Project Overview

Goal: Predict air pollution levels based on historical air quality data using time-series forecasting models (LSTMs).

Libraries Required: pandas, numpy – Data handling matplotlib, seaborn – Visualization scikit-learn – Data preprocessing tensorflow.keras or torch – LSTM model training

Step 1: Install and Import Dependencies

Run this in Google Colab

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout


from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
```

Step 2: Load and Explore the Dataset

Download the dataset and load it into a Pandas DataFrame.

```
import pandas as pd

file_path = "/content/drive/My Drive/AirQuality.csv"


df = pd.read_csv(file_path, sep=";", encoding="utf-8")

# Display first few rows and column names
print(df.head())
print(df.columns)
```

```
         Date      Time CO(GT)  PT08.S1(CO)  NMHC(GT) C6H6(GT)  PT08.S2(NMHC)
0  10/03/2004  18.00.00    2,6       1360.0     150.0     11,9         1046.0
1  10/03/2004  19.00.00      2       1292.0     112.0      9,4          955.0
2  10/03/2004  20.00.00    2,2       1402.0      88.0      9,0          939.0
3  10/03/2004  21.00.00    2,2       1376.0      80.0      9,2          948.0
4  10/03/2004  22.00.00    1,6       1272.0      51.0      6,5          836.0

   NOx(GT)  PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)     T    RH  \
0    166.0        1056.0    113.0        1692.0       1268.0  13,6  48,9
1    103.0        1174.0     92.0        1559.0        972.0  13,3  47,7
2    131.0        1140.0    114.0        1555.0       1074.0  11,9  54,0
3    172.0        1092.0    122.0        1584.0       1203.0  11,0  60,0
4    131.0        1205.0    116.0        1490.0       1110.0  11,2  59,6

       AH  Unnamed: 15  Unnamed: 16
0  0,7578          NaN          NaN
1  0,7255          NaN          NaN
2  0,7502          NaN          NaN
3  0,7867          NaN          NaN
4  0,7888          NaN          NaN
Index(['Date', 'Time', 'CO(GT)', 'PT08.S1(CO)', 'NMHC(GT)', 'C6H6(GT)',
       'PT08.S2(NMHC)', 'NOx(GT)', 'PT08.S3(NOx)', 'NO2(GT)', 'PT08.S4(NO2)',
       'PT08.S5(O3)', 'T', 'RH', 'AH', 'Unnamed: 15', 'Unnamed: 16'],
      dtype='object')
```

```
# Remove extra spaces and special characters
df.columns = df.columns.str.strip().str.replace(r'\W+', '_', regex=True)

# Print cleaned column names
print(df.columns)
```

```
Index(['Date', 'Time', 'CO_GT_', 'PT08_S1_CO_', 'NMHC_GT_', 'C6H6_GT_',
       'PT08_S2_NMHC_', 'NOx_GT_', 'PT08_S3_NOx_', 'NO2_GT_', 'PT08_S4_NO2_',
       'PT08_S5_O3_', 'T', 'RH', 'AH', 'Unnamed_15', 'Unnamed_16'],
      dtype='object')
```

Step 3: Data Preprocessing

1. Select Features

```
df = df[['CO_GT_', 'T', 'RH']].copy()
df.rename(columns={'T': 'Temperature', 'RH': 'Humidity', 'CO_GT_': 'CO_Level'}, i
```

2. Handle Missing Values

```
print(df.isnull().sum())  # Check missing values

# Fill missing values using forward fill (or change as needed)
df.fillna(method='ffill', inplace=True)
```

```
CO_Level       114
Temperature    114
Humidity       114
dtype: int64
<ipython-input-104-8c19cd319783>:4: FutureWarning: DataFrame.fillna with 'metl
  df.fillna(method='ffill', inplace=True)
```

3. Normalize Data

```
# Convert columns with potential comma separators to numeric
for col in ['CO_Level', 'Temperature', 'Humidity']:
    df[col] = pd.to_numeric(df[col].astype(str).str.replace(',', '.', regex=False

# Now apply scaling
df_scaled = scaler.transform(df)
```

```
import joblib
scaler = MinMaxScaler()
scaler.fit(df[['CO_Level', 'Temperature', 'Humidity']])  # Fit first!

df_scaled = scaler.transform(df[['CO_Level', 'Temperature', 'Humidity']])  # Then


# Save the scaler
joblib.dump(scaler, 'scaler.pkl')
```

```
['scaler.pkl']
```

Step 4: Create Train-Test Splits

Define time-series windows for LSTM input.

```
def create_sequences(data, time_steps=10):
    X, y = [], []
    for i in range(len(data) - time_steps):
        X.append(data[i:i+time_steps])
        y.append(data[i+time_steps, 0])  # Predict CO Level
    return np.array(X), np.array(y)

time_steps = 10
X, y = create_sequences(df_scaled, time_steps)

split = int(0.8 * len(X))  # 80% training, 20% testing
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]
```

Step 5: Build & Train LSTM Model

Define an LSTM-based neural network:

```
model = Sequential([
    LSTM(50, return_sequences=True, input_shape=(X_train.shape[1], X_train.shape[
    Dropout(0.2),
    LSTM(50, return_sequences=False),
    Dropout(0.2),
    Dense(25),
    Dense(1)  # Predict PM2.5
])

model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserW
  super().__init__(**kwargs)
Model: "sequential_4"
```

| Layer (type) | Output Shape | |
|---|---|---|
| lstm_8 (LSTM) | (None, 10, 50) | |
| dropout_8 (Dropout) | (None, 10, 50) | |
| lstm_9 (LSTM) | (None, 50) | |
| dropout_9 (Dropout) | (None, 50) | |
| dense_8 (Dense) | (None, 25) | |
| dense_9 (Dense) | (None, 1) | |

```
 Total params: 32,301 (126.18 KB)
 Trainable params: 32,301 (126.18 KB)
 Non-trainable params: 0 (0.00 B)
```

Train the model:

```
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50
```

```
Epoch 1/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 9s 11ms/step - loss: 0.0817 - val_loss: 0.0270
Epoch 2/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 9ms/step - loss: 0.0387 - val_loss: 0.0232
Epoch 3/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0306 - val_loss: 0.0224
```

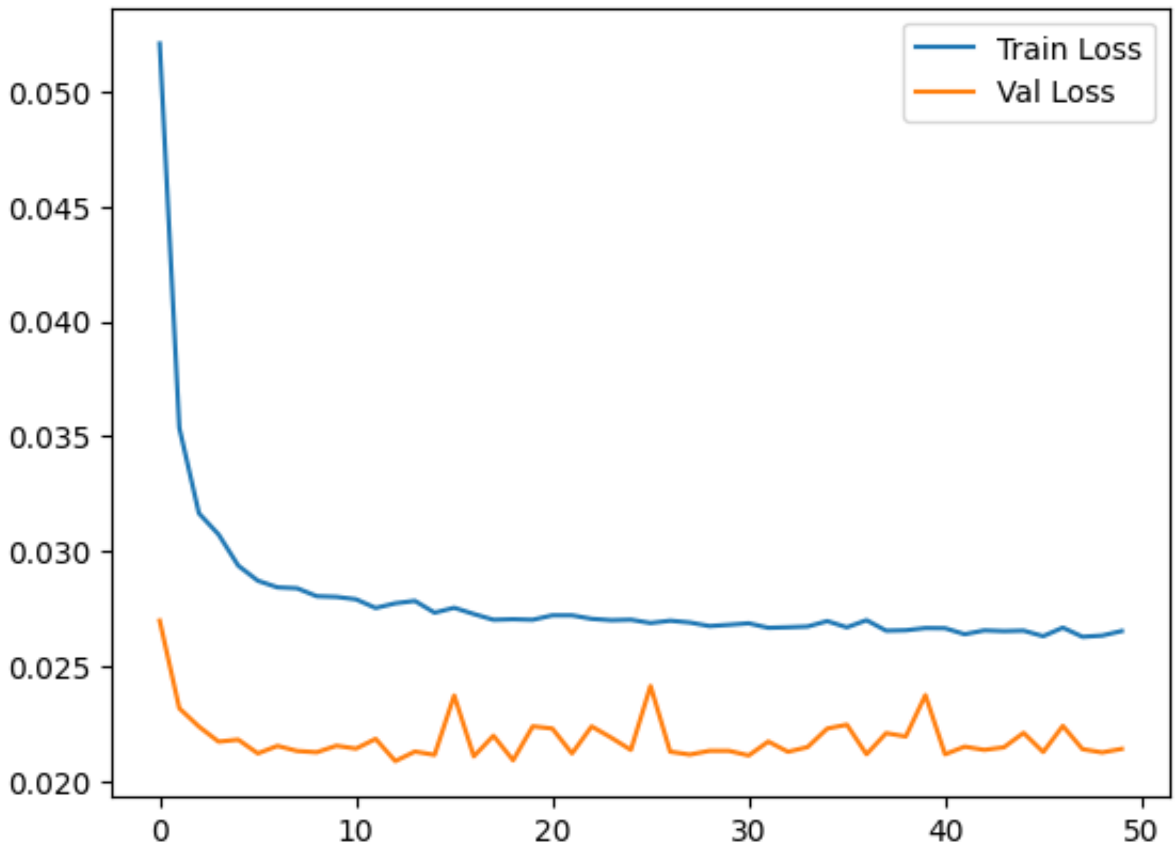
```
Epoch 4/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 9s 9ms/step - loss: 0.0337 - val_loss: 0.0217
Epoch 5/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0284 - val_loss: 0.0218
Epoch 6/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 8s 8ms/step - loss: 0.0271 - val_loss: 0.0212
Epoch 7/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0312 - val_loss: 0.0215
Epoch 8/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 9s 9ms/step - loss: 0.0316 - val_loss: 0.0213
Epoch 9/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0290 - val_loss: 0.0212
Epoch 10/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - loss: 0.0267 - val_loss: 0.0215
Epoch 11/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 5s 9ms/step - loss: 0.0275 - val_loss: 0.0214
Epoch 12/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 11ms/step - loss: 0.0287 - val_loss: 0.0218
Epoch 13/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 9ms/step - loss: 0.0290 - val_loss: 0.0209
Epoch 14/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 9ms/step - loss: 0.0261 - val_loss: 0.0213
Epoch 15/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 10ms/step - loss: 0.0262 - val_loss: 0.0211
Epoch 16/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - loss: 0.0259 - val_loss: 0.0237
Epoch 17/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 5s 10ms/step - loss: 0.0269 - val_loss: 0.0211
Epoch 18/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 5s 10ms/step - loss: 0.0295 - val_loss: 0.0220
Epoch 19/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - loss: 0.0290 - val_loss: 0.0209
Epoch 20/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 5s 10ms/step - loss: 0.0261 - val_loss: 0.0224
Epoch 21/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 5s 11ms/step - loss: 0.0265 - val_loss: 0.0223
Epoch 22/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 10s 11ms/step - loss: 0.0265 - val_loss: 0.0212
Epoch 23/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 9s 9ms/step - loss: 0.0277 - val_loss: 0.0224
Epoch 24/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0279 - val_loss: 0.0219
Epoch 25/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 9s 9ms/step - loss: 0.0281 - val_loss: 0.0213
Epoch 26/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0272 - val_loss: 0.0241
Epoch 27/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 9s 9ms/step - loss: 0.0268 - val_loss: 0.0213
Epoch 28/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 6s 12ms/step - loss: 0.0262 - val_loss: 0.0211
```

```
Epoch 29/50
473/473 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - loss: 0.0280 - val_loss: 0.0213
Epoch 30/50
```

Step 7: Evaluate the Model

Plot loss curve:

```
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.legend()
plt.show()
```

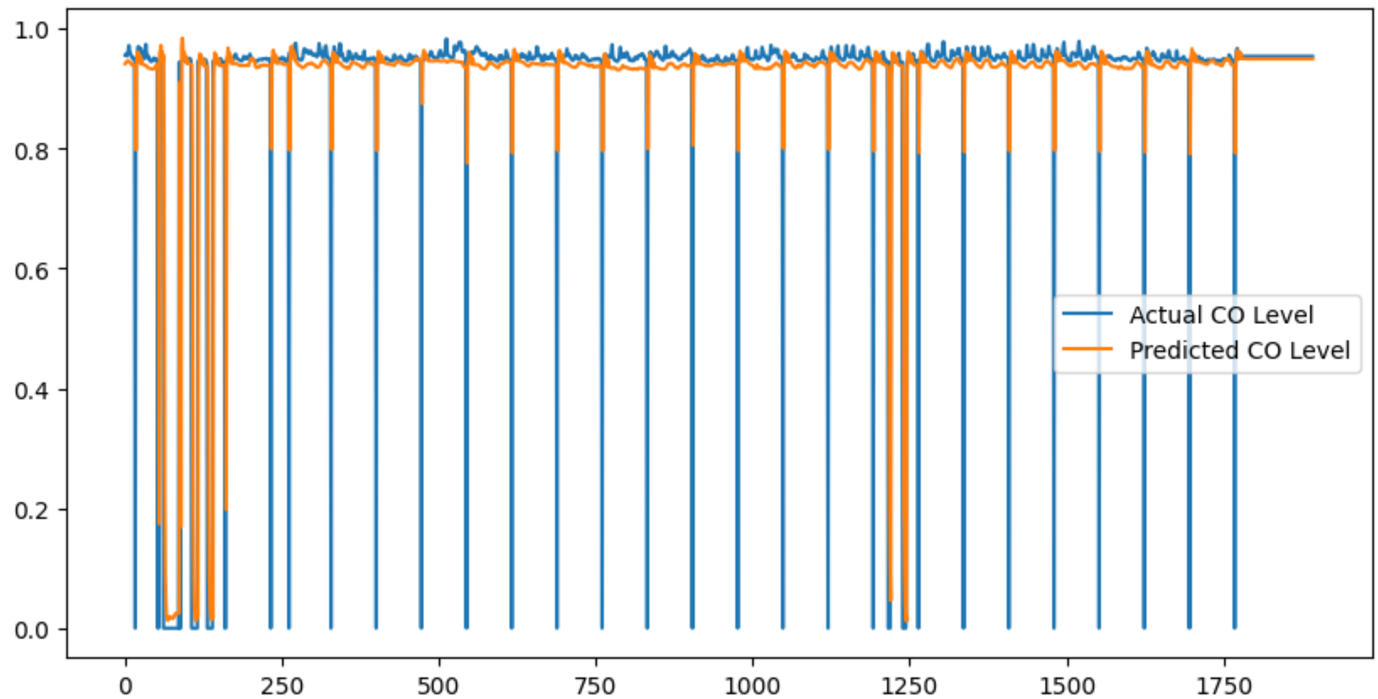



Predict and compare with actual values:

```
y_pred = model.predict(X_test.reshape(-1, time_steps, 3))


plt.figure(figsize=(10,5))
plt.plot(y_test, label='Actual CO Level')
plt.plot(y_pred, label='Predicted CO Level')
plt.legend()
plt.show()
```

```
60/60 ━━━━━━━━━━━━━━━━━━━━ 1s 9ms/step
```




Step 7: Deploy trained model using Streamlit for an interactive dashboard

```
from google.colab import files

joblib.dump(scaler, 'scaler.pkl')
files.download('scaler.pkl')

# Save the model
model.save('air_quality_model.h5')
files.download('air_quality_model.h5')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `
```

```
model.summary()
```

**Model: "sequential_4"**

| Layer (type) | Output Shape | |
|---|---|---|
| lstm_8 (LSTM) | (None, 10, 50) | |
| dropout_8 (Dropout) | (None, 10, 50) | |
| lstm_9 (LSTM) | (None, 50) | |
| dropout_9 (Dropout) | (None, 50) | |
| dense_8 (Dense) | (None, 25) | |
| dense_9 (Dense) | (None, 1) | |

**Total params:** 96,905 (378.54 KB)
**Trainable params:** 32,301 (126.18 KB)
**Non-trainable params:** 0 (0.00 B)
**Optimizer params:** 64,604 (252.36 KB)