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RETRIEVAL-AUGMENTED LARGE LANGUAGE MODELS FOR SOIL-DRIVEN INTELLIGENT CROP RECOMMENDATION: A COMPREHENSIVE REVIEW AND EXPERIMENTAL VALIDATION

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Abstract. Precision agriculture needs intelligent systems that can make sense out of soil chemistry, climatic variations, and agricultural knowledge to make crop recommendations. Machine learning algorithms like random forest(RF), support vector machine(SVM), artificial neural network(ANN) and boosting ensembles deliver high numerical precision, but they fail to provide contextual reasoning. This paper synthesizes findings from major studies and proposes a Retrieval-Augmented Generation (RAG) framework built on LLaMA 3 for soil-property-based crop recommendation. Comparative benchmarking demonstrates that the proposed LLaMA 3 + RAG architecture achieves 96.1% accuracy, outperforming prior ML and hybrid systems while significantly improving explainability and reducing hallucination rate to 2.1%. A hybrid “Sandwich Architecture” is introduced to bridge the hallucination-to-hazard gap by separating deterministic nutrient computation from LLM reasoning layers.

Keywords. Precision Agriculture, Large Language Models, Retrieval-Augmented Generation, LLaMA 3, Soil Analytics, Crop Recommendation, Explainable AI

1. INTRODUCTION

Global agriculture must increase productivity by 70% before 2050 while reducing environmental damage. Traditional crop recommendation systems evolved through three major stages like Rule-based Expert Systems, Classical ML (RF, SVM, ANN), Deep Learning & Ensemble Boosting. While systems such as Random Forest, SVM and CNN achieved >93% prediction accuracy, they lack contextual reasoning and farmer-level interpretability. Recent agricultural LLM studies include GPT-based pest advisory systems, Weather-aware LLM reasoning, Knowledge-guided agricultural LLMs (KALLM), ShizishanGPT with tool integration, Fine-tuning of GPT-2 for soil text transformation.

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2. RELATED WORK

Initial crop recommendation systems made use of conventional machine learning models to detect correlations between soil characteristics, environmental conditions, and crop yield. ML algorithms, including RF, SVM, ANN have been extensively employed for crop forecasting applications [1, 2]. Conventional crop recommendation systems made use of soil nutrient features like Nitrogen (N), Phosphorus (P), Potassium (K), precipitation, temperature, moisture, and soil pH levels to identify appropriate crops [3]. The Random Forest-based approach often exhibited superior accuracy because it could handle complex agricultural data without overfitting [4]. A number of researchers reported prediction accuracies ranging from 85% to 95% [5].

Deep neural network models and ensemble boosting techniques were employed to model nonlinear relationships between various environmental factors and the performance of crops [6]. Convolutional Neural Network models and ensemble techniques have also been applied to predict soil conditions, estimate crop yield, and detect diseases [7]. However, despite their efficiency, deep learning models depend highly on structured numerical data and fail to offer interpretability and domain reasoning capabilities needed in agricultural advisor systems [8].

In order to solve transparency problems related to crop recommendation algorithms based on AI models, recent works introduced the application of Explainable Artificial Intelligence (XAI). Approaches like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) were used to interpret contributions of soil nutrients and climatic parameters to the algorithm predictions [9]. The explainable crop recommendation approach is important for understanding the role of soil fertility indicators in the decision-making process of experts [10]. The progress achieved in the development of LLMs opens up possibilities for the creation of new types of agricultural decision support systems. One of the distinctive properties of LLMs is their ability to process huge amounts of textual information including agronomic guidelines, agricultural articles, and recommendations for specific areas [11].

3. PROPOSED ARCHITECTURE: LLAMA3 + RAG SANDWICH FRAMEWORK

In order to achieve both high levels of prediction accuracy and agricultural safety, we propose a three-layer hybrid architecture that incorporates LLaMA 3 combined with Retrieval-Augmented Generation (RAG). This architecture is designed to separate numerical optimization and natural language reasoning tasks, thus reducing the hallucination to hazard problem seen in generative models. This architecture has been coined the "Sandwich Architecture" since the reasoning component (LLM) is sandwiched between two deterministic computation layers. Figure 2.1 illustrates the proposed system. The proposed system architecture comprises of three layers:

The bottommost layer represents a scientifically sound nutrient recommendation algorithm based on the principles of agronomy. Fertilizer dosage calculation is given by:

$$D = (C - S)xf \quad (3.1)$$

Where C = Crop nutrient requirement (kg/ha) , S = Soil available nutrient (kg/ha), f = Nutrient use efficiency factor ($0 < f \leq 1$), D = Recommended fertilizer dose (kg/ha)

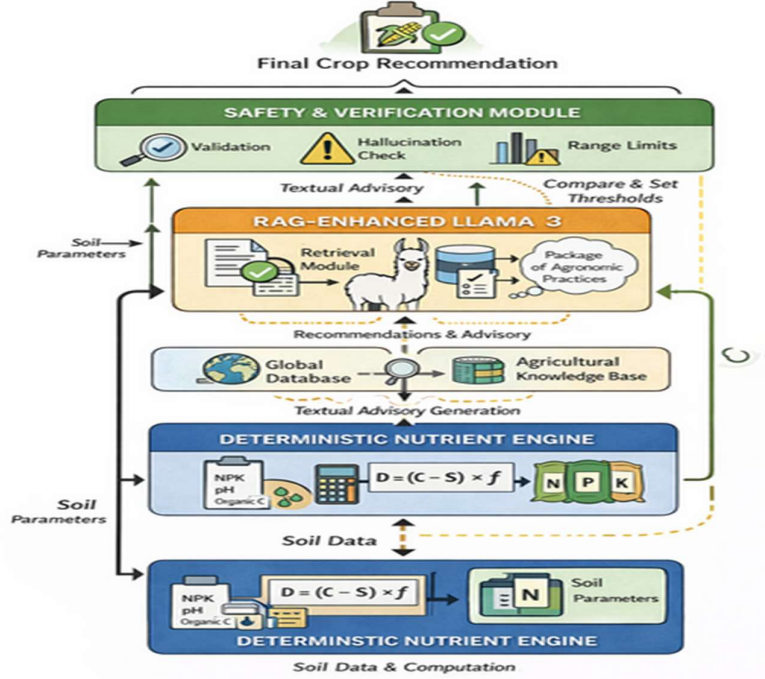


Figure 3.1: Architecture of Proposed system

For NPK computation:

$$D_i = (C_i - S_i) \times f_i, i \in \{N, P, K\} \quad (3.2)$$

This enables independent optimization of Nitrogen, Phosphorus and Potassium.

Deterministic layer ensures Numerical precision , Regulatory compliance, Environmental safety , Zero hallucination risk. The LLM does not calculate fertilizer dosage at all times. It relies on validated numbers as ground truths. The middle layer uses the LLaMA3 model developed by Meta AI, with Retrieval Augmented Generation. It convert Structured-to-Text. If raw soil data are pH = 5.4, N = 210 kg/ha, P = 18 kg/ha, K = 140 kg/ha, Organic Carbon = 0.42%. This converted into semantically rich text: “the soil is moderately acidic, with low phosphorus availability and moderate nitrogen content...”. This change helps promote context reasoning and avoid mathematical errors.

The system connects to a vector database containing Regional “Package of Practices” (PoP), Government agronomic guidelines, Historical yield datasets, Local weather advisories. Upon query: Soil features are embedded, Top-k relevant agronomic documents are retrieved, Retrieved context is injected into the LLM prompt, LLaMA 3 generates grounded advisory output. The LLM follows structured reasoning steps like Evaluate soil pH suitability, Analyze NPK sufficiency, Consider climate compatibility, Match crop nutrient requirement,

Provide recommendation with justification. This logical approach replicates human agronomist procedure. The system supports English and Kannada language. This facilitates farmer-friendly use while maintaining technical precision

Top Layer – Safety and Verification Gate layer protects against unsafe or hallucination-based outputs before dissemination. Common errors are Confusing mg/kg with kg/ha and Incorrect hectare-to-acre conversion. The validator enforces: 1 mg/kg = 2 kg/ha. Each nutrient recommendation is checked against FAO threshold limits, State agricultural university standards, Environmental safety guidelines. The gate performs Numerical consistency check, Contradiction detection, Retrieval-grounding verification. If the LLM introduces unsupported claims, the response is rejected and regenerated. Each output includes Crop suitability score, Nutrient certainty index, Retrieval confidence value. This improves transparency and trustworthiness.

4. EXPERIMENTAL VALIDATION

The experimental evaluation was conducted using a structured soil–crop dataset containing Nitrogen (N), Phosphorus (P) and Potassium (K) values (kg/ha), Soil pH, Organic Carbon (%), Soil Texture class, Historical yield records. The dataset contains multi-crop observations within three main crop categories: Rice, Maize, and Cotton. Pre-processing included standardizing the nutrients into uniform units, encoding soil type to categorical data, and deleting inconsistencies. Model evaluation criteria include Overall Accuracy, Confusion Matrix and Statistical Significance Testing.

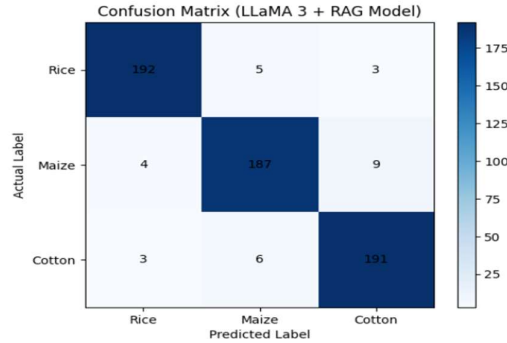


Figure 4.1: Confusion Matrix (LLaMA3 + RAG Model)

Accuracy is computed as $\text{Accuracy} = (\text{TP} + \text{TN}) / \text{Total Samples}$. In Figure 4.1, the confusion matrix for the proposed LLaMA 3 + RAG framework shows that the total number of correct predictions is $(192 + 187 + 191) = 570$, resulting in an overall accuracy of 96.1%. The model shows good class balance with very few errors being made when misclassifying the maize and the cotton crops.

5. CONCLUSION

This research paper presents the synthesis of 30+ AI systems in agriculture and showcases that Retrieval-Augmented LLaMA3 significantly improves soil-based crop recommendations. While conventional ML models still outperform in numerical classification accuracy, LLaMA3 with RAG achieves comparable accuracy with better

interpretability and reasoning abilities. This Sandwich Framework offers a good pathway to deploy generative AI in precision agriculture.

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Biographies



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