Machine Learning-Based Crop Recommendation System

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***Abstract*— Crop recommendation refers to the process of suggesting suitable crop varieties for cultivation in a specific agricultural area or on a particular piece of land based on various factors and data analysis. The goal of crop recommendation systems is to assist farmers and agricultural stakeholders in making informed decisions about what crops to plant to maximize yield, minimize resource usage, and enhance overall agricultural sustainability. Crop recommendation is necessary to optimize agricultural productivity, minimize resource waste, and promote sustainability, ensuring food security for a growing global population. After going through a rigorous survey, we found the various existing techniques for crop recommendation which include IOT-based, Geospatial, Weather Data integration, Remote Sensing, etc. The agriculture sector faces the dual challenge of meeting the growing demand for food production while optimizing resource usage and mitigating environmental impacts. Precision agriculture, powered by machine learning and data-driven approaches, has emerged as a solution to address these challenges.**

Keywords*— *Machine Learning, Soil Parameters, Precision agriculture.

I. INTRODUCTION

Crop recommendation refers to the process of suggesting suitable crop varieties for cultivation in a specific agricultural area or on a particular piece of land based on various factors and data analysis. A crop recommendation system is a technology-driven solution that provides personalized advice to farmers regarding the selection of crops and best agricultural practices. It uses data analytics, including climate, soil, and historical crop yield data, to make informed suggestions. A crop recommendation system is an innovative agricultural tool designed to assist farmers in making informed decisions regarding crop selection and cultivation practices. A crop recommendation system is an intelligent solution that harnesses data analytics, including factors like soil characteristics, weather patterns, historical crop performance, and market trends, to provide personalized guidance to farmers. This guidance includes crop selection recommendations and optimized farming practices tailored to specific agricultural conditions. Crop recommendation techniques encompass various methods and technologies that assist farmers in making informed decisions about crop selection and farming practices.

The need for crop recommendation systems is to assist farmers and agricultural stakeholders in making informed decisions about what crops to plant to maximize yield, minimize resource usage, and enhance overall agricultural sustainability. Crop recommendation is necessary to optimize agricultural productivity, minimize resource waste, and promote sustainability, ensuring food security for a growing global population. In a world facing climate change, resource scarcity, and a growing population, agricultural efficiency is paramount. Crop recommendation systems address the need for sustainable and productive farming by helping farmers adapt to changing conditions, reduce resource wastage, and maximize yields.

The evolution of crop recommendation systems from ancient practices to modern-day technology signifies a remarkable advancement in agricultural techniques. In the olden days, farmers heavily relied on traditional wisdom and local knowledge to make crop-related decisions, with limited data and manual assessments of soil and climate conditions. However, as technology progressed, so did the methods for guiding farmers in their agricultural endeavors. The transition to modern crop recommendation systems ushered in the era of data-driven approaches, incorporating soil testing, satellite imagery, and real-time weather forecasts for more precise recommendations. Expert systems and rule-based algorithms were introduced to facilitate structured decision-making, while Geographic Information Systems (GIS) and remote sensing technologies added spatial data integration, enhancing recommendation accuracy. The advent of machine learning and artificial intelligence revolutionized crop recommendations, enabling the handling of vast datasets, pattern recognition, and adaptability to changing conditions. Today, crop recommendation systems are highly personalized and accessible through mobile apps, focusing on sustainability and continuous improvement, resulting in more efficient and sustainable agricultural practices that empower farmers to optimize yields and adapt to an ever-changing agricultural landscape.

Machine learning is essential in crop recommendation systems because it elevates the accuracy and adaptability of recommendations, tailors advice to individual farmers, and contributes to sustainable and efficient farming practices. It empowers farmers to make data-driven decisions and harness the benefits of technology in an ever-evolving agricultural landscape. Machine learning is crucial in crop recommendation systems as it enables data-driven decision-making by analyzing extensive agricultural data, recognizing complex patterns, and adapting recommendations to changing conditions. It offers highly personalized advice, optimizes multi-dimensional decisions, and continuously improves over time. Machine learning enhances resource efficiency, contributes to sustainability goals, and can address global food security challenges by increasing agricultural productivity, making it a significant and indispensable component of modern crop recommendation systems.

II. LITERATURE REVIEW

U. Barman et al [1] appears that the paper discusses the use of K-means segmentation and HSV (Hue, Saturation, Value) color image processing techniques to predict soil pH values. This suggests that the paper likely focuses on using image analysis methods to determine soil pH levels, which is a common approach in the field of soil science and agriculture. H. Wang et al [2] This paper appears to focus on the application of hyperspectral technology, specifically the use of hyperspectral data, in combination with a Bat Algorithm-AdaBoost model for the prediction of soil nutrient levels in field conditions. The paper likely discusses the methodology used to integrate hyperspectral technology, the Bat Algorithm, and AdaBoost for accurate soil nutrient prediction. They have also explored the advantages and effectiveness of this combined approach for soil nutrient analysis. A.K. Patel et al [3] This paper focuses on the use of deep learning techniques for estimating the fractional abundance of nitrogen in soil based on hyperspectral data. The paper likely discusses the development and application of a deep learning model for accurately estimating nitrogen content in soil using hyperspectral data as input. This approach can provide valuable insights into soil nutrient levels, which is crucial for agriculture and environmental monitoring. H. K. Sharma et al [4] This paper appears to focus on the application of image processing techniques for soil classification and characterization. The authors likely discuss the methodology and techniques used to process images of soil samples and extract information related to soil classification and characterization. This could involve the analysis of soil texture, color, and other visual features to classify and characterize different soil types or properties. K. M. Anand Vijay et al [5] This paper likely presents a system for agriculture monitoring and management using a mobile application (Agri-App) to enhance crop production. The authors may discuss the design and implementation of the Agri-App, its features, and how it contributes to better crop production and agriculture management. This system involves data collection, analysis, and decision-making support for farmers. E.O. Babalolaet al [6] This paper appears to focus on the classification of soil surface texture using RGB images acquired in uncontrolled field conditions. The authors likely discuss the methodology and techniques used to process RGB images captured under real-world, uncontrolled environments to classify soil surface textures. This research is valuable for applications in agriculture, geology, and environmental science where knowledge of soil texture is important.

K. Srunitha et al [7] This paper appears to focus on evaluating the performance of Support Vector Machine (SVM) classifier for the task of soil classification based on images. The authors likely discuss the methodology, dataset, and results related to using SVM as a classifier for classifying soil types or characteristics from image data. SVM is a commonly used machine learning algorithm for classification tasks. J. V. Rissati et al [8] This paper likely discusses the classification of hyperspectral images using two types of algorithms: Random Forest and Deep Learning. The authors may present the methodology and results related to the use of these algorithms for classifying hyperspectral remote sensing data. Hyperspectral imaging allows for detailed spectral analysis and is widely used in remote sensing applications. Xudong Zhang et al [9] This paper likely discusses a methodology for classifying soil texture using remote sensing data. The authors have employed wavelet transform techniques in combination with the Maximum Likelihood Approach for soil texture classification. Soil texture classification is important in agriculture and environmental studies.

H. S. Abdullahi et al [10] This paper likely discusses the use of Convolutional Neural Networks (CNNs) in precision agriculture for recognizing and classifying plant images. The authors describe how CNNs are employed to automate the recognition and classification of plants based on their images. Precision agriculture benefits from such techniques for crop monitoring and management. H. Alshahrani et al [11] This paper appears to discuss the application of a Chaotic Jaya Optimization Algorithm in combination with computer vision techniques for soil type classification in the context of smart farming. The authors describe how this optimization algorithm is used to improve the performance of computer vision-based soil classification. This research aims to enhance soil analysis and decision-making in agriculture. S. Agarwal et al [12] This paper likely discusses the application of colorimetry (a technique that measures color properties) for determining soil fertility. The authors use the Naive Bayes classification algorithm to classify soil samples based on colorimetry data. The aim is to develop a method for assessing soil fertility through color analysis, which can be valuable in agriculture. M. Van Rooyen et al [13] This paper likely discusses the automation of soil classification and identification using machine vision techniques. The authors describe how machine vision technology is applied to analyse and classify soil samples based on visual data. Such automation can be valuable in various applications, including agriculture and environmental monitoring

P. A. Harlianto et al [14] This paper likely presents a comparative study of different machine learning algorithms applied to soil type classification. The authors have evaluated and compared the performance of various machine learning techniques for classifying soil types based on different features or data sources. The study could provide insights into the effectiveness of different algorithms for this specific task. R. Jin et al [15] This paper likely discusses the development and application of a decision tree algorithm for the classification of surface soil as either freeze or thaw using data from the Special Sensor Microwave/Imager (SSM/I). The authors describe how decision tree-based algorithms are used to classify the freeze/thaw status of surface soil based on remote sensing data. Such classification is valuable in environmental and climate studies. S. A. Z. Rahman Li et al [16] This paper likely discusses the use of machine learning methods for soil classification and crop suggestion based on soil series. The authors describe how machine learning techniques are employed to classify soil types and how this classification is then used to provide recommendations for suitable crops to be grown in specific soil types. This type of research can be valuable in precision agriculture and optimizing crop production.

III. PROPOSED METHODOLOGY

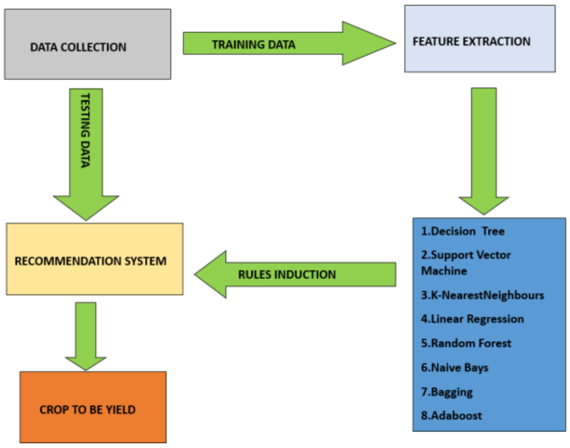

Fig. 1. Data flow within an Operational ML crop classifier

A. Problem Definition

The goal of the Crop Recommendation System is to assist farmers in selecting suitable crops for cultivation based on various factors such as soil type, climate, and other environmental conditions. This helps optimize agricultural yield and resource utilization.

B. Input Dataset

Data collection is the most common approach for gathering and analyzing information from various sources. The dataset must have the following qualities to provide an approximate data set for the system. These criteria will be considered for crop recommendation: Nitrogen (N), Phosphorus (P), Potassium (K) value, temperature, humidity, PH, and rainfall.

C. Data Pre-Processing

Data preprocessing for machine learning-based crop recommendation involves initial data collection on factors like soil type, temperature, humidity, and rainfall, followed by cleaning to handle missing values and outliers. Feature selection and extraction focus on relevant crop-growth impacting variables, while normalization or scaling ensures consistency across features. The dataset is then split into training and testing sets for model evaluation. For Logistic Regression, Naive Bayes, and SVM, categorical variables are encoded and continuous ones are scaled; Decision Tree, Random Forest, and Extra Trees handle categorical variables naturally but might benefit from scaled continuous ones. Bagging and AdaBoost, as ensemble methods, undergo similar preprocessing to their base models. After training and hyperparameter tuning, model evaluation using metrics like accuracy or precision helps select the most suitable algorithm for crop recommendation based on the dataset and problem characteristics.

D. Feature Engineering

Feature engineering for machine learning-based crop recommendation involves identifying and selecting relevant agricultural factors like soil type, temperature, humidity, and rainfall as input variables. For Logistic Regression, Naive Bayes, and SVM, categorical variables are encoded (e.g., one-hot encoding), and continuous variables are scaled to ensure compatibility. Decision Tree, Random Forests, and Extra Trees benefit from domain-specific features impacting crop growth and might benefit from explicit feature selection or importance analysis. Bagging and AdaBoost focus on diverse feature sets to leverage ensemble learning, emphasizing the creation of features that enable weak learners to capture different aspects of the agricultural data. Overall, feature engineering tailors input variables to suit each algorithm's strengths, aiming to improve the accuracy and robustness of the crop recommendation system.

E. Testing set

In machine learning-based crop recommendation systems, the testing phase involves splitting the dataset into training and testing sets, training the models (Logistic Regression, Naive Bayes, SVM, Decision Tree, Random Forest, Bagging, AdaBoost, Extra Trees) on the training data to learn patterns between agricultural features and recommended crops, and then evaluating their performance using the unseen testing set. Each algorithm predicts crop suitability based on the testing set's agricultural conditions, allowing for the calculation of performance metrics such as accuracy, precision, recall, or F1-score. This comparative analysis across algorithms enables the selection of the most effective model for providing accurate crop recommendations in real-world scenarios with previously unseen agricultural data.

F. Machine Learning Algorithms

Machine learning is a subset of artificial intelligence that uses data to train computer models to make predictions or decisions. In crop recommendation systems, machine learning is employed to suggest the best crops for farmers to plant based on factors like weather, soil conditions, and historical data, helping optimize agricultural productivity. The following algorithms are used for recommending the crop.

1) *Logistic Regression:* Logistic Regression in crop recommendation processes agricultural features like soil type, temperature, humidity, and rainfall to predict the probability of a crop being suitable. By learning the relationships between these features and crop suitability. Logistic Regression establishes a decision boundary in the feature space, allowing it to classify crops accordingly. When presented with new agricultural data, the model computes the probability of a crop being suitable based on these learned relationships, facilitating recommendations based on predetermined thresholds.

a) Mathematical Model:

- $h\theta(x)$ represents the predicted probability that the crop is suitable.
- θ is the parameter vector.
- x is the input feature vector.

Input Features (x): Let's say x consists of N. P, K values, Temperature, Humidity, pH level, Rainfall

2) *Naive Bayes:* Naive Bayes contributes to crop recommendation systems by utilizing conditional probability estimation based on agricultural features like soil type, temperature, humidity, and rainfall. Operating under the assumption of feature independence, this algorithm calculates the likelihood of a crop being suitable given these features by employing Bayes' theorem. During model training, it learns the probabilities associated with each feature given the class of crop suitability. When presented with new agricultural conditions, Naive Bayes computes the probability of crop

suitability for each class and selects the class with the highest probability as the recommended crop. While Naive Bayes is efficient and effective for handling numerous features with limited data, its assumption of feature independence might not fully capture complex relationships among variables, potentially affecting its accuracy in more intricate agricultural scenarios.

a) Mathematical Model:

$P(Y \mid X) = P(X \mid Y) \times P(Y) / P(X)$

Where:

- $P(Y \mid X)$ is the posterior probability of class Y given predictor X.
- $P(X \mid Y)$ is the likelihood of predictor X given class Y.
- $P(Y)$ is the prior probability of class Y.
- $P(X)$is the probability of predictor X.

3) Support Vector Machine (SVM): Support Vector Machines (SVM) aid crop recommendation systems by delineating a decision boundary in the agricultural feature space to classify crops based on their suitability. By mapping agricultural features like soil type, temperature, humidity, and rainfall into a higher-dimensional space, SVM aims to find the optimal hyperplane that best separates different classes of crops.

a) Mathematical Model: For simplicity, let's consider a classification problem where the goal is to recommend crops based on input features.

b) Input Features: Let X = (N, P, K, temperature, humidity, pH, rainfall) represent the input feature vector for a particular region.

c) Output/Classes: The output will represent the classes of crops suitable for the given conditions (e.g., Wheat, Rice, Corn, etc.).

d) SVM Objective: SVM aims to find a hyperplane that best separates the classes while maximizing the margin between the classes.

e) Mathematical Representation: The decision boundary in SVM is represented by: $w^T \cdot x + b = 0$

* w is the weight vector perpendicular to the hyperplane.
* b is the bias term.
* x is the input feature vector.

4) K-Nearest Neighbors (K-NN): K-Nearest Neighbors (KNN) is employed in crop recommendation systems by leveraging the similarity of agricultural features to predict the suitability of crops. Operating on the principle that similar agricultural conditions often correspond to similar crop recommendations, KNN identifies the 'k' most similar data points (neighbors) to the new agricultural conditions in the dataset. By considering the majority class among these neighbors, KNN assigns the crop recommendation to the new input based on a voting mechanism. For instance, if most of the 'k' nearest agricultural conditions suggest a particular crop as suitable, KNN predicts the same crop for the new input. KNN's simplicity and intuitive nature make it a valuable choice for crop recommendation, particularly when the relationship between features and suitability relies on local similarity patterns within the dataset. However, its performance might be affected by high dimensionality or noisy data.

a) Mathematical Model: Input features (Nitrogen, Phosphorus, Potassium, temperature, humidity, pH, rainfall). K: Number of nearest neighbors to consider.

b) Calculate Distance: Use a distance metric (e.g., Euclidean distance) to measure the distance between X and all other data points in the dataset.

c) Find K Nearest Neighbors: Select the K-data points with the smallest distances to X

d) Majority Vote or Weighted Average: For classification: Assign the most frequent class among the K neighbors as the predicted crop. For regression: Take the average of the target values of the K neighbors as the predicted value.

5) Decision Tree: Decision Trees are utilized in crop recommendation systems to create hierarchical structures that represent decision rules based on agricultural features, enabling the prediction of suitable crops. By recursively partitioning the feature space, Decision Trees identify the most influential agricultural factors for classifying crops. Each node in the tree represents a feature and each branch represents a decision based on that feature, leading to the prediction of crop suitability at the leaf nodes. When presented with new agricultural data, the Decision Tree navigates through its branches based on the input features, ultimately recommending a crop based on the traversal path. Decision Trees are interpretable and effective at handling both categorical and numerical data, making them valuable for crop recommendation systems, though they might overfit with complex or noisy datasets, which can be mitigated through techniques like pruning or ensemble methods.

a) Decision Nodes: Splitting criteria decision trees make decisions based on features to create branches. For instance, "Is N > 40?" could be a decision node. Information gain measures the homogeneity of a node. For classification, Gini Impurity or Information Gain is commonly used to determine the best split.

b) Leaf Nodes: Predictions of the Leaf nodes represent the final decision or classification. For crop recommendation, it could be the suggested crop based on the conditions.

6) Random Forest: Random Forests are instrumental in crop recommendation systems by leveraging an ensemble of Decision Trees to enhance prediction accuracy and robustness. They operate by constructing multiple Decision Trees on random subsets of the agricultural data and features, each tree providing its prediction. When making a recommendation for a new set of agricultural conditions, the Random Forest aggregates the predictions from all individual trees through a voting or averaging mechanism, ultimately offering a more stable and accurate recommendation. Random Forests mitigate overfitting tendencies of individual trees and handle high-dimensional data while maintaining the interpretability and feature importance assessment provided by Decision Trees. This ensemble method excels in handling complex relationships between agricultural features and crop suitability, making it a potent tool in crop recommendation systems.

a) Decision Trees: Random Forest is an ensemble of decision trees. Each decision tree is constructed using a subset of the training data and a random subset of features.Trees are trained recursively by splitting the data based on feature values until certain conditions are met (e.g., purity of nodes, maximum depth).

b) Ensemble Method: Multiple decision trees are built independently. For classification tasks, each tree predicts the class and, in regression, predicts a continuous value. The final prediction is often the mode (for classification) or average (for regression) of predictions made by individual trees.

7) AdaBoost: AdaBoost, a boosting technique, contributes to crop recommendation systems by iteratively training weak learners (often Decision Trees) on subsets of agricultural data, assigning higher weights to incorrectly classified instances in each iteration. This process emphasizes the misclassified data points, enabling subsequent models to focus more on getting those instances correct. When predicting the suitability of crops for new agricultural conditions, AdaBoost combines the outputs of these weak learners to form a strong ensemble model. Each weak learner contributes their prediction, and their combined result, weighted by their performance, generates the final crop recommendation. AdaBoost adapts well to complex relationships in agricultural data, continuously improving its prediction accuracy by learning from previous model errors, making it effective in crop recommendation systems where precise classification is essential.

IV. Results & Discussions

Machine learning is instrumental in modernizing and improving agriculture through the development of crop recommendation systems. By harnessing the power of data and predictive modeling, these systems empower farmers with actionable insights for more efficient and sustainable farming practices. The classification algorithms exhibit varying levels of accuracy, with Naive Bayes, Random Forest, and Bagging standing out as top-performing choices, each achieving a high accuracy of 99%. These algorithms are well-suited for accurately categorizing crops based on input data, but the final selection should also consider factors such as computational efficiency, and interpretability.

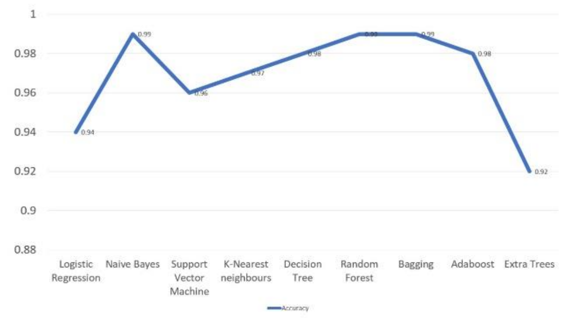

Fig. 2. Comparison of training time accuracy

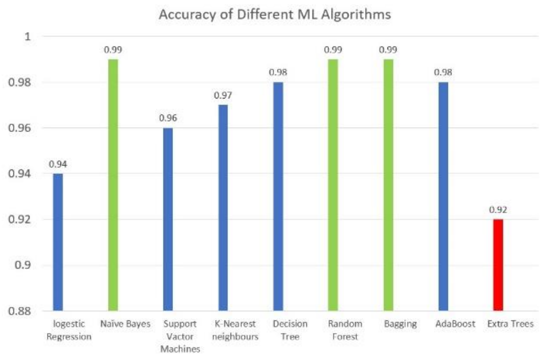

Fig. 3. Comparision of accuracy

These accuracy percentages represent how well each algorithm performs in classifying data into different categories, with higher percentages indicating greater accuracy in making correct predictions. The choice of algorithm depends on the specific problem and the balance between accuracy and other considerations, such as model complexity and interpretability.

V. Summary

Crop recommendation systems have advanced by integrating traditional methods with machine learning techniques, utilizing historical data, climate insights, soil quality, and crop characteristics to offer tailored suggestions to farmers. Machine learning algorithms like decision trees, random forests, and neural networks enhance accuracy by analyzing vast datasets and identifying complex patterns. IoT sensors and remote sensing technology provide real-time data on soil moisture, weather, and crop health for dynamic adjustments. The synergy of agricultural knowledge and machine learning empowers farmers to optimize yields, resource usage, and sustainability. Machine learning plays a crucial role in data-driven decision-making, contributing to efficient resource utilization and addressing global food security challenges, making it a vital component of modern crop recommendation systems.

VI. Conclusion

Machine Learning crop recommendation system for different crops is based on soil dataset features that as Nitrogen (N), Phosphorus (P), Potassium (K) values, temperature, humidity, pH, and rainfall values through these values, we recommend the crop-based on that's values. Overall, they make farming smarter, more efficient, and better for the environment.

We proposed the system using a well-trained ml model to recommend the crop that will make smart farming. This improves the accuracy of crop recommendations, promotes sustainable resource usage, enhances climate resilience, ensures accessibility for all farmers, addresses data processing challenges, and prepares for future agricultural needs. These project collectively work toward addressing the problem of inefficient and imprecise agricultural recommendations, benefiting both farmers and the agriculture sector as a whole.

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