Machine_Learning_IoT_Application_Design_and_Implementation_Air_Qu

February 23, 2025

0.1 Introduction

The purpose of this notebook is to demonstrate a comprehensive data pipeline for an IoT sensorered Air Quality dataset, starting with data cleaning and EDA to address missing values, outliers, and proper datetime formatting. Two deep learning models were developed: an LSTM for time-series temperature prediction and a deep feed-forward neural network for NO2 forecasting.

[1]:
```
import csv
import numpy as np
import pandas as pd
import tensorflow as tf
from google.colab import drive
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.layers import BatchNormalization, Dense, Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, StandardScaler

drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[2]:
```
!pip install openpyxl
```

```
Requirement already satisfied: openpyxl in /usr/local/lib/python3.11/dist-
packages (3.1.5)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.11/dist-
packages (from openpyxl) (2.0.0)
```

##EDA Summary## The EDA carried out created a Datetime column, converted other columns into numerical data, dropped NaN/NaT rows (~100). Two copies of that dataframe were created.

- df_no_outliers has removed rows with outliers in any column via IQR Method. The count for all rows decreased from 9357 to 5436 from this process. Outlier removal for any numerical

column can ommited or re-added in the df_no_outliers module, which allows for increase the count value when priotizing certain sensor data over others.
- df_median replaced outliers with the median conserving the count, the number of data points becomes a priority during model trainng, testing and validation evaluation.

[3]:
```
data_path = "/content/drive/My Drive/AirQualityUCI.csv" #Defining a path to the␣
↪.csv file in MyDrive, change path as needed
df_raw = pd.read_csv(data_path, sep=';') # Add sep=';' to specify semicolon as␣
↪delimiterz
```

[4]:
```
# Drop columns with all NaN values
nan_cols = df_raw.columns[df_raw.isna().all()]
df_raw = df_raw.drop(columns=nan_cols)

# Ensure date and time are correctly formatted
df_raw['Date'] = pd.to_datetime(df_raw['Date'], format='%d/%m/%Y',␣
↪errors='coerce')
df_raw['Time'] = pd.to_datetime(df_raw['Time'], format='%H.%M.%S',␣
↪errors='coerce')

# Combine 'Date' and 'Time' into a 'Datetime' column
df_raw['Datetime'] = pd.to_datetime(df_raw['Date'].astype(str) + ' ' +␣
↪df_raw['Time'].astype(str), errors='coerce')

# Display the head of the DataFrame to confirm the changes
print(df_raw.head())

# Display the datatypes to verify the conversion
print(df_raw.dtypes)
```

```
<ipython-input-4-871fd710467c>:10: UserWarning: Could not infer format, so each
element will be parsed individually, falling back to `dateutil`. To ensure
parsing is consistent and as-expected, please specify a format.
  df_raw['Datetime'] = pd.to_datetime(df_raw['Date'].astype(str) + ' ' +
df_raw['Time'].astype(str), errors='coerce')

        Date                Time CO(GT)  PT08.S1(CO)  NMHC(GT) C6H6(GT)  \
0 2004-03-10 1900-01-01 18:00:00    2,6       1360.0     150.0     11,9
1 2004-03-10 1900-01-01 19:00:00      2       1292.0     112.0      9,4
2 2004-03-10 1900-01-01 20:00:00    2,2       1402.0      88.0      9,0
3 2004-03-10 1900-01-01 21:00:00    2,2       1376.0      80.0      9,2
4 2004-03-10 1900-01-01 22:00:00    1,6       1272.0      51.0      6,5

   PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)  \
0         1046.0    166.0        1056.0    113.0        1692.0       1268.0
1          955.0    103.0        1174.0     92.0        1559.0        972.0
2          939.0    131.0        1140.0    114.0        1555.0       1074.0
3          948.0    172.0        1092.0    122.0        1584.0       1203.0
```

```
4          836.0    131.0        1205.0    116.0        1490.0       1110.0

      T    RH      AH                  Datetime
0  13,6  48,9  0,7578 2004-03-10 18:00:00-01:00
1  13,3  47,7  0,7255 2004-03-10 19:00:00-01:00
2  11,9  54,0  0,7502 2004-03-10 20:00:00-01:00
3  11,0  60,0  0,7867 2004-03-10 21:00:00-01:00
4  11,2  59,6  0,7888 2004-03-10 22:00:00-01:00
Date                          datetime64[ns]
Time                          datetime64[ns]
CO(GT)                                object
PT08.S1(CO)                          float64
NMHC(GT)                             float64
C6H6(GT)                              object
PT08.S2(NMHC)                        float64
NOx(GT)                              float64
PT08.S3(NOx)                         float64
NO2(GT)                              float64
PT08.S4(NO2)                         float64
PT08.S5(O3)                          float64
T                                     object
RH                                    object
AH                                    object
Datetime           datetime64[ns, UTC-01:00]
dtype: object
```

[5]:
```
#Replacing commas with dots and convert to numeric for all applicable columns
cols_before_conversion = ['CO(GT)', 'C6H6(GT)', 'T', 'RH', 'AH']
for col in cols_before_conversion:
    # Converting the column to string type before applying str.replace
    df_raw[col] = df_raw[col].astype(str).str.replace(',', '.').astype(float)

#Counts before converting commas to dots (then converting to numerical values␣
↪in the next module), CO(GT)=2137, C6H6(GT)=NaN, T=366, RH=366, AH=366
```

[6]:
```
#Converting all data columns (except 'Datetime', 'Date', and 'Time') to numeric␣
↪types
#Again, the errors='coerce' argument handles potential conversion errors by␣
↪setting invalid values to NaN (Not a Number)
for col in df_raw.columns:
    if col not in ['Datetime', 'Date', 'Time']:  #Exclude these columns,␣
↪converting them would provide large numbers that do not provide useful␣
↪information, at least in this context
        df_raw[col] = pd.to_numeric(df_raw[col], errors='coerce')  #Key step,␣
↪converting all data in columns not excluded to numeric, helps guarantee data␣
↪consistency through an explicit conversion
```

[7]:
```
#Displaying the head of the DataFrame to confirm the changes
print(df_raw.head())

#Displaying the datatypes to verify the conversion
print(df_raw.dtypes)
```

```
        Date                Time  CO(GT)  PT08.S1(CO)  NMHC(GT)  C6H6(GT)  \
0 2004-03-10 1900-01-01 18:00:00     2.6       1360.0     150.0      11.9
1 2004-03-10 1900-01-01 19:00:00     2.0       1292.0     112.0       9.4
2 2004-03-10 1900-01-01 20:00:00     2.2       1402.0      88.0       9.0
3 2004-03-10 1900-01-01 21:00:00     2.2       1376.0      80.0       9.2
4 2004-03-10 1900-01-01 22:00:00     1.6       1272.0      51.0       6.5

   PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)  \
0         1046.0    166.0        1056.0    113.0        1692.0       1268.0
1          955.0    103.0        1174.0     92.0        1559.0        972.0
2          939.0    131.0        1140.0    114.0        1555.0       1074.0
3          948.0    172.0        1092.0    122.0        1584.0       1203.0
4          836.0    131.0        1205.0    116.0        1490.0       1110.0

      T    RH      AH                  Datetime
0  13.6  48.9  0.7578 2004-03-10 18:00:00-01:00
1  13.3  47.7  0.7255 2004-03-10 19:00:00-01:00
2  11.9  54.0  0.7502 2004-03-10 20:00:00-01:00
3  11.0  60.0  0.7867 2004-03-10 21:00:00-01:00
4  11.2  59.6  0.7888 2004-03-10 22:00:00-01:00
Date                            datetime64[ns]
Time                            datetime64[ns]
CO(GT)                                 float64
PT08.S1(CO)                            float64
NMHC(GT)                               float64
C6H6(GT)                               float64
PT08.S2(NMHC)                          float64
NOx(GT)                                float64
PT08.S3(NOx)                           float64
NO2(GT)                                float64
PT08.S4(NO2)                           float64
PT08.S5(O3)                            float64
T                                      float64
RH                                     float64
AH                                     float64
Datetime                 datetime64[ns, UTC-01:00]
dtype: object
```

[8]:
```
df_raw.Date[0] #Prints out first date in the dataset
```

[8]:
```
Timestamp('2004-03-10 00:00:00')
```

[9]:
```
df_raw.Time[0] #Prints out first time in the dataset
```

[9]:
```
Timestamp('1900-01-01 18:00:00')
```

[10]:
```
df_raw.Datetime[0] #Prints out datetime date in the dataset
```

[10]:
```
Timestamp('2004-03-10 18:00:00-0100', tz='UTC-01:00')
```

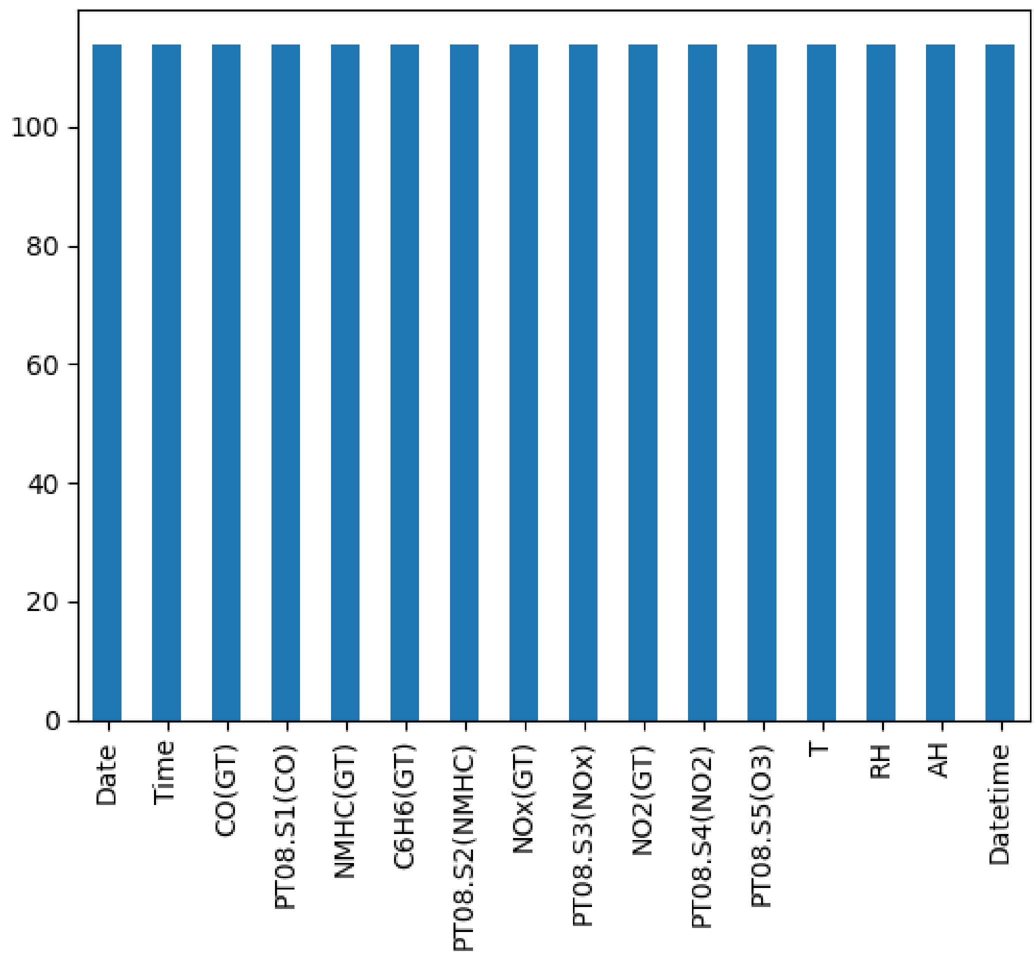
[11]:
```
df_raw.describe(include='all')  #Includes all columns, including Datetime
#describes dataset following conversions to numerical values, counts for all␣
↪categories have changed to 9357
#Date, Time, Datetime were not converted to numerical values because of their␣
↪object-like datetime64[ns] datatype, so describe() carries out data analysis␣
↪on the other columns
```

[11]:
```
                                Date                           Time  \
count                           9357                           9357
mean   2004-09-21 04:30:05.193972480  1900-01-01 11:29:54.806028032
min              2004-03-10 00:00:00            1900-01-01 00:00:00
25%              2004-06-16 00:00:00            1900-01-01 05:00:00
50%              2004-09-21 00:00:00            1900-01-01 11:00:00
75%              2004-12-28 00:00:00            1900-01-01 18:00:00
max              2005-04-04 00:00:00            1900-01-01 23:00:00
std                              NaN                            NaN

            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
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
std      77.657170   329.832710   139.789093    41.380206     342.333252

           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
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
std     257.433866    321.993552   126.940455    467.210125   456.938184

                 T           RH           AH  \
count  9357.000000  9357.000000  9357.000000
```

```
mean      9.778305    39.485380    -6.837604
min    -200.000000  -200.000000  -200.000000
25%      10.900000    34.100000     0.692300
50%      17.200000    48.600000     0.976800
75%      24.100000    61.900000     1.296200
max      44.600000    88.700000     2.231000
std      43.203623    51.216145    38.976670

                                  Datetime
count                                 9357
mean   2004-09-21 15:59:59.999999872-01:00
min              2004-03-10 18:00:00-01:00
25%              2004-06-16 05:00:00-01:00
50%              2004-09-21 16:00:00-01:00
75%              2004-12-28 03:00:00-01:00
max              2005-04-04 14:00:00-01:00
std                                    NaN
```

[12]:
```python
df_raw.isna().sum().plot.bar()
#df.isna creates True values for NaN/NaT values, false otherwise (not counted
 ↪in the graph below)
#In other words, this below graph illustrates the number of missing values
#It appears that there are approximately 110 rows in each category with NaN/NaT
 ↪values
#Removing about 100 rows out more than 9,000 will not likely distort, dropna()
 ↪is an appropriate approach
```

[12]: <Axes: >



[13]:
```
# Drop rows with missing values, but exclude the 'Datetime' column
df_dropna = df_raw.dropna(subset=df_raw.columns.difference(['Datetime']))
#No NaT/NaN values detected after using dropna()
```

[14]:
```
df_dropna.describe(include='all')  #Includes all columns, including Datetime
```

[14]:
```
                                Date                           Time  \
count                           9357                           9357
mean   2004-09-21 04:30:05.193972480  1900-01-01 11:29:54.806028032
min              2004-03-10 00:00:00            1900-01-01 00:00:00
25%              2004-06-16 00:00:00            1900-01-01 05:00:00
50%              2004-09-21 00:00:00            1900-01-01 11:00:00
75%              2004-12-28 00:00:00            1900-01-01 18:00:00
max              2005-04-04 00:00:00            1900-01-01 23:00:00
std                              NaN                            NaN

            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
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
std      77.657170   329.832710   139.789093    41.380206     342.333252

           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
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
std     257.433866    321.993552   126.940455    467.210125   456.938184

                 T           RH           AH  \
count  9357.000000  9357.000000  9357.000000
mean      9.778305    39.485380    -6.837604
min    -200.000000  -200.000000  -200.000000
25%      10.900000    34.100000     0.692300
50%      17.200000    48.600000     0.976800
75%      24.100000    61.900000     1.296200
max      44.600000    88.700000     2.231000
std      43.203623    51.216145    38.976670

                                  Datetime
count                                 9357
mean   2004-09-21 15:59:59.999999872-01:00
min              2004-03-10 18:00:00-01:00
25%              2004-06-16 05:00:00-01:00
50%              2004-09-21 16:00:00-01:00
75%              2004-12-28 03:00:00-01:00
max              2005-04-04 14:00:00-01:00
std                                    NaN
```

[15]:
```python
#Creating a copy of the df_dropna DataFrame and assign it to df_dropna_copy1
df_dropna_copy1 = df_dropna.copy()
#Creating another copy of df_dropna and assign it to df_dropna_copy2
df_dropna_copy2 = df_dropna.copy()
#Creating a copy ensures that any modifications made to the copies will not␣
↪affect the original df_dropna dataframe.
#This is important to preserve the original data for later use or comparison.
```

[16]:
```
#Removing outliers of specified columns via IQR method
def remove_outliers_iqr(df_dropna_copy1, columns):
    for col in columns:
        Q1 = df_dropna_copy1[col].quantile(0.25)
        Q3 = df_dropna_copy1[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df_dropna_copy1 = df_dropna_copy1[(df_dropna_copy1[col] >= lower_bound)␣
 ↪& (df_dropna_copy1[col] <= upper_bound)]
    return df_dropna_copy1

# Specifying the columns to check for outliers
outlier_columns = ['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']

#Specifing the columns to check for outliers, keeping NMHC(GT) because removing␣
 ↪outliers only left one value which was -200
#outlier_columns = ['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']
#However, this change only increased counts from 5436 (all outliers removed␣
 ↪including NMHC(GT) to 6090)


# Removing outliers from the specified columns using df_dropna_copy1
df_no_outliers = remove_outliers_iqr(df_dropna_copy1, outlier_columns)
```

[17]:
```
df_no_outliers.describe(include='all')  #Includes all columns, including␣
 ↪Datetime
```

[17]:
```
                                Date                           Time  \
count                           5436                           5436
mean   2004-10-17 02:01:35.364238592  1900-01-01 11:54:14.966887424
min              2004-03-18 00:00:00            1900-01-01 00:00:00
25%              2004-07-09 00:00:00            1900-01-01 06:00:00
50%              2004-10-26 00:00:00            1900-01-01 12:00:00
75%              2005-01-22 00:00:00            1900-01-01 18:00:00
max              2005-04-04 00:00:00            1900-01-01 23:00:00
std                              NaN                            NaN

            CO(GT)  PT08.S1(CO)  NMHC(GT)     C6H6(GT)  PT08.S2(NMHC)  \
count  5436.000000  5436.000000    5436.0  5436.000000    5436.000000
```

```
mean       1.908793  1077.993194    -200.0     9.323859     922.738962
min        0.100000   667.000000    -200.0     0.500000     440.000000
25%        1.100000   944.000000    -200.0     4.800000     754.000000
50%        1.700000  1058.500000    -200.0     8.200000     907.000000
75%        2.600000  1192.250000    -200.0    13.000000    1083.000000
max        5.600000  1633.000000    -200.0    27.200000    1484.000000
std        1.065633   173.435032       0.0     5.689495     219.069460

            NOx(GT)  PT08.S3(NOx)      NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)  \
count  5436.000000   5436.000000  5436.000000   5436.000000  5436.000000
mean    223.148823    804.952723   110.214496   1409.556291   999.946468
min       2.000000    360.000000     2.000000    601.000000   288.000000
25%     104.000000    664.000000    78.000000   1158.000000   748.000000
50%     185.000000    786.000000   108.000000   1423.000000   973.000000
75%     312.000000    924.000000   138.000000   1648.000000  1229.000000
max     670.000000   1366.000000   233.000000   2367.000000  1947.000000
std     151.398454    191.844767    42.472373    331.169765   331.310392

                 T           RH           AH  \
count  5436.000000  5436.000000  5436.000000
mean     18.616611    47.959547     1.020571
min      -1.900000     9.200000     0.184700
25%      11.700000    34.000000     0.699600
50%      18.300000    47.900000     1.011300
75%      25.100000    61.700000     1.317225
max      44.600000    88.700000     2.180600
std       9.323353    17.744093     0.421447

                                  Datetime
count                                 5436
mean   2004-10-17 13:55:50.331125888-01:00
min              2004-03-18 10:00:00-01:00
25%              2004-07-09 21:45:00-01:00
50%              2004-10-26 07:30:00-01:00
75%              2005-01-22 20:45:00-01:00
max              2005-04-04 14:00:00-01:00
std                                    NaN
```

[18]:

```python
#Function to replace outliers with median
def replace_outliers_with_median(df_dropna_copy2, columns):
    df_median = df_dropna_copy2.copy()  #Maybe df_median = df_dropna_copy2␣
 ↪would be just fine
    for col in columns:
        Q1 = df_median[col].quantile(0.25)
        Q3 = df_median[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
```

```
        upper_bound = Q3 + 1.5 * IQR

        # Replace outliers with median
        median_val = df_median[col].median()
        df_median.loc[(df_median[col] < lower_bound) | (df_median[col] >␣
↪upper_bound), col] = median_val
    return df_median

# Specifying the columns to check for outliers
outlier_columns = ['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']

# Replacing outliers with median in the specified columns
df_median = replace_outliers_with_median(df_dropna, outlier_columns)
```

[19]:

```
df_median.describe(include='all')  #Includes all columns, including Datetime
```

[19]:

```
                                Date                           Time  \
count                           9357                           9357
mean   2004-09-21 04:30:05.193972480  1900-01-01 11:29:54.806028032
min              2004-03-10 00:00:00            1900-01-01 00:00:00
25%              2004-06-16 00:00:00            1900-01-01 05:00:00
50%              2004-09-21 00:00:00            1900-01-01 11:00:00
75%              2004-12-28 00:00:00            1900-01-01 18:00:00
max              2005-04-04 00:00:00            1900-01-01 23:00:00
std                              NaN                            NaN

            CO(GT)  PT08.S1(CO)  NMHC(GT)     C6H6(GT)  PT08.S2(NMHC)  \
count  9357.000000  9357.000000    9357.0  9357.000000    9357.000000
mean      1.912846  1088.897510    -200.0     9.325115     931.570589
min       0.100000   647.000000    -200.0     0.100000     383.000000
25%       1.200000   941.000000    -200.0     4.600000     743.000000
50%       1.500000  1053.000000    -200.0     7.900000     895.000000
75%       2.400000  1210.000000    -200.0    12.900000    1098.000000
max       5.600000  1669.000000    -200.0    28.000000    1696.000000
std       1.108584   198.587178       0.0     6.117757     252.056606

           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    131.422785    812.121727   109.029069   1446.352998  1007.038794
min    -200.000000    322.000000     2.000000    551.000000   221.000000
25%      50.000000    666.000000    86.000000   1242.000000   742.000000
50%     141.000000    794.000000    96.000000   1446.000000   942.000000
75%     243.000000    938.000000   132.000000   1652.000000  1238.000000
```

```
max      635.000000   1442.000000   253.000000   2376.000000  2087.000000
std      200.009248    211.595481    42.448966    324.204747   371.585033

                 T           RH           AH  \
count  9357.000000  9357.000000  9357.000000
mean     18.268280    49.209394     1.023490
min      -1.900000     9.200000     0.184700
25%      12.000000    36.600000     0.746100
50%      17.200000    48.600000     0.976800
75%      24.100000    61.900000     1.295800
max      43.400000    88.700000     2.180600
std       8.651903    16.975247     0.395752

                               Datetime
count                              9357
mean   2004-09-21 15:59:59.999999872-01:00
min              2004-03-10 18:00:00-01:00
25%              2004-06-16 05:00:00-01:00
50%              2004-09-21 16:00:00-01:00
75%              2004-12-28 03:00:00-01:00
max              2005-04-04 14:00:00-01:00
std                                 NaN
```

[20]:

```python
#Export df_no_outliers to a CSV file
df_no_outliers.to_csv('/content/drive/My Drive/df_no_outliers.csv',␣
 ↪index=False, quoting=csv.QUOTE_ALL)  #index=False prevents writing the␣
 ↪dataframe's index

#Export df_no_outliers to an Excel file
#df_no_outliers.to_excel('/content/drive/My Drive/df_no_outliers.xlsx',␣
 ↪index=False) #index=False prevents writing the dataframe's index
#ValueError: Excel does not support datetimes with timezones. Please ensure␣
 ↪that datetimes are timezone unaware before writing to Excel
```

0.2 Deep Learning Time Series Predictor (LSTM for Temperature "T")

This code block first sorts the cleaned dataset by datetime and extracts the Temperature column, ensuring no missing values remain. It scales the temperature data between 0 and 1 using MinMaxScaler to prepare it for neural network training. Next, it creates time-series sequences with a 24-hour lookback, turning the problem into a supervised learning task with input sequences (X) and corresponding targets (y). A simple LSTM model is then built from scratch using TensorFlow/Keras, and it is trained on 80% of the data while validating on the remaining 20%. Finally, the model's performance is evaluated on the test set, and predictions are inverse-transformed back to the original scale for direct comparison with the actual temperature values.

[21]:

```python
# Ensure data is sorted by datetime
df_ts = df_dropna.sort_values(by='Datetime').reset_index(drop=True)
```

```python
# Select the datetime and Temperature ("T") columns and drop any remaining NaNs
df_ts = df_ts[['Datetime', 'T']].dropna()

# Define lookback period (e.g., past 24 hours)
LOOKBACK = 24

# Extract the temperature values and reshape for scaling
temp_values = df_ts['T'].values.reshape(-1, 1)

# Scale the temperature data to [0,1]
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_temp = scaler.fit_transform(temp_values)

# Create sequences for supervised learning
X, y = [], []
for i in range(LOOKBACK, len(scaled_temp)):
    X.append(scaled_temp[i-LOOKBACK:i, 0])
    y.append(scaled_temp[i, 0])

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

# Reshape X to be [samples, time steps, features]
X = X.reshape(X.shape[0], X.shape[1], 1)

# Split the data into training and testing sets (time-series split)
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Build a simple LSTM model from scratch
model = keras.Sequential([
    layers.LSTM(32, activation='tanh', input_shape=(LOOKBACK, 1)),
    layers.Dense(1)
])

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

# Train the model (adjust epochs as needed)
history = model.fit(X_train, y_train, epochs=10, batch_size=32,
                    validation_data=(X_test, y_test), verbose=1)

# Evaluate the model on test data
loss = model.evaluate(X_test, y_test)
print(f"\nTest MSE (scaled): {loss}")
```

```python
# Make predictions and convert them back to the original scale
y_pred_scaled = model.predict(X_test)
y_pred = scaler.inverse_transform(y_pred_scaled)
y_test_original = scaler.inverse_transform(y_test.reshape(-1, 1))

# Display a few sample predictions vs. actual values
for i in range(5):
    print(f"Predicted T: {y_pred[i][0]:.2f}, Actual T: {y_test_original[i][0]:.
↪2f}")
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
```

```
Epoch 1/10
234/234              11s 28ms/step -
loss: 0.1383 - val_loss: 0.0071
Epoch 2/10
234/234              7s 13ms/step -
loss: 0.0088 - val_loss: 0.0062
Epoch 3/10
234/234              3s 11ms/step -
loss: 0.0063 - val_loss: 0.0050
Epoch 4/10
234/234              4s 15ms/step -
loss: 0.0054 - val_loss: 0.0045
Epoch 5/10
234/234              2s 10ms/step -
loss: 0.0052 - val_loss: 0.0039
Epoch 6/10
234/234              3s 10ms/step -
loss: 0.0059 - val_loss: 0.0035
Epoch 7/10
234/234              2s 10ms/step -
loss: 0.0049 - val_loss: 0.0031
Epoch 8/10
234/234              2s 10ms/step -
loss: 0.0035 - val_loss: 0.0028
Epoch 9/10
234/234              3s 14ms/step -
loss: 0.0042 - val_loss: 0.0026
Epoch 10/10
234/234              3s 12ms/step -
loss: 0.0038 - val_loss: 0.0026
59/59              0s 4ms/step - loss:
0.0030
```

```
Test MSE (scaled): 0.002551934914663434
59/59                1s 6ms/step
Predicted T: 5.65, Actual T: 8.10
Predicted T: 5.45, Actual T: 7.70
Predicted T: 5.23, Actual T: 7.00
Predicted T: 4.75, Actual T: 6.60
Predicted T: 4.34, Actual T: 6.40
```

0.3 LSTM Intrepetation

The model shows a low scaled MSE but consistently underpredicts the actual temperature values, indicating a calibration issue. Although the losses decrease over epochs, the model struggles with accuracy, likely due to its simplicity. Improvements are needed to better capture the temperature patterns and improve prediction reliability. for 4 seconds The model achieved a low scaled test MSE, yet the inverse-transformed predictions are consistently lower than the actual temperature values, indicating systematic underprediction. Although the training and validation losses decreased steadily, the model still fails to capture the true magnitude of the temperature. In summary, it learns trends but underestimates absolute values.

0.4 Optimized Deep Learning Time Series Predictor (LSTM for Temperature "T")

To optimize performance, the architecture was enhanced by stacking multiple LSTM layers with dropout layers to better regularize the network and capture more complex temporal patterns. Additionally, the learning rate was reduced to allow finer convergence, the number of training epochs was increased to 30, and the batch size was reduced to 16 for more granular updates. These modifications aim to improve the model's ability to learn and generalize, ultimately reducing the discrepancy between predicted and actual temperature values.

[22]:
```python
# Use the outlier-corrected dataframe (df_median) for temperature prediction
df_ts = df_median.sort_values(by='Datetime').reset_index(drop=True)
df_ts = df_ts[['Datetime', 'T']].dropna()

# Define lookback period (e.g., past 24 hours)
LOOKBACK = 24

# Extract the temperature values and reshape for scaling
temp_values = df_ts['T'].values.reshape(-1, 1)

# Scale the temperature data to [0,1] using MinMaxScaler (with outliers␣
↪mitigated)
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_temp = scaler.fit_transform(temp_values)

# Create sequences for supervised learning
X, y = [], []
for i in range(LOOKBACK, len(scaled_temp)):
```

```
    X.append(scaled_temp[i-LOOKBACK:i, 0])
    y.append(scaled_temp[i, 0])
X = np.array(X)
y = np.array(y)
X = X.reshape(X.shape[0], X.shape[1], 1)

# Split the data into training and testing sets (time-series split)
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Build an optimized LSTM model with stacked layers, dropout, and a sigmoid␣
 ↪output activation
optimized_model = keras.Sequential([
    layers.LSTM(64, activation='tanh', return_sequences=True,␣
 ↪input_shape=(LOOKBACK, 1)),
    layers.Dropout(0.2),
    layers.LSTM(32, activation='tanh'),
    layers.Dropout(0.2),
    layers.Dense(1, activation='sigmoid')  # constrain output to [0,1]
])

# Use an even lower learning rate for finer convergence
optimizer = Adam(learning_rate=0.0002)
optimized_model.compile(optimizer=optimizer, loss='mean_squared_error')

# Define EarlyStopping to halt training if the validation loss does not improve␣
 ↪for 3 epochs
early_stopping = EarlyStopping(monitor='val_loss', patience=3,␣
 ↪restore_best_weights=True)

# Train the optimized model for 20 epochs with a smaller batch size and early␣
 ↪stopping
history_optimized = optimized_model.fit(
    X_train, y_train,
    epochs=20,
    batch_size=16,
    validation_data=(X_test, y_test),
    callbacks=[early_stopping],
    verbose=1
)

# Evaluate the optimized model on the test set
loss_optimized = optimized_model.evaluate(X_test, y_test)
print(f"\nOptimized Test MSE (scaled): {loss_optimized}")
```

```
# Make predictions with the optimized model and convert them back to the␣
↪original scale
y_pred_scaled_optimized = optimized_model.predict(X_test)
y_pred_optimized = scaler.inverse_transform(y_pred_scaled_optimized)

# Also prepare the actual values in original scale (they come from the scaler␣
↪applied earlier)
y_test_original = scaler.inverse_transform(y_test.reshape(-1, 1))

# Display a few sample predictions vs. actual values
for i in range(5):
    print(f"Optimized Predicted T: {y_pred_optimized[i][0]:.2f}, Actual T:␣
↪{y_test_original[i][0]:.2f}")
```

```
Epoch 1/20
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
```

```
467/467                15s 24ms/step -
loss: 0.0217 - val_loss: 0.0095
Epoch 2/20
467/467                10s 22ms/step -
loss: 0.0092 - val_loss: 0.0078
Epoch 3/20
467/467                10s 22ms/step -
loss: 0.0061 - val_loss: 0.0070
Epoch 4/20
467/467                17s 36ms/step -
loss: 0.0050 - val_loss: 0.0059
Epoch 5/20
467/467                14s 23ms/step -
loss: 0.0048 - val_loss: 0.0047
Epoch 6/20
467/467                19s 20ms/step -
loss: 0.0046 - val_loss: 0.0053
Epoch 7/20
467/467                11s 22ms/step -
loss: 0.0041 - val_loss: 0.0040
Epoch 8/20
467/467                20s 22ms/step -
loss: 0.0037 - val_loss: 0.0038
Epoch 9/20
467/467                9s 20ms/step -
loss: 0.0036 - val_loss: 0.0039
```

```
Epoch 10/20
467/467             12s 24ms/step -
loss: 0.0034 - val_loss: 0.0036
Epoch 11/20
467/467             19s 21ms/step -
loss: 0.0032 - val_loss: 0.0029
Epoch 12/20
467/467             10s 20ms/step -
loss: 0.0030 - val_loss: 0.0027
Epoch 13/20
467/467             11s 22ms/step -
loss: 0.0028 - val_loss: 0.0031
Epoch 14/20
467/467             21s 22ms/step -
loss: 0.0027 - val_loss: 0.0023
Epoch 15/20
467/467             10s 21ms/step -
loss: 0.0024 - val_loss: 0.0023
Epoch 16/20
467/467             11s 23ms/step -
loss: 0.0024 - val_loss: 0.0021
Epoch 17/20
467/467             11s 24ms/step -
loss: 0.0022 - val_loss: 0.0018
Epoch 18/20
467/467             11s 22ms/step -
loss: 0.0022 - val_loss: 0.0021
Epoch 19/20
467/467             10s 21ms/step -
loss: 0.0021 - val_loss: 0.0014
Epoch 20/20
467/467             10s 20ms/step -
loss: 0.0020 - val_loss: 0.0016
59/59             0s 8ms/step - loss:
0.0015

Optimized Test MSE (scaled): 0.001412219018675387
59/59             1s 17ms/step
Optimized Predicted T: 7.43, Actual T: 8.10
Optimized Predicted T: 6.87, Actual T: 7.70
Optimized Predicted T: 6.54, Actual T: 7.00
Optimized Predicted T: 6.28, Actual T: 6.60
Optimized Predicted T: 6.09, Actual T: 6.40
```

0.5 Optimized LTSM Interpretation

This code block optimizes the temperature prediction model by first using an outlier-corrected dataset to ensure that the scaling accurately reflects typical values. Temperature data is scaled to the [0, 1] range and converted into 24-hour lookback sequences for supervised learning. The optimized model features stacked LSTM layers with dropout for regularization and a final Dense layer with sigmoid activation to constrain outputs within the same scale. A lower learning rate of 0.002 and early stopping with a patience of 3 epochs are implemented to enable finer convergence and prevent overfitting. Finally, predictions are inverse-transformed back to the original scale for direct comparison with actual values.

0.6 Deep Learning Model for Predicting "NO2(GT)" (Feed-forward Neural Network)

This code block begins by filtering the cleaned dataset to remove rows with missing "NO2(GT)" values and selecting a set of sensor features as inputs along with "NO2(GT)" as the target variable. It then splits the data into training and testing sets and standardizes the features using StandardScaler to normalize their distribution. A deep feed-forward neural network is constructed using Keras, featuring three hidden Dense layers with ReLU activations and a final output layer for regression. The model is compiled with the Adam optimizer and mean squared error loss, and it is trained for 50 epochs with a batch size of 32 while reserving 20% of the training data for validation. Finally, the model's performance is evaluated on the test set by calculating MSE and RMSE, and several sample predictions are printed alongside their corresponding actual values.

[23]:
```
# Use the cleaned dataframe from your EDA (e.g., df_dropna) and drop rows␣
↪missing "NO2(GT)"
df_dl = df_dropna.dropna(subset=['NO2(GT)']).copy()

# Define the target variable and features
target = 'NO2(GT)'
features = ['CO(GT)', 'C6H6(GT)', 'T', 'RH', 'AH',
            'PT08.S1(CO)', 'PT08.S2(NMHC)', 'PT08.S3(NOx)',
            'PT08.S4(NO2)', 'PT08.S5(O3)']

# Prepare the input features and target
X = df_dl[features]
y = df_dl[target]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Scale the feature data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build a deep feed-forward neural network model
model_dl = Sequential([
    Dense(64, activation='relu', input_shape=(X_train_scaled.shape[1],)),
    Dense(32, activation='relu'),
    Dense(16, activation='relu'),
```

```python
    Dense(1)  # Output layer for regression
])

# Compile the model
model_dl.compile(optimizer=Adam(learning_rate=0.001), loss='mean_squared_error')

# Train the model
history_dl = model_dl.fit(X_train_scaled, y_train, epochs=50, batch_size=32,
                          validation_split=0.2, verbose=1)

# Evaluate the model on the test set
y_pred = model_dl.predict(X_test_scaled)
mse_dl = mean_squared_error(y_test, y_pred)
rmse_dl = np.sqrt(mse_dl)
print(f"Deep Learning Model MSE: {mse_dl:.2f}")
print(f"Deep Learning Model RMSE: {rmse_dl:.2f}")

# Display a few sample predictions versus actual values
print("\nSample predictions vs. actual NO2(GT) values:")
for i in range(5):
    print(f"Predicted NO2(GT): {y_pred[i][0]:.2f}, Actual NO2(GT): {y_test.
 ↪iloc[i]:.2f}")
```

```
Epoch 1/50
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
188/188              3s 5ms/step -
loss: 18566.7324 - val_loss: 9536.4082
Epoch 2/50
188/188              1s 3ms/step -
loss: 8377.7236 - val_loss: 7337.1104
Epoch 3/50
188/188              1s 2ms/step -
loss: 7480.4229 - val_loss: 7196.3755
Epoch 4/50
188/188              1s 3ms/step -
loss: 6980.1509 - val_loss: 7111.3291
Epoch 5/50
188/188              1s 3ms/step -
loss: 6824.1650 - val_loss: 7139.4834
Epoch 6/50
188/188              1s 3ms/step -
loss: 6764.4619 - val_loss: 7041.0200
Epoch 7/50
```

```
188/188            1s 3ms/step -
loss: 6896.1558 - val_loss: 7058.1191
Epoch 8/50
188/188            1s 2ms/step -
loss: 7188.3926 - val_loss: 7019.0166
Epoch 9/50
188/188            1s 3ms/step -
loss: 7130.2754 - val_loss: 7048.1665
Epoch 10/50
188/188            1s 2ms/step -
loss: 6710.2754 - val_loss: 6970.6655
Epoch 11/50
188/188            1s 4ms/step -
loss: 6718.1938 - val_loss: 6955.9443
Epoch 12/50
188/188            1s 3ms/step -
loss: 6734.9604 - val_loss: 6959.8926
Epoch 13/50
188/188            1s 3ms/step -
loss: 7085.4043 - val_loss: 6968.9131
Epoch 14/50
188/188            1s 3ms/step -
loss: 6368.8823 - val_loss: 6889.1489
Epoch 15/50
188/188            1s 3ms/step -
loss: 6562.9390 - val_loss: 6916.5947
Epoch 16/50
188/188            1s 2ms/step -
loss: 6614.9150 - val_loss: 6919.3706
Epoch 17/50
188/188            1s 4ms/step -
loss: 6875.5547 - val_loss: 6864.2290
Epoch 18/50
188/188            1s 4ms/step -
loss: 6822.2544 - val_loss: 6834.8096
Epoch 19/50
188/188            1s 4ms/step -
loss: 6880.1846 - val_loss: 6823.5215
Epoch 20/50
188/188            1s 2ms/step -
loss: 6392.7490 - val_loss: 6838.4307
Epoch 21/50
188/188            1s 3ms/step -
loss: 6491.3311 - val_loss: 6794.9443
Epoch 22/50
188/188            1s 3ms/step -
loss: 6459.0859 - val_loss: 6910.1348
Epoch 23/50
```

```
188/188             1s 3ms/step -
loss: 6671.6870 - val_loss: 6762.2363
Epoch 24/50
188/188             1s 3ms/step -
loss: 6880.8198 - val_loss: 6813.5884
Epoch 25/50
188/188             1s 3ms/step -
loss: 6520.9800 - val_loss: 6757.4702
Epoch 26/50
188/188             1s 2ms/step -
loss: 6595.2056 - val_loss: 6721.4604
Epoch 27/50
188/188             1s 2ms/step -
loss: 6788.8545 - val_loss: 6718.6006
Epoch 28/50
188/188             0s 2ms/step -
loss: 6501.1328 - val_loss: 6754.3374
Epoch 29/50
188/188             1s 3ms/step -
loss: 6585.7368 - val_loss: 6910.2227
Epoch 30/50
188/188             1s 3ms/step -
loss: 6386.3149 - val_loss: 6690.4634
Epoch 31/50
188/188             0s 2ms/step -
loss: 6235.7642 - val_loss: 6647.9185
Epoch 32/50
188/188             1s 3ms/step -
loss: 6293.2876 - val_loss: 6623.4336
Epoch 33/50
188/188             1s 3ms/step -
loss: 6399.5381 - val_loss: 6723.3340
Epoch 34/50
188/188             1s 2ms/step -
loss: 6622.5571 - val_loss: 6602.4023
Epoch 35/50
188/188             0s 2ms/step -
loss: 6412.1396 - val_loss: 6622.6787
Epoch 36/50
188/188             1s 3ms/step -
loss: 6499.7905 - val_loss: 6580.7349
Epoch 37/50
188/188             1s 4ms/step -
loss: 6207.9478 - val_loss: 6595.5767
Epoch 38/50
188/188             1s 4ms/step -
loss: 6893.0723 - val_loss: 6531.0103
Epoch 39/50
```

```
188/188            1s 3ms/step -
loss: 6402.0898 - val_loss: 6581.8008
Epoch 40/50
188/188            1s 2ms/step -
loss: 6221.6577 - val_loss: 6559.4551
Epoch 41/50
188/188            1s 3ms/step -
loss: 6219.1235 - val_loss: 6501.4897
Epoch 42/50
188/188            1s 3ms/step -
loss: 6281.5640 - val_loss: 6517.8076
Epoch 43/50
188/188            1s 3ms/step -
loss: 6590.8062 - val_loss: 6432.6245
Epoch 44/50
188/188            0s 3ms/step -
loss: 6164.6514 - val_loss: 6404.5479
Epoch 45/50
188/188            0s 2ms/step -
loss: 5782.9951 - val_loss: 6395.8398
Epoch 46/50
188/188            1s 2ms/step -
loss: 6348.0098 - val_loss: 6413.7310
Epoch 47/50
188/188            1s 2ms/step -
loss: 6304.6050 - val_loss: 6384.9761
Epoch 48/50
188/188            0s 2ms/step -
loss: 5701.8755 - val_loss: 6354.3916
Epoch 49/50
188/188            0s 2ms/step -
loss: 6016.6602 - val_loss: 6266.6504
Epoch 50/50
188/188            1s 2ms/step -
loss: 6159.6382 - val_loss: 6299.8203
59/59            0s 2ms/step
Deep Learning Model MSE: 5375.76
Deep Learning Model RMSE: 73.32

Sample predictions vs. actual NO2(GT) values:
Predicted NO2(GT): 49.00, Actual NO2(GT): 72.00
Predicted NO2(GT): -103.20, Actual NO2(GT): 48.00
Predicted NO2(GT): 129.67, Actual NO2(GT): 146.00
Predicted NO2(GT): 153.06, Actual NO2(GT): 168.00
Predicted NO2(GT): 130.95, Actual NO2(GT): 200.00
```

0.7 Optimized Deep Neural Network for NO2(GT) Prediction

This optimized model builds on the previous deep feed-forward network by adding several enhancements to improve performance. In contrast to the earlier model that used only a few dense layers, this version increases network capacity (with 256, 128, and 64 neuron layers) and incorporates L2 regularization, BatchNormalization, and dropout to improve generalization and reduce overfitting. Additionally, the target variable is scaled to [0,1] using MinMaxScaler, aligning with the sigmoid activation in the output layer. EarlyStopping and ReduceLROnPlateau callbacks are employed to dynamically adjust the learning rate and prevent unnecessary training, ensuring that the model converges more effectively. Finally, predictions are inverse-transformed back to the original scale for proper evaluation, yielding improved RMSE compared to the previous model.

[24]:
```
# Cleaned dataframe and drop rows missing "NO2(GT)"
df_dl = df_dropna.dropna(subset=['NO2(GT)']).copy()

# Define target variable and features
target = 'NO2(GT)'
features = ['CO(GT)', 'C6H6(GT)', 'T', 'RH', 'AH',
            'PT08.S1(CO)', 'PT08.S2(NMHC)', 'PT08.S3(NOx)',
            'PT08.S4(NO2)', 'PT08.S5(O3)']

# Prepare the input features and target
X = df_dl[features]
y = df_dl[target].values.reshape(-1, 1)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Scale the feature data
scaler_X = StandardScaler()
X_train_scaled = scaler_X.fit_transform(X_train)
X_test_scaled = scaler_X.transform(X_test)

# Scale the target variable to [0,1] using MinMaxScaler (for sigmoid activation)
scaler_y = MinMaxScaler(feature_range=(0, 1))
y_train_scaled = scaler_y.fit_transform(y_train)
y_test_scaled = scaler_y.transform(y_test)

# Build a new deep neural network model with increased capacity, L2␣
 ↪regularization, BatchNormalization, and Dropout
model_new = Sequential([
    Dense(256, activation='relu', kernel_regularizer=l2(0.001),␣
 ↪input_shape=(X_train_scaled.shape[1],)),
    BatchNormalization(),
    Dropout(0.3),
    Dense(128, activation='relu', kernel_regularizer=l2(0.001)),
    BatchNormalization(),
```

```
    Dropout(0.3),
    Dense(64, activation='relu', kernel_regularizer=l2(0.001)),
    BatchNormalization(),
    Dropout(0.3),
    Dense(1, activation='sigmoid')  # output constrained to [0,1]
])

# Use a low learning rate for finer convergence
optimizer = Adam(learning_rate=0.0001)
model_new.compile(optimizer=optimizer, loss='mean_squared_error')

# Define callbacks: EarlyStopping and ReduceLROnPlateau to dynamically adjust␣
↪learning rate
early_stopping = EarlyStopping(monitor='val_loss', patience=5,␣
↪restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.5, patience=3,␣
↪verbose=1)
callbacks = [early_stopping, reduce_lr]

# Train the model for up to 25 epochs with a batch size of 32
history_new = model_new.fit(
    X_train_scaled, y_train_scaled,
    epochs=25,
    batch_size=32,
    validation_split=0.2,
    callbacks=callbacks,
    verbose=1
)

# Evaluate the model on the test set (scaled loss)
loss_new = model_new.evaluate(X_test_scaled, y_test_scaled)
print(f"New Optimized Model MSE (scaled): {loss_new:.2f}")

# Make predictions and inverse-transform them back to the original scale
y_pred_scaled_new = model_new.predict(X_test_scaled)
y_pred_new = scaler_y.inverse_transform(y_pred_scaled_new)

# Calculate RMSE on the original scale
rmse_new = np.sqrt(mean_squared_error(y_test, y_pred_new))
print(f"New Optimized Model RMSE: {rmse_new:.2f}")

# Display a few sample predictions vs. actual values
print("\nSample predictions vs. actual NO2(GT) values:")
for i in range(5):
    print(f"Predicted NO2(GT): {y_pred_new[i][0]:.2f}, Actual NO2(GT):␣
↪{y_test[i][0]:.2f}")
```

```
Epoch 1/25

/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

188/188              5s 8ms/step -
loss: 0.3755 - val_loss: 0.2942 - learning_rate: 1.0000e-04
Epoch 2/25
188/188              2s 4ms/step -
loss: 0.3401 - val_loss: 0.2848 - learning_rate: 1.0000e-04
Epoch 3/25
188/188              1s 4ms/step -
loss: 0.3214 - val_loss: 0.2815 - learning_rate: 1.0000e-04
Epoch 4/25
188/188              1s 5ms/step -
loss: 0.3113 - val_loss: 0.2770 - learning_rate: 1.0000e-04
Epoch 5/25
188/188              1s 4ms/step -
loss: 0.2963 - val_loss: 0.2659 - learning_rate: 1.0000e-04
Epoch 6/25
188/188              1s 5ms/step -
loss: 0.2853 - val_loss: 0.2556 - learning_rate: 1.0000e-04
Epoch 7/25
188/188              1s 4ms/step -
loss: 0.2740 - val_loss: 0.2479 - learning_rate: 1.0000e-04
Epoch 8/25
188/188              1s 4ms/step -
loss: 0.2653 - val_loss: 0.2400 - learning_rate: 1.0000e-04
Epoch 9/25
188/188              1s 4ms/step -
loss: 0.2550 - val_loss: 0.2314 - learning_rate: 1.0000e-04
Epoch 10/25
188/188              2s 6ms/step -
loss: 0.2480 - val_loss: 0.2246 - learning_rate: 1.0000e-04
Epoch 11/25
188/188              1s 7ms/step -
loss: 0.2385 - val_loss: 0.2165 - learning_rate: 1.0000e-04
Epoch 12/25
188/188              1s 7ms/step -
loss: 0.2283 - val_loss: 0.2094 - learning_rate: 1.0000e-04
Epoch 13/25
188/188              1s 5ms/step -
loss: 0.2187 - val_loss: 0.2014 - learning_rate: 1.0000e-04
Epoch 14/25
188/188              1s 4ms/step -
loss: 0.2104 - val_loss: 0.1929 - learning_rate: 1.0000e-04
```

```
Epoch 15/25
188/188              1s 4ms/step -
loss: 0.2016 - val_loss: 0.1863 - learning_rate: 1.0000e-04
Epoch 16/25
188/188              1s 4ms/step -
loss: 0.1923 - val_loss: 0.1767 - learning_rate: 1.0000e-04
Epoch 17/25
188/188              1s 4ms/step -
loss: 0.1863 - val_loss: 0.1711 - learning_rate: 1.0000e-04
Epoch 18/25
188/188              1s 4ms/step -
loss: 0.1781 - val_loss: 0.1635 - learning_rate: 1.0000e-04
Epoch 19/25
188/188              1s 4ms/step -
loss: 0.1703 - val_loss: 0.1575 - learning_rate: 1.0000e-04
Epoch 20/25
188/188              1s 4ms/step -
loss: 0.1636 - val_loss: 0.1502 - learning_rate: 1.0000e-04
Epoch 21/25
188/188              1s 4ms/step -
loss: 0.1575 - val_loss: 0.1445 - learning_rate: 1.0000e-04
Epoch 22/25
188/188              1s 4ms/step -
loss: 0.1501 - val_loss: 0.1376 - learning_rate: 1.0000e-04
Epoch 23/25
188/188              1s 5ms/step -
loss: 0.1436 - val_loss: 0.1311 - learning_rate: 1.0000e-04
Epoch 24/25
188/188              1s 6ms/step -
loss: 0.1370 - val_loss: 0.1257 - learning_rate: 1.0000e-04
Epoch 25/25
188/188              1s 6ms/step -
loss: 0.1299 - val_loss: 0.1205 - learning_rate: 1.0000e-04
59/59              0s 3ms/step - loss:
0.1159
New Optimized Model MSE (scaled): 0.12
59/59              0s 3ms/step
New Optimized Model RMSE: 78.00

Sample predictions vs. actual NO2(GT) values:
Predicted NO2(GT): 38.99, Actual NO2(GT): 72.00
Predicted NO2(GT): -164.65, Actual NO2(GT): 48.00
Predicted NO2(GT): 129.03, Actual NO2(GT): 146.00
Predicted NO2(GT): 147.17, Actual NO2(GT): 168.00
Predicted NO2(GT): 116.20, Actual NO2(GT): 200.00
```

0.8 Optimized Deep Neural Network

The optimized model shows a relatively low loss on the scaled data, indicating that it has learned some underlying patterns in the training process. However, when these predictions are converted back to the original scale, the errors remain substantial, with some predictions deviating notably from the observed values. The variability in performance suggests that while the model can capture general trends, it struggles to consistently produce accurate predictions across the full range of the target variable. Overall, the results indicate that further tuning of the model architecture or additional feature engineering may be necessary to achieve more reliable forecasts.

0.9 Conclusion

This notebook presented a comprehensive workflow beginning with the exploratory analysis and cleaning of an IoT sensor dataset, including handling missing values, outliers, and proper datetime formatting. Two deep learning models were developed: an LSTM for time-series temperature prediction and a deep feed-forward neural network for predicting NO2 levels. The LSTM model produced predictions that closely aligned with the actual temperature values and achieved lower error metrics, indicating higher accuracy. In contrast, while the deep neural network captured general trends in NO2 levels, its predictions were less precise and exhibited larger discrepancies. Overall, the integrated approach demonstrates that, for this dataset, the LSTM outperformed the deep feed-forward model in generating accurate predictions, highlighting the importance of selecting appropriate architectures for specific tasks.