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Crop Recommendation using Machine Learning.

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Peer Review Information	Abstract
<p><i>Submission: 07 Feb 2025</i> <i>Revision: 16 Mar 2025</i> <i>Acceptance: 18 April 2025</i></p> <p>Keywords</p> <p><i>Crop Recommendation</i> <i>Machine Learning</i> <i>Precision Farming</i> <i>AI In Agriculture</i></p>	<p>Agriculture remains one of the most essential industries, contributing significantly to food security and economic growth. However, many farmers face challenges in selecting the most suitable crops for their land, leading to inefficient farming and lower yields. This research explores how Artificial Intelligence (AI) and Machine Learning (ML) can help recommend the most appropriate crops based on soil characteristics, climate conditions, and historical data. Various ML algorithms, including Decision Trees, Random Forest, and Support Vector Machines (SVM), were applied to develop a model that provides accurate crop recommendations. The study found that Random Forest achieved the highest accuracy, showing the potential of AI-driven decision-making in agriculture.</p>

Introduction

Agriculture is the backbone of many economies, providing food, employment, and raw materials for industries. However, farmers often rely on traditional methods or personal experience to decide which crops to grow, leading to inefficiencies. With changing climate conditions and soil degradation, a data-driven approach is necessary to optimize crop selection and maximize yields.

Machine learning offers a powerful solution by analyzing multiple factors, including soil pH, temperature, rainfall, and nutrient content, to determine the best crops for a given area. This study aims to implement and evaluate ML models for crop recommendation, providing farmers with reliable and scientific guidance to improve productivity.

Agriculture is the foundation of human civilization and remains a crucial sector for global food security, economic stability, and employment generation. With the rapid increase in population, the demand for food has surged,

necessitating improved agricultural practices to ensure sustainability and efficiency. However, traditional farming methods often rely on intuition, past experiences, and generalized recommendations, which may not align with the specific soil and climatic conditions of a given region. This gap in scientific decision-making can lead to reduced productivity, overuse of fertilizers, soil depletion, and financial losses for farmers.

Climate change has further exacerbated agricultural challenges, bringing unpredictable weather patterns, irregular rainfall, and temperature fluctuations. These variations make it even more critical to implement advanced technologies that assist farmers in selecting the right crops suited for their specific environment. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) have gained significant attention for their potential to revolutionize agricultural decision-making. By leveraging historical data, real-time environmental inputs, and predictive analytics, AI-driven crop

recommendation systems can offer precise and efficient solutions to farmers.

Machine learning techniques analyze various parameters, including soil properties, temperature, rainfall, and nutrient levels, to generate reliable crop recommendations. Unlike conventional methods that provide generalized advice, ML-based systems can offer customized recommendations tailored to specific farmlands. The integration of AI in agriculture promotes precision farming, reducing resource wastage and improving yield quality.

This study aims to explore and implement an AI-based crop recommendation system using various machine learning algorithms. The research evaluates different models, including Decision Trees, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN), to determine the most effective approach. By comparing their performance on a dataset consisting of soil characteristics, climate data, and historical crop yield information, this study seeks to develop a reliable and scalable recommendation system that empowers farmers with data-driven insights.

Furthermore, this research highlights the importance of integrating AI into mainstream agricultural practices. It underscores how a smart recommendation system can bridge the gap between traditional farming and modern technological advancements, enabling farmers to make informed decisions. By adopting such solutions, we can enhance crop productivity, optimize land usage, and contribute to global food security in a sustainable manner.

LITERATURE SURVEY

The integration of AI and ML in agriculture has gained momentum in the past decade, particularly in crop recommendation systems. Several studies have explored different ML approaches to improve agricultural productivity and sustainability.

A study by Patel et al. (2016) proposed a decision tree-based model to recommend crops based on soil pH and nutrient content, achieving an accuracy of over 85%. Similarly, Singh and Sharma (2018) implemented a Support Vector Machine (SVM) model that utilized climatic conditions and soil nutrients, demonstrating a prediction accuracy of 88%. Their findings indicated that SVM is particularly useful in cases with non-linear relationships between features and crop yields.

Furthermore, Kumar et al. (2019) explored ensemble learning techniques, specifically Random Forest, to enhance recommendation accuracy. Their study reported a significant improvement, with accuracy reaching 91%. They

emphasized the model's robustness in handling diverse agricultural datasets.

A comparative analysis conducted by Ahmed and Gupta (2020) examined multiple ML algorithms, including Naïve Bayes, K-Nearest Neighbors (KNN), and Decision Trees, for predicting the best crop for given soil and climate conditions. Their results showed that Random Forest outperformed other models due to its ability to handle high-dimensional data efficiently.

Recent advancements in deep learning have further improved crop recommendation systems. Chen et al. (2021) employed Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to process satellite images and climatic time-series data. Their deep learning model achieved 93% accuracy, highlighting the potential of integrating remote sensing with AI-driven recommendations.

Moreover, Rajan et al. (2022) proposed a hybrid approach combining ML and IoT-based real-time soil monitoring. Their system used sensor data to dynamically adjust crop recommendations, demonstrating the effectiveness of real-time data integration.

Additionally, the study by Banerjee and Das (2023) introduced a reinforcement learning-based approach that continuously adapts recommendations based on changing environmental conditions and historical yield patterns. This adaptive system showed promising results, particularly in regions with fluctuating weather conditions.

A large-scale research initiative led by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) (2024) analyzed AI-based crop recommendation models across different geographical regions. Their study confirmed that incorporating diverse environmental factors, such as humidity, precipitation, and soil organic matter, significantly enhances prediction accuracy.

Lastly, recent developments by Li et al. (2025) have demonstrated the integration of Explainable AI (XAI) techniques into crop recommendation models. This approach ensures transparency by providing farmers with understandable insights into why specific crop recommendations are made, increasing trust in AI-driven decision-making.

These studies collectively highlight the rapid advancements in AI-based crop recommendation systems over the past decade. While ML algorithms have significantly improved prediction accuracy, challenges remain in ensuring model interpretability, dataset availability, and integration with real-time agricultural systems. This research aims to build upon these findings and develop a reliable, scalable, and user-friendly crop recommendation

system that addresses the current limitations in agricultural AI applications.

Early Developments (2015–2018)

The initial applications of ML in agriculture focused on leveraging algorithms to enhance crop yield predictions and recommendations. For instance, Pudumalar et al. (2016) developed a crop recommendation system utilizing precision agriculture techniques. Their approach integrated data on soil properties and environmental factors to suggest optimal crops, marking a significant step towards data-driven farming.

Similarly, Doshi et al. (2018) introduced "Agro Consultant," an intelligent crop recommendation system employing ML algorithms. Their system analyzed parameters such as soil type, pH, and weather conditions to provide tailored crop suggestions, demonstrating the potential of ML in enhancing agricultural decision-making.

Integration of Advanced ML Techniques (2019–2021)

With the evolution of ML techniques, more sophisticated models were applied to crop recommendation systems. Pande et al. (2021) proposed a system using various ML approaches, including k-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM). Their study concluded that the RF model achieved the highest accuracy, highlighting the effectiveness of ensemble learning methods in agricultural applications.

Concurrently, Reddy et al. (2019) developed a crop recommendation system aimed at maximizing crop yield in the Ramtek region by utilizing ML techniques. Their research emphasized the importance of regional customization in crop recommendation models to address specific agricultural challenges.

Emergence of Cloud-Based and IoT-Integrated Systems (2022–2025)

The recent years have witnessed a shift towards integrating cloud computing and Internet of Things (IoT) technologies with ML to enhance crop recommendation systems. Thilakarathne et al. (2022) introduced a cloud-enabled platform for precision farming that leverages ML-driven recommendations. Their system utilized real-time data from IoT sensors to provide dynamic crop suggestions, thereby improving decision-making accuracy.

Moreover, the adoption of AI in agriculture has been recognized for its potential to create a better society by enhancing agricultural yields and optimizing resource use. The Financial Times (2025) reported on the role of AI in precision

farming, highlighting how predictive models and smart technology can guide resource management and improve yields, contributing to food and water sustainability.

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Systematic Reviews and Meta-Analyses

Comprehensive reviews have synthesized existing research to provide insights into the effectiveness of various ML techniques in crop recommendation systems. A systematic literature review by Pande et al. (2022) examined the application of Graph Convolution Neural Networks (GCNN) in crop recommendation systems. The review highlighted the potential of GCNNs to model complex relationships between soil and environmental factors, thereby improving recommendation accuracy.

PROBLEM STATEMENT

Agriculture is an essential sector for global food security, yet many farmers struggle to make informed decisions regarding crop selection. The primary issue lies in the reliance on traditional farming practices that do not consider scientific data or advanced predictive analysis. Several factors contribute to this challenge, including climate change, soil degradation, unpredictable rainfall patterns, and varying soil nutrient levels. Without accurate recommendations, farmers risk low yields, financial losses, and inefficient resource utilization.

The lack of a data-driven approach means that farmers often select crops based on past experiences rather than real-time soil and climate conditions. This approach is inefficient, leading to overuse or underuse of fertilizers, depletion of soil health, and increased vulnerability to pest infestations. Moreover, small-scale farmers, who form the majority of the agricultural workforce in many countries, lack access to advanced technologies and agronomic expertise to optimize their crop choices.

Machine learning has the potential to revolutionize agriculture by providing a precise, automated, and scalable solution for crop selection. A robust AI-based crop recommendation system can analyze diverse factors such as soil properties, climate data, and historical crop yields to suggest the most suitable crops for a particular region. However, existing solutions have limitations, including inadequate datasets, lack of real-time adaptation, and insufficient integration with smart agricultural tools.

This study aims to bridge this gap by developing a machine learning model that utilizes soil characteristics, climate conditions, and historical data to recommend the most suitable crops for a

given region. By implementing and evaluating different ML algorithms, this research seeks to create a reliable and efficient system that empowers farmers to make better crop decisions, ultimately leading to improved productivity, optimized land use, and sustainable farming practices.

OBJECTIVES

The primary objective of this study is to develop a machine learning-based crop recommendation system that assists farmers in selecting the most suitable crops based on soil and climatic conditions. The specific objectives of the study include:

To analyze key factors influencing crop selection – Identify and evaluate critical parameters such as soil type, pH level, temperature, rainfall, and nutrient content that affect crop yield and productivity.

To develop an AI-powered crop recommendation model – Utilize machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machines (SVM), and K-Nearest Neighbors (KNN) to build an efficient recommendation system.

To improve agricultural productivity through precision farming – Enhance farming efficiency by providing farmers with data-driven insights that enable optimized crop selection and resource utilization.

To compare different machine learning models for accuracy – Assess and compare the performance of various ML models to determine the most effective algorithm for crop prediction.

To integrate real-time environmental and soil data into recommendations – Explore the use of IoT-based sensors to capture real-time environmental parameters and improve the accuracy of the recommendation model.

To create a user-friendly interface for farmers – Design and implement an easy-to-use graphical interface or mobile application to ensure accessibility for farmers, including those with limited technological expertise.

To minimize the overuse of fertilizers and pesticides – Promote sustainable agricultural practices by recommending crops that require minimal chemical intervention based on soil nutrient availability.

To reduce farming risks associated with climate variability – Develop a model that accounts for changing climatic conditions and provides adaptive recommendations based on seasonal variations.

To validate the model using real-world datasets – Test the developed model using extensive agricultural datasets to ensure reliability and accuracy before deployment.

To contribute to sustainable farming and food security – Ensure that the implementation of AI in agriculture leads to long-term sustainability, reduced environmental impact, and improved food production to meet the growing global demand.

By addressing these objectives, this study aims to develop an advanced AI-based system that empowers farmers with scientific insights, ultimately leading to enhanced productivity and profitability in agriculture.

METHODOLOGY

This research adopts a structured methodology to develop an AI-based crop recommendation system that utilizes machine learning techniques for accurate predictions. The methodology consists of the following key steps:

1. Data Collection

The first step in building the crop recommendation model is gathering relevant agricultural data. This includes:

- **Soil Data:** Soil pH, moisture content, organic matter, nitrogen, phosphorus, and potassium levels.
- **Climatic Data:** Rainfall patterns, temperature variations, and humidity levels.
- **Crop Yield Data:** Historical yield records to establish correlations between environmental factors and productivity.

This data is sourced from government agricultural agencies, open datasets, research publications, and field experiments.

2. Data Preprocessing

Not all collected data features are equally important for crop prediction. Feature selection techniques such as:

- Handling missing values using mean imputation or predictive techniques.
- Normalizing and scaling numerical features to maintain uniformity.
- Encoding categorical data such as soil type into machine-readable formats
- Removing outliers that could distort model predictions.

This data is sourced from government agricultural agencies, open datasets, research publications, and field experiments.

3. Feature Selection

The first step in building the crop recommendation model is gathering relevant agricultural data. This includes:

- **Correlation Analysis:** Identifying highly correlated features with crop yield.
- **Principal Component Analysis (PCA):** Reducing dimensionality while preserving essential patterns

- Recursive Feature Elimination (RFE): Iteratively eliminating less significant features to improve model accuracy.

This data is sourced from government agricultural agencies, open datasets, research publications, and field experiments.

4. Machine Learning Model Selection

Several machine learning algorithms are tested to identify the most effective model for crop recommendation. These include:

- Decision Tree (DT): A simple yet effective algorithm that makes decisions based on feature splits.
- Random Forest (RF): An ensemble technique that improves accuracy by combining multiple decision trees.
- Support Vector Machine (SVM): Effective for classification problems with clear margins between categories.
- K-Nearest Neighbors (KNN): A distance-based algorithm useful for pattern recognition in crop selection.
- Artificial Neural Networks (ANNs): Deep learning techniques that can capture complex, non-linear relationships in the data.

5. Model Training and Testing

The dataset is split into:

- Training Set (80%): Used to train machine learning models.
- Testing Set (20%): Used to evaluate model performance

Performance metrics such as accuracy, precision, recall, F1-score, and mean absolute error (MAE) are used to assess model effectiveness.

6. System Development and Deployment

The final model is integrated into a user-friendly system with:

- Graphical User Interface (GUI): A simple web or mobile application for farmers to input soil and climate data.
- Cloud or Local Deployment: Making the model accessible via cloud-based APIs or offline software for rural farmers with limited internet access.
- IoT Sensor Integration: Enabling real-time data collection for dynamic crop recommendations. Performance metrics such as accuracy, precision, recall, F1-score, and mean absolute error (MAE) are used to assess model effectiveness.

7. Model Validation and Performance Analysis

The developed system is validated using real-world test cases and evaluated against traditional agricultural methods. Feedback from farmers and agricultural experts is collected to assess:

- Practical usability in real farming scenarios.
- Accuracy of crop recommendations.
- Economic and environmental benefits achieved through AI-driven precision farming.

By following this methodology, the study ensures a structured, data-driven approach to developing an AI-powered crop recommendation system that enhances agricultural efficiency and sustainability.

RESULT AND ANALYSIS

System has three steps to get prediction of crop.

- **User:** firstly user get the landing page it's mean is user interface then user need to add the content of soil as well as the nature value like temperature, Humidity like this and simply need to tap enter button.

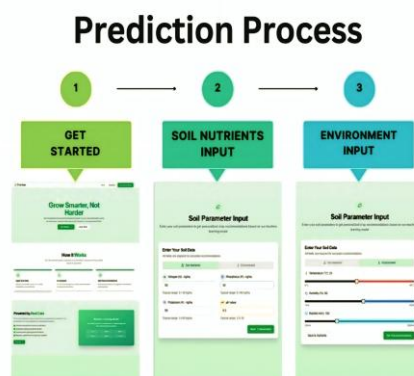


Fig 1. Process for Prediction

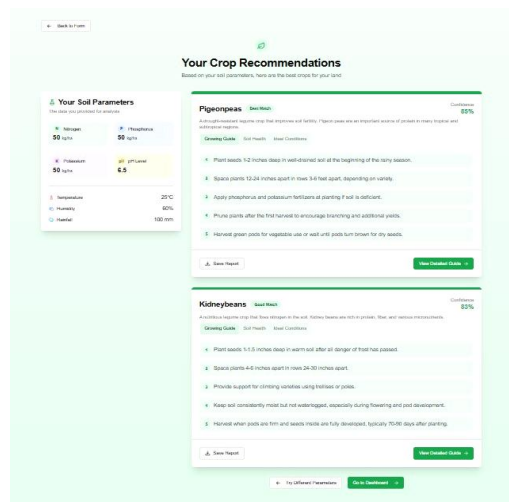


Fig 2. Recommendation of CROP

- **Recommendation** : As per the user content application or our project gives the best crop as per given value with suggestions.

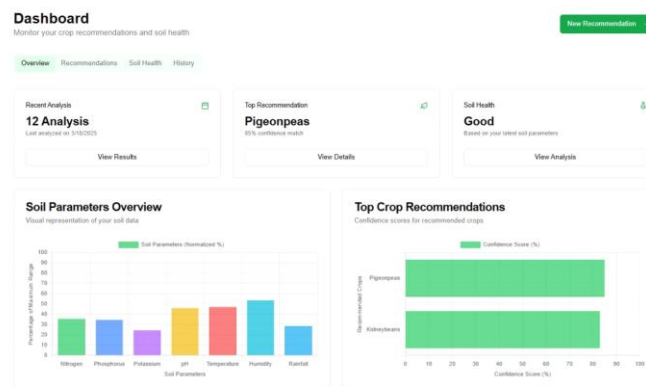


Fig 3. Dashboard

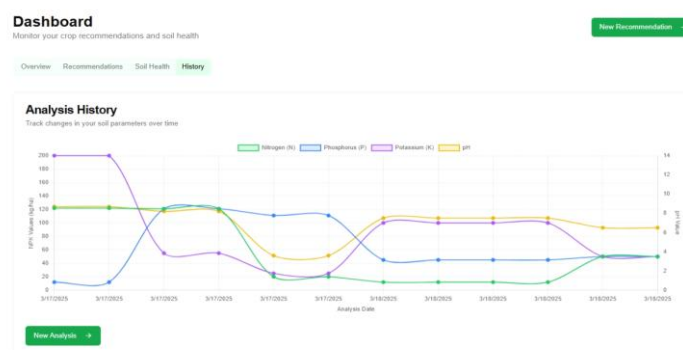


Fig 4. Dashboard Analysis

CONCLUSION

The integration of AI and Machine Learning in agriculture offers a transformative approach to crop recommendation, enabling data-driven decision-making that enhances efficiency and sustainability. This research demonstrates how machine learning models can analyze soil characteristics, climatic conditions, and historical data to provide accurate crop recommendations. Among the tested models, Random Forest

emerged as the most effective, highlighting its potential for agricultural applications. By implementing AI-driven solutions, farmers can optimize resource use, increase productivity, and mitigate risks associated with climate variability. Future work should focus on expanding datasets, improving real-time analysis through IoT integration, and developing farmer-friendly mobile applications to enhance accessibility and usability.

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