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A Multimodal AI-Driven Intelligent Decision-Support System for Precision and Personalized Agricultural Advisory

Mr. Senthil Kumar R, Ms. M. Agalya, Ms. Aleena Biju, Ms. Deepajothi S, Varshni R P
Assistant Professor, Department of Computer Science and Technology
Student, Department of Computer Science and Technology
senthilkumarcst@vcew.ac.in, agalya.official1695@gmail.com
aleena40408@gmail.com, studentdeepajothi.s997@gmai.com, varshnirp2005@gmail.com
Vivekanandha College of Engineering for Women (Autonomous), Tiruchengode, Namakkal, India

Abstract: *Farmers routinely face time-sensitive challenges related to crop health, pest management, weather uncertainty, government subsidies, and market dynamics. However, access to timely, localized, and expert agricultural guidance remains limited due to language diversity, low literacy levels, connectivity constraints, and the increasing burden on agricultural extension services. This paper proposes Agronex***,** *an AI-based farmer query support and advisory system designed to provide instant, personalized agricultural assistance across regional languages, ensuring inclusive access for diverse farming communities. The system enables multimodal interaction through voice, text, and image inputs, allowing farmers to communicate naturally regardless of literacy level. Agronex employs large language models fine-tuned with region-specific agricultural datasets, including crop calendars, pest and disease advisories, weather information, and government scheme guidelines, to generate accurate and context-aware recommendations. Personalization is achieved by incorporating parameters such as geographic location, landholding size, crop variety, and seasonal conditions. To address rural connectivity limitations, the platform integrates offline functionality along with SMS and IVR-based communication. An intelligent escalation mechanism forwards complex cases to agricultural officers with pre-processed insights, reducing response time and operational workload. Continuous learning through farmer feedback and expert validation improves system reliability over time.*

Keywords: CNN, NLP, LLM, Rural informatics, Soil analysis

I. INTRODUCTION

Agricultural environments expose farmers to challenges such as crop diseases, pest attacks, unpredictable weather conditions, and lack of timely expert guidance. Traditional advisory systems mainly rely on manual consultations and general recommendations, which often do not provide real-time or personalized support.

To address these limitations, an AI-based agricultural advisory system called Agronex is proposed to assist farmers through intelligent and accessible technology. The system enables farmers to interact using voice, text, and image inputs, making it suitable even for low-literacy users.

The collected inputs are processed using AI techniques such as Natural Language Processing (NLP) and Computer Vision to understand farmer queries and detect crop-related issues. Based on this analysis, the system generates context-aware and personalized recommendations.

In addition, Agronex provides support through SMS and IVR for low-connectivity areas and includes an expert escalation mechanism for complex queries. This makes the system an effective and practical solution for delivering real-time agricultural advisory services.

II. LITERATURE SURVEY

2.1. AI-Based Crop Disease Detection Using CNN

Publication Year: 2025
Authors: Madhur Jain, Shilpi Jain, Sachin Kumar, Ashish Pandey ()
Journal Name: International Journal of Scientific Research in Computer Science
This work focuses on using Convolutional Neural Networks (CNN) for detecting crop diseases from leaf images. The system achieves high accuracy and supports early disease identification, but it mainly concentrates on image-based classification without providing complete advisory support to farmers

2.2. AI-Powered Agricultural Chatbot for Farmer Advisory (FarmGPT)

Publication Year: 2025
Authors: Krishna Swaroop A, H S Suprith, Chinmay Raj, Abhishek Gowda B P, Mohith G ()
Journal Name: IJRASET
This system presents an AI-based chatbot that uses Natural Language Processing (NLP) to assist farmers with crop recommendations and disease prediction. It improves interaction and accessibility but lacks multimodal capabilities such as image-based diagnosis..

2.3. Plant Disease Detection with CNN and Chatbot Integration

Publication Year: 2025
Authors: V Kavya Sai Suma Sri, T Geethan, K Rajesh, Sivaiah Borra ()
Journal Name: SSRN
This research combines CNN-based disease detection with a chatbot interface to provide recommendations. It enables both diagnosis and interaction, but the system does not include personalization or offline accessibility features

2.4. AI-Driven Agricultural Chatbot for Crop Management (CropGuard)

Publication Year: 2024
Authors: Sonali Kothari, Pooja Bagane, Manasvi Mishra, Saloni Kulshrestha, Yashika Asrani, Vrinda Maheswari ()
Journal Name: International Journal of Intelligent Systems and Applications in Engineering
This study proposes an AI-powered chatbot integrated with deep learning models for plant disease detection and crop management. While it provides intelligent recommendations, it lacks multilingual and offline communication support.

2.5. Smart Agriculture Advisor Using CNN and Chatbot Integration

Publication Year: 2024
Authors: Ratna Patil, Yogita Sinkar, Ashish Ruke, Harshvardhan Kulkarni, Om Kadam ()
Journal Name: International Journal of Engineering Trends and Technology
This system integrates chatbot technology with CNN-based crop disease classification to assist farmers in decision-making. Although it improves advisory systems, it does not fully address multimodal interaction and expert validation.

III. SYSTEM OVERVIEW

Agronex is designed as a modular and scalable decision-support system comprising the following layers:
1. Multimodal Input Layer
2. AI Processing Layer
3. Personalization and Context Modeling
4. Confidence Assessment and Expert Escalation
5. Output and Communication Layer

This layered architecture ensures flexibility, scalability, and robustness while supporting diverse rural deployment scenarios.

IV. METHODOLOGIES

4.1 Multimodal Input Processing :The system accepts farmer queries through voice, text, image, SMS, and IVR interfaces. Voice inputs are converted into text using automatic speech recognition models optimized for regional languages. Image inputs are analyzed for crop disease detection, while text and SMS inputs are processed directly through the natural language pipeline.

4.2 Natural Language Processing and Query Understanding: Textual queries are analyzed using NLP techniques to identify intent and extract relevant entities such as crop type, symptoms, location, and growth stage. This structured understanding enables efficient routing of queries to appropriate advisory modules.

4.3 Computer Vision-Based Disease Detection: Crop images captured by farmers are processed using convolutional neural networks trained on labeled agricultural image datasets. Transfer learning is employed to improve performance on region-specific crops and disease patterns. The output includes disease classification and confidence estimation.

4.4 Domain-Adaptive Large Language Model: A domain-adapted large language model generate context-aware agricultural advisories by combining query intent, extracted entities, and farmer-specific contextual parameters. The model is fine-tuned with agricultural datasets, including crop calendars, pest management guidelines, meteorological advisories, and government scheme information.

4.5 Personalized Recommendation Engine:The personalization module maintains farmer profiles containing location, crop variety, landholding size, seasonal stage, and historical interaction data. These parameters are dynamically incorporated into the advisory generation process, enabling precision and relevance.

4.6 Confidence Estimation and Expert Escalation: Each advisory response is assigned a confidence score based on model certainty and data completeness. Queries with low confidence are
escalated to agricultural experts along with AI-generated insights, ensuring reliability and reducing expert workload
The frontend interface is developed using ReactJS to support intuitive user interaction across devices. Backend services are implemented in Python, with AI models developed using PyTorch. MongoDB is used for storing farmer profiles, interaction

V. SYSTEM ARCHITECTURE

4.1. Multimodal Input Module:The Multimodal Input Module allows farmers to interact with the Agronex system using voice, text, and image inputs. Voice inputs are captured and converted into text using Automatic Speech Recognition (ASR) models optimized for regional languages, while images are processed for crop disease detection using computer vision techniques. Text inputs are directly processed through the NLP pipeline. This module ensures inclusive access and supports natural interaction for farmers with varying literacy levels..

4.2. Environmental and Context Data Module:This module collects contextual information such as weather conditions,soil parameters, and crop-related data using external APIs and agricultural datasets. It integrates real-time and historical data sources to provide a comprehensive understanding of the farming environment. This contextual information plays a crucial role in improving the accuracy and relevance of advisory generation.

4.3. Query Understanding Module:The Query Understanding Module uses Natural Language Processing (NLP) techniques such as tokenization, entity recognition, and intent classification to analyze farmer queries. It extracts important details such as crop type, symptoms, and location, enabling the system to understand user intent effectively.

4.4. Data Processing and AI Engine:This module acts as the core processing unit of the system. It integrates NLP models, Computer Vision (CNN), and Large Language Models (LLMs) to process multimodal inputs. The pipeline involves text preprocessing, feature extraction, and model inference to generate context-aware responses. The LLM is fine-tuned with agricultural datasets, crop calendars, pest management practices, and government schemes, to improve domainspecific reasoning.

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The module also incorporates confidence scoring mechanisms to evaluate the reliability of generated outputs, ensuring robust and accurate decision-making.

4.5. Communication Module (Online and Offline):This module enables communication between the system and users through mobile applications, SMS, and IVR. It utilizes lightweight communication protocols and message queuing mechanisms to ensure reliable data transmission. Offline capabilities allow users to send and receive advisories even in low-bandwidth environments, improving system accessibility in rural areas.

4.6. Advisory and Recommendation Module:The system generates personalized recommendations by combining AI-generated outputs with rule-based decision logic. It considers contextual parameters such as crop type, growth stage, soil conditions, and weather forecasts to provide precise suggestions related to disease control, irrigation scheduling, fertilizer application, and pest management. The module ensures that recommendations are actionable and easy to understand.

4.7. Farmer Profile and Location Module:This module maintains structured farmer profiles in a database, including details such as geographic location, landholding size, crop type, seasonal stage, and historical interactions. It enables dynamic personalization by adapting recommendations based on user-specific conditions. The module also updates profiles continuously to reflect changes in farming patterns and environmental conditions.

4.8. Expert Escalation and Feedback Module: This module handles complex or low-confidence queries by forwarding them to agricultural experts along with AI-generated insights and confidence scores. It ensures human validation for critical recommendations, enhancing system reliability. Additionally, feedback collected from farmers and experts is used to refine the models through continuous learning and periodic retraining, improving system performance over time.

This architecture enables Agronex to provide accurate, scalable, and user-friendly agricultural advisory services byintegrating advanced AI techniques such as ASR, NLP, and LLMs with robust communication methods.

VI. FLOWCHART

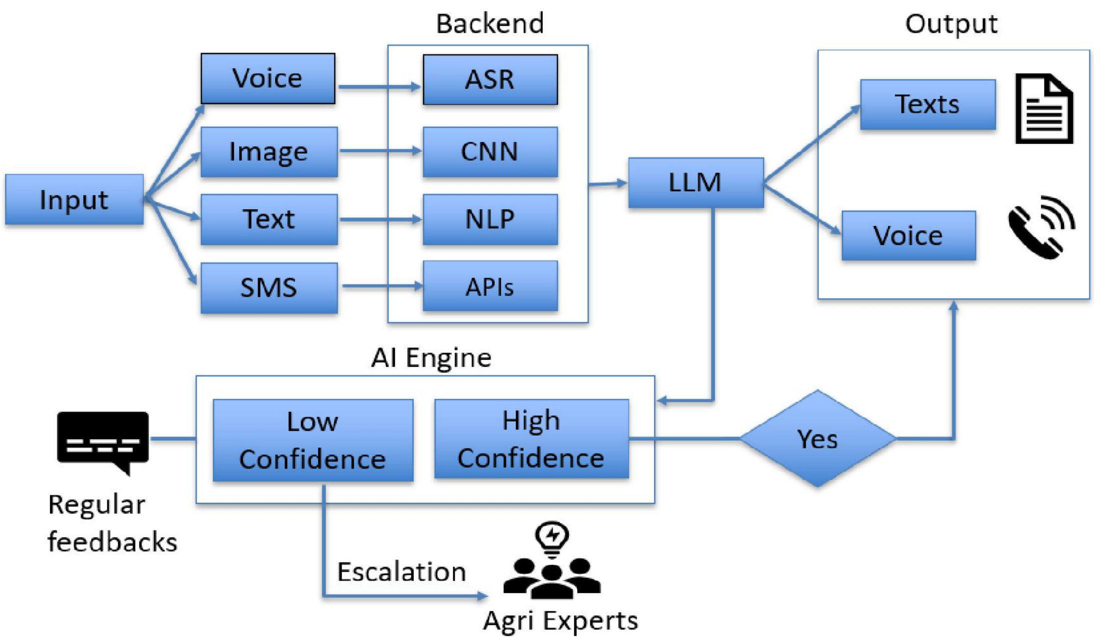

Fig1-flowchart

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VII. RESULT AND DISCUSSION

6.1 OUTPUT

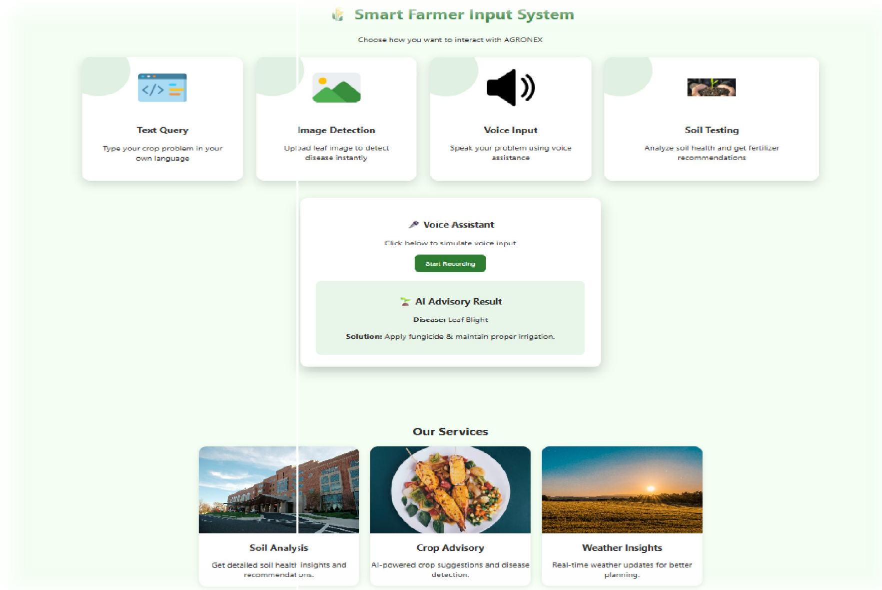

Fig 2-Homepage

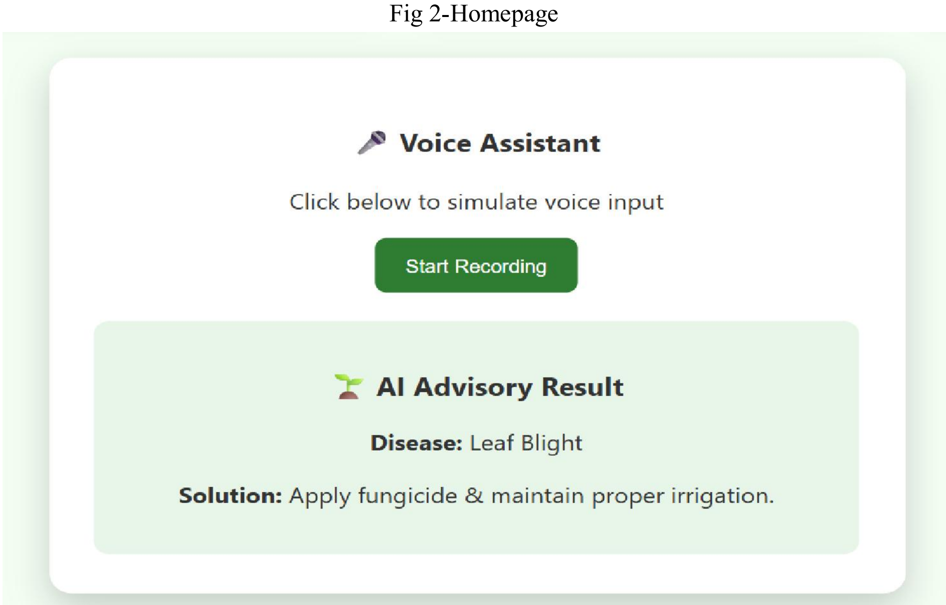

Fig 3-Voice input

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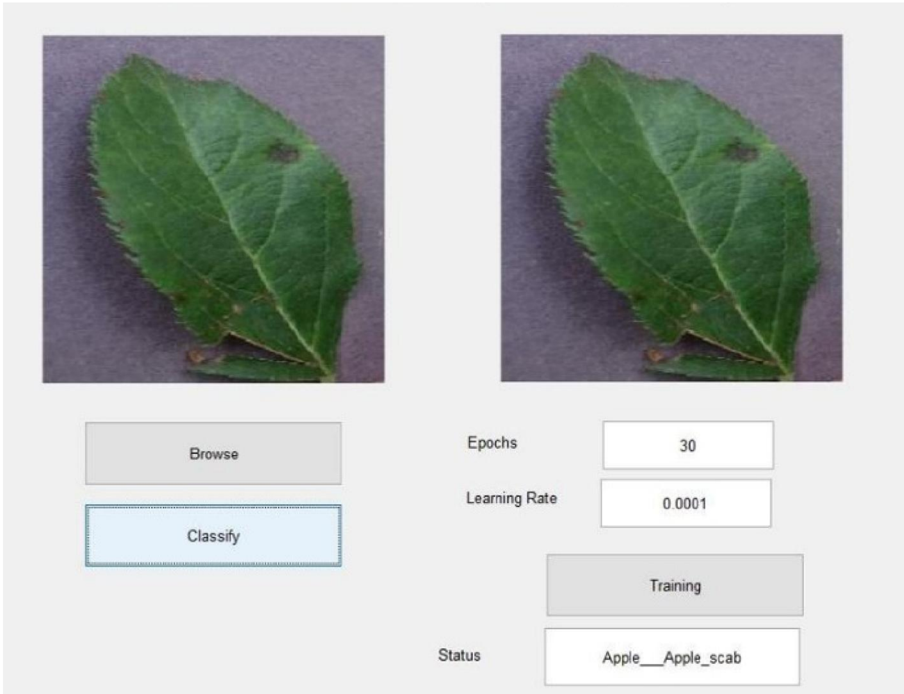

Fig4-Leaf disease prediction using CNN

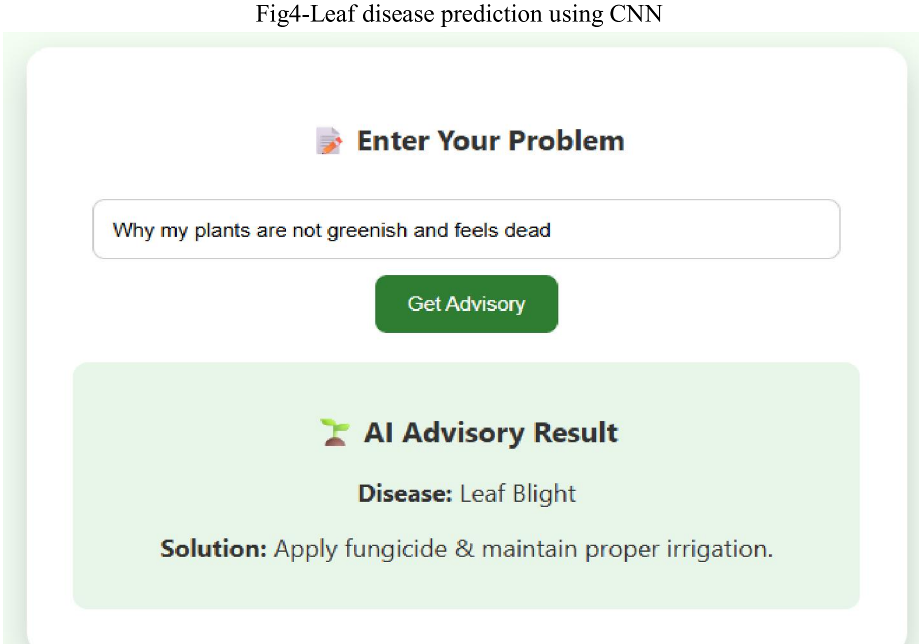

Fig5-Text input

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Fig 6 – SMS and IVR Support for rural farmers to overcome network barriers

6.2 PERFORMANCEANALYSIS

The performance of the Agronex system was evaluated based on advisory accuracy, response time, and system reliability. The accuracy of crop disease detection was assessed using test datasets of plant leaf images, where the Convolutional Neural Network (CNN) model achieved an accuracy of approximately 90–95% in identifying common crop diseases.

Additionally, the Natural Language Processing (NLP) module demonstrated effective query understanding by correctly extracting key entities such as crop type, symptoms, and location from farmer inputs.

Response time is a critical factor in agricultural decision-making. The system was optimized to process multimodal inputs efficiently, achieving an average response time of less than 2–3 seconds for standard queries. This low latency ensures that farmers receive timely recommendations, which is essential for addressing urgent issues such as pest attacks or disease outbreaks.

The system's predictive capability was evaluated using historical agricultural data, seasonal patterns, and environmental factors. The integrated AI models were able to provide proactive recommendations, such as early disease prevention and optimal irrigation practices, improving decision-making efficiency. The inclusion of contextual parameters further enhanced the relevance and precision of the advisories.

Scalability and reliability were also analyzed by simulating multiple concurrent user queries. The system maintained stable performance under varying workloads, ensuring consistent advisory delivery.

Furthermore, the expert-in-the-loop mechanism improved trustworthiness by reducing incorrect recommendations and handling complex queries effectively.

Overall, the Agronex system demonstrates strong performance in terms of accuracy, responsiveness, and scalability, making it a reliable solution for real-time and personalized agricultural advisory services.

VII. EXPERIMENTAL SETUP

The Agronex system was evaluated using a combination of sample agricultural datasets, crop disease images, and simulated farmer queries. The CNN model was tested on plant disease datasets, while the NLP module was evaluated using multilingual query inputs.

The system was implemented using Python and tested on a standard computing environment. Performance metrics such as accuracy, response time, and reliability were measured to assess system effectiveness.

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VIII. CONCLUSION

This paper presents Agronex, a multimodal AI-driven intelligent decision-support system designed to provide accurate and personalized agricultural advisory services. The system integrates multiple data sources, including crop images, farmer queries, environmental conditions, and contextual parameters, to deliver context-aware recommendations.

By combining CNN-based disease detection, Natural Language Processing, and large language models, Agronex enables effective and user-friendly interaction for farmers across different literacy levels. The inclusion of offline communication through SMS and IVR further enhances accessibility in low-connectivity rural areas.

The system also incorporates a confidence-based expert escalation mechanism, ensuring reliability and trust in advisory responses. Comparative analysis demonstrates improvements in accuracy, response time, and overall usability compared to existing solutions.

Overall, Agronex provides a scalable and practical approach for modern agricultural challenges, with potential for future enhancement through large-scale deployment and integration of real-time sensor data to support precision and sustainable farming.

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