

AQI Predictor Prototype

Goal: Predict the next 24 hour AQI, based on the past 12-hour data (30 mins-interval)

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Training Pipeline

```
# 1. Import Libraries
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.multioutput import MultiOutputRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
import joblib
import matplotlib.pyplot as plt

# 2. Load Data
df = pd.read_csv("input.csv", parse_dates=['timestamp'])
df = df.sort_values("timestamp")

# For prototype, we'll use: Subset last X days
x_days = 2
df = df[df['timestamp'] >= df['timestamp'].max() -
pd.Timedelta(days=x_days)]
print(df.shape)
df.head(2)

(97, 37)
```

		created_at	updated_at
id \			
6691	2025-05-24 11:53:53.958527+00	2025-05-29 09:23:37.76187+00	
13559			
6692	2025-05-24 11:53:53.961339+00	2025-05-29 09:30:38.84316+00	
13560			

	timestamp	PM25	PM10	O3	S02
N0 \					
6691	2025-05-22 18:30:00+00:00	17.0167	28.0616	18.6344	6.9171
2.2333					
6692	2025-05-22 19:00:00+00:00	26.7487	40.9343	21.5069	6.9354
1.0469					

	N02	...	AQI
AQI_detail \			

```

6691 35.3888 ... 78 {"CO": 21, "O3": 11, "CH4": 4, "NO2": 29,
"S02"...
6692 25.4352 ... 77 {"CO": 21, "O3": 11, "CH4": 4, "NO2": 28,
"S02"...

```

	AQI_parameter	PM25_AQI	PM10_AQI	O3_AQI	S02_AQI	NO2_AQI
CO_AQI \						
6691	PM25	78	40	11	9	29
21						
6692	PM25	77	40	11	9	28
21						

	CH4_AQI
6691	4
6692	4

```
[2 rows x 37 columns]
```

3. Feature Selection

```

features = ['PM25', 'PM10', 'O3', 'S02', 'NO', 'NO2', 'NOX', 'CO',
'CH4',
            'NMHC', 'THC', 'wind_speed', 'wind_gust_speed',
            'wind_direction', 'air_humidity', 'air_temperature',
            'container_humidity', 'container_temperature',
'solar_radiation']
target = 'AQI'

```

4. Framing the problem as Supervised Learning

```

input_len = 24 # past 12 hours (30min x 24 = 12hr)
output_len = 48 # next 24 hours (30min x 48 = 24hr)

```

```

X, y = [], []
for i in range(input_len, len(df) - output_len):
    X.append(df[features].iloc[i - input_len:i].values.flatten())
    y.append(df[target].iloc[i:i + output_len].values)

```

```

X = np.array(X)
y = np.array(y)

```

```
X.shape, y.shape
```

```
((25, 456), (25, 48))
```

5. Train-Test Split

```

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, shuffle=False)

```

6. Normalize

```

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

```

```

# 7. Model Training
# Caution: Might takes time! Please be patient, monitor your CPU &
Memory usage.
base_model = GradientBoostingRegressor()
model = MultiOutputRegressor(base_model)
model.fit(X_train_scaled, y_train)

MultiOutputRegressor(estimator=GradientBoostingRegressor())

# 8. Save Model
joblib.dump(model, 'aqi_forecast_model.pkl')
joblib.dump(scaler, 'aqi_scaler.pkl')

['aqi_scaler.pkl']

```

Inference Pipeline

```

X_test_scaled.shape

(5, 456)

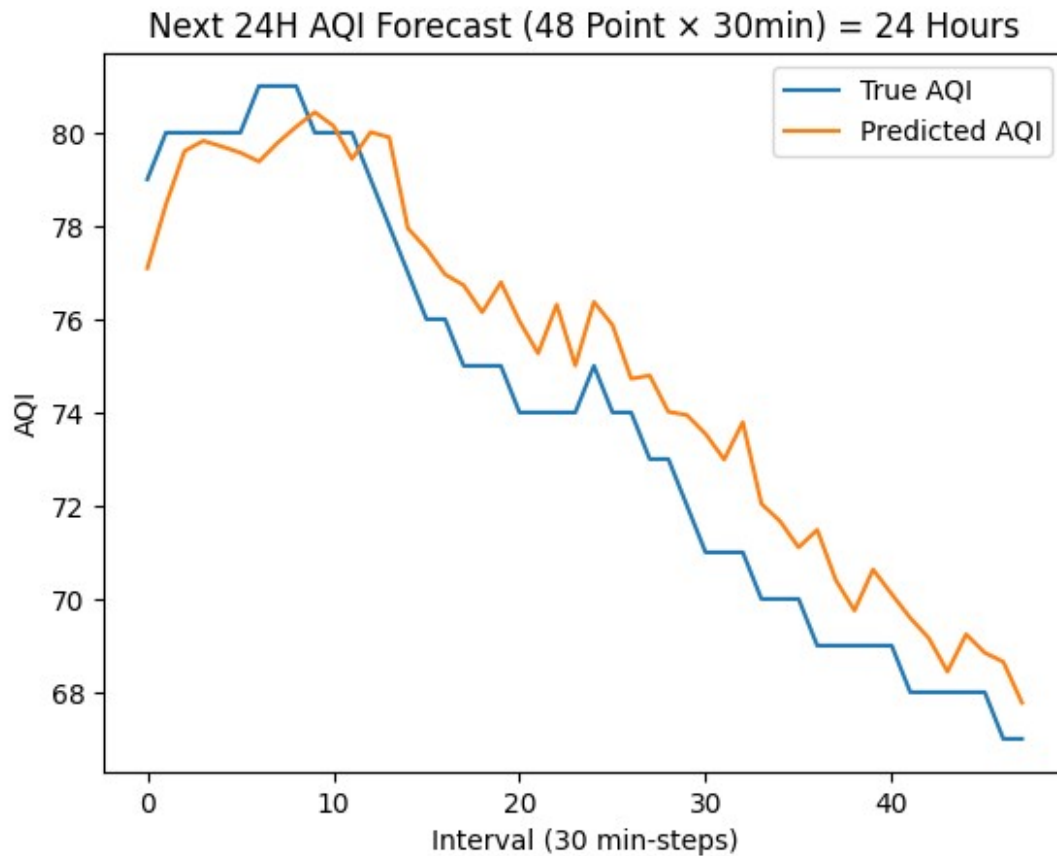
# 9. Inference
y_pred = model.predict(X_test_scaled)
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test,
y_pred))

Mean Absolute Error (MAE): 2.427852716662926

# 10. Visualization Example of the first 24 hours rolling window
plt.plot(y_test[0], label='True AQI')
plt.plot(y_pred[0], label='Predicted AQI')
plt.title('Next 24H AQI Forecast (48 Point × 30min) = 24 Hours')
plt.legend()

plt.xlabel("Interval (30 min-steps)")
plt.ylabel("AQI")
plt.show()

```



Summary

- In this prototype, for the sake of efficiency & proof-of-concept, we only use the most recent **2 days** of data during the **training**.
- We could always increase the time window to (possibly) get more (seasonal/monthly) context.
- Accuracy is not bad, as visualize on the above graph!