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

data=pd.read_csv('C:/Users/Admin/Downloads/Crop_recommendation.csv')
data

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

[2200 rows x 8 columns]

print("Shape of the dataset:", data.shape)

Shape of the dataset: (2200, 8)

data.head(11)

     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
10  91  53  40    26.527235  81.417538  5.386168  264.614870  rice
```

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

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

```
data["label"].value_counts()
```

```
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
```

```
print("Average ratio of Nitrogen in Soil:
{0: .2f}".format(data["N"].mean()))
print("Average ratio of Phosphorus in Soil:
{0: .2f}".format(data["P"].mean()))
print("Average ratio of Potassium in Soil:
{0: .2f}".format(data["K"].mean()))
print("Average ratio of Temperature in celcius:
```

```
{0: .2f}".format(data["temperature"].mean()))
print("Average relative humdity in %:
{0: .2f}".format(data["humidity"].mean()))
print("Average pH value of the Soil:
{0: .2f}".format(data["ph"].mean()))
print("Average rainfall in mm:
{0: .2f}".format(data["rainfall"].mean()))
```

```
Average ratio of Nitrogen in Soil: 50.55
Average ratio of Phosphorus in Soil: 53.36
Average ratio of Potassium in Soil: 48.15
Average ratio of Temperature in celcius: 25.62
Average relative humdity in %: 71.48
Average pH value of the Soil: 6.47
Average rainfall in mm: 103.46
```

```
@interact
def summary(crops = list(data['label'].value_counts().index)):
    x = data[data['label'] == crops]
    print("---------------------------------------------")
    print("Statistics for Nitrogen")
    print("Minimum Nitrogen required:", x['N'].min())
    print("Average Nitrogen required:", x['N'].mean())
    print("Maximum Nitrogen required:", x['N'].max())
    print("---------------------------------------------")
    print("Statistics for Phosphorus")
    print("Minimum Phosphorus required:", x['P'].min())
    print("Average Phosphorus required:", x['P'].mean())
    print("Maximum Phosphorus required:", x['P'].max())
    print("---------------------------------------------")
    print("Statistics for Potassium")
    print("Minimum Potassium required:", x['K'].min())
    print("Average Potassium required:", x['K'].mean())
    print("Maximum Potassium required:", x['K'].max())
    print("---------------------------------------------")
    print("Statistics for Temperature")
    print("Minimum Temperature required:
{:.2f}".format(x['temperature'].min()))
    print("Average Temperature required:
{:.2f}".format(x['temperature'].mean()))
    print("Maximum Temperature required:
{:.2f}".format(x['temperature'].max()))
    print("---------------------------------------------")
    print("Statistics for Humidity")
    print("Minimum Humidity required:
{:.2f}".format(x['humidity'].min()))
    print("Average Humidity required:
{:.2f}".format(x['humidity'].mean()))
    print("Maximum Humidity required:
{:.2f}".format(x['humidity'].max()))
```

```
    print("---------------------------------------------")
    print("Statistics for pH")
    print("Minimum pH required: {:.2f}".format(x['ph'].min()))
    print("Average pH required: {:.2f}".format(x['ph'].mean()))
    print("Maximum pH required: {:.2f}".format(x['ph'].max()))
    print("---------------------------------------------")
    print("Statistics for Rainfall")
    print("Minimum Rainfall required:
{:.2f}".format(x['rainfall'].min()))
    print("Average Rainfall required:
{:.2f}".format(x['rainfall'].mean()))
    print("Maximum Rainfall required:
{:.2f}".format(x['rainfall'].max()))
```

{"model_id":"bb2b5f4ada524d43be1c64bf8eadc908","version_major":2,"vers
ion_minor":0}

```
@interact
def compare(conditions =
['N','P','K','temperature','ph','humidity','rainfall']):
    print("Average Value for", conditions, "is
{0:.2f}".format(data[conditions].mean()))
    print("----------------------------------------------")
    print("Rice : {0:.2f}".format(data[(data['label'] == 'rice')]
[conditions].mean()))
    print("Black Grams : {0:.2f}".format(data[(data['label'] ==
'blackgrams')][conditions].mean()))
    print("Banana : {0:.2f}".format(data[(data['label'] == 'banana')]
[conditions].mean()))
    print("Jute : {0:.2f}".format(data[(data['label'] == 'jute')]
[conditions].mean()))
    print("Coconut : {0:.2f}".format(data[(data['label'] ==
'coconut')][conditions].mean()))
    print("Apple : {0:.2f}".format(data[(data['label'] == 'apple')]
[conditions].mean()))
    print("Papaya : {0:.2f}".format(data[(data['label'] == 'papaya')]
[conditions].mean()))
    print("Muskmelon : {0:.2f}".format(data[(data['label'] ==
'muskmelon')][conditions].mean()))
    print("Grapes : {0:.2f}".format(data[(data['label'] == 'grapes')]
[conditions].mean()))
    print("Watermelon : {0:.2f}".format(data[(data['label'] ==
'watermelon')][conditions].mean()))
    print("Kidney Beans : {0:.2f}".format(data[(data['label'] ==
'kidney beans')][conditions].mean()))
    print("Mung Beans : {0:.2f}".format(data[(data['label'] == 'mung
beans')][conditions].mean()))
    print("Oranges : {0:.2f}".format(data[(data['label'] ==
'oranges')][conditions].mean()))
    print("Chick Peas : {0:.2f}".format(data[(data['label'] == 'chick
```

```
peas')][conditions].mean()))
    print("Lentils : {0:.2f}".format(data[(data['label'] ==
'lentils')][conditions].mean()))
    print("Cotton : {0:.2f}".format(data[(data['label'] == 'cotton')]
[conditions].mean()))
    print("Maize : {0:.2f}".format(data[(data['label'] == 'maize')]
[conditions].mean()))
    print("Moth Beans : {0:.2f}".format(data[(data['label'] == 'moth
beans')][conditions].mean()))
    print("Pigeon Peas : {0:.2f}".format(data[(data['label'] ==
'pigeon peas')][conditions].mean()))
    print("Mango : {0:.2f}".format(data[(data['label'] == 'mango')]
[conditions].mean()))
    print("Pomegranate : {0:.2f}".format(data[(data['label'] ==
'pomegranate')][conditions].mean()))
    print("Coffee : {0:.2f}".format(data[(data['label'] == 'coffee')]
[conditions].mean()))
```

{"model_id":"60c15a454a6b408399023a19665835d7","version_major":2,"version_minor":0}

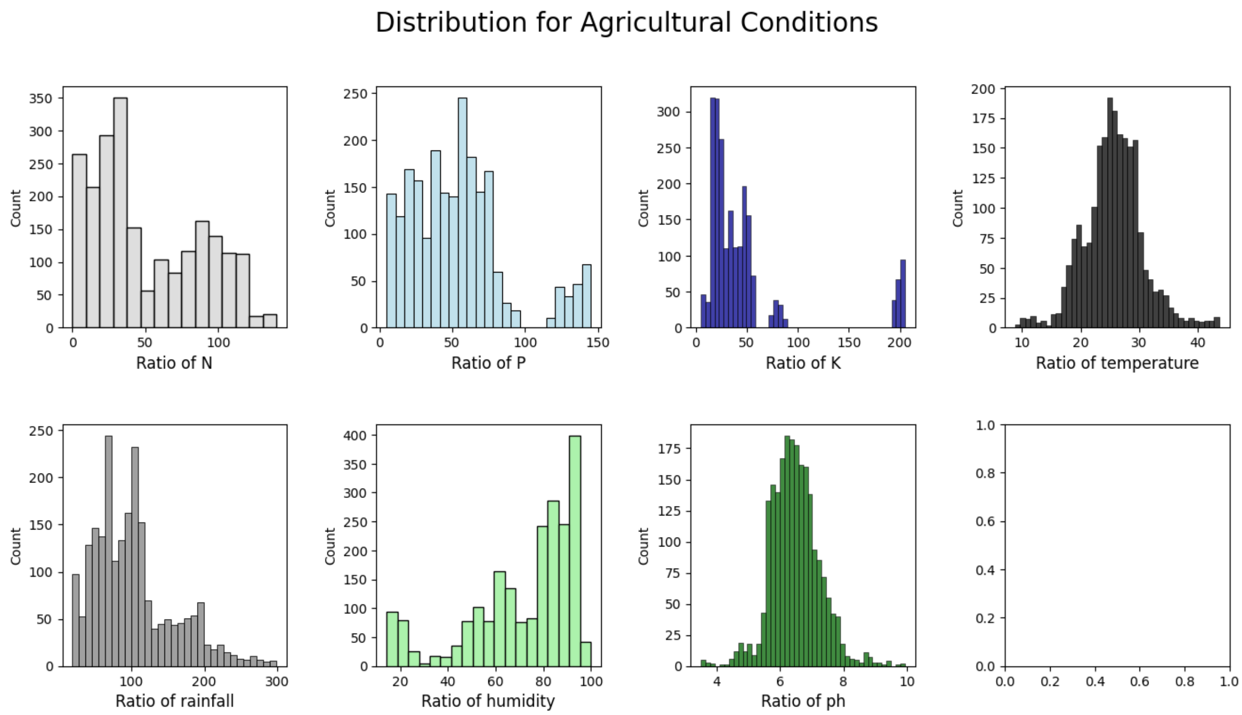
```
@interact
def compare(conditions =
['N','P','K','temperature','ph','humidity','rainfall']):
    print("Crops which require greater than average", conditions, '\
n')
    print(data[data[conditions] > data[conditions].mean()]
['label'].unique())
    print("---------------------------------------")
    print("Crops which require less than average", conditions,'\n')
    print(data[data[conditions] <=data[conditions].mean()]
['label'].unique())
```

{"model_id":"3c58b05f5a2c400f8f42aadf862413b6","version_major":2,"version_minor":0}

Distribution for Agricultural Conditions

```
import seaborn as sns
import matplotlib.pyplot as plt

# Create subplots with 2 rows and 4 columns
fig, axes = plt.subplots(2, 4, figsize=(16, 8))

# Define the data columns and colors
columns = ['N', 'P', 'K', 'temperature', 'rainfall', 'humidity', 'ph']
colors = ['lightgrey', 'lightblue', 'darkblue', 'black', 'grey',
'lightgreen', 'darkgreen']

# Loop through the subplots and create the distribution plots
```

```
for i, col in enumerate(columns):
    row = i // 4
    col_num = i % 4

    sns.histplot(data[col], color=colors[i], ax=axes[row, col_num])
    axes[row, col_num].set_xlabel(f'Ratio of {col}', fontsize=12)

# Adjust the spacing between subplots
plt.subplots_adjust(wspace=0.4, hspace=0.4)

# Add a title for the entire figure
plt.suptitle('Distribution for Agricultural Conditions', fontsize=20)

# Show the plot
plt.show()
```




```
print("Some Interesting Patterns")
print("---------------------------")
print("Crops which requires very High Ratio of Nirtogen Content in
Soil:", data[data['N'] > 120]['label'].unique())
print("Crops which requires very High Ratio of Phosphorous Content in
Soil:", data[data['P'] > 100]['label'].unique())
print("Crops which requires very High Ratio of Potassium Content in
Soil:", data[data['K'] > 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("Crops 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']
Crops which requires very Low pH: ['mothbeans']
```

Seasonal Crops Recommendations (Summer, Winter, Rainy)

```
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())
```

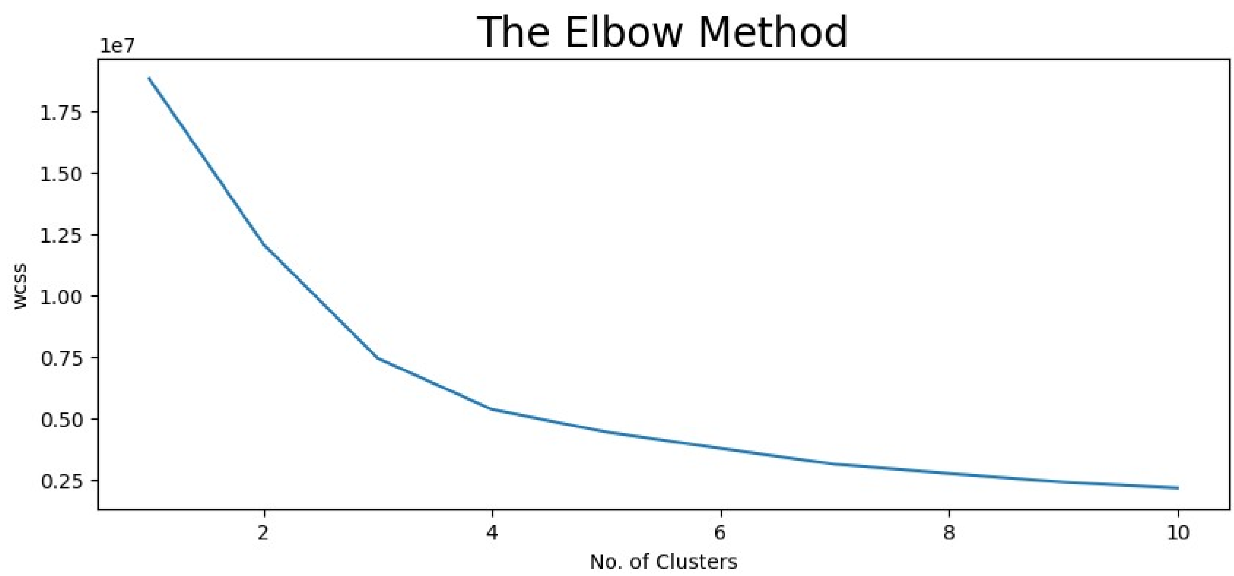
```
Summer Crops
['pigeonpeas' 'mothbeans' 'blackgram' 'mango' 'grapes' 'orange'
'papaya']
-----------------------------------------
Winter Crops
['maize' 'pigeonpeas' 'lentil' 'pomegranate' 'grapes' 'orange']
-----------------------------------------
Rainy Crops
['rice' 'papaya' 'coconut']
```

Removing of columns to find some more Insights

```
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)
```

To determine the Optimum Number of Clusters within the Dataset

```
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()
```



Implementation of K Means to perform Clustering Analysis

```
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 Results
a = data['label']
y_means = pd.DataFrame(y_means)
z = pd.concat([y_means, a], axis = 1)
z = z.rename(columns = {0: 'cluster'})

# Lets check the Clusters 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: ['grapes' 'apple']
```

```
----------------------------------------------------------------
Crops in Second cluster: ['maize' 'chickpea' 'kidneybeans'
'pigeonpeas' 'mothbeans' 'mungbean'
 'blackgram' 'lentil' 'pomegranate' 'mango' 'orange' 'papaya'
'coconut']
----------------------------------------------------------------
Crops in Third cluster: ['maize' 'banana' 'watermelon' 'muskmelon'
'papaya' 'cotton' 'coffee']
----------------------------------------------------------------
Crops in Forth cluster: ['rice' 'pigeonpeas' 'papaya' 'coconut' 'jute'
'coffee']
```

Splitting up of 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,)
```

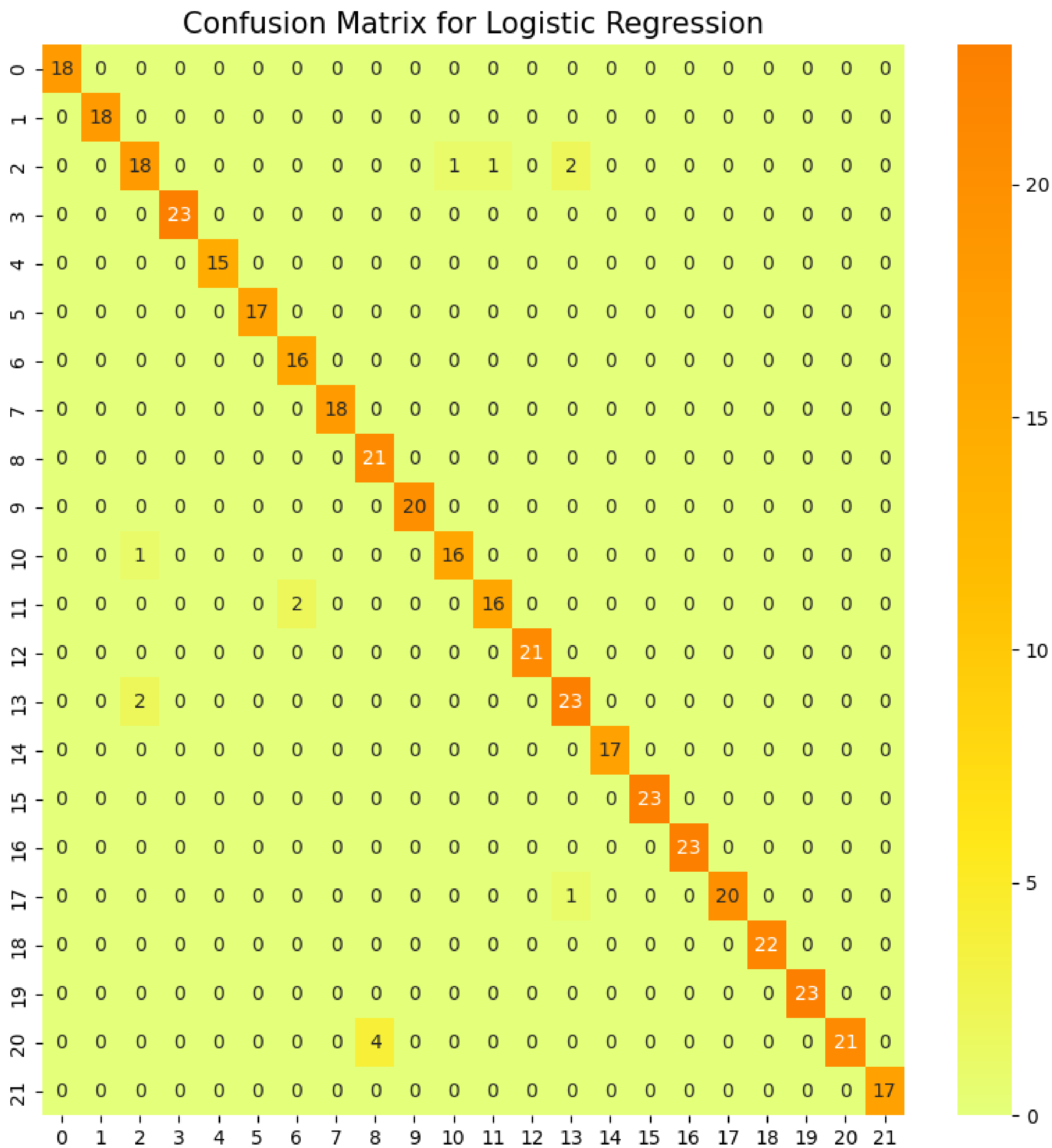
Creations of the Training and Testing Sets for Validation of Results

```
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)
```

Evaluation of a Model Performance

```
from sklearn.metrics import confusion_matrix

# Printing the Confusion matrix
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()
```



Printing out the Classification Report

```
from sklearn.metrics import classification_report
```

```
cr = classification_report(y_test, y_pred)
print(cr)
```

```
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        18
      banana       1.00      1.00      1.00        18
   blackgram       0.86      0.82      0.84        22
    chickpea       1.00      1.00      1.00        23
     coconut       1.00      1.00      1.00        15
      coffee       1.00      1.00      1.00        17
      cotton       0.89      1.00      0.94        16
      grapes       1.00      1.00      1.00        18
        jute       0.84      1.00      0.91        21
 kidneybeans       1.00      1.00      1.00        20
      lentil       0.94      0.94      0.94        17
       maize       0.94      0.89      0.91        18
       mango       1.00      1.00      1.00        21
   mothbeans       0.88      0.92      0.90        25
    mungbean       1.00      1.00      1.00        17
   muskmelon       1.00      1.00      1.00        23
      orange       1.00      1.00      1.00        23
      papaya       1.00      0.95      0.98        21
  pigeonpeas       1.00      1.00      1.00        22
 pomegranate       1.00      1.00      1.00        23
        rice       1.00      0.84      0.91        25
  watermelon       1.00      1.00      1.00        17

    accuracy                           0.97       440
   macro avg       0.97      0.97      0.97       440
weighted avg       0.97      0.97      0.97       440
```

```
from sklearn.metrics import classification_report

# Assuming that 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

       apple       1.00      1.00      1.00        18
      banana       1.00      1.00      1.00        18
   blackgram       0.86      0.82      0.84        22
    chickpea       1.00      1.00      1.00        23
     coconut       1.00      1.00      1.00        15
      coffee       1.00      1.00      1.00        17
      cotton       0.89      1.00      0.94        16
      grapes       1.00      1.00      1.00        18
```

```
         jute       0.84      1.00      0.91        21
  kidneybeans       1.00      1.00      1.00        20
       lentil       0.94      0.94      0.94        17
        maize       0.94      0.89      0.91        18
        mango       1.00      1.00      1.00        21
    mothbeans       0.88      0.92      0.90        25
     mungbean       1.00      1.00      1.00        17
    muskmelon       1.00      1.00      1.00        23
       orange       1.00      1.00      1.00        23
       papaya       1.00      0.95      0.98        21
   pigeonpeas       1.00      1.00      1.00        22
  pomegranate       1.00      1.00      1.00        23
         rice       1.00      0.84      0.91        25
   watermelon       1.00      1.00      1.00        17

     accuracy                           0.97       440
    macro avg       0.97      0.97      0.97       440
 weighted avg       0.97      0.97      0.97       440
```

Inspecting the Head of the Dataset

```
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
```

The Final Prediction

```
prediction = model.predict((np.array([[90,
                                       40,
                                       40,
                                       20,
                                       80,
                                       7,
                                      200]])))
print("The Suggested Crop for Given Climatic Condition is :",
prediction)
```

```
The Suggested Crop for Given Climatic Condition is : ['rice']

C:\Users\Admin\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\base.py:465: UserWarning: X does not have valid
feature names, but LogisticRegression was fitted with feature names
  warnings.warn(
```