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Crop Recommendation System Using Machine Learning: A Comparative Study

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Abstract

Agriculture, as a fundamental aspect of human existence, faces challenges in crop selection, impacting resource allocation and productivity. This project addresses these challenges by proposing a stable system employing a soft voting classifier ensemble method. The ensemble comprises Naive Bayes, Support Vector Machine (SVM), Decision Tree, and Random Forest classifiers, offering personalized crop recommendations. Feasibility analysis encompasses technical, operational, economic, and scheduling aspects, ensuring practicality and efficacy. Development follows an incremental model, emphasizing continuous enhancement through feedback. Results indicate accuracies for individual classifiers ('Decision Tree': 98.38%, 'Random Forest': 98.90%, 'Naive Bayes': 98.14%, 'SVM': 98.50%), with an ensemble accuracy of 98.99%. Cross-validation confirms robustness. Evaluation metrics such as recall, precision, and F1 score demonstrate that the soft voting ensemble outperforms individual classifiers, highlighting its effectiveness in optimizing crop selection processes in agriculture and facilitating improved resource management and productivity.

Keywords: Ensemble, Recommendation, Cross Validation, Robustness, Recall

1. Introduction

Agriculture is also a growing industry; however, farmers have still relied on inherited knowledge and local practices to make crop selection decisions.

Lack of guidance leads to reduced productivity. Traditional farming, dependent on outdated techniques, faces limitations. The need for skilled guidance is crucial for better productivity, benefiting farmers. Existing traditional knowledge lacks a system to detect environmental factors and suggest the best crops for farming (Bandara, et al., 2020). A key challenge in conventional farming is farmers frequently neglecting to choose crops according to soil needs, significantly impacting overall productivity (S Kiruthika, 2023).

Agriculture struggles with crop selection challenges due to limited resources and technical expertise. This hinders informed decisions for sustainable choices. The absence of personalized recommendations, coupled with traditional methods lacking precision, contributes to low productivity. Urgently needed is an advanced crop recommendation system utilizing machine learning to enhance productivity, optimize resources, and improve livelihoods (Abdullahi, et al., 2015). The digital revolution in agriculture, driven by artificial intelligence and machine learning, enhances management practices by extracting value from extensive data. This study specifically focuses on machine learning's role in addressing challenges in knowledge-based farming systems, particularly "crop recommendation." It highlights the efficiency of ensemble learning approaches (Benos, et al., 2021).

2. Related Works

The researchers in (Kalimuthu, et al., 2020) highlight the persistent challenge of escalating food security issues in India. The paper addresses the depletion of food production and prediction due to disruption in natural climatic conditions and stresses on trend of diminishing GDP in the agricultural sector, where over 80% of the GDP is derived from rural areas, directly affecting the livelihoods of farmers in such areas. The paper suggests the implementation of modern technology to tackle this problem and mentions the deployment of machine learning technology with Naive Bayes as a supervised learning algorithm is a way to actually suggest and guide the farmers in India to sow the reasonable crops in their lands. The system outlined in the paper uses mobile application to take the input parameters in order to predict the most suitable crops, providing farmers with a tailored list of cost-effective crop options for their specific plots of land. The authors in (Vaishnavi, et al., 2021) highlight the inadequacy in agricultural productivity in southern India where words-of-mouth proved beneficial for productivity in past decades but doesn't really benefit at present due to changing climatic factors. There is a necessity for developing efficient technique to facilitate crop cultivation. The paper acknowledges IT sector as helpful in improving the situation and focuses on integration of modern technological methods, particularly data analytics and machine learning in addressing the challenges faced by the farmers. The paper suggests data analytics as a means to pave a way for extracting useful insights from agricultural database, and such insights may help future agriculturalists to have better agricultural productivity. The paper provides recommendation system as an approach to provide the suggestions to the users. The paper (Reddy, et al., 2020) addresses the growing trend of digital storage for health records as it has become tedious to maintain and operate on manually written records. The researchers have chosen Diabetic Retinopathy as a field of study where time and resource utilization play huge role to combat atrocities pertinent to this disease. They have highlighted the failure of various machine learning models as each of these models failed to provide satisfactory results in prediction and detection of this disease. The researchers then proposed a model that ensembles the existing machine learning models as a way to get best predictive results, which comprised of Random Forest classifier, Decision Tree classifier, Adaboost classifier, K-Nearest Neighbor classifier and Logistic Regression classifier. The paper also emphasizes the normalization of datasets using min-max normalization method. In the paper, the researchers primarily deal with understanding of how ensemble learning can improve healthcare diagnostics, specifically in diabetic retinopathy cases. The researchers in (Nagendra Kumar, et al., 2020) acknowledge the necessity for increasing production in agriculture as the demand for food products has been increasing exponentially with time. Even with various modern techniques available, people are still ignorant on using them (Chapagain, 2023) properly leading to degrading soil quality and further environmental harm. The paper suggests machine learning as a crucial perspective to make the producers familiar with proper and accurate information on the crop yield. The machine learning model suggested in the paper utilizes various machine learning algorithms like Random Forest algorithm, Decision Tree algorithm and Support Vector Regression algorithm in the initial development phase. The paper suggests Random Forest algorithm as the best model that reduces the overfitting problem caused by decision tree algorithm and largely improves the accuracy as compared to SVR model. With all the data provided the proposed model processes all the data using random forest and predicts the crop yield. The paper (AKYOL, et al., 2022) addresses heart disease as one of the leading causes of death around the world and considers the routine clinical data analysis as difficult means to provide early diagnosis of cardiac diseases. The paper suggests that the use of machine learning benefits the identification of cardiac diseases and potentially prevent deaths in much significant amount. The author emphasizes using the maximum voting ensemble technique of classification and using inter quartile range method for removing outliers and min-max method for normalization while preprocessing. Among various machine learning models like XGboost, Decision Tree, Gradient Boost, K-Nearest Neighbor and SVM, the max-voting ensemble technique chooses the best possible model to provide the output. The paper (Korkontzelos & Nnamoko, 2020) proposes a computer-aided diagnosis system for otitis media, addressing challenges like high costs and subjectivity. It introduces a novel approach using a voting ensemble framework with five pretrained CNN models trained on the Public Ear Imagery dataset. Achieving exceptional classification performance, the soft voting ensemble framework attains 98.8% accuracy, 97.5% sensitivity, and 99.1% specificity for various

tympanic membrane conditions. These results indicate significant improvement over existing methods, promising enhanced accuracy and stability in automatic diagnosis of otitis media.
The utilization of classification-based algorithms, including Support Vector Machines (SVM), Naive Bayes, Decision Trees, and Random Forest, as well as meticulous data preprocessing techniques such as normalization and under sampling, has been identified in the literature as pivotal for the development of this research.

3. Methodology

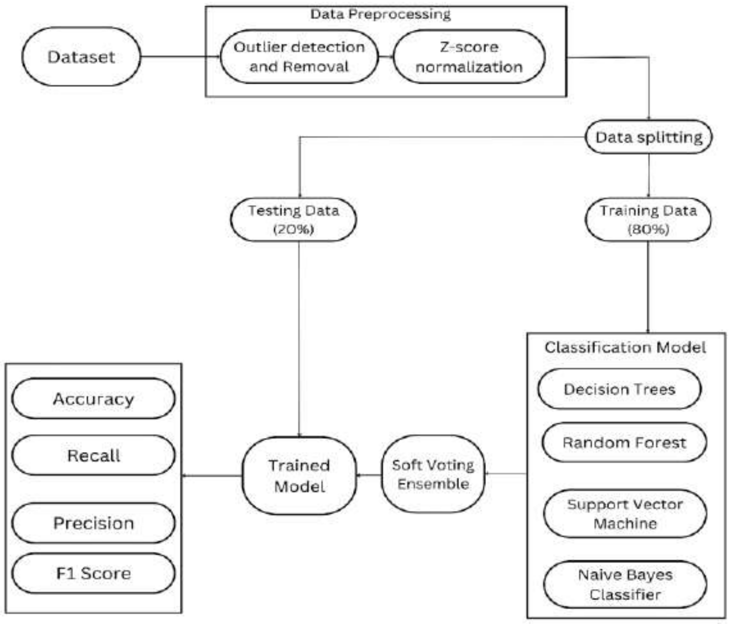

Figure 1. Working Mechanism of Crop Recommendation System

3.1. Dataset Description

The dataset was constructed by compiling rainfall, climate, and fertilizer data available, where Urea represents the ratio of urea content in soil, P represents the ratio of Phosphorous content in soil, K represents the ratio of Potassium content in soil, temperature is measured in degrees Fahrenheit and pH indicates the soil's acidity or alkalinity. The dataset consisted of 1,00,000 observations, encompassing a diverse set of variables including Urea, Phosphorus (P), pH, Temperature and Potassium (K). The dataset covered information on 10 unique crops with each crop having 10,000 observations. The subsequent step involved building the system using this dataset.

	pH	Soil EC	Phosphorus	Potassium	Urea	T.S.P	M.O.P	Moisture	Temperature	Plant Type
0	6.021428	0.237700	15.987947	133.206193	45.627373	16.952809	23.362074	79.234006	52.094083	Carrots
1	6.342420	0.211844	15.305906	137.856536	59.460887	18.378723	22.143606	75.612889	51.349760	Carrots
2	6.684784	0.290343	14.778959	132.994257	53.567383	17.207365	27.448977	77.277833	61.162072	Carrots
3	6.552203	0.407055	12.328408	109.766048	41.053263	12.086209	21.630035	76.426754	72.280843	Carrots
4	6.705262	0.533824	11.215420	102.429536	37.250965	14.953550	24.008938	76.718368	58.710557	Carrots

Figure 2. Raw Dataset

Figure 1 shows minimal portion of the dataset to familiarize with the value content in different features.

3.2. Algorithm Description

In our crop recommendation system, we employ different algorithms to provide valuable insights to farmers seeking the most suitable crop for their agricultural conditions. The algorithm relies on historical datasets containing essential parameters such as Urea, Phosphorous, Potassium, pH, Temperature and plant type. In the first step, we gather and pre-process the dataset, organizing the information into relevant features and corresponding crop labels.

3.2.1. Naïve Bayes

The Naïve Bayes algorithm, a form of supervised learning, relies on Bayes' theorem and is primarily utilized for classification tasks. Text classification, a common application of Naïve Bayes, often involves extensive training data with high dimensionality. Despite its simplicity, Naïve Bayes is remarkably effective in classification tasks, facilitating the rapid construction of machine learning models capable of swift predictions. Operating on the probability of an object, it earns its moniker as a probabilistic classifier.

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \quad \text{(Equation 1)}$$

where, P(A|B) is the Posterior probability, P(B|A) is the Likelihood probability, P(A) is the Prior probability, P(B) is the Marginal probability (Raj, et al., 2021).

In the research, the classes denoted by A include various crop items like tomatoes, rice, wheat, cinnamon, and carrots, while B represents features such as pH level, temperature, potassium content, phosphorus content, and urea content. These class-feature combinations form the basis for applying the Naïve Bayes algorithm in the study.

3.2.2. Support Vector Machine

Support Vector Machine (SVM) is a powerful method for building a classifier in a crop recommendation system. It aims to create a decision boundary, known as the hyperplane, between different classes of crops based on the input features such as pH, temperature, potassium, phosphorus, and urea levels. The goal is to accurately predict the suitable crop type based on these features. Given a labeled training dataset, (x1, y1), ..., (x5, y5), where x_i is a feature vector representing the features and y_i is the class label of a training dataset. The optimal hyperplane can be defined as:

$$wx^T + b = 0 \quad \text{(Equation 2)}$$

where, w is the weight vector that determines the orientation of the hyperplane in the feature space, x is the input feature vector representing environmental conditions and b is the bias term. The decision boundary created by the hyperplane is positioned to maximize the margin between the different classes of crops. The data points closest to the hyperplane on either side, known as support vectors, are critical in defining the hyperplane. To ensure that the hyperplane effectively separates the classes, the following conditions must be satisfied for all elements of the training set:

$$wx_i^T + b \geq +1 \; if \; y_i = 1 \; (indicating \; a \; positive \; class) \quad \text{(Equation 3)}$$

$$wx_i^T + b \geq -1 \; if \; y_i = -1 \; (indicating \; a \; negative \; class) \quad \text{(Equation 4)}$$

The objective of training an SVM model is to find the optimal values of w and b that maximize the margin between the classes while satisfying the above conditions. This is achieved by solving an optimization problem to minimize 1/w2, subject to the constraints mentioned earlier (Huang, et al., 2018).

3.2.3. Decision Tree

Decision tree generates a tree like structure, operating as a classifier. The nodes of tree indicate data attributes and the edge encapsulates decision rules. The classifier, in this system, calculates information gain for each attribute and finds the highest information gain difference between the target attribute (i.e., plant type) and other attributes (temperature, pH, Phosphorous, Potassium, Urea) to find the most relevant node for the iteration. Commencing from then root node with the decision rules, descendant nodes are selected until a terminal node is reached. The information gain for attribute selection is given by:

Information Gain = Entropy(S) - [(Weighted Average) * Entropy (Each feature)] (Equation 5)

$$Entropy(S) = -P(yes)log_2\big(P(yes)\big) - P(no)log_2(P(no)) \quad \text{(Equation 6)}$$

where, S = Total number of data sample, P(Yes) = Probability of yes, P(No) = Probability of no (Chapagain, 2023).

3.2.4. Random Forest

The Random Forest algorithm is a potent ensemble learning technique widely employed in crop recommendation systems for classification tasks. In contrast to the Support Vector Machine (SVM), which focuses on establishing a hyperplane for class separation, Random Forest constructs multiple decision trees and amalgamates their outputs to generate robust predictions.

A Random Forest constitutes a classifier composed of an assembly of tree-structured classifiers, where independent random vectors are distributed uniformly. Each tree independently makes a decision for the most prevalent class based on input x, as illustrated in the figure. A random vector is generated autonomously of previous random vectors, maintaining the same distribution, and a tree is constructed using the training set [8,9]. The key advantages of employing the Random Forest algorithm include enhanced accuracy, resilience to outliers' faster execution compared to bagging and boosting, and simplicity, making it easy to parallelize. The Random Forest operates in two phases: the first involves creating the random forest by amalgamating N decision trees, and the second entails making predictions for each tree generated in the initial phase.

Algorithm for Random Forest in Machine Learning:

Step 1: Select random K data points from the training set.

Step 2: Build the decision trees associated with the selected data points (Subsets).

Step 3: Choose the number N for decision trees that you want to build.

Step 4: Repeat Step 1 & 2.

Step 5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes (Radhimeenakshi. & Buvaanyaa, 2023).

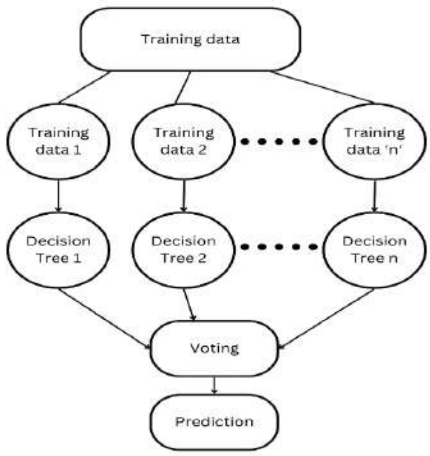

Figure 3. Random Forest

3.2.5. Ensemble Model

Ensemble learning enhances the performance of individual machine learning models by training multiple models to generate improved predictions. It involves using predictors, often decision trees for quantitative problems, and aggregating their results to make conclusive decisions (Reddy, et al., 2020).

In the research, ensemble learning builds a model that learns from the dataset comprising of soil contents and plant type. The dataset contains different variables (Urea, Phosphorous, Potassium, pH, Temperature) and also 5 different types of crops (tomatoes, rice, wheat, cinnamon, and carrots). In this process, diverse models are tested, compared based on accuracy, and their varied learning techniques and assumptions allow compensating errors made by one model with correct predictions from others. It recommends the farmers the right crop to increase in yielding hence increase in overall productivity with the proposed ensemble model with individual base learners Gaussian Naive Bayes, SVM, Decision tree, Random Forest.

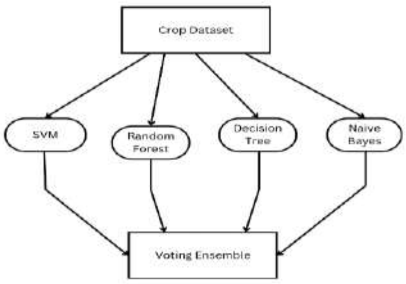

Figure 4. Ensemble Model

3.3. Performance Analysis

3.3.1 Outlier Detection and Removal

In this particular study, a dataset sourced from Kaggle is utilized, noted for its lack of null values. Consequently, during the data preprocessing phase, outlier detection and removal, along with normalization, are carried out. Detecting outliers involves identifying patterns within the data that fall beyond the expected range of normal behavior. These outliers, which deviate from anticipated statistical distributions, can significantly affect the accuracy of the system. They can arise from various factors such as malicious activity, errors in instrumentation, environmental changes, or human error. The Interquartile Range (IQR) is a preprocessing technique used to identify outliers and extreme values in a dataset. It assesses dispersion by dividing the dataset into four equal parts known as quartiles. These quartiles, denoted as Q1, Q2, and Q3, represent specific values within the dataset's distribution. Q1 and Q3 represent the middle values of the first and second halves of the dataset respectively, while Q2 is the median value of the entire dataset. The IQR is then calculated as the difference between Q3 and Q1.

Outliers are identified as data instances falling below Q1 – 1.5 IQR or above Q3 + 1.5 IQR.

Lower Boundary: $Q1 - 1.5 * IQR$ (Equation 7)

Upper Boundary: $Q3 + 1.5 * IQR$ (Equation 8)

The data resides outside of the lower and upper boundary are outliers and are removed to clean the dataset (Korkontzelos & Nnamoko, 2020).

Outliers have been detected in the pH, urea, and potassium features, which introduce noise into the datasets. The Interquartile Range (IQR) method is employed to identify and remove these outliers, utilizing a threshold of 1.5 for outlier removal. As a result, there is a decrease in the number of datasets within the Wheat class to 8437 and within the Tomato class to 8082. To address this reduction, under sampling techniques have been implemented to balance the dataset, ensuring representative samples for analysis.

Figure 5 shows that there is significant number of outliers in pH that are essential to be removed. Figure 6 shows that there is a smaller number of outliers in potassium that are to be removed. Figure 7 shows that there is significant number of outliers in urea that are essential be removed.

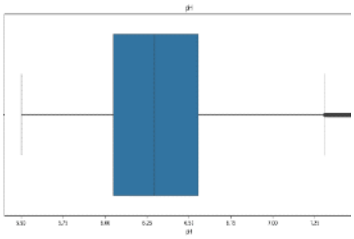

Figure 5. Outliers in pH

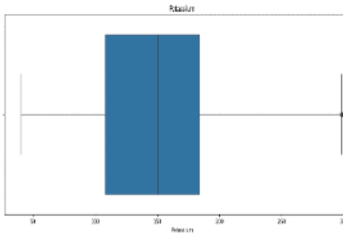

Figure 6. Outliers in Potassium

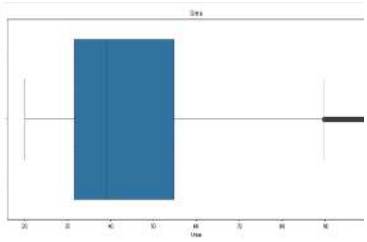

Figure 7. Outliers in Urea

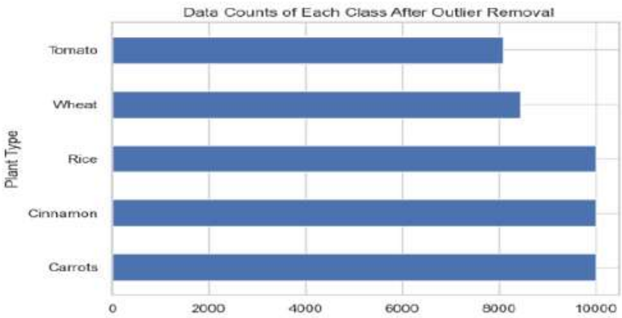

Figure 8. Data Counts After Outlier Removal

Figure 8 shows the number of data counts in each class after the successful removal of outliers. Under sampling is done in order to bring uniformity in data counts for each class, shown by figure 9 below.

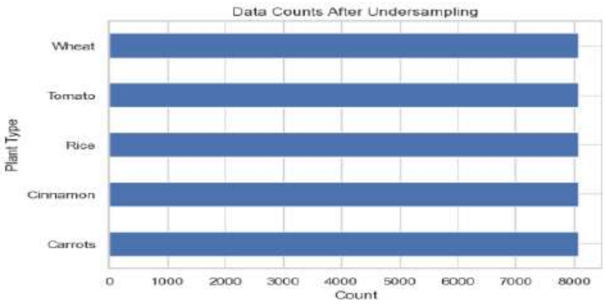

Figure 9. Data Count After Under Sampling

3.3.2 Z-score Normalization

Z-score normalization is implemented in under sampled datasets, given the wide-ranging values observed for features like pH, temperature, potassium, phosphorus, and urea levels across the various classes. This normalization method ensures that all features are on a comparable scale, which is essential for optimal model performance. By standardizing the data in this manner, it has been expected that it will enhance the model's ability to accurately interpret and make predictions based on the diverse input variables present in the dataset.

$$x'_i = \frac{x_i - \mu}{\sigma} \qquad \text{(Equation 9)}$$

where x'_i is normalized data, x_i is original data, μ is the average of data, and σ is the standard deviation of the data.

3.3.3 Exploratory Data Analysis

The analysis reveals distinct nutrient requirements and environmental preferences among different crop classes. Rice exhibits the highest demand for phosphorus, followed by Wheat and Tomato. Wheat requires the most potassium, followed by Tomato and Rice. Regarding temperature preference, Rice prefers the highest levels, followed by Tomato and Cinnamon. Additionally, Tomato requires the most urea for optimal production, followed by Rice and Carrots.

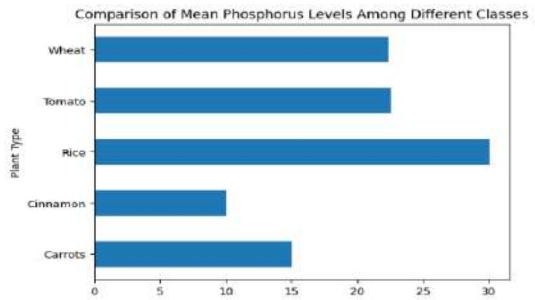

Figure 10: Comparison of Mean Phosphorus with Classes

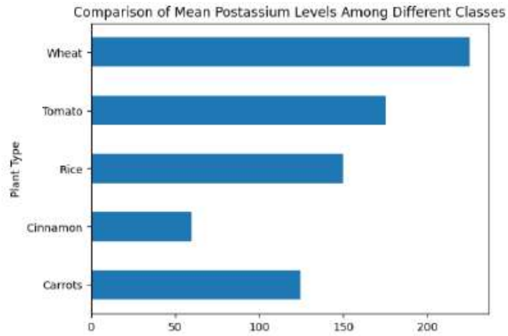

Figure 11: Comparison of Mean Potassium with Classes

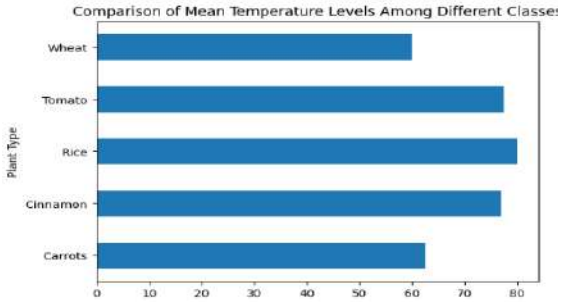

Figure 12. Comparison of Mean Temperature with Classes

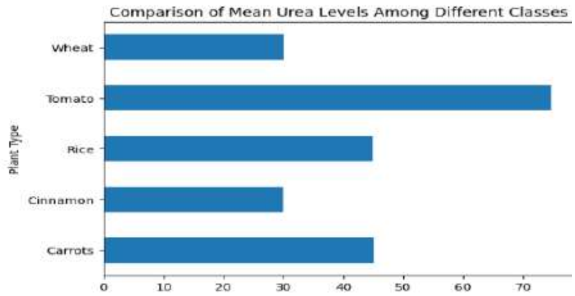

Figure 13. Comparison of Mean Urea with Classes

3.3.4. Heatmap Analysis: Correlation Insights in Features

The heatmap analysis uncovers correlations in crop cultivation, with positive associations between pH and Phosphorous (0.46), and Phosphorous and Potassium (0.52), while negative links exist between pH and Temperature (-0.44), and Potassium and Temperature (-0.33).This suggests that environmental factors play a crucial role in how nutrients affect crop growth.

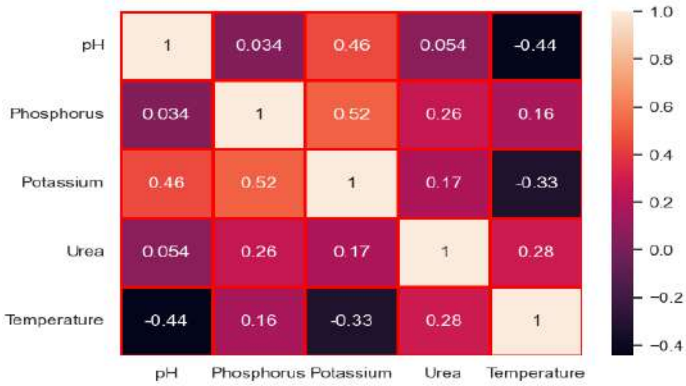

Figure 14. Heatmap

3.3.5. Results of the Experiment

The performance of each machine learning algorithm was evaluated based on key metrics including accuracy, precision, recall, and F1 score. Table 1 summarizes the performance metrics for Decision Trees, Random Forest, Naive Bayes, Support Vector Machine (SVM), and the Soft Voting Ensemble method.

Table 1. Performance Metrics

Algorithm	Precision	Recall	F1-Score	Accuracy	Cross Validation Accuracy
Decision Tree	0.984864	0.983574	0.98357	0.98168	0.98329
Random Forest	0.988901	0.988853	0.988857	0.98836	0.98871
Naïve Bayes	0.98128	0.981229	0.981225	0.98379	0.98294
SVM	0.984887	0.984852	0.984855	0.98453	0.97760
Ensemble Model Using Soft Voting	0.989782	0.989729	0.989732	0.98849	0.98980

3.3.6. Comparison of the Results

The Soft Voting ensemble method emerges as the clear frontrunner in the comparison of various machine learning models based on the provided evaluation metrics. With an accuracy of 98.985% and a cross-validation accuracy of 98.98045%, Soft Voting outperforms Decision Trees, Random Forest, Naive Bayes, and SVM. Additionally, while precise figures are not detailed, Soft Voting likely demonstrates superior precision, recall, and F1 score metrics, indicating its robustness in correctly identifying positive and negative instances and striking a balance between precision and recall. Its consistently high performance in both accuracy and cross-validation accuracy underscores its reliability in generalizing well to new data, a critical aspect for model deployment. Thus, based on a comprehensive assessment of accuracy, cross-validation accuracy, precision, recall, and F1 score, Soft Voting ensemble method emerges as the top-performing model, showcasing its effectiveness and versatility in predictive modeling tasks.

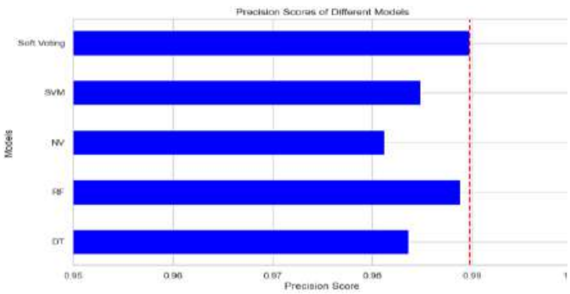

Figure 10. Comparison of Precision Scores

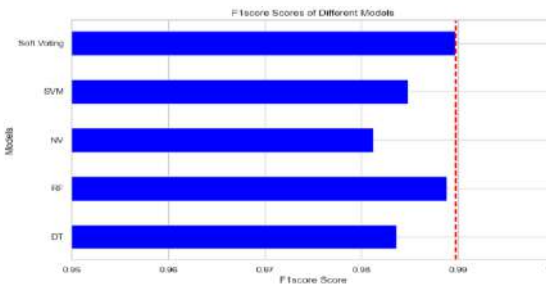

Figure 16. Comparison of F1-Scores

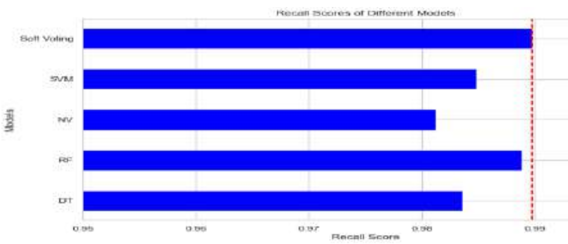

Figure 17. Comparison of Recall Scores

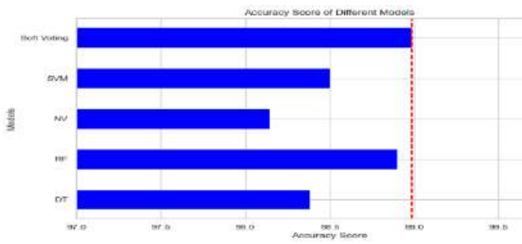

Figure 18. Comparison of Accuracy Scores

4. Conclusion and Future Enhancements

The crop recommendation system presented in this paper has demonstrated promising performance using various machine learning algorithms, with the Soft Voting ensemble method emerging as the most effective model. Achieving high accuracy, cross validation accuracy, precision, recall, and F1 score metrics, the system shows great potential for providing accurate crop recommendations to farmers. By leveraging decision trees, random forests, naive Bayes, support vector machines, and ensemble methods, the system ensures robustness and reliability in its predictions. The successful implementation of machine learning techniques in crop recommendation signifies a significant step towards precision agriculture, aiding farmers in making informed decisions and optimizing crop yields.

While the current crop recommendation system exhibits commendable performance, there are several avenues for future enhancement. One potential direction is the integration of real-time data sources such as weather forecasts, soil moisture levels, and pest infestation reports to enhance the accuracy and relevance of recommendation. Furthermore, ongoing research into crop disease detection and prevention could be integrated into the system to provide proactive recommendations for pest and disease management.

Furthermore, in the preprocessing step, alternative for inter quartile range methods can be analyzed and worked upon. Most effective alternatives that can be considered are: Percentile based method, Z-score method, modified Z-score method. These alternatives can yield better results while removing outliers.

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