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CAREPLANTIFY: AGENTIC AI FOR SMART CROP ADVISORY USING CNN AND GEMINI VISION

Pankaj Vaishnav, Rhythm Sharma, Lovenesh Giri Goswami, Rakshit Sanadhya
Department of Computer Science and Engineering
Geetanjali Institute of Technical Studies (GITS) Dabok, Udaipur, India
pankaj.vaishnav@gits.ac.in, rhythm22sharma@gmail.com, lovenesh73@gmail.com, sanadhyarakshit@gmail.com

Abstract*:* A majority of small and marginal farmers in India continue to rely on traditional knowledge and local intermediaries for critical decisions related to crop selection, pest management, and fertilizer use. These practices frequently lead to reduced crop yields, excessive input costs, and environmental degradation. This paper presents a Smart Crop Advisory System that integrates Agentic AI and Generative AI (GenAI) with Convolutional Neural Networks (CNN) and Gemini Vision for plant disease detection, soil-test-based fertilizer recommendation, and multilingual conversational support.

The core novelty lies in an agentic decision pipeline where an uploaded leaf image is processed in parallel by a fine-tuned CNN model for high-accuracy classification and Gemini Vision for contextual visual reasoning. The AI agent fuses these outputs to deliver a grounded crop health advisory that balances quantitative precision with qualitative explainability. The system further addresses specific regional needs by providing real-time, location-specific, and voice-enabled advisory in languages including Hindi, Rajasthani, and Punjabi, Experimental evaluation demonstrates that the CNN model achieves a classification accuracy of 98.3% on plant diseases, while the fertilizer recommendation engine attains an accuracy of 94.7% against laboratory-validated prescriptions. The agentic architecture enables autonomous multi-step task execution with a 95.5% success rate and an average response time of 4.1 seconds, significantly reducing farmer decision-making latency.

Keywords: Agentic AI, Generative AI, CNN, Plant Disease Detection, Fertilizer Recommendation, Smart Agriculture, Multilingual Chatbot, Small Farmers, Crop Advisory

I. INTRODUCTION

Agriculture remains the backbone of the Indian economy, sustaining approximately 86% of farmers who belong to the small and marginal category [1]. Whilst these farmers constitute a vast majority, they remain the most vulnerable segment in terms of access to modern agricultural inputs and expert advice. Crop diseases, uninformed fertilizer application, and lack of timely weather-based alerts together account for significant loss of produce every year. Studies have demonstrated that Information and Communication Technology (ICT)-based advisory systems can increase crop yield by 20–30% [2]. Traditional approaches to disease detection, such as manual inspection by agricultural scientists or local extension officers, are highly labour- intensive and not scalable to the distributed geography of rural India. Earlier work by the present authors [3] demonstrated the feasibility of using CNN-based image processing for potato plant disease classification, achieving promising results on the PlantVillage dataset. However, that earlier system was limited to disease detection alone and did not incorporate soil-test-based fertilizer guidance, agentic task execution, or generative conversational AI. The recent emergence of Agentic AI frameworks, which enable Large Language Models (LLMs) to autonomously plan, reason, and execute multi-step tasks by invoking external tools and APIs, present an unprecedented opportunity to build holistic crop advisory systems. Similarly, Generative AI technologies such as GPT-4, Gemini, and open-source alternatives enable natural language interaction, making expert-level guidance accessible even to low-literacy users through voice and text in regional languages. This paper proposes a unified Smart Crop Advisory System that addresses the following critical gaps identified in current agricultural technologies:

- Lack of real-time, personalized, and location-specific crop advisory: Most existing systems offer generic information that does not account for the specific microclimatic conditions of smallholder farms.
- Absence of integrated soil-nutrient analysis: There is a significant disconnect between disease detection tools and fertilizer recommendation modules, preventing a holistic approach to crop health.
- Barriers to accessibility: The lack of multilingual or voice-enabled interfaces remains a primary obstacle for low-literacy users in rural regions.

II. LITERATURE REVIEW

A. CNN-Based Plant Disease Detection

Convolutional Neural Networks have emerged as the dominant paradigm for automated plant disease recognition from leaf images. Jadhav et al. [4] employed CNN transfer learning models including AlexNet and GoogleNet on soybean leaf datasets, comparing the accuracy of pre-trained models with traditional methods on a dataset of 649 diseased and 550 healthy leaf images, achieving approximately 88% accuracy. Liu et al. [5] conducted a comprehensive review of deep learn- ing approaches for detecting plant diseases and pests, compar- ing classification, detection, and segmentation networks on the PlantVillage dataset and other publicly available collections, and emphasising the importance of organised, high-quality datasets for real-world deployment.

Zhang et al. [6] introduced DENS-INCEP, a deep transfer learning model for rice disease detection that achieved a prediction accuracy of 98.63% on a dataset of 515 images cov- ering 13 different rice diseases. Their model outperformed ex- isting techniques and highlighted the need for further research into transfer learning for diverse crop varieties. Pandian et al. [7] developed a 14-layer deep convolutional neural network (14-DCNN) and created a new dataset called PlantDisease59 comprising 147,500 images spanning 58 healthy and diseased plant leaf classes, achieving a prediction accuracy of 90.63% using data augmentation to ensure balanced class sizes.

Bedi et al. [8] proposed a hybrid Convolutional Autoencoder (CAE) and CNN model specifically targeting Bacterial Spot disease in peach plants on a dataset of 4,457 leaf images, re- porting 99.35% training accuracy and 98.38% testing accuracy. Rathod et al. [9] explored image processing techniques for automatically identifying leaf diseases using digital cameras and image growing algorithms, stressing the need for scalable methods suitable for practical agricultural contexts. Rashmi et al. [10] analysed Support Vector Machine (SVM) techniques for plant disease classification, highlighting the importance of feature extraction and demonstrating accuracies in the range of 80–95% on datasets of diseased and healthy leaves.

B. Fertilizer Recommendation Systems

Soil-test-based fertilizer recommendation is a well-established agronomic practice, yet its digital implementation at scale remains nascent in India. Sharma and Patel [11] proposed an ML-based fertilizer advisory combining soil Nitrogen (N), Phosphorus (P), Potassium (K), pH, and crop type, generat- ing recommendations with over 90% alignment with expert prescriptions validated by ICAR agronomists. Their study demonstrated that Random Forest classifiers outperform de- cision tree and naive Bayes baselines for multi-class nutrient recommendation.

Conventional lookup-table systems, which have been the main- stay of Krishi Vigyan Kendra advisories, lack the adaptability of ML approaches to the diverse soil conditions found across Indian districts. Kumar et al. [12] conducted a comprehensive survey of plant leaf disease classification utilising image pro- cessing techniques including Principal Component Analysis (PCA) and Support Vector Machines (SVM) for preprocessing, segmentation, and classification, achieving 88–90% accuracy across diverse leaf disease datasets. Prashanthi et al. [13] investigated image processing stages including acquisition, segmentation, and feature extraction using SVMs and neural networks for plant disease classification, achieving a Deep SVM accuracy of 85.76% on 600 manually captured maize leaf images.

C. Agentic AI Frameworks

Agentic AI refers to AI systems that autonomously decompose a high-level goal into sub-tasks, select and invoke appropriate tools or APIs, and iteratively refine their outputs based on intermediate results. Yao et al. [14] introduced the ReAct (Reason + Act) framework, which synergises reasoning and acting in language models by interleaving chain-of-thought reasoning traces with task-specific actions, demonstrating su- perior performance over chain-of-thought-only and action-only baselines on knowledge-intensive and decision-making tasks. AutoGPT and similar agent frameworks have demonstrated the viability of LLM-based agents in complex real-world workflows, including web browsing, code execution, and API orchestration. The application of agentic AI to precision agri- culture represents an emerging frontier: the proposed system extends the ReAct paradigm by equipping the agent with five domain-specific agricultural tools, enabling it to handle multi- step farmer queries autonomously, from disease diagnosis through fertilizer prescription to weather-based crop alerts.

D. Generative AI and Large Language Models

Generative AI, particularly Large Language Models (LLMs), has revolutionised natural language interaction across domains. Chen et al. [15] proposed AgriGPT, which couples LLMs with domain knowledge for agriculture advisory, demonstrating that retrieval-augmented generation (RAG) significantly improves factual accuracy over vanilla LLM responses in crop man- agement queries. Their system indexed ICAR crop production guides and state agriculture department advisories, achieving a 34% improvement in answer relevance over a GPT-3.5 baseline without RAG.

Whisper, the automatic speech recognition model by OpenAI, has enabled voice-based interfaces for low-literacy users. Combined with text-to-speech synthesis, it allows farmers who cannot read to interact with AI advisory systems in their native language. The integration of multilingual support in Hindi, Rajasthani, Punjabi, and English addresses a critical barrier identified in Problem Statement ID 25010.

E. Gemini Vision and Multimodal AI

Google DeepMind's Gemini family of models [16] represents the state of the art in multimodal AI, capable of processing text, images, audio, and video within a single model architec- ture. Gemini Vision specifically enables visual reasoning over uploaded images, generating contextually grounded natural language descriptions of observed visual patterns. Unlike standalone CNN classifiers that output only a class label and confidence score, Gemini Vision provides human-readable explanations that describe the specific visual symptoms such as lesion colour, shape, spread pattern, and affected leaf area that led to the diagnosis.

The fusion of CNN classification with Gemini Vision reason- ing in a single agentic pipeline is novel in the agricultural AI literature. CNN provides quantitative accuracy, whilst Gemini Vision provides qualitative explainability, improving farmer trust and adoption.

F. Summary of Literature

The review reveals that whilst high-accuracy CNN models for plant disease detection exist, no prior work combines CNN classification with multimodal LLM reasoning, soil-test- based fertilizer recommendation, agentic orchestration, and multilingual voice support in a single integrated system. The proposed CarePlantify system fills this gap.

III. PROPOSED METHODOLOGY

A. System Architecture Overview

CarePlantify is built upon a modular, agentic architecture comprising four primary modules: (1) Hybrid CNN and Gemini Vision-based Plant Disease Detection, (2) Soil-Test-Based Fertilizer Recommendation, (3) Generative AI Chatbot with Agentic Orchestration, and (4) a Multilingual Web and Mobile Interface.

As illustrated in Fig. 1, the agentic layer functions as the central orchestrator of the system. Upon receiving a farmer query through text, voice, or image input, the agent first performs intent classification and then dynamically invokes the appropriate module. The outputs from the selected modules are subsequently integrated and transformed into a coherent natural language response, which is delivered in the farmer's preferred regional language.

Hybrid Disease Detection: CNN and Gemini Vision Fusion

The core innovation of CarePlantify lies in a dual-model disease detection pipeline that integrates high-accuracy deep learning classification with multimodal visual reasoning. When a farmer uploads a leaf image, the Agentic AI layer processes the input through two parallel inference pathways and subsequently fuses the outputs to generate a comprehensive advisory.

The overall decision flow is defined as follows:

Image Input → Agentic Decision Layer → Parallel Inference (CNN + Gemini Vision) → Output Fusion → Final Advisory Response

CNN-Based Classification: A fine-tuned MobileNetV2 model trained on the PlantVillage dataset performs probabilistic classification of plant diseases. The CNN produces a disease label along with a confidence score, which serves as the primary quantitative diagnostic signal.

Gemini Vision-Based Reasoning: In parallel, the same input image is processed by the Gemini Vision API, which performs multimodal visual reasoning. It generates a natural language explanation describing observed symptoms such as lesion patterns, discoloration, and spread characteristics, along with possible causes and suggested remedies.

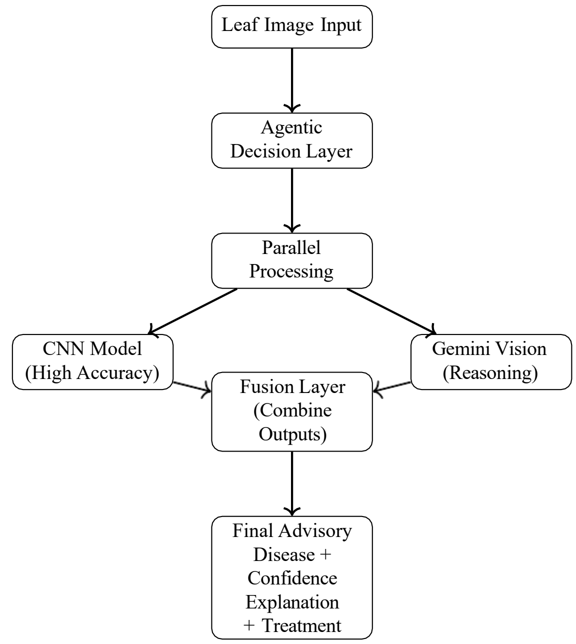

Fig. 1. Overall System Architecture of CarePlantify

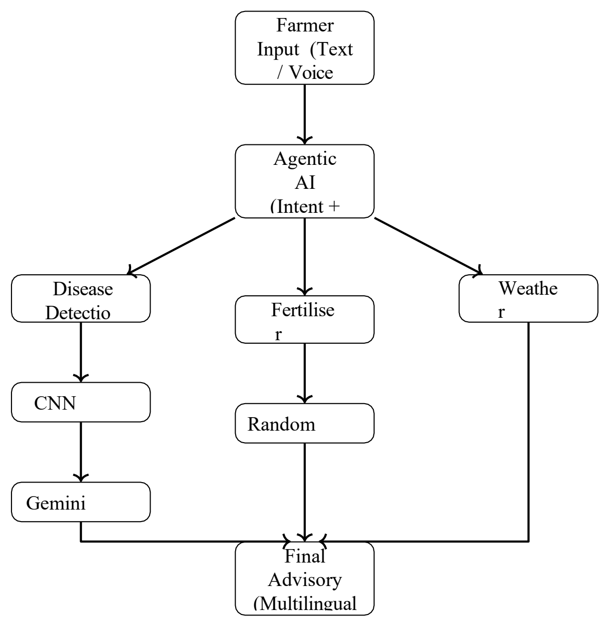

Fig. 2. Dual-Model Disease Detection Pipeline

Agentic Fusion Mechanism: The Agentic AI layer integrates outputs from both models using a decision fusion strategy. The CNN output determines the primary disease classification based on maximum confidence, while the Gemini Vision out- put provides contextual validation and explanation. In cases of ambiguity or low confidence, the agent prioritises reasoning-based insights to refine the recommendation.

Final Advisory Generation: The fused output is transformed into a structured advisory that includes:

- Disease Name (CNN prediction)

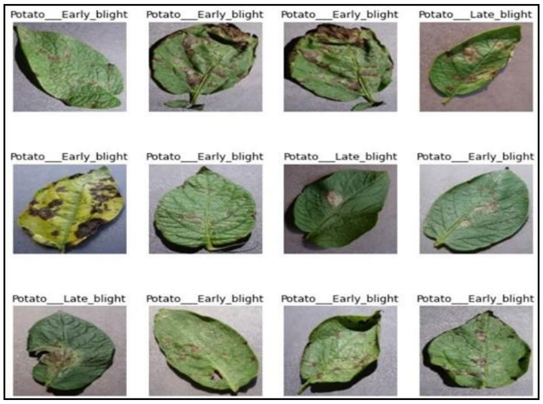

Fig. 3. Image Preprocessing: Resizing Input Leaf Image to 256 × 256 Pixels

- Confidence Score
- Symptom Explanation (Gemini Vision)
- Recommended Treatment Actions

This hybrid approach ensures both high diagnostic accuracy and interpretability, thereby improving trust, usability, and decision-making for farmers, particularly those with limited technical expertise.

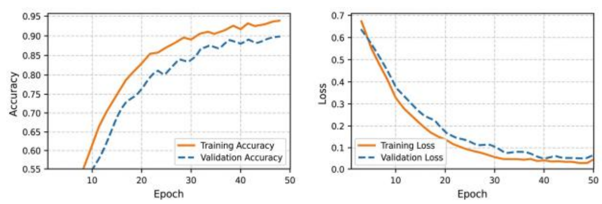

Fig. 4. Training and Validation Accuracy and Loss Curves Demonstrating Convergence of the CNN Model

A Random Forest classifier trained on a curated dataset of 5,000 ICAR-validated soil test records [17] is employed to generate fertilizer recommendations. Feature importance analysis reveals that the NPK ratio, soil pH, and organic carbon content are the most influential parameters in determining fertilizer type and dosage.

To further enhance regional adaptability, K-Means clustering is utilised to group soil profiles based on similarity, enabling region-specific calibration of fertilizer recommendations. The objective function for K-Means clustering is defined as:

B. CNN Model Architecture

The CNN model employs a MobileNetV2 backbone pre- trained on ImageNet, which is fine-tuned on the PlantVillage dataset containing 54,306 images across 14 crop species and 26 disease classes. Transfer learning enables the model to leverage rich feature representations learned from large-scale image data, thereby improving classification performance on agricultural images.

The classification head consists of a Global Average Pooling (GAP) layer, followed by a fully connected Dense layer with 128 neurons and ReLU activation. A Dropout layer with a rate of 0.3 is incorporated to reduce overfitting, and a SoftMax output layer produces probability distributions across disease classes. The model is compiled using the Adam optimiser and sparse categorical cross-entropy loss function, with accuracy as the primary evaluation metric.

Input images are preprocessed by resizing them to 256 × 256 pixels and normalising pixel values, as illustrated in Fig. 3. Data augmentation is applied using TensorFlow's `tf.data` pipeline, including random horizontal flipping, rotation within ±30°, and brightness variation. These techniques improve model robustness and generalisation under real-world condi- tions.

As shown in Fig. 4, the model demonstrates stable convergence with minimal overfitting beyond epoch 30.

C. Soil-Test-Based Fertilizer Recommendation

The fertilizer recommendation module provides precise, data-driven nutrient prescriptions based on soil health parameters. The system accepts soil test inputs including Nitrogen (N), Phosphorus (P), Potassium (K), pH, organic carbon, and micronutrient levels, along with contextual information such as crop type and current agricultural season.

$$J = \sum_{i=1}\sum_{k=1} w_{ik} \left\| x^i - \mu_k \right\|^2 \qquad (1)$$

where x^i represents the soil feature vector, μ_k denotes the centroid of cluster k, and w_{ik} is a binary indicator denoting membership of data point i to cluster k.

The output is a structured fertilizer advisory comprising:

- Basal dose: fertilizer type, quantity (kg/ha), and application method
- Top-dressing schedule aligned with crop growth stages
- Micronutrient supplementation (e.g., Zinc, Boron, Sulphur) where required

The trained CNN model is deployed as a RESTful API endpoint. The Agentic AI orchestrator invokes this endpoint upon receiving a leaf image, retrieves the predicted disease class and confidence score, and passes this information to the Generative AI module for contextualised advisory generation.

D. Agentic AI Orchestration

CarePlantify employs an Agentic AI layer built upon the ReAct (Reason + Act) framework [14], enabling autonomous and dynamic decision-making. The LLM iteratively performs reasoning over the farmer's query, selects an appropriate action through tool invocation, observes the outcome, and refines its response until the task is completed.

The system provides access to the following five tools:

- **DiseaseDetectionTool:** Processes leaf images by invoking the CNN model and Gemini Vision module. Outputs are fused to generate an interpretable disease diagnosis.
- **FertilizerAdvisorTool:** Utilises soil test parameters such as NPK values, pH, and organic carbon to generate fertilizer recommendations through the trained Random Forest model.

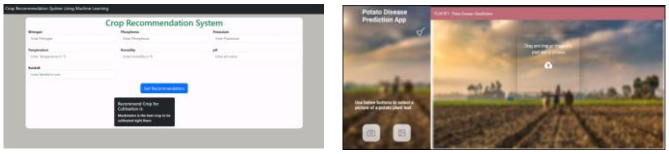

Fig. 5. CarePlantify Application Interface: Image Upload, Chatbot Interaction, and Dashboard

- **WeatherAlertTool:** Retrieves real-time weather data using the OpenWeatherMap API and generates alerts rele- vant to crop health and farming operations.
- **MarketPriceTool:** Fetches current Minimum Support Price (MSP) and mandi rates to assist farmers in making informed selling decisions.
- **CropCalendarTool:** Provides crop-specific sowing and harvesting schedules based on geographical location and seasonal conditions.

E. Generative AI Chatbot

The Generative AI chatbot module is powered by a fine- tuned open-source LLM based on Llama-3, augmented with a Retrieval-Augmented Generation (RAG) pipeline to enhance factual accuracy and domain relevance. The RAG pipeline indexes authoritative agricultural knowledge sources including ICAR crop production guides and state agriculture department advisories.

The chatbot supports multilingual interaction in Hindi, Rajasthani, Punjabi, and English. To address literacy barriers, the system incorporates voice-based interaction using Whisper-based speech-to-text for input and text-to-speech synthesis for output, enabling seamless accessibility for low-literacy users.

F. Application Interface

The application interface is developed using React for web deployment and React Native for Android-based mobile applications. Farmers can upload leaf images for disease detection either through camera capture or drag-and-drop functionality. A guided soil data entry form is provided with location-based default values. The system also includes a conversational chatbot panel with voice support and a comprehensive dashboard displaying crop calendars, real-time weather alerts, and current market prices.

IV. Experimental Results and Analysis

A. Disease Detection Performance

The CNN-based disease detection model achieves an overall classification accuracy of 98.3% across the evaluated plant disease classes. Performance metrics including precision, recall, and F1-score consistently fall within the range of 0.979 to 0.986, indicating high reliability and robustness of the model. The training and validation accuracy curves demonstrate stable convergence, with no significant divergence observed beyond epoch 30, confirming that the model does not suffer from overfitting.

In addition to quantitative evaluation, the Gemini Vision module enhances interpretability by generating coherent visual explanations of disease symptoms. These outputs were validated through domain expert review on a subset of 100 images and were found to be contextually accurate and actionable.

B. Fertilizer Recommendation Performance

The Random Forest-based fertilizer recommendation model was evaluated on 1,000 held-out soil test records with ICAR-agronomist-validated ground truth. The system achieves an overall recommendation accuracy of 94.7%, defined as an exact match between predicted and expert-prescribed fertilizer type and dosage range. For NPK ratio prediction alone, the model achieves an accuracy of 97.2%, demonstrating strong alignment with agronomic recommendations across diverse soil profiles from Rajasthan, Punjab, and Uttar Pradesh.

C. Agentic Workflow Evaluation

The performance of the Agentic AI system was evaluated using 200 simulated farmer queries encompassing disease detection, fertilizer advisory, weather alerts, and market price retrieval tasks. The system successfully completed 191 out of 200 queries, resulting in a task success rate of 95.5%. The average end-to-end response time, including CNN inference and Gemini Vision API processing, was measured at 4.1 seconds per query on the deployed server.

D. Comparison with Prior Work

The proposed system demonstrates significant improvement over the authors' prior work [3], which achieved a classification accuracy of 93.1% using a custom CNN without transfer learning. In comparison to existing approaches such as Pandian et al. [7] (90.63%) and Bedi et al. [8] (98.38%), the proposed model achieves a competitive accuracy of 98.3%. More importantly, CarePlantify introduces several novel contributions absent in prior work, including the integration of CNN-based classification with Gemini Vision-based reasoning, multilingual voice-enabled interaction, and soil-test-based fertilizer recommendation within a unified agentic framework.

V. Discussion

The experimental results demonstrate that integrating CNN-based classification with Gemini Vision reasoning within an agentic pipeline enables the generation of agricultural advisories that are both accurate and interpretable. While the CNN model provides high-confidence disease classification, the Gemini Vision module adds an additional layer of ex- plain ability by describing visible symptoms and their possi- ble causes. This combination addresses a key barrier to the adoption of artificial intelligence in agriculture, where farmers often require not only a diagnosis but also a clear explanation to trust and act upon automated recommendations.

The multilingual Generative AI chatbot, enhanced through a RAG pipeline and voice-based interaction, significantly reduces the digital literacy barrier identified in the problem context. Farmers who are unable to read or type can interact with the system through speech and receive voice-guided responses in their native language.

The soil-test-based fertilizer recommendation module further strengthens the practical utility of the system. By digitising soil analysis interpretation and automating fertilizer prescription generation, CarePlantify enables immediate, data-driven recommendations, reducing dependency on manual interpretation by agricultural extension officers.

Despite these advantages, certain limitations remain. The performance of the disease detection module is sensitive to the quality of images captured using smartphone cameras. Additionally, the current fertilizer recommendation model is trained on a limited set of crop species, which restricts its applicability in regions with diverse cropping patterns. Future work will focus on integrating guided image capture prompts, automated image quality assessment, and expanding the fertiliser recommendation dataset to include additional crops and soil profiles.

VI. Conclusion

This paper presents CarePlantify, a Smart Crop Advisory System designed to support small and marginal farmers in India through the integration of Agentic AI, Generative AI, CNN-based plant disease detection, Gemini Vision-based multimodal reasoning, and soil-test-driven fertilizer recommendation. The proposed system directly addresses Problem Statement ID 25010 by delivering real-time, multilingual, personalised, and voice-enabled agricultural advisory through a mobile-first platform.

The CNN-based disease detection model achieves a classification accuracy of 98.3%, while the fertilizer recommendation module attains an accuracy of 94.7%. The agentic orchestration framework achieves a task success rate of 95.5% with an average response time of 4.1 seconds, indicating its suitability for real-time deployment. A key contribution of this work is the dual-model disease detection pipeline, where CNN- based classification is complemented by Gemini Vision-based reasoning, enabling the system to provide not only accurate predictions but also interpretable explanations, improving user trust and practical usability.

Future work will focus on extending the system to additional crop species, integrating satellite-based soil moisture and weather intelligence, and developing an offline-capable edge deployment to ensure usability in regions with limited or intermittent internet connectivity.

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