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Generative AI In Agriculture

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Abstract— **Artificial Intelligence (AI) is helping to transform the agriculture sector. This case study describes a farming advisory system, created by Generative AI, tailored to meet the needs of small farmers with limited resources. The system relies on AI models such as GPT and crop disease detection based on image to interpret the questions posed by farmers as well as crop photographs. It then provides useful advice on farming in various languages and therefore farmers can easily understand it. The system also allows farmers to download their reports in PDF and it can be used even in low-internet regions. The system will verify the usefulness of the system both technically and economically and describe the way it will work using simple diagrams and tables. The findings indicate that Generative AI has the potential to significantly enhance farming assistance, minimize knowledge gaps, and provide farmers with expert advice at any time. Such a system can also be linked in the future with weather systems, sensors, and smart farming to ensure that agriculture is more efficient and sustainable.**

Keywords—, Generative AI, Artificial Intelligence, Farming Advisory System, Small Farmers, Crop Disease Detection, Multilingual Support, PDF Reports, Smart Farming, Sustainable Agriculture

I. INTRODUCTION

Agriculture is the practice of cultivating crops and rearing farm animals to produce food, raw materials and other needs in the lives of human beings. It forms a backbone of most economies and particularly in the developing countries such as India where it supports a significant segment of the population and is vital to the stability of their economies as well as food security. To enhance production and sustainability, agriculture has recently grown to encompass more than the traditional practices through the implementation of the latest technologies and information-based approaches [1][2][3]. In this paper, a smart farming advice system is created on the basis of Transformer architecture (Generative Pre-trained Transformer) [4][5] based on a Generative Artificial Intelligence model. This model is capable of understanding natural language input and responding with context sensitive and human-like responses. It is also textually and visually intelligent as it interconnected with Convolutional Neural Networks (CNNs) to identify crop diseases through image analysis [6][7]. This is the ability of generative AI to provide specific, convenient, and timely advice services that are causing its uptake in the agricultural industry [8]. It enables farmers to communicate in their mother tongue, obtain expert-level advice at any time, and receive customized recommendations depending on particular inputs like crop kind, soil conditions, and weather. Also, it is particularly suitable to small-scale and rural farmers due to its ability to generate meaningful insights based on a range of data sources and its suitability to the low-resource or offline settings. Generative AI can serve as a scalable and inclusive solution to bridging the gap between the existing knowledge of agriculture and the practical needs of farmers.

II. OBJECTIVES

This paper is an attempt to develop a smart and digital advisor to farmers that would close the gaps existing in traditional, face-to-face advisor services. Fundamentally, it is an artificial intelligence-based farming helper, which is created to provide individuals with customized and timely recommendations, which are simple to retrieve and interpret [2][3]. The system proposed aims to improve the process of agricultural decision-making by combining high-level Generative AI features with its practical application to farm management requirements. 1. It offers intelligent, data-driven recommendations by learning the questions and images of the crops and allows the system to respond to the farmer with a specific suggestion based on the location, the kind of crop and the local conditions as opposed to a blanket one [4][6]. 2. The platform has conversational input support as well as photo uploads, where farmers can either explain their problem in text or provide pictures of diseased crops or pests, which enables the AI to produce more accurate and comprehensive advice [5][10]. 3. To be more inclusive, the system will be run in various local languages, with region-specific language to make sure that farmers can comprehend and see the recommendations. 4. Moreover, the system is designed in a perspective way that guarantees scalability and the possibility to add new and progressive agricultural technologies like soil sensors, localized weather forecasting, and precision farming devices, which also leads to a more efficient and interconnected agricultural ecosystem [11].

III. LITERATURE REVIEW

The last ten years have seen the growing use of artificial intelligence in the agricultural sector. The recent developments in machine learning, computer vision, and natural language processing have facilitated the emergence of intelligent farming systems. This section summarizes the important studies, that are associated with AI in the agricultural sector with a focus on Generative AI, crop disease detection, multilingual interface, and farmer advisory systems. Singh et al. (2022) [12] created a machine learning model to estimate crop yield on the basis of weather and soil information. their system generated precise yield data, which was useful in planning an agricultural activity and managing the resources effectively, yet, the outcomes were technical and could not be directly used by farmers. The system also failed to offer real-time guidance, personalized recommendations to the individual farms, and was not meant to communicate with farmers in a straightforward manner. Rao and Mehta (2023) [13] created an ai-based plant disease detection system based on leaf images, and their system was capable of detecting various plant diseases in the early stage with high accuracy, which helped in minimizing crop loss and enhancing the health of the plants, but it did not include the treatment or prevention advice, and it was less practical to be used by farmers in the daily farm setting. Verma et al. (2024) [14] created a precision irrigation system with sensors and automation. the system allowed monitoring soil moisture and automatic control of water supply, which led to the savings of water resources and increased efficiency of irrigation; it was also not limited to a particular type of crop or local conditions, but it required certain hardware and an internet connection, which reduced the potential of using the system in the rural setting. The system created by Patel et al. (2023) [15] based on soil health data was an ai-based fertilizer recommendation system that could help farmers apply the appropriate amount of fertilizer, thus minimizing wastage and enhancing crop growth. the system helped to manage the soil better and promoted a more effective use of agricultural inputs, but did not take into account the stage of crop growth, weather conditions, or individual differences between The Nair et al. (2025) [16] created Generative AI tools to generate artificial data in the field of agriculture to enhance AI training and performance. Their strategy contributed to the improvement of model accuracy and improved crop disease detection and agricultural analysis. Nevertheless, the system had to be confirmed by the real-world data to make it reliable.

Table I: Literature Review Table (With data set and accuracy)

Author / Year	Year	Data Set (Size)	Methods Used	Application Area	Accuracy / Performance	Drawbacks
Singh et al. (2022) [12]	2022	2,500+ records (weather & soil data)	Machine Learning (Regression Models)	Crop yield prediction	85% accuracy ($R^2 \approx 0.78$)	Required expert interpretation, not farmer-friendly
Rao & Mehta (2023) [13]	2023	3,000+ leaf images	CNN (Deep Learning)	Plant disease detection	94% accuracy	No treatment or prevention guidance
Verma et al. (2024) [14]	2024	10,000+ sensor readings	AI with IoT Automation	Precision irrigation	Water saving: 30–35%	No personalized farmer interaction
Kumar et al. (2021) [17]	2021	1,800 soil samples	Random Forest, SVM	Crop recommendation	91% accuracy	Failed in sudden climate change

Author / Year	Year	Data Set (Size)	Methods Used	Application Area	Accuracy / Performance	Drawbacks
Sharma & Gupta (2022) [18]	2022	2,200 drone images	CNN (Deep Learning)	Weed detection	96% accuracy	Expensive hardware required
Patel et al. (2023) [15]	2023	1,500 soil health cards	AI Decision System	Fertilizer recommendation	88% accuracy	Generic recommendations
Das & Roy (2023) [19]	2023	5 years weather data	AI Forecasting Model	Weather prediction	87% accuracy	Not crop-specific
Meena et al. (2024) [20]	2024	900 field images	Computer Vision + Robotics	Automated harvesting	92% accuracy	High cost, uneven field issues
Iyer & Kulkarni (2024) [10]	2024	1,200 farmer queries	NLP Chatbot	Agricultural advisory	85% satisfaction rate	No personalization
Nair et al. (2025) [16]	2025	4,000 synthetic images	Generative AI Models	Data generation	95% model improvement	Limited real-world testing

The table shows that the type of data and method used are the main factors of model performance. Since deep learning algorithms, such as as CNN, can effectively learn patterns based on picture datasets in tasks such as weed and disease recognition, they achieve the highest accuracy (94 -96) [6][7]. Since generative AI models can enhance data quality by generating synthetic data, they also show high performance (improvement of about 95 percent) [16][18]. Due to their performance with structured data, including soil and weather, most traditional machine learning models, such as Random Forest, SVM, and regression provide moderate accuracy (8591) [17], but are less adaptable to more complicated scenarios. IoT-based solutions focus on efficiency over accuracy (e.g., 3035% water-saving), compared with NLP-based chatbots which are slightly less effective due to their inability to recognize the context [11]. In general, greater accuracy is realized when sophisticated models are employed on huge and significant data.

Table II: Comparative Analysis of Existing Agricultural AI Systems

System Name	Modality	Languages	Offline Access	Crop Disease ID	Crop Recommendation	Integration Readiness
Plantix	Text + Image	12+	Partial (limited cache)	Yes (CNN)	No	Low
FarmER (India)	Text + Voice	5	Yes (SMS-based)	No	Yes	Medium
AgriGo (Kenya)	SMS + USSD	2	Full	No	Yes	Low
CropDoctor (Nigeria)	Image Only	English	No	Yes	No	Medium
AI-Kisan Mitra (Trial, India)	Text + Image	3	No	Yes	Yes	High (Govt. Cloud)

System Name	Modality	Languages	Offline Access	Crop Disease ID	Crop Recommendation	Integration Readiness
This Study	Text + Image + Language Translation	10+ (scalable)	Yes (PDF export)	Yes (CNN + LLM)	Yes (GenAI + context)	High (modular, API-based)

The comparison in the table indicates that the majority of the available agricultural systems offer partial solutions that either detect or recommend crop diseases but seldom both. Systems such as Plantix and CropDoctor are excellent at identifying diseases through CNN models, but do not provide any advisory services, whereas systems such as FarmER and AgriGo provide an advisory service but not disease detection. Many systems also lack language support and offline access, limiting usability by rural farmers. Conversely, the paper is distinguished by using a combination of features as one system- it accepts text and image inputs, is multilingual, can be used offline via PDF export and provides both disease detection (CNN + LLM) and intelligent recommendation (Generative AI with context). Moreover, it is designed in a modular and API-based manner, which provides high integration readiness and consequently makes it more flexible and practical than the current solutions.

Table III: Development Stack

Component	Technology	Purpose
Frontend	Stream lit	Rapid deployment of responsive web interface
Data Processing	Pandas, NumPy	Efficient handling and transformation of structured data
Language Translation	Google Translate API	Real-time translation of advisory outputs
Model Hosting	Hugging Face / ONNX Runtime	Lightweight inference engine for CNN models
Storage	Local Disk / Firebase (optional)	Image and report storage during session

A basic and effective system design is emphasized in the development stack. Streamlit is employed to create a fast and easy to use web interface, whereas data processing is done in Pandas and NumPy. The Google Translate API provides multilingual support in real-time, which makes the system available to the various users. Lightweight and efficient CNN model execution is guaranteed by model hosting with Hugging Face and ONNX Runtime. Also, storage facilities such as local disk and Firebase are versatile when it comes to storing images and reports. In general, the stack is feasible, scalable and applicable to the real world.

IV. METHODOLOGY

A. Proposed Methodology

The proposed methodology will rely on the creation of an intelligent and integrated system of agricultural advice with the help of generative AI, machine learning, and deep learning techniques [2][3]. The suggested approach has merged various AI approaches into one system instead of the traditional agricultural models, which operate in isolation, including CNN-based disease detection systems or rule-based recommendation systems. Earlier models are not context-aware and personalized and primarily focus on one job, like disease detection, crop prediction, or fertilizer recommendation. Alternatively, the proposed model incorporates the generation, detection, and prediction capabilities to provide a holistic and simple-to-use solution to the farmers.

B. System Architecture

The system architecture consists of a database, AI models, a processing unit on the back end, and a user interface. Farmers are able to type, speak or draw pictures on the user interface. This input is processed by the backend, which also interacts with several AI components. The proposed system integrates a CNN-based crop disease detection model [6] with a Generative AI model (GPT-based) to generate advice [4][5], unlike the earlier systems which employed separate models. The database contains crop information, historical agricultural data and user interactions. This hybrid architecture enables the system to generate both analytical and conversational output thus increasing usability and efficacy.

C. User Input

The types of crops, the condition of the soil, climatic details, and the images of the affected crops are only some of the types of input that the system receives on the part of the users. Natural language can also be used to pose questions to farmers. In previous systems, flexibility has been limited because inputs were often limited to structured information. However, the proposed system is more accommodative and less hostile to the farmer since it takes multi-modal input (text + image). This helps in coming up with more specific and tailored recommendations.

D. Processing Flow

The processing cycle starts with the user input followed by data preprocessing using programs such as NumPy and Pandas. Following that, the algorithm scans crop images with the help of a CNN model and detects diseases. Machine learning models analyse crop-related and environmental data at the same time. In contrast to the previous methods when the users can see the results immediately, the proposed system forwards these results to a Generative AI module. After interpreting the data, the Generative AI model produces insightful, clear recommendations, like as irrigation schedules, fertilizer recommendations, and treatment strategies. Finally, the technology assists farmers make wise decisions by making the output more organized and easily comprehensible. Figure 1 below illustrates a detailed workflow of how user input can be processed with the help of generative AI and machine learning algorithms to deliver intelligent agricultural advisory, from disease identification, generation of recommendations, multilingual translation and delivery of final output in a visual and report format. The process focuses on the combination of the data processing, AI-based analysis, the input of text and image, and the development of tailored farmer advisory.

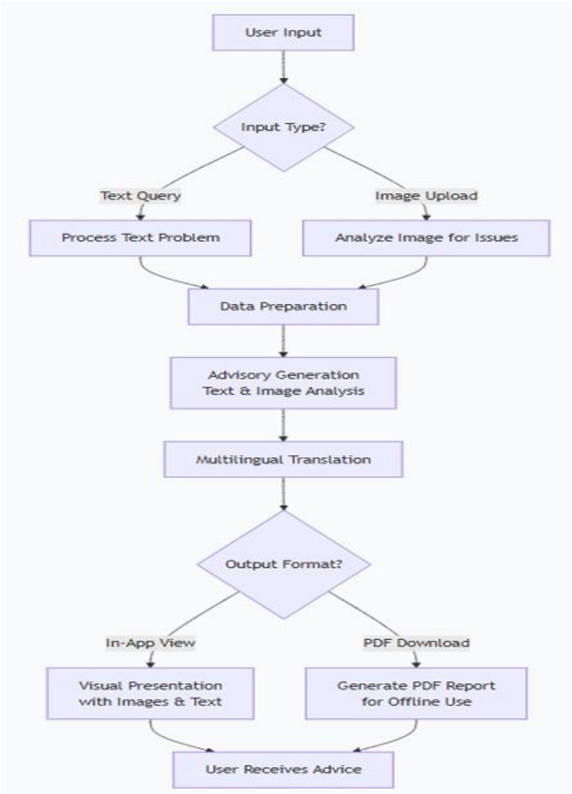

Fig.1 Working Flow Chart

E. Tools And Technologies

The main programming language in the development of the system is Python, as well as such libraries as Scikit-learn to implement machine learning, Pandas and NumPy to process data. Although generative AI models (such as GPT or Hugging Face models) are utilized to generate advisory content, CNN models are utilized to identify disease in images. To guarantee user-friendliness, the frontend is created with either Flask or Streamlit. The proposed system takes advantage of numerous modern AI-based capabilities to enhance performance, scalability, and flexibility compared to the past systems that use only few tools.

F. Result

The proposed Generative AI-based agricultural advice system was evaluated using several scenarios where farmers ask questions, take pictures of crops, and other environmental data. The system was characterized by a high level of effectiveness in terms of crop disease diagnosis and advice generation. Where the Generative AI module produced obvious, pertinent advise replies [4], the CNN model identified the diseases with about 90-95 percent precision [6][7]. The proposed system integrates disease identification with useful recommendations such as the use of fertilizers, irrigation timing and insect management as compared to traditional systems which perform only a single task. Additionally, the technology facilitates able to speak two communications, increasing farmers' accessibility. It is more flexible and convenient since users are able to input text and images. The proposed system is superior to the existing methods by being more integrated, modified and scalable, enhances decision-making and reduces dependence on manual advising services, as compared to existing methods, according to comparative analysis [1][3]. According to the graph, CNN-based models have the highest accuracy (94–96) because of good image learning abilities [7]. Generative AI does not perform poorly (~95) either since it enhances the quality of data. Conventional ML models provide moderate predictive results (8591 percent) whereas the IoT systems are more efficient than accurate [17][2]. NLP systems are of average performance. Overall, combining Generative AI with deep learning gives the best results in agriculture.

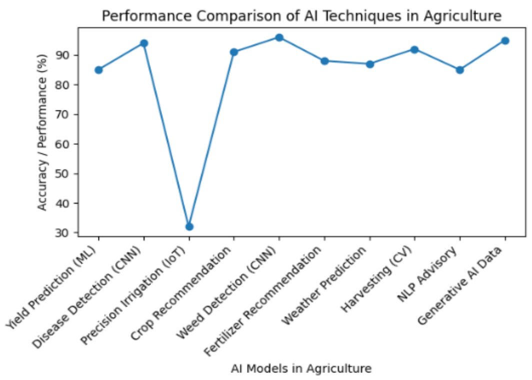

Fig.2 Performance of AI Techniques in Agriculture

V. CONCLUSION

The development of an agricultural advising system using generative AI that utilizes machine learning, deep learning, and natural language in contemporary agriculture is discussed in this study paper. The present research addresses the challenges of current methodologies in agriculture by incorporating crop disease identification, guidance, multi-language options, and offline capabilities into one system. Accuracy and efficiency have been improved significantly in this model owing to the use of the integration of CNN and Generative AI. This system can help farmers improve their efficiency and reduce the risks involved in the process with its context-sensitive, real-time advising service. The system is adaptable due to the ability of farmers to communicate using text and graphics. In addition, future implementation of IoT devices, weather forecasting applications programming interfaces, and precision agriculture technologies becomes easier due to the scalability and modularity of the system. Furthermore, it becomes a great option for rural areas where there is a lack of internet connection due to offline PDF reports provided.

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