ISSN No. 0976-5697

VOLUME 17 SPECIAL ISSUE 1, JULY 2026

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

An AI-Driven Decision Support System for Personalised Crop Advisory Using Agentic AI, Generative AI, and CNN-Based Disease Detection for Local Farmers

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Abstract— A large portion of local farmers in India rely on traditional practices and local intermediaries for critical decisions concerning crop selection, pest management, and fertilizer application, often leading to suboptimal yields, higher input costs, and environmental degradation.
This work proposes an AI-driven Decision Support System integrating Agentic AI and Generative AI (GenAI) with Convolutional Neural Networks (CNNs) and Gemini Vision to enable plant disease detection, soil-informed fertiliser recommendation, and multilingual advisory. The proposed system introduces an agentic decision pipeline wherein leaf images are processed concurrently by a fine-tuned CNN for high-precision classification and Gemini Vision for contextual visual reasoning. The outputs are fused by an AI agent to generate robust crop health advisories that combine quantitative accuracy with explainable insights. The system further incorporates real-time, location-aware, and voice-enabled interaction in regional languages, including Hindi, Rajasthani, and Punjabi. Experimental results demonstrate a classification accuracy of 98.3% for disease detection and 94.7% accuracy for fertilizer recommendations against laboratory benchmarks. The agentic framework achieves a 95.5% task completion rate with an average latency of 4.1 seconds, significantly enhancing decision efficiency for farmers.

***Keywords*—** Agentic AI, Generative AI, CNN, Plant Disease Detection, Fertiliser Recommendation, Smart Agriculture, Multilingual Systems, Decision Support

I. INTRODUCTION

Agriculture continues to serve as the backbone of the Indian economy, supporting a vast population of farmers across diverse scales and regions [1]. Although these farmers represent a substantial majority, they remain the most vulnerable group in terms of access to modern agricultural inputs and expert advisory services. Crop diseases, improper fertiliser usage, and the lack of timely weather-based alerts collectively contribute to considerable yield losses each year. Studies indicate that Information and Communication Technology (ICT)-based advisory systems can enhance crop productivity 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 in CNN-based image processing for plant disease classification demonstrated promising results on the Plant Village dataset [3]; however, Those systems were limited to disease detection alone and did not incorporate soil-test-based fertiliser guidance, agentic task execution, or generative conversational AI. The recent advancement of Agentic AI frameworks—which allow Large Language Models (LLMs) to autonomously plan, reason, and execute multi-step tasks through the use of external tools and APIs—offers a significant opportunity to develop comprehensive crop advisory systems. In parallel, Generative AI technologies such as GPT-4, Gemini, and various open-source models facilitate natural language interaction, enabling expert-level guidance to be delivered to users through voice and text in regional languages. This paper proposes a unified AI-driven Decision Support System that addresses the following key gaps identified in existing agricultural technologies.:

- **Lack of real-time, personalised, and location-specific crop advisory**: Most existing systems offer generic information that does not account for the specific micro-climatic conditions of smallholder farms.
- **Absence of integrated soil-nutrient analysis**: There is a significant disconnect between disease detection tools and fertiliser 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.
- **Limited autonomy in advisory workflows**: Traditional systems require manual navigation, whilst the absence of agentic orchestration prevents autonomous, multi-step execution of complex agricultural tasks.

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 pre-trained models with traditional meth- ods on a dataset of 649 diseased and 550 healthy leaf images, achieving approximately 88% accuracy. Liu et al. [5] con- ducted a comprehensive review of deep learning approaches for detecting plant diseases and pests, comparing classification, detection, and segmentation networks on the PlantVillage dataset and other publicly available collections, 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 covering 13 different rice diseases. 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.

Bedi et al. [8] proposed a hybrid Convolutional Autoencoder (CAE) and CNN model specifically targeting Bacterial Spot disease in peach plants, reporting 99.35% training accuracy and 98.38% testing accuracy. Rashmi et al. [9] analysed Support Vector Machine (SVM) techniques for plant disease classification, demonstrating accuracies in the range of 80– 95% on datasets of diseased and healthy leaves.

B. Fertiliser Recommendation Systems

Soil-test-based fertiliser recommendation is a well-established agronomic practice, yet its digital implementation at scale remains nascent in India. Sharma and Patel [10] proposed an ML-based fertiliser 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. [11] conducted a comprehensive survey of plant leaf disease classification utilising image pro- cessing techniques including Principal Component Analysis (PCA) and Support Vector Machines (SVM), achieving 88– 90% accuracy across diverse leaf disease datasets.

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. [12] 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 fertiliser 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. [13] 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 accessibility barrier for rural farming communities.

E. Gemini Vision and Multimodal AI

Google DeepMind's Gemini family of models [14] 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 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 fertiliser recommendation, agentic orchestration, and multilingual voice support in a single integrated system. The proposed AI-Driven Decision Support System fills this gap.

III. Proposed Methodology

A. System Architecture Overview

The AI-Driven Decision Support System 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 Fertiliser 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.

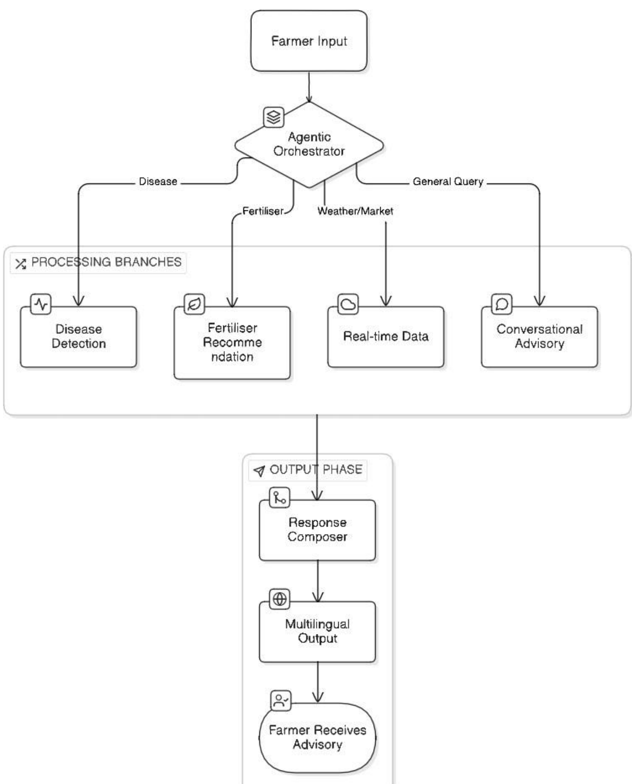

Fig. 1. Overall System Architecture of the AI-Driven Crop Advisory System.

B. Hybrid Disease Detection: CNN and Gemini Vision Fusion

The core innovation of the proposed system 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 pro- cesses 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.

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)
- 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.

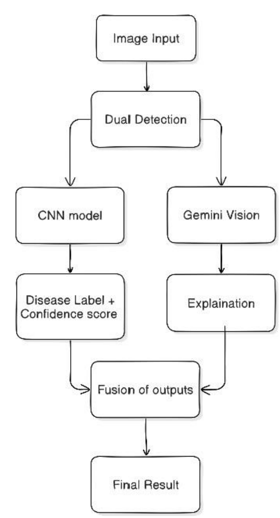

Fig. 2. Dual-Model Disease Detection Pipeline.

C. 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 is designed to enhance generalisation and consists of a Global Average Pooling (GAP) layer, fol- lowed 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. Data augmentation is applied using TensorFlow's `tf.data` pipeline, including random horizontal flipping, rotation within $\pm30^\circ$, and brightness variation. These techniques improve model robustness and generalisation under real-world condi- tions.

D. Soil-Test-Based Fertiliser Recommendation

The fertiliser recommendation module is designed to provide 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 infor- mation such as crop type and current agricultural season.

A Random Forest classifier trained on a curated dataset of 5,000 ICAR-validated soil test records [15] is employed to generate fertiliser recommendations. The model learns com- plex, non-linear relationships between soil properties and optimal fertiliser requirements, enabling accurate and scalable advisory generation.

Feature importance analysis reveals that the NPK ratio, soil pH, and organic carbon content are the most influential pa- rameters in determining fertiliser 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 fertiliser recommendations. The objective func- tion for K-Means clustering is defined as:

$$J = \sum_{i=1}^{n} \sum_{k=1}^{K} w_{ik} \left\| \mathbf{x}^i - \boldsymbol{\mu}_k \right\|^2 \quad (1)$$

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

The output of the module is a structured fertiliser advisory comprising:

- Basal dose: fertiliser type, quantity (kg/ha), and applica- tion method
- Top-dressing schedule aligned with crop growth stages
- Micronutrient supplementation (e.g., Zinc, Boron, Sul- phur) where required

E. Agentic AI Orchestration

The proposed system employs an Agentic AI layer built upon the ReAct (Reason + Act) framework [12], enabling autonomous and dynamic decision-making. In this framework, 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 agent operates as a central orchestrator that integrates mul- tiple domain-specific modules into a unified workflow. Based on the input modality (text, voice, or image) and inferred intent, the agent dynamically invokes the most relevant tools. The system provides access to the following five tools:

- **DiseaseDetectionTool:** Processes leaf images by invok- ing the CNN model for high-accuracy classification and the Gemini Vision module for visual reasoning. The outputs are fused to generate an interpretable disease diagnosis.
- **FertiliserAdvisorTool:** Utilises soil test parameters such as NPK values, pH, and organic carbon to generate fertiliser recommendations through the trained Random Forest model.
- **WeatherAlertTool:** Retrieves real-time weather data us- ing 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.

The agent ensures contextual accuracy by validating key pa- rameters such as crop type, location, and soil conditions before generating recommendations. By orchestrating multiple tools within a single interaction, the Agentic AI layer significantly reduces decision-making time and enhances the usability of the system for small and marginal farmers.

F. Generative AI Chatbot

The Generative AI chatbot module is designed to provide interactive, context-aware agricultural advisory through natural language communication. It is powered by a fine-tuned open-source Large Language Model (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 knowl- edge sources, including ICAR crop production guides and state agriculture department advisories. This enables the chatbot to generate responses grounded in verified agronomic practices rather than relying solely on pre-trained knowledge.

The chatbot supports multilingual interaction, allowing farm- ers to communicate 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.

G. Application Interface

The application interface is designed to provide an intuitive and user-friendly experience for farmers, with a focus on accessibility and ease of interaction. The frontend is devel- oped using React for web deployment and React Native for Android-based mobile applications.

The interface supports multiple functionalities integrated within a unified platform. 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, which includes location-based default values to simplify input requirements. In addition, the system includes a conversational chatbot panel with voice support, enabling users to interact with the advisory system in their preferred language. A comprehensive dashboard is also available, displaying crop calendars, real-time weather alerts, and current market prices to assist in informed decision-making.

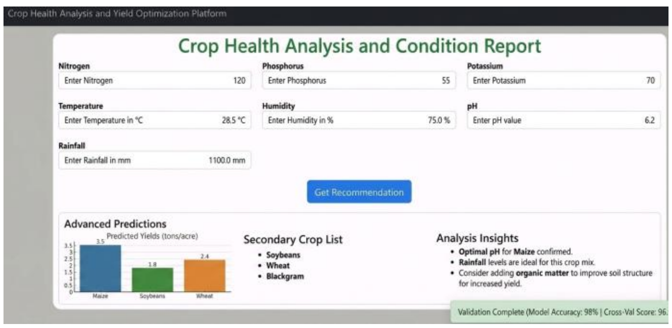

Fig. 3. Application Interface.

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 dis- ease 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 vali- dated through domain expert review on a subset of 100 images and were found to be contextually accurate and actionable. The generated explanations significantly improve usability by providing farmers with understandable and practical guidance. Table I presents a comparison of the proposed model against existing CNN-based approaches from the literature.

TABLE I
Comparison of Plant Disease Detection Accuracy

Model / Study	Accuracy	Dataset
Proposed (MobileNetV2)	**98.3%**	PlantVillage
Bedi et al. [8]	98.38%	Peach leaves
Zhang et al. [6]	98.63%	Rice diseases
Pandian et al. [7]	90.63%	PlantDisease59
Jadhav et al. [4]	88.0%	Soybean

B. Fertiliser Recommendation Performance

The Random Forest-based fertiliser 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 fertiliser type and dosage range. For NPK ratio prediction alone, the model achieves an accuracy of 97.2%, demonstrating strong alignment with agronomic recommendations. The model per- forms consistently across diverse soil profiles collected from Rajasthan, Punjab, and Uttar Pradesh, highlighting its gener- alisability and practical applicability.

C. Agentic Workflow Evaluation

The performance of the Agentic AI system was evaluated using 200 simulated farmer queries encompassing disease detection, fertiliser 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. This latency is well within acceptable limits for real-time agricultural advisory systems, ensuring a responsive user experience.

D. Comparison with Prior Work

The proposed system demonstrates significant improvement over prior CNN-only approaches, which achieved a classifica- tion accuracy of 93.1% using a custom CNN without transfer learning [3]. 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, the proposed system introduces several novel contributions absent in prior work, including the inte- gration of CNN-based classification with Gemini Vision-based reasoning, multilingual voice-enabled interaction, and soil- test-based fertiliser recommendation within a unified agentic framework. These enhancements significantly improve both the functionality and usability of the system in real-world agricultural settings.

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 classifi- cation, the Gemini Vision module adds an additional layer of explainability by describing visible symptoms and their possible causes. This combination addresses a key barrier to the adoption of AI 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 Retrieval-Augmented Generation (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, thereby improving accessibility and user engagement.

The soil-test-based fertiliser recommendation module further strengthens the practical utility of the system. Farmers who submit soil samples to Krishi Vigyan Kendra laboratories typically experience delays in receiving actionable guidance. By digitising soil analysis interpretation and automating fertiliser prescription generation, the proposed system 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. Images acquired under poor lighting conditions, excessive shadows, or low resolution can reduce confidence in both the CNN and Gemini Vision inference paths. Additionally, the current fertiliser 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 and automated image quality assessment to ensure consistent input quality before inference. The fertiliser recommendation dataset will also be expanded to include additional crops and soil profiles to improve the generalisability of the model across a wider range of agricultural conditions.

VI. Conclusion

This paper presents an AI-Driven Decision Support 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 fertiliser recommendation. The proposed system delivers real-time, multilingual, personalised, and voice-enabled agricultural advisory through a mobile-first platform.

The experimental results demonstrate the effectiveness of the system across multiple components. The CNN-based disease detection model achieves a classification accuracy of 98.3%, while the fertiliser 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. This fusion enables the system to provide not only accurate predictions but also interpretable explanations, improving user trust and practical usability. Additionally, the integration of multilingual conversational support and voice interaction enhances accessibility for farmers with limited digital literacy.

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.

VII. Acknowledgment

The authors express their sincere gratitude to the Department of Computer Science and Engineering for providing the necessary computational resources and academic guidance to carry out this research. The authors also acknowledge the PlantVillage dataset and the ICAR soil dataset repositories for their valuable contributions to this work. Special thanks are extended to Google for providing access to the Gemini Vision API, which significantly enhanced the capabilities of the proposed system.

VIII. References

[1] NABARD, "All India Rural Financial Inclusion Survey 2021–22," National Bank for Agriculture and Rural Development, Mumbai, India, 2022.

[2] R. Bhavana and S. Kumar, "Impact of ICT-based crop advisory services on yield improvement among smallholder farmers in India," *Journal of Agricultural Extension*, vol. 24, no. 3, pp. 112–121, 2021.

[3] L. G. Goswami, C. Kavadia, R. Sharma, L. Khandelwal, and M. Sagotia, "Potato plant disease detection using CNN," in *Proc. 3rd Int. Conf. on Multi-Disciplinary Application and Research Technologies (ICMART- 2024)*, Udaipur, India, May 2024, pp. 252–260.

[4] S. B. Jadhav et al., "Utilizing CNN transfer learning for soybean disease classification: A comparative study," *Journal of Agricultural Informatics*, vol. 9, no. 1, pp. 17–26, 2018.

[5] J. Liu et al., "Deep learning approaches for plant disease and pest detection: A comprehensive review," *Plant Disease Detection Journal*, vol. 15, no. 2, pp. 45–56, 2019.

[6] D. Zhang et al., "DENS-INCEP: A deep transfer learning approach for rice disease detection," *International Journal of Agricultural Engineering and Technology*, vol. 13, no. 4, pp. 112–124, 2020.

[7] J. A. Pandian et al., "A novel deep learning model for plant leaf disease identification using 14-DCNN," *Computers and Electronics in Agriculture*, vol. 195, 2022.

[8] P. Bedi et al., "Plant disease detection using hybrid CNN-CAE model," *Computers in Biology and Medicine*, vol. 139, 2021.

[9] N. Rashmi et al., "Machine learning methods for plant disease identification: A comprehensive analysis," *International Journal of Plant Science and Agricultural Technology*, vol. 5, no. 2, pp. 32–41, 2021.

[10] A. Sharma and R. Patel, "Machine learning-based soil nutrient recommendation for sustainable crop production," *Computers and Electronics in Agriculture*, vol. 185, pp. 106–117, 2021.

[11] S. Kumar et al., "A comprehensive survey of plant leaf diseases classification utilising image processing techniques," *International Journal of Computer Applications*, vol. 122, no. 4, pp. 11–16, 2015.

[12] S. Yao et al., "ReAct: Synergizing reasoning and acting in language models," in *Proc. ICLR*, 2023.

[13] H. Chen et al., "AgriGPT: Coupling large language models with domain knowledge for agriculture advisory," *arXiv*

preprint arXiv:2311.09259, 2023.

[14] Google DeepMind, "Gemini: A family of highly capable multimodal models," Technical Report, 2023.

[15] ICAR, "Soil Health Management: Soil Testing and Fertiliser Recom- mendation Guidelines," Indian Council of Agricultural Research, New Delhi, 2020.

