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Survey Paper On Machine Learning-Based Crop Recommendation Systems

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Abstract - **As agriculture faces increasing pressure from climate change, limited natural resources, and growing population demands, the need for intelligent, data-driven support systems has become more urgent. Machine Learning (ML)-based crop recommendation systems are proving to be valuable tools that assist farmers in selecting the most suitable crops based on factors like soil properties, weather patterns, and regional agricultural practices. This literature survey reviews recent developments in such systems, comparing different machine learning models, their accuracy, and performance evaluation methods. It also discusses current limitations and areas where existing systems fall short. By compiling and analyzing findings from various studies, this paper offers insights that can inform future advancements in precision agriculture and contribute to more sustainable, efficient farming practices.**

I.Introduction

A. Background and Rationale

Agriculture remains a cornerstone of many economies, particularly in developing nations, where it plays a vital role in livelihoods and food security. However, modern farmers face increasingly complex challenges, including climate variability, declining soil health, and limited access to natural resources. Traditional methods of crop selection—often based on inherited knowledge or localized advice—are no longer sufficient in the face of these dynamic environmental conditions.

Recent advancements in machine learning (ML) have given rise to crop recommendation systems that aim to support more informed agricultural decisions. Typically, these systems use basic parameters such as temperature, rainfall, and soil nutrients to suggest appropriate crops. While valuable, many existing solutions are overly simplistic and fail to reflect the complex realities of farming today. They often overlook critical factors like groundwater levels, soil salinity and alkalinity, and local agricultural practices. Furthermore, most tools lack regional specificity, offer limited interpretability, and are not tailored for easy use by smallholder or less tech-savvy farmers.

This study proposes a more comprehensive and practical crop recommendation system. By integrating a wider range of environmental and agronomic variables—alongside explainable, region-aware intelligence—this system seeks to provide actionable and scientifically grounded insights. The goal is to empower farmers with reliable, context-rich recommendations that enhance decision-making, improve crop suitability, and support sustainable agricultural practices.

B. Problem Statement

Despite technological progress, many farmers continue to rely on traditional knowledge or informal advice when choosing crops—a practice that is increasingly inadequate under the pressures of a changing climate and evolving soil conditions. Existing crop recommendation tools, while helpful, often rely on limited datasets and fail to account for important variables such as groundwater availability, soil salinity and alkalinity, or prevailing regional cropping patterns.

Moreover, these systems are frequently designed without consideration for usability in rural or low-literacy settings, limiting their accessibility and real-world utility. There is a clear and pressing need for an intelligent, adaptive system that delivers accurate, localized, and easy-to-understand crop recommendations—one that bridges the gap between scientific data and practical farming needs.

C. Research Objectives

This research aims to develop a data-driven crop recommendation system that meaningfully supports farmers in making informed, site-specific decisions. The project is driven by the following objectives:

- To design a robust recommendation system that evaluates a wide array of agronomic and environmental factors—including soil health metrics, climatic conditions, groundwater availability, and regional crop preferences.
- To build a machine learning model that leverages real-world agricultural data and improves over time through adaptive learning.
- To incorporate often-overlooked variables such as soil salinity, alkalinity, and local dietary staples, enhancing the system's contextual relevance.
- To ensure usability and accessibility, particularly for farmers with limited technical expertise, through an intuitive and user-friendly interface.
- To support long-term agricultural sustainability and profitability, enabling farmers to choose

crops that are ecologically suitable and economically viable.

D. Scope of the Study

This study focuses on the development of a machine learning-based crop recommendation platform that integrates environmental, soil, and socio-agricultural data to generate precise, location-specific crop suggestions. Key parameters include rainfall, temperature, soil moisture, fertility indicators, and groundwater availability. The system also takes into account local cropping trends and staple food preferences to tailor its recommendations to the specific needs of the farming community.

The project encompasses the full pipeline of system development—from data collection and preprocessing to model training, evaluation, and user interface design. While initially targeted at select regions, the system is structured for scalability and adaptability across diverse agro-climatic zones.

E. Significance of the Study

In an era marked by ecological uncertainty and agricultural transformation, farmers are increasingly in need of reliable tools to guide their planting decisions. Poor crop selection can have serious repercussions—leading to resource wastage, lower yields, and economic hardship. This research addresses a critical gap by developing a machine learning-based crop recommendation system that prioritizes both scientific accuracy and farmer usability.

The study is significant in several ways. First, it expands the scope of traditional crop recommendation models by including variables like soil salinity, alkalinity, moisture content, groundwater levels, and local food habits—factors often overlooked yet vital to realistic agricultural planning. Second, the system is being designed with an emphasis on accessibility, ensuring that even farmers with minimal digital literacy can benefit from its insights.

From an academic standpoint, the study contributes to the growing field of precision agriculture, showcasing the practical application of machine learning in environmental and agronomic contexts. Practically, it offers a scalable solution that can enhance crop planning, reduce trial-and-error farming, and support the resilience of rural economies. Ultimately, this research aims to empower farmers with the knowledge and tools necessary for sustainable, profitable, and environmentally aligned agricultural practices.

II.Review of Literature

A. Algorithm Comparisons and Model Effectiveness

A significant body of research has focused on evaluating the performance of various machine learning (ML) algorithms for crop recommendation systems. Commonly tested models include Logistic Regression (LR), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees (DT), Random Forests (RF), and Gradient Boosting (GB). Among these, Random Forest has consistently demonstrated superior performance. In one comprehensive comparative analysis involving nine algorithms, the Random Forest model achieved a remarkable accuracy of 99.31%, outperforming all other models tested [1]. This finding aligns with broader evidence suggesting that ensemble learning methods like Random Forest and Gradient Boosting generally offer improved generalization and robustness when compared to individual classifiers [4].

B. Integration of IoT and Real-Time Data Collection

The integration of Internet of Things (IoT) technology has introduced dynamic capabilities to crop recommendation systems. For instance, Mahesh Korde and colleagues developed a hybrid ML-IoT framework that utilizes real-time data from sensors measuring nitrogen, phosphorus, potassium, soil pH, moisture levels, and temperature [3]. This system enables adaptive crop recommendations based on real-time environmental inputs, allowing farmers to respond quickly to changing field conditions. Such integration makes the model more responsive and scalable for use in precision agriculture applications.

C. Feature Engineering and Data Preprocessing

The accuracy and reliability of crop recommendation systems are heavily dependent on the quality of the input features. Research highlights the importance of selecting relevant attributes such as soil nutrient content (NPK), climatic conditions (temperature, humidity, rainfall), and in some cases, socioeconomic indicators. Preprocessing techniques—such as normalization, outlier detection and removal, and data balancing using methods like Synthetic Minority Over-sampling Technique (SMOTE)—have proven effective in enhancing model stability and predictive performance [1].

D. Emerging Frameworks and Hybrid Models

Innovative hybrid frameworks are gaining traction in the literature. These systems combine machine learning models with rule-based logic to leverage both data-driven insights and domain knowledge. One such example is the Agro-Consultant framework, which integrates multiple algorithms—such as Random Forest, KNN, and Neural Networks—with expert-defined rules based on local environmental conditions. This model achieved an accuracy exceeding 91%, demonstrating the potential of combining statistical models with contextual intelligence for agricultural decision support [4].

E. Regional Relevance and Scalability

Despite promising results, many crop recommendation models are developed using datasets constrained to specific geographic regions, which limits their applicability elsewhere. As noted by Prity et al., enhancing model generalizability requires incorporating regional variables such as historical cropping patterns, soil quality indexes, and dominant crop varieties [1]. Moreover, integrating Geographic Information System (GIS) data and crop market analytics has been recommended to expand the practical scope and adaptability of these systems across diverse agro-climatic zones.

III.Existing Crop Recommendation System

Over the past decade, various crop recommendation systems have been developed, each utilizing distinct methodologies to assist farmers in making informed decisions about crop selection. Traditional rule-based systems, which operate on fixed "if-then" logic derived from expert knowledge, have been among the earliest tools in this domain. While these systems offer straightforward decision rules, they lack adaptability to dynamic environmental conditions and real-time data updates, limiting their effectiveness in practical, evolving agricultural settings [2].

Decision Support Systems (DSS) represent another early category of tools. These systems often incorporate simulations based on soil characteristics, climate data, and crop growth models to provide recommendations. However, their reliance on detailed and often hard-to-obtain input parameters, coupled with a level of complexity that may be overwhelming for smallholder farmers, has limited their widespread adoption [2].

GIS-based systems have further enhanced decision-making by enabling spatial analysis of crop suitability using geographic and environmental data layers. Though useful for location-based planning, these systems typically neglect socioeconomic variables and market dynamics, which are critical for real-world agricultural decisions [2].

In recent years, machine learning (ML)-based systems have gained prominence due to their ability to learn patterns from historical and environmental datasets. These models—such as those using Random Forests, Decision Trees, or Neural Networks—offer dynamic and data-driven crop recommendations. Solutions like the Agro-Consultant framework have demonstrated strong predictive performance; however, they often face challenges with regional scalability and may require users to possess a certain level of technical proficiency [1][4][5].

Mobile and web-based applications, such as AgriApp, have improved accessibility by delivering crop advisory services directly to farmers' smartphones. These platforms, while user-friendly, may rely on simplified algorithms and are often dependent on consistent internet access, which can be a limiting factor in remote rural areas [2]. Some of the most advanced systems integrate IoT sensors with ML algorithms to provide real-time, location-specific crop recommendations. These platforms analyze live data from soil sensors measuring moisture, nutrient content, temperature, and more to deliver hyper-personalized advice. Although highly accurate and responsive, such systems tend to be cost-intensive and require robust infrastructure, making them less accessible to resource-constrained farming communities [3].

Despite the technological progress, several common limitations remain across existing systems. These include limited scalability, user inaccessibility due to technical complexity or digital divide, and insufficient integration of real-time environmental and economic data. Addressing these challenges is crucial to developing next-generation crop recommendation systems that are not only intelligent and adaptive but also practical and inclusive for everyday farmers.

IV.Limitations of Existing Crop Recommendation Systems

Despite significant advancements in crop recommendation systems—particularly with the integration of machine learning and smart technologies—several critical challenges remain. These limitations often hinder the practical adoption and long-term effectiveness of such systems, especially in real-world agricultural settings.

A. Dependence on Outdated or Static Data

Many current models primarily rely on historical datasets to generate crop suggestions. While past data offers useful trends, it often lacks the responsiveness needed to reflect current, on-the-ground realities. Changes in soil health, rainfall patterns, or unexpected weather conditions can render these recommendations obsolete. This limitation becomes particularly problematic in regions experiencing rapid climate variability or irregular seasonal cycles.

B. Insufficient Regional Adaptability

Agricultural environments vary significantly across different geographies—even within the same country. However, many crop recommendation systems are developed using data from specific locations and often struggle to adapt to new regions with distinct soil profiles, climate conditions, or farming practices. Without local calibration, these systems risk making unsuitable recommendations that could lead to poor yields or resource mismanagement.

C. Limited User Accessibility

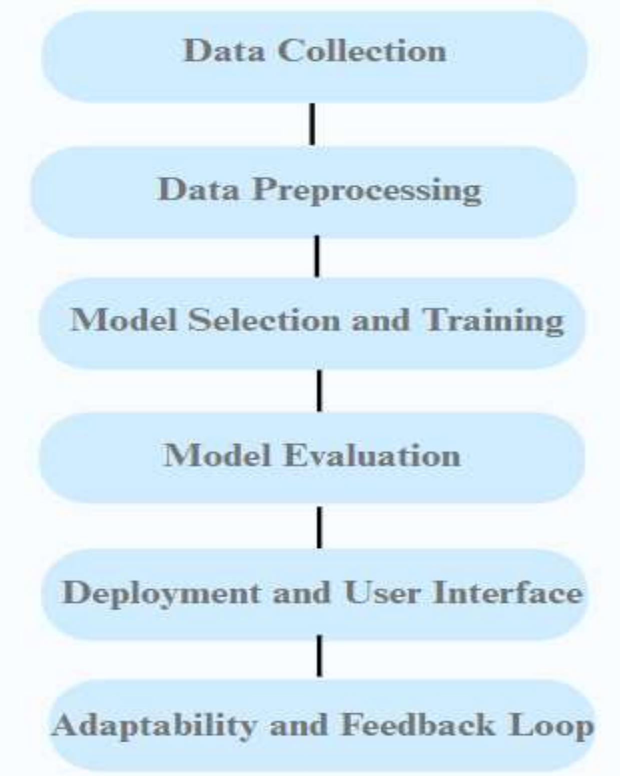
Advanced systems that incorporate complex algorithms and detailed environmental modeling are often designed for use by researchers or technically skilled professionals. This can alienate the very users these tools are meant to serve—smallholder or rural farmers—who may face barriers in terms of digital literacy, time constraints, or lack of confidence in using such interfaces. Simpler, farmer-friendly tools are still in short supply.

D. Economic Factors Often Overlooked

While many systems focus heavily on agronomic suitability, such as soil compatibility or climate conditions, they tend to overlook economic realities. Factors like market demand, expected profitability, and the cost of cultivation are rarely integrated into the recommendation logic. As a result, a farmer may be advised to grow a crop that is technically viable but unprofitable, inaccessible, or oversupplied in the local market.

E. Inadequate Real-Time Responsiveness

Only a handful of existing systems are equipped to incorporate real-time data inputs or adapt



dynamically to sudden changes, such as pest outbreaks or unexpected rainfall. Most models require manual updates or retraining to respond to new conditions. This lack of adaptability can leave farmers without timely support during critical phases of the crop cycle, potentially compromising productivity.

F. Lack of Transparency and Interpretability

Many high-performing machine learning models, such as Random Forests and Neural Networks, are often treated as "black boxes." They produce outputs—like crop recommendations—without offering clear explanations of the decision-making process. This opaqueness can make farmers hesitant to trust the system's advice, especially when the recommendations impact their livelihood and financial risk.

G. Infrastructure and Accessibility Constraints

Advanced systems that rely on IoT devices or mobile applications often assume the availability of stable internet access, electricity, and smartphones—resources that remain limited or inconsistent in many rural farming communities. Additionally, installing and maintaining sensor networks or digital infrastructure can be costly and impractical for small-scale farmers with limited budgets.

V. Methodology

The development of machine learning-based crop recommendation systems generally follows a systematic, multi-stage approach. While the choice of algorithms, tools, and data sources may vary across studies, most successful implementations follow a common framework. This begins with comprehensive data collection from sources such as soil records, weather data, and IoT sensors, followed by data preprocessing to clean and prepare the inputs for modeling.

Next, machine learning algorithms are trained to learn patterns between environmental factors and suitable crops. The model's performance is evaluated using standard metrics to ensure accuracy and reliability. Advanced systems often include user interfaces for real-time interaction and feedback loops to adapt over time based on new data. The following sections outline each of these core stages in detail, forming the foundation of an effective and scalable crop recommendation system.

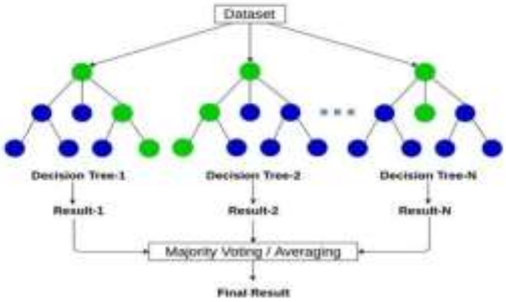


Fig 1: Methodology

A. Data Collection

The foundation of any crop recommendation system lies in gathering a rich and relevant dataset. This includes both soil characteristics—such as nitrogen (N), phosphorus (P), and potassium (K) levels, pH value, and moisture content—and environmental conditions, including temperature, humidity, and rainfall. In some cases, historical cropping patterns and previous yield data are also integrated to improve prediction accuracy. Recent advancements have further enhanced data collection through IoT-enabled sensors and publicly available government datasets, providing real-time and region-specific agricultural information [1][3].

B. Data Preprocessing

Once the data is collected, it undergoes rigorous cleaning and transformation to prepare it for model training. This step involves handling missing values, encoding categorical variables (such as crop type or soil category), and applying normalization or standardization techniques to bring all features to a comparable scale. Many studies also implement feature selection methods to isolate the most influential variables, thereby improving model efficiency and reducing the risk of overfitting [1][5]. In cases where the dataset is imbalanced—meaning some crop classes are underrepresented—techniques like SMOTE (Synthetic Minority Over-sampling Technique) are used to generate synthetic examples and balance the dataset for more reliable learning outcomes [5].

C. Model Selection and Training

At the heart of the system is the machine learning model that learns to associate environmental conditions with suitable crop choices. A variety of algorithms are employed, depending on the nature of the dataset and project goals:

- Random Forest – widely preferred due to its high accuracy and robustness against noise.
- Decision Trees – favored for their simplicity and interpretability.
- K-Nearest Neighbors (KNN) – effective for smaller datasets and low-dimensional problems.
- Support Vector Machines (SVM) – suitable for datasets with many features.
- Neural Networks – used in advanced or hybrid systems requiring deep learning capabilities.

In this study, emphasis is placed on the Random Forest algorithm, which has demonstrated superior performance in several comparative evaluations[1][2][5]. We are focusing mainly on random-forest algorithm as it gives the most accurate results compared to other algorithms.

Fig 2: Random forest algorithm[3]

D. Model Evaluation

After training, the model's performance is assessed using various evaluation metrics, which provide insight into both overall accuracy and the quality of predictions:

- Accuracy – measures the percentage of correct predictions.
- Precision and Recall – evaluate how effectively the model identifies relevant crop classes.
- F1-Score – balances precision and recall for a more comprehensive assessment.
- Confusion Matrix – visualizes the distribution of actual versus predicted labels.
- Cross-validation, particularly K-Fold, is commonly used to ensure the model generalizes well to new data and is not overfitting to the training set [1][4].

E. Deployment and User Interface

To make the system practical and accessible, some studies move beyond model development and deploy the system as a user-friendly application. These are typically web- or mobile-based platforms where farmers or extension agents can input key parameters—such as soil pH, temperature, or rainfall—and receive crop suggestions. In more advanced setups, the platform is linked to IoT sensors, enabling the model to adjust recommendations dynamically based on real-time environmental changes [3].

F. Adaptability and Continuous Learning

A few cutting-edge systems incorporate a feedback mechanism to enable continuous improvement. As new data becomes available—such as crop yield after harvest or user feedback—it is re-integrated into the dataset, allowing the model to retrain and refine its recommendations over time. This adaptive learning loop is particularly valuable in addressing the challenges of changing climate patterns, soil degradation, and evolving agricultural practices [2][5].

VI. Proposed System

The proposed system is a machine learning–based crop recommendation platform developed to support farmers, agronomists, and agricultural planners in choosing the most suitable crop for cultivation in a given geographic area. By leveraging a broad spectrum of environmental, soil, and regional factors, the system aims to provide accurate, context-aware crop suggestions that enhance agricultural productivity and promote sustainable land use.

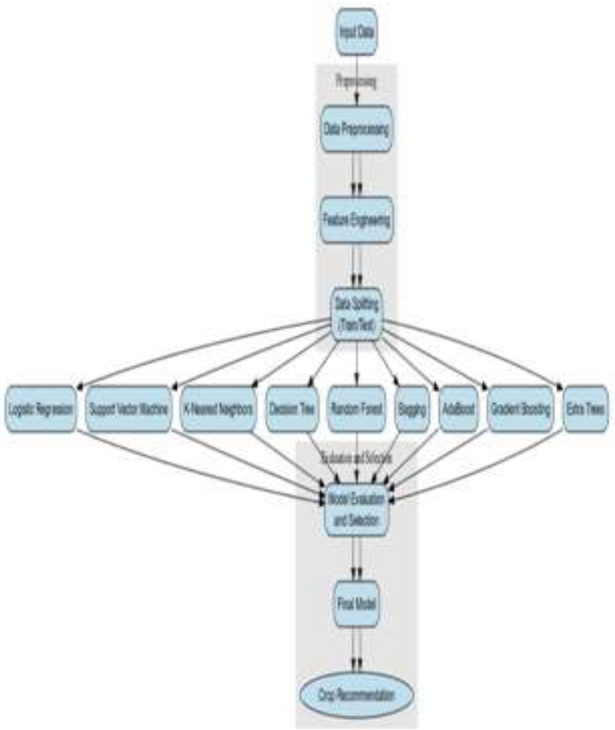


Fig 3: Proposed System Architecture

A. Data Integration

The system starts by aggregating diverse datasets that reflect both environmental and agronomic variables. These include climatic data such as rainfall, temperature, and humidity, as well as soil-related attributes like moisture content, nutrient availability (NPK), pH, salinity, alkalinity, and groundwater levels. Importantly, the model also integrates regional cropping trends, including dominant staple crops and commonly cultivated varieties, making it sensitive to local agricultural practices and needs.

B. Data Preprocessing and Feature Engineering

To ensure that the input data is clean, consistent, and usable by machine learning algorithms, a thorough preprocessing phase is carried out. This involves data cleaning to remove noise and inconsistencies, normalization or standardization to align feature scales, and handling of missing values through appropriate imputation techniques. Additionally, feature engineering is applied to extract or select the most relevant variables, thereby enhancing model efficiency and predictive power.

C. Machine Learning Model Development

At the heart of the system is a supervised machine learning model trained on historical agricultural data. Several algorithms—such as Decision Trees, Random Forests, and Support Vector Machines

(SVM)—are evaluated to determine the most effective model based on the characteristics of the dataset. These models learn patterns between environmental conditions and successful crop outcomes, enabling them to recommend optimal crops when provided with new input data.

D. Region-Specific Recommendations
A key strength of the system lies in its regional adaptability. Unlike generic models, this system factors in local dietary preferences, traditional cropping systems, and regional agricultural norms. This ensures that the recommendations are not only ecologically suitable but also culturally acceptable and economically viable, increasing the likelihood of adoption by the farming community.

E. User Interface
To make the tool accessible and user-friendly, an intuitive interface is designed for both desktop and mobile platforms. This allows users—especially farmers and agricultural extension workers—to input real-time parameters such as soil pH, temperature, or rainfall levels. The system processes this input and returns actionable crop recommendations instantly, even for users with minimal technical expertise.

F. Model Validation
To evaluate the system's accuracy and reliability, various performance metrics are applied, including accuracy, precision, recall, and F1-score. These metrics help assess how well the model performs under different scenarios, ensuring that its outputs are both consistent and trustworthy for field application.

G. Decision Support Capabilities
Ultimately, the proposed system is designed to function as a decision support tool for informed agricultural planning. By offering data-driven, region-specific crop suggestions, it reduces reliance on intuition or trial-and-error methods. This not only minimizes the risk of crop failure but also helps farmers optimize resource use, increase yields, and transition toward more sustainable agricultural practices. The system is expected to provide accurate and region-specific crop recommendations based on environmental and soil parameters. It will help farmers make informed decisions, leading to improved crop yields and efficient resource use. By tailoring suggestions to local practices and conditions, the system promotes sustainable agriculture. Overall, it aims to reduce risk and support smarter, data-driven farming.

Fig 4:Expected Outcome

VII. Future Scope and Discussion

As agriculture continues to evolve with the support of emerging technologies, crop recommendation systems are poised to become more intelligent, adaptive, and farmer-centric. While current models demonstrate impressive accuracy and technical sophistication, there remains significant scope to address real-world challenges and improve usability, relevance, and impact.

A. Real-Time Adaptability
A key area of advancement lies in enabling real-time responsiveness. Most existing systems are built on static or historical datasets, which limits their ability to respond to rapidly changing field conditions. In reality, parameters such as rainfall, temperature, soil moisture, and pest outbreaks can fluctuate significantly within short timeframes. Future systems are expected to incorporate live data streams through sources like satellite imagery, weather APIs, and IoT sensors. This would allow the recommendation engine to dynamically adjust its output, offering timely support during critical stages of farming—such as sowing, fertilization, and irrigation planning [1][3].

B. Integration of Economic Intelligence
Beyond agronomic suitability, farmers must make decisions based on economic viability. Current systems often overlook this aspect, focusing only on crop-environment compatibility. However, crop selection also depends on market demand, expected profitability, input costs, labor availability, and government incentives. Integrating real-time market prices, subsidy data, and local supply-demand trends into crop recommendation logic could help ensure that suggestions are not just environmentally feasible, but also financially beneficial for farmers [1][5].

C. Explainable and Transparent AI

Trust is a major factor in the adoption of AI-driven tools, especially in sensitive domains like agriculture. Many high-performing machine learning models—such as Random Forests or Neural Networks—are often treated as "black boxes," providing recommendations without clear justifications. The future will likely see a shift toward Explainable AI (XAI), where the system can articulate why a specific crop is being recommended. For instance, a system might state, "Maize is recommended due to low rainfall forecast, acidic soil condition, and projected high market value for the upcoming season." Such transparency enhances farmer trust, adoption, and actionability of the recommendations [5].

D. User-Centric Design and Accessibility

No matter how accurate a model is, its success depends largely on its usability. Many rural farmers operate in low-resource environments with limited digital literacy. Future systems must therefore be designed with the end-user in mind. Interfaces should be mobile-friendly, support native languages, and offer simple input methods—such as drop-down menus, icons, or even voice-based interaction. Accessibility improvements will ensure that the technology is inclusive and usable by smallholder farmers, not just researchers or tech-savvy users [2][4].

E. Modularity and Regional Scalability

Another challenge is that models trained on one region's dataset may not generalize well to other regions due to differences in soil types, climate, cropping patterns, and cultural preferences. A more sustainable approach would involve modular model architecture, where each region has a tailored version of the recommendation engine. These localized models could be fine-tuned over time using farmer feedback, post-harvest results, and on-ground corrections. This continuous learning loop would enhance system accuracy, regional relevance, and long-term effectiveness [1][3]. The system's modular design allows easy customization for different regions. This ensures scalability and accurate crop recommendations across diverse agro-climatic zones.

VIII. Conclusion

The review of existing research makes it evident that machine learning-based crop recommendation systems have significantly evolved—from static, rule-based approaches to intelligent, data-driven solutions. However, as we move toward designing and implementing our own system, it becomes equally clear that there are important limitations and lessons to draw from prior work.

Most existing systems primarily rely on core environmental and soil-related features such as nitrogen, phosphorus, potassium (NPK), pH, temperature, and rainfall. While these parameters are indeed essential, they represent only part of the picture. Our proposed system builds on this foundation by incorporating additional variables, including groundwater availability, soil salinity, alkalinity, and even cultural factors such as local food preferences and staple crop patterns. These dimensions, though often overlooked, play a critical role in making recommendations that are both agronomically viable and socially relevant.

One of the major challenges observed in the literature is the gap between lab-tested accuracy and real-world usability. Many models perform well in controlled datasets but lack the flexibility, accessibility, and regional adaptability needed for real deployment. Our system addresses these gaps by using a comprehensive and diverse dataset, emphasizing ease of use for non-technical users, and designing the architecture to be modular and scalable. This means it can be tailored to different regions with minimal adjustments, increasing its practical value and reach. Furthermore, while many high-performing models operate as black boxes, offering little insight into how decisions are made, our system integrates transparency and interpretability. By leveraging principles from Explainable AI (XAI), we aim to ensure that users not only receive a recommendation but also understand the rationale behind it. This builds trust and supports better-informed decision-making by farmers.

Another critical insight from our review is the frequent disconnect between agronomic suitability and economic feasibility. A crop may grow well in a particular region, but if it has low market demand or high input costs, it may not be a wise choice. Our system is being developed with the long-term goal of integrating economic indicators such as market prices, crop profitability, and subsidy information, making it possible to provide recommendations that are both biologically appropriate and economically sound.

In conclusion, the literature strongly supports the potential of machine learning to revolutionize agricultural decision-making. However, for these tools to be truly transformative, they must be localized, real-time responsive, user-friendly, and economically aware. Our proposed crop recommendation system is built with these priorities at its core, aiming not only to support sustainable farming but also to empower the farmers who form the backbone of global food systems.

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