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MULTI AGENT DECISON SUPPORT SYSTEM USING LLM's FOR CROP MANAGEMENT AND RESOURCE OPTIMIZATION

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ABSTRACT
Modern agriculture increasingly depends on data-driven decision-making to improve crop productivity, reduce resource waste, and ensure long-term environmental sustainability. However, traditional farm management systems often operate in isolation, lack real-time intelligence, and fail to integrate the diverse data sources required for precise decision support. To address these challenges, this project proposes a Multi Agent Decision Support System (MADSS) powered by Large Language Models (LLMs) to optimize crop management and resource allocation.
The proposed MADSS architecture is designed as a collection of autonomous yet coordinated agents, each responsible for a specialized task such as soil monitoring, crop health assessment, weather forecasting, and resource planning. By combining sensor data, farm records, and external knowledge sources, each agent uses LLM-based reasoning to interpret data, generate insights, and provide context-aware recommendations. These agents communicate through a central orchestrator, enabling collaborative problem-solving, adaptive learning, and consistent decision generation across the system.A key strength of MADSS lies in its ability to process dynamic, uncertain, and multimodal agricultural data. Through natural language interactions, farmers receive clear suggestions on irrigation schedules, fertilizer usage, pest control measures, and yield predictions. The system also supports real-time alerts, anomaly detection, and scenario simulation, helping farmers anticipate risks and choose optimal strategies. Furthermore, the LLMdriven agents continuously improve through user feedback, promoting long-term adaptability and scalability for diverse crop systems and field environments.
Overall, MADSS represents a modern, intelligent, and holistic approach to sustainable agriculture. By integrating autonomous agents with advanced language models, the system enhances decision accuracy, minimizes resource wastage, and empowers farmers with actionable insights. This project demonstrates how AI-based multi-agent frameworks can significantly transform agricultural practices, moving toward more efficient, resilient, and sustainable farm ecosystems.

INTRODUCTION
Modern agriculture is becoming more complex as farmers face challenges such as climate change, unpredictable weather, limited resources, and increasing demand for food production. To manage these challenges effectively, farming must shift from traditional methods to smart, data-driven practices. Today, technologies like sensors, automation, and artificial intelligence are helping farmers make better decisions and use resources more efficiently. However, there is still a need for an intelligent system that can combine different types of information and provide clear, reliable guidance to farmers. This project introduces a Multi-Agent Decision Support System (MADSS) powered by Large Language Models (LLMs).
The system is designed to support farmers by analyzing real-time field data and offering accurate recommendations for crop management. MADSS consists of several specialized software agents, with each agent focusing on a specific area such as irrigation, soil nutrients, pest control, or crop monitoring. These agents continuously collect data from sensors placed in the field and interpret the information using LLM-based reasoning.
A central LLM coordinator brings all the agents' suggestions together, compares them, and selects the most optimal plan for the farm. This makes the system more reliable and reduces the chances of mistakes. By using intelligent

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agents and advanced language models, MADSS helps farmers save water, reduce fertilizer and pesticide usage, prevent crop diseases, and improve yield predictions. Overall, the introduction of MADSS aims to promote smarter farming practices, reduce waste, improve overall productivity, and support sustainable agriculture in the long run. This system has the potential to transform modern farming by making decisions faster, more accurate, and more environmentally friendly.

Crop management and resource optimization play a crucial role in modern agriculture by ensuring that crops are grown efficiently, sustainably, and with maximum productivity. As the global demand for food continues to rise, farmers and agricultural experts are increasingly relying on scientific methods and technology-driven strategies to make smarter decisions. Crop management involves planning, monitoring, and controlling various aspects of farming—such as soil preparation, seed selection, irrigation, pest control, and nutrient management—to support healthy plant growth. When combined with resource optimization, the focus shifts toward using available resources like water, fertilizers, land, labour, and energy in the most efficient way possible. Advancements in technology have significantly transformed traditional farming practices. Tools such as IoT-based soil sensors, weather forecasting systems, drone imagery, and satellite-based crop monitoring help farmers collect accurate and real-time data from their fields. This information allows them to determine the exact needs of their crops, such as where irrigation is required, which areas need fertilizer, or where pest infestation is likely to occur. By applying inputs only where necessary, farmers can reduce wastage, lower production costs, and minimize environmental impacts.

Machine learning and AI models further enhance crop management by predicting crop yields, identifying diseases early, and recommending optimal farming practices. Automated irrigation systems and precision farming techniques ensure that water and nutrients are supplied efficiently, avoiding overuse and improving soil health. Resource optimization not only increases productivity but also supports sustainable agriculture by conserving natural resources, reducing greenhouse gas emissions, and maintaining ecological balance.

Overall, crop management and resource optimization provide a data-driven, efficient, and environmentally responsible approach to farming. These practices help farmers achieve higher yields, improve crop quality, and ensure long-term agricultural sustainability, making them essential components of modern agricultural systems.

LITERATURE SURVEY

Pajak et al. (2025) Strength: The study offers a powerful multi-agent LLM architecture capable of coordinating several autonomous agents for complex decision-making. Its sustainability-focused workflow supports efficient resource use and demonstrates strong hierarchical planning suitable for agricultural tasks. Limitation: However, the framework is not agriculture-specific and does not address crop-related variables like soil moisture or pest risk. It also requires high-quality domain data and significant computational resources, which may limit use in rural farming contexts.

Chen et al. (2024) Strength: The work presents a scalable multi-agent orchestration system with a conductor agent coordinating planners and tool-calling agents. Its real-time API integration and modular architecture make it suitable for dynamic crop advisory systems and flexible deployment. Limitation: Despite this, the system was designed for smart-city applications, meaning agricultural models for soil, crop physiology, and climate must be added. It also lacks farm-specific sensor integration and does not include agricultural case studies.

Sapkota et al. (2024) Strength: This review highlights the potential of multimodal LLMs to combine satellite images, sensor streams, and textual data, offering valuable insights for agricultural monitoring. The domainspecific focus supports accurate crop assessment and field condition analysis. Limitation: Yet, the review remains conceptual, providing limited implementation guidance and lacking algorithms or multi-agent workflows. It also offers no benchmark comparisons across agricultural datasets.

Arsanjani (2022) Strength: The study demonstrates practical patterns for LLM function-calling, enabling integration with external tools like weather APIs and soil sensors—key for real-time precision farming. It connects conceptual AI capabilities with field-level operational needs. Limitation: However, it is conceptual and not peer-reviewed, reducing its academic reliability. It focuses mainly on single-agent patterns and provides limited guidance for multi-agent coordination or generalization across diverse agricultural environments. Zheng.et.al(2023) Strength: AgriBERT offers domain-adapted language understanding, improving the accuracy of interpreting crop diseases, soil terminology, and farming practices. Its specialized NLP abilities enhance agricultural question-answering performance. Limitation: But AgriBERT is text-focused and lacks multimodal abilities for images or sensor data. It cannot run as a real-time system and is not designed for multi-agent collaboration or dynamic tool interactions. Ge et al. (2024) Strength: The work provides a directly applicable agricultural agent architecture that supports real-time crop monitoring and resource assessment. It serves as a

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strong reference model for MADSS development with clear agricultural relevance. Limitation: Even so, the system has limited real-world validation and only basic optimization capabilities. Multi agent interactions are simple compared to advanced LLM-based frameworks, and economic modeling for inputs is minimal. Ahemed et al. (2024) Strength: This review traces the evolution from rule-based and ML-driven DSS to modern AI-enhanced systems, supporting the rationale for LLM-based MADSS. Limitation: However, it does not focus on LLM-specific or multi-agent architectures and lacks concrete system designs. Challenges like privacy, hallucination, and model misalignment in LLM-driven agriculture are not addressed.

3.PROBLEM STATEMENT

In today's agricultural landscape, crop management and resource planning remain complex and inefficient processes that require farmers to rely on fragmented sources of information such as weather updates, soil reports, and traditional knowledge. Existing systems lack integration, personalization, and intelligent automation, forcing farmers to manually analyze multiple factors like soil conditions, crop suitability, irrigation needs, and fertilizer usage.

Moreover, these conventional approaches do not effectively utilize advanced Artificial Intelligence techniques to provide real-time, context-aware recommendations. The absence of coordination between different agricultural services and data sources leads to poor decision-making, inefficient resource utilization, increased costs, and reduced crop productivity.

Therefore, there is a need for an intelligent, automated, and collaborative system that can integrate diverse agricultural data, understand farmer requirements, and generate optimized crop management strategies using advanced AI technologies such as multi-agent systems and Large Language Models (LLMs).

4.PROPOSED SYSTEM

The proposed crop management system introduces an intelligent and integrated approach by leveraging advanced Artificial Intelligence techniques such as multi-agent systems and Large Language Models (LLMs). Unlike traditional systems, this solution is designed to handle multiple agricultural tasks in a coordinated and collaborative manner, providing farmers with accurate, real-time, and context-aware decision support.

In this system, different specialized agents are responsible for handling specific functions such as soil analysis, weather monitoring, crop recommendation, irrigation planning, and pest management. These agents work together as a multi-agent system, continuously sharing information and collaborating to generate comprehensive and optimized recommendations. This coordinated approach ensures that all critical factors affecting crop growth are considered simultaneously, improving decision accuracy.

The system integrates real-time data sources, including live weather APIs, soil condition data, and environmental parameters. By utilizing up-to-date information, the system can adapt to changing conditions and provide dynamic recommendations, making it more reliable and practical for real-world agricultural scenarios.

A key component of the proposed system is the use of Large Language Models (LLMs), which act as an intelligent decision-making layer. The LLM processes inputs from multiple agents, understands the context of the farmer's query, and generates clear, human-readable recommendations. This enables farmers to interact with the system using natural language, making it more user-friendly and accessible even for non-technical users.

Furthermore, the system focuses on resource optimization, helping farmers efficiently utilize water, fertilizers, and other inputs. By analyzing multiple parameters together, it suggests optimal strategies that not only improve crop yield but also promote sustainable farming practices.

Overall, the proposed system overcomes the limitations of existing solutions by providing an integrated, collaborative, real-time, and intelligent decision support platform for modern agriculture.

5. SYSTEM ARCHITECTURE

The architecture of the proposed multi-agent decision support system for crop management and resource optimization consists of several interconnected layers that enable intelligent, coordinated, and real-time decision-making.

1) **User Interface Layer** – Provides an interactive platform for farmers or users to enter agricultural inputs such as soil parameters (N, P, K values), location, rainfall conditions, and crop preferences. It also displays the final recommendations, including crop suggestions, fertilizer advice, and weather insights in a clear and user-friendly format.

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2) **Application / Controller Layer** – This layer is represented by the Main Controller (CropManagement class), which acts as the central unit of the system. It handles user requests, validates input data, and manages the overall workflow by coordinating with different agents and system components.
3) **Agent Management Layer** – This layer consists of multiple specialized agents collectively referred to as Crop Management Agents. Each agent is assigned a specific responsibility:
    - Soil Agent performs soil analysis
    - Weather Agent handles rainfall forecasting
    - Crop Agent provides crop recommendations
    - Fertilizer Agent gives fertilizer advice

    These agents operate independently but collaboratively, generating outputs based on their respective tasks.
4) **Task Processing Layer** – Each agent executes specific tasks such as soil analysis, rainfall forecasting, crop recommendation, and fertilizer suggestion. The outputs from these tasks are generated in structured formats (JSON context), ensuring consistency and easy integration.
5) **AI Processing Layer** – This layer integrates the system with an LLM Service (e.g., GPT-based model). The LLM processes outputs from all agents, applies contextual reasoning, and generates intelligent, human-readable recommendations by combining multiple factors.
6) **Coordination / Decision Support Layer** – Represented as the Simple Decision-Support Layer, this layer combines and refines outputs from different agents to ensure consistency, accuracy, and completeness before final aggregation.
7) **Data Aggregation Layer –** The Final Output Aggregator collects all processed data and integrates it into a structured format known as Comprehensive Crop Management JSON, which includes all recommendations in an organized manner.
8) **Output Layer** – The final processed result is delivered to the user, providing a complete decision-support solution for crop management and resource optimization.

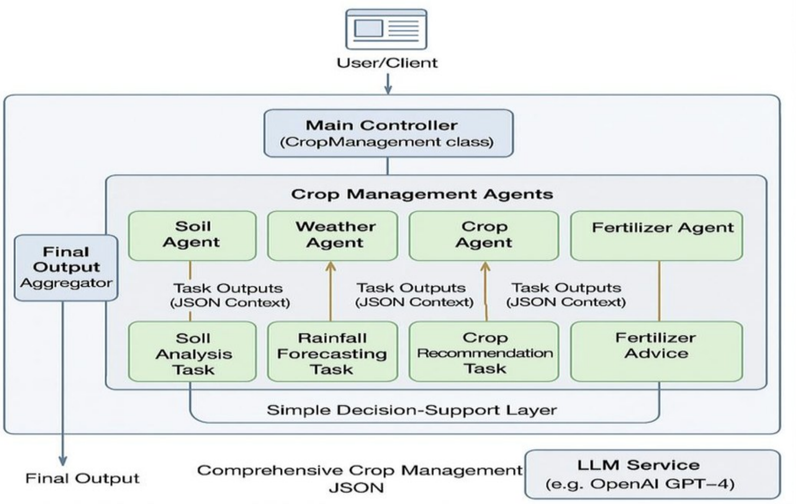

fig.1: system architecture

5.1 WORK FLOW OF THE PROPOSED SYSTEM

The workflow of the proposed multi-agent crop management system follows a structured sequence of operations that ensures efficient interaction between the user, agents, and AI components.

Initially, the user accesses the system through the interface and provides input data such as soil parameters, location, rainfall conditions, and crop preferences. The Main Controller receives this input, validates it, and initiates the processing workflow.

Next, the input data is distributed among multiple specialized agents within the system. The Soil Agent analyzes soil conditions, the Weather Agent performs rainfall forecasting using available data, the Crop Agent determines

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suitable crops based on combined factors, and the Fertilizer Agent suggests appropriate fertilizer usage. Each agent performs its respective task and generates outputs in a structured format (JSON context).
These outputs are then passed to the Decision-Support Layer, where initial integration and validation of results take place. After this, the combined data is sent to the LLM Processing Layer, where advanced reasoning is applied. The LLM analyzes all inputs collectively, understands the context, and generates meaningful, human-readable recommendations.
Finally, the processed outputs are collected by the Final Output Aggregator, which organizes them into a comprehensive crop management plan. This final output is then displayed to the user through the interface, providing clear and actionable insights for better decision-making.
Overall, the system ensures intelligent collaboration between multiple agents, real-time adaptability, and efficient resource optimization, making it highly effective for modern agricultural practices.

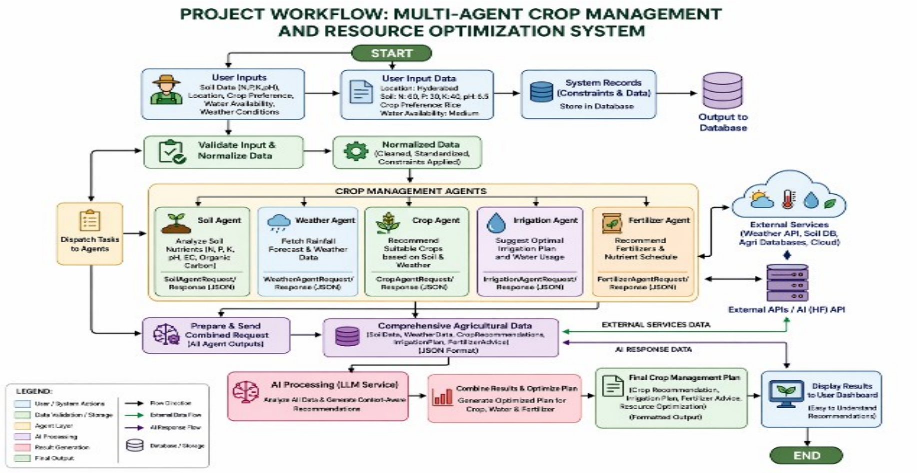

fig.2: work flow

6. METHODOLOGY

The proposed system follows a structured methodology for developing an AI-based multi-agent decision support system that enables intelligent crop management and efficient resource optimization. Initially, agricultural data is collected from users through the application interface, where farmers provide inputs such as soil parameters (nitrogen, phosphorus, potassium values), location, rainfall conditions, and crop preferences. The collected data is then validated and processed to ensure accuracy and proper organization before initiating the analysis process.
The system utilizes multiple intelligent agents to handle different agricultural tasks. The Soil Agent analyzes soil conditions and nutrient levels, while the Weather Agent retrieves and processes rainfall and environmental data. The Crop Agent suggests suitable crops based on combined soil and weather factors, and the Fertilizer Agent provides recommendations for optimal fertilizer usage to improve productivity. Each agent performs its task independently and generates outputs in a structured format.
The platform incorporates advanced Artificial Intelligence technologies, particularly Large Language Models (LLMs), to enhance decision-making and improve recommendation accuracy. Each agent communicates with the AI processing layer to obtain context-aware insights. The outputs generated by individual agents are then collected and combined into a unified decision-support plan.
All activities are efficiently managed through backend services, ensuring smooth data flow, proper coordination between agents, and reliable system performance. The integrated results are processed further to generate meaningful, human-readable recommendations that are easy for farmers to understand and apply.
Finally, the processed information is presented to users through an interactive interface that displays clear and organized recommendations, including crop selection, fertilizer usage, and resource optimization strategies. This methodology ensures efficient data processing, seamless collaboration between multiple agents, real-time adaptability, and improved decision-making in modern agriculture.
The system collects user inputs such as soil parameters, location, and weather conditions. Data is validated and processed using multiple agents for soil analysis, crop recommendation, irrigation, and fertilizer planning. Outputs

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are combined using LLM-based reasoning to generate optimized, real-time, and context-aware crop management recommendations for efficient resource utilization and improved agricultural productivity. It ensures seamless coordination between agents, supports real-time data integration, enhances decision accuracy, and delivers user-friendly recommendations for sustainable and smart farming practices.

7. ALGORITHM

Input: User agricultural data (soil parameters such as N, P, K, pH, location, water availability, weather conditions, crop preference)
Output: Generated crop management plan including crop recommendation, irrigation plan, fertilizer advice, and resource optimization strategy
Step 1: Collect agricultural details from users through the application interface.
Step 2: Accept user inputs such as soil nutrient values (N, P, K, pH), location, rainfall conditions, water availability, and crop preferences.
Step 3: Preprocess and validate the collected data to ensure accuracy, consistency, and completeness.
Step 4: Send the validated data to the system processing module (Main Controller).
Step 5: Process and normalize input data (e.g., standardize soil values, location data).
Step 6: Assign agricultural tasks to specialized agents such as Soil Agent, Weather Agent, Crop Agent, Irrigation Agent, and Fertilizer Agent.
Step 7: The Soil Agent analyzes soil conditions and nutrient levels.
Step 8: The Weather Agent retrieves and processes real-time weather and rainfall data.
Step 9: The Crop Agent recommends suitable crops based on soil and weather conditions.
Step 10: The Irrigation Agent suggests optimal water usage and irrigation planning.
Step 11: The Fertilizer Agent provides fertilizer recommendations for better yield.
Step 12: Send outputs from all agents to the AI processing layer (LLM service).
Step 13: Apply intelligent processing using LLMs to combine agent outputs and generate context-aware recommendations.
Step 14: Generate final outputs including crop recommendation, irrigation strategy, fertilizer plan, and resource optimization.
Step 15: Combine outputs from all agents into a single structured crop management plan.
Step 16: Display the generated plan to users through the application interface.
Step 17: Update system records and store results in the database.
Step 18: Provide final recommendations to the user.

8. EXPERIMENTAL SUPPORT

The experimental setup for the proposed system includes various software and hardware components required for the development and evaluation of the AI-based multi-agent crop management and resource optimization platform. The system is developed using modern web technologies, with HTML, CSS, and JavaScript used for the frontend interface, while the backend is implemented using the Django framework in Python to manage user authentication, request handling, and coordination between different system components. The system utilizes Django's built-in authentication module to support secure user registration, login, and logout functionalities.
Artificial Intelligence capabilities are integrated into the system through advanced AI services such as Large Language Model (LLM) APIs (e.g., Hugging Face or similar platforms), which are used to generate intelligent agricultural recommendations such as crop selection, irrigation planning, fertilizer advice, and resource optimization strategies. The system processes user inputs including soil parameters (N, P, K, pH), location, weather conditions, and water availability, and sends structured requests to the AI service to obtain context-aware responses.
The system also incorporates external data sources such as weather APIs and agricultural datasets to ensure real-time and accurate information. Backend services communicate with the frontend through HTTP requests and APIs, enabling smooth data exchange and efficient interaction between users and the system.
The multi-agent architecture is implemented within the backend, where different agents handle specific tasks such as soil analysis, weather forecasting, crop recommendation, irrigation planning, and fertilizer suggestion. These agents generate intermediate outputs that are combined and processed through the AI layer to produce final recommendations.
Overall, the experimental setup ensures reliable system performance, efficient data processing, seamless integration of multiple components, and accurate decision support for modern agricultural practices.

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9. PERFORMANCE METRICS

To evaluate the effectiveness of the proposed AI-based multi-agent crop management and resource optimization system, several performance metrics are considered:

1) **System Accuracy** – Measures the correctness of crop recommendations, irrigation planning, fertilizer suggestions, and overall decision support generated by the system based on user inputs.
2) **Response Time** – Indicates the time taken by the system to process user inputs such as soil data, location, and weather conditions, and generate recommendations.
3) **Precision** – Represents the proportion of relevant recommendations (crop selection, fertilizer advice, irrigation plan) correctly generated according to the given agricultural inputs.
4) **Recall –** Measures the system's ability to provide all necessary recommendations required for complete crop management, including soil analysis, weather insights, crop suggestions, and resource optimization.
5) **Reliability –** Evaluates the system's ability to consistently produce accurate outputs without failures or errors under different input conditions.
6) **Processing Time** – Time taken by the system to complete the full analysis cycle from input submission to final recommendation display.
7) **System Throughput** – Number of user requests (farmers' queries) that the system can handle within a specific time period.
8) **Scalability** – Evaluates the system's ability to handle increasing numbers of users and agricultural data without performance degradation.

10. RESULTS AND ANALYSIS

The proposed system, "Multi-Agent Decision Support System using LLMs for Crop Management and Resource Optimization," demonstrates effective performance in generating accurate and structured agricultural recommendations based on user inputs. The system allows users to provide details such as soil nutrients (N, P, K, pH), location, weather conditions, and water availability through a simple and user-friendly interface.

The coordination of multiple intelligent agents ensures efficient processing of soil analysis, weather forecasting, crop recommendation, irrigation planning, and fertilizer suggestions. The integration of these agents improves decision accuracy compared to traditional single-model systems.

The performance of the system was evaluated using metrics such as response time and system efficiency. The system shows minimal delay in processing inputs and generating recommendations. The integration of LLM-based AI services enables fast, reliable, and context-aware outputs.

The system was tested with multiple input scenarios representing different soil and environmental conditions. It showed stable performance with consistent response times and reliable outputs. The results indicate that the proposed system improves agricultural decision-making, reduces manual effort, optimizes resource utilization, and enhances overall farming productivity.

11. FUTURE ENHANCEMENT

Future improvements to the proposed system may include integration with real-time agricultural services such as IoT-based soil sensors, advanced weather forecasting APIs, and market price analysis systems to provide more accurate and dynamic recommendations.

The system can be extended to support mobile applications, enabling farmers to access recommendations easily through smartphones. Additionally, advanced machine learning and deep learning techniques can be incorporated to further improve prediction accuracy and personalization based on historical farming data.

Integration with drone technology and satellite imaging can enhance monitoring capabilities for crop health and pest detection. Cloud-based deployment can improve scalability and system performance, allowing the platform to handle large-scale agricultural data.

Furthermore, multilingual support can be implemented to make the system accessible to farmers from different regions. Features such as automated alerts, voice-based interaction, and real-time advisory services can further enhance usability and effectiveness in real-world agricultural applications.

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The authors also extend their thanks to the institution for providing the necessary resources and environment to carry out this work effectively.

13. CONCLUSION

This research presented a “Multi-Agent Decision Support System using LLMs for Crop Management and Resource Optimization,” designed to improve efficiency and decision-making in modern agriculture. The proposed system integrates advanced web technologies with intelligent features such as soil analysis, weather forecasting, crop recommendation, irrigation planning, and fertilizer optimization to provide a complete agricultural decision-support solution.

The platform supports secure user interaction through the Django framework and utilizes advanced AI technologies such as Large Language Models (LLMs) to generate intelligent, context-aware agricultural recommendations. The integration of a multi-agent architecture enables efficient collaboration between different components, improving the overall accuracy and reliability of the system.

The results demonstrate that combining multi-agent systems with AI significantly enhances agricultural decision-making, reduces manual effort, and optimizes the use of resources such as water and fertilizers. Overall, the proposed system highlights the potential of AI-driven solutions in transforming traditional farming into smart, efficient, and sustainable agriculture.

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