Smart Crop Recommendation for Modern Farming using Machine Learning

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***Abstract*—The agricultural sector plays a key role in global food security and livelihoods, emphasizing the importance of improving agricultural practices. In this research, we present a crop recommendation system (CRS) designed to help farmers optimize the crop selection process. CRS uses machine learning algorithms that incorporate a diverse dataset containing soil properties, climate conditions, and historical crop yield data.**

Our methodology includes a multi-stage approach. Initially, we conducted comprehensive data collection from various sources, including government databases and research publications. Subsequently, data pre-processing techniques are applied to clean, normalize, and integrate different data sets into a uniform format suitable for analysis.

Whereas we receive basic attributes like soil pH, moisture content, temperature, and rainfall levels, structural engineering is crucial. We provide an ensemble learning framework by utilizing sophisticated machine learning models such as CatBoost classifiers, Naive Bayes Gaussians, decision trees, and support vector machines (SVMs). This framework uses fused data to estimate which crops will be most suited.

CRS also has an easy-to-use interface that can be accessed on mobile and web platforms. With this interface, farmers may input the properties of their soil and get recommendations for treatments in real-time.

To ensure the system's reliability and scalability, we tested the system extensively across a variety of geographic locations and climate zones. The efficacy of CRS in recommending crops for various soil and climate conditions is verified by performance metrics like accuracy, precision, and recall. A promising accuracy rate of more than 95% is demonstrated by the data, demonstrating how useful CRS is in assisting farmers in selecting the best crops. In order to increase agricultural productivity and sustainability, farmers can use the intelligent decision support system developed by this research to acquire data-driven insights.

***Index Terms*—Crop Recommendation System, N-P-K, ML, Naive Bayes, SVM, CatBoost**

I. Introduction

The agricultural sector stands as a cornerstone of global sustenance, playing a pivotal role in supporting the world's population. Climate conditions, soil quality, and crop selection represent merely a fraction of the multitude of variables influencing the efficacy and profitability of agricultural endeavors. The process of determining the crops that are most suited for a certain location entail taking into account several intricate factors, including market demands, weather patterns, soil composition, and past crop performance. Traditional farming practices often rely on experience and local knowledge, but with advancements in technology and data analysis, we can optimize crop recommendations and significantly enhance agricultural productivity. With advancement of machine learning algorithms like deep learning and transfer learning [1][2]. different crop issues of crop disease detection [3][4][5][11] and crop recommendation [12][19] easily can be solved.

The primary challenge in modern agriculture is to maximize yield while minimizing resource usage and environmental impact. Based on the distinctive features of their land and the regional environmental circumstances, farmers have a tough time deciding which crops to cultivate. Inaccurate information results in less-than-ideal crop choices, leading to decreased yields and economic losses. To solve this issue, a precise crop recommendation system that uses data analytics and machine learning to recommend the best crops for certain farming sites is needed. Effective crop selection has a direct influence on agricultural productivity and farmers' financial well-being. We can increase production, cut down on resource waste, and support sustainable agricultural practices by appropriately advising crops based on a region's geographical and environmental characteristics. Moreover, a well-designed Crop Recommendation System can empower farmers, especially those with limited resources or expertise, to make informed decisions, ultimately leading to improved livelihoods and food security.

II. Literature Review

Shafiola Sharif et al. [6] used machine learning algorithms to assist farmers in selecting the best goods to produce based on environmental and geographic parameters. There was use of KNN, random forests, decision trees, and neural networks. When neural networks are used, accuracy increases.

S. Sudaresan et al. [7] applied machine learning and IoT-based approach for smart agriculture to recommend the crop. They look at a number of variables, including pH levels, meteorological conditions, and nutrients like phosphorus (P) and nitrogen (N). potassium, a slow variable (K). The primary factors

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used to determine fertilizer recommendations are crop type and the quantities of accessible soil nutrients. Autonomous irrigation systems also consider the present soil moisture levels and weather forecasts in order to automate irrigation. They demonstrate how machine learning has enhanced fertilizer recommendations and product selection by summarising the successes and triumphs of product recommendation systems. Thomas van Klempenburg et al. [8] explored the complex endeavor of forecasting crop yields in precision agriculture using machine learning. The article discussed various models proposed for this task, including neural networks, random forests, gradient-boosted trees, and linear regression. Accurate crop yield predictions are essential for farmers to make informed decisions about crop choice and planting schedules.

Druvi Gosai et al. [9] presented a thorough product recommendation system using machine learning methods. The study evaluates the effectiveness of various ML algorithms for product recommendations, with Naive Bayes and Random Forests (RF) showing high prediction accuracy.

Anantha Reddy Dasari et al. [10] described a product recommendation system designed to maximize crop performance in the Ramtek region using machine learning. The methodology relies on factors such as soil types, soil features, and crop yield data to recommend suitable crops for cultivation. The system employs various ML algorithms, including Naive Bayes, K-Nearest Neighbour, CHAID, and RF, to forecast state and district values as well as specific crops under particular meteorological conditions.

Shraban Kumar Apat et al. [13] introduced an AI-based crop recommendation system utilizing Categorial Boosting (CatBoost), which achieved outstanding performance with an accuracy score of 99.5129, an F-measure of 0.9916, a precision of 0.9918, and a Kappa of 0.8870. The system outperformed others, including Gaussian Naive Bayes (GNB), in the classification, regression, and boosting families of machine learning algorithms.

Pradeepa Bandara et al. [14] described a crop recommendation system using Naive Bayes and SVM to predict the most suitable crop type for a given plot based on environmental conditions. The system identifies four probable crops with a probability above 90% and incorporates farmer feedback to improve prediction accuracy.

Soumya Gite et al. [15] presented an online crop recommendation system using various ML algorithms on historical datasets. The system suggests the most appropriate crop based on specified conditions like rainfall and soil factors, evaluating multiple algorithms to deliver accurate recommendations.

Anusha K et al. [16] integrated Machine Learning algorithms with IoT technologies in a crop recommendation system. Using datasets that include environmental metrics and soil properties, the system employs sensors and IoT devices, such as an ESP32 development board, to gather data for crop recommendations.

Uma Pujeri et al. [17] made a smart fertilizer recommendation system using machine learning and IoT. The system helps farmers choose the optimal fertilizer based on factors like nutrient levels, humidity, temperature, and soil moisture. ML methods such as XGBoost Classifier, Random Forest, k-Nearest Neighbour, and SVM are proposed to enhance precision agriculture.

Santosh Kumar Upadhyay et al. [18] focused on an automated plant disease detection system utilizing the InceptionV3 model, a sophisticated deep learning technique. This system is designed to identify and classify various diseases affecting rice crops by processing a large dataset of 2,550 images of infected rice leaves from five disease classes. The model employs advanced image processing methods, such as contrast stretching and image augmentation, to enhance training accuracy. Achieving 100% overall accuracy, this model provides a reliable and efficient method for early disease detection and management, which is crucial for maintaining crop health and ensuring high yields.

Santosh Kumar Upadhyay et al. [19] address the critical need for an intelligent crop recommendation system using ma- chine learning to assist farmers in making informed decisions. By analyzing environmental conditions and soil properties, their system predicts the most suitable crop to plant with a remarkable 99% accuracy. Their study highlights the potential of this system to maximize agricultural productivity and minimize risks by recommending optimal crop choices based on precise data analysis.

III. Proposed Approach

A. Gaussian Naive Bayes

GNB, a foundational algorithm in ML, is renowned for its simplicity and efficiency, particularly in classification tasks. It operates on the principle of Bayes' theorem, facilitating the calculation of posterior probabilities by combining prior knowledge with new evidence. The 'Gaussian' aspect of the algorithm refers to the assumption that features follow a Gaussian (normal) distribution, simplifying the computation of probabilities and enabling swift predictions. Despite its seemingly naive assumption of feature independence, Gaussian Naive Bayes remains a formidable tool in various domains due to its computational efficiency and effectiveness in handling high-dimensional datasets.

This algorithm is particularly adept at handling classification tasks where the features are continuous and can be modeled using a Gaussian distribution. By estimating the mean and variance of each feature for each class during training, Gaussian Naive Bayes effectively calculates the probability of each class based on the observed features (as shown in Fig. 1). Its simplicity and scalability make it an attractive choice for real-world applications such as text classification, spam detection, and medical diagnosis. Additionally, its robust performance, even with the simplifying assumption of feature independence, underscores its utility and widespread adoption across diverse domains in machine learning research and practice.

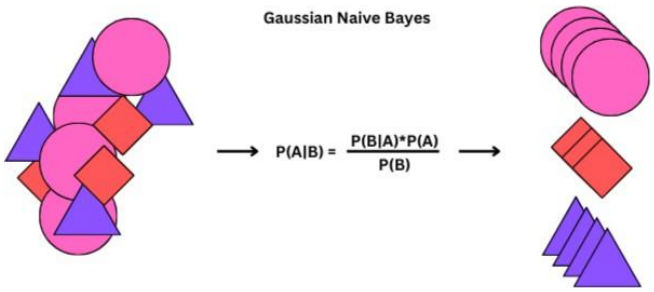

Fig. 1. Gaussian Naive Bayes

B. CatBoost Classifier

The CatBoost classifier is an advanced gradient-boosting algorithm specifically designed to efficiently handle classified features. It combines several weak learners, typically Decision Trees, to forge a single robust lerarner. What sets CatBoost apart is its capability to manage variables implicitly without the necessity for preprocessing, making it exceptionally well-suited for real-world datasets characterized with mixed data types.

The algorithm uses a technique called ordered boosting, which optimizes the learning process by adjusting the order in which classified features are processed during tree construction. This approach helps reduce overfitting and increases the generalizability of the model. Additionally, CatBoost incorporates advanced regularization techniques to further improve model performance and prevent overfitting.

CatBoost classifier provides high accuracy and robustness in various classification tasks including unbalanced classes and noisy data. The efficient handling of its unique features, coupled with its ability to automatically tune hyperparameters, makes it a popular choice for both research and practical applications. Additionally, its compatibility with GPU acceleration allows for faster training times, making it suitable for large-scale datasets. Overall, the CatBoost classifier stands out as a powerful and versatile algorithm for classification tasks, especially in situations where distinct features play a significant role in the data.

C. Decision Tree Classifier

This model is employed in classification as well as various prediction tasks, where various paths are composed of a series of decisions to be made to reach a particular class. When you review an example in the tutorial, you will be asked a series of questions. Non-terminal nodes, including root nodes and internal nodes, have deterministic properties. The decision-making process involves comparing samples and decision attributes, which leads to splitting and proceeding to the next node. The cycle persists until a leaf node is encountered, producing a subtree and assigning the class label to that instance (as shown in Fig. 2). Recursive partitioning, which splits the tree, contributes to the ability to process high-dimensional data with high precision. Decision trees are easily explained and understood in the form of flowcharts that resemble human-level thinking.

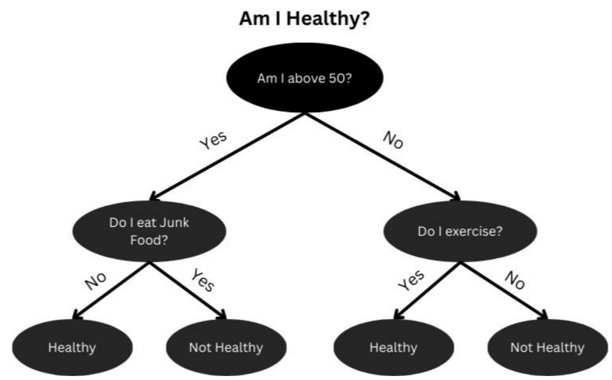

Fig. 2. Decision Tree

D. Support Vector Machine

SVM algorithms are well utilized in tasks involving prediction or classification challenges. It is renowned for its adeptness in managing high-dimensional sample sets. SVM finds applications across various domains, including bioinformatics, image classification, and text categorization.

Fundamentally, SVM seeks to maximize the model's capacity for generalisation by identifying the ideal hyperplane in the feature space that divides several classes of data points with the greatest amount of margin. This entails selecting the hyperplane that maximizes the distance from the closest data point of each class, thus distinctly delineating class boundaries. SVM can effectively handle linearly separable and nonlinear datasets.

SVM's primary strength lies in its ability to handle datasets with high number of features, surpassing the number of samples. Additionally, because SVM aims to maximize the margin between classes, it is resistant to overfitting and improves generalization to missing data. Even while SVM training can be computationally demanding, particularly for large datasets, improvements in parallel computing and optimization strategies have made it more and more practical for practical uses. All things considered, SVM is a strong and adaptable algorithm in the machine learning toolbox, providing strong performance and excellent accuracy on a range of problems.

IV. METHODOLOGY

This section consists of data gathering, data preprocessing, data splitting, model fitting and performance evaluation processes. Work flow diagram of proposed system is shown in Fig. 3.

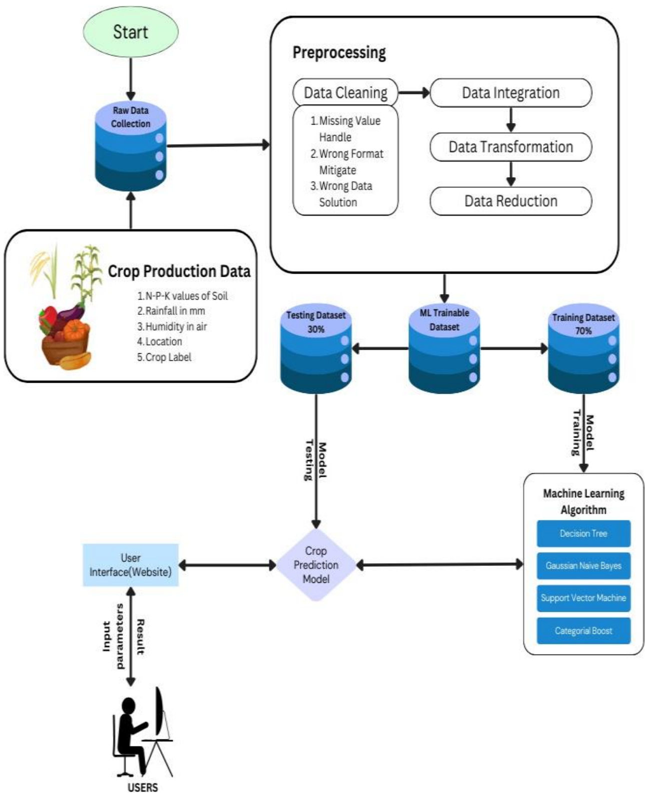

Fig. 3. System Workflow Diagram

A. Collecting Raw Data

It is essential to evaluate historical events and enable data analysis to uncover recurrent trends through the process of data collection, which entails obtaining and evaluating information from a variety of sources. The sample data used in this project was sourced from the Kaggle[20] platform and has been cited in numerous prior research studies. Comprising of 2200 different examples of 22 different crops classified in labels(apple, maize, lentil, watermelon, pomegranate, blackgram, chickpea, mothbeans, banana, mango, pigeonpeas, muskmelon, rice, and others), considering 7 different attributes of soil which affect the crop selection: (i) relative humidity percentage, (ii) Potassium content ratio in Soil (K), (iii) Tem- perature expressed in degrees Celsius, (iv) Nitrogen content ratio in soil (N), (v) Phosphorus content ratio in soil (P), (vi) pH value of the soil and (vii) rainfall measured in millimeters. Sample of dataset is shown in Fig.4.

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...	...	...	...
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

Fig. 4. Dataset

B. Data Preprocessing

This involves the conversion of raw data into a format suitable for machine learning algorithms, aiding analysts and data scientists to gain insights or predict outcomes. In this step, the focus lies on addressing missing values in the dataset. Ensuring complete data for each entry in a dataset can be challenging due to empty cells or placeholders like null values or specific characters (e.g., question marks) indicating missing information. It is worth noting that the dataset used in this project has no missing values.

C. Train and Test Split

The `train_test_split()` function from the scikit-learn module is used to employed to partition the sample data into a training set and a test set. To be more precise, out of the 2200 data points in the dataset, 70% are allocated to the training sample (1760 data points), while the remaining 30% are allocated to the testing dataset (440 data points).

D. Fitting the Model

Fitting a model involves adjusting its parameters to improve accuracy. In order to allow the model to train, this involves using an algorithm on data that contains known target variables. Model accuracy is assessed by contrasting the target variable's observed values with the model's predictions. In order to make sure that the machine learning model can accurately predict the output when faced with unknown inputs, the model fitting procedure evaluates the model's generalization to the training data.

E. Assessing Performance on the Training Set

Evaluating performance, commonly referred to as inference, involves employing a trained ML model to generate predictions from new input data. The training dataset's scores for each model are determined using the 'model.score()' method. This score gives information about the model's learning ca- pacity and predictive power using training data.

F. Predicting the Model

"Prediction" in the context of machine learning refers to calculating the possibility or probability of a specific result. This estimate is the result of an algorithm that is applied to fresh data after being trained on an earlier dataset. The test feature dataset is used to call the 'predict()' method, which predicts the model. An array with the expected values that the model produced for the provided test data is the end result.

G. Evaluating Model Precision

The precision of a model is determined by the accurate classification of instances relative to the total number of predictions. This assessment metric is computed using the `accuracy_score()` function from the scikit-learn metrics module.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

In this equation, the terms stand for:

- TP (True Positive): Prediction correctly identified as belonging to the positive class.
- FP (False Positive): Prediction incorrectly identified as belonging to the positive class.
- TN (True Negative): Prediction correctly identified as belonging to the negative class.
- FN (False Negative): Prediction incorrectly identified as belonging to the negative class.

Accuracy signifies the proportion of correct predictions out of the total predictions made, providing a comprehensive evaluation of the performance of the ML model.

V. Results and Discussion

In the comprehensive evaluation of four distinct ML models (CatBoost, Decision Tree, SVM, and Gaussian Naive Bayes) for crop prediction, Gaussian Naive Bayes emerged as the most accurate model, achieving an impressive accuracy rate of 99.09% as shown in Fig.6. Following closely behind, CatBoost demonstrated a high accuracy rate of 98.86% as shown in Fig.8., while SVM exhibited an accuracy of 97.95% as shown in Fig. 7. Decision Tree, although slightly lower in accuracy compared to the others, still performed well with an accuracy rate of 90% as shown in Fig 5.

DecisionTrees's Accuracy is: 90.0

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	0.59	1.00	0.74	16
chickpea	1.00	1.00	1.00	21
coconut	0.91	1.00	0.95	21
coffee	1.00	1.00	1.00	22
cotton	1.00	1.00	1.00	20
grapes	1.00	1.00	1.00	18
jute	0.74	0.93	0.83	28
kidneybeans	0.00	0.00	0.00	14
lentil	0.68	1.00	0.81	23
maize	1.00	1.00	1.00	21
mango	1.00	1.00	1.00	26
mothbeans	0.00	0.00	0.00	19
mungbean	1.00	1.00	1.00	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	0.84	0.91	19
pigeonpeas	0.62	1.00	0.77	18
pomegranate	1.00	1.00	1.00	17
rice	1.00	0.62	0.77	16
watermelon	1.00	1.00	1.00	15
accuracy			0.90	440
macro avg	0.84	0.88	0.85	440
weighted avg	0.86	0.90	0.87	440

Fig. 5. Decision Tree Result

Naive Bayes's Accuracy is: 0.990909090909091

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	1.00	1.00	1.00	16
chickpea	1.00	1.00	1.00	21
coconut	1.00	1.00	1.00	21
coffee	1.00	1.00	1.00	22
cotton	1.00	1.00	1.00	20
grapes	1.00	1.00	1.00	18
jute	0.88	1.00	0.93	28
kidneybeans	1.00	1.00	1.00	14
lentil	1.00	1.00	1.00	23
maize	1.00	1.00	1.00	21
mango	1.00	1.00	1.00	26
mothbeans	1.00	1.00	1.00	19
mungbean	1.00	1.00	1.00	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	1.00	1.00	19
pigeonpeas	1.00	1.00	1.00	18
pomegranate	1.00	1.00	1.00	17
rice	1.00	0.75	0.86	16
watermelon	1.00	1.00	1.00	15
accuracy			0.99	440
macro avg	0.99	0.99	0.99	440
weighted avg	0.99	0.99	0.99	440

Fig. 6. Gaussian Naive Bayes Result

```
SVM's Accuracy is:  0.9795454545454545
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       1.00      1.00      1.00        17
   blackgram       1.00      1.00      1.00        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      1.00      1.00        21
      coffee       1.00      0.95      0.98        22
      cotton       0.95      1.00      0.98        20
      grapes       1.00      1.00      1.00        18
        jute       0.83      0.89      0.86        28
 kidneybeans       1.00      1.00      1.00        14
      lentil       1.00      1.00      1.00        23
       maize       1.00      0.95      0.98        21
       mango       1.00      1.00      1.00        26
   mothbeans       1.00      1.00      1.00        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       1.00      1.00      1.00        19
  pigeonpeas       1.00      1.00      1.00        18
 pomegranate       1.00      1.00      1.00        17
        rice       0.80      0.75      0.77        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           0.98       440
   macro avg       0.98      0.98      0.98       440
weighted avg       0.98      0.98      0.98       440
```

Fig. 7. SVM Result

```
CatBoost's Accuracy is:  0.9886363636363636
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        13
      banana       1.00      1.00      1.00        17
   blackgram       0.94      1.00      0.97        16
    chickpea       1.00      1.00      1.00        21
     coconut       1.00      1.00      1.00        21
      coffee       1.00      1.00      1.00        22
      cotton       1.00      1.00      1.00        20
      grapes       1.00      1.00      1.00        18
        jute       0.96      0.89      0.93        28
 kidneybeans       1.00      1.00      1.00        14
      lentil       1.00      1.00      1.00        23
       maize       1.00      1.00      1.00        21
       mango       1.00      1.00      1.00        26
   mothbeans       1.00      0.95      0.97        19
    mungbean       1.00      1.00      1.00        24
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        29
      papaya       1.00      1.00      1.00        19
  pigeonpeas       1.00      1.00      1.00        18
 pomegranate       1.00      1.00      1.00        17
        rice       0.83      0.94      0.88        16
  watermelon       1.00      1.00      1.00        15

    accuracy                           0.99       440
   macro avg       0.99      0.99      0.99       440
weighted avg       0.99      0.99      0.99       440
```

Fig. 8. CatBoost Result

A comparison of performance parameters for all four models is given in Table. 1.

TABLE I
PERFORMANCE COMPARISON

ML Algorithm	Accuracy	Precision	Recall	F1 Score
GNB	99.09%	99%	99%	99%
Decision Tree	90%	84%	88%	90%
SVM	97.95%	98%	98%	98%
Cat Boost	98.86%	99%	99%	99%

- **Gaussian Naive Bayes (GNB)** demonstrates the highest accuracy at 99.09%, with Precision, Recall, and F1 Score all at 99%.
- **Decision Tree** shows an accuracy of 90%, with Precision at 84%, Recall at 88%, and an F1 Score of 90%.
- **Support Vector Machine (SVM)** achieves an accuracy of 97.95%, and similar to GNB, it has high Precision, Recall, and F1 Score, all at 98%.
- **Cat Boost** has an accuracy of 98.86%, with Precision, Recall, and F1 Score all at 99%.

Overall, GNB and Cat Boost perform the best across all metrics, with Decision Tree showing the lowest performance among the four algorithms.

VI. Conclusion and Future Scope

Results of Table 1. underscore the efficacy of Gaussian Naive Bayes in accurately predicting the best-suited crop for a particular land, followed by CatBoost and SVM. These models offer valuable insights for farmers to optimize crop growth efficiently based on the characteristics of their land.

In light of the promising results obtained from evaluating various supervised machine-learning models for crop prediction, there are several prospective avenues for future exploration and advancement in this domain. One potential direction involves the integration of advanced techniques such as ensemble learning, which combines predictions from multiple models to improve accuracy and robustness further. Furthermore, exploring the incorporation of deep learning algorithms such as ANN or CNN could offer deeper insights into crop prediction by leveraging complex patterns and relationships within the data.

Furthermore, there is a growing interest in the use of remote sensing data and satellite imagery for crop monitoring and prediction. Integrating these sources of information with machine learning models could provide real-time updates on crop health, yield estimation, and disease detection, thereby enabling proactive decision-making for farmers. Moreover, addressing the challenges of data scarcity and imbalance in agricultural datasets remains a crucial area for future research. Developing techniques to handle missing or incomplete data, as well as strategies for addressing class imbalances, could enhance the reliability and generalization capability of crop prediction models.Overall, the future of crop prediction using machine learn- ing holds immense potential for revolutionizing agricultural practices, improving crop yield, and ensuring food security. By leveraging advancements in technology and data analytics, researchers can continue to innovate and develop solutions that benefit farmers, policymakers, and the agricultural industry as a whole.

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