

Review Of Ai-Driven Farmer Support Systems Using Llm's and Real-Time Data Integration

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Abstract

Agriculture plays a vital role in economic development and food security, particularly in developing countries where farmers rely on timely and accurate agricultural guidance. Conventional advisory systems generally provide static and generalized information, limiting their effectiveness in real-time decision-making and personalized support. Recent advancements in Artificial Intelligence (AI), Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and multimodal learning have enabled the development of intelligent and interactive agricultural advisory systems capable of delivering context-aware recommendations. This review paper presents a comprehensive overview of AI-based farmer advisory systems with a focus on conversational AI, retrieval-based frameworks, tool-augmented reasoning, and image-based crop disease detection. The study reviews existing research on machine learning-based crop recommendation systems, IoT-enabled smart agriculture, deep learning approaches, and LLM-powered agricultural assistants. The role of vector databases, external tool integration, and real-time data processing in improving the accuracy, relevance, and personalization of agricultural responses is also examined. Furthermore, the paper discusses major challenges, limitations, and future research opportunities associated with designing efficient, scalable, and reliable smart agricultural advisory systems. The review highlights the growing potential of integrating LLMs with retrieval mechanisms and multimodal technologies to enhance the effectiveness of next-generation agricultural support systems.

Keywords: Conversational AI; Deep Learning; FAISS; Large Language Models (LLMs); Multimodal Learning

1. Introduction

Agriculture is one of the most important sectors contributing to economic growth and food security. Especially in developing countries where a large population depends on farming for livelihood. Farmers need timely and accurate information on crop selection, irrigation, fertilizers, pest control, weather conditions and disease management for increasing productivity and minimizing losses. However, traditional agricultural advisory systems mainly offer static and generalized information, which constrains their ability of facilitating real-time and personalized decision-making. The rapid development of Artificial Intelligence(AI) and Natural Language Processing(NLP) has attracted more attention to intelligent advisory systems in modern agriculture. Machine learning (ML), deep

learning (DL), Internet of Things (IoT) and conversational AI technologies are increasingly being leveraged to develop smart farming solutions. One of these technologies, Large Language Models (LLMs), has been shown to be powerful at understanding natural language queries and generating human-like responses, making them very well suited for interactive farmer support systems. However, stand-alone LLMs still suffer from hallucination, lack of domain-specific knowledge, and unavailability of real-time information. To overcome these limitations, more sophisticated approaches including Retrieval-Augmented Generation (RAG), vector databases, and tool-augmented reasoning have been proposed. These technologies enhance the reliability and context

understanding of AI systems by incorporating external knowledge sources and real-time tools. Moreover, multimodal learning approaches have facilitated crop disease detection and visual agricultural assistance through the use of image analysis and deep learning. The present review paper aims to comprehensively study intelligent farmer advisory systems using AI technologies, including LLMs, RAG, conversational AI, multimodal learning, and real-time data integration. The paper presents a survey of existing research works, comparison of different approaches, major challenges and limitations and future directions for developing efficient and reliable smart agricultural advisory systems.

2. Related Work

The development of intelligent agricultural advisory systems has increased significantly with the advancement of the Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP). Several researchers have proposed various methods to improve agricultural productivity, crop monitoring, disease detection and assist farmers. This section reviews important research works related to AI based farmer advisory systems[1].

- A) Shinn et al. (2023) propose an agent-based framework for LLMs that improves reasoning ability through feedback and iteration. Their work showed how LLMs can interact with external tools to enhance response generation. However, the framework was not tailored for agricultural applications and not domain-specific optimized[2].
- B) Sujatha et al. (2021) proposed a crop recommendation system using Machine Learning algorithms like Decision Trees and Random Forest. The system looked at soil and environmental conditions to recommend suitable crops. The model was able to achieve good prediction accuracy but it was focused on structured data and did not have the ability to converse or give real-time advice.
- C) Rajput and Kumar (2020) developed an IoT-based smart agriculture monitoring system which used sensors for monitoring soil moisture, humidity and temperature. The system was equipped with smart irrigation and environmental monitoring, but it was not interactive and did not provide personalised farmer guidance.
- D) Lewis et al. (2020) proposed the Retrieval-Augmented Generation (RAG) framework, which combines external document retrieval with Large Language Models to enhance the reliability of responses and reduce hallucination. The framework significantly improved knowledge-grounded text generation, but the framework lacks dynamic real-time decision making and domain-specific agricultural integration[3].
- E) Brown et al. (2020) demonstrated the effectiveness of Large Language Models by showing the ability of the GPT-3 to perform multiple natural language tasks with few-shot learning. They improved conversational AI systems but were limited by hallucination challenges and lack of real-time information.
- F) Kumar et al. (2020) developed an AI-based agricultural chatbot to answer general agricultural questions of farmers. The chatbot improved accessibility and communication but lacked advanced features like retrieval-based knowledge integration, multimodal analysis and contextual personalisation.
- G) The Food and Agriculture Organization (FAO) (2018) stressed the role of Information and Communication Technology (ICT) in agriculture to enhance knowledge sharing and farmer support services. The report pointed out the digital platforms used for agricultural communication, but most of the systems were static and did not have intelligent reasoning abilities.
- H) Mohanty et al. (2017) created a deep learning system based on convolutional neural networks to detect diseases in crops using plant leaf images. The model exhibited high accuracy of disease classification and the effectiveness of deep learning in agriculture. But the approach only focused on classifying images and did not provide comprehensive advisory support.

Based on the literature studied, it can be seen that the existing systems of agricultural advisory are mainly designed for particular tasks like crop recommendation, monitoring, disease detection or chatbot interaction. There is limited research on combining LLMs, Retrieval-Augmented Generation, multimodal analysis and real-time tool integration into a single farmer advisory system. Hence, intelligent systems integrating these technologies have a great potential to improve the accuracy, reliability and the usability of agricultural advisory services[4].

3. Analysis Of Existing Approaches

The development of Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT) and Large Language Models (LLMs) has led to a significant evolution of Artificial Intelligence-based agricultural advisory systems. There are many proposals for approaches to improve agricultural productivity, monitoring of crops, detection of disease and support services for farmers. This section reviews the main technologies and approaches used in current farmer advisory systems.

3.1. Machine Learning Based Advisory Systems

Crop recommendation, yield prediction, soil analysis and irrigation management are popular application areas for Machine Learning techniques in agriculture. Algorithms like Decision Trees, Random Forests, Support Vector Machines and others are used extensively for analysis of agricultural data and recommendations. These systems can accurately predict using structured datasets, but often lack conversational interaction and real-time adaptability.

Advantages:

- Prediction accuracy is good
- Efficient for structured data in agriculture
- Support for crop and soil analysis

Limitations:

- Poor conversational ability
- Needs pre-defined data sets
- No real-time contextual understanding

3.2. Smart Agriculture Systems on IoT

In IoT-enabled agricultural systems, sensors and connected devices are used to keep an eye on

environmental conditions, including temperature, humidity and soil moisture. These systems enable farmers to automate irrigation and monitoring of crops. IoT systems may enhance the real-time monitoring, but they typically do not provide intelligent reasoning and personalised advisory.

Advantages[5]:

- Real time environment monitoring
- Irrigation automatic assist
- Better resource management

Limitations:

- Limited user interaction
- Needs sensor infrastructure
- No conversational AI integration

3.3. Large Language Model (LLM) based systems

Large Language Models have been employed to boost the conversational capabilities of agricultural advisory systems. These models can understand natural language queries and generate human-like responses, thus making agricultural support more accessible to farmers. However, standalone LLMs may generate erroneous or hallucinated information due to a lack of grounding in a specific domain[6].

Advantages:

- Communication in natural language
- Human like response generation
- Farmers' improved accessibility

Limitations:

- Issues of hallucination
- Lack of real-time knowledge
- Dependence on pre-trained data

3.4. Retrieval-Augmented Generation (RAG) Systems

Retrieval-Augmented Generation improves the reliability of LLM-based systems by retrieving relevant information from external knowledge sources prior to response generation. Vector databases such as FAISS are often utilised for fast document retrieval. RAG-based systems reduce hallucination and improve accuracy on domain-specific information.

Advantages:

- Better response accuracy
- Knowledge-based recommendations
- Lower hallucination in LLMs

Limitations:

- Depends on the quality of knowledge base
- More complexity of the system
- Needs efficient retrieval mechanisms

3.5. Multimodal and Deep Learning Based Systems

In multimodal agricultural systems, text and image analysis are combined to holistically support farmers. Deep Learning models, especially Convolutional Neural Networks (CNNs) are widely used for the detection of crop diseases based on leaf images. These systems improve the accuracy of disease diagnosis but are generally focused on specific tasks rather than comprehensive advisory support[7].

Advantages:

- Disease detection accuracy
- Allows analysis based on images
- Intensifies agricultural monitoring

Limitations:

- Image quality sensitive:
- Large training datasets needed
- Absence of contextual reasoning

3.6. Chatbot and Conversational AI systems

Agricultural chatbot systems offer conversational interfaces for interactive support for farmers. These systems increase accessibility and user engagement by enabling farmers to pose questions in natural language. Many chatbot systems, however, can only provide pre-defined or static responses and lack advanced reasoning abilities.

Advantages:

- Basic farmer engagement
- Fast response generation
- Better accessibility

Limitations:

- Lack of contextual understanding
- Fixed response generation
- No sophisticated AI reasoning

Analysis of the existing approaches reveals that most of the agricultural advisory systems are based on specific functionalities like prediction, monitoring, chatbot interaction, and disease detection. Few systems successfully integrate conversational AI, Retrieval-Augmented Generation, multimodal learning, and real-time tool integration under a single umbrella. Therefore, the integration of these

technologies has the potential to significantly enhance the efficiency, reliability and intelligence of future agricultural advisory systems.

4. Challenges And Limitations

Artificial Intelligence-based agricultural advisory systems have shown significant advancements in farmer support and decision making, but current methods still have some challenges and limitations. These limitations affect the reliability, scalability and practical applicability of intelligent advisory systems in real-world agricultural environments[8].

- **Large Language Models and Hallucination**
One of the biggest problems with Large Language Models (LLMs) is hallucination, or the model producing incorrect or misleading information. Erroneous responses can lead to dire consequences since agricultural recommendations are directly related to crop productivity and decisions made by farmers. While Retrieval-Augmented Generation (RAG) mitigates hallucination, full reliability remains challenging.
- **Lack of Real-Time Context Understanding**
Most of the agricultural advisory systems depend largely on pre-trained datasets and static sources of information. Hence they may not give recommendations depending on changing environmental conditions like weather, soil moisture, temperature and pest outbreaks. Real-time contextual understanding is still a major challenge in building useful advisory systems.
- **Restricted domain knowledge**
General purpose AI models are not specifically trained for agricultural purposes. So they may not have enough knowledge on the crops, fertilisers, irrigation methods, and local farming practices." Accurate domain-specific knowledge bases require continuous data collection and maintenance.
- **Limitations of the Dataset and Data Quality**
The quality and availability of data for training is critical for the performance of AI and deep learning models. In agriculture, it is difficult to obtain large scale and diverse datasets due to the variations in crops, soil

conditions, climate and farming techniques. Low quality datasets can reduce the accuracy and reliability of the model.

- **Multimodal Analysis Challenges** Image based crop disease detection systems are often sensitive to image quality, lighting conditions and dataset diversity. Blurred or poor quality images may reduce the accuracy of detection. Furthermore, the challenge of integrating text, image and sensor data into a unified intelligent framework still exists.
- **Infrastructure & Internet Reliance** Good internet connectivity, cloud platforms, and computational resources are common features of sophisticated AI based agricultural systems. Rural areas may not have the digital infrastructure, and the internet access, to make these systems work in practice.
- **Privacy and Security Issues** Farmer advisory systems may collect sensitive user data, such as location, crop information and farming practices. Secured storage and protection against unauthorised access is important to maintain user trust and reliability of the system.
- **But continuous development in Artificial Intelligence, Retrieval-Augmented Generation, multimodal learning, and real-time data integration is creating new opportunities for the improvement of intelligent agricultural advisory systems. Addressing these limitations can lead to more reliable, scalable and farmer-friendly smart agriculture solutions.**

5. Future Scope

The rapid development of Artificial Intelligence (AI), Large Language Models (LLMs) and smart agriculture technologies has created great opportunities for improving intelligent farmer advisory systems. Such systems can be further improved in terms of accuracy, scalability, accessibility and real time performance by future research and development

- **Progressive Agentic AI Architectures** Advanced agent-based AI frameworks that are able to perform multi-step reasoning and

autonomous decision-making can be used in future agricultural advisory systems. They have the ability to intelligently combine retrieval mechanisms, external tools and contextual understanding to offer more accurate and personalised recommendations .

- **Integration of real-time data** Contextual awareness in advisory systems can be enhanced by integrating real-time data from weather services, IoT sensors, and satellite systems. Future systems could provide dynamic recommendations on irrigation, fertiliser application, pest control and crop monitoring based on ever-changing environmental conditions.
- **Multilingual Conversational Systems** The future systems should be able to support multiple regional languages and dialects, so that the farmers from different regions can access them more easily. Multilingual conversational AI can help farmers to interact with advisory systems in a more natural and effective way.
- **Enhanced Multimodal Learning** In the future, agricultural systems will be able to integrate data from text, images, audio and sensors to deliver richer analysis and decision support. Advanced multimodal learning techniques might improve accuracy of crop disease detection, soil analysis and agricultural monitoring.
- **Trustworthy and Explainable AI** Future research efforts should be directed at the development of explainable AI systems that offer transparent and comprehensible recommendations. This can improve farmers' trust and help users better understand the logic behind the advisory suggestions.
- **Integration with Government and Agriculture Databases** Future advisory systems will combine government agricultural schemes, crop guidelines and market information to give farmers more comprehensive support. The integration can boost awareness on subsidies, crop insurance and agricultural policies

- Scalable Agricultural Platforms on the Cloud
Cloud computing technologies can be used to build scalable and efficient advisory systems that can cope with large numbers of users and agricultural datasets. Hosting on the cloud can enhance the system's availability, storage, and processing efficiency.
- Improved Crop Disease Detection Models
Larger and more diverse datasets and advanced deep learning architectures and transfer learning techniques can be used to improve future systems for crop disease detection. This would increase disease detection accuracy across various crop varieties and environmental conditions."

The use of advanced AI technologies, real-time analytics, multimodal learning, and scalable intelligent frameworks has great potential to transform agricultural advisory systems. Progress in these areas in the future could make a major contribution to the development of smarter, more accessible and more reliable solutions for digital agriculture.

Conclusion

AI-based advisory systems for agriculture are helping modern agriculture with their intelligent and context-aware assistance. Techniques like LLM, RAG, conversational AI, and multimodal learning have made agricultural advisory systems highly accurate and effective. In this review paper, several techniques based on AI technology in smart agriculture were investigated. These include crop recommendation systems, IoT-based monitoring, disease detection, and conversational advisory systems. Several challenges in AI-based agricultural advisory systems were discussed, including the issue of hallucination in LLMs, absence of real-time comprehension, inadequate datasets, and multi-language support. The conclusion drawn from this review is that incorporating AI-based technology with retrieval models and real-time sources can enhance the performance of agricultural advisory systems in the future.

References

- [1]. S. Shinn et al., "Reflexion: Language Agents with Verbal Reinforcement Learning," 2023.
- [2]. R. Sujatha, P. Isakki, and S. Raj, "Crop

Recommendation System using Machine Learning," 2021.

- [3]. A. Rajput and S. Kumar, "IoT Based Smart Agriculture Monitoring System," 2020.
- [4]. P. Lewis et al., "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks," 2020.
- [5]. T. B. Brown et al., "Language Models are Few-Shot Learners," 2020.
- [6]. R. Kumar et al., "Agricultural Chatbot for Farmers using Artificial Intelligence," 2020.
- [7]. Food and Agriculture Organization (FAO), "Information and Communication Technology in Agriculture," 2018.
- [8]. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," 2017.