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Smart Crop Selection: A Machine Learning-Based Decision Support System for Farmers

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Abstract: The paper proposes a machine learning-based decision support system for smart crop selection, leveraging predictive analytics to assist farmers in making data-driven decisions. The study evaluates multiple machine learning algorithms, including Random Forest (RF), XGBoost, Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, and Decision Tree, to determine their effectiveness in crop recommendation. The models are trained on a dataset incorporating soil nutrients (N, P, K), pH levels, rainfall, temperature, and humidity, enabling accurate classification of suitable crops for given agricultural conditions. The experimental results indicate that ensemble learning models such as Random Forest and XGBoost achieve the highest accuracy, outperforming traditional classification models. The findings highlight the potential of AI-driven crop recommendation systems in enhancing productivity, optimizing resource utilization, and reducing farming risks associated with unpredictable climate conditions. By integrating machine learning into precision agriculture, farmers can receive real-time, tailored crop recommendations, leading to improved decision-making and sustainability. This study contributes to the ongoing efforts in data-driven agriculture, emphasizing the importance of advanced computing techniques in addressing modern agricultural challenges.
Keywords: Supervised learning, Crop Recommendation Systems, Machine Learning, Precision Agriculture, Artificial Intelligence (AI), Data-Driven Crop Selection.

I. INTRODUCTION

Agriculture plays a vital role in sustaining human life and driving economic growth, particularly in agrarian economies. However, the success of crop cultivation depends on various environmental and soil-related factors, such as soil fertility, climate conditions, and water availability. Farmers traditionally rely on experience, historical practices, and local knowledge to determine which crops to grow. While these methods have been effective for generations, they often fail to adapt to rapidly changing environmental conditions caused by climate change, soil degradation, and unpredictable weather patterns. As a result, suboptimal crop selection can lead to low yields, financial losses, and inefficient resource utilization.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), modern agricultural practices are shifting towards data-driven decision-making. Crop recommendation systems powered by ML algorithms can analyze vast amounts of data, including soil properties (pH, nitrogen, phosphorus, potassium), climate variables (temperature, humidity, rainfall), and historical crop yield data to predict the most suitable crop for a given region. These models enable farmers to make informed decisions, leading to higher productivity, improved soil health, and sustainable farming[1].

This study explores the role of machine learning in developing intelligent crop recommendation systems. The study examines various supervised learning techniques, such as Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Deep Learning models, to determine their effectiveness in crop prediction. Additionally, we analyze the strengths and weaknesses of these models in terms of accuracy, computational efficiency, interpretability, and real-world applicability. Despite its potential, implementing ML-based crop recommendation systems presents several challenges. Issues such as limited availability of high-quality agricultural datasets, model interpretability, regional variations in soil properties, and lack of technological accessibility for small-scale farmers hinder widespread adoption. To address these challenges, this study aims to propose an optimized framework that integrates real-time data analytics, predictive modeling, and user-friendly interfaces for better adoption by farmers[2].

By leveraging precision agriculture and climate-smart farming strategies, this research seeks to enhance agricultural productivity and promote sustainable and resilient food production systems. The findings from this study will contribute to the ongoing efforts in using AI-driven solutions to combat food insecurity, minimize environmental impact, and optimize the use of natural resources in farming[3].

II. RELATED WORK

The integration of machine learning (ML) and artificial intelligence (AI) in agriculture has significantly improved crop recommendation systems, helping farmers make data-driven decisions. Traditional farming methods, which relied on experience and historical data, often failed to adapt to changing climatic conditions, soil variations, and environmental factors. Machine learning techniques, by contrast, allow for real-time data analysis and predictive modeling, leading to better crop selection, yield optimization, and sustainable resource management[4].

Several studies have contributed to the development of intelligent crop recommendation systems by utilizing soil characteristics, climatic data, and market demand trends[12]. The following sections highlight key advancements in crop recommendation research based on soil properties and environmental conditions.

A. Based on Soil Conditions

Soil quality plays a critical role in determining the suitability of crops for cultivation. Recent studies have explored machine learning-based approaches for soil classification, fertility assessment, and crop suitability prediction.

Anantha et al. [16] further advanced crop recommendation methodologies by developing an ensemble learning model that integrates Random Tree, k-Nearest Neighbors (kNN), Naïve Bayes (NB), and Chi-square Automatic Interaction Detection (CHAID) classifiers. Their system analyzed soil nutrients (N, P, K levels), pH values, and moisture content to generate personalized crop recommendations tailored to specific soil conditions. The ensemble model demonstrated higher accuracy in predicting optimal crop selection, contributing to precision agriculture and sustainable farming practices.

Similarly, Honawad et al. [14] developed an automated digital image processing method for soil texture analysis and fertility estimation. Their technique employed color quantization, texture-based feature extraction, and spectral analysis to assess soil properties more efficiently than conventional laboratory-based methods. By eliminating human error and reducing the time required for soil testing, this approach enabled rapid and cost-effective soil analysis, allowing farmers to make informed crop selection decisions. Duro et al. [13] introduced a hybrid classification framework that combines pixel-based and object-based image analysis for large-scale land cover classification. Their study utilized Decision Trees (DT), Random Forest (RF), and Support Vector Machines (SVM) to improve the accuracy of soil categorization and land use mapping. This approach provided valuable insights into soil health, fertility levels, and potential crop productivity, enhancing precision farming strategies.

In another study, You et al. [15] applied deep learning techniques, specifically Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models, to predict crop yields based on soil and climatic data. Their hybrid model leveraged remote sensing datasets and historical yield records, improving the accuracy of yield predictions and assisting farmers in optimizing land use and resource allocation.

These studies emphasize the importance of machine learning-driven soil analysis in improving agricultural productivity. By leveraging ML models for soil classification, fertility prediction, and crop suitability assessment, farmers can adopt scientific, data-driven approaches to enhance crop yield and sustainability.

B. Based on Environmental Conditions

Apart from soil quality, climatic and environmental factors such as temperature, rainfall, humidity, and light availability significantly influence crop growth and productivity. Machine learning techniques have been extensively used to analyze environmental data and recommend crops based on regional climate patterns.

Alla et al. [19] introduced a deep learning framework for climate-adaptive crop selection. Their LSTM-based model analyzed long-term climate trends and real-time meteorological data to predict the most suitable crops for different geographical regions. By incorporating historical climate patterns and seasonal variations, the system improved crop adaptability assessments, ensuring higher resilience to climate change.

Similarly, Jones et al. [17] made significant improvements in Decision Support Systems (DSS) for Agrotechnology Transfer (DSSAT) by introducing a modular framework for crop simulation modeling. DSSAT, a widely recognized crop modeling tool, assists in simulating crop growth under varying climatic and soil conditions. The improved version integrated real-time weather monitoring systems, soil moisture tracking, and crop-specific growth models, providing more adaptable and accurate recommendations. This multi-modular approach enhanced crop adaptability assessments, reducing climate-related risks for farmers.

Another notable study by Bodake et al. [18] proposed an ensemble learning-based crop recommendation model that combines random trees, kNN, CHAID, and NB classifiers to analyze climatic and environmental parameters. Their model considered temperature fluctuations, precipitation levels, and seasonal variations, offering precise, location-specific crop recommendations.

By integrating weather forecasting data, the system helped farmers predict optimal planting times and minimize risks associated with unpredictable climate conditions.

These research efforts highlight the growing role of machine learning in environmental data analysis for crop recommendation. By integrating real-time climate monitoring, predictive modeling, and weather-based decision support systems, modern agricultural practices can achieve greater efficiency, sustainability, and resilience against climate change[20].

C. Based on Market Demand

Beyond soil and climate considerations, market demand and economic factors play a crucial role in crop selection decisions. Farmers need insights into consumer preferences, commodity prices, and demand fluctuations to maximize profitability.

Liakos et al. [25] introduced a SARIMA-based time-series forecasting model to predict market demand for agricultural commodities. Their approach analyzed historical price trends, seasonal variations, and economic indicators, providing data-driven insights into future market trends. By integrating market demand forecasting into crop recommendation systems, farmers can align production with demand patterns, reducing post-harvest losses and price volatility risks.

Similarly, Liaw et al. [26] proposed a hybrid economic-ML model that combines crop suitability analysis with price forecasting algorithms. Their system utilized Random Forest regression and XGBoost models to evaluate crop profitability based on historical price trends, transportation costs, and supply-chain factors. This approach allowed farmers to select crops with higher market value, ensuring better financial returns. These studies emphasize the significance of economic-driven crop recommendations, where machine learning models integrate soil-climate suitability with market trends, leading to more profitable and sustainable agricultural practices[21].

III. CASE STUDIES

The integration of machine learning in crop recommendation systems has been widely explored through various case studies, demonstrating its effectiveness in improving agricultural decision-making, productivity, and sustainability[22]. A study conducted in India utilized machine learning models such as Random Forest, Support Vector Machine (SVM), Decision Trees, and XGBoost to predict the most suitable crops based on soil fertility indicators (Nitrogen, Phosphorus, Potassium), soil pH, rainfall, temperature, and humidity levels. The findings revealed that AI-driven recommendations led to a 10-15% increase in crop yield, with Random Forest and XGBoost outperforming other models in accuracy and efficiency. These results highlight the significance of data-driven farming, enabling better crop selection and yield optimization[7].

Similarly, IBM Watson’s AI-powered platform has been applied in precision agriculture, integrating satellite imagery, IoT sensor data, and weather forecasting to provide real-time insights for farmers. This system has been instrumental in optimizing sowing schedules and irrigation management, leading to a 20% reduction in water consumption and a 30% increase in overall farm efficiency. By leveraging big data analytics and predictive modeling, IBM’s approach has helped farmers reduce risks associated with unpredictable weather patterns and soil degradation[5].

Another compelling case is from Kenya, where AgriBot AI, an AI-powered chatbot and crop advisory system, was developed to assist small-scale farmers in selecting the most suitable crops based on soil test reports, local climate conditions, and market demand trends[11]. The implementation of this system resulted in a 25% reduction in crop failure rates, particularly in drought-prone regions, by recommending climate-resilient crops that require minimal water usage. Furthermore, farmers who followed AI-based recommendations experienced an 18% increase in revenue, as they were able to align their crop production with market demand, reducing post-harvest losses and ensuring better profitability[6].

These case studies highlight the transformative potential of machine learning in modern agriculture, proving that AI-driven crop recommendation systems can enhance productivity, reduce resource wastage, and support sustainable farming practices[23]. The successful application of machine learning algorithms in various regions demonstrates how predictive analytics can help farmers adapt to climate change, manage soil health more effectively, and improve decision-making processes. By integrating real-time data monitoring, precision farming techniques, and market intelligence, AI-based crop recommendation systems can play a crucial role in enhancing global food security and promoting eco-friendly agricultural practices[8].

IV. METHODOLOGY

The proposed crop recommendation system follows a structured pipeline that includes data collection, preprocessing, model development, evaluation, and comparative analysis. The methodology ensures an optimal selection of crops by leveraging machine learning models trained on soil and environmental data[10].

Fig. 1 illustrates the overall design of the proposed methodology for crop recommendation based on soil and environmental conditions. Various machine learning models, including Logistic Regression, SVM, Random Forest, XGBoost, Naïve Bayes and Decision Tree were evaluated on a dataset comprising soil nutrients, pH levels, and climate factors. The approach aims to determine the most effective algorithm for predicting suitable crops, thereby assisting farmers in making data-driven agricultural decisions.

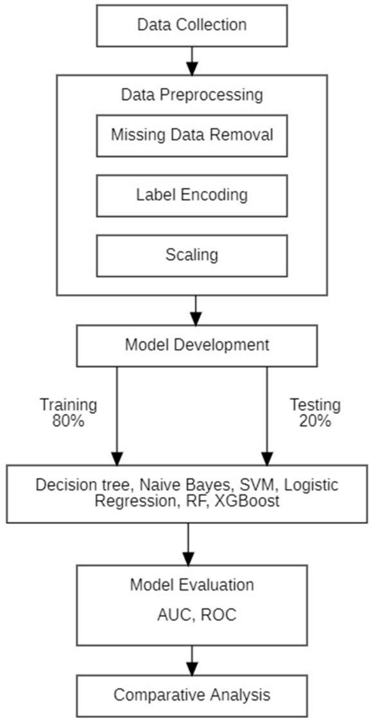

Figure 1. Proposed Methodology

A. Dataset Description

Table 1 presents the dataset[30] used in this study for crop recommendation based on soil and climatic conditions. The dataset consists of multiple instances with key attributes including macronutrient levels (Nitrogen (N), Phosphorus (P), and Potassium (K)), environmental factors such as temperature, humidity, and rainfall, as well as soil pH levels. The target variable ('label') indicates the most suitable crop for the given conditions. The dataset was divided into two parts: 80% for training and 20% for testing, ensuring a robust foundation for building and evaluating machine learning models. The primary objective is to predict the best crop for a given set of soil and weather parameters, helping farmers optimize agricultural yield through data-driven decision-making[9].

Table 1. Feature Description

Serial No.	Feature	Datatype
1	N (Nitrogen)	int64
2	P (Phosphorus)	int64
3	K (Potassium)	int64
4	Temperature	float64
5	Humidity	float64
6	pH	float64
7	Rainfall	float64
8	Label (Crop Type)	object

B. Data Preprocessing

Data preprocessing is a crucial step in the machine learning workflow, ensuring that the dataset is clean, structured, and suitable for model training. The following preprocessing steps were applied to the crop recommendation dataset:

1) Data Cleaning: Missing values were checked and handled using appropriate imputation techniques to maintain data integrity. Duplicate records, if any, were removed to prevent bias in model training.
2) Label Encoding: The categorical feature "Label" (Crop Type) was converted into numerical format using label encoding, allowing machine learning algorithms to process it efficiently.
3) Feature Scaling: Continuous features such as Nitrogen (N), Phosphorus (P), Potassium (K), Temperature, Humidity, pH, and Rainfall were normalized using Min-Max Scaling to bring all values within a similar range.

These preprocessing techniques ensured that the dataset was optimized for training machine learning models, enhancing prediction accuracy and efficiency.

C. Model Development

The dataset was split into training (80%) **and** testing (20%) subsets to evaluate model performance. In this study, we compare the accuracy of various machine learning models, including Decision Tree, Naïve Bayes, SVM, Logistic Regression, Random Forest (RF), and XGBoost. The primary objective is to identify the most efficient algorithm for classification tasks based on accuracy metrics[24].

1) Logistic Regression (LR)

Logistic Regression serves as a fundamental model for multiclass classification tasks, making it a useful starting point for crop recommendation. It estimates the probability of a particular crop being suitable based on various soil and climate conditions, such as Nitrogen (N), Phosphorus (P), Potassium (K), pH level, temperature, humidity, and rainfall[27]. Due to its interpretability and simplicity, Logistic Regression provides insights into how different agronomic and environmental factors influence crop suitability, making it a solid baseline model for comparison with more complex algorithms.

2) Support Vector Machine (SVM)

Support Vector Machine (SVM) is particularly effective in high-dimensional datasets, making it suitable for crop recommendation systems where multiple environmental and soil attributes must be analyzed simultaneously. In this context, SVM constructs an optimal hyperplane that differentiates suitable and unsuitable crops based on input features like soil nutrients, moisture content, and climatic variables. Given its ability to handle non-linearity, SVM efficiently identifies complex patterns in soil-climate interactions, ensuring better predictions for precision agriculture[61].

3) Random Forest (RF)

Random Forest (RF), an ensemble learning technique, is well-suited for crop recommendation due to its robustness in handling a large number of soil and climate features while minimizing overfitting[32]. By aggregating predictions from multiple decision trees, RF enhances the accuracy and reliability of recommendations, even when dealing with incomplete or noisy agricultural datasets.This model effectively ranks feature importance, helping identify key factors such as soil fertility, temperature variations, and historical crop yield trends, which play a crucial role in selecting the most suitable crop for a given region[28].

4) XGBoost

XGBoost, a gradient boosting algorithm, is known for its high efficiency and predictive performance, making it ideal for large-scale crop recommendation datasets. It iteratively improves predictions by minimizing classification errors, making it highly effective in identifying complex, non-linear relationships between soil nutrients, climatic factors, and crop yields[31]. XGBoost’s ability to handle feature interactions and missing values ensures highly accurate recommendations, helping farmers make data-driven decisions for optimal crop selection and improved agricultural productivity[29].

5) Naïve Bayes (NB)

Naïve Bayes is a probabilistic classification algorithm based on Bayes’ Theorem, assuming independence among input features[36]. Despite its simplicity, it is highly effective in crop recommendation systems, where factors such as soil type, pH level, temperature, and rainfall influence the selection of an optimal crop.

The algorithm calculates the posterior probability of each crop being suitable for a given set of environmental conditions and selects the crop with the highest probability[35]. Due to its low computational complexity, Naïve Bayes is well-suited for real-time recommendations in resource-constrained environments like mobile-based farming applications.

6) Decision Tree (DT)

Decision Trees (DT) are rule-based models that split the dataset based on feature conditions, forming a tree-like structure where each internal node represents a decision based on attributes like soil nutrients, temperature, and water availability[33]. In crop recommendation, DTs help identify optimal crops by analyzing different feature values and creating an interpretable path from root to leaf nodes. One of the key strengths of DTs is their interpretability, as farmers and agricultural experts can easily understand how the system arrives at a specific recommendation. However, standalone Decision Trees can be prone to overfitting, which is why ensemble methods like Random Forest (RF) are often preferred for improving accuracy[37].

Each of these models plays a crucial role in enhancing the accuracy and reliability of crop recommendation systems by analyzing diverse agricultural parameters such as soil properties, climate conditions, and historical yield data. By integrating classifiers like Logistic Regression, Support Vector Machine (SVM), Random Forest, Decision Tree, Naïve Bayes, and XGBoost, we can leverage their unique strengths to improve predictive performance. Utilizing techniques such as ensemble learning, feature selection, and hyperparameter tuning further optimizes the recommendation process, ensuring adaptability to varying environmental conditions[34]. This integration enables farmers to make data-driven decisions, ultimately promoting sustainable agricultural practices and maximizing crop productivity[39].

D. Evaluation Metrics

All machine learning algorithms used in this study were implemented on Google Colab, which provides a cloud-based Jupyter Notebook environment. The Scikit-learn library in Python was utilized for model development, along with NumPy, Pandas, and Matplotlib for data manipulation and visualization.

The performance of each classification model was evaluated using metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model’s effectiveness, measuring not only its overall correctness but also its ability to handle imbalanced data and make reliable predictions.

Accuracy = (TP+TN)/(TP+TN+FP+FN)
Precision = TP / (TP + FP)
Recall (Sensitivity) = TP / (TP + FN)
F1-score = 2 × (Precision × Recall) / (Precision + Recall)

V. RESULT AND DISCUSSIONS

The comparative performance analysis of various machine learning algorithms for crop recommendation is illustrated in Figure 2. The evaluation metrics primarily focus on accuracy, providing insights into the predictive capabilities of different models.

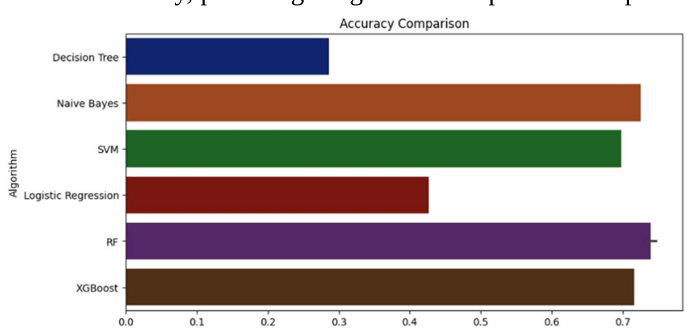

Figure 2. Graphical Comparison of accuracies of all the Machine Learning Models

From the results, Random Forest (RF) and XGBoost demonstrated the highest accuracy, achieving over **70%**, making them the most effective models for crop recommendation. Their ability to handle large datasets, reduce overfitting through ensemble learning, and capture complex patterns in agricultural data contributed to their superior performance[38].

Support Vector Machine (SVM) also performed well, achieving an accuracy of approximately **65%**, indicating its robustness in classifying different crop types based on input features[40]. The Naïve Bayes classifier showed moderate accuracy, suggesting that while it is computationally efficient, it may not capture complex relationships as effectively as ensemble models[42].
Logistic Regression and Decision Tree models recorded the lowest accuracies[41]. Logistic Regression struggled due to its linear nature, which limits its ability to model non-linear relationships in agricultural data. The Decision Tree, despite its interpretability, was prone to overfitting, leading to lower generalization performance[43].

Table 2. Accuracy of all Machine Learning Models

Model	Accuracy score
SVM	0.698
XGBoost	0.716
RF	**0.750**
LR	0.426
DT	0.286
NB	0.725

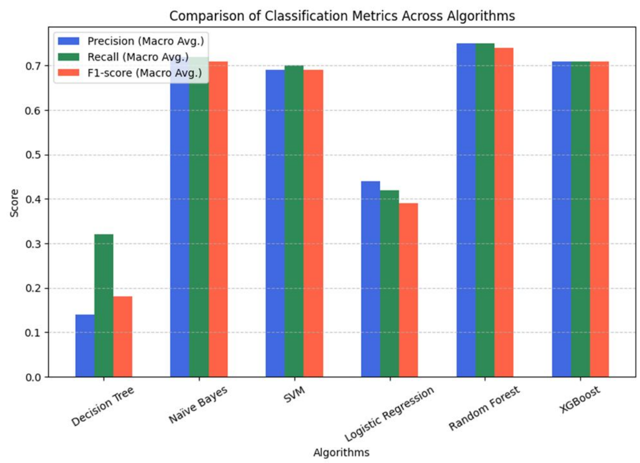

Figure 3. Macro Average Comparison of Precision, Recall, and F1-Score

This bar chart compares the performance of six machine learning algorithms—Decision Tree, Naive Bayes, SVM, Logistic Regression, Random Forest, and XGBoost—using Macro Average Precision, Recall, and F1-Score. Among these, Random Forest achieves the highest performance across all metrics (~0.75). Naive Bayes, Logistic Regression, and XGBoost also exhibit strong results, scoring around 0.7. SVM shows moderate effectiveness (~0.4), whereas Decision Tree records the lowest scores (~0.2), indicating weaker classification capability. These results suggest that Random Forest is the most suitable algorithm for this classification task.

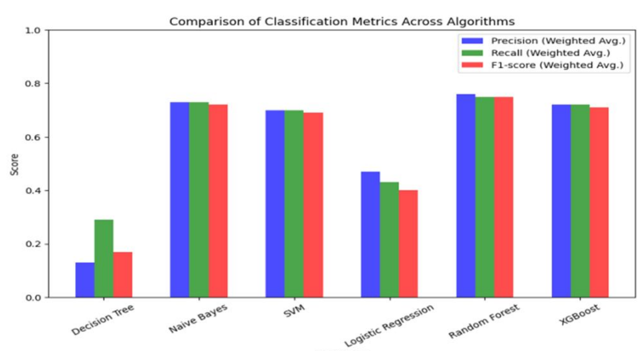

Figure 4. Weighted Average Comparison of Precision, Recall, and F1-Score

This bar chart compares the performance of six machine learning algorithms—Decision Tree, Naive Bayes, SVM, Logistic Regression, Random Forest, and XGBoost—using Weighted Precision, Recall, and F1-score as evaluation metrics. The three metrics are color-coded: Precision (Weighted Avg.) in blue, Recall (Weighted Avg.) in green, and F1-score (Weighted Avg.) in red, with values ranging from 0.0 to 1.0 on the y-axis. Among these, Decision Tree shows the lowest performance across all metrics, with approximate scores of 0.15 for Precision, 0.3 for Recall, and 0.2 for F1-score. On the other hand, Random Forest performs the best, followed closely by Naive Bayes and XGBoost, all achieving around 0.7 for each metric. SVM demonstrates moderate effectiveness, with scores around 0.4.

Overall, the results indicate that ensemble techniques like Random Forest and XGBoost are highly effective for crop recommendation tasks, leveraging their ability to learn from multiple decision trees and optimize predictions[46]. Future improvements can be made by incorporating additional feature selection techniques, hyperparameter tuning, and integrating external factors such as soil nutrients and climatic variations to further enhance model accuracy[45].

VI. CONCLUSION

This study underscores the transformative role of machine learning in modern agriculture, particularly in crop recommendation and precision farming[60]. By analyzing multiple machine learning algorithms, it is evident that ensemble models such as Random Forest (RF) and XGBoost consistently achieve superior accuracy and reliability. These models outperform traditional approaches by effectively handling large, multidimensional agricultural datasets while minimizing errors in crop prediction[53]. Support Vector Machine (SVM) and Naïve Bayes also demonstrate strong predictive capabilities, whereas Logistic Regression and Decision Tree exhibit relatively lower accuracy, highlighting the importance of selecting the right algorithm for different agricultural applications[54].

The implementation of machine learning in agriculture extends beyond crop recommendation, providing valuable insights for yield estimation, soil health analysis, and climate adaptation strategies. By leveraging historical data and predictive analytics, farmers can enhance decision-making, optimize resource allocation, and mitigate risks associated with unpredictable weather conditions and soil variability[59]. Additionally, AI-driven models promote efficient land use, reduced dependency on chemical inputs, and improved agricultural sustainability, ultimately contributing to higher productivity and economic benefits[58].

Furthermore, the integration of these models into user-friendly digital platforms and mobile applications can enable broader accessibility for farmers, ensuring real-time recommendations tailored to specific geographical and climatic conditions. The adoption of such AI-based solutions can lead to a paradigm shift in farming, moving towards data-driven, technology-assisted agricultural practices that enhance food security and sustainability. As machine learning continues to evolve, its role in agriculture will remain vital in addressing global challenges and improving overall farming efficiency[55].

In conclusion, the continuous integration of machine learning and smart technologies into agriculture is vital for improving efficiency and sustainability in the face of global challenges[57]. By focusing on relevant crops based on local conditions and economic significance, our research supports farmers and policymakers in navigating the complexities of modern agriculture[56]. Ultimately, this work advocates for a future where integrated AI frameworks not only contribute to enhanced productivity but also play a crucial role in achieving food security and fostering a resilient agricultural sector equipped to meet the demands of a growing global population.

VII. FUTURE DIRECTIONS

The findings of this study highlight the potential of machine learning models in improving crop recommendation systems. However, several areas require further exploration to enhance the accuracy, reliability, and applicability of these models. One promising direction is the integration of real-time environmental and soil sensor data, which can provide dynamic insights into changing agricultural conditions[47]. Additionally, incorporating deep learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), may improve model performance by capturing complex patterns in large-scale agricultural datasets[44].

Another important avenue for future research is the development of explainable AI (XAI) techniques to enhance the interpretability of crop recommendation models[49]. Farmers often require clear and understandable reasoning behind AI-driven recommendations, and implementing transparent machine learning approaches can improve trust and adoption. Furthermore, integrating remote sensing data from satellite imagery and drones can provide valuable geospatial insights that complement traditional soil and weather-based prediction models[48].

Expanding datasets to include diverse climatic zones and region-specific agricultural practices can improve model generalization, making recommendations more adaptable to different farming environments[50]. Additionally, hybrid models that combine multiple algorithms, such as ensemble learning and meta-learning, could further optimize crop selection strategies. Future work could also focus on the socio-economic aspects of crop recommendation, ensuring that AI-driven solutions align with market demands, farmer preferences, and sustainable farming practices[52].

Finally, collaboration with agricultural experts, policymakers, and technology developers will be essential to bridge the gap between AI research and real-world implementation. By addressing these challenges, future advancements in machine learning can significantly contribute to precision agriculture, resource-efficient farming, and increased crop yields[51].

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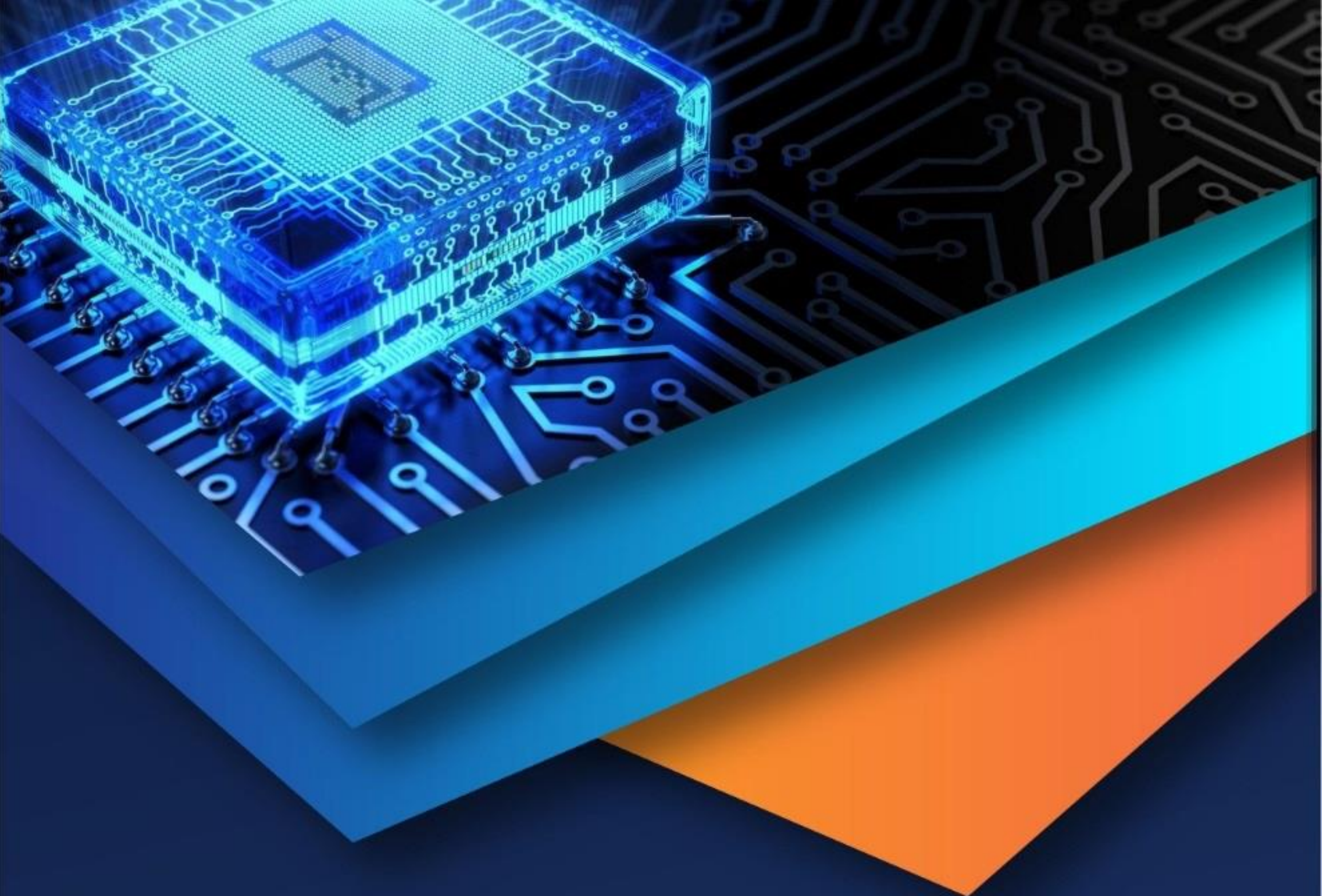

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IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429