Import The following packages

```
import numpy as np # for complex mathematical problems
import pandas as pd # for data analysis and manipulation
import seaborn as sns # for data visualization
from matplotlib import pyplot as plt
from ipywidgets import interact # for interactivity
```

Retrieving the dataset

```
In [9]:
           data =pd.read csv('E:/archive/data.csv')
In [10]:
           # Lets check the head of the Dataset
           data.head()
Out[10]:
                     K temperature humidity
                                                          rainfall label
                                                   ph
          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
            60 55 44
                          23.004459 82.320763 7.840207 263.964248
                                                                   rice
            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
In [11]:
           print("The shape of the Dataset is:",data.shape)
          The shape of the Dataset is: (2200, 8)
In [12]:
           # To check the null value in the dataset
           data.isnull().sum()
Out[12]:
                          0
          temperature
          humidity
          ph
          rainfall
                          0
          label
          dtype: int64
```

- Fill-Na function is sued to replace these missing values such as mean, median, mode.
- Na means not available
- Pandas have function like fill_na, drop-Na to treat missing values

```
In [13]: # Lets check the crops present in ths dataset
```

```
data['label'].value counts()
                        100
Out[13]: grapes
                        100
         mungbean
         pigeonpeas
                        100
         coconut
                        100
                        100
         blackgram
         lentil
                        100
         coffee
                        100
         banana
                        100
                        100
         chickpea
                        100
         mango
                        100
         papaya
                        100
         cotton
                        100
         mothbeans
         muskmelon
                        100
         watermelon
                        100
                        100
         rice
                        100
         orange
         pomegranate
                        100
         apple
                        100
         maize
                        100
         jute
                        100
         kidneybeans
                        100
         Name: label, dtype: int64
In [14]:
          # Lets check the summary
          print("Average Ratio of Nitrogen in the soil: {0:.2f}".format(data['N'].mean()))
          print("Average Ratio of Phosphorous in the soil: {0:.2f}".format(data['P'].mean()))
          print("Average Ratio of Potassium in the soil: {0:.2f}".format(data['K'].mean()))
          print("Average Temperature in celcius: {0:.2f}".format(data['temperature'].mean()))
          print("Average Relative Humidity 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 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 celcius: 25.62
         Average Relative Humidity in %: 71.48
         Average Ph value of the soil: 6.47
         Average Rainfall in mm: 103.46
In [15]:
          # Lets check the summary Statistics for each of the crops
          @interact
          def summary(crops = list(data['label'].value counts().index)):
              x =data[data['label'] ==crops]
              print("----")
              print("Statistics for Nitrogen")
              print("Minimum Nitrigen required:",x['N'].min())
              print("Average Nitrigen required:",x['N'].mean())
              print("Maximum Nitrigen required:",x['N'].max())
              print("-----")
              print("Statistics for Phosphorous")
              print("Minimum Phosphorous required:",x['P'].min())
              print("Average Phosphorous required:",x['P'].mean())
              print("Maximum Phosphorous 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:",x['temperature'].min())
print("Average Temperature required:",x['temperature'].mean())
print("Maximum Temperature required:",x['temperature'].max())
print("----")
print("Statistics for Humidity")
print("Minimum Humidity required:",x['humidity'].min())
print("Average Humidityrequired:",x['humidity'].mean())
print("Maximum Humidity required:",x['humidity'].max())
print("----")
print("Statistics for PH")
print("Minimum PH required:",x['ph'].min())
print("Average PHrequired:",x['ph'].mean())
print("Maximum PH required:",x['ph'].max())
print("-----")
print("Statistics for Rainfall")
print("Minimum Rainfall required:",x['rainfall'].min())
print("Average Rainfall required:",x['rainfall'].mean())
print("Maximum rainfall required:",x['rainfall'].max())
print("-----")
```

```
In [16]:
          data['label'].value_counts()
                       100
Out[16]: grapes
                       100
         mungbean
                       100
         pigeonpeas
                       100
         coconut
                       100
         blackgram
         lentil
                       100
         coffee
                       100
         banana
                       100
                       100
         chickpea
                       100
         mango
                       100
         papaya
         cotton
                       100
                       100
         mothbeans
         muskmelon
                       100
                       100
         watermelon
         rice
                       100
                       100
         orange
                       100
         pomegranate
                       100
         apple
                       100
         maize
                       100
         jute
         kidneybeans
                       100
         Name: label, dtype: int64
In [17]:
          # Lets compare the Average for eachcrops with average conditions
          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("Maize:{0:.2f}".format(data[(data['label'] =='maize')][conditions].mean()))
              print("Mothbeans:{0:.2f}".format(data[(data['label'] =='mothbeans'))][conditions].me
```

```
print("Apple:{0:.2f}".format(data[(data['label'] =='apple')][conditions].mean()))
print("Grapes:{0:.2f}".format(data[(data['label'] =='grapes')][conditions].mean()))
print("Muskmelon:{0:.2f}".format(data[(data['label'] =='muskmelon')][conditions].me
print("Lentil:{0:.2f}".format(data[(data['label'] =='lentil'))][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("Rice:{0:.2f}".format(data[(data['label'] =='rice')][conditions].mean()))
print("Pigeonpeas:{0:.2f}".format(data[(data['label'] =='pigeonpeas')][conditions].
print("Kidneybeans:{0:.2f}".format(data['label'] =='kidneybeans')][conditions
print("Coffee:{0:.2f}".format(data[(data['label'] =='coffee')][conditions].mean()))
print("Papaya:{0:.2f}".format(data['label'] =='papaya')][conditions].mean()))
print("Mango:{0:.2f}".format(data[(data['label'] =='mango')][conditions].mean()))
print("Chickpea:{0:.2f}".format(data[(data['label'] =='chickpea'))][conditions].mean
print("Orange:{0:.2f}".format(data[(data['label'] =='orange')][conditions].mean()))
print("Mungbean:{0:.2f}".format(data[(data['label'] =='mungbean'))][conditions].mean
print("Blackgram:{0:.2f}".format(data[(data['label'] =='blackgram'))][conditions].me
print("Pomegrenate:{0:.2f}".format(data[(data['label'] =='pomegranate'))][conditions
print("Cotton:{0:.2f}".format(data[(data['label'] =='cotton')][conditions].mean()))
print("Watermelon:{0:.2f}".format(data[(data['label'] =='watermelon')][conditions].
```

```
# Lets make this function more promptive
@interact
def compare(conditions=['N','P','K','temperature','ph','humidity','rainfall']):
    print(" Average value of",conditions,"is: {0:.2f}".format(data[conditions].mean
    print("Crops which require greater than average",conditions,'\n')
    print(data[data[conditions] > data[conditions].mean()]['label'].unique())
    print("Crops which require less than average",conditions,'\n')
    print(data[data[conditions] <data[conditions].mean()]['label'].unique())</pre>
```

```
In [19]:
          plt.subplot(3,4,1)
          sns.distplot(data['N'], color ='yellow')
          plt.xlabel('Ratio of Nitrogen', fontsize =12)
          plt.grid()
          plt.subplot(3,4,2)
          sns.distplot(data['P'],color ='lightpink')
          plt.xlabel('Ratio of Phosphorous',fontsize =12)
          plt.grid()
          plt.subplot(3,4,3)
          sns.distplot(data['K'],color ='black')
          plt.xlabel('Ratio of Potassim', fontsize =12)
          plt.grid()
          plt.subplot(3,4,4)
          sns.distplot(data['temperature'],color ='grey')
          plt.xlabel('Temperature', fontsize =12)
          plt.grid()
          plt.subplot(3,4,5)
          sns.distplot(data['rainfall'],color ='lightgreen')
          plt.xlabel('Rainfall', fontsize=12)
          plt.grid()
```

```
Optimizing Agriculture Production
 plt.subplot(3,4,6)
 sns.distplot(data['humidity'],color ='darkgreen')
 plt.xlabel('humidity',fontsize=12)
plt.grid()
plt.subplot(3,4,7)
 sns.distplot(data['ph'],color ='lightblue')
 plt.xlabel('Ph Level', fontsize=12)
plt.grid()
plt.suptitle('Distribution for Agriculture Conditions', fontsize =20)
plt.show()
C:\Users\asus\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adap
t your code to use either `displot` (a figure-level function with similar flexibility) o
r `histplot` (an axes-level function for histograms).
 warnings.warn(msg, FutureWarning)
C:\Users\asus\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please adap
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`distplot` is a deprecated function and will be removed in a future version. Please adap
```

t your code to use either `displot` (a figure-level function with similar flexibility) o

r `histplot` (an axes-level function for histograms).

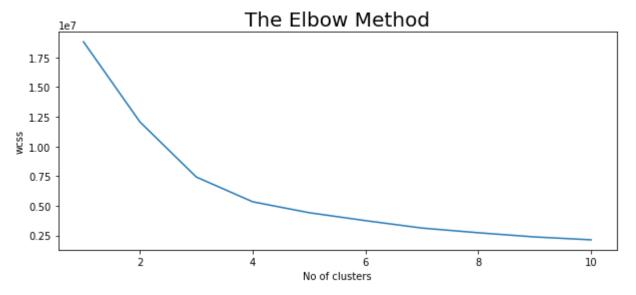
warnings.warn(msg, FutureWarning)

Distribution for Agriculture Conditions

```
Density
200
               0.01
 0.01
                                                    0.d5
 0.00
                  0.00
                                   0.00
               100
                                                  200
                  0.04
                                   0.5kRai
0.01R.a
                                                      imTemperature
                  0.02
0.005
0.000
              200
                                  100
          Rainfall
                         humidity
                                           Ph Level
```

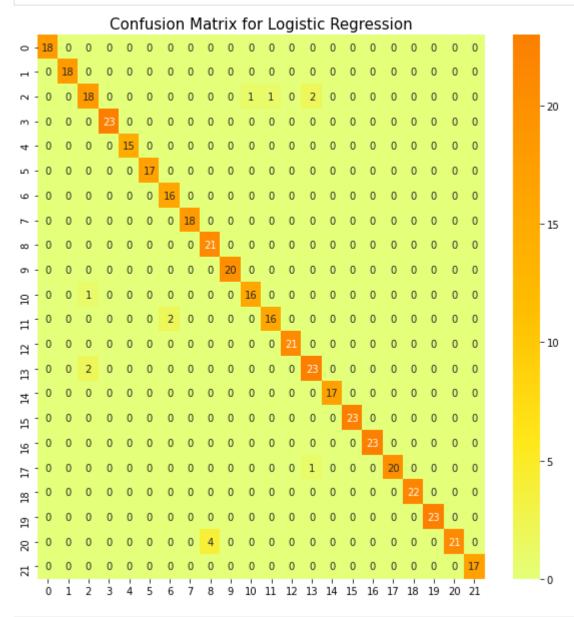
```
In [20]:
         # Lets find out something more
          print("Some intresting fact:")
          print("-----")
         print("Crops which require very High Ratio of Nitrogen Content in soil:",data[data['N']
         print("Crops which requires very High Ratio of Phosphorous in the soil:",data[data['P']
          print("Crops which requires Very High Ratio of Potassiu in the soil",data[data['K'] > 2
          print("Crops which requires very High Rainfall:",data[data['rainfall'] >200]['label'].u
          print("Crops which requires very low Rainfall:",data[data['rainfall'] <60]['label'].uni</pre>
         print("Crops which rquires very High Temperature",data[data['temperature'] >40]['label'
         print("Crops which requires very Low Temperature",data[data['temperature']<10]['label']</pre>
         Some intresting fact:
         Crops which require very High Ratio of Nitrogen Content in soil: ['cotton']
         Crops which requires very High Ratio of Phosphorous in the soil: ['grapes' 'apple']
         Crops which requires Very High Ratio of Potassiu in the soil ['grapes' 'apple']
         Crops which requires very High Rainfall: ['rice' 'papaya' 'coconut']
         Crops which requires very low Rainfall: ['mothbeans' 'mungbean' 'lentil' 'watermelon' 'm
         uskmelon' 'papaya']
         Crops which rquires very High Temperature ['grapes' 'papaya']
         Crops which requires very Low Temperature ['grapes']
In [21]:
         ### Lets understand which crops can only be grown in summer, winter and rainy season
         print("SUMMER CROPS")
         print(data[(data['temperature'] >40) & (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
         ['grapes' 'papaya']
         WINTER CROPS
         ['maize' 'pigeonpeas' 'lentil' 'pomegranate' 'grapes' 'orange']
         RAINY CROPS
         ['rice' 'papaya' 'coconut']
In [22]:
         from sklearn.cluster import KMeans
         # removing the labels column
         x=data.drop(['label'], axis =1)
          # selcting all the values of data
```

```
x=x.values
          # checking the shape
          print(x.shape)
          (2200, 7)
In [23]:
          x.shape
Out[23]: (2200, 7)
In [34]:
          # Lets determine the optimum no of clusters within the clusters
          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)
              wcss.append(km.inertia_)
          # Lets plot the result
          plt.plot(range(1,11),wcss)
          plt.title('The Elbow Method',fontsize =20)
          plt.xlabel('No of clusters')
          plt.ylabel('wcss')
          plt.show()
```



```
print("Crops in Third Cluster:",z[z['cluster'] == 2]['label'].unique())
          print("-----")
          print("Crops in Fourth Cluster:",z[z['cluster'] == 3]['label'].unique())
         Lets check the results after applying the K means clustering analysis
         Crops in First clustering: ['maize' 'chickpea' 'kidneybeans' 'pigeonpeas' 'mothbeans' 'm
         ungbean'
          'blackgram' 'lentil' 'pomegranate' 'mango' 'orange' 'papaya' 'coconut']
         Crops in Second Cluster: ['maize' 'banana' 'watermelon' 'muskmelon' 'papaya' 'cotton' 'c
         Crops in Third Cluster: ['grapes' 'apple']
         -----
         Crops in Fourth Cluster: ['rice' 'pigeonpeas' 'papaya' 'coconut' 'jute' 'coffee']
In [39]:
          # Lets split the dataset for predectvive Modeling
          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,)
In [41]:
          # Lets try to 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:",y 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,)
In [43]:
          # Lets create a Predective Model
          from sklearn.linear model import LogisticRegression
          model =LogisticRegression()
          model.fit(x train, y train)
          y pred = model.predict(x test)
         C:\Users\asus\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:763: Converg
         enceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regression
           n iter i = check optimize result(
In [49]:
          # 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()
```



```
In [51]: # Lets print 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

```
0.84
                               1.00
                                          0.91
                                                       21
        jute
 kidneybeans
                    1.00
                               1.00
                                          1.00
                                                       20
                                                       17
      lentil
                               0.94
                                          0.94
                    0.94
       maize
                    0.94
                               0.89
                                          0.91
                                                       18
                    1.00
                               1.00
                                          1.00
                                                       21
       mango
                               0.92
                                          0.90
                                                       25
   mothbeans
                    0.88
                                                       17
    mungbean
                    1.00
                               1.00
                                          1.00
   muskmelon
                    1.00
                               1.00
                                          1.00
                                                       23
                               1.00
                                                       23
      orange
                    1.00
                                          1.00
                                                       21
      papaya
                    1.00
                               0.95
                                          0.98
                               1.00
                                                       22
  pigeonpeas
                    1.00
                                          1.00
 pomegranate
                    1.00
                               1.00
                                          1.00
                                                       23
        rice
                    1.00
                               0.84
                                          0.91
                                                       25
                                                       17
  watermelon
                    1.00
                               1.00
                                          1.00
                                          0.97
                                                      440
    accuracy
                    0.97
                                          0.97
                                                      440
   macro avg
                               0.97
weighted avg
                    0.97
                               0.97
                                          0.97
                                                      440
```

In [55]:

In []:

data.head(100)

ut[55]:		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
	•••								
	95	88	46	42	22.683191	83.463583	6.604993	194.265172	rice
	96	93	47	37	21.533463	82.140041	6.500343	295.924880	rice
	97	60	55	45	21.408658	83.329319	5.935745	287.576694	rice
	98	78	35	44	26.543481	84.673536	7.072656	183.622266	rice
	99	65	37	40	23.359054	83.595123	5.333323	188.413665	rice

100 rows × 8 columns

localhost:8888/nbconvert/html/Optimizing Agriculture Production.ipynb?download=false