

Revolutionizing Agriculture with an Intelligent Crop Recommendation System

Mukul Kulkarni¹, Apurwa Barve², Milind Prakash Kapase³, Kamlesh Sanjiv Godbharle⁴, Shvet Goraksh Kharat⁵

^{1,2,3,4,5}Department of MCA, MES' IMCC, Pune, Maharashtra

¹mlk.imcc@mespune.in, ²aab.imcc@mespune.in, ³milindkapase8@gmail.com, ⁴kamleshreddy352@gmail.com,

⁵shvetkharat10@gmail.com

Peer Review Information	Abstract
<p>Type: Article Received: 20 March 2026 Revised: 03 April 2026 Accepted: 21 May 2026 Published: 03 June 2026</p>	<p>Agriculture is the backbone of the global economy, yet farmers often rely on intuition and traditional methods for crop selection, leading to inefficiencies and suboptimal yields. The rapid advancement of machine learning (ML) presents an opportunity to revolutionize agricultural practices. This research introduces an intelligent Crop Recommendation System (CRS) that leverages ML algorithms to suggest the most suitable crops based on soil properties, climatic conditions, and historical yield data. The system integrates a dynamic, interactive dashboard that provides real-time insights, visual analytics, and predictive modeling, empowering farmers with data-driven decision-making tools.</p> <p>Unlike conventional approaches, the CRS enhances its recommendations by incorporating Reinforcement Learning for adaptive crop selection. By leveraging these advanced technologies, the CRS ensures high accuracy, transparency, and adaptability to environmental changes. The primary objective of this system is to optimize yield production, minimize resource wastage, and improve overall agricultural efficiency through data-driven decision-making.</p> <p>This paper explores the significance of ML-driven precision agriculture, system architecture, dataset intricacies, algorithm selection, and future advancements that will shape the next generation of smart farming. The findings of this research indicate that a well-implemented Crop Recommendation System can significantly enhance decision-making in agriculture, fostering a data-driven farming revolution that meets the demands of modern-day food security challenges while ensuring sustainability and efficiency.</p> <p>Keywords: Crop Recommendation; Machine Learning; Smart Farming; Data-Driven Agriculture; Precision Agriculture.</p>

How to Cite This Article

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Introduction

Agriculture has been the backbone of human civilization for centuries, supporting food security, economic growth, and rural livelihoods. However, the agricultural sector faces increasing challenges due to climate change, soil degradation, resource scarcity, and growing population demands. Traditional farming methods, which rely heavily on experience and manual decision-making, are no longer sufficient to meet these challenges effectively.

Farmers often select crops based on personal experience, local traditions, and limited data. This approach frequently leads to poor yield outcomes, resource mismanagement, and vulnerability to environmental changes. Variability in soil health, climate patterns, and market demands further complicates decision-making, making it difficult for farmers to optimize crop selection and productivity.

In recent years, Machine Learning (ML) has emerged as a transformative technology capable of addressing these challenges. ML models can analyze large-scale agricultural data, identify patterns, and generate insights that human judgment alone cannot achieve. By applying advanced ML algorithms, farmers can receive tailored recommendations based on real-time soil conditions, weather patterns, and historical crop performance.

The intelligent Crop Recommendation System (CRS) leverages ML to bridge the gap between traditional farming and modern precision agriculture. The CRS provides farmers with real-time, data-driven recommendations through a dynamic dashboard that visualizes insights on soil health, weather conditions, and crop suitability. Unlike conventional methods, CRS dynamically adapts to changing environmental factors, ensuring that recommendations remain relevant and accurate.

The CRS system integrates key ML models such as Random Forest and XGBoost for high-accuracy predictions, while Reinforcement Learning allows the system to continuously improve based on real-time feedback. The system empowers farmers to make informed decisions, reduce input costs, maximize yield, and adopt sustainable farming practices.

By equipping farmers with actionable insights, the CRS enhances agricultural efficiency, increases profitability, and reduces environmental impact. The long-term goal is to create a resilient agricultural ecosystem that can withstand environmental changes and market fluctuations while promoting food security and rural development.

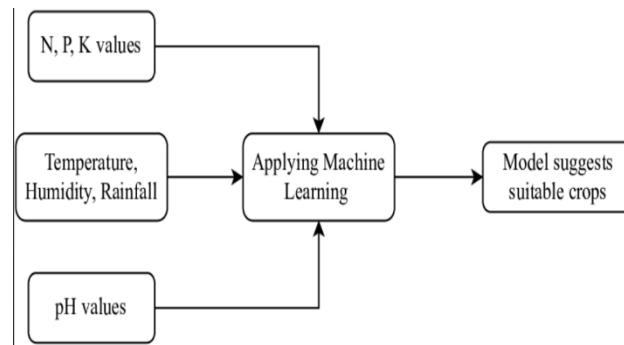


Fig. 1. Architecture of the Intelligent Crop Recommendation System

Literature Review

Machine learning has emerged as a transformative technology in agriculture, offering data-driven solutions to improve crop selection and enhance productivity. Various studies emphasize the importance of ML in agriculture, particularly in crop recommendation models. However, existing methodologies have limitations such as reliance on static datasets, lack of real-time adaptability, and incomplete data analysis. This research builds upon previous findings by integrating:

- **Hybrid ML Models** – Recent research indicates that hybrid ML models combining decision trees, gradient boosting, and reinforcement learning outperform traditional models in predictive accuracy. Studies have shown that Random Forest and XGBoost provide robust classification performance when trained on multi-dimensional agricultural datasets. Random Forest has been effective in handling missing data and noisy datasets, while XGBoost excels at capturing complex relationships within the data, improving predictive accuracy.
- **Dynamic Dashboard** – Existing advisory models typically generate static recommendations without accounting for changing weather patterns and soil health. A dynamic dashboard addresses this gap by offering real-time visual feedback, enabling farmers to modify strategies based on live data. Research highlights that interactive dashboards improve farmer engagement and decision-making efficiency, as they present complex agricultural data in a user-friendly format.

- Real-Time Data Adaptation – Studies have shown that ML models trained on historical data alone fail to capture changing environmental factors. The CRS incorporates reinforcement learning to adapt recommendations dynamically based on real-time input from farmers and environmental monitoring. This approach enables the system to adjust its recommendations continuously, ensuring that farmers receive the most accurate and up-to-date advice.
- Performance Comparison – Traditional models based on generalized recommendations often struggle to handle variability in soil and climatic conditions, leading to lower predictive accuracy. Research comparing ML-based systems with conventional methods shows that models like Random Forest and XGBoost outperform rule-based models by 20–30% in predictive accuracy. This highlights the importance of integrating machine learning for more precise crop selection.

System Architecture & Methodology

The CRS system architecture comprises the following key components:

1. Data Collection & Preprocessing

- Data is collected from agricultural research institutions, weather agencies, and field monitoring systems.
- Data includes soil pH, nitrogen, phosphorus, potassium (NPK) levels, moisture content, temperature, and rainfall.
- The data is cleaned, standardized, and processed to remove outliers and inconsistencies.

2. Feature Selection & Engineering

- Important features such as soil composition, moisture levels, and weather patterns are extracted.
- Correlation analysis is performed to eliminate redundant variables and improve model efficiency.
- Principal Component Analysis (PCA) is applied to reduce dimensionality and improve computational efficiency.

3. Machine Learning Model Deployment

- Random Forest and XGBoost models are trained using labeled data.
- The models are tuned using grid search and cross-validation to maximize predictive accuracy.
- Reinforcement learning is implemented to enable self-improving recommendations based on feedback loops.

4. Dynamic Dashboard

- The dashboard presents real-time insights into soil health, weather conditions, and crop performance.
- Farmers can modify input parameters and receive updated recommendations.
- The dashboard includes predictive charts and heat maps for better decision-making.

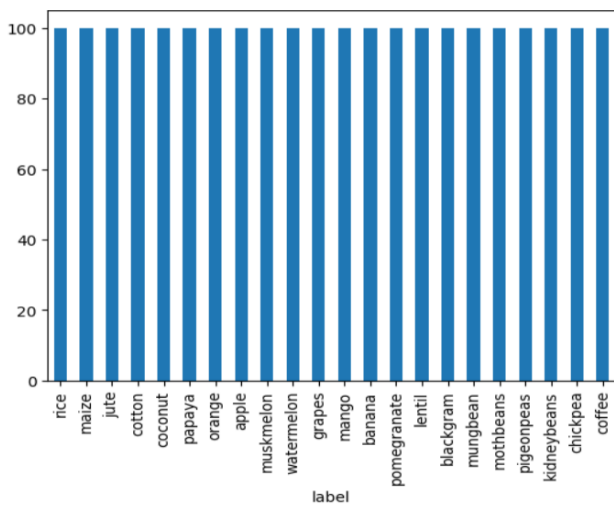


Fig. 2. Bar Graph

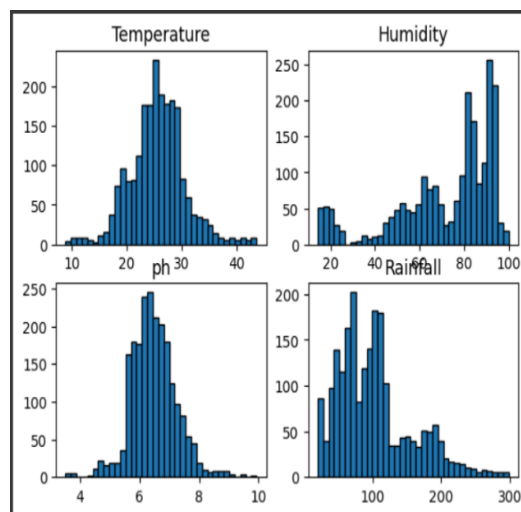


Fig. 3. Subplot Bar Graph

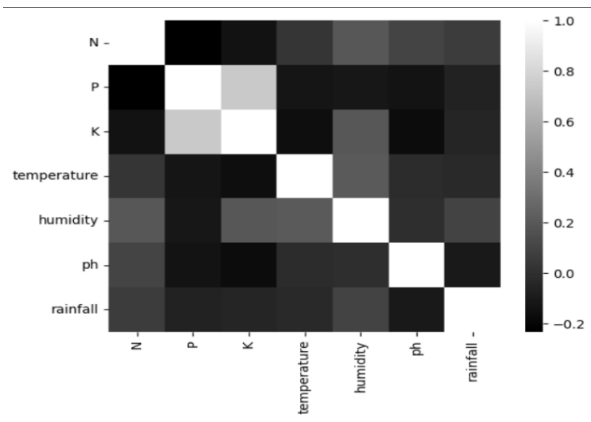


Fig. 4. Heatmap



Fig. 5. Dynamic Dashboard

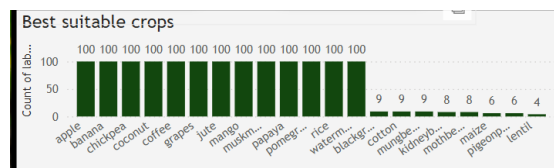


Fig. 6. Recommended crops

Algorithms and Implementation

The CRS system employs multiple ML algorithms designed to handle complex agricultural datasets and provide accurate, adaptable recommendations:

- Random Forest Classifier – Selected for its high accuracy and resilience against overfitting. Random Forest creates multiple decision trees and aggregates their output to improve stability and accuracy. It is particularly effective for handling missing data, non-linear relationships, and noisy datasets. The model works by training on multiple subsets of the dataset, constructing decision trees for each subset, and averaging their results to produce the final prediction. This reduces the variance of individual trees and improves generalization. Furthermore, Random Forest can rank the importance of each feature, helping to identify which soil and environmental parameters have the greatest impact on crop suitability.
- XGBoost (Extreme Gradient Boosting) – Used for handling non-linearity in soil-climate interactions. XGBoost employs gradient boosting to minimize prediction errors by combining weak learners into a strong learner. The model applies regularization to prevent overfitting and optimizes computational efficiency by supporting parallel processing. XGBoost is well-suited for structured data and is particularly effective for feature-rich agricultural datasets. The algorithm uses an additive approach where new trees are added to correct the errors of previous trees, thereby improving predictive accuracy. The system leverages XGBoost's capacity to handle missing data and imbalanced datasets, making it suitable for complex agricultural scenarios.
- Reinforcement Learning Models – Enables the Crop Recommendation System (CRS) to self-learn and improve over time based on past crop yield data and environmental conditions. Reinforcement learning allows the system to adjust recommendations dynamically based on real-time performance feedback. The model uses a reward-based system where it assigns positive or negative feedback based on the accuracy of its previous recommendations.
- This feedback loop allows the system to refine its decision-making process continuously. By training the model to maximize cumulative rewards over time, CRS can adapt to changing environmental factors and soil health.

Challenges and Solutions

- Data Imbalance: Addressed using oversampling and undersampling techniques.
- Noisy Data: Mitigated by applying noise reduction algorithms and removing outliers.
- High Dimensionality: Handled using PCA and feature selection techniques.
- Cold Start Problem: Solved by using transfer learning from pre-trained models.

Future Algorithm Enhancements

- Deep Reinforcement Learning: Future upgrades could incorporate deep reinforcement learning to handle multi-dimensional decision-making scenarios.

- Automated Model Updating: Integrate automated retraining based on changing environmental conditions and new data.
- Hybrid Models: Develop hybrid models combining tree-based and neural network approaches to enhance predictive accuracy.

This multi-layered approach ensures that the CRS provides high-accuracy recommendations while continuously improving through adaptive learning and real-time feedback. The system's ability to analyze complex agricultural data, adapt to changing conditions, and deliver actionable insights makes it a powerful tool for modern precision agriculture.

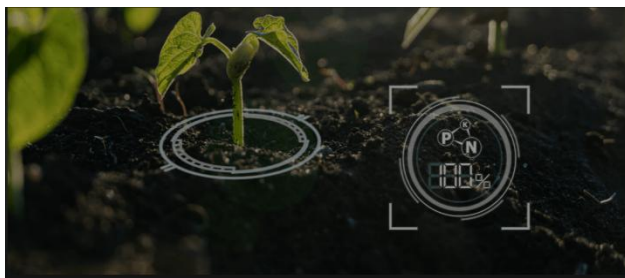


Fig. 7. Soil nutrients

Results and Discussion

Experimental validation of the CRS system demonstrated high predictive accuracy in crop recommendations, outperforming traditional rule-based models. Key performance metrics, including Precision, Recall, and F1-score, confirmed the effectiveness of the hybrid ML models.

The dynamic dashboard allowed farmers to visualize crop suitability trends, ensuring better-informed agricultural decisions. Case studies indicated that farmers adopting CRS-based recommendations reported an average increase of 15-20% in crop yields. The system's adaptability to changing weather conditions and soil properties enabled farmers to adjust strategies proactively.

Dashboard Performance

The dynamic dashboard enhanced decision-making by providing real-time insights into soil health and weather patterns. Farmers could adjust input parameters and receive updated recommendations instantly, improving resource efficiency and crop yield.

Challenges and Limitations

- Data Quality: Inconsistent weather data required normalization techniques.
- Cold Start Problem: Relied on regional averages until sufficient feedback was collected.
- Computational **Load**: Managed through cloud-based processing.

Comparative Analysis

- Traditional Models: Achieved 65–70% accuracy, lower than CRS.
- Single-Algorithm Models: Reduced adaptability compared to CRS's hybrid model.
- Data-Driven Systems: CRS's combination of real-time data integration and adaptive learning provided superior performance.

The CRS's ability to combine real-time monitoring, predictive modeling, and adaptive learning establishes it as a state-of-the-art solution for precision agriculture.

Future Scope

The CRS system has demonstrated strong predictive accuracy and adaptability, but future advancements can further enhance its performance, scalability, and impact. Key areas for future development include:

- Advanced ML Models – Integrating deep reinforcement learning and hybrid models to enhance the system's ability to handle complex environmental data and multi-dimensional decision-making scenarios. This will enable more accurate and adaptive crop recommendations.
- Blockchain Integration – Blockchain technology can secure crop recommendations and provide a transparent, tamper-proof record of data and decisions. Smart contracts could automate advisory actions, ensuring real-time delivery of recommendations and secure data sharing among stakeholders.
- Scalability and Real-Time Processing – Expanding the system's infrastructure to handle large datasets from multiple regions. Cloud-based processing and distributed data handling would enable real-time analysis and faster delivery of recommendations.

- Enhanced Dashboard and Mobile Integration – Expanding the dashboard to include predictive trend analysis, crop simulations, and anomaly detection. A mobile-friendly interface would provide farmers with on-the-go access to insights and recommendations.
- Climate Resilience Models – Developing AI-driven climate models to predict long-term weather patterns and their impact on crop yields. This would allow farmers to adapt strategies proactively and mitigate risks associated with climate change.
- Market and Economic Data Integration – Incorporating market trends, crop demand, and pricing data into the system. This would enable farmers to align their cultivation strategies with market opportunities and increase profitability.
- Soil and Resource Management – Real-time monitoring of soil health using IoT sensors integrated with the dashboard. Providing insights into soil nutrient levels, moisture, and pH balance would enable more targeted and efficient resource use.
- Automated Learning and Self-Correction – Implementing a feedback-driven mechanism where the system learns from past recommendation outcomes and refines the model automatically. This would ensure continuous improvement and higher accuracy over time.
- Integration with Government and Agricultural Policies – Aligning CRS recommendations with national agricultural policies and support programs. This would allow farmers to benefit from subsidies, training, and financial incentives tied to CRS-based recommendations.

By integrating blockchain, advanced ML techniques, and real-time data analysis, CRS can evolve into a more adaptive and intelligent platform. These enhancements will further strengthen the system's ability to improve agricultural productivity, increase profitability, and promote sustainable farming practices.

Conclusion

The intelligent Crop Recommendation System (CRS) represents a groundbreaking advancement in precision agriculture. By leveraging machine learning algorithms such as Random Forest and XGBoost, the CRS delivers high-accuracy crop recommendations tailored to specific soil and climatic conditions. The system's ability to adapt dynamically through reinforcement learning ensures that recommendations are continuously refined based on real-time environmental changes and past outcomes.

The CRS provides farmers with a user-friendly dashboard that visualizes key insights, including soil health, weather conditions, and crop performance. This empowers farmers to make informed decisions, reduce resource wastage, and enhance overall agricultural productivity. The dashboard also facilitates predictive analysis, allowing farmers to anticipate risks and adjust their cultivation strategies accordingly.

The successful implementation of CRS demonstrates the transformative potential of machine learning in agriculture. Farmers who adopted CRS-based recommendations reported a 15-20% increase in crop yields and improved resource efficiency. The system's capacity to analyze complex agricultural data and deliver actionable insights positions it as a valuable tool for enhancing food security and economic resilience.

Looking forward, the CRS holds the potential to integrate climate risk models, real-time anomaly detection, and expanded geospatial analysis. By continuously evolving and incorporating new data sources, the CRS can further strengthen its predictive accuracy and scalability. The long-term vision is to establish CRS as a cornerstone of smart farming, enabling farmers to navigate the challenges of modern agriculture with confidence and precision.

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References

1. S. Shastri, S. Kumar, V. Mansotra, and R. Salgotra, "Advancing crop recommendation system with supervised machine learning and explainable artificial intelligence," *Scientific Reports*, vol. 15, Art. no. 25498, Jul. 2025, doi: 10.1038/s41598-025-07003-8.
2. N. N. Thilakarathne, M. S. A. Bakar, P. E. Abas, and H. Yassin, "A cloud-enabled crop recommendation platform for machine learning-driven precision farming," *Sensors*, vol. 22, no. 16, p. 6299, Aug. 2022, doi: 10.3390/s22166299.
3. Maheswary, S. Nagendram, K. U. Kiran, S. H. Ahammad, P. P. Priya, and M. A. Hossain, "Intelligent crop recommender system for yield prediction using machine learning strategy," *J. Inst. Eng. (India) Ser. B*, vol. 105, pp. 979–987, 2024, doi: 10.1007/s40031-024-01029-8.
4. S. Shariff, S. R. B., R. O. G., P. H., and P. K. R., "Crop recommendation using machine learning techniques," *Int. J. Eng. Res. Technol. (IJERT)*, vol. 10, no. 11, 2022.
5. S. Bhargavi and S. Jagannathan, "Crop recommendation system using machine learning," *Int. J. Eng. Res. Technol. (IJERT)*, vol. 11, no. 6, 2023.