



SCIENCE RESEARCH ANNALS (PHYSICAL SCIENCES)

Published by Faculty of Science, Adekunle Ajasin University, Akungba-Akoko (AAUA)

Journal website: <https://sra.com.ng/index.php/sra-physical>



SCIENTIFIC ARTICLE

DOI: <https://doi.org/10.63112/rfcd6x82>

Leveraging AI chat assistants for enhanced food security in Africa: A comprehensive integration of large language models, retrieval augmented generation, and vector embedding techniques

Abdulmajid Mujtaba^{1,*}, Isah Abdulsamad¹, Abu Zibri Ismail², Maryam Ibrahim Mukhtar²,
Muhammad Abdulkadir Yola²

¹ Technology and R&D Department, Extension Africa Consulting Limited, Abuja, Nigeria

² Department of Software Engineering and Computer Science, Faculty of Computing and Information Technology, Bayero University Kano, PMB 3011 Kano, Kano State, Nigeria

*Correspondence: a.mujtaba@extensionafrica.com (A. Mujtaba)

ARTICLE INFORMATION

Keywords:

Artificial intelligence
Agricultural extension and advisory
Food security
Large language models (LLMs)
Retrieval-augmented generation (RAG)

Handling Editor: M.B. Aminu

Disclaimer: All opinions expressed are solely the authors, and do not necessarily represent that of the Journal's Editorial Board, Management, or workers.

License: SRA, AAUA, Nigeria.

ABSTRACT

Agricultural productivity in Africa faces significant challenges due to limited access to timely, localized information and expert guidance, leading to suboptimal farming practices that threaten food security and economic development. The increasing demands of food security and sustainable agriculture necessitate cutting-edge technological solutions. This study introduces an Artificial Intelligence (AI) chat assistant powered by Large Language Models (LLMs) and AI agents, utilizing Retrieval-Augmented Generation (RAG) and vector database embeddings to transform agricultural practices. By integrating LLMs with domain-specific data through RAG, the assistant delivers precise, context-aware responses to complex agricultural inquiries. The use of vector embeddings enables efficient semantic search across extensive agricultural datasets, enhancing information retrieval and decision-making processes for frontline extension workers, agronomists, and farmers. The AI agents facilitate autonomous task execution, such as analysis of crop health, disease identification, and predictive modelling based on weather patterns. Natural language processing ensures intuitive user interactions, making advanced agricultural insights accessible regardless of technical proficiency. AI chat assistance leads to increased access to much-needed information on a wide range of agricultural practices, empowering farmers to optimize their practices, enhance crop yields, and significantly contribute to food security and sustainable economic development in Africa.

Highlights

- AI chat assistant, Abikn Noma, RAG and vector embeddings for agronomic advice.
- Deep-learning CNN identifies crop diseases with 88.3 % validation accuracy.
- Tool can cut 35-40 % yield losses via timely AI-driven interventions.

1. Introduction

Achieving Sustainable Development Goal 2 (SDG 2) to end global hunger requires universal access to safe, nutritious food and resilient systems that incorporate sustainable agriculture, poverty reduction, and equitable distribution. Currently, nearly 690 million people face hunger, a figure that has increased by 60 million over the last five years (Chamara et al., 2020). The global demand for food continues to rise due to

population growth, posing significant challenges to sustainability and threatening food security worldwide (Chamara et al., 2020).

Traditionally, agricultural experts have visited farms to provide training and advice on various practices, including crop pest and disease detection, to support farmers in enhancing their agricultural techniques (Momaya, 2021; Omara et al., 2023). However, crop pests and diseases represent a major threat in sub-Saharan Africa, leading to annual yield losses exceeding 35–40% (Omara et al., 2023). Furthermore, limited

access to modern farming technologies remains a significant challenge for rural communities (Ekanayake & Saputhanthri, 2020).

Information is a critical resource for rural development, enabling small-scale farmers to make timely, informed decisions (Ekanayake and Saputhanthri 2020). Unfortunately, the lack of real-time information on soil properties, seeds, fertilizers, pests, modern tools, and best agricultural practices often results in poor crop productivity and low yields (Usif et al., 2023; Omara et al., 2023).

Artificial Intelligence (AI), particularly through machine learning, holds promise in providing farmers with chatbots, virtual assistants, and voice-based interfaces for accessing real-time information (Kansal *et al.*, 2023). Since its emergence in 2015, the use of AI in agricultural food production has garnered attention but remains in its early stages (Chamara et al., 2020). Despite its potential, the agricultural sector has been slow to adopt AI technologies, and its application for enhancing food security is not as advanced as in fields like IT, transportation, economics, social media, and business (Chamara *et al.*, 2020).

Recently, there has been a significant shift from relying on agricultural experts to utilizing machine learning and computer vision techniques for crop inspection via mobile devices (Omara *et al.*, 2023). The establishment of mobile chatbots for crop farmers is recognized as a key contributor to achieving sustainable development goals (Usip *et al.*, 2023). Extension workers and smallholder farmers can leverage mobile applications for the early detection and diagnosis of crop diseases and pest manifestations, as well as for various other farming-related activities (Omara et al., 2023; Rane et al., 2024).

Numerous chatbots and applications have been developed to assist farmers in obtaining real-time information. Omara *et al.* (2023) aimed to integrate a smartphone-based disease diagnostic application with a real-time feedback tool that farmers can utilize at any time in their gardens. Yadav et al. (2023) developed a mobile application to assist farmers that includes a technology library, plant disease identification and diagnosis, an automated chatbot, weather alerts, and information on nearby warehouses and market prices. Vankatesh et al. (2023) developed an automated chatbot model that utilizes artificial intelligence to address the fundamental needs of farmers and agriculture, including soil type, crop selection, and environmental factors. Usif et al. (2022) focused on creating a mobile chatbot that offers useful answers, advice, and recommendations on specific farming concerns for crop farmers in Uyo and its surrounding areas. Momaya (2021) developed a chatbot that assists farmers by providing solutions to agricultural queries, addressing questions related to crop sowing, crop diseases, and seasonal issues. Kaviya et al. (2021) presented the design and development of an intelligent voice recognition chatbot that allows users to query any farmer-related activities. Maduri et al. (2021) developed a voice-enabled chatbot that helps farmers with questions regarding specific fertilizer dosage predictions and optimal crop selection based on climate conditions. Ekanayake and Saputhanthri (2020) developed a chat room and a chatbot to discuss prevailing farming issues with peers and experts, supporting farmers in making timely decisions regarding their agricultural practices.

This paper presents a real-time chatbot designed to assist farmers and extension agents in analysing crop health, identifying pests and diseases, and providing advice based on weather conditions. By utilizing the chatbot, farmers can receive instant guidance without waiting for expert intervention, enhancing crop management through timely responses. This early intervention has the potential to significantly improve livelihoods and contribute to alleviating food security challenges in Africa.

2. Methodology

This study employs a comprehensive framework integrating Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and vector embedding techniques to develop an AI chat assistant aimed at enhancing agricultural productivity and food security in Africa. The methodology encompasses the selection and configuration of appropriate AI models, the implementation of an agent framework, and the utilization of advanced data retrieval and embedding techniques to ensure the delivery of precise and context-aware information to end-users. The following sections detail each component of the methodology.

2.1 System Architecture

The proposed AI chat assistant is structured into five processing layers: the Language Processing Layer, the vector embedding layer, the Retrieval-Augmented Generation Layer, the Deep Learning CNN Layer, and the AI Agent Framework. This architecture facilitates seamless integration of domain-specific agricultural data with advanced language and image recognition models to provide actionable knowledge to farmers and agronomists.

2.1.1 Large Language Model (LLM)

At the core of the system lies the OpenAI GPT-4o-mini, a variant of the Generative Pre-trained Transformer (GPT) architecture (Vaswani et al., 2017; OpenAI, 2023). GPT-4o-mini was selected due to its balance between computational efficiency and linguistic proficiency, enabling real-time interactions essential for agricultural decision-making.

2.1.2 Retrieval-Augmented Generation (RAG)

To address the limitations of static knowledge within LLMs, the study integrates Retrieval-Augmented Generation (RAG) techniques (Lewis et al., 2020). RAG combines the generative capabilities of LLMs with a retrieval mechanism that accesses external databases, thereby providing up-to-date and contextually relevant information. The implementation leverages OpenAI's File Search tool, which automatically parses, chunks, and embeds user-provided documents into a vector database. This setup enables both keyword and semantic searches, facilitating the retrieval of pertinent information in response to user queries.

2.1.3 Vector Embedding Techniques

Vector embeddings play a critical role in enhancing the semantic search capabilities of the AI assistant. Utilizing vector database embeddings, the system transforms textual data into high-dimensional vectors that capture the semantic relationships between different pieces of information (Mikolov et al., 2013). The OpenAI File Search tool employs these embeddings to enable efficient and accurate retrieval of relevant agricultural data from extensive datasets. Each vector store can accommodate up to 10,000 files, ensuring scalability and comprehensive coverage of agricultural knowledge.

2.1.4 Deep Learning CNN for Disease Identification

In addition to language-based functionalities, the AI assistant incorporates a deep learning Convolutional Neural Network (CNN) model for plant disease identification. This model is trained on the PlantVillage dataset, which includes images of various crops such as tomato and maize labeled with different disease symptoms (Kaggle, 2020). The CNN architecture was selected for its proven effectiveness in image classification tasks (LeCun et al., 2015). During user interactions, farmers can upload images of their crops, and the CNN model analyzes these images to identify potential diseases, providing timely and accurate diagnostic information. This integration enhances the AI assistant's capability to support farmers in disease management and crop health monitoring.

2.1.5 AI Agent Framework

The AI Assistant API provided by OpenAI serves as the foundation for the agent framework, enabling the creation of autonomous agents capable of executing specific tasks within the application (OpenAI, 2023). This agent leverages the integrated LLM, RAG, and CNN components to perform functions such as real-time crop health analysis, disease identification, and predictive modeling based on weather patterns. The framework supports the deployment of multiple agents, each specialized in different aspects of agricultural support, thereby enhancing the overall functionality and responsiveness of the AI assistant.

2.2 Implementation Process

The implementation of the AI chat assistant followed a structured process:

- 1. Data Collection and Preparation:** Agricultural documents, including local farming guidelines, were collected and digitized. Additionally, the PlantVillage dataset was acquired, containing labelled images of various crops affected by different diseases. These documents and images were then parsed and segmented into manageable chunks for embedding and training purposes.
- 2. Embedding Generation:** The segmented documents were processed using vector embedding techniques to create high-dimensional representations stored in the vector store database. This step ensures that the system can perform both keyword and semantic searches efficiently.
- 3. Model Integration:** The OpenAI GPT-4o-mini was integrated with the RAG framework using the File Search tool, enabling the model to access and retrieve relevant information dynamically during user interactions.
- 4. CNN Model Training and Integration:** The CNN model was trained on the PlantVillage dataset to accurately classify plant diseases based on uploaded images. The trained model was then integrated into the AI assistant, allowing it to process and analyze visual data provided by users.
- 5. Agent Configuration:** Utilizing the OpenAI Assistant API, specialized AI agents are configured using a function (Tools) calling to handle specific tasks such as crop health analysis, disease identification, and weather-based predictive modelling. This agent is programmed to autonomously execute its

designated functions based on user inputs and retrieved data. A deep learning model was trained using a convolutional neural network.

- 6. User Interface Development:** A user-friendly interface was developed to facilitate intuitive interactions between farmers, extension agents, and the AI assistant.

Figure 1 illustrates the Sequence interaction flow between the User, Chatbot, Assistant API, and Assistant Tools to process user queries. The User initiates the process by sending a message to the Chatbot, which forwards it to the Assistant API along with details of available tools. The API analyzes the request, decides on the appropriate tool (e.g., a deep learning CNN model for disease identification or weather forecasting tools), and executes it with relevant arguments. The tool processes the input and returns a response to the API, which updates the Chatbot with the results. The Chatbot integrates the tool's response, refines it if needed, and delivers the final output to the User. This flow ensures dynamic, tool-based query handling for accurate and efficient responses.

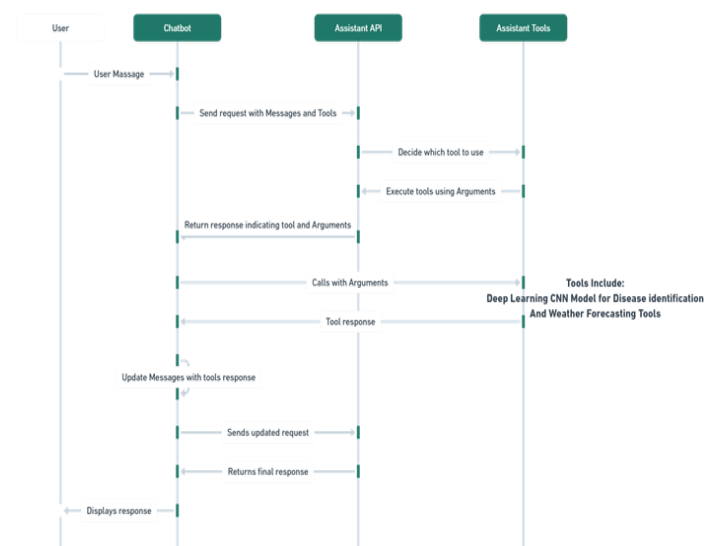


Figure 1: Assistant interaction process.

2.3 Evaluation and Validation

To assess the effectiveness of the AI chat assistant, a series of evaluations were conducted:

- 1. CNN Model Performance:** The accuracy of the CNN model in identifying plant diseases was evaluated using a separate validation set from the PlantVillage dataset (Kaggle, 2020), which achieved 88.28% Validation accuracy. Figure 2 shows the accuracy of the CNN deep learning model for both training and validation datasets. As observed, the training accuracy improves consistently, achieving a peak value of 97.60% Similarly, the validation accuracy shows a steady increase, reaching 88.28%. The model demonstrates strong generalization with a validation accuracy of 88.28%.
- 2. User Satisfaction and Usability:** Surveys and user interviews were conducted with a sample of farmers and agronomists to evaluate the usability and satisfaction levels associated with the AI assistant. Feedback was systematically analyzed to identify specific areas for improvement, ensuring that the system aligns with the practical needs and preferences of end-users across

diverse farming environments. Table 1 gives a summary of sample prompts, the AI's responses, and observations gathered during testing.

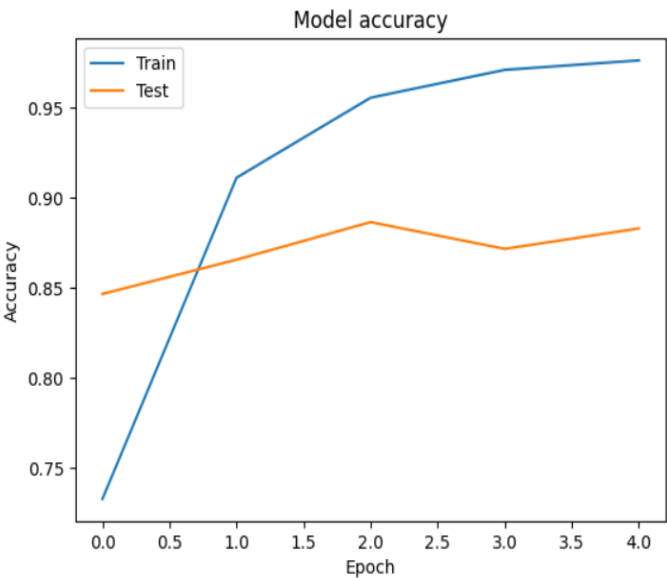


Figure 2: Model accuracy graph.

Table 1: Survey responses.

S/N	Prompt	Response	Observation
1	What do you is best to farm in Jos?	<p>In Jos, which is located in Plateau State, the climate and soil conditions are suitable for growing several high-yielding crops. Here are some of the best options:</p> <ol style="list-style-type: none">1) Maize: This is a major cereal and can thrive in various soil types. Recommended varieties include SAMMAZ 15 and SAMMAZ 17, known for their drought tolerance and high yield potential.2) Cassava: This root crop grows well in loamy, well-drained soils and can withstand drought conditions. Varieties such as TMS 90257 and NR 8082 are recommended for their high yields and disease resistance.3) Rice: Suitable for both upland and lowland areas with adequate rainfall. Varieties like FARO 44 are known for their high yields and adaptability to the local climate.4) Sorghum: This drought-resistant crop is also well-suited for the region and can adapt to different soils. <p>It's also important to consider market demand and the specific conditions of your farm when choosing which crops to plant. If you're interested in learning more about agriculture practices, you can explore courses at the Extension Africa Academy. If you have more specific questions or need assistance, feel free to ask!</p>	The response is informative and provides specific crop recommendations, with varieties that are well-suited to Jos' climate and soil. Additionally, users might benefit from more localized advice on planting schedules or specific pest/disease risks in Jos.
2	Hello, I need help and advice with regards to rice farming	<p>Hello! I'm Abokin Noma, your agricultural assistant. How can I assist you specifically with rice farming? Are you looking for advice on planting, disease management, harvesting, or something else? Let me know so I can provide the most helpful information from our resources.</p>	The response is user-friendly and engages the user by clarifying their specific needs, which can improve the quality of advice given.
3	This is a picture of a plant from my farm. Please give me some advice?	<p>The plant in your picture is affected by the Tomato Mosaic Virus. Although your concern was about rice, I'll provide advice specific to dealing with this virus since it's related to your uploaded plant picture:</p> <p>Management Tips for Tomato Mosaic Virus:</p> <ol style="list-style-type: none">1) Crop Rotation: Avoid planting tomatoes in the same location every year. Rotate with non-susceptible crops.2) Sanitation:<ul style="list-style-type: none">• Remove and destroy infected plants immediately to prevent the spread of the virus.	The response correctly identifies the disease affecting the plant in the picture. The assistant provides relevant and actionable advice, although the user initially asked for rice-related help. Additionally, the assistant could encourage ongoing monitoring of nearby plants for similar symptoms.

3. Results and discussions

The results from implementing the AI chat assistant reveal its transformative potential in addressing agricultural challenges in Africa. By leveraging technologies such as Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), vector embeddings, and deep learning CNN models, the system effectively enhances access to real-time, context-specific agricultural information. This section elaborates on the system's effectiveness, practical applications, performance metrics, and implications for food security and agricultural sustainability.

3.1 Improved Access to Agricultural Information

The AI assistant has transformed the way farmers and extension workers access essential agricultural knowledge. By offering detailed, context-specific advice tailored to regional soil conditions, crop types, and pest challenges, it provides invaluable support. Its real-time capabilities eliminate the delays often encountered with traditional advisory services or waiting for expert consultations. Additionally, the assistant's ability to deliver swift and actionable insights on pest outbreaks, disease identification, and weather-adaptive practices has significantly contributed to reducing potential yield losses.

	<ul style="list-style-type: none"> • Clean tools and equipment regularly with disinfectant solutions. 	
	<ol style="list-style-type: none"> 3) Resistant Varieties: Consider using tomato varieties that are resistant to Tomato Mosaic Virus for future plantings. 4) Quarantine New Plants: Keep new tomato plants isolated until you can ensure they are not infected. 5) Pest Control: Control insect pests that can serve as vectors for virus transmission. 	
	If you need specific help regarding rice farming, feel free to ask more questions or upload additional images if you suspect any issues with your rice crop.	
4	<p>Analyze the picture and give me a solution?</p> <p>Hello! It seems that the plant in your picture is affected by the Tomato Mosaic Virus. Here's what you can do:</p> <ol style="list-style-type: none"> 1) Isolate Infected Plants: Remove and destroy all infected plants to prevent the virus from spreading. 2) Sanitize Tools: Make sure to clean and disinfect gardening tools regularly to avoid transferring the virus from one plant to another. 3) Rotate Crops: Practice crop rotation with non-susceptible plants to reduce the virus in the soil. 4) Control Weeds: Weeds can host the virus, so maintain your garden by removing them frequently. 5) Resistant Varieties: Consider planting tomato varieties that are resistant to the Tomato Mosaic Virus. <p>Encourage good sanitation practices in your garden and monitor your plants regularly. If the problem persists, seeking further advice through the Extension Africa Academy can be beneficial. If you need additional help, please call 080000222333.</p>	The response provides a clear and actionable solution for managing the Tomato Mosaic Virus, offering practical steps such as isolation, sanitation, crop rotation, and weed control.
5	<p>My farm is currently in Abuja. Based on the weather, do you think I should water it today and tomorrow?</p> <p>Here's the weather forecast for Abuja over the next three days:</p> <ol style="list-style-type: none"> 1) Today (2024-11-09): Few clouds with temperatures ranging from 22.88°C to 32.91°C. Humidity is at 36%. 2) Tomorrow (2024-11-10): Overcast clouds with temperatures from 22.88°C to 31.85°C. Humidity increases to 42%. <p>Watering Advice:</p> <ol style="list-style-type: none"> 1) Given the relatively high temperatures and moderate humidity, you might consider watering your crops today to ensure they don't suffer from a lack of moisture. 2) Tomorrow, with overcast conditions and slightly higher humidity, the need for watering might be less urgent, but it depends on the soil moisture level and the specific needs of your crop. <p>Always check the soil moisture manually to ensure it aligns with the requirements of rice, which usually needs consistent moisture for optimal growth. If you have any further questions or need more specific advice, feel free to ask!</p>	The response is thorough and provides a detailed weather forecast followed by practical watering advice, which is helpful. The assistant could improve by offering a more crop-specific recommendation (since rice generally needs more moisture) and reminding the user to account for any recent rainfall. Including a simple soil moisture test tip (e.g., checking soil depth for moisture) could enhance the response's practicality.

3.3 Efficiency of Semantic Search

By using advanced vector embedding techniques, the system enhanced semantic understanding and data retrieval. This allowed the assistant to provide precise, contextually relevant information efficiently, even for complex queries. The assistant's search scalability supports up to 10,000 files, ensuring comprehensive agricultural coverage for a wide user base. Figure 3 shows the interface of the chat assistant with a user query asking for an assistant and receiving a response from the assistant.

3.4 User Satisfaction and Usability

Farmers and extension workers appreciated the intuitive interface, reliability, and timely responses. The system's design emphasized user accessibility, catering to non-technical users through a conversational interface. Extension workers benefited from tools for field-specific challenges, while farmers utilized predictive modelling for disease iden-

tification and prevention. The disease diagnostic functionality was particularly highlighted as a game-changer for smallholder farmers. The findings are similar to those of Ekanayake and Saputhanthri (2020), where the majority of farmers found the interface easy to use and were impressed with the system.

4. Discussion

The discussion delves into the transformative potential of the AI chat assistant in addressing key agricultural challenges across Africa. By integrating advanced technologies such as Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), vector embeddings, and deep learning, the assistant bridges the gap between traditional farming practices and modern, data-driven solutions. This section evaluates the assistant's effectiveness in empowering farmers and extension workers, explores its contributions to enhancing food security, and critically analyzes its scalability.

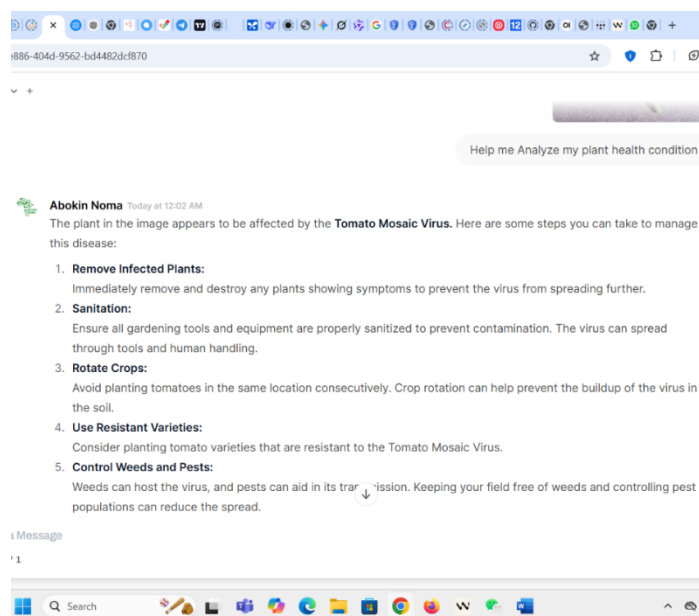


Figure 3: Chat assistant interface.

4.1 Enhancing Food Security through AI

The AI assistant plays a crucial role in addressing food insecurity across Africa by facilitating precision farming. Through timely diagnosis of diseases, it can help reduce the 35–40% annual yield losses commonly reported in sub-Saharan Africa. By providing actionable recommendations, the assistant will enable farmers to implement more efficient practices, including irrigation, pest control, and fertilizer application. Additionally, its predictive analytics, based on weather data, can empower farmers to proactively adapt to changing climatic conditions, further safeguarding their yields.

4.2 Scalability and Adaptability

The system's design makes it easy to scale up for wider use. With its vector embedding model and semantic search capabilities, it's ready to integrate new datasets, making it adaptable to different agricultural needs. By training the models to recognize region-specific crops, pests, and diseases, the assistant can effectively support farmers across diverse environments in Africa.

4.3. Bridging Knowledge Gaps for Extension Workers

The AI assistant can significantly enhance the capacity of extension services by providing access to a comprehensive digital repository of agricultural knowledge. It enables real-time responses to farmers' queries, reducing the need for frequent physical field visits. The assistant supports scalable operations by lessening the reliance on a limited pool of human experts, allowing extension services to reach more farmers efficiently and effectively.

5. Conclusions and Recommendations

Limited access to productive resources, including extension and advisory services, has been a significant challenge for smallholder farmers across Africa. The public extension system, responsible for

knowledge transfer, suffers from insufficient funding for content development and dissemination through both in-person interactions and digital tools. Since the withdrawal of World Bank funding, which previously supported the Training & Visit (T&V) approach, private and development partners have stepped in to explore alternative solutions.

Integrating AI chat assistants has shown a positive impact on the capabilities of frontline extension agents by enhancing their awareness, improving pest and disease diagnostics, and enabling more effective advisory services for farmers. The AI assistant's ability to identify crop issues and provide immediate recommendations reduces the need to consult subject matter specialists, streamlining support for farmers. Additionally, the AI's tolerance for typographical and sentence-structure errors makes it accessible to extension agents with basic literacy skills. Despite these benefits, there is a critical need to ensure the AI system provides verified agronomic advice, climate-smart practices, and weather-related recommendations. Agricultural research institutions and extension agencies should prioritize making accurate, up-to-date content accessible for AI platforms through standardized digital formats and APIs or via dedicated content partnerships with AI platform developers to maximize their value for extension agents and farmers. They should also establish sustainable processes for content review and updates to ensure long-term relevance and ownership of information. However, limited internet connectivity and poor network infrastructure in rural areas restrict access to these digital tools. Adding voice and speech functionalities could further extend AI's reach to over 30% of smallholder farmers who cannot read or write.

Utilizing AI chat assistance has the potential to significantly improve access to extension and advisory services, which can lead to increased productivity, higher incomes, greater resilience, and enhanced food security for smallholder farmers. To realize the full benefits of AI and other digital tools in agriculture, it is essential to invest in rural infrastructure that supports connectivity and digital access for agricultural practitioners.

Acknowledgments

The authors are grateful to all the anonymous reviewers whose contributions and comments have greatly improved this manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Competing Interest

The authors affirm that there are no identifiable conflicts of interest, either financial or personal, that could be perceived as influencing the work presented in this paper.

Data Availability Statement

All data generated or analyzed during this study are included in this published article.

Ethics Approval

No institutional review board operates at the authors' home institution; therefore, the study underwent an internal minimal-risk

assessment and was judged to meet the criteria for exempt human-subjects research. All survey and interview participants were adults who received an information sheet describing the study purpose, data uses, and their right to withdraw; written informed consent was obtained before any questions were asked. Data were pseudonymised, stored on encrypted drives, and analysed only in aggregate. Processing complied with the Nigeria Data Protection Regulation 2019 and the Nigeria Data Protection Act 2023, which require “freely given, specific, informed and unambiguous” consent and appropriate security safeguards. No personally identifying information is reported in this article. The secondary PlantVillage images and other open datasets contain no personal data and are therefore exempt from further review.

References

- Chamara, R. M. S. R., Senevirathne, S. M. P., Samarasinghe, S. A. I. L. N., Premasiri, M. W. R. C., Sandaruwani, K. H. C., Dissanayake, D. M. N. N., and Marambe, B. (2020). Role of artificial intelligence in achieving global food security: a promising technology for future. *Sri Lanka Journal of Food and Agriculture*, 6(2). <https://doi.org/10.4038/sljfa.v6i2.88>
- Ekanayake, J., & Saputhanthri, L. (2020). E-AGRO: Intelligent chat-bot. *Agris On-Line Papers in Economics and Informatics*, 12(1), 15-21. <https://doi.org/10.7160/aol.2020.120102>
- Kaggle. (2020). *PlantVillage dataset*. <https://www.kaggle.com/datasets/emmarex/plantdisease>
- Kansal, M., Singh, P., Srivastava, M., & Chaurasia, P. (2023). Empowering Agriculture With Conversational AI: An Application for Farmer Advisory and Communication. In *Convergence of Cloud Computing, AI, and Agricultural Science* (pp. 210-227). IGI Global. <https://doi.org/10.4018/979-8-3693-0200-2.ch011>
- Kaviya, P., Bhavyashree, M., Krishnan, M. D., & Sugacini, M. (2021). Artificial intelligence based farmer assistant chatbot. *International Journal of Research in Engineering, Science and Management*, 4(4), 26-29. <https://journal.ijresm.com/index.php/ijresm/article/view/631>
- Lewis, P., Perez, E., Piktus, A., et al. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. In *Advances in Neural Information Processing Systems*, 33 (pp. 9459-9474). <https://doi.org/10.48550/arXiv.2005.11401>
- Maduri, P. K., Dhiman, P., Shukla, M. R., Anand, S., & Singh, S. P. (2021, December). Farmers agriculture assistance chatbot. In *Proceedings of the 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)* (pp. 1884-1889). IEEE. <https://doi.org/10.1109/ICAC3N53548.2021.9725634>
- Manning, C. D., Raghavan, P., & Schütze, H. (2008). *Introduction to information retrieval*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511809071>
- Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In *Advances in Neural Information Processing Systems*, 26 (pp. 3111-3119). <https://doi.org/10.48550/arXiv.1310.4546>
- Momaya, M., Khanna, A., Sadavarte, J., & Sankhe, M. (2021, June). Krushi – the farmer chatbot. In *2021 International Conference on Communication, Information and Computing Technology (ICCICT)* (pp. 1-6). IEEE. <https://doi.org/10.1109/ICCICT50803.2021.9510040>
- Omara, J., Talavera, E., Otim, D., Turcza, D., Ofumbi, E., & Owomugisha, G. (2023). A field-based recommender system for crop disease detection using machine learning. *Frontiers in Artificial Intelligence*, 6, Article 1010804. <https://doi.org/10.3389/frai.2023.1010804>
- OpenAI. (2023). *OpenAI API documentation*. <https://platform.openai.com/docs>
- Rane, J., Kaya, O., Mallick, S. K., & Rane, N. L. (2024). Smart farming using artificial intelligence, machine learning, deep learning, and ChatGPT: Applications, opportunities, challenges, and future directions. In *Generative artificial intelligence in agriculture, education, and business* (pp. 218-272). Deep Science Publishing. https://doi.org/10.70593/978-81-981271-7-4_6
- Usip, P. U., Udo, E. N., Asuquo, D. E., & James, O. R. (2022, September). A machine learning-based mobile chatbot for crop farmers. In *International Conference on Electronic Governance with Emerging Technologies* (pp. 192-211). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-22950-3_15
- Usip, P. U., James, O. R., Asuquo, D. E., Udo, E. N., & Osang, F. B. (2023). Usability evaluation of an intelligent mobile chatbot for crop farmers. In F. Ortiz-Rodríguez, S. Tiwari, P. Usoro Usip, & R. Palma (Eds.), *Electronic governance with emerging technologies* (Vol. 1888, pp. 101-111). Springer. https://doi.org/10.1007/978-3-031-43940-7_9
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems*, 30 (pp. 5998-6008). <https://doi.org/10.48550/arXiv.1706.03762>
- Venkatesh, V., Kunju, K., Suresh, S., Natesan, S., & Kumar, S. (2023, August). AI-based farmer assistant talkbot. In *AIP Conference Proceedings* (Vol. 2857, 020031). AIP Publishing. <https://doi.org/10.1063/5.0166565>
- Yadav, T., Sable, P., & Kalbande, D. (2023, July). SMART KISAN: A mobile app for farmers' assistance in agricultural activities. In *2023 International Conference on Smart Systems for Applications in Electrical Sciences (ICSSES)* (pp. 1-6). IEEE. <https://doi.org/10.1109/ICSSES58299.2023.10199471>

How to Cite: Mujtaba et al. (2025). Leveraging AI chat assistants for enhanced food security in Africa: A comprehensive integration of large language models, retrieval-augmented generation, and vector embedding techniques. *Science Research Annals—Physical Sciences*, 1(1), 34–40. <https://doi.org/10.63112/rfcd6x82>