Air Quality Index (AQI) Prediction

This notebook demonstrates AQI prediction using a **Random Forest Regressor** and **XG Boost Regressoe** model. To improve performance, **GridSearchCV** is used for hyperparameter tuning.

Dataset link : https://github.com/cp099/India-Air-Quality-Dataset/blob/main/Delhi_AQI_Dataset.csv

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

In [2]:
```
df = pd.read_csv('/content/Delhi_AQI_Dataset.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	City	Date	AQI	PM2.5	PM10	NO2	SO2	CO	O3	Unnamed: 9	Unnamed: 10
0	Delhi	01/01/18	406	223.3	438.48	336.98	462.84	4.26	385.7	NaN	NaN
1	Delhi	02/01/18	418	229.9	451.44	346.94	476.52	4.39	397.1	NaN	NaN
2	Delhi	03/01/18	382	210.1	412.56	317.06	435.48	4.01	362.9	NaN	NaN
3	Delhi	04/01/18	366	201.3	395.28	303.78	417.24	3.84	347.7	NaN	NaN
4	Delhi	05/01/18	390	214.5	421.20	323.70	444.60	4.10	370.5	NaN	NaN

In [4]:
```
df = df.drop(columns=['Unnamed: 10','Unnamed: 9','City'])
```

In [5]:
```
df.head()
```

Out[5]:

	Date	AQI	PM2.5	PM10	NO2	SO2	CO	O3
0	01/01/18	406	223.3	438.48	336.98	462.84	4.26	385.7
1	02/01/18	418	229.9	451.44	346.94	476.52	4.39	397.1
2	03/01/18	382	210.1	412.56	317.06	435.48	4.01	362.9
3	04/01/18	366	201.3	395.28	303.78	417.24	3.84	347.7
4	05/01/18	390	214.5	421.20	323.70	444.60	4.10	370.5

In [6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2191 entries, 0 to 2190
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Date    2191 non-null   object 
 1   AQI     2191 non-null   int64  
 2   PM2.5   2191 non-null   float64
 3   PM10    2191 non-null   float64
 4   NO2     2191 non-null   float64
 5   SO2     2191 non-null   float64
 6   CO      2191 non-null   float64
 7   O3      2191 non-null   float64
dtypes: float64(6), int64(1), object(1)
memory usage: 137.1+ KB
```

In [7]:
```python
df['Date'] = pd.to_datetime(df['Date'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2191 entries, 0 to 2190
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype         
---  ------  --------------  -----         
 0   Date    2191 non-null   datetime64[ns]
 1   AQI     2191 non-null   int64         
 2   PM2.5   2191 non-null   float64       
 3   PM10    2191 non-null   float64       
 4   NO2     2191 non-null   float64       
 5   SO2     2191 non-null   float64       
 6   CO      2191 non-null   float64       
 7   O3      2191 non-null   float64       
dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 137.1 KB
```

```
/tmp/ipython-input-7-2345423161.py:1: UserWarning: Could not infer format, so each element will be parsed individually, falling bac
k to `dateutil`. To ensure parsing is consistent and as-expected, please specify a format.
  df['Date'] = pd.to_datetime(df['Date'])
```

In [8]:
```python
df.head(12)
```

Out[8]:

	Date	AQI	PM2.5	PM10	NO2	SO2	CO	O3
0	2018-01-01	406	223.30	438.48	336.98	462.84	4.26	385.70
1	2018-02-01	418	229.90	451.44	346.94	476.52	4.39	397.10
2	2018-03-01	382	210.10	412.56	317.06	435.48	4.01	362.90
3	2018-04-01	366	201.30	395.28	303.78	417.24	3.84	347.70
4	2018-05-01	390	214.50	421.20	323.70	444.60	4.10	370.50
5	2018-06-01	405	222.75	437.40	336.15	461.70	4.25	384.75
6	2018-07-01	355	195.25	383.40	294.65	404.70	3.73	337.25
7	2018-08-01	288	158.40	311.04	239.04	328.32	3.02	273.60
8	2018-09-01	359	197.45	387.72	297.97	409.26	3.77	341.05
9	2018-10-01	352	193.60	380.16	292.16	401.28	3.70	334.40
10	2018-11-01	309	169.95	333.72	256.47	352.26	3.24	293.55
11	2018-12-01	298	163.90	321.84	247.34	339.72	3.13	283.10

In [9]:

```
print(df['Date'].min())
print(df['Date'].max())
```

```
2018-01-01 00:00:00
2024-12-31 00:00:00
```

In [10]:

```
df = df.sort_values('Date')
df.head()
```

Out[10]:

	Date	AQI	PM2.5	PM10	NO2	SO2	CO	O3
0	2018-01-01	406	223.30	438.48	336.98	462.84	4.26	385.70
31	2018-01-02	274	150.70	295.92	227.42	312.36	2.88	260.30
59	2018-01-03	257	141.35	277.56	213.31	292.98	2.70	244.15
90	2018-01-04	195	107.25	210.60	161.85	222.30	2.05	185.25
120	2018-01-05	177	97.35	191.16	146.91	201.78	1.86	168.15

In [11]:

```
df.drop(columns=['Date']).describe()
```

Out[11]:

	AQI	PM2.5	PM10	NO2	SO2	CO	O3
count	2191.000000	2191.000000	2191.000000	2191.000000	2191.000000	2191.000000	2191.000000
mean	208.285714	114.557143	224.948571	172.877143	237.445714	2.187307	197.871429
std	106.614654	58.638060	115.143827	88.490163	121.540706	1.119494	101.283922
min	41.000000	22.550000	44.280000	34.030000	46.740000	0.430000	38.950000
25%	117.000000	64.350000	126.360000	97.110000	133.380000	1.230000	111.150000
50%	190.000000	104.500000	205.200000	157.700000	216.600000	2.000000	180.500000
75%	289.000000	158.950000	312.120000	239.870000	329.460000	3.030000	274.550000
max	494.000000	271.700000	533.520000	410.020000	563.160000	5.190000	469.300000

In [12]:

```
year = range(2018,2025)

for y in year:
  print(y,len(df[df['Date'].dt.year == y]))
```

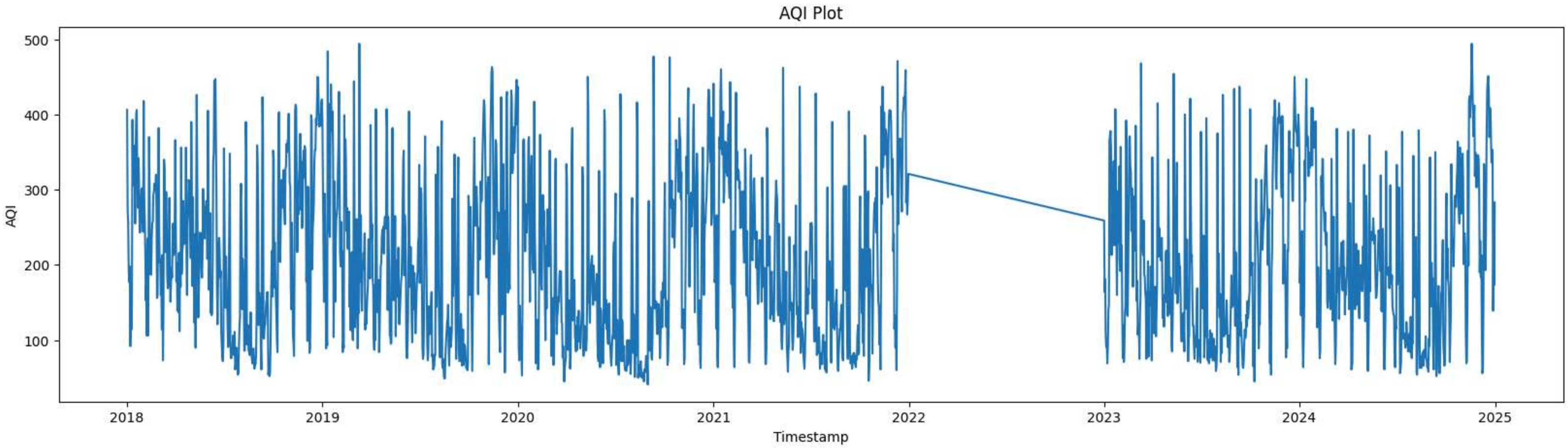
```
2018 365
2019 365
2020 365
2021 365
2022 0
2023 365
2024 366
```

In [13]:

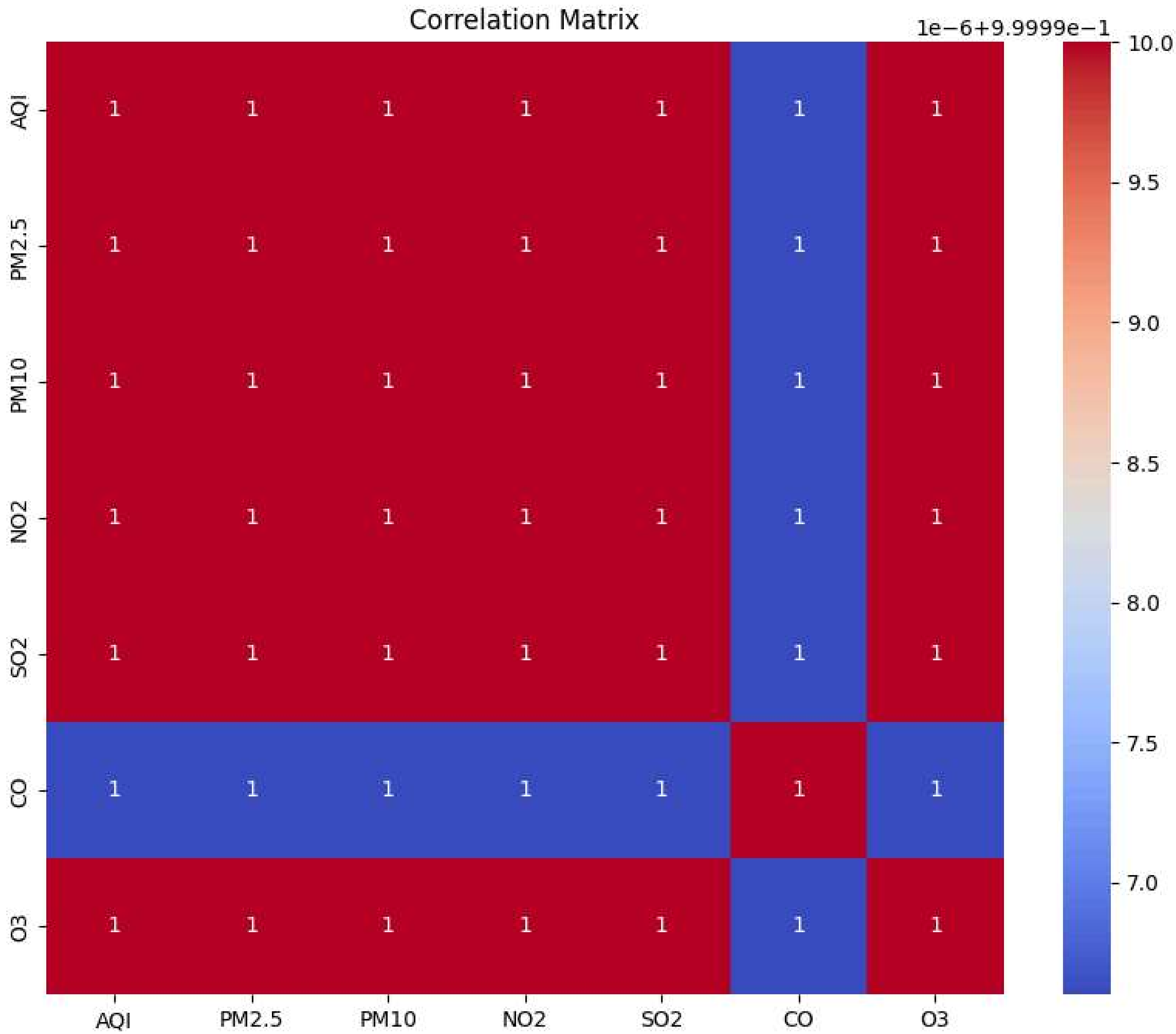
```
import matplotlib.pyplot as plt
import seaborn as sns
```

In [14]:

```
plt.figure(figsize=(20,5))
plt.plot(df['Date'],df['AQI'])
plt.xlabel('Timestamp')
plt.ylabel('AQI')
plt.title(f'AQI Plot')
plt.show();
```



In [15]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.drop(columns=['Date']).corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Matrix")
plt.show()
```



In [16]:
```
df_numeric = df.drop(columns=['Date'])
constant_cols = [
    col for col in df_numeric.columns
    if df_numeric[col].nunique() == 1
]
```

```
print("Constant columns:", constant_cols)
```

```
Constant columns: []
```

In [17]:

```
# Check pairwise identical columns
for i, col1 in enumerate(df_numeric.columns):
    for col2 in df_numeric.columns[i+1:]:
        if df_numeric[col1].equals(df_numeric[col2]):
            print(f"Columns {col1} and {col2} are identical!")
else:
  print("No Duplicate Columns")
```

```
No Duplicate Columns
```

In [18]:

```
X = df.drop(columns=["AQI","Date"])
y = df["AQI"]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1752, 6)
(439, 6)
(1752,)
(439,)
```

Random Forest Regressor

In [19]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.model_selection import GridSearchCV
```

In [20]:

```
param_grid = {
    'n_estimators': list(range(5,105,5)),
    'max_depth': [10,20,30,40,None],
}

grid_search = GridSearchCV(
    RandomForestRegressor(random_state=42),
    param_grid,
    cv=5,
    scoring='neg_mean_absolute_error',
```

```python
    n_jobs=-1
)

grid_search.fit(X_train, y_train)
```

Out[20]:

```
▸ GridSearchCV
▸ best_estimator_: RandomForestRegressor
    ▸ RandomForestRegressor
```

In [21]:

```python
print(f"Best parameters: {grid_search.best_params_}")
print(f"Best CV MAE: {-grid_search.best_score_:.4f}")
```

```
Best parameters: {'max_depth': 20, 'n_estimators': 65}
Best CV MAE: 0.0846
```

In [22]:

```python
final_model = grid_search.best_estimator_
```

In [23]:

```python
y_pred = final_model.predict(X_test)
```

In [24]:

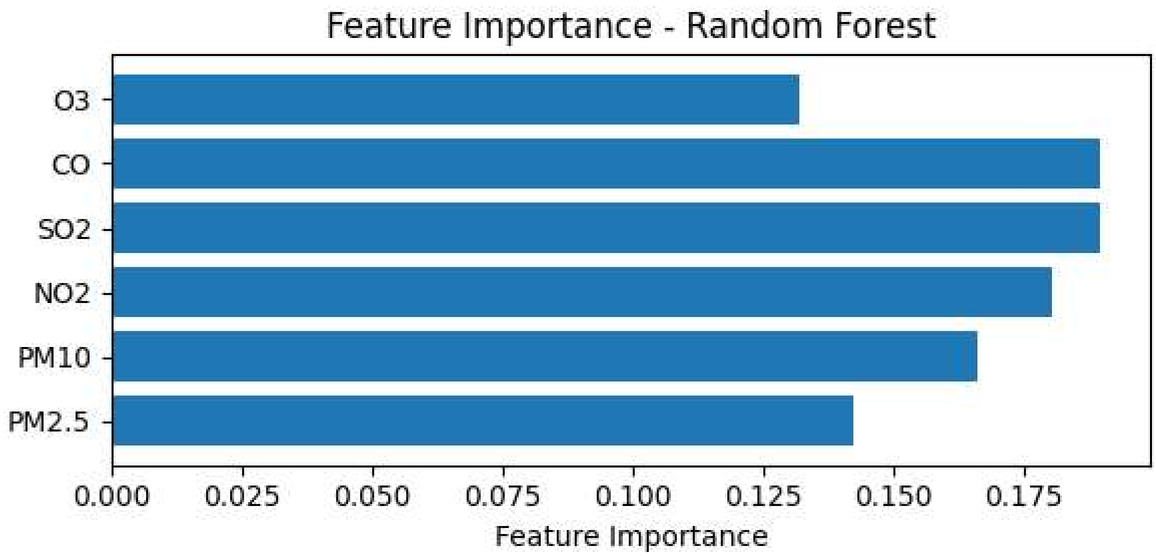
```python
mae = mean_absolute_error(y_test, y_pred)
print("Test MAE:", round(mae,5))
```

```
Test MAE: 0.02835
```

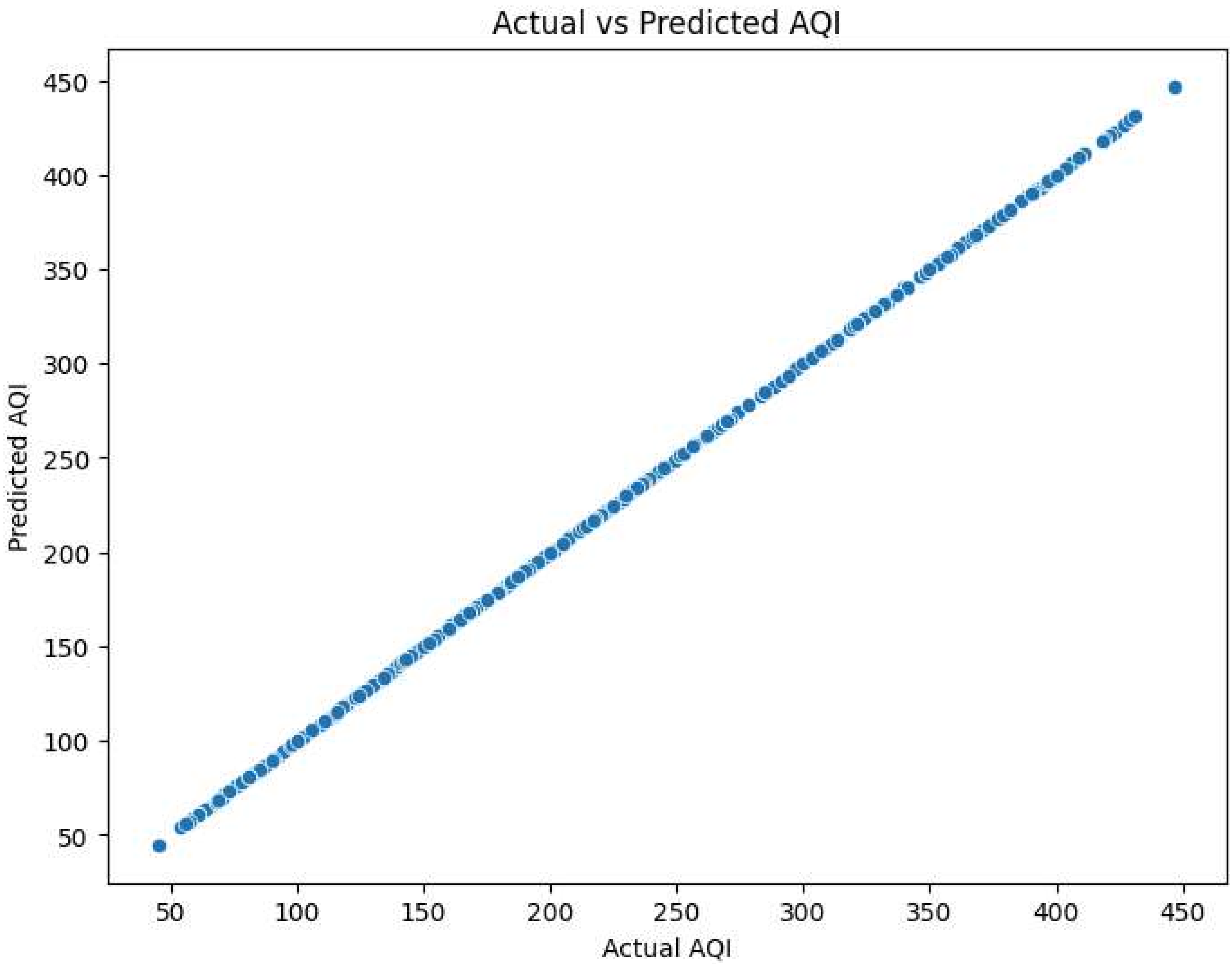
In [25]:

```python
feature_importances = final_model.feature_importances_
feature_names = X_train.columns

plt.figure(figsize=(6, 3))
plt.barh(feature_names, feature_importances)
plt.xlabel('Feature Importance')
plt.title('Feature Importance - Random Forest')
plt.tight_layout()
plt.show();
```



In [26]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(x=y_test, y=y_pred)
plt.xlabel("Actual AQI")
plt.ylabel("Predicted AQI")
plt.title("Actual vs Predicted AQI")
plt.show();
```



XGBoost Regressor

In [27]:
```
from xgboost import XGBRegressor
```

In [28]:
```
param_grid = {
    'n_estimators': list(range(5,105,5)),
    'max_depth': [10,20,30,40,None],
}

grid_search_xg = GridSearchCV(
    XGBRegressor(random_state=42),
    param_grid,
```

```
    cv=5,
    scoring='neg_mean_absolute_error',
    n_jobs=-1
)

grid_search_xg.fit(X_train, y_train)
```

Out[28]:

```
▸ GridSearchCV
▸ best_estimator_: XGBRegressor
  ▸ XGBRegressor
```

In [29]:

```
print(f"Best parameters: {grid_search_xg.best_params_}")
print(f"Best CV MAE: {-grid_search_xg.best_score_:.4f}")
```

```
Best parameters: {'max_depth': 40, 'n_estimators': 75}
Best CV MAE: 0.4609
```

In [30]:

```
final_model_xg = grid_search.best_estimator_
```

In [31]:

```
y_pred_xg = final_model.predict(X_test)
```

In [32]:

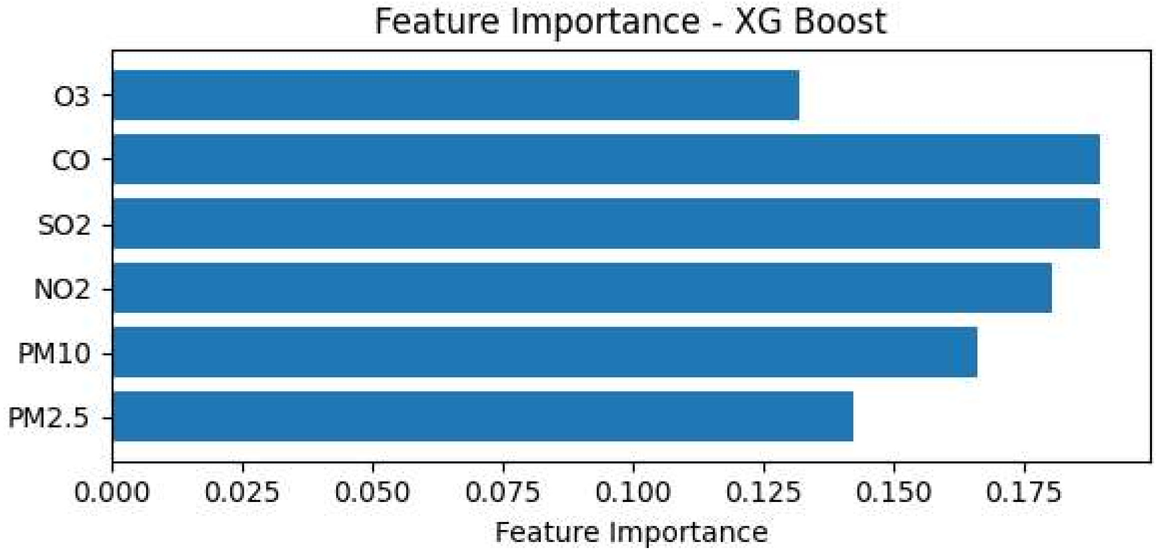
```
mae_xg = mean_absolute_error(y_test, y_pred_xg)
print("Test MAE:", round(mae,5))
```

```
Test MAE: 0.02835
```

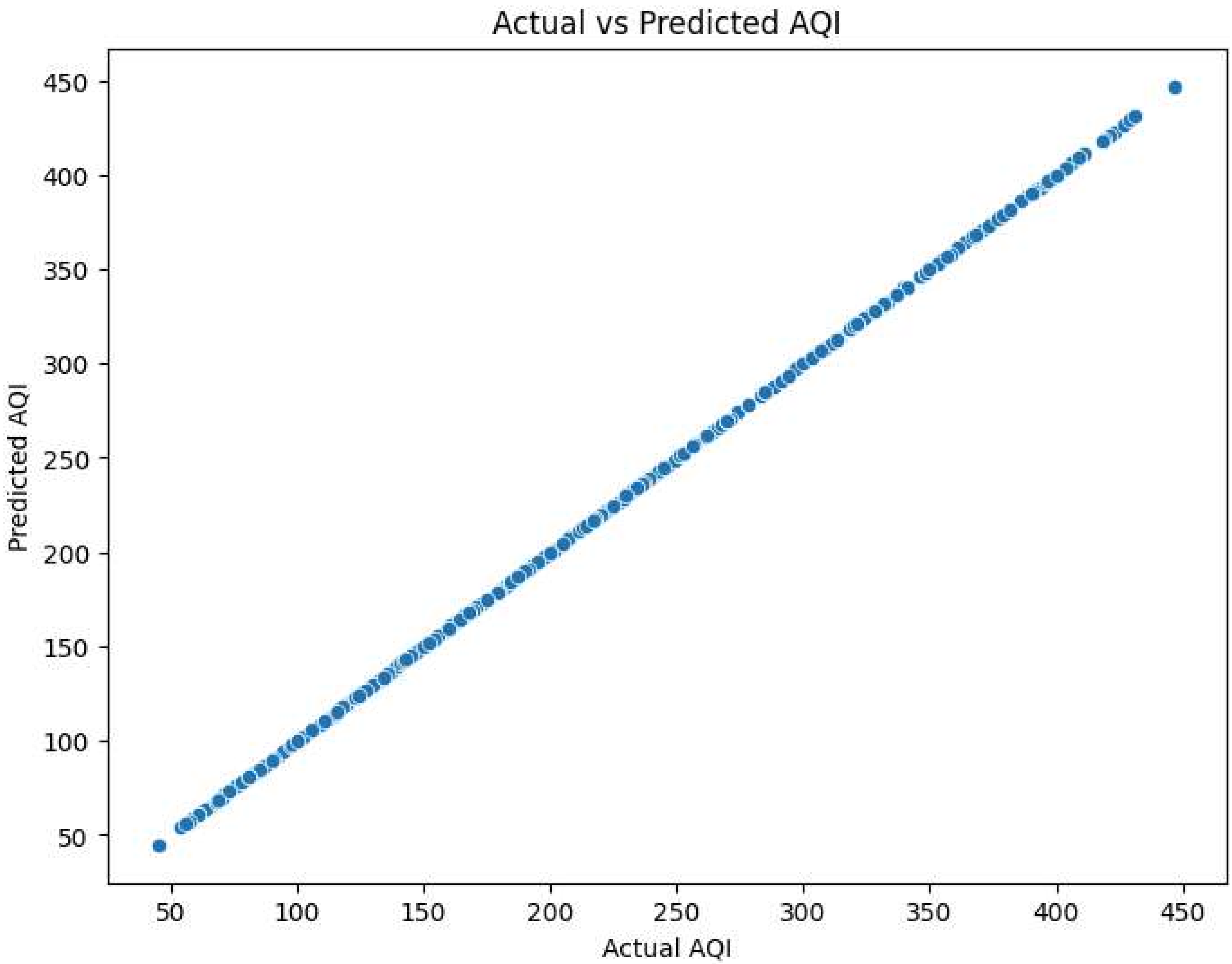
In [33]:

```
feature_importances_xg = final_model_xg.feature_importances_
feature_names_xg = X_train.columns

plt.figure(figsize=(6, 3))
plt.barh(feature_names_xg, feature_importances_xg)
plt.xlabel('Feature Importance')
plt.title('Feature Importance - XG Boost')
plt.tight_layout()
plt.show();
```



In [34]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(x=y_test, y=y_pred_xg)
plt.xlabel("Actual AQI")
plt.ylabel("Predicted AQI")
plt.title("Actual vs Predicted AQI")
plt.show();
```



Results

In [37]:
```
print("Random Forest Regressor")
print(f"Best Parameters: {grid_search.best_params_}")
print("Test MAE:", round(mae,5))
print("Most Important Feature: ", feature_names[feature_importances.argmax()])
print("-"*100)
print("XG Boost Regressor")
print(f"Best Parameters: {grid_search_xg.best_params_}")
print("Test MAE:", round(mae_xg,5))
print("Most Important Feature: ", feature_names_xg[feature_importances_xg.argmax()])
```

```
Random Forest Regressor
Best Parameters: {'max_depth': 20, 'n_estimators': 65}
Test MAE: 0.02835
Most Important Feature:  CO
----------------------------------------------------------------------------------------------------
XG Boost Regressor
Best Parameters: {'max_depth': 40, 'n_estimators': 75}
Test MAE: 0.02835
Most Important Feature:  CO
```

In [ ]: