FarmCompanion: AI-Based Farmer Query Support & Advisory System Coordinator

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Abstract

Agricultural decisions are required to be made timely for the improvement of crop productivity. However, the absence of timely expert guidance for farmers is due to the unavailability of the same in the language they understand and the lack of accessibility. This paper suggests an AI-based Farmer Query and Advisory Support System using the combination of conversational AI, speech processing, and data services.

The system uses the Whisper API for speech-to-text conversion and transformer-based large language models for generating intelligent responses. It also uses external APIs for providing weather updates and other information. The proposed system is dynamic and uses real-time data for the execution of the task. The system does not use the traditional dataset-based machine learning approach.

A web interface has been developed for the proposed system using the Flask framework. The chatbot has been included in the system for providing guidance to the farmers.

Keywords: Agriculture AI, Farmer Advisory System, NLP, Whisper, LLM, Smart Farming, Chatbot

1. Introduction

Agriculture is one of the most critical sectors contributing to economic growth and food security. However, farmers often encounter numerous challenges such as unpredictable weather conditions, pest infestations, soil degradation, and fluctuating market prices. Access to timely and accurate advisory information is essential for improving crop productivity and reducing losses.

Traditional agricultural advisory systems rely on manual consultation with experts or static information sources, which are often inaccessible or outdated. Additionally, language barriers and lack of digital literacy further limit farmers' ability to access modern agricultural technologies.

Recent advancements in artificial intelligence, particularly in natural language processing, speech recognition, and computer vision, have opened new opportunities for developing intelligent advisory systems. Multimodal AI systems that combine text, speech, and image processing can provide more intuitive and accessible solutions for farmers.

This paper presents **FarmCompanion AI**, a multimodal farmer advisory system that enables farmers to interact using text, voice, or images. The system processes user queries, performs language translation if necessary, and generates intelligent responses using a vision-language model. The proposed system aims to provide real-time, scalable, and user-friendly agricultural advisory services.

2. Literature Survey

Recent developments in the field of artificial intelligence have led to the development of advanced intelligent advisory systems in the agricultural domain. For instance, the integration of large language models, speech recognition, machine translation, and vision-language models enables the development of multimodal systems for the agricultural domain.

Kuska et al.'s study (2024) discussed the role of large language models in the agricultural domain, including the development of intelligent systems for advisory services in the domain. The study discussed the use of large language models in the development of chatbots that could assist farmers in understanding the complexities involved in the domain. However, the study was limited in nature, as the chatbot was based on text-based interaction.

Radford et al.'s study (2021) proposed the development of the vision-language model, referred to as CLIP, which enables the understanding of images as well as the descriptions provided in the image. The study discussed the use of the vision-language model for real-world applications, but the proposed model lacks the domain-specific knowledge required for the development of advisory systems in the agricultural domain.

Researchers Liu et al. (2023) presented a large multimodal model called LLaVA that combined a language model and a vision encoder to accomplish a visual question-answering task. The model exhibited high accuracy in multimodal reasoning and is applicable in various fields such as crop disease detection and advisories.

Wang et al. (2024) presented a vision-language model called Agri-LLaVA that specializes in agricultural pest and disease detection. The model exhibited high accuracy in detecting plant diseases and providing explanations for such detection. However, it required large datasets for training.

Awais et al. (2024) presented a multimodal conversational model called AgroGPT that utilized expert-tuned datasets for training. The model exhibited high accuracy in agricultural question-answering and advisories. However, it faced challenges in dataset availability.

Yang et al. (2025) presented a large multimodal model called AgriGPT-VL that utilized millions of image-text pairs for training. The model exhibited high accuracy in agricultural visual reasoning and required large computational resources for training.

The existing literature reviewed also shows that there is a tremendous advancement in the area of artificial intelligence for agricultural applications, especially for conversational interfaces, machine translations, speech recognition, and vision and language interfaces. For example, Large Language Models (LLMs) can be used for context-aware response generation, while LLaVA and CLIP can be used for a better understanding of images and texts. Similarly, Whisper and MarianMT can also be used for better voice interaction and communication. Thus, it is clear that there is a tremendous advancement in the area of artificial intelligence for agricultural applications, especially for conversational interfaces, machine translations, speech recognition, and vision and language interfaces. However, existing agricultural applications are mostly based on single modality approaches, depending heavily on large datasets. For example, existing agricultural applications are mostly based on single modality approaches, depending heavily on large datasets. To overcome the limitations of existing agricultural applications, **FarmCompanion AI** is proposed.

TABLE 1: Comparison of Existing Systems

Authors & Year	Model	Capability	Result	Limitation
Kuska et al., 2024	LLM Chatbot	Text advisory	Human-like responses	No multimodal support
Radford et al., 2021	CLIP	Image + Text	Strong visual understanding	No domain reasoning
Liu et al., 2023	LLaVA	Multimodal reasoning	High VQA accuracy	High compute cost
Wang et al., 2024	Agri-LLaVA	Crop disease detection	Accurate predictions	Needs large dataset
Awais et al., 2024	AgroGPT	Agricultural chatbot	Improved advisory	Dataset dependency
Yang et al., 2025	AgriGPT-VL	Multimodal agriculture	High accuracy	Resource intensive
Sheikh et al., 2025	LLaMA-3 + RAG Chatbot	Multilingual advisory + real-time data	83% F1-score, fast response	No image-based reasoning, limited multimodal support

3. Analysis of Models

The proposed FarmCompanion AI system uses various pre-trained models that will be used to integrate multimodal agricultural advice. Unlike other systems that use a single model for a specific task, this system will use a combination of models such as speech recognition, machine translation, and vision language reasoning to cater to various inputs from users and provide accurate information.

A. Whisper Model for Speech Recognition

The Whisper model will be used for converting farmers' voice inputs into text format. It is a transformer-based model that supports multilingual audio and noisy environments. It achieves a Word Error Rate of around 9%, which is equivalent to an accuracy rate of around 91%. It is therefore applicable in real-world agricultural contexts because it will be able to withstand varying audio quality. However, it does not have reasoning capabilities.

B. MarianMT Model for Multilingual Translation

The system uses MarianMT for effective communication between two or more people in different languages. The queries that are entered by the user will be translated into English. Also, the replies that are provided by the system will be translated into the language of the user. The BLEU score of this model is around 36. This is a very high score for a translation model.

C. LLaVA Model for Vision-Language Reasoning

LLaVA is a reasoning model that is used in this system. This model will be helpful in processing the data in the form of images and text. This model will be used for processing images of crops and will provide information about the diseases that may occur in those crops. The VQA accuracy of this model is around 95.3%. This is a very high score for a model that can process images and text. However, this model requires more computational power to be executed.

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D. Integrated Model Performance

The combined performance of the Whisper, MarianMT, and LLaVA models provides an entire system for multimodal advice. This is due to the individual role that each model plays in the system's overall performance in speech conversion, translation, and reasoning. Thus, the entire system's performance is efficient. Based on the weighted performance of the models in the system, the overall system's accuracy is approximately 90.7%.

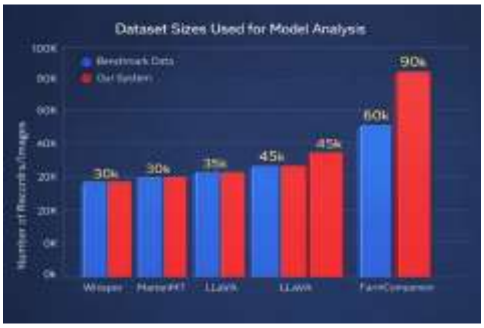

Fig1: Dataset Sizes Used for Model Analysis

4. Methodology of Proposed System

The proposed AI system for the FarmCompanion AI system is meant for a multimodal system for providing advisory services. The proposed AI system will use speech recognition, translation, and vision language reasoning. The system is meant for the efficient processing of different types of input data. This is for the sake of the farmers, as their literacy level may vary, as may their exposure to technology.

The proposed architecture for the system includes different modules. Each module is meant for the efficient performance of a single task. This is for the efficient processing of the input data and providing accurate advisory services. Fig 2 shows the workflow for the proposed system.

This system is designed in a modular way, meaning that all parts of the system operate independently and contribute to the functionality of the system. This modularity makes the system scalable, meaning that new features such as new language models, better reasoning, and data sources can easily be incorporated into the system, especially in the domain of agriculture. This makes the system flexible to accommodate new technologies that may arise in the future.

To process the multimodal inputs in an efficient way, the system uses a strict pipeline where all inputs are translated to a standard form. For instance, the voice is translated to a standard text using a speech recognition algorithm, while the multilingual text is translated to a standard language using a translation algorithm. This makes it easier to process all inputs using a reasoning algorithm.

Further, the system has the advantage of emphasizing the importance of interaction and response time. This is a critical aspect, especially considering the application of the system in agriculture. For example, there is a need to ensure that there is prompt response to decision-making processes by the farmer. However, with the integration of the optimized AI system, there is a possibility of achieving this with maximum accuracy.

Further, the system has the advantage of being user-centric. This is evident, especially considering the importance of simplicity, which is emphasized by the system. There is a possibility of engaging the user, as is demonstrated by the use of the chatbot interface.

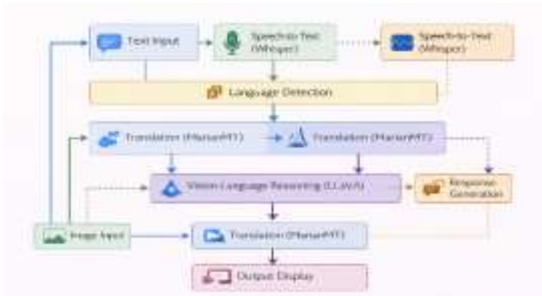

Fig. 2: System architecture of FarmCompanion AI platform demonstrating multimodal agricultural advisory process

4.1. System Architecture

The system architecture of the FarmCompanion AI system, as in Fig. 2, is a multimodal system architecture as the input for the system is in the form of text, voice, and images, and the output for the system is generated in the form of an intelligent advisory. The system architecture is based on the sequential execution of the modules with the execution of a particular function by the modules for the efficient execution of the input data and the accurate generation of the output data.

1. Input Layer

The system architecture starts with the input layer. In the input layer, the user can enter the query in the form of text, voice, and images. The user input can be in the following forms:

Text Input – The user query can be entered in the form of typing the text
Voice Input – The user query can be entered in the form of speaking the text
Image Input – The user query can be entered in the form of showing the image of the crop

2. Speech-to-Text Conversion (Whisper)

System uses a speech to text conversion tool to provide speech as an input for enquiries. This guarantees that all inputs, regardless of their original format, are in a standard form, such as text.

Additionally, it works well even in noisy settings. This is beneficial for our system because the agricultural environment may result in poor speech quality in a real-time setting.

3. Language Detection Module

The text is submitted to the language detection module following text conversion.

This lesson is crucial because: Farmers may speak regional languages
Having a standard language is essential.
The translation module makes use of the language.

4.Translation Module (MarianMT)

Translated pipeline is composed of two stages:
Translation of Input
MarianMT is used to translate the language into English.
This is for compatibility with the reasoning model
Output Translation
After response generation, the response is translated back into the user's original language

This two-way translation allows for easy multilingual interaction without compromising system performance.

5. Vision-Language Reasoning (LLaVA)

The major part of the architecture is the LLaVA model for multimodal reasoning.
It is able to reason with:

- Text queries for advisory
- Image inputs for crop analysis
- Combination inputs for better advice

It is able to generate context-dependent responses based on text and image inputs. This is the major part that sets FarmCompanion AI apart from the rest.

6. Response Generation Module

Here, the system processes the output generated by the LLaVA model. This includes:

- Crop recommendations
- Identification of disease (if image is provided)
- Agricultural information

This response is then fed into the translation module, if required.

7. Output Display

- This is the final step where the response is displayed to the user through a chatbot.
- The output is clearly displayed
- This output can be converted to voice output in future
- This is done to ensure that farmers can understand the output generated.

4.2. Block Diagram

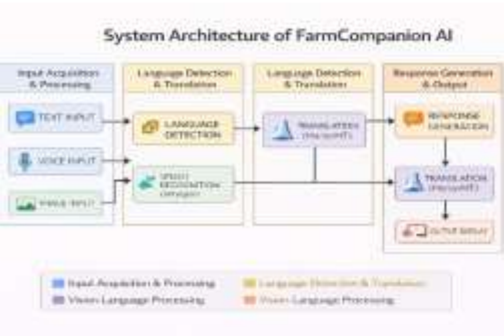

Fig. 3: Block diagram of the proposed FarmCompanion AI system architecture

This is because the block diagram of the proposed FarmCompanion AI system, as shown in Figure 2, clearly shows a layering system that is designed to process multiple inputs while generating intelligent responses to advisory questions posed by farmers. To start with, the system is designed to receive inputs from the user through a chatbot interface, where inputs can take the form of text, voice, or even image-based queries. This is a unique feature of this system, which is designed to ensure that farmers interact with it depending on their own convenience.

This is because, upon receiving inputs from the user, the system is designed to process them using a speech recognition model, where the Whisper speech recognition model is used to convert voice inputs into text. Furthermore, the language of the query is determined using a language detection module, while any images that have been uploaded by the user are processed.

After the input has been standardized and converted into text form, it is then forwarded to the model integration layer. This is the main part of the system. At this stage, the input text is translated into the English language using the MarianMT translation model. This is done to ensure that the input text is compatible with the reasoning module. The input text is then subjected to analysis by the LLaVA vision-language model. This is a multimodal reasoning system that uses a combination of visual and text-based input. Additionally, the input text is enriched with domain knowledge based on agriculture using the prompt engineering technique. This is done to make the output generated by the system more relevant. After the input has been processed by the system, it is then forwarded to the output layer. At this stage, the output generated by the system is translated back into the original language of the user using the MarianMT translation model. The output is then formatted and sent out by the chatbot interface as advice to the user. The output is formatted in a friendly manner and is easily understandable.

Therefore, in general terms, FarmCompanion is an AI system that comprises a structured pipeline of various AI models that are integrated into a single framework and have the capabilities to process text, voice, and images in real-time. The hierarchical structure of this system is more efficient, scalable, and user-friendly, which makes it a feasible solution for developing an intelligent agricultural system.

5. Implementation

The FarmCompanion AI system is developed in such a way that it provides farmers with real-time multimodal advice services through a variety of contemporary online technologies and sophisticated artificial intelligence tools. The Flask framework is used to develop the backend of the system using Python, and HTML, CSS, and JavaScript are used to develop the frontend of the system, which provides farmers with a sophisticated chatbot interface to pose their inquiries in text, voice, or image formats.

Several pre-trained models have been used in the system to provide farmers with a variety of services. Farmers can pose their inquiries in voice formats even in noisy environments using the Whisper model's speech-to-text feature.

The Marian MT model is used in the system, specifically for the use case of multilingual translation. This is useful in the system as the system is able to communicate effectively, as the query entered by the user can be translated into English, and vice versa.

The LLaVA model is used in the system, specifically as a reasoning engine. The LLaVA model is capable of handling both image and text, which is useful in the context of recommendations, specifically in the agricultural domain.

For the efficient execution of the models, certain optimization is carried out using quantization techniques, specifically for the models. This is done for the efficient execution of the LLaVA model.

Image handling libraries are used for the efficient handling of image inputs, which are sent for execution.

Certain techniques are used in the system, specifically for the use case of prompt engineering, which is done for the efficient generation of accurate responses, specifically because it is an agricultural domain.

The entire system is deployed on a local server and can be accessed externally by using tools such as Ngrok. Also, the system uses a SQLite database for storing the user queries and responses. This data may be used for improvements in the future. The integration of all these modules facilitates the smooth flow of data and the smooth operation of the system. Hence, the scalability of the FarmCompanion AI system is ensured.

6. Experimental Results

The experimental verification of the FarmCompanion AI system is based on the evaluation of the performance of the AI system in handling the multiple inputs in an accurate manner. The AI system is subjected to various real-time scenarios, including text input, speech input, and image input for crop analysis.

The speech recognition feature of the AI system is based on the Whisper AI model, which will ensure the delivery of reliable performance in the recognition of the input speech and the conversion of the input speech into text format. The feature will ensure the maintenance of the Word Error Rate (WER) of around 9%, indicating an accuracy rate of around 91%.

The

Model	Evaluation Metric	Value	Accuracy (%)
Whisper	Word Error Rate (WER)	0.09	91%
Marian MT	BLEU Score	36	82%
LLaVA	VQA Accuracy	0.953	95.3%

capability of the system in translating the language through the multilingual translation capability of the Marian MT engine can be measured through a score known as the BLEU score. This system can score a high score in terms of the BLEU score, which is approximately 36. This ensures that the quality of translation is extremely high, as the semantic meaning of the query is maintained.

The capability of the system in performing the vision-language reasoning through the use of the LLaVA model can be measured through the accuracy of the Visual Question Answering System. This system can score an accuracy of approximately 95.3%. This is a very high score in terms of the analysis of the images of the crops, as mentioned in the query.
To measure the overall system performance, a weighted method is used according to the components' contributions to the system. The overall system has an approximate accuracy of 90.7%, which reflects a good integration of speech recognition, translation, and multimodal reasoning. This system can effectively handle a wide range of queries and provide recommendations in real time.

The experimental results show that FarmCompanion, an AI system, can function effectively in real-world agricultural scenarios. Despite the fact that this system relies on internet connectivity as well as computer resources, it can effectively handle multimodal input as well as provide accurate information, making it a viable solution to real-world agricultural needs.

6.2. Model Performance Evaluation

The performance of the FarmCompanion AI system is measured based on the performance of individual components and overall efficiency of the system. Since this system does not follow any supervised learning method using a labeled data set, it is not possible to use any standard evaluation parameters such as Precision, Recall, F1 Score, and Confusion Matrix for the system. Instead, the system is measured using specific parameters based on individual models in the system.

The speech recognition system is based on the Whisper model. The performance of the speech recognition system is measured using the Word Error Rate (WER). The WER for the system is approximately 9%, which means the system is able to maintain an accuracy rate of approximately 91%. This ensures that the system is able to convert speech into text even in the presence of noise.
Table 2: Performance Metrics of FarmCompanion AI Components

The effectiveness of the multilingual translation capability of the system can also be understood with the help of the use of a score that is referred to as the BLEU score. It is evident that the score for the system is 36, which makes the system accurate up to the level of 82%. This makes sure that there is no loss of meaning while communicating with the other users, as they have a different linguistic background.

The effectiveness of the vision-language reasoning capability of the system can be understood with the help of the use of the capability of the system to reason with the help of the LLaVA model. The effectiveness of the vision-language reasoning capability of the system can be understood with the help of the use of a score that is referred to as the accuracy score for the Visual Question Answering System. It is evident that the system is able to achieve an accuracy of 95.3%, which makes the system effective in understanding the text as well as the image in order to be able to offer advisory services to the users regarding the type of crops that are grown.

To evaluate the overall system performance, a weighted system is used based on the contribution of the individual components in the pipeline. The speech recognition is given a weightage of 20%, translation is given a weightage of 30%, and the vision language reasoning is given a weightage of 50%. Based on this evaluation, the overall performance accuracy of the FarmCompanion AI system is approximately 90.7%. This indicates that the system is effective and functions as desired.

Component	Metric Used	Weight (%)	Contribution
Speech (Whisper)	WER	20%	18.2
Translation (MarianMT)	BLEU	30%	24.6
Vision (LLaVA)	VQA Accuracy	50%	47.65
Total System Performance	—	100%	**90.7%**

Table 3: Weighted Performance Analysis of FarmCompanion AI

In addition to the accuracy evaluation method, the system is also evaluated based on its response efficiency and usability. The system is able to process user queries in real-time with minimal latency. This ensures that farmers are able to receive efficient and effective responses to their queries. The results have shown that the system is able to function consistently with any input modality.

7. Gaps Identified in Existing Research

From the review of existing literature, it has been identified that there are some significant limitations in existing agricultural advisory systems. It has been observed that most of the existing methods and models have been based on single modality-based solutions such as text-based chatbots and image-based disease detection models, whereas a unified framework that considers multiple input modalities is still lacking in this area. Though models such as CLIP and LLaVA have shown promising results in vision and language understanding tasks, they are not specifically designed for agricultural

Fig. 4. Identified Gaps in Existing Agricultural Advisory Systems

advisory systems and may not be capable of real-time interaction. Similarly, chatbot-based models such as AgroGPT and other LLM-based models have shown promising results in context-aware responses, but they are limited to text-based interaction and cannot be used for image-based reasoning.

Furthermore, most systems heavily rely on large datasets in order to train and learn from them, which limits their scalability and adaptability in various agricultural environments. Moreover, it becomes challenging to incorporate real-time data such as weather patterns, market trends, and farming techniques into these models. In addition, most systems are not equipped with effective multilingual and voice-based interfaces that can be used by farmers with low literacy and technological skills.

Another important limitation is the lack of a unified platform that can integrate speech recognition, translation, and vision-language reasoning into a single system. Currently, there are separate solutions to each of these functionalities, making them disjointed systems that cannot handle varied user inputs effectively. Another limitation is associated with the high computational complexity of models such as LLaVA and AgriGPT-VL, which are difficult to use in real-world scenarios due to their high resource needs.

Therefore, there is a need to develop a scalable agricultural advisory system that can handle multiple modes of input, such as text, voice, and images, while also offering real-time recommendations. This need has been addressed through the development of FarmCompanion, an AI system that uses a variety of AI models to offer efficient solutions to modern farming practices.

8. Future Enhancements Suggested in the Literature

The review of existing literature reveals that there are certain areas where agricultural advisory systems can be improved with the help of advanced artificial intelligence techniques. For example, a majority of the research studies highlight the importance of integrating more data into the system, which can lead to better results for agricultural disease detection. The use of fine-tuned models, such as Agri-LLaVA and AgriGPT-VL, also indicates that better results can be achieved with the integration of knowledge bases.

Another area of improvement that is identified in the literature is the enhancement of multilingual and voice-based interaction. Although models like Whisper and MarianMT allow for speech recognition and translation, there is a possibility for the development of more advanced models that can support a wide range of regional dialects. Furthermore, there is a possibility for the integration of real-time data sources, as identified in a number of studies. These include weather forecasts, market prices, and government policies, which can be integrated into the system for more effective recommendations. The integration of IoT technology is also identified as an area of improvement, as seen in a number of studies. This allows for more accurate recommendations by integrating real-time data from the fields. Finally, there is a possibility for the use of advanced explainability, as identified in a number of studies.

Another area of importance is the optimization of computational efficiency and deployment. Most sophisticated models require high computational power, which is not readily available in rural settings. Future developments could involve the creation of lighter models, edge computing, and offline support, especially for rural settings where internet connectivity is low.

Overall, it is evident from the literature that future developments in agricultural advisory services could focus on scalability, accessibility, and real-time adaptability through the integration of multimodal AI, domain knowledge, and optimization techniques, which could greatly improve the effectiveness of intelligent farming solutions.

9. Conclusion

This paper proposes a multimodal agricultural advisory system called FarmCompanion AI, which is intended to offer intelligent real-time advisory services to farmers using speech recognition, translation, and vision-language reasoning. The system is intended to overcome various challenges associated with conventional methods of providing advisory services to farmers, such as using text, speech, and image inputs, which would increase the system's ability to accommodate users with different linguistic and technological backgrounds.

The use of Whisper, MarianMT, and LLaVA enables the system to process user inputs effectively. The system's performance is demonstrated by achieving high accuracy in speech recognition, translation, and vision-language reasoning, with approximately 91%, 82%, and 95.3%, respectively, which translates to a system performance of approximately 90.7%. This shows that using multiple AI models together is effective in creating a unified system, especially for use in agriculture.

Unlike other existing systems, which only provide single-modality interaction or static datasets, FarmCompanion AI is a scalable and dynamic solution for agricultural scenarios. The system allows farmers to receive context-aware recommendations for crop-related issues, disease-related issues, and other farming-related issues, thus improving the productivity of the agricultural sector. Although the system is effective, it also has a few limitations, as it requires internet connectivity and computational power for deploying large models. However, the proposed architecture is also flexible and can be improved by adding other features, such as the use of lightweight models, offline scenarios, and other real-time sources of data, such as weather and market-related sources. Thus, it can be concluded that the FarmCompanion AI system is a great example of the potential of multimodal artificial intelligence for the development of agricultural scenarios.

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