INTEGRATING MACHINE LEARNING TECHNIQUES WITH THE CONVENTIONAL CROP RECOMMENDATION SYSTEMP.

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***Abstract*—**
In India, agriculture is a significant sector. It is essential to the survival and expansion of the Indian economy. India is a significant producer of a wide range of agricultural goods. An essential element in the development of crops is soil. In the past, farmers with practical expertise would cultivate crops. The traits and attributes of a crop are no longer enough to determine which one is ideal for a farmer's land. As a result, a machine learning algorithm-based recommendation system has been created to suggest the crop that might be harvested in that specific soil. Numerous machine learning techniques are used by this system, including Bagging Classifier, K-Nearest Neighbors (KNN), Gradient Boosting Classifier, Support Vector Machine, and Light Gradient Boosting Machine (LGBM) Classifier. Crop suggestion functions as a kind of intelligent farm assistant, assisting farmers in selecting the most suitable crops for their farms. This system looks at weather, soil health, and other significant elements using cutting edge technologies. It all comes down to helping farmers make decisions by providing them with individualized counsel. Imagine that a farmer in a hamlet could use their phone to obtain recommendations on which crops will grow the best. They can choose what to grow much more easily thanks to this technology, which will improve yields. The best thing is that it also contributes to resource conservation, making farming environmentally benign in addition to productive. Thus, this initiative aims to make farming smarter and simpler for farmers by providing them with a high-tech assistant.

***Keywords*—**
Crop Suggestion, Soil Characteristics, Machine Learning, Decision Tree, Random Forest.

INTRODUCTION

Using data and algorithms, machine learning-based crop recommendation finds the best crops for a given piece of land. First, a variety of data sets, including those on soil quality, temperature, past crop yields, and even satellite images, are gathered. After that, machine learning algorithms examine this data to find trends and connections between many variables and the growth of fruitful crops. Through a knowledge of these linkages, the algorithms are able to forecast which crops will do well in a certain location.

The purpose of using machine learning for crop recommendation is to increase production and efficiency in agriculture. Farmers are able to make better judgments about what to plant, when to plant it, and how to maintain their crops by utilizing data analysis and predictive modeling. Higher yields, less use of resources, and eventually more profitability for farmers are possible outcomes of this. Additionally, machine learning may support sustainable farming methods and lessen the risks connected with climate change by suggesting crops that are well-suited to the local climatic circumstances.

Ultimately, the goal of crop recommendation based on machine learning is to give farmers relevant information to optimize their agricultural practices. By employing cutting-edge technology to tailor crop selections to specific meteorological conditions, machine learning can contribute to the development of a more robust and productive food system. This has wider ramifications for global food security and sustainability in addition to helping individual farmers.

ISSN: 2278-4632
Vol-14, Issue-7, No.02,July: 2024

LITERATURE REVIEW

A method to forecast a crop utilizing variables including temperature, humidity, pH, and rainfall was presented by Spandana et al. [1]. Decision tree algorithms can be used to anticipate this harvest. Using random forests will get more accurate results.

Dhawan et al. [2] talked about the data sets gathered over a number of years for projecting the output of soybean crops. This article employs a variety of prediction techniques, including Bagging. It is concluded that, among the aforementioned algorithms, Bagging is the most predictive.

The class was predicted and the ground dataset was proven by Santosh et al. [3]. The crop was determined based on the projected soil class. KNN and Naive Bayes algorithms are employed to make predictions. The future is already under construction.

Anantha et al.'s investigation [4] focused on criteria such crop yield data gathering, soil type, and property characteristics. Based on those parameters, the researchers advise farmers on which crops to plant. It may be used with many machine learning methods, including naïve bias, K closest neighbors, and random forests. Crops, state and district values, and meteorological conditions may all be predicted by this approach.

A system designed by Nidhi et al. [5] recommends crops depending on temperature, average rainfall, and type of soil. It may be used with a variety of machine learning techniques, including random forests, naïve arrays, and linear SVMs. Crop varieties like Rabi and Kharif will be suggested by the algorithm.

A method for identifying cream based on a soil database was suggested by Rohit Kumar et al. [6] and may be used to a variety of crops, including vegetables, beans, cotton, and peanuts. ANN classifiers, Random Forest, Naive Bayes, and support vector machines are just a few of the machine learning algorithms that employ this to successfully and efficiently recommend crops.

Manikandan et al. [7] developed a method to identify a particular crop using the information given. The Support Vector Machine (SVM) was employed to boost accuracy and output. The two datasets that this research article primarily examined were the crop data sample and the location data sample. For a number of crops, including rice, maize, black gram, carrot, and radish, this recommended method assessed the available nutrient values and required fertilizer levels. It then recommended a specific crop based on the nutrient values of that crop.

Reddy et al. [8] looked at three factors: crop yield data collecting, soil types, and soil characteristics. Based on these factors, The farmer was given recommendations by the researchers on the ideal crop to grow. It operates on many Ml algorithms and CHAID. We are able to forecast a certain crop based on state, district, and weather conditions. By helping farmers plant the appropriate seed according to the needs of the land, this program would increase national production.

Rajak et al. developed a method for identifying a certain crop based on soil information [9]. This method worked well for a variety of crops, such as vegetables, sorghum, sugarcane, coriander, bananas, groundnuts, cotton, and vegetables; it also worked well for a variety of soil properties, such as color, permeability, drainage, water retention, and erosion.

This technique used a variety of machine learning classifiers to accurately and efficiently choose a crop for a site-specific characteristic ,including as Random Forest, Naïve Bayes. Farmers will be able to increase agricultural productivity, reduce the amount of chemicals used to grow crops, halt soil erosion on farmed land, and better manage water resources with the help of this study.

Avinash et al. [16] have described a method that predicts the best crop based on a number of factors, including pH, depth, texture, water-holding capacity, and erosion. This technique was effective with a variety of crops, including coriander, sorghum, groundnuts, and pulses. Decision Trees, and ANN may all be used to forecast crops. Using the XGBoost algorithm produced the most accurate value result. Farmers might boost their profit margins by increasing productivity with the aid of this article.

In order to anticipate the ideal crop, Jayanthi et al. [17] have implemented a system that employs an IOT device to gather data on a number of factors, including pH, moisture, humidity, temperature, and erosion. A Graphical User Interface (GUI) was created by them. Random Forest (RF) and Naïve Bayes

Classifier may both be used to forecast crops. The Naïve Bayes algorithm produced the highest accurate value result with a 96.89% accuracy rate.
Shreedhara et al. have proposed a technique that considers a variety of variables, such as the soil's texture, depth, color, permeability, pH, and water-holding capacity[18]. There are around nine distinct crops in the sample. The algorithms were the learners employed in this model. The most accurate results were produced using the Naïve Bayes algorithm.
A method that takes into account meteorological factors such sun exposure, rainfall, average temperature, humidity, and the frequency of rainy days has been studied by Merlinda et al. [19]. takes harvest-related factors like productivity and yields in tons into account. Naïve Bayes may be used to predict crops, and the greatest accuracy was about 85.71% with a mean absolute error of about 0.1051.

SYSTEM ANALYSIS

The suggested crop selection system aims to assist farmers in selecting crops to grow based on features specific to their land and environment. The system gathers information on temperature, humidity, pH, rainfall, and levels of nitrogen, phosphorus, and potassium. To guarantee consistency, this data is standardized and pre-processed to accommodate missing values. The processed data is used to train a variety of machine learning methods, such as K-Nearest Neighbours, Bagging Classifier, Gradient Boost Classifier, and Light Gradient Boost Machine Classifier. The system evaluates each model's performance using several , in order to determine which model performs best for crop prediction. The result is a crop suggestion that maximizes agricultural production and resource efficiency given the input parameters. In order to make the system easily available to farmers with varied degrees of technical skill, next additions include increasing the dataset, adding disease prediction, and building a user-friendly interface through a website and mobile application.

A. PROBLEM STATEMENT

Farmers sometimes find it difficult to select the best crops to plant, particularly when dealing with the complexity of different soil types, climates, and market needs. The issue is that farmers could find it difficult to manage resources responsibly while maximizing yields and profits in the absence of precise instructions. This problem is intended to be addressed by crop recommendation utilizing machine learning, which offers farmers customized recommendations based on data analysis. This method aims to provide farmers with useful information so they can decide which crops to put on their property by using algorithms to analyze variables like soil quality, weather patterns, and past yields. The main problem is that there isn't a trustworthy and effective way to suggest crops that are in line with the unique circumstances of every farm. Conventional crop selection methods can depend on general suggestions or specific knowledge, which might not always yield the best outcomes. The goal is to develop a system that can assess large datasets using machine learning techniques and identify patterns that humans might overlook. In the end, this system will be able to provide farmers with individualized suggestions that will increase agricultural output, profitability, and sustainability.

B. PROPOSED SYSTEM

The suggested system is a clever crop selection tool that helps farmers choose the best crops to grow according to certain soil and environmental circumstances. Key soil nutrients (nitrogen, phosphorus, and potassium) as well as important climatic variables (temperature, humidity, pH levels, and rainfall) are all recorded by this system. The technology cleans and normalizes this data through a thorough preparation step to improve its suitability for machine learning models. To analyze the data and predict the best crop for a given set of conditions, a variety of algorithms are trained, including K-Nearest Neighbors, Bagging Classifier, Gradient Boost Classifier, and Light Gradient Boost Machine Classifier and more.

ISSN: 2278-4632
Vol-14, Issue-7, No.02,July: 2024

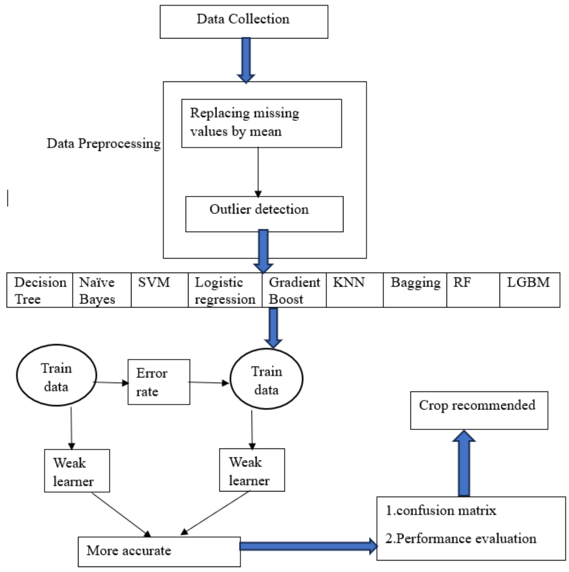

Fig.1. The proposed system's architecture

To identify the best course of action, the performance of the models is evaluated using measures including accuracy, precision, recall, and F1-score. The ultimate objective is to give farmers practical advice that will boost crop yields and boost agricultural productivity. In order to enable wider utilization among farmers, future projects plan to increase the dataset, add disease prediction capabilities, and make easily navigable online and mobile apps.

C. METHODOLOGY

The intelligent crop recommendation system's approach consists of many crucial elements that are necessary to provide precise and practical forecasts for farmers. The following is an outline of the workflow:

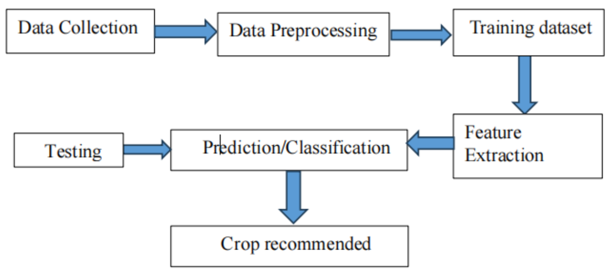

Fig.2.Workflow of Crop Recommendation System.

1. Data Collection:

The first stage is to gather all of the data, which should include soil-specific characteristics such the amounts of nitrogen (N), phosphorus (P), and potassium (K) as well as environmental variables like rainfall, temperature, humidity, and pH. This dataset serves as the foundation for data-driven recommendations aimed at optimizing agricultural output.

	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

2200 rows × 8 columns

Fig.3. Dataset of 2200 records

2. Data Preprocessing:

Data preparation, or converting raw data into a comprehensible and useful format, is an essential stage in the process for analysis of data and machine learning. This procedure usually entails a number of activities, including data normalization or scaling to ensure that features are on a comparable size, improving algorithm efficiency, and addressing missing values, where techniques like imputation or removal are performed.

3. Training Dataset:

A crop recommendation training dataset would include a variety of data points on different fields and the crops that are successfully grown on them. Every data point would be collected. Crop suggested Feature Deletion Forecast/Categorization Preparing Data training set Information on soil type, climate (temperature, humidity, rainfall), soil pH, and other pertinent agricultural characteristics are all tested for. It would also contain the matching crop that was cultivated under such circumstances with success.

4. Feature Extraction:

The process of feature extraction entails locating essential traits from many agricultural data sources that may be used to forecast the best crops for a certain region. This might include elements like the kind of soil, the climate, past crop yields, and consumer demand. For example, the system may extract variables like soil pH levels, nutrient content, and texture instead of utilizing raw soil data. In a similar manner, characteristics such as the length of the growing season, rainfall patterns, and average temperature might be extracted from climatic data. The system can gain a deeper understanding of the particular situations by extracting these pertinent aspects.

5. Prediction Classification:

Using a machine learning model to classify a particular field into one of many crop categories based on its features is known as prediction classification for crop recommendation. For example, the model may examine information from a specific field about the kind of soil, temperature, rainfall, and pH level. The program will categorize the field and suggest the best crop to plant based on patterns discovered from a training dataset. This results in increased yields and more effective use of resources by assisting farmers in making judgments about which crops are most likely to flourish in their farms.

6. Model Training:

The models are trained using a variety of machine learning methods, such as Bagging Classifier, Gradient Boost Classifier, Decision Tree, Naive Bayes, Support Vector Machine (SVM), Logistic Regression, Random Forest, and K-Nearest Neighbors (KNN) (LGBM). In order to understand the connections between input characteristics and crop outcomes, each algorithm is trained using the dataset.

7. Model Evaluation:

The trained models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. This assessment aids in figuring out how well each algorithm predicts the best harvest under particular circumstances. In order to visualize the performance and spot any misclassifications, confusion matrices are also employed.

8. Crop Recommendation:

With the highest accuracy and performance indicators, the approach recommends the best crop to plant in a certain area. These suggestions are derived from the final model, which is usually the one with the greatest assessment findings, assisting farmers in making well-informed decisions.

MODELS USED IN RECOMMENDATION SYSTEM

The crop recommendation system uses a number of machine learning algorithms to identify the best crop for a given set of soil and climate conditions. Every model presents distinct advantages and methods for solving categorization issues. The models employed in this undertaking are:

1. The Decision Tree:

A decision tree-like model is produced using the Decision Tree algorithm, which divides the data into branches according to feature values. Every leaf denotes a result, every branch denotes a decision rule, and every node indicates a feature. Decision trees manage both numerical and categorical data effectively and are simple to understand.

 ISSN: 2278-4632
Vol-14, Issue-7, No.02,July: 2024

2. Naive Bayes (NB) model
Based on the Bayes theorem and the assumption of predictor independence, the Naive Bayes classifier is a probabilistic method. It operates effectively with big datasets and is incredibly efficient despite its simplicity. It works especially well with text categorization and issues involving categorical input characteristics.

3. Support Vector Machine
To divide several classes, SVM creates hyperplanes in a multidimensional space. It seeks to identify the best border so as to optimize the gap between classes. SVMs work well in situations when there are more dimensions than samples, and they are particularly strong in high-dimensional domains.

4. The Logistic Regression Model
Based on one or more predictor factors, the likelihood of a binary outcome is modeled using logistic regression. It is helpful for binary classification jobs since it squeezes the output between 0 and 1 using the logistic function. It is a linear model appropriate for binary and multiclass classification tasks, despite its name.

5. The Random Forest (RF)
Using an ensemble approach called Random Forest, several decision trees are constructed and then combined to get a forecast that is more reliable and accurate. By averaging the predictions from different trees, it lowers the chance of overfitting and enhances generalization. It is strong and does a great job managing a lot of features.

6. K-Nearest Neighbours:
KNN is a simple, instance-based learning method that clusters data points in the feature space based on their k-nearest neighbors' majority class. It is intuitive and easy to use, but for large datasets, it can be computationally expensive.

7. Bagging Classifier:
Training many models on various random subsets of the training data and then aggregating their predictions is known as bagging (Bootstrap Aggregating). By lowering variance, this ensemble approach improves accuracy and resilience.

8. Gradient Boost Classifier:
Usually decision trees, it constructs an orderly ensemble of weak learners. Each new model minimizes a loss function in an effort to repair the mistakes of the prior models. It is quite good at handling complicated patterns in the data and is very successful for classification jobs.

9. Light Gradient Boost Machine Classifier(LGBM):
LightGBM is a large-scale data-handling, performant gradient boosting method. It employs split finding techniques based on histograms and a leaf-wise growth method, which expedites training and utilizes less memory. LGBM is renowned for its exceptional accuracy and performance across a range of machine learning applications.

IMPLEMENTATION AND RESULTS

A. Code Implementation:

1. Importing Libraries and Loading Data:

```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report
from sklearn import metrics
from sklearn import tree
import warnings
warnings.filterwarnings('ignore')

# Mounting Google Drive and loading dataset
from google.colab import drive
drive.mount('/content/drive')

df = pd.read_csv("/content/drive/MyDrive/Crop_recommendation.csv")
```

The required libraries for machine learning (sklearn), data processing (pandas, numpy), and visualization (matplotlib, seaborn) are imported in this block. Additionally, it loads the dataset into a DataFrame from Google Drive.

 ISSN: 2278-4632
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2. Data Exploration and Visualization:

```
# Checking the structure and summary statistics
df.describe()
df['label'].value_counts().plot(kind="bar")
plt.show()

# Visualizing feature distributions
plt.figure(figsize=(15,13))
for i, column in enumerate(df.columns[:-1], 1):
    plt.subplot(3, 3, i)
    sns.histplot(df[column])
plt.show()

# Correlation heatmap
sns.heatmap(df.corr(), annot=True)
plt.show()
```

This block shows the distribution of crop kinds and characteristics and gives an overview of the dataset. Histograms illustrate feature distributions, a heatmap reveals feature correlations, and a bar plot depicts the frequency of each crop type.

3. Splitting Data into Training and Testing Sets:

```
from sklearn.model_selection import train_test_split
features = df[['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall']]
target = df['label']
Xtrain, Xtest, Ytrain, Ytest = train_test_split(features, target, test_size=0.2, random_state=2)
```

This block separates the features (independent variables) from the objective (dependent variable) by dividing the dataset into training (80%) and testing (20%) sets. This allows for the evaluation of model performance.

4. Building and Evaluating Models:

a. Decision Tree Classifier:

```
from sklearn.tree import DecisionTreeClassifier
DecisionTree = DecisionTreeClassifier(criterion="entropy", random_state=2, max_depth=5)
DecisionTree.fit(Xtrain, Ytrain)
predicted_values = DecisionTree.predict(Xtest)
print("Decision Tree's Accuracy is: ", metrics.accuracy_score(Ytest, predicted_values)*100)
print(classification report(Ytest, predicted values))
```

The Decision Tree classifier is constructed and assessed in this block. On the training set, the model is trained, and on the test set, predictions are made. To assess performance, the accuracy and classification report are printed.

b. Random Forest Classifier:

```
from sklearn.ensemble import RandomForestClassifier
RF = RandomForestClassifier(n_estimators=20, random_state=0)
RF.fit(Xtrain, Ytrain)
predicted_values = RF.predict(Xtest)
print("Random Forest's Accuracy is: ", metrics.accuracy_score(Ytest, predicted_values)*100)
print(classification report(Ytest, predicted values))
```

This block creates and assesses a Random Forest classifier in a similar manner. The model's performance is revealed via the accuracy and classification report.

5. Accuracy Comparison and Model Selection:

```
acc = [metrics.accuracy_score(Ytest, DecisionTree.predict(Xtest)),
       metrics.accuracy_score(Ytest, RF.predict(Xtest))]
model = ['Decision Tree', 'Random Forest']

plt.figure(figsize=[10,5], dpi=100)
plt.title('Accuracy Comparison')
plt.xlabel('Accuracy')
plt.ylabel('Algorithm')
sns.barplot(x=acc, y=model, palette='dark')
plt.show()
```

This block uses a bar plot to compare the Decision Tree and Random Forest models' accuracy. The best-performing model for predictions may be chosen with the aid of this graphic.

6. Making a Prediction:


```
data = np.array([[7, 5, 4, 20.8, 80, 6.5, 190]])
prediction = RF.predict(data)
dic = {'Telangana': 'Red and Yellow', 'Andhra pradesh': 'Red and Yellow', 'Assam': 'alluvial',
       'Bihar': 'alluvial', 'Karnataka': 'Black', 'Tamilnadu': 'Red', 'Chattisgarh': 'Red and Yellow',
       'Goa': 'Red and Yellow', 'Gujarat': 'Black', 'Haryana': 'alluvial', 'Himachal pradesh': 'alluvial',
       'Jharkhand': 'Red and Yellow', 'Kerela': 'laterite', 'Madhya Pradesh': 'Black', 'Maharastra': 'Black',
       'Manipur': 'Red and Yellow', 'Meghalaya': 'alluvial', 'Mizoram': 'Red', 'Nagaland': 'Red',
       'Odisha': 'Red', 'Punjab': 'alluvial', 'Rajasthan': 'Desert', 'Sikkim': 'Mountain', 'Tripura': 'Red',
       'Uttar Pradesh': 'Alluvial', 'West bengal': 'Alluvial', 'Arunachal Pradesh': 'Red'}
geoloc = input("Enter the GeoLocation:")
print(prediction, "is the BEST CROP to grow")
print(geoloc.capitalize(), "is majorly covered by", dic[geoloc.capitalize()], "Soil.")
```

Based on input features, this block predicts which crop would grow best using the Random Forest model. After the user enters a place, the system suggests the ideal crop based on the kind of soil at that specific spot.

B. Validation Results:

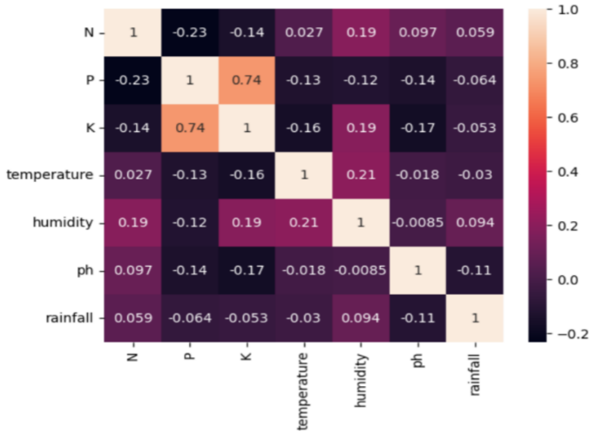

Fig.4. Confusion Matrix

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.Evaluation metrics of Decision Tree

Naive Bayes's Accuracy is: 0.9909090909090909091

	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. Evaluation metrics of Naïve Bayes

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. Evaluation metrics of SVMs

Logistic Regression's Accuracy is: 0.9522727272727273

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	13
banana	1.00	1.00	1.00	17
blackgram	0.86	0.75	0.80	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	0.86	0.90	0.88	20
grapes	1.00	1.00	1.00	18
jute	0.84	0.93	0.88	28
kidneybeans	1.00	1.00	1.00	14
lentil	0.88	1.00	0.94	23
maize	0.90	0.86	0.88	21
mango	0.96	1.00	0.98	26
mothbeans	0.84	0.84	0.84	19
mungbean	1.00	0.96	0.98	24
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	29
papaya	1.00	0.95	0.97	19
pigeonpeas	1.00	1.00	1.00	18
pomegranate	1.00	1.00	1.00	17
rice	0.85	0.69	0.76	16
watermelon	1.00	1.00	1.00	15
accuracy			0.95	440
macro avg	0.95	0.95	0.95	440
weighted avg	0.95	0.95	0.95	440

Fig.8.Evaluation metrics of Logistic Regression

RF'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	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	0.90	1.00	0.95	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	1.00	0.81	0.90	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.9. Evaluation metrics of Random Forest

KNN's Accuracy is: 0.9772727272727273

	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	0.95	1.00	0.98	20
grapes	1.00	1.00	1.00	18
jute	0.89	0.89	0.89	28
kidneybeans	0.93	1.00	0.97	14
lentil	0.96	1.00	0.98	23
maize	1.00	0.95	0.98	21
mango	1.00	1.00	1.00	26
mothbeans	1.00	0.89	0.94	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	0.94	0.97	18
pomegranate	1.00	1.00	1.00	17
rice	0.81	0.81	0.81	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.10. KNNs' evaluation metrics

ISSN: 2278-4632
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Bagging Classifier's Accuracy is: 0.9863636363636363

	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	0.90	1.00	0.95	28
kidneybeans	1.00	1.00	1.00	14
lentil	1.00	0.91	0.95	23
maize	1.00	1.00	1.00	21
mango	1.00	1.00	1.00	26
mothbeans	0.90	0.95	0.92	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	0.81	0.90	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.11. Evaluation metrics of Bagging Classifiers

Gradient Boost's Accuracy is: 0.9931818181818182

	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	1.00	0.93	0.96	28
kidneybeans	1.00	1.00	1.00	14
lentil	1.00	0.96	0.98	23
maize	1.00	1.00	1.00	21
mango	1.00	1.00	1.00	26
mothbeans	0.95	1.00	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	0.89	1.00	0.94	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.12. Evaluation metrics of Gradient Boost Classifier

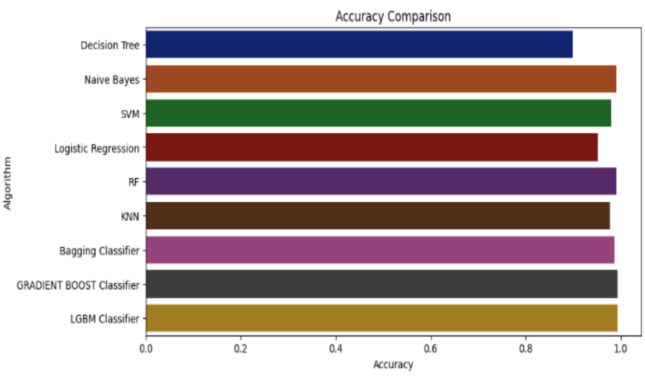

Fig.13.Accuracy Comparison of ML models

```
Enter the GeoLocation:Assam
['coconut'] is BEST CROP to grow
Assam is majorly covered by alluvial Soil.
```

```
data = np.array([[83, 45, 60, 28, 70.3, 7.0, 150.9]])
prediction = RF.predict(data)
print(prediction)
```

```
['jute']
```

Fig.14. Prediction of Output based on input values

Conclusion

We have built and deployed an intelligent crop recommendation technology that farmers may readily utilize throughout India. Based on a number of variables, such as temperature, humidity, rainfall, PH value, nitrogen, phosphorus, and potassium, this system would help farmers choose which crop to grow. We might use this strategy to raise national output and make money by using the study findings. Farmers may plant the correct crop in this way, boosting both their yield and the nation's total profitability. Numerous machine learning techniques have been employed in this work to provide suggestions for a range of Indian crops.

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