Major Project Synopsis

on

AIR QUALITY INDEX PREDICTOR SOURCE CODE FILE

In partial fulfilment of requirements for the degree

of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE & ENGINEERING

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JUL.-DEC-2022

SHRI VAISHNAV INSTITUTE OF INFORMATION TECHNOLOGY

SOURCE CODE

```
df['AQI_Bucket'].fillna('Good')
```

```
0                Good
1                Good
2                Good
3                Good
4                Good
              ...
29526            Good
29527    Satisfactory
29528    Satisfactory
29529    Satisfactory
29530            Good
Name: AQI_Bucket, Length: 29531, dtype: object
```

```
print(df)
```

```
                City        Date  PM2.5   PM10     NO    NO2    NOx    NH3  \
0          Ahmedabad  2015-01-01    NaN    NaN   0.92  18.22  17.15    NaN
1          Ahmedabad  2015-01-02    NaN    NaN   0.97  15.69  16.46    NaN
2          Ahmedabad  2015-01-03    NaN    NaN  17.40  19.30  29.70    NaN
3          Ahmedabad  2015-01-04    NaN    NaN   1.70  18.48  17.97    NaN
4          Ahmedabad  2015-01-05    NaN    NaN  22.10  21.42  37.76    NaN
...              ...         ...    ...    ...    ...    ...    ...    ...
29526  Visakhapatnam  2020-06-27  15.02  50.94   7.68  25.06  19.54  12.47
29527  Visakhapatnam  2020-06-28  24.38  74.09   3.42  26.06  16.53  11.99
29528  Visakhapatnam  2020-06-29  22.91  65.73   3.45  29.53  18.33  10.71
29529  Visakhapatnam  2020-06-30  16.64  49.97   4.05  29.26  18.80  10.03
29530  Visakhapatnam  2020-07-01  15.00  66.00   0.40  26.85  14.05   5.20

          CO    SO2      O3  Benzene  Toluene  Xylene    AQI    AQI_Bucket
0       0.92  27.64  133.36     0.00     0.02    0.00    NaN           NaN
1       0.97  24.55   34.06     3.68     5.50    3.77    NaN           NaN
2      17.40  29.07   30.70     6.80    16.40    2.25    NaN           NaN
3       1.70  18.59   36.08     4.43    10.14    1.00    NaN           NaN
4      22.10  39.33   39.31     7.01    18.89    2.78    NaN           NaN
...      ...    ...     ...      ...      ...     ...    ...           ...
29526   0.47   8.55   23.30     2.24    12.07    0.73   41.0          Good
29527   0.52  12.72   30.14     0.74     2.21    0.38   70.0  Satisfactory
29528   0.48   8.42   30.96     0.01     0.01    0.00   68.0  Satisfactory
29529   0.52   9.84   28.30     0.00     0.00    0.00   54.0  Satisfactory
29530   0.59   2.10   17.05      NaN      NaN     NaN   50.0          Good
```

```
print(df.head(10))
```

```
        City        Date  PM2.5  PM10     NO    NO2     NOx  NH3     CO  \
0  Ahmedabad  2015-01-01    NaN   NaN   0.92  18.22   17.15  NaN   0.92
1  Ahmedabad  2015-01-02    NaN   NaN   0.97  15.69   16.46  NaN   0.97
2  Ahmedabad  2015-01-03    NaN   NaN  17.40  19.30   29.70  NaN  17.40
3  Ahmedabad  2015-01-04    NaN   NaN   1.70  18.48   17.97  NaN   1.70
4  Ahmedabad  2015-01-05    NaN   NaN  22.10  21.42   37.76  NaN  22.10
5  Ahmedabad  2015-01-06    NaN   NaN  45.41  38.48   81.50  NaN  45.41
6  Ahmedabad  2015-01-07    NaN   NaN 112.16  40.62  130.77  NaN 112.16
7  Ahmedabad  2015-01-08    NaN   NaN  80.87  36.74   96.75  NaN  80.87
8  Ahmedabad  2015-01-09    NaN   NaN  29.16  31.00   48.00  NaN  29.16
9  Ahmedabad  2015-01-10    NaN   NaN    NaN   7.04    0.00  NaN    NaN

     SO2      O3  Benzene  Toluene  Xylene  AQI AQI_Bucket
0  27.64  133.36     0.00     0.02    0.00  NaN        NaN
1  24.55   34.06     3.68     5.50    3.77  NaN        NaN
2  29.07   30.70     6.80    16.40    2.25  NaN        NaN
3  18.59   36.08     4.43    10.14    1.00  NaN        NaN
4  39.33   39.31     7.01    18.89    2.78  NaN        NaN
5  45.76   46.51     5.42    10.83    1.93  NaN        NaN
6  32.28   33.47     0.00     0.00    0.00  NaN        NaN
7  38.54   31.89     0.00     0.00    0.00  NaN        NaN
8  58.68   25.75     0.00     0.00    0.00  NaN        NaN
9   8.29    4.55     0.00     0.00    0.00  NaN        NaN
```

```
print(df.tail(10))
```

```
              City        Date  PM2.5    PM10    NO    NO2    NOx    NH3  \
29521  Visakhapatnam  2020-06-22  33.17  108.22  5.58  42.45  27.06  13.70
29522  Visakhapatnam  2020-06-23  25.40   83.38  2.76  34.09  19.92  13.13
29523  Visakhapatnam  2020-06-24  34.36   90.90  1.22  23.38  13.12  14.45
29524  Visakhapatnam  2020-06-25  13.45   58.54  2.30  21.60  13.09  12.27
29525  Visakhapatnam  2020-06-26   7.63   32.27  5.91  23.27  17.19  11.15
29526  Visakhapatnam  2020-06-27  15.02   50.94  7.68  25.06  19.54  12.47
29527  Visakhapatnam  2020-06-28  24.38   74.09  3.42  26.06  16.53  11.99
29528  Visakhapatnam  2020-06-29  22.91   65.73  3.45  29.53  18.33  10.71
29529  Visakhapatnam  2020-06-30  16.64   49.97  4.05  29.26  18.80  10.03
29530  Visakhapatnam  2020-07-01  15.00   66.00  0.40  26.85  14.05   5.20

         CO    SO2     O3  Benzene  Toluene  Xylene    AQI    AQI_Bucket
29521  0.73  13.65  34.85     3.99    10.24    2.32   95.0  Satisfactory
29522  0.54  10.40  43.27     2.88    12.03    1.33  100.0  Satisfactory
29523  0.56  10.92  35.12     2.99     3.15    1.60   86.0  Satisfactory
29524  0.41   8.19  29.38     1.28     5.64    0.92   77.0  Satisfactory
29525  0.46   6.87  19.90     1.45     5.37    1.45   47.0          Good
29526  0.47   8.55  23.30     2.24    12.07    0.73   41.0          Good
29527  0.52  12.72  30.14     0.74     2.21    0.38   70.0  Satisfactory
29528  0.48   8.42  30.96     0.01     0.01    0.00   68.0  Satisfactory
29529  0.52   9.84  28.30     0.00     0.00    0.00   54.0  Satisfactory
29530  0.59   2.10  17.05      NaN      NaN     NaN   50.0          Good
```

```
print(df.describe())
```

```
              PM2.5          PM10            NO           NO2           NOx  \
count  24933.000000  18391.000000  25949.000000  25946.000000  25346.000000
mean      67.450578    118.127103     17.574730     28.560659     32.309123
std       64.661449     90.605110     22.785846     24.474746     31.646011
min        0.040000      0.010000      0.020000      0.010000      0.000000
25%       28.820000     56.255000      5.630000     11.750000     12.820000
50%       48.570000     95.680000      9.890000     21.690000     23.520000
75%       80.590000    149.745000     19.950000     37.620000     40.127500
max      949.990000   1000.000000    390.680000    362.210000    467.630000

                NH3            CO           SO2            O3       Benzene  \
count  19203.000000  27472.000000  25677.000000  25509.000000  23908.000000
mean      23.483476      2.248598     14.531977     34.491430      3.280840
std       25.684275      6.962884     18.133775     21.694928     15.811136
min        0.010000      0.000000      0.010000      0.010000      0.000000
25%        8.580000      0.510000      5.670000     18.860000      0.120000
50%       15.850000      0.890000      9.160000     30.840000      1.070000
75%       30.020000      1.450000     15.220000     45.570000      3.080000
max      352.890000    175.810000    193.860000    257.730000    455.030000

             Toluene        Xylene           AQI
count  21490.000000  11422.000000  24850.000000
mean       8.700972      3.070128    166.463581
std       19.969164      6.323247    140.696585
min        0.000000      0.000000     13.000000
25%        0.600000      0.140000     81.000000
50%        2.970000      0.980000    118.000000
75%        9.150000      3.350000    208.000000
max      454.850000    170.370000   2049.000000
```

```
print(df.isnull().sum())
```

```
City              0
Date              0
PM2.5          4598
PM10          11140
NO             3582
NO2            3585
NOx            4185
NH3           10328
CO             2059
SO2            3854
O3             4022
Benzene        5623
Toluene        8041
Xylene        18109
AQI            4681
AQI_Bucket     4681
dtype: int64
```

```
print(df.corr())
```

```
             PM2.5     PM10        NO       NO2       NOx       NH3       CO  \
PM2.5     1.000000  0.846498  0.433491  0.350709  0.436792  0.275086  0.089912
PM10      0.846498  1.000000  0.502349  0.464380  0.527768  0.376816  0.112588
NO        0.433491  0.502349  1.000000  0.478070  0.794890  0.185621  0.212607
NO2       0.350709  0.464380  0.478070  1.000000  0.627627  0.234938  0.356521
NOx       0.436792  0.527768  0.794890  0.627627  1.000000  0.166224  0.226992
NH3       0.275086  0.376816  0.185621  0.234938  0.166224  1.000000  0.104891
CO        0.089912  0.112588  0.212607  0.356521  0.226992  0.104891  1.000000
SO2       0.132325  0.256974  0.170322  0.392233  0.238397 -0.038998  0.489697
O3        0.161238  0.244919  0.014580  0.293349  0.093170  0.094972  0.041736
Benzene   0.023911  0.022265  0.035771  0.025260  0.039121 -0.015650  0.061861
Toluene   0.117080  0.169335  0.150857  0.273926  0.189386  0.013227  0.277904
Xylene    0.114579  0.081700  0.094237  0.171701  0.087398 -0.019813  0.154889
AQI       0.659181  0.803313  0.452191  0.537071  0.486450  0.252019  0.683346

              SO2        O3   Benzene   Toluene    Xylene       AQI
PM2.5    0.132325  0.161238  0.023911  0.117080  0.114579  0.659181
PM10     0.256974  0.244919  0.022265  0.169335  0.081700  0.803313
NO       0.170322  0.014580  0.035771  0.150857  0.094237  0.452191
NO2      0.392233  0.293349  0.025260  0.273926  0.171701  0.537071
NOx      0.238397  0.093170  0.039121  0.189386  0.087398  0.486450
NH3     -0.038998  0.094972 -0.015650  0.013227 -0.019813  0.252019
CO       0.489697  0.041736  0.061861  0.277904  0.154889  0.683346
SO2      1.000000  0.162142  0.036110  0.296139  0.251195  0.490586
O3       0.162142  1.000000  0.020255  0.130209  0.111410  0.198991
Benzene  0.036110  0.020255  1.000000  0.739286  0.415427  0.044407
Toluene  0.296139  0.130209  0.739286  1.000000  0.421432  0.279992
Xylene   0.251195  0.111410  0.415427  0.421432  1.000000  0.165532
AQI      0.490586  0.198991  0.044407  0.279992  0.165532  1.000000
```

```
print(df.columns)
```

```
Index(['City', 'Date', 'PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2',
       'O3', 'Benzene', 'Toluene', 'Xylene', 'AQI', 'AQI_Bucket'],
      dtype='object')
```

Lable of encoding

from sklearn.preprocessing import LabelEncoder

le=LabelEncoder()

df['AQI_Bucket']=le.fit_transform(df['AQI_Bucket'])

print(df['AQI_Bucket'].value_counts())

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df['AQI_Bucket']=le.fit_transform(df['AQI_Bucket'])
print(df['AQI_Bucket'].value_counts() )
```

```
1    8829
3    8224
6    4681
2    2781
5    2337
0    1341
4    1338
Name: AQI_Bucket, dtype: int64
```

Declaring independent and dependent

x=df.iloc[:,2:14]

y=df.iloc[:,0:16:15]

print(x)

print(y)

```
x=df.iloc[:,2:14]
y=df.iloc[:,0:16:15]
print(x)
print(y)
```

```
       PM2.5   PM10     NO    NO2    NOx    NH3     CO    SO2     O3  \
0        NaN    NaN   0.92  18.22  17.15    NaN   0.92  27.64  133.36
1        NaN    NaN   0.97  15.69  16.46    NaN   0.97  24.55   34.06
2        NaN    NaN  17.40  19.30  29.70    NaN  17.40  29.07   30.70
3        NaN    NaN   1.70  18.48  17.97    NaN   1.70  18.59   36.08
4        NaN    NaN  22.10  21.42  37.76    NaN  22.10  39.33   39.31
...      ...    ...    ...    ...    ...    ...    ...    ...     ...
29526  15.02  50.94   7.68  25.06  19.54  12.47   0.47   8.55   23.30
29527  24.38  74.09   3.42  26.06  16.53  11.99   0.52  12.72   30.14
29528  22.91  65.73   3.45  29.53  18.33  10.71   0.48   8.42   30.96
29529  16.64  49.97   4.05  29.26  18.80  10.03   0.52   9.84   28.30
29530  15.00  66.00   0.40  26.85  14.05   5.20   0.59   2.10   17.05
```

```
        Benzene  Toluene  Xylene
0          0.00     0.02    0.00
1          3.68     5.50    3.77
2          6.80    16.40    2.25
3          4.43    10.14    1.00
4          7.01    18.89    2.78
...         ...      ...     ...
29526      2.24    12.07    0.73
29527      0.74     2.21    0.38
29528      0.01     0.01    0.00
29529      0.00     0.00    0.00
29530       NaN      NaN     NaN

[29531 rows x 12 columns]
                City  AQI_Bucket
0          Ahmedabad           6
1          Ahmedabad           6
2          Ahmedabad           6
3          Ahmedabad           6
4          Ahmedabad           6
...              ...         ...
29526  Visakhapatnam           0
29527  Visakhapatnam           3
29528  Visakhapatnam           3
29529  Visakhapatnam           3
29530  Visakhapatnam           0
```

TRAIN TEST SPLIT

from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=,25)

print(x_train.shape, x_test.shape, y_train.shape,y_test.shape)

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x, y, test_size = .25)
print(x_train.shape, x_test.shape, y_train.shape,y_test.shape)
```

```
(22148, 12) (7383, 12) (22148, 2) (7383, 2)
```

Logistic Regression

import algorithm

from sklearn.linear_model

import LogisticRegression

lr=LogisticRegression()

```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()
print(lr)
```

```
LogisticRegression()
```

train model and prediction

from sklearn.linear_model import LogisticRegression

lr=LogisticRegression()

lr.fit(x_train,y_train)

y_pred_lr = lr.predict(x_test)

print(y_pred_lr[:5],y_test.values[:5])

print(lr.score(x_train,y_train))

print(lr.score(x_test, y_test))

```
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression()

lr.fit(x_train,y_train)

y_pred_lr = lr.predict(x_test)
print(y_pred_lr[:5],y_test.values[:5] )

print(lr.score(x_train,y_train))
print(lr.score(x_test, y_test))
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:993: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y t
  y = column_or_1d(y, warn=True)
[2 3 1 0 1] [[2]
 [3]
 [3]
 [0]
 [3]]
0.5736583279880265
0.5567671584348942
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: ConvergenceWarning: 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
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

evalution

print(lr.score(x_train,y_train))

print(lr.score(x_test, y_test))

from sklearn.metrics import confusion_matrix,classification_report, accuracy_score

print(confusion_matrix(y_pred_lr, y_test))

print(classification_report(y_pred_1r, y_test))

print(f'model_score- {lr.score(x_test,y_test)}')

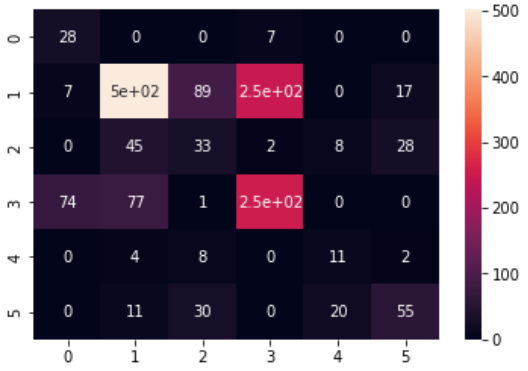
print(f'accuracy_score- {accuracy_score(y_pred_lr, y_test)}')

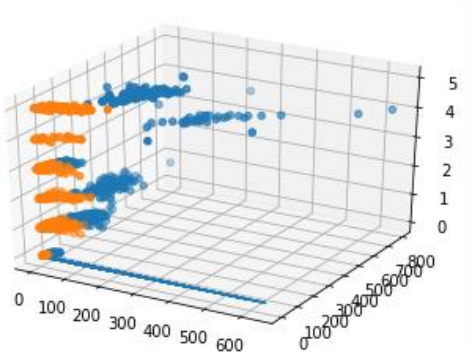
```
print(lr.score(x_train,y_train))
print(lr.score(x_test, y_test))

from sklearn.metrics import confusion_matrix,classification_report, accuracy_score
print(confusion_matrix(y_pred_lr, y_test))
print(classification_report(y_pred_1r, y_test))
print(f'model_score- {lr.score(x_test,y_test)}')
print(f'accuracy_score- {accuracy_score(y_pred_lr, y_test)}')
```

```
0.5736583279880265
0.5567671584348942
[[ 32   1   0  11   0   0]
 [  3 464  71 248   3  16]
 [  0  61  45   2   4  35]
 [ 84  89   0 267   0   1]
 [  0   3   6   0  11   6]
 [  0  12  24   2   9  49]]
              precision    recall  f1-score   support

           0       0.27      0.73      0.39        44
           1       0.74      0.58      0.65       805
           2       0.31      0.31      0.31       147
           3       0.50      0.61      0.55       441
           4       0.41      0.42      0.42        26
           5       0.46      0.51      0.48        96

    accuracy                           0.56      1559
   macro avg       0.45      0.52      0.47      1559
weighted avg       0.59      0.56      0.57      1559

model_score- 0.5567671584348942
accuracy_score- 0.5567671584348942
```

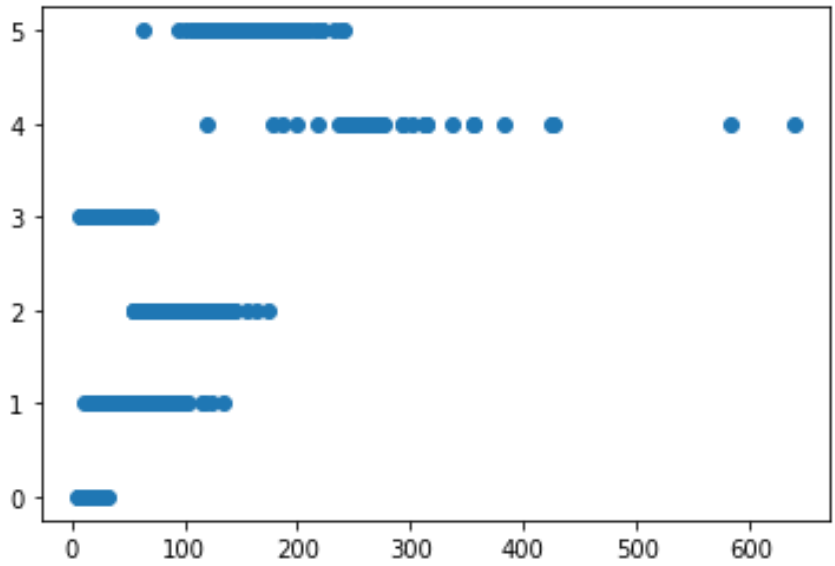
visualization

```
cm=confusion_matrix(y_pred_lr,y_test)
sns.heatmap(cm,annot=True)
plt.show()

ax = plt.axes(projection = '3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['NO'],x_test['NO2'],y_pred_lr, 'black')
plt.plot(x_test['PM2.5'], y_pred_lr)
plt.show()
```






```
plt.scatter(x_test['PM2.5'], y_test)
plt.show()
```



Evalution

print(I=lr.score(x_train,y_train))

print(lr.score(x_test, y_test))

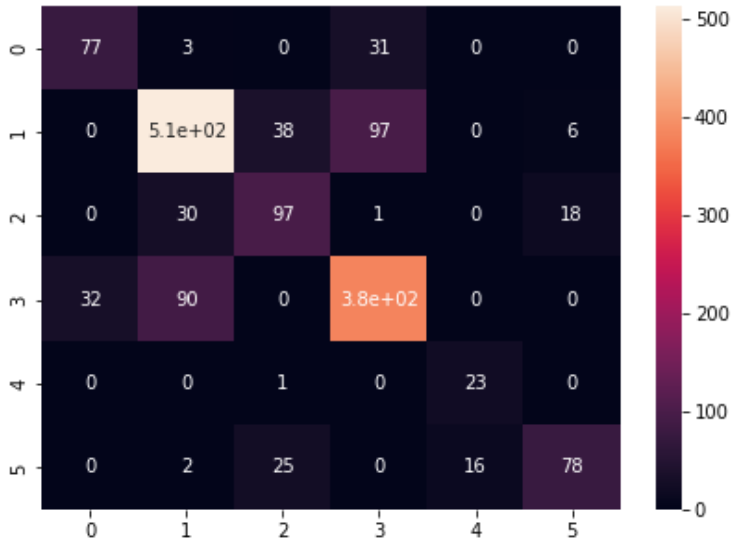
```
print(lr.score(x_train,y_train))
print(lr.score(x_test, y_test))
```

```
0.5736583279880265
0.5567671584348942
```

Decision Tree Classifier

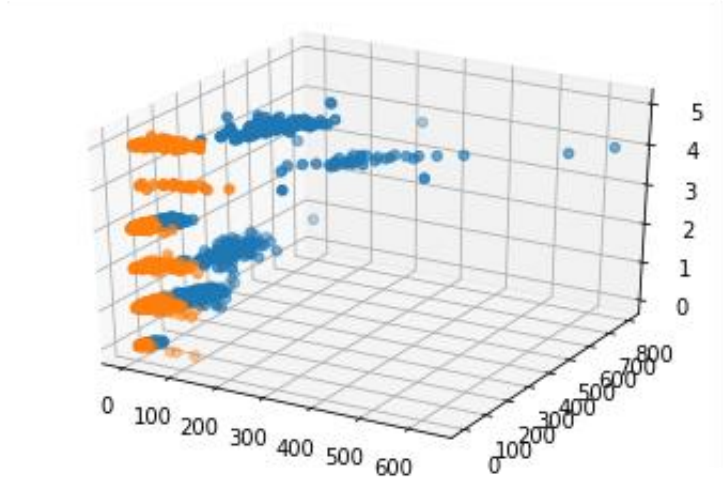
```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier()
dtc.fit(x_train,y_train)
y_pred_dtc=dtc.predict(x_test)
print(f'Predicted_y{y_pred_dtc[:5]} Actual_y{y_test.values[:5]}')
print(confusion_matrix(y_pred_dtc,y_test))

from sklearn.metrics import confusion_matrix,classification_report, accuracy_score
cm=confusion_matrix(y_pred_dtc, y_test)
plt.figure(figsize=(7,5))
print(sns.heatmap(cm, annot=True))
plt.show()
print(classification_report(y_pred_dtc, y_test))
print(f'model_score- {dtc.score(x_test, y_test)} ')
print(f'accuracy_score- {accuracy_score(y_pred_dtc, y_test)}')
ax = plt.axes (projection ='3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['NO'],x_test['NO2'], y_pred_dtc,'black')
plt.show()
```

```
Predicted_y[0 4 0 3 1] Actual_y[[3]
 [4]
 [0]
 [3]
 [1]]
[[ 77   3   0  31   0   0]
 [  0 513  38  97   0   6]
 [  0  30  97   1   0  18]
 [ 32  90   0 381   0   0]
 [  0   0   1   0  23   0]
 [  0   2  25   0  16  78]]
AxesSubplot(0.125,0.125;0.62x0.755)
```



	precision	recall	f1-score	support
0	0.71	0.69	0.70	111
1	0.80	0.78	0.79	654
2	0.60	0.66	0.63	146
3	0.75	0.76	0.75	503
4	0.59	0.96	0.73	24
5	0.76	0.64	0.70	121
accuracy			0.75	1559
macro avg	0.70	0.75	0.72	1559
weighted avg	0.75	0.75	0.75	1559

model_score- 0.7498396407953817
accuracy score- 0.7498396407953817



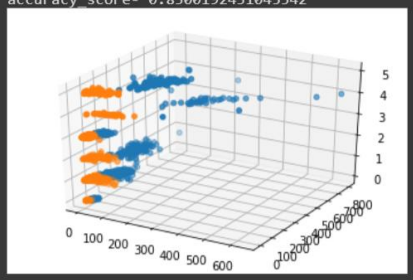
Random forest Classifier

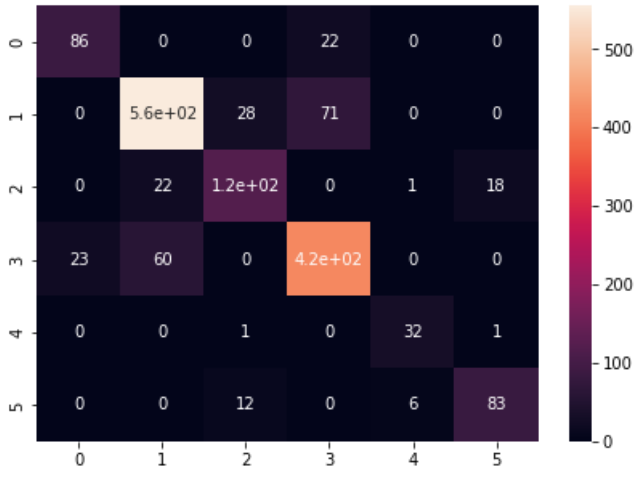
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(x_train, y_train)
y_pred_rfc = rfc.predict(x_test)
print(f'predicted_y-{y_pred_rfc} actual_y-{y_test.values}')
print(confusion_matrix(y_pred_rfc,y_test))
cm=confusion_matrix(y_pred_rfc,y_test)
plt.figure(figsize=(7,5))
sns.heatmap(cm, annot=True)
plt.show()
print(classification_report(y_pred_rfc, y_test))
print(f'model_score- {rfc.score(x_test,y_test)}')
print(f'accuracy_score- {accuracy_score(y_pred_rfc, y_test)}')
ax = plt.axes (projection ='3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['NO'],x_test['NO2'],y_pred_rfc,'black')
plt.show()
```

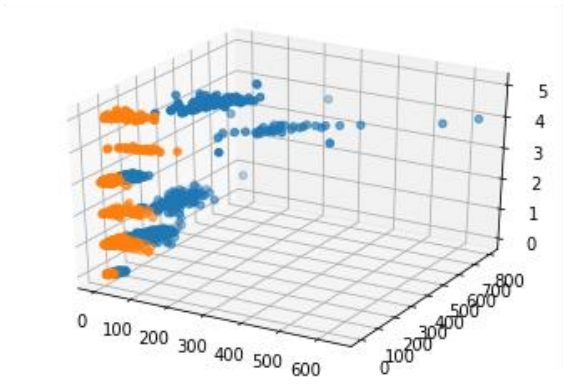
```
predicted_y-[3 4 0 ... 3 0 3] actual_y-[[3]
 [4]
 [0]
 ...
 [3]
 [0]
 [3]]
[[ 86   0   0  22   0   0]
 [  0 556  28  71   0   0]
 [  0  22 120   0   1  18]
 [ 23  60   0 417   0   0]
 [  0   0   1   0  32   1]
 [  0   0  12   0   6  83]]
```

	precision	recall	f1-score	support
0	0.79	0.80	0.79	108
1	0.87	0.85	0.86	655
2	0.75	0.75	0.75	161
3	0.82	0.83	0.83	500
4	0.82	0.94	0.88	34
5	0.81	0.82	0.82	101
accuracy			0.83	1559
macro avg	0.81	0.83	0.82	1559
weighted avg	0.83	0.83	0.83	1559

```
model_score- 0.8300192431045542
accuracy_score- 0.8300192431045542
```



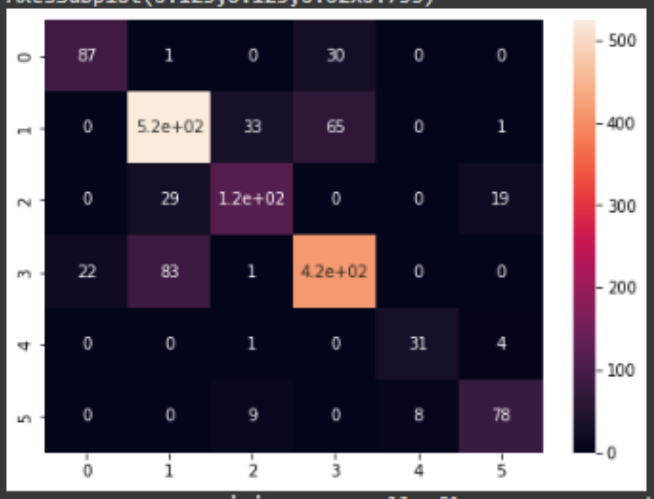




K-Nearest Neighbours

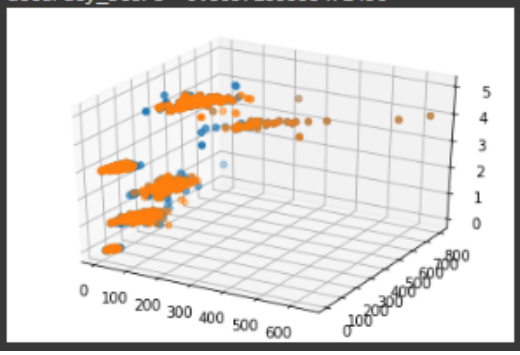
```
from sklearn.neighbors import KNeighborsClassifier
knc=KNeighborsClassifier()
knc.fit(x_train, y_train)
y_pred_knc=knc.predict(x_test)
print(f'Predicted_y{y_pred_knc[:5]} Actual_y{y_test.values[:5]}')
print(confusion_matrix(y_pred_knc,y_test))
from sklearn.metrics import confusion_matrix,classification_report, accuracy_score
cm=confusion_matrix(y_pred_knc,y_test)
plt.figure(figsize=(7,5))
print(sns.heatmap(cm, annot=True))
plt.show()
print(classification_report(y_pred_knc, y_test))
print(f'model_score- {dtc.score(x_test, y_test)} ')
print(f'accuracy_score- {accuracy_score(y_pred_knc, y_test)}')
ax = plt.axes(projection  = '3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_pred_knc, 'black')
plt.show()
```

```
Predicted_y[0 4 0 3 1] Actual_y[[3]
 [4]
 [0]
 [3]
 [1]]
[[ 87   1   0  30   0   0]
 [  0 525  33  65   0   1]
 [  0  29 117   0   0  19]
 [ 22  83   1 415   0   0]
 [  0   0   1   0  31   4]
 [  0   0   9   0   8  78]]
AxesSubplot(0.125,0.125;0.62x0.755)
```



	precision	recall	f1-score	support
0	0.80	0.74	0.77	118
1	0.82	0.84	0.83	624
2	0.73	0.71	0.72	165
3	0.81	0.80	0.81	521
4	0.79	0.86	0.83	36
5	0.76	0.82	0.79	95
accuracy			0.80	1559
macro avg	0.79	0.79	0.79	1559
weighted avg	0.80	0.80	0.80	1559

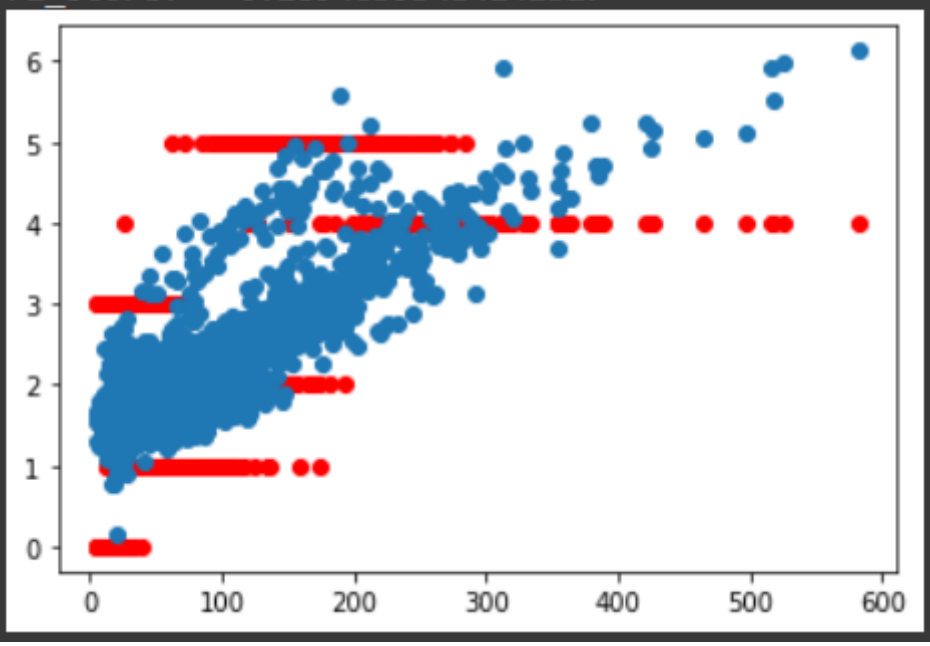
```
              precision    recall  f1-score   support

           0       0.80      0.74      0.77       118
           1       0.82      0.84      0.83       624
           2       0.73      0.71      0.72       165
           3       0.81      0.80      0.81       521
           4       0.79      0.86      0.83        36
           5       0.76      0.82      0.79        95

    accuracy                           0.80      1559
   macro avg       0.79      0.79      0.79      1559
weighted avg       0.80      0.80      0.80      1559

model_score- 0.7498396407953817
accuracy_score- 0.8037203335471456
```



Simple linear Regression

```
from sklearn.linear_model import LinearRegression
slr=LinearRegression()

slr.fit(x_train, y_train)
y_pred=slr.predict(x_test)

print(slr.score(x_train,y_train))
print(slr.score(x_test,y_test))

from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score

print("Mean Absolute Error:- ",mean_absolute_error(y_test, y_pred))
print("Mean Squared Error:- ",mean_squared_error(y_test,y_pred))
print("r2_score:- ",r2_score(y_test,y_pred))

a=slr.coef_
b=slr.intercept_


plt.scatter(x_test['PM2.5'],y_test,color='r')
plt.scatter(x_test['PM2.5'],y_pred)

plt.show()
```

```
0.1961930096682737
0.18946593484141327
Mean Absolute Error:-  1.0708636884898894
Mean Squared Error:-  1.384272714993072
r2_score:-  0.18946593484141327
```



Multi Linear Regression

```
from sklearn.linear_model import LinearRegression
mlr=LinearRegression()
```

```
[8] mlr.fit(x_train, y_train)
```

```
LinearRegression()
```

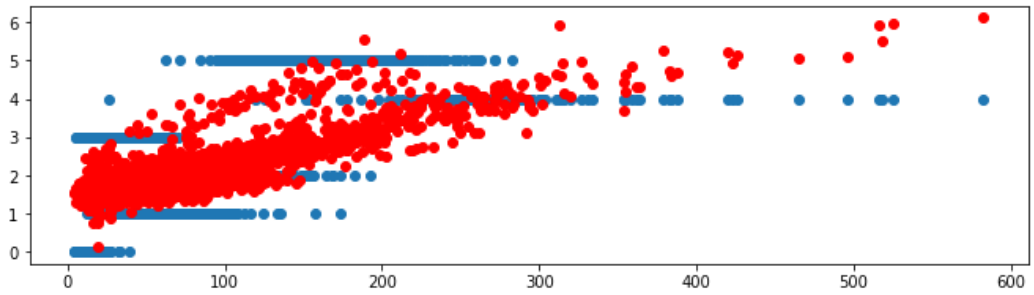
```
[9] y_pred=mlr.predict(x_test)

print(y_pred[:5],y_test.values[:5] )
```

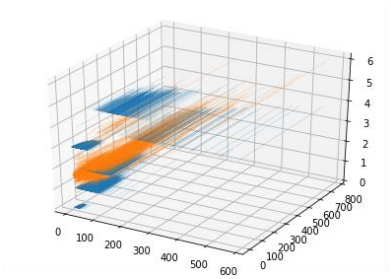
```
[1.74839761 1.64013322 1.90306688 2.35022822 1.79697298] [3 3 1 2 3]
```

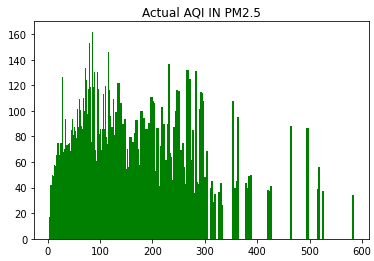
```
print(mlr.score(x_test,y_test))

from sklearn.metrics import mean_absolute_error, mean_squared_error,r2_score
print("Mean Absolute Error:- ",mean_absolute_error(y_test, y_pred))
print("Mean Squared Error:- ",mean_squared_error(y_test,y_pred))
print("r2_score:- ",r2_score(y_test,y_pred))
```

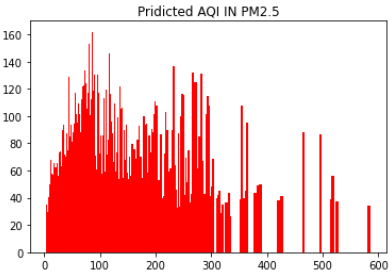
```
0.18946593484141327
Mean Absolute Error:-  1.0708636884898894
Mean Squared Error:-  1.384272714993072
r2_score:-  0.18946593484141327
```

```
plt.figure(figsize=(25,3))
plt.subplot(1,2,1)

plt.scatter(x_test['PM2.5'],y_test)

plt.scatter(x_test['PM2.5'],y_pred, color='red')

plt.show()

plt.figure(figsize=(7,5))

plt.subplot(1,2,2)

ax=plt.axes (projection='3d')

ax.bar(x_test['PM2.5'],x_test['PM10'],y_test)

ax.bar(x_test['PM2.5'],x_test['PM10'],y_pred)

plt.show()
plt.title("Actual AQI IN PM2.5")
plt.bar(x_test['PM2.5'],x_test['O3'],y_test,color='g')

plt.show()
plt.title("Pridicted AQI IN PM2.5")
plt.bar(x_test['PM2.5'],x_test['O3'],y_pred,color='r')

plt.show()
```





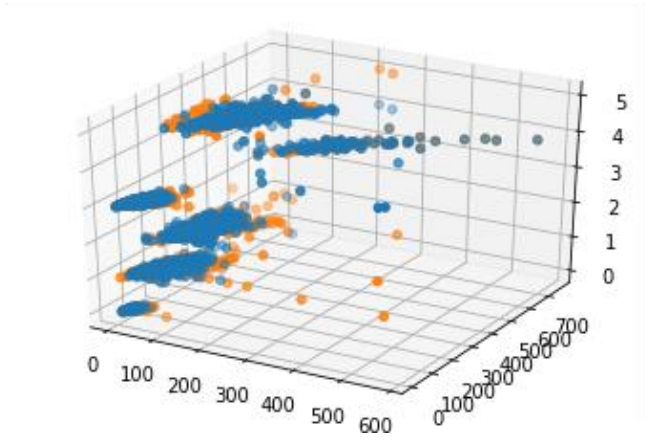




Decision Tree Regression

```
from sklearn.tree import DecisionTreeRegressor
dtr=DecisionTreeRegressor()

print(dtr. fit(x_train, y_train))

y_pred_dtr=dtr.predict(x_test)

print(y_pred_dtr[:5])
print(y_test.values[:5])

print('------accuracy score--------')
from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score
from math import sqrt

print('mean_absolute_error:-',mean_absolute_error(y_test,y_pred_dtr))
print('mean_squared_error:-', mean_squared_error(y_test,y_pred_dtr))

mse=mean_squared_error(y_test,y_pred_dtr)

print('r2_score',r2_score(y_test,y_pred_dtr))
print('MODEL SCORE', dtr.score(x_test,y_test))

print(sqrt(mse))

ax = plt.axes (projection ='3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_pred_dtr, 'red')
plt.show()
```

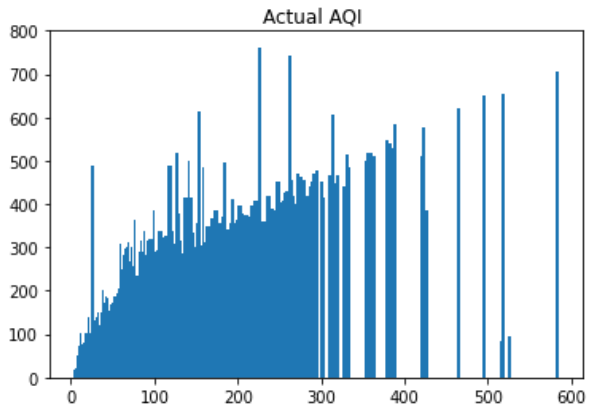
```
DecisionTreeRegressor()
[3. 3. 1. 2. 3.]
[3 3 1 2 3]
------accuracy score--------
mean_absolute_error:- 0.5558228101824013
mean_squared_error:- 1.3223090799759472
r2_score 0.22574754065395342
MODEL SCORE 0.22574754065395342
1.149916988297828
```

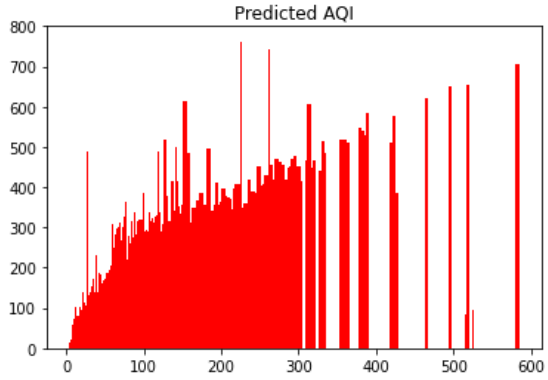


RandomForestRegressor

```
from sklearn.ensemble import RandomForestRegressor

rfr=RandomForestRegressor(n_estimators=5, max_depth=3)

rfr.fit(x_train, y_train)
y_pred_rfr=rfr.predict(x_test)
print(y_pred_rfr[:5],y_test.values[:5])

print('------accuracy score--------')

from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from math import sqrt
print('mean_absolute_error', mean_absolute_error(y_test,y_pred_rfr))

print('mean_squared_error', mean_squared_error(y_test,y_pred_rfr))

mse=mean_squared_error(y_test,y_pred_rfr)

print('r2_score',r2_score(y_test,y_pred_rfr))
print('MODEL SCORE',rfr.score(x_test, y_test))
print(sqrt(mse))
#ax = plt.axes (projection ='3d')
plt.title("Actual AQI ")
plt.bar(x_test['PM2.5'],x_test['PM10'],y_test)
plt.show()
plt.title("Predicted AQI")
plt.bar(x_test['PM2.5'],x_test['PM10'],y_pred_rfr,color='r')

plt.show()
```

```
[2.51016458 2.51016458 1.26229664 2.06206346 2.51016458] [3 3 1 2 3]
------accuracy score--------
mean_absolute_error 0.7114287654731594
mean_squared_error 0.8692705832775914
r2_score 0.4910154538513113
MODEL SCORE 0.4910154538513113
0.9323468149125579
```





K-Neighbors Regressor

```
from sklearn.neighbors import KNeighborsRegressor

knn=KNeighborsRegressor(n_neighbors=5)
knn.fit(x_train, y_train)

y_pred_knn=knn.predict(x_test)

print(y_pred_knn[:5],y_test.values[:5])

print('------accuracy score--------')

from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score
from math import sqrt

print('mean_absolute_error', mean_absolute_error(y_test,y_pred_knn))

print('mean_squared_error', mean_squared_error(y_test,y_pred_knn))
print('r2_score',r2_score(y_test, y_pred_knn))
print('MODEL SCORE', knn.score(x_test,y_test))
```

```
[3.  3.  1.8 1.4 2.6] [3 3 1 2 3]
------accuracy score--------
mean_absolute_error 0.5708558829424735
mean_squared_error 0.7983644016837042
r2_score 0.5325331945318057
MODEL SCORE 0.5325331945318057
```