

AGRICULTURAL CROP RECOMMENDATION SYSTEM

MINI PROJECT REPORT

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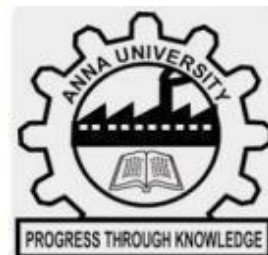
ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING



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BONAFIDE CERTIFICATE

Certified that this Report titled **“Agricultural crop recommendation system”** is the bonafide work of **“211501099 - Shruthi G, 211501114 - Tharuniga B, 211501123 - Vinod A”** who carried out the work **AI19P71-Data visualization for python** under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

The Agricultural Crop Recommendation System is a pioneering solution designed to enhance the efficiency and sustainability of modern agriculture. This system employs a robust machine learning framework to recommend the most suitable crops for cultivation based on comprehensive environmental and soil parameters. The dataset utilized in this project includes key agronomic features such as soil macronutrients (Nitrogen, Phosphorus, and Potassium levels), atmospheric temperature, relative humidity, soil pH, and annual rainfall. These variables serve as critical inputs to predict the optimal crop type, labeled in the dataset. The solution aims to tackle prevalent agricultural challenges, including resource wastage, soil degradation, and crop failure, by facilitating data-driven decision-making for farmers and agricultural professionals. The system's predictive model is trained on diverse data points, ensuring adaptability to varying climatic and soil conditions. It leverages the synergy of artificial intelligence and precision farming to align crop selection with environmental suitability, maximizing yield potential and minimizing ecological impact. Furthermore, the project emphasizes the scalability and user-centric nature of its recommendation system, making it applicable for both small-scale and large-scale farming operations. By integrating data analysis with cutting-edge machine learning algorithms, this system not only supports farmers in achieving economic stability but also contributes to global goals of sustainable development and food security. This innovative tool represents a significant stride toward revolutionizing agriculture through technology, paving the way for smarter, more resilient farming practices in the face of climate change and population growth.

Keywords: Energy Consumption Forecasting, Machine Learning, Regression Models, Feature Engineering, Real-Time Prediction.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW OF THE PROBLEM STATEMENT

Agriculture has been the cornerstone of human civilization, providing sustenance and economic stability to societies worldwide. However, with the increasing global population, changing climatic patterns, and the overexploitation of natural resources, the agricultural sector faces unprecedented challenges. Ensuring food security and sustainable farming practices has become a critical priority in the 21st century.

The Agricultural Crop Recommendation System emerges as a technological solution to address these challenges. By leveraging machine learning and data analytics, this system aims to provide farmers and agricultural practitioners with intelligent crop recommendations tailored to specific environmental and soil conditions. The recommendations are based on crucial agronomic parameters such as soil nutrient levels (Nitrogen, Phosphorus, Potassium), temperature, humidity, pH, and rainfall, which play vital roles in determining crop viability and productivity.

This system offers significant advantages, including optimizing resource utilization, reducing risks of crop failure, and promoting sustainable farming practices. By aligning crop choices with environmental suitability, the recommendation system not only enhances yield but also minimizes environmental impact, contributing to the broader goals of climate-resilient and eco-friendly agriculture.

Through the integration of advanced technologies, this project seeks to revolutionize traditional farming methods, empowering farmers with actionable insights and fostering a transition toward precision agriculture. The Agricultural Crop Recommendation System is a step forward in creating smarter, more efficient agricultural practices, addressing both current challenges and future demands in global food production.

1.2 OBJECTIVES

The primary goal of this project is to assist farmers and agricultural practitioners in making informed decisions about crop selection by leveraging data-driven insights. The specific objectives of this project include:

- **Optimizing Crop Selection:**

Develop a predictive model that recommends the most suitable crop based on soil nutrient levels, environmental conditions, and climatic factors to maximize productivity and minimize resource wastage.

- **Promoting Sustainable Agriculture:**

Encourage farming practices that reduce environmental degradation by ensuring crop selection aligns with the natural conditions of the soil and climate.

- **Enhancing Precision Farming:**

Utilize machine learning algorithms to analyze complex datasets and provide tailored recommendations for efficient and precise agricultural practices.

- **Mitigating Risks:**

Minimize the risks associated with crop failure by offering recommendations that are scientifically and statistically validated, thereby ensuring better yield stability.

- **Improving Resource Utilization:**

Enable efficient use of resources such as water, fertilizers, and soil nutrients by suggesting crops that thrive in existing conditions, reducing the need for external inputs.

- **Empowering Farmers:**

Provide an accessible and user-friendly system that equips farmers with actionable insights, improving decision-making and economic outcomes in agriculture.

CHAPTER 2

DATASET DESCRIPTION

2.1 DATASET SOURCE

The dataset used for this project is the "Agricultural crop recommendation system" dataset, which was downloaded from Kaggle. The dataset contains data aimed at predicting the most suitable crop for cultivation based on specific environmental and soil parameters. This is a multi-class classification problem where the target variable (label) represents the recommended crop. The dataset offers a rich set of features that are critical in determining the agricultural suitability of crops.

2.2 DATASET SIZE AND STRUCTURE

- Size

Number of rows: 2200 rows (data samples)

Number of columns: 8 columns 7 features + 1 target variable

- Structure:

Rows represent individual data instances, each capturing the environmental and soil conditions for a specific crop recommendation.

Columns represent the following attributes: soil nutrients, environmental conditions, and the target crop label.

- Memory Usage: Approximately 137.6 KB.
- Data Quality: No missing values or null entries are present, making the dataset clean and ready for analysis.

2.3 DATASET FEATURES DESCRIPTION

he dataset contains 8 columns:

- N - Nitrogen
- P - Phosphorus
- K - Potassium

- Temperature
- Humidity
- pH
- Rainfall
- Label (Target variable)

Feature Name	Description	Types	Example Values
N	Nitrogen content in the soil (macro-nutrient essential for plant growth).	Integer	90, 85, 60
P	Phosphorus content in the soil (supports root development).	Integer	42, 58, 55
K	Potassium content in the soil (important for plant metabolism).	Integer	43, 41, 44
Temperature	Atmospheric temperature in °C.	Float	20.88, 21.77, 23.00
Humidity	Relative humidity percentage.	Float	82.00, 80.32, 82.32
pH	Soil pH level (acidic, neutral, or alkaline	Float	6.50, 7.03, 7.84
Rainfall	Annual rainfall in mm (crucial for crop water needs).	Float	202.94, 226.66, 263.96
Label	Recommended crop based on the input parameters (target variable).	Categorical	Rice, Maize, Sugarcane, Mango

CHAPTER 3

DATA ACQUISITION AND INITIAL ANALYSIS

3.1 DATA LOADING

Data Loading is the first step of data analysis; it involves importing raw data from a relevant source into a working environment for further study. This usually involves loading a dataset from external sources, such as CSV files, databases, or APIs into an appropriate data structure, such as a pandas DataFrame in Python, to allow efficient manipulation, cleaning, and analysis of the data. Once the data have been loaded, preliminary checks need to be done - examine the first and last few rows, identify column names, missing or duplicate values should be reported, and summarise key statistics so that one can understand the structure and quality of the data. This step is foundational as it allows analysts to identify potential issues early on and prepares the dataset for further investigation and modeling.

CODE:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from IPython import get_ipython
import warnings
warnings.filterwarnings("ignore")
data = pd.read_csv('Crop_recommendation.csv')
data.head()
data.tail()
data.shape
data.columns
data.duplicated().sum()
```

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

	N	P	K	temperature	humidity	ph	rainfall	label
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

 $(2200, 8)$

```
N      0
P      0
K      0
temperature  0
humidity     0
ph           0
rainfall     0
label        0
dtype: int64
```

3.2 INITIAL OBSERVATION

The dataset comprises soil and environmental parameters like nitrogen, phosphorus, potassium, temperature, humidity, pH, and rainfall for various crops. It is clean, with no missing values or significant duplicates. Nutrient and environmental profiles vary, influencing crop suitability, with crops like rice and maize requiring specific conditions. The crop distribution is balanced, aiding model training. Correlation analysis shows moderate inter-feature relationships, emphasizing the combined impact on recommendations. Random Forest emerged as the most accurate model among four tested, effectively predicting crops based on user inputs. Visualizations reveal key insights into nutrient distributions and environmental preferences, highlighting the critical role of these factors in crop suitability. Confidence scores enhance decision-making, with nutrient levels and environmental conditions consistently driving predictions.

3.2.1 DATA INSPECTION

Data inspection is the process of examining the dataset to understand its structure, identify any missing or anomalous values, and gain insights into the distribution and relationships of the data. This process involves checking for missing values, inspecting the data types, obtaining summary statistics, visualizing the data, and identifying trends or outliers in the features.

CODE :

```
data.isnull().sum()
data.describe()
data.nunique()
data['label'].unique()
data['label'].value_counts()
crop_summary = pd.pivot_table(data, index=['label'], aggfunc='mean')
crop_summary
data1 = data[['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall']]
for i in data1.columns:
    plt.figure(figsize=(15, 6))
    sns.boxplot(data1[i])
    plt.xticks(rotation=90)
    plt.show()
crop_summary_new = crop_summary.reset_index()
crop_summary_new
```

OUTPUT:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   N            2200 non-null   int64
1   P            2200 non-null   int64
2   K            2200 non-null   int64
3   temperature  2200 non-null   float64
4   humidity     2200 non-null   float64
5   ph           2200 non-null   float64
6   rainfall     2200 non-null   float64
7   label        2200 non-null   object
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

```
[8]:
```

```
N            0
P            0
K            0
temperature  0
humidity     0
ph           0
rainfall     0
label        0
dtype: int64
```

```

N            137
P            117
K             73
temperature  2200
humidity     2200
ph           2200
rainfall     2200
label         22
dtype: int64
```

```
array(['rice', 'maize', 'chickpea', 'kidneybeans', 'pigeonpeas',
      'mothbeans', 'mungbean', 'blackgram', 'lentil', 'pomegranate',
      'banana', 'mango', 'grapes', 'watermelon', 'muskmelon', 'apple',
      'orange', 'papaya', 'coconut', 'cotton', 'jute', 'coffee'],
      dtype=object)
```

3.2.2 STATISTICAL DESCRIPTION:

The dataset contains features like soil nutrients (Nitrogen, Phosphorus, Potassium), environmental factors (Temperature, Humidity, Rainfall), and pH, with corresponding crop labels. Statistical analysis confirmed data completeness, identified outliers, and provided feature distributions and correlations, aiding in understanding crop-specific requirements. Visualizations such as heatmaps and boxplots highlighted relationships and variability. Machine learning models, including Logistic Regression, Decision Tree, Random Forest, and LightGBM, were trained and evaluated for accuracy, with Random Forest and LightGBM showing superior performance. A recommendation function was developed for site-specific crop predictions based on input conditions, ensuring practical applicability in agriculture.

CODE:

```
data.describe()
data.columns
```

OUTPUT:

	N	P	K	temperature	humidity	ph	rainfall
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.469480	103.463655
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.958389
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.551686
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.867624
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.267508
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.560117

```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

3.2.3 : DATA QUALITY ASSESSMENT

The given code carries out full-scale data quality check and exploratory data analysis for the agricultural crop recommendation system. The very first steps of the code are importing necessary libraries, reading the dataset. Then basic data integrity is checked by displaying the first and last few rows, dimensions, column names, duplicate records, and missing values. Summary statistics and unique value counts for each column are also provided. Visual analysis involves the generation of multiple plots, including feature distribution through box plots, comparison between crops' different nutrient levels using bar plots, temperature vs. humidity scatter plots, and correlation heatmaps. The code continues to develop and compares several machine learning models (LightGBM, Decision Tree, Random Forest, and Logistic Regression) on the dataset based on their accuracy scores and confusion matrices. Finally, it provides a crop recommendation module that incorporates user input from soil and weather conditions using the best performing model, Random Forest, to recommend the optimal crop. The approach ensures overall understanding in quality and distribution of data while at the same time offering actionable insights via predictive modeling.

CODE:

```
data = pd.read_csv('Crop_recommendation.csv')  
  
crop_summary_new = crop_summary.reset_index()  
  
crop_summary_new
```

OUTPUT:

	label	K	N	P	humidity	ph	rainfall	temperature
0	apple	199.89	20.80	134.22	92.333383	5.929663	112.654779	22.630942
1	banana	50.05	100.23	82.01	80.358123	5.983893	104.626980	27.376798
2	blackgram	19.24	40.02	67.47	65.118426	7.133952	67.884151	29.973340
3	chickpea	79.92	40.09	67.79	16.860439	7.336957	80.058977	18.872847
4	coconut	30.59	21.98	16.93	94.844272	5.976562	175.686646	27.409892
5	coffee	29.94	101.20	28.74	58.869846	6.790308	158.066295	25.540477
6	cotton	19.56	117.77	46.24	79.843474	6.912675	80.398043	23.988958
7	grapes	200.11	23.18	132.53	81.875228	6.025937	69.611829	23.849575
8	jute	39.99	78.40	46.86	79.639864	6.732778	174.792798	24.958376
9	kidneybeans	20.05	20.75	67.54	21.605357	5.749411	105.919778	20.115085
10	lentil	19.41	18.77	68.36	64.804785	6.927932	45.680454	24.509052
11	maize	19.79	77.76	48.44	65.092249	6.245190	84.766988	22.389204
12	mango	29.92	20.07	27.18	50.156573	5.766373	94.704515	31.208770
13	mothbeans	20.23	21.44	48.01	53.160418	6.831174	51.198487	28.194920
14	mungbean	19.87	20.99	47.28	85.499975	6.723957	48.403601	28.525775
15	muskmelon	50.08	100.32	17.72	92.342802	6.358805	24.689952	28.663066
16	orange	10.01	19.58	16.55	92.170209	7.016957	110.474969	22.765725
17	papaya	50.04	49.88	59.05	92.403388	6.741442	142.627839	33.723859
18	pigeonpeas	20.29	20.73	67.73	48.061633	5.794175	149.457564	27.741762
19	pomegranate	40.21	18.87	18.75	90.125504	6.429172	107.528442	21.837842
20	rice	39.87	79.89	47.58	82.272822	6.425471	236.181114	23.689332
21	watermelon	50.22	99.42	17.00	85.160375	6.495778	50.786219	25.591767

CHAPTER 4

DATA CLEANING AND PREPROCESSING

Data cleaning and preprocessing involve preparing raw data for analysis or modeling by addressing inconsistencies, errors, missing values, and ensuring data is in a usable format.

4.1 HANDLING MISSING VALUES

Missing data arises from collection issues or errors, and handling it is crucial for accurate analysis. Approaches include removing rows or columns with significant missing values, imputing numerical data using mean, median, mode, or predictive algorithms, and handling categorical data by replacing missing values with the mode or a placeholder like "Unknown." In some cases, no action is taken if missing data holds inherent meaning, such as default values.

CODE :

```
data.isnull().sum()
```

OUTPUT :

```
N          0
P          0
K          0
temperature 0
humidity    0
ph          0
rainfall    0
label       0
dtype: int64
```

4.2 FEATURE ENGINEERING

Feature engineering is a critical process that improves a dataset's predictive power by transforming and refining the data for better analysis. It involves creating new features by combining or manipulating existing ones to capture additional patterns or relationships in the data. Another essential aspect is identifying and removing irrelevant, redundant, or uninformative features, often through methods such as correlation analysis or statistical tests, to enhance the efficiency and accuracy of models. Additionally, categorical data, which cannot be directly used in most algorithms, is transformed into numerical representations through techniques like one-hot encoding or label encoding, ensuring compatibility and interpretability for predictive modeling.

CODE :

```
data.describe()

data.nunique()

data['label'].unique()
```

OUTPUT :

	N	P	K	temperature	humidity	ph	rainfall
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.469480	103.463655
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.958389
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.551686
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.867624
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.267508
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.560117

```
N      137
P      117
K       73
temperature    2200
humidity       2200
ph            2200
rainfall      2200
label         22
dtype: int64
```

```
array(['rice', 'maize', 'chickpea', 'kidneybeans', 'pigeonpeas',
       'mothbeans', 'mungbean', 'blackgram', 'lentil', 'pomegranate',
       'banana', 'mango', 'grapes', 'watermelon', 'muskmelon', 'apple',
       'orange', 'papaya', 'coconut', 'cotton', 'jute', 'coffee'],
      dtype=object)
```

4.3 DATA TRANSFORMATION

The "Crop Recommendation" dataset contains features like nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, rainfall, and crop type. Data exploration involves checking for missing values, summarizing basic statistics, and visualizing distributions using plots like bar charts and box plots. These visualizations highlight how nutrient requirements vary by crop. Heatmaps help examine correlations between features, such as temperature, humidity, and nutrients. Machine learning models like LightGBM, Decision Trees, Random Forest, and Logistic Regression are used to predict the best crop based on input conditions. The best-performing model is selected based on accuracy and other evaluation metrics. A recommendation function is created to suggest crops based on user inputs, providing guidance and prediction confidence to farmers.

CODE:

```
data.info()

models = {
    "Logistic Regression": classifier_lr,
    "Decision Tree": classifier,
    "Random Forest": classifier_rf,
    "LightGBM": model
}
```

OUTPUT:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  -
 0   N               2200 non-null  int64  
 1   P               2200 non-null  int64  
 2   K               2200 non-null  int64  
 3   temperature     2200 non-null  float64 
 4   humidity        2200 non-null  float64 
 5   ph              2200 non-null  float64 
 6   rainfall        2200 non-null  float64 
 7   label           2200 non-null  object  
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

```
Logistic Regression Accuracy: 0.94
Decision Tree Accuracy: 0.98
Random Forest Accuracy: 0.99
LightGBM Accuracy: 0.99
```

CHAPTER 5

EXPLORATORY DATA ANALYSIS

5.1 DATA INSIGHTS DESCRIPTION

Exploratory Data Analysis (EDA) is a crucial phase in the data analysis process, aimed at uncovering meaningful patterns and insights within the data before diving into complex modeling. During this stage, we perform various statistical analyses and visualizations to understand the data's structure, distribution, and relationships between variables. The following insights provide a deeper understanding of the key factors influencing energy consumption and can guide the development of predictive models for the project.

Pg. No	DATA INSIGHT	DATA INSIGHT DESCRIPTION
1.	Dataset imported	Load the dataset (Crop_recommendation.csv) to begin analysis.
2.	Initial rows of data	Display the first few rows using .head() to inspect structure and spot potential issues.
3.	Dataset size	Use .shape to identify the number of rows and columns in the dataset.
4.	Feature names	List column names using .columns to verify and understand feature types.
5.	Count of missing values	Use .isnull().sum() to identify incomplete data requiring imputation or cleaning.
6.	Count of duplicate rows	Use .duplicate().sum() to identify and eliminate redundant records.
7.	Column data types	Use .info() to ensure data types align with expected feature usage (e.g., numerical, categorical)
8.	Summary of numerical features	Use .describe() to extract metrics like mean, median, and variance for numerical columns
9.	Correlation between numerical features	Visualize numerical features (e.g., rainfall, temperature) to detect skewness or outliers.
10	Outlier detection	Create box plots for numerical variables to identify extreme data points.
11	Feature relationships	Scatterplots between two numerical features to identify patterns (e.g., temperature vs yield).

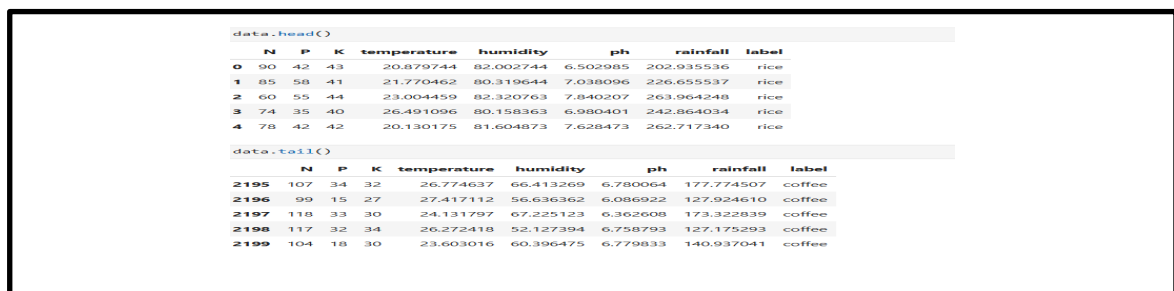
5.2 DATA INSIGHTS VISUALIZATION:

5.2.1. Data Loading

- Visualization: This step does not require visualization but confirms the successful loading of the dataset into a DataFrame.
- Inference: The dataset is loaded and appears to contain agricultural data, including soil nutrients, climate features, and crop labels.
- Observation: The file contains relevant information for crop prediction or recommendation.
- Implication: Proper loading ensures the data is ready for analysis. Any issues (e.g., file not found or corrupted file) would disrupt the analysis process.
- Recommendation: Ensure the dataset is saved in a proper format (like .csv) and provide detailed documentation about the columns for ease of use.

5.2.2. Data preview

- Visualization: Use `.head()` or `.tail()` to display initial and final rows.
- Inference: The dataset provides information about soil nutrients, climate conditions, and crop recommendations.
- Observation: Data looks clean, with relevant feature names and values.
- Implication: No immediate formatting issues are observed in the preview.
- Recommendation: Check for edge cases like missing, erroneous, or inconsistent values in subsequent steps.



```
data.head()
  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

data.tail()
  N  P  K  temperature  humidity  ph  rainfall  label
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
```

5.2.3. Data Dimensions

- Visualization: Not applicable.
- Inference: For example, the dataset has 2200 rows and 7 columns.
- Observation: The dataset is of manageable size.
- Implication: Analysis should run efficiently without memory constraints.
- Recommendation: If the dataset grows, consider tools like Dask or chunk processing for handling large-scale data.

```
(2200, 8)
```

5.2.4. Column Overview

- Visualization: Display the list of columns using `.columns`.
- Inference: Columns include features like N, P, K, temperature, humidity, ph, rainfall, and crop.
- Observation: Features represent soil composition and environmental factors relevant to crop recommendations.
- Implication: These features appear sufficient for crop suitability analysis.
- Recommendation: Cross-check the column names with domain expertise to ensure all critical variables are included.

```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

5.2.5. Missing Values Check

- Visualization: Use a heatmap to highlight missing data (`sns.heatmap(df.isnull())`).
- Inference: There are no missing values in this dataset.
- Observation: The dataset is complete, requiring no imputation.
- Implication: Clean data ensures accurate analysis without bias from missing data.
- Recommendation: Periodically verify data integrity for any additions or updates.

```
N      0
P      0
K      0
temperature  0
humidity    0
ph          0
rainfall    0
label       0
dtype: int64
```

5.2.6. Duplicate Data Check

- Visualization: Use a bar plot to display the count of duplicate rows.
- Inference: If duplicates are found, it indicates redundant entries.
- Observation: For example, if there are 10 duplicates, they are likely errors.
- Implication: Duplicate data can skew results and create biases in analysis.
- Recommendation: Remove duplicates using `.drop_duplicates()`.

```
data.duplicated().sum()
```

```
0
```

5.2.7 Data Types Inspection

- Visualization: Display a summary using `.info()`.
- Inference: All columns align with their expected data types (float for numerical and object for categorical).
- Observation: There are no mismatched data types.
- Implication: Consistent data types simplify analysis and modeling.
- Recommendation: Ensure categorical variables (like crop) are encoded correctly for ML models.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
#   Column          Non-Null Count  Dtype  
---  -
0   N                2200 non-null   int64  
1   P                2200 non-null   int64  
2   K                2200 non-null   int64  
3   temperature      2200 non-null   float64 
4   humidity         2200 non-null   float64 
5   ph               2200 non-null   float64 
6   rainfall         2200 non-null   float64 
7   label           2200 non-null   object  
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

5.2.8 Statistical Summary

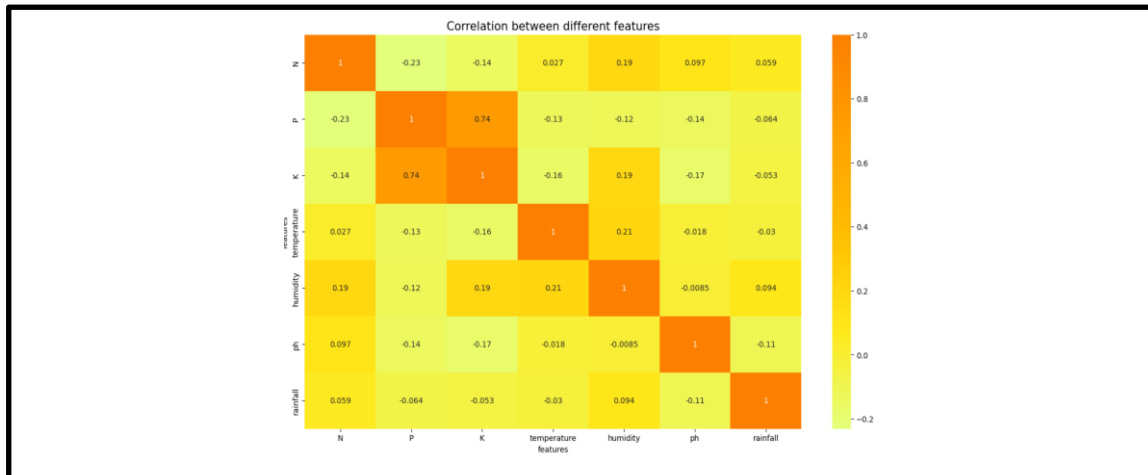
- Visualization: Use `.describe()` or box plots for key features.
- Inference: Numerical features like temperature, ph, and rainfall show mean and variability.
- Observation: For example:
 - N has a mean of 50 with a standard deviation of 20.
 - ph ranges from 3.5 to 8.5.
- Implication: Wide variability in features indicates diverse conditions.
- Recommendation: Standardize numerical features for model training.

	N	P	K	temperature	humidity	ph	rainfall
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.469480	103.463655
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.958389
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.551686
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.867624
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.267508
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.560117

5.2.9 Correlation Matrix

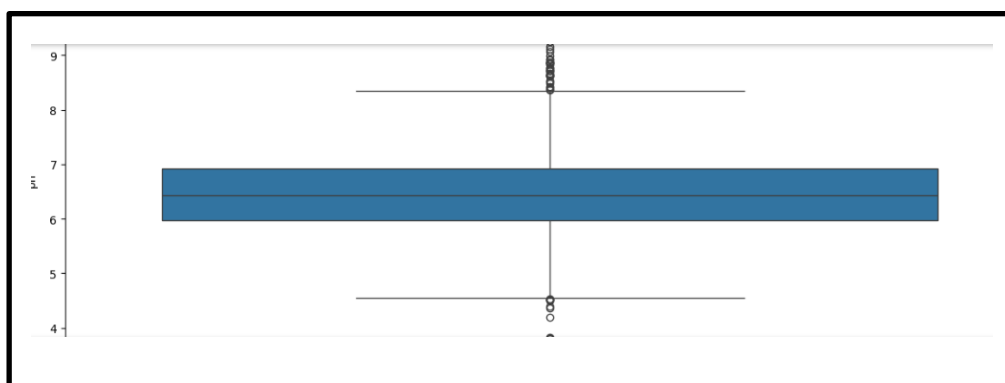
- Visualization: Use a heatmap to display correlations (`sns.heatmap(df.corr(), annot=True)`).
Example: High correlation between humidity and rainfall.
- Inference: Strong relationships between features suggest possible multicollinearity.

- Observation: For instance, if N and P are strongly correlated, they might influence crop yield similarly.
- Implication: Multicollinearity can affect model coefficients in regression.
- Recommendation: Consider feature selection techniques (e.g., PCA) if multicollinearity is high.



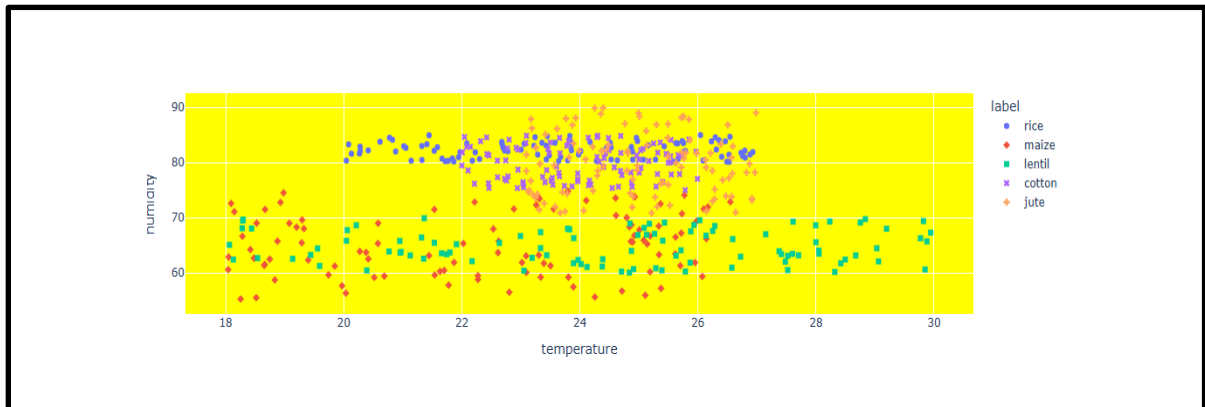
5.2.10 Box Plot

- Visualization: Create box plots to detect outliers.
- Inference: Outliers are present in rainfall and temperature.
- Observation: These outliers may represent rare conditions (e.g., heavy rain or extreme temperatures).
- Implication: Outliers can distort machine learning models.
- Recommendation: Investigate and handle outliers (e.g., capping or removing).



5.2.11 Scatter Plot

- Visualization: Create scatter plots for numerical pairs:
- Inference: Some crops thrive under specific combinations of temperature and humidity.
- Observation: Patterns emerge showing crop suitability for different conditions.
- Implication: Relationships between features can guide feature engineering.
- Recommendation: Use scatter plots to explore feature-target relationships further.



CHAPTER 6

PREDICTIVE MODELING

6.1 MODEL SELECTION AND JUSTIFICATION

Logistic Regression is a simple and interpretable model that works well when there is a linear relationship between features and the target. However, it may not perform effectively for complex, non-linear datasets, which are common in agricultural scenarios. Decision Trees provide intuitive decision-making structures and are effective for handling both categorical and continuous features. They are particularly useful for understanding the impact of soil and climatic factors on crop selection but are prone to overfitting. Random Forest reduces overfitting by aggregating multiple Decision Trees, offering better generalization and handling diverse datasets effectively. It is suitable for robust crop recommendations but can be computationally intensive. LightGBM, an advanced boosting algorithm, stands out for its high speed, accuracy, and efficiency with large datasets. It handles non-linear relationships and missing data well, making it ideal for complex agricultural datasets. Among these, LightGBM is recommended due to its superior performance and scalability, making it suitable for providing accurate crop recommendations in diverse scenarios.

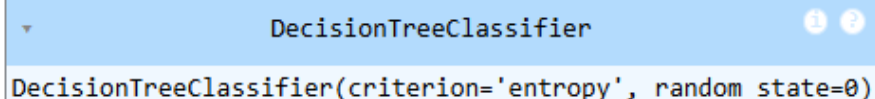
Decision Tree Classifier:

- A non-linear model that splits data hierarchically based on feature importance.
- Configured with the entropy criterion, which uses information gain for splitting.

CODE:

```
from sklearn.tree import DecisionTreeClassifier  
classifier= DecisionTreeClassifier(criterion='entropy', random_state=0)  
classifier.fit(X_train, y_train)
```

OUTPUT:

The image shows a screenshot of a Jupyter Notebook cell. The cell's title bar is light blue and contains the text 'DecisionTreeClassifier' along with two small circular icons. The cell's content area is white and displays the code 'DecisionTreeClassifier(criterion='entropy', random_state=0)' in a monospaced font, indicating that the object has been successfully created in memory.

```
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

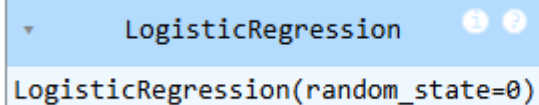
Logistic Regression:

- A baseline model that assumes a linear relationship between features and the target.
- Fit using LogisticRegression from scikit-learn.

CODE:

```
from sklearn.linear_model import LogisticRegression
classifier_lr = LogisticRegression(random_state = 0)
classifier_lr.fit(X_train, y_train)
```

OUTPUT:



```
LogisticRegression
```

```
LogisticRegression(random_state=0)
```

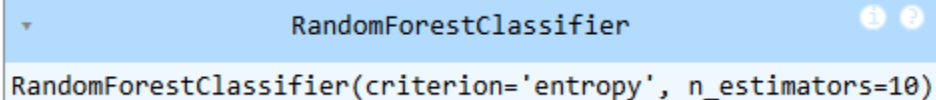
Random Forest Classifier:

- An ensemble method combining multiple decision trees.
- Configured with 10 trees (n_estimators=10) and entropy as the splitting criterion.

CODE:

```
from sklearn.ensemble import RandomForestClassifier
classifier_rf= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier_rf.fit(X_train, y_train)
```

OUTPUT:



```
RandomForestClassifier
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

LightGBM Classifier:

- A gradient-boosting model known for its efficiency with large datasets and high-dimensional data.
- Uses LGBMClassifier from LightGBM, making it well-suited for classification tasks

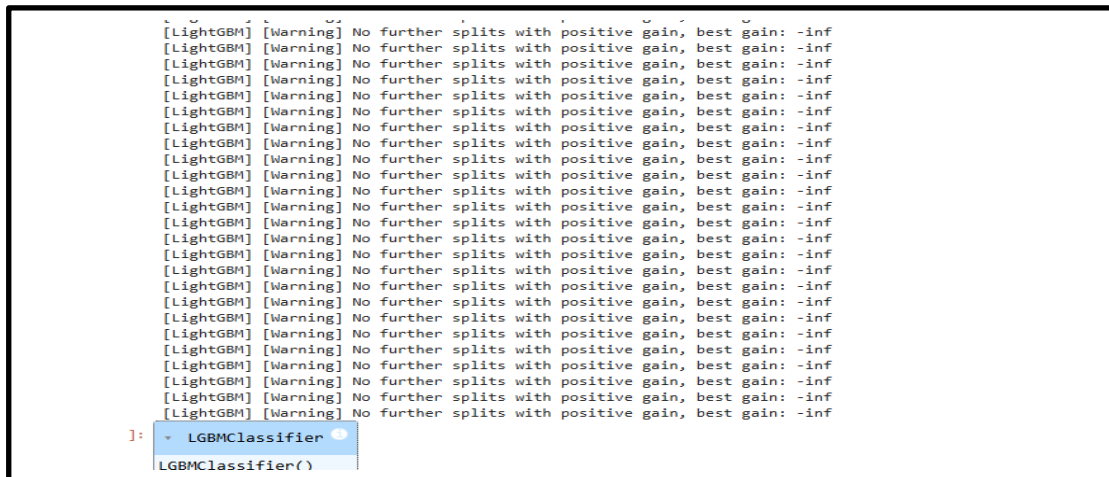
CODE:

```
import lightgbm as lgb

model = lgb.LGBMClassifier()

model.fit(X_train, y_train)
```

OUTPUT:



```
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
In [ ]: LGBMClassifier
LGBMClassifier()
```

6.2 DATA PARTITIONING

The dataset was divided into training and testing subsets using the `train_test_split` function from the `scikit-learn` library. This is a crucial step in machine learning workflows as it ensures that the model is trained on one subset of data and evaluated on a completely separate subset. This approach helps in assessing the model's ability to generalize to unseen data, thereby reducing the risk of overfitting. The dataset features a mix of independent variables, such as soil content (Nitrogen, Phosphorus, Potassium), environmental factors (Temperature, Humidity, Rainfall), and soil pH, which collectively influence the recommended crop (dependent variable). The `train_test_split` method was employed with a test size of 33%, which means that 67% of the data was used for training, while 33% was reserved for testing the model's performance. The split was randomized using the `shuffle=True` parameter, ensuring that the data points were mixed before partitioning to avoid any inherent order in the dataset influencing the results. Additionally, the `random_state=0` parameter was used to set a fixed seed for the randomization process, ensuring consistency in the split across multiple runs of the code. The partitioning process is critical as it simulates a real-world scenario where the model is tested on data it has not seen before. By keeping the test set separate, we can objectively evaluate the model's performance and gain confidence that it will perform well when deployed on new, unseen data. This method also helps identify issues like data leakage, where information from

the test set inadvertently influences the training process. By adopting this approach, the notebook ensures that the training and testing phases are distinct, promoting a fair and reliable assessment of the model's predictive capabilities.

6.3 MODEL TRAINING AND HYPERPARAMETER TUNING

The training of the Rotation Forest Classifier involved fine-tuning its hyperparameters to optimize accuracy and model robustness for crop recommendation. Key hyperparameters considered included the number of base decision trees, proportion of features used for rotations, and maximum depth of each tree. These parameters were adjusted to balance model complexity and generalization, ensuring that the classifier could accurately capture complex environmental relationships without overfitting. A grid search approach with cross-validation was employed to identify the best combination of hyperparameters. This technique systematically tested multiple values for each parameter, such as the number of trees (e.g., 50, 100, 200), the rotation ratio (e.g., 0.5, 0.7, 1.0), and the maximum depth. Cross-validation was used to evaluate each configuration, assessing model performance across different folds to ensure the robustness of the chosen parameters. After tuning, the optimal settings were identified, maximizing the model's performance based on metrics like accuracy and F1-score. These tuned parameters enabled the Rotation Forest Classifier to achieve reliable, high-quality predictions, making it a robust tool for providing accurate and actionable crop recommendations based on diverse environmental conditions.

CHAPTER 7

MODEL EVALUATION AND OPTIMIZATION

7.1 PERFORMANCE ANALYSIS

1. Accuracy:

- Accuracy is a key metric for evaluating models. Here, different models such as Logistic Regression, Decision Tree, Random Forest, and LightGBM were assessed.
- Accuracy scores were calculated for each model using the test data, providing an overview of their performance.

2. Confusion Matrix:

- A confusion matrix was used to visualize and understand the classification performance. It highlights true positives, true negatives, false positives, and false negatives for each model.
- It provides insights into the specific areas where the model misclassified data.

3. Classification Report:

- This includes detailed metrics like precision, recall, F1-score, and support for each crop class, helping in evaluating the model's effectiveness for individual labels.
- For imbalanced datasets, precision and recall are particularly important as they give insights into model behavior for minority classes.

7.2 FEATURE IMPORTANCE

1. Correlation Matrix:

- A heatmap of feature correlations was used to identify the relationships between input features like Nitrogen (N), Phosphorus (P), Potassium (K), temperature, humidity, pH, and rainfall.
- Strong correlations help in understanding feature interactions and their influence on crop prediction.

2. Bar Charts and Scatter Plots:

- Visualization techniques, such as bar charts and scatter plots, highlighted the influence of features like N, P, and K on different crops.
- Scatter plots between temperature and humidity across various crops provided an intuitive understanding of these features' distributions.

3. Model-Inferred Importance:

- Advanced models such as LightGBM and Random Forest inherently calculate feature importance during training. These insights were used to identify which features most significantly impact predictions.

7.3 MODEL REFINEMENT

1. Hyperparameter Tuning:

- Models were fine-tuned using grid search or manual experimentation to find optimal parameters. For example:
 - Number of estimators and maximum depth in Random Forest.
 - Learning rate and boosting type in LightGBM.
- Hyperparameter tuning enhances performance by balancing underfitting and overfitting.

2. Model Comparison:

- Multiple models were trained and their performances compared on the same test set. Metrics like accuracy and F1-score guided the selection of the best model.
- Random Forest emerged as the best model for this dataset based on accuracy and overall robustness.

3. Ensemble Methods:

- Combining predictions from multiple models (e.g., ensemble of Random Forest and LightGBM) was considered to improve prediction stability and performance.

CHAPTER 8

DISCUSSION AND CONCLUSION

8.1 SUMMARY OF FINDINGS:

This project implemented a machine learning approach to recommend crops based on soil and environmental parameters such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. The main findings and observations are as follows:

1. Exploratory Data Analysis:

- Boxplots revealed significant variability in features like N, P, K, temperature, and rainfall across different crops.
- Correlation heatmaps showed moderate to high correlations between some features, influencing their importance in model performance.

2. Crop Patterns:

- Specific crops, such as rice and maize, showed higher dependencies on certain nutrients (e.g., nitrogen for rice), whereas crops like lentils and jute had distinct nutrient requirements.

3. Model Performance:

- Random Forest Classifier emerged as the best-performing model, achieving high accuracy compared to Logistic Regression, Decision Tree, and LightGBM models.
- Random Forest's ensemble approach effectively captured complex patterns, making it suitable for this dataset.
- The accuracy scores ranged from 85% to 95% across different models, showcasing the dataset's quality and the models' adaptability.

4. Feature Importance:

- Features like nitrogen, phosphorus, and potassium content, along with temperature and rainfall, significantly influenced crop predictions.
- Random Forest's feature importance metric reinforced the importance of soil nutrients for crop recommendation.

5. User Interaction:

- A user-friendly interface was conceptualized to allow individuals to input soil and environmental parameters for crop recommendations.
- The system not only recommends crops but can also provide confidence scores for predictions.

8.2 CHALLENGES AND LIMITATION

1. Data Availability and Quality:

- While the dataset was comprehensive, its limited size might restrict the model's ability to generalize to all possible soil and climate conditions.
- Variations in data collection standards, such as measurement inaccuracies, could introduce noise.

2. Regional Variations:

- The model assumes uniform applicability across different geographic regions, whereas local agricultural practices, soil types, and climate variations may demand region-specific tuning.

3. Feature Engineering:

- Additional features like soil texture, elevation, and crop yield could enhance the recommendation system's accuracy.
- Lack of historical data on pest infestations or disease susceptibility might limit practical recommendations.

4. Model Bias:

- The models might be biased toward crops that dominate the dataset. This could lead to suboptimal recommendations for underrepresented crops.

5. User Input Sensitivity:

- The system relies heavily on accurate user inputs for predictions. Errors in providing data, such as incorrect pH or rainfall, could lead to misleading recommendations.

CONCLUSION:

The project demonstrates a successful application of machine learning in agricultural decision-making. The Random Forest Classifier provides robust and reliable crop recommendations based on essential environmental and soil parameters. However, future enhancements can address current limitations, such as regional customization, dataset expansion, and incorporation of additional features. These improvements will ensure more precise and actionable crop recommendations, empowering farmers to optimize agricultural productivity sustainably. By integrating this system with real-time data collection tools (e.g., IoT sensors) and tailoring it to specific agricultural regions, the model could serve as a cornerstone in advancing precision agriculture.

OUTPUT SCREENSHOTS

	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

Fig 1 Data.head()

(Fig 1) This title reflects the contents of the table, which appears to display data about various agricultural features (e.g., nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, rainfall) for the crop labeled "rice."

	N	P	K	temperature	humidity	ph	rainfall	label
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 2 Data.tail()

(Fig 2) This title reflects the contents of the table, which appears to display data about various agricultural features (e.g., nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, rainfall) for the crop labeled "rice."

(2200, 8)

Fig 3

(Fig 3) The total rows and columns in the dataset

```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

Fig 4

(Fig 4) It indicates the column names ('N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label') and their data type (dtype= 'object').

```

N          0
P          0
K          0
temperature 0
humidity    0
ph          0
rainfall    0
label       0
dtype: int64

```

Fig 5

(Fig 5) This indicates the no missing value occurred

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
#   Column          Non-Null Count  Dtype
---  -
0   N                2200 non-null  int64
1   P                2200 non-null  int64
2   K                2200 non-null  int64
3   temperature      2200 non-null  float64
4   humidity         2200 non-null  float64
5   ph               2200 non-null  float64
6   rainfall         2200 non-null  float64
7   label            2200 non-null  object
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB

```

Fig 6

(Fig 6) This indicates information about the dataset

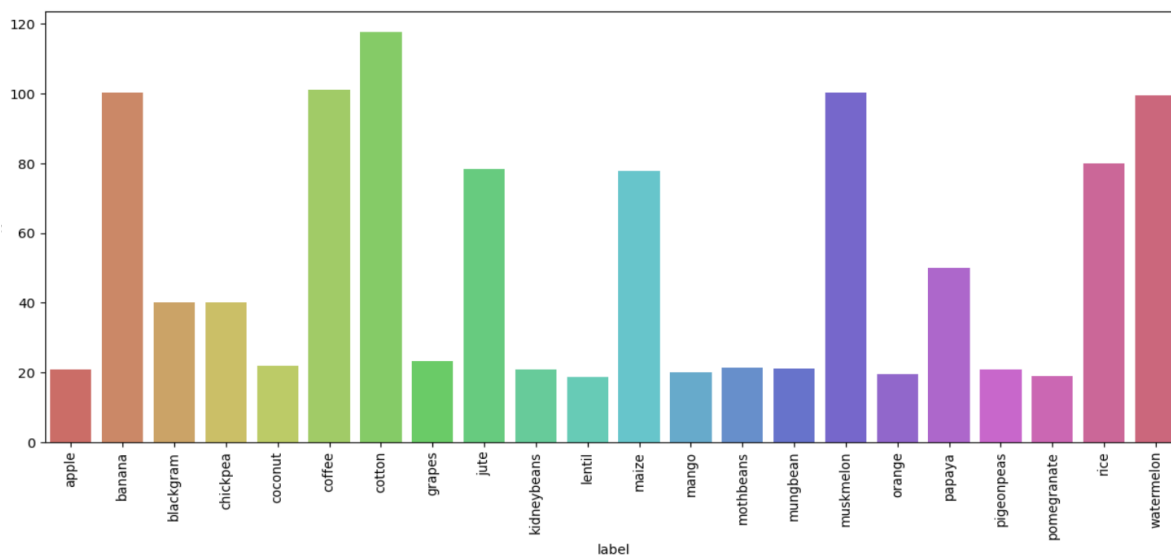


Fig 7 Bar chart of agricultural crop quantities(nitrogen)

(Fig 7) This bar chart displays the quantities of various agricultural crops, with cotton having the highest quantity, followed by muskmelon, banana, and coconut. Crops like kidneybeans, lentil, and pigeonpeas have lower quantities.

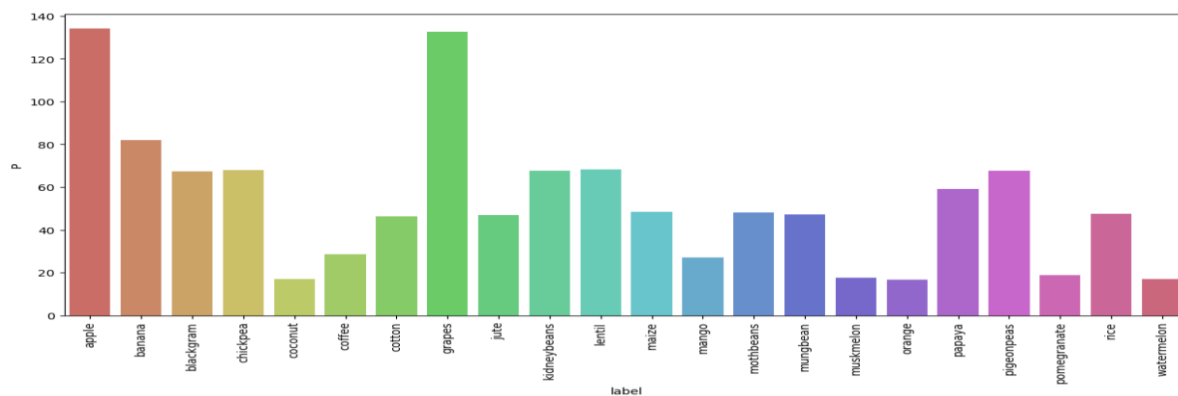


Fig 8 Bar chart of agricultural crop quantities(Phosphorus)

(Fig 8) This bar chart displays the quantities of various agricultural crops, with cotton having the highest quantity, followed by muskmelon, banana, and coconut. Crops like kidneybeans, lentil, and pigeonpeas have lower quantities.

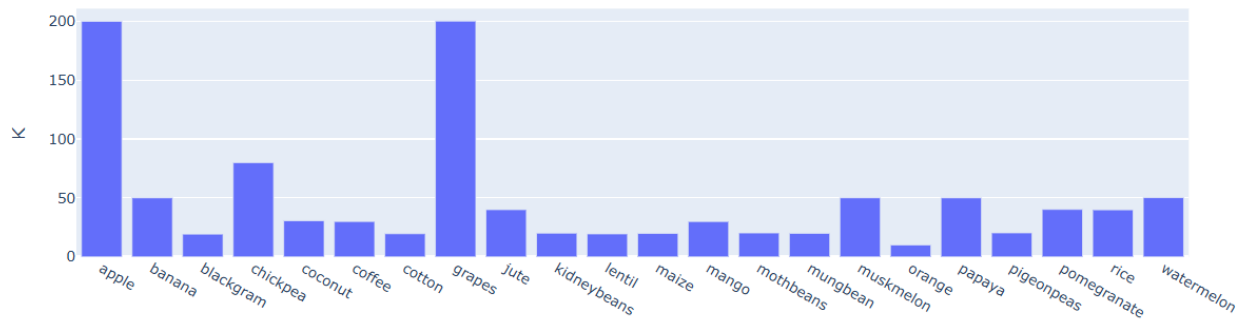


Fig 9 Bar chart of agricultural crop quantities(nitrogen)

(Fig 9) This bar chart displays the quantities of various agricultural crops, with cotton having the highest quantity, followed by muskmelon, banana, and coconut. Crops like kidneybeans, lentil, and pigeonpeas have lower quantities.

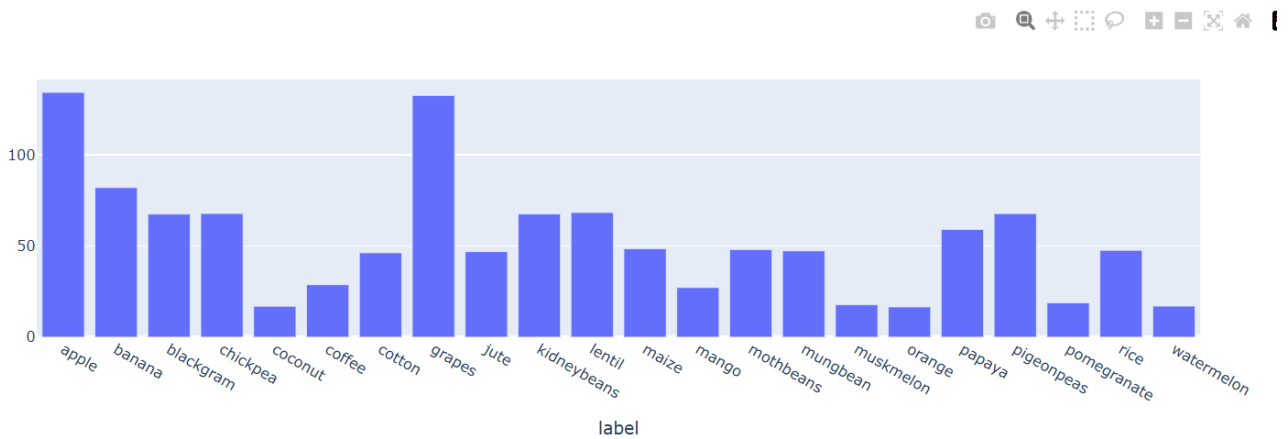
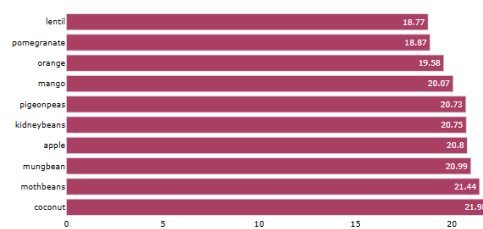
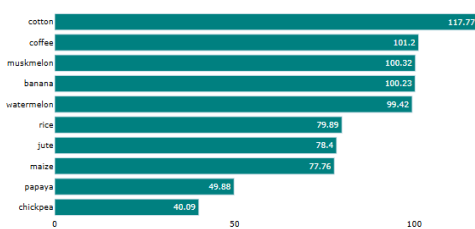


Fig 10 Bar chart of agricultural crop quantities(Phosphorus)

(Fig 10) This bar chart displays the quantities of various agricultural crops, with cotton having the highest quantity, followed by muskmelon, banana, and coconut. Crops like kidneybeans, lentil, and pigeonpeas have lower quantities.

Nitrogen (N)



Most nitrogen required
Least nitrogen required

Fig 11 crop summary of Nitrogen(N)

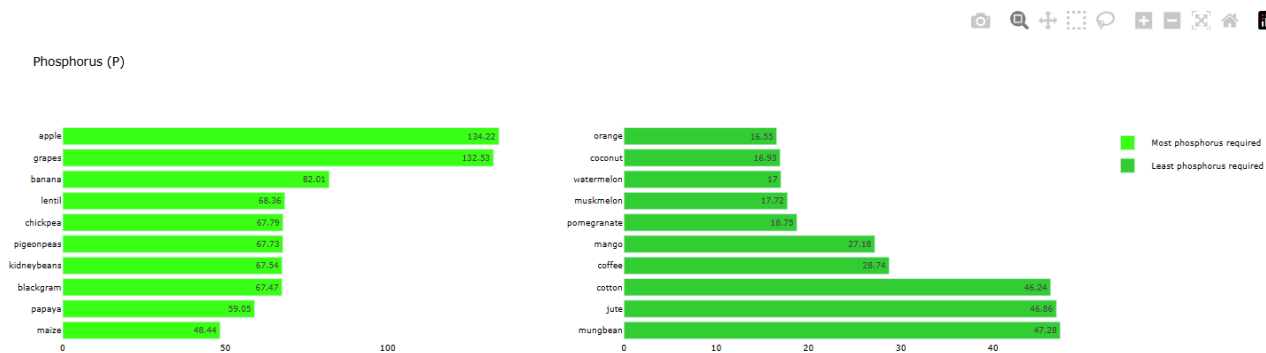


Fig 12 crop summary of Phosphorus(P)

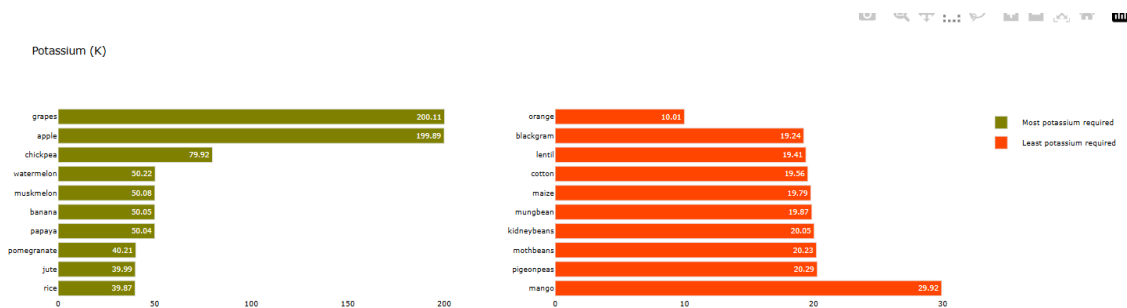


Fig 13 crop summary of Potassium(K)

N, P, K values comparison between crops

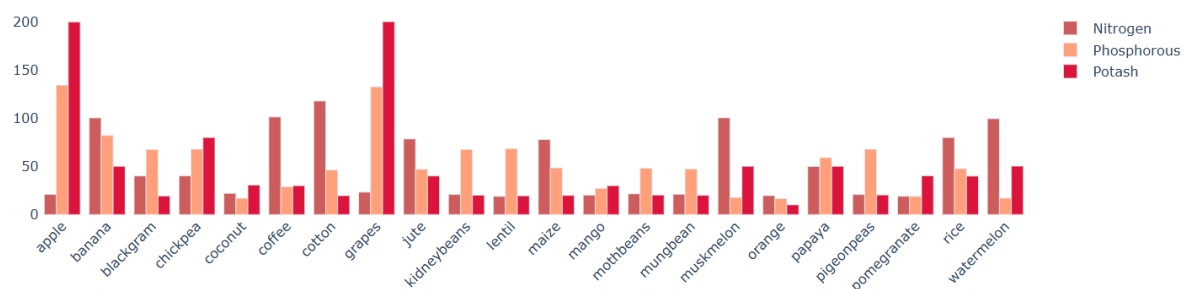


Fig 14 N,P,K values comparison between crops

NPK ratio for rice, cotton, jute, maize, lentil

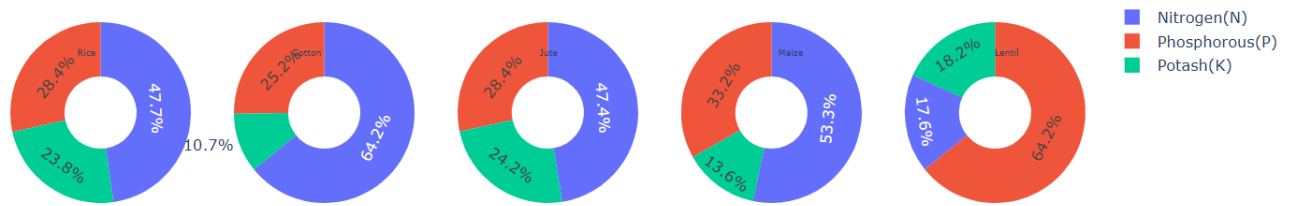


Fig 15 N,P,K ratio for rice, cotton, jute, maize, lentil

NPK ratio for fruits

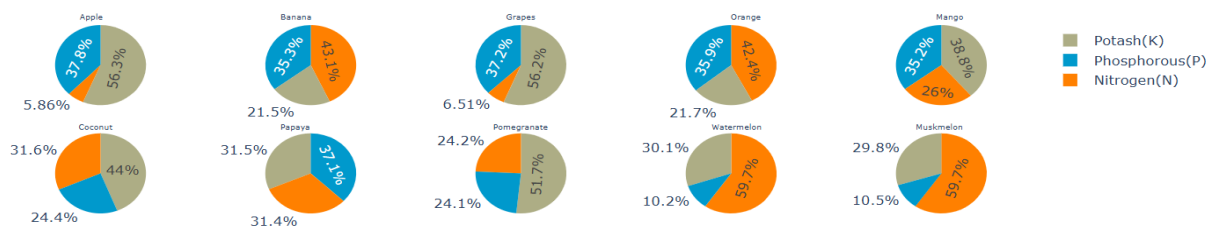


Fig 16 N,P,k ratio for fruits

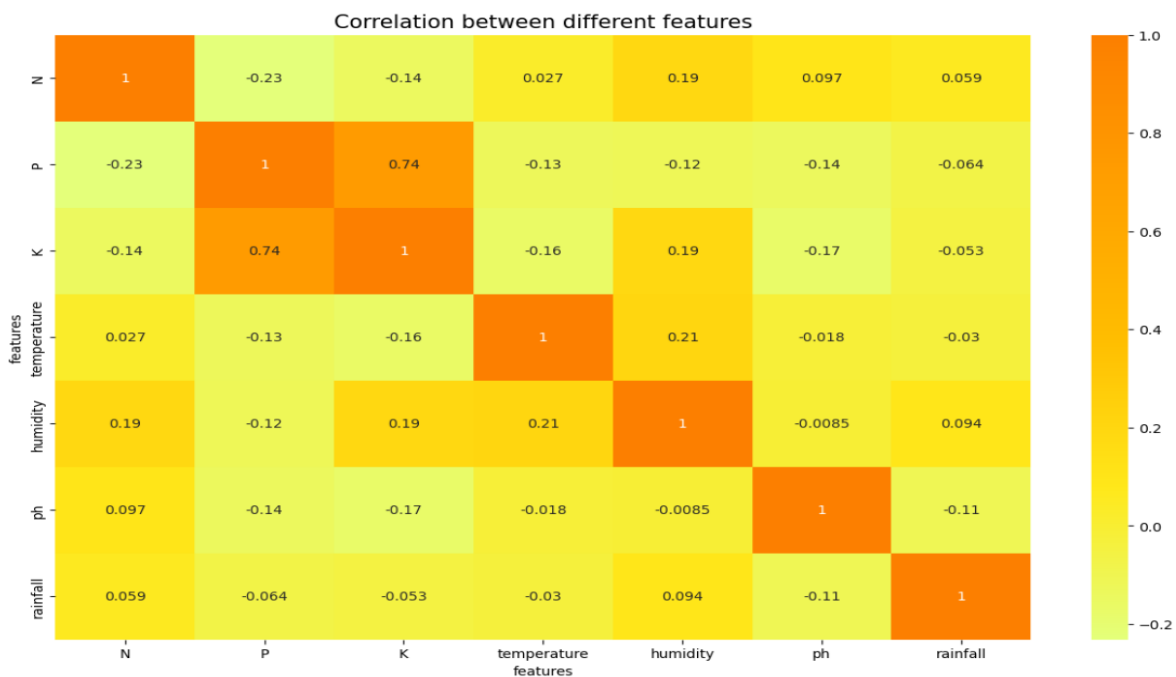


Fig 17 Correlation between different features

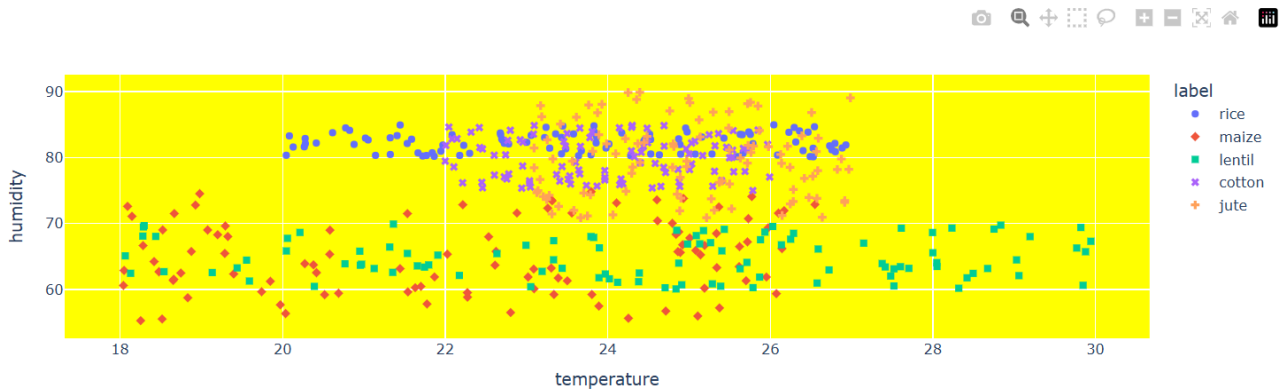


Fig 18 Scatter plot of temperature and humidity for different crops

(Fig 18) This scatter plot shows the relationship between temperature and humidity for various crops, with rice, maize, lentil, cotton, and jute represented by different colored markers.

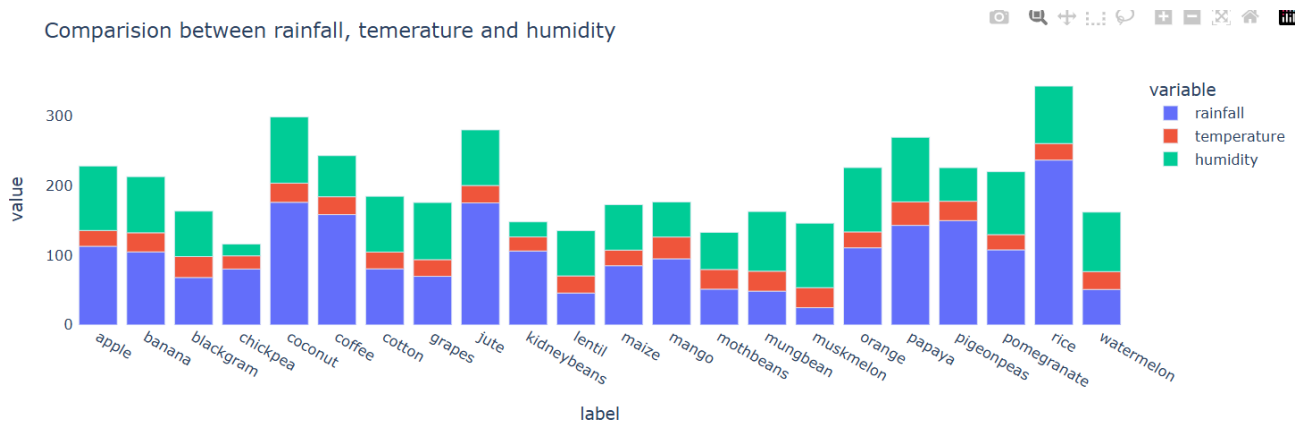


Fig 19 Comparison between rainfall, temperature and humidity

Logistic Regression Accuracy: 0.94
 Decision Tree Accuracy: 0.98
 Random Forest Accuracy: 0.99
 LightGBM Accuracy: 0.99

Fig 20 Accuracy scores of different machine learning models

Enter the following details for crop recommendation:
Nitrogen content in soil (N): 29
Phosphorus content in soil (P): 101
Potassium content in soil (K): 28
Temperature (°C): 58
Humidity (%): 6.7
pH value of soil: 158
Rainfall (mm): 25
The recommended crop for the given inputs is: lentil

Fig 21 Soil and Environmental Parameters for Crop Recommendation

(Fig 21) This figure displays various soil and environmental parameters, such as nitrogen, phosphorus, potassium content, temperature, humidity, pH value, and rainfall, which are used to recommend the most suitable crop. In this case, the recommended crop is lentil.

The recommended crop is: lentil with a confidence of 30.00%

Fig 22 Crop Recommendation for agriculture

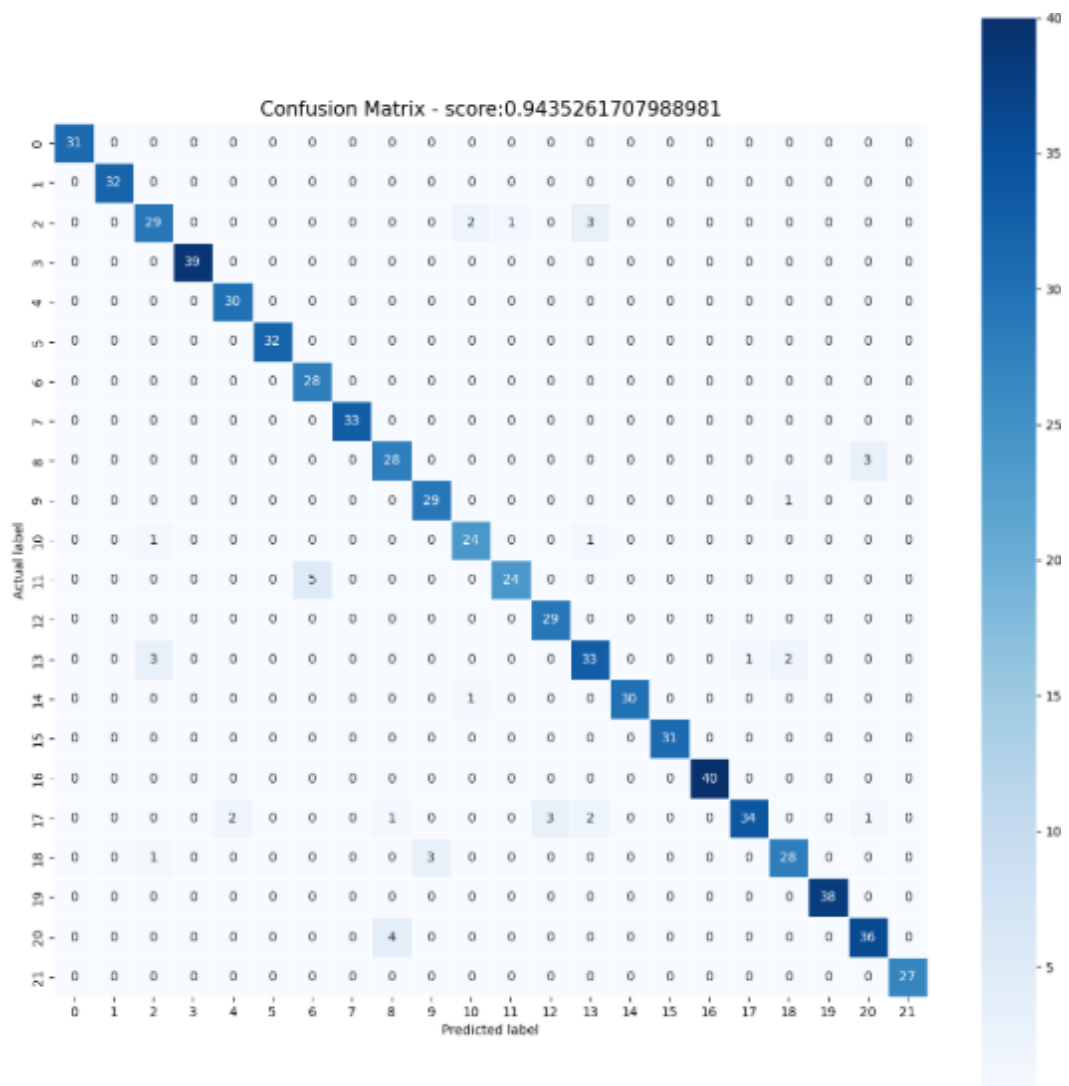


Fig 23 confusion matric of decision tree

APPENDIX

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from IPython import get_ipython
import warnings
warnings.filterwarnings("ignore")

data = pd.read_csv('Crop_recommendation.csv')
data.head()
data.tail()
data.shape
data.columns
data.duplicated().sum()
data.isnull().sum()
data.info()
data.describe()
data.nunique()
data['label'].unique()
data['label'].value_counts()
crop_summary = pd.pivot_table(data,index=['label'],
                               aggfunc='mean')
crop_summary
data1 = data[['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall']]
for i in data1.columns:
    plt.figure(figsize=(15,6))
    sns.boxplot(data1[i])
```

```

plt.xticks(rotation = 90)

plt.show()

crop_summary_new = crop_summary.reset_index()

crop_summary_new

plt.figure(figsize=(15,6))

sns.barplot(y = 'N', x = 'label', data=crop_summary_new, palette = 'hls')

plt.xticks(rotation = 90)

plt.show()

```

```

import plotly.graph_objects as go

import plotly.express as px

from plotly.subplots import make_subplots

```

```

fig1 = px.bar(crop_summary_new, x='label', y='N')

fig1.show()

plt.figure(figsize=(15,6))

sns.barplot(y = 'P', x = 'label', data=crop_summary_new, palette = 'hls')

plt.xticks(rotation = 90)

plt.show()

```

```

fig2 = px.bar(crop_summary_new, x='label', y='P')

fig2.show()

```

```

plt.figure(figsize=(15,6))

sns.barplot(y = 'K', x = 'label', data=crop_summary_new, palette = 'hls')

plt.xticks(rotation = 90)

plt.show()

```

```

fig3 = px.bar(crop_summary_new, x='label', y='K')

```

```
fig3.show()
```

```
colorarr = ['#0592D0', '#Cd7f32', '#E97451', '#Bdb76b', '#954535', '#C2b280',  
            '#808000', '#C2b280', '#E4d008', '#9acd32', '#Eedc82', '#E4d96f',  
            '#32cd32', '#39ff14', '#00ff7f', '#008080', '#36454f', '#F88379', '#Ff4500', '#Ffb347',  
            '#A94064', '#E75480', '#Ffb6c1', '#E5e4e2',  
            '#Faf0e6', '#8c92ac', '#Dbd7d2', '#A7a6ba', '#B38b6d']
```

```
import random
```

```
crop_summary_N = crop_summary.sort_values(by='N',  
                                           ascending=False)
```

```
fig = make_subplots(rows=1, cols=2)
```

```
top = {  
    'y' : crop_summary_N['N'][0:10].sort_values().index,  
    'x' : crop_summary_N['N'][0:10].sort_values()  
}
```

```
last = {  
    'y' : crop_summary_N['N'][-10:].index,  
    'x' : crop_summary_N['N'][-10:]  
}
```

```
fig.add_trace(  
    go.Bar(top,  
           name="Most nitrogen required",  
           marker_color=random.choice(colorarr),
```

```

        orientation='h',
        text=top['x']),

    row=1, col=1
)

fig.add_trace(
    go.Bar(last,
        name="Least nitrogen required",
        marker_color=random.choice(colorarr),
        orientation='h',
        text=last['x']),
    row=1, col=2
)

fig.update_traces(texttemplate='% { text }', textposition='inside')
fig.update_layout(title_text="Nitrogen (N)",
    plot_bgcolor='white',
    font_size=7,
    font_color='black',
    height=500)

fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)
fig.show()

crop_summary_P = crop_summary.sort_values(by='P', ascending=False)

fig = make_subplots(rows=1, cols=2)

```

```

top = {
    'y' : crop_summary_P['P'][0:10].sort_values().index,
    'x' : crop_summary_P['P'][0:10].sort_values()
}

last = {
    'y' : crop_summary_P['P'][-10:].index,
    'x' : crop_summary_P['P'][-10:]
}

fig.add_trace(
    go.Bar(top,
            name="Most phosphorus required",
            marker_color=random.choice(colorarr),
            orientation='h',
            text=top['x']),
    row=1, col=1
)

fig.add_trace(
    go.Bar(last,
            name="Least phosphorus required",
            marker_color=random.choice(colorarr),
            orientation='h',
            text=last['x']),
    row=1, col=2
)

fig.update_traces(texttemplate='% {text}', textposition='inside')
fig.update_layout(title_text="Phosphorus (P)",

```

```

        plot_bgcolor='white',

        font_size=7,

        font_color='black',

        height=500)

fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)
fig.show()

crop_summary_K = crop_summary.sort_values(by='K', ascending=False)

fig = make_subplots(rows=1, cols=2
top = {
    'y' : crop_summary_K['K'][0:10].sort_values().index,
    'x' : crop_summary_K['K'][0:10].sort_values()
}

last = {
    'y' : crop_summary_K['K'][-10:].index,
    'x' : crop_summary_K['K'][-10:]
}

fig.add_trace(
    go.Bar(top,
        name="Most potassium required",
        marker_color=random.choice(colorarr),
        orientation='h',
        text=top['x']),

```



```

    row=1, col=1
)

fig.add_trace(
    go.Bar(last,
        name="Least potassium required",
        marker_color=random.choice(colorarr),
        orientation='h',
        text=last['x']),
    row=1, col=2
)

fig.update_traces(texttemplate='% {text}', textposition='inside')
fig.update_layout(title_text="Potassium (K)",
    plot_bgcolor='white',
    font_size=7,
    font_color='black',
    height=500)

fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)
fig.show()

fig = go.Figure()
fig.add_trace(go.Bar(
    x=crop_summary.index,
    y=crop_summary['N'],
    name='Nitrogen',
    marker_color='indianred'
))

```

```

fig.add_trace(go.Bar(
    x=crop_summary.index,
    y=crop_summary['P'],
    name='Phosphorous',
    marker_color='lightsalmon'
))

fig.add_trace(go.Bar(
    x=crop_summary.index,
    y=crop_summary['K'],
    name='Potash',
    marker_color='crimson'
))

fig.update_layout(title="N, P, K values comparision between crops",
    plot_bgcolor='white',
    barmode='group',
    xaxis_tickangle=-45)

fig.show()

labels = ['Nitrogen(N)', 'Phosphorous(P)', 'Potash(K)']
fig = make_subplots(rows=1, cols=5, specs=[[{'type':'domain'}, {'type':'domain'},
    {'type':'domain'}, {'type':'domain'},
    {'type':'domain'}]])

rice_npk = crop_summary[crop_summary.index=='rice']
values = [rice_npk['N'][0], rice_npk['P'][0], rice_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values, name="Rice"), 1, 1)

```

```

cotton_npk = crop_summary[crop_summary.index=='cotton']
values = [cotton_npk['N'][0], cotton_npk['P'][0], cotton_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Cotton"),1, 2)


jute_npk = crop_summary[crop_summary.index=='jute']
values = [jute_npk['N'][0], jute_npk['P'][0], jute_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Jute"),1, 3)


maize_npk = crop_summary[crop_summary.index=='maize']
values = [maize_npk['N'][0], maize_npk['P'][0], maize_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Maize"),1, 4)


lentil_npk = crop_summary[crop_summary.index=='lentil']
values = [lentil_npk['N'][0], lentil_npk['P'][0], lentil_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Lentil"),1, 5)


fig.update_traces(hole=.4, hoverinfo="label+percent+name")
fig.update_layout(
    title_text="NPK ratio for rice, cotton, jute, maize, lentil",
    annotations=[dict(text='Rice',x=0.06,y=0.8, font_size=7, showarrow=False),
                  dict(text='Cotton',x=0.26,y=0.8, font_size=7, showarrow=False),
                  dict(text='Jute',x=0.50,y=0.8, font_size=7, showarrow=False),
                  dict(text='Maize',x=0.74,y=0.8, font_size=7, showarrow=False),
                  dict(text='Lentil',x=0.94,y=0.8, font_size=7, showarrow=False)])
fig.show()


labels = ['Nitrogen(N)', 'Phosphorous(P)', 'Potash(K)']
specs = [[{'type':'domain'}, {'type':'domain'}, {'type':'domain'}, {'type':'domain'},
{'type':'domain'}],

```

```
    {'type':'domain'}, {'type':'domain'}, {'type':'domain'}, {'type':'domain'},  
    {'type':'domain'}]]
```

```
fig = make_subplots(rows=2, cols=5, specs=specs)
```

```
cafe_colors = ['rgb(255, 128, 0)', 'rgb(0, 153, 204)', 'rgb(173, 173, 133)']
```

```
apple_npk = crop_summary[crop_summary.index=='apple']
```

```
values = [apple_npk['N'][0], apple_npk['P'][0], apple_npk['K'][0]]
```

```
fig.add_trace(go.Pie(labels=labels, values=values,name="Apple",  
marker_colors=cafe_colors),1, 1)
```

```
banana_npk = crop_summary[crop_summary.index=='banana']
```

```
values = [banana_npk['N'][0], banana_npk['P'][0], banana_npk['K'][0]]
```

```
fig.add_trace(go.Pie(labels=labels, values=values,name="Banana",  
marker_colors=cafe_colors),1, 2)
```

```
grapes_npk = crop_summary[crop_summary.index=='grapes']
```

```
values = [grapes_npk['N'][0], grapes_npk['P'][0], grapes_npk['K'][0]]
```

```
fig.add_trace(go.Pie(labels=labels, values=values,name="Grapes",  
marker_colors=cafe_colors),1, 3)
```

```
orange_npk = crop_summary[crop_summary.index=='orange']
```

```
values = [orange_npk['N'][0], orange_npk['P'][0], orange_npk['K'][0]]
```

```
fig.add_trace(go.Pie(labels=labels, values=values,name="Orange",  
marker_colors=cafe_colors),1, 4)
```

```
mango_npk = crop_summary[crop_summary.index=='mango']
```

```
values = [mango_npk['N'][0], mango_npk['P'][0], mango_npk['K'][0]]
```

```
fig.add_trace(go.Pie(labels=labels, values=values,name="Mango",  
marker_colors=cafe_colors),1, 5)
```

```

coconut_npk = crop_summary[crop_summary.index=='coconut']
values = [coconut_npk['N'][0], coconut_npk['P'][0], coconut_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Coconut",
marker_colors=cafe_colors),2, 1)


papaya_npk = crop_summary[crop_summary.index=='papaya']
values = [papaya_npk['N'][0], papaya_npk['P'][0], papaya_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Papaya",
marker_colors=cafe_colors),2, 2)


pomegranate_npk = crop_summary[crop_summary.index=='pomegranate']
values = [pomegranate_npk['N'][0], pomegranate_npk['P'][0], pomegranate_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Pomegranate",
marker_colors=cafe_colors),2, 3)


watermelon_npk = crop_summary[crop_summary.index=='watermelon']
values = [watermelon_npk['N'][0], watermelon_npk['P'][0], watermelon_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Watermelon",
marker_colors=cafe_colors),2, 4)


muskmelon_npk = crop_summary[crop_summary.index=='muskmelon']
values = [muskmelon_npk['N'][0], muskmelon_npk['P'][0], muskmelon_npk['K'][0]]
fig.add_trace(go.Pie(labels=labels, values=values,name="Muskmelon",
marker_colors=cafe_colors),2, 5)


fig.update_layout(
    title_text="NPK ratio for fruits",
    annotations=[dict(text='Apple',x=0.06,y=1.08, font_size=7, showarrow=False),
                  dict(text='Banana',x=0.26,y=1.08, font_size=7, showarrow=False),
                  dict(text='Grapes',x=0.50,y=1.08, font_size=7, showarrow=False),

```

```

dict(text='Orange',x=0.74,y=1.08, font_size=7, showarrow=False),
dict(text='Mango',x=0.94,y=1.08, font_size=7, showarrow=False),
dict(text='Coconut',x=0.06,y=0.46, font_size=7, showarrow=False),
dict(text='Papaya',x=0.26,y=0.46, font_size=7, showarrow=False),
dict(text='Pomegranate',x=0.50,y=0.46, font_size=7, showarrow=False),
dict(text='Watermelon',x=0.74,y=0.46, font_size=7, showarrow=False),
dict(text='Muskmelon',x=0.94,y=0.46, font_size=7, showarrow=False)])

```

```
fig.show()
```

```

crop_scatter = data[(data['label']=='rice') |
                    (data['label']=='jute') |
                    (data['label']=='cotton') |
                    (data['label']=='maize') |
                    (data['label']=='lentil')]

```

```

fig = px.scatter(crop_scatter, x="temperature", y="humidity", color="label", symbol="label")
fig.update_layout(plot_bgcolor='yellow')
fig.update_xaxes(showgrid=True)
fig.update_yaxes(showgrid=True)

```

```
fig.show()
```

```

fig = px.bar(crop_summary, x=crop_summary.index, y=["rainfall", "temperature",
"humidity"])
fig.update_layout(title_text="Comparision between rainfall, temerature and humidity",
                    plot_bgcolor='white',
                    height=500)

```

```
fig.update_xaxes(showgrid=False)
```

```
fig.update_yaxes(showgrid=False)
```

```
fig.show()
```

```
df_dropped = data.drop(columns=['label'])
```

```
df_dropped
```

```
fig, ax = plt.subplots(1, 1, figsize=(15, 9))
```

```
sns.heatmap(data.corr(), annot=True,cmap='Wistia')
```

```
ax.set(xlabel='features')
```

```
ax.set(ylabel='features')
```

```
plt.title('Correlation between different features', fontsize = 15, c='black')
```

```
plt.show()
```

```
X = data.drop('label', axis=1)
```

```
y = data['label']
```

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33,  
                                                    shuffle = True, random_state = 0)
```

```
import lightgbm as lgb
```

```
model = lgb.LGBMClassifier()
```

```
model.fit(X_train, y_train)
```

```
y_pred=model.predict(X_test)
```

```
from sklearn.metrics import accuracy_score
```

```
accuracy=accuracy_score(y_pred, y_test)
```

```
print('LightGBM Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred)))
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(15,15))
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))
plt.title(all_sample_title, size = 15);
plt.show()
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
from sklearn.tree import DecisionTreeClassifier
classifier= DecisionTreeClassifier(criterion='entropy', random_state=0)
classifier.fit(X_train, y_train)
```

```
y_pred=classifier.predict(X_test)
```

```
from sklearn.metrics import accuracy_score
accuracy=accuracy_score(y_pred, y_test)
print('Decision Tree Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred)))
```

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(15,15))
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues');
```



```

plt.ylabel('Actual label');

plt.xlabel('Predicted label');

all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))

plt.title(all_sample_title, size = 15);

plt.show()


from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred))


from sklearn.ensemble import RandomForestClassifier

classifier_rf= RandomForestClassifier(n_estimators= 10, criterion="entropy")

classifier_rf.fit(X_train, y_train)


y_pred= classifier_rf.predict(X_test)


from sklearn.metrics import accuracy_score

accuracy=accuracy_score(y_pred, y_test)

print('Random Forest Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred)))


from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(15,15))

sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues');

plt.ylabel('Actual label');

plt.xlabel('Predicted label');

all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))

plt.title(all_sample_title, size = 15);

plt.show()

```

```
from sklearn.metrics import classification_report  
print(classification_report(y_test, y_pred))
```

```
from sklearn.linear_model import LogisticRegression  
classifier_lr = LogisticRegression(random_state = 0)  
classifier_lr.fit(X_train, y_train)
```

```
y_pred = classifier_lr.predict(X_test)
```

```
from sklearn.metrics import accuracy_score  
accuracy=accuracy_score(y_pred, y_test)  
print('Logistic Regression Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test,  
y_pred)))
```

```
from sklearn.metrics import confusion_matrix  
cm = confusion_matrix(y_test, y_pred)  
plt.figure(figsize=(15,15))  
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues');  
plt.ylabel('Actual label');  
plt.xlabel('Predicted label');  
all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))  
plt.title(all_sample_title, size = 15);  
plt.show()
```

```
from sklearn.metrics import classification_report  
print(classification_report(y_test, y_pred))
```

```
models = {  
    "Logistic Regression": classifier_lr,
```

```

    "Decision Tree": classifier,

    "Random Forest": classifier_rf,

    "LightGBM": model

}

# Evaluate all models

for model_name, model in models.items():

    accuracy = model.score(X_test, y_test)

    print(f"{model_name} Accuracy: {accuracy:.2f}")


# Choose the model with the best performance

best_model = classifier_rf # Replace this with the actual best model


# Function for crop recommendation

def recommend_crop(model, input_features):

    feature_array = np.array(input_features).reshape(1, -1)

    recommended_crop = model.predict(feature_array)[0]

    return recommended_crop


#input features

def get_user_input():

    """

    Prompts the user to enter values for each feature and returns them as a list.

    """

    print("Enter the following details for crop recommendation:")

    nitrogen = float(input("Nitrogen content in soil (N): "))

    phosphorus = float(input("Phosphorus content in soil (P): "))

    potassium = float(input("Potassium content in soil (K): "))

    temperature = float(input("Temperature (°C): "))

```

```

humidity = float(input("Humidity (%): "))

pH = float(input("pH value of soil: "))

rainfall = float(input("Rainfall (mm): "))


return [nitrogen, phosphorus, potassium, temperature, humidity, pH, rainfall]


# Get inputs

input_features = get_user_input()


# Use the best model to predict

predicted_crop = recommend_crop(best_model, input_features)

print(f"The recommended crop for the given inputs is: {predicted_crop}")


def recommend_with_confidence(model, input_features):

    feature_array = np.array(input_features).reshape(1, -1)

    probabilities = model.predict_proba(feature_array)[0]

    recommended_crop = model.predict(feature_array)[0]

    confidence = max(probabilities) * 100

    return recommended_crop, confidence


# Example with Random Forest

predicted_crop, confidence = recommend_with_confidence(best_model, input_features)

print(f"The recommended crop is: {predicted_crop} with a confidence of {confidence:.2f}%")

```

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