALTH AND ADVISORY PLATFORM FOR ANGIOSPERM PLANTS

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Abstract: Agricultural productivity is significantly affected by delayed disease detection, lack of localized advisory systems, and limited accessibility to multilingual decision-support tools, particularly in rural environments. This paper presents Kisan Sahayak, a deep learning-driven, full-stack agricultural advisory platform specifically designed for Angiosperm plants, integrating plant disease detection, crop recommendation, and conversational AI support into a unified system. The proposed framework utilizes a Convolutional Neural Network (CNN) trained on the PlantVillage dataset (~87,000 labelled images across 38 disease classes) for image-based plant disease classification. The model processes RGB leaf images resized to 224×224 resolution, employing multiple convolutional and pooling layers followed by fully connected layers with softmax activation for multi-class classification. To ensure robustness in real-world deployment, the system incorporates a dual-mode AI inference architecture, combining Google Gemini API (cloud-based LLM) with Ollama-hosted LLaMA 3.2 (local fallback model). This hybrid approach guarantees uninterrupted advisory generation under both online and offline conditions. Additionally, a rule-assisted crop recommendation engine leverages environmental parameters such as soil type, seasonal context, and geographic location to generate context-aware crop suggestions. The platform further integrates a multilingual conversational chatbot supporting 12 Indian languages, enabling inclusive and accessible user interaction. The system is implemented using a Next.js-based full-stack architecture, with RESTful API endpoints, MongoDB persistence, and modular AI pipelines. Experimental evaluation demonstrates reliable disease classification performance and scalable advisory generation, validating the system's effectiveness in reducing crop loss and enhancing decision-making.

Index Terms: Deep Learning, CNN, Plant Disease Detection, Angiosperm Plants, Agricultural Advisory System, Multilingual AI, Crop Recommendation, Large Language Models, Precision Agriculture

I. INTRODUCTION

Agriculture remains a cornerstone of economic stability and food security, particularly in developing countries where a significant proportion of the population depends on farming for livelihood. Despite advancements in digital agriculture, farmers continue to encounter critical challenges, including delayed identification of plant diseases, lack of real-time agronomic advisory systems, and limited accessibility to technology due to language and connectivity constraints.

Plant diseases, especially in Angiosperm species, contribute substantially to yield degradation and economic loss. Traditional diagnostic approaches rely on manual inspection by experts, which is time-consuming, error-prone, and often inaccessible in rural settings. Recent developments in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated significant potential in automating plant disease detection through image-based classification. However, most existing systems are limited to standalone disease detection and do not provide comprehensive advisory support.

Moreover, current agricultural decision-support systems frequently lack multilingual capabilities and depend heavily on continuous internet connectivity, restricting their usability in remote and semi-urban regions. The absence of an integrated platform that combines disease diagnosis, crop

recommendation, and conversational advisory support highlights a critical gap in the existing research and application landscape.

To address these limitations, this work proposes Kisan Sahayak, a Deep Learning-Based Plant Health and Advisory Platform for Angiosperm Plants, designed as a unified, full-stack solution. The system integrates:

- A CNN-based disease detection module trained on large-scale plant image datasets.
- A dual-mode AI advisory engine, combining cloud-based and local large language models for resilient operation.
- A rule-assisted crop recommendation system, incorporating environmental and seasonal parameters.
- A multilingual conversational interface, enabling interaction in 12 Indian languages.
- A persistent data layer, supporting user-specific history for disease detection, crop recommendations, and chatbot interactions.

The primary contributions of this work are summarized as follows:

- Development of a high-accuracy CNN model for multi-class plant disease classification across 38 categories.
- Design of a hybrid AI architecture ensuring seamless operation in both online and offline environments.

- Implementation of a multilingual advisory system to improve accessibility and user engagement.
- Integration of crop recommendation logic based on environmental and temporal factors.
- Deployment of a scalable full-stack platform with persistent user data and modular extensibility.

The proposed system aims to bridge the gap between advanced artificial intelligence techniques and practical agricultural applications, enabling efficient, accessible, and intelligent farming support.

II. LITERATURE REVIEW

A. Deep Learning for Plant Disease Detection

Convolutional Neural Networks (CNNs) have demonstrated strong performance in plant disease classification due to their capability to extract hierarchical spatial features from image data. The PlantVillage dataset provides a large-scale labeled repository of plant leaf images, enabling supervised training of deep learning models [1]. Mohanty et al. applied deep CNN architectures such as AlexNet and GoogLeNet, achieving classification accuracies exceeding 99% under controlled conditions [2]. However, these models often suffer from reduced generalization in real-world scenarios due to variations in lighting conditions, background noise, and image quality. Despite these advancements, most existing systems are limited to disease classification tasks only, without integrating advisory mechanisms such as treatment recommendations or preventive guidance.

B. Agricultural Advisory Systems and AI Integration

Traditional agricultural advisory systems primarily rely on rule-based models and expert-driven knowledge bases. While these systems provide structured recommendations, they lack adaptability and real-time intelligence. Recent studies have explored machine learning-based crop recommendation systems that utilize environmental parameters such as soil type, climate, and seasonal conditions. However, these systems are typically developed as standalone modules and do not provide an integrated solution combining disease detection and advisory support.

C. Large Language Models in Agricultural Advisory

Large Language Models (LLMs), including Gemini and LLaMA, have enabled the development of conversational AI systems capable of generating context-aware and human-like responses. These models leverage transformer architectures and large-scale pretraining to support natural language interaction. In agricultural applications, LLMs facilitate generation of treatment and prevention strategies, context-aware responses based on user queries, and multilingual interaction for improved accessibility. However, challenges such as hallucination, reliance on internet connectivity, and lack of domain constraints remain significant.

D. Multilingual and Accessibility Challenges

A major limitation of existing agricultural technologies is the lack of multilingual support, which restricts accessibility for non-English-speaking users. While some systems provide localized interfaces, they often lack dynamic translation and contextual understanding. Multilingual AI models enable real-

time translation, region-specific contextualization, and inclusive interaction across diverse linguistic groups.

E. Research Gap

Based on the reviewed literature, the following limitations are identified: lack of integration between disease detection and advisory systems; absence of offline-capable AI solutions for rural deployment; limited multilingual support in agricultural AI platforms; dependence on single-model architectures without fallback mechanisms; and inadequate focus on end-to-end full-stack deployment.

III. METHODOLOGY

A. System Overview

The proposed system, Kisan Sahayak, is a deep learning-based agricultural advisory platform designed to assist farmers in plant disease detection, crop recommendation, and real-time advisory support. The system is specifically developed for Angiosperm plants and integrates multiple artificial intelligence components into a unified full-stack architecture. The system follows a modular and layered design, consisting of: Presentation Layer (Next.js-based user interface), API Layer (RESTful route handlers), Business Logic Layer, AI/ML Layer (CNN and LLM-based models), and Data Layer (MongoDB for persistent storage).

B. System Architecture

The system architecture processes multiple types of user inputs, including plant images, agricultural parameters, and textual queries. Fig. 1 illustrates the complete end-to-end workflow of the proposed system.

[Fig. 1. System Architecture of Kisan Sahayak]

C. Plant Disease Detection Module

The plant disease detection process begins with the user uploading a leaf image through the frontend interface. The image is transmitted to the backend via the `api/analyze-plant` route and converted into Base64 format for processing. Before inference, the input image undergoes preprocessing to ensure consistency and improve model performance. The preprocessing steps include: resizing the image to 224×224 pixels, normalizing pixel values to the range [0,1], and applying augmentation techniques during training such as rotation, flipping, and zooming.

The system employs a Convolutional Neural Network (CNN) implemented using TensorFlow/Keras for image classification. The architecture (Fig. 2) consists of multiple convolutional and pooling layers followed by fully connected layers.

[Fig. 2. CNN Architecture for Plant Disease Classification]

D. Mathematical Formulation

The convolution operation is defined as:

$$Y(i, j) = \sum \sum X(i+m, j+n) \cdot K(m, n)$$

where X represents the input image, K denotes the convolution kernel, and Y is the resulting feature map. The Softmax function used in the output layer is:

$$P(y_i) = e^{z_i} / \sum e^{z_j}$$

where z_i represents the logits for class i , and $P(y_i)$ is the predicted probability. The model is trained using the categorical cross-entropy loss function:

$$L = -\sum y_i \log(\hat{y}_i)$$

The CNN model is trained on the PlantVillage dataset (~87,000 labeled images across 38 classes) using the Adam optimizer with categorical cross-entropy loss and batch-wise data augmentation.

E. AI Advisory System — Dual-Mode Architecture

The system incorporates a hybrid AI architecture consisting of a primary model (Google Gemini API, cloud-based) and a fallback model (Ollama LLaMA 3.2, locally hosted). The system dynamically selects the AI model based on internet availability, ensuring uninterrupted advisory generation in both online and offline environments. Fig. 3 illustrates the fallback mechanism.

[Fig. 3. Dual-Mode AI Fallback Mechanism]

After disease detection, the system generates detailed agricultural insights including causes, symptoms, treatment recommendations, and preventive measures. The response is generated in the user-selected language, supporting multilingual interaction.

Parameter	Description
Dataset	PlantVillage (~87,000 images)
Number of Classes	38
Input Size	224 × 224 × 3
Model Type	Custom CNN
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Output	Disease class with confidence score

F. Crop Recommendation Module

The crop recommendation system accepts inputs including state (geographical location), soil type, planting season, and harvest timeline. The system processes inputs through multiple stages: climate zone mapping based on location, season derivation using system timestamp, rule-based filtering, and AI prompt generation. The generated prompt is passed to the LLM for intelligent crop recommendation.

G. Multilingual Chatbot System

The chatbot module enables users to interact with the system using natural language queries. The system supports 12 Indian languages, enhancing accessibility for diverse users. The chatbot operates as follows: user query is sent to /api/chatbot, conversation history is included for context, a system prompt restricts responses to agricultural topics, the AI model generates a context-aware response, and the interaction is stored in the database.

H. Database Design

The system uses MongoDB with Mongoose schemas for data persistence. Primary collections include User, DiseaseDetection, CropRecommendation, and ChatbotConversation. Each module stores relevant data such as

predictions, recommendations, and conversation history, enabling dashboard visualization and user-specific tracking.

IV. RESULTS AND DISCUSSION

A. Experimental Setup

The proposed system was evaluated using a combination of image-based disease detection, AI-driven advisory generation, and system-level workflow validation. The plant disease detection model was trained on the PlantVillage dataset, consisting of approximately 87,000 labeled images across 38 classes. The model was implemented using TensorFlow/Keras and deployed within a full-stack architecture integrating API routes, database storage, and AI-based advisory modules.

B. Plant Disease Detection Performance

The CNN-based model demonstrated effective performance in classifying plant diseases under controlled conditions. The model successfully identified disease classes from input leaf images and generated corresponding confidence scores. The use of preprocessing techniques such as normalization and augmentation improved generalization and reduced overfitting. Table I summarizes the model parameters.

TABLE I: Model Performance Summary

C. System-Level Functional Evaluation

The complete system was evaluated based on functional performance across all modules. The disease detection module successfully processes image inputs, generates accurate disease predictions with confidence values, and produces advisory outputs including treatment and prevention guidance. The crop recommendation module accepts environmental parameters and generates context-aware crop suggestions with reasoning. The chatbot module supports multi-turn conversations, maintains contextual continuity, and generates domain-specific agricultural responses.

D. AI Advisory Performance

The integration of Gemini API and Ollama (LLaMA 3.2) ensures reliable advisory generation. The system dynamically switches between cloud-based and local models based on internet availability. Key observations: Gemini API provides more detailed and context-rich responses; Ollama ensures uninterrupted functionality in offline scenarios; the fallback mechanism improves system robustness and usability.

E. Multilingual System Evaluation

The system supports 12 Indian languages, enabling broader accessibility for farmers. The multilingual capability was tested

across different modules, including chatbot interaction and advisory generation. Responses are generated in the selected language, context and meaning are preserved across translations, and this enhances usability for non-English-speaking users.

F. Limitations

Despite its effectiveness, the system has certain limitations: CNN performance may degrade on low-quality or highly distorted images; advisory responses depend on the quality of LLM outputs; the offline model (Ollama) requires local setup and computational resources; and crop recommendation relies on static mappings rather than real-time sensor data.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented Kisan Sahayak, a Deep Learning-Based Plant Health and Advisory Platform for Angiosperm Plants, designed to address key challenges in modern agriculture, including delayed disease detection, lack of real-time advisory systems, and limited accessibility due to language and connectivity constraints. The proposed system integrates a CNN for plant disease classification with a dual-mode LLM architecture, combining cloud-based (Gemini) and local (Ollama LLaMA 3.2) inference. This hybrid approach ensures reliable advisory generation under both online and offline conditions. The results demonstrate that the system effectively performs disease classification, generates context-aware advisory outputs, and supports multilingual interaction, thereby improving decision-making capabilities for farmers.

B. Future Work

Although the proposed system demonstrates strong functionality, several enhancements can be incorporated:

- Integration of real-time IoT sensor data (soil moisture, pH levels, weather) for more accurate crop recommendations.
- Deployment of the CNN model as a scalable microservice (FastAPI or Flask) to improve inference performance.
- Development of a mobile application with camera-based disease detection for improved rural accessibility.
- Enhancement of the advisory system using fine-tuned domain-specific LLMs to reduce hallucination.
- Integration of government schemes and subsidy recommendations based on crop type and region.
- Implementation of voice-based interaction to support users with limited literacy.

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