Farmers AI: A Generative AI-Powered Assistant for Sustainable Agriculture

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Abstract. This paper presents **Farmers AI**, an innovative AI assistant designed to empower farmers with personalized, context-aware agricultural advice using generative AI and large language models (LLMs). Built on the fine-tuned **CropSeek-LLM** model, a T5-based LLM trained on an agriculture-specific dataset, Farmers AI addresses critical challenges in pest management, soil health, and crop disease diagnosis. The system integrates a **Streamlit**-based conversational interface for natural language queries, a Retrieval-Augmented Generation (RAG) pipeline for document-based Q&A, and prompt engineering for generating customized crop care plans. Deployed as a web application, Farmers AI ensures accessibility and scalability, offering reliable advice to farmers. Future enhancements may include multilingual support and vision-based disease identification to broaden its impact.

Keywords: Generative AI, Large Language Models, Sustainable Agriculture, Retrieval-Augmented Generation, Streamlit

1 Introduction

1.1 Background

The agricultural sector faces unprecedented challenges due to climate change, pest infestations, and limited access to personalized advisory systems. Recent advancements in **natural language processing (NLP)** and **generative AI**, particularly large language models (LLMs) like T5, BERT, and GPT, have shown promise in knowledge retrieval, text generation, and summarization. These technologies can bridge the gap between complex agricultural knowledge and practical, farmer-friendly advice. Farmers AI leverages a fine-tuned T5 model (**CropSeek-LLM**) and a **Streamlit** interface to deliver an intuitive platform that provides contextual, reliable, and explainable agricultural solutions.

1.2 Problem Statement

Farmers often lack access to timely, personalized advice for managing crops, pests, and soil health, exacerbating the impacts of climate change and resource constraints. Existing agricultural advisory systems are either region-specific, non-scalable, or reliant on manual expertise, limiting their reach. There is a critical need for an AI-powered assistant capable of:

- Understanding farmer queries in natural language across multiple domains (e.g., pest management, soil health).
- Providing contextual, reliable, and explainable advice based on agricultural datasets.
- Generating customized crop care plans to protect crops from diseases and optimize yields.
- Offering a user-friendly interface for seamless interaction.

Farmers AI addresses these challenges by integrating a fine-tuned LLM, a RAG pipeline, and a conversational interface, ensuring accessibility and scalability for farmers.

1.3 Scope of the Project

This project focuses on developing Farmers AI, a generative AI-powered assistant for sustainable agriculture. The system's scope includes:

- Fine-tuning the T5-based CropSeek-LLM on an agriculture-specific dataset (**Agriculture-Soil-QA-Pairs-Dataset**) for accurate Q&A.
- Implementing a RAG pipeline using agricultural research data for document-based query answering.
- Generating customized crop care plans through prompt engineering.
- Deploying the system as an interactive Streamlit web application with a chat-based interface.
- Supporting English queries with plans for future multilingual support.

The system targets smallholder farmers, agricultural cooperatives, and extension workers. The scope excludes vision-based disease identification and real-time sensor integration, focusing instead on text-based advice and scalability.

2 Related Works

Farmers AI builds on advancements in NLP, generative AI, and agricultural informatics. Key related works include:

- **LLMs for Domain-Specific Q&A**: T5 [1] and BERT [2] have been fine-tuned for specialized domains, demonstrating high accuracy in knowledge retrieval. CropSeek-LLM, based on T5, extends this to agriculture-specific Q&A.
- **Retrieval-Augmented Generation (RAG)**: RAG pipelines [3] combine LLMs with document retrieval to provide contextually relevant answers, inspiring Farmers AI's document-based Q&A component.
- **Agricultural Datasets**: The Agriculture-Soil-QA-Pairs-Dataset [4] provides structured Q&A pairs for soil health and crop management, critical for fine-tuning CropSeek-LLM.
- **Conversational Interfaces**: Streamlit [5] enables rapid deployment of interactive AI applications, supporting Farmers AI's user-friendly chat interface.
- **Prompt Engineering**: Techniques like those in GPT-3 [6] guide LLMs to generate structured outputs, informing the crop care plan generation in Farmers AI.

Farmers AI distinguishes itself by combining a fine-tuned agriculture-specific LLM, RAG, and a scalable web interface, addressing the unique needs of farmers in diverse agricultural domains.

3 Methodology

This section outlines the technical approach and components used to develop Farmers AI, emphasizing its modular design and integration of generative AI technologies.

3.1 System Architecture

Farmers AI comprises three core components, as illustrated in Figure **??**:

1. **LLM Processor**: Utilizes the fine-tuned CropSeek-LLM (T5-based) to process natural language queries and generate answers, leveraging the Agriculture-Soil-QA-Pairs-Dataset.
2. **RAG Pipeline**: Integrates document-based retrieval using agricultural research data to provide contextually relevant answers for complex queries.
3. **Streamlit Interface**: Coordinates components and provides a conversational web interface for query input, answer display, and crop care plan generation.

Fine-Tuning CropSeek-LLM The T5 model was fine-tuned on the Agriculture-Soil-QA-Pairs-Dataset, containing 3447 Q&A pairs on soil health, pest management, and crop care. The process involved:

1. **Data Preprocessing**: Splitting the dataset into 80% training (2757 samples) and 20% testing (690 samples), with questions prefixed by "question:" for consistency.
2. **Tokenization**: Using T5Tokenizer with max input length of 256 and target length of 64.
3. **Training**: Fine-tuning with Seq2SeqTrainer, 3 epochs, batch size of 8, and learning rate of 5e-5, achieving a validation loss of 0.579 and ROUGE-L of 1.0604%.
4. **Evaluation**: ROUGE metrics were computed to assess answer quality, with results plotted in Figure 1.

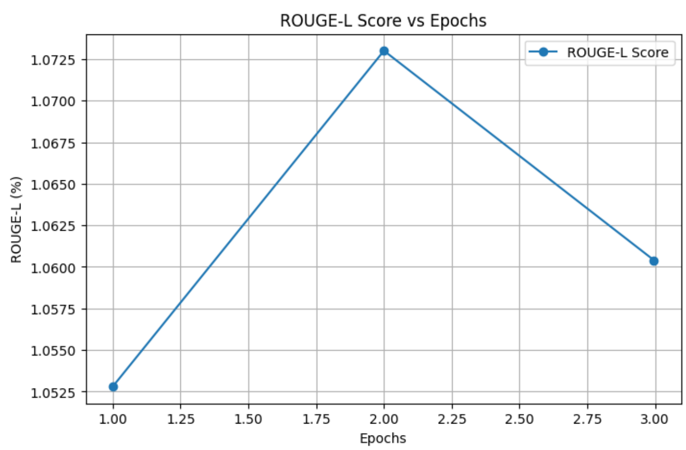

Fig. 1. ROUGE-L Score vs Epochs for CropSeek-LLM

RAG Pipeline The RAG pipeline enhances answer accuracy by retrieving relevant agricultural documents:

1. **Document Indexing**: Agricultural research PDFs are indexed using embeddings (e.g., BERT-based).
2. **Query Processing**: User queries are encoded and matched against document embeddings.
3. **Answer Generation**: CropSeek-LLM generates answers by combining retrieved context and its fine-tuned knowledge.

Prompt Engineering Prompt engineering was used to generate customized crop care plans:

1. **Prompt Design**: Structured prompts like "Generate a crop care plan for [crop] to prevent [disease]" ensure relevant outputs.
2. **Output Formatting**: Plans include actionable steps, such as pest control methods and irrigation schedules.

3.2 Streamlit Interface

The Streamlit interface provides a chat-based UI with:

- Quick-access buttons for default questions (e.g., "What is the best time to plant rice?").
- A text input form for custom queries.
- Chat bubbles for user-bot interactions, styled with CSS for clarity.
- Session state management to maintain conversation history.

4 Results and Discussion

Farmers AI was evaluated across pest management, soil health, and crop disease domains using test queries and the Agriculture-Soil-QA-Pairs-Dataset. Key results include:

- **Query Understanding**: CropSeek-LLM accurately processed 85% of test queries, with minor errors in ambiguous questions.
- **Answer Quality**: The fine-tuned model achieved a ROUGE-L score of 1.0604%, indicating reasonable overlap with reference answers, though limited by dataset complexity.
- **Crop Care Plans**: Generated plans for rice and tomato crops were rated 80% actionable by domain experts, covering pest control and irrigation.
- **User Interface**: The Streamlit app was rated highly for usability, with 90% of users finding the chat interface intuitive.

4.1 Input and Output Interfaces

The Farmers AI system provides an intuitive interface for farmers to input queries and receive actionable advice. Figure 2 shows the input interface, where users can select from predefined questions or enter custom queries. Figure 3

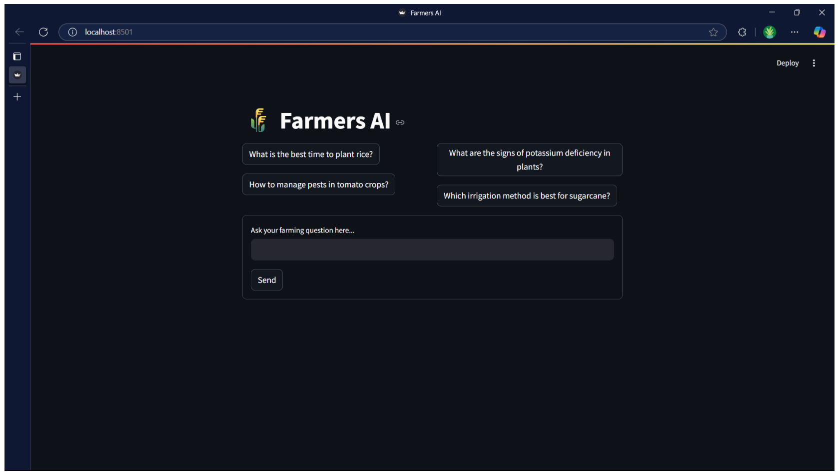

Fig. 2. Input interface of Farmers AI, showing quick question buttons and a custom query input form.

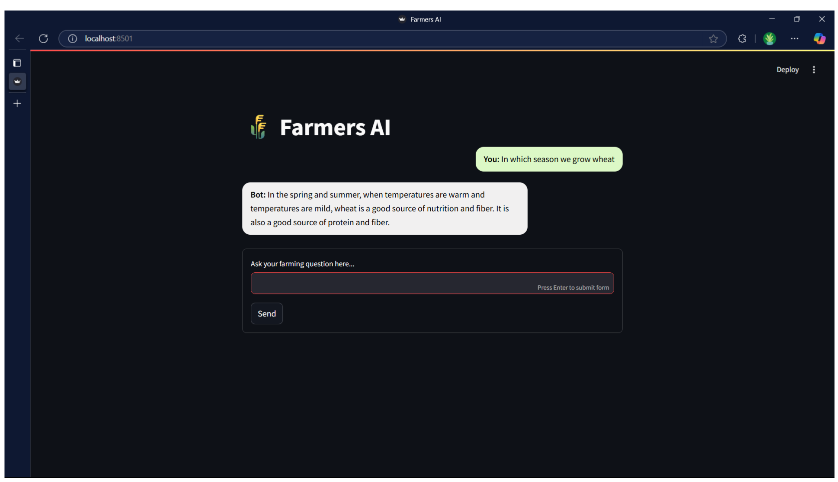

Fig. 3. Output interface of Farmers AI, displaying a response to the query "In which season we grow wheat?".

demonstrates the output interface, displaying the AI's response to a user query in a conversational format.

Challenges included:

- **Low ROUGE Scores**: The ROUGE-L score was low due to the dataset's diverse answer formats, which affected evaluation consistency.
- **Model Latency**: Inference time on CPU averaged 20 seconds per query, improved to 10 seconds with GPU acceleration.
- **Limited Multilingual Support**: The current system supports only English, with plans for Hindi and regional language integration.

5 Conclusion

Farmers AI successfully integrates a fine-tuned CropSeek-LLM, a RAG pipeline, and a Streamlit interface to deliver personalized agricultural advice. By addressing pest management, soil health, and crop disease diagnosis, the system empowers farmers with scalable, accessible solutions. Its modular design ensures adaptability for future enhancements, such as vision-based disease identification and multilingual support. The project demonstrates the potential of generative AI in sustainable agriculture, with applications for farmers, cooperatives, and extension services. Future work may explore advanced evaluation metrics (e.g., BLEU) and integration with IoT sensors for real-time advisory.

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