##BITS F464 - Semester 1 - MACHINE LEARNING

PROJECT - MACHINE LEARNING FOR SUSTAINABLE DEVELOPMENT GOALS (SDGs)

Team number: 46

Project number : 3 (Air quality prediction)

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Id number of all students in the team:

2021A3PS1551H , 2021A7PS0372H ,2021A3PS0777H ,2021A7PS0225H,2021A8PS1475H

1. Preprocessing of Dataset

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from tqdm import tqdm

# Set a seed value for NumPy random number generator
SEED=42
np.random.seed(SEED)
```

Read Dataset

1. Upload dataset file in proejct read directory.
2. keep csv file name as 'dataset.csv'

Dataset Link

```
df = pd.read_csv('dataset.csv', decimal=",")
df.head()

         Date      Time  CO(GT)  PT08.S1(CO)  NMHC(GT)  C6H6(GT)  \
0  10/03/2004  18.00.00     2.6         1360       150      11.9
1  10/03/2004  19.00.00     2.0         1292       112       9.4
```

```
2  10/03/2004  20.00.00     2.2         1402        88        9.0
3  10/03/2004  21.00.00     2.2         1376        80        9.2
4  10/03/2004  22.00.00     1.6         1272        51        6.5

   PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)
PT08.S5(O3)  \
0           1046      166          1056      113          1692
1268
1            955      103          1174       92          1559
972
2            939      131          1140      114          1555
1074
3            948      172          1092      122          1584
1203
4            836      131          1205      116          1490
1110

      T    RH      AH
0  13.6  48.9  7.578
1  13.3  47.7  7.255
2  11.9  54.0  7.502
3  11.0  60.0  7.867
4  11.2  59.6  7.888
```

Convert Date and Time in single column for calculating AQI.

This conversion is necessary because AQI calculation depends on 24H and 8H time window.

```
# convert Date time column as Date object and also add new column
Date_time for AQI calculation
df['Date'] = pd.to_datetime(df['Date'], format='%d/%m/%Y')
df['Time'] = pd.to_datetime(df['Time'], format='%H.%M.%S').dt.time
df['Date_Time'] = pd.to_datetime(df['Date'].astype(str) + ' ' +
df['Time'].astype(str), format='%Y-%m-%d %H:%M:%S')

df = df.sort_values('Date_Time',
ascending=True).reset_index(drop=True)
df.head()

        Date      Time  CO(GT)  PT08.S1(CO)  NMHC(GT)  C6H6(GT)  \
0 2004-03-10  18:00:00     2.6         1360       150      11.9
1 2004-03-10  19:00:00     2.0         1292       112       9.4
2 2004-03-10  20:00:00     2.2         1402        88       9.0
3 2004-03-10  21:00:00     2.2         1376        80       9.2
4 2004-03-10  22:00:00     1.6         1272        51       6.5

   PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)
```

```
PT08.S5(O3)  \
0           1046      166          1056      113          1692
1268
1            955      103          1174       92          1559
972
2            939      131          1140      114          1555
1074
3            948      172          1092      122          1584
1203
4            836      131          1205      116          1490
1110

      T    RH     AH           Date_Time
0  13.6  48.9  7.578 2004-03-10 18:00:00
1  13.3  47.7  7.255 2004-03-10 19:00:00
2  11.9  54.0  7.502 2004-03-10 20:00:00
3  11.0  60.0  7.867 2004-03-10 21:00:00
4  11.2  59.6  7.888 2004-03-10 22:00:00
```

#Exploratory data analysis (EDA) Analysis data is very importend to undertand data pattern which help to build and train ML model.

```python
# shape of our dataset
# df.shape
print("No of rows in dataset:",df.shape[0])
print("No of columns in dataset:",df.shape[1])
```

```
No of rows in dataset: 9357
No of columns in dataset: 16
```

```python
# getting the dtypes of the all columns
df.dtypes
```

```
Date                 datetime64[ns]
Time                         object
CO(GT)                      float64
PT08.S1(CO)                   int64
NMHC(GT)                      int64
C6H6(GT)                    float64
PT08.S2(NMHC)                 int64
NOx(GT)                       int64
PT08.S3(NOx)                  int64
NO2(GT)                       int64
PT08.S4(NO2)                  int64
PT08.S5(O3)                   int64
T                           float64
RH                          float64
AH                          float64
Date_Time            datetime64[ns]
dtype: object
```

```
# getting the numerical estimates of all the numerical column
df.describe()
```

```
                CO(GT)  PT08.S1(CO)     NMHC(GT)     C6H6(GT)
PT08.S2(NMHC)  \
count  9357.000000  9357.000000  9357.000000  9357.000000
9357.000000
mean    -34.207524  1048.990061  -159.090093     1.865683
894.595276
std      77.657170   329.832710   139.789093    41.380206
342.333252
min    -200.000000  -200.000000  -200.000000  -200.000000    -
200.000000
25%       0.600000   921.000000  -200.000000     4.000000
711.000000
50%       1.500000  1053.000000  -200.000000     7.900000
895.000000
75%       2.600000  1221.000000  -200.000000    13.600000
1105.000000
max      11.900000  2040.000000  1189.000000    63.700000
2214.000000

           NOx(GT)  PT08.S3(NOx)      NO2(GT)  PT08.S4(NO2)
PT08.S5(O3)  \
count  9357.000000   9357.000000  9357.000000   9357.000000
9357.000000
mean    168.616971    794.990168    58.148873   1391.479641
975.072032
std     257.433866    321.993552   126.940455    467.210125
456.938184
min    -200.000000   -200.000000  -200.000000   -200.000000  -
200.000000
25%      50.000000    637.000000    53.000000   1185.000000
700.000000
50%     141.000000    794.000000    96.000000   1446.000000
942.000000
75%     284.000000    960.000000   133.000000   1662.000000
1255.000000
max    1479.000000   2683.000000   340.000000   2775.000000
2523.000000

                 T           RH           AH
count  9357.000000  9357.000000  9357.000000
mean      9.778305    39.485380     2.031145
std      43.203623    51.216145    40.955855
min    -200.000000  -200.000000  -200.000000
25%      10.900000    34.100000     6.923000
50%      17.200000    48.600000     9.768000
75%      24.100000    61.900000    12.962000
max      44.600000    88.700000    22.310000
```

Dataset insights based on data description

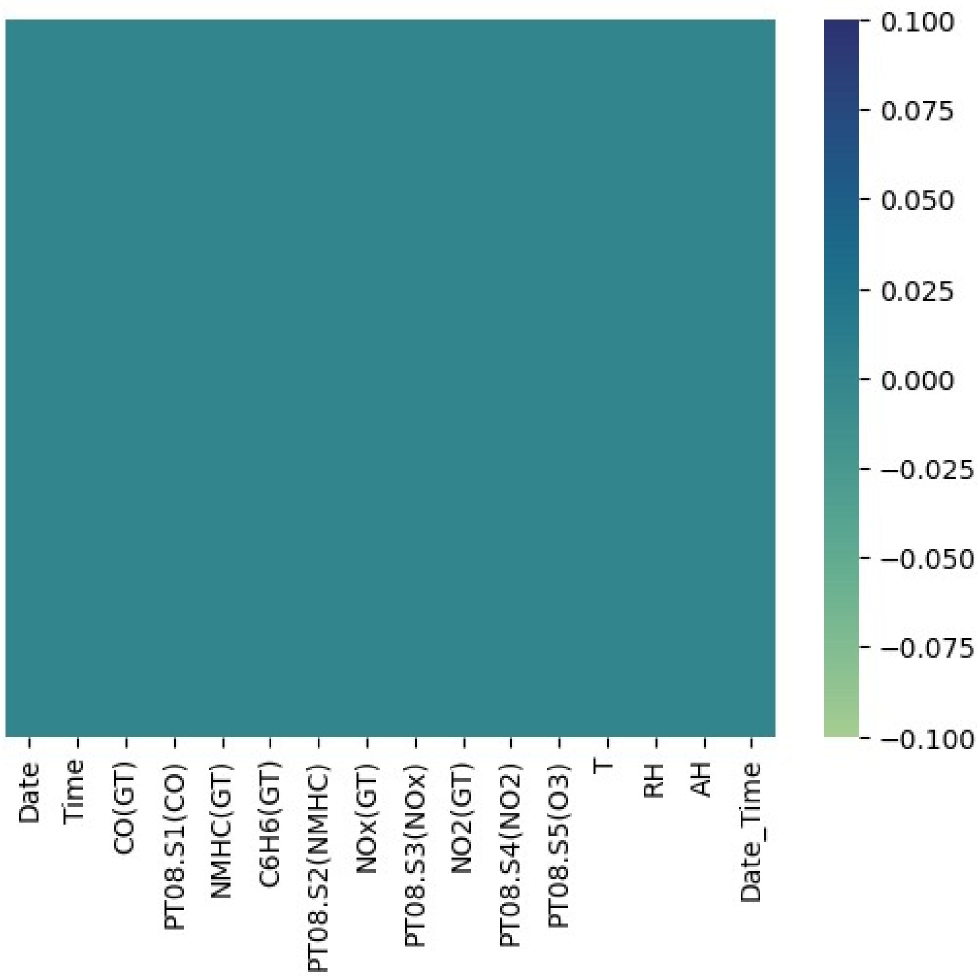
This dataset consists of 9357 entries with measurements related to air quality. The columns include various parameters such as carbon monoxide levels (CO), non-methane hydrocarbons (NMHC), benzene (C6H6), nitrogen oxides (NOx), nitrogen dioxide (NO2), and ozone (O3), among others. The data provides information on mean, standard deviation, minimum, maximum, and quartile values for each parameter. Notably, some entries have missing or invalid values represented as -200. The dataset covers a range of air quality indicators and can be used for analysis and modeling to understand the patterns and trends in air pollution.

Next step based on this data analysis

1. Need to handle missing value (None/np.na)
2. Need to handle mislabel -200 value
3. Need to handle outliner

None value and -200 handling

```
# no null values are now present in the dataset which was provided
sns.heatmap(df.isna(),yticklabels=False,cmap='crest')
plt.show()
```

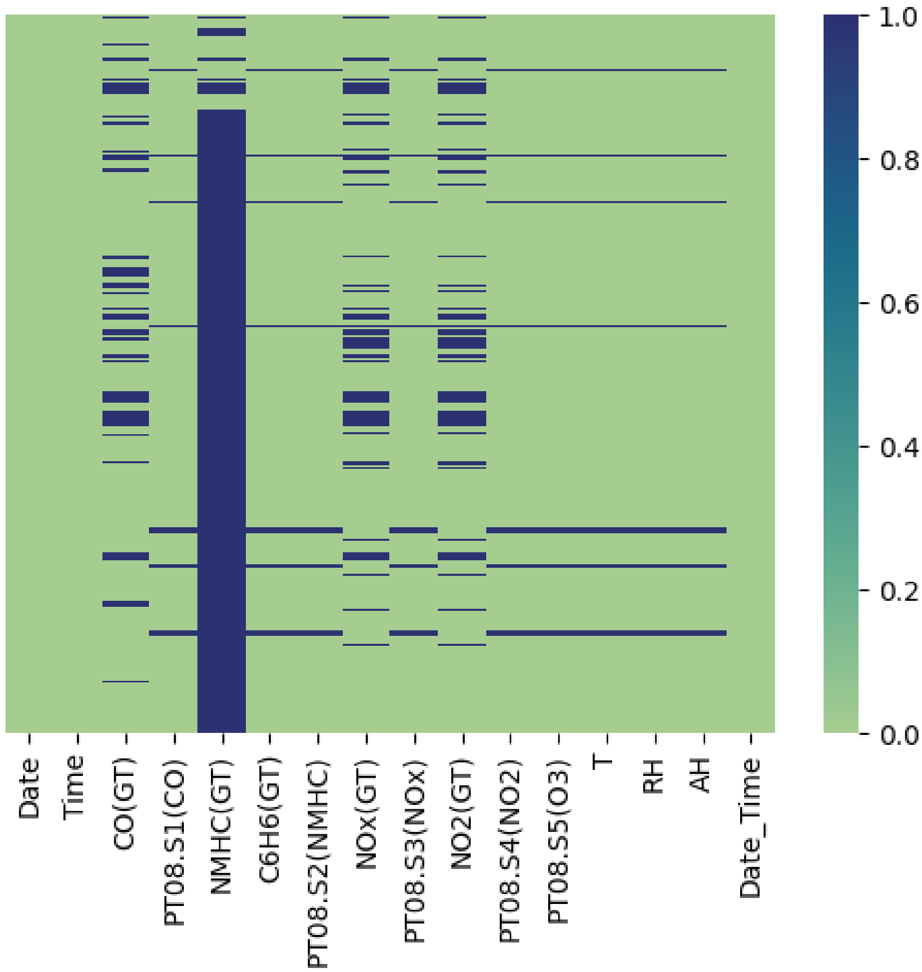


Based on this heatmap, we found there is no missing or None value. Now need to handle -200 valuee.

Step:

1. At first need to replace -200 as np.nan
2. Then generage Heat map again to insight visualized
3. After That need to take necessary steps

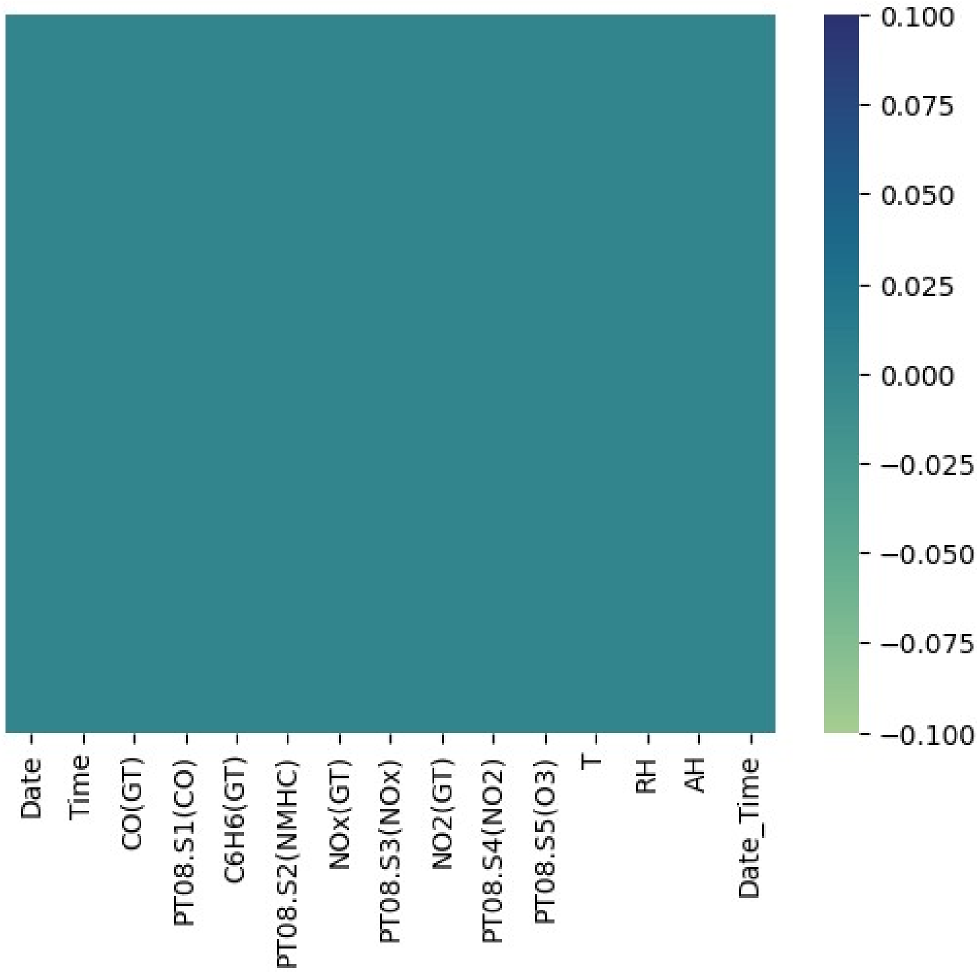
```
#first labelling -200 value as null value
df.replace(to_replace=-200,value=np.nan,inplace=True)

# heat map
sns.heatmap(df.isna(),yticklabels=False,cmap='crest')
plt.show()
```



Action

1. This heat map shows MNHC(GT) colum is mostly None or -200, Therefore we can remove this column.
2. Others columns need to full fill missing value with mean of the column value.

```
#NMHC column has a lot of null values. We can drop the column!
df.drop(columns=['NMHC(GT)'],inplace=True)

#Since the data is real valued, we should replace all the null values
with mean of each column
col = ['CO(GT)', 'PT08.S1(CO)', 'C6H6(GT)','PT08.S2(NMHC)', 'NOx(GT)',
'PT08.S3(NOx)', 'NO2(GT)', 'PT08.S4(NO2)','PT08.S5(O3)', 'T', 'RH',
'AH']

for i in col:
    df[i] = df[i].fillna(df[i].mean())

# heat map
sns.heatmap(df.isna(),yticklabels=False,cmap='crest')
plt.show()
```



So now again dataset have no missing or misslebel data.

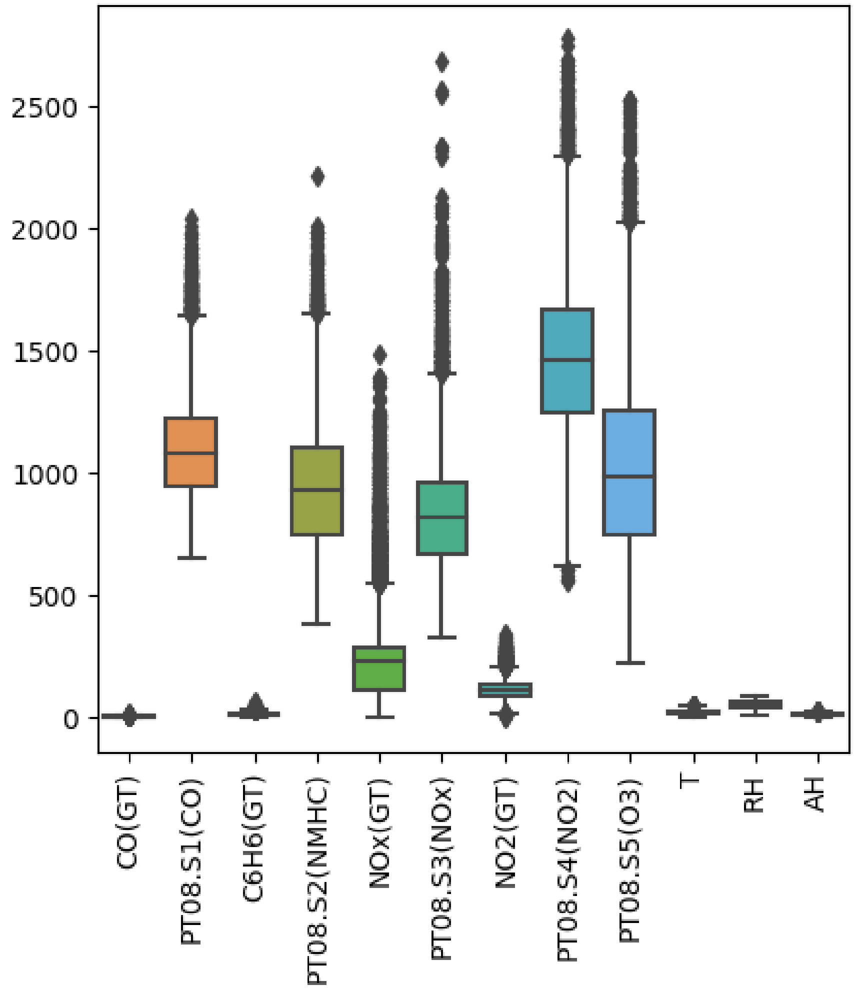
Now need to handle outliers

Handling Outliers

Box plot help us to understand outliers values and pattern Step:

1. Getting the quartile one and quartile 3 values of each column
2. if the values fall behind Q1 - (1.5 * IQR) or above Q3 + 1.5*IQR, then it is been defined as outlier
3. Replacing all the outliers using the median of that particular column

```
# plotting a boxplot
plt.figure(figsize=(5,5))
sns.boxplot(data=df)
plt.xticks(rotation='vertical')
plt.show()
```

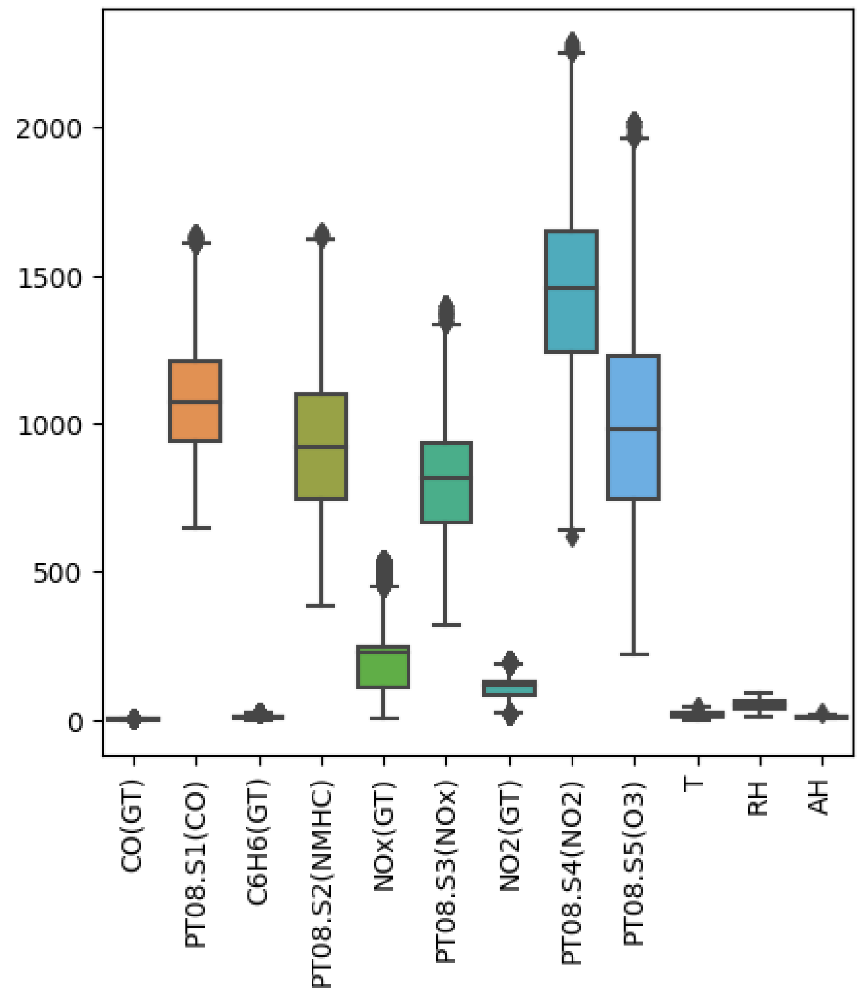



```
# getting the quartile one and quartile 3 values of each column
Q1 = df[col].quantile(0.25)
Q3 = df[col].quantile(0.75)
# finally calculating the interquartile range IQR
IQR = Q3 - Q1

# if the values fall behind Q1 - (1.5 * IQR) or above Q3 + 1.5*IQR,
#then it is been defined as outlier
((df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR))).sum()

CO(GT)           454
PT08.S1(CO)      145
C6H6(GT)         286
PT08.S2(NMHC)     91
NOx(GT)          778
PT08.S3(NOx)     278
NO2(GT)          380
PT08.S4(NO2)     131
PT08.S5(O3)      131
```

```
T                 10
RH                 0
AH                 7
dtype: int64

mask = (df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR))
mask.head()

   CO(GT)  PT08.S1(CO)  C6H6(GT)  PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)
\
0   False        False     False          False    False         False

1   False        False     False          False    False         False

2   False        False     False          False    False         False

3   False        False     False          False    False         False

4   False        False     False          False    False         False


   NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)      T     RH     AH
0    False         False        False  False  False  False
1    False         False        False  False  False  False
2    False         False        False  False  False  False
3    False         False        False  False  False  False
4    False         False        False  False  False  False

# now replacing all the outliers using the median of that particular
column
for i in mask.columns:
    df[i].astype('float')
    temp = df[i].median()
    df.loc[mask[i], i] = temp

# outliers are now being handled and are replaced with that column's
median value
((df[col] < (Q1 - 1.5 * IQR)) | (df[col] > (Q3 + 1.5 * IQR))).sum()

CO(GT)           0
PT08.S1(CO)      0
C6H6(GT)         0
PT08.S2(NMHC)    0
NOx(GT)          0
PT08.S3(NOx)     0
NO2(GT)          0
PT08.S4(NO2)     0
PT08.S5(O3)      0
T                0
RH               0
```

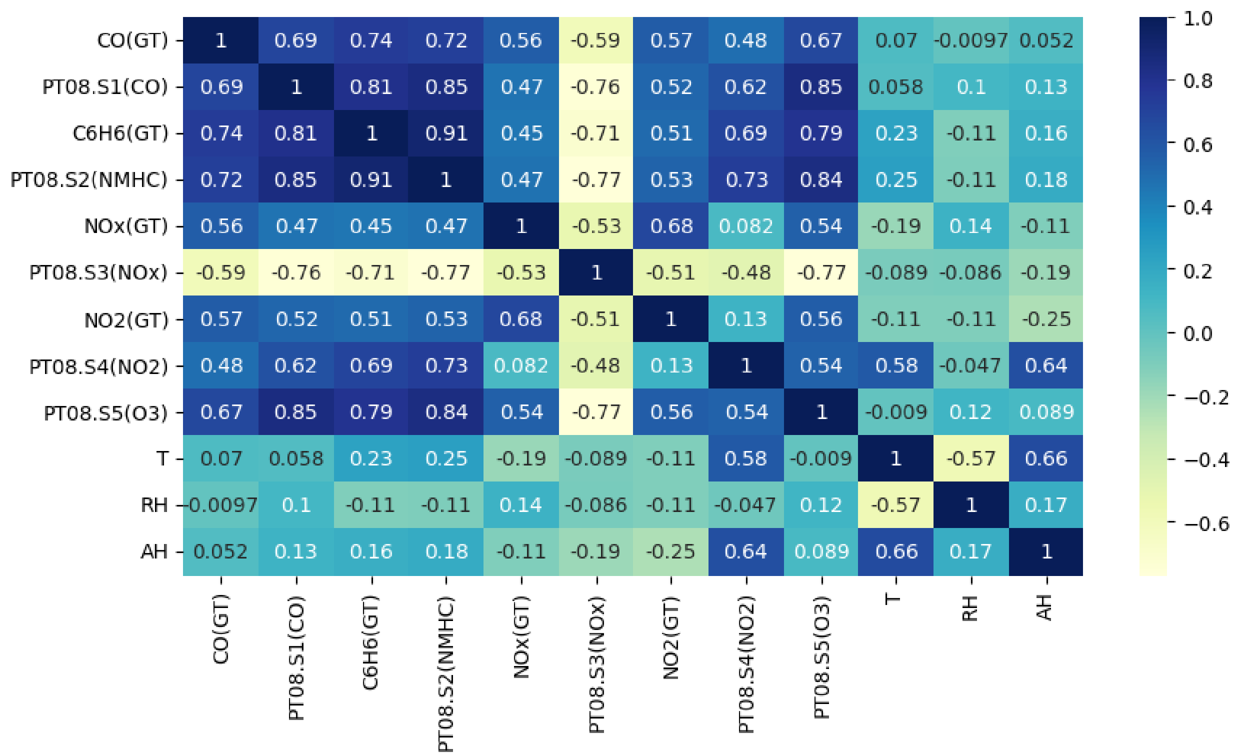
```
AH                  0
dtype: int64
```

```
plt.figure(figsize=(5,5))
sns.boxplot(data=df)
plt.xticks(rotation='vertical')
plt.show()
```



Find correlations between attributes

```
plt.figure(figsize=(10,5))
sns.heatmap(df[col].corr(),cmap='YlGnBu',annot=True)
plt.show()
```



Calculating AQI

The Air Quality Index (AQI) is a numerical scale used to convey the level of air pollution and its potential health effects to the public. The calculation involves several steps:

1. Pollutant Selection: Choose specific air pollutants to assess, such as particulate matter (PM2.5 and PM10), ground-level ozone (O3), sulfur dioxide (SO2), nitrogen dioxide (NO2), and carbon monoxide (CO).

2. Concentration Measurement: Obtain the concentrations of selected pollutants from monitoring stations. These concentrations should be in standardized units like micrograms per cubic meter ($\mu g/m^3$) or parts per million (ppm).

3. Sub-Index Calculation: For each pollutant, calculate a sub-index using a formula that involves the pollutant concentration, breakpoint values, and the AQI range for that pollutant. Breakpoint values represent concentration ranges associated with different AQI categories.

4. Overall AQI Determination: Identify the highest sub-index among all pollutants as the overall AQI. This is crucial because the air quality is often dominated by the pollutant with the highest concentration.

5. Interpretation of AQI: Match the overall AQI to predefined categories such as Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and

Hazardous. Each category corresponds to a range of AQI values and indicates the level of health concern associated with the air quality.

More Detaisl Here

##Step 1,2:

Calculate 24H and 8H time window's individual particals pollutant concentration

```
df['CO_avg'] = df.rolling(window='8H', on='Date_Time', min_periods =
1)['CO(GT)'].mean()
df['O3_avg'] = df.rolling(window='8H', on='Date_Time', min_periods =
1)['PT08.S5(O3)'].mean()
df['NO2_avg'] = df.rolling(window='24H', on='Date_Time', min_periods =
16)['NO2(GT)'].mean()
df['NOx_avg'] = df.rolling(window='24H', on='Date_Time', min_periods =
16)['PT08.S3(NOx)'].mean()
```

Step 3: Sub-index calculation

CO (Carbon Monoxide)

CO is measured in mg / m3 (milligrams per cubic meter of air). The predefined groups are defined in the function below:

```
def calculate_aqi_for_co(co_concentration):
    if co_concentration <= 4.4:
        IAQI_low, IAQI_high = 0, 50
        Conc_low, Conc_high = 0, 4.4
    elif 4.5 <= co_concentration <= 9.4:
        IAQI_low, IAQI_high = 51, 100
        Conc_low, Conc_high = 4.5, 9.4
    elif 9.5 <= co_concentration <= 12.4:
        IAQI_low, IAQI_high = 101, 150
        Conc_low, Conc_high = 9.5, 12.4
    elif 12.5 <= co_concentration <= 15.4:
        IAQI_low, IAQI_high = 151, 200
        Conc_low, Conc_high = 12.5, 15.4
    elif 15.5 <= co_concentration <= 30.4:
        IAQI_low, IAQI_high = 201, 300
        Conc_low, Conc_high = 15.5, 30.4
    else:
        IAQI_low, IAQI_high = 301, None
        Conc_low, Conc_high = 30.5, None

    if IAQI_high is not None:
```

```
        aqi = ((IAQI_high - IAQI_low) / (Conc_high - Conc_low)) *
(co_concentration - Conc_low) + IAQI_low
    else:
        aqi = IAQI_low

    return round(aqi)

df["CO_sub_index"] = df["CO_avg"].apply(lambda x:
calculate_aqi_for_co(x))
```

O3 (Ozone or Trioxygen)

O3 is measured in ug / m3 (micrograms per cubic meter of air). The predefined groups are defined in the function below:

```
def calculate_aqi_for_o3(o3_concentration):
    if o3_concentration <= 50:
        IAQI_low, IAQI_high = 0, 50
        Conc_low, Conc_high = 0, 50
    elif 51 <= o3_concentration <= 100:
        IAQI_low, IAQI_high = 51, 100
        Conc_low, Conc_high = 51, 100
    elif 101 <= o3_concentration <= 168:
        IAQI_low, IAQI_high = 101, 150
        Conc_low, Conc_high = 101, 168
    elif 169 <= o3_concentration <= 208:
        IAQI_low, IAQI_high = 151, 200
        Conc_low, Conc_high = 169, 208
    elif 209 <= o3_concentration <= 748:
        IAQI_low, IAQI_high = 201, 300
        Conc_low, Conc_high = 209, 748
    else:
        IAQI_low, IAQI_high = 301, None
        Conc_low, Conc_high = 749, None

    if IAQI_high is not None:
        aqi = ((IAQI_high - IAQI_low) / (Conc_high - Conc_low)) *
(o3_concentration - Conc_low) + IAQI_low
    else:
        aqi = IAQI_low

    return round(aqi)

df["O3_sub_index"] = df["O3_avg"].apply(lambda x:
calculate_aqi_for_o3(x))
```

NO2 and NOx (Any Nitric x-oxide)

NOx is measured in ppb (parts per billion). The predefined groups are defined in the function below:

```
def calculate_aqi_for_no2(no2_concentration):
    if no2_concentration <= 40:
        IAQI_low, IAQI_high = 0, 50
        Conc_low, Conc_high = 0, 40
    elif 41 <= no2_concentration <= 80:
        IAQI_low, IAQI_high = 51, 100
        Conc_low, Conc_high = 41, 80
    elif 81 <= no2_concentration <= 180:
        IAQI_low, IAQI_high = 101, 200
        Conc_low, Conc_high = 81, 180
    elif 181 <= no2_concentration <= 280:
        IAQI_low, IAQI_high = 201, 300
        Conc_low, Conc_high = 181, 280
    elif 281 <= no2_concentration <= 400:
        IAQI_low, IAQI_high = 301, 400
        Conc_low, Conc_high = 281, 400
    else:
        IAQI_low, IAQI_high = 401, None
        Conc_low, Conc_high = 401, None

    if IAQI_high is not None:
        aqi = ((IAQI_high - IAQI_low) / (Conc_high - Conc_low)) * 
(no2_concentration - Conc_low) + IAQI_low
    else:
        aqi = IAQI_low

    return round(aqi)

df["NO2_sub_index"] = df["NO2_avg"].apply(lambda x: 
calculate_aqi_for_no2(x))
df["NOx_sub_index"] = df["NOx_avg"].apply(lambda x: 
calculate_aqi_for_no2(x))
```

Step 4, 5:

Label based on this documentation

0-50: This range defines air quality as good as it shows minimal or no impact on health.

51-100: This is a satisfactory air quality range and it can show effects such as breathing difficulty in sensitive groups.

101-200: The range shows moderate air quality with impacts such as breathing discomfort for children and elderly people, and people already suffering from lung disorders and heart disease.

201-300: AQI falling in this range communicates that the air quality is poor and shows health effects on people when exposed for the long term. People already suffering from heart diseases can experience discomfort from short exposure.

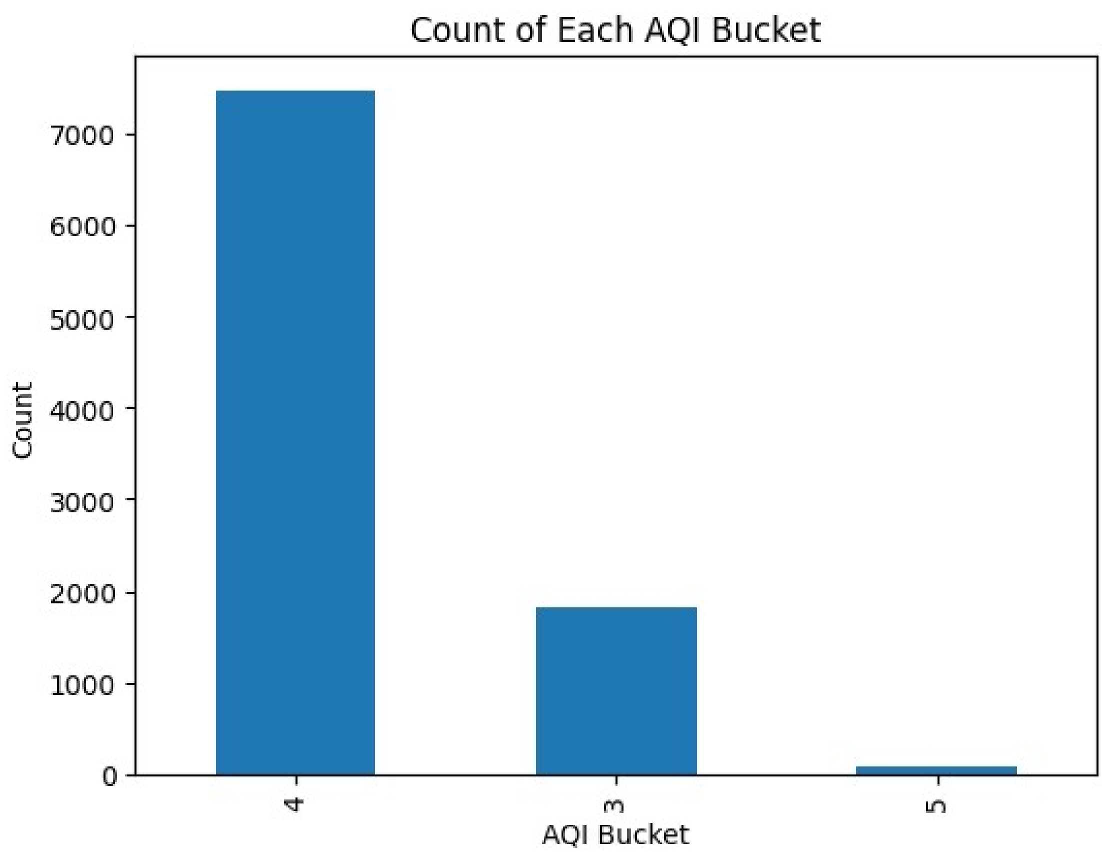
301-400: This range shows very poor air quality and causes respiratory illness for a longer duration of exposure.

401-500: This is the severe range of AQI causing health impacts to normal and diseased people. It also causes severe health impacts on sensitive groups.

```
AQI_label_map = {
    'Good': 0,
    'Satisfactory': 1,
    'Moderate': 2,
    'Poor': 3,
    'Very Poor': 4,
    'Severe': 5
}

AQI_index_map = {
    0: 'Good',
    1: 'Satisfactory',
    2: 'Moderate',
    3: 'Poor',
    4: 'Very Poor',
    5: 'Severe'
}

## AQI bucketing
def get_AQI_bucket(x):
    if x <= 50:
        return AQI_label_map["Good"]
    elif x <= 100:
        return AQI_label_map["Satisfactory"]
    elif x <= 200:
        return AQI_label_map["Moderate"]
    elif x <= 300:
        return AQI_label_map["Poor"]
    elif x <= 400:
        return AQI_label_map["Very Poor"]
    elif x > 400:
        return AQI_label_map["Severe"]
    else:
        return np.NaN


df["Checks"] = (df["CO_sub_index"] > 0).astype(int) + \
                (df["O3_sub_index"] > 0).astype(int) + \
```

```
                (df["NO2_sub_index"] > 0).astype(int) + \
                (df["NOx_sub_index"] > 0).astype(int)


df["AQI_calculated"] = round(df[["CO_sub_index", "O3_sub_index",
"NO2_sub_index"]].max(axis = 1))
# df["AQI_calculated"] = round(df[["CO_sub_index", "O3_sub_index",
"NO2_sub_index", "NOx_sub_index"]].max(axis = 1))

df.loc[df.Checks < 3, "AQI_calculated"] = np.NaN

df["AQI_bucket_calculated"] = df["AQI_calculated"].apply(lambda x:
get_AQI_bucket(x))
df[~df.AQI_calculated.isna()].head()

        Date      Time  CO(GT)  PT08.S1(CO)  C6H6(GT)  PT08.S2(NMHC)
NOx(GT)  \
0 2004-03-10  18:00:00     2.6       1360.0      11.9         1046.0
166.0
1 2004-03-10  19:00:00     2.0       1292.0       9.4          955.0
103.0
2 2004-03-10  20:00:00     2.2       1402.0       9.0          939.0
131.0
3 2004-03-10  21:00:00     2.2       1376.0       9.2          948.0
172.0
4 2004-03-10  22:00:00     1.6       1272.0       6.5          836.0
131.0

   PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)  ...       O3_avg  NO2_avg
NOx_avg  \
0        1056.0    113.0        1692.0  ...  1268.000000      NaN
NaN
1        1174.0     92.0        1559.0  ...  1120.000000      NaN
NaN
2        1140.0    114.0        1555.0  ...  1104.666667      NaN
NaN
3        1092.0    122.0        1584.0  ...  1129.250000      NaN
NaN
4        1205.0    116.0        1490.0  ...  1125.400000      NaN
NaN

   CO_sub_index O3_sub_index  NO2_sub_index  NOx_sub_index  Checks  \
0            30          301            401            401       4
1            26          301            401            401       4
2            26          301            401            401       4
3            26          301            401            401       4
4            24          301            401            401       4

   AQI_calculated  AQI_bucket_calculated
0           401.0                      5
```

```
1           401.0                      5
2           401.0                      5
3           401.0                      5
4           401.0                      5

[5 rows x 26 columns]

df = df[~df.AQI_bucket_calculated.isna()]
print(df['AQI_bucket_calculated'].isna().sum())
print(df.shape)

0
(9357, 26)

value_counts = df['AQI_bucket_calculated'].value_counts()

# Plot the counts
value_counts.plot(kind='bar')
plt.title('Count of Each AQI Bucket')
plt.xlabel('AQI Bucket')
plt.ylabel('Count')
plt.show()
```



Summary of AQA

1. We found most of the data set have label 4 which mean, most of the rows represent Very Poor Air quality. After that next lavel is 3 that mean Poor air index and some are Severe index.

2. Other's 3 label are missing in this dataset. Thefore we need to make model wich will predict this 3 label.

Training and Test data selecting

```
data_df = df[['CO(GT)', 'PT08.S1(CO)', 'C6H6(GT)', 'PT08.S2(NMHC)',
'NOx(GT)', 'PT08.S3(NOx)',
              'NO2(GT)', 'PT08.S4(NO2)', 'PT08.S5(O3)', 'T', 'RH',
'AH', 'AQI_bucket_calculated']]

data_df.head()
```

```
   CO(GT)  PT08.S1(CO)  C6H6(GT)  PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)
\
0     2.6       1360.0      11.9         1046.0    166.0        1056.0

1     2.0       1292.0       9.4          955.0    103.0        1174.0

2     2.2       1402.0       9.0          939.0    131.0        1140.0

3     2.2       1376.0       9.2          948.0    172.0        1092.0

4     1.6       1272.0       6.5          836.0    131.0        1205.0


   NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)     T    RH      AH  \
0    113.0        1692.0       1268.0  13.6  48.9  7.578
1     92.0        1559.0        972.0  13.3  47.7  7.255
2    114.0        1555.0       1074.0  11.9  54.0  7.502
3    122.0        1584.0       1203.0  11.0  60.0  7.867
4    116.0        1490.0       1110.0  11.2  59.6  7.888

   AQI_bucket_calculated
0                      5
1                      5
2                      5
3                      5
4                      5
```

As we have most of the dataset label is 3, so this is imblance dataset. Therefore we must need to split dataset based on label value nor random value.

Here, iterate each label and split 80% for train and 20% data for test. So that both test and train have all 3 labels

```
np.random.seed(100)
# Normalize data

# data_df =  data_df/ data_df.abs().max()

# Randomize the rows
df_randomized = data_df.sample(frac=1, random_state=42)  # Set a
random_state for reproducibility
train_ratio = 0.8

# Assuming your target column is named 'AQI_bucket_calculated'
X = df_randomized.drop(columns=['AQI_bucket_calculated'])
y = df_randomized['AQI_bucket_calculated']

# Get unique levels present in the data
unique_levels = y.unique()

# Initialize empty DataFrames for train and test sets
train_set = pd.DataFrame()
test_set = pd.DataFrame()

# Loop through each level and split data based on level if available
for level in unique_levels:
    level_data = df_randomized[y == level]

    # Calculate the number of samples to include in the training set
    train_size_level = int(train_ratio * len(level_data))

    # Split the level_data into train and test sets
    train_level, test_level = level_data.iloc[:train_size_level],
level_data.iloc[train_size_level:]

    # Append the level-specific splits to the overall train and test
sets
    # Concatenate the level-specific splits to the overall train and
test sets
    train_set = pd.concat([train_set, train_level])
    test_set = pd.concat([test_set, test_level])

# Shuffle the train and test sets to ensure randomness
train_set = train_set.sample(frac=1, random_state=42)
test_set = test_set.sample(frac=1, random_state=42)
```

```
# Verify the distribution of levels in the train and test sets
print("Train Set Distribution:")
print(train_set['AQI_bucket_calculated'].value_counts())

print("\nTest Set Distribution:")
print(test_set['AQI_bucket_calculated'].value_counts())
```

```
Train Set Distribution:
4    5968
3    1456
5      60
Name: AQI_bucket_calculated, dtype: int64

Test Set Distribution:
4    1492
3     365
5      16
Name: AQI_bucket_calculated, dtype: int64
```

One hot encoding for categorial classfication

```
np.random.seed(100)

X_train = train_set.drop(['AQI_bucket_calculated'], axis=1)
y_train = train_set[['AQI_bucket_calculated']]-3 # -3 for makeing 3-0,
4-1, 5-2 beacuse we have only this label.
# print(y_train.head())
y_train_onehot = pd.get_dummies(y_train,
columns=['AQI_bucket_calculated'], prefix='AQI')



y_train_onehot = y_train_onehot.values

print(X_train.shape)
print(y_train_onehot.shape)

X_test = test_set.drop(['AQI_bucket_calculated'], axis=1)
y_test = test_set[['AQI_bucket_calculated']] -3 # # -3 for makeing 3-
0, 4-1, 5-2 beacuse we have only this label.

y_test_onehot = pd.get_dummies(y_test,
columns=['AQI_bucket_calculated'], prefix='AQI')
# for col in range(3):
#     y_test_onehot[f'AQI_{col}'] = 0
# y_test_onehot = y_test_onehot[sorted(y_test_onehot.columns)]

y_test_onehot = y_test_onehot.values

#Normalize_data between -1 to 1
```

```
X_train =  X_train/ X_train.abs().max()
X_test =  X_test/ X_test.abs().max()

print(X_test.shape)
print(y_test_onehot.shape)
```

```
(7484, 12)
(7484, 3)
(1873, 12)
(1873, 3)
```

Accuracy matrix

```
def get_accurcy_matrix(y_pred_labels, y_true_labels):
    # Calculate classification metrics
    accuracy = np.mean(y_pred_labels == y_true_labels)

    # Calculate confusion matrix
    confusion_matrix = np.zeros((6, 6))
    for true_label, pred_label in zip(y_true_labels, y_pred_labels):
        confusion_matrix[true_label, pred_label] += 1

    # Calculate precision, recall, and F1 score for each class
    precision = np.zeros(6)
    recall = np.zeros(6)
    f1_score = np.zeros(6)

    for i in range(6):
        tp = confusion_matrix[i, i]
        fp = np.sum(confusion_matrix[:, i]) - tp
        fn = np.sum(confusion_matrix[i, :]) - tp

        # Handle zero denominators
        precision[i] = tp / (tp + fp) if (tp + fp) != 0 else 0
        recall[i] = tp / (tp + fn) if (tp + fn) != 0 else 0
        f1_score[i] = 2 * (precision[i] * recall[i]) / (precision[i] +
recall[i]) if (precision[i] + recall[i]) != 0 else 0

    # Average precision, recall, and F1 score over all classes
    avg_precision = np.mean([p for p in precision if p !=0])
    avg_recall = np.mean([r for r in recall if r!=0])
    avg_f1_score = np.mean([f for f in f1_score if f !=0])

    # Print or use the classification metrics as needed
    print()
    print(f"Accuracy: {accuracy}")
    print(f"Average Precision: {avg_precision}")
    print(f"Average Recall: {avg_recall}")
```

```
    print(f"Average F1 Score: {avg_f1_score}")

    return accuracy, avg_precision, avg_recall, avg_f1_score
```

2. ML Model 1

ANN

```
class ANN:
    def __init__(self, input_size, hidden_size, output_size):
        # Initialize weights and biases
        np.random.seed(100)
        self.weights_input_hidden = np.random.randn(input_size,
hidden_size)
        self.bias_hidden = np.zeros((1, hidden_size))
        self.weights_hidden_output = np.random.randn(hidden_size,
output_size)
        self.bias_output = np.zeros((1, output_size))

    def softmax(self, x):
        exp_values = np.exp(x - np.max(x, axis=1, keepdims=True))
        return exp_values / np.sum(exp_values, axis=1, keepdims=True)

    def softmax_derivative(self, x):
        # Calculate the softmax function
        softmax_output = self.softmax(x)

        # Calculate the Jacobian matrix (derivative of softmax with
respect to its input)
        jac_matrix = softmax_output[:, :, np.newaxis] *
(np.eye(softmax_output.shape[1])[np.newaxis, :, :] - softmax_output[:,
np.newaxis, :])

        return jac_matrix

    def fit(self, X, y, epochs=1000, learning_rate=0.01):
        for epoch in tqdm(range(epochs)):
            # Forward pass
            hidden_layer_input = np.dot(X, self.weights_input_hidden)
+ self.bias_hidden
            hidden_layer_output = self.softmax(hidden_layer_input)
            output_layer_input = np.dot(hidden_layer_output,
self.weights_hidden_output) + self.bias_output
            predicted_output = self.softmax(output_layer_input)

            # Backward pass
            error = y - predicted_output
```

```
            # Update weights and biases
            self.weights_hidden_output +=
hidden_layer_output.T.dot(error) * learning_rate
            self.bias_output += np.sum(error, axis=0, keepdims=True) *
learning_rate

            self.weights_input_hidden +=
X.T.dot((error.dot(self.weights_hidden_output.T)) *
np.sum(self.softmax_derivative(hidden_layer_output), axis=1)) *
learning_rate
            self.bias_hidden +=
np.sum((error.dot(self.weights_hidden_output.T)) *
np.sum(self.softmax_derivative(hidden_layer_output), axis=1), axis=0,
keepdims=True) * learning_rate

    def predict(self, X):
        # Forward pass for prediction
        hidden_layer_input = np.dot(X, self.weights_input_hidden) +
self.bias_hidden
        hidden_layer_output = self.softmax(hidden_layer_input)
        output_layer_input = np.dot(hidden_layer_output,
self.weights_hidden_output) + self.bias_output
        predicted_output = self.softmax(output_layer_input)

        return predicted_output

    def calculate_metrics(self, X_test, y_test):
        y_pred_prob = self.predict(X_test)

        # Convert probabilities to class labels
        y_pred_labels = np.argmax(y_pred_prob, axis=1)
        y_true_labels = np.argmax(y_test, axis=1)

        return get_accurcy_matrix(y_pred_labels, y_true_labels)

ann_model = ANN(input_size=X_train.shape[1], hidden_size=2,
output_size=3)
ann_model.fit(X_train.to_numpy(), y_train_onehot, epochs=12,
learning_rate=0.00001)

ann_model_accuracy, ann_model_precision, ann_model_recall,
ann_model_f1_score = ann_model.calculate_metrics(
    X_test.to_numpy(), y_test_onehot
)
```

```
100%|██████████| 12/12 [00:00<00:00, 121.37it/s]
```

```
Accuracy: 0.6721836625734117
Average Precision: 0.4782637180797496
```

```
Average Recall: 0.48296668992618164
Average F1 Score: 0.48054423861829154
```

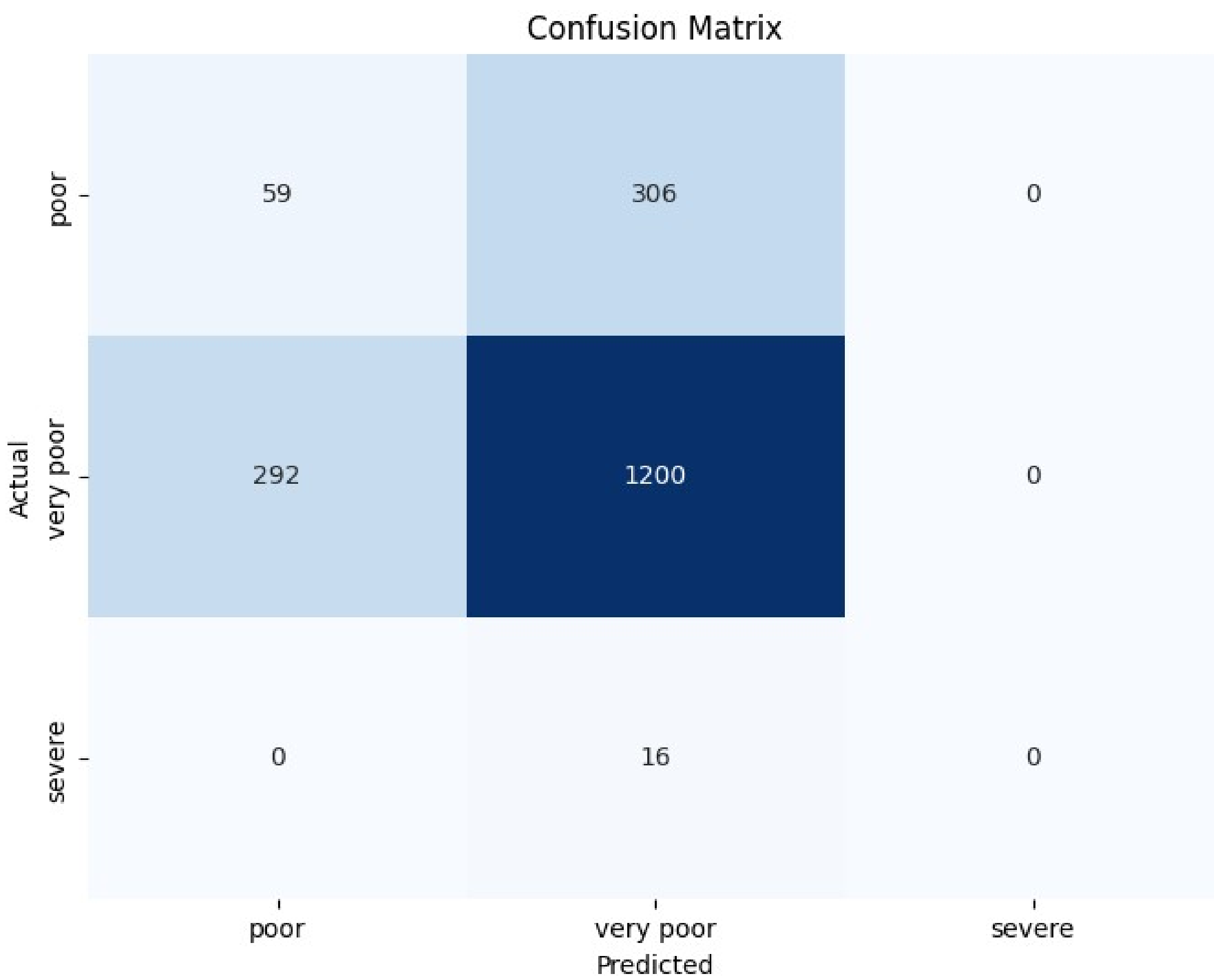
Evaluation model

```
X_test_temp = X_test.to_numpy()
X_test_for_print = X_test_temp[0:10]
y_test_onehot_for_print = y_test_onehot[0:10]

for x,y in zip(X_test_for_print, y_test_onehot_for_print):
    pred  = ann_model.predict(x)
    pred_aqi_index = np.argmax(pred) + 3
    actual_aqi_index = np.argmax(y) + 3

    print(f"Actual AQI Index: {AQI_index_map[actual_aqi_index]} ->
Predicted AQI Index: {AQI_index_map[pred_aqi_index]}")
```

```
Actual AQI Index: Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Poor
```

```
preds = ann_model.predict(X_test)
preds = np.argmax(preds, axis=1)
actuals = np.argmax(y_test_onehot, axis=1)


# Define your class labels and their corresponding names
labels = [0, 1, 2]
class_names = ['poor', 'very poor', 'severe']

# Compute confusion matrix using NumPy
conf_matrix = np.zeros((len(labels), len(labels)), dtype=int)

for actual, pred in zip(actuals, preds):
    conf_matrix[actual, pred] += 1

conf_df = pd.DataFrame(conf_matrix, index=class_names,
columns=class_names)

# Visualize the confusion matrix using seaborn and matplotlib
plt.figure(figsize=(8, 6))
```

```
sns.heatmap(conf_df, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Summary:

Row Labels (Actual Classes): The rows represent the actual classes.

Column Labels (Predicted Classes): The columns represent the predicted classes.

In the cell at the intersection of the "poor" row and "poor" column (top-left), there are 59 instances where both the actual and predicted classes are "poor."

In the cell at the intersection of the "very poor" row and "very poor" column (center), there are 1200 instances where both the actual and predicted classes are "very poor."

In the cell at the intersection of the "severe" row and "severe" column (bottom-right), there are 0 instances where both the actual and predicted classes are "severe." Notice dataset have only

16 Sever class, for only this small number all are predicted as Very poor because of imblance data.

3. ML Model 2

KNN

```
import numpy as np

class KNN:
    def __init__(self, k=3):
        np.random.seed(100)
        self.k = k

    def fit(self, X_train, y_train):
        self.X_train = X_train
        self.y_train = y_train

    def predict(self, X_test, verbose=True):
        predictions = []
        for x in tqdm(X_test, disable=not verbose):
            predictions.append(self._predict(x))
        return np.array(predictions)

    def _predict(self, x):
        # Calculate distances between x and all examples in the
training set
        distances = [np.linalg.norm(x - x_train) for x_train in
self.X_train]

        # Get indices of k-nearest training data points
        k_neighbors_indices = np.argsort(distances)[:self.k]

        # Get the labels of the k-nearest training data points
        k_neighbor_labels = [self.y_train[i] for i in
k_neighbors_indices]

        # Return the most common class label among the k-nearest
neighbors
        most_common = np.bincount(k_neighbor_labels).argmax()
        return most_common

    def calculate_metrics(self, X_test, y_test):
        y_pred = self.predict(X_test)

        y_pred_labels = np.array(y_pred)
        y_true_labels = np.array(y_test)
```

```python
        return get_accurcy_matrix(y_pred_labels, y_true_labels)


knn_model = KNN(k=3)
knn_model.fit(X_train.to_numpy(), y_train.to_numpy().flatten())
knn_model_accuracy, knn_model_precision, knn_model_recall,
knn_model_f1_score = knn_model.calculate_metrics(X_test.to_numpy(),
y_test.to_numpy().flatten())
```

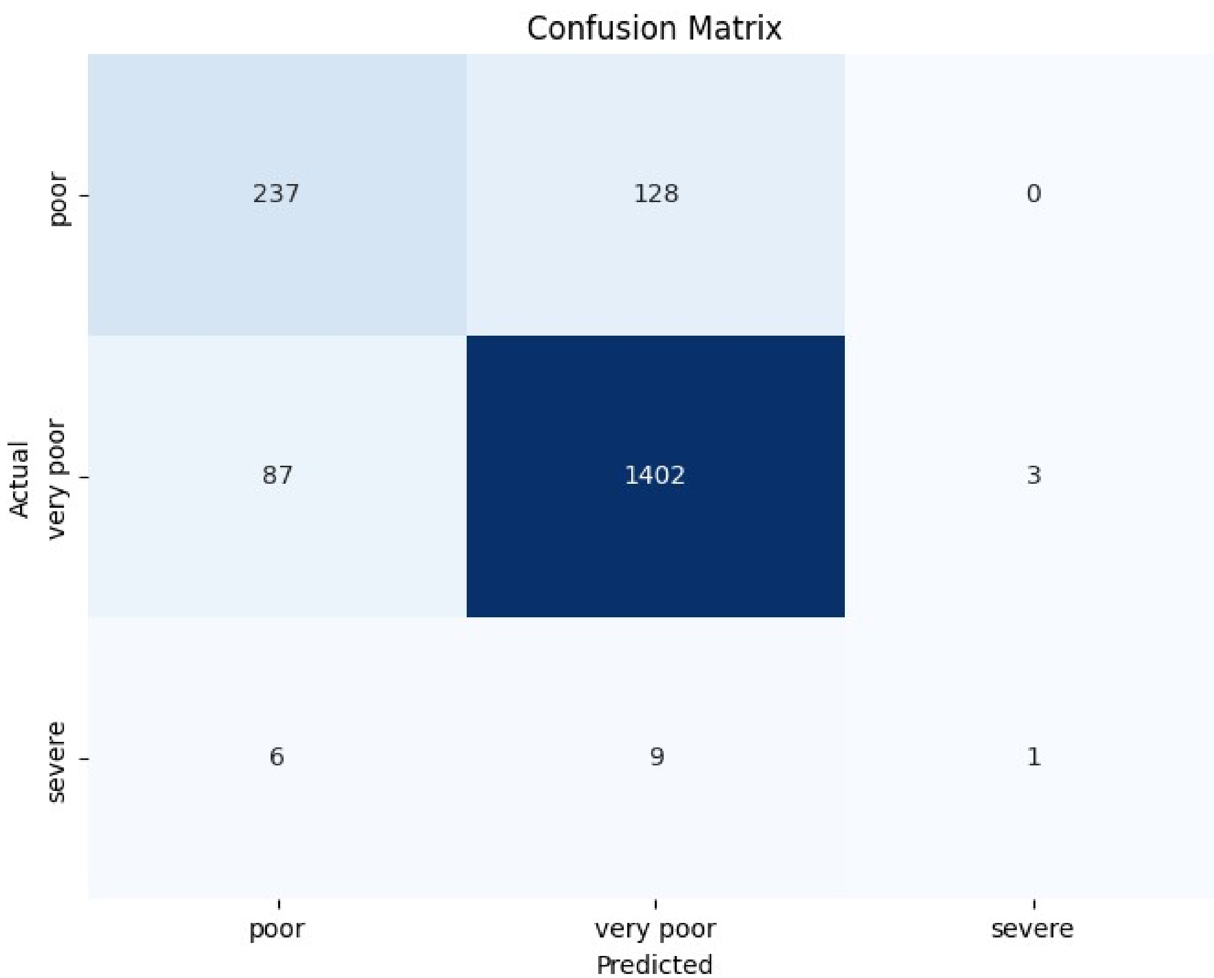
```
100%|██████████| 1873/1873 [01:11<00:00, 26.14it/s]


Accuracy: 0.8756006406833956
Average Precision: 0.6263876582590032
Average Recall: 0.550497784225152
Average F1 Score: 0.5690405379424602
```

```python
X_test_temp = X_test.to_numpy()
y_test_temp = y_test.to_numpy()
X_test_for_print = X_test_temp[0:10]
y_test_for_print = y_test_temp[0:10]

for x,y in zip(X_test_for_print, y_test_for_print):
    pred  = knn_model.predict(x, False)
    pred_aqi_index = pred[0]+3
    actual_aqi_index = y[0] + 3

    print(f"Actual AQI Index: {AQI_index_map[actual_aqi_index]} ->
Predicted AQI Index: {AQI_index_map[pred_aqi_index]}")
```

```
Actual AQI Index: Poor -> Predicted AQI Index: Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
```

```python
preds = knn_model.predict(X_test.to_numpy())
actuals = y_test.to_numpy()


# Define your class labels and their corresponding names
labels = [0, 1, 2]
class_names = ['poor', 'very poor', 'severe']

# Compute confusion matrix using NumPy
```

```
conf_matrix = np.zeros((len(labels), len(labels)), dtype=int)

for actual, pred in zip(actuals, preds):
    conf_matrix[actual[0], pred] += 1

conf_df = pd.DataFrame(conf_matrix, index=class_names,
columns=class_names)

# Visualize the confusion matrix using seaborn and matplotlib
plt.figure(figsize=(8, 6))
sns.heatmap(conf_df, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

100%|██████████| 1873/1873 [01:12<00:00, 25.68it/s]
```



Summary:

Row Labels (Actual Classes): The rows represent the actual classes.

Column Labels (Predicted Classes): The columns represent the predicted classes.

In the cell at the intersection of the "poor" row and "poor" column (top-left), there are 237 instances where both the actual and predicted classes are "poor."

In the cell at the intersection of the "very poor" row and "very poor" column (center), there are 1402 instances where both the actual and predicted classes are "very poor."

In the cell at the intersection of the "severe" row and "severe" column (bottom-right), there are 1 instances where both the actual and predicted classes are "severe." Notice dataset have only 16 Sever class, for only this small number one as prediced rightly and others are predicted wrongly.

4. ML Model 3

RandomForest

```
class DecisionTree:
    def __init__(self, output_class, max_depth=None):
        self._output_class = output_class
        self.max_depth = max_depth
        self.tree = None

    def fit(self, X, y_proba, depth=0):
        self.tree = self._fit(X, y_proba, depth)
        return self.tree

    def _fit(self, X, y_proba, depth=0):
        if depth == self.max_depth or np.all(np.sum(y_proba, axis=0)
== 0):
            # Create a leaf node
            return {'value': np.sum(y_proba, axis=0) /
np.sum(y_proba), 'is_leaf': True}

        num_features = X.shape[1]
        # Select the best split based on Gini impurity for multi-class
classification
        best_feature, best_value = self.find_best_split(X, y_proba,
num_features)

        if best_feature is None:
            # Create a leaf node
            return {'value': np.sum(y_proba, axis=0) /
```

```
np.sum(y_proba), 'is_leaf': True}

        # Split the data
        left_mask = X[:, best_feature] <= best_value
        right_mask = ~left_mask

        # Recursively build the tree
        left_subtree = self._fit(X[left_mask], y_proba[left_mask],
depth + 1)
        right_subtree = self._fit(X[right_mask], y_proba[right_mask],
depth + 1)

        # Save the split information
        return {'feature_index': best_feature,
                'split_value': best_value,
                'left': left_subtree,
                'right': right_subtree,
                'is_leaf': False,
                'value': None}  # Add the 'value' key for non-leaf
nodes

    def find_best_split(self, X, y_proba, num_features):
        best_feature, best_value, best_gini = None, None, float('inf')

        for feature in range(num_features):
            feature_values = np.unique(X[:, feature])
            for value in feature_values:
                left_mask = X[:, feature] <= value
                right_mask = ~left_mask

                if np.sum(left_mask) > 0 and np.sum(right_mask) > 0:
                    gini = self.gini_impurity(y_proba[left_mask],
y_proba[right_mask])
                    if np.any(gini < best_gini):
                        best_feature, best_value, best_gini = feature,
value, gini

        return best_feature, best_value

    def gini_impurity(self, left, right):
        total_samples_left = np.sum(left, axis=0)
        total_samples_right = np.sum(right, axis=0)
        total_samples = total_samples_left + total_samples_right

        gini_right = 1.0 - np.sum((right /
np.where(total_samples_right == 0, 1, total_samples_right))**2,
axis=0)
        gini_left = 1.0 - np.sum((left / np.where(total_samples_left
== 0, 1, total_samples_left))**2, axis=0)
```

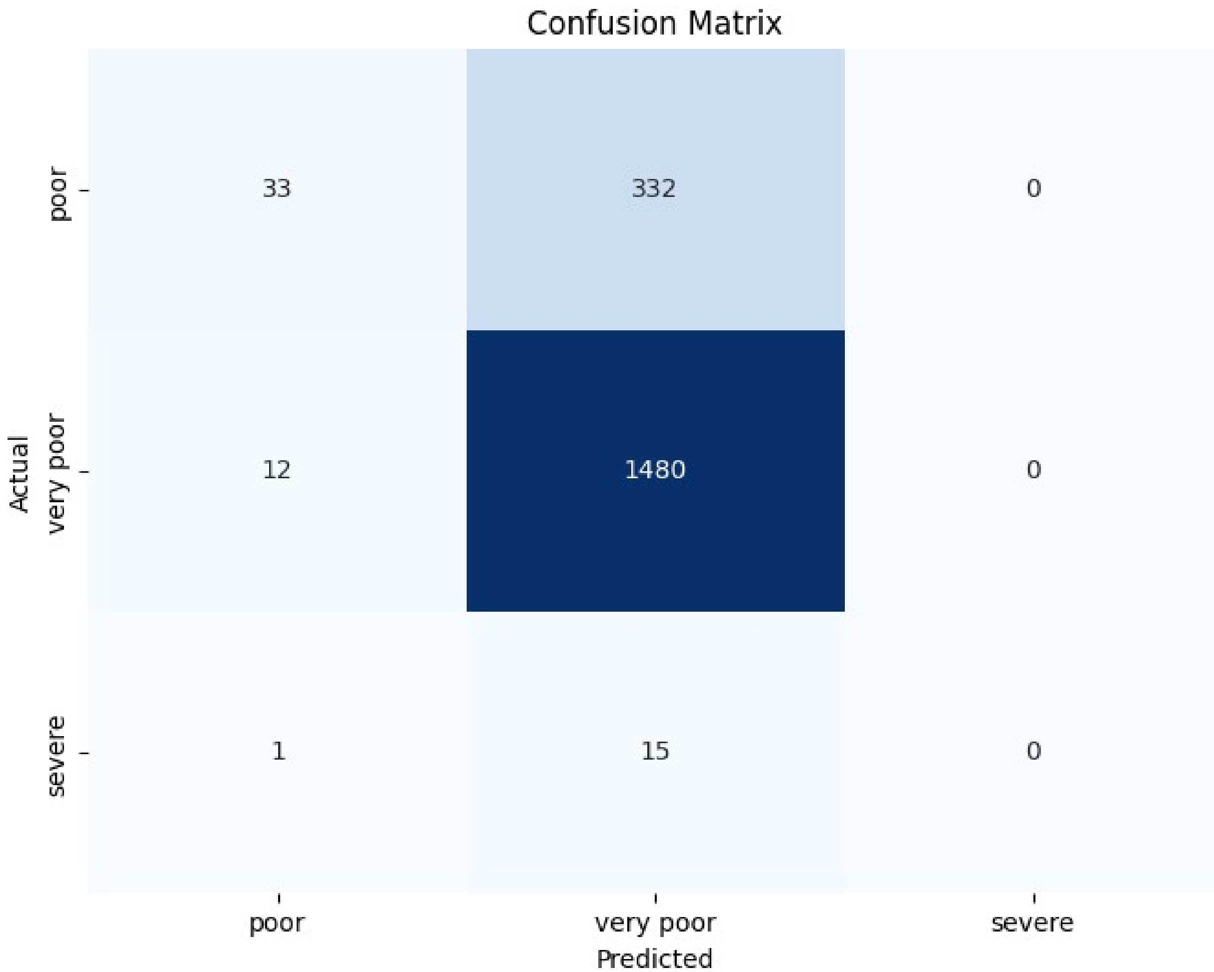
```
        gini = (total_samples_left / total_samples) * gini_left +
(total_samples_right / total_samples) * gini_right
        return gini

    def predict_proba(self, sample):
        if self.tree is None:
            raise ValueError("Decision tree not fitted")

        return self._predict_sample(sample)['value']

    def _predict_sample(self, sample):
        current_node = self.tree

        while not current_node['is_leaf']:
            split_value = current_node['split_value']
            feature_value = sample[current_node['feature_index']]

            if feature_value <= split_value:
                current_node = current_node['left']
            else:
                current_node = current_node['right']

        return current_node

class RandomForest:
    def __init__(self, n_trees=100, max_depth=None, sample_size=None,
output_class=3):
        np.random.seed(100)
        self.n_trees = n_trees
        self.max_depth = max_depth
        self.sample_size = sample_size
        self.trees = []
        self._output_class = output_class

    def fit(self, X, y):
        y_proba = self.calculate_class_probabilities(y)
        for _ in tqdm(range(self.n_trees)):
            tree = DecisionTree(output_class=self._output_class,
max_depth=self.max_depth)
            sample_indices = np.random.choice(len(X),
size=self.sample_size, replace=True)
            xx = X[sample_indices]
            yy = y_proba[sample_indices]
            tree.fit(xx, yy)
            self.trees.append(tree)

    def calculate_class_probabilities(self, y_int):
        # Convert integer labels to one-hot encoded class
probabilities
        return np.eye(self._output_class)[y_int]
```

```
    def predict_proba(self, X):
        predictions = np.zeros((X.shape[0], self.n_trees,
self._output_class))
        for i, tree in enumerate(self.trees):
            predictions[:, i, :] = [tree.predict_proba(sample) for
sample in X]

        # Sum probabilities across trees
        return np.sum(predictions, axis=1) / self.n_trees

    def calculate_error(self, X_test, y_test):
        y_pred = self.predict_proba(X_test)

        y_pred_labels = np.argmax(y_pred, axis=1)
        y_true_labels = np.array(y_test)

        return get_accurcy_matrix(y_pred_labels, y_true_labels)

rf_model = RandomForest(n_trees=10, max_depth=3,
sample_size=len(X_train.to_numpy()), output_class=3)
rf_model.fit(X_train.to_numpy(),
y_train.astype(int).to_numpy().flatten())
rf_model_accuracy, rf_model_precision, rf_model_recall,
rf_model_f1_score = rf_model.calculate_error(X_test.to_numpy(),
y_test.astype(int).to_numpy())

 10%|█         | 1/10 [00:28<04:14, 28.32s/it]<ipython-input-40-
021c7890a30b>:64: RuntimeWarning: invalid value encountered in divide
  gini = (total_samples_left / total_samples) * gini_left +
(total_samples_right / total_samples) * gini_right
100%|██████████| 10/10 [04:34<00:00, 27.40s/it]


Accuracy: 0.7818053441022266
Average Precision: 0.7637312296232837
Average Recall: 0.5411840317308751
Average F1 Score: 0.526209415816478



X_test_temp = X_test.to_numpy()
y_test_temp = y_test.to_numpy()
X_test_for_print = X_test_temp[0:10]
y_test_for_print = y_test_temp[0:10]

for x,y in zip(X_test_for_print, y_test_for_print):
    x = x.reshape(1, -1)
    pred  = rf_model.predict_proba(x)
    pred = np.argmax(pred, axis=1)
    pred_aqi_index = pred[0]+3
```

```
    actual_aqi_index = y[0] + 3

    print(f"Actual AQI Index: {AQI_index_map[actual_aqi_index]} ->
Predicted AQI Index: {AQI_index_map[pred_aqi_index]}")
```

```
Actual AQI Index: Poor -> Predicted AQI Index: Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
```

```
preds = rf_model.predict_proba(X_test.to_numpy())
preds = np.argmax(preds, axis=1)
actuals = y_test.to_numpy()


# Define your class labels and their corresponding names
labels = [0, 1, 2]
class_names = ['poor', 'very poor', 'severe']

# Compute confusion matrix using NumPy
conf_matrix = np.zeros((len(labels), len(labels)), dtype=int)

for actual, pred in zip(actuals, preds):
    conf_matrix[actual[0], pred] += 1

conf_df = pd.DataFrame(conf_matrix, index=class_names,
columns=class_names)

# Visualize the confusion matrix using seaborn and matplotlib
plt.figure(figsize=(8, 6))
sns.heatmap(conf_df, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Summary

Row Labels (Actual Classes): The rows represent the actual classes.

Column Labels (Predicted Classes): The columns represent the predicted classes.

In the cell at the intersection of the "poor" row and "poor" column (top-left), there are 33 instances where both the actual and predicted classes are "poor."

In the cell at the intersection of the "very poor" row and "very poor" column (center), there are 1480 instances where both the actual and predicted classes are "very poor."

In the cell at the intersection of the "severe" row and "severe" column (bottom-right), there are 1 instances where both the actual and predicted classes are "severe." Notice dataset have only 16 Sever class, for only this small number one as prediced rightly and others are predicted wrongly.

5. ML Model 4 (Based on research literature)

XGBoostRegressor

```
class XGBoostClassifier:
    def __init__(self, n_estimators=100, output_class=3,
learning_rate=0.1, max_depth=3):
        self.n_estimators = n_estimators
        self.learning_rate = learning_rate
        self.max_depth = max_depth
        self.trees = []
        self._output_class = output_class

    def fit(self, X, y):
        y_proba = self.calculate_class_probabilities(y)
        # print(y_proba)

        for i in tqdm(range(self.n_estimators)):
            tree = DecisionTree(output_class=self._output_class,
max_depth=self.max_depth)
            tree.fit(X, y_proba)  # Pass class probabilities to the
tree
            self.trees.append(tree)

            # Update pseudo-residuals for the next iteration
            residuals = y_proba -
self.learning_rate*self.predict_proba(X)
            y_proba = residuals

    def calculate_class_probabilities(self, y_int):
        # Convert integer labels to one-hot encoded class
probabilities
        return np.eye(self._output_class)[y_int]

    def predict_proba(self, X):
        # Aggregate predictions from all trees
        predictions = np.zeros((X.shape[0], len(self.trees),
self._output_class))

        for i, tree in enumerate(self.trees):
            predictions[:, i, :] = [tree.predict_proba(sample) for
sample in X]

        # Sum probabilities across trees
        return np.sum(predictions, axis=1) / len(self.trees)

    def calculate_error(self, X_test, y_test):
        y_pred = self.predict_proba(X_test)

        y_pred_labels = np.argmax(y_pred, axis=1)
```

```
        y_true_labels = np.array(y_test)

        return get_accurcy_matrix(y_pred_labels, y_true_labels)
```

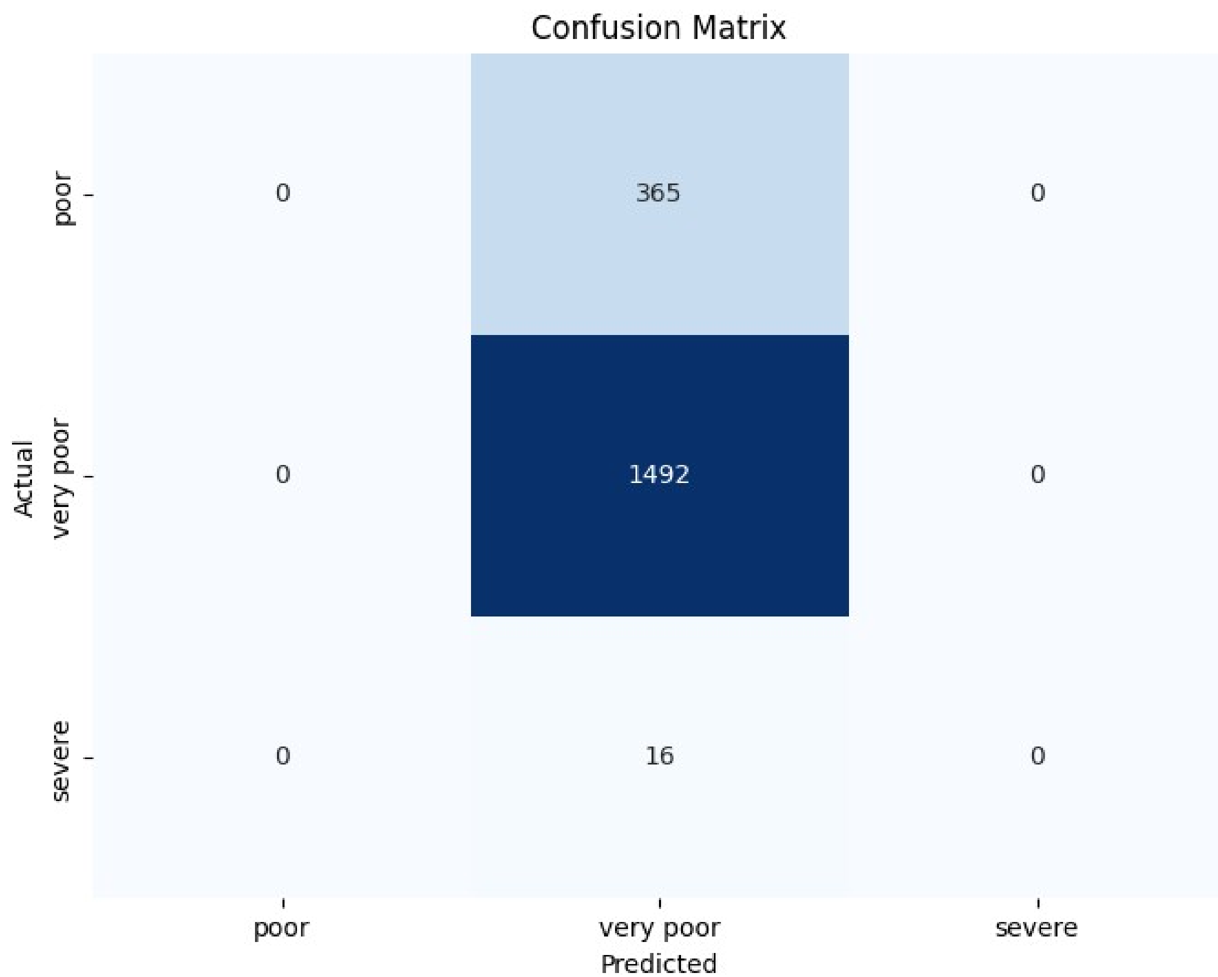
```
xgb_model = XGBoostClassifier(n_estimators=10, learning_rate=0.01,
max_depth=3)
xgb_model.fit(X_train.to_numpy(),
y_train.to_numpy().astype(int).flatten())
xgb_model_accuracy, xgb_model_precision, xgb_model_recall,
xgb_model_f1_score = xgb_model.calculate_error(X_test.to_numpy(),
y_test.to_numpy().flatten())
```

```
  0%|          | 0/10 [00:00<?, ?it/s]<ipython-input-40-
021c7890a30b>:64: RuntimeWarning: invalid value encountered in divide
  gini = (total_samples_left / total_samples) * gini_left +
(total_samples_right / total_samples) * gini_right
100%|██████████| 10/10 [07:03<00:00, 42.37s/it]


Accuracy: 0.7965830218900161
Average Precision: 0.7965830218900161
Average Recall: 1.0
Average F1 Score: 0.886775631500743
```

```
X_test_temp = X_test.to_numpy()
y_test_temp = y_test.to_numpy()
X_test_for_print = X_test_temp[0:10]
y_test_for_print = y_test_temp[0:10]

for x,y in zip(X_test_for_print, y_test_for_print):
    x = x.reshape(1, -1)
    pred  = xgb_model.predict_proba(x)
    pred = np.argmax(pred, axis=1)
    pred_aqi_index = pred[0]+3
    actual_aqi_index = y[0] + 3

    print(f"Actual AQI Index: {AQI_index_map[actual_aqi_index]} ->
Predicted AQI Index: {AQI_index_map[pred_aqi_index]}")
```

```
Actual AQI Index: Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
Actual AQI Index: Very Poor -> Predicted AQI Index: Very Poor
```

```python
preds = xgb_model.predict_proba(X_test.to_numpy())
preds = np.argmax(preds, axis = 1)
actuals = y_test.to_numpy()


# Define your class labels and their corresponding names
labels = [0, 1, 2]
class_names = ['poor', 'very poor', 'severe']

# Compute confusion matrix using NumPy
conf_matrix = np.zeros((len(labels), len(labels)), dtype=int)

for actual, pred in zip(actuals, preds):
    conf_matrix[actual[0], pred] += 1

conf_df = pd.DataFrame(conf_matrix, index=class_names,
columns=class_names)

# Visualize the confusion matrix using seaborn and matplotlib
plt.figure(figsize=(8, 6))
sns.heatmap(conf_df, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Summary

Row Labels (Actual Classes): The rows represent the actual classes.

Column Labels (Predicted Classes): The columns represent the predicted classes.

In the cell at the intersection of the "poor" row and "poor" column (top-left), there are 0 instances where both the actual and predicted classes are "poor."

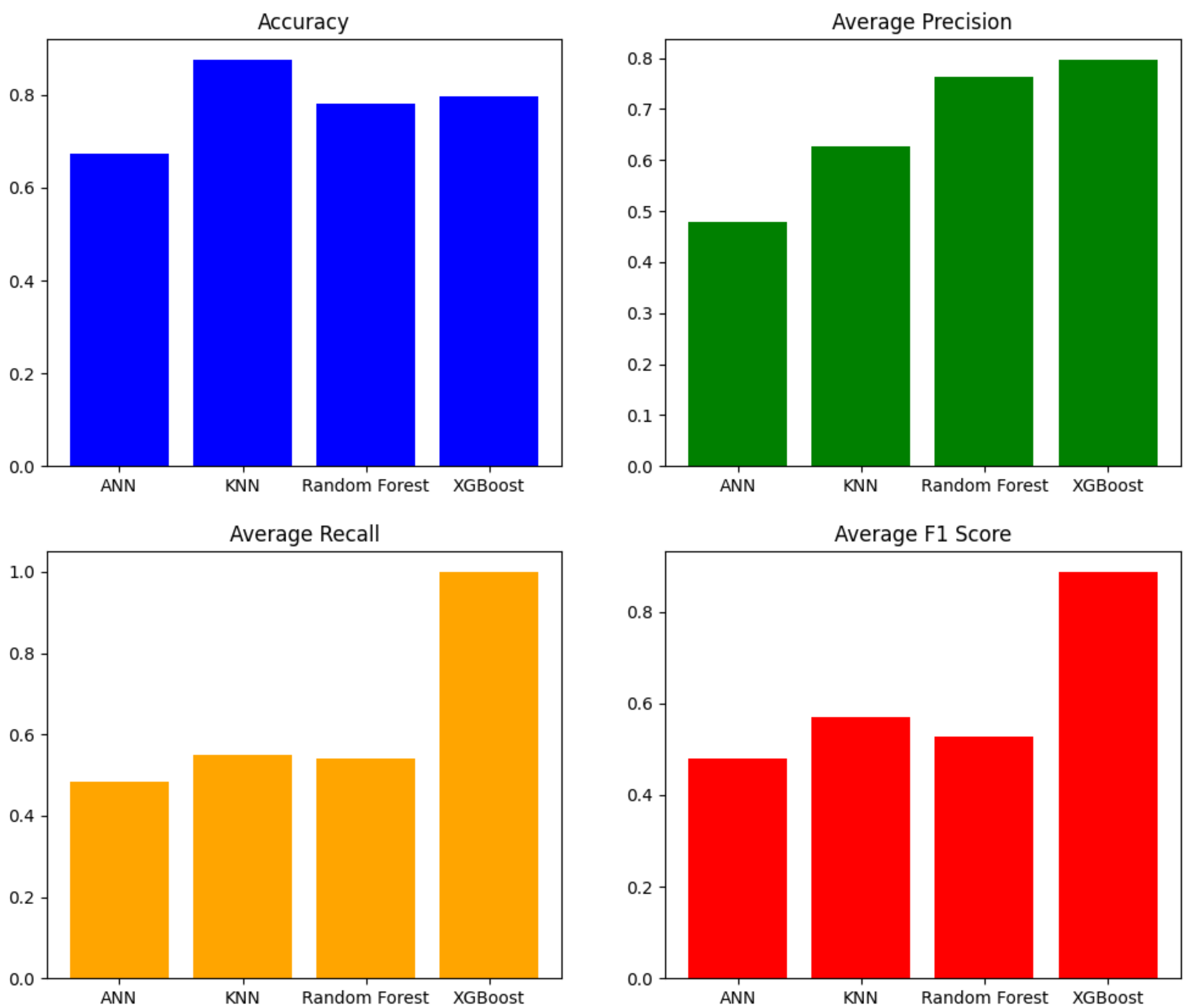
In the cell at the intersection of the "very poor" row and "very poor" column (center), there are 1492 instances where both the actual and predicted classes are "very poor."

In the cell at the intersection of the "severe" row and "severe" column (bottom-right), there are 1 instances where both the actual and predicted classes are "severe." Notice dataset have only 16 Sever class, for only this small number one as prediced rightly and others are predicted wrongly.

6. Comparison of insights drawn from the models

```
# Model names
models = ['ANN', 'KNN', 'Random Forest', 'XGBoost']
# Performance metrics
accuracy = [ann_model_accuracy, knn_model_accuracy, rf_model_accuracy,
xgb_model_accuracy ]
avg_precision = [ann_model_precision, knn_model_precision,
rf_model_precision,xgb_model_precision]
avg_recall = [ann_model_recall, knn_model_recall, rf_model_recall,
xgb_model_recall]
avg_f1_score = [ann_model_f1_score, knn_model_f1_score,
rf_model_f1_score, xgb_model_f1_score]

# print(accuracy)
# print(avg_precision)
# print(avg_recall)
# print(avg_f1_score)

# Individual bar graphs
fig, axs = plt.subplots(2, 2, figsize=(12, 10))

# Accuracy
axs[0, 0].bar(models, accuracy, color='blue')
axs[0, 0].set_title('Accuracy')

# Average Precision
axs[0, 1].bar(models, avg_precision, color='green')
axs[0, 1].set_title('Average Precision')

# Average Recall
axs[1, 0].bar(models, avg_recall, color='orange')
axs[1, 0].set_title('Average Recall')

# Average F1 Score
axs[1, 1].bar(models, avg_f1_score, color='red')
axs[1, 1].set_title('Average F1 Score')
```

```
Text(0.5, 1.0, 'Average F1 Score')
```



Model Recommendation Summary

KNN:

Accuracy (0.876): KNN demonstrates the highest accuracy, indicating strong overall predictive performance. Precision (0.626), Recall (0.550), F1 Score (0.569): KNN shows moderate precision, recall, and F1 Score. Consideration: Suitable for scenarios where high accuracy is a priority, and a balanced trade-off between precision and recall is acceptable.

###ANN:

Accuracy (0.672): ANN has a lower accuracy compared to other models. Precision (0.478), Recall (0.483), F1 Score (0.481): ANN exhibits balanced precision, recall, and F1 Score. Consideration: Despite lower accuracy, ANN is well-balanced, making it suitable for scenarios where a balance between precision and recall is crucial.

Random Forest:

Accuracy (0.782): Random Forest achieves a good level of accuracy. Precision (0.764), Recall (0.541), F1 Score (0.526): Random Forest shows a trade-off between precision and recall. Consideration: Suitable for scenarios where a balance between precision and recall is important, and high accuracy is desirable.

XGBoost:

Accuracy (0.797): XGBoost demonstrates a high level of accuracy. Precision (0.797), Recall (1.0), F1 Score (0.887): XGBoost exhibits high precision, recall, and F1 Score. Consideration: Suitable for scenarios where high accuracy and a strong balance between precision and recall are critical.

Overall Recommendations:

For High Accuracy:

Choose XGBoost for the highest accuracy, precision, recall, and F1 Score.

###For a Balance Between Precision and Recall:

Consider Random Forest for a trade-off between precision and recall.

For a Balanced Approach:

ANN exhibits a balanced performance and may be suitable for scenarios where a balance between precision and recall is crucial.

7. References

1. Dataset
2. AQI Index
3. Paper for AQI
4. XGBoost
5. AQI Calculation 6.ANN tutorial
6. KNN tutorial
7. Random Forest
8. XGBoost tutorial
9. Random Forest Turorial
10. XGBoost implementaiton Example