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Project :

Solving Classification Predication For "weather_classification" Dataset using logistic Regression, Naives Bayes Classification, Support Vector Classifier, K Nearest Neighbour, Desicion Tree Classifier, BaggingClassifier, VotingClassifier, StackingClassifier, BoostingClassifier

Data

1.Temperature : present in positive and negative temperature

2.Humidity : Humidity is the concentration of water vapor present in the air.

3.Wind Speed : Air moving from high to low pressure,due to change in temperature

4.Precipitation (%) :i.e rain

5.Cloud Cover :'partly cloudy' 'clear' 'overcast' 'cloudy'

6.Atmospheric Pressure : air pressure on earth

7.UV Index : ultra violet index

8.Season :'Winter', 'Spring', 'Summer','Autumn'

9.Visibility (km) :

10.Location :'inland','mountain','coastal'

11.Weather Type :'Rainy','Cloudy','Sunny','Snowy

Approach

1.Load the required libraries such as pandas,numpy,seaborn,matplotlib along with given dataset.

2.Perform EDA on given dataset.

3.Explore about the numerical variables like using libries seaborn and matplotlib

4.Explore about the categorical variables like using libries seaborn and matplotlib.

5.Finding relationship between features.

6.Finding out outliers in given data set using Boxplot

7.Cleaning data i.e raw data converted in useful data

8.Handling missing values like that mean,mode,median

9.Convert all required categorical columns to numerical columns like using a get dummies

10.Scaling down the data using a standarization or normalization.

11.Import machine learning Algoritham by using logistic Regression,Naives Bayes Classification, Support Vector Classifier, KNeighbourClassifier, Desicion Tree Classifier, BaggingClassifier, VotingClassifier, StackingClassifier, BoostingClassifier

12.Split the given dataset training data and testing data using a function train_test_split ,then calculate accuracy score using sklearn library by importing metrics.

13.Once we get accuracy score of all models for both training and testing data , create a dataframe and load all the accuracy of all models.

14.Once the dataset is created plot the accuracies of all the models using matplotlib for barplot.

15.They find out conclusion,which model gives best accuracy.

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
X=pd.read_csv(r"C:\Users\HP\Downloads\data analysis\weather_classification_data.csv")
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
X
```

Out[2]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Cloud Cover	Atmospheric Pressure	UV Index	Season	Visibility (km)	Location	Weather Type
0	14.0	73	9.5	82.0	partly cloudy	1010.82	2	Winter	3.5	inland	Rainy
1	39.0	96	8.5	71.0	partly cloudy	1011.43	7	Spring	10.0	inland	Cloudy
2	30.0	64	7.0	16.0	clear	1018.72	5	Spring	5.5	mountain	Sunny
3	38.0	83	1.5	82.0	clear	1026.25	7	Spring	1.0	coastal	Sunny
4	27.0	74	17.0	66.0	overcast	990.67	1	Winter	2.5	mountain	Rainy
...	...	...	...	...	...	...	...	...	...	...	...
13195	10.0	74	14.5	71.0	overcast	1003.15	1	Summer	1.0	mountain	Rainy
13196	-1.0	76	3.5	23.0	cloudy	1067.23	1	Winter	6.0	coastal	Snowy
13197	30.0	77	5.5	28.0	overcast	1012.69	3	Autumn	9.0	coastal	Cloudy
13198	3.0	76	10.0	94.0	overcast	984.27	0	Winter	2.0	inland	Snowy
13199	-5.0	38	0.0	92.0	overcast	1015.37	5	Autumn	10.0	mountain	Rainy

13200 rows × 11 columns

In [3]:
```
X.info()                                                      ## showing in columns in
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13200 entries, 0 to 13199
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Temperature           13200 non-null  float64
 1   Humidity              13200 non-null  int64  
 2   Wind Speed            13200 non-null  float64
 3   Precipitation (%)     13200 non-null  float64
 4   Cloud Cover           13200 non-null  object 
 5   Atmospheric Pressure  13200 non-null  float64
 6   UV Index              13200 non-null  int64  
 7   Season                13200 non-null  object 
 8   Visibility (km)       13200 non-null  float64
 9   Location              13200 non-null  object 
 10  Weather Type          13200 non-null  object 
dtypes: float64(5), int64(2), object(4)
memory usage: 1.1+ MB
```

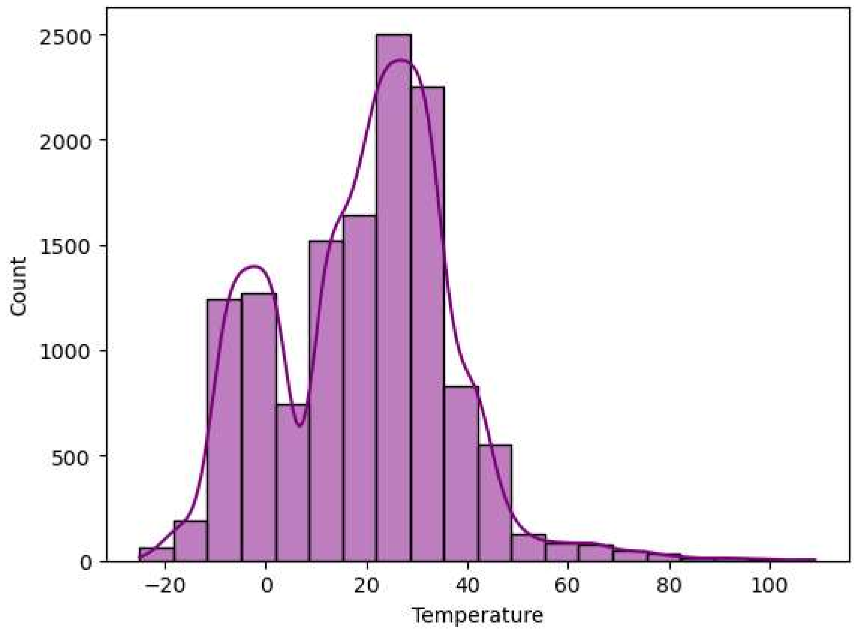
In [4]:
```
X.isnull().sum()                        ## This will display the count of missing values
```

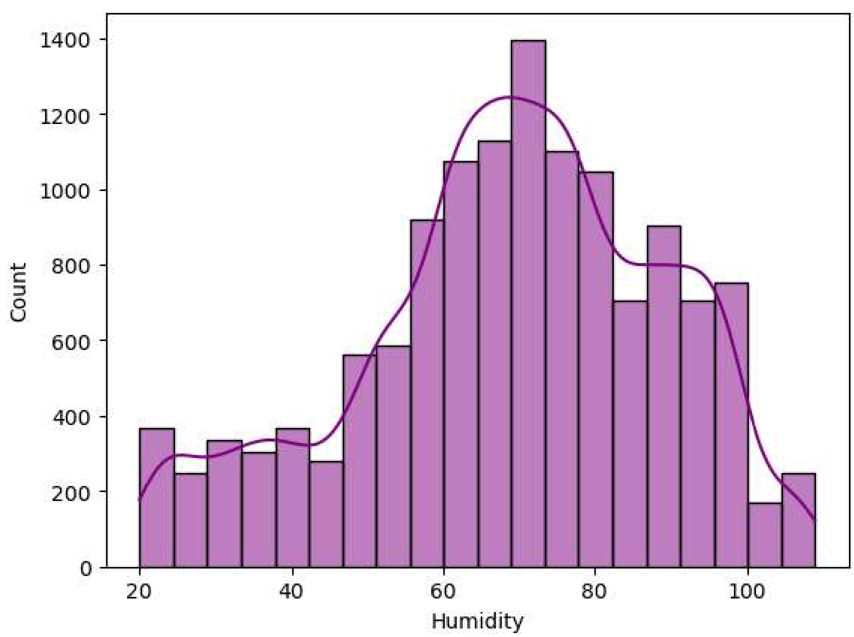
Out[4]:
```
Temperature             0
Humidity                0
Wind Speed              0
Precipitation (%)       0
Cloud Cover             0
Atmospheric Pressure    0
UV Index                0
Season                  0
Visibility (km)         0
Location                0
Weather Type            0
dtype: int64
```

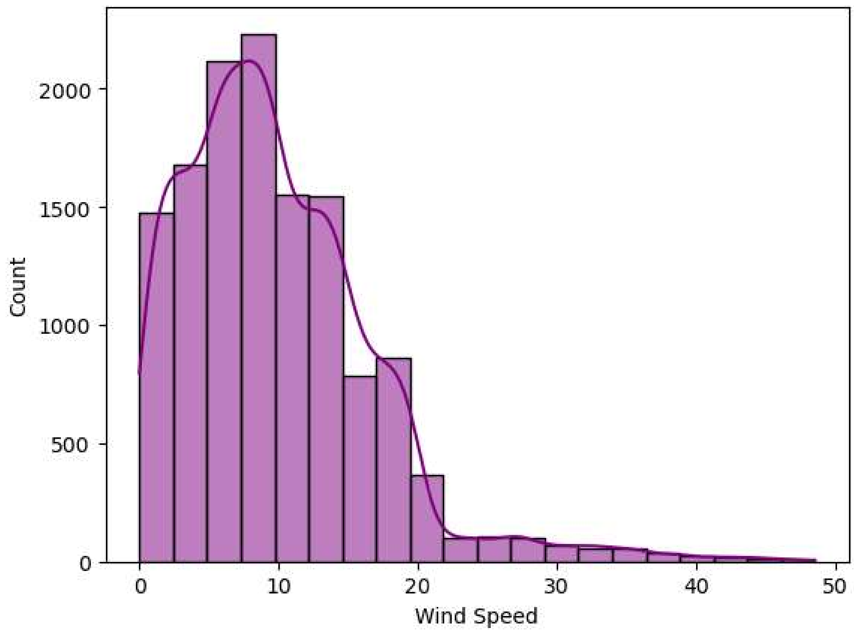
```
In [5]: for i in X.columns:                               ## This will display an array of unique values present in the sp
            print(i)
            a = X[i].unique()
            print(a)
```

```
Temperature
[ 14.  39.  30.  38.  27.  32.  -2.   3.  28.  35.  12. -10.  24.  10.
  33.  43.  13.  -7.  26.   4.  17.  40.   2.  15.  29.  11.  -9.  36.
  42.  21.  22.  25.  -4.  -1.  -5.  41.  31.  16.  34.  49.  19.  23.
  20.  -3.  18.   1.   0.  46.  44. -13.  -6.  78.  63.  73.   8. -12.
 -24.  -8.  60.  48.   5.  51. -14.  50.  37.  54.  47.  70.   9.  66.
 -16. -15.  59.  80. -19.  52.  45.   6. -18. -11.  74.  76.  55. -20.
  57.  91.  82. -17.  61.   7.  53.  65.  77.  67.  64.  58.  68.  72.
  62.  71.  56. 107. -22.  75.  85.  97.  84. -21.  92. -25.  81. 109.
  98.  94.  90. -23.  88.  99.  69. 100.  89. 102.  86. 108.  87.  95.]
Humidity
[ 73  96  64  83  74  55  97  85  45  43  59  87  21  50  27  51  46 102
  67  88  36  79  72  57  61  70  95  69  90 105  49  37  22  54  66  25
  91  98  94  41  84  63  75  52  89  47  81  62  31  68  35  78  56  93
  44  38  24  82  65  80  39  48  60  29  99  92  76  77  86  32  58  42
  30 100  33  71 107 108  26 106  28 109 101  34 103  40  23 104  53  20]
Wind Speed
[ 9.5  8.5  7.   1.5 17.   3.5  8.   6.   2.  10.5 15.   6.5  0.5 12.
 12.5  7.5 13.5  1.   4.  16.  16.5  2.5 23.   3.  10.  25.5 19.  11.5
  0.   9.  18.5 11.  20.  14.   5.5 13.  46.5  5.  18.  28.5 14.5  4.5
 15.5 28.  19.5 21.5 34.  17.5 47.  34.5 35.5 23.5 42.5 33.  31.5 26.
 22.  36.5 27.5 20.5 35.  30.  26.5 21.  32.5 32.  24.  27.  22.5 31.
 30.5 24.5 29.5 37.  44.5 41.  41.5 40.5 37.5 46.  25.  39.  29.  45.
 43.5 45.5 36.  38.  44.  38.5 33.5 40.  42.  47.5 39.5 43.  48.5]
Precipitation (%)
[ 82.  71.  16.  66.  26.  86.  96. 107.  25.  67.   8.  46.  13.  27.
  15.  72.  75.  98.  18.  29. 101.  85.  62.  12.   3.  54.  97.  63.
  56.  91.   6.  76. 109.  58.  37.   9.   0.  39.  11.  14.  88.  78.
  55.  90.   4.  69.  68.  32.  87.  17.  89.  57.  41.  84.  83.  47.
  99.  92.  19.  60.  65.   5.  43.   2.  59.  79.  94.  42.  53.  73.
  81.  52.  36.  45.  21.  22.  40.  50.  51.  10.  35.  95. 103.   7.
  74.  48.  61.  64.  31. 106.  93.  24.   1.  80.  23.  70.  20. 104.
  77.  30.  33.  38.  34.  49.  28. 100.  44. 108. 105. 102.]
Cloud Cover
['partly cloudy' 'clear' 'overcast' 'cloudy']
Atmospheric Pressure
[1010.82 1011.43 1018.72 ... 1022.86 1067.23  984.27]
UV Index
[ 2  7  5  1  0  8 11  3  9  4 13 10 14  6 12]
Season
['Winter' 'Spring' 'Summer' 'Autumn']
Visibility (km)
[ 3.5 10.   5.5  1.   2.5  5.   4.   7.5  1.5  8.5  6.   8.   3.   9.5
  9.   4.5  2.  16.5 12.5  6.5  7.   0.  17.5 17.  13.  11.   0.5 16.
 18.  10.5 11.5 19.  18.5 13.5 15.5 15.  14.5 14.  12.  20.  19.5]
Location
['inland' 'mountain' 'coastal']
Weather Type
['Rainy' 'Cloudy' 'Sunny' 'Snowy']
```

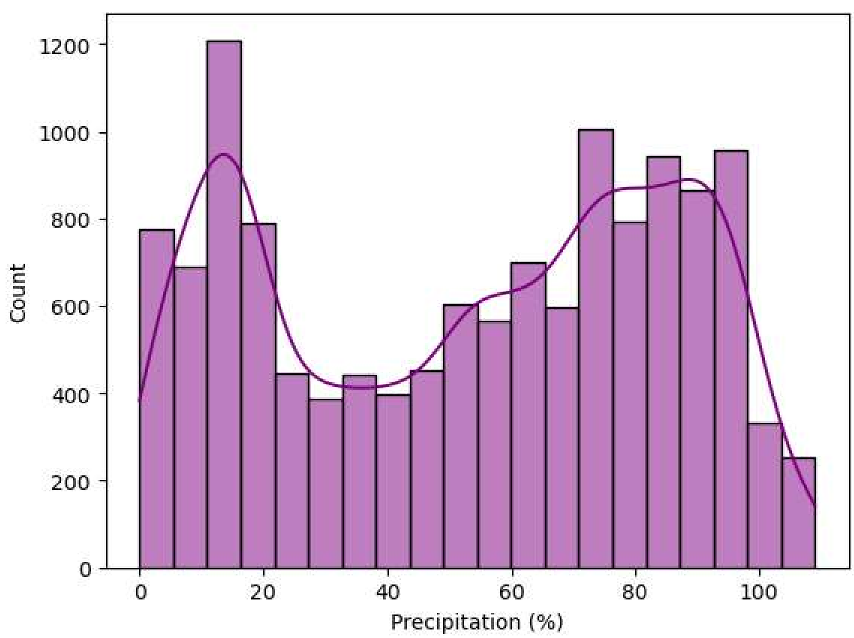
In [6]:
```
import matplotlib.pyplot as plt
import seaborn as sns
for i in X.columns:
    sns.histplot(X[i],bins=20,kde=True,color="purple")                                        ## showing distribut
    plt.show()
```



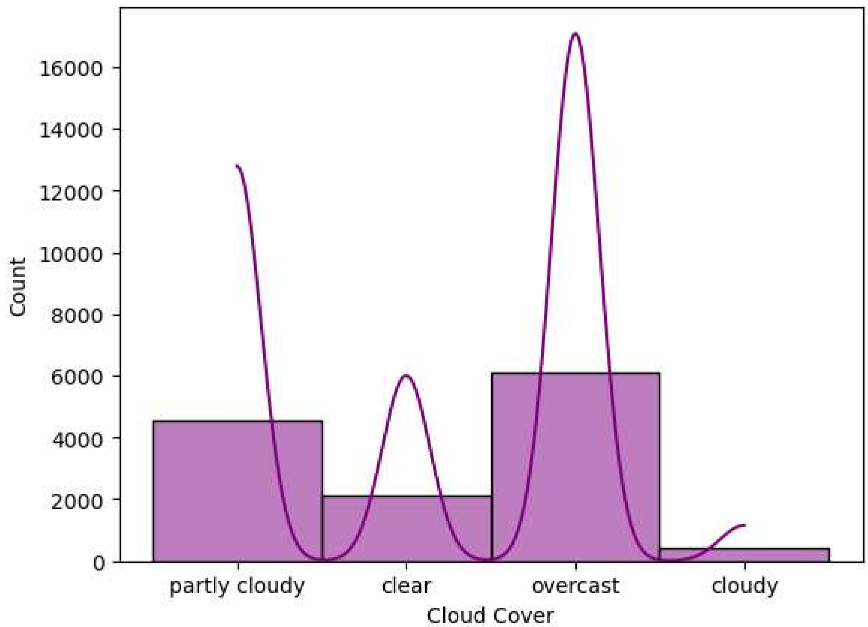


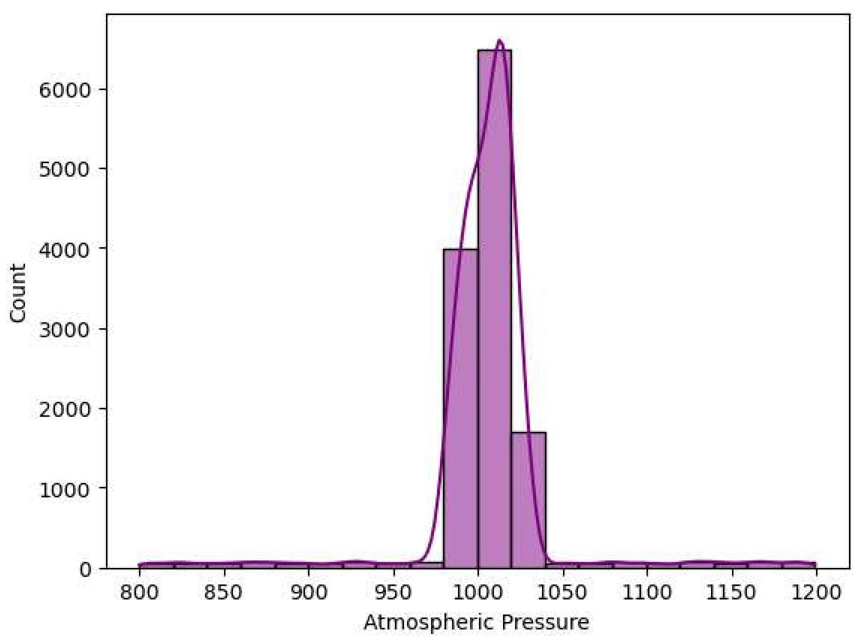


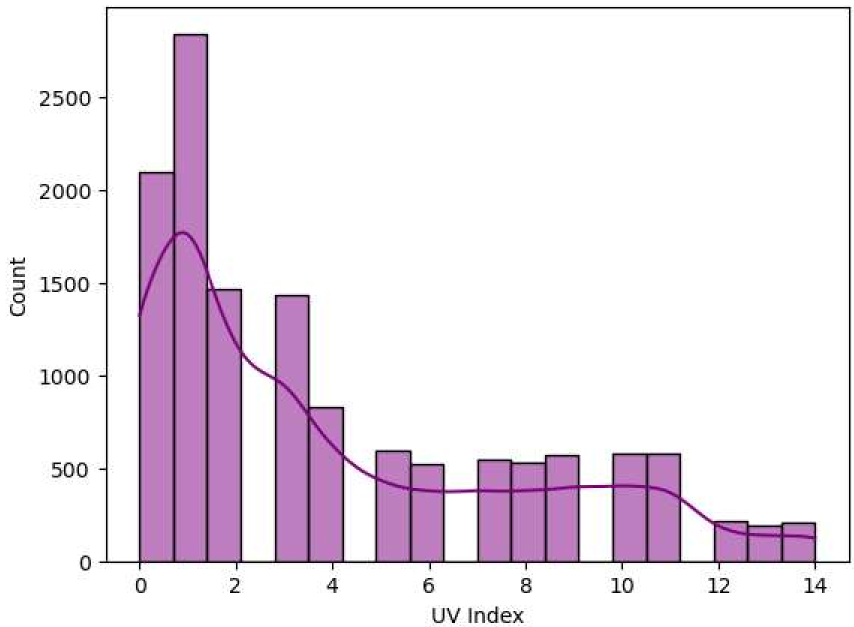
Count
Wind Speed
0
500
1000
1500
2000
0
10
20
30
40
50

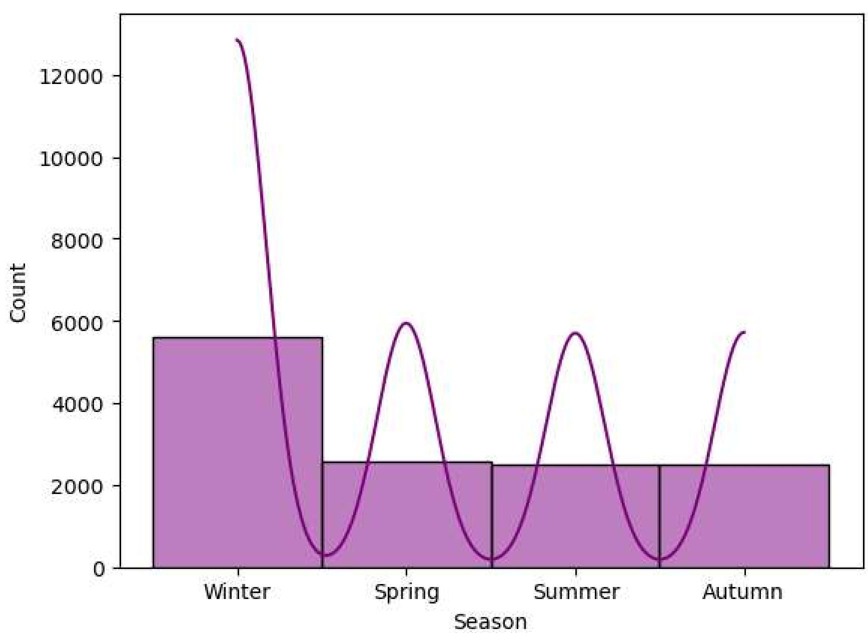


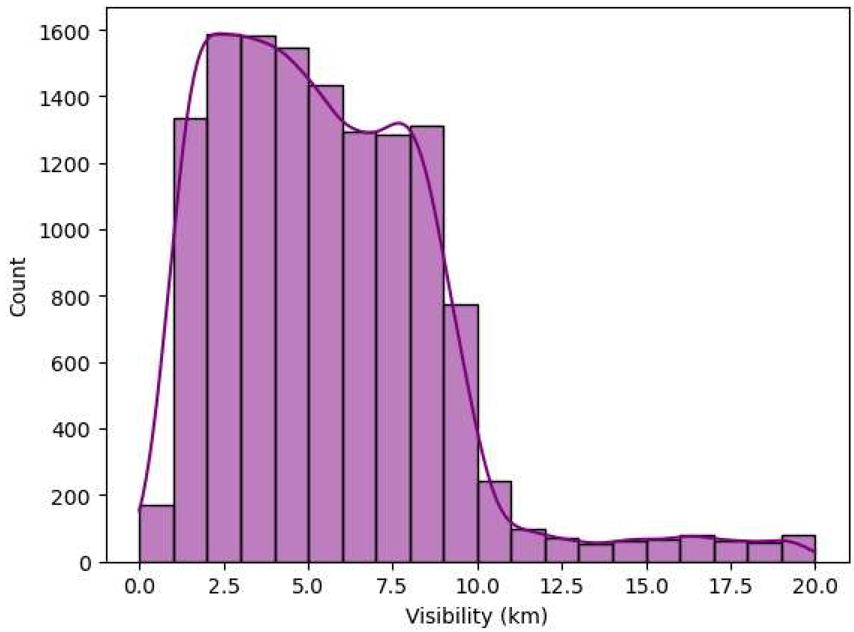
Count
Precipitation (%)
0
200
400
600
800
1000
1200
0
20
40
60
80
100

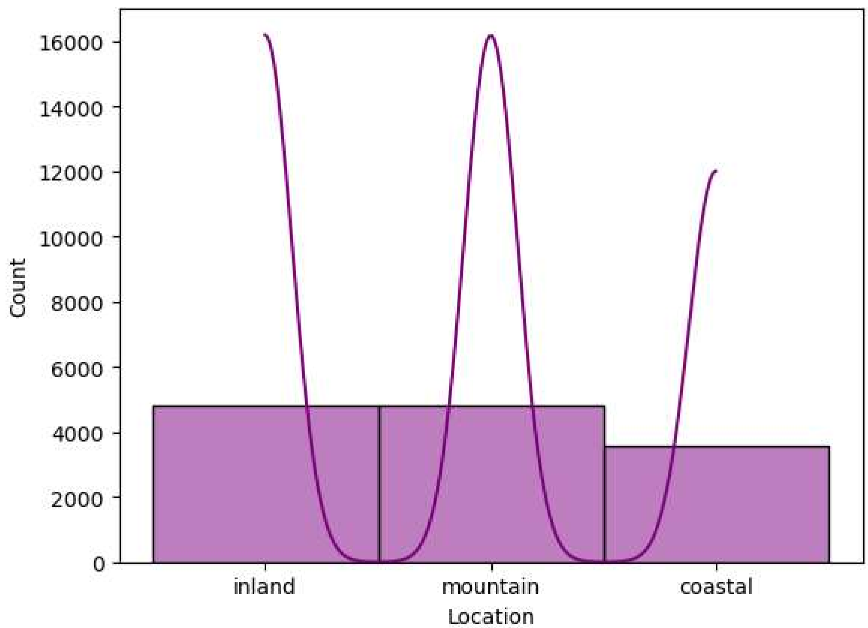

16000
14000
12000
10000
8000
6000
4000
2000
0
Count
partly cloudy
clear
overcast
cloudy
Cloud Cover

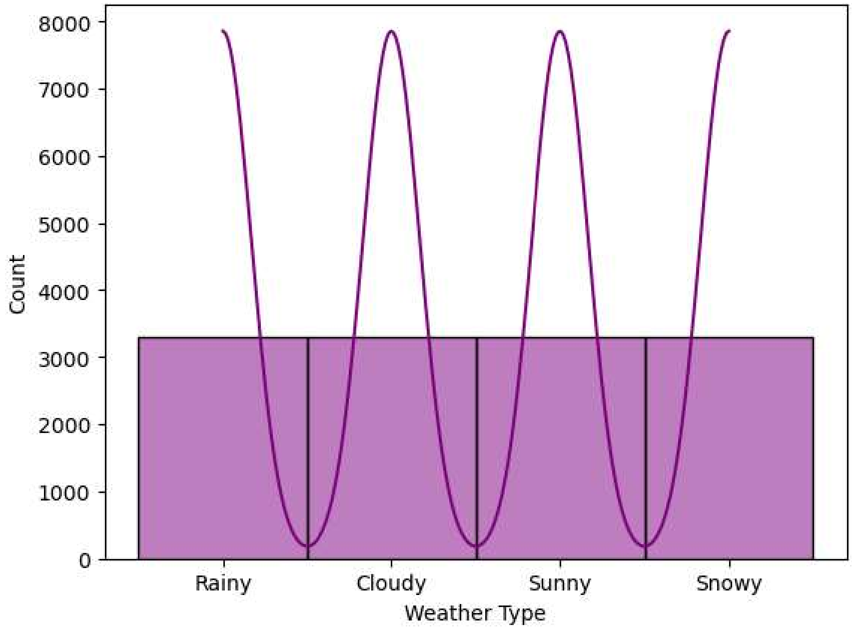

6000
5000
4000
3000
2000
1000
0
Count
800
850
900
950
1000
1050
1100
1150
1200
Atmospheric Pressure


2500
2000
1500
1000
500
0
Count
0
2
4
6
8
10
12
14
UV Index


12000
10000
8000
6000
4000
2000
0
Count
Winter
Spring
Summer
Autumn
Season

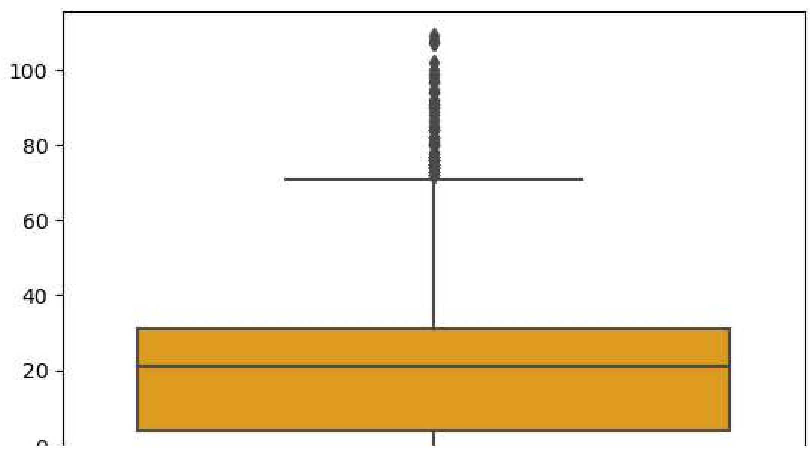

1600
1400
1200
1000
800
600
400
200
0
Count
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Visibility (km)


16000
14000
12000
10000
8000
6000
4000
2000
0
Count
inland
mountain
coastal
Location



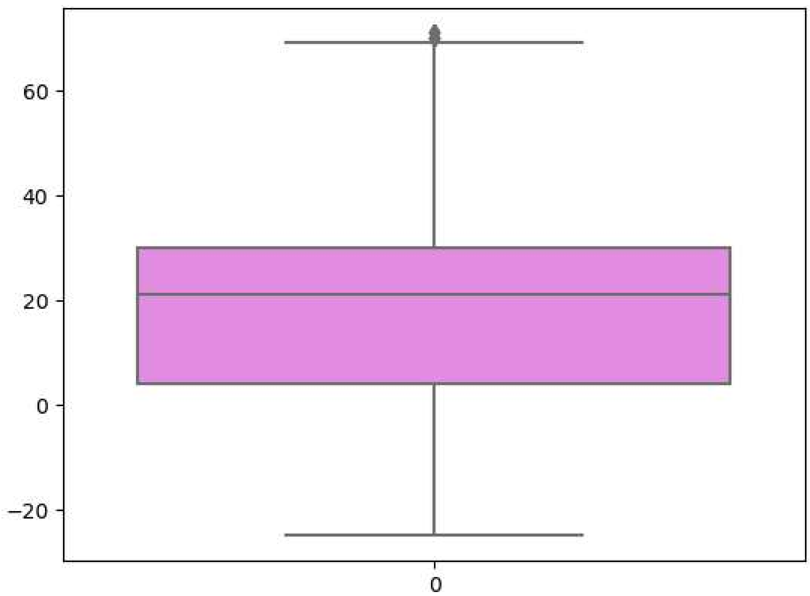
In [7]:
```
for i in X.columns:
     if(X[i].dtype=="int64") | (X[i].dtype=="float64"):
        print(i)
        sns.boxplot(X[i],color="orange")          ## display summary of dataset
        plt.show()
```

Temperature

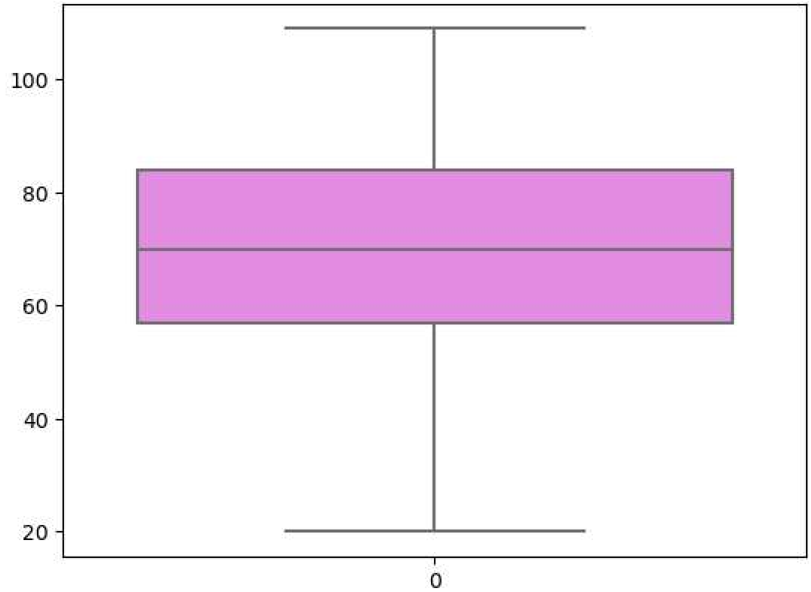


In [8]:
```
for i in X.columns:
    if(X[i].dtype=="int64") | (X[i].dtype=="float64"):
        print(i)
        Q1=X[i].quantile(0.25)
        print("Q1=",Q1)
        Q2=X[i].median()
        print("Q2=",Q2)
        Q3=X[i].quantile(0.75)
        print("Q3=",Q3)
        IQR=Q3-Q1
        print("IQR=",IQR)
        low_bound=Q1-(1.5*IQR)
        high_bound=Q3+(1.5*IQR)
        Z=X.loc[(X[i]>low_bound)&(X[i]<high_bound)]
        sns.boxplot(Z[i],color="violet")
        plt.show()
```

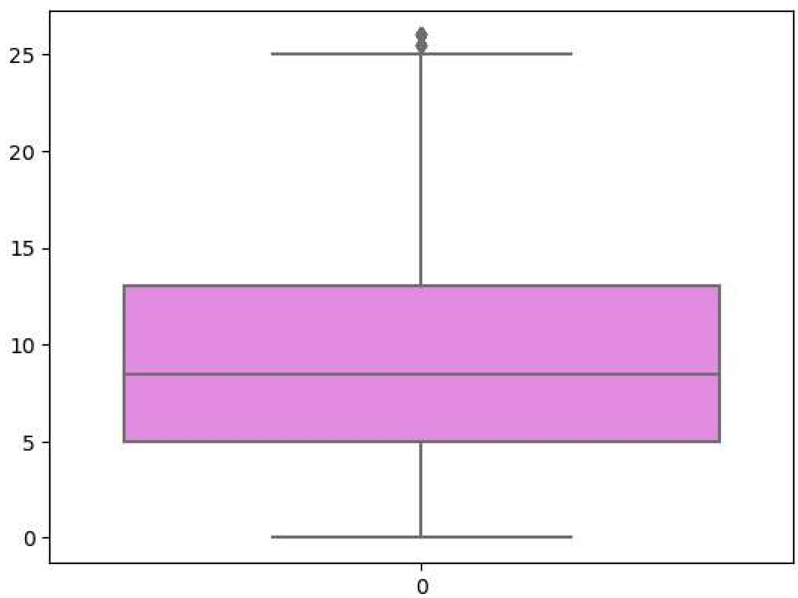
```
Temperature
Q1= 4.0
Q2= 21.0
Q3= 31.0
IQR= 27.0
```



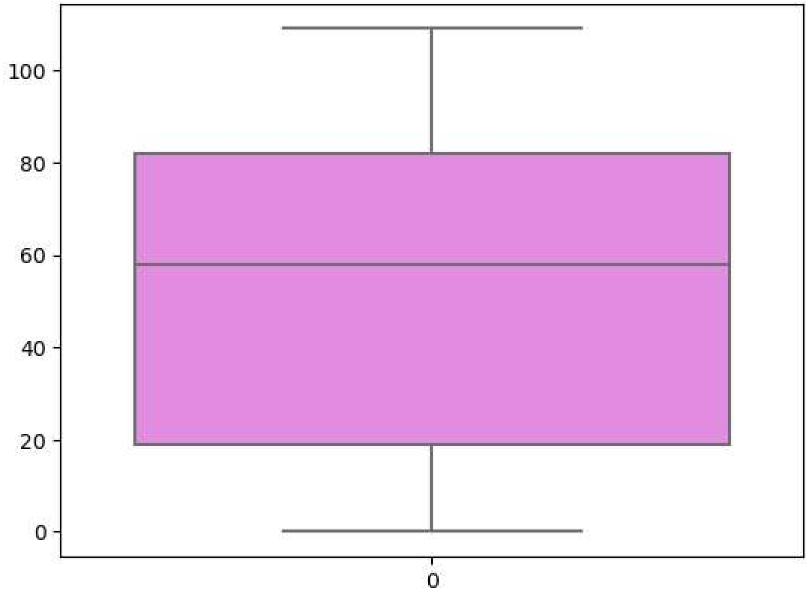

```
Humidity
Q1= 57.0
Q2= 70.0
Q3= 84.0
IQR= 27.0
```



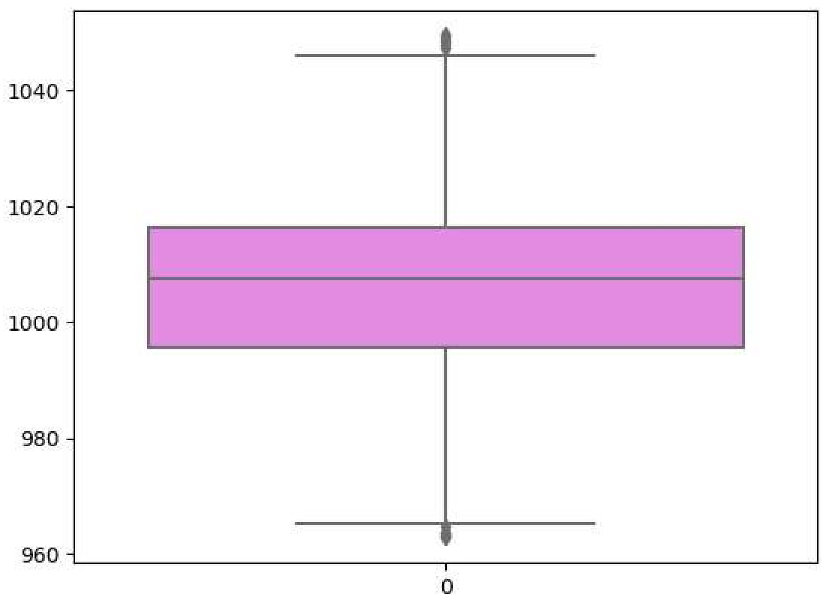
Wind Speed
Q1= 5.0
Q2= 9.0
Q3= 13.5
IQR= 8.5



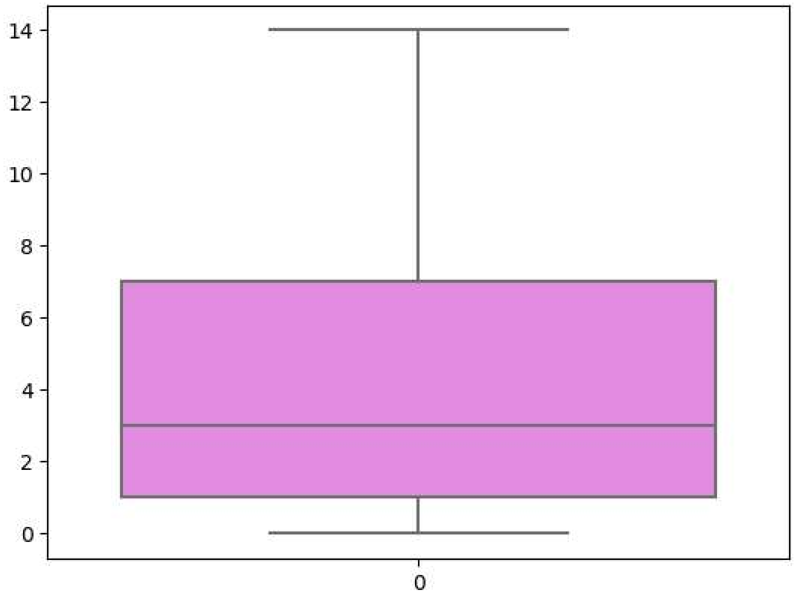
Precipitation (%)
Q1= 19.0
Q2= 58.0
Q3= 82.0
IQR= 63.0



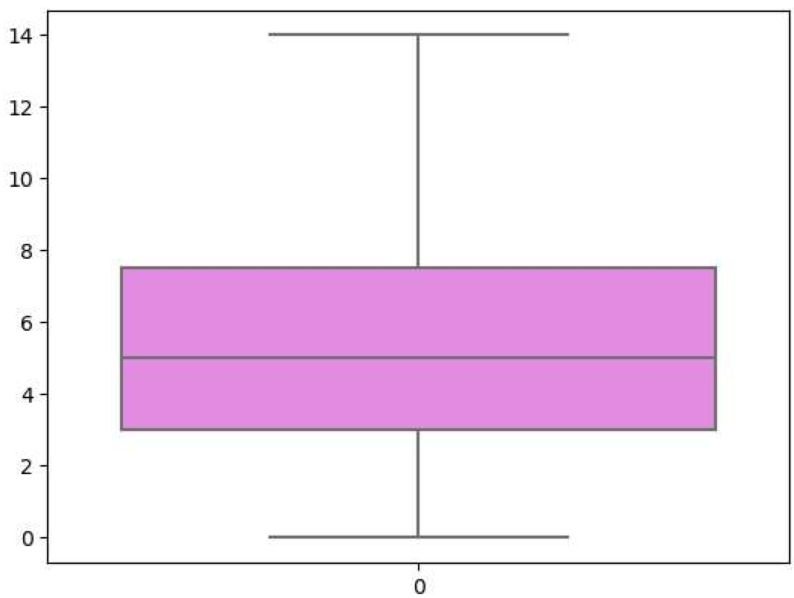

```
Atmospheric Pressure
Q1= 994.8
Q2= 1007.65
Q3= 1016.7725
IQR= 21.972500000000082
```




```
UV Index
Q1= 1.0
Q2= 3.0
Q3= 7.0
IQR= 6.0
```

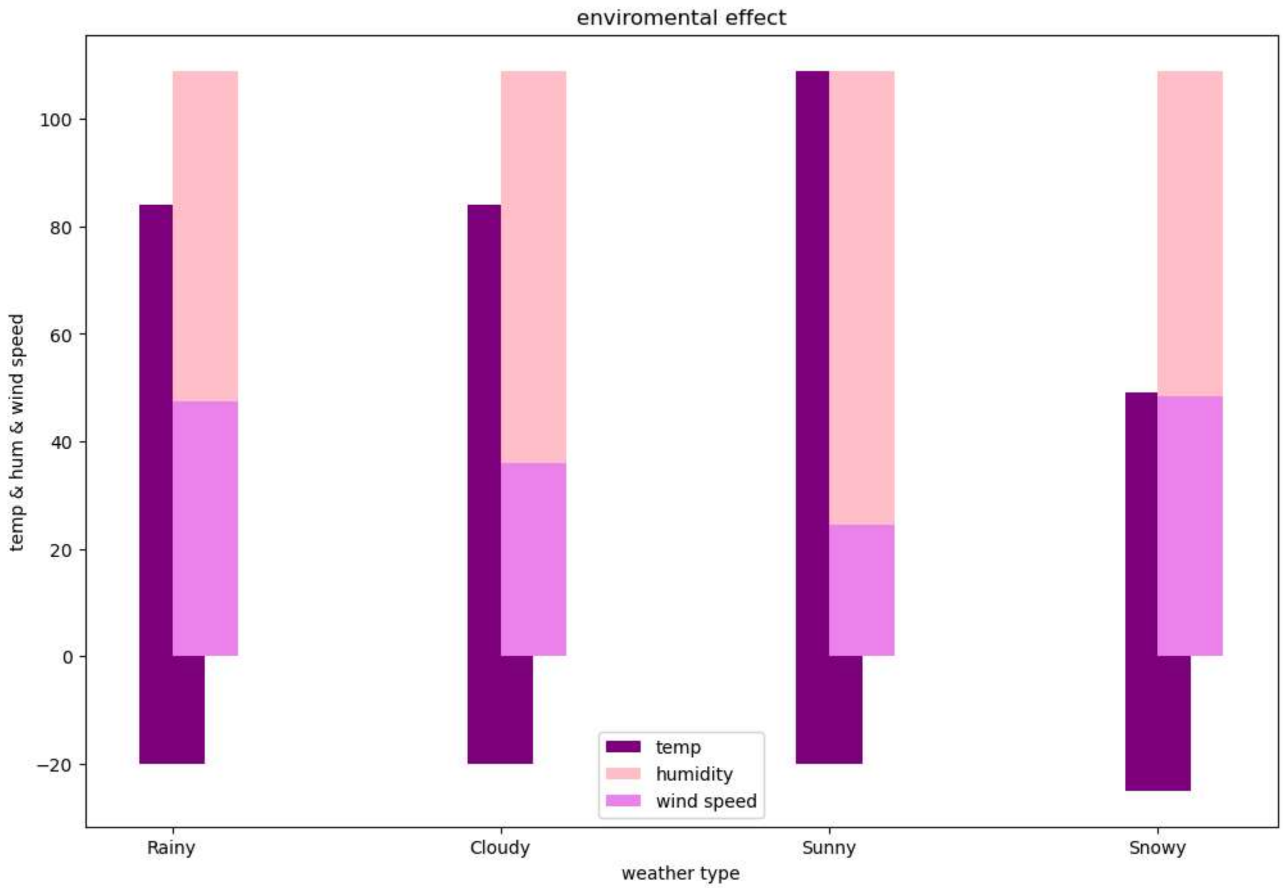



```
Visibility (km)
Q1= 3.0
Q2= 5.0
Q3= 7.5
IQR= 4.5
```



In [9]:
```
#U=Z.sample(1000)
```

In [10]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(12,8))
plt.bar(Z["Weather Type"],Z['Temperature'], color="purple",label="temp",width=0.2,align="center")
plt.bar(Z["Weather Type"],Z['Humidity'], color="pink",label="humidity",width=0.2,align="edge")
plt.bar(Z["Weather Type"],Z['Wind Speed'], color="violet",label="wind speed",width=0.2,align="edge")
plt.xlabel("weather type")
plt.ylabel("temp & hum & wind speed")
plt.title("enviromental effect")
plt.legend()
plt.show()
```



In [11]:
```
X.describe()                                    ## calculating some statistical summary for
```

Out[11]:

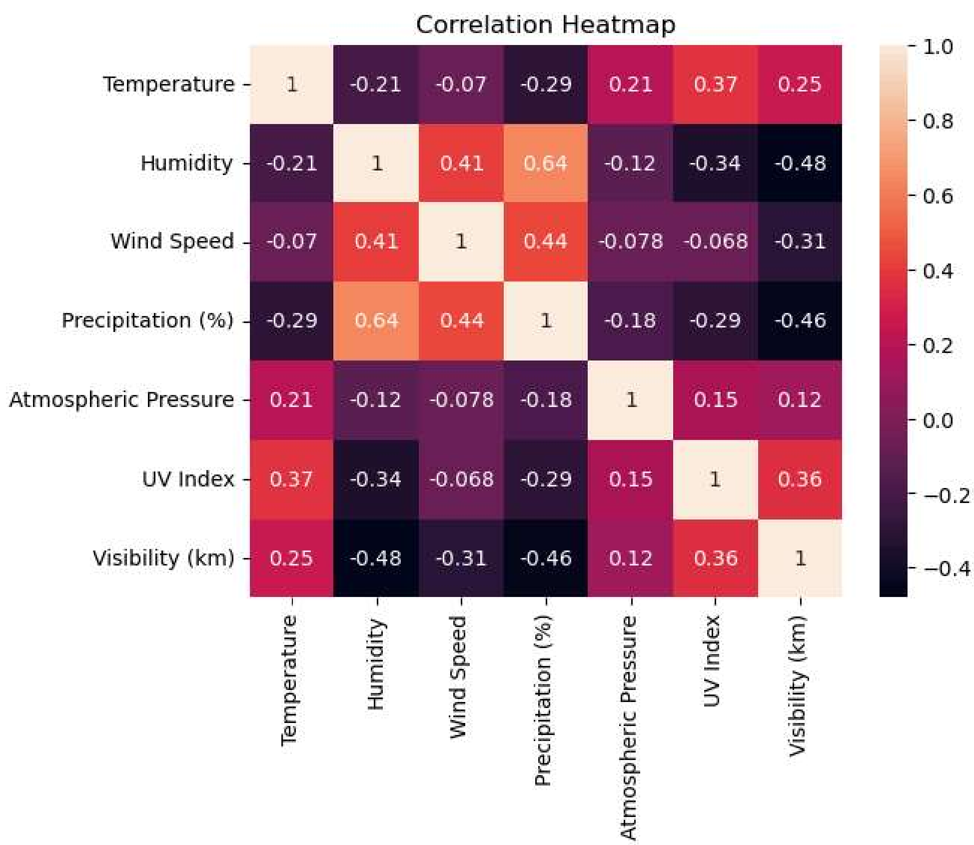
	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Visibility (km)
count	13200.000000	13200.000000	13200.000000	13200.000000	13200.000000	13200.000000	13200.000000
mean	19.127576	68.710833	9.832197	53.644394	1005.827896	4.005758	5.462917
std	17.386327	20.194248	6.908704	31.946541	37.199589	3.856600	3.371499
min	-25.000000	20.000000	0.000000	0.000000	800.120000	0.000000	0.000000
25%	4.000000	57.000000	5.000000	19.000000	994.800000	1.000000	3.000000
50%	21.000000	70.000000	9.000000	58.000000	1007.650000	3.000000	5.000000
75%	31.000000	84.000000	13.500000	82.000000	1016.772500	7.000000	7.500000
max	109.000000	109.000000	48.500000	109.000000	1199.210000	14.000000	20.000000

In [12]:
```
X.corr()                                              ## statistical summary of the relationship between two set
```

Out[12]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Visibility (km)
Temperature	1.000000	-0.207969	-0.070022	-0.287206	0.209188	0.374773	0.250751
Humidity	-0.207969	1.000000	0.406079	0.638631	-0.120653	-0.342694	-0.479969
Wind Speed	-0.070022	0.406079	1.000000	0.443770	-0.077757	-0.068147	-0.311828
Precipitation (%)	-0.287206	0.638631	0.443770	1.000000	-0.177444	-0.291601	-0.457444
Atmospheric Pressure	0.209188	-0.120653	-0.077757	-0.177444	1.000000	0.154128	0.120182
UV Index	0.374773	-0.342694	-0.068147	-0.291601	0.154128	1.000000	0.362922
Visibility (km)	0.250751	-0.479969	-0.311828	-0.457444	0.120182	0.362922	1.000000

In [13]:
```
corr_matrix = X.corr()
sns.heatmap(corr_matrix, xticklabels=corr_matrix.columns, yticklabels=corr_matrix.columns, annot=True)
#values representing various shades
plt.title("Correlation Heatmap")
plt.show()
```



In [14]:
```
Z1=Z.groupby(["Season"])[["Atmospheric Pressure","Temperature","Humidity","Wind Speed","Precipitation (%)","UV In
```

In [15]:
```
Z1
```

Out[15]:

	Season	Atmospheric Pressure	Temperature	Humidity	Wind Speed	Precipitation (%)	UV Index	Visibility (km)
0	Autumn	1011.228190	26.239130	65.425585	9.644440	46.640050	4.670569	5.808319
1	Spring	1011.025288	26.190400	65.156800	9.197000	46.108800	4.705200	5.822400
2	Summer	1009.788920	26.467193	66.121678	9.635797	46.800249	4.766611	5.788414
3	Winter	999.513538	10.017763	74.187058	10.435110	62.953598	2.843756	4.205275

In [16]:
```
Z2=Z.groupby(["Weather Type"])[["Atmospheric Pressure","Temperature","Humidity","Wind Speed","Precipitation (%)",
```

In [17]:
```
Z2
```

Out[17]:

	Weather Type	Atmospheric Pressure	Temperature	Humidity	Wind Speed	Precipitation (%)	UV Index	Visibility (km)
3	Sunny	1018.289377	33.000312	51.368142	6.033510	23.992207	7.810474	7.287562
0	Cloudy	1009.804812	23.059025	66.990991	8.633582	39.785648	3.476546	6.820286
1	Rainy	1004.486740	23.056268	79.326039	13.845264	75.446702	2.573929	3.208503
2	Snowy	990.824779	-2.070824	79.506111	11.092918	75.353808	1.761517	3.131150

In [18]:
```
Z3=Z.groupby(["Location"])[["Atmospheric Pressure","Temperature","Humidity","Wind Speed","Precipitation (%)","UV
```

In [19]:
```
Z3
```

Out[19]:

	Location	Atmospheric Pressure	Temperature	Humidity	Wind Speed	Precipitation (%)	UV Index	Visibility (km)
0	coastal	1010.826830	26.145724	65.917394	9.576934	47.280105	4.618674	5.691390
1	inland	1004.494720	16.906070	70.802769	10.134931	56.123536	3.695421	4.881257
2	mountain	1003.625877	16.647737	70.208796	9.890371	55.678053	3.602263	4.932536

In [20]:
```
Z4=Z.groupby(["Cloud Cover"])[["Atmospheric Pressure","Temperature","Humidity","Wind Speed","Precipitation (%)","
```

In [21]:
```
Z4
```

Out[21]:

	Cloud Cover	Atmospheric Pressure	Temperature	Humidity	Wind Speed	Precipitation (%)	UV Index	Visibility (km)
0	clear	1019.948109	34.293870	51.990173	5.930042	22.636874	7.871315	7.322649
3	partly cloudy	1007.848062	21.589668	68.166253	9.736522	49.379878	3.932326	5.595646
2	overcast	999.776205	12.476606	77.229415	11.550394	67.796579	2.312762	3.913886
1	cloudy	997.267183	13.556338	49.640845	7.485915	53.866197	7.246479	6.323944

In [22]:
```
X.shape                                                                    ## showing ro
```

Out[22]: (13200, 11)

In [23]:
```
Z.shape
```

Out[23]: (12817, 11)

In [24]:
```
M=pd.get_dummies(Z['Cloud Cover'],drop_first=True)
```

In [25]:
```
M
```

Out[25]:

	cloudy	overcast	partly cloudy
0	0	0	1
1	0	0	1
2	0	0	0
3	0	0	0
4	0	1	0
...	...	...	...
13195	0	1	0
13196	1	0	0
13197	0	1	0
13198	0	1	0
13199	0	1	0

12817 rows × 3 columns

In [26]:
```
F=pd.concat([Z,M],axis=1)
F
```

Out[26]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Cloud Cover	Atmospheric Pressure	UV Index	Season	Visibility (km)	Location	Weather Type	cloudy	overcast
0	14.0	73	9.5	82.0	partly cloudy	1010.82	2	Winter	3.5	inland	Rainy	0	0
1	39.0	96	8.5	71.0	partly cloudy	1011.43	7	Spring	10.0	inland	Cloudy	0	0
2	30.0	64	7.0	16.0	clear	1018.72	5	Spring	5.5	mountain	Sunny	0	0
3	38.0	83	1.5	82.0	clear	1026.25	7	Spring	1.0	coastal	Sunny	0	0
4	27.0	74	17.0	66.0	overcast	990.67	1	Winter	2.5	mountain	Rainy	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
13195	10.0	74	14.5	71.0	overcast	1003.15	1	Summer	1.0	mountain	Rainy	0	1
13196	-1.0	76	3.5	23.0	cloudy	1067.23	1	Winter	6.0	coastal	Snowy	1	0
13197	30.0	77	5.5	28.0	overcast	1012.69	3	Autumn	9.0	coastal	Cloudy	0	1
13198	3.0	76	10.0	94.0	overcast	984.27	0	Winter	2.0	inland	Snowy	0	1
13199	-5.0	38	0.0	92.0	overcast	1015.37	5	Autumn	10.0	mountain	Rainy	0	1

12817 rows × 14 columns

In [27]:
```
F.drop(columns='Cloud Cover',inplace=True)
F
```

Out[27]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Season	Visibility (km)	Location	Weather Type	cloudy	overcast	partly cloudy
0	14.0	73	9.5	82.0	1010.82	2	Winter	3.5	inland	Rainy	0	0	1
1	39.0	96	8.5	71.0	1011.43	7	Spring	10.0	inland	Cloudy	0	0	1
2	30.0	64	7.0	16.0	1018.72	5	Spring	5.5	mountain	Sunny	0	0	0
3	38.0	83	1.5	82.0	1026.25	7	Spring	1.0	coastal	Sunny	0	0	0
4	27.0	74	17.0	66.0	990.67	1	Winter	2.5	mountain	Rainy	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
13195	10.0	74	14.5	71.0	1003.15	1	Summer	1.0	mountain	Rainy	0	1	0
13196	-1.0	76	3.5	23.0	1067.23	1	Winter	6.0	coastal	Snowy	1	0	0
13197	30.0	77	5.5	28.0	1012.69	3	Autumn	9.0	coastal	Cloudy	0	1	0
13198	3.0	76	10.0	94.0	984.27	0	Winter	2.0	inland	Snowy	0	1	0
13199	-5.0	38	0.0	92.0	1015.37	5	Autumn	10.0	mountain	Rainy	0	1	0

12817 rows × 13 columns

In [28]:
```
Y=pd.get_dummies(F['Season'],drop_first=True)
Y
```

Out[28]:

	Spring	Summer	Winter
0	0	0	1
1	1	0	0
2	1	0	0
3	1	0	0
4	0	0	1
...	...	...	...
13195	0	1	0
13196	0	0	1
13197	0	0	0
13198	0	0	1
13199	0	0	0

12817 rows × 3 columns

In [29]:
```python
T=pd.concat([F,Y],axis=1)
T
```

Out[29]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Season	Visibility (km)	Location	Weather Type	cloudy	overcast	partly cloudy
0	14.0	73	9.5	82.0	1010.82	2	Winter	3.5	inland	Rainy	0	0	1
1	39.0	96	8.5	71.0	1011.43	7	Spring	10.0	inland	Cloudy	0	0	1
2	30.0	64	7.0	16.0	1018.72	5	Spring	5.5	mountain	Sunny	0	0	0
3	38.0	83	1.5	82.0	1026.25	7	Spring	1.0	coastal	Sunny	0	0	0
4	27.0	74	17.0	66.0	990.67	1	Winter	2.5	mountain	Rainy	0	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
13195	10.0	74	14.5	71.0	1003.15	1	Summer	1.0	mountain	Rainy	0	1	0
13196	-1.0	76	3.5	23.0	1067.23	1	Winter	6.0	coastal	Snowy	1	0	0
13197	30.0	77	5.5	28.0	1012.69	3	Autumn	9.0	coastal	Cloudy	0	1	0
13198	3.0	76	10.0	94.0	984.27	0	Winter	2.0	inland	Snowy	0	1	0
13199	-5.0	38	0.0	92.0	1015.37	5	Autumn	10.0	mountain	Rainy	0	1	0

12817 rows × 16 columns

In [30]:
```python
T.drop(columns='Season',inplace=True)
T
```

Out[30]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Visibility (km)	Location	Weather Type	cloudy	overcast	partly cloudy	Spring
0	14.0	73	9.5	82.0	1010.82	2	3.5	inland	Rainy	0	0	1	0
1	39.0	96	8.5	71.0	1011.43	7	10.0	inland	Cloudy	0	0	1	1
2	30.0	64	7.0	16.0	1018.72	5	5.5	mountain	Sunny	0	0	0	1
3	38.0	83	1.5	82.0	1026.25	7	1.0	coastal	Sunny	0	0	0	1
4	27.0	74	17.0	66.0	990.67	1	2.5	mountain	Rainy	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
13195	10.0	74	14.5	71.0	1003.15	1	1.0	mountain	Rainy	0	1	0	0
13196	-1.0	76	3.5	23.0	1067.23	1	6.0	coastal	Snowy	1	0	0	0
13197	30.0	77	5.5	28.0	1012.69	3	9.0	coastal	Cloudy	0	1	0	0
13198	3.0	76	10.0	94.0	984.27	0	2.0	inland	Snowy	0	1	0	0
13199	-5.0	38	0.0	92.0	1015.37	5	10.0	mountain	Rainy	0	1	0	0

12817 rows × 15 columns

In [31]:
```
T1=pd.get_dummies(T['Location'],drop_first=True)
T1
```

Out[31]:

	inland	mountain
0	1	0
1	1	0
2	0	1
3	0	0
4	0	1
...	...	...
13195	0	1
13196	0	0
13197	0	0
13198	1	0
13199	0	1

12817 rows × 2 columns

In [32]:
```
F1=pd.concat([T,T1],axis=1)
F1
```

Out[32]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Visibility (km)	Location	Weather Type	cloudy	overcast	partly cloudy	Spring	Su
0	14.0	73	9.5	82.0	1010.82	2	3.5	inland	Rainy	0	0	1	0	
1	39.0	96	8.5	71.0	1011.43	7	10.0	inland	Cloudy	0	0	1	1	
2	30.0	64	7.0	16.0	1018.72	5	5.5	mountain	Sunny	0	0	0	1	
3	38.0	83	1.5	82.0	1026.25	7	1.0	coastal	Sunny	0	0	0	1	
4	27.0	74	17.0	66.0	990.67	1	2.5	mountain	Rainy	0	1	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
13195	10.0	74	14.5	71.0	1003.15	1	1.0	mountain	Rainy	0	1	0	0	
13196	-1.0	76	3.5	23.0	1067.23	1	6.0	coastal	Snowy	1	0	0	0	
13197	30.0	77	5.5	28.0	1012.69	3	9.0	coastal	Cloudy	0	1	0	0	
13198	3.0	76	10.0	94.0	984.27	0	2.0	inland	Snowy	0	1	0	0	
13199	-5.0	38	0.0	92.0	1015.37	5	10.0	mountain	Rainy	0	1	0	0	

12817 rows × 17 columns

In [33]:
```
F1.drop(columns='Location',inplace=True)
```

In [34]:
```
F1
```

Out[34]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Visibility (km)	Weather Type	cloudy	overcast	partly cloudy	Spring	Summer	Wi
0	14.0	73	9.5	82.0	1010.82	2	3.5	Rainy	0	0	1	0	0	
1	39.0	96	8.5	71.0	1011.43	7	10.0	Cloudy	0	0	1	1	0	
2	30.0	64	7.0	16.0	1018.72	5	5.5	Sunny	0	0	0	1	0	
3	38.0	83	1.5	82.0	1026.25	7	1.0	Sunny	0	0	0	1	0	
4	27.0	74	17.0	66.0	990.67	1	2.5	Rainy	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
13195	10.0	74	14.5	71.0	1003.15	1	1.0	Rainy	0	1	0	0	1	
13196	-1.0	76	3.5	23.0	1067.23	1	6.0	Snowy	1	0	0	0	0	
13197	30.0	77	5.5	28.0	1012.69	3	9.0	Cloudy	0	1	0	0	0	
13198	3.0	76	10.0	94.0	984.27	0	2.0	Snowy	0	1	0	0	0	
13199	-5.0	38	0.0	92.0	1015.37	5	10.0	Rainy	0	1	0	0	0	

12817 rows × 16 columns

In [35]:
```
F1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12817 entries, 0 to 13199
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Temperature           12817 non-null  float64
 1   Humidity              12817 non-null  int64  
 2   Wind Speed            12817 non-null  float64
 3   Precipitation (%)     12817 non-null  float64
 4   Atmospheric Pressure  12817 non-null  float64
 5   UV Index              12817 non-null  int64  
 6   Visibility (km)       12817 non-null  float64
 7   Weather Type          12817 non-null  object 
 8   cloudy                12817 non-null  uint8  
 9   overcast              12817 non-null  uint8  
 10  partly cloudy         12817 non-null  uint8  
 11  Spring                12817 non-null  uint8  
 12  Summer                12817 non-null  uint8  
 13  Winter                12817 non-null  uint8  
 14  inland                12817 non-null  uint8  
 15  mountain              12817 non-null  uint8  
dtypes: float64(5), int64(2), object(1), uint8(8)
memory usage: 1.5+ MB
```

In [36]:
```
X["Weather Type"].unique()
```

Out[36]:
```
array(['Rainy', 'Cloudy', 'Sunny', 'Snowy'], dtype=object)
```

In [37]:
```
from sklearn.preprocessing import LabelEncoder
L=LabelEncoder()
```

In [38]:
```
F1["Weather Type"]=L.fit_transform(F1["Weather Type"])
```

In [39]:
```
F1
```

Out[39]:

	Temperature	Humidity	Wind Speed	Precipitation (%)	Atmospheric Pressure	UV Index	Visibility (km)	Weather Type	cloudy	overcast	partly cloudy	Spring	Summer	Wi
0	14.0	73	9.5	82.0	1010.82	2	3.5	1	0	0	1	0	0	
1	39.0	96	8.5	71.0	1011.43	7	10.0	0	0	0	1	1	0	
2	30.0	64	7.0	16.0	1018.72	5	5.5	3	0	0	0	1	0	
3	38.0	83	1.5	82.0	1026.25	7	1.0	3	0	0	0	1	0	
4	27.0	74	17.0	66.0	990.67	1	2.5	1	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
13195	10.0	74	14.5	71.0	1003.15	1	1.0	1	0	1	0	0	1	
13196	-1.0	76	3.5	23.0	1067.23	1	6.0	2	1	0	0	0	0	
13197	30.0	77	5.5	28.0	1012.69	3	9.0	0	0	1	0	0	0	
13198	3.0	76	10.0	94.0	984.27	0	2.0	2	0	1	0	0	0	
13199	-5.0	38	0.0	92.0	1015.37	5	10.0	1	0	1	0	0	0	

12817 rows × 16 columns

In [40]:
```
F1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 12817 entries, 0 to 13199
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Temperature           12817 non-null  float64
 1   Humidity              12817 non-null  int64  
 2   Wind Speed            12817 non-null  float64
 3   Precipitation (%)     12817 non-null  float64
 4   Atmospheric Pressure  12817 non-null  float64
 5   UV Index              12817 non-null  int64  
 6   Visibility (km)       12817 non-null  float64
 7   Weather Type          12817 non-null  int32  
 8   cloudy                12817 non-null  uint8  
 9   overcast              12817 non-null  uint8  
 10  partly cloudy         12817 non-null  uint8  
 11  Spring                12817 non-null  uint8  
 12  Summer                12817 non-null  uint8  
 13  Winter                12817 non-null  uint8  
 14  inland                12817 non-null  uint8  
 15  mountain              12817 non-null  uint8  
dtypes: float64(5), int32(1), int64(2), uint8(8)
memory usage: 1.4 MB
```

In [41]:
```
F=F1.drop('Weather Type',axis=1)
T=F1['Weather Type']
```

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(F,T,train_size=0.85,random_state=200)
```

In [43]:
```
from sklearn.preprocessing import StandardScaler
M=StandardScaler()
```

In [44]:
```
X_train[["Temperature","Humidity","Wind Speed","Precipitation (%)","Atmospheric Pressure"]]=M.fit_transform(X_tra
X_test[["Temperature","Humidity","Wind Speed","Precipitation (%)","Atmospheric Pressure"]]=M.transform(X_test[["T
```

LogisticRegression

In [45]:
```
from sklearn.linear_model import LogisticRegression
L=LogisticRegression()
```

In [46]:
```
L.fit(X_train,y_train)
```

Out[46]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [47]:
```
L.score(X_train,y_train)
```

Out[47]:
```
0.9034330824306958
```

In [48]:
```
L.score(X_test,y_test)
```

Out[48]:
```
0.9022360894435777
```

SVC

In [49]:
```
from sklearn.svm import SVC
s=SVC()
```

In [50]:
```
s.fit(X_train,y_train)
```

Out[50]:
```
SVC()
```

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In [51]:
```
s.score(X_train,y_train)
```

Out[51]:
```
0.9316137323297228
```

In [52]:
```
s.score(X_test,y_test)
```

Out[52]:
```
0.9230369214768591
```

KNeighborsClassifier

In [53]:
```
from sklearn.neighbors import KNeighborsClassifier
K=KNeighborsClassifier()
```

In [54]:
```
K1=K.fit(X_train,y_train)
K1
```

Out[54]:
```
KNeighborsClassifier()
```

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In [55]:
```
K1.score(X_train,y_train)
```

Out[55]:
```
0.9333578116394345
```

In [56]:
```
K1.score(X_test,y_test)
```

Out[56]:
```
0.9089963598543942
```

naive_bayes

In [57]:
```
from sklearn.naive_bayes import GaussianNB,MultinomialNB,BernoulliNB,ComplementNB
G=GaussianNB()
M=MultinomialNB()
B=BernoulliNB()
C=ComplementNB()
```

In [58]:
```
G.fit(X_train,y_train)
```

Out[58]:
```
GaussianNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [59]:
```
G.score(X_train,y_train)
```

Out[59]:
```
0.8632274646594456
```

In [60]:
```
G.score(X_test,y_test)
```

Out[60]:
```
0.8653146125845034
```

In [61]:
```
B.fit(X_train,y_train)
```

Out[61]:
```
BernoulliNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [62]:
```
B.score(X_train,y_train)
```

Out[62]:
```
0.8249495134936662
```

In [63]:
```
B.score(X_test,y_test)
```

Out[63]:
```
0.827873114924597
```

In [64]:
```
from sklearn.tree import DecisionTreeClassifier
D=DecisionTreeClassifier(max_depth=5,criterion='gini',min_samples_split=8)
```

In [65]:
```
D.fit(X_train,y_train)
```

Out[65]:
```
DecisionTreeClassifier(max_depth=5, min_samples_split=8)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [66]:
```
D.score(X_train,y_train)
```

Out[66]:
```
0.924362034147237
```

In [67]:
```
D.score(X_test,y_test)
```

Out[67]:
```
0.9152366094643786
```

DecisionTreeClassifier

In [68]:
```
from sklearn.tree import DecisionTreeClassifier
D=DecisionTreeClassifier()
from sklearn.model_selection import GridSearchCV
params={"max_depth":[5,6,8,9],"criterion":['gini'],"min_samples_split":[6,9,8,6]}
G1=GridSearchCV(D,param_grid=params,scoring="accuracy",cv=7)
```

In [69]:
```
G1.fit(X_train,y_train)
```

Out[69]:
```
GridSearchCV(cv=7, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['gini'], 'max_depth': [5, 6, 8, 9],
                         'min_samples_split': [6, 9, 8, 6]},
             scoring='accuracy')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [70]:
```
G1.best_params_
```

Out[70]:
```
{'criterion': 'gini', 'max_depth': 9, 'min_samples_split': 6}
```

In [71]:
```
G1.score(X_train,y_train)
```

Out[71]:
```
0.9622728107214981
```

In [72]:
```
G1.score(X_test,y_test)
```

Out[72]:
```
0.9329173166926678
```

In [73]:
```
from sklearn.tree import DecisionTreeClassifier
D=DecisionTreeClassifier()
from sklearn.model_selection import GridSearchCV
params={"max_depth":[5,6,8,9],"criterion":['entropy'],"min_samples_split":[6,9,8,6]}
G1=GridSearchCV(D,param_grid=params,scoring="accuracy",cv=7)
```

In [74]:
```
G1.fit(X_train,y_train)
```

Out[74]:
```
GridSearchCV(cv=7, estimator=DecisionTreeClassifier(),
             param_grid={'criterion': ['entropy'], 'max_depth': [5, 6, 8, 9],
                         'min_samples_split': [6, 9, 8, 6]},
             scoring='accuracy')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [75]:
```
G1.best_params_
```

Out[75]:
```
{'criterion': 'entropy', 'max_depth': 9, 'min_samples_split': 6}
```

In [76]:
```
G1.score(X_train,y_train)
```

Out[76]:
```
0.9634661281439324
```

In [77]:
```
G1.score(X_test,y_test)
```

Out[77]:
```
0.9349973998959958
```

BaggingClassifier,RandomForestClassifier

In [78]:
```
from sklearn.ensemble import BaggingClassifier,RandomForestClassifier
A=RandomForestClassifier(n_estimators=20)
```

In [79]:
```
A.fit(X_train,y_train)
```

Out[79]:
```
RandomForestClassifier(n_estimators=20)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [80]:
```
A.score(X_train,y_train)
```

Out[80]:
```
0.9998164127042408
```

In [81]:
```
A.score(X_test,y_test)
```

Out[81]:
```
0.9386375455018201
```

BaggingClassifier

In [82]:
```
from sklearn.ensemble import BaggingClassifier
B=BaggingClassifier(estimator=KNeighborsClassifier(),n_estimators=60)
```

In [83]:
```
B.fit(X_train,y_train)
```

Out[83]:
```
BaggingClassifier(estimator=KNeighborsClassifier(), n_estimators=60)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [84]:
```
B.score(X_train,y_train)
```

Out[84]:
```
0.9365705893152194
```

In [85]:
```
B.score(X_test,y_test)
```

Out[85]:
```
0.9131565262610505
```

VotingClassifier

In [86]:
```
from sklearn.ensemble import VotingClassifier
A=VotingClassifier(estimators=[("logi",LogisticRegression()),("nb",GaussianNB()),("svc",SVC())])
```

In [87]:
```
A.fit(X_train,y_train)
```

Out[87]:
```
VotingClassifier(estimators=[('logi', LogisticRegression()),
                             ('nb', GaussianNB()), ('svc', SVC())])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [88]:
```
A.score(X_train,y_train)
```

Out[88]:
```
0.9137139709932073
```

In [89]:
```
A.score(X_test,y_test)
```

Out[89]:
```
0.9105564222568903
```

StackingClassifier

In [90]:
```
from sklearn.ensemble import StackingClassifier
s=StackingClassifier(estimators=[("nb",GaussianNB()),("svc",SVC()),("knn",KNeighborsClassifier())],final_estimato
```

In [91]:
```
s.fit(X_train,y_train)
```

Out[91]:
```
StackingClassifier(estimators=[('nb', GaussianNB()), ('svc', SVC()),
                               ('knn', KNeighborsClassifier())],
                   final_estimator=LogisticRegression())
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [92]:
```
s.score(X_train,y_train)
```
Out[92]: 0.9358362401321828

In [93]:
```
s.score(X_test,y_test)
```
Out[93]: 0.9157566302652106

AdaBoostClassifier

In [94]:
```
from sklearn.ensemble import AdaBoostClassifier
A=AdaBoostClassifier(n_estimators=50)
```

In [95]:
```
A.fit(X_train,y_train)
```
Out[95]: AdaBoostClassifier()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [96]:
```
A.score(X_train,y_train)
```
Out[96]: 0.8817697815311181

In [97]:
```
A.score(X_test,y_test)
```
Out[97]: 0.8928757150286012

In [100]:
```
Svc","knn","Gaussian","bernoulli","DecisionTree","BaggingClassifier","VotingClassifier","StackingClassifier","AdaE
```

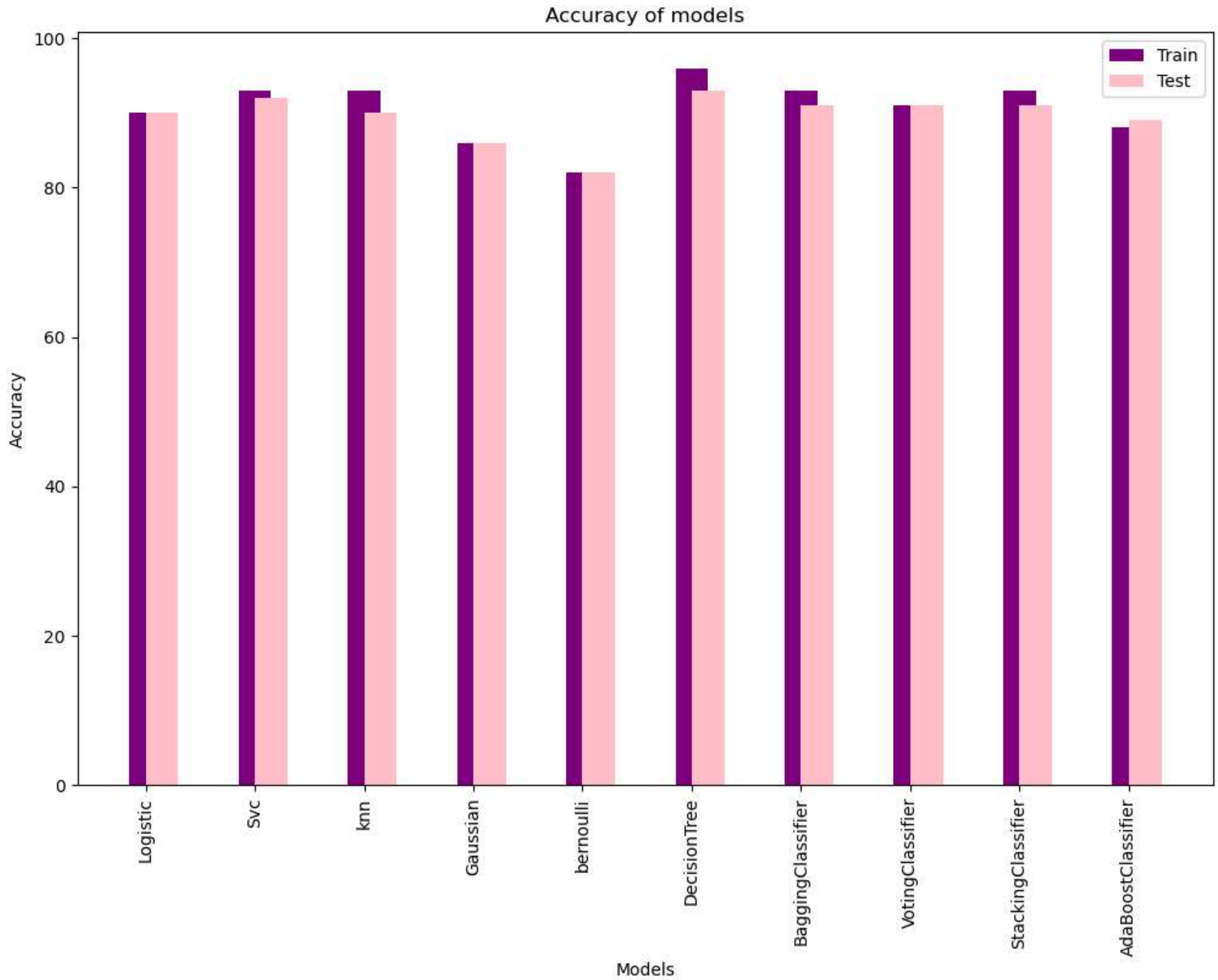
In [101]:
```
A=pd.DataFrame(A)
```

In [102]:
```
A
```
Out[102]:

	Methods	Train	Test
0	Logistic	90	90
1	Svc	93	92
2	knn	93	90
3	Gaussian	86	86
4	bernoulli	82	82
5	DecisionTree	96	93
6	BaggingClassifier	93	91
7	VotingClassifier	91	91
8	StackingClassifier	93	91
9	AdaBoostClassifier	88	89

In [110]:

```
plt.figure(figsize=(12,8))
plt.bar(A["Methods"],A["Train"],width=0.3,label="Train",color="purple")
plt.bar(A["Methods"],A["Test"],align="edge",width=0.3,label="Test",color="pink")
plt.xticks(rotation=90)
plt.legend(bbox_to_anchor=[1,0,0,1])
plt.xlabel("Models")
plt.ylabel("Accuracy")
plt.title("Accuracy of models")
plt.show()
```



On basis of this chart assume that"StackingClassifier" model working is fine as comapred to other.

In [ ]: