

```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

#Reading the dataset
crop=pd.read_csv("/Crop_recommendation.csv")
crop
```

	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 × 8 columns

```
crop.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

```
crop.tail()
```

	N	P	K	temperature	humidity	ph	rainfall	label
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

```
crop.isna().sum()
```

N	0
P	0
K	0
temperature	0
humidity	0
ph	0
rainfall	0

```
label      0
dtype: int64
```

```
print("The size of the dataset:",crop.size)
print("Shape of the dataset:",crop.shape)
```

```
The size of the dataset: 17600
Shape of the dataset: (2200, 8)
```

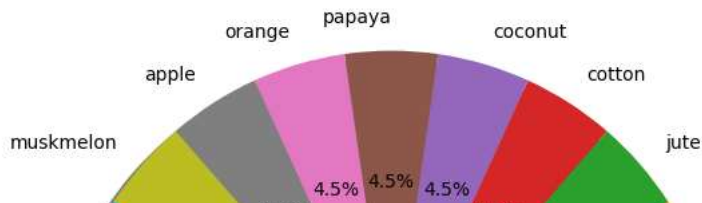
```
print("Number of columns in the dataset:\n",crop.columns)
```

```
Number of columns in the dataset:
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

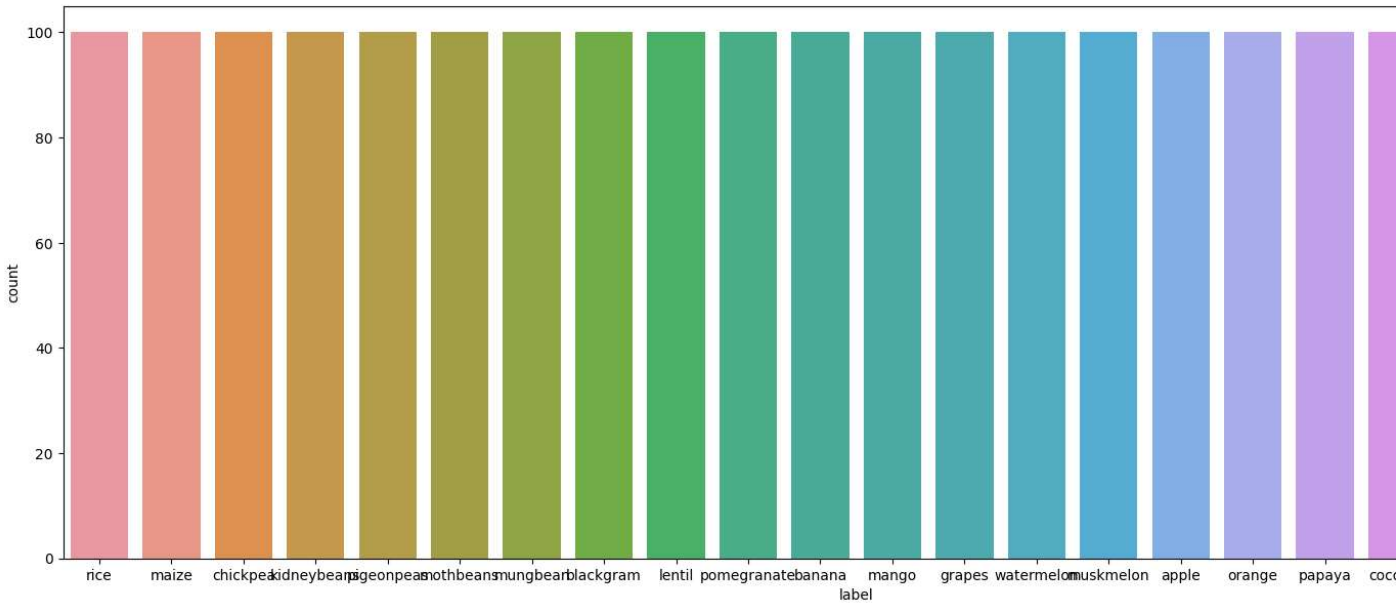
```
print("Value count of the labels:\n",crop['label'].value_counts())
```

```
Value count of the labels:
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: label, dtype: int64
```

```
#Data visualization
#Pie chart for label column
data_viz_df = crop.copy()
data_viz_df.head()
label_name = data_viz_df['label'].value_counts().index
val = data_viz_df['label'].value_counts().values
plt.figure(figsize = (8,8))
plt.pie(x = val , labels = label_name , shadow = True , autopct = '%1.1f%%')
plt.show()
```



```
#Bar graph for Label column
plt.figure(figsize = (20 , 7))
sns.countplot(x = 'label' , data = data_viz_df)
plt.show()
```



```
#Label Encoding
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
crop['label'] = le.fit_transform(crop['label'])
crop.head()
```

	N	P	K	temperature	humidity	ph	rainfall	label	
0	90	42	43	20.879744	82.002744	6.502985	202.935536	20	
1	85	58	41	21.770462	80.319644	7.038096	226.655537	20	
2	60	55	44	23.004459	82.320763	7.840207	263.964248	20	
3	74	35	40	26.491096	80.158363	6.980401	242.864034	20	
4	78	42	42	20.130175	81.604873	7.628473	262.717340	20	

```
x=crop.drop('label',axis=1)
x
```

	N	P	K	temperature	humidity	ph	rainfall
0	90	42	43	20.879744	82.002744	6.502985	202.935536
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



```
y=crop['label']
```

```
y
```

```
0      20
1      20
2      20
3      20
4      20
```

```
..
2195    5
2196    5
2197    5
2198    5
2199    5
```

```
Name: label, Length: 2200, dtype: int64
```

```
#Train_Test_Split
```

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.33,random_state=0)
print("xtrain shape:",xtrain.shape)
print("xtest shape:",xtest.shape)
print("ytrain shape:",ytrain.shape)
print("ytest shape:",ytest.shape)
```

```
xtrain shape: (1474, 7)
xtest shape: (726, 7)
ytrain shape: (1474,)
ytest shape: (726,)
```

```
#LogisticRegression()
```

```
from sklearn.linear_model import LogisticRegression
LG = LogisticRegression()
LG.fit(xtrain,ytrain)
```

```
▼ LogisticRegression
LogisticRegression()
```

```
#To check intercept and co-efficient
```

```
print('Intercept:',LG.intercept_)
print('Co-efficient:',LG.coef_)
```

```
Intercept: [-0.00780263 -0.01053188 -0.01657645  0.00332404 -0.00463209  0.00217817
 -0.01441515 -0.00392094 -0.00192072  0.01139565  0.00604579  0.01981117
  0.02530411  0.04437446 -0.00247394  0.00067193  0.00319134 -0.04082406
 -0.00357376  0.00243646 -0.0123666  0.00030511]
Co-efficient: [[-4.95073484e-01  2.37818458e-01  8.81830732e-01 -2.02632762e-01
 -2.15887867e-01 -5.59788206e-02 -2.65260000e-01]
 [ 4.05127140e-01  1.36164301e-01  1.71382690e-01 -1.54910037e-01
 -2.87219947e-01 -8.73894529e-02  6.77969943e-02]
 [-1.22341138e-01  4.17528443e-01 -4.32713598e-01  1.84071457e-01
  6.03238407e-02 -6.94249117e-02  6.43785233e-02]
 [ 7.08325343e-02  2.80986905e-01  4.72444119e-01 -2.58743623e-03
 -4.93916277e-01  3.47613283e-02  7.42472131e-02]
 [-3.39645974e-01 -5.62047213e-01 -1.45093902e-01 -4.47995478e-02
  2.49809393e-01 -5.68238347e-02  3.57349018e-01]
 [ 6.51856484e-01 -4.63425638e-01 -1.74397966e-01  7.00590637e-02
 -4.16995783e-01  2.76565987e-02  2.26341134e-01]
 [ 6.07064022e-01 -1.34120586e-01 -5.74851007e-01 -1.85494873e-01
  6.30183028e-02 -2.64960924e-02 -1.90339861e-02]
 [-4.88437684e-01  3.87346469e-01  1.04059784e+00 -1.27822994e-01
 -2.31305090e-01 -2.88194601e-02 -8.50592446e-01]
 [ 1.87619254e-01 -1.72504463e-01  8.65556339e-03 -1.27720022e-01
 -8.28986040e-02  6.62274965e-02  2.66109022e-01]
 [-1.94869829e-01  6.75571604e-01 -6.24381826e-02  2.12318514e-02
 -7.24283208e-01  6.29970737e-02  1.97017331e-01]
 [-2.03451192e-01  5.39442203e-01 -3.12328384e-01 -1.59233261e-01
  2.65899943e-01  5.12321440e-02 -1.67062430e-01]
 [ 4.51779041e-01 -4.11379427e-02 -3.08784109e-01  5.16554953e-02
 -7.66516820e-02  4.94236731e-02  9.55319619e-02]
```

```

[-2.92335907e-01 -1.84513905e-01 3.09791378e-01 5.71415316e-01
 -8.67931805e-02 9.61871208e-02 1.93947179e-01]
[-2.00695183e-01 1.74360039e-01 -7.08670458e-02 8.14513299e-01
 -2.31985140e-02 3.17598068e-01 -5.12918666e-02]
[-2.48551961e-01 2.41566023e-02 -4.41589441e-01 4.31574548e-03
 5.82246788e-01 -1.62197926e-02 -7.35054258e-02]
[ 5.58967400e-01 -3.63880997e-01 1.26053947e-01 7.76629075e-02
 3.39145879e-01 1.00746460e-03 -8.97768988e-01]
[-3.13038618e-01 -3.93235362e-01 -5.19932385e-01 -1.69364564e-02
 5.04927147e-01 4.25652560e-02 1.96768632e-01]
[-2.54664016e-01 1.16083229e-01 4.07403242e-01 -2.03504842e-01
 1.11101751e-01 -2.34937289e-01 1.65237761e-01]
[-2.47777779e-01 3.75688193e-01 -5.17238715e-01 8.52964584e-02
 -4.56960960e-02 -5.08523340e-02 2.60099344e-01]
[-3.01581873e-01 -3.96251359e-01 2.55926764e-01 -1.43333131e-01
 4.29057822e-01 2.21824551e-02 1.02038234e-01]
[ 1.91756984e-01 -2.23053944e-01 -2.53887706e-01 -4.75647887e-01
 -2.32198055e-02 -1.46840662e-01 3.54096485e-01]
[ 5.77461776e-01 -4.30975036e-01 1.40036163e-01 -3.55983415e-02
 1.02535187e-01 1.94397099e-03 -2.96443689e-01]]

```

```
#Predictions
```

```
y_pred=LG.predict(xtest)
```

```
y_pred
```

```

array([21, 21, 7, 3, 2, 8, 13, 9, 15, 1, 13, 5, 10, 14, 12, 0, 5,
       10, 5, 12, 4, 2, 9, 8, 6, 5, 10, 16, 13, 9, 19, 20, 11, 15,
       4, 6, 12, 12, 21, 13, 11, 2, 18, 21, 18, 14, 9, 9, 6, 14, 13,
       2, 0, 15, 18, 1, 17, 12, 10, 6, 16, 14, 21, 20, 15, 0, 7, 5,
       0, 16, 4, 19, 9, 11, 7, 13, 3, 11, 8, 12, 20, 13, 21, 21, 15,
       6, 11, 10, 13, 17, 2, 8, 14, 7, 14, 11, 5, 8, 10, 3, 16, 8,
       14, 1, 1, 20, 21, 5, 18, 15, 15, 12, 5, 7, 16, 19, 14, 10, 11,
       8, 19, 10, 16, 3, 3, 2, 19, 16, 3, 12, 13, 2, 15, 14, 6, 14,
       4, 19, 16, 2, 10, 7, 0, 5, 3, 0, 8, 12, 21, 17, 16, 4, 13,
       1, 19, 3, 21, 11, 0, 8, 10, 18, 8, 9, 9, 15, 20, 15, 1, 16,
       9, 0, 13, 4, 6, 14, 9, 19, 17, 16, 20, 17, 17, 9, 9, 1, 4,
       18, 20, 17, 11, 8, 13, 20, 11, 5, 18, 4, 3, 12, 4, 19, 6, 13,
       18, 16, 15, 11, 18, 1, 3, 2, 18, 16, 13, 14, 12, 17, 15, 19, 8,
       20, 2, 17, 2, 5, 11, 5, 16, 20, 13, 14, 16, 9, 19, 4, 12, 14,
       6, 20, 3, 14, 0, 18, 13, 20, 21, 2, 19, 16, 11, 7, 3, 18, 8,
       17, 19, 5, 12, 13, 8, 21, 19, 20, 7, 4, 8, 10, 3, 5, 5, 17,
       19, 11, 20, 3, 18, 16, 19, 18, 4, 9, 19, 15, 13, 12, 10, 1, 2,
       12, 9, 12, 6, 14, 4, 7, 7, 18, 17, 20, 20, 3, 15, 5, 21, 8,
       8, 13, 7, 15, 2, 13, 13, 3, 2, 12, 1, 12, 19, 8, 16, 15, 3,
       10, 6, 17, 7, 9, 10, 0, 20, 15, 0, 17, 2, 8, 3, 13, 10, 7,
       20, 9, 15, 12, 7, 17, 20, 5, 15, 13, 1, 17, 16, 9, 21, 18, 0,
       21, 21, 18, 9, 2, 9, 8, 4, 6, 9, 16, 6, 18, 19, 6, 6, 0,
       6, 0, 16, 11, 7, 1, 0, 13, 20, 9, 1, 20, 10, 3, 19, 1, 3,
       15, 19, 0, 10, 15, 16, 2, 15, 13, 12, 3, 19, 12, 3, 4, 15, 1,
       18, 17, 8, 2, 6, 20, 1, 4, 20, 2, 11, 16, 21, 20, 0, 7, 18,
       7, 3, 12, 8, 19, 11, 12, 7, 1, 14, 18, 1, 6, 2, 0, 0, 8,
       8, 21, 3, 1, 19, 1, 9, 7, 11, 5, 6, 8, 7, 5, 14, 2, 8,
       16, 18, 18, 15, 2, 21, 14, 21, 17, 14, 14, 14, 19, 16, 13, 0, 5,
       4, 11, 4, 7, 7, 3, 3, 12, 9, 12, 16, 14, 17, 18, 2, 17, 15,
       2, 1, 20, 5, 6, 7, 8, 3, 15, 1, 7, 21, 15, 9, 8, 18, 6,
       21, 19, 5, 4, 11, 20, 14, 9, 21, 14, 0, 0, 21, 1, 18, 14, 0,
       14, 6, 20, 17, 6, 17, 3, 0, 19, 13, 20, 2, 12, 16, 8, 1, 13,
       5, 6, 12, 5, 4, 19, 6, 7, 2, 3, 8, 3, 17, 16, 6, 1, 2,
       15, 17, 0, 16, 19, 11, 18, 17, 12, 19, 17, 7, 20, 6, 8, 13, 10,
       13, 9, 1, 13, 0, 17, 21, 4, 3, 10, 9, 13, 7, 7, 16, 20, 2,
       1, 6, 6, 13, 20, 20, 4, 13, 6, 5, 17, 5, 14, 10, 16, 19, 3,
       10, 6, 12, 16, 5, 20, 17, 17, 4, 20, 6, 13, 4, 20, 7, 0, 1,
       4, 1, 11, 12, 17, 17, 20, 8, 15, 6, 10, 9, 2, 5, 20, 16, 4,
       1, 2, 0, 11, 12, 3, 4, 15, 5, 19, 16, 7, 17, 3, 8, 21, 16,
       9, 16, 16, 10, 11, 12, 9, 19, 4, 13, 11, 10, 14, 20, 9, 16, 10,
       5, 14, 15, 4, 7, 4, 19, 18, 4, 10, 17, 1, 3, 13, 17, 16, 10,
       19, 2, 20, 16, 20, 3, 2, 18, 5, 3, 7, 4, 3, 7, 5, 19, 19,
       1, 3, 2, 18, 13, 0, 19, 0, 13, 0, 21, 18])

```

```
#Evaluating the model
```

```
train_accuracy=LG.score(xtrain,ytrain)
```

```
print('Train_accuracy(R_Squared):',train_accuracy)
```

```
test_accuracy=LG.score(xtest,ytest)
```

```
print('Test_accuracy(R_Squared):',test_accuracy)
```

```
Train_accuracy(R_Squared): 0.9721845318860244
```

```
Test_accuracy(R_Squared): 0.9435261707988981
```

```
import math
```

```
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

```
print('Mean Absolute Error:',mean_absolute_error(ytest,y_pred))
print('Mean Squared Error:',mean_squared_error(ytest,y_pred))
print('Root Mean Squared Error:',math.sqrt(mean_squared_error(ytest,y_pred)))
```

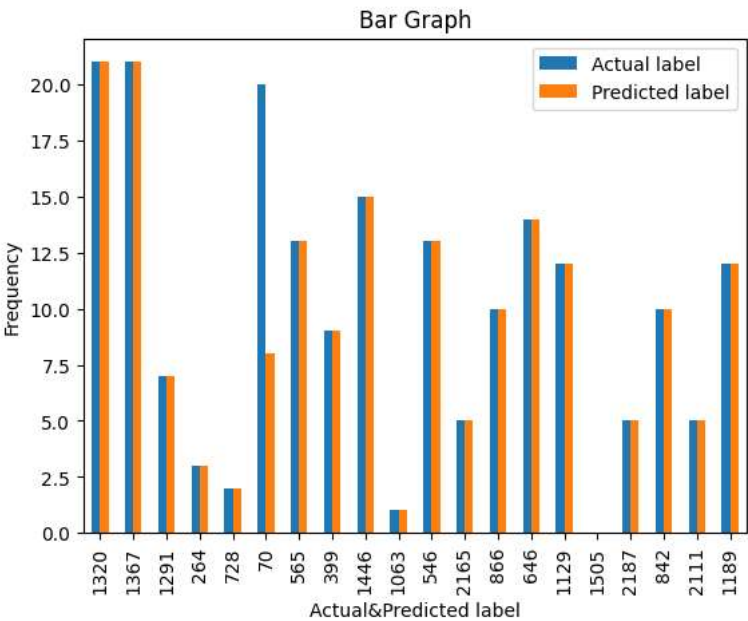
Mean Absolute Error: 0.47107438016528924  
Mean Squared Error: 4.597796143250688  
Root Mean Squared Error: 2.1442472206466046

```
#To check the actual label,predicted label
dfr=pd.DataFrame({'Actual label':ytest,'Predicted label':y_pred})
dfr
```

	Actual label	Predicted label
1320	21	21
1367	21	21
1291	7	7
264	3	3
728	2	2
...	...	...
1523	0	0
731	2	13
1545	0	0
1358	21	21
383	9	18

726 rows × 2 columns

```
#Plotting the Bar graph for above actual,predicted label
graph=dfr.head(20)
graph.plot(kind='bar')
plt.title('Bar Graph')
plt.xlabel('Actual&Predicted label')
plt.ylabel('Frequency')
plt.show()
```



```
#RandomForestClassifier()
from sklearn.ensemble import RandomForestRegressor
RF = RandomForestRegressor()
RF.fit(xtrain,ytrain)
```

```
▼ RandomForestRegressor
RandomForestRegressor()

#Evaluating model
train_accuracy = RF.score(xtrain,ytrain)
print("Train_accuracy(R_Squared):",train_accuracy)
test_accuracy = RF.score(xtest,ytest)
print("Test_accuracy(R_Squared):",test_accuracy)

Train_accuracy(R_Squared): 0.994821238022106
Test_accuracy(R_Squared): 0.9715513770838728

#Comparison between Linear and RandomForestRegression using boxplot
logistic_regression_accuracy=0.9435261707988981
random_forest_accuracy=0.9715513770838728
accuracy_scores=[logistic_regression_accuracy,random_forest_accuracy]
model_names=['LogisticRegression','RandomForestRegression']
plt.bar(model_names,accuracy_scores)
plt.xlabel('Models')
plt.ylabel('Test_Accuracy')
plt.title('Comparison of Test_Accuracy:LogisticRegression v/s RandomForestRegression')
plt.show()
```

Comparison of Test\_Accuracy:LogisticRegression v/s RandomForestRegression

