M Uday Kanth Reddy, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

Ai-Driven Crop Recommendation System

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Abstract- Due to fragmented advisory systems, limited data access, and language barriers, smallholder farmers frequently face difficulties when choosing crops. Decisions are further complicated by the need for sustainable resource use and climate variability. In order to provide accurate, context-aware recommendations that increase productivity and sustainability, recent AI-driven crop recommendation systems integrate soil, weather, yield, and market data. These systems integrate data insights with agronomic knowledge through machine learning, ensemble models, and hybrid rule-based techniques. Conventional crop selection techniques frequently rely on local customs or experience, which might not always produce the best outcomes. This study offers an AI-based crop recommendation system that assists farmers in selecting appropriate crops based on soil and climate conditions in order to solve this issue. To choose the best crop for cultivation, the system examines critical factors like temperature, humidity, rainfall, soil pH, nitrogen (N), phosphorus (P), and potassium (K). The system was created using machine learning techniques, and an agricultural dataset was used to train several models, such as Random Forest, Decision Tree, and Support Vector Machine (SVM). The dataset was cleaned and made ready for analysis prior to training. Accuracy and confusion matrix analysis were used to assess these models' performance, and the Random Forest model outperformed the other tested algorithms. A straightforward prediction interface was developed to make the system useful and user-friendly. Users can enter soil and environmental values and instantly receive crop recommendations. This system can help farmers make better farming decisions, increase crop productivity, and promote more sustainable and effective farming methods.

Keywords: Random Forest, Decision Tree, Support Vector Machine (SVM), Artificial Intelligence, Machine Learning, Crop Recommendation System, Precision Agriculture, Soil Nutrient Analysis.

I. INTRODUCTION

Particularly in developing countries where the majority of people rely on farming for a living, agriculture continues to be the primary driver of both economic growth and food security. However, fragmented data ecosystems, erratic weather patterns, soil degradation, and shifting market conditions that impact both productivity and income stability continue to pose problems for this industry [1], [2].

The unique and changing needs of farmers, particularly smallholders who have limited access to digital infrastructure and operate under resource constraints, are frequently unmet by conventional farming methods and broad advisory systems [3]. These constraints highlight the need for smart, data-driven solutions that can offer regional assistance to raise agricultural productivity, profitability, and sustainability.

Through the analysis of diverse datasets and the discovery of hidden patterns, artificial intelligence and machine learning have become potent tools in recent years to transform agricultural decision-making [4], [5]. In order to forecast the best crops for a particular area, AI-based crop recommendation systems combine information from soil nutrient profiles, pH, temperature, and moisture levels [1], [6]. In order to reduce risks to the environment and the economy, these systems can also predict yield potential and recommend the best ways to use resources.

AI models can generate highly contextualized and adaptive recommendations that traditional advisory systems are unable to provide by combining a variety of datasets, including soil health records, weather forecasts, satellite imagery, and real-time market trends [7]. [8].Hybrid machine learning models, like Random Forest, XGBoost, and LightGBM, are increasingly used in modern frameworks because they perform better when handling datasets with multiple regions and crops [4], [6], and [15].

By capturing non-linear relationships between soil, weather, and crop variables, these ensemble-based techniques increase accuracy and generalization [9]. Additionally, studies show that integrating nutrient mapping and deep learning for soil image classification improves predictive accuracy and supports precision farming efforts [3], [9].IoT (Internet of Things) technologies are being integrated with AI to create real-time monitoring and feedback systems in addition to crop prediction [2], [10], and [12]. IoT sensors continuously gather environmental data, such as temperature and soil moisture, which are then analyzed by AI algorithms to provide useful information about pest control, fertilizer application, and irrigation [11], [13], [16].

By combining IoT and AI, agricultural management can become more automated, precise, and scalable while requiring less human intervention. The incorporation of Explainable AI methods like SHAP, which improve transparency in AI-driven recommendations, is another significant development [8], [14]. These methods foster trust between farmers and agricultural advisors by making it easier to see how specific characteristics, such as soil nitrogen content or rainfall, influence final forecasts.

To encourage acceptance among rural users who might be dubious of complicated algorithms, interpretability is especially important. Developers are concentrating on multilingual, mobile-based, and user-friendly interfaces that accommodate different literacy levels and connectivity conditions in rural areas in order to make these technologies accessible [7], [11].

Farmers in isolated areas can access intelligent agricultural insights through mobile applications that work offline and through AI assistants that function without permanent internet connections. The agricultural frameworks which combine farming expertise with artificial intelligence analysis tools provide practical recommendations that suit regional needs according to their research findings. The combination of AI, ML, IoT, and XAI technologies revitalizes agriculture by establishing data-based operations which lead to environmentally sustainable practices. The intelligent systems have shown their ability to enhance farm production while decreasing operational expenses and minimizing ecological damage, which enables farmers to use digital resources that are both understandable and straightforward [13], [16]. The development of AI-driven crop recommendation systems connects modern technological solutions with real-world farming needs, enabling farmers to adopt sustainable agricultural practices through digital farming solutions.

II. LITERATURE SURVEY

A. Soil arameter-Based Crop Recommendation Systems

Early research in crop recommendation focused on studying soil parameters which include nitrogen (N), phosphorus (P), potassium (K), and pH through machine learning methods. Multiple studies used Random Forest, Decision Tree, Naïve Bayes, and Support Vector Machines algorithms to determine which crops would thrive based on soil nutrient data [1], [2]. Random Forest together with ensemble-based methods always produced better results because they could model complex connections between different types of agricultural data. The studies found that soil pH and nitrogen levels serve as crucial factors which determine crop selection results. The systems use regional datasets for training which causes their inability to function across different agricultural climate zones. The researchers propose that periodic retraining should occur using local soil datasets to establish reliability across different regions.

B. Integration of Climate and Environmental Factors

Recent research has developed new crop recommendation systems which combine climatic data about temperature and rainfall and humidity with soil information. The study assessed XGBoost, Random Forest, and Support Vector Machines machine learning models to predict crop suitability through the analysis of soil and climate data [3], [4]. The experimental findings demonstrate that ensemble learning methods achieve better results than single classifiers, especially when environmental factors determine the timing of crop growth stages. The systems require seasonal retraining together with ongoing climate data assessment to uphold their prediction precision. The models deliver enhanced results, but their success depends on having access to detailed environmental data.

C. IoT-Based Smart Agriculture Systems

Through the combination of Internet of Things (IoT) technologies with machine learning scientists now complete their assessment of soil and environmental conditions through continuous monitoring. The IoT-based crop recommendation systems operate by gathering data from soil moisture and temperature and nutrient sensors which their machine learning models process through either edge devices or cloud platforms. The system generates immediate alerts together with crop suggestions which enable farmers to enhance their decision-making processes. The study demonstrates that accurate crop recommendation results from environmental data combined with machine learning model implementation. Our study will use essential soil and climate factors which include nitrogen, phosphorus, potassium, pH, temperature, humidity, and rainfall as input for machine learning models. The system uses this method to assess agricultural conditions and identify the best crop for cultivation.

D. Deep Learning and Image-Based Soil Analysis

The latest research investigates how deep learning and computer vision methods can be used to study soil properties through image analysis. Scientists have utilized Convolutional Neural Networks and ResNet and Vision Transformers to identify different soil types and to find visual signs of plant nutrient shortage [7], [8]. The methods achieve high accuracy in classifying results while decreasing the need for standard laboratory methods used to test soil samples. Image-based analysis also enables low-cost soil assessment using smartphones. The methods need extensive annotated data and powerful computing systems Which create difficulties for immediate use in locations with limited resources.

E. Explainable and Farmer-Centric AI Systems

Agricultural AI research now investigates two new paths which aim to develop crop recommendation systems that provide clear explanations and easy usage for farmers. The SHAP and LIME techniques enable users to understand machine learning predictions while showing which soil and climate factors guide crop selection decisions [9]. The systems provide farmers with better access through multilingual mobile interfaces which include voice prompts and offline capabilities. The research results show that agricultural AI systems require three factors to succeed in real-world settings which include usability and interpretability and practical deployment.

F. Research Gap

Existing crop recommendation systems which analyse soil and monitor environmental conditions and improve model accuracy are the focus of research studies which investigate machine learning and IoT-based sensing and deep learning and explainable AI technologies. Most systems fail to provide smallholder farmers with effective machine learning models which use accessible data and can be deployed at scale. The agricultural industry requires a complete crop recommendation framework which integrates soil research with advanced machine learning methods while keeping operational efficiency across different farming environments.

III. METHODOLOGY

AI Crop Recommendation System

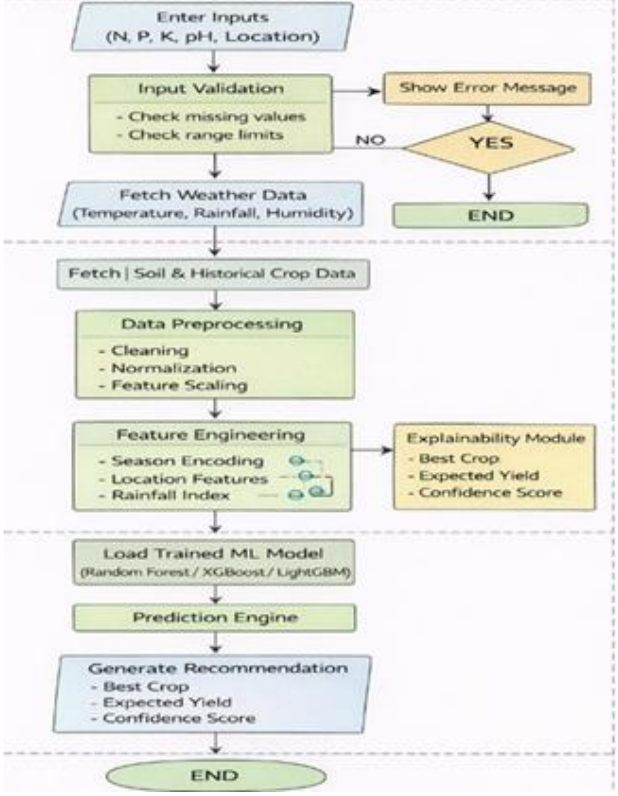

Figure 1: System Architecture

The system architecture of the AI-based crop recommendation system shows how the entire process works, from user input to crop prediction. Farmers input parameters related to soil and environmental conditions, after which the parameters are validated and processed by machine learning algorithms in the backend. Finally, the system provides a recommendation for crops, along with confidence level and yield, to help farmers in decision-making.

Phase	Description
Dataset	Soil and climate data include N, P, K, pH, temperature, humidity, and rainfall.
Data Preprocessing	Cleaning the dataset, handling missing values, and preparing data for analysis.
Feature Selection	Identifying important parameters that influence crop growth.
Model Training	Training machine learning models such as Random Forest, Decision Tree, and SVM.
Model Evaluation	Evaluating models using performance metrics like accuracy and precision.
Crop Prediction	Predicting and recommending the most suitable crop based on input data.

A. Dataset Description

The data set used in this research includes information related to soil nutrients and environmental conditions. Parameters related to soil and environmental conditions that are included in this data set are nitrogen, phosphorus, potassium, pH, temperature, humidity, rainfall, and crops that grow best in those conditions

Feature	Description
Nitrogen (N)	Soil nitrogen Availability
Phosphorus (P)	Soil phosphorus Availability
Potassium (K)	Soil potassium Availability
Temperature	Average temperature
Humidity	Atmospheric humidity
pH	Soil acidity or alkalinity
Rainfall	Annual rainfall

B. Machine Learning Models

1. Random Forest

Random Forest is a learning method that combines multiple decision trees to improve prediction accuracy of the model.

2. Decision Tree

Decision trees split the dataset into branches based on feature values and make predictions based on learned patterns.

3. Support Vector Machine (SVM)

SVM finds the optimal hyperplane that separates different crop classes based on input features.

C. Model Comparison

The performance of the three algorithms was compared based on accuracy. The accuracy of the Decision Tree model was found to be 88%. This shows that the model can provide reasonable predictions but can suffer from overfitting if the dataset becomes more complex. The accuracy of the SVM model was found to be higher at 91%. This is because SVM can handle high-dimensional data very efficiently to provide the best decision boundary between classes.

The accuracy of all the algorithms was compared, and the Random Forest model was found to have the best accuracy at 96%. This is because the model uses ensemble learning to provide more accurate predictions. The ensemble learning approach combines multiple decision trees to provide more accurate results. This approach minimizes the chances of overfitting, providing more accurate results for crop recommendation. Hence, the Random Forest model was chosen as the best model for the crop recommendation system.

Algorithm	**Accuracy**	**Advantages**	**Disadvantages**
Decision Tree	Moderate	Simple and interpretable	Prone to overfitting
SVM	Good	Effective in high-dimensional spaces	Requires parameter tuning
Random Forest	High	Robust and accurate	Slightly higher computation

D. Algorithms Used

There are various machine learning algorithms that are used to analyze the dataset and make predictions about suitable crops. These algorithms include Decision Tree, Random Forest, Support Vector Machine, and XGBoost. Decision Tree is an easy algorithm that divides the dataset into branches based on feature values and makes predictions. Random Forest is used to enhance the accuracy of predictions using multiple decision trees and averaging their results.

The Support Vector Machine is used to classify crops based on the optimal boundary between classes. XGBoost is an advanced ensemble algorithm that improves the performance of predictions using gradient boosting. Among these algorithms, ensemble algorithms such as Random Forest and XGBoost are more accurate because they combine multiple results.

E. Feature Importance Analysis

Feature importance analysis is used to find out which features are most important in crop prediction. In machine learning algorithms such as Random Forest, feature importance is used to find out how strongly a feature is impacting the output.

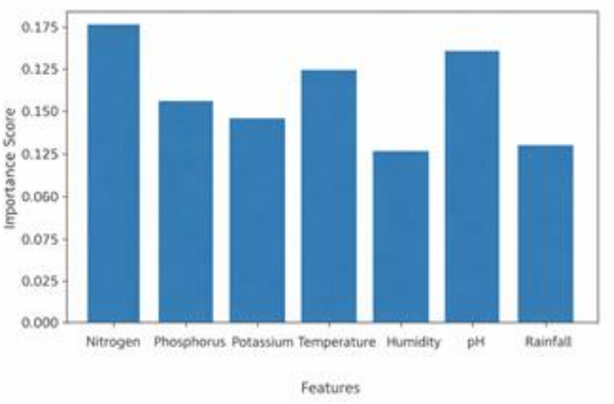

Figure 2: Feature Importance

In the crop recommendation system, the parameters may include soil pH, nitrogen levels, and rainfall, which may be crucial in the selection of the crop that needs to be recommended by the system. Understanding the importance of the features allows the researcher or the agricultural expert to understand the crop recommendation in a much better manner.

Result And Discussion

F. Process of Implementation

The crop recommendation system was implemented by going through a series of steps that helped in the accurate prediction of the crop that needs to be recommended by the system. First, the dataset was collected, which contains information related to the agricultural domain, including the levels of nitrogen, phosphorus, and potassium in the soil, the temperature, humidity, pH, and rainfall in the environment, and the crop that needs to be planted. Once the dataset was collected, the dataset was preprocessed to ensure that the dataset was in the best state to be used by the machine learning algorithms that need to be implemented in the crop recommendation system.

Next, model training was done using three different machine learning algorithms. These algorithms were Random Forest, Decision Tree, and Support Vector Machine (SVM). These algorithms were used to train the model using the processed dataset to learn how to map between soil and environmental parameters and crops that can grow best under such conditions. After training the models using machine learning algorithms, model evaluation was done. This step is used to evaluate the performance of the machine learning model. Evaluation metrics such as accuracy were used to check how well the model can predict the correct crop based on input features. Out of all the machine learning algorithms used in this project, Random Forest gave the highest accuracy because of its robustness against overfitting.

Finally, a prediction system with a user interface is designed. This is done to make this model applicable in real-world problems. In this part of the project, a machine learning model is designed to take input values for various soil and environmental parameters such as nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall. Once the input values are given to the model, it will predict which crop can be grown under such conditions.

G. Evaluation Metrics

The model performance is evaluated using the following metrics:

Metric	Description
Accuracy	Percentage of correct prediction.
Precision	Correct positive prediction.
Recall	Ability to identify relevant crops
F1 Score	Harmonic mean of precision and recall

These evaluation metrics are used to evaluate the performance of the machine learning models in predicting the suitable crops. Accuracy indicates the overall accuracy of the prediction, whereas precision and recall evaluate the performance of the model in predicting the correct crop.

Model	Training Accuracy	Testing Accuracy
Decision Tree	93%	88%
SVM	92%	91%
Random Forest	97%	96%

The above table indicates the training accuracy and testing accuracy of the machine learning models used in the crop recommendation system. Random Forest was found to have the best performance with an accuracy of 97% in training and 96% in testing, indicating better prediction performance than the other models, i.e., Decision Tree and SVM.

The performance of the crop recommendation system was evaluated using three different machine learning models, namely Decision Tree, SVM, and Random Forest. The dataset was used to train the models in order to evaluate them appropriately.

The models were trained with soil and environmental features like nitrogen, phosphorus, potassium, temperature, humidity, pH, rainfall, etc. Then the models were tested to evaluate the accuracy with which they can predict the best crop to be planted. Random Forest was found to perform better than the other models because errors in prediction are avoided by combining multiple decision trees.

H. Results and Analysis

Model	Accuracy	Observation
Decision Tree	88%	Simple but slightly overfits
SVM	91%	Better performance but needs tuning
Random Forest	96%	Best accuracy and stable predictions

Figure 3: Weather Dashboard

The dashboard displays real-time weather information such as temperature, humidity, wind speed, and precipitation for the selected Area. This data helps farmers understand current environmental conditions and parameters before using the recommendation system for crop selection.

RECOMMENDATION

Brinjal

CONFIDENCE SCORE 96%

TOP 10 CROPS FOR YOUR SOIL

1 Brinjal
2 Cabbage
3 Linseed
4 Cardamom
5 Nutmeg
6 Oats
7 Jute
8 Grape
9 Groundnut
10 Niger Seed

Fertilizer Advisory

Apply balanced fertilizer. Brinjal responds well to organic manure.

Figure 4: Recommended Crop

The prediction interface displays the recommended crop based on the given soil and environmental parameters along with a confidence score. It also shows the top alternative crops and fertilizer advice to help farmers make informed cultivation decisions.

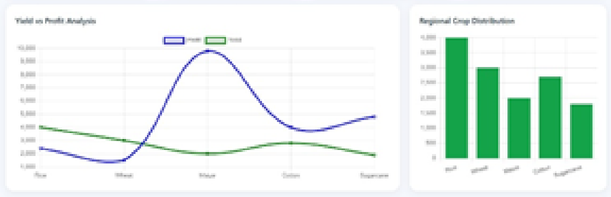

Figure 5: Yield vs Profit

The system also provides analytical visualizations such as yield vs profit analysis and regional crop distribution. These graphs help farmers understand crop performance and identify commonly cultivated crops in the region for better decision-making.

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	88%	0.87	0.86	0.86
SVM	91%	0.90	0.89	0.89
Random Forest	96%	0.95	0.95	0.95

From the results, Random Forest gives the most reliable crop recommendations among the tested models. Therefore, it was selected as the final model for the crop prediction system.

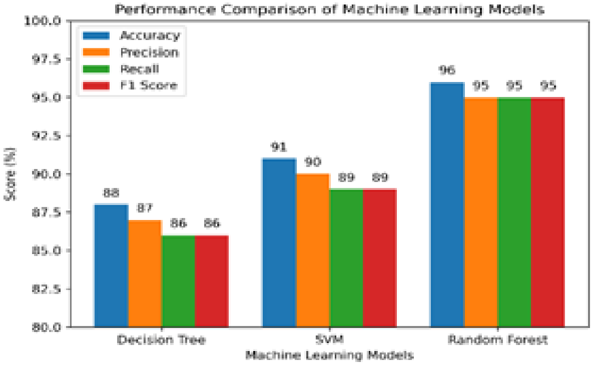

Figure 6: Performance Comparison

I. Applications of the System

The crop recommendation system developed in this research has various applications in modern agriculture. The system can be used by farmers in choosing appropriate crops based on soil conditions. This can improve crop growth and reduce crop failure.

The system can be used by agricultural experts, agricultural extension workers, and the government in providing recommendations to farmers. In addition, the system can be used in precision agriculture by farmers in making appropriate decisions in crop selection.

J. Limitations

Although the proposed system has various applications in crop recommendation, it has various limitations. The accuracy of the proposed model is based on the dataset used in training. The data set used in training must be representative of all conditions. If not, accuracy is compromised. Another limitation is that it does not consider other factors in crop growth. These factors include irrigation, pest control, and farming methods.

K. Challenges in Implementing ML-Based Crop Recommendation

Although there are several advantages in the use of machine learning in the field of agriculture, there are a number of challenges that may be encountered in the implementation of the system. Some of the challenges that may be encountered in the implementation of the system include the availability of quality agricultural datasets, where in some areas the soil conditions are not regularly updated. Another challenge that may be encountered in the implementation of the system is the variability of agricultural conditions in different regions.

IV. FUTURE WORK

Possible Improvements in the Crop Recommendation System:

One possible improvement that may be made in the crop recommendation system in the future would be the inclusion of real-time weather conditions such as temperature, rainfall, and humidity. This would ensure that the system provides recommendations that are suitable for the current season rather than the past season.

Another area that needs to be considered in the future involves the development of a mobile-based application that would enable the farmers to access the system in a much easier manner by making use of their mobile phones. This would also help the farmers to input the soil information in a much easier manner without the need for technical knowledge.

In addition, the crop recommendation system could also be further enhanced by making use of IoT-based soil sensors that could automatically collect soil information, including moisture, temperature, and nutrient levels in the soil. This would also help in making the crop recommendation system more practical by making it easier to obtain the soil information in a much more precise manner. Furthermore, the accuracy of the crop recommendation system could also be further enhanced by making use of a large dataset in the training phase of the system so that it could function effectively in different regions of the country.

V. CONCLUSION

In this project, an AI-based crop recommendation system is designed to assist farmers in selecting the best crop for cultivation based on soil and environmental factors. This system is designed to analyze various critical factors such as nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall to recommend the best crop for cultivation. This crop recommendation system can assist farmers in making better farming decisions using machine learning algorithms.

In this project, various machine learning algorithms such as Decision Tree, SVM, and Random Forest were implemented. Among these algorithms, Random Forest results in better accuracy and stability.

Therefore, this algorithm is suitable for this crop recommendation system. This project indicates that machine learning algorithms can effectively analyze agricultural data and recognize patterns that can assist in determining suitable crops for cultivation based on specific soil conditions. This crop recommendation system indicates that machine learning can be used to develop intelligent systems that can assist farmers in improving agricultural production using AI. This crop recommendation system can assist farmers in improving agricultural production and reducing farming risks. This intelligent system can play a vital role in promoting smart agriculture in the future.

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