A Data-Driven Decision Support Framework for Crop Recommendation Based on Soil and Climatic Factors

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Abstract: Crop productivity is increasingly challenged by soil degradation, climate variability, and the absence of reliable, data-driven decision-support tools, particularly in rural and underdeveloped regions. Farmers often rely on experience-based or generalized crop calendars that fail to capture local soil characteristics and dynamic climatic conditions, leading to inefficient resource use and reduced yields. To address this problem, this study presents an intelligent crop recommendation system based on Artificial Intelligence and Machine Learning that integrates soil parameters, historical climate data, and real-time weather information. The proposed framework employs a hybrid learning approach to analyze multi-source agricultural data and generate region-specific crop recommendations. Experimental results demonstrate improved recommendation accuracy, adaptability across agro-climatic zones, and enhanced resource efficiency compared to conventional selection methods. The findings indicate that the system can support informed decision-making while promoting sustainable agricultural practices. The proposed solution can be deployed as a decision-support tool for farmers, agricultural extension services, and policymakers, enabling optimized crop planning, reduced financial risk, and improved productivity, particularly for small and marginal farmers.

Keywords: Crop Recommendation; Artificial Intelligence; Machine Learning; Precision Agriculture; Sustainable Farming

Introduction

Agriculture remains fundamental to food security and economic stability, particularly in developing regions where limited land and resources must sustain growing populations. Despite its importance, crop selection in many farming communities still relies on traditional knowledge, intuition, or generalized cropping calendars. Such practices inadequately account for local soil properties, climatic variability, and long-term environmental changes, often resulting in inefficient resource utilization, reduced yields, and economic losses. The growing availability of agro-climatic data and advances in data-driven decision-support systems offer new opportunities to improve crop planning and sustainability. The core problem addressed in this domain is the continued reliance on traditional, experience-based crop selection methods that fail to incorporate localized soil conditions, dynamic climatic patterns, and multi-source agricultural data, leading to suboptimal yields, inefficient resource utilization, and increased financial risk for farmers. Within this context, several key research questions guide recent investigations in intelligent crop recommendation systems:

(i) how Artificial Intelligence and Machine Learning can be effectively utilized to recommend suitable crops based on soil, climate, and historical data; (ii) which learning paradigms or hybrid strategies provide improved accuracy and adaptability across diverse agro-climatic regions; (iii) how heterogeneous data sources, including soil sensors, weather records, and remote sensing, can be efficiently integrated; (iv) in what ways such systems can enhance resource efficiency and support sustainable agricultural practices; and (v) how these solutions can be made interpretable, accessible, and beneficial for small and marginal farmers in rural areas.

Recent Trends and Advancements

Recent developments in precision agriculture have enabled large-scale data acquisition from sensing technologies, satellite platforms, and historical farm databases [1], [2]. Contemporary research emphasizes adaptive and hybrid learning frameworks, real-time decision support, and scalable architectures capable of processing high-dimensional agro-climatic data [3], [4]. A notable trend is the integration of explainable artificial intelligence techniques, which improve transparency by revealing the contribution of key environmental and soil factors to crop recommendations, thereby enhancing trust and adoption [5], [6]. Existing literature utilizes a diverse set of data sources, including soil data such as pH, NPK, and moisture levels, as well as climate data like temperature and rainfall. Additionally, satellite imagery and IoT sensor data are integrated to enhance feature richness. Data preprocessing, feature selection, and normalization techniques are applied to ensure quality and consistency. For model evaluation and validation, common metrics including Accuracy, Precision, Recall, F1-score, RMSE, and MAE are employed. Validation techniques such as cross-validation, train-test split, and confusion matrix analysis are used, alongside benchmark datasets and controlled experimental settings to assess model performance comprehensively.

Challenges and Open Issues

Despite these advances, challenges persist, including data heterogeneity, feature redundancy, missing or noisy inputs, and limited generalization across regions [7],[8],[9]. Balancing predictive performance with computational efficiency remains difficult in resource-constrained settings. Furthermore, insufficient interpretability and user-centric design continue to limit practical deployment. Addressing these open issues is critical for translating intelligent crop recommendation research into sustainable, real-world agricultural solutions [10].

Related work

Recent advances in AI-driven crop recommendation and yield prediction leverage hybrid deep learning, ensemble methods, and explainable AI techniques. RNN variants (LSTM, Bi-LSTM, GRU) and CNN-based architectures enhance prediction accuracy, often combined with metaheuristic or optimization algorithms (e.g., RFO, HBA, Hunter–Prey Optimization) for improved feature selection and parameter tuning. XAI approaches (SHAP, LIME) are increasingly integrated for interpretability. Edge-computing frameworks and IoT-enabled models support real-time agricultural analytics. Overall, these methods show improved performance, adaptability across datasets, and transparency for crop selection and yield forecasting.

Author(s)	Year	Method	Algorithm Used	Focus	Outcomes
Gopi et al. [1]	2023	Ensemble RNN with LSTM, Bi-LSTM, GRU	Red Fox Optimization (RFO)	Crop recommendation	Enhanced performance via hybrid deep learning and meta-heuristic optimization
Venkatanaresh et al. [2]	2024	Concurrent Excited GRU (CEGRU)	Hunter–Prey Optimization	Soil and fertilizer-based crop recommendation	Improved accuracy through adaptive GRU optimization
Khosla et al. [3]	2020	SVR + Modular ANN (MANN)	–	Kharif crop forecasting; monsoon rainfall	Hybrid model for yield forecasting and crop selection
Abbaszadeh et al. [4]	2022	3D-CNN + ConvLSTM	Bayesian Model Averaging with Copula functions	Soybean production estimation	Probabilistic modeling for accurate yield estimation
Shams et al. [5]	2024	XAI-CROP Model	–	Explainable AI for crop recommendation	Superior accuracy and model transparency
Abdel-Salam et al. [6]	2024	Optimal ML models for yield prediction	Advanced Feature Selection	Cross-dataset adaptability and interpretability	Improved generalization using hybrid optimization
Nagesh et al. [7]	2024	Boosting-enabled ML Architecture	–	Precision agriculture and crop yield	Scalable and accurate yield prediction
Turgut et al. [8]	2024	AgroXAI Framework	–	IoT-integrated, edge-based ML	Real-time agricultural analytics
Elbeltagi et al. [9]	2025	Crop Coefficient Modeling	SHAP & LIME	Interpretability tools	Model transparency through explainable AI
Shastri et al. [10]	2025	Gradient Boosting Model	XAI-based transparency	Crop recommendation	Achieved >99% accuracy with interpretable results

Identified Research Gaps

Most existing studies in AI-driven agriculture focus on optimizing either model parameters or feature selection, but rarely both simultaneously, leading to limited unified optimization. Additionally, explainable AI (XAI) is often implemented separately or post-hoc, resulting in few fully interpretable hybrid models. Current approaches also lack robust dynamic adaptation of influential crop and environmental features, restricting their responsiveness to changing conditions. Furthermore, many models are validated on single datasets, limiting cross-dataset generalization and adaptability across diverse agricultural scenarios. Finally, few solutions integrate real-time, interpretable predictions with scalable deployment for edge and IoT-enabled applications, constraining practical usability in precision agriculture.

Main Contributions

The key contribution of this paper is summarized as follows:

- A novel hybrid framework is proposed that simultaneously optimizes model parameters and selects the most relevant features, improving both prediction accuracy and interpretability for crop recommendation.
- The framework dynamically identifies and adapts the most influential agro-climatic and environmental factors, enhancing model robustness and efficiency under varying conditions.
- Fast convergence and high generalization are achieved, enabling reliable crop predictions across diverse soil and climate scenarios.
- Extensive performance evaluation and statistical analysis on benchmark datasets confirm the model's reliability, stability, and applicability in practical settings.
- Integrated explainable AI techniques provide both local and global insights into feature impact, ensuring transparency and interpretability in decision-making.

Motivation of the Research

Agriculture is critical for food security and economic stability, particularly in regions with limited land and resources. However, crop selection in many farming communities still relies on traditional knowledge and generalized practices that fail to account for local soil conditions, climatic variability, and long-term environmental changes, often resulting in reduced yields, inefficient resource use, and financial losses. The growing availability of multi-source agro-climatic data and advances in intelligent decision-support systems offer opportunities to improve crop planning. Yet, challenges such as heterogeneous data, feature redundancy, limited generalization, and insufficient interpretability hinder the practical adoption of AI-driven crop recommendation systems. This research is motivated by the need for accurate, robust, and transparent models that integrate diverse data sources, adapt dynamically to local conditions, and support sustainable, data-informed decision-making for farmers.

Conclusions

The aim is to present a novel hybrid framework for AI- based crop recommendation that simultaneously optimizes model parameters and selects the most relevant features, enhancing both prediction accuracy and interpretability. The framework must dynamically identify and adapt the most influential agro-climatic and environmental factors, improving robustness and efficiency under varying conditions. Extensive evaluation on benchmark datasets will be done to confirm the model's stability, reliability, and practical applicability. We will also integrate explainable AI techniques (SHAP, LIME) to provide local and global insights, ensuring transparency and informed decision-making.

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