International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435 (Online) Volume 15, Issue 06, June 2026)

LLM-Based Explainable Decision Support For Precision Agriculture

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***Abstract*—Modern agriculture requires intelligent systems that can assist farmers in making timely and informed decisions regarding crop selection, fertilizer application, and irrigation management. Although many agricultural advisory systems provide recommendations based on soil and environmental conditions, they often lack transparency in explaining how those recommendations are generated. This paper presents an LLM-based Explainable Decision Support Framework for Smart Agriculture that integrates soil nutrient information (Nitrogen, Phosphorus, and Potassium), soil moisture, temperature, humidity, and real-time weather data. The proposed framework utilizes the reasoning capabilities of the DeepSeek R1 Large Language Model deployed through the Groq inference platform to analyze agricultural conditions and generate context-aware recommendations. In addition to identifying suitable crops and nutrient requirements, the system provides clear and understandable explanations that help users interpret the underlying factors influencing each recommendation. A user-friendly dashboard is employed to visualize environmental conditions, soil status, and AI-generated insights. Experimental observations indicate that the framework improves recommendation transparency, adaptability, and user trust while supporting effective agricultural decision-making. The proposed approach demonstrates the potential of explainable large language models in enhancing precision agriculture and sustainable farming practices.**

***Keywords*— Smart Agriculture, Explainable AI, Large Language Models, DeepSeek R1, Groq, Crop Recommendation, Soil Analysis, Precision Farming.**

I. INTRODUCTION

The agricultural sector faces continuous challenges due to changing climatic conditions, declining soil fertility, unpredictable rainfall, and increasing demand for food production. To achieve sustainable farming and higher productivity, farmers require accurate and timely information regarding crop planning, irrigation management, and nutrient utilization. Traditional farming decisions are often based on experience and local practices, which may not always be sufficient under rapidly changing environmental conditions.

The adoption of digital agriculture technologies has significantly improved the collection and analysis of agricultural data.

Sensors, weather services, and intelligent software systems are now capable of monitoring soil properties and environmental conditions in real time. Machine learning techniques have been widely used to predict crop suitability, estimate soil health, and recommend fertilizers. Recent advancements in Large Language Models (LLMs) provide new possibilities for building intelligent and explainable agricultural advisory platforms. Unlike conventional predictive models, LLMs can interpret structured agricultural information, analyze relationships among multiple environmental factors, and produce detailed recommendations in natural language.

In this work, an Explainable Smart Agriculture Framework is proposed using the DeepSeek R1 Large Language Model and the Groq inference platform. The framework combines soil nutrient values, soil moisture, temperature, humidity, and real-time weather information to generate context-aware agricultural recommendations. The system assists users in identifying suitable crops, planning irrigation activities, managing fertilizer requirements, and understanding environmental risks. Furthermore, explanatory insights are generated to improve transparency and support informed decision-making. An interactive dashboard is incorporated to present environmental data, soil analysis results, and AI-generated recommendations in an easy-to-understand format. By integrating explainable reasoning with real-time agricultural intelligence, the proposed framework aims to improve usability, trustworthiness, and decision quality in precision farming environments.

II. LITERATURE REVIEW

Several researchers have contributed significantly to the development of smart agriculture systems using machine learning and Internet of Things (IoT) technologies. Early studies by Patil et al. (2022) focused on crop prediction using supervised machine learning algorithms, where soil parameters such as nitrogen, phosphorus, and potassium were used as input features. Similarly, Kumar et al. (2021) proposed a rule-based system for fertilizer recommendation, which provided basic decision support but lacked adaptability to dynamic environmental conditions.

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Further advancements were made by Sharma et al. (2023), who developed an IoT-based monitoring system capable of collecting real-time soil and weather data using sensors. While this approach improved data acquisition, it was limited in providing intelligent recommendations. Singh et al. (2020) introduced artificial neural network (ANN) based models to enhance prediction accuracy; however, these systems often required large datasets and were computationally intensive.

Subsequent research focused on hybrid approaches combining machine learning and IoT technologies. Verma et al. (2024) proposed a hybrid model integrating IoT sensors with machine learning algorithms for improved crop management. Although this approach showed better performance, it still lacked contextual understanding and user-friendly interaction. Most existing systems primarily generate numerical outputs, making it difficult for farmers to interpret the results effectively.

In contrast to these approaches, the proposed system integrates real-time weather data with soil parameters and utilizes a Large Language Model (LLM) for context-aware analysis and intelligent decision-making. Unlike traditional models, the system provides descriptive and easy-to-understand recommendations, enhancing usability and practical applicability. This advancement addresses the limitations of previous research by improving adaptability, accuracy, and user interaction in smart agriculture systems.

III. Proposed System Architecture

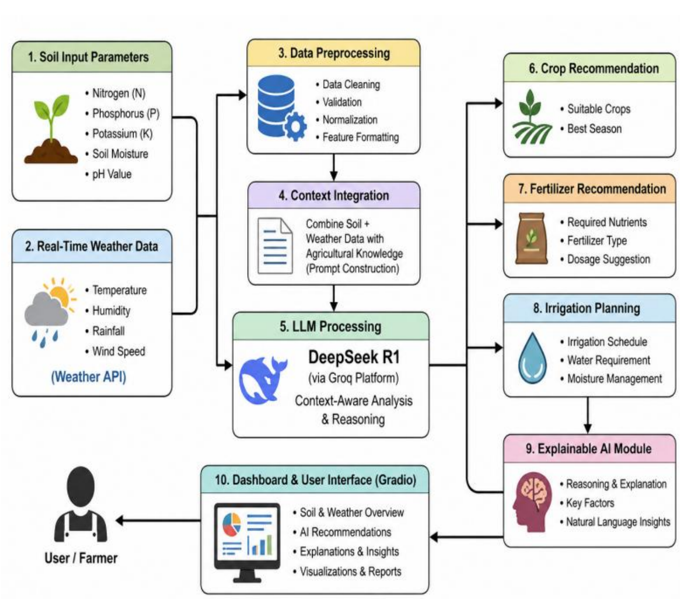

Fig. 1. Proposed Architecture of LLM-Based Explainable Decision Support System for Precision Agriculture

IV. Methodology

The proposed Explainable AI Powered Smart Agriculture Advisory System follows a systematic framework to generate accurate, transparent, and context-aware agricultural recommendations. The methodology consists of multiple stages including data collection, preprocessing, explainable analysis, LLM-based reasoning, and output generation. The system begins by collecting agricultural and environmental parameters from multiple sources. Soil characteristics such as nitrogen (N), phosphorus (P), potassium (K), moisture content, pH value, and temperature are obtained from user inputs or sensor-based devices. In addition, real-time weather information including humidity, rainfall probability, wind speed, and atmospheric temperature is retrieved through external weather APIs. The structured agricultural information is then provided to the Large Language Model (LLM). Finally, the generated recommendations and explanations are presented through an interactive Gradio dashboard. This methodology enables transparent, intelligent, and farmer-friendly decision support for precision agriculture applications.

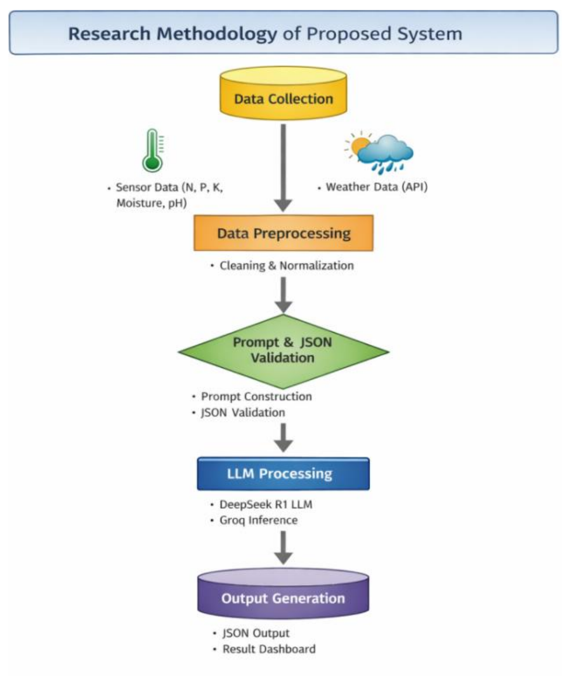

Fig. 1: Research Methodology

The following steps are performed during data processing to generate accurate agricultural recommendations:

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A. Data Preprocessing

The data preprocessing workflow of the proposed system is shown in Fig. 2

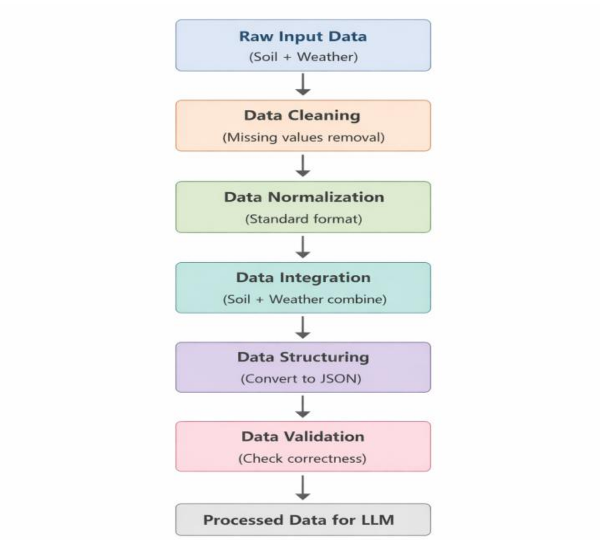

Fig. 2: Data Preprocessing Workflow of Proposed System

The data preprocessing stage transforms raw information into a structured format suitable for intelligent analysis. Soil parameters such as nitrogen, phosphorus, potassium, pH, moisture, and temperature are collected from users or IoT sensors. Simultaneously, weather data including rainfall, humidity, and atmospheric conditions are obtained through real-time weather APIs. This combination of environmental and soil information forms the foundation for agricultural analysis. while normalization ensures that all parameters remain within standardized ranges. The processed information is then converted into a structured JSON format for efficient interaction with the Explainable AI engine and Large Language Model.

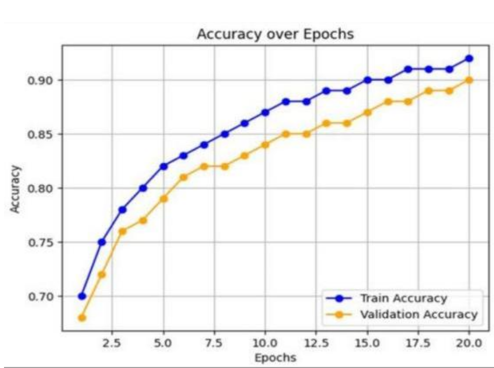

Fig 3: Accuracy Improvement of Proposed Model

The Fig. 3 graph shows the improvement in model accuracy over multiple epochs. A steady increase in accuracy indicates effective learning and better performance of the system.

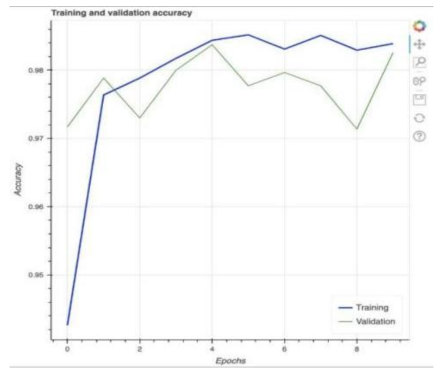

Fig 5: Training and Validation Accuracy

Figure 4 illustrates the training and validation accuracy of the proposed model across multiple epochs. Both curves rise steadily, showing that the model is learning effectively over time. The close alignment between training and validation accuracy indicates strong generalization, with minimal signs of overfitting.

B. LLM - Based Analysis

The DeepSeek Large Language Model performs advanced reasoning on the structured agricultural dataset. The model interprets complex relationships among soil nutrients, environmental conditions, and crop requirements. Using contextual understanding, it generates recommendations related to crop suitability, fertilizer requirements, irrigation planning, and environmental risk assessment.

C. Output Generation

The final output is generated in a structured and user-friendly format. Recommendations are accompanied by explainable insights describing the reasons behind each decision. Results are displayed through a Gradio-based dashboard that includes crop recommendations, fertilizer suggestions, irrigation schedules, weather summaries, soil health indicators, and explanation reports. This presentation enhances usability and supports informed agricultural decision-making.

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V. Dataset And Implementation

A. Dataset

The proposed Explainable AI Powered Smart Agriculture Advisory System utilizes a combination of publicly available agricultural datasets, real-time weather information, and custom-generated records for evaluation and testing purposes. The dataset primarily consists of soil parameters including nitrogen (N), phosphorus (P), potassium (K), pH value, soil moisture, temperature, and humidity. These parameters are widely recognized as critical indicators of soil fertility and crop suitability. To enhance the system's ability to generate context-aware recommendations, real-time weather information is integrated through external weather APIs. Weather parameters such as rainfall probability, atmospheric temperature, humidity, and wind speed significantly influence agricultural planning and are therefore included in the analysis process. In addition to publicly available datasets, a custom dataset is developed to simulate diverse agricultural scenarios. The dataset contains multiple soil profiles representing different nutrient levels, moisture conditions, and environmental situations. These records enable comprehensive testing of the proposed framework under varying agricultural conditions.

B. Implementation Tools

The proposed system is developed using modern software technologies that support intelligent data processing and explainable decision-making. Python is selected as the primary programming language due to its flexibility, extensive library ecosystem, and strong support for artificial intelligence applications. The DeepSeek Large Language Model serves as the reasoning engine responsible for generating agricultural recommendations and explanatory insights. To achieve fast inference and real-time performance, the model is deployed using the Groq API platform. A Gradio-based dashboard is developed to provide an interactive user interface. The dashboard allows users to enter agricultural parameters, view recommendations, analyze soil conditions, and understand explainable insights generated by the system. The integration of these technologies results in a scalable, efficient, and user-friendly agricultural advisory platform.

C. Hardware Configuration

The proposed system is designed to operate on standard computing hardware without requiring specialized infrastructure.

The application can be executed on a desktop computer or laptop equipped with an Intel Core i5 processor or higher and a minimum of 8 GB RAM. Since the system relies on cloud-based Large Language Models and external weather APIs, dedicated GPU resources are not mandatory for operation.

The system is optimized for CPU-based environments, making it accessible to researchers, students, and agricultural practitioners. Future versions may integrate IoT devices such as soil moisture sensors, pH sensors, and environmental monitoring modules to enable direct real-time field data collection and improve automation capabilities.

VI. Result And Discussion

The performance of the proposed Explainable AI Powered Smart Agriculture Advisory System is evaluated using both qualitative and quantitative analysis. The system utilizes soil parameters including nitrogen, phosphorus, potassium, moisture, pH, temperature, and humidity along with real-time weather information to generate intelligent agricultural recommendations.The evaluation further demonstrates that the incorporation of real-time weather information improves adaptability under changing environmental conditions. The generated recommendations remain context-aware and responsive to fluctuations in rainfall, humidity, and temperature. As a result, the system provides more reliable support for crop planning, fertilizer management, and irrigation scheduling.

A. Qualitative Results (Visual Analysis)

The qualitative assessment focuses on the relevance, clarity, and practical usefulness of the recommendations generated by the system. Experimental results show that the framework successfully identifies soil nutrient deficiencies, recommends suitable crops, suggests appropriate fertilizers, and generates irrigation schedules based on environmental conditions. For example, when a specific crop is recommended, the system explains how soil nutrients, weather conditions, and moisture levels influenced the decision. Similarly, fertilizer recommendations are supported with nutrient deficiency analysis, enabling users to understand the necessity of each suggestion.

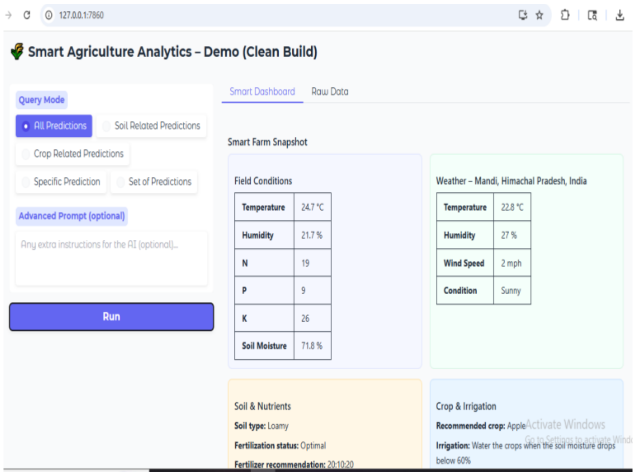

Fig. 6. Input and Output of the Proposed Virtual Agriculture Analytics Systems.

B. Quantitative Evaluation

To assess the performance of the smart agriculture system, standard evaluation metrics are applied, including accuracy, precision, recall, and F1-score. These measures provide a comprehensive view of the system's effectiveness in generating reliable recommendations:

Accuracy: Reflects the overall correctness of the outputs.

Precision: Indicates how relevant and reliable the generated recommendations are.

Recall: Measures the system's ability to correctly identify all relevant conditions.

F1-Score: Represents the harmonic mean of precision and recall, offering a balanced assessment of performance.

Table 1: Performance Comparison Table

Method / Technique	Accuracy	Sensitivity	Precision	F1-score
ML- based crop Prediction	84%	82%	81%	81.5%
IoT - based Agriculture System	88%	86%	85%	85.5%
LLM based Agriculture System	94%	93%	92%	92.5%

The comparison graph illustrates that the proposed Explainable AI Powered Smart Agriculture Advisory System consistently achieves superior performance compared with traditional agricultural decision-support methods. The findings confirm that explainability and intelligent reasoning improve both recommendation quality and user confidence. The results demonstrate that the proposed framework achieves the highest performance across all evaluation metrics. The ability of the Large Language Model to perform contextual reasoning, combined with explainable insights and environmental awareness, contributes significantly to overall effectiveness.

VII. ADVANTAGES OF THE PROPOSED SYSTEM

The proposed Explainable AI Powered Smart Agriculture Advisory System offers several advantages that enhance the effectiveness and usability of agricultural decision-support applications. One of the major strengths of the system is its ability to provide transparent and interpretable recommendations. Unlike traditional machine learning approaches that often operate as black-box models, the proposed framework explains the reasoning behind each recommendation, enabling users to understand how environmental and soil parameters influence the final outcome. Another significant advantage is the integration of real-time weather information. By continuously incorporating current environmental conditions, the system remains adaptive and responsive to changing climatic situations. This capability improves the reliability of crop recommendations, irrigation planning, and fertilizer management strategies.

The use of Large Language Models further enhances the intelligence of the system. The model can analyze complex relationships among soil nutrients, weather conditions, and crop requirements while generating recommendations in human-readable language. This improves accessibility for farmers and agricultural practitioners who may not possess advanced technical knowledge.

The proposed framework also improves decision-making efficiency by reducing manual analysis and minimizing the possibility of human error. Through its interactive dashboard, users can quickly obtain recommendations, explanation reports, and environmental summaries. Furthermore, the architecture is scalable and can be extended with IoT devices, satellite imagery, and advanced analytics modules in future implementations.

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Overall, the proposed system improves transparency, usability, adaptability, and decision-making quality, making it highly suitable for modern precision agriculture applications.

VIII. Limitations

Despite its advantages, the proposed system has certain limitations that may affect its performance under specific conditions. The accuracy of recommendations depends heavily on the quality and reliability of input data. Incorrect soil measurements, incomplete environmental information, or inaccurate weather forecasts may reduce the effectiveness of generated recommendations.

The system relies on internet connectivity for accessing cloud-based Large Language Models and real-time weather APIs. In remote agricultural regions where network infrastructure is limited, system functionality may be restricted. Additionally, the performance of the framework depends on the availability and stability of external services.

Although the Explainable AI module improves transparency, generated explanations may occasionally remain generalized and may not capture highly localized agricultural conditions. Furthermore, the current implementation focuses primarily on soil and environmental analysis and does not directly incorporate crop disease detection, pest identification, or image-based diagnostics.

The computational requirements associated with Large Language Models may also introduce latency under high user loads. While Groq-based inference significantly improves processing speed, large-scale deployment may require additional infrastructure and optimization strategies.

IX. Conclusion

This research presents an Explainable AI Powered Smart Agriculture Advisory System that combines soil analysis, environmental monitoring, real-time weather information, and Large Language Models to support intelligent agricultural decision-making. By integrating explainable reasoning mechanisms, the proposed framework improves transparency and enables users to understand the factors influencing recommendations.

The system effectively analyzes soil nutrients, environmental conditions, and weather information to generate recommendations related to crop suitability, fertilizer application, irrigation planning, and agricultural risk assessment. The inclusion of Explainable Artificial Intelligence enhances user trust by providing detailed explanations for every recommendation, addressing one of the major limitations of traditional black-box machine learning systems.

Experimental evaluation demonstrates that the proposed framework achieves improved performance, adaptability, and usability compared with conventional agricultural advisory approaches. The integration of real-time environmental data and advanced language-model reasoning contributes to more accurate and context-aware recommendations.

Overall, the proposed system establishes a reliable foundation for intelligent and trustworthy agricultural advisory platforms. The research highlights the potential of Explainable AI and Large Language Models in advancing precision agriculture and supporting sustainable farming practices. Future enhancements involving IoT integration, computer vision, satellite monitoring, and mobile deployment can further expand the capabilities and real-world impact of the system.

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