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# AI-Based Farmer Query Support and Advisory System

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***Abstract:*** Agriculture plays a Big role in India, but many farmers often face challenges in accessing timely and accurate information related to crop diseases, weather conditions, and market prices. This research proposes an AI-Based Farmer Query Support and Advisory System that provides real-time assistance using modern technologies such as Large Language Models (LLMs), workflow automation, and API integration. The system enables farmers to interact through WhatsApp/Website by sending text or images, which are processed using Google Gemini AI. The platform enriches user queries with real-time weather and market data to generate accurate and actionable responses in local languages. The proposed solution aims to bridge the information gap, improve decision-making, and reduce crop losses by delivering instant advisory services in an accessible and scalable manner.

***Keywords:*** Artificial Intelligence, Smart Agriculture, Chatbot/WhatsApp, Gemini AI, n8n Automation, Crop Advisory, RAG System

## I. INTRODUCTION

Agriculture plays a very important role in the economic development of many countries, especially in India where a significant portion of the population depends on farming for their livelihood. It contributes not only to food security but also to employment generation and industrial growth. Despite its importance, the agricultural sector faces numerous challenges due to limited access to timely, accurate, and actionable information. Farmers often rely on traditional knowledge or delayed advisory systems, which can lead to inefficient decision-making and reduced crop productivity.

In recent years, the rapid advancement of digital technologies and Artificial Intelligence (AI) has opened new opportunities to transform the agricultural sector. Smart farming solutions, powered by machine learning and data analytics, are enabling farmers to make informed decisions based on real-time insights. However, many existing solutions are either too complex, not localized, or inaccessible to rural populations due to language barriers and lack of technical awareness.

One of the major challenges faced by farmers is the inability to quickly identify crop diseases and pests, which can significantly affect yield and quality. Additionally, access to real-time weather forecasts and market prices is often fragmented, making it difficult for farmers to plan irrigation, harvesting, and selling strategies effectively. Traditional advisory systems such as agricultural helplines or extension services are often slow, limited in reach, and not available 24/7.

To address these challenges, this research proposes an AI-Based Farmer Query Support and Advisory System that leverages modern technologies such as Large Language Models (LLMs), workflow automation, and API integration. The system provides a simple and accessible interface through WhatsApp, a widely used communication platform among farmers. By allowing users to submit queries in the form of text or images, the system enables seamless interaction without requiring any technical expertise.

The proposed system utilizes Google Gemini AI for processing and understanding user queries, including multimodal inputs such as images of crops. It integrates real-time data from external sources, such as weather and market price APIs, to generate accurate and context-aware responses. The use of n8n workflow automation ensures efficient orchestration of the entire process, from receiving the query to delivering the response.

## II. Related Work

### A. *Agriculture Advisory System*

Agricultural advisory systems have evolved from traditional expert-based approaches to modern digital platforms aimed at improving farmer decision-making. Earlier systems relied on agricultural extension services and helplines, which often suffered from delays and limited accessibility. With the advancement of digital technologies, smart agriculture solutions have been introduced to provide farmers with timely information related to crops, weather, and market conditions.

Recent studies highlight that integrating artificial intelligence and modern technologies into agriculture can significantly enhance productivity and efficiency [8], [15]. These systems aim to provide better decision support; however, many existing platforms still lack real-time responsiveness and personalized interaction, limiting their practical usability in rural environments.

### B. *AI and Machine Learning in Agriculture*

Artificial Intelligence and Machine Learning have been widely applied in agriculture for tasks such as crop disease detection, yield prediction, and crop recommendation. Deep learning techniques, particularly image-based models, have shown strong performance in identifying plant diseases from leaf images [2]. These approaches demonstrate the potential of AI in improving crop monitoring and early disease detection.

In addition, machine learning-based recommendation systems have been developed to assist farmers in selecting suitable crops based on environmental conditions [9], [14]. Research also emphasizes the broader impact of AI in agriculture, including improvements in productivity and sustainability [1], [11].

Furthermore, the use of satellite data and predictive models has contributed to more accurate crop yield estimation and agricultural planning [10]. Despite these advancements, many systems operate in isolation and do not incorporate real-time contextual data, which limits their effectiveness in practical farming scenarios.

### C. *Data-Driven and Intelligent Farming System*

Recent developments in smart farming highlight the importance of big data and intelligent systems in enhancing agricultural practices. Studies indicate that big data analytics can improve farming efficiency by enabling data-driven decision-making [13]. Similarly, machine learning techniques have been used to build intelligent advisory systems that provide recommendations based on environmental and historical data [12].

However, most existing systems do not offer a unified platform that integrates conversational interaction, multimodal input handling, and real-time data sources. While APIs such as weather services and communication platforms enable real-time data exchange [4], [6], their integration with intelligent advisory systems remains limited.

The proposed system addresses these challenges by combining conversational AI, multimodal processing, and real-time data integration into a single platform. It also leverages workflow automation techniques [7] to ensure efficient orchestration and scalability, providing a more practical and user-friendly solution for agricultural advisory services.

## III. Methodology

The development of the proposed AI-based Farmer Query Support and Advisory System follows a modular and scalable architecture designed to ensure real-time responsiveness, high accuracy, and ease of accessibility for users. The system integrates multiple functional components, including data acquisition, processing, enrichment, and intelligent response generation, all coordinated through a centralized workflow mechanism. By adopting a structured pipeline, the system ensures that farmer queries—whether text-based or image-based—are handled efficiently and provide context-aware recommendations.

The methodology emphasizes seamless interaction, real-time data utilization, and intelligent decision-making. The system is designed to operate continuously, allowing farmers to access advisory services at any time without dependency on manual intervention. Each stage of the workflow contributes to improving the quality, relevance, and usability of the generated responses.

### A. *System Components*

The system is composed of several interconnected modules that work together to process user queries and generate meaningful outputs.

- Multimodal Input Layer:

  This layer captures user inputs in the form of text messages and images through a messaging platform. It as the entry point of the system and ensures that different types of queries can be handled efficiently.

- Processing and Orchestration Layer:

  The core processing layer manages the entire workflow, including input validation, routing, and integration with external services. It ensures smooth coordination between different components and maintains system reliability.

- Advisory Output Layer:

  The final responses are generated in a simplified and user-friendly format, often in local language, ensuring that farmers can easily understand and apply the recommendations.

### B. *Requirement Analysis*

A detailed requirement analysis was conducted to understand the practical challenges faced by farmers and to identify the key functionalities needed in the system. This involved studying common agricultural problems such as

crop diseases, pest infestations, unpredictable weather conditions, and fluctuating market prices.
In addition, existing digital platforms and advisory systems were reviewed to identify their limitations, such as lack of real-time interaction, poor accessibility, and limited language support. Based on this analysis, the system was designed to provide instant, accurate, and localized advisory services while maintaining simplicity in user interaction.

### C. *System Design*

The system design focuses on creating a smooth and intuitive interaction flow while ensuring consistency and reliability in the generated responses.

- User Interaction Flow:

  The interaction workflow is designed to handle different types of inputs, including text queries and image submissions. The system ensures that users can easily send queries without requiring technical knowledge.

- Data Enrichment Strategy:

  To improve the quality of responses, the system integrates real-time data such as weather conditions and market prices. This ensures that the advisory provided is not only accurate but also relevant to the current situation.

- Prompt Structuring:

  Structured input formats are used to combine user queries with external data before sending them to the AI model. This helps in generating consistent and context-aware responses.

- Fallback Mechanism:

  In cases where the system is uncertain or unable to provide a confident response, fallback strategies are implemented to handle such scenarios gracefully and avoid misleading information.

### D. *Implementation*

The implementation of the system involves integrating multiple components to create a unified and efficient workflow.
The frontend interaction is handled through a messaging interface, allowing users to communicate with the system in a familiar environment. This eliminates the need for installing additional applications and improves accessibility.
On the backend, an automated workflow system manages incoming requests, processes data, and coordinates with external services. It handles tasks such as request validation, data fetching, and response delivery in a structured manner.
The core intelligence of the system is powered by a large language model that processes both text and image inputs. For text queries, the model interprets the intent and generates appropriate recommendations. For image-based queries, it analyzes visual features to identify possible crop diseases or issues.
After processing, the generated responses undergo a post-processing stage where they are formatted into a clear and concise structure. The responses are also adapted to local language where necessary, ensuring better understanding and usability for farmers.

### E. *System Flow Representation*

The diagram illustrates the overall workflow of the proposed system. It begins with user input in the form of text or images, which is received through a webhook. The system then processes the input and enriches it with real-time data such as weather and market information. This enriched data is analyse using an AI model capable of multimodal understanding. Finally, the system generates a relevant response and delivers it back to the user, ensuring quick and accurate advisory support.

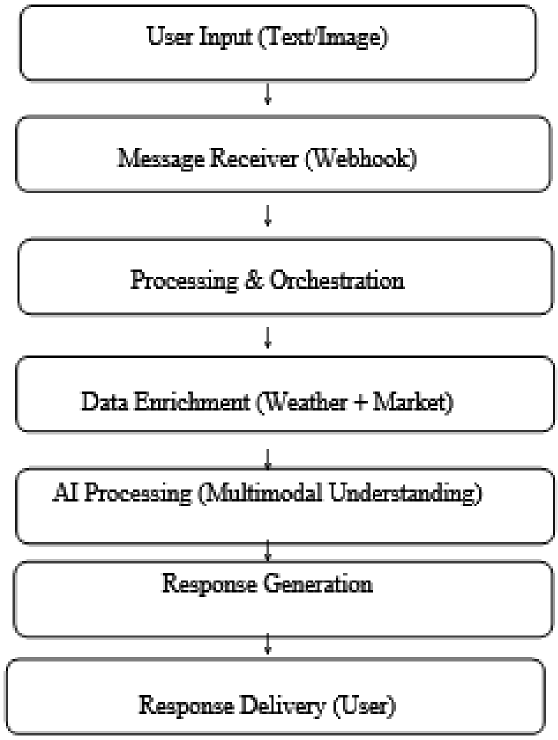


Figure1. System Flow Representation

## IV. RESULTS

The developed system was tested using a variety of real-world scenarios to evaluate its performance in handling farmer queries. The testing included both text-based and image-based inputs to ensure that the system works effectively under different conditions.

For text-based queries, the system successfully provided accurate responses related to weather conditions, crop guidance, and market prices. The responses were generated by combining user input with real-time data, which improved the relevance of the output. The average response time observed during testing was within a few seconds, making the system suitable for real-time usage.

For image-based queries, the system was able to analyse crop images and provide possible disease identification along with suggested remedies. The results were generally reliable when the image quality was clear and properly focused. In most cases, the system provided useful preliminary guidance that could help farmers take immediate action.

The system also demonstrated good performance in terms of usability. Users were able to interact with the system easily through a messaging interface without requiring any technical knowledge. The responses generated in local language further improved understanding and user satisfaction.

Table I. Performance Comparison

| *parameter* | *Traditional Systems* | *Proposed System* |
|---|---|---|
| Response Time | High (hours/Day) | Low (Seconds) |
| Query Handing | Limited | Text+ Image |
| Accessibility | Modarate | High |
| Language Support | Limited | Local Language |
| Real-Time Data Usage | NO | Yes |

The comparison clearly indicates that the proposed system outperforms traditional methods in terms of speed, flexibility, and accessibility. However, certain limitations were observed during testing. The system's performance depends on internet connectivity and the availability of external APIs. In some cases, ambiguous queries or low-quality images may lead to less accurate responses. These challenges highlight the need for further improvements in robustness and data handling.

Another limitation is that the system provides advisory based on available data and AI interpretation, which may not always replace expert-level diagnosis in complex cases. Therefore, it is better suited as a support tool rather than a complete replacement for agricultural experts.

### B. *Error and Uncertainty Analysis*

In real-world applications, handling uncertainty is an important aspect of system performance. During testing, certain scenarios were identified where the system produced less accurate or incomplete responses.

Most inaccuracies occurred in the following cases:

[1] Ambiguous Queries:

When users provided incomplete or unclear questions, the system sometimes generated generalized responses due to lack of sufficient context.

Overall, the results demonstrate that the system is capable of providing efficient and reliable agricultural advisory services. By combining AI capabilities with real-time data integration and a user-friendly interface, the proposed solution offers a practical approach to addressing key challenges in modern agriculture.

## V. DISCUSSION

### A. *System Strengths and Limitations*

The experimental results highlight several strengths of the proposed AI-based advisory system. One of the most significant advantages is its ability to provide real-time responses by integrating user queries with live data sources. This reduces dependency on traditional advisory methods and enables faster decision-making for farmers. The system also supports multimodal input, allowing users to submit both text and images, which improves flexibility and usability in real-world scenarios.

Another key strength is the accessibility of the system. By utilizing a messaging platform, the system eliminates the need for complex applications, making it easier for farmers to interact without technical knowledge. The inclusion of local language responses further enhances usability and ensures that the advisory is understandable and actionable.

The system also demonstrates good scalability due to its modular design. Each component of the workflow operates independently, allowing future enhancements without affecting the entire system. This makes it suitable for deployment across different regions and agricultural use cases.

However, certain limitations were observed during testing. The performance of the system is dependent on internet connectivity and the availability of external data sources. In areas with poor network access, response time and data accuracy may be affected. Additionally, the accuracy of image-based analysis depends on the quality of the input image. Poor lighting, low resolution, or improper angles can reduce the effectiveness of disease identification.

[2] Low-Quality Images:

Image-based queries with blurred or poorly captured images reduced the system's ability to correctly identify crop diseases.

[3] Dynamic Environmental Factors:

Agricultural conditions can vary significantly depending on location and time. In some cases, limited or delayed real-time data affected the precision of recommendations.

[4] Domain-Specific Edge Cases:

Certain rare crop diseases or region-specific issues were not fully captured by the system, leading to less accurate outputs.

These observations highlight the importance of improving input quality, enhancing contextual understanding, and continuously updating the system with new agricultural knowledge.


 

The results indicate that the proposed system performs effectively in delivering real-time agricultural advisory services. Compared to traditional methods, the system significantly reduces response time and provides more accessible and user-friendly interaction.

One of the major strengths observed is the integration of real-time data, which allows the system to generate context-aware recommendations. This improves the practical usefulness of the advice provided to farmers. Additionally, the use of a messaging platform simplifies user interaction and increases the likelihood of adoption, especially in rural areas.

However, certain limitations were identified during testing. The accuracy of image-based analysis depends heavily on the quality of the input image. Poor lighting or unclear images can affect the system's ability to correctly identify crop issues. Furthermore, the system relies on external APIs for data, which means that performance may be affected by network connectivity or API availability.

Despite these limitations, the overall performance of the system is promising. It demonstrates the potential of combining artificial intelligence with real-time data integration to create scalable and practical solutions for agriculture. With further improvements, the system can become more robust and capable of handling a wider range of agricultural scenarios.

## VI. Conclusion and Future Work

This paper presented an AI-Based Farmer Query Support and advisory system designed to support farmers by providing timely, accurate, and accessible agricultural guidance. The system effectively addresses key challenges such as lack of real-time information, difficulty in disease identification, and limited access to expert advice. By integrating intelligent processing with real-time data sources, the proposed solution is able to generate context-aware recommendations that are both practical and easy to understand.

One of the major strengths of the system lies in its accessibility and simplicity. By utilizing a familiar communication platform, farmers can interact with the system without requiring technical expertise or additional training. The ability to handle both text and image-based queries further enhances its usability, allowing farmers to seek help in a more natural and convenient way. The integration of real-time weather and market data ensures that the responses are not only accurate but also relevant to current conditions, thereby supporting better decision-making.

The system also demonstrates the potential of combining conversational AI with real-world data to create scalable and efficient solutions for agriculture. Its modular architecture allows for easy expansion and adaptation to different use cases, making it suitable for deployment in diverse agricultural environments.

In the future, the system can be further enhanced by incorporating voice-based interaction to support users with limited literacy, enabling more inclusive access. The integration of IoT-based sensors can provide real-time soil and environmental data, allowing the system to offer more precise and predictive recommendations. Additionally, expanding support for multiple regional languages and dialects can improve adoption across different regions. Advanced predictive analytics and machine learning models can also be incorporated to forecast crop yield, detect early-stage diseases, and provide proactive advisory services. These improvements can transform the system from a reactive support tool into a comprehensive smart farming assistant.

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