optimizing-agricultural-production

January 7, 2024

[1]:
```
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

```
/kaggle/input/smart-agricultural-production-optimizing-
engine/Crop_recommendation.csv
```

1 Problem Statement:

Build a predictive model so as to suggest the most suitable crops to grow based on the available climatic and soil conditions

1.1 Goal:

Achieve Precision Farming by Optimizing the Agricultural Production

2 About the Dataset

This dataset will help in recommending the crop for the suitable soil. This will be very useful in Optimizing Agricultural Production.

2.1 Variable Names and their Uses:

Nitrogen *is one of chemical elements that become a part of amino acids. Plants synthesize nitrogen from soils along with other primary elements and turn them into amino acids. These chemical compounds are utilized by plants to increase the production and quality of crops.*

Phosphorus *plays a major role in the growth of new tissue and division of cells. Plants perform complex energy transmissions, a function that requires phosphorus.*

Potassium *is a paramount macro-element for overall survival of living things. It is an abundant mineral macronutrient present in both plant and animals tissues. It is necessary for the proper functionality of all living cells.*

Temperature: *Germination is a miraculous event that involves a number of factors that include air, water, light, and, of course, temperature. Germination increases in higher temperatures – up to a point. Once the seeds reach optimum temperatures, which depends on the plant, germination begins to decline.*

The **pH** *range 5.5–6.5 is optimal for plant growth as the availability of nutrients is optimal. Besides disease, rainfall can also determine how fast a crop will grow from seed, including when it will be ready for harvesting. A good balance of rain and proper irrigation can lead to , which can cut down on germination time and the length between seeding and harvest*

2.2 Importing Libraries and Loading dataset

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from ipywidgets import interact

import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
data=pd.read_csv("/kaggle/input/smart-agricultural-production-optimizing-engine/
↪Crop_recommendation.csv")
```

2.3 To check the shape (number of rows & columns) of the dataset

[4]:
```
print("Shape of the dataset:", data.shape)
```

```
Shape of the dataset: (2200, 8)
```

2.4 Inspecting the first 10 rows of the Dataset

[5]:
```
data.head(10)
```

[5]:
```
    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
5  69  37  42    23.058049  83.370118  7.073454  251.055000  rice
6  69  55  38    22.708838  82.639414  5.700806  271.324860  rice
7  94  53  40    20.277744  82.894086  5.718627  241.974195  rice
8  89  54  38    24.515881  83.535216  6.685346  230.446236  rice
9  68  58  38    23.223974  83.033227  6.336254  221.209196  rice
```

2.4.1 Checking for Null values if any

[6]:
```
print("Missing/Null values in the our data set:")
data.isnull().sum()
```

```
Missing/Null values in the our data set:
```

[6]:
```
N              0
P              0
K              0
temperature    0
humidity       0
ph             0
rainfall       0
label          0
dtype: int64
```

2.4.2 Describe (statistical) detail of data

[7]:
```
data.describe()
```

[7]:
```
                 N            P            K  temperature     humidity  \
count  2200.000000  2200.000000  2200.000000  2200.000000  2200.000000
mean     50.551818    53.362727    48.149091    25.616244    71.481779
std      36.917334    32.985883    50.647931     5.063749    22.263812
min       0.000000     5.000000     5.000000     8.825675    14.258040
25%      21.000000    28.000000    20.000000    22.769375    60.261953
50%      37.000000    51.000000    32.000000    25.598693    80.473146
75%      84.250000    68.000000    49.000000    28.561654    89.948771
max     140.000000   145.000000   205.000000    43.675493    99.981876
```

```
                ph     rainfall
count  2200.000000  2200.000000
mean      6.469480   103.463655
std       0.773938    54.958389
min       3.504752    20.211267
25%       5.971693    64.551686
50%       6.425045    94.867624
75%       6.923643   124.267508
max       9.935091   298.560117
```

2.4.3 Note:

There are outliers present in the dataset

2.4.4 To check the unique value in the label(crops) column of the dataset

[8]:
```
data['label'].value_counts()
```

[8]:
```
label
rice           100
maize          100
jute           100
cotton         100
coconut        100
papaya         100
orange         100
apple          100
muskmelon      100
watermelon     100
grapes         100
mango          100
banana         100
pomegranate    100
lentil         100
blackgram      100
mungbean       100
mothbeans      100
pigeonpeas     100
kidneybeans    100
chickpea       100
coffee         100
Name: count, dtype: int64
```

[9]:
```
data.info()
```

```
<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
```

[10]:
```
# To check for duplicates

data.duplicated().sum()

#No duplicates observed
```

[10]: 0

[11]:
```
#Renaming columns

data.columns =␣
↪['Nitrogen','Phosphorus','Potassium','Temperature','Humidity','pH','Rainfall','Label']
```

2.4.5 To check the overall summary for all variables

[12]:
```
print("Average Ratio of Nitrogen in the soil : {0:.2f}".format(data['Nitrogen'].
↪mean()))
print("Average Ratio of Phosphorous in the soil : {0:.2f}".
↪format(data['Phosphorus'].mean()))
print("Average Ratio of Potassium in the soil : {0:.2f}".
↪format(data['Potassium'].mean()))
print("Average Temperature in celsius : {0:.2f}".format(data['Temperature'].
↪mean()))
print("Average Humidity in the soil : {0:.2f}".format(data['Humidity'].mean()))
print("Average Ph_scale in the soil : {0:.2f}".format(data['pH'].mean()))
print("Average Rain_fall in the soil : {0:.2f}".format(data['Rainfall'].mean()))
```

```
Average Ratio of Nitrogen in the soil : 50.55
Average Ratio of Phosphorous in the soil : 53.36
Average Ratio of Potassium in the soil : 48.15
Average Temperature in celsius : 25.62
Average Humidity in the soil : 71.48
Average Ph_scale in the soil : 6.47
```

```
Average Rain_fall in the soil : 103.46
```

2.4.6 Let's check the summary statistics of each for the crops

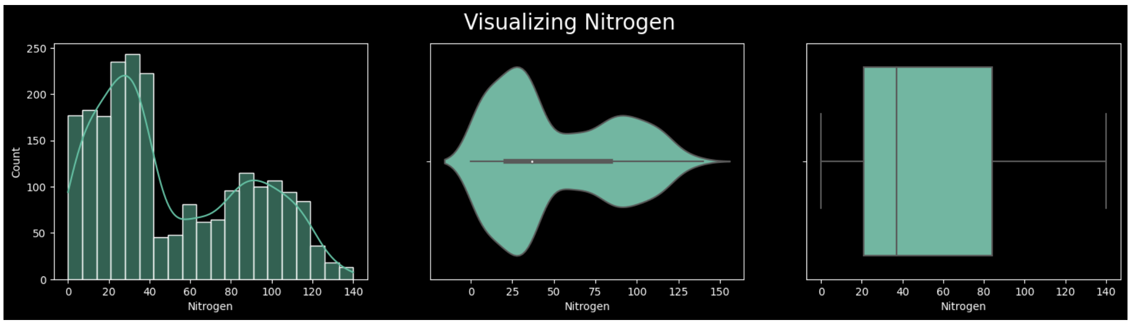
Use of Interactive function(@interact) from ipywidget library; to find the best optimum climatic condition for any specific crop

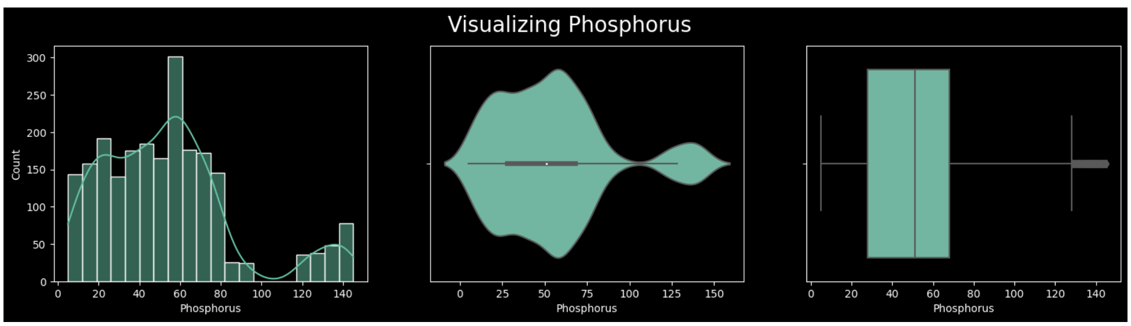
[13]:
```
@interact #for dropdodwn box
def summary(crops=list(data['Label'].value_counts().index)):
    x=data[data['Label'] == crops]
    print("---------------------------------------------")
    print("Statistics for Nitrogen")
    print("Minimum Nitrogen required:", x['Nitrogen'].min())
    print("Average Nitrogen required:", x['Nitrogen'].mean())
    print("Maximum Nitrogen required:", x['Nitrogen'].max())
    print("---------------------------------------------")
    print("Statistics for Potassium")
    print("Minimum Potassium required:",x['Potassium'].min())
    print("Average Potassium required:",x['Potassium'].mean())
    print("Maximum Potassium required:",x['Potassium'].max())
    print("---------------------------------------------")
    print("Statistics for Temperature")
    print("Minimum Temperature required:{0:.2f}".format(x['Temperature'].min()))
    print("Average Temperature required:{0:.2f}".format(x['Temperature'].
 ↪mean()))
    print("Maximum Temperature required:{0:.2f}".format(x['Temperature'].max()))
    print("---------------------------------------------")
    print("Statistics for Humidity")
    print("Minimum Humidity required:{0:.2f}".format(x['Humidity'].min()))
    print("Average Humidity required:{0:.2f}".format(x['Humidity'].mean()))
    print("Maximum Humidity required:{0:.2f}".format(x['Humidity'].max()))
    print("---------------------------------------------")
    print("Statistics for Phscale")
    print("Minimum Phscale required:{0:.2f}".format(x['pH'].min()))
    print("Average Phscale required:{0:.2f}".format(x['pH'].mean()))
    print("Maximum Phscale require:{0:.2f}".format(x['pH'].max()))
    print("---------------------------------------------")
    print("Statistics for Rainfall")
    print("Minimum Rainfall required:{0:.2f}".format(x['Rainfall'].min()))
    print("Average Rainfall required:{0:.2f}".format(x['Rainfall'].mean()))
    print("Maximum Rainfall required:{0:.2f}".format(x['Rainfall'].max()))
```

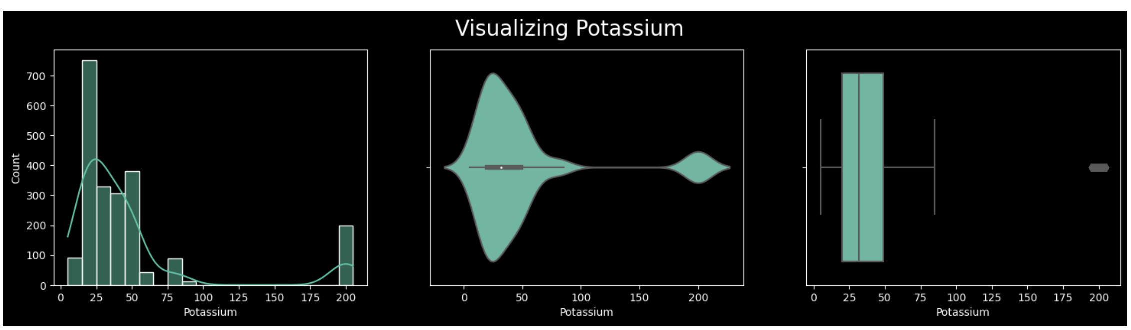
```
interactive(children=(Dropdown(description='crops', options=('rice', 'maize',␣
 ↪'jute', 'cotton', 'coconut', 'pa…
```

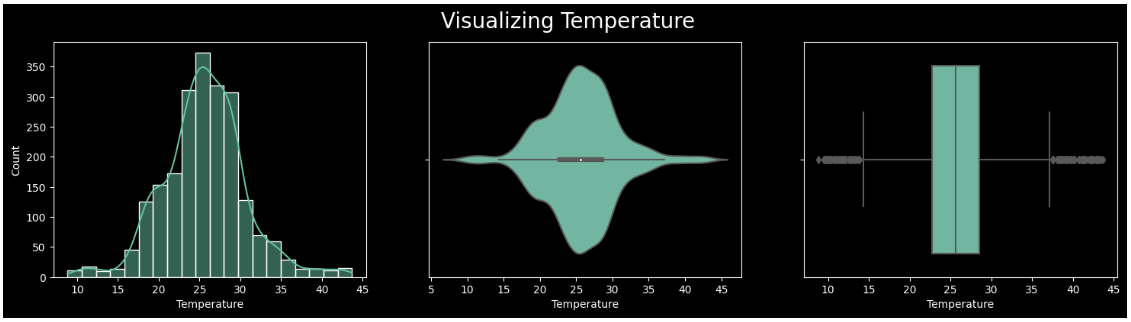
3 EDA - Exploratory Data Analysis

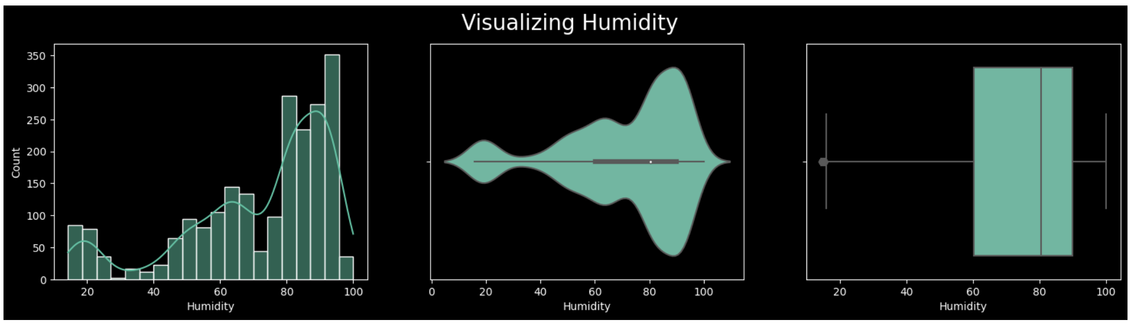
[14]:
```
plt.style.use('dark_background')
sns.set_palette("Set2")
for i in data.columns[:-1]:
    fig,ax=plt.subplots(1,3,figsize=(18,4))
    sns.histplot(data=data,x=i,kde=True,bins=20,ax=ax[0])
    sns.violinplot(data=data,x=i,ax=ax[1])
    sns.boxplot(data=data,x=i,ax=ax[2])
    plt.suptitle(f'Visualizing {i}',size=20)
```

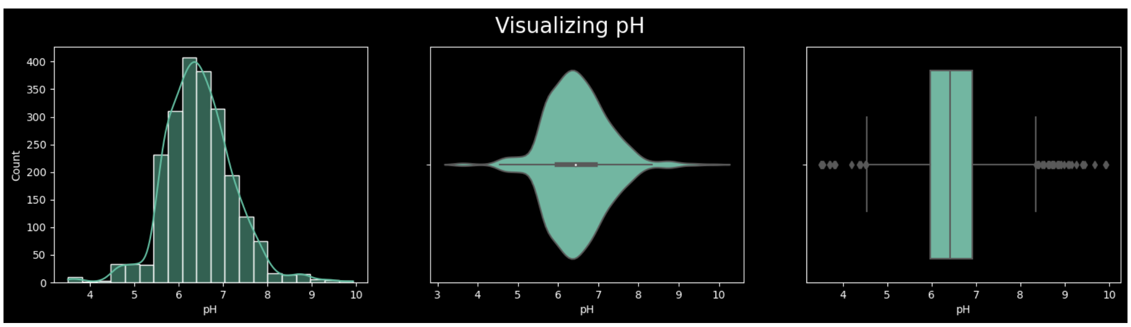


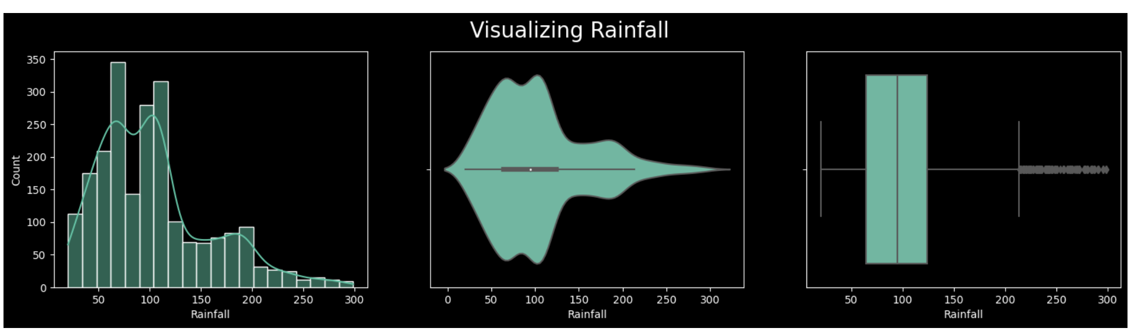





Visualizing Temperature
Count
Temperature
Temperature
Temperature


Visualizing Humidity
Count
Humidity
Humidity
Humidity


Visualizing pH
Count
pH
pH
pH


Visualizing Rainfall
Count
Rainfall
Rainfall
Rainfall

3.1 Note:

These graphs confirm that there are outliers present in the data. Also it helps us understand the overall distribution of the dataset

[15]:
```
# The GROUP BY statement groups rows that have the same values into summary
↪rows.

grouped = data.groupby(by='Label').mean().reset_index()
```

[16]:
```
grouped
```

[16]:

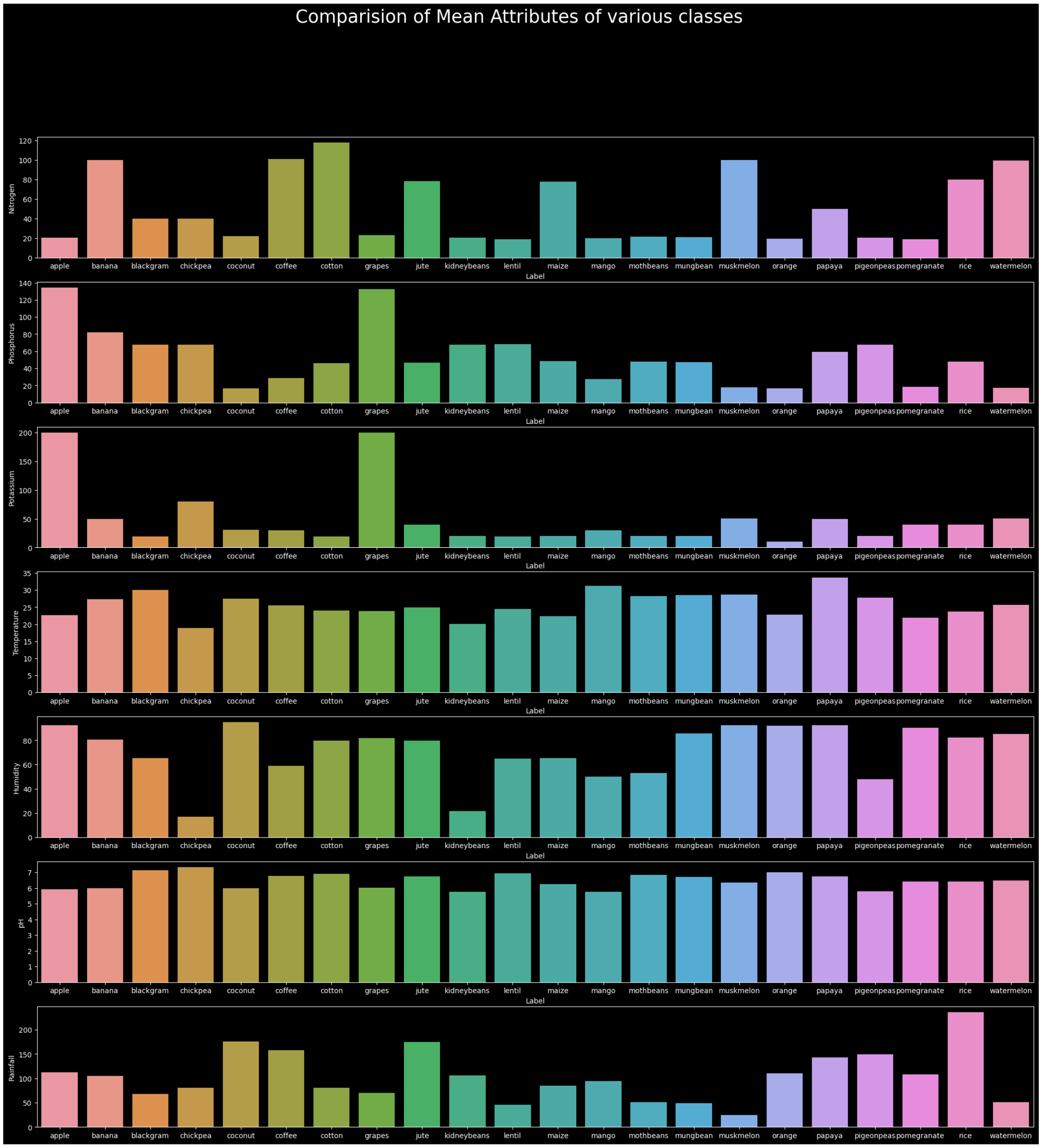
	Label	Nitrogen	Phosphorus	Potassium	Temperature	Humidity
0	apple	20.80	134.22	199.89	22.630942	92.333383
1	banana	100.23	82.01	50.05	27.376798	80.358123
2	blackgram	40.02	67.47	19.24	29.973340	65.118426
3	chickpea	40.09	67.79	79.92	18.872847	16.860439
4	coconut	21.98	16.93	30.59	27.409892	94.844272
5	coffee	101.20	28.74	29.94	25.540477	58.869846
6	cotton	117.77	46.24	19.56	23.988958	79.843474
7	grapes	23.18	132.53	200.11	23.849575	81.875228
8	jute	78.40	46.86	39.99	24.958376	79.639864
9	kidneybeans	20.75	67.54	20.05	20.115085	21.605357
10	lentil	18.77	68.36	19.41	24.509052	64.804785
11	maize	77.76	48.44	19.79	22.389204	65.092249
12	mango	20.07	27.18	29.92	31.208770	50.156573
13	mothbeans	21.44	48.01	20.23	28.194920	53.160418
14	mungbean	20.99	47.28	19.87	28.525775	85.499975
15	muskmelon	100.32	17.72	50.08	28.663066	92.342802
16	orange	19.58	16.55	10.01	22.765725	92.170209
17	papaya	49.88	59.05	50.04	33.723859	92.403388
18	pigeonpeas	20.73	67.73	20.29	27.741762	48.061633
19	pomegranate	18.87	18.75	40.21	21.837842	90.125504
20	rice	79.89	47.58	39.87	23.689332	82.272822
21	watermelon	99.42	17.00	50.22	25.591767	85.160375

	pH	Rainfall
0	5.929663	112.654779
1	5.983893	104.626980
2	7.133952	67.884151
3	7.336957	80.058977
4	5.976562	175.686646
5	6.790308	158.066295
6	6.912675	80.398043
7	6.025937	69.611829
8	6.732778	174.792798
9	5.749411	105.919778
10	6.927932	45.680454

```
11  6.245190   84.766988
12  5.766373   94.704515
13  6.831174   51.198487
14  6.723957   48.403601
15  6.358805   24.689952
16  7.016957  110.474969
17  6.741442  142.627839
18  5.794175  149.457564
19  6.429172  107.528442
20  6.425471  236.181114
21  6.495778   50.786219
```

3.1.1 Lets compare the Average Requirement of each crops for an average condition

[17]:
```
fig,ax=plt.subplots(7,1,figsize=(25,25))
for index,i in enumerate(grouped.columns[1:]):
    sns.barplot(data=grouped,x='Label',y=i,ax=ax[index])
    plt.suptitle("Comparision of Mean Attributes of various classes",size=25)
    plt.xlabel("")
```



3.2 Note:

- *Cotton requires most Nitrogen.*
- *Apple requires most Phosphorus.*
- *Grapes require most Potassium.*
- *Papaya requires a hot climate.*
- *Coconut requires a humid climate.*

- *Chickpea requires high pH in soil.*
- *Rice requires huge amount of Rainfall.*

3.2.1 Identifying the crops that requires unusual or specific weather and soil mineral conditions

[18]:
```
print(f'--------------------------------')
for i in grouped.columns[1:]:
    print(f'Top 5 Most {i} requiring crops:')
    print(f'--------------------------------')
    for j ,k in grouped.sort_values(by=i,ascending=False)[:5][['Label',i]].
 ↪values:
        print(f'{j} --> {k}')
    print(f'-------------------------------')
```

```
--------------------------------
Top 5 Most Nitrogen requiring crops:
--------------------------------
cotton --> 117.77
coffee --> 101.2
muskmelon --> 100.32
banana --> 100.23
watermelon --> 99.42
-------------------------------
Top 5 Most Phosphorus requiring crops:
--------------------------------
apple --> 134.22
grapes --> 132.53
banana --> 82.01
lentil --> 68.36
chickpea --> 67.79
-------------------------------
Top 5 Most Potassium requiring crops:
--------------------------------
grapes --> 200.11
apple --> 199.89
chickpea --> 79.92
watermelon --> 50.22
muskmelon --> 50.08
-------------------------------
Top 5 Most Temperature requiring crops:
--------------------------------
papaya --> 33.7238587388
mango --> 31.2087701513
blackgram --> 29.9733396789
muskmelon --> 28.663065756
mungbean --> 28.5257747353
```

```
-------------------------------
Top 5 Most Humidity requiring crops:
--------------------------------
coconut --> 94.84427180610001
papaya --> 92.4033876826
muskmelon --> 92.34280196089999
apple --> 92.3333828756
orange --> 92.17020876340001
-------------------------------
Top 5 Most pH requiring crops:
--------------------------------
chickpea --> 7.33695662374
blackgram --> 7.13395162948
orange --> 7.01695745276
lentil --> 6.927931571609999
cotton --> 6.91267549578
-------------------------------
Top 5 Most Rainfall requiring crops:
--------------------------------
rice --> 236.181113594
coconut --> 175.686645804
jute --> 174.792797536
coffee --> 158.066294882
pigeonpeas --> 149.4575638135
-------------------------------
```

3.3 Lets Find out Some Intersting Facts

[19]:
```
print("Some Interesting Patterns:")
print("---------------------------")
print("Crops which requires very High Ratio of Nirtogen Content in Soil:", 
 ↪data[data['Nitrogen'] > 120]['Label'].unique())
print("Crops which requires very High Ratio of Phosphorous Content in Soil:", 
 ↪data[data['Phosphorus'] > 100]['Label'].unique())
print("Crops which requires very High Ratio of Potassium Content in Soil:", 
 ↪data[data['Potassium'] > 200]['Label'].unique())
print("Crops which requires very High Rainfall:", data[data['Rainfall'] > 
 ↪200]['Label'].unique())
print("Crops which requires very Low Temperature:", data[data['Temperature'] > 
 ↪10]['Label'].unique())
print("Crops which requires very High Temperature:", data[data['Temperature'] > 
 ↪40]['Label'].unique())
print("Crops which requires very Low Humidty:", data[data['Humidity'] > 
 ↪20]['Label'].unique())
print("Crops which requires very Low pH:", data[data['pH'] < 4]['Label'].
 ↪unique())
```

```
print("Cr0ps which requires very Low pH:", data[data['pH'] > 9]['Label'].
 ↪unique())
```

```
Some Interesting Patterns:
--------------------------
Crops which requires very High Ratio of Nirtogen Content in Soil: ['cotton']
Crops which requires very High Ratio of Phosphorous Content in Soil: ['grapes'
'apple']
Crops which requires very High Ratio of Potassium Content in Soil: ['grapes'
'apple']
Crops which requires very High Rainfall: ['rice' 'papaya' 'coconut']
Crops which requires very Low Temperature: ['rice' 'maize' 'chickpea'
'kidneybeans' 'pigeonpeas' 'mothbeans'
 'mungbean' 'blackgram' 'lentil' 'pomegranate' 'banana' 'mango' 'grapes'
 'watermelon' 'muskmelon' 'apple' 'orange' 'papaya' 'coconut' 'cotton'
 'jute' 'coffee']
Crops which requires very High Temperature: ['grapes' 'papaya']
Crops which requires very Low Humidty: ['rice' 'maize' 'kidneybeans'
'pigeonpeas' 'mothbeans' 'mungbean'
 'blackgram' 'lentil' 'pomegranate' 'banana' 'mango' 'grapes' 'watermelon'
 'muskmelon' 'apple' 'orange' 'papaya' 'coconut' 'cotton' 'jute' 'coffee']
Crops which requires very Low pH: ['mothbeans']
Cr0ps which requires very Low pH: ['mothbeans']
```

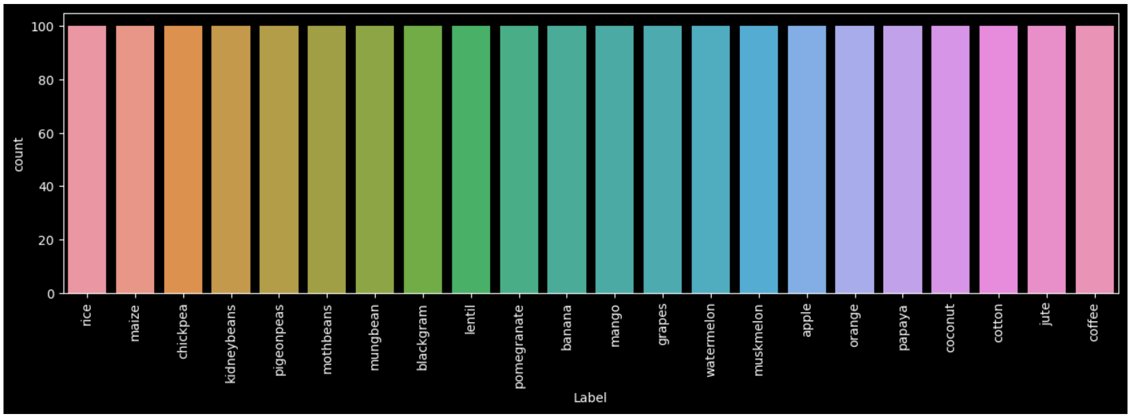
4 Seasonal Crops Recommendations

[20]:
```
### Lets understand which crops can only be Grown in Summer Season, Winter␣
 ↪Season and Rainy Season

print("Summer Crops")
print(data[(data['Temperature'] > 30) & (data['Humidity'] > 50)]['Label'].
 ↪unique())
print("-----------------------------------------")
print("Winter Crops")
print(data[(data['Temperature'] < 20) & (data['Humidity'] > 30)]['Label'].
 ↪unique())
print("-----------------------------------------")
print("Rainy Crops")
print(data[(data['Rainfall'] > 200) & (data['Humidity'] > 30)]['Label'].
 ↪unique())
```

```
Summer Crops
['pigeonpeas' 'mothbeans' 'blackgram' 'mango' 'grapes' 'orange' 'papaya']
-----------------------------------------
Winter Crops
['maize' 'pigeonpeas' 'lentil' 'pomegranate' 'grapes' 'orange']
-----------------------------------------
```

```
Rainy Crops
['rice' 'papaya' 'coconut']
```

[21]:
```python
plt.figure(figsize=(15,4))
sns.countplot(data=data,x='Label')
plt.xticks(rotation = 90)
plt.show()
```



4.0.1 Note:

The classes are balanced. Accuracy would be a good metric.

[22]:
```python
import plotly.express as px

from sklearn.decomposition import PCA
pca=PCA(n_components=2)
data_pca=pca.fit_transform(data.drop(['Label'],axis=1))
data_pca=pd.DataFrame(data_pca)
fig = px.
  ↪scatter(x=data_pca[0],y=data_pca[1],color=data['Label'],title="Decomposed␣
  ↪using PCA")
fig.show()
```

[23]:
```python
pca3=PCA(n_components=3)
data_pca3=pca3.fit_transform(data.drop(['Label'],axis=1))
data_pca3=pd.DataFrame(data_pca3)
fig = px.
  ↪scatter_3d(x=data_pca3[0],y=data_pca3[1],z=data_pca3[2],color=data['Label'],title=f"Varianc
  ↪Explained : {pca3.explained_variance_ratio_.sum() * 100}%")
fig.show()
```

[24]:

```
fig = px.
 ↪scatter(x=data['Nitrogen'],y=data['Phosphorus'],color=data['Label'],title="Nitrogen␣
 ↪VS Phosphorus")
fig.show()
```

[25]:
```
fig = px.
 ↪scatter(x=data['Phosphorus'],y=data['Potassium'],color=data['Label'],title="Phosphorus␣
 ↪VS Potassium")
fig.show()
```

[26]:
```
#would be required in future to get the names of crops back from encoded form

names = data['Label'].unique()
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
data['Label']=encoder.fit_transform(data['Label'])
data.head()
```

[26]:
```
   Nitrogen  Phosphorus  Potassium  Temperature   Humidity        pH  \
0        90          42         43    20.879744  82.002744  6.502985
1        85          58         41    21.770462  80.319644  7.038096
2        60          55         44    23.004459  82.320763  7.840207
3        74          35         40    26.491096  80.158363  6.980401
4        78          42         42    20.130175  81.604873  7.628473

     Rainfall  Label
0  202.935536     20
1  226.655537     20
2  263.964248     20
3  242.864034     20
4  262.717340     20
```

4.1 Note:

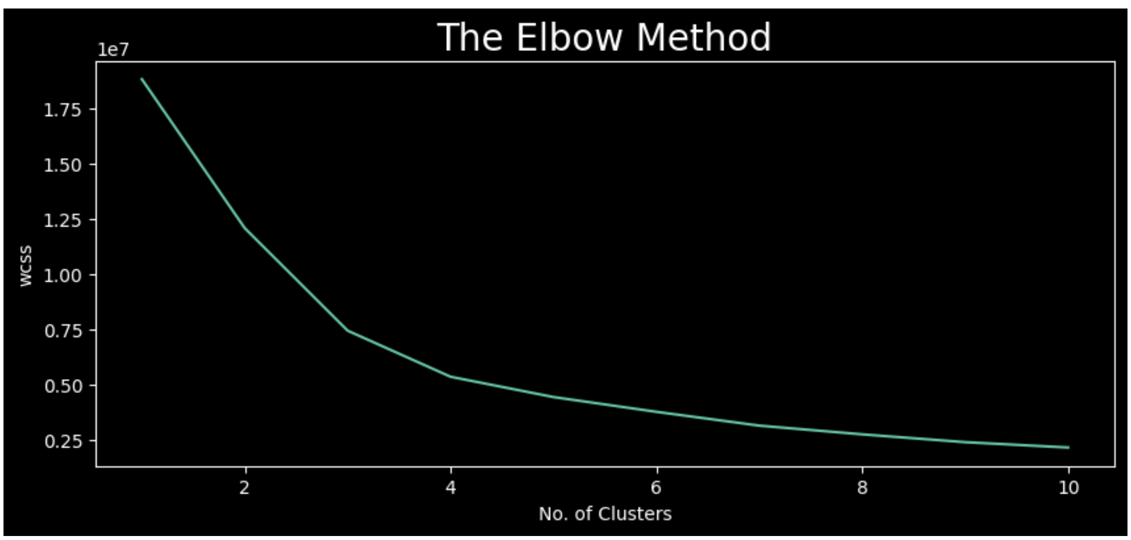
Encoding the target values to its respective numerical value is necessary because our machine learning model won't be able to understand strings!

[27]:
```
from sklearn.cluster import KMeans

# removing the labels column
x = data.drop(['Label'], axis=1)

# selecting all the values of the data
x = x.values

# checking the shape
print(x.shape)
```

```
(2200, 7)
```

4.2 Lets determine the Optimum Number of Clusters within the Dataset by using the Elbow Algorithm

[28]:
```
plt.rcParams['figure.figsize'] = (10, 4)

wcss = []
for i in range(1, 11):
    km = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init =␣
 ↪10, random_state = 0)
    km.fit(x)
    wcss.append(km.inertia_)

# Lets plot the results
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method', fontsize = 20)
plt.xlabel('No. of Clusters')
plt.ylabel('wcss')
plt.show()
```



4.3 Note:

There are two elbows first at 3 & second at 4; always select the last Elbow.

Hence our Cluster should be 4

4.4 Lets implement the K means algorithm to perform Clustering analysis

[29]:
```
km = KMeans(n_clusters=4,init='k-means++',max_iter = 300,n_init=10,random_state=0)
y_means =km.fit_predict(x)

#Lets find out the Result
a=data['Label']
y_means=pd.DataFrame(y_means)
z=pd.concat([y_means,a],axis=1)
z=z.rename(columns={0:'cluster'})

# let check the Cluster  of each Crops
print(" Lets check the Results After Applying the K Means Clustering Analysis: \n")
print("Crops in First Cluster:", z[z['cluster']==0]['Label'].unique())
print("--------------------------------------------------------------")
print(" Crops in Second cluster:", z[z['cluster']==1]['Label'].unique())
print('---------------------------------------------------------------')
print("Crops in Third cluster:", z[z['cluster'] ==2]['Label'].unique())
print("----------------------------------------------------------------")
print("Crops in Forth Cluster:",z[z['cluster']==3]['Label'].unique())
```

```
 Lets check the Results After Applying the K Means Clustering Analysis:

Crops in First Cluster: [11  3  9 18 13 14  2 10 19 12 16 17  4]
--------------------------------------------------------------
 Crops in Second cluster: [11  1 21 15 17  6  5]
---------------------------------------------------------------
Crops in Third cluster: [7 0]
----------------------------------------------------------------
Crops in Forth Cluster: [20 18 17  4  8  5]
```

4.5 Note:

This will help Farmers in adopting similar kind of crops and yield maximum productivity

5 Splitting up the Dataset for Predictive Modelling

[30]:
```
# Lets split the Dataset for Predictive Modelling
y = data['Label']
x = data.drop(['Label'], axis = 1)

print("Shape of x:", x.shape)
print("shape of y:", y.shape)
```

```
Shape of x: (2200, 7)
shape of y: (2200,)
```

6 Now, its time to divide the data into two sets; train_data & test_data

[31]:
```
# Lets create Training and Testing Sets for Validation of Results

from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
 ↪random_state = 0)

print("The Shape of x train:", x_train.shape)
print("The Shape of x test:", x_test.shape)
print("The Shape of y train:", y_train.shape)
print("The Shape of y test:", x_test.shape)
```

```
The Shape of x train: (1760, 7)
The Shape of x test: (440, 7)
The Shape of y train: (1760,)
The Shape of y test: (440, 7)
```

6.1 Let's build a predictive model guiding us about the best productive crop as per the climatic condition and minerals; for which we need to use machine learning algorithm to train our model.

After our model is trained, we will use the model for further predictions.

We are using logistic regression algorithm to train our model.

Logistic regression is a probabilistic model; Suitable for cases of probabilistic - or multiple - class types.

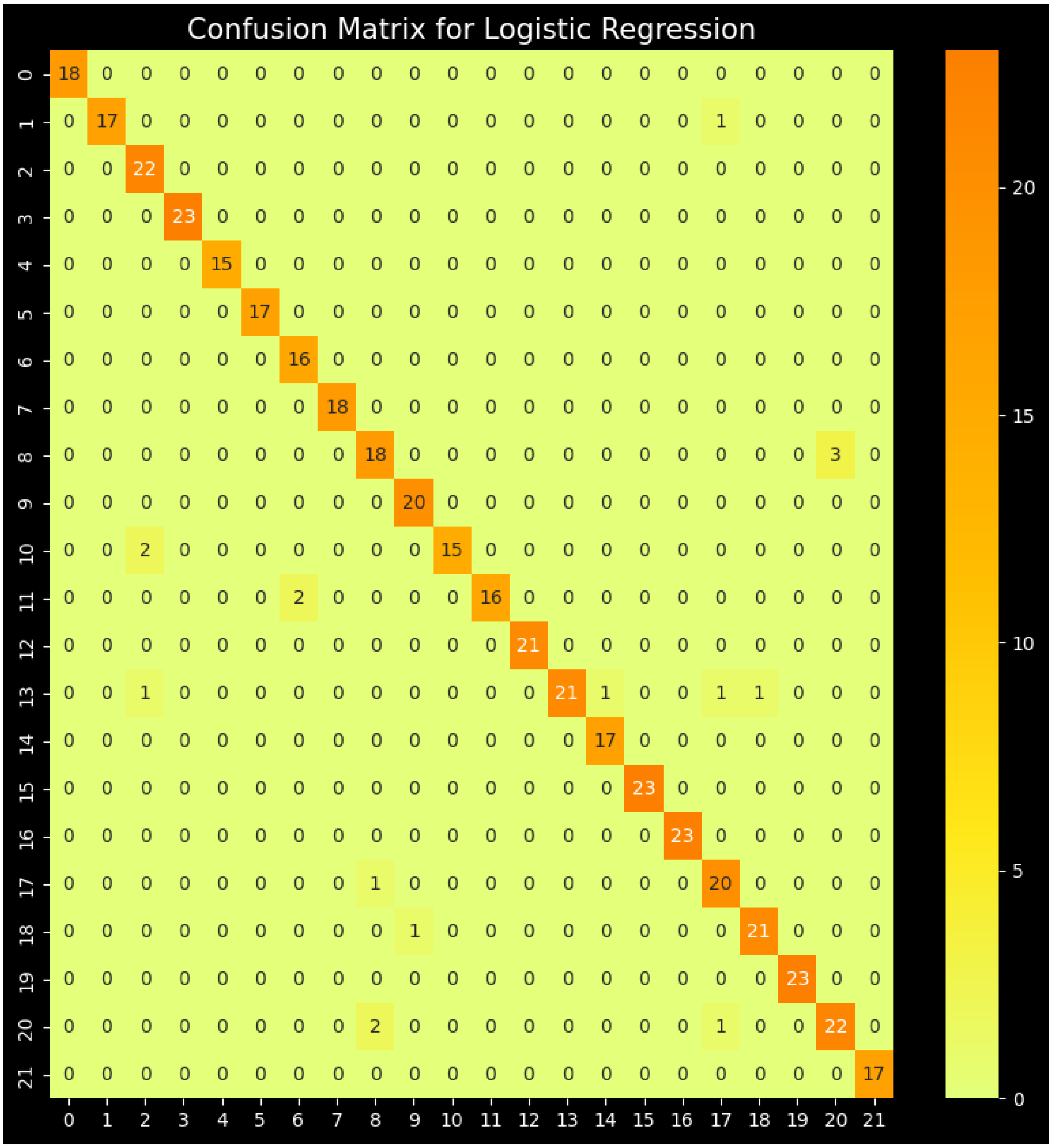
We have 22 classes in our cases.

7 Creation of a Predictive Model

[32]:
```
# Lets creat a Predictive Model

from sklearn.linear_model import LogisticRegression
# Importing LogisticRegression from SKlearn to make our predective model

model = LogisticRegression(solver = 'liblinear')
# Storing our Algorithm in varriable name model

#model=LogisticRegression()
model=model.fit(x_train, y_train)
```

```
# Our model hase been trained from the data stored into training data set, Our␣
↪model is fully trained now , further function used to predection

y_pred = model.predict(x_test)
#  we predict our model for x_test data set and further stored it into y_pred␣
↪variable
```

[33]:
```
# Lets evaluate the Model Performance
from sklearn.metrics import confusion_matrix

# Lets print the Confusion matrix first
plt.rcParams['figure.figsize'] = (10, 10)
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, cmap='Wistia')
plt.title('Confusion Matrix for Logistic Regression', fontsize=15)
plt.show()
```



8 To print the Classification Report:

[34]:
```python
from sklearn.metrics import classification_report

# Assuming we have defined and populated y_test and y_pred correctly
cr = classification_report(y_test, y_pred)
print(cr)
```

```
              precision    recall  f1-score   support
```

```
           0       1.00      1.00      1.00        18
           1       1.00      0.94      0.97        18
           2       0.88      1.00      0.94        22
           3       1.00      1.00      1.00        23
           4       1.00      1.00      1.00        15
           5       1.00      1.00      1.00        17
           6       0.89      1.00      0.94        16
           7       1.00      1.00      1.00        18
           8       0.86      0.86      0.86        21
           9       0.95      1.00      0.98        20
          10       1.00      0.88      0.94        17
          11       1.00      0.89      0.94        18
          12       1.00      1.00      1.00        21
          13       1.00      0.84      0.91        25
          14       0.94      1.00      0.97        17
          15       1.00      1.00      1.00        23
          16       1.00      1.00      1.00        23
          17       0.87      0.95      0.91        21
          18       0.95      0.95      0.95        22
          19       1.00      1.00      1.00        23
          20       0.88      0.88      0.88        25
          21       1.00      1.00      1.00        17

    accuracy                           0.96       440
   macro avg       0.96      0.96      0.96       440
weighted avg       0.96      0.96      0.96       440
```

8.1 Note:

With the help of classification report; we got the value of Precision & Recall, further if both precicion and recall are at optimum value, it indicates strong accuracy of our training model.

96% Accuracy for our predictive model has been achived.

8.2 Inspecting the Head of the Dataset

[35]:
```
# Checking the Head of the Dataset

data.head()
```

[35]:
```
   Nitrogen  Phosphorus  Potassium  Temperature   Humidity        pH  \
0        90          42         43    20.879744  82.002744  6.502985
1        85          58         41    21.770462  80.319644  7.038096
2        60          55         44    23.004459  82.320763  7.840207
3        74          35         40    26.491096  80.158363  6.980401
4        78          42         42    20.130175  81.604873  7.628473
```

```
    Rainfall  Label
0  202.935536     20
1  226.655537     20
2  263.964248     20
3  242.864034     20
4  262.717340     20
```

9 To Pridict a suitable Crop for Given Climatic Condition

[36]:
```
prediction = model.predict((np.array([[50, #for Nitrogen
                                       45,  #for Phosphorous
                                       10,  #for Potassium
                                       20,  #for Temperature
                                       80,  #for Humidity
                                       7,   #for pH
                                       200]])))#for Rainfall
print("The suggested crop for given climatic condition is:",prediction)
```

```
The suggested crop for given climatic condition is: [16]
```

10 Key Insights:

1. Crops and Nutrient Requirements:

• Certain crops have distinct requirements for nitrogen, phosphorus, and potassium. • Cotton requires the most nitrogen, while apple and grapes demand the highest phosphorus and potassium, respectively.

2. Climate and Soil Preferences:

• Different crops have varying preferences for temperature, humidity, pH, and rainfall. • Papaya and mango require high temperatures, while coconut needs a humid climate. • Chickpeas thrive in higher pH soils, whereas rice demands significant rainfall.

3. Seasonal Crop Recommendations:

- Identified crops suitable for different seasons:
- **Summer Crops**: *Pigeonpeas, mothbeans, mango, grapes, orange, papaya.*
- **Winter Crops**: *Maize, lentil, pomegranate, grapes, orange.*
- **Rainy Crops**: *Rice, papaya, coconut.*

4. Outliers and Data Distribution:

- Outliers are present across the dataset affecting nutrient levels and climatic conditions.
- Visualizations highlight the distribution and variability of data attributes.

5. Clustering Analysis:

- Implemented K-means clustering to group crops based on similar conditions.
- Identified clusters with crops having comparable requirements for optimal growth.

11 Recommendations:

1. Precision Farming Strategies:

• Employ precision farming techniques based on identified nutrient and climatic requirements for different crops.

2. Crop-Specific Planning:

• Farmers should plan crops based on seasonal and regional suitability for better yields.

3. Outlier Management:

• Address outliers in the dataset to ensure accurate predictive modeling.

4. Machine Learning Application:

• Deploy machine learning models to predict suitable crops for given soil and climatic conditions.

5. Further Research:

• Explore advanced techniques to handle outliers and improve predictive accuracy.

Implementing these recommendations can significantly enhance agricultural productivity and assist farmers in making informed decisions based on climatic and soil conditions.

12 Contact:

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Thank you!