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Data-Driven Crop Suitability Recommendation Using Random Forest And Soil-Climate Feature Analysis

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Abstract
Efficient crop selection is a crucial component of sustainable agriculture, improved productivity, and long-term food security. Selecting an appropriate crop depends on multiple soil and environmental conditions, while conventional farming practices often rely on farmers' experience and traditional cultivation patterns. This study presents a data-driven crop suitability recommendation system using the Random Forest algorithm and soil-climate feature analysis to support accurate and reliable crop selection.
The proposed system uses key agricultural parameters, including Nitrogen, Phosphorus, Potassium, soil pH, temperature, humidity, and rainfall, to evaluate soil fertility and prevailing climatic conditions. Data preprocessing and exploratory analysis are performed to improve data quality and identify significant relationships between agricultural features and crop suitability. A Random Forest Classifier is then employed to learn complex patterns from historical agricultural data. By combining the predictions of multiple decision trees, the model improves classification performance while reducing the risk of overfitting.
The developed system can recommend 22 different crop varieties based on varying soil and climatic conditions. Its performance is assessed using accuracy, precision, recall, F1-score, and a confusion matrix. Experimental results show that the Random Forest model achieves approximately 99% accuracy on the test dataset, demonstrating strong predictive performance and reliability. The proposed approach can support farmers and agricultural stakeholders in making informed, data-driven decisions, thereby contributing to efficient crop planning, sustainable farming practices, and enhanced agricultural productivity.

Keywords: *Crop Recommendation, Random Forest, Precision Agriculture, Soil Analysis, Climate Analysis, Machine Learning, Crop Suitability, Data-Driven Agriculture, Sustainable Farming.*

1. Introduction

Agriculture remains strongly influenced by the interaction between soil characteristics, climatic conditions, and crop-specific requirements. Choosing a suitable crop for a particular field is therefore not simply a matter of selecting a crop with high market demand; it also requires consideration of whether the available soil nutrients and environmental conditions can support healthy crop development. Variations in nitrogen, phosphorus, potassium, soil pH, temperature, humidity, and rainfall can significantly influence crop growth and productivity. Climate variability has further increased the difficulty of making reliable crop-selection decisions, particularly for smallholder farming systems that may have limited access to advanced agricultural advisory services. Aryal *et al.* discussed the importance of adaptation strategies for agricultural systems under changing climatic conditions and highlighted the need to consider local environmental and production conditions when making agricultural decisions [10].

Traditional crop-selection practices frequently depend on farmers' experience, previous cultivation patterns, and locally established practices. Although such knowledge remains valuable, it may not adequately capture complex relationships among several agricultural variables simultaneously. The increasing availability of agricultural datasets has created opportunities to complement traditional knowledge with computational methods capable of identifying patterns from historical observations. Machine learning has consequently become an important research direction in agriculture because it can process multiple variables and learn relationships that may be difficult to establish through conventional statistical approaches. Liakos *et al.* reviewed machine learning applications in agriculture and demonstrated its growing use across agricultural monitoring, prediction, and decision-support applications [25].

Crop yield and crop suitability are closely related but distinct prediction problems. A yield-oriented model generally attempts to estimate the expected production of a selected crop, whereas a suitability or recommendation system attempts to determine which crop is more appropriate under a given set of conditions. Successful crop recommendation therefore requires a model capable of distinguishing among several crop classes while considering the combined influence of soil and climatic attributes. Van Klompenburg, Kassahun, and Catal reported that machine learning methods have been increasingly investigated for agricultural prediction because they can incorporate diverse environmental and agronomic variables into predictive models [6].

Soil properties constitute an important component of crop recommendation. Nutrient availability and soil characteristics influence root development, vegetative growth, flowering, and final productivity. In particular, nitrogen, phosphorus, and potassium are widely used as indicators of soil fertility, while soil pH affects nutrient availability and the suitability of the soil for different crops. Zhang *et al.* demonstrated that changes in soil conditions can have a measurable influence on crop yield, emphasizing the importance of understanding soil characteristics when evaluating agricultural performance [4].

Climatic parameters provide another major source of information for determining crop suitability. Temperature, humidity, and rainfall influence water availability, nutrient uptake, disease development, and the physiological processes associated with crop growth. Consequently, a recommendation system based only on soil nutrients may provide incomplete results. Tseng, Cho, and Wu demonstrated the potential of big-data-based approaches for intelligent crop-selection analysis, showing how agricultural information can be integrated to support more informed crop decisions [15].

Machine learning-based crop recommendation systems have therefore emerged as a practical approach for combining soil and climatic information. Pudumalar *et al.* proposed a crop recommendation approach for precision agriculture, illustrating the potential of computational recommendation methods to assist agricultural decision-making [23]. Similarly, Madhuri and Indiramma investigated an artificial-neural-network-based crop recommendation system using soil and climatic parameters, demonstrating the relevance of combining multiple agricultural attributes rather than relying on an individual variable [20].

Feature selection and agricultural variable analysis are also important for developing reliable recommendation systems. When several soil and environmental attributes are supplied to a predictive model, some variables may contribute more strongly to the classification decision than others. Identifying useful features can reduce unnecessary complexity and improve the interpretability of the resulting model. Madhuri and Indiramma examined hybrid filter and wrapper feature-selection methods for crop recommendation, highlighting the importance of selecting informative agricultural attributes before model development [2].

Crop-protection research has further demonstrated the value of data-driven approaches in agricultural decision-making. Ip *et al.* discussed the application of big data and machine learning to crop protection and emphasized how large agricultural datasets can support improved analysis and decision-making [13]. Such approaches are particularly relevant to crop suitability systems because agricultural observations often contain nonlinear relationships among environmental variables, and these relationships may not be adequately represented by simple rule-based methods.

The present study develops a data-driven crop suitability recommendation system using the Random Forest classification algorithm and soil-climate feature analysis. The system considers nitrogen, phosphorus, potassium, soil pH, temperature, humidity, and rainfall as principal input variables and predicts the most appropriate crop among 22 crop categories. Random Forest is selected because it combines multiple decision trees and can model nonlinear relationships between agricultural attributes and crop classes while reducing the dependence on a single decision tree. The proposed system is evaluated using accuracy, precision, recall, F1-score, and a confusion matrix to determine its classification performance. The overall objective is to provide a practical computational approach that can assist farmers and agricultural stakeholders in making more informed crop-selection decisions.

2. Literature Review

Liakos, Busato, Moshou, Pearson, and Bochtis presented a comprehensive review of machine learning applications in agriculture. Their study examined the use of machine learning across several agricultural activities and showed that data-driven techniques can assist with prediction, monitoring, and decision support. The review is particularly relevant to crop recommendation because agricultural systems generate multiple interacting variables that can be analyzed through machine learning models rather than conventional single-variable approaches [25].

Van Klompenburg, Kassahun, and Catal conducted a systematic literature review of machine learning approaches for crop yield prediction. Their analysis showed that machine learning models have been increasingly applied to agricultural prediction tasks using environmental, climatic, and crop-related variables. The study also demonstrated the growing interest in combining multiple sources of agricultural information to improve predictive performance, providing a foundation for developing data-driven crop decision systems [6].

Tseng, Cho, and Wu investigated the application of big data to intelligent agriculture-based crop selection analysis. Their work demonstrated how agricultural datasets can be processed to identify relationships that support crop-selection decisions. The study is significant for the present research because it establishes the importance of integrating agricultural attributes within an intelligent decision-support framework rather than treating crop selection as a purely experience-based activity [15].

Pudumalar, Ramanujam, Rajashree, Kavya, Kiruthika, and Nisha developed a crop recommendation system for precision agriculture. Their work demonstrated that machine learning-based recommendation can be used to assist farmers in selecting crops according to available agricultural conditions. The study provides an important foundation for the present work because it establishes crop recommendation as a practical application of data-driven agricultural decision support [23].

Madhuri and Indiramma proposed an artificial neural network-based integrated crop recommendation system using soil and climatic parameters. Their study emphasized the importance of combining environmental and soil information when making crop recommendations. The use of multiple agricultural variables provides a more comprehensive representation of field conditions and supports the development of intelligent recommendation systems capable of distinguishing among different crop requirements [20].

Madhuri and Indiramma further examined hybrid filter and wrapper methods for feature selection in crop recommendation. Their research highlighted the importance of identifying informative variables before constructing a predictive model. Feature-selection methods can help reduce redundant information and provide a more meaningful representation of the factors influencing crop suitability. This concept directly supports the feature-analysis component of the present study [2].

Kumar, Sarkar, and Pradhan investigated a recommendation system for crop identification and pest-control techniques in agriculture. Their work demonstrated the potential for integrating computational intelligence into agricultural decision-making. Although their study extends beyond crop suitability alone, it illustrates how recommendation systems can transform agricultural observations into actionable information for farmers and other stakeholders [11].

Aryal, Sapkota, Khurana, Khatri-Chhetri, Rahut, and Jat examined climate change and adaptation options in smallholder agricultural production systems in South Asia. Their research emphasized that changing climatic conditions create additional challenges for agricultural planning and require adaptation strategies suited to local farming environments. The findings support the inclusion of climatic variables in crop-related decision systems, particularly where temperature and rainfall patterns influence agricultural outcomes [10].

Zhang, Huang, Rong, Duan, Zhang, Li, and Guan investigated the relationship between soil erosion depth and crop yield using a meta-analysis. Their findings demonstrated that alterations in soil conditions can influence crop productivity, reinforcing the importance of soil characteristics in agricultural modelling. The study supports the inclusion of soil-related attributes in computational systems designed to assess crop suitability [4].

Ip, Ang, Seng, Broster, and Pratley examined big data and machine learning applications for crop protection. Their work highlighted how agricultural datasets can be used to improve decision-making by identifying patterns across large numbers of observations. The study is relevant to the present research because it demonstrates the broader value of machine learning for extracting useful agricultural information from heterogeneous datasets [13].

Elavarasan, Vincent, Sharma, Zomaya, and Srinivasan reviewed approaches for forecasting agricultural yield by integrating agrarian factors with machine learning models. Their work emphasized the value of combining multiple agricultural variables when constructing predictive models. The findings indicate that machine learning can provide useful agricultural predictions when soil, climatic, and other agrarian factors are jointly considered [22].

Ransom *et al.* evaluated statistical and machine learning methods for incorporating soil and weather information into corn nitrogen recommendations. Their study demonstrated the importance of combining soil and weather variables when generating agricultural recommendations. The research also illustrates how machine learning can capture relationships among environmental conditions and agricultural management requirements, supporting the broader application of data-driven models in agricultural decision-support systems [17].

Overall, the reviewed studies indicate a clear movement toward data-driven agricultural decision-making. Existing research has established the usefulness of machine learning, soil analysis, climatic variables, feature selection, and recommendation frameworks for agricultural applications. However, there remains scope for developing a compact crop suitability framework that directly combines soil nutrient attributes with climatic parameters and uses an ensemble learning method for multiclass crop recommendation. The present study addresses this requirement by employing Random Forest to classify 22 crop categories using nitrogen, phosphorus, potassium, soil pH, temperature, humidity, and rainfall. The approach further incorporates exploratory feature analysis and standard classification metrics to evaluate the reliability of the resulting recommendations.

3. Methodology

The proposed project aims to develop a Data-Driven Crop Suitability Recommendation System capable of identifying suitable crops from soil and climatic information. The framework applies the Random Forest Classifier to historical agricultural data and uses measurable environmental characteristics to support crop-selection decisions. The system is intended to assist users in selecting crops that are compatible with existing conditions, thereby supporting improved agricultural productivity, efficient resource utilization, and sustainable cultivation practices.

1. Crop Recommendation Based on Soil and Climate Features

The main purpose of the system is to determine an appropriate crop by jointly examining important soil and environmental attributes. The input parameters include Nitrogen, Phosphorus, Potassium, temperature, humidity, soil pH, and rainfall. These variables provide information about nutrient availability, soil conditions, and the surrounding climate, all of which can affect plant growth and crop productivity. The model is trained using agricultural records containing multiple crop categories so that it can learn the relationships between different combinations of input features and suitable crops.

2. Implementation of Random Forest Classifier

The crop prediction component is developed using the Random Forest Classifier, which is a supervised ensemble learning algorithm. Rather than depending on a single decision tree, the algorithm constructs multiple trees using different samples of the training data and subsets of available features. Each tree independently produces a classification result, and the final crop recommendation is determined by aggregating the predictions through majority voting. This ensemble strategy helps improve the stability of the classifier and can reduce the tendency of an individual decision tree to overfit the training data.

3. Improvement over Traditional Crop Selection Methods

Conventional crop selection often depends on personal farming experience, local practices, and observations of seasonal conditions. Although these approaches provide valuable practical knowledge, they may not always account for several agricultural variables simultaneously. The proposed system provides a complementary data-driven mechanism by analyzing multiple soil and climatic features together. This approach can produce more consistent recommendations based on patterns learned from agricultural data and can support informed decision-making under varying environmental conditions.

4. Soil–Climate Feature Analysis

The proposed framework also examines the role of individual agricultural variables in the prediction process. Feature analysis is used to study the relative contribution of soil nutrients and climatic conditions to the classification results. The Random Forest model can provide feature importance information that indicates which variables are particularly influential within the trained model. This analysis helps in understanding how the model uses the available agricultural data and can provide useful insights for researchers and agricultural decision-makers.

5. User-Friendly Prediction System

A simple interface is incorporated to make the prediction system accessible to users. The required soil and climatic values are entered through the application interface, after which the information is processed and supplied to the trained model. The system then returns the predicted crop in a clear format. This workflow is designed to reduce the complexity of interacting directly with the machine learning model and support practical use of the recommendation system.

6. Practical Application in Agriculture

The developed framework can function as a decision-support tool for farmers, agricultural personnel, researchers, and students. It can be particularly useful where immediate access to agricultural expertise is limited. By considering measurable soil and climatic conditions before cultivation, users can obtain analytical support for crop planning, potentially reducing the risk associated with unsuitable crop selection and encouraging more effective use of available agricultural resources.

7. Data-Driven Agricultural Planning

The project demonstrates the application of Artificial Intelligence and Machine Learning in precision agriculture. Historical agricultural observations are used to train a predictive model capable of recognizing patterns between environmental conditions and crop categories. The resulting system illustrates how agricultural planning can be supported by data analysis and predictive modeling.

System Architecture

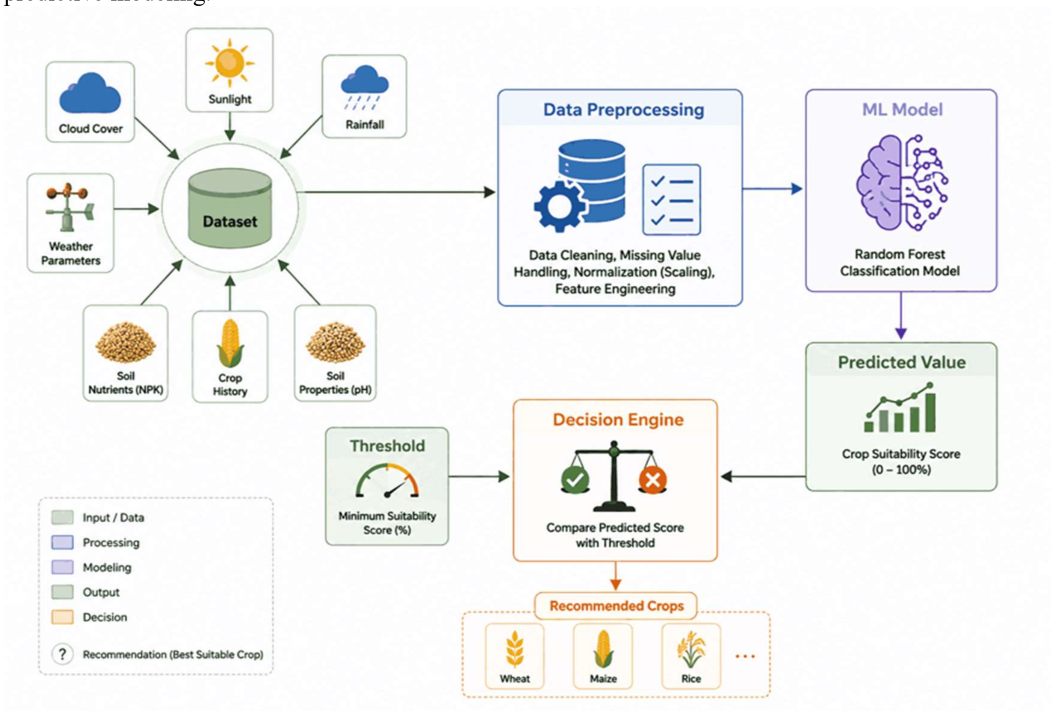

Fig. 1: System Architecture

Explanation

The system architecture represents the flow of information from agricultural input to crop recommendation. Users enter the required soil and climatic values through the web interface. The application receives these values and performs the necessary preprocessing before forwarding the prepared data to the trained Random Forest model. The model analyzes the combined input features and generates a crop prediction based on patterns learned from the agricultural dataset.

The overall architecture establishes communication among the user interface, application layer, dataset, preprocessing operations, machine learning model, and visualization components. This integrated workflow enables the system to transform raw agricultural measurements into a meaningful crop recommendation for decision-support purposes.

Development Tools

Python is used as the primary programming language for developing the proposed crop recommendation system. It is a high-level programming language known for its readable syntax, flexibility, and extensive support for scientific and computational applications. These characteristics make it suitable for implementing the different stages of the proposed framework.

In this project, Python supports data preparation, exploratory analysis, soil-climate feature examination, machine learning model development, prediction, and result generation. Its broad ecosystem of data science and machine learning libraries enables different components of the agricultural application to be developed within a common programming environment.

4. Result and Snapshots

The developed system is implemented as a Python-based web application that integrates the crop recommendation model with an interactive user interface. The application processes the soil and climatic information submitted by the user and communicates with the trained Random Forest model to generate a crop recommendation. The interface design is supported by web technologies such as HTML and Cascading Style Sheets, while the application logic and prediction operations are managed through the backend framework.

The snapshots presented in this section illustrate the main interfaces and stages of system operation. They demonstrate how users interact with the application, provide agricultural input values, and receive the predicted crop as output.

Various Snapshots

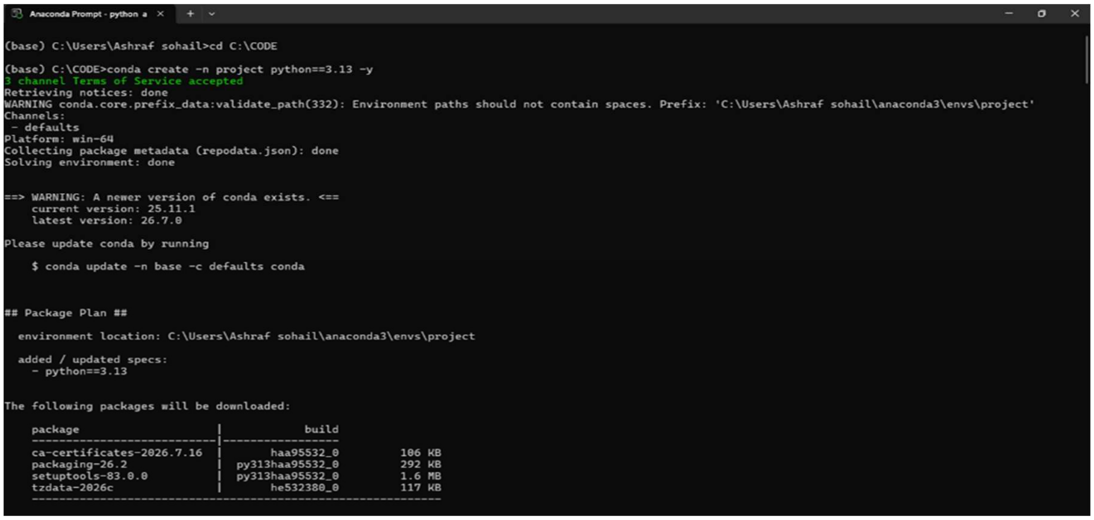

Fig. 2

Fig. 3

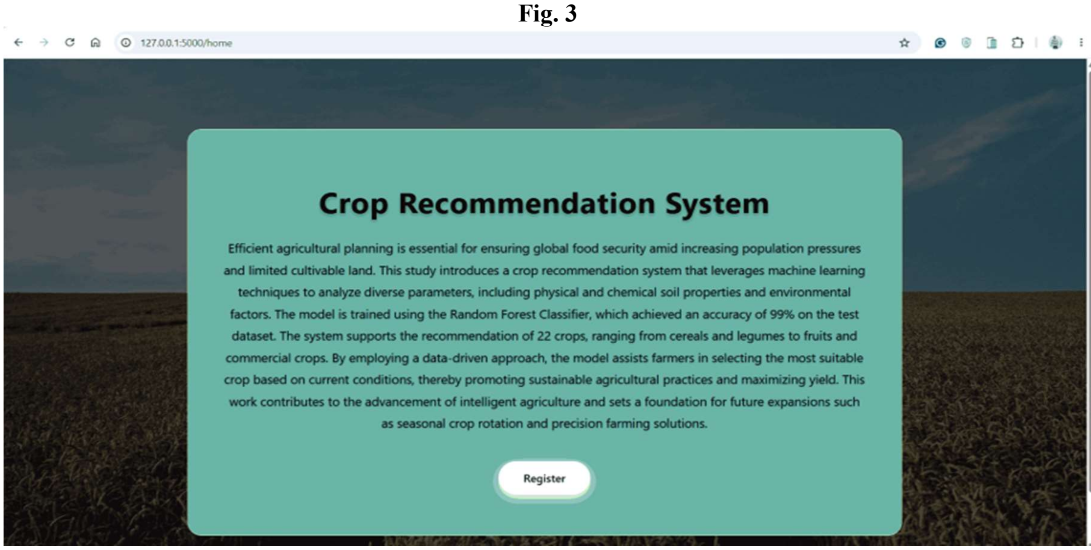

Fig. 4

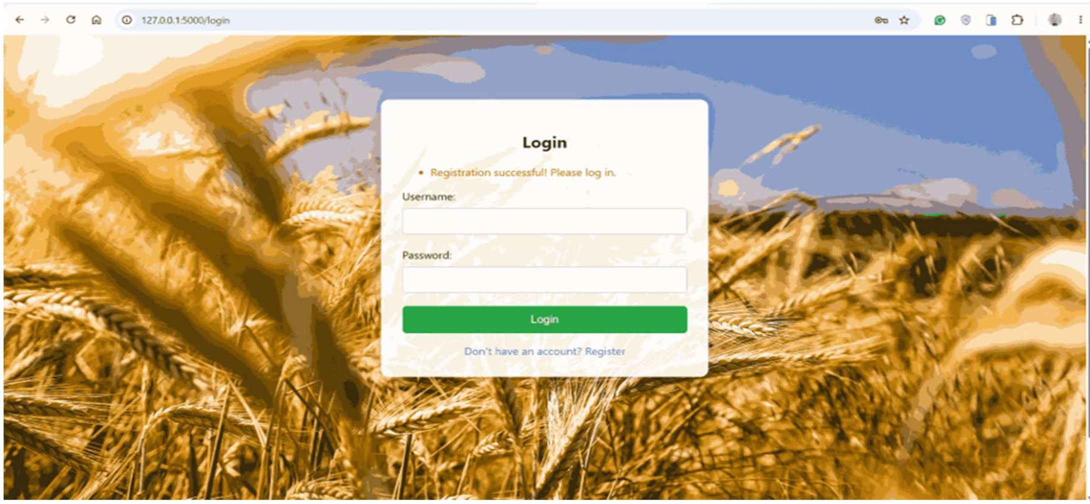
127.0.0.1:5000/login
Login
Registration successful! Please log in.
Username:
Password:
Login
Don't have an account? Register

Fig. 5

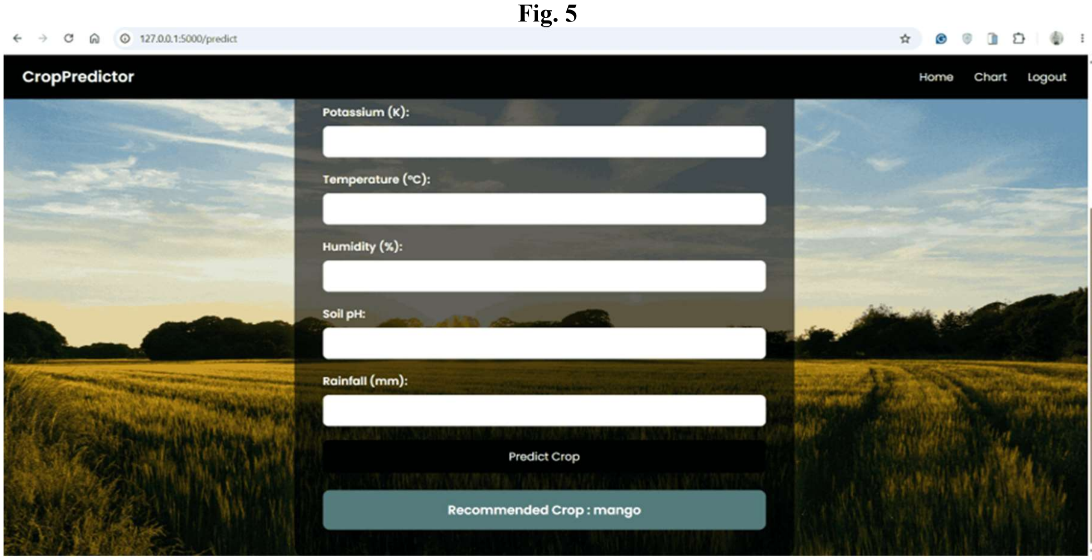
127.0.0.1:5000/predict
CropPredictor
Home
Chart
Logout
Potassium (K):
Temperature (°C):
Humidity (%):
Soil pH:
Rainfall (mm):
Predict Crop
Recommended Crop : mango

Fig. 6

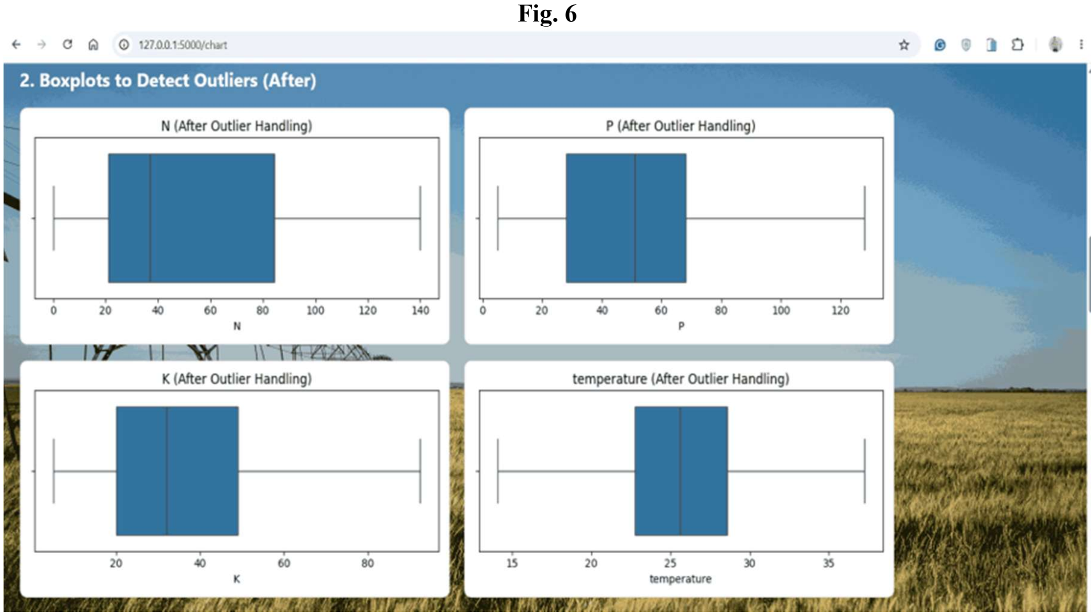
127.0.0.1:5000/chart
2. Boxplots to Detect Outliers (After)
N (After Outlier Handling)
0 20 40 60 80 100 120 140
N
P (After Outlier Handling)
0 20 40 60 80 100 120
P
K (After Outlier Handling)
20 40 60 80
K
temperature (After Outlier Handling)
15 20 25 30 35
temperature

Fig. 7

The following snapshots represent the important screens and operational stages of the proposed crop recommendation application, including the input interface and the presentation of prediction results.

Software Testing

Software testing is an essential activity in the development of the proposed Data-Driven Crop Suitability Recommendation System. Testing is performed to identify implementation errors and verify that the application operates correctly under different input and operating conditions. The process evaluates whether the system satisfies its expected functional and operational requirements while generating crop recommendations from soil and climatic information.

The testing process covers the major components of the application, including data preparation, model operation, crop prediction, feature analysis, and the user interface. Different testing approaches are used to examine the correctness of individual components as well as their behavior after integration. The objective is to ensure that the system responds appropriately to user input and produces consistent results when processing agricultural data.

Future Enhancements

The proposed data-driven crop suitability recommendation system can be further developed to improve its predictive capability, accessibility, and usefulness in real agricultural environments. A major enhancement would be the integration of Internet of Things (IoT)-enabled sensors capable of continuously monitoring soil conditions such as nutrient levels, moisture, temperature, and other relevant parameters. Combining these observations with real-time weather information would allow the system to generate recommendations based on current field conditions rather than relying solely on previously collected datasets.

Cloud deployment represents another important direction for future development. A cloud-based implementation could make the application accessible through smartphones, tablets, and computers, allowing users to obtain recommendations from different locations. Such an architecture could also support centralized data storage, periodic model updates, improved scalability, and simultaneous access by a large number of users.

The predictive component may also be strengthened by evaluating advanced algorithms, including XGBoost, CatBoost, LightGBM, and hybrid ensemble approaches. Comparing these techniques with the existing Random Forest model could help identify algorithms that offer improved accuracy and generalization for particular agricultural datasets. In addition, future datasets may incorporate variables such as soil texture and type, geographical characteristics, irrigation facilities, cropping season, historical climate patterns, and satellite-derived observations. The inclusion of these factors could support more localized and context-aware crop recommendations.

The application may eventually evolve into a broader agricultural decision-support platform. Additional services could include fertilizer selection, irrigation planning, soil quality assessment, crop rotation guidance, pest and disease warnings, and crop yield estimation. A multilingual mobile application with voice-based interaction could further improve accessibility, particularly for users who may find conventional text-based interfaces difficult to use.

5. Conclusion

This work demonstrates the potential of machine learning to support crop selection through the systematic analysis of soil and climatic information. The proposed system uses Nitrogen, Phosphorus, Potassium, temperature, humidity, soil pH, and rainfall as input variables to determine a suitable crop using the Random Forest classification approach. By considering these parameters collectively, the model provides a data-oriented alternative to crop selection based exclusively on traditional experience or individual environmental factors.

The use of Random Forest is beneficial because its ensemble structure combines the decisions of multiple trees, enabling the model to capture complex relationships among agricultural variables while reducing the risk associated with reliance on a single decision tree. The developed application also provides a straightforward interface through which users can enter relevant field and environmental values and obtain a crop recommendation without requiring extensive technical knowledge.

The proposed approach has practical value for farmers, agricultural researchers, students, and other stakeholders involved in crop planning. Selecting crops that are better aligned with prevailing soil and climatic conditions can support more effective use of agricultural inputs and may reduce the risks associated with unsuitable cultivation choices. The system therefore illustrates the role that Artificial Intelligence and Machine Learning can play in developing modern, data-supported agricultural practices.

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