```
In [1]: import numpy as np
import pandas as pd
```

Read the Data

```
In [2]: #Importing the data
crop = pd.read_csv('Crop_recommendation.csv')
```

In [3]: crop

Out[3]:

		N	Р	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
2	195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2	196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2	197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2	198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2	199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

2200 rows × 8 columns

In [4]: crop.head()

Out[4]:

		N	Р	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

In [5]: #Shape of Data
crop.shape

Out[5]: (2200, 8)

```
In [6]: crop.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 2200 entries, 0 to 2199
         Data columns (total 8 columns):
           #
               Column
                              Non-Null Count Dtype
           0
                              2200 non-null
                                                int64
           1
               Ρ
                              2200 non-null
                                                int64
           2
               Κ
                              2200 non-null
                                                int64
           3
               temperature 2200 non-null
                                                float64
           4
               humidity
                              2200 non-null
                                                float64
                                                float64
          5
               ph
                              2200 non-null
          6
               rainfall
                              2200 non-null
                                                float64
                              2200 non-null
           7
               label
                                                object
         dtypes: float64(4), int64(3), object(1)
         memory usage: 137.6+ KB
In [7]: | crop.isna().sum()
Out[7]: N
                          0
                          0
                          0
         temperature
         humidity
                          0
         ph
                          0
                          0
         rainfall
         label
                          0
         dtype: int64
In [8]:
         crop.duplicated().sum()
Out[8]: 0
         #describing the data
In [9]:
         crop.describe()
Out[9]:
                                      Ρ
                                                     temperature
                                                                     humidity
                                                                                      ph
          count 2200.000000
                             2200.000000
                                         2200.000000
                                                                  2200.000000
                                                                              2200.000000
                                                     2200.000000
                                                                                          2200.
                                                                                           103.
          mean
                   50.551818
                               53.362727
                                           48.149091
                                                        25.616244
                                                                    71.481779
                                                                                 6.469480
                   36.917334
                               32.985883
                                           50.647931
                                                         5.063749
                                                                    22.263812
                                                                                 0.773938
                                                                                            54.
            std
                    0.000000
                                5.000000
                                            5.000000
                                                         8.825675
                                                                    14.258040
                                                                                 3.504752
                                                                                            20.
            min
            25%
                   21.000000
                               28.000000
                                           20.000000
                                                        22.769375
                                                                    60.261953
                                                                                 5.971693
                                                                                            64.
            50%
                   37.000000
                               51.000000
                                           32.000000
                                                        25.598693
                                                                    80.473146
                                                                                 6.425045
                                                                                            94.
            75%
                   84.250000
                               68.000000
                                           49.000000
                                                        28.561654
                                                                    89.948771
                                                                                 6.923643
                                                                                           124.
                  140.000000
                                                                                            298.
            max
                              145.000000
                                          205.000000
                                                        43.675493
                                                                    99.981876
                                                                                 9.935091
```

Exploring data

In [10]: correlation = crop.corr()
 correlation

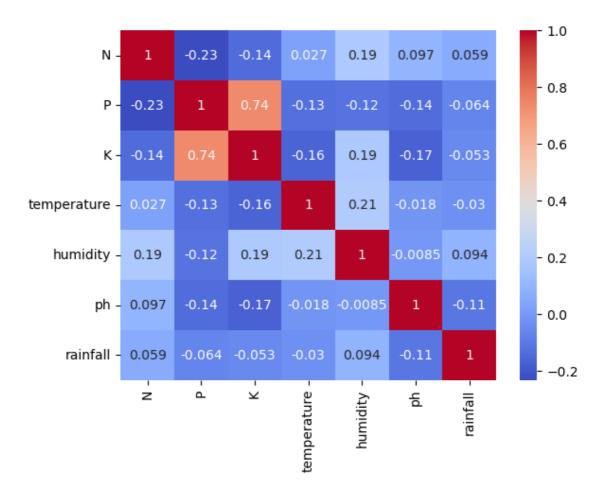
C:\Users\Dell\AppData\Local\Temp\ipykernel_11968\1129341823.py:1: FutureW
arning: The default value of numeric_only in DataFrame.corr is deprecate
d. In a future version, it will default to False. Select only valid colum
ns or specify the value of numeric_only to silence this warning.
 correlation = crop.corr()

Out[10]:

	N	Р	K	temperature	humidity	ph	rainfall
N	1.000000	-0.231460	-0.140512	0.026504	0.190688	0.096683	0.059020
Р	-0.231460	1.000000	0.736232	-0.127541	-0.118734	-0.138019	-0.063839
K	-0.140512	0.736232	1.000000	-0.160387	0.190859	-0.169503	-0.053461
temperature	0.026504	-0.127541	-0.160387	1.000000	0.205320	-0.017795	-0.030084
humidity	0.190688	-0.118734	0.190859	0.205320	1.000000	-0.008483	0.094423
ph	0.096683	-0.138019	-0.169503	-0.017795	-0.008483	1.000000	-0.109069
rainfall	0.059020	-0.063839	-0.053461	-0.030084	0.094423	-0.109069	1.000000

In [11]: import seaborn as sns
sns.heatmap(correlation, annot=True, cbar=True, cmap='coolwarm')

Out[11]: <Axes: >



```
In [12]: crop['label'].unique()
Out[12]: 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)
In [13]: crop['label'].value_counts()
Out[13]: rice
                           100
                           100
          maize
          jute
                           100
                           100
          cotton
          coconut
                           100
                           100
          papaya
                           100
          orange
          apple
                           100
          muskmelon
                           100
          watermelon
                           100
                           100
          grapes
          mango
                           100
                           100
          banana
          pomegranate
                           100
          lentil
                           100
          blackgram
                           100
          mungbean
                           100
          mothbeans
                           100
          pigeonpeas
                           100
                           100
          kidneybeans
          chickpea
                           100
          coffee
                           100
          Name: label, dtype: int64
```

Data Encoding

```
In [14]:
         crop_dict = {
              'rice': 1,
              'maize': 2,
              'jute': 3,
              'cotton': 4,
              'coconut': 5,
              'papaya': 6,
              'orange': 7,
              'apple': 8,
              'muskmelon': 9,
              'watermelon': 10,
              'grapes': 11,
              'mango': 12,
              'banana': 13,
              'pomegranate': 14,
              'lentil': 15,
              'blackgram': 16,
              'mungbean': 17,
              'mothbeans': 18,
              'pigeonpeas': 19,
              'kidneybeans': 20,
              'chickpea': 21,
              'coffee': 22
          crop['crop_num']=crop['label'].map(crop_dict)
In [15]: crop['crop_num'].value_counts()
Out[15]: 1
                100
          2
                100
          3
                100
          4
                100
          5
                100
          6
                100
          7
                100
          8
                100
          9
                100
          10
                100
                100
          11
          12
                100
          13
                100
          14
                100
          15
                100
          16
                100
          17
                100
          18
                100
          19
                100
          20
                100
          21
                100
          22
                100
```

Name: crop_num, dtype: int64

```
In [16]: crop.sample(2)
```

Out[16]:

	N	Р	K	temperature	humidity	ph	rainfall	label	crop_num
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice	1
714	51	56	18	28.127878	64.209777	6.706506	70.863408	blackgram	16

Train Test Split

```
In [17]: | X = crop.drop(['crop_num', 'label'], axis=1)
          y = crop['crop_num']
In [18]: X
Out[18]:
                  Ν
                      Ρ
                          K temperature
                                         humidity
                                                       ph
                                                               rainfall
                 90
                     42
                         43
                              20.879744 82.002744 6.502985
                                                           202.935536
              0
              1
                  85
                     58
                         41
                              21.770462 80.319644 7.038096
                                                           226.655537
              2
                  60
                     55 44
                              23.004459 82.320763 7.840207
                                                           263.964248
              3
                 74
                     35 40
                              26.491096 80.158363 6.980401
                                                           242.864034
                  78
                    42 42
                              20.130175 81.604873 7.628473
                                                           262.717340
                 107
                     34 32
                              26.774637 66.413269 6.780064
                                                          177.774507
           2195
                 99
           2196
                    15 27
                              27.417112 56.636362 6.086922 127.924610
           2197
                118
                    33
                         30
                              24.131797 67.225123 6.362608
                                                          173.322839
           2198
                117
                     32 34
                              26.272418 52.127394 6.758793
                                                          127.175293
           2199
                104
                    18 30
                              23.603016 60.396475 6.779833 140.937041
          2200 rows × 7 columns
In [19]:
          X.shape
Out[19]: (2200, 7)
In [20]:
          y.shape
Out[20]: (2200,)
In [21]:
          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, rand)
In [22]: X_train.shape
Out[22]: (1760, 7)
```

```
In [23]: X_test.shape
Out[23]: (440, 7)
In [24]: X_train
```

Out[24]:

	N	Р	K	temperature	humidity	ph	rainfall
1656	17	16	14	16.396243	92.181519	6.625539	102.944161
752	37	79	19	27.543848	69.347863	7.143943	69.408782
892	7	73	25	27.521856	63.132153	7.288057	45.208411
1041	101	70	48	25.360592	75.031933	6.012697	116.553145
1179	0	17	30	35.474783	47.972305	6.279134	97.790725
1638	10	5	5	21.213070	91.353492	7.817846	112.983436
1095	108	94	47	27.359116	84.546250	6.387431	90.812505
1130	11	36	31	27.920633	51.779659	6.475449	100.258567
1294	11	124	204	13.429886	80.066340	6.361141	71.400430
860	32	78	22	23.970814	62.355576	7.007038	53.409060

1760 rows × 7 columns

Scale the features using MinMaxScaler

```
In [25]: from sklearn.preprocessing import MinMaxScaler
         ms = MinMaxScaler()
         X_train = ms.fit_transform(X_train)
         X test = ms.fit transform(X test)
In [26]: X_train
Out[26]: array([[0.12142857, 0.07857143, 0.045
                                                   , ..., 0.9089898 , 0.48532225,
                 0.29685161],
                [0.26428571, 0.52857143, 0.07
                                                   , ..., 0.64257946, 0.56594073,
                 0.17630752],
                                                   , ..., 0.57005802, 0.58835229,
                        , 0.48571429, 0.1
                [0.05
                 0.08931844],
                [0.07857143, 0.22142857, 0.13
                                                   , ..., 0.43760347, 0.46198144,
                 0.28719815],
                [0.07857143, 0.85
                                       , 0.995
                                                   , ..., 0.76763665, 0.44420505,
                 0.18346657],
                [0.22857143, 0.52142857, 0.085
                                                   , ..., 0.56099735, 0.54465022,
                 0.11879596]])
```

Standarization

```
In [27]: from sklearn.preprocessing import StandardScaler
         sc = StandardScaler()
         sc.fit(X_train)
         X train = sc.transform(X train)
         X_test = sc.transform(X_test)
In [28]: | X_train
Out[28]: array([[-9.03426596e-01, -1.12616170e+00, -6.68506601e-01, ...,
                  9.36586183e-01, 1.93473784e-01, 5.14970176e-03],
                [-3.67051340e-01, 7.70358846e-01, -5.70589522e-01, ...,
                 -1.00470485e-01, 8.63917548e-01, -6.05290566e-01],
                [-1.17161422e+00, 5.89737842e-01, -4.53089028e-01, ...,
                 -3.82774991e-01, 1.05029771e+00, -1.04580687e+00],
                [-1.06433917e+00, -5.24091685e-01, -3.35588533e-01, ...,
                 -8.98381379e-01, -6.34357580e-04, -4.37358211e-02],
                [-1.06433917e+00, 2.12501638e+00, 3.05234239e+00, ...,
                  3.86340190e-01, -1.48467347e-01, -5.69036842e-01],
                [-5.01145154e-01, 7.40255346e-01, -5.11839275e-01, ...,
                 -4.18045489e-01, 6.86860180e-01, -8.96531475e-01]])
```

Training Models

```
from sklearn.linear_model import LogisticRegression
In [29]:
         from sklearn.naive_bayes import GaussianNB
         from sklearn.svm import SVC
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.tree import ExtraTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.ensemble import BaggingClassifier
         from sklearn.ensemble import GradientBoostingClassifier
         from sklearn.ensemble import AdaBoostClassifier
         from sklearn.metrics import accuracy score
         # create instance of all models
         models = {
             'Logistic Regression': LogisticRegression(),
             'Naive Bayes': GaussianNB(),
             'Support Vector Machine': SVC(),
             'K-Nearest Neighbors': KNeighborsClassifier(),
             'Decision Tree': DecisionTreeClassifier(),
             'Random Forest': RandomForestClassifier(),
             'Bagging': BaggingClassifier(),
             'AdaBoost': AdaBoostClassifier(),
             'Gradient Boosting': GradientBoostingClassifier(),
             'Extra Trees': ExtraTreeClassifier(),
         }
         for name, md in models.items():
             md.fit(X_train, y_train)
             ypred = md.predict(X_test)
             print(f"{name} with accuracy : {accuracy_score(y_test,ypred)}")
         Logistic Regression with accuracy : 0.9568181818181818
         Naive Bayes with accuracy : 0.99318181818182
         Support Vector Machine with accuracy : 0.9704545454545455
         K-Nearest Neighbors with accuracy : 0.9568181818181818
         Decision Tree with accuracy : 0.98181818181818
         Random Forest with accuracy : 0.990909090909091
         Bagging with accuracy: 0.98181818181818
         AdaBoost with accuracy : 0.1409090909090909
         Gradient Boosting with accuracy: 0.9636363636363636
         Extra Trees with accuracy : 0.925
In [38]: rfc = GaussianNB()
         rfc.fit(X_train,y_train)
         ypred = rfc.predict(X_test)
```

```
Predictive System
```

Out[38]: 0.9931818181818182

accuracy score(y test,ypred)

```
In [39]: def recommendation(N,P,K,temperature,humidity, ph, rainfall):
             features = np.array([[N,P,K,temperature,humidity, ph, rainfall]])
             prediction = rfc.predict(features).reshape(1,-1)
             return prediction[0]
In [60]:
         N = 90
         P = 42
         K = 43
         temperature = 20
         humidity = 82
         ph = 6.5
         rainfall = 202
         predict = recommendation(N,P,K,temperature,humidity, ph, rainfall)
         crop_dict = {1: "Rice", 2: "Maize", 3: "Jute", 4: "Cotton", 5: "Coconut", 6
                          8: "Apple", 9: "Muskmelon", 10: "Watermelon", 11: "Grapes'
                          14: "Pomegranate", 15: "Lentil", 16: "Blackgram", 17: "Mur
                          19: "Pigeonpeas", 20: "Kidneybeans", 21: "Chickpea", 22:
         if predict[0] in crop_dict:
             crop = crop_dict[predict[0]]
             print("{} is a best crop to be cultivated ".format(crop))
         else:
             print("Sorry are not able to recommend a proper crop for this environme
         Pigeonpeas is a best crop to be cultivated
In [59]: import pickle
         pickle.dump(rfc, open('model.pkl','wb'))
In [34]: import sklearn
         print(sklearn.__version__)
         1.2.2
 In [ ]:
```