International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 06 June 2026
Page No: 4413 - 4416
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0576

Llm-Based Farmer Advisory System Using Retrieval and Tool-Augmented Reasoning

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Abstract
Timely, accurate, and context-aware advisory support is essential for improving agricultural productivity and decision-making. Traditional agricultural advisory systems often provide generalized recommendations and lack real-time adaptability to individual farmer requirements. To address these limitations, this paper presents an intelligent LLM-based Farmer Advisory System that integrates conversational artificial intelligence with Retrieval-Augmented Generation (RAG), tool-based reasoning, and multimodal analysis. The proposed system utilizes a LangGraph-based orchestration framework in which the Large Language Model dynamically determines whether to retrieve information from a FAISS-based knowledge repository, invoke external tools such as weather APIs, or generate responses directly based on user queries. The system further incorporates farmer-specific contextual information, including crop type, geographical location, and soil conditions, to provide personalized and relevant recommendations. In addition, a vision-based crop disease detection module is integrated to analyze crop images and assist farmers in identifying possible diseases. The system is implemented as a web-based application using Flask, enabling seamless interaction through a user-friendly interface. The proposed hybrid framework improves the reliability, adaptability, and usability of agricultural advisory services compared to conventional approaches. Experimental observations indicate that combining LLM reasoning with retrieval mechanisms and external tools significantly enhances the effectiveness of AI-driven agricultural assistance systems in real-world farming environments.
Keywords: *Conversational AI; Crop Disease Detection; FAISS; Farmer Advisory System; Large Language Model (LLM)*

1. Introduction
Particularly in developing nations where a sizable section of the population relies on farming, agriculture is essential to maintaining food security and boosting the economy. Farmers often need accurate and timely information about weather, pest control, fertilizer use, crop selection, and irrigation techniques. However, because they rely on static information sources and constrained interaction mechanisms, traditional advisory systems frequently fall short of offering individualized and real-time guidance. Large Language Models (LLMs) have become potent tools for facilitating human-like interaction with machines due to the quick development of Artificial Intelligence (AI), especially in the area of Natural Language Processing (NLP). By enabling natural language communication, these models increase the accessibility of technology for non-technical users like farmers. By enabling natural language communication, these models increase the accessibility of technology for non-technical users like farmers. Despite their potential, standalone LLMs are constrained by their reliance on pre-trained knowledge and their inability to dynamically access real-time or domain-specific data. This study proposes an intelligent Farmer Advisory System that integrates multimodal analysis, tool integration, retrieval mechanisms, and LLM-based conversational capabilities. The system makes use of a LangGraph-based framework to facilitate dynamic

decision-making, in which the model chooses whether to use external tools, retrieve data from a document database, or directly generate responses. In order to provide tailored recommendations, farmer-specific contextual data like location, crop type, and soil conditions are also included. The system is a complete advisory platform since it has a vision-based module for evaluating crop photos and helping to identify diseases. The suggested system seeks to enhance the precision, applicability, and usability of agricultural advisory services by combining various technologies into a single framework. This work shows how hybrid AI systems can improve farmers' decision support and solve real-world problems.

2. Literature Review

Artificial intelligence and digital technologies have led to the evolution of agricultural advisory systems. To help farmers make decisions, a variety of methods have been employed, including conversational systems, deep learning, and machine learning. Although current approaches yield encouraging outcomes, they frequently do not incorporate real-time data, personalization, and interactive features. These methods are expanded upon in this work to create a cohesive and intelligent farmer advisory system[1].

2.1. Shinn et al. (2023) – LLM Agent-Based Systems

In order to improve task performance, Shinn et al. proposed an agent-based framework that enhances Large Language Models with reasoning and feedback mechanisms. The system shows how LLMs can interact with external tools and iteratively improve their responses. Although the method works well for enhancing reasoning skills, it is not designed for domain-specific applications like agriculture and necessitates structured orchestration[2].

2.2. Sujatha et al. (2021) – Crop Recommendation using Machine Learning

Sujatha and others made a system that uses machine learning algorithms like Decision Trees and Random Forest to recommend crops. The system looks at the soil and environmental conditions to recommend the best crops. The model makes accurate predictions, but it can only work with structured data and can't handle natural language queries or give interactive advice.

2.3. Rajput and Kumar (2020) – IoT-Based Smart Agriculture

Rajput and Kumar put forward an IoT-based smart agriculture system that uses sensors to keep an eye on things like temperature, humidity, and soil moisture. The system helps people make choices about watering plants and taking care of them. But it doesn't have a conversational interface and doesn't give farmers personalized suggestions[3].

2.4. Lewis et al. (2020) – Retrieval-Augmented Generation

Lewis et al. came up with the Retrieval-Augmented Generation (RAG) framework, which uses language models and external document retrieval to make sure that generated responses are more accurate. This method makes things more reliable, but it doesn't allow for real-time data integration or dynamic decision-making about how to use tools[4].

2.5. Brown et al. (2020) – Large Language Models (GPT-3)

Brown et al. showed that big language models can write text that sounds like a person and do a lot of other natural language tasks. These models make conversational AI systems a lot better. But they are likely to have hallucinations and don't have access to real-time or domain-specific information.

2.6. Kumar et al. (2020) – Agricultural Chatbot Systems

Kumar et al. made a chatbot system that uses AI to help farmers with simple questions about farming. The system makes things easier to get to and gives quick answers. But it doesn't have advanced features like knowledge-grounded retrieval, real-time data integration, and multimodal analysis[5].

2.7. Food and Agriculture Organization (FAO) (2018) – ICT in Agriculture

The FAO report talks about how Information and Communication Technology (ICT) can help people get advice on farming. It stresses how important digital platforms are for making agricultural knowledge more accessible. These systems, on the other hand, are mostly static and don't have smart decision-making or personalization features.

2.8. Mohanty et al. (2017) – Deep Learning for Plant Disease Detection

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Mohanty et al. suggested an intelligent system based on deep learning technology using Convolutional Neural Networks for plant disease detection through leaf images. The system has achieved good accuracy, which shows the efficiency of deep learning in agriculture. The system is only based on image classification and does not offer overall advisory services by incorporating other factors[6].

3. Methodology And Implementations

The proposed system is aimed at providing intelligent and contextual agricultural advisories through the use of a hybrid model based on LLMs, retrieval methods, and external tool support. The system architecture is aimed at ensuring efficient query processing for users, dynamic decision-making, and effective interaction between various components[7].

3.1.System Architecture

The proposed system is based on a modular system architecture, which includes the frontend interface, backend server, database, and AI processing layer. The frontend interface is based on a web interface, which is implemented using web-based technology. The backend is based on Flask, which is used for efficient processing of requests, authentication, and interaction between various components. The AI layer is based on the integration of LLM and LangGraph for workflow execution and decision-making. The system also utilizes a vector database based on FAISS for efficient retrieval of agricultural documents. In addition, external APIs are used for retrieving real-time data from external sources.

3.2.Working of the System

The system follows a series of steps to generate a response for user queries. When a farmer asks a question, it is first processed and enriched with additional information. Then, it is passed on to the decision engine, where it is processed by LangGraph. Depending on the output of this engine, a response is generated by the LLM. Thus, it ensures that the output is accurate, relevant, and easy to understand.

3.3.Retrieval-Augmented Generation

To ensure that the output is reliable, Retrieval-Augmented Generation is used in this system. Here, a FAISS database is used to store vector embeddings of all agricultural documents. When required, it uses this information to generate a response. Thus, it ensures that the output is reliable, and there is no chance of incorrect information being provided.

3.4.Tool-Based Integration

To make this system more useful, several tools are integrated into it. For instance, a weather API is integrated into this system[8]. This API is used to fetch information regarding weather conditions. Thus, it ensures that context-aware information is provided to farmers.

3.5.Farmer Profile Personalization

The system has a farmer profile that includes information about their location, type of crops, and soil conditions. This information is used to personalize the response so that it is relevant to the user. This enhances the usability of the system.

3.6.Multimodal Analysis

In addition to text, images are used for input in the system. This is used for detecting possible diseases in crops. A deep learning model is used for analyzing images of crops. This information is then used in conjunction with the explanation provided by the LLM to give a comprehensive output to the farmer.

3.7.Implementation Details

The system is developed by using Flask for developing the back end. Various libraries are used for developing the system. LangGraph is used for workflow management, thus enabling dynamic decision-making. FAISS is used for efficient search in the knowledge base.

4. Results And Discussion

The proposed Farmer Advisory System based on LLM was evaluated based on its capability to provide accurate, relevant, and context-aware responses to the queries made to the system. The proposed Farmer Advisory System was tested with different types of inputs to the system, including general queries on agriculture, weather-related queries, and images regarding crop disease.

4.1.Response Accuracy and Relevance

The accuracy of the response generated by the proposed Farmer Advisory System was enhanced through the integration of Retrieval-Augmented Generation with the Large Language Model. The relevant information was retrieved from the knowledge base, enabling the generation of more accurate responses to the queries made to the system.

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The addition of context to the query, like the farmer profile, also enhanced the relevance of the response generated by the system.

4.2.Real-Time Decision Support

The integration of weather-related tools with the proposed Farmer Advisory System enabled the generation of real-time decision support to the farmers. The proposed Farmer Advisory System was able to generate recommendations on irrigation, usage of fertilizers, and disease management based on the weather conditions.

4.3.Multimodal Functionality

The system can accommodate both text and image input. This makes it more flexible than other advisory systems. This image-based part of the system can recognize crop diseases and make recommendations. This feature contributes to the overall functionality of the system.

4.4.User Interaction and Usability

The conversational interface enabled farmers to interact with the system. This made it easier for users to interact with the system. This is because farmers can interact using natural language. Personalized recommendations were also made based on farmer profiles.

4.5. Comparison with Existing Systems

The proposed system, when compared to traditional rule-based and machine learning-based advisory systems, provides a more integrated and intelligent approach. While traditional systems are designed to perform a single task, such as prediction or detection, the proposed system provides a comprehensive approach through the combination of conversation AI, retrieval, and real-time data integration.

4.6.Limitations

The proposed system has a few limitations. First, the system depends on a good knowledge base and external data. Second, the image-based disease detection may be influenced by image quality. Further improvements can be made by increasing the dataset and improving the accuracy of the model.

Conclusion And Future Work

Conclusion

The Farmer Advisory System is a good example of how Large Language Models can be used in conjunction with retrieval-augmented generation and tools to develop intelligent and context-aware agricultural advisory systems. This system can help address the limitations associated with conventional advisory systems. This is because it is interactive, personalized, and real-time. Additionally, the incorporation of farmer-specific information and multimodal analysis can make this system even more usable. Therefore, this proposed approach is quite promising in terms of improving decision support for farmers.

Future work

The system can also be improved further by incorporating other data sources such as satellite imagery, soil sensor data, and government agricultural data. The disease detection module can also be improved using larger and diverse data sets. Other improvements that can be made to the system in the future include incorporating multiple languages to support farmers of various regions. In addition to that, incorporating more advanced agent-based frameworks and real-time tool integration can also improve the system.

References

[1]. S. Shinn et al. (2023) Reflexion: Language Agents with Verbal Reinforcement Learning
[2]. R. Sujatha, P. Isakki and S. Raj (2021) Crop Recommendation System using Machine Learning
[3]. A. Rajput and S. Kumar (2020) IoT Based Smart Agriculture Monitoring System
[4]. P. Lewis et al. (2020) Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks
[5]. T. B. Brown et al. (2020) Language Models are Few-Shot Learners
[6]. R. Kumar et al. (2020) Agricultural Chatbot for Farmers using Artificial Intelligence
[7]. Food and Agriculture Organization (FAO) (2018) Information and Communication Technology in Agriculture
[8]. S. P. Mohanty, D. P. Hughes and M. Salathé (2017) Using Deep Learning for Image-Based Plant Disease Detection