

Importing all the libraries

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from catboost import CatBoostRegressor
from xgboost import XGBRegressor
from sklearn.svm import SVR, NuSVR
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import make_scorer
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LeakyReLU

from warnings import filterwarnings
filterwarnings("ignore")
```

Importing the dataset

```
In [2]: df = pd.read_csv("/kaggle/input/biomass-cleaned-dataset/biomass_data.csv")
```

Exploratory Data Analysis

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

	sl no	MC	VM	FC	Ash	C	H	O
count	450.000000	450.000000	450.000000	450.000000	450.000000	450.000000	450.000000	450.000000
mean	225.500000	8.527356	71.909667	15.288511	4.289467	49.434578	6.090178	43.443067
std	130.048068	3.672753	7.987731	4.021544	5.753450	3.342011	1.229714	3.929314
min	1.000000	4.560000	52.560000	3.120000	0.010000	43.300000	0.080000	31.010000
25%	113.250000	6.110000	66.900000	12.570000	0.500000	46.920000	5.620000	41.340000
50%	225.500000	8.000000	75.180000	15.610000	1.510000	50.200000	6.210000	42.990000
75%	337.750000	9.800000	77.710000	16.940000	5.330000	50.820000	6.780000	46.420000
max	450.000000	27.000000	86.740000	26.450000	19.520000	58.340000	8.660000	51.830000

```
In [4]: df.head()
```

```
Out[4]:
```

	sl no	Biomass species	MC	VM	FC	Ash	C	H	O	N	S	oC	ER	S/B	CO
0	1.0	Corn Stover	6.34	67.25	15.64	10.68	52.26	6.03	40.67	0.97	0.07	650.0	0.0	1.0	27.26
1	2.0	Vermont Wood	4.56	81.51	13.55	0.38	54.51	6.21	39.15	0.11	0.03	650.0	0.0	1.0	25.66
2	3.0	Wheat Straw	5.18	67.89	14.89	12.04	58.34	6.40	34.79	0.36	0.11	650.0	0.0	1.0	30.15
3	4.0	Switchgrass	8.38	69.63	14.66	7.33	50.61	5.82	42.77	0.71	0.10	650.0	0.0	1.0	35.66
4	5.0	Rice Husk	9.84	65.07	16.13	8.96	45.09	5.93	46.87	0.59	1.52	850.0	0.0	0.3	37.28

```
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```

```
In [5]: df.columns
```

```
Out[5]: Index(['sl no', 'Biomass species', 'MC', 'VM', 'FC', 'Ash', 'C', 'H', 'O', 'N',  
              'S', 'oC', 'ER', 'S/B', 'CO', 'CO2', 'H2', 'CH4', 'Gas (m3/kg)',  
              'Tar (g/m^3)'],  
              dtype='object')
```

```
In [6]: df.drop(columns = ['sl no'], inplace = True)
```

```
In [7]: df.columns
```

```
Out[7]: Index(['Biomass species', 'MC', 'VM', 'FC', 'Ash', 'C', 'H', 'O', 'N', 'S',  
              'oC', 'ER', 'S/B', 'CO', 'CO2', 'H2', 'CH4', 'Gas (m3/kg)',  
              'Tar (g/m^3)'],  
              dtype='object')
```

```
In [8]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 453 entries, 0 to 452  
Data columns (total 19 columns):  
 #   Column           Non-Null Count  Dtype    
---  --  
 0   Biomass species  450 non-null    object   
 1   MC               450 non-null    float64  
 2   VM               450 non-null    float64  
 3   FC               450 non-null    float64  
 4   Ash              450 non-null    float64  
 5   C                450 non-null    float64  
 6   H                450 non-null    float64  
 7   O                450 non-null    float64  
 8   N                450 non-null    float64  
 9   S                450 non-null    float64  
 10  oC              450 non-null    float64  
 11  ER              450 non-null    float64  
 12  S/B             450 non-null    float64  
 13  CO              414 non-null    float64  
 14  CO2             414 non-null    float64  
 15  H2              414 non-null    float64  
 16  CH4             414 non-null    float64  
 17  Gas (m3/kg)     268 non-null    float64  
 18  Tar (g/m^3)     124 non-null    float64  
dtypes: float64(18), object(1)  
memory usage: 67.4+ KB
```

```
In [9]: df['Biomass species'].value_counts()
```

```
Out[9]: Biomass species
Pine Sawdust                                70
Rice Husk                                    32
Wood Residue                                 25
Sawdust                                     23
Pine wood                                    19
Empty Fruit Bunch                           19
Wood Pellets                                 17
Rice husk                                    17
Rice Straw                                   15
Pine Chips                                   15
Artificial waste (including wood chips)    14
Groundnut Shell                             13
Sugarcane Bagasse                           13
Corn Straw                                   12
Ecualyptus Sawdust                          10
Peat                                         9
Palm Oil Wastes                            9
Legume Straw                                 9
Wood Chips                                   9
Coconut Shell                               8
Rubber Woodchip                            7
Pine waste                                  7
Olive Stone                                 7
C. cardunculus L                           5
Olive Tree Cuttings                         5
Rubber Wood Chip                           5
Miscanthus Pellet                           5
Olive kernels                               5
Poultry litter                             4
Sunflower                                   4
Orujillo                                    4
Crushed Peat Pellets                      4
Willow                                       4
Holm-oak                                    4
Woody biomass                               4
Eucalyptus                                  4
Wood Pellet                                 3
Spruce Wood Pellets                        3
Vermont Wood                               1
Corn Stover                                 1
Switchgrass                                 1
Wheat Straw                                 1
Artificial waste(including wood chips)   1
Dried Grains                               1
Woody Biomass                              1
Bark Pellet                                 1
Name: count, dtype: int64
```

Pair plot

```
In [10]: # sns.pairplot(df, hue='Biomass species')
# plt.show()
```

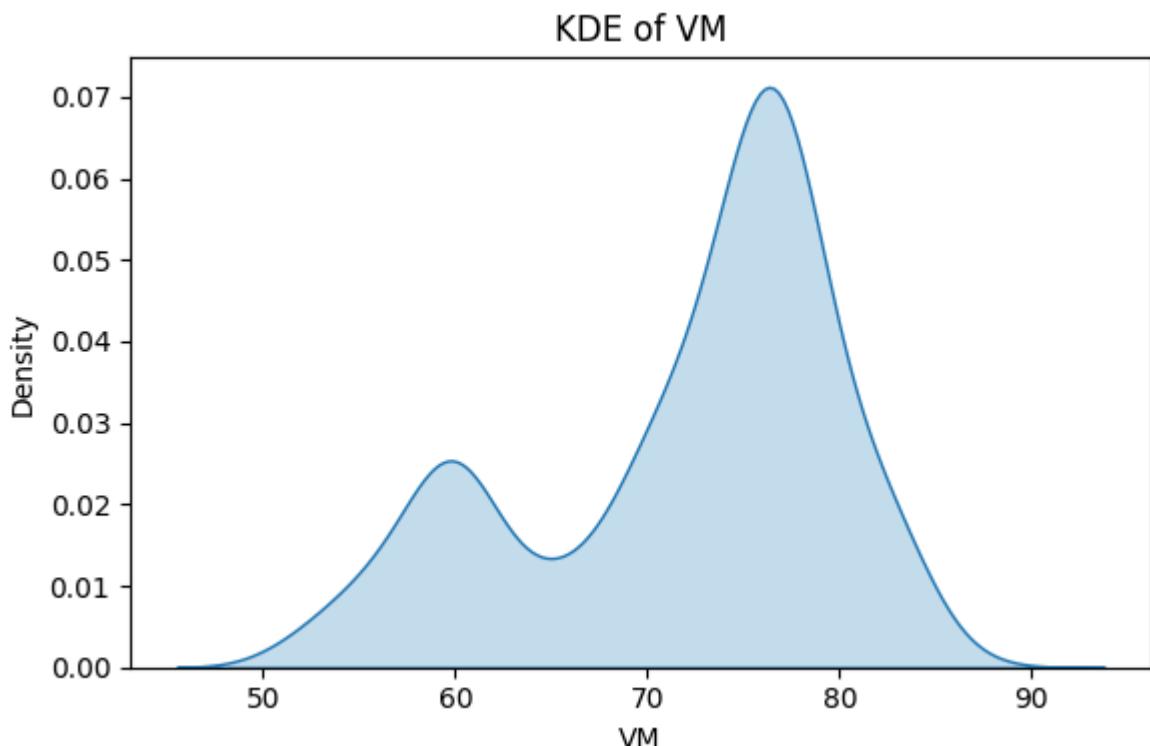
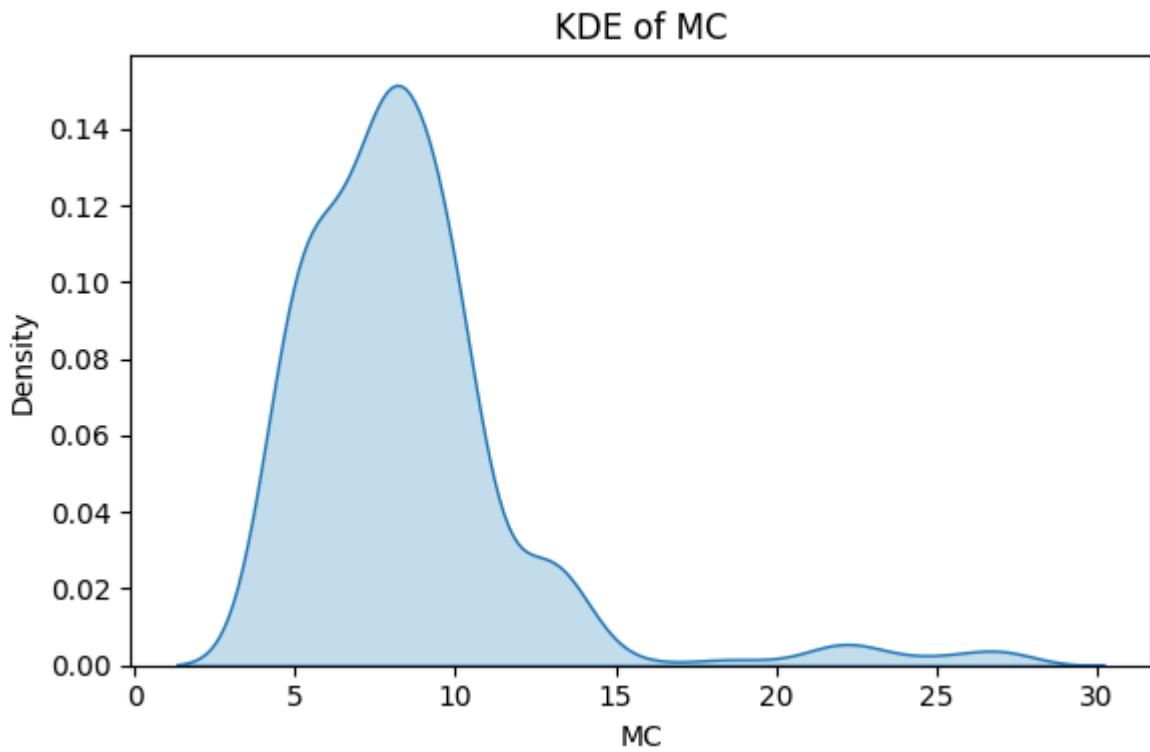
```
In [11]: categorical_col = ['Biomass species']
numerical_col = df.select_dtypes(include='float').columns.tolist()
target_col = numerical_col[12:18]
numerical_col = numerical_col[:12]
```

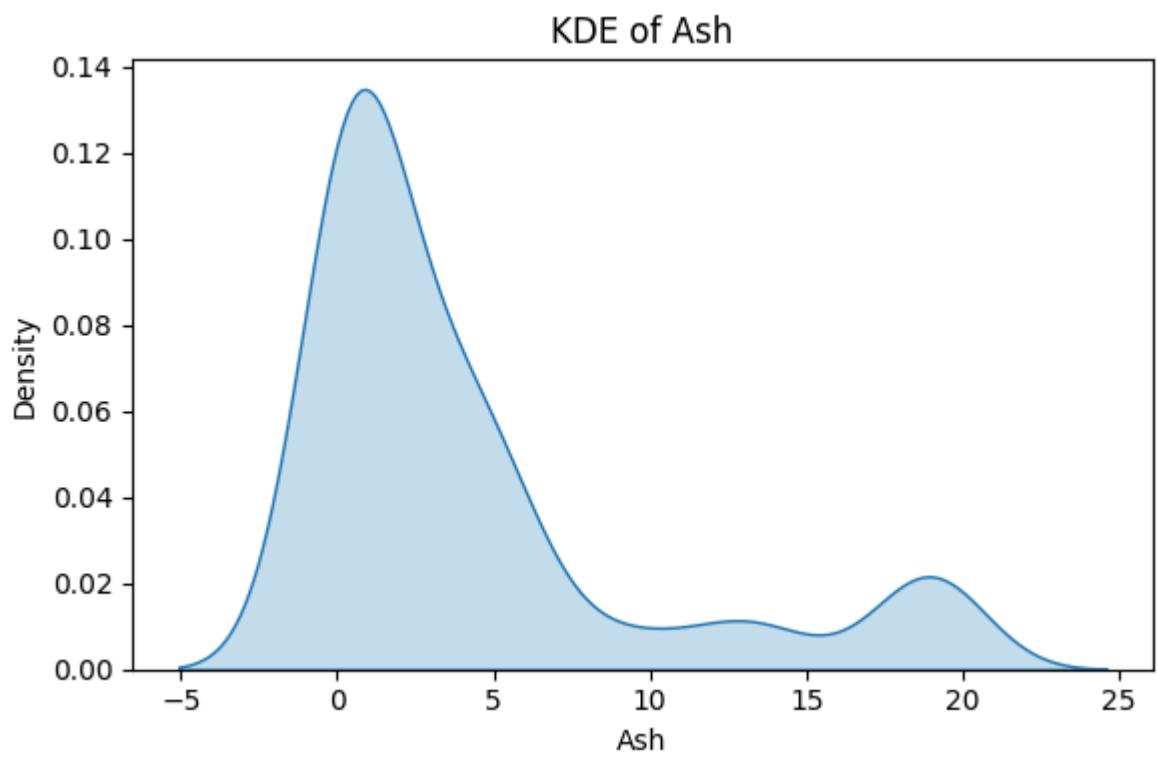
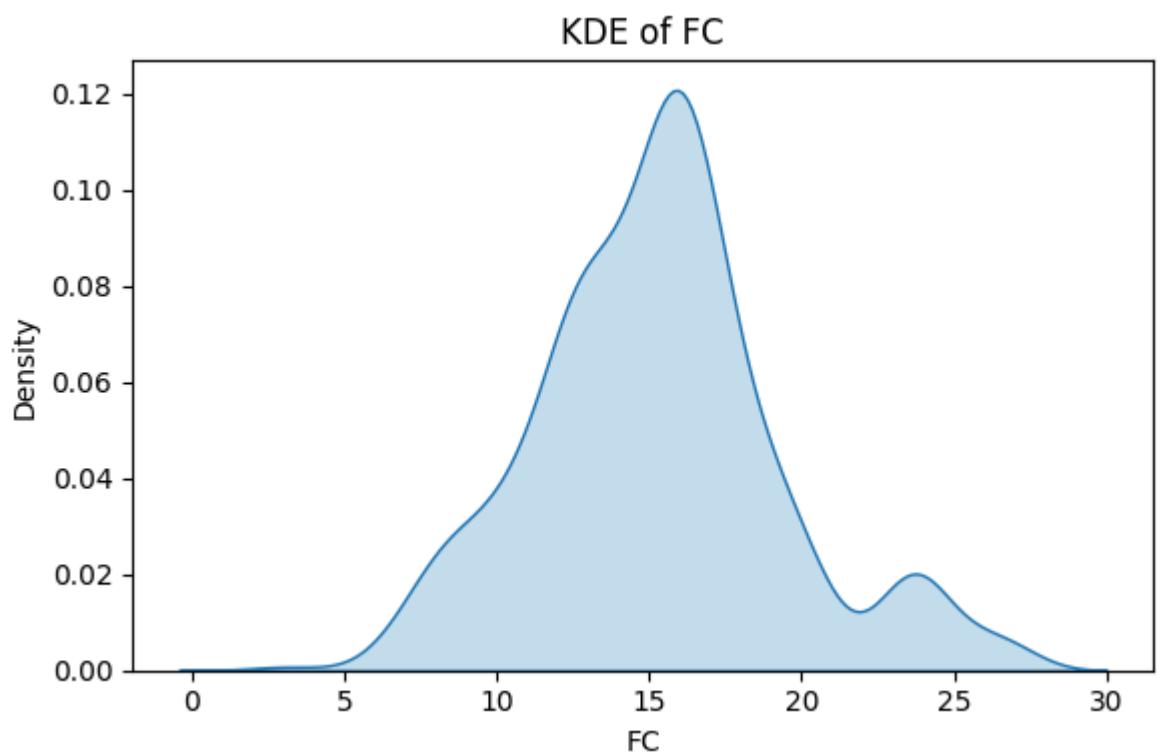
```
In [12]: print(numerical_col)
print(target_col)
print(categorical_col)
```

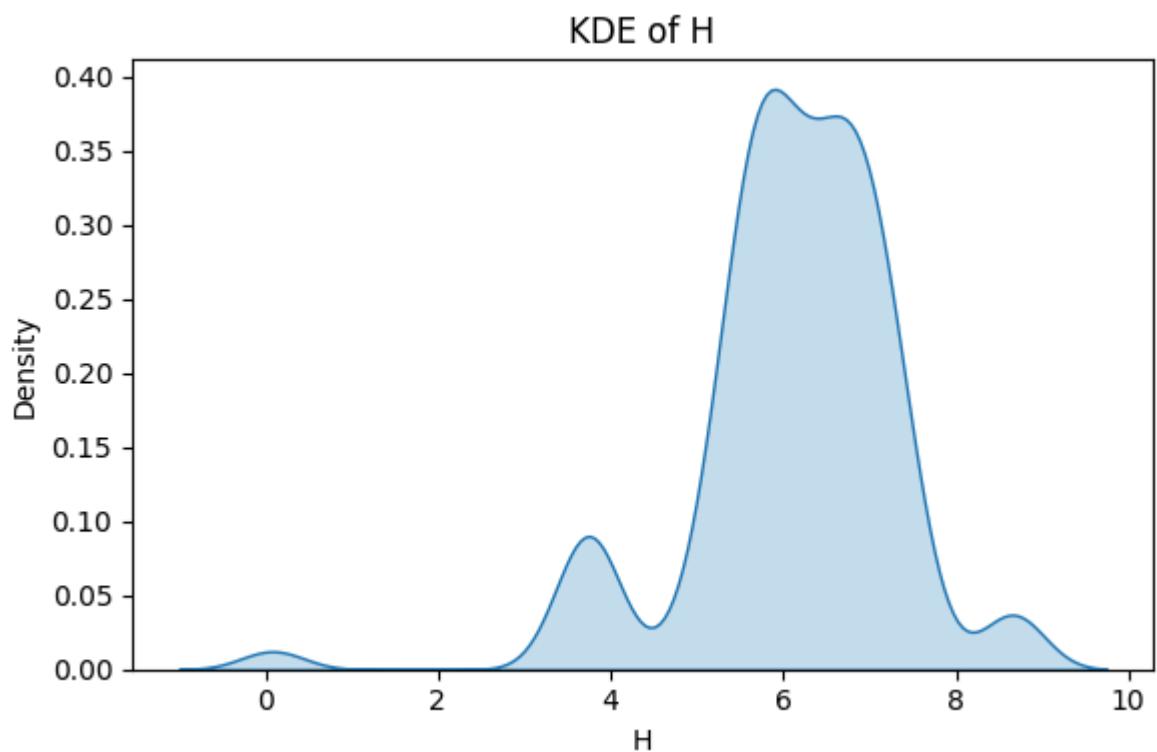
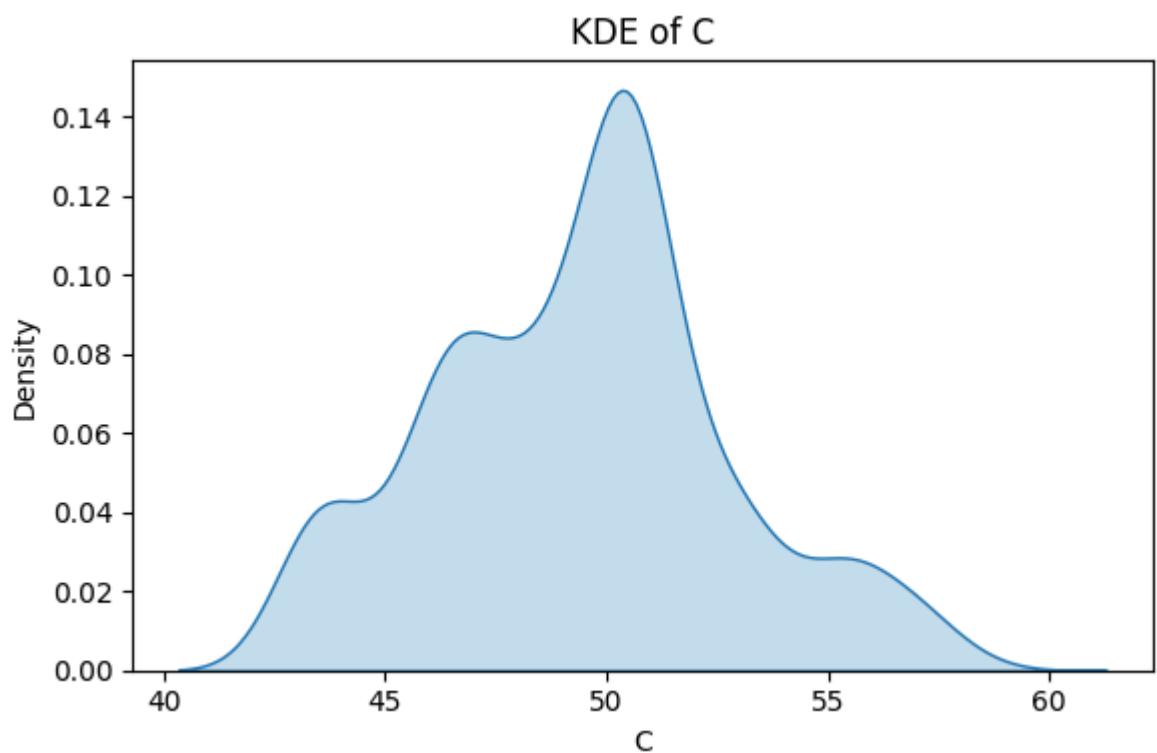
```
['MC', 'VM', 'FC', 'Ash', 'C', 'H', 'O', 'N', 'S', 'oC', 'ER', 'S/B']
['CO', 'CO2', 'H2', 'CH4', 'Gas (m3/kg)', 'Tar (g/m^3)']
['Biomass species']
```

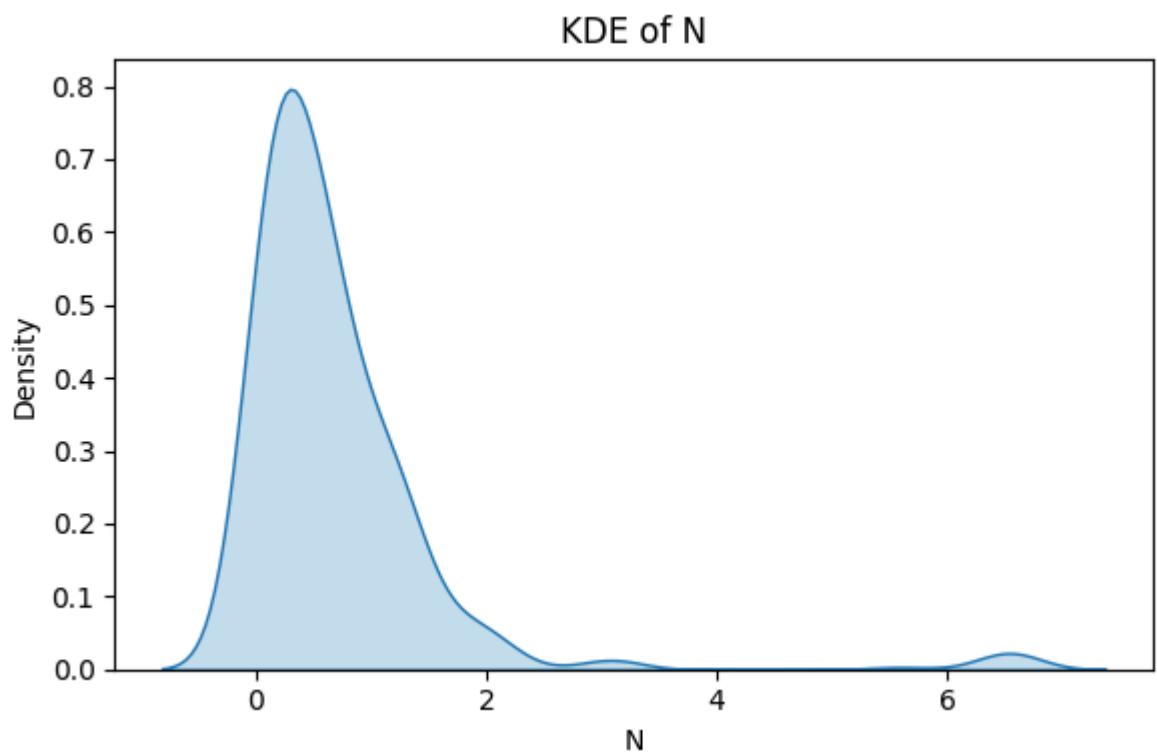
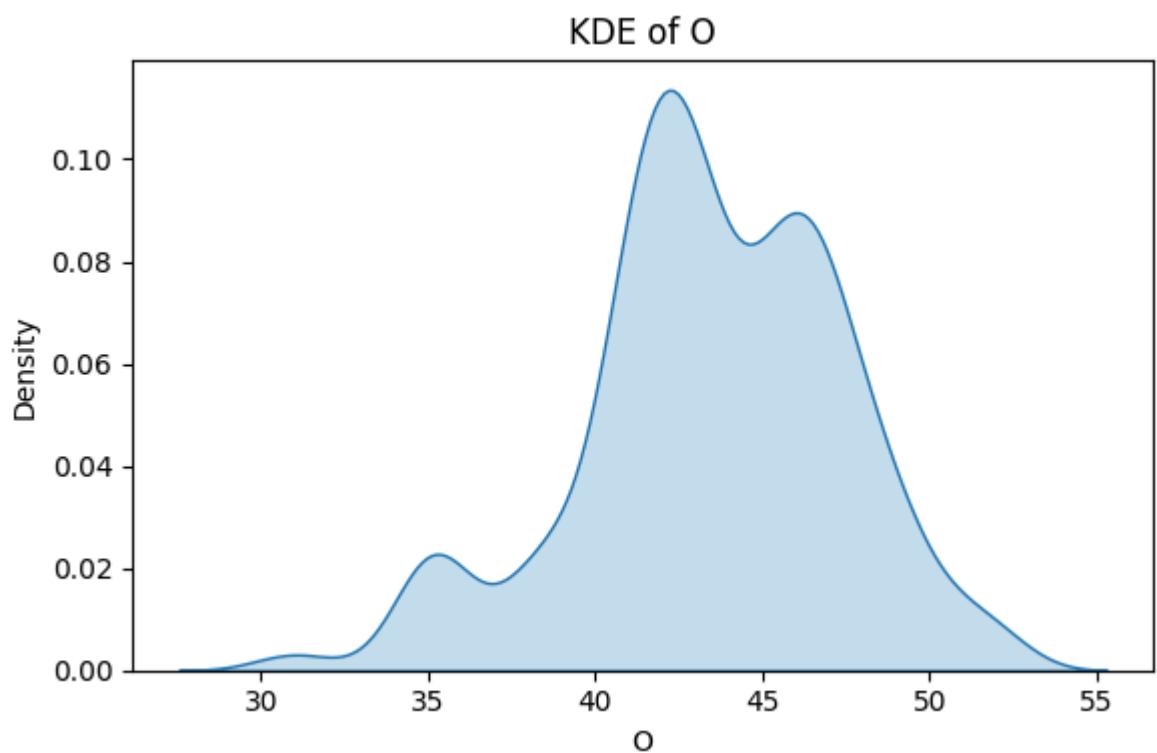
Histplot

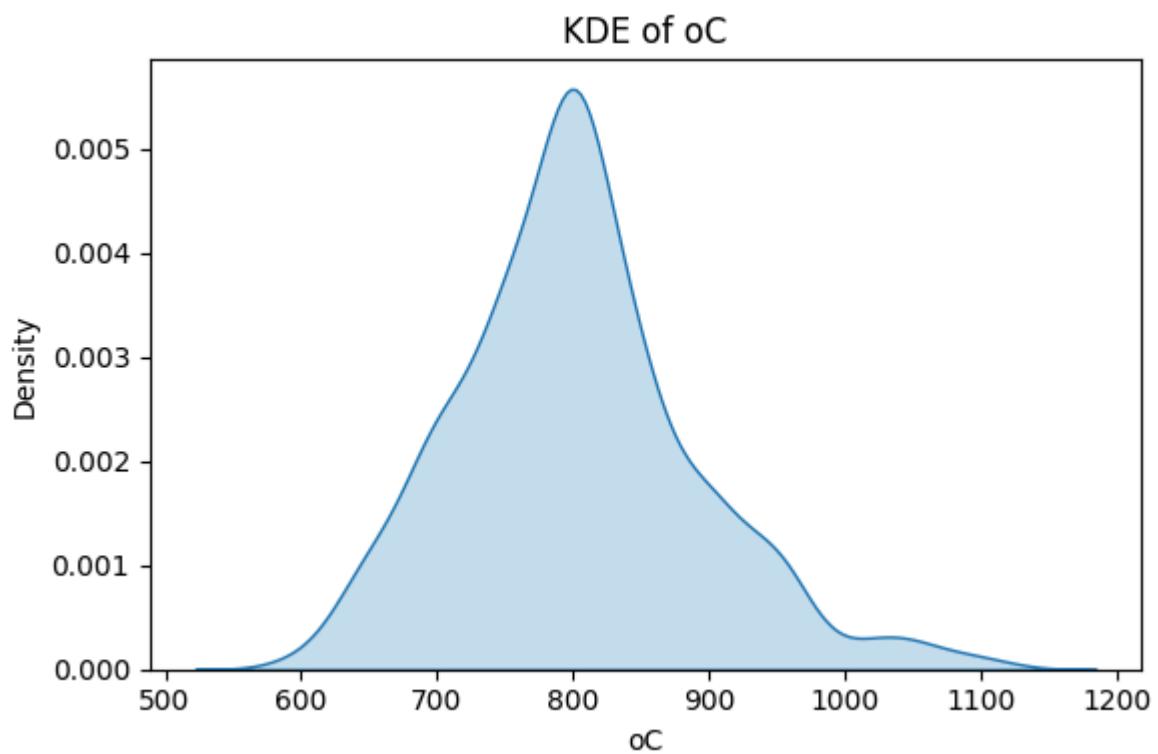
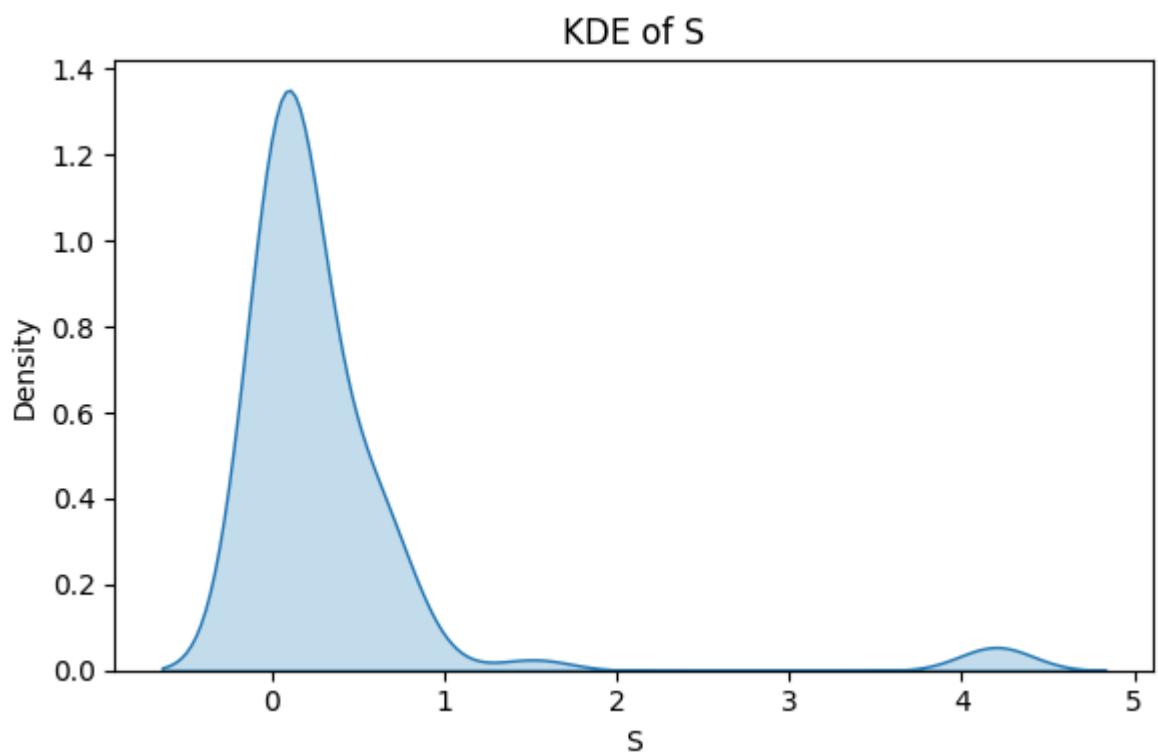
```
In [13]: for col in numerical_col:
    plt.figure(figsize=(6, 4))
    sns.kdeplot(data=df[col], fill=True)
    plt.title(f'KDE of {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.tight_layout()
    plt.show()
```

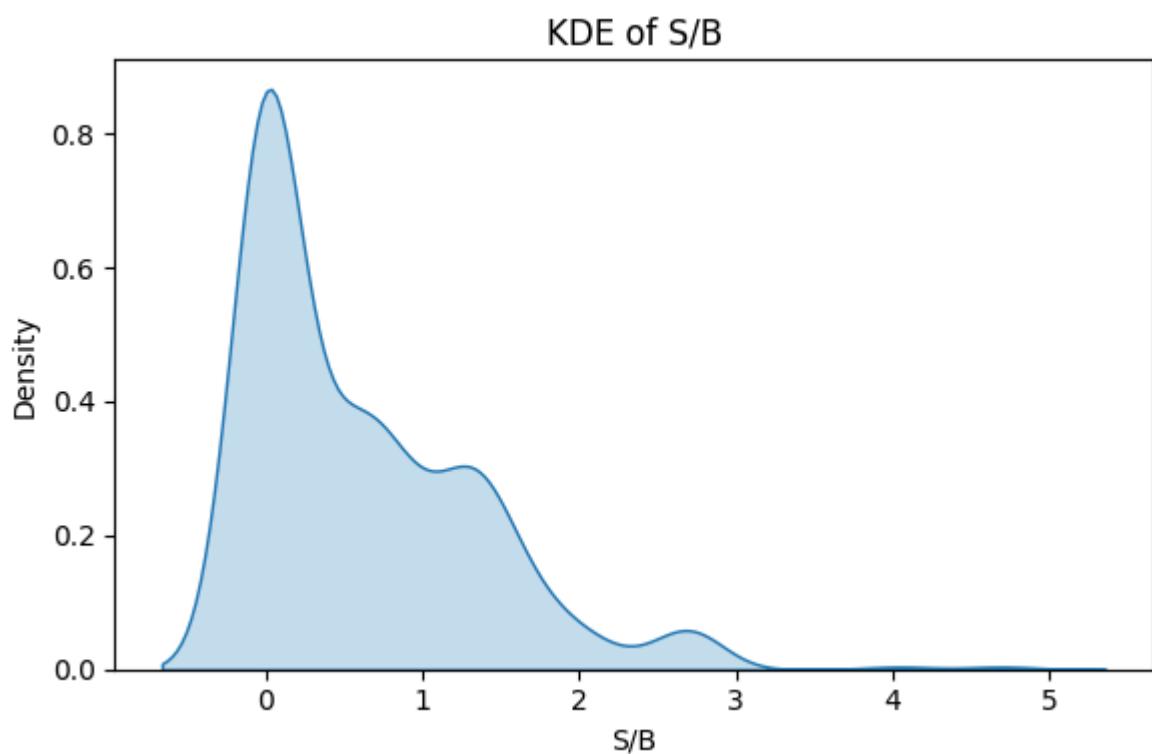
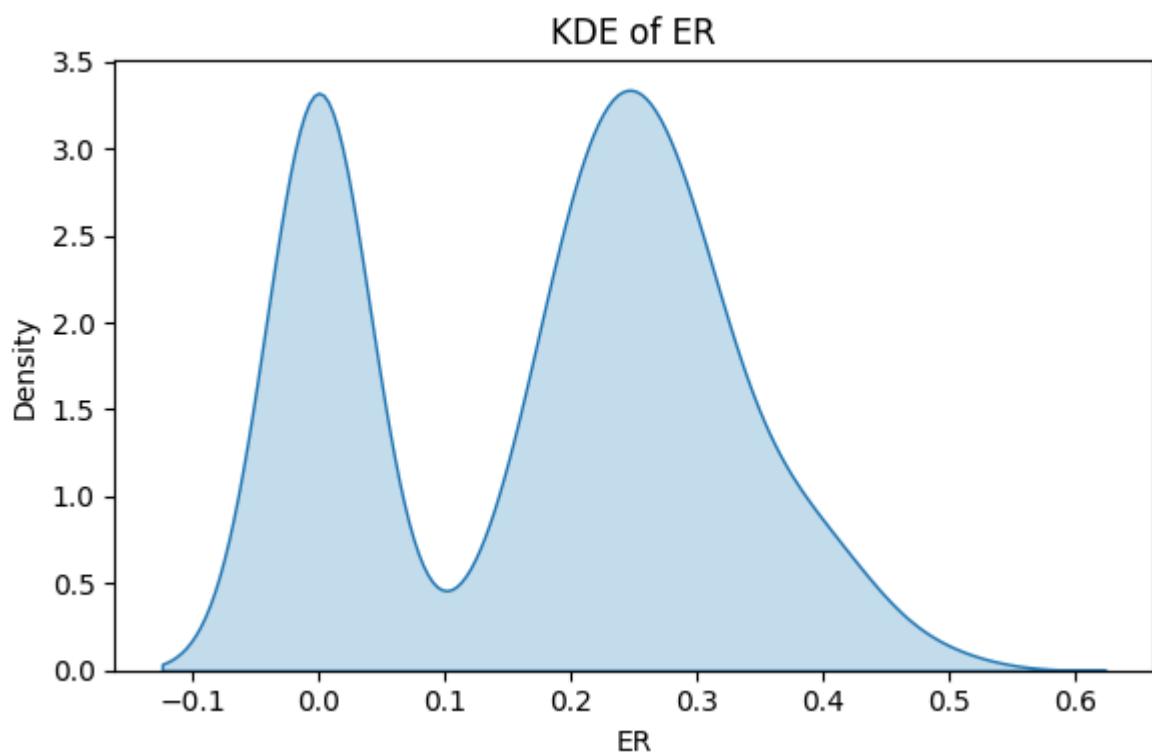






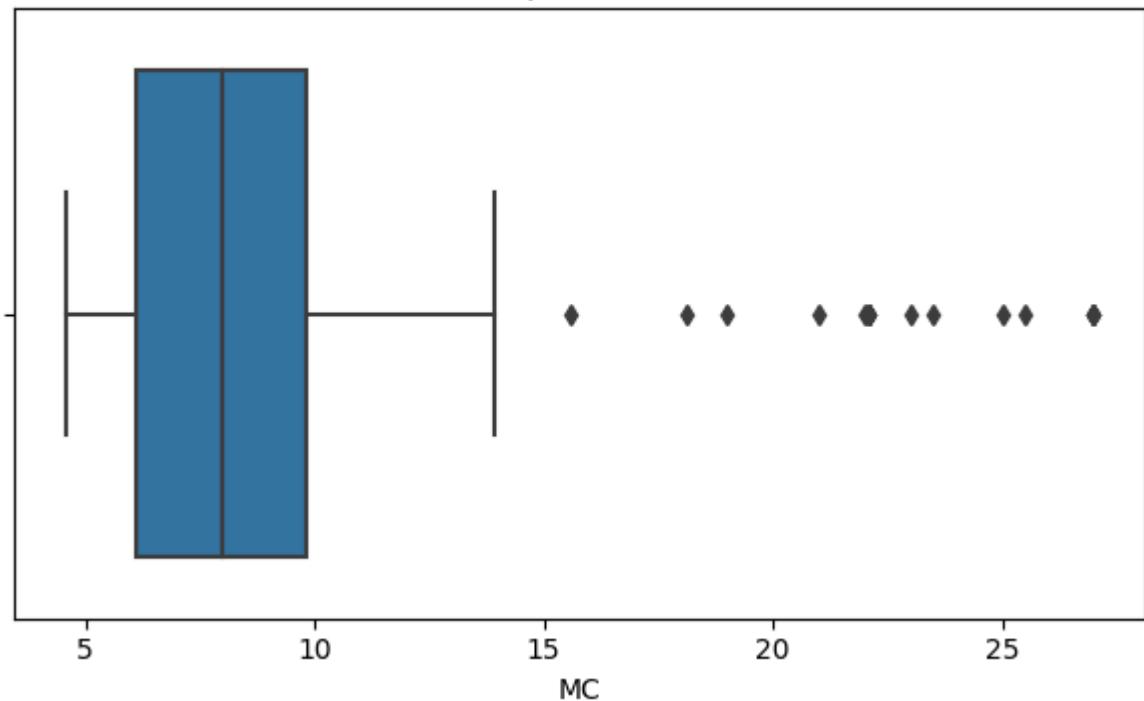




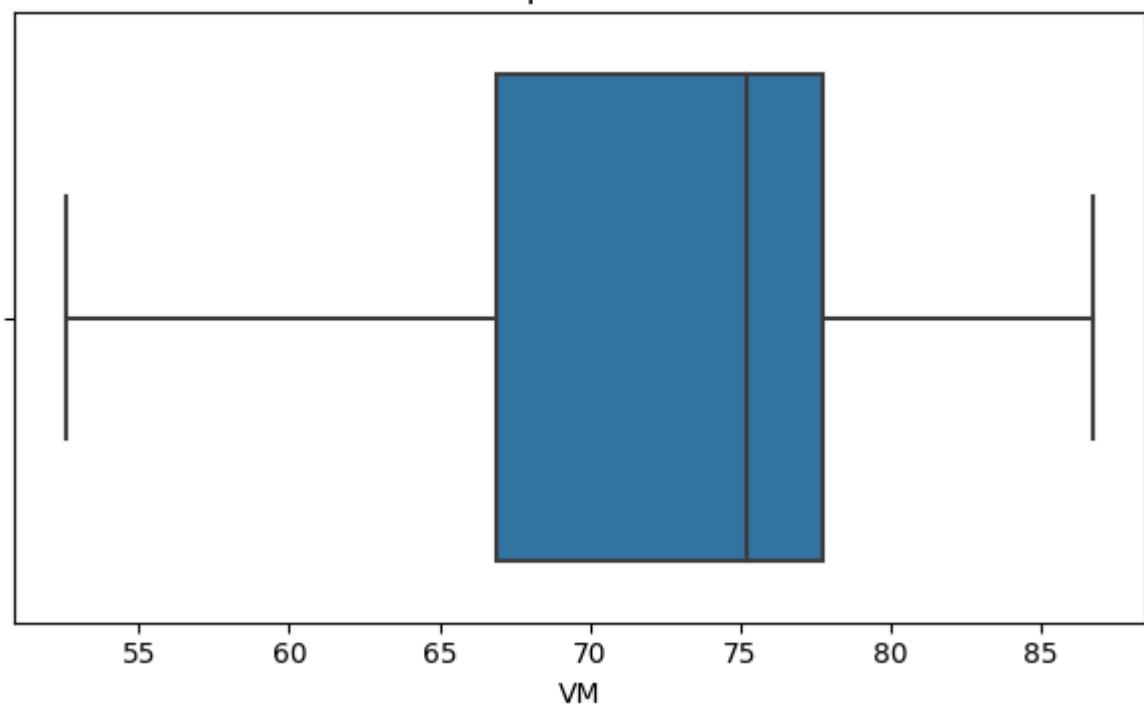


```
In [14]: for col in numerical_col:  
    plt.figure(figsize=(6, 4))  
    sns.boxplot(x=df[col])  
    plt.title(f'Boxplot of {col}')  
    plt.tight_layout()  
    plt.show()
```

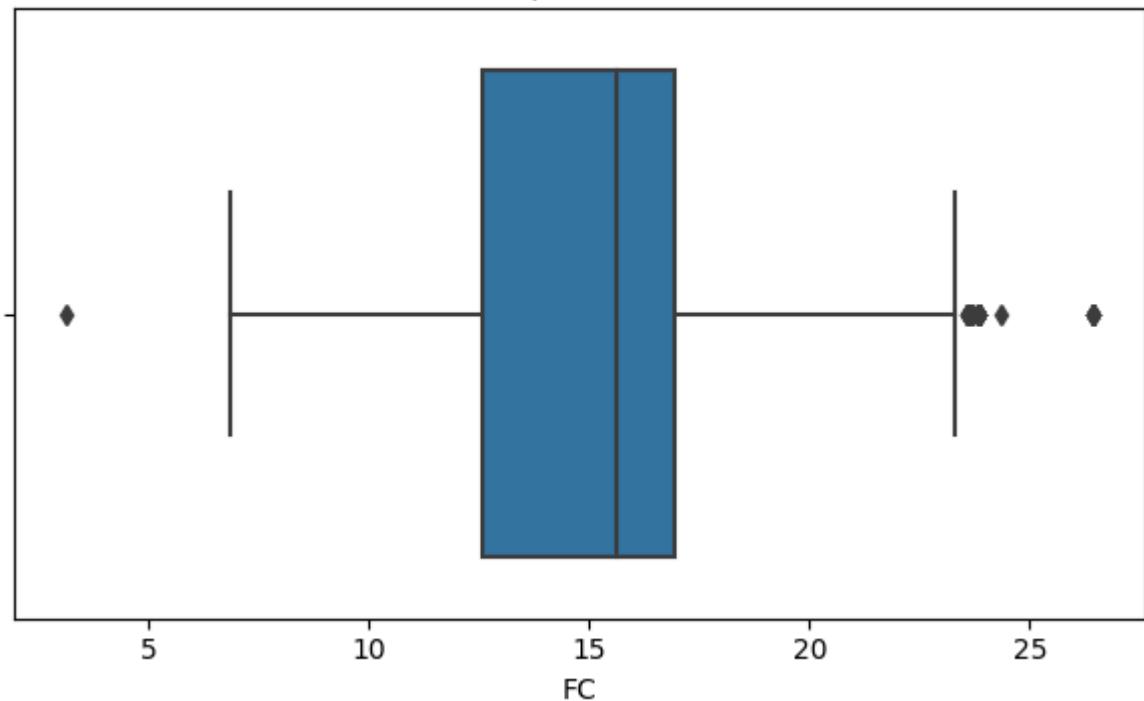
Boxplot of MC



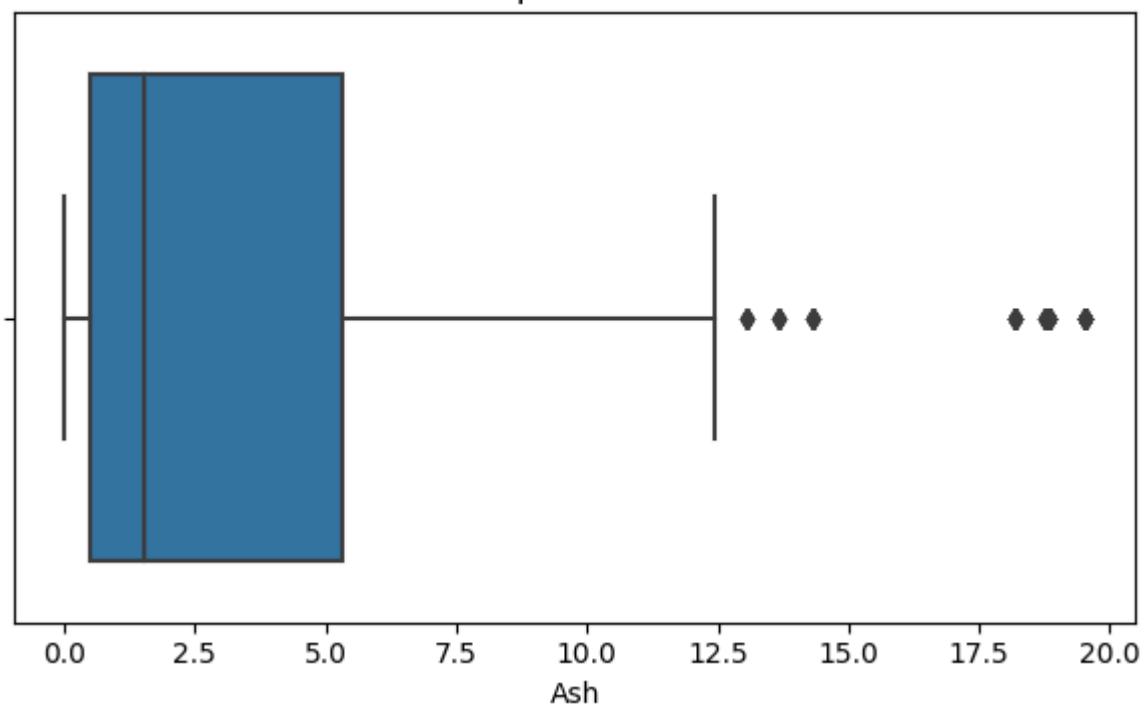
Boxplot of VM



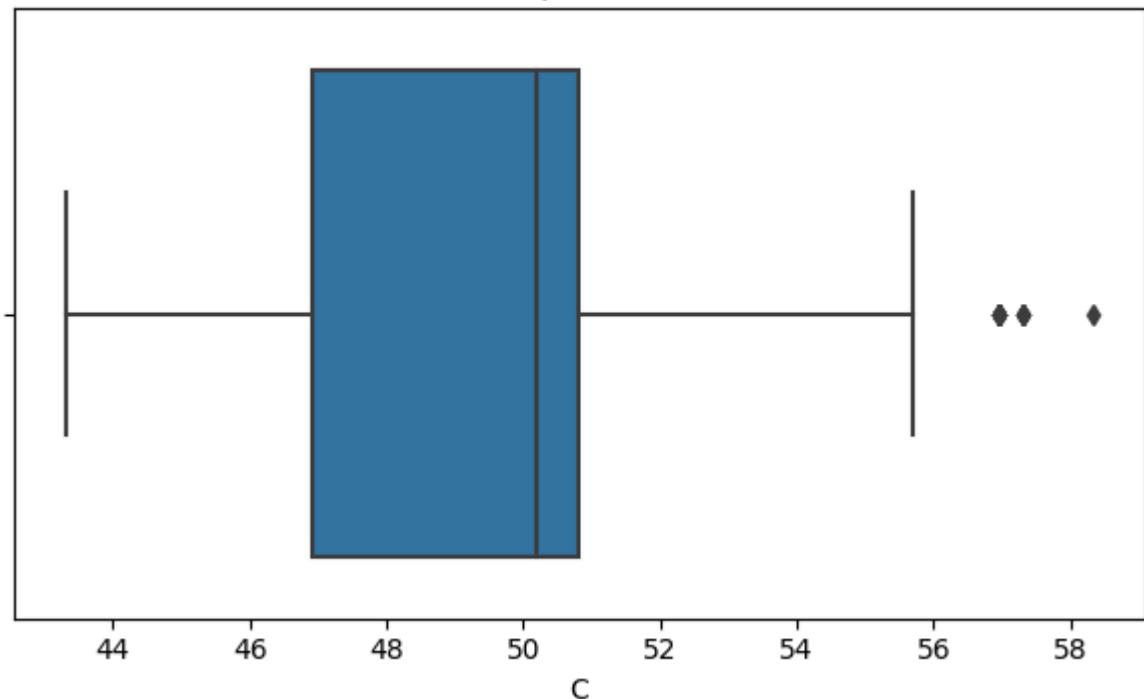
Boxplot of FC



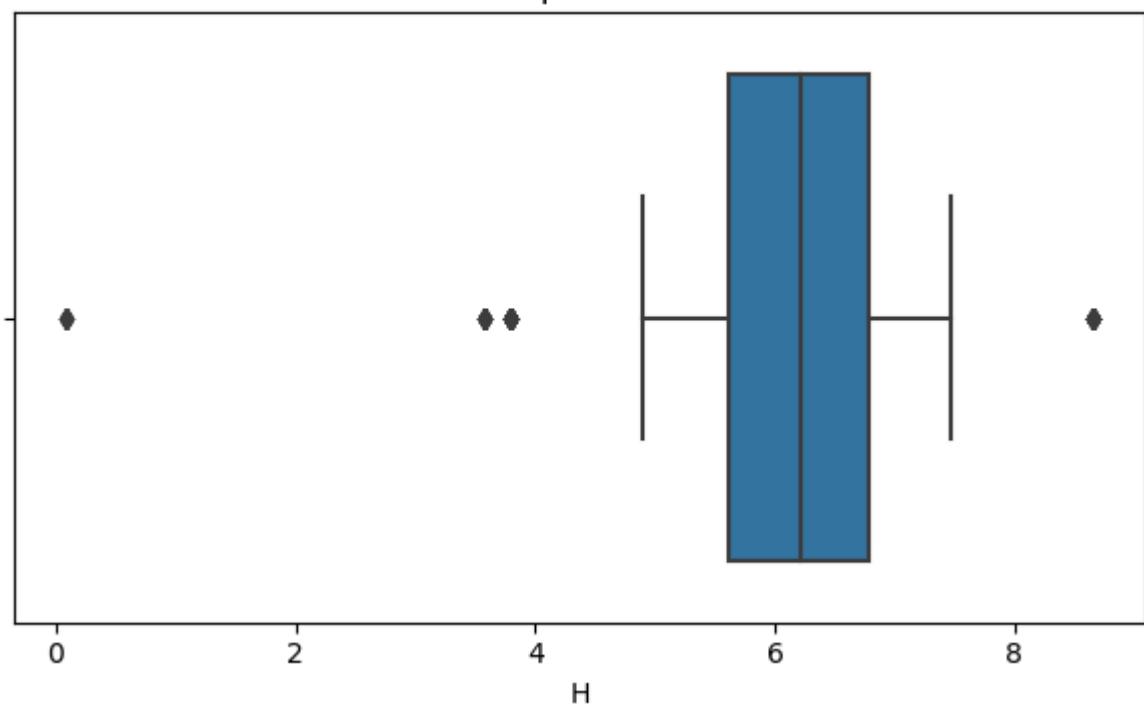
Boxplot of Ash



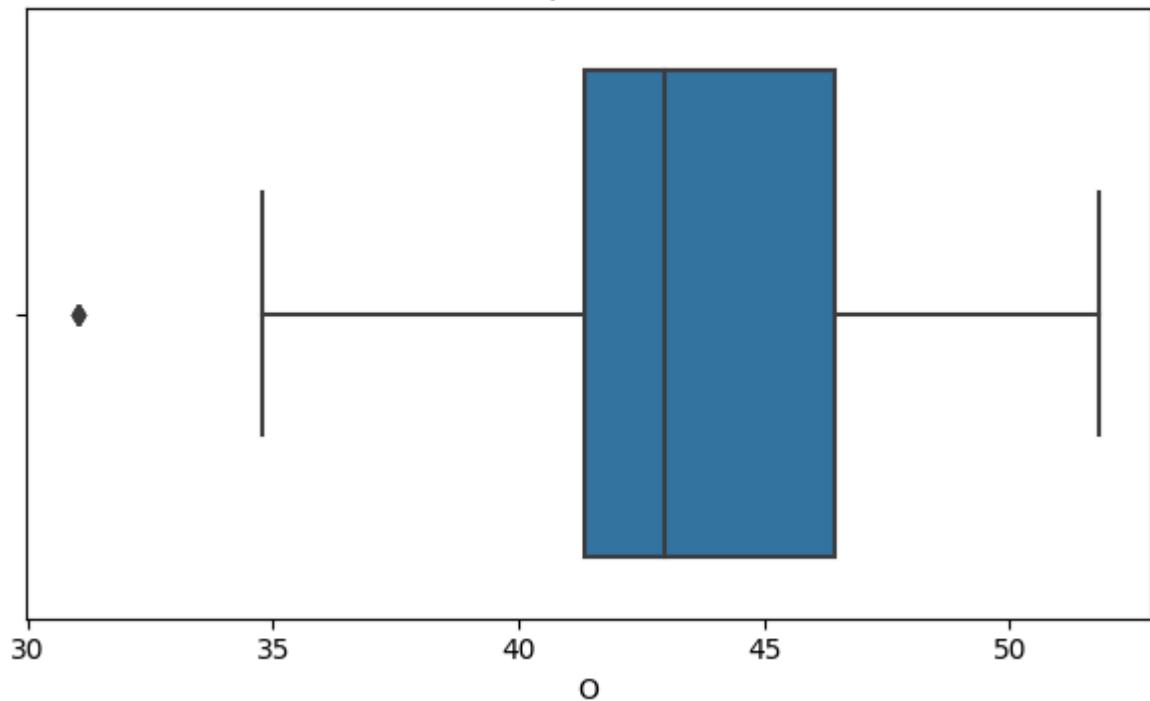
Boxplot of C



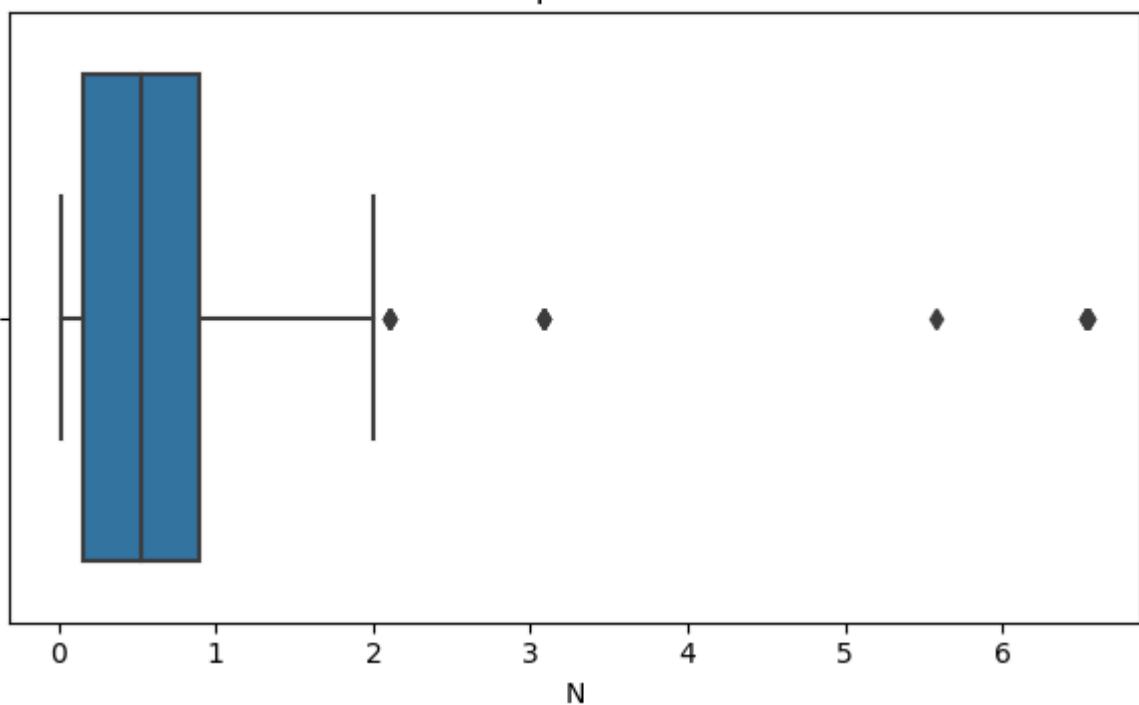
Boxplot of H



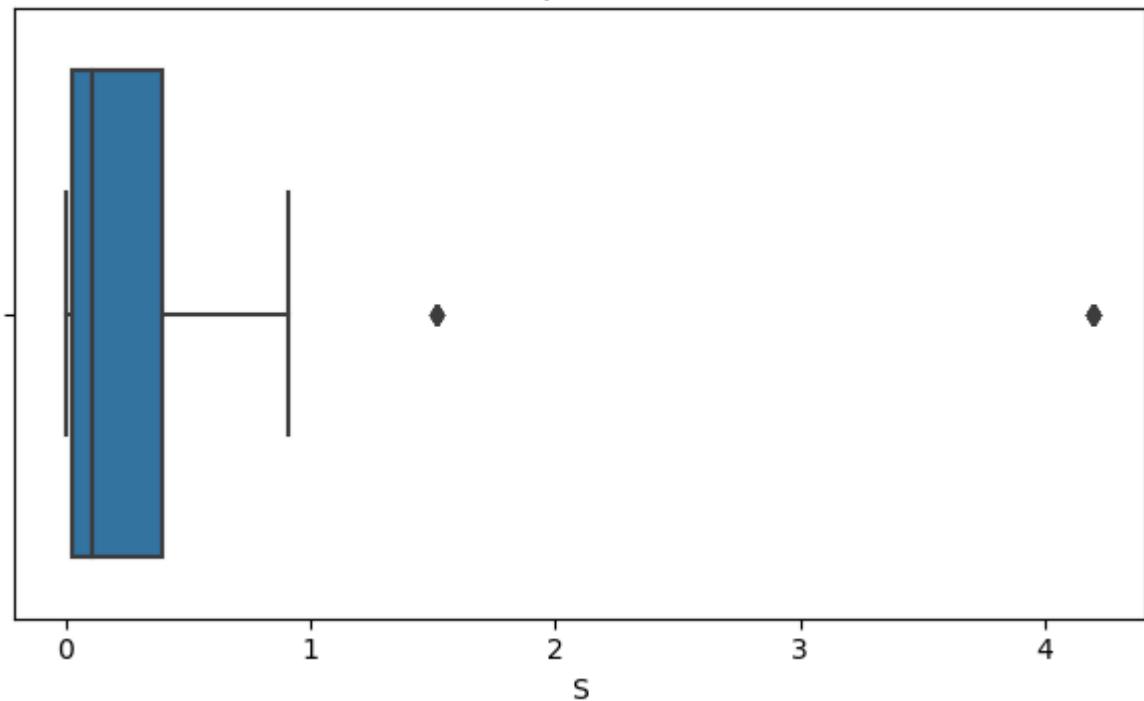
Boxplot of O



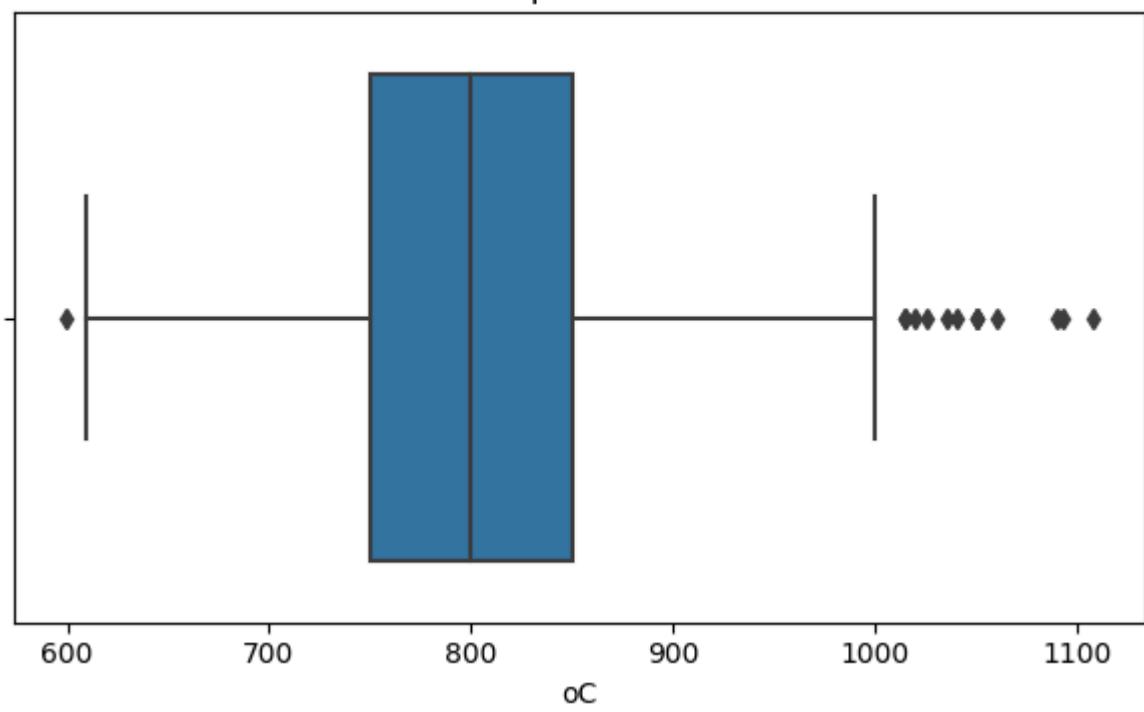
Boxplot of N



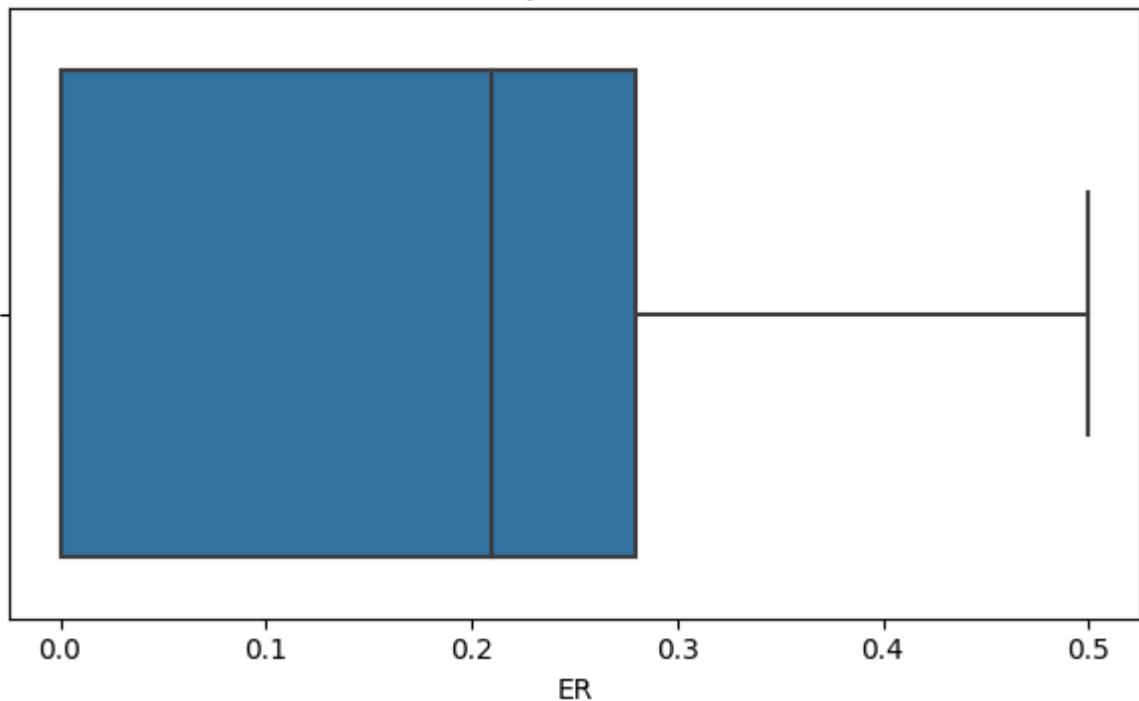
Boxplot of S



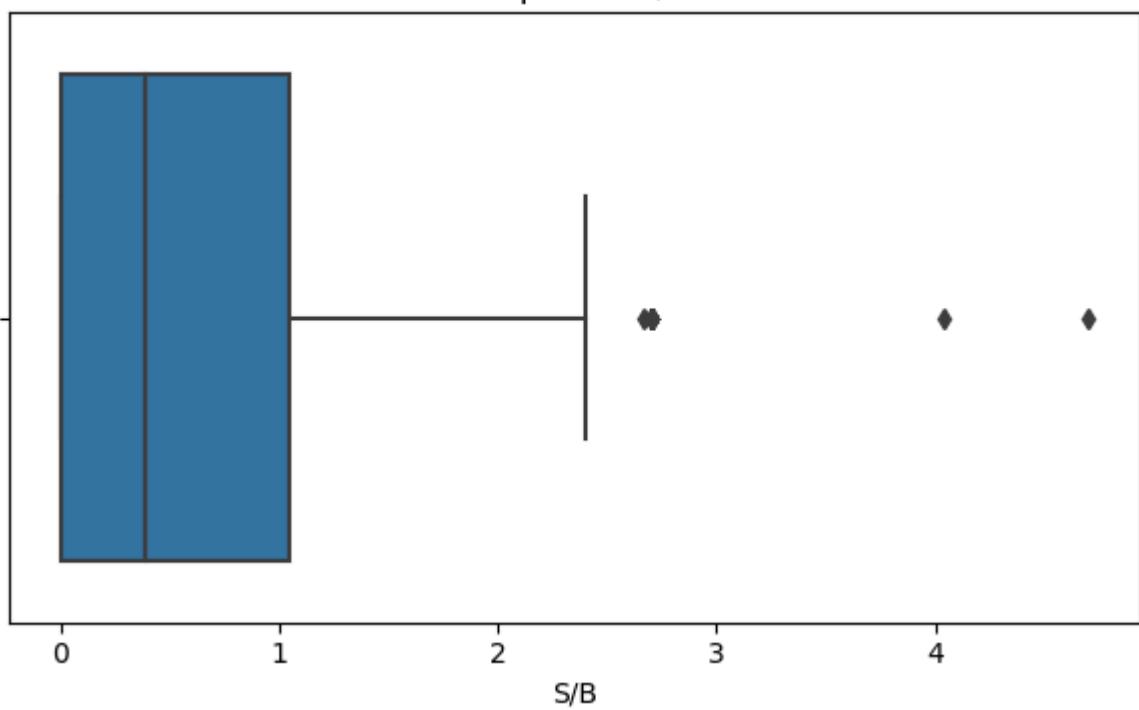
Boxplot of oC



Boxplot of ER

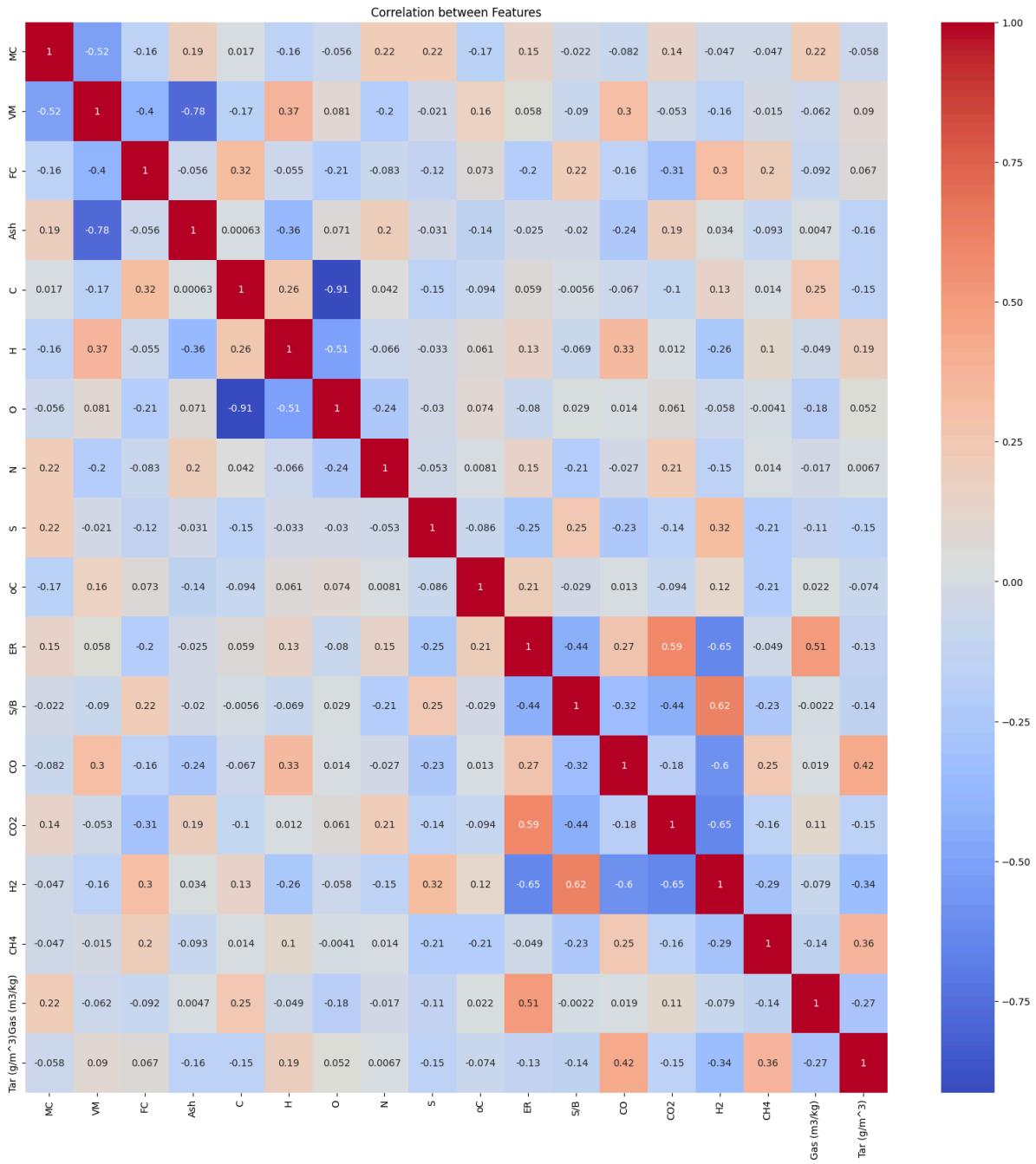


Boxplot of S/B



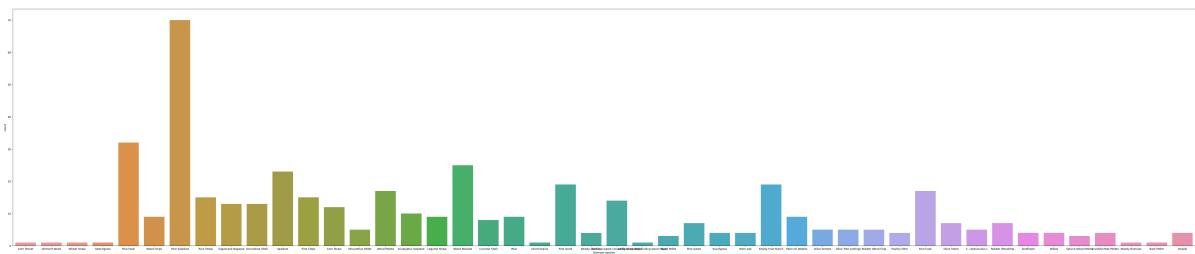
There are a few outliers present in the dataset

```
In [15]: plt.figure(figsize= (20,20))
corr = df.select_dtypes(include='number').corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation between Features')
plt.show()
```



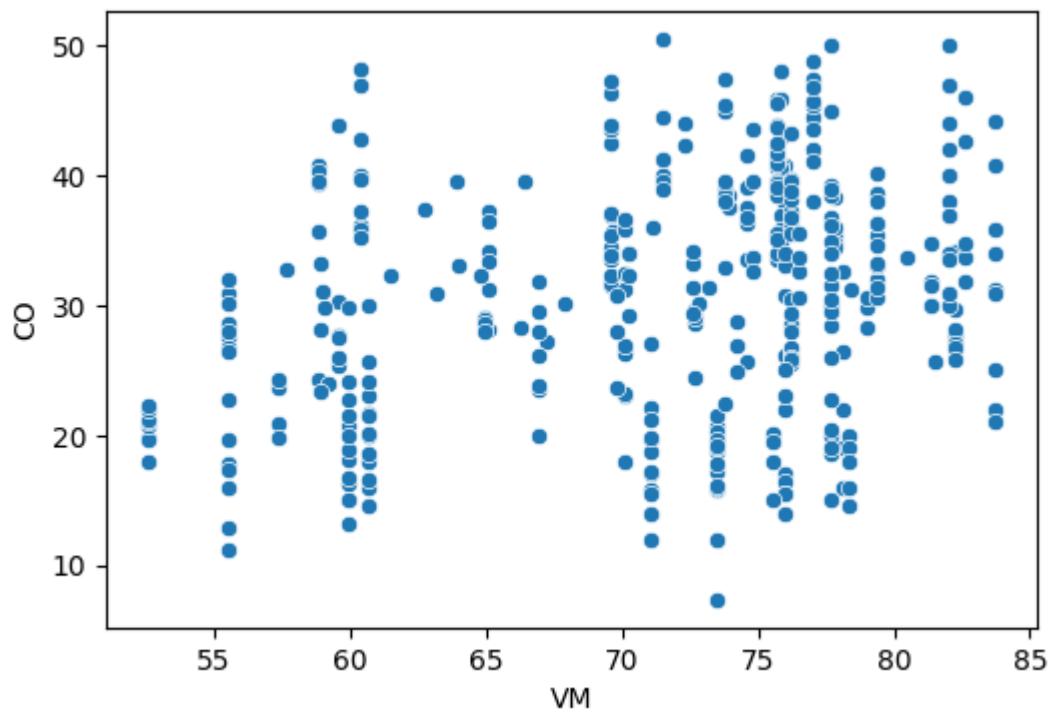
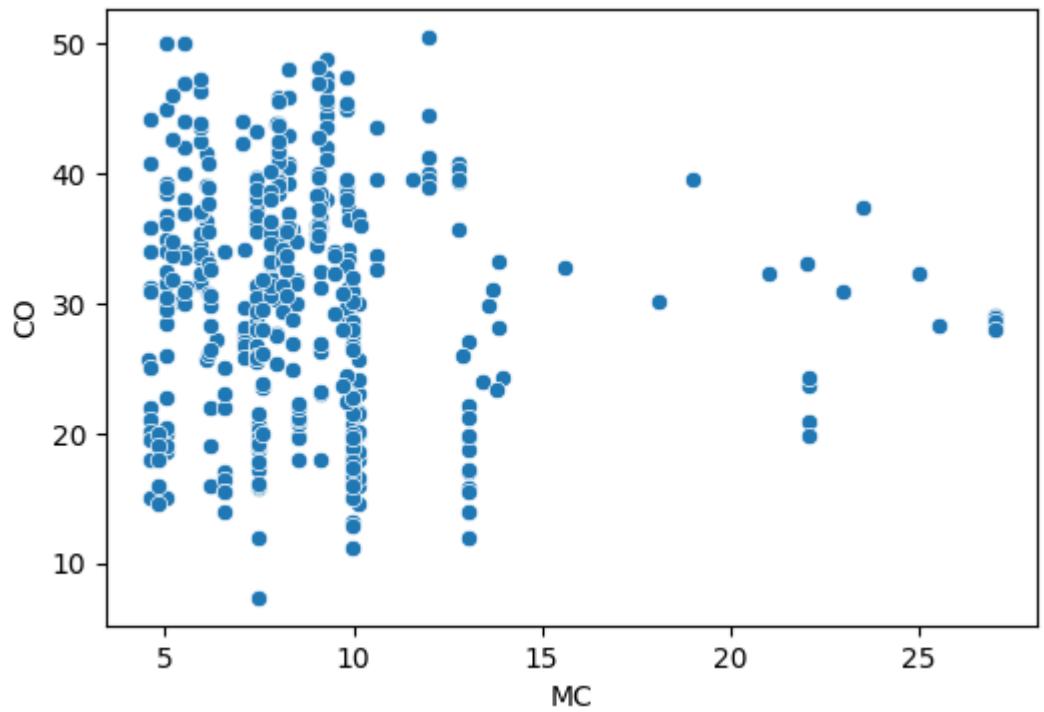
Ash and VM has 0.78 neg correlation and O and C have very high negative correlation

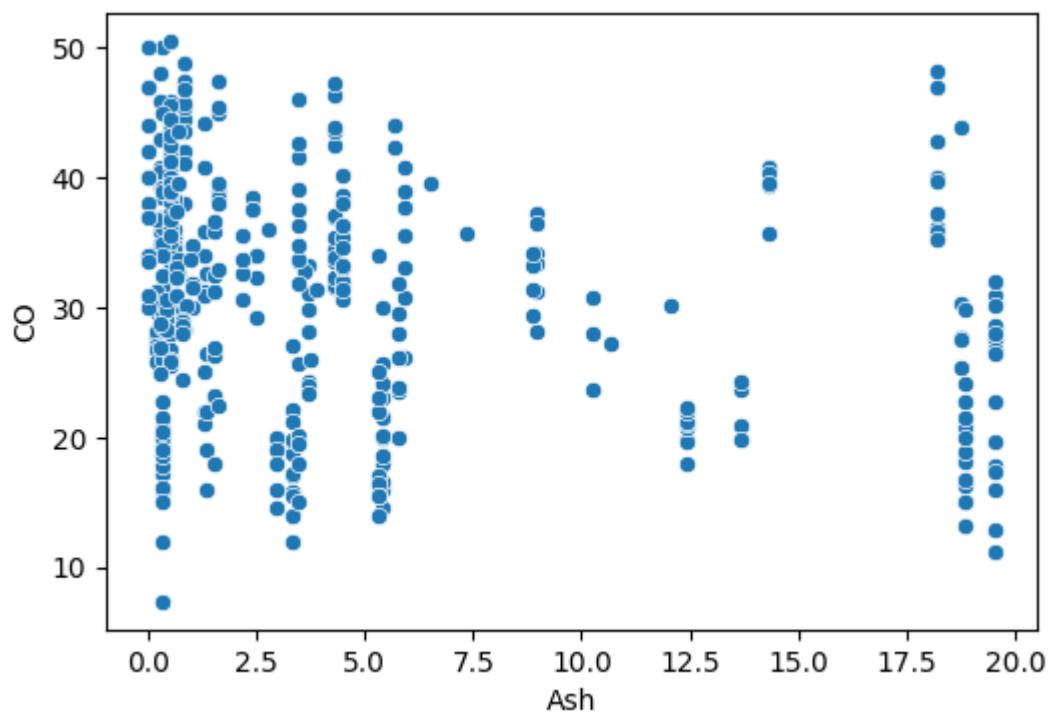
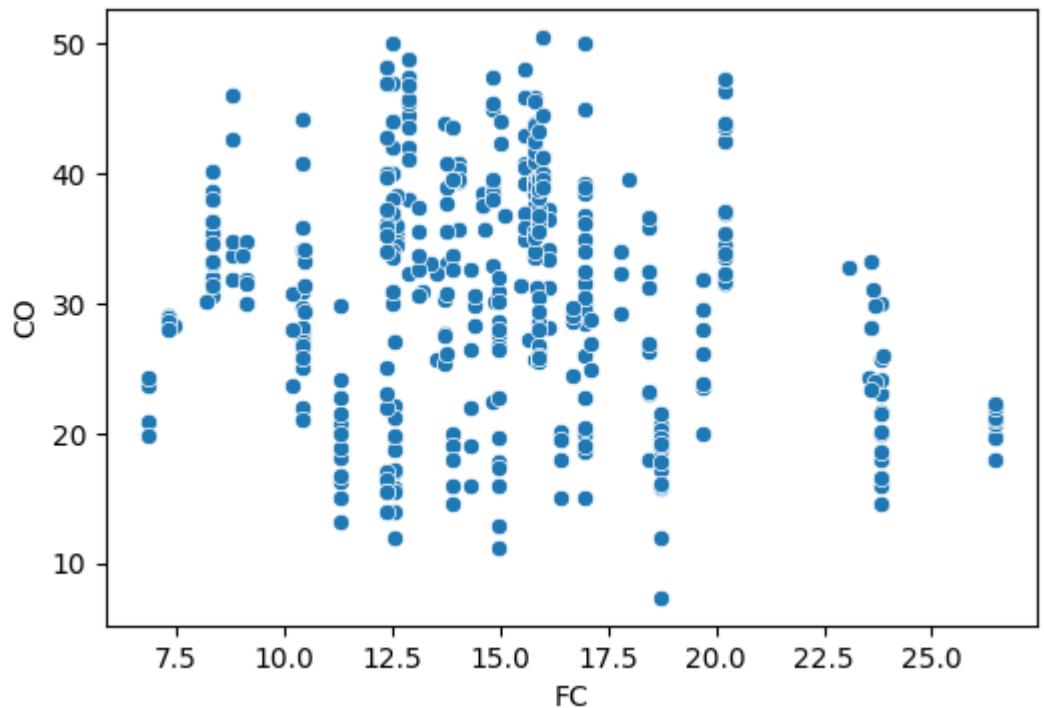
```
In [16]: plt.figure(figsize=(80,16))
sns.countplot(x = 'Biomass species', data = df);
```

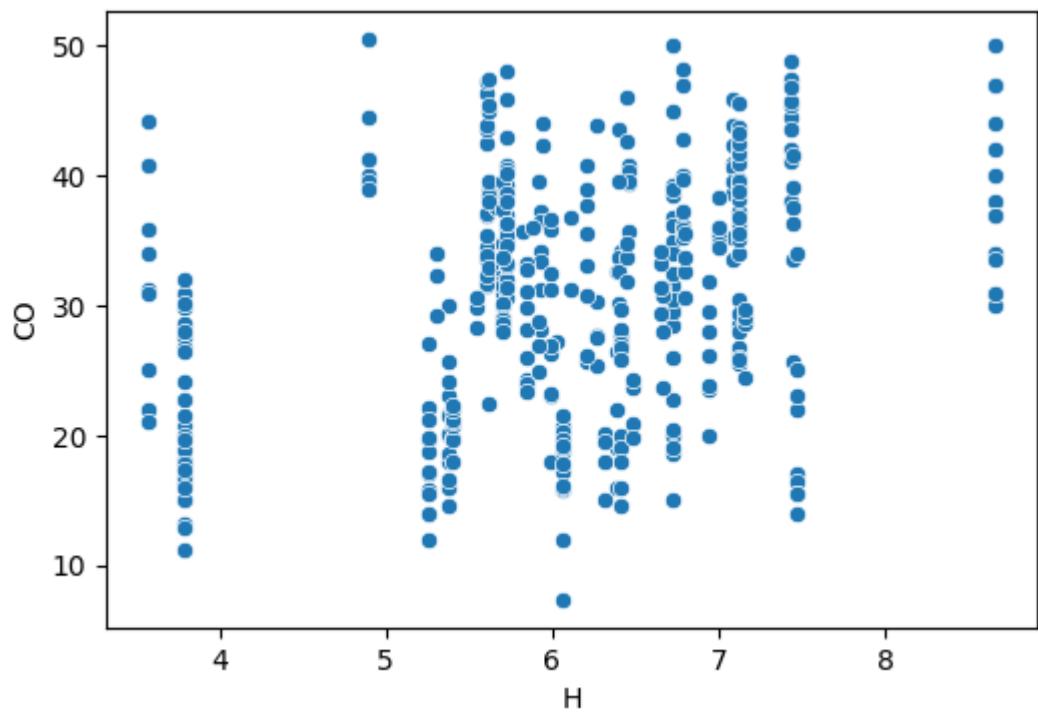
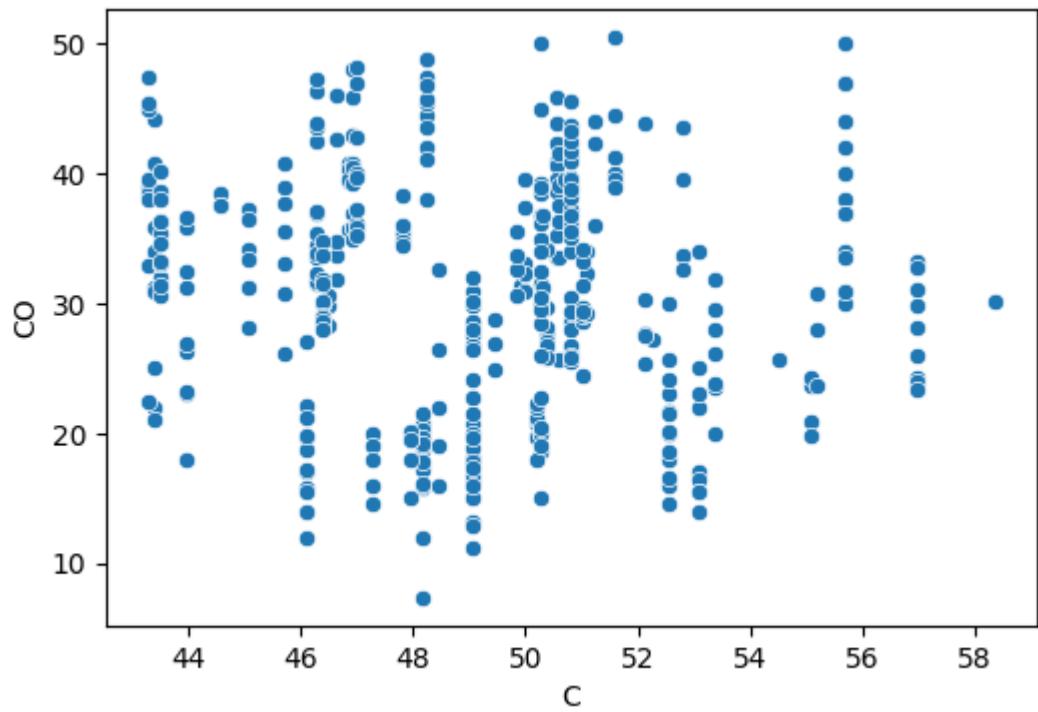


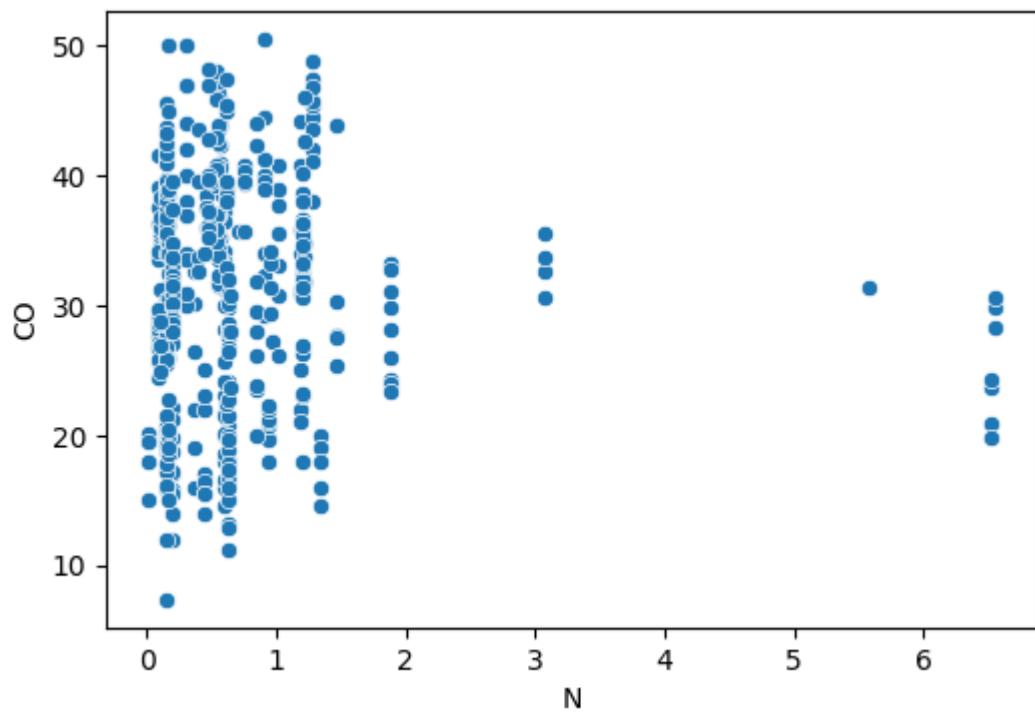
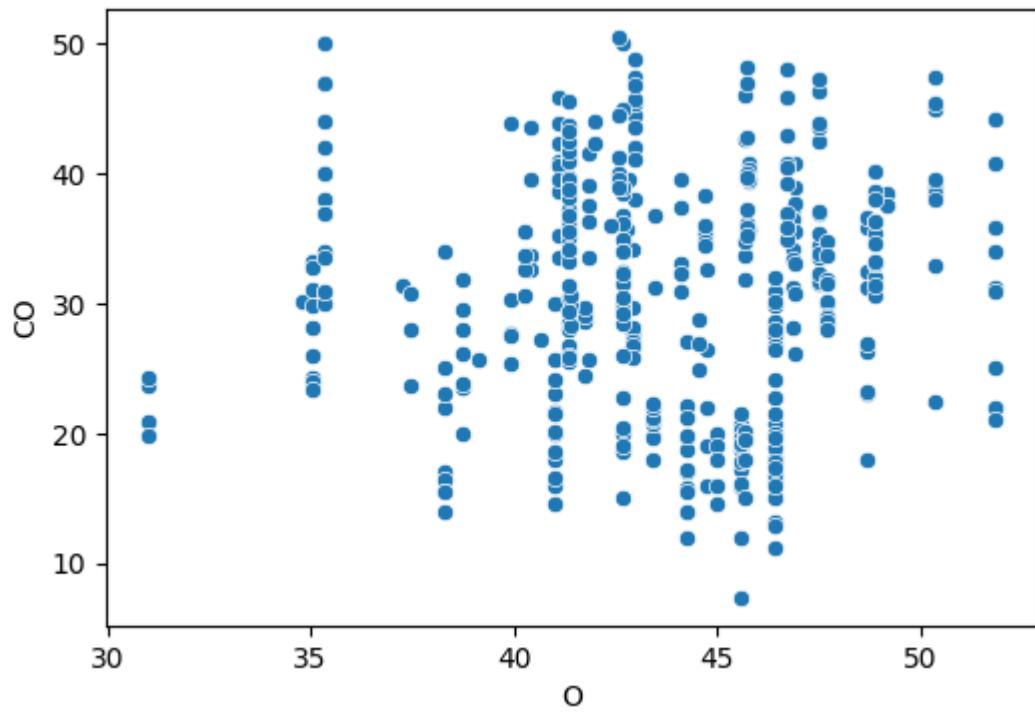
There is an uneven distribution in the count of categorical values

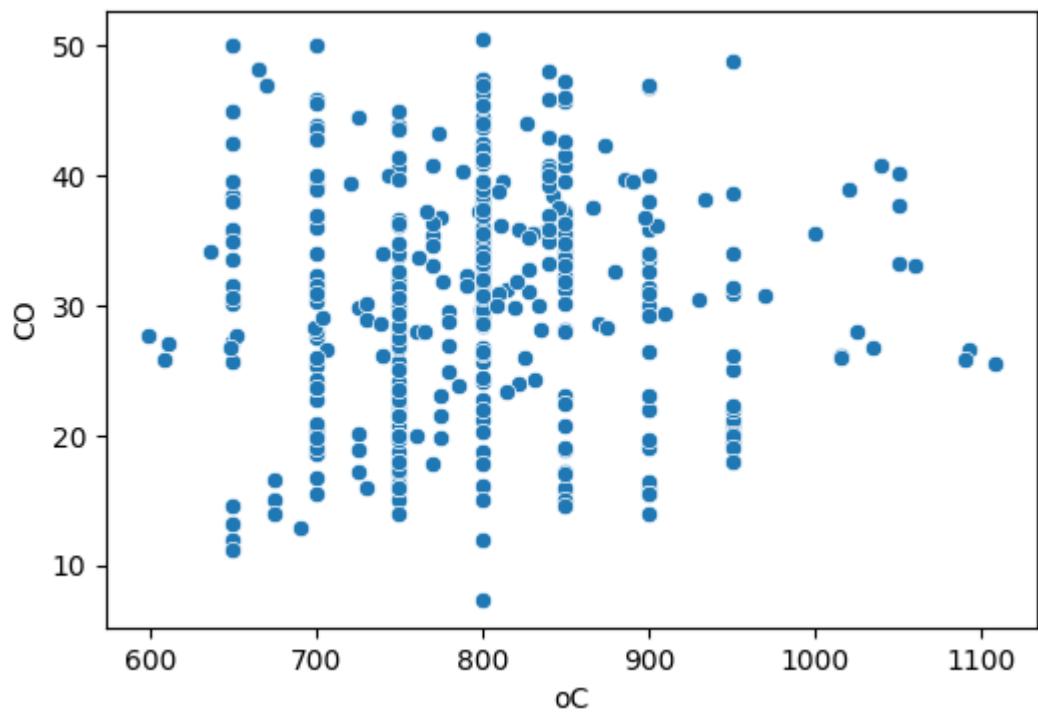
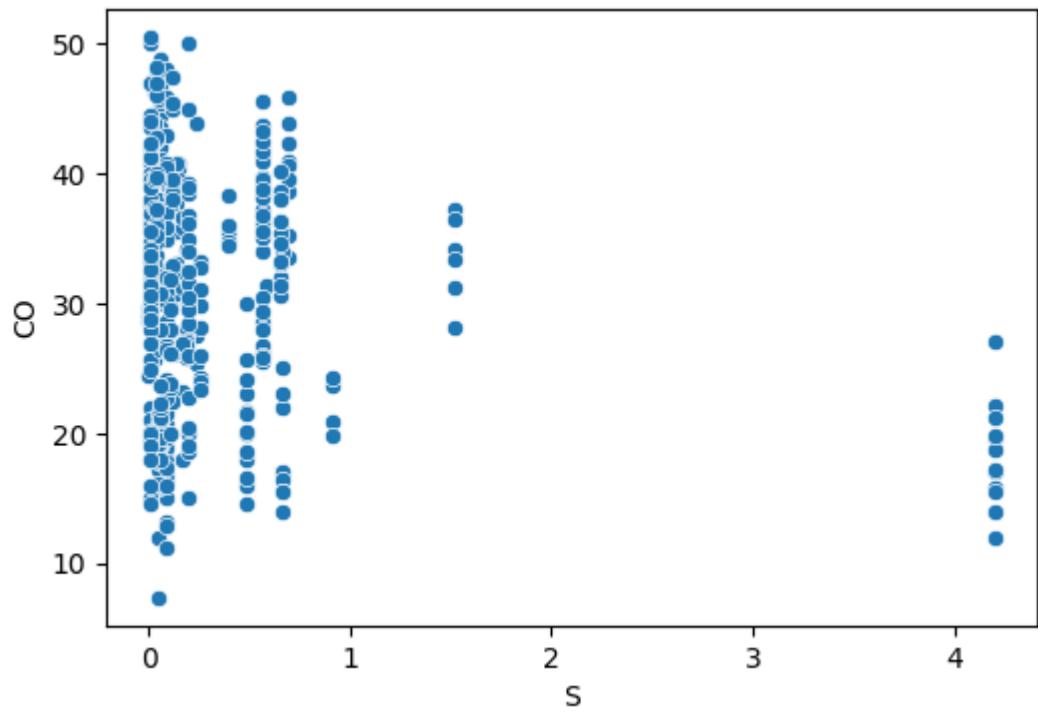
```
In [17]: for tar_col in target_col:  
    for num_col in numerical_col:  
        plt.figure(figsize=(6,4))  
        sns.scatterplot(x = df[num_col], y = df[tar_col])  
        plt.show()
```

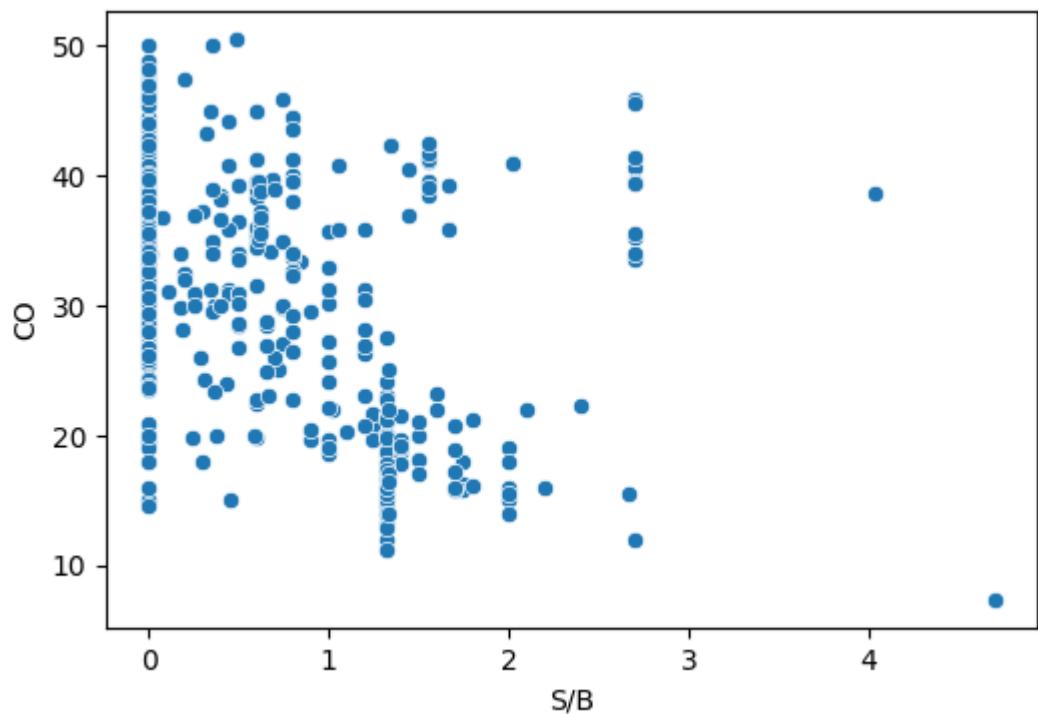
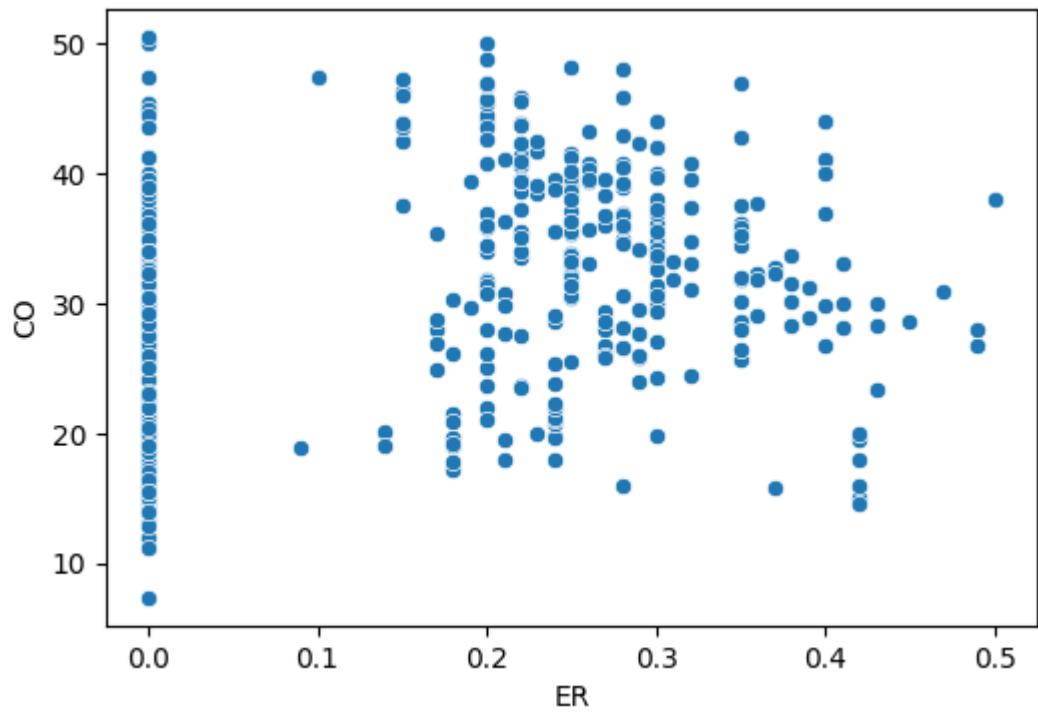


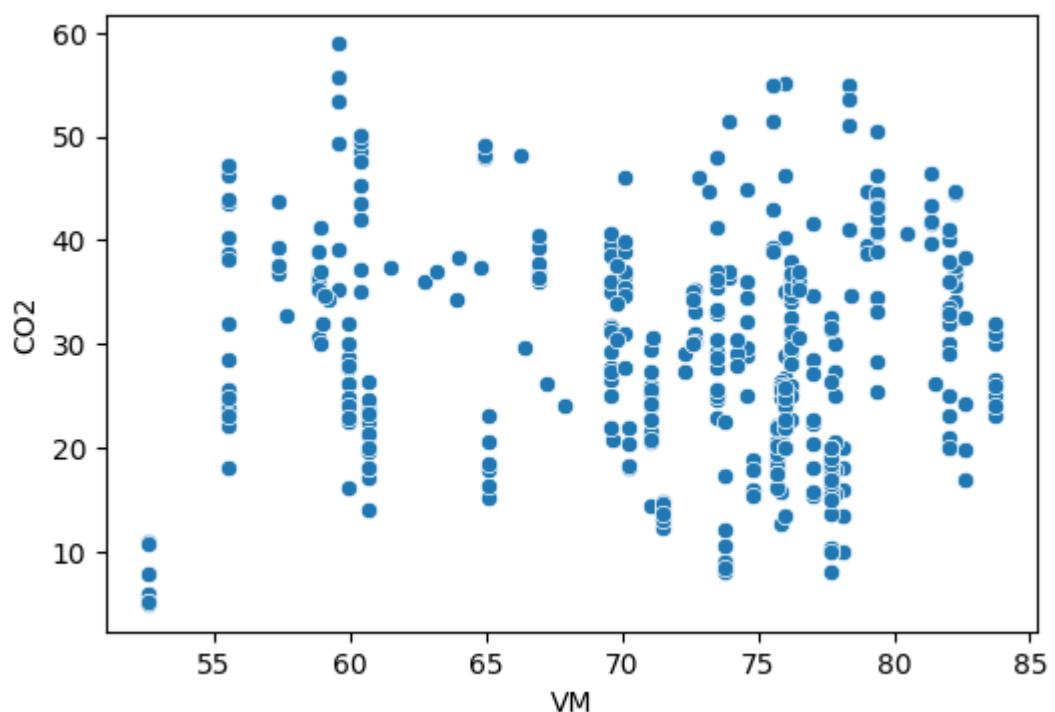
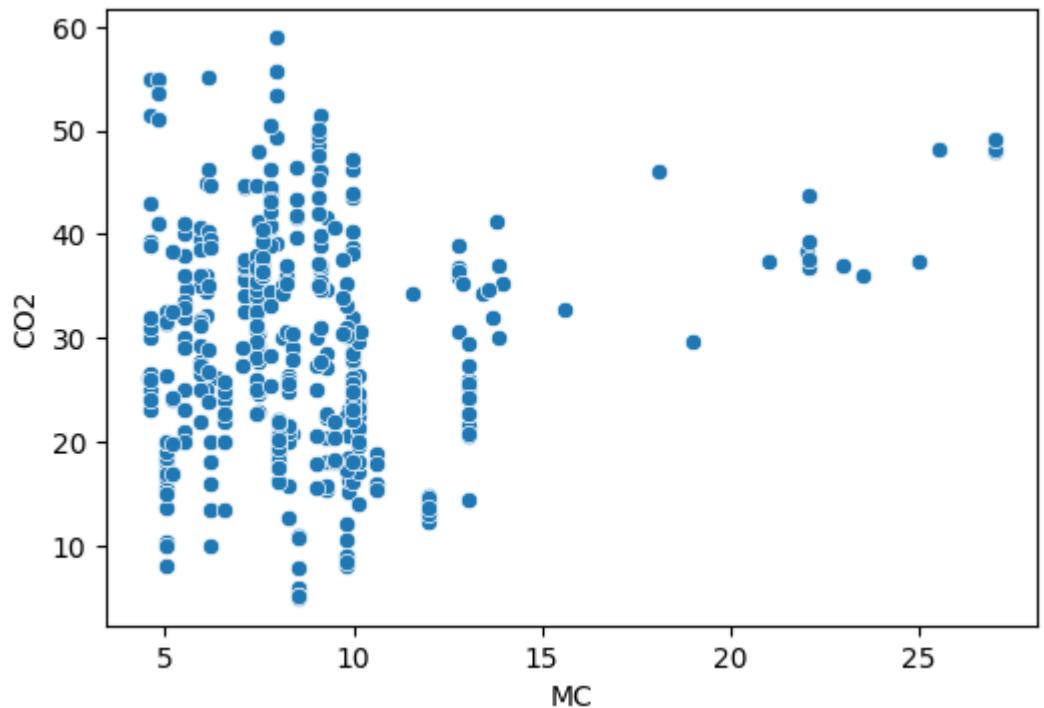


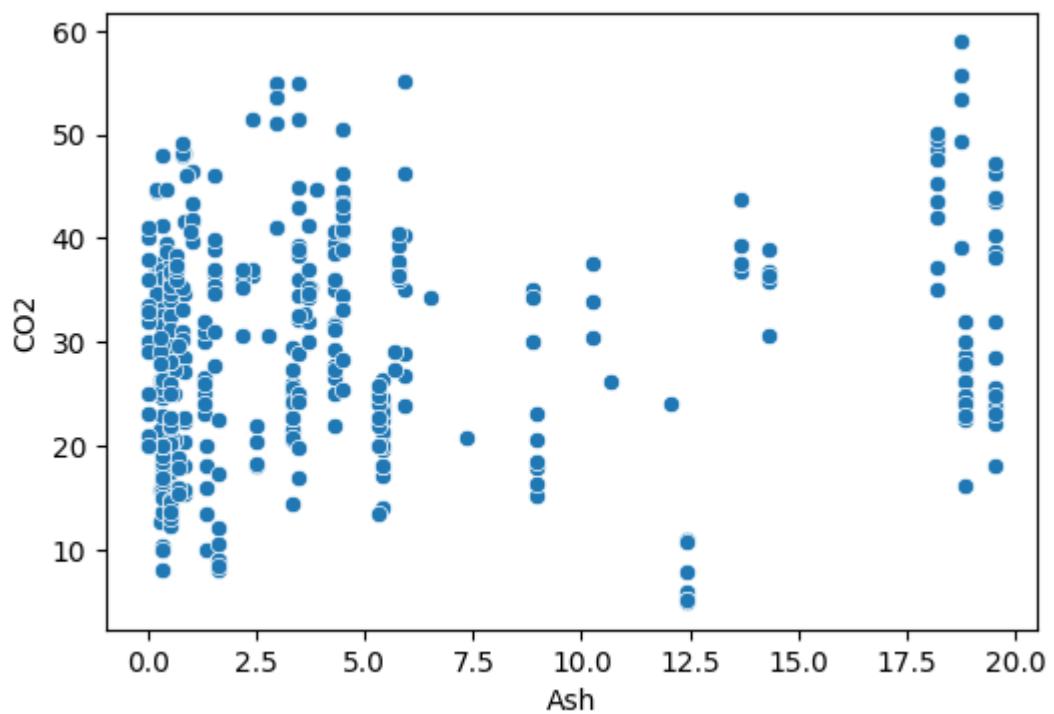
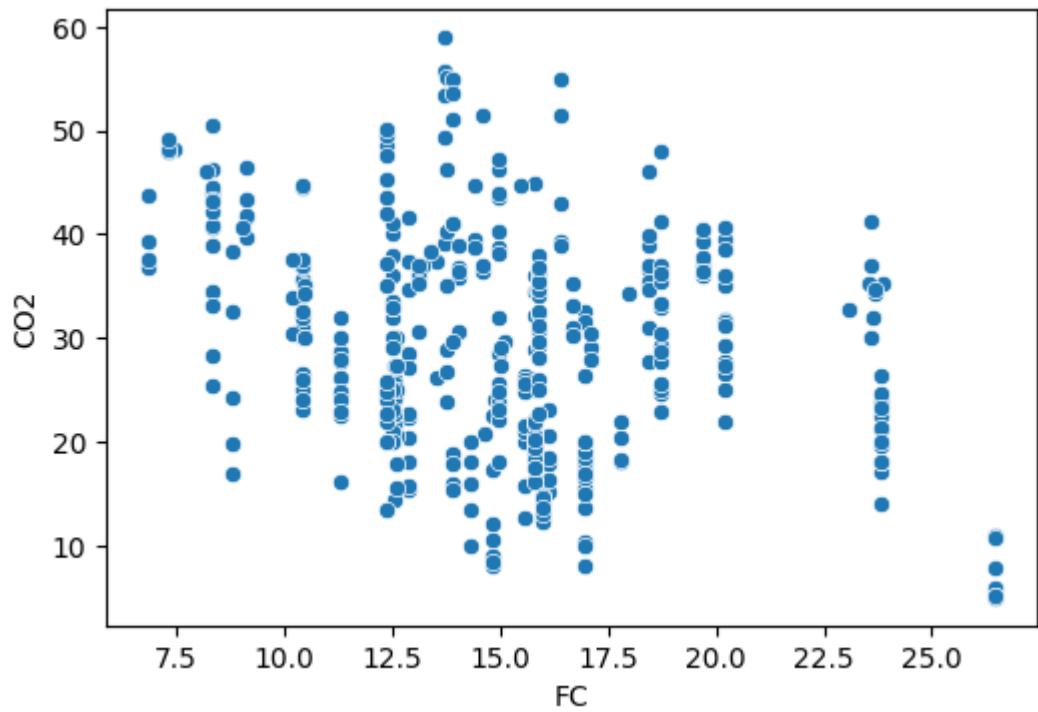


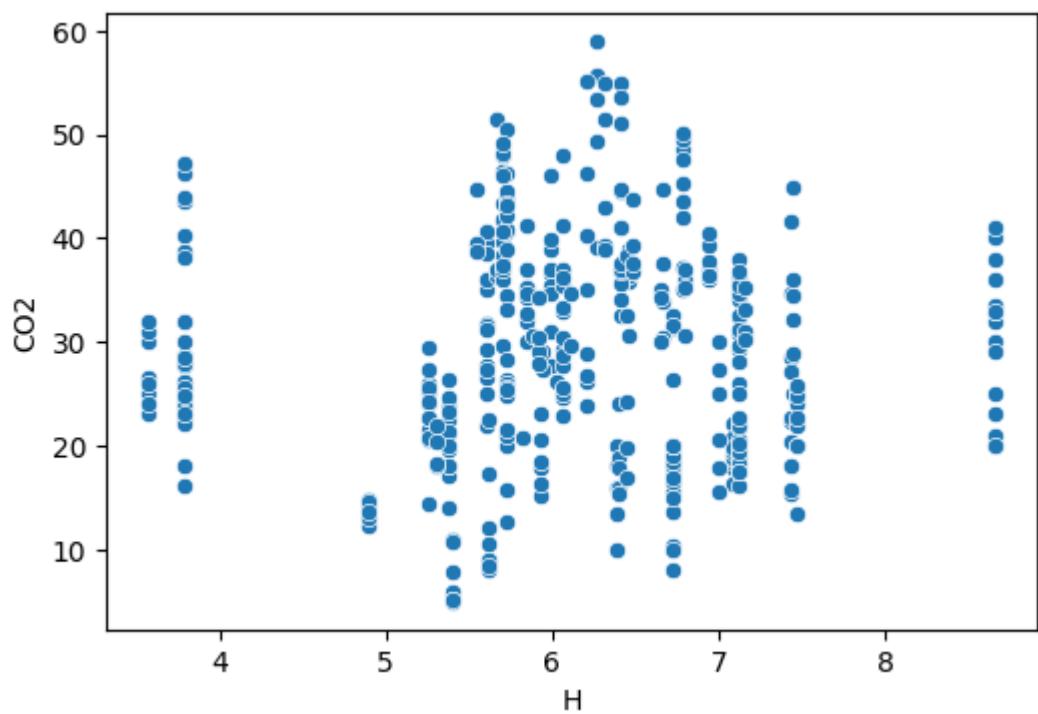
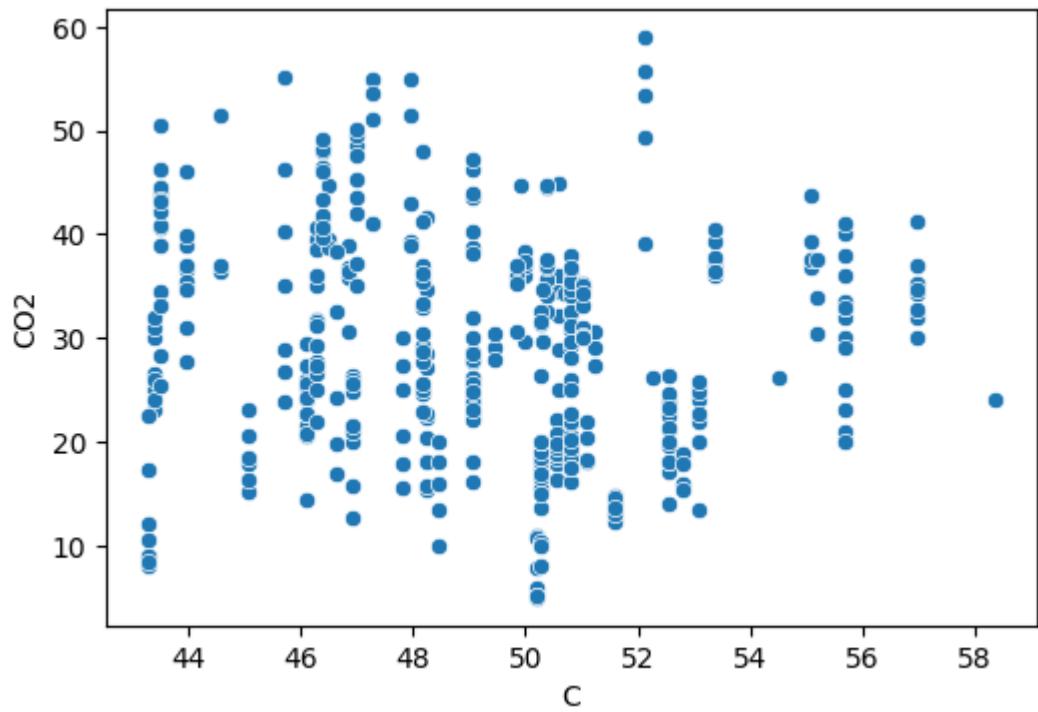


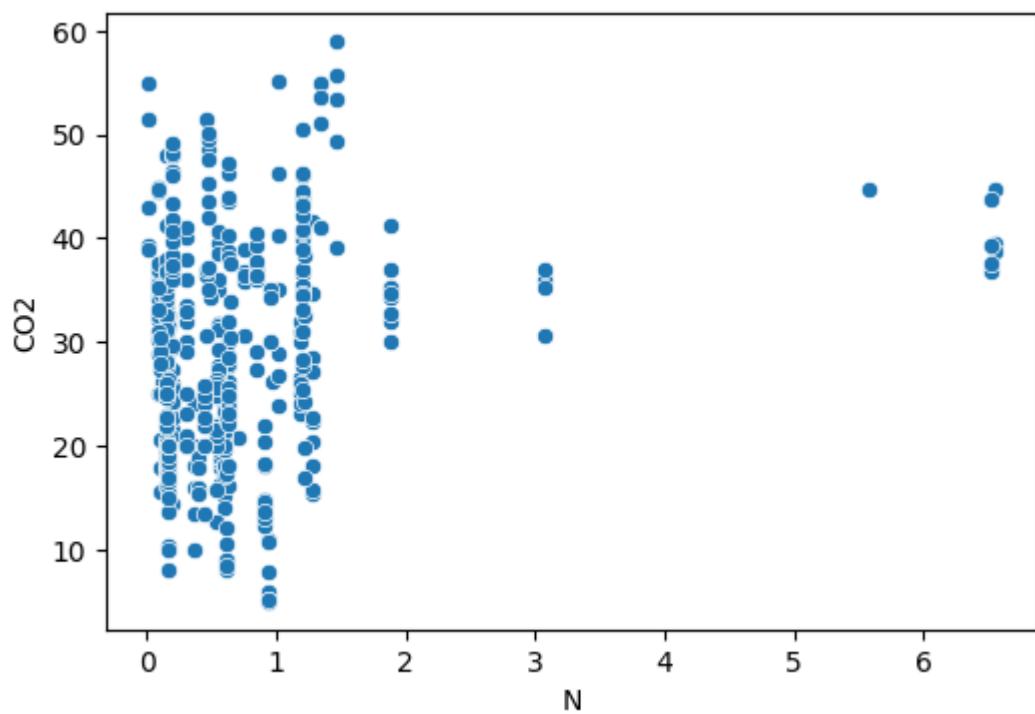
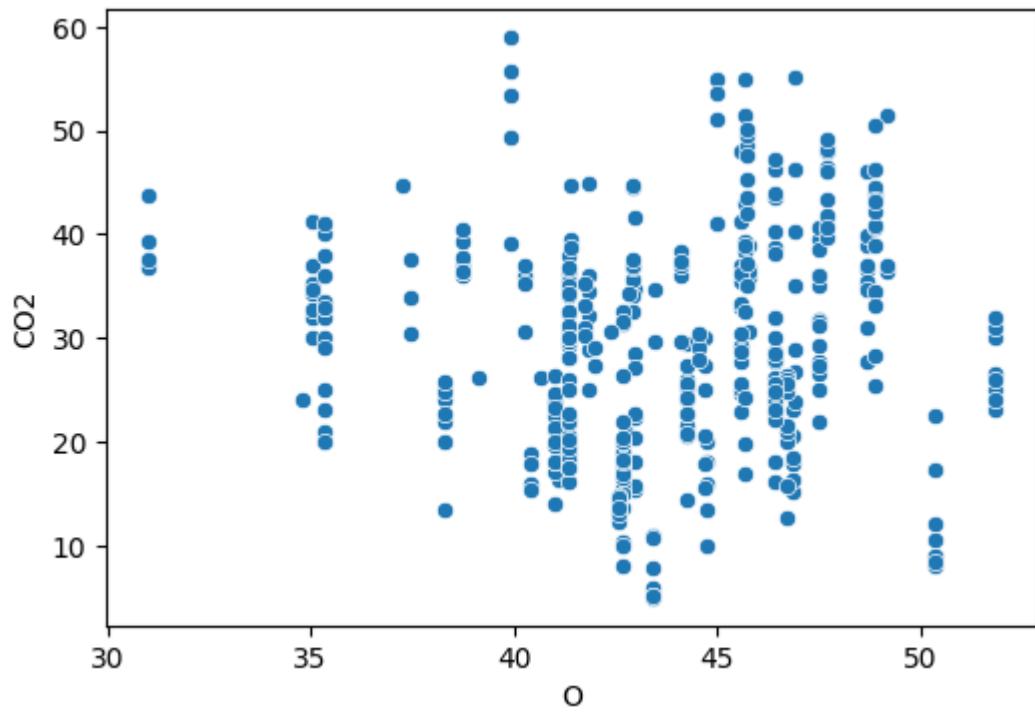


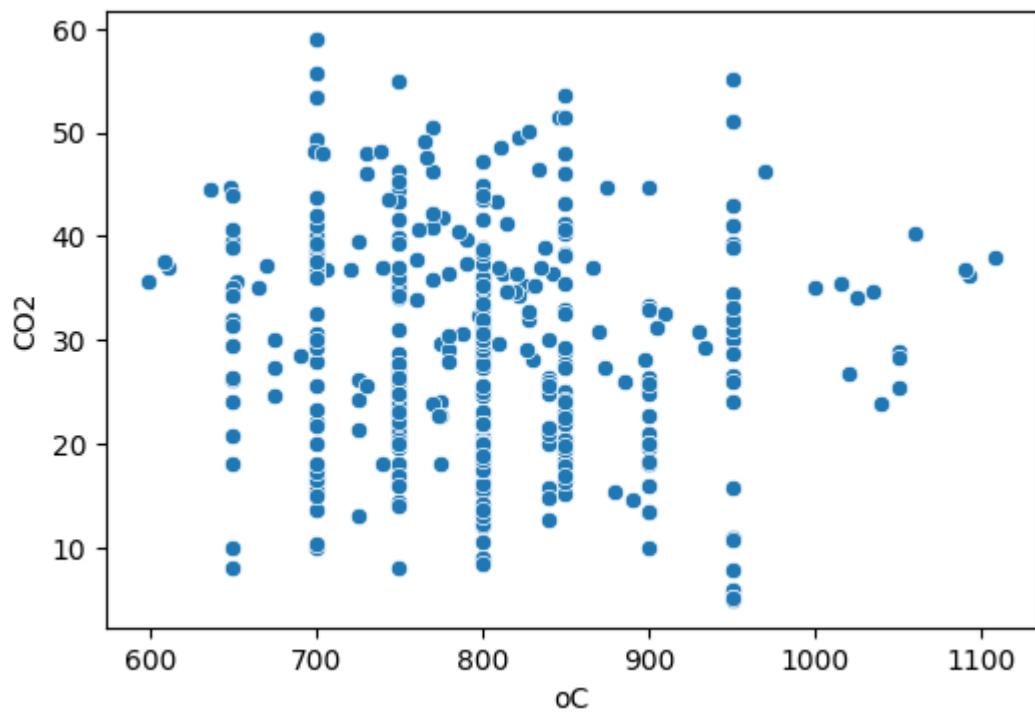
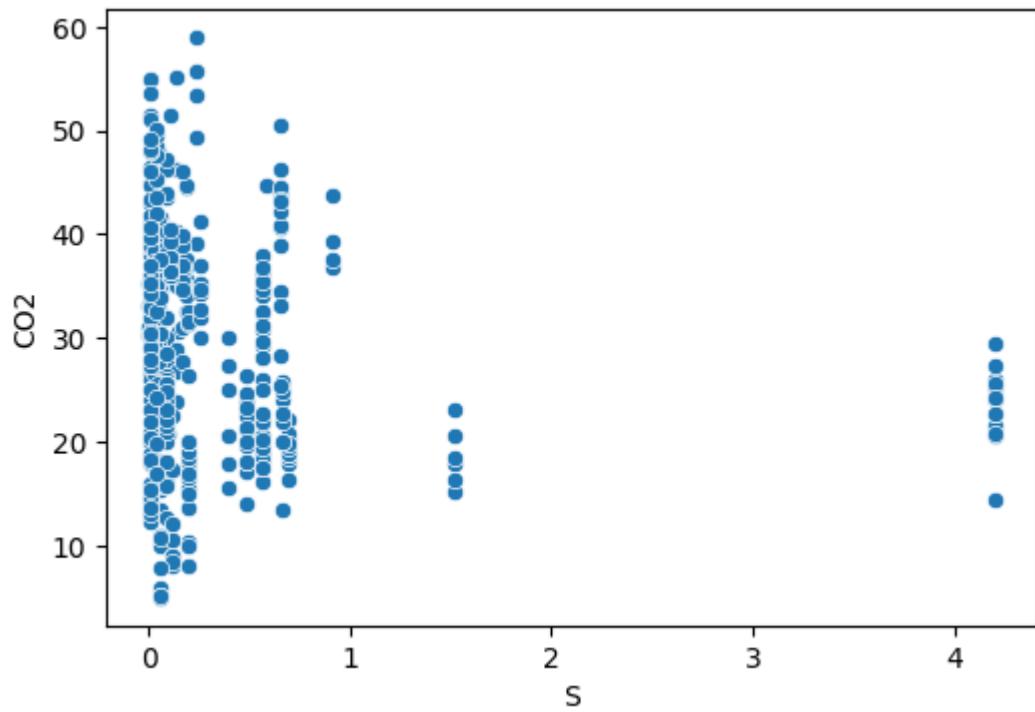


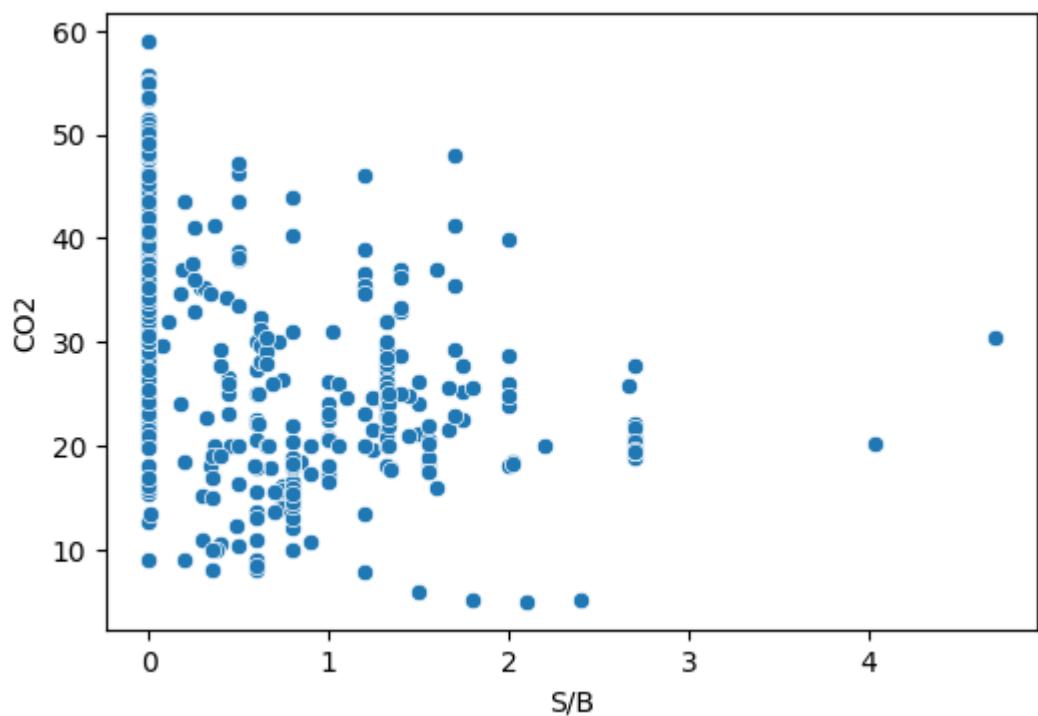
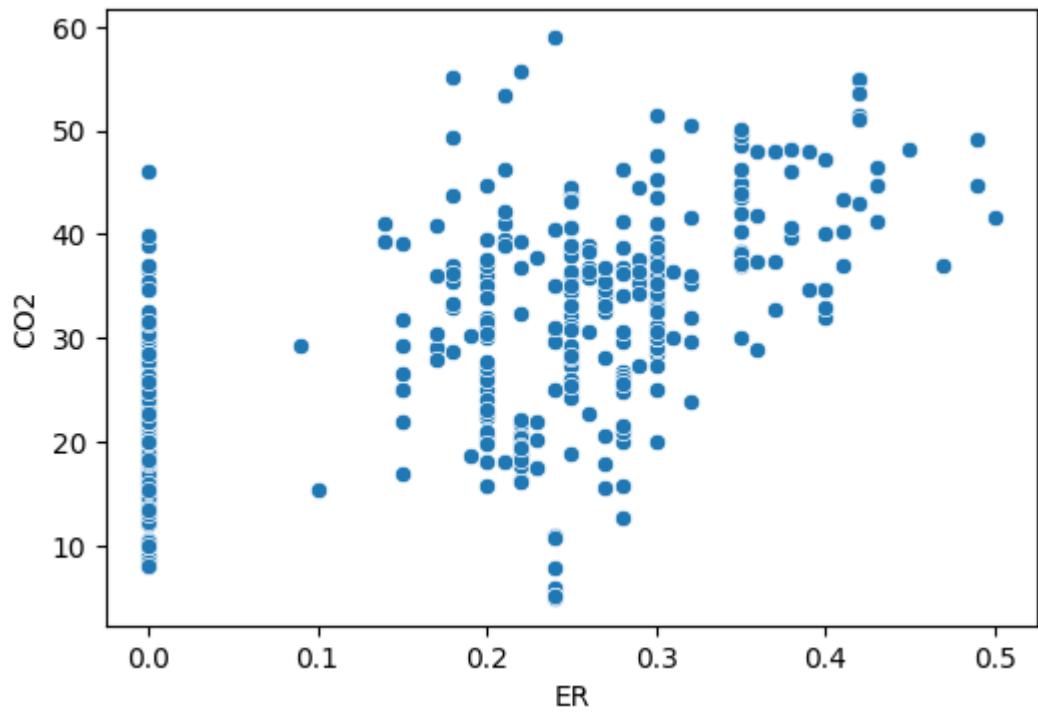


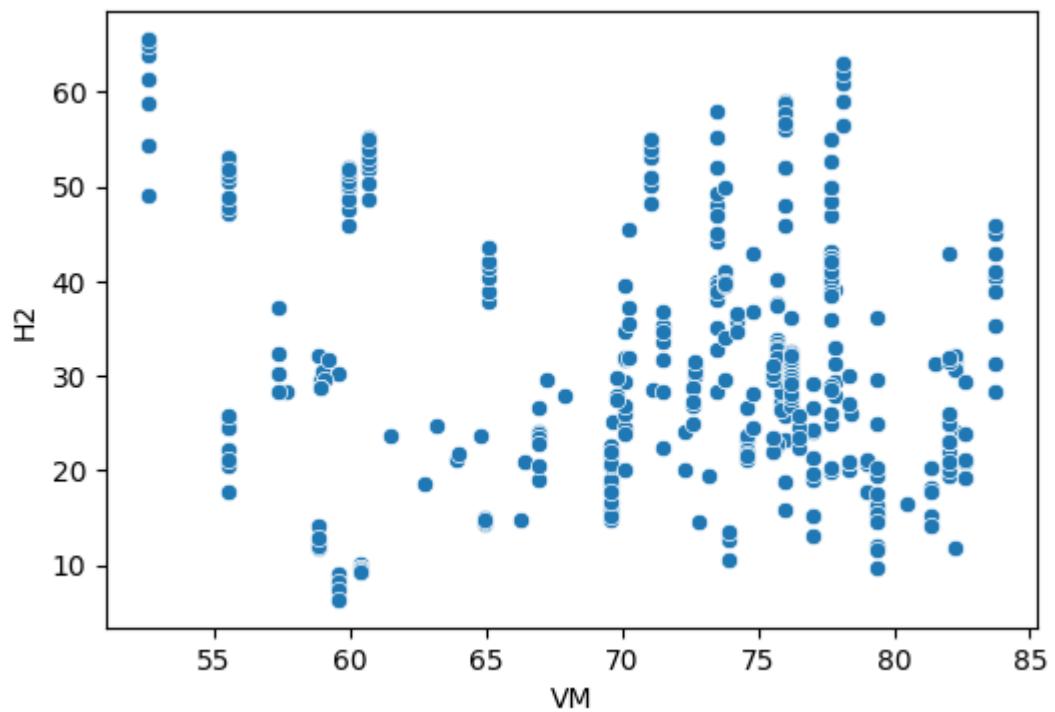
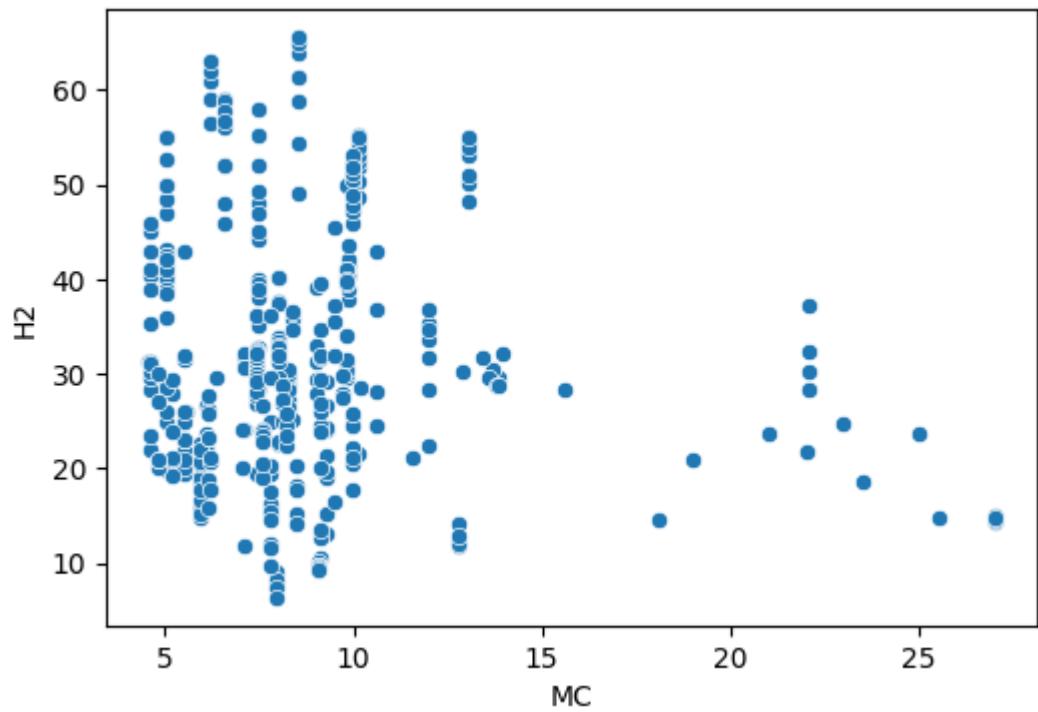


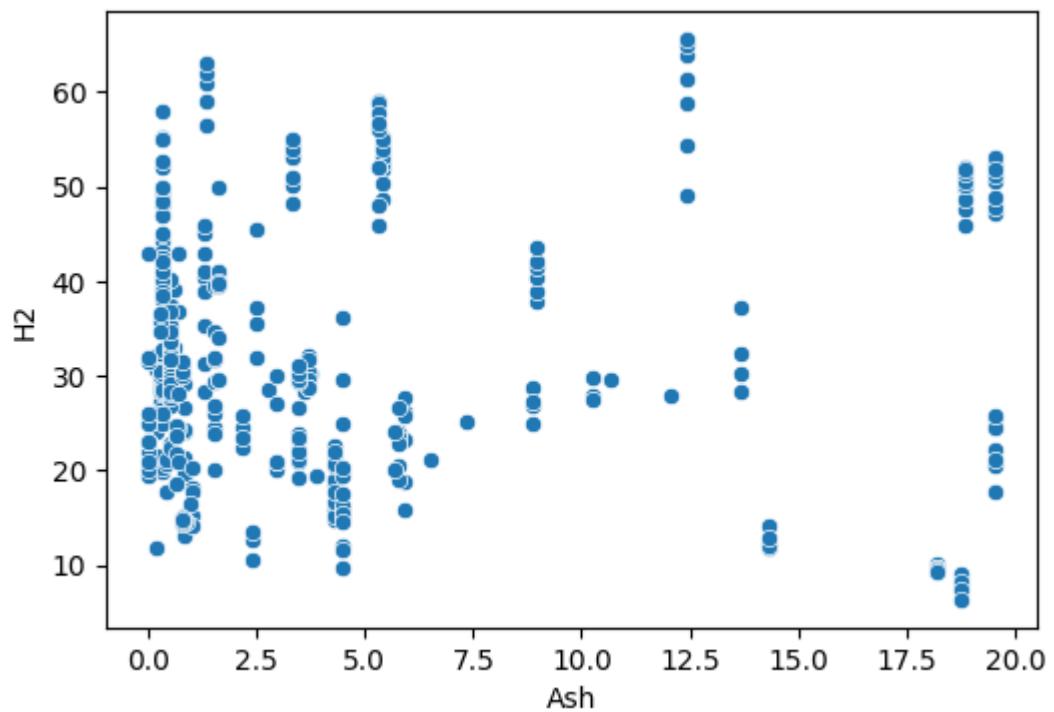
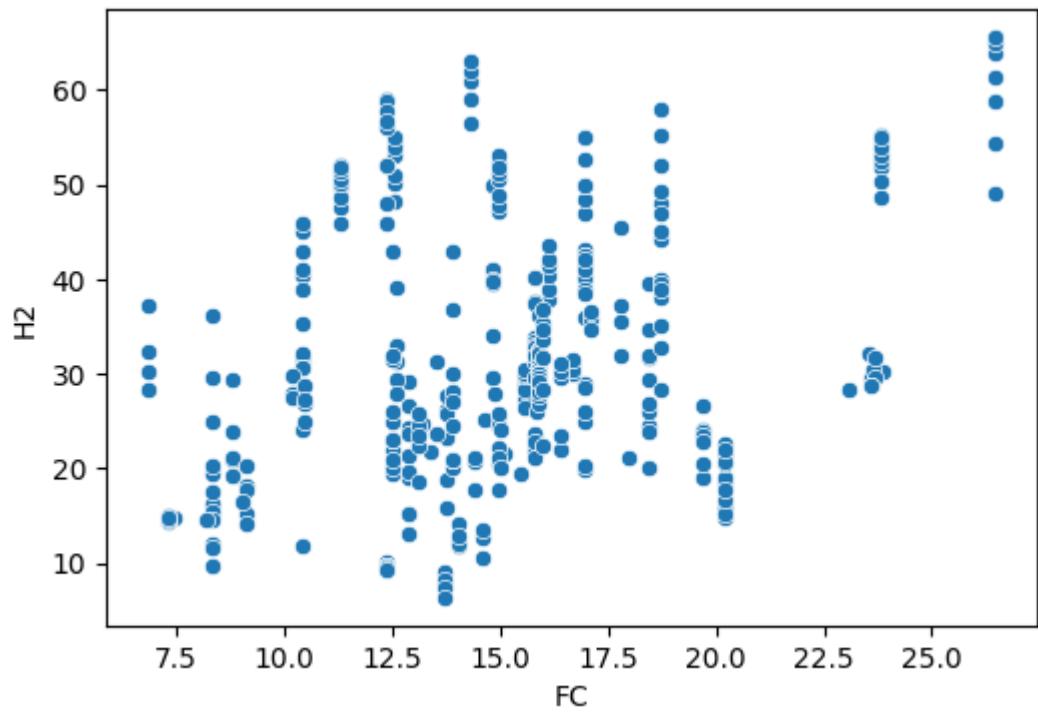


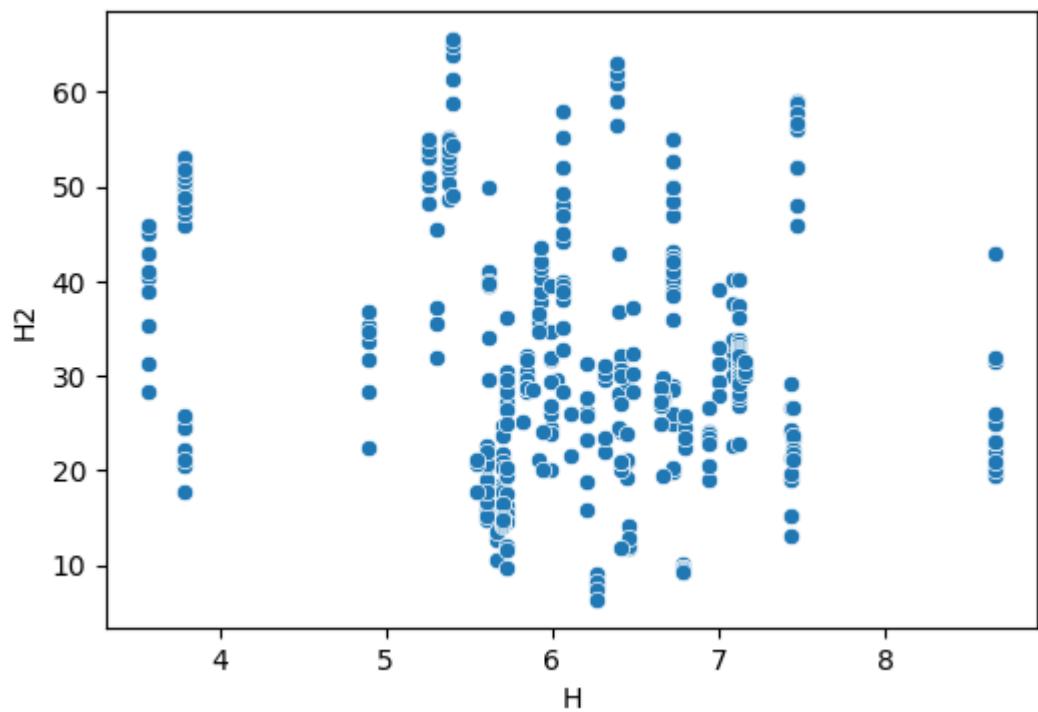
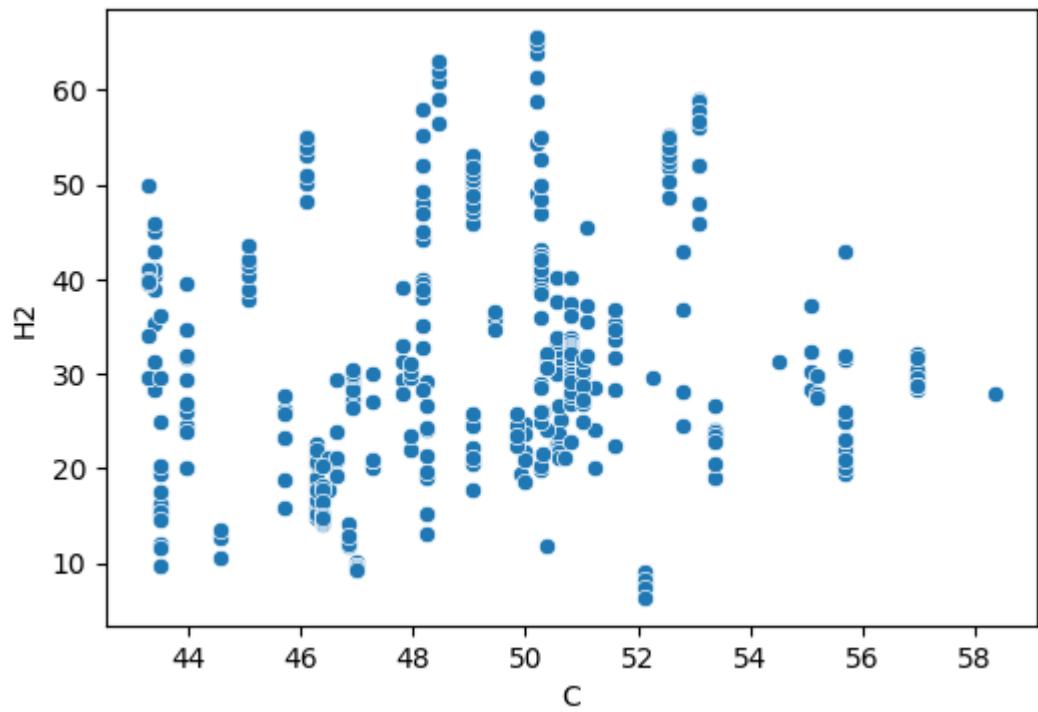


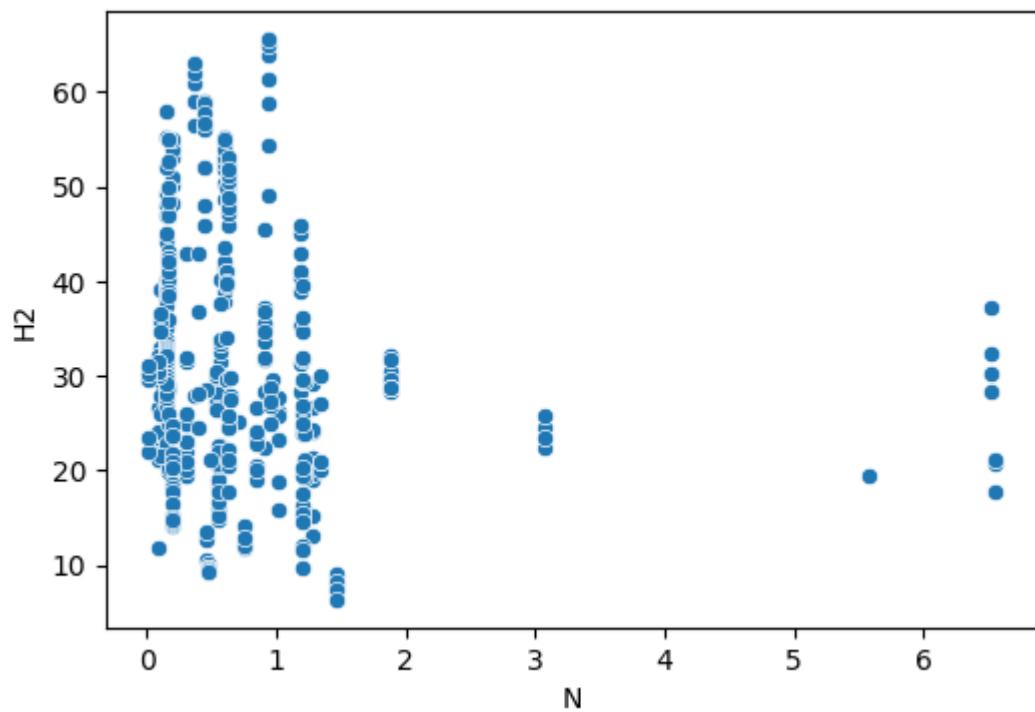
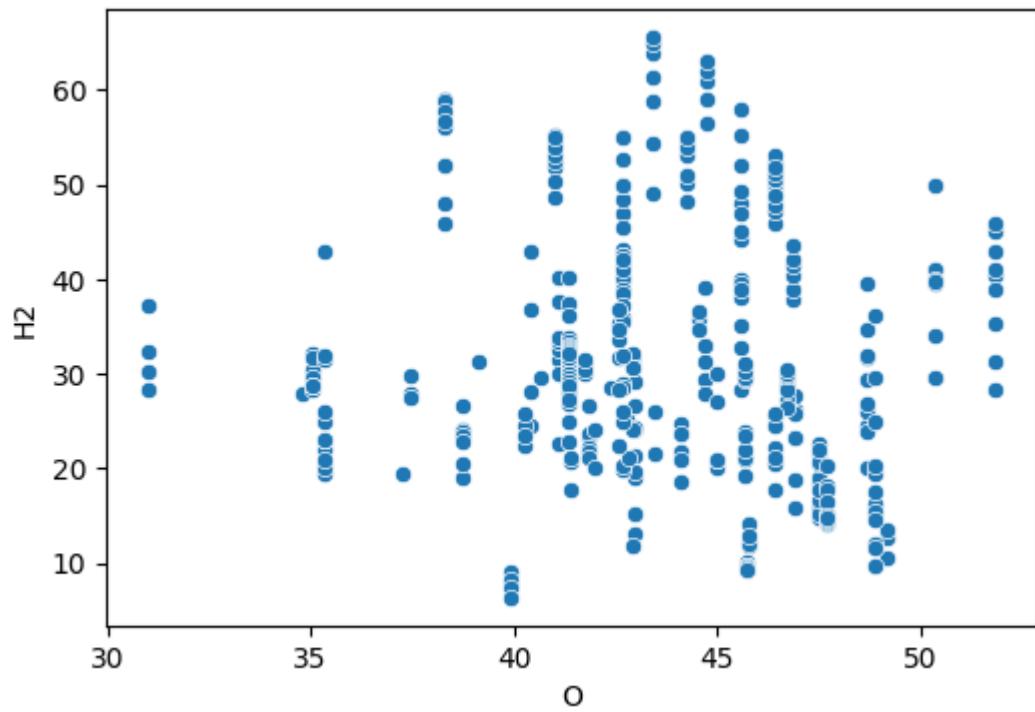


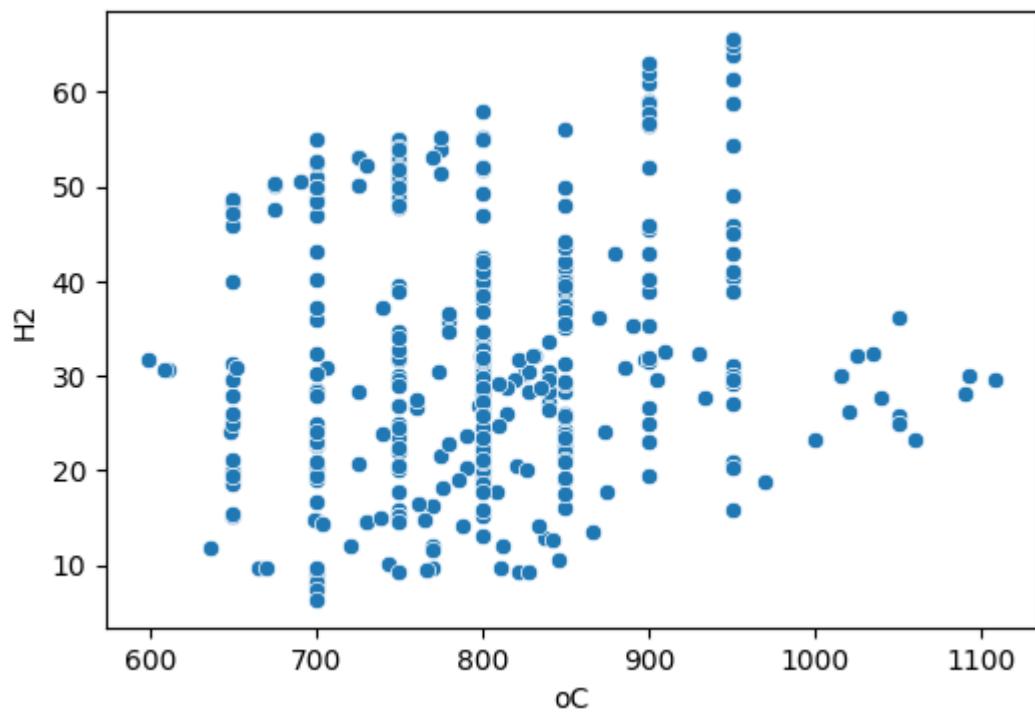
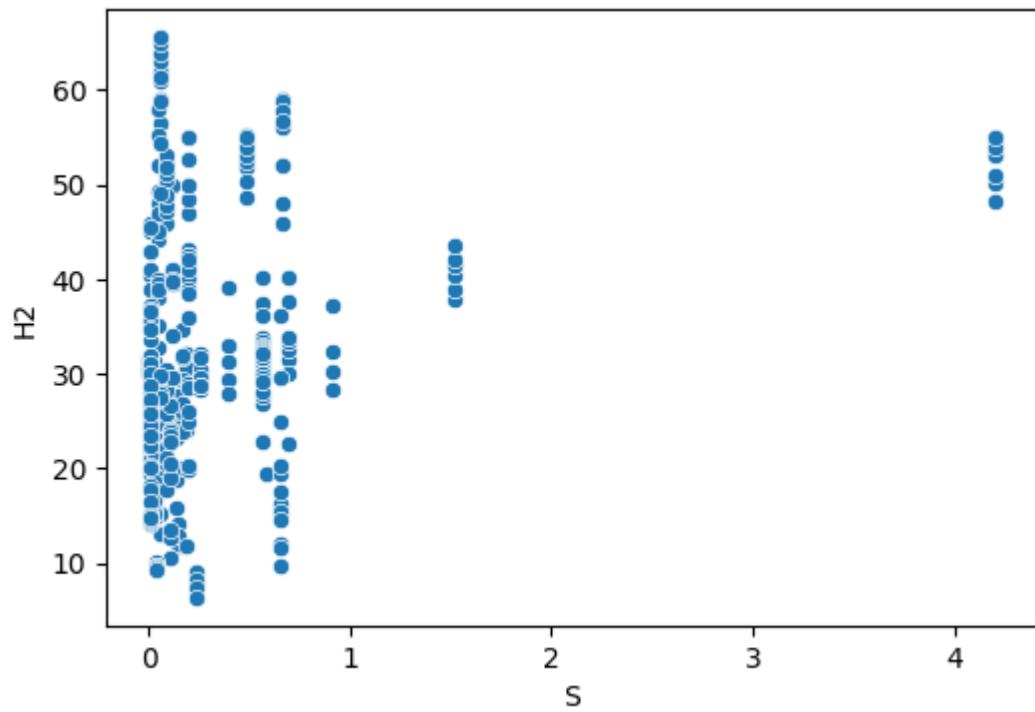


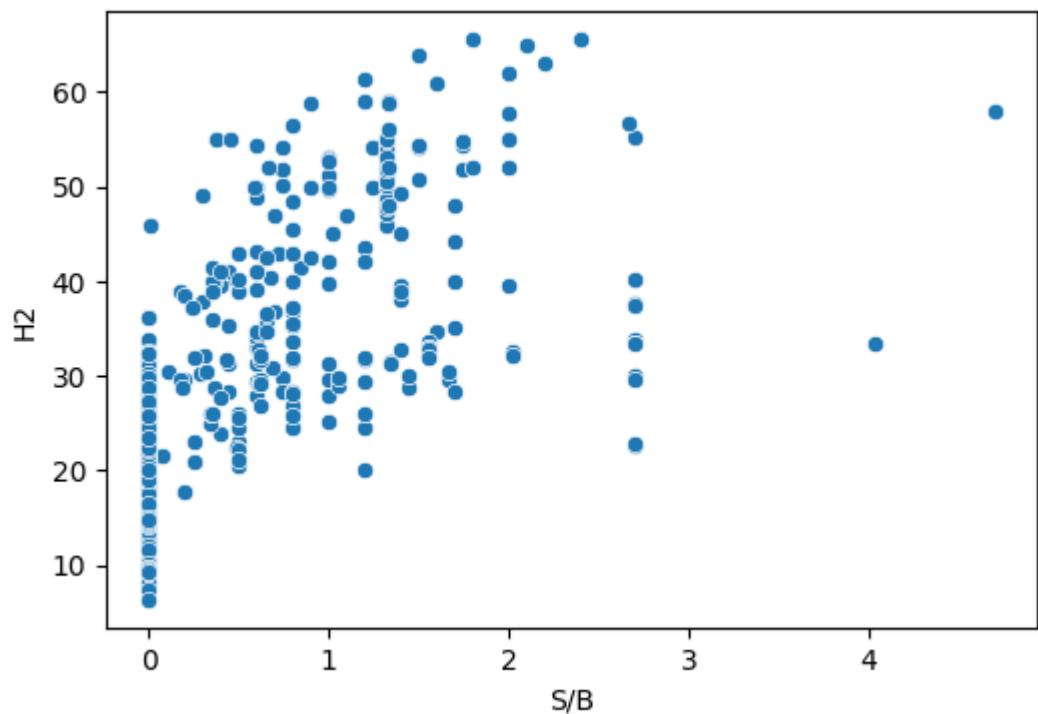
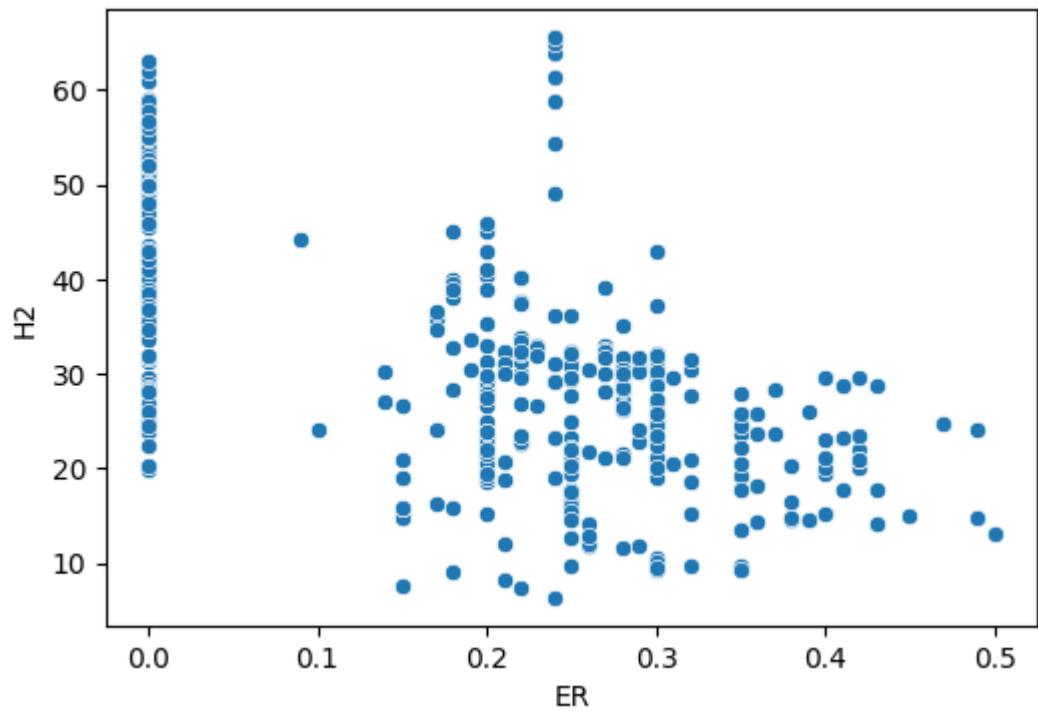


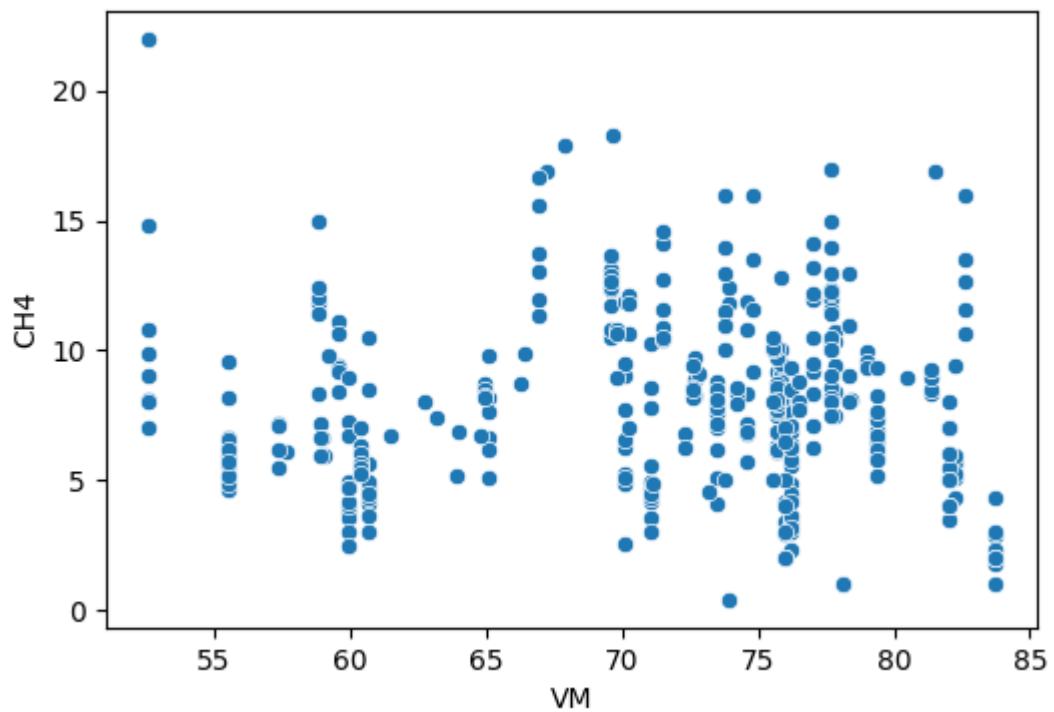
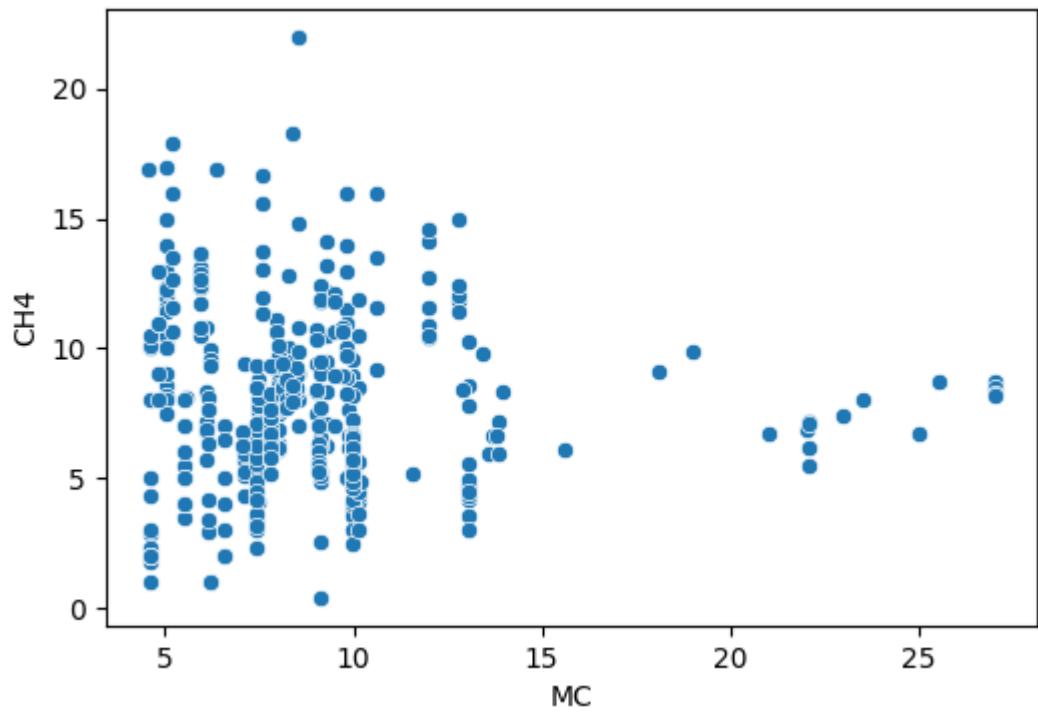


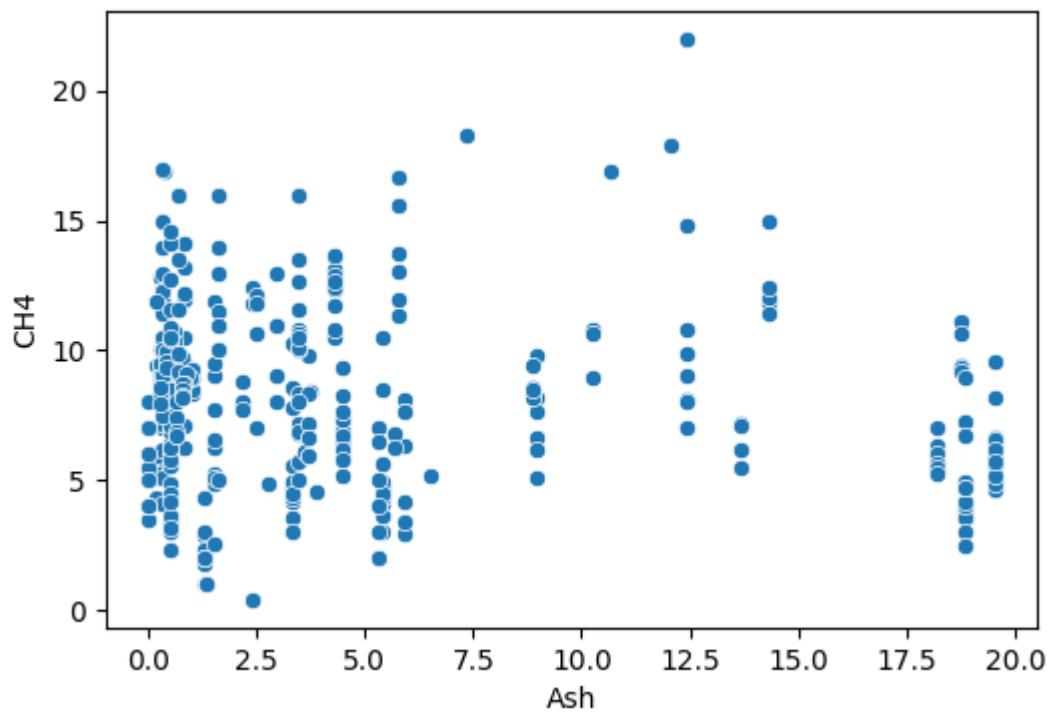
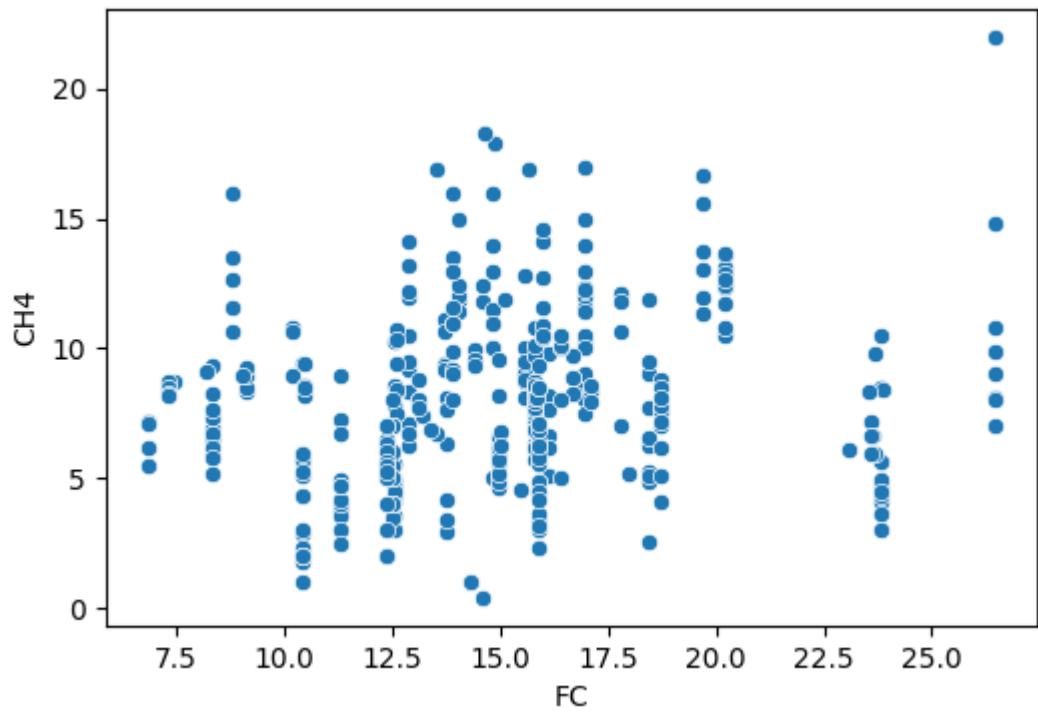


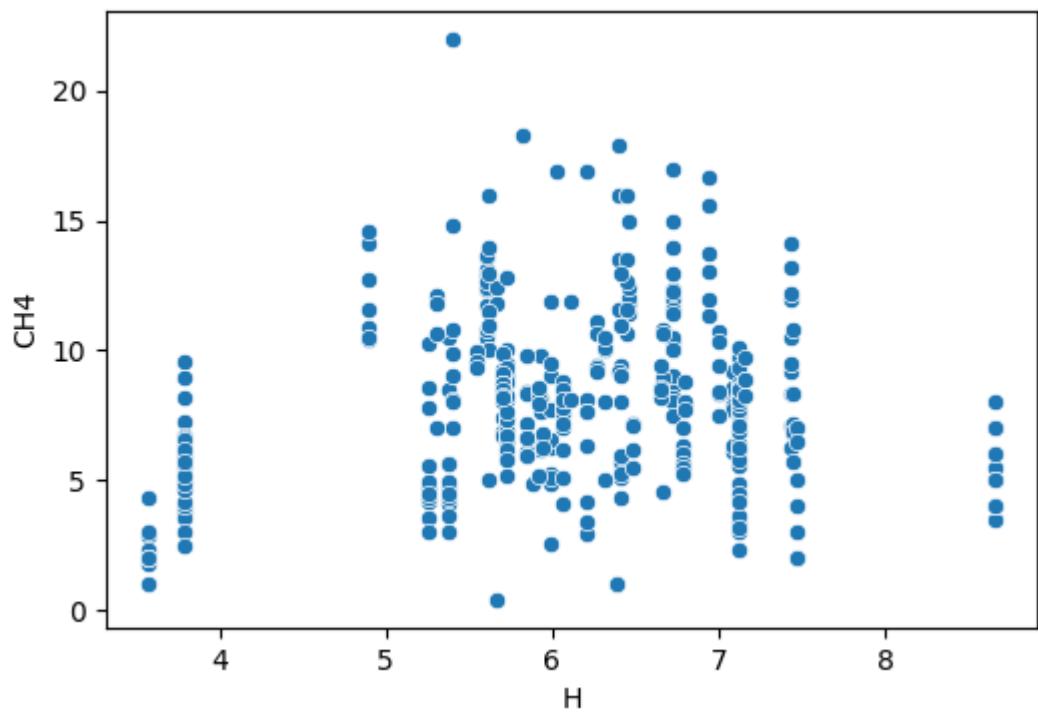
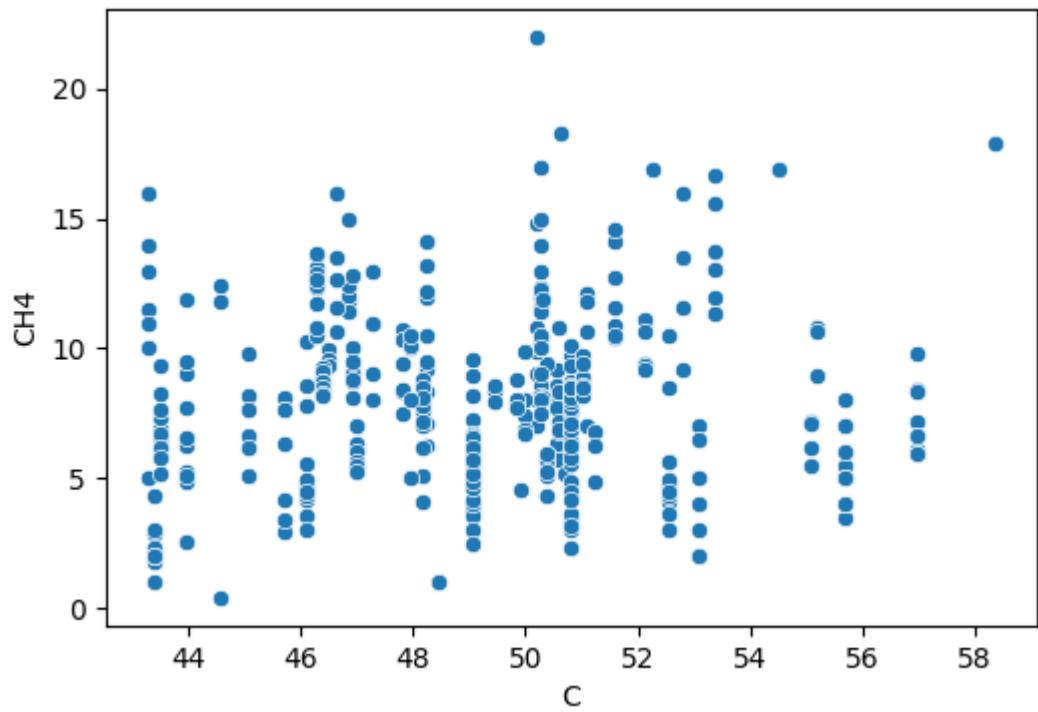


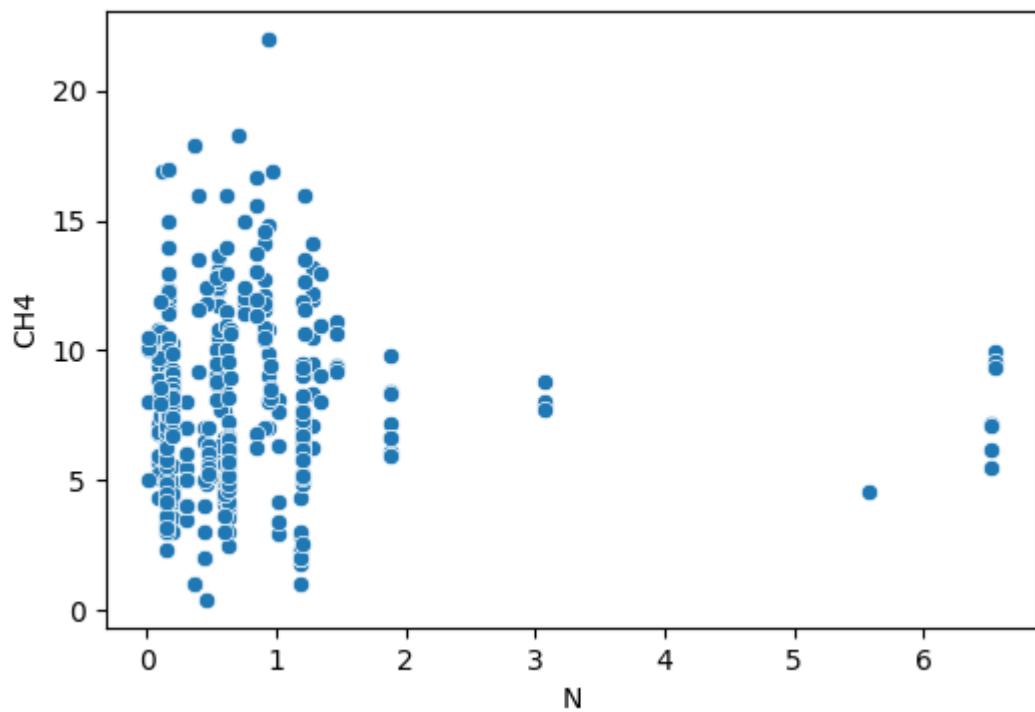
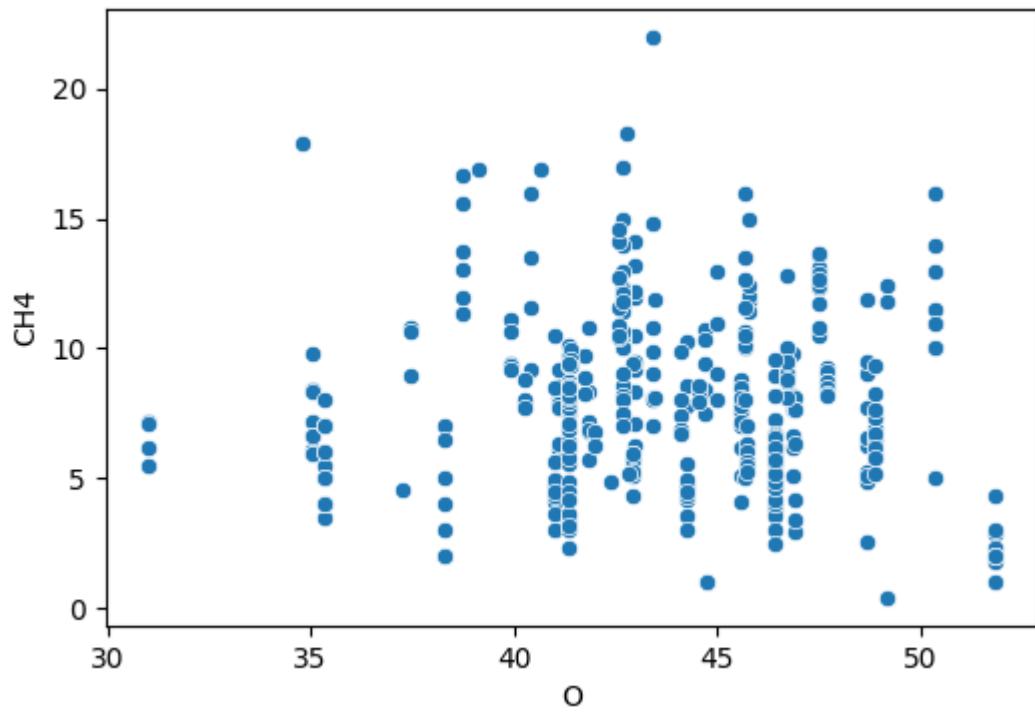


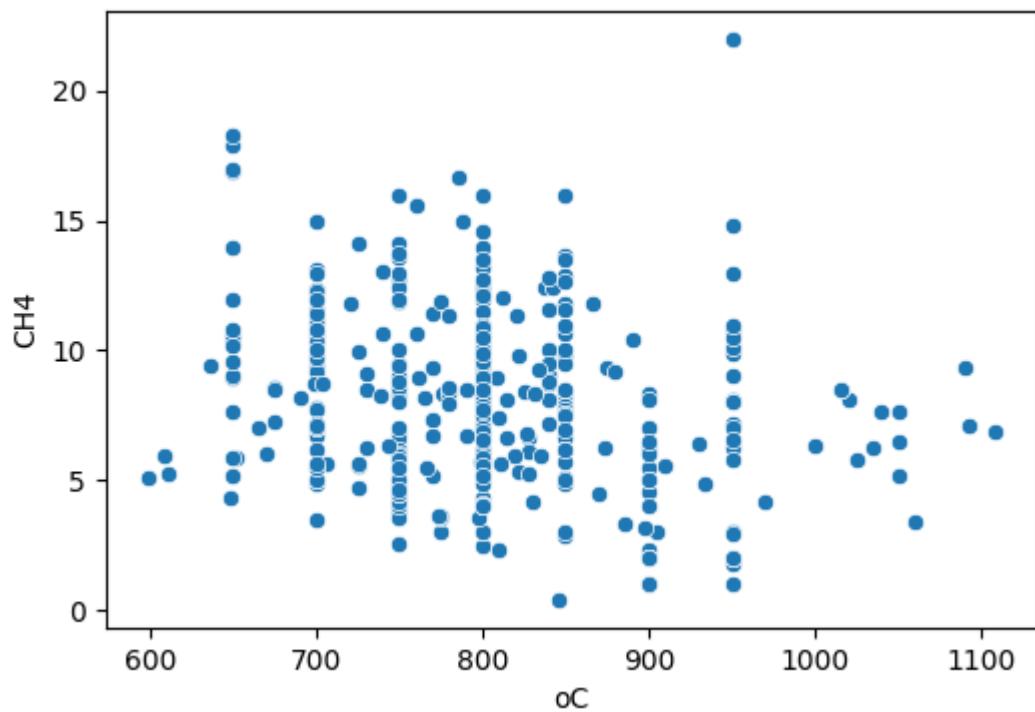
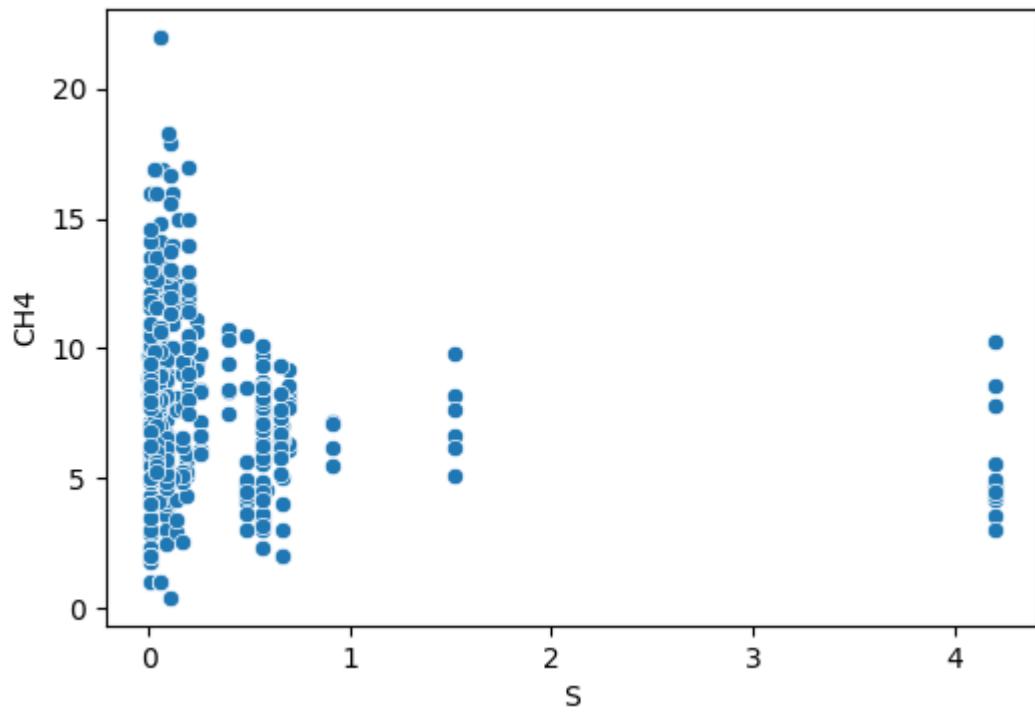


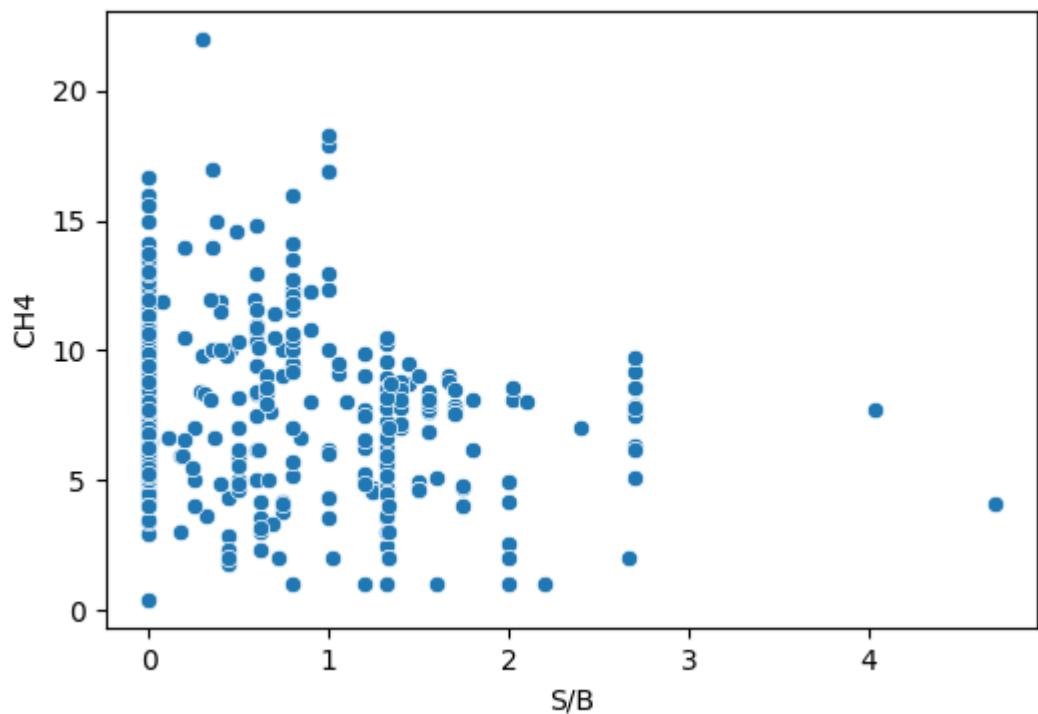
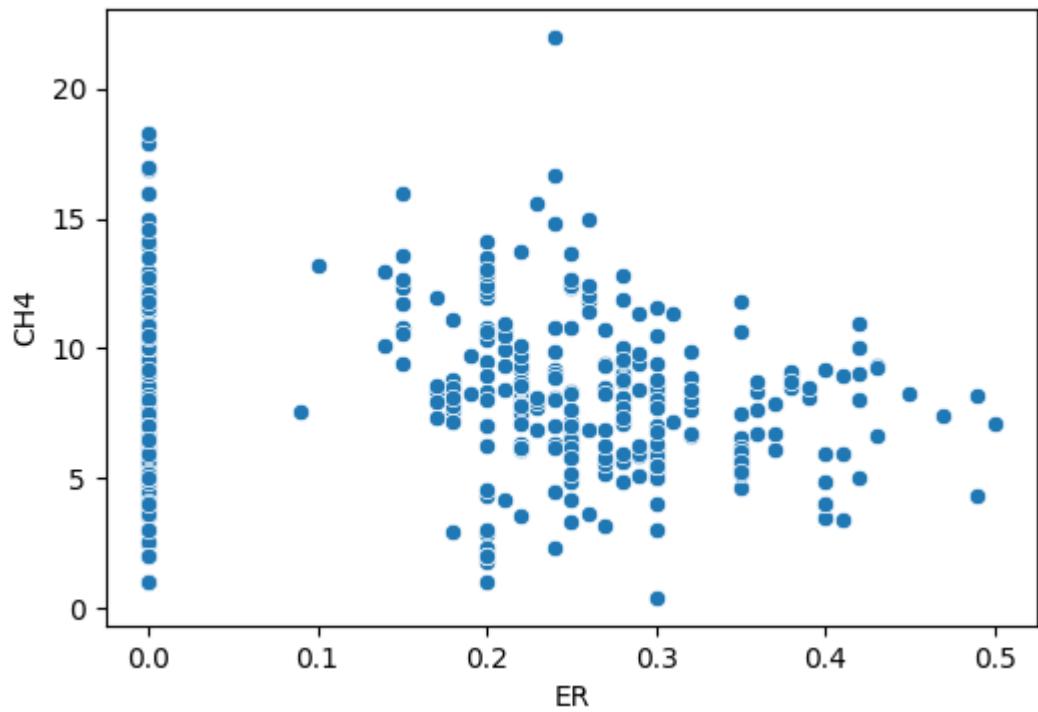


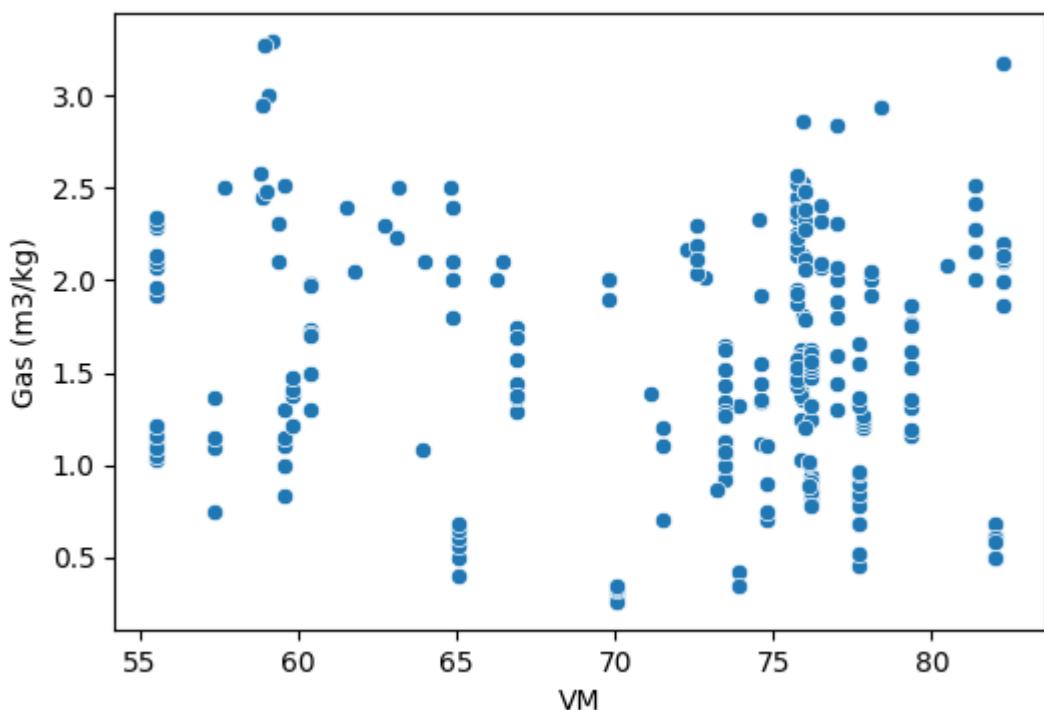
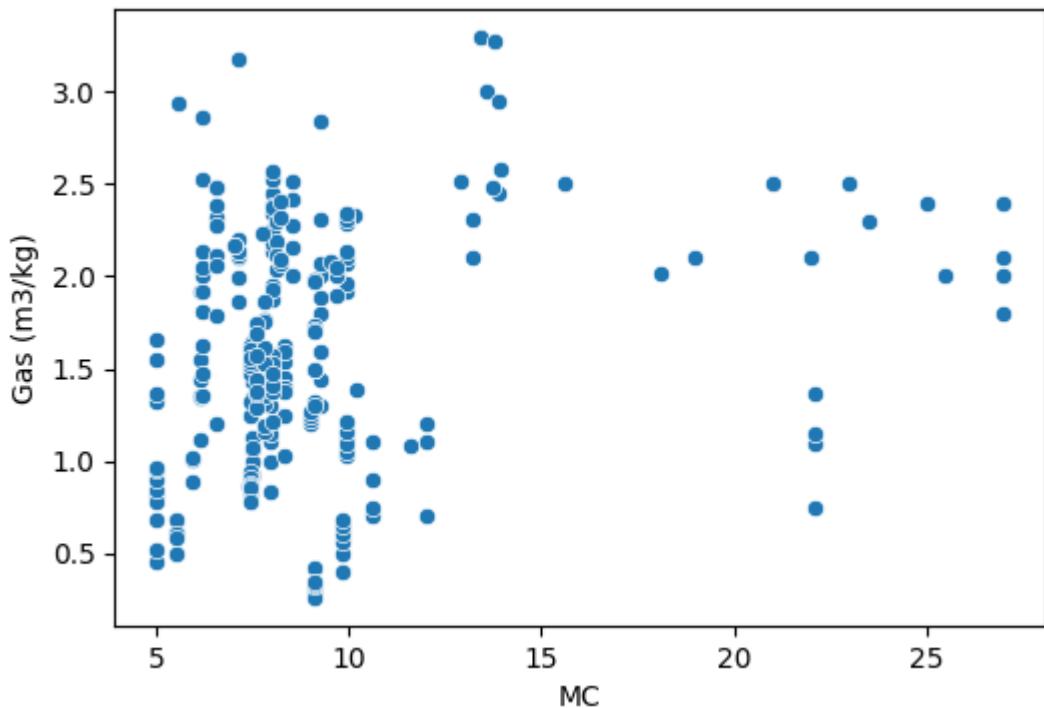


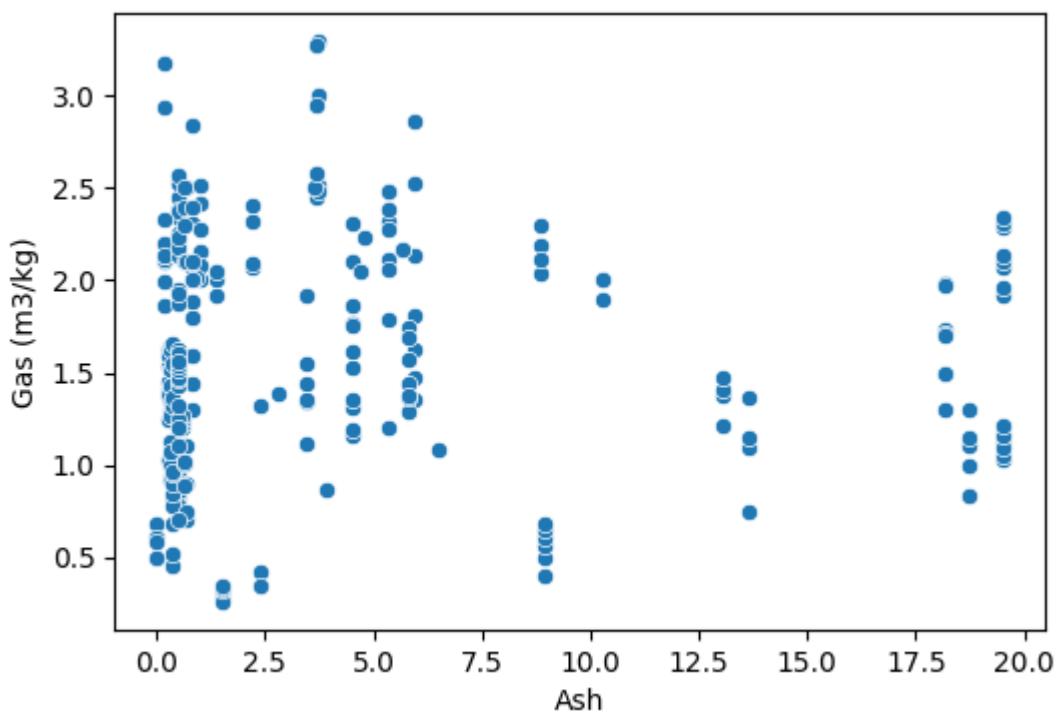
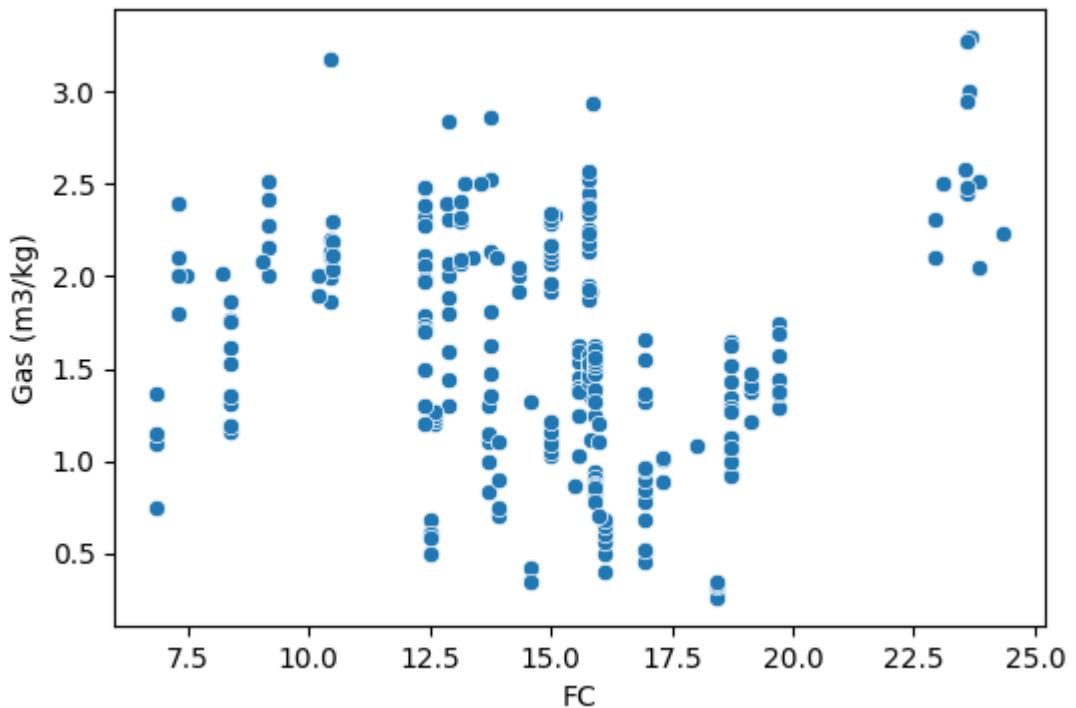


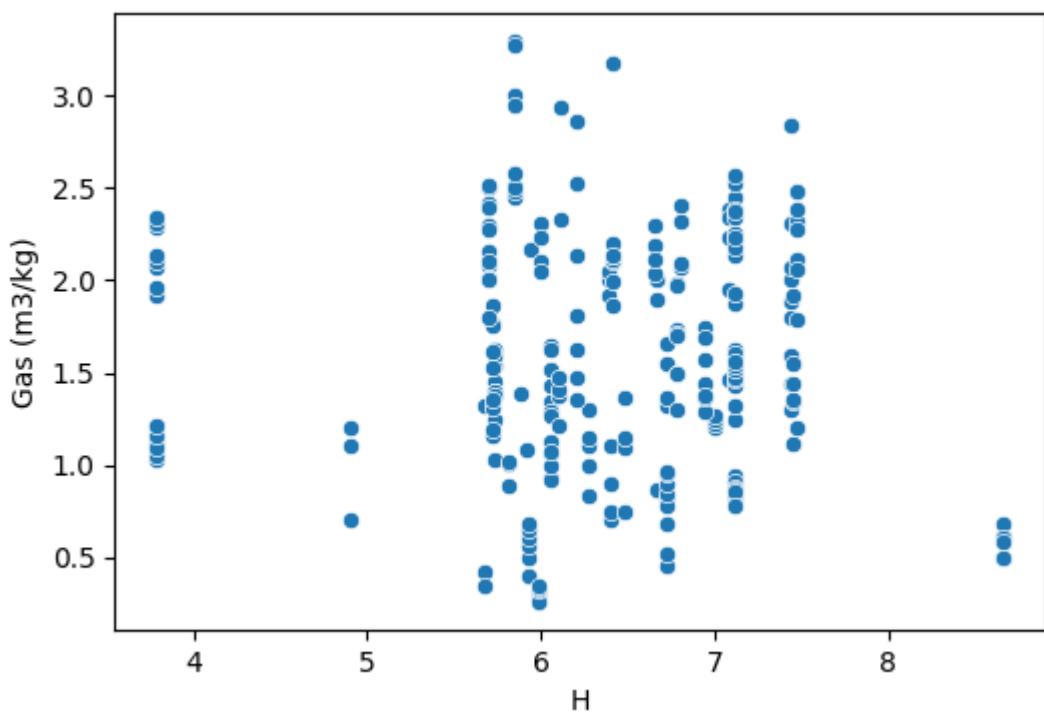
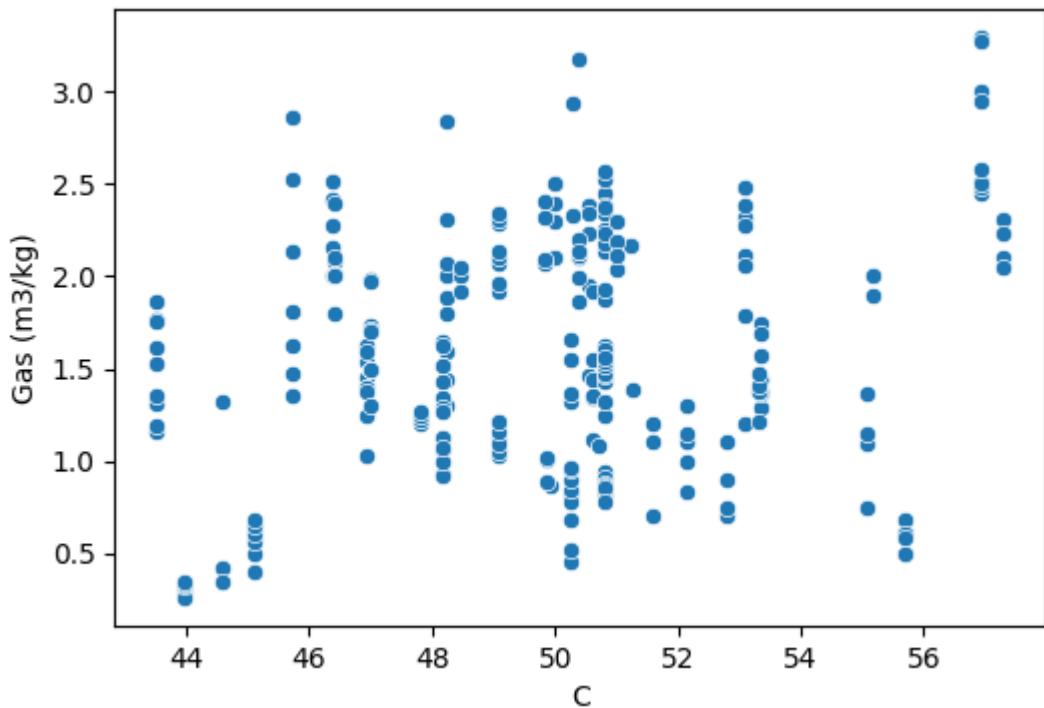


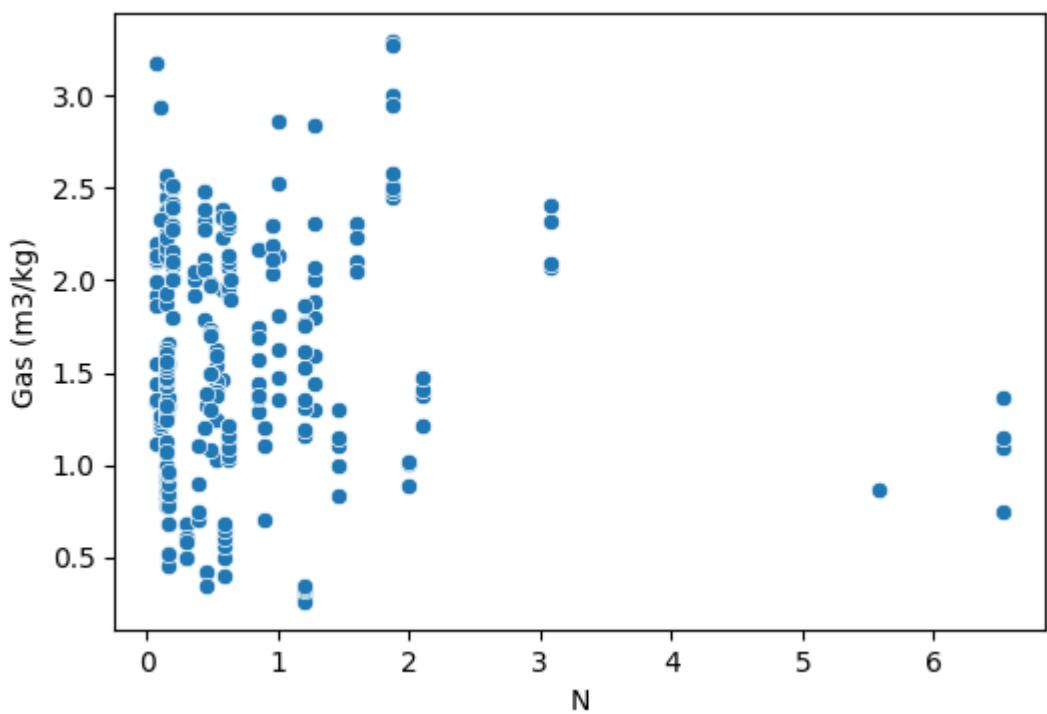
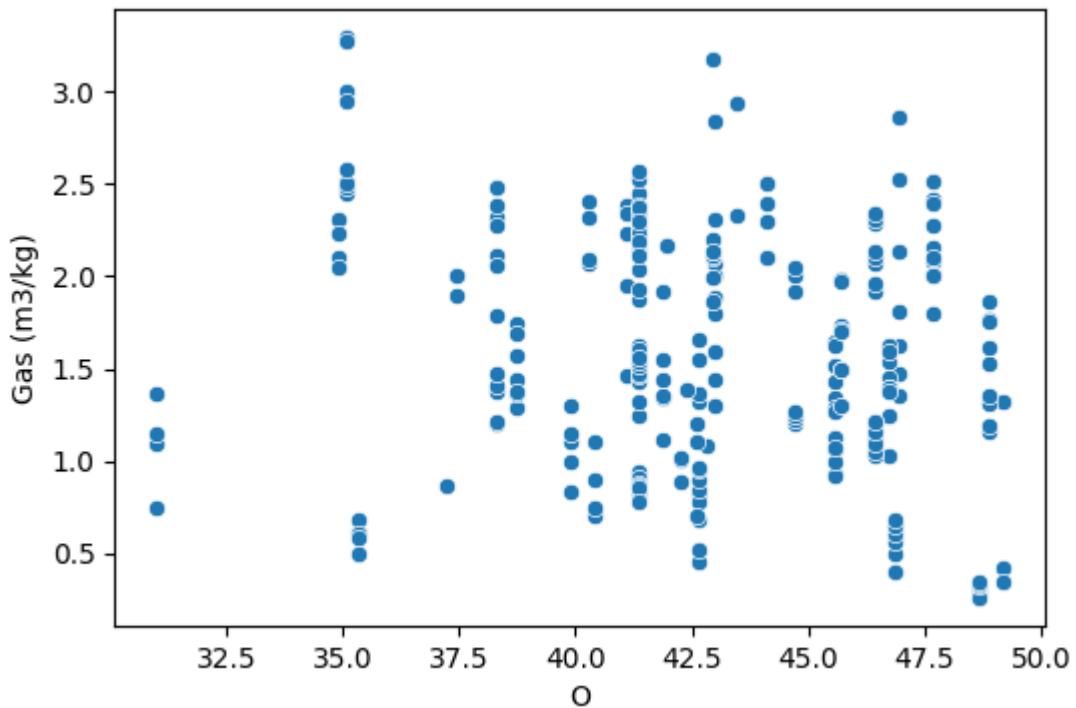


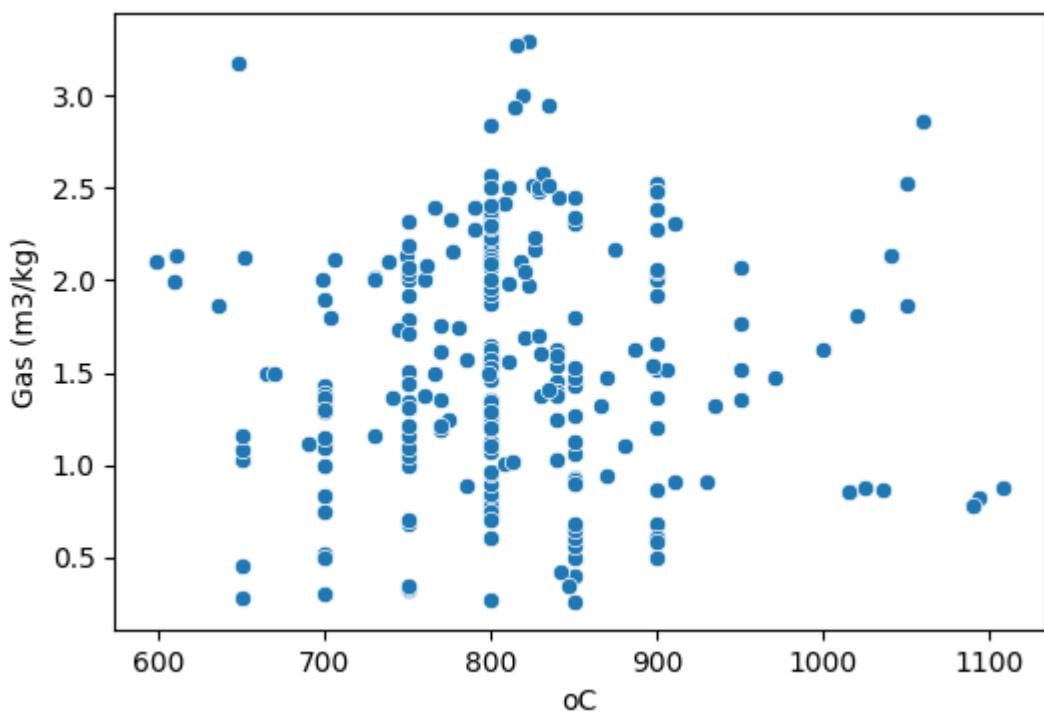
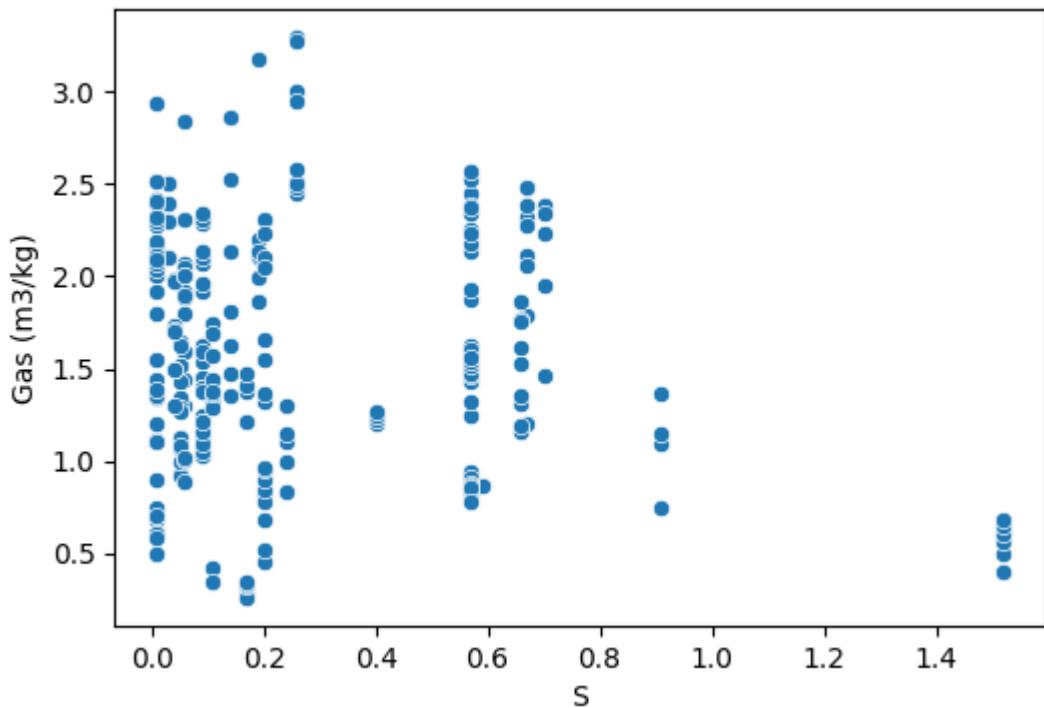


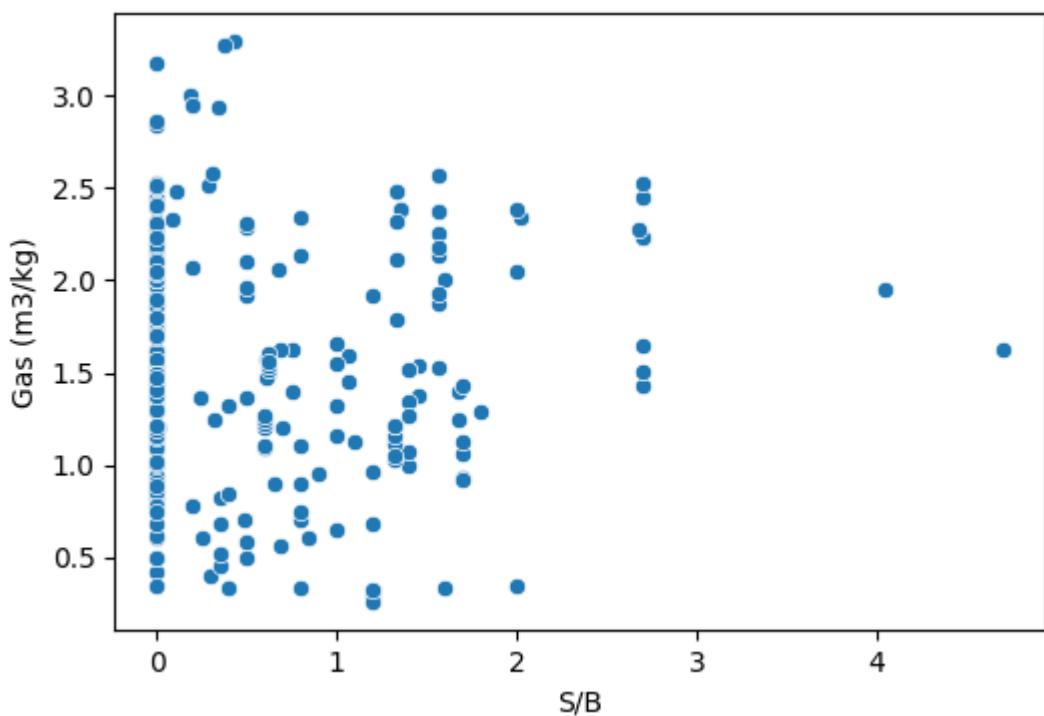
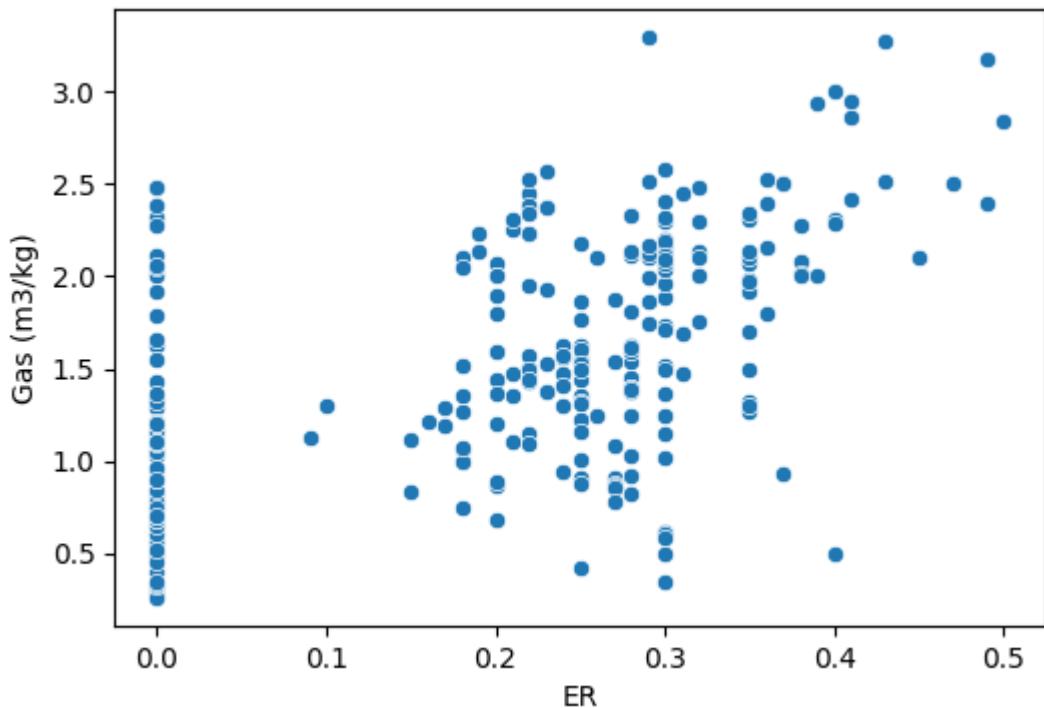


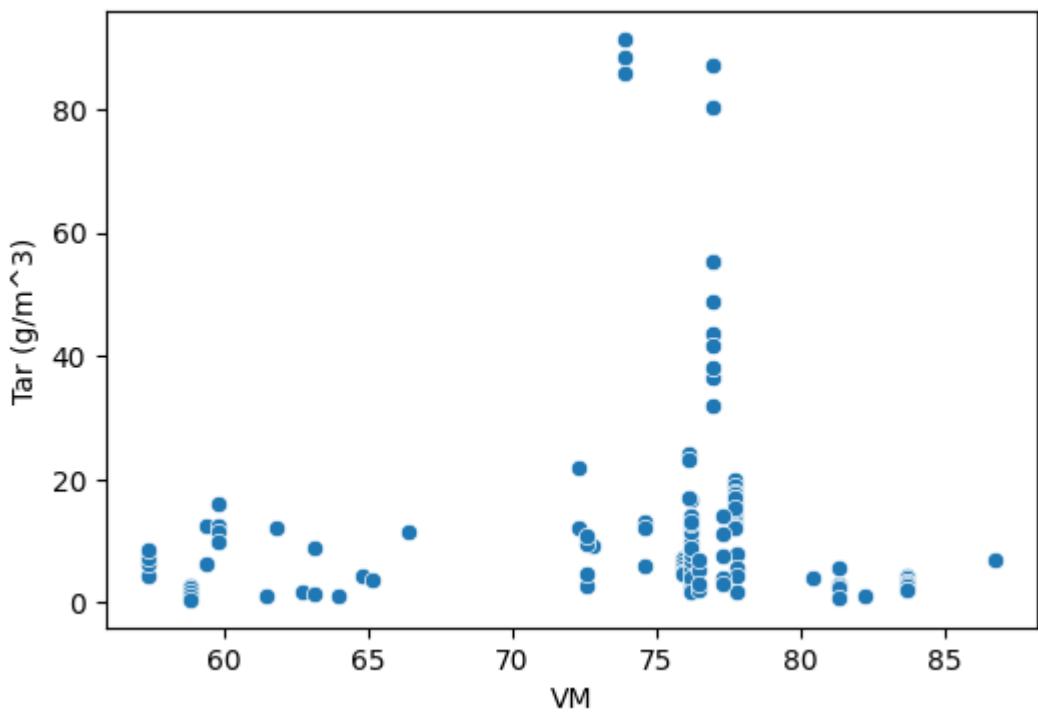
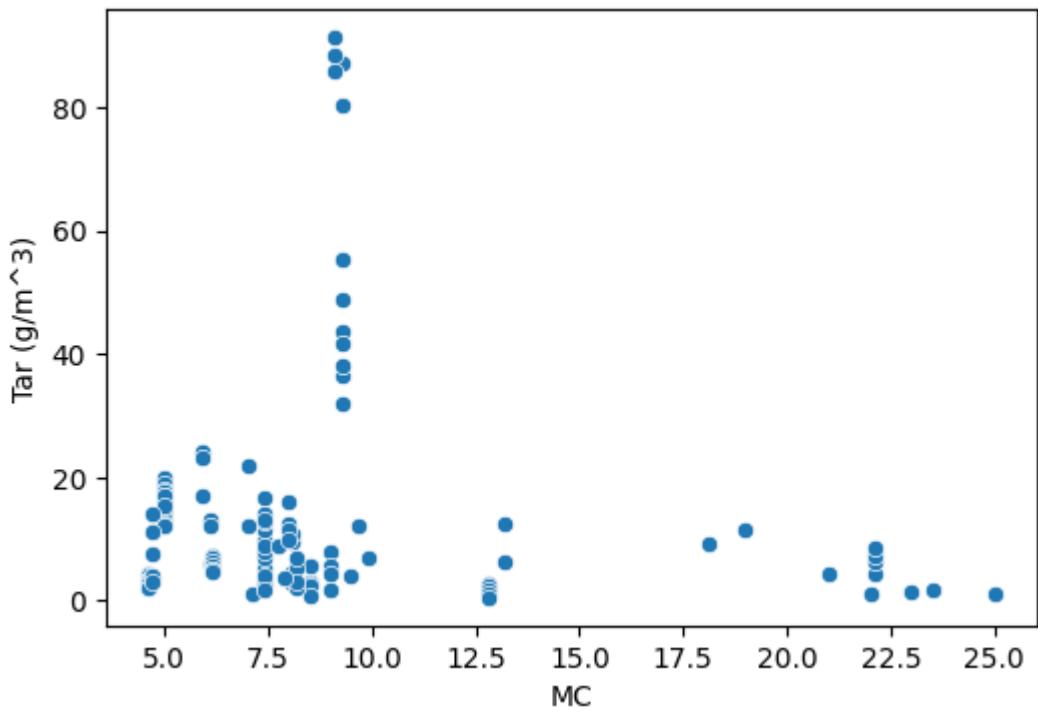


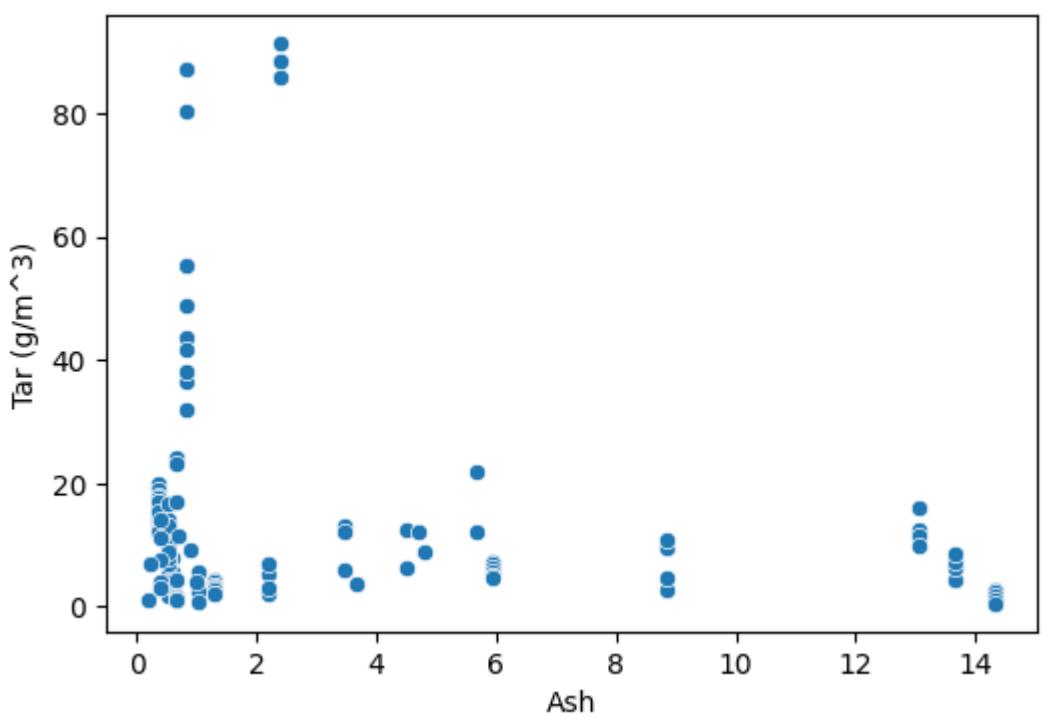
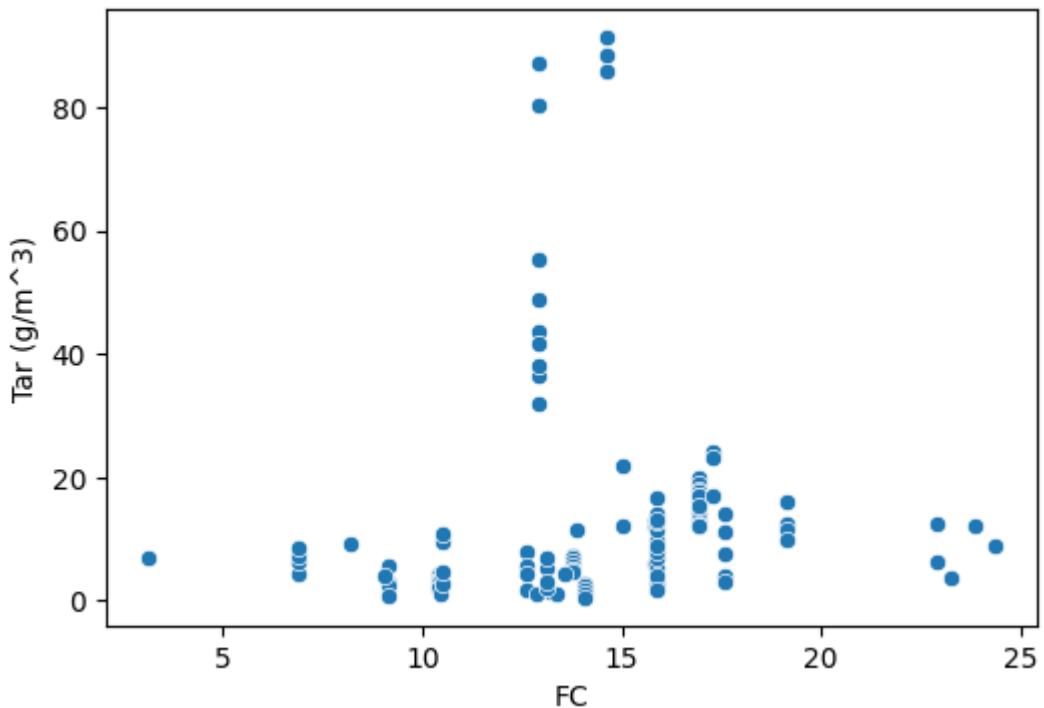


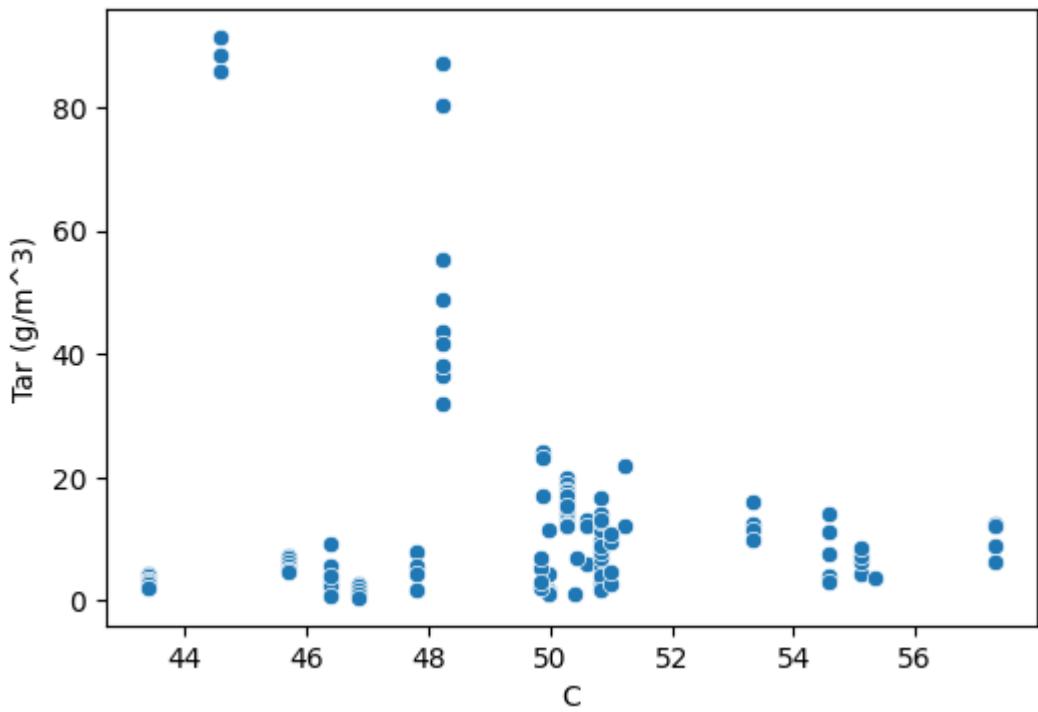


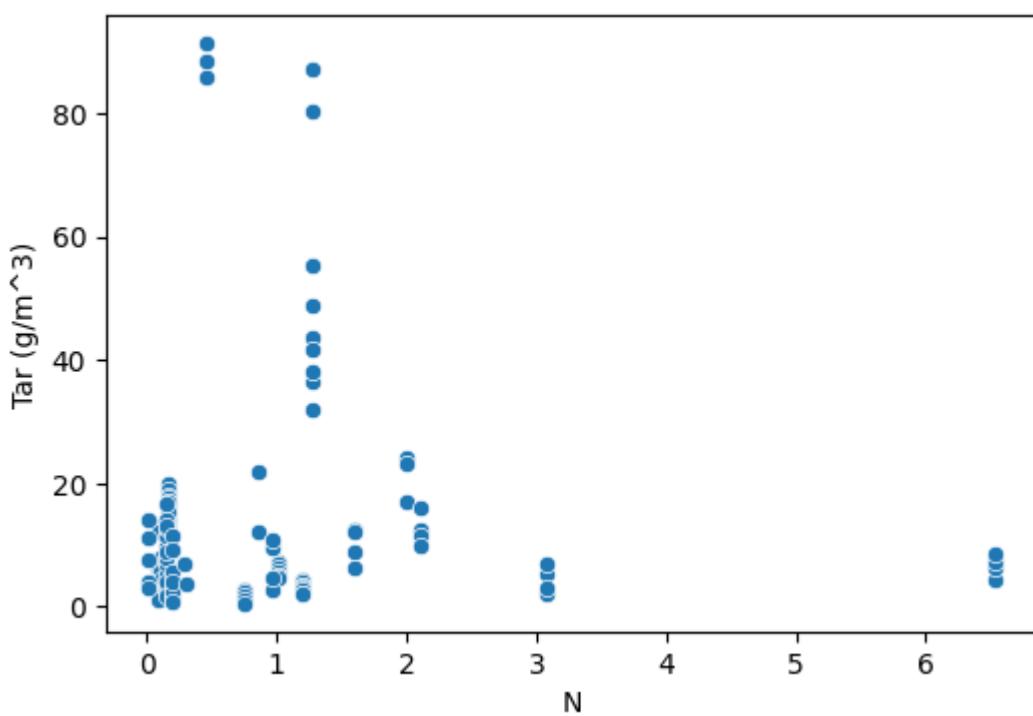
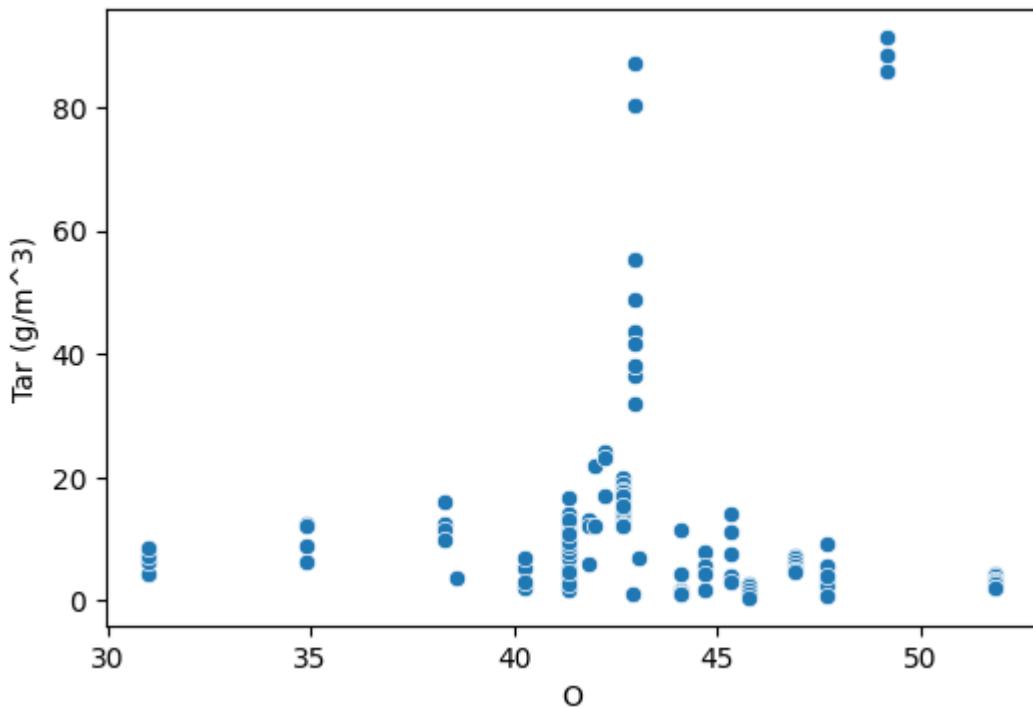


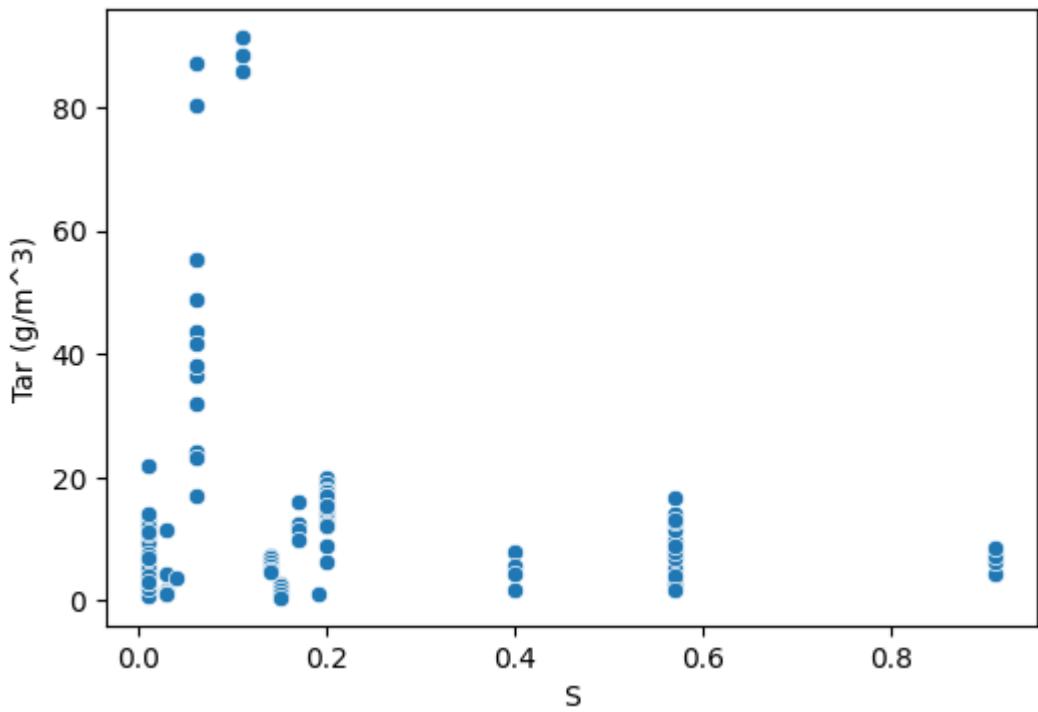


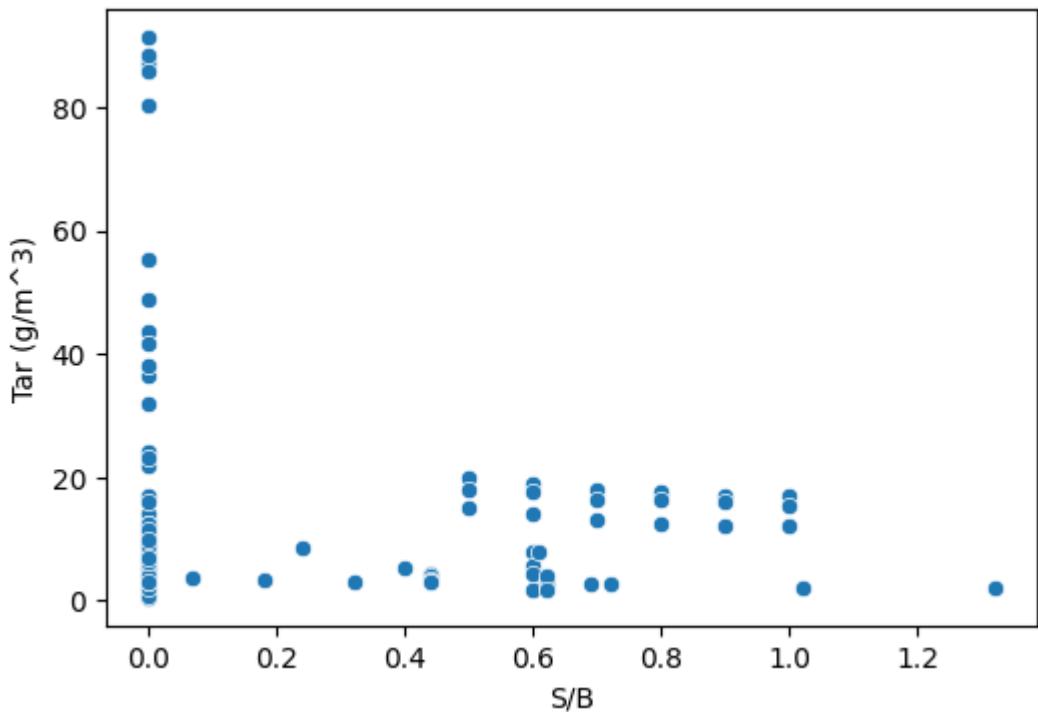
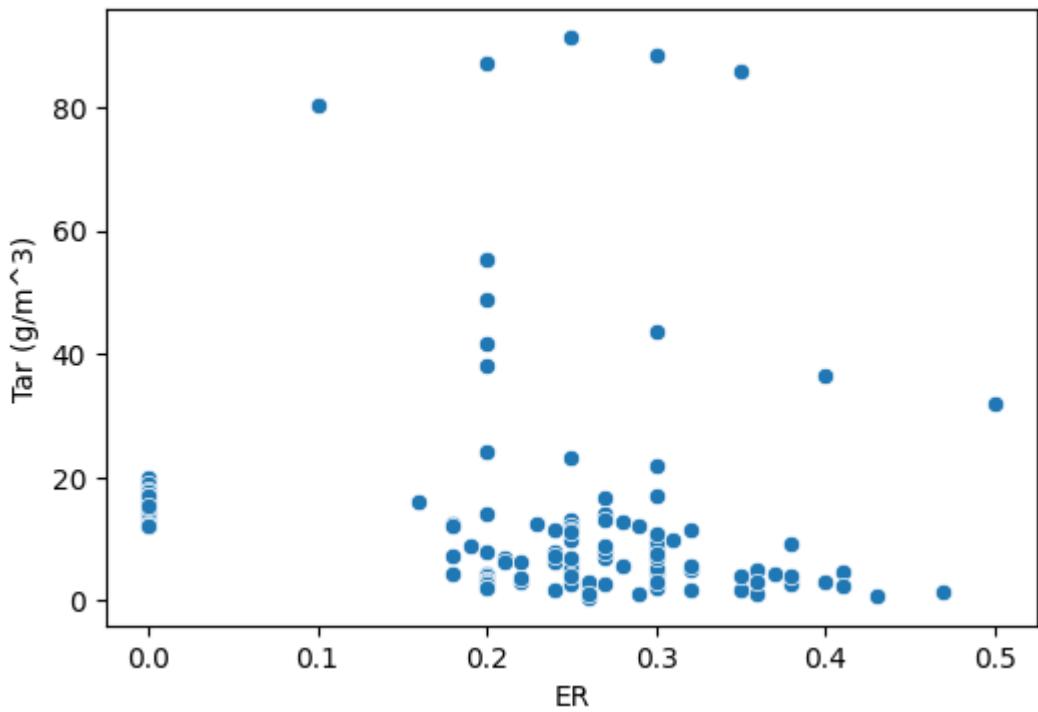












Preprocessing

```
In [18]: df = df.iloc[:-3]
df.tail()
```

Out[18]:

	Biomass species	MC	VM	FC	Ash	C	H	O	N	S	oC	ER	S/B	CO	CO2
445	Wood Pellets	5.92	76.13	17.29	0.66	49.87	5.81	42.26	2.0	0.06	813.0	0.30	0.0	NaN	NaN
446	Orujillo	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	770.0	0.16	0.0	NaN	NaN
447	Orujillo	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	830.0	0.23	0.0	NaN	NaN
448	Orujillo	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	835.0	0.24	0.0	NaN	NaN
449	Orujillo	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	870.0	0.31	0.0	NaN	NaN

In [19]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['Biomass species'] = le.fit_transform(df['Biomass species'])
```

In [20]:

```
df['Biomass species'].unique().shape
```

Out[20]:

```
(46,)
```

In [21]:

```
df.tail()
```

Out[21]:

	Biomass species	MC	VM	FC	Ash	C	H	O	N	S	oC	ER	S/B	CO	CO2
445	42	5.92	76.13	17.29	0.66	49.87	5.81	42.26	2.0	0.06	813.0	0.30	0.0	NaN	NaN
446	19	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	770.0	0.16	0.0	NaN	NaN
447	19	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	830.0	0.23	0.0	NaN	NaN
448	19	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	835.0	0.24	0.0	NaN	NaN
449	19	8.00	59.83	19.12	13.05	53.32	6.10	38.31	2.1	0.17	870.0	0.31	0.0	NaN	NaN

In [22]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 450 entries, 0 to 449
Data columns (total 19 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Biomass species  450 non-null    int64  
 1   MC                450 non-null    float64 
 2   VM                450 non-null    float64 
 3   FC                450 non-null    float64 
 4   Ash               450 non-null    float64 
 5   C                 450 non-null    float64 
 6   H                 450 non-null    float64 
 7   O                 450 non-null    float64 
 8   N                 450 non-null    float64 
 9   S                 450 non-null    float64 
 10  oC                450 non-null    float64 
 11  ER                450 non-null    float64 
 12  S/B               450 non-null    float64 
 13  CO                414 non-null    float64 
 14  CO2               414 non-null    float64 
 15  H2                414 non-null    float64 
 16  CH4               414 non-null    float64 
 17  Gas (m3/kg)      268 non-null    float64 
 18  Tar (g/m^3)       124 non-null    float64 
dtypes: float64(18), int64(1)
memory usage: 66.9 KB
```

```
In [23]: from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
data = df[['Ash', 'VM']]

# Scale the data
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data)

# Step 2: Perform PCA
# Since we have two features, we can set n_components to 2 (or less, if you want to
pca = PCA(n_components=2)
principal_components = pca.fit_transform(data_scaled)

# Step 3: Create a DataFrame with the principal components
pc_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])

print("Principal Components:")
print(pc_df)

print("\nExplained Variance Ratio:")
print(pca.explained_variance_ratio_)
```

```
Principal Components:
      PC1      PC2
0    1.199231 -0.373327
1   -1.331820 -0.369793
2    1.309845 -0.597378
3    0.576132 -0.172071
4    1.180803  0.031496
..     ...
445 -0.820580  0.072546
446  2.148411 -0.007348
447  2.148411 -0.007348
448  2.148411 -0.007348
449  2.148411 -0.007348
```

[450 rows x 2 columns]

```
Explained Variance Ratio:
[0.88808869 0.11191131]
```

Between Ash and VM the PC1 has captured 88% variance as it is not more than 90 so I am not replacing them in the original dataframe

```
In [24]: from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
data = df[['O', 'C']]

# Scale the data
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data)
# Step 2: Perform PCA
# Since we have two features, we can set n_components to 2 (or less, if you want to
pca = PCA(n_components=2)
principal_components = pca.fit_transform(data_scaled)

# Step 3: Create a DataFrame with the principal components
pc_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])

print("Principal Components:")
print(pc_df)

print("\nExplained Variance Ratio:")
print(pca.explained_variance_ratio_)
```

```
Principal Components:
      PC1      PC2
0    1.098059  0.098884
1    1.848486  0.301633
2    3.445228  0.327406
3    0.370232  0.127716
4   -1.537640 -0.302868
..     ...
445  0.305368 -0.120908
446  1.747756 -0.101761
447  1.747756 -0.101761
448  1.747756 -0.101761
449  1.747756 -0.101761
```

[450 rows x 2 columns]

```
Explained Variance Ratio:
[0.95675092 0.04324908]
```

```
In [25]: # Optionally, if you're sure, drop the original 'O' and 'C' columns
df_reduced = df.drop(['O', 'C'], axis=1)
```

```
df_reduced['PC1'] = principal_components[:, 0]
```

replaced the C and O column with PC1 and the variance captured by PC1 is more than 95%

In [26]: `df_reduced.head()`

	Biomass species	MC	VM	FC	Ash	H	N	S	oC	ER	S/B	CO	CO2	H2	CH4
0	5	6.34	67.25	15.64	10.68	6.03	0.97	0.07	650.0	0.0	1.0	27.26	26.16	29.69	16.89
1	37	4.56	81.51	13.55	0.38	6.21	0.11	0.03	650.0	0.0	1.0	25.66	26.20	31.22	16.92
2	38	5.18	67.89	14.89	12.04	6.40	0.36	0.11	650.0	0.0	1.0	30.15	24.12	27.85	17.87
3	36	8.38	69.63	14.66	7.33	5.82	0.71	0.10	650.0	0.0	1.0	35.66	20.84	25.24	18.26
4	27	9.84	65.07	16.13	8.96	5.93	0.59	1.52	850.0	0.0	0.3	37.28	15.11	37.78	9.82

In [27]: `df_reduced.describe()`

	Biomass species	MC	VM	FC	Ash	H	N
count	450.000000	450.000000	450.000000	450.000000	450.000000	450.000000	450.000000
mean	23.642222	8.527356	71.909667	15.288511	4.289467	6.090178	0.699333
std	11.366676	3.672753	7.987731	4.021544	5.753450	1.229714	0.935660
min	0.000000	4.560000	52.560000	3.120000	0.010000	0.080000	0.010000
25%	16.000000	6.110000	66.900000	12.570000	0.500000	5.620000	0.160000
50%	23.000000	8.000000	75.180000	15.610000	1.510000	6.210000	0.530000
75%	31.000000	9.800000	77.710000	16.940000	5.330000	6.780000	0.900000
max	45.000000	27.000000	86.740000	26.450000	19.520000	8.660000	6.550000

Train test split

In [28]: `df['Biomass species'].value_counts().sort_index()`

```
Out[28]: Biomass species
```

```
0      14  
1      1  
2      1  
3      5  
4      8  
5      1  
6     12  
7      4  
8      1  
9     10  
10     19  
11     4  
12     13  
13     4  
14     9  
15     5  
16     7  
17     5  
18     5  
19     4  
20     9  
21     9  
22    15  
23    70  
24     7  
25    19  
26     4  
27    32  
28    15  
29    17  
30     5  
31     7  
32    23  
33     3  
34    13  
35     4  
36     1  
37     1  
38     1  
39     4  
40     9  
41     3  
42    17  
43    25  
44     1  
45     4
```

```
Name: count, dtype: int64
```

```
In [29]: null_counts = df.groupby('Biomass species')[['CO', 'CO2', 'H2', 'CH4']].apply(lambda x: x.isnull().sum())  
print(null_counts)
```

Biomass species	CO	CO2	H2	CH4
0	0	0	0	0
1	0	0	0	0
2	1	1	1	1
3	0	0	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	4	4	4	4
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0
11	0	0	0	0
12	0	0	0	0
13	0	0	0	0
14	0	0	0	0
15	0	0	0	0
16	0	0	0	0
17	0	0	0	0
18	0	0	0	0
19	4	4	4	4
20	0	0	0	0
21	0	0	0	0
22	0	0	0	0
23	0	0	0	0
24	0	0	0	0
25	0	0	0	0
26	0	0	0	0
27	0	0	0	0
28	0	0	0	0
29	0	0	0	0
30	0	0	0	0
31	0	0	0	0
32	0	0	0	0
33	0	0	0	0
34	0	0	0	0
35	0	0	0	0
36	0	0	0	0
37	0	0	0	0
38	0	0	0	0
39	0	0	0	0
40	0	0	0	0
41	0	0	0	0
42	8	8	8	8
43	18	18	18	18
44	1	1	1	1
45	0	0	0	0

```
In [30]: strings_to_remove = ['Gas (m3/kg)', 'Tar (g/m^3)']
target_col = [item for item in target_col if item not in strings_to_remove]
```

```
In [31]: df.drop(['Gas (m3/kg)', 'Tar (g/m^3)'], axis =1, inplace = True)
```

```
In [32]: x_test = df[df['CO'].isna()]

# Remove those rows from the original DataFrame
df_up = df[~df['CO'].isna()]
```

```
In [33]: x_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 36 entries, 192 to 449
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Biomass species  36 non-null    int64  
 1   MC                36 non-null    float64 
 2   VM                36 non-null    float64 
 3   FC                36 non-null    float64 
 4   Ash               36 non-null    float64 
 5   C                 36 non-null    float64 
 6   H                 36 non-null    float64 
 7   O                 36 non-null    float64 
 8   N                 36 non-null    float64 
 9   S                 36 non-null    float64 
 10  oC               36 non-null    float64 
 11  ER               36 non-null    float64 
 12  S/B              36 non-null    float64 
 13  CO               0 non-null     float64 
 14  CO2              0 non-null     float64 
 15  H2               0 non-null     float64 
 16  CH4              0 non-null     float64 
dtypes: float64(16), int64(1)
memory usage: 5.1 KB
```

In [34]: `df_up.info()`

```
<class 'pandas.core.frame.DataFrame'>
Index: 414 entries, 0 to 431
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Biomass species  414 non-null    int64  
 1   MC                414 non-null    float64 
 2   VM                414 non-null    float64 
 3   FC                414 non-null    float64 
 4   Ash               414 non-null    float64 
 5   C                 414 non-null    float64 
 6   H                 414 non-null    float64 
 7   O                 414 non-null    float64 
 8   N                 414 non-null    float64 
 9   S                 414 non-null    float64 
 10  oC               414 non-null    float64 
 11  ER               414 non-null    float64 
 12  S/B              414 non-null    float64 
 13  CO               414 non-null    float64 
 14  CO2              414 non-null    float64 
 15  H2               414 non-null    float64 
 16  CH4              414 non-null    float64 
dtypes: float64(16), int64(1)
memory usage: 58.2 KB
```

In [35]: `category_counts = df_up['Biomass species'].value_counts()`

```
# Separate rare (count == 1) and common (count >= 2) categories
rare_categories = category_counts[category_counts <= 2].index
common_categories = category_counts[category_counts > 2].index

# 1. Put rare category rows directly into x_train and y_train
df_rare = df_up[df_up['Biomass species'].isin(rare_categories)]
x_train_rare = df_rare.drop(columns=target_col)
y_train_rare = df_rare[target_col]

# 2. Use stratified split on the rest (common categories)
```

```

df_common = df_up[df_up['Biomass species'].isin(common_categories)]

X_common = df_common.drop(columns=target_col)
y_common = df_common[target_col]

x_train_common, x_val, y_train_common, y_val = train_test_split(
    X_common, y_common, test_size=0.3, stratify=df_common['Biomass species'], random_state=42)

# 3. Combine both parts into final x_train and y_train
x_train = pd.concat([x_train_common, x_train_rare]).reset_index(drop=True)
y_train = pd.concat([y_train_common, y_train_rare]).reset_index(drop=True)

```

In [36]: `print(x_train.shape, y_train.shape, x_val.shape, y_val.shape)`

```
(291, 13) (291, 4) (123, 13) (123, 4)
```

In [37]: `sc = StandardScaler()`
`X_train_scaled = sc.fit_transform(x_train)`
`X_val_scaled = sc.transform(x_val)`

Models

Linear Regression

In [38]: `y_val`

Out[38]:

	CO	CO2	H2	CH4
373	32.08	43.56	17.80	6.56
166	16.16	25.51	52.13	6.20
277	29.40	32.45	32.58	5.57
61	16.24	27.77	51.93	4.06
230	19.80	10.89	54.46	14.85
...
351	16.00	55.00	20.00	9.00
219	39.57	20.56	32.97	6.90
84	23.12	18.05	55.17	3.65
428	33.70	35.20	23.40	7.70
22	39.57	18.76	33.76	7.91

123 rows × 4 columns

In [39]: `lr = LinearRegression()`
`lr.fit(X_train_scaled, y_train)`
`y_pred_lr = lr.predict(X_val_scaled)`
`r2 = r2_score(y_val, y_pred_lr)`
`print(r2)`

0.4642857004670947

SVR

```
In [40]: from sklearn.multioutput import MultiOutputRegressor as MOR
```

```
In [41]: svr = MOR(SVR(kernel='rbf', C = 100, gamma=0.1, epsilon =0.1))
svr.fit(X_train_scaled, y_train)
y_pred_svr = svr.predict(X_val_scaled)
r2 = r2_score(y_val, y_pred_svr)
r2
```

```
Out[41]: 0.8597656722127263
```

Random Forest

```
In [42]: rf = MOR(RandomForestRegressor(n_estimators = 100, random_state = 0))
rf.fit(X_train_scaled, y_train)
y_pred_rf = rf.predict(X_val_scaled)
r2 = r2_score(y_val, y_pred_rf)
r2
```

```
Out[42]: 0.8593649636831314
```

XG Boost

```
In [43]: xgbr = MOR(XGBRegressor())
xgbr.fit(X_train_scaled, y_train)
y_pred_xgbr = xgbr.predict(X_val_scaled)
r2 = r2_score(y_val, y_pred_xgbr)
r2
```

```
Out[43]: 0.8437070181957863
```

CatBoost

```
In [44]: catr = MOR(CatBoostRegressor(verbose = 0, iterations = 100))
catr.fit(X_train_scaled, y_train)
y_pred_catr = catr.predict(X_val_scaled)
r2 = r2_score(y_val, y_pred_catr)
r2
```

```
Out[44]: 0.8757567617515191
```

Prediction for CO

```
In [45]: ANN_model = Sequential([
    Dense(32, input_dim=13), # No activation here
    LeakyReLU(alpha=0.1), # LeakyReLU activation
    Dense(32, activation='tanh'), # Tanh for richer non-linearity
    Dense(16, activation='relu'), # ReLU for simplicity
    Dense(1, activation='linear') # Linear for regression output
])

# Compile the model
ANN_model.compile(optimizer='adam',
                   loss='mean_squared_error',
```

```
metrics=[ 'mae'])

# Train the model
ANN_model.fit(X_train_scaled, y_train.C0, epochs=500, verbose=1)

# Evaluate the model
loss, mae = ANN_model.evaluate(X_train_scaled, y_train.C0, verbose=0)
print(f"\nModel evaluation:\nLoss (MSE): {loss:.2f}, MAE: {mae:.2f}")
```

Epoch 1/500
10/10 3s 73ms/step - loss: 1049.5668 - mae: 31.1556
Epoch 2/500
10/10 0s 2ms/step - loss: 990.8082 - mae: 30.2402
Epoch 3/500
10/10 0s 2ms/step - loss: 997.6783 - mae: 30.2056
Epoch 4/500
10/10 0s 2ms/step - loss: 946.1098 - mae: 29.4611
Epoch 5/500
10/10 0s 2ms/step - loss: 875.7856 - mae: 28.1450
Epoch 6/500
10/10 0s 2ms/step - loss: 812.5873 - mae: 27.0314
Epoch 7/500
10/10 0s 2ms/step - loss: 784.5808 - mae: 26.4351
Epoch 8/500
10/10 0s 2ms/step - loss: 629.8642 - mae: 23.3735
Epoch 9/500
10/10 0s 2ms/step - loss: 604.7215 - mae: 22.6841
Epoch 10/500
10/10 0s 2ms/step - loss: 474.7732 - mae: 19.9527
Epoch 11/500
10/10 0s 2ms/step - loss: 386.4395 - mae: 17.4614
Epoch 12/500
10/10 0s 2ms/step - loss: 305.8181 - mae: 15.1905
Epoch 13/500
10/10 0s 2ms/step - loss: 233.2466 - mae: 12.9242
Epoch 14/500
10/10 0s 2ms/step - loss: 193.7127 - mae: 11.7246
Epoch 15/500
10/10 0s 2ms/step - loss: 150.3445 - mae: 10.4185
Epoch 16/500
10/10 0s 2ms/step - loss: 121.2733 - mae: 9.2584
Epoch 17/500
10/10 0s 2ms/step - loss: 106.8774 - mae: 8.6945
Epoch 18/500
10/10 0s 2ms/step - loss: 90.4864 - mae: 8.0807
Epoch 19/500
10/10 0s 2ms/step - loss: 87.8201 - mae: 7.8085
Epoch 20/500
10/10 0s 2ms/step - loss: 74.9877 - mae: 7.2468
Epoch 21/500
10/10 0s 2ms/step - loss: 76.6438 - mae: 7.2888
Epoch 22/500
10/10 0s 2ms/step - loss: 73.5152 - mae: 7.1648
Epoch 23/500
10/10 0s 2ms/step - loss: 71.0906 - mae: 6.9862
Epoch 24/500
10/10 0s 2ms/step - loss: 73.8597 - mae: 7.1195
Epoch 25/500
10/10 0s 2ms/step - loss: 64.4932 - mae: 6.5665
Epoch 26/500
10/10 0s 2ms/step - loss: 68.5440 - mae: 6.7592
Epoch 27/500
10/10 0s 2ms/step - loss: 68.2444 - mae: 6.7819
Epoch 28/500
10/10 0s 2ms/step - loss: 54.3098 - mae: 5.9240
Epoch 29/500
10/10 0s 2ms/step - loss: 66.5484 - mae: 6.6636
Epoch 30/500
10/10 0s 2ms/step - loss: 59.9352 - mae: 6.1679
Epoch 31/500
10/10 0s 2ms/step - loss: 58.0923 - mae: 6.1950
Epoch 32/500
10/10 0s 2ms/step - loss: 59.9825 - mae: 6.2434

Epoch 33/500
10/10 0s 2ms/step - loss: 64.6556 - mae: 6.3879
Epoch 34/500
10/10 0s 2ms/step - loss: 59.0059 - mae: 6.1226
Epoch 35/500
10/10 0s 2ms/step - loss: 55.5718 - mae: 5.8198
Epoch 36/500
10/10 0s 2ms/step - loss: 57.1887 - mae: 5.9417
Epoch 37/500
10/10 0s 2ms/step - loss: 55.4530 - mae: 6.0229
Epoch 38/500
10/10 0s 2ms/step - loss: 57.8251 - mae: 6.1345
Epoch 39/500
10/10 0s 2ms/step - loss: 57.2762 - mae: 6.0623
Epoch 40/500
10/10 0s 2ms/step - loss: 58.1037 - mae: 6.1595
Epoch 41/500
10/10 0s 2ms/step - loss: 57.7948 - mae: 6.0099
Epoch 42/500
10/10 0s 2ms/step - loss: 59.4623 - mae: 6.0884
Epoch 43/500
10/10 0s 2ms/step - loss: 58.5125 - mae: 6.0615
Epoch 44/500
10/10 0s 2ms/step - loss: 60.8963 - mae: 6.2569
Epoch 45/500
10/10 0s 2ms/step - loss: 55.7482 - mae: 6.0097
Epoch 46/500
10/10 0s 2ms/step - loss: 50.2650 - mae: 5.6216
Epoch 47/500
10/10 0s 2ms/step - loss: 52.2891 - mae: 5.7414
Epoch 48/500
10/10 0s 2ms/step - loss: 56.5041 - mae: 5.9530
Epoch 49/500
10/10 0s 2ms/step - loss: 50.2919 - mae: 5.5421
Epoch 50/500
10/10 0s 2ms/step - loss: 49.1641 - mae: 5.5442
Epoch 51/500
10/10 0s 2ms/step - loss: 45.6205 - mae: 5.2689
Epoch 52/500
10/10 0s 2ms/step - loss: 48.7371 - mae: 5.5629
Epoch 53/500
10/10 0s 2ms/step - loss: 48.2250 - mae: 5.5235
Epoch 54/500
10/10 0s 2ms/step - loss: 50.6296 - mae: 5.5812
Epoch 55/500
10/10 0s 2ms/step - loss: 42.4191 - mae: 5.1308
Epoch 56/500
10/10 0s 2ms/step - loss: 43.2791 - mae: 5.1268
Epoch 57/500
10/10 0s 2ms/step - loss: 46.3677 - mae: 5.4436
Epoch 58/500
10/10 0s 2ms/step - loss: 47.5146 - mae: 5.3818
Epoch 59/500
10/10 0s 2ms/step - loss: 45.9024 - mae: 5.3736
Epoch 60/500
10/10 0s 2ms/step - loss: 45.0861 - mae: 5.2716
Epoch 61/500
10/10 0s 2ms/step - loss: 43.4712 - mae: 5.1133
Epoch 62/500
10/10 0s 2ms/step - loss: 39.0592 - mae: 4.8002
Epoch 63/500
10/10 0s 2ms/step - loss: 43.6977 - mae: 5.2156
Epoch 64/500
10/10 0s 2ms/step - loss: 40.8246 - mae: 4.9551

Epoch 65/500
10/10 0s 2ms/step - loss: 39.5400 - mae: 4.8716
Epoch 66/500
10/10 0s 2ms/step - loss: 40.3137 - mae: 4.9308
Epoch 67/500
10/10 0s 2ms/step - loss: 40.6637 - mae: 4.9948
Epoch 68/500
10/10 0s 2ms/step - loss: 46.0055 - mae: 5.3520
Epoch 69/500
10/10 0s 2ms/step - loss: 37.6940 - mae: 4.8441
Epoch 70/500
10/10 0s 2ms/step - loss: 38.4222 - mae: 4.9042
Epoch 71/500
10/10 0s 2ms/step - loss: 37.4353 - mae: 4.7259
Epoch 72/500
10/10 0s 2ms/step - loss: 35.1792 - mae: 4.6057
Epoch 73/500
10/10 0s 2ms/step - loss: 39.6806 - mae: 4.7793
Epoch 74/500
10/10 0s 2ms/step - loss: 38.8105 - mae: 4.8041
Epoch 75/500
10/10 0s 2ms/step - loss: 35.2362 - mae: 4.5829
Epoch 76/500
10/10 0s 2ms/step - loss: 35.0303 - mae: 4.5737
Epoch 77/500
10/10 0s 2ms/step - loss: 36.8052 - mae: 4.7044
Epoch 78/500
10/10 0s 2ms/step - loss: 32.3093 - mae: 4.4273
Epoch 79/500
10/10 0s 2ms/step - loss: 31.5110 - mae: 4.3561
Epoch 80/500
10/10 0s 2ms/step - loss: 37.6505 - mae: 4.7359
Epoch 81/500
10/10 0s 2ms/step - loss: 32.3553 - mae: 4.5196
Epoch 82/500
10/10 0s 2ms/step - loss: 31.5304 - mae: 4.4196
Epoch 83/500
10/10 0s 2ms/step - loss: 28.1999 - mae: 4.1188
Epoch 84/500
10/10 0s 2ms/step - loss: 35.5382 - mae: 4.6962
Epoch 85/500
10/10 0s 2ms/step - loss: 32.0853 - mae: 4.3008
Epoch 86/500
10/10 0s 2ms/step - loss: 29.7146 - mae: 4.2753
Epoch 87/500
10/10 0s 2ms/step - loss: 28.1309 - mae: 4.0398
Epoch 88/500
10/10 0s 2ms/step - loss: 31.4374 - mae: 4.2591
Epoch 89/500
10/10 0s 2ms/step - loss: 29.4820 - mae: 4.1664
Epoch 90/500
10/10 0s 2ms/step - loss: 26.1225 - mae: 3.8892
Epoch 91/500
10/10 0s 2ms/step - loss: 27.2259 - mae: 3.9730
Epoch 92/500
10/10 0s 2ms/step - loss: 24.5490 - mae: 3.7907
Epoch 93/500
10/10 0s 2ms/step - loss: 27.6922 - mae: 4.0293
Epoch 94/500
10/10 0s 2ms/step - loss: 25.6301 - mae: 3.9065
Epoch 95/500
10/10 0s 2ms/step - loss: 26.7401 - mae: 3.9771
Epoch 96/500
10/10 0s 2ms/step - loss: 27.9769 - mae: 3.9282

Epoch 97/500
10/10 0s 2ms/step - loss: 25.4226 - mae: 3.8476
Epoch 98/500
10/10 0s 2ms/step - loss: 22.9323 - mae: 3.5304
Epoch 99/500
10/10 0s 2ms/step - loss: 27.3618 - mae: 3.9609
Epoch 100/500
10/10 0s 2ms/step - loss: 24.9963 - mae: 3.7854
Epoch 101/500
10/10 0s 2ms/step - loss: 24.6444 - mae: 3.7258
Epoch 102/500
10/10 0s 2ms/step - loss: 22.9058 - mae: 3.5608
Epoch 103/500
10/10 0s 2ms/step - loss: 21.8688 - mae: 3.5154
Epoch 104/500
10/10 0s 2ms/step - loss: 27.2191 - mae: 3.9576
Epoch 105/500
10/10 0s 2ms/step - loss: 28.1785 - mae: 3.8518
Epoch 106/500
10/10 0s 2ms/step - loss: 22.8801 - mae: 3.5336
Epoch 107/500
10/10 0s 2ms/step - loss: 24.9918 - mae: 3.6878
Epoch 108/500
10/10 0s 2ms/step - loss: 19.1551 - mae: 3.3090
Epoch 109/500
10/10 0s 2ms/step - loss: 22.7038 - mae: 3.5484
Epoch 110/500
10/10 0s 2ms/step - loss: 22.0876 - mae: 3.5077
Epoch 111/500
10/10 0s 2ms/step - loss: 24.2354 - mae: 3.6588
Epoch 112/500
10/10 0s 2ms/step - loss: 23.2939 - mae: 3.6849
Epoch 113/500
10/10 0s 2ms/step - loss: 21.6588 - mae: 3.4449
Epoch 114/500
10/10 0s 2ms/step - loss: 19.5717 - mae: 3.2436
Epoch 115/500
10/10 0s 2ms/step - loss: 19.8740 - mae: 3.3301
Epoch 116/500
10/10 0s 2ms/step - loss: 19.3815 - mae: 3.2860
Epoch 117/500
10/10 0s 2ms/step - loss: 21.1956 - mae: 3.4279
Epoch 118/500
10/10 0s 2ms/step - loss: 19.5456 - mae: 3.3085
Epoch 119/500
10/10 0s 2ms/step - loss: 22.0018 - mae: 3.3917
Epoch 120/500
10/10 0s 2ms/step - loss: 21.5345 - mae: 3.3947
Epoch 121/500
10/10 0s 2ms/step - loss: 18.6902 - mae: 3.1535
Epoch 122/500
10/10 0s 2ms/step - loss: 20.5010 - mae: 3.3366
Epoch 123/500
10/10 0s 2ms/step - loss: 20.4733 - mae: 3.2849
Epoch 124/500
10/10 0s 2ms/step - loss: 21.2049 - mae: 3.3962
Epoch 125/500
10/10 0s 2ms/step - loss: 17.7079 - mae: 3.0630
Epoch 126/500
10/10 0s 2ms/step - loss: 17.8997 - mae: 3.0776
Epoch 127/500
10/10 0s 2ms/step - loss: 17.1731 - mae: 2.9640
Epoch 128/500
10/10 0s 2ms/step - loss: 17.4506 - mae: 3.0995

Epoch 129/500
10/10 0s 2ms/step - loss: 18.2497 - mae: 3.0618
Epoch 130/500
10/10 0s 2ms/step - loss: 20.5432 - mae: 3.2767
Epoch 131/500
10/10 0s 2ms/step - loss: 17.9494 - mae: 3.1669
Epoch 132/500
10/10 0s 2ms/step - loss: 15.6547 - mae: 2.9171
Epoch 133/500
10/10 0s 2ms/step - loss: 16.7346 - mae: 3.0229
Epoch 134/500
10/10 0s 2ms/step - loss: 18.9137 - mae: 3.1245
Epoch 135/500
10/10 0s 2ms/step - loss: 19.5400 - mae: 3.3215
Epoch 136/500
10/10 0s 2ms/step - loss: 19.6561 - mae: 3.2664
Epoch 137/500
10/10 0s 2ms/step - loss: 17.0565 - mae: 3.0045
Epoch 138/500
10/10 0s 2ms/step - loss: 16.9809 - mae: 3.1107
Epoch 139/500
10/10 0s 2ms/step - loss: 18.3218 - mae: 3.1368
Epoch 140/500
10/10 0s 2ms/step - loss: 17.4129 - mae: 3.0626
Epoch 141/500
10/10 0s 2ms/step - loss: 17.9193 - mae: 3.0643
Epoch 142/500
10/10 0s 2ms/step - loss: 18.4840 - mae: 3.1768
Epoch 143/500
10/10 0s 2ms/step - loss: 17.2585 - mae: 3.0968
Epoch 144/500
10/10 0s 2ms/step - loss: 18.4544 - mae: 3.1746
Epoch 145/500
10/10 0s 2ms/step - loss: 17.4295 - mae: 3.0693
Epoch 146/500
10/10 0s 2ms/step - loss: 17.2559 - mae: 3.0132
Epoch 147/500
10/10 0s 2ms/step - loss: 16.7293 - mae: 2.9369
Epoch 148/500
10/10 0s 2ms/step - loss: 18.7350 - mae: 3.1985
Epoch 149/500
10/10 0s 2ms/step - loss: 19.5996 - mae: 3.1382
Epoch 150/500
10/10 0s 2ms/step - loss: 16.1582 - mae: 2.9745
Epoch 151/500
10/10 0s 2ms/step - loss: 14.4522 - mae: 2.7548
Epoch 152/500
10/10 0s 2ms/step - loss: 15.2458 - mae: 2.8222
Epoch 153/500
10/10 0s 2ms/step - loss: 14.9354 - mae: 2.7755
Epoch 154/500
10/10 0s 2ms/step - loss: 15.5355 - mae: 2.8087
Epoch 155/500
10/10 0s 2ms/step - loss: 14.6071 - mae: 2.6840
Epoch 156/500
10/10 0s 2ms/step - loss: 15.7906 - mae: 2.8778
Epoch 157/500
10/10 0s 2ms/step - loss: 16.3160 - mae: 2.9861
Epoch 158/500
10/10 0s 2ms/step - loss: 13.5215 - mae: 2.6492
Epoch 159/500
10/10 0s 2ms/step - loss: 14.7714 - mae: 2.8399
Epoch 160/500
10/10 0s 2ms/step - loss: 17.2373 - mae: 2.9664

Epoch 161/500
10/10 0s 2ms/step - loss: 16.0783 - mae: 2.9210
Epoch 162/500
10/10 0s 2ms/step - loss: 14.8620 - mae: 2.7460
Epoch 163/500
10/10 0s 2ms/step - loss: 15.6127 - mae: 2.8041
Epoch 164/500
10/10 0s 2ms/step - loss: 18.4618 - mae: 3.0441
Epoch 165/500
10/10 0s 2ms/step - loss: 15.2178 - mae: 2.7968
Epoch 166/500
10/10 0s 2ms/step - loss: 14.6241 - mae: 2.7654
Epoch 167/500
10/10 0s 2ms/step - loss: 12.4566 - mae: 2.5760
Epoch 168/500
10/10 0s 2ms/step - loss: 15.8734 - mae: 2.8540
Epoch 169/500
10/10 0s 2ms/step - loss: 13.5075 - mae: 2.7120
Epoch 170/500
10/10 0s 1ms/step - loss: 15.3931 - mae: 2.9061
Epoch 171/500
10/10 0s 2ms/step - loss: 13.7793 - mae: 2.6955
Epoch 172/500
10/10 0s 2ms/step - loss: 18.2681 - mae: 3.0696
Epoch 173/500
10/10 0s 2ms/step - loss: 13.7597 - mae: 2.6869
Epoch 174/500
10/10 0s 2ms/step - loss: 13.9697 - mae: 2.7104
Epoch 175/500
10/10 0s 2ms/step - loss: 15.3552 - mae: 2.8191
Epoch 176/500
10/10 0s 2ms/step - loss: 12.9031 - mae: 2.6247
Epoch 177/500
10/10 0s 2ms/step - loss: 15.6405 - mae: 2.7684
Epoch 178/500
10/10 0s 2ms/step - loss: 14.6220 - mae: 2.6508
Epoch 179/500
10/10 0s 2ms/step - loss: 14.4352 - mae: 2.6886
Epoch 180/500
10/10 0s 2ms/step - loss: 15.2032 - mae: 2.7976
Epoch 181/500
10/10 0s 2ms/step - loss: 13.1606 - mae: 2.5459
Epoch 182/500
10/10 0s 2ms/step - loss: 11.9826 - mae: 2.5154
Epoch 183/500
10/10 0s 2ms/step - loss: 14.3524 - mae: 2.6852
Epoch 184/500
10/10 0s 2ms/step - loss: 14.3347 - mae: 2.7753
Epoch 185/500
10/10 0s 2ms/step - loss: 13.7059 - mae: 2.6754
Epoch 186/500
10/10 0s 2ms/step - loss: 16.7382 - mae: 2.9608
Epoch 187/500
10/10 0s 2ms/step - loss: 13.5628 - mae: 2.5736
Epoch 188/500
10/10 0s 2ms/step - loss: 10.1552 - mae: 2.3583
Epoch 189/500
10/10 0s 2ms/step - loss: 12.8257 - mae: 2.5482
Epoch 190/500
10/10 0s 2ms/step - loss: 14.6458 - mae: 2.7296
Epoch 191/500
10/10 0s 2ms/step - loss: 13.6867 - mae: 2.6346
Epoch 192/500
10/10 0s 2ms/step - loss: 12.4644 - mae: 2.5646

Epoch 193/500
10/10 0s 2ms/step - loss: 11.8776 - mae: 2.4346
Epoch 194/500
10/10 0s 2ms/step - loss: 11.2379 - mae: 2.3383
Epoch 195/500
10/10 0s 2ms/step - loss: 14.0399 - mae: 2.6771
Epoch 196/500
10/10 0s 2ms/step - loss: 15.1619 - mae: 2.7304
Epoch 197/500
10/10 0s 2ms/step - loss: 11.3813 - mae: 2.3802
Epoch 198/500
10/10 0s 2ms/step - loss: 11.4387 - mae: 2.3931
Epoch 199/500
10/10 0s 2ms/step - loss: 12.2842 - mae: 2.4844
Epoch 200/500
10/10 0s 2ms/step - loss: 10.9771 - mae: 2.2233
Epoch 201/500
10/10 0s 2ms/step - loss: 13.0037 - mae: 2.5338
Epoch 202/500
10/10 0s 2ms/step - loss: 11.8396 - mae: 2.4309
Epoch 203/500
10/10 0s 2ms/step - loss: 13.0599 - mae: 2.5229
Epoch 204/500
10/10 0s 2ms/step - loss: 12.4750 - mae: 2.4653
Epoch 205/500
10/10 0s 2ms/step - loss: 10.7590 - mae: 2.3797
Epoch 206/500
10/10 0s 2ms/step - loss: 12.3996 - mae: 2.4322
Epoch 207/500
10/10 0s 2ms/step - loss: 10.8096 - mae: 2.4042
Epoch 208/500
10/10 0s 2ms/step - loss: 14.2821 - mae: 2.6146
Epoch 209/500
10/10 0s 2ms/step - loss: 10.8340 - mae: 2.3436
Epoch 210/500
10/10 0s 2ms/step - loss: 10.3319 - mae: 2.3593
Epoch 211/500
10/10 0s 2ms/step - loss: 12.8783 - mae: 2.4590
Epoch 212/500
10/10 0s 2ms/step - loss: 11.6279 - mae: 2.4054
Epoch 213/500
10/10 0s 2ms/step - loss: 11.2264 - mae: 2.3728
Epoch 214/500
10/10 0s 2ms/step - loss: 11.9747 - mae: 2.3688
Epoch 215/500
10/10 0s 2ms/step - loss: 10.0189 - mae: 2.3585
Epoch 216/500
10/10 0s 2ms/step - loss: 9.6053 - mae: 2.2643
Epoch 217/500
10/10 0s 2ms/step - loss: 10.4804 - mae: 2.3079
Epoch 218/500
10/10 0s 2ms/step - loss: 11.6690 - mae: 2.3054
Epoch 219/500
10/10 0s 2ms/step - loss: 10.1003 - mae: 2.2849
Epoch 220/500
10/10 0s 2ms/step - loss: 10.7362 - mae: 2.3402
Epoch 221/500
10/10 0s 2ms/step - loss: 9.7143 - mae: 2.2660
Epoch 222/500
10/10 0s 2ms/step - loss: 12.1649 - mae: 2.4281
Epoch 223/500
10/10 0s 2ms/step - loss: 10.4735 - mae: 2.3397
Epoch 224/500
10/10 0s 2ms/step - loss: 10.9349 - mae: 2.2391

Epoch 225/500
10/10 0s 2ms/step - loss: 9.4857 - mae: 2.2126
Epoch 226/500
10/10 0s 2ms/step - loss: 8.8658 - mae: 2.0347
Epoch 227/500
10/10 0s 2ms/step - loss: 9.4893 - mae: 2.2164
Epoch 228/500
10/10 0s 2ms/step - loss: 10.8990 - mae: 2.2382
Epoch 229/500
10/10 0s 2ms/step - loss: 8.6970 - mae: 2.0715
Epoch 230/500
10/10 0s 2ms/step - loss: 9.2404 - mae: 2.1493
Epoch 231/500
10/10 0s 2ms/step - loss: 10.6201 - mae: 2.2906
Epoch 232/500
10/10 0s 2ms/step - loss: 9.9761 - mae: 2.2215
Epoch 233/500
10/10 0s 2ms/step - loss: 10.1878 - mae: 2.1658
Epoch 234/500
10/10 0s 2ms/step - loss: 8.4778 - mae: 2.0545
Epoch 235/500
10/10 0s 2ms/step - loss: 10.0767 - mae: 2.1459
Epoch 236/500
10/10 0s 2ms/step - loss: 11.6867 - mae: 2.3378
Epoch 237/500
10/10 0s 2ms/step - loss: 9.2053 - mae: 2.1621
Epoch 238/500
10/10 0s 2ms/step - loss: 9.1747 - mae: 2.0918
Epoch 239/500
10/10 0s 2ms/step - loss: 9.1489 - mae: 2.1063
Epoch 240/500
10/10 0s 2ms/step - loss: 9.0646 - mae: 2.0497
Epoch 241/500
10/10 0s 2ms/step - loss: 9.3317 - mae: 2.0287
Epoch 242/500
10/10 0s 2ms/step - loss: 11.1991 - mae: 2.3062
Epoch 243/500
10/10 0s 2ms/step - loss: 9.7304 - mae: 2.0722
Epoch 244/500
10/10 0s 2ms/step - loss: 8.0453 - mae: 1.9254
Epoch 245/500
10/10 0s 2ms/step - loss: 7.8318 - mae: 1.9011
Epoch 246/500
10/10 0s 2ms/step - loss: 10.1199 - mae: 2.1026
Epoch 247/500
10/10 0s 2ms/step - loss: 7.7387 - mae: 1.9115
Epoch 248/500
10/10 0s 2ms/step - loss: 10.8999 - mae: 2.2430
Epoch 249/500
10/10 0s 2ms/step - loss: 9.3109 - mae: 2.0055
Epoch 250/500
10/10 0s 2ms/step - loss: 9.0610 - mae: 2.0578
Epoch 251/500
10/10 0s 2ms/step - loss: 8.1976 - mae: 1.8884
Epoch 252/500
10/10 0s 2ms/step - loss: 9.4156 - mae: 2.0387
Epoch 253/500
10/10 0s 2ms/step - loss: 8.4914 - mae: 2.0217
Epoch 254/500
10/10 0s 2ms/step - loss: 7.7322 - mae: 1.8796
Epoch 255/500
10/10 0s 2ms/step - loss: 8.5904 - mae: 2.0052
Epoch 256/500
10/10 0s 2ms/step - loss: 8.5525 - mae: 1.9877

Epoch 257/500
10/10 0s 2ms/step - loss: 8.0220 - mae: 1.8718
Epoch 258/500
10/10 0s 2ms/step - loss: 7.9664 - mae: 1.9287
Epoch 259/500
10/10 0s 2ms/step - loss: 8.0896 - mae: 1.8996
Epoch 260/500
10/10 0s 2ms/step - loss: 8.7437 - mae: 1.9473
Epoch 261/500
10/10 0s 2ms/step - loss: 8.8119 - mae: 2.0272
Epoch 262/500
10/10 0s 2ms/step - loss: 8.7180 - mae: 1.9775
Epoch 263/500
10/10 0s 2ms/step - loss: 8.1631 - mae: 1.9030
Epoch 264/500
10/10 0s 2ms/step - loss: 7.2763 - mae: 1.8540
Epoch 265/500
10/10 0s 2ms/step - loss: 8.5749 - mae: 2.0115
Epoch 266/500
10/10 0s 2ms/step - loss: 8.6657 - mae: 1.9886
Epoch 267/500
10/10 0s 2ms/step - loss: 8.2563 - mae: 1.9849
Epoch 268/500
10/10 0s 2ms/step - loss: 9.2689 - mae: 2.0956
Epoch 269/500
10/10 0s 2ms/step - loss: 7.9055 - mae: 1.9312
Epoch 270/500
10/10 0s 2ms/step - loss: 7.6906 - mae: 1.9254
Epoch 271/500
10/10 0s 2ms/step - loss: 6.8792 - mae: 1.8277
Epoch 272/500
10/10 0s 2ms/step - loss: 7.5770 - mae: 1.7990
Epoch 273/500
10/10 0s 2ms/step - loss: 7.0742 - mae: 1.8560
Epoch 274/500
10/10 0s 2ms/step - loss: 8.0556 - mae: 1.9480
Epoch 275/500
10/10 0s 2ms/step - loss: 7.7471 - mae: 1.8695
Epoch 276/500
10/10 0s 2ms/step - loss: 7.5108 - mae: 1.8963
Epoch 277/500
10/10 0s 2ms/step - loss: 8.5517 - mae: 1.9656
Epoch 278/500
10/10 0s 2ms/step - loss: 7.2174 - mae: 1.7889
Epoch 279/500
10/10 0s 2ms/step - loss: 9.1950 - mae: 1.9930
Epoch 280/500
10/10 0s 2ms/step - loss: 7.9053 - mae: 1.8311
Epoch 281/500
10/10 0s 2ms/step - loss: 7.5292 - mae: 1.8490
Epoch 282/500
10/10 0s 2ms/step - loss: 7.4859 - mae: 1.8373
Epoch 283/500
10/10 0s 2ms/step - loss: 9.6827 - mae: 2.1537
Epoch 284/500
10/10 0s 2ms/step - loss: 7.8376 - mae: 1.9251
Epoch 285/500
10/10 0s 2ms/step - loss: 9.7059 - mae: 2.1337
Epoch 286/500
10/10 0s 2ms/step - loss: 8.2716 - mae: 1.9498
Epoch 287/500
10/10 0s 2ms/step - loss: 8.1108 - mae: 2.0148
Epoch 288/500
10/10 0s 2ms/step - loss: 6.7163 - mae: 1.8074

Epoch 289/500
10/10 0s 2ms/step - loss: 8.0859 - mae: 2.0185
Epoch 290/500
10/10 0s 2ms/step - loss: 8.2522 - mae: 2.0603
Epoch 291/500
10/10 0s 2ms/step - loss: 7.9490 - mae: 1.9155
Epoch 292/500
10/10 0s 2ms/step - loss: 7.4364 - mae: 1.8066
Epoch 293/500
10/10 0s 2ms/step - loss: 6.4390 - mae: 1.7193
Epoch 294/500
10/10 0s 2ms/step - loss: 7.5727 - mae: 1.9158
Epoch 295/500
10/10 0s 2ms/step - loss: 7.8665 - mae: 1.8765
Epoch 296/500
10/10 0s 2ms/step - loss: 7.5139 - mae: 1.8384
Epoch 297/500
10/10 0s 2ms/step - loss: 7.7506 - mae: 1.8647
Epoch 298/500
10/10 0s 2ms/step - loss: 7.9047 - mae: 1.8560
Epoch 299/500
10/10 0s 2ms/step - loss: 7.6695 - mae: 1.8330
Epoch 300/500
10/10 0s 2ms/step - loss: 7.7294 - mae: 1.8861
Epoch 301/500
10/10 0s 2ms/step - loss: 5.6524 - mae: 1.6692
Epoch 302/500
10/10 0s 2ms/step - loss: 7.1935 - mae: 1.7689
Epoch 303/500
10/10 0s 2ms/step - loss: 7.4361 - mae: 1.7489
Epoch 304/500
10/10 0s 2ms/step - loss: 7.0978 - mae: 1.7748
Epoch 305/500
10/10 0s 2ms/step - loss: 6.4466 - mae: 1.7551
Epoch 306/500
10/10 0s 2ms/step - loss: 8.2721 - mae: 1.8647
Epoch 307/500
10/10 0s 2ms/step - loss: 6.9718 - mae: 1.8209
Epoch 308/500
10/10 0s 2ms/step - loss: 7.7737 - mae: 1.8163
Epoch 309/500
10/10 0s 2ms/step - loss: 6.4438 - mae: 1.6935
Epoch 310/500
10/10 0s 2ms/step - loss: 6.5852 - mae: 1.7142
Epoch 311/500
10/10 0s 2ms/step - loss: 7.7172 - mae: 1.8537
Epoch 312/500
10/10 0s 2ms/step - loss: 7.2375 - mae: 1.8387
Epoch 313/500
10/10 0s 2ms/step - loss: 6.7704 - mae: 1.7844
Epoch 314/500
10/10 0s 2ms/step - loss: 8.4139 - mae: 1.9312
Epoch 315/500
10/10 0s 2ms/step - loss: 7.1177 - mae: 1.7583
Epoch 316/500
10/10 0s 2ms/step - loss: 6.8768 - mae: 1.8250
Epoch 317/500
10/10 0s 2ms/step - loss: 6.2011 - mae: 1.6893
Epoch 318/500
10/10 0s 2ms/step - loss: 6.7330 - mae: 1.7523
Epoch 319/500
10/10 0s 2ms/step - loss: 6.6161 - mae: 1.7083
Epoch 320/500
10/10 0s 2ms/step - loss: 7.0959 - mae: 1.7774

Epoch 321/500
10/10 0s 2ms/step - loss: 7.6171 - mae: 1.8303
Epoch 322/500
10/10 0s 2ms/step - loss: 6.8782 - mae: 1.6791
Epoch 323/500
10/10 0s 2ms/step - loss: 7.7185 - mae: 1.7284
Epoch 324/500
10/10 0s 2ms/step - loss: 7.9616 - mae: 1.8105
Epoch 325/500
10/10 0s 2ms/step - loss: 7.4696 - mae: 1.7610
Epoch 326/500
10/10 0s 2ms/step - loss: 6.8729 - mae: 1.6935
Epoch 327/500
10/10 0s 2ms/step - loss: 7.1664 - mae: 1.7357
Epoch 328/500
10/10 0s 2ms/step - loss: 6.6704 - mae: 1.7434
Epoch 329/500
10/10 0s 2ms/step - loss: 7.3001 - mae: 1.8465
Epoch 330/500
10/10 0s 2ms/step - loss: 7.8150 - mae: 1.9558
Epoch 331/500
10/10 0s 2ms/step - loss: 6.2932 - mae: 1.7034
Epoch 332/500
10/10 0s 2ms/step - loss: 7.2603 - mae: 1.7853
Epoch 333/500
10/10 0s 2ms/step - loss: 6.5499 - mae: 1.6925
Epoch 334/500
10/10 0s 1ms/step - loss: 8.7210 - mae: 1.9415
Epoch 335/500
10/10 0s 2ms/step - loss: 5.9925 - mae: 1.6494
Epoch 336/500
10/10 0s 2ms/step - loss: 8.2069 - mae: 1.8744
Epoch 337/500
10/10 0s 2ms/step - loss: 6.6790 - mae: 1.6815
Epoch 338/500
10/10 0s 2ms/step - loss: 6.3123 - mae: 1.7971
Epoch 339/500
10/10 0s 2ms/step - loss: 5.2852 - mae: 1.5632
Epoch 340/500
10/10 0s 2ms/step - loss: 5.6461 - mae: 1.5981
Epoch 341/500
10/10 0s 2ms/step - loss: 7.3203 - mae: 1.8182
Epoch 342/500
10/10 0s 2ms/step - loss: 5.6392 - mae: 1.5989
Epoch 343/500
10/10 0s 2ms/step - loss: 6.1923 - mae: 1.6714
Epoch 344/500
10/10 0s 2ms/step - loss: 6.3421 - mae: 1.6650
Epoch 345/500
10/10 0s 2ms/step - loss: 7.3046 - mae: 1.6799
Epoch 346/500
10/10 0s 2ms/step - loss: 6.4212 - mae: 1.6465
Epoch 347/500
10/10 0s 2ms/step - loss: 6.3622 - mae: 1.7005
Epoch 348/500
10/10 0s 2ms/step - loss: 6.2949 - mae: 1.6205
Epoch 349/500
10/10 0s 2ms/step - loss: 6.5990 - mae: 1.7172
Epoch 350/500
10/10 0s 2ms/step - loss: 5.6478 - mae: 1.6617
Epoch 351/500
10/10 0s 2ms/step - loss: 5.3573 - mae: 1.5831
Epoch 352/500
10/10 0s 2ms/step - loss: 5.9858 - mae: 1.6435

Epoch 353/500
10/10 0s 2ms/step - loss: 6.2687 - mae: 1.6461
Epoch 354/500
10/10 0s 2ms/step - loss: 6.4730 - mae: 1.6991
Epoch 355/500
10/10 0s 2ms/step - loss: 6.3315 - mae: 1.6084
Epoch 356/500
10/10 0s 2ms/step - loss: 7.1780 - mae: 1.7549
Epoch 357/500
10/10 0s 2ms/step - loss: 5.6276 - mae: 1.6008
Epoch 358/500
10/10 0s 2ms/step - loss: 7.5822 - mae: 1.8368
Epoch 359/500
10/10 0s 2ms/step - loss: 7.0110 - mae: 1.6983
Epoch 360/500
10/10 0s 2ms/step - loss: 6.9595 - mae: 1.7618
Epoch 361/500
10/10 0s 2ms/step - loss: 6.9245 - mae: 1.7864
Epoch 362/500
10/10 0s 2ms/step - loss: 7.4756 - mae: 1.7513
Epoch 363/500
10/10 0s 2ms/step - loss: 6.1827 - mae: 1.6452
Epoch 364/500
10/10 0s 2ms/step - loss: 6.6116 - mae: 1.6548
Epoch 365/500
10/10 0s 2ms/step - loss: 6.2185 - mae: 1.6619
Epoch 366/500
10/10 0s 2ms/step - loss: 5.9426 - mae: 1.6803
Epoch 367/500
10/10 0s 2ms/step - loss: 6.6353 - mae: 1.7295
Epoch 368/500
10/10 0s 2ms/step - loss: 6.7616 - mae: 1.7835
Epoch 369/500
10/10 0s 2ms/step - loss: 7.2137 - mae: 1.8449
Epoch 370/500
10/10 0s 2ms/step - loss: 6.8921 - mae: 1.7813
Epoch 371/500
10/10 0s 2ms/step - loss: 5.7580 - mae: 1.6400
Epoch 372/500
10/10 0s 2ms/step - loss: 5.6586 - mae: 1.6028
Epoch 373/500
10/10 0s 2ms/step - loss: 6.0027 - mae: 1.6208
Epoch 374/500
10/10 0s 2ms/step - loss: 5.6781 - mae: 1.6282
Epoch 375/500
10/10 0s 2ms/step - loss: 7.0329 - mae: 1.7236
Epoch 376/500
10/10 0s 2ms/step - loss: 6.2406 - mae: 1.6525
Epoch 377/500
10/10 0s 2ms/step - loss: 6.5417 - mae: 1.6719
Epoch 378/500
10/10 0s 2ms/step - loss: 5.6530 - mae: 1.5459
Epoch 379/500
10/10 0s 2ms/step - loss: 4.9457 - mae: 1.4770
Epoch 380/500
10/10 0s 2ms/step - loss: 5.7267 - mae: 1.5772
Epoch 381/500
10/10 0s 2ms/step - loss: 5.1328 - mae: 1.4794
Epoch 382/500
10/10 0s 2ms/step - loss: 5.4178 - mae: 1.5186
Epoch 383/500
10/10 0s 2ms/step - loss: 5.6627 - mae: 1.5477
Epoch 384/500
10/10 0s 2ms/step - loss: 6.4242 - mae: 1.6301

Epoch 385/500
10/10 0s 2ms/step - loss: 5.5287 - mae: 1.6035
Epoch 386/500
10/10 0s 2ms/step - loss: 7.2384 - mae: 1.7793
Epoch 387/500
10/10 0s 2ms/step - loss: 6.1052 - mae: 1.6029
Epoch 388/500
10/10 0s 2ms/step - loss: 5.7544 - mae: 1.5868
Epoch 389/500
10/10 0s 2ms/step - loss: 6.6347 - mae: 1.7125
Epoch 390/500
10/10 0s 2ms/step - loss: 7.2089 - mae: 1.7078
Epoch 391/500
10/10 0s 2ms/step - loss: 6.1454 - mae: 1.5662
Epoch 392/500
10/10 0s 2ms/step - loss: 6.2118 - mae: 1.6337
Epoch 393/500
10/10 0s 2ms/step - loss: 6.0658 - mae: 1.6319
Epoch 394/500
10/10 0s 2ms/step - loss: 6.3664 - mae: 1.5995
Epoch 395/500
10/10 0s 2ms/step - loss: 5.8452 - mae: 1.5705
Epoch 396/500
10/10 0s 2ms/step - loss: 6.1546 - mae: 1.7064
Epoch 397/500
10/10 0s 2ms/step - loss: 6.7117 - mae: 1.6970
Epoch 398/500
10/10 0s 2ms/step - loss: 5.6622 - mae: 1.5288
Epoch 399/500
10/10 0s 2ms/step - loss: 5.9905 - mae: 1.5109
Epoch 400/500
10/10 0s 2ms/step - loss: 5.5553 - mae: 1.5088
Epoch 401/500
10/10 0s 2ms/step - loss: 6.2241 - mae: 1.5894
Epoch 402/500
10/10 0s 2ms/step - loss: 5.9552 - mae: 1.6867
Epoch 403/500
10/10 0s 2ms/step - loss: 6.8616 - mae: 1.7147
Epoch 404/500
10/10 0s 2ms/step - loss: 6.6028 - mae: 1.6715
Epoch 405/500
10/10 0s 2ms/step - loss: 5.3296 - mae: 1.5118
Epoch 406/500
10/10 0s 2ms/step - loss: 6.6093 - mae: 1.6317
Epoch 407/500
10/10 0s 2ms/step - loss: 4.8440 - mae: 1.4820
Epoch 408/500
10/10 0s 2ms/step - loss: 5.4591 - mae: 1.5597
Epoch 409/500
10/10 0s 2ms/step - loss: 5.9434 - mae: 1.4812
Epoch 410/500
10/10 0s 2ms/step - loss: 5.5675 - mae: 1.5753
Epoch 411/500
10/10 0s 2ms/step - loss: 4.6233 - mae: 1.4234
Epoch 412/500
10/10 0s 2ms/step - loss: 4.8615 - mae: 1.4194
Epoch 413/500
10/10 0s 2ms/step - loss: 5.3310 - mae: 1.5204
Epoch 414/500
10/10 0s 2ms/step - loss: 5.7428 - mae: 1.5519
Epoch 415/500
10/10 0s 2ms/step - loss: 6.2236 - mae: 1.6342
Epoch 416/500
10/10 0s 2ms/step - loss: 5.8963 - mae: 1.5419

Epoch 417/500
10/10 0s 2ms/step - loss: 5.7184 - mae: 1.5612
Epoch 418/500
10/10 0s 2ms/step - loss: 5.6425 - mae: 1.5444
Epoch 419/500
10/10 0s 2ms/step - loss: 6.2338 - mae: 1.5956
Epoch 420/500
10/10 0s 2ms/step - loss: 6.1304 - mae: 1.6586
Epoch 421/500
10/10 0s 2ms/step - loss: 5.6684 - mae: 1.5646
Epoch 422/500
10/10 0s 2ms/step - loss: 5.2657 - mae: 1.5120
Epoch 423/500
10/10 0s 2ms/step - loss: 6.0610 - mae: 1.6318
Epoch 424/500
10/10 0s 2ms/step - loss: 7.0312 - mae: 1.6603
Epoch 425/500
10/10 0s 2ms/step - loss: 6.4145 - mae: 1.6181
Epoch 426/500
10/10 0s 2ms/step - loss: 6.2241 - mae: 1.6323
Epoch 427/500
10/10 0s 2ms/step - loss: 5.0105 - mae: 1.4643
Epoch 428/500
10/10 0s 2ms/step - loss: 6.0263 - mae: 1.5387
Epoch 429/500
10/10 0s 2ms/step - loss: 5.8204 - mae: 1.5309
Epoch 430/500
10/10 0s 2ms/step - loss: 4.9397 - mae: 1.4441
Epoch 431/500
10/10 0s 2ms/step - loss: 5.8087 - mae: 1.5140
Epoch 432/500
10/10 0s 2ms/step - loss: 6.0648 - mae: 1.4644
Epoch 433/500
10/10 0s 2ms/step - loss: 5.3057 - mae: 1.5018
Epoch 434/500
10/10 0s 2ms/step - loss: 4.8582 - mae: 1.4008
Epoch 435/500
10/10 0s 2ms/step - loss: 4.8165 - mae: 1.4377
Epoch 436/500
10/10 0s 2ms/step - loss: 5.1185 - mae: 1.4699
Epoch 437/500
10/10 0s 2ms/step - loss: 5.5749 - mae: 1.5116
Epoch 438/500
10/10 0s 2ms/step - loss: 5.9733 - mae: 1.5844
Epoch 439/500
10/10 0s 2ms/step - loss: 4.4861 - mae: 1.4467
Epoch 440/500
10/10 0s 2ms/step - loss: 3.8616 - mae: 1.3272
Epoch 441/500
10/10 0s 2ms/step - loss: 6.1900 - mae: 1.6252
Epoch 442/500
10/10 0s 2ms/step - loss: 4.5820 - mae: 1.3972
Epoch 443/500
10/10 0s 2ms/step - loss: 5.0918 - mae: 1.4767
Epoch 444/500
10/10 0s 2ms/step - loss: 6.3299 - mae: 1.5987
Epoch 445/500
10/10 0s 2ms/step - loss: 5.7869 - mae: 1.5129
Epoch 446/500
10/10 0s 2ms/step - loss: 5.9886 - mae: 1.5265
Epoch 447/500
10/10 0s 2ms/step - loss: 5.6581 - mae: 1.4699
Epoch 448/500
10/10 0s 2ms/step - loss: 5.6576 - mae: 1.5441

Epoch 449/500
10/10 0s 2ms/step - loss: 5.1280 - mae: 1.4364
Epoch 450/500
10/10 0s 2ms/step - loss: 5.6271 - mae: 1.5258
Epoch 451/500
10/10 0s 2ms/step - loss: 4.9385 - mae: 1.4117
Epoch 452/500
10/10 0s 2ms/step - loss: 4.5694 - mae: 1.3875
Epoch 453/500
10/10 0s 2ms/step - loss: 5.5401 - mae: 1.4993
Epoch 454/500
10/10 0s 2ms/step - loss: 4.9672 - mae: 1.4045
Epoch 455/500
10/10 0s 2ms/step - loss: 4.9416 - mae: 1.4278
Epoch 456/500
10/10 0s 2ms/step - loss: 5.3139 - mae: 1.4943
Epoch 457/500
10/10 0s 2ms/step - loss: 5.4715 - mae: 1.4818
Epoch 458/500
10/10 0s 2ms/step - loss: 4.4714 - mae: 1.3555
Epoch 459/500
10/10 0s 2ms/step - loss: 4.6679 - mae: 1.3837
Epoch 460/500
10/10 0s 2ms/step - loss: 5.3692 - mae: 1.4775
Epoch 461/500
10/10 0s 2ms/step - loss: 4.9616 - mae: 1.4848
Epoch 462/500
10/10 0s 2ms/step - loss: 6.2197 - mae: 1.4827
Epoch 463/500
10/10 0s 2ms/step - loss: 4.6465 - mae: 1.3731
Epoch 464/500
10/10 0s 2ms/step - loss: 5.1985 - mae: 1.4664
Epoch 465/500
10/10 0s 2ms/step - loss: 4.8643 - mae: 1.4402
Epoch 466/500
10/10 0s 2ms/step - loss: 5.3455 - mae: 1.4653
Epoch 467/500
10/10 0s 2ms/step - loss: 5.3018 - mae: 1.5030
Epoch 468/500
10/10 0s 2ms/step - loss: 6.1616 - mae: 1.5486
Epoch 469/500
10/10 0s 2ms/step - loss: 4.8834 - mae: 1.3952
Epoch 470/500
10/10 0s 2ms/step - loss: 5.8562 - mae: 1.4746
Epoch 471/500
10/10 0s 2ms/step - loss: 4.5395 - mae: 1.4132
Epoch 472/500
10/10 0s 2ms/step - loss: 4.8587 - mae: 1.3960
Epoch 473/500
10/10 0s 2ms/step - loss: 5.0071 - mae: 1.3938
Epoch 474/500
10/10 0s 2ms/step - loss: 4.6593 - mae: 1.3721
Epoch 475/500
10/10 0s 2ms/step - loss: 5.1358 - mae: 1.4420
Epoch 476/500
10/10 0s 2ms/step - loss: 5.3344 - mae: 1.4666
Epoch 477/500
10/10 0s 2ms/step - loss: 5.2943 - mae: 1.3883
Epoch 478/500
10/10 0s 2ms/step - loss: 4.1035 - mae: 1.3060
Epoch 479/500
10/10 0s 2ms/step - loss: 4.8962 - mae: 1.3939
Epoch 480/500
10/10 0s 2ms/step - loss: 3.9681 - mae: 1.2708

```
Epoch 481/500
10/10 ██████████ 0s 2ms/step - loss: 5.0422 - mae: 1.4280
Epoch 482/500
10/10 ██████████ 0s 2ms/step - loss: 4.0126 - mae: 1.3127
Epoch 483/500
10/10 ██████████ 0s 2ms/step - loss: 5.0385 - mae: 1.5372
Epoch 484/500
10/10 ██████████ 0s 2ms/step - loss: 4.0688 - mae: 1.3264
Epoch 485/500
10/10 ██████████ 0s 2ms/step - loss: 5.0267 - mae: 1.4433
Epoch 486/500
10/10 ██████████ 0s 2ms/step - loss: 4.7391 - mae: 1.4071
Epoch 487/500
10/10 ██████████ 0s 2ms/step - loss: 4.9989 - mae: 1.4683
Epoch 488/500
10/10 ██████████ 0s 2ms/step - loss: 6.5448 - mae: 1.6161
Epoch 489/500
10/10 ██████████ 0s 2ms/step - loss: 5.2658 - mae: 1.4413
Epoch 490/500
10/10 ██████████ 0s 2ms/step - loss: 4.3288 - mae: 1.3699
Epoch 491/500
10/10 ██████████ 0s 2ms/step - loss: 4.3687 - mae: 1.3123
Epoch 492/500
10/10 ██████████ 0s 2ms/step - loss: 5.3377 - mae: 1.4158
Epoch 493/500
10/10 ██████████ 0s 2ms/step - loss: 4.4964 - mae: 1.3429
Epoch 494/500
10/10 ██████████ 0s 2ms/step - loss: 4.1610 - mae: 1.3191
Epoch 495/500
10/10 ██████████ 0s 2ms/step - loss: 2.9518 - mae: 1.0940
Epoch 496/500
10/10 ██████████ 0s 2ms/step - loss: 5.3821 - mae: 1.4393
Epoch 497/500
10/10 ██████████ 0s 2ms/step - loss: 4.3060 - mae: 1.3377
Epoch 498/500
10/10 ██████████ 0s 2ms/step - loss: 4.7516 - mae: 1.3700
Epoch 499/500
10/10 ██████████ 0s 2ms/step - loss: 4.3595 - mae: 1.3024
Epoch 500/500
10/10 ██████████ 0s 2ms/step - loss: 5.8172 - mae: 1.5220
```

Model evaluation:

Loss (MSE): 4.56, MAE: 1.35

```
In [46]: models = {
    "Linear Regression": LinearRegression(),
    "Lasso": Lasso(),
    "K-Neighbors Regressor": KNeighborsRegressor(),
    "Decision Tree": DecisionTreeRegressor(),
    "Random Forest Regressor": RandomForestRegressor(),
    "Gradient Boosting": GradientBoostingRegressor(),
    "XGBRegressor": XGBRegressor(),
    "CatBoosting Regressor": CatBoostRegressor(verbose=0, iterations = 100),
    "AdaBoost Regressor": AdaBoostRegressor(),
    "ExtraTreesRegressor": ExtraTreesRegressor(),
    "Support Vector Regressor(RBF)": SVR(kernel="rbf"),
    "Support Vector Regressor(linear)": SVR(kernel="linear"),
    "Nu SVR(rbf)": NuSVR(kernel="rbf"),
    "ANN": ANN_model
}
```

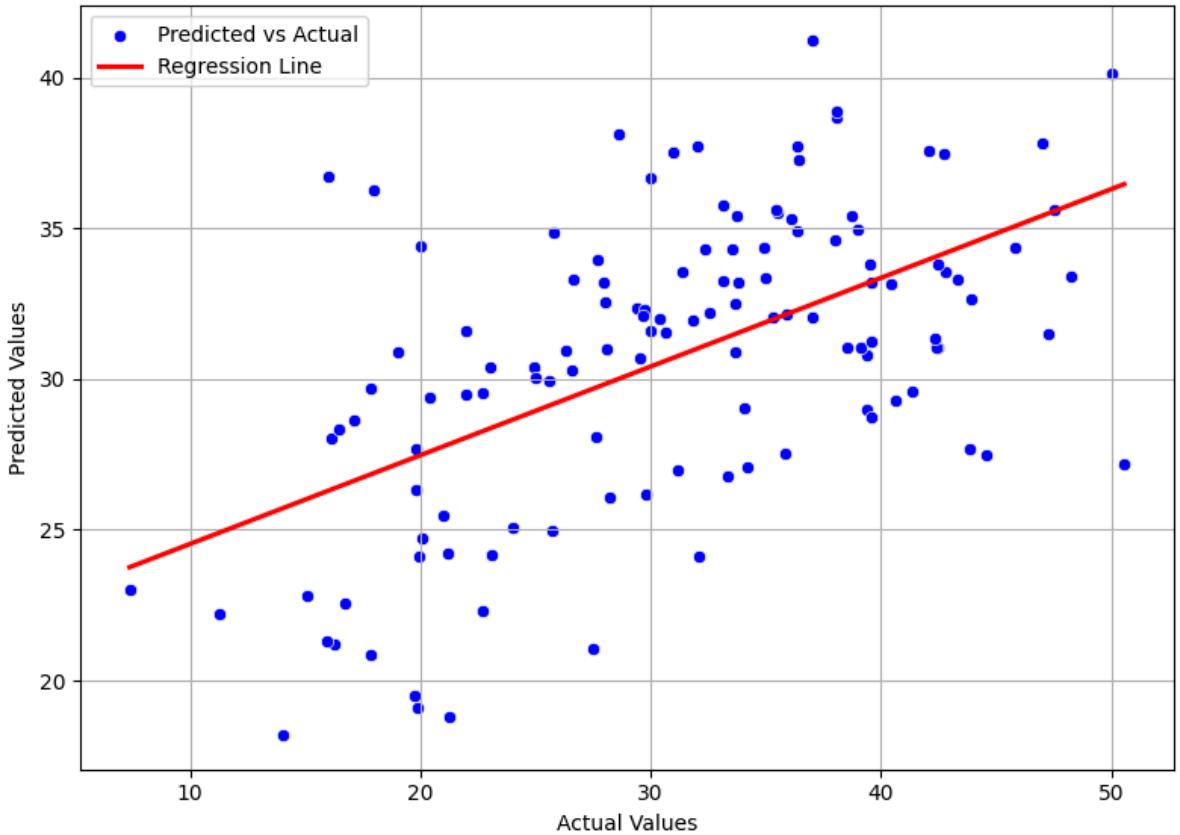
```
In [47]: def safe_flatten(y_pred):
    """
    Flattens the array if it's a 2D array with shape (n, 1).
    """
```

```
    Useful for ANN predictions.  
    """  
    if isinstance(y_pred, (np.ndarray, list)) and len(np.shape(y_pred)) == 2 and y_  
        return y_pred.flatten()  
    return y_pred
```

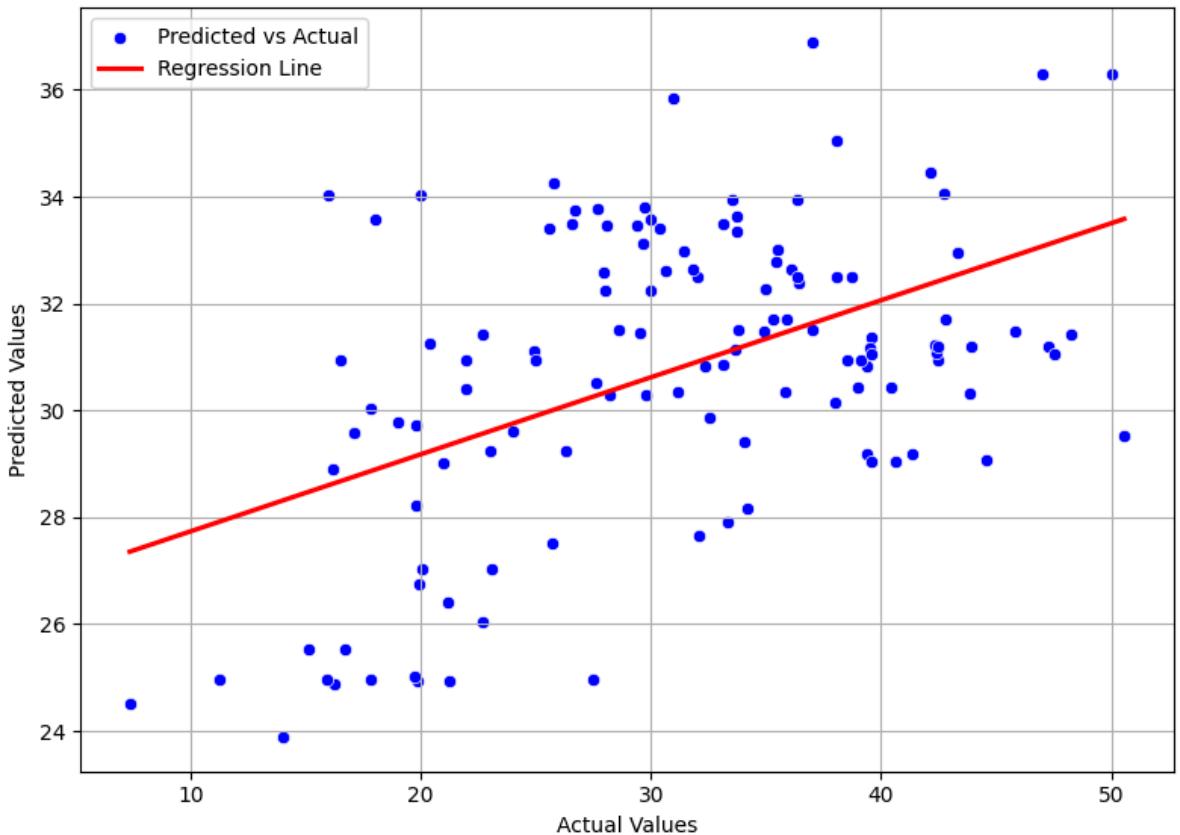
```
In [48]: r2_train_score = {}  
r2_test_score = {}  
def evaluate_model(models, X_train, y_train, X_val, y_val):  
    for model_name, model in models.items():  
        model.fit(X_train, y_train)  
  
        y_train_pred = model.predict(X_train)  
        y_test_pred = model.predict(X_val)  
  
        y = y_val  
        y_pred = safe_flatten(y_test_pred)  
  
        plt.figure(figsize=(8, 6))  
        r2 = r2_score(y, y_pred)  
  
        sns.scatterplot(x=y, y=y_pred, label='Predicted vs Actual', color='blue')  
        sns.regplot(x=y, y=y_pred, scatter=False, label='Regression Line', color='red')  
  
        plt.xlabel('Actual Values')  
        plt.ylabel('Predicted Values')  
        plt.title(f'CO Actual vs Predicted Values (R2 Score: {r2:.4f}) for {model_name}')  
        plt.legend()  
        plt.grid(True)  
        plt.tight_layout()  
        plt.savefig(f'CO Actual vs Predicted Values (R2 Score: {r2:.4f}) for {model_name}.png')  
        plt.show()  
  
    r2_train_score[model_name] = r2_score(y_train, y_train_pred)  
    r2_test_score[model_name] = r2_score(y_val, y_test_pred)
```

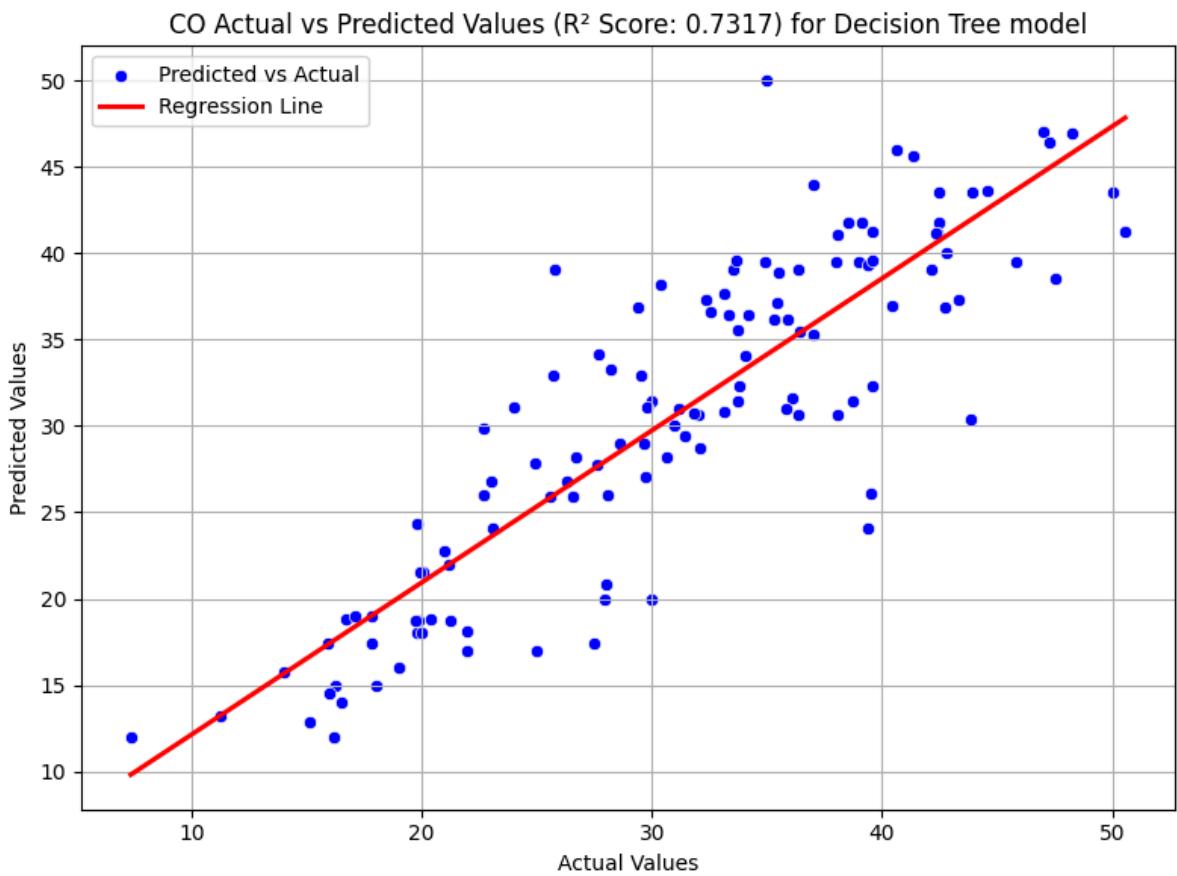
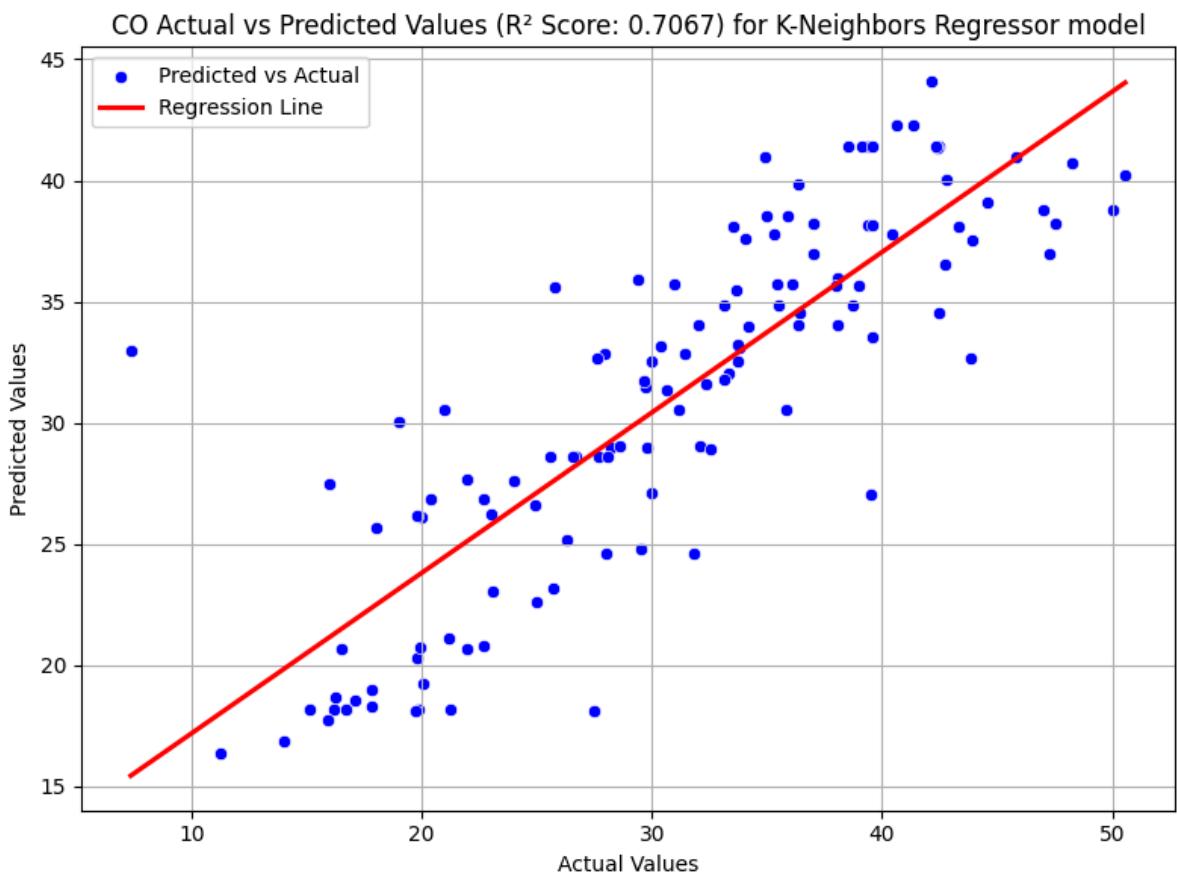
```
In [49]: evaluate_model(models, X_train_scaled, y_train.CO, X_val_scaled, y_val.CO)
```

CO Actual vs Predicted Values (R^2 Score: 0.3103) for Linear Regression model

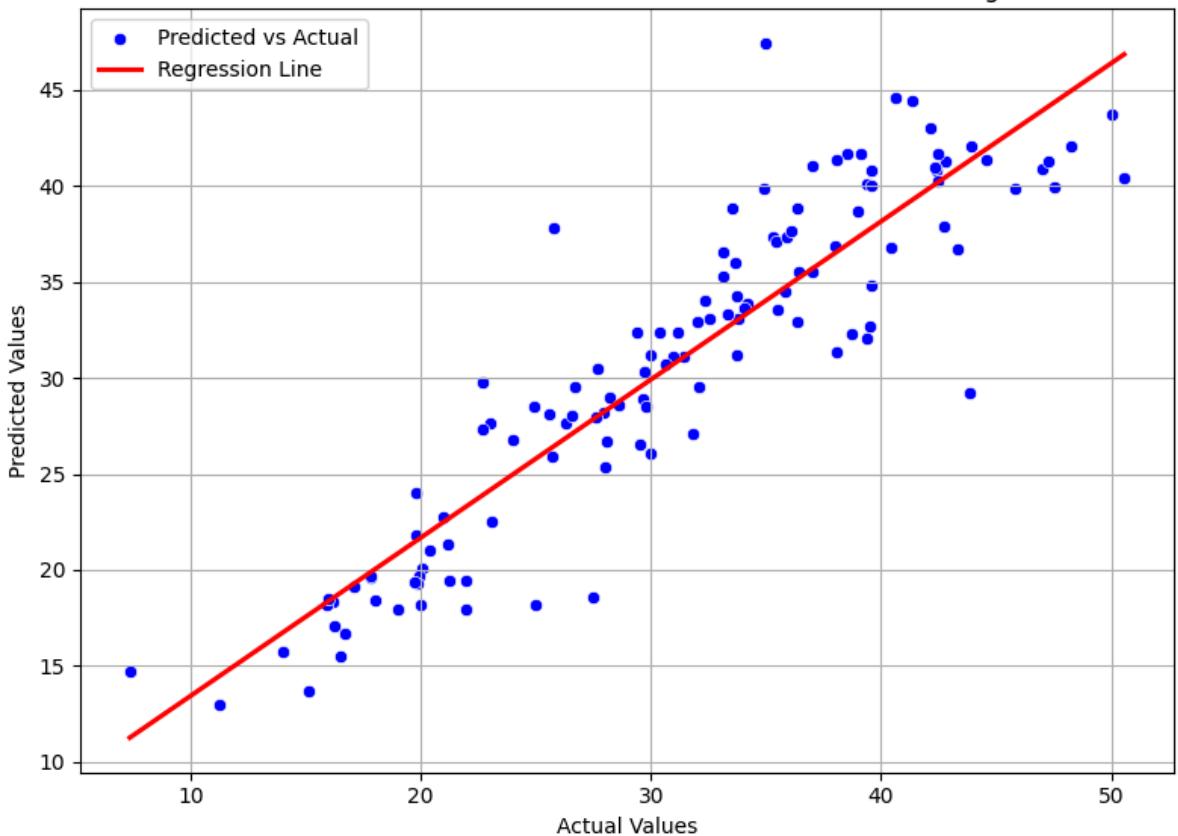


CO Actual vs Predicted Values (R^2 Score: 0.1988) for Lasso model

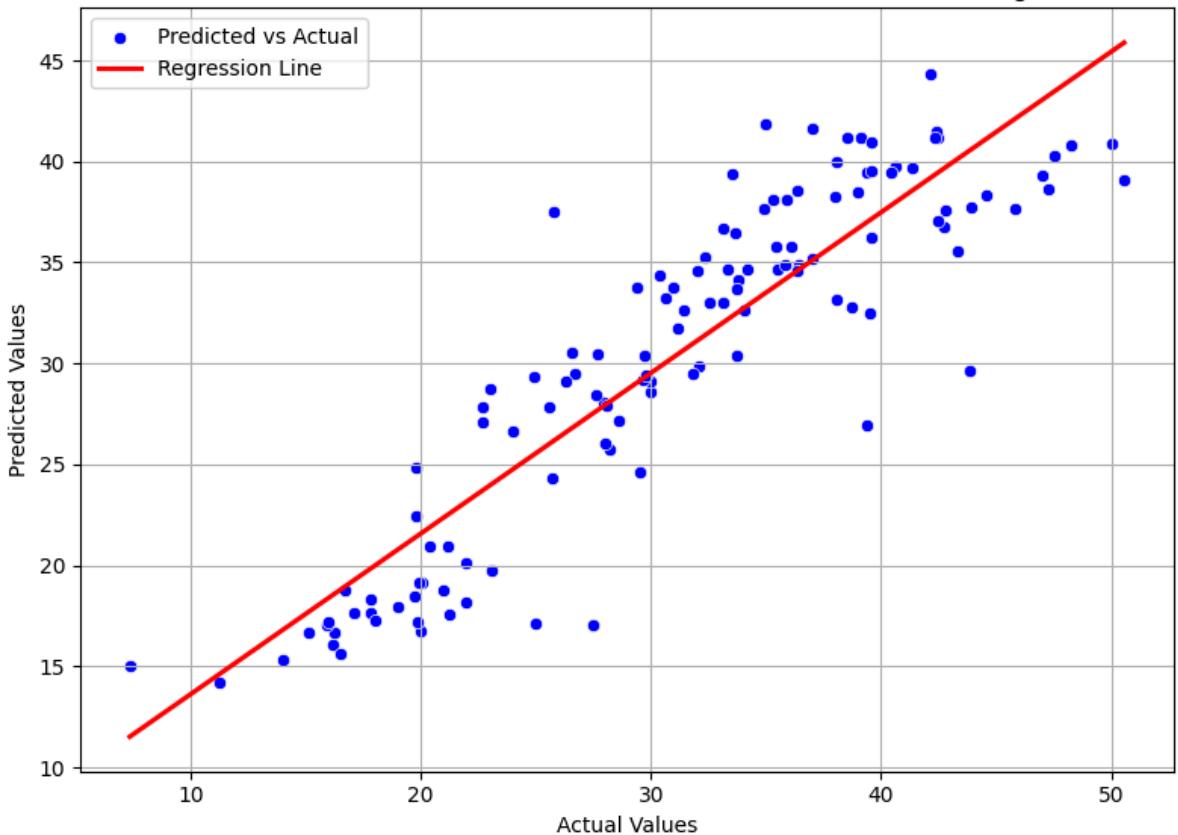




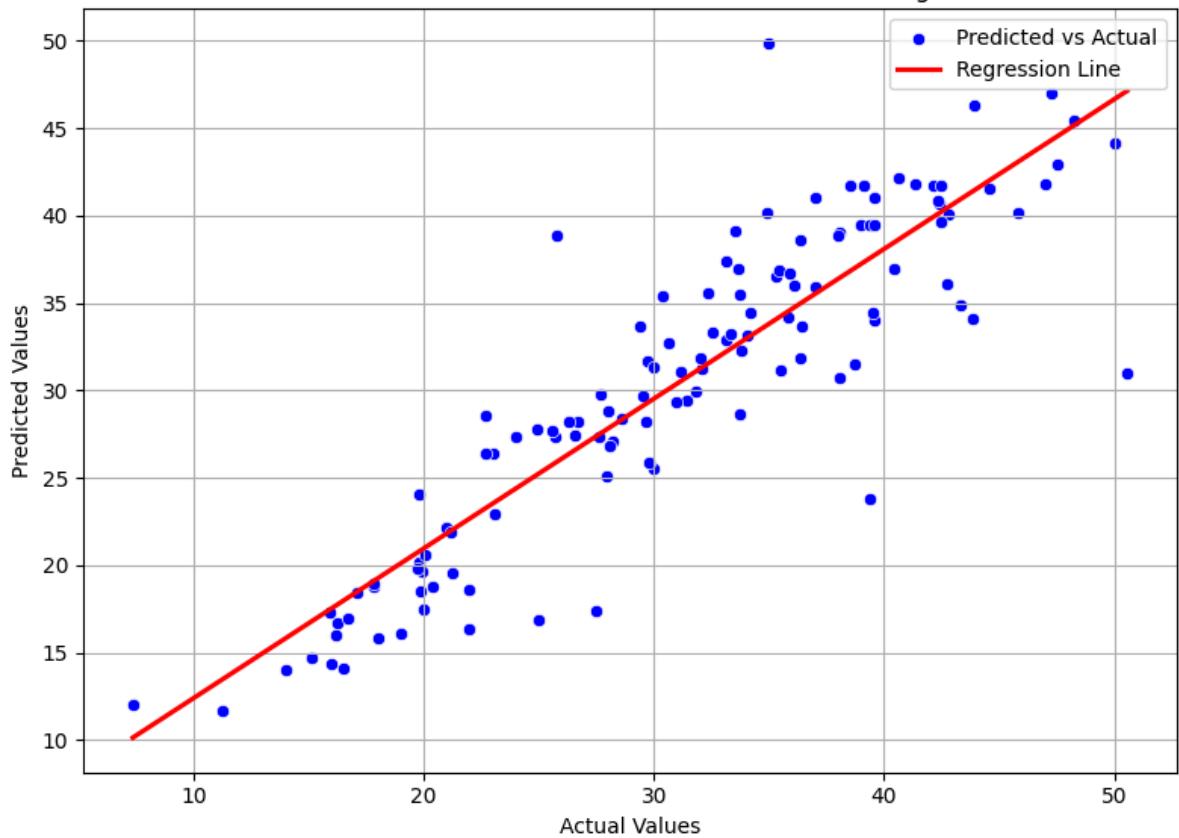
CO Actual vs Predicted Values (R^2 Score: 0.8279) for Random Forest Regressor model



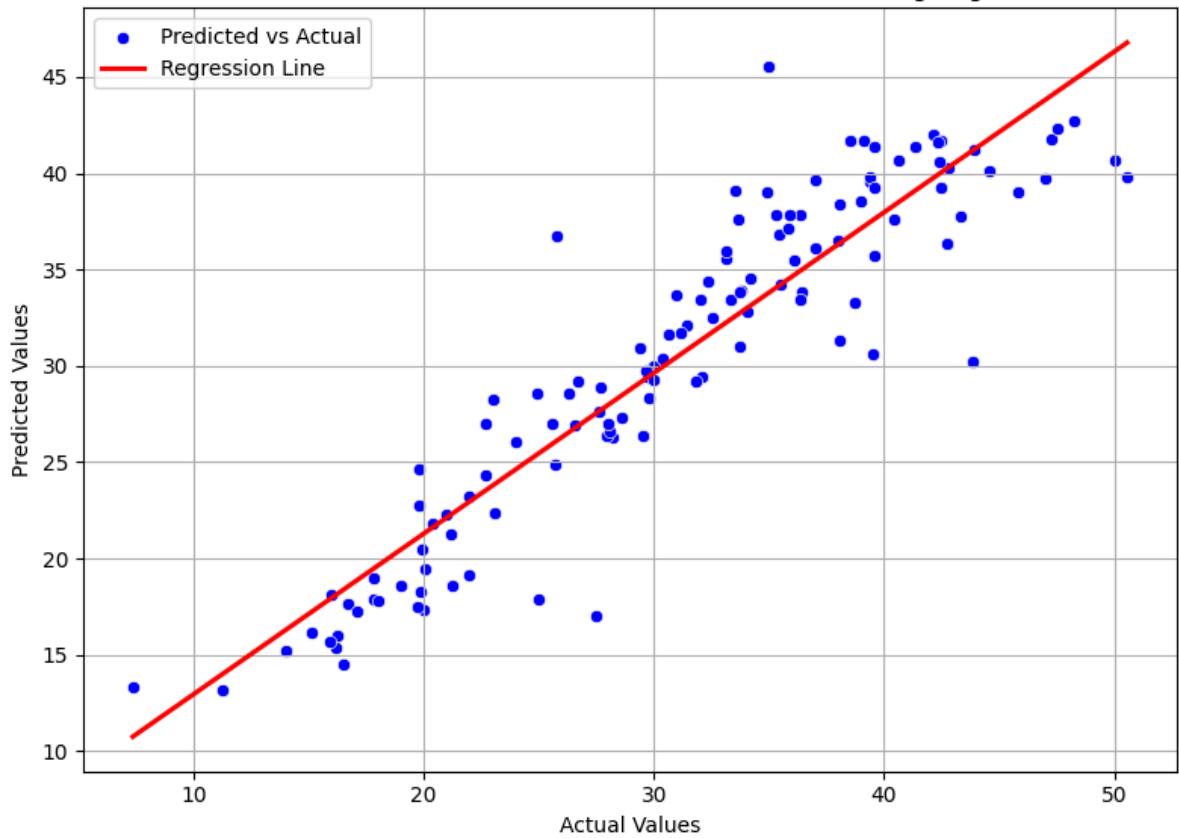
CO Actual vs Predicted Values (R^2 Score: 0.7976) for Gradient Boosting model

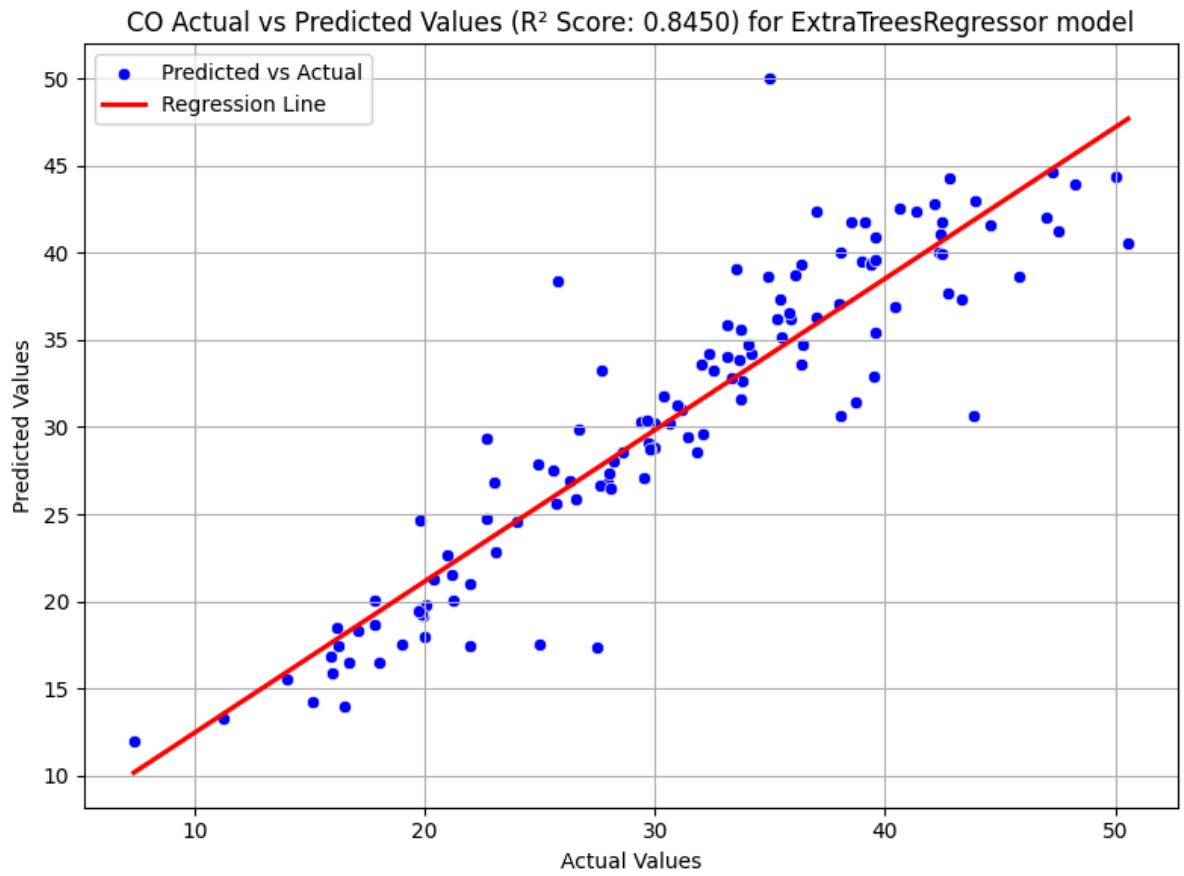
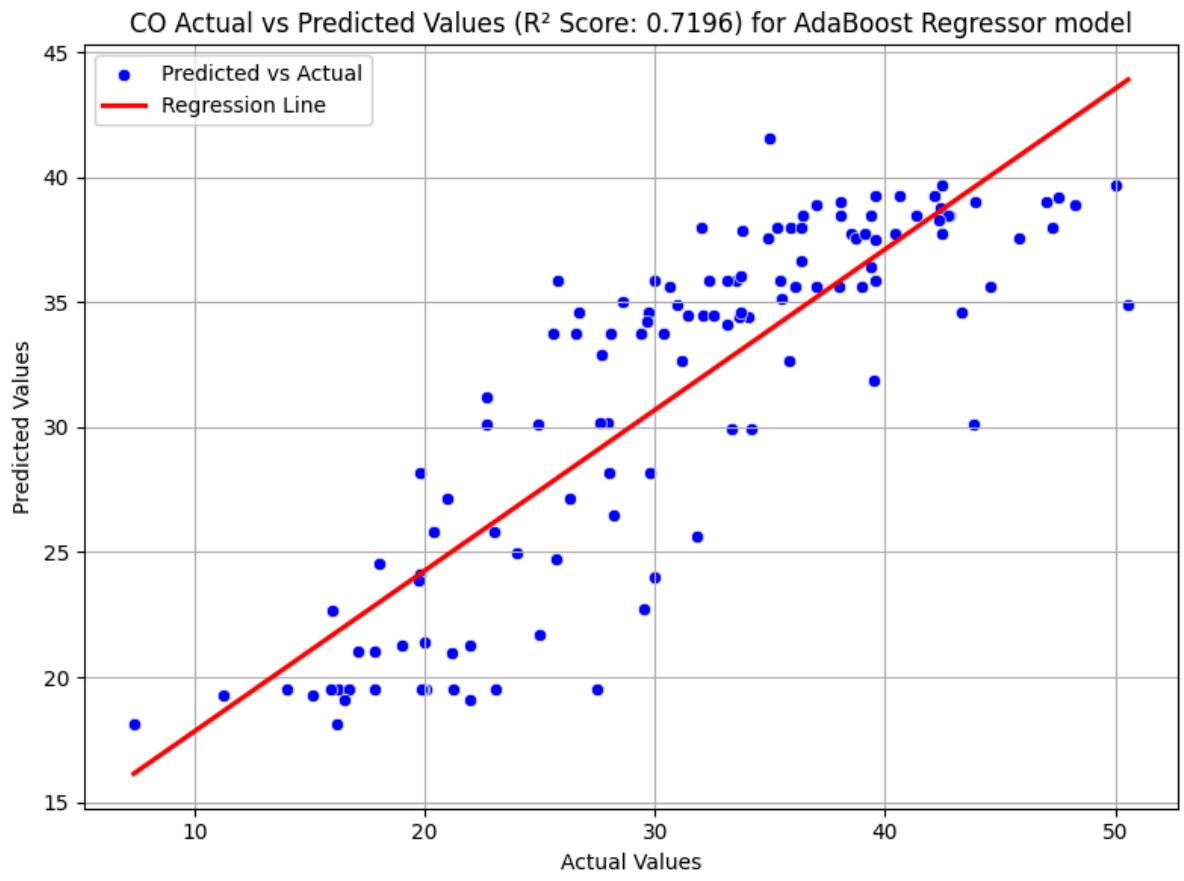


CO Actual vs Predicted Values (R^2 Score: 0.7885) for XGBRegressor model

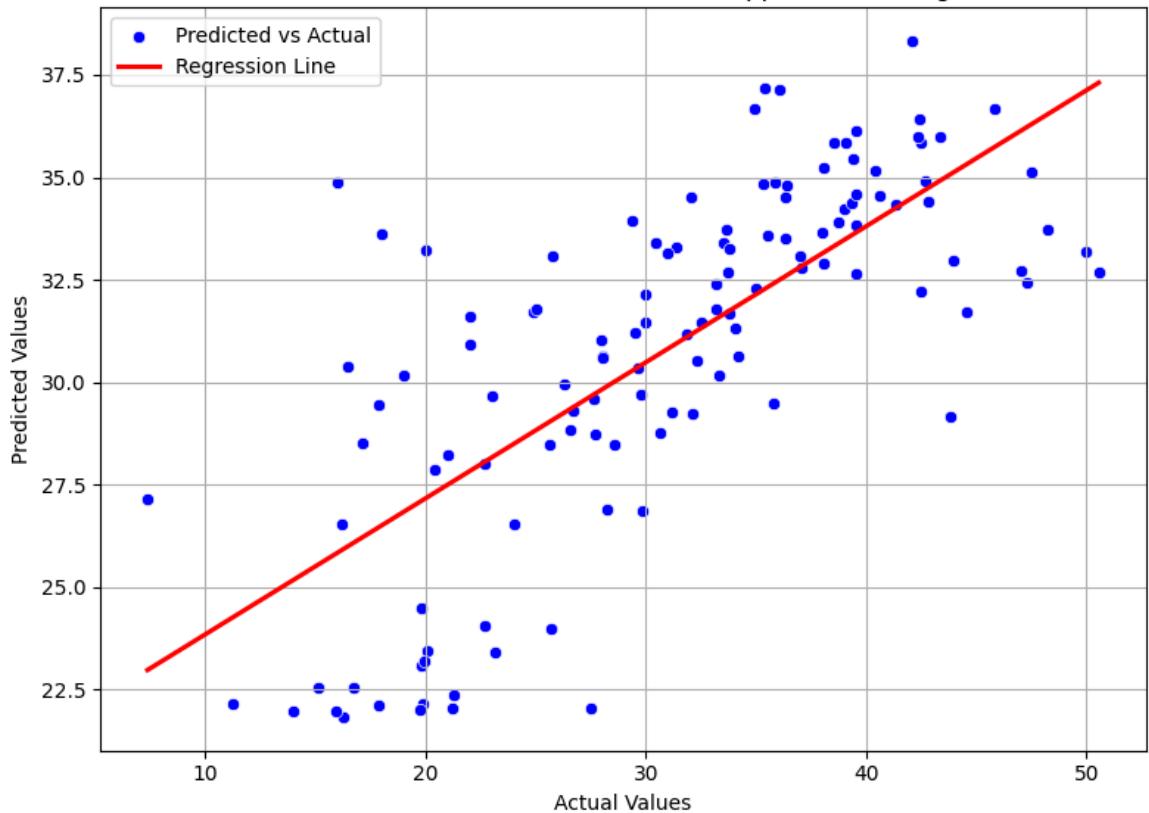


CO Actual vs Predicted Values (R^2 Score: 0.8457) for CatBoosting Regressor model

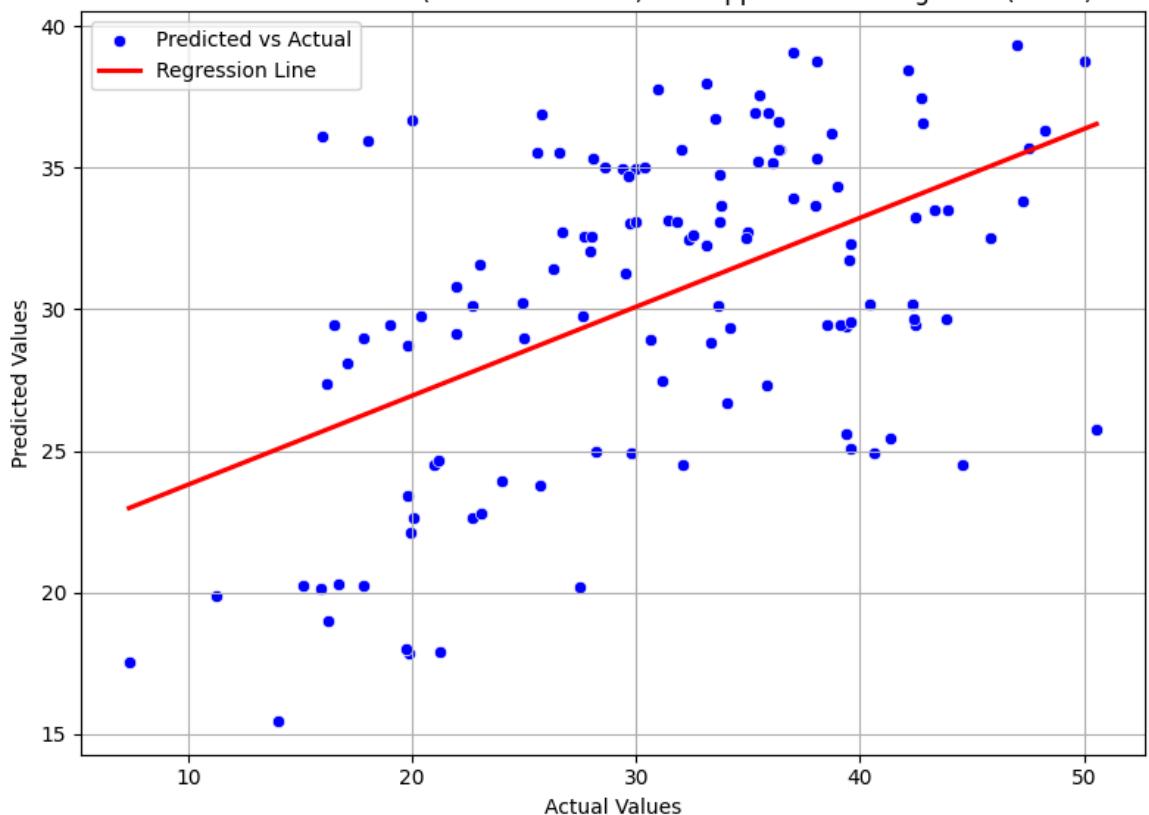




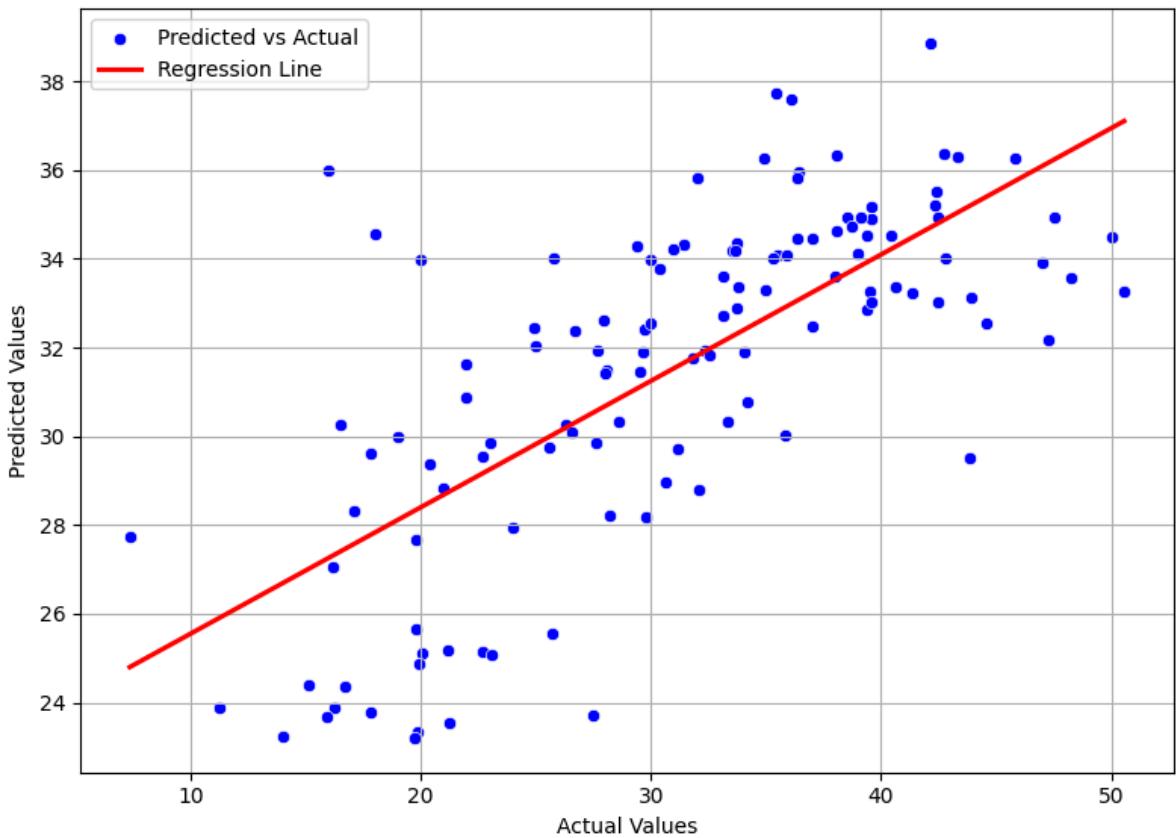
CO Actual vs Predicted Values (R^2 Score: 0.4564) for Support Vector Regressor(RBF) model



CO Actual vs Predicted Values (R^2 Score: 0.2617) for Support Vector Regressor(linear) model



CO Actual vs Predicted Values (R^2 Score: 0.4048) for Nu SVR(rbf) model

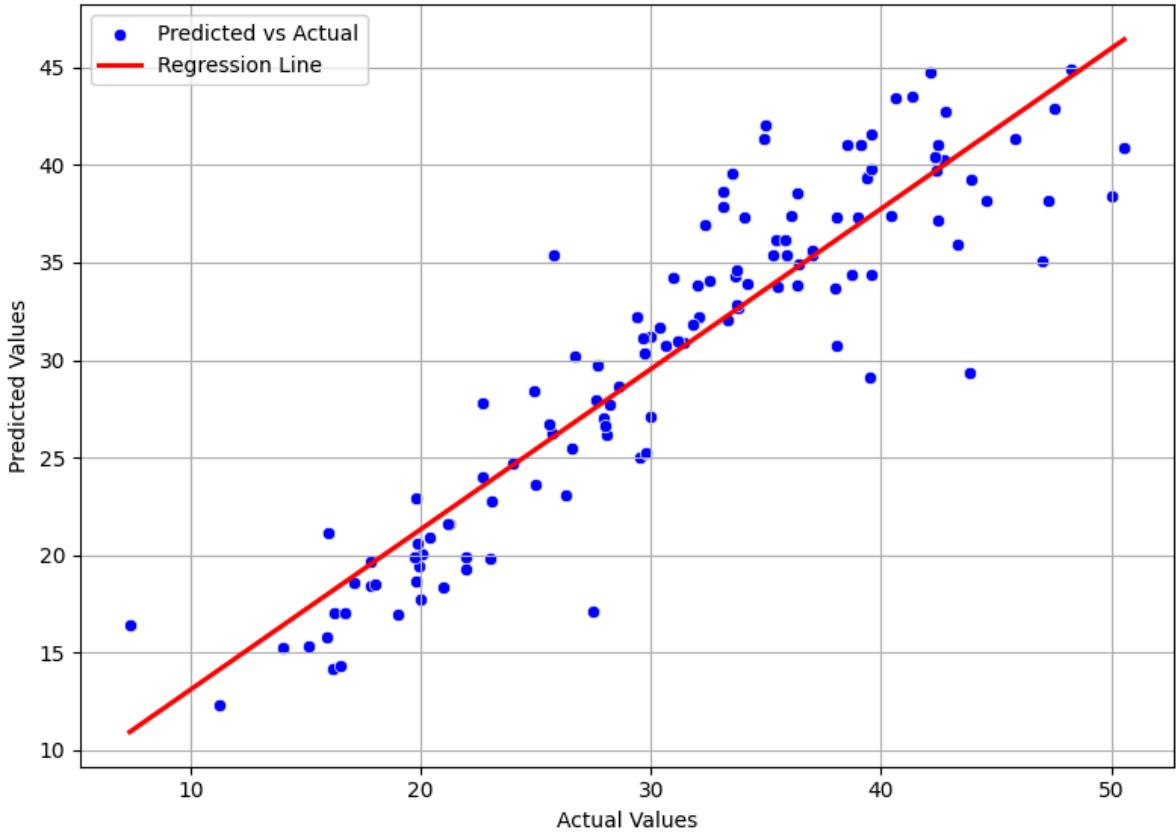


10/10 ————— 0s 2ms/step - loss: 5.2083 - mae: 1.4006

10/10 ————— 0s 18ms/step

4/4 ————— 0s 81ms/step

CO Actual vs Predicted Values (R^2 Score: 0.8223) for ANN model



```
In [50]: score = pd.DataFrame(list(zip(models.keys(), r2_train_score.values(), r2_test_score
score
```

Out[50]:

	Model	r2_train_score	r2_test_score
0	Linear Regression	0.298496	0.310329
1	Lasso	0.205461	0.198758
2	K-Neighbors Regressor	0.794460	0.706655
3	Decision Tree	0.997006	0.731715
4	Random Forest Regressor	0.970487	0.827927
5	Gradient Boosting	0.919220	0.797646
6	XGBRegressor	0.996926	0.788515
7	CatBoosting Regressor	0.968410	0.845676
8	AdaBoost Regressor	0.746776	0.719574
9	ExtraTreesRegressor	0.997006	0.844978
10	Support Vector Regressor(RBF)	0.473190	0.456430
11	Support Vector Regressor(linear)	0.253874	0.261680
12	Nu SVR(rbf)	0.433602	0.404798
13	ANN	0.943367	0.822314

In [51]:

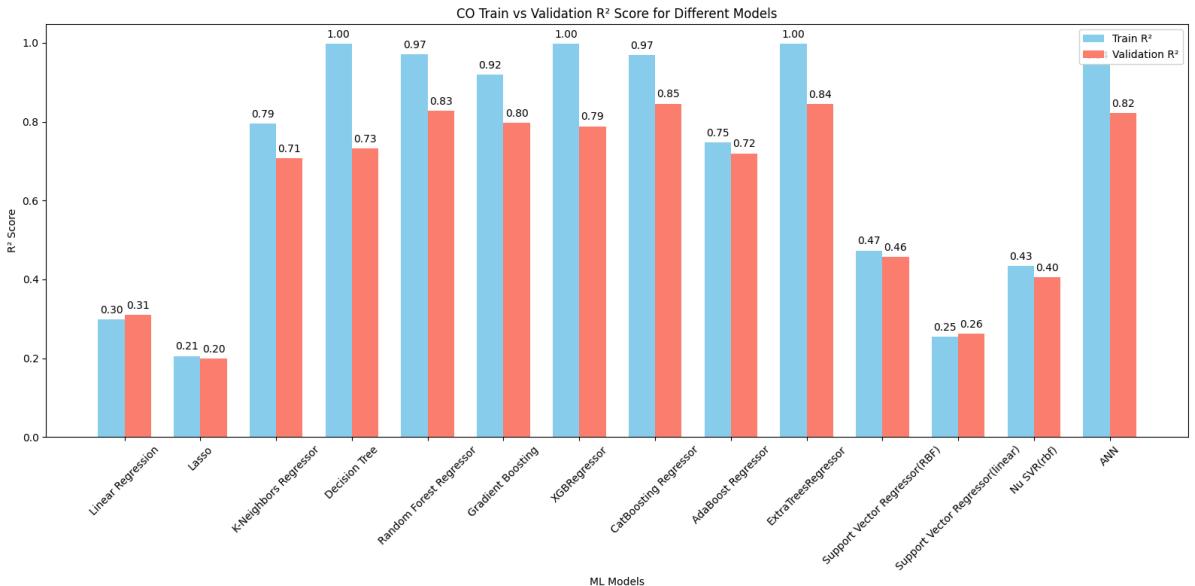
```
# Set positions
x = np.arange(len(score['Model']))
width = 0.35 # Width of the bars

# Create plot
fig, ax = plt.subplots(figsize=(16, 8))
bars1 = ax.bar(x - width/2, score['r2_train_score'], width, label='Train R2', color='blue')
bars2 = ax.bar(x + width/2, score['r2_test_score'], width, label='Validation R2', color='red')

# Add labels and title
ax.set_xlabel('ML Models')
ax.set_ylabel('R2 Score')
ax.set_title('CO Train vs Validation R2 Score for Different Models')
ax.set_xticks(x)
ax.set_xticklabels(score['Model'], rotation=45)
ax.legend()

# Add R2 score text on top of bars
for bar in bars1 + bars2:
    yval = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2.0, yval + 0.01, f'{yval:.2f}', ha='center')

plt.tight_layout()
plt.savefig("CO Train vs Validation R2 Score for Different Models")
plt.show()
```



Predicting the value of CO2

```
In [52]: ANN_model = Sequential([
    Dense(32, input_dim=13),
    LeakyReLU(alpha=0.1),
    Dense(32, activation='tanh'),
    Dense(16, activation='relu'),
    Dense(1, activation='linear')
])

# Compile the model
ANN_model.compile(optimizer='adam',
                   loss='mean_squared_error',
                   metrics=['mae'])

# Train the model
ANN_model.fit(X_train_scaled, y_train.CO2, epochs=500, verbose=1)

# Evaluate the model
loss, mae = ANN_model.evaluate(X_train_scaled, y_train.CO2, verbose=0)
print(f"\nModel evaluation:\nLoss (MSE): {loss:.2f}, MAE: {mae:.2f}")
```

Epoch 1/500
10/10 2s 35ms/step - loss: 971.2888 - mae: 29.2199
Epoch 2/500
10/10 0s 2ms/step - loss: 852.4738 - mae: 27.1535
Epoch 3/500
10/10 0s 2ms/step - loss: 897.0617 - mae: 27.5853
Epoch 4/500
10/10 0s 2ms/step - loss: 816.9807 - mae: 26.5347
Epoch 5/500
10/10 0s 2ms/step - loss: 758.8616 - mae: 25.5917
Epoch 6/500
10/10 0s 2ms/step - loss: 720.9613 - mae: 24.7938
Epoch 7/500
10/10 0s 2ms/step - loss: 647.0811 - mae: 23.1684
Epoch 8/500
10/10 0s 2ms/step - loss: 618.7953 - mae: 22.4222
Epoch 9/500
10/10 0s 2ms/step - loss: 553.5217 - mae: 21.1887
Epoch 10/500
10/10 0s 2ms/step - loss: 463.5688 - mae: 18.8825
Epoch 11/500
10/10 0s 2ms/step - loss: 391.7823 - mae: 17.1454
Epoch 12/500
10/10 0s 2ms/step - loss: 332.0067 - mae: 15.5609
Epoch 13/500
10/10 0s 2ms/step - loss: 268.2933 - mae: 13.7168
Epoch 14/500
10/10 0s 2ms/step - loss: 217.2852 - mae: 12.0998
Epoch 15/500
10/10 0s 2ms/step - loss: 192.3208 - mae: 11.0861
Epoch 16/500
10/10 0s 2ms/step - loss: 163.3085 - mae: 10.0014
Epoch 17/500
10/10 0s 2ms/step - loss: 148.8390 - mae: 9.6554
Epoch 18/500
10/10 0s 2ms/step - loss: 129.5284 - mae: 8.8581
Epoch 19/500
10/10 0s 2ms/step - loss: 111.0075 - mae: 8.3567
Epoch 20/500
10/10 0s 2ms/step - loss: 109.2474 - mae: 8.3348
Epoch 21/500
10/10 0s 2ms/step - loss: 111.4418 - mae: 8.3495
Epoch 22/500
10/10 0s 2ms/step - loss: 100.5414 - mae: 8.0990
Epoch 23/500
10/10 0s 2ms/step - loss: 87.0583 - mae: 7.3503
Epoch 24/500
10/10 0s 2ms/step - loss: 91.5189 - mae: 7.5758
Epoch 25/500
10/10 0s 2ms/step - loss: 86.7589 - mae: 7.2348
Epoch 26/500
10/10 0s 2ms/step - loss: 80.0594 - mae: 6.9449
Epoch 27/500
10/10 0s 2ms/step - loss: 79.8378 - mae: 6.9428
Epoch 28/500
10/10 0s 2ms/step - loss: 78.9295 - mae: 6.8522
Epoch 29/500
10/10 0s 2ms/step - loss: 68.9338 - mae: 6.3111
Epoch 30/500
10/10 0s 2ms/step - loss: 71.8124 - mae: 6.5123
Epoch 31/500
10/10 0s 2ms/step - loss: 69.4678 - mae: 6.3512
Epoch 32/500
10/10 0s 2ms/step - loss: 70.8776 - mae: 6.6940

Epoch 33/500
10/10 0s 2ms/step - loss: 61.6333 - mae: 6.1062
Epoch 34/500
10/10 0s 2ms/step - loss: 61.0036 - mae: 6.1099
Epoch 35/500
10/10 0s 2ms/step - loss: 58.2509 - mae: 5.9578
Epoch 36/500
10/10 0s 2ms/step - loss: 60.7742 - mae: 6.0740
Epoch 37/500
10/10 0s 2ms/step - loss: 60.5848 - mae: 6.0946
Epoch 38/500
10/10 0s 2ms/step - loss: 59.7367 - mae: 6.1034
Epoch 39/500
10/10 0s 2ms/step - loss: 56.5720 - mae: 5.7739
Epoch 40/500
10/10 0s 2ms/step - loss: 51.8915 - mae: 5.7104
Epoch 41/500
10/10 0s 2ms/step - loss: 47.9939 - mae: 5.3694
Epoch 42/500
10/10 0s 2ms/step - loss: 51.5936 - mae: 5.5273
Epoch 43/500
10/10 0s 2ms/step - loss: 49.7496 - mae: 5.5159
Epoch 44/500
10/10 0s 2ms/step - loss: 46.5658 - mae: 5.2398
Epoch 45/500
10/10 0s 2ms/step - loss: 51.0932 - mae: 5.5899
Epoch 46/500
10/10 0s 2ms/step - loss: 50.0542 - mae: 5.4831
Epoch 47/500
10/10 0s 2ms/step - loss: 42.8194 - mae: 5.0390
Epoch 48/500
10/10 0s 2ms/step - loss: 44.5907 - mae: 5.0486
Epoch 49/500
10/10 0s 2ms/step - loss: 40.4311 - mae: 4.8723
Epoch 50/500
10/10 0s 2ms/step - loss: 41.4721 - mae: 4.8772
Epoch 51/500
10/10 0s 2ms/step - loss: 42.0994 - mae: 4.8855
Epoch 52/500
10/10 0s 2ms/step - loss: 37.5851 - mae: 4.5207
Epoch 53/500
10/10 0s 2ms/step - loss: 34.4494 - mae: 4.3824
Epoch 54/500
10/10 0s 2ms/step - loss: 37.7001 - mae: 4.6922
Epoch 55/500
10/10 0s 2ms/step - loss: 32.5776 - mae: 4.2685
Epoch 56/500
10/10 0s 2ms/step - loss: 37.6299 - mae: 4.5828
Epoch 57/500
10/10 0s 2ms/step - loss: 32.6874 - mae: 4.2509
Epoch 58/500
10/10 0s 2ms/step - loss: 32.1981 - mae: 4.1700
Epoch 59/500
10/10 0s 2ms/step - loss: 30.9978 - mae: 4.0709
Epoch 60/500
10/10 0s 2ms/step - loss: 32.9333 - mae: 4.3929
Epoch 61/500
10/10 0s 2ms/step - loss: 32.1816 - mae: 4.3212
Epoch 62/500
10/10 0s 2ms/step - loss: 29.9763 - mae: 4.0720
Epoch 63/500
10/10 0s 2ms/step - loss: 30.6256 - mae: 4.1386
Epoch 64/500
10/10 0s 2ms/step - loss: 30.9484 - mae: 4.0547

Epoch 65/500
10/10 0s 2ms/step - loss: 31.5012 - mae: 4.1652
Epoch 66/500
10/10 0s 2ms/step - loss: 30.0958 - mae: 4.1425
Epoch 67/500
10/10 0s 2ms/step - loss: 29.2075 - mae: 4.0200
Epoch 68/500
10/10 0s 2ms/step - loss: 24.8771 - mae: 3.7245
Epoch 69/500
10/10 0s 2ms/step - loss: 25.5529 - mae: 3.7960
Epoch 70/500
10/10 0s 2ms/step - loss: 27.2648 - mae: 3.8462
Epoch 71/500
10/10 0s 2ms/step - loss: 24.0162 - mae: 3.6635
Epoch 72/500
10/10 0s 2ms/step - loss: 27.9976 - mae: 3.8432
Epoch 73/500
10/10 0s 2ms/step - loss: 27.6230 - mae: 3.9056
Epoch 74/500
10/10 0s 2ms/step - loss: 25.1281 - mae: 3.7212
Epoch 75/500
10/10 0s 2ms/step - loss: 24.9558 - mae: 3.6680
Epoch 76/500
10/10 0s 2ms/step - loss: 25.2152 - mae: 3.6010
Epoch 77/500
10/10 0s 2ms/step - loss: 24.6198 - mae: 3.6775
Epoch 78/500
10/10 0s 2ms/step - loss: 24.1574 - mae: 3.5959
Epoch 79/500
10/10 0s 2ms/step - loss: 23.8615 - mae: 3.5766
Epoch 80/500
10/10 0s 2ms/step - loss: 21.8738 - mae: 3.5123
Epoch 81/500
10/10 0s 2ms/step - loss: 19.7147 - mae: 3.3153
Epoch 82/500
10/10 0s 2ms/step - loss: 21.0796 - mae: 3.4543
Epoch 83/500
10/10 0s 2ms/step - loss: 24.8496 - mae: 3.5379
Epoch 84/500
10/10 0s 2ms/step - loss: 24.4565 - mae: 3.5608
Epoch 85/500
10/10 0s 2ms/step - loss: 20.3060 - mae: 3.3647
Epoch 86/500
10/10 0s 2ms/step - loss: 21.5074 - mae: 3.4104
Epoch 87/500
10/10 0s 2ms/step - loss: 21.8676 - mae: 3.4403
Epoch 88/500
10/10 0s 2ms/step - loss: 21.6501 - mae: 3.4304
Epoch 89/500
10/10 0s 2ms/step - loss: 22.4576 - mae: 3.6158
Epoch 90/500
10/10 0s 2ms/step - loss: 18.9229 - mae: 3.1636
Epoch 91/500
10/10 0s 2ms/step - loss: 20.2548 - mae: 3.3057
Epoch 92/500
10/10 0s 2ms/step - loss: 22.4314 - mae: 3.3893
Epoch 93/500
10/10 0s 2ms/step - loss: 21.8139 - mae: 3.4199
Epoch 94/500
10/10 0s 2ms/step - loss: 19.8418 - mae: 3.2225
Epoch 95/500
10/10 0s 2ms/step - loss: 20.1343 - mae: 3.2271
Epoch 96/500
10/10 0s 2ms/step - loss: 21.3820 - mae: 3.3501

Epoch 97/500
10/10 0s 2ms/step - loss: 21.2544 - mae: 3.3067
Epoch 98/500
10/10 0s 2ms/step - loss: 20.9168 - mae: 3.1676
Epoch 99/500
10/10 0s 2ms/step - loss: 18.2320 - mae: 3.0297
Epoch 100/500
10/10 0s 2ms/step - loss: 17.2101 - mae: 2.9583
Epoch 101/500
10/10 0s 2ms/step - loss: 18.3682 - mae: 3.0407
Epoch 102/500
10/10 0s 2ms/step - loss: 21.3420 - mae: 3.1874
Epoch 103/500
10/10 0s 2ms/step - loss: 18.1227 - mae: 3.0070
Epoch 104/500
10/10 0s 2ms/step - loss: 17.2004 - mae: 2.9861
Epoch 105/500
10/10 0s 2ms/step - loss: 21.6553 - mae: 3.2881
Epoch 106/500
10/10 0s 2ms/step - loss: 19.2212 - mae: 3.0393
Epoch 107/500
10/10 0s 2ms/step - loss: 18.5478 - mae: 3.0555
Epoch 108/500
10/10 0s 2ms/step - loss: 15.9787 - mae: 2.8014
Epoch 109/500
10/10 0s 2ms/step - loss: 16.3722 - mae: 2.9790
Epoch 110/500
10/10 0s 2ms/step - loss: 17.9630 - mae: 2.9683
Epoch 111/500
10/10 0s 2ms/step - loss: 17.1403 - mae: 2.9139
Epoch 112/500
10/10 0s 2ms/step - loss: 16.7631 - mae: 2.8454
Epoch 113/500
10/10 0s 2ms/step - loss: 17.0715 - mae: 2.8679
Epoch 114/500
10/10 0s 2ms/step - loss: 14.9353 - mae: 2.7678
Epoch 115/500
10/10 0s 2ms/step - loss: 14.5872 - mae: 2.6647
Epoch 116/500
10/10 0s 2ms/step - loss: 18.8832 - mae: 2.9775
Epoch 117/500
10/10 0s 2ms/step - loss: 18.1620 - mae: 2.9049
Epoch 118/500
10/10 0s 2ms/step - loss: 16.4629 - mae: 2.7852
Epoch 119/500
10/10 0s 2ms/step - loss: 15.3947 - mae: 2.7458
Epoch 120/500
10/10 0s 2ms/step - loss: 18.2059 - mae: 2.9202
Epoch 121/500
10/10 0s 2ms/step - loss: 14.6663 - mae: 2.7972
Epoch 122/500
10/10 0s 2ms/step - loss: 15.6063 - mae: 2.8079
Epoch 123/500
10/10 0s 2ms/step - loss: 15.0874 - mae: 2.7518
Epoch 124/500
10/10 0s 2ms/step - loss: 16.0720 - mae: 2.7614
Epoch 125/500
10/10 0s 2ms/step - loss: 12.9881 - mae: 2.6036
Epoch 126/500
10/10 0s 2ms/step - loss: 17.1759 - mae: 2.8811
Epoch 127/500
10/10 0s 2ms/step - loss: 14.9151 - mae: 2.7088
Epoch 128/500
10/10 0s 2ms/step - loss: 13.1569 - mae: 2.5561

Epoch 129/500
10/10 0s 2ms/step - loss: 15.2690 - mae: 2.6289
Epoch 130/500
10/10 0s 2ms/step - loss: 13.9103 - mae: 2.7369
Epoch 131/500
10/10 0s 2ms/step - loss: 14.0609 - mae: 2.6313
Epoch 132/500
10/10 0s 2ms/step - loss: 13.4980 - mae: 2.5778
Epoch 133/500
10/10 0s 2ms/step - loss: 18.2210 - mae: 2.8224
Epoch 134/500
10/10 0s 2ms/step - loss: 15.4969 - mae: 2.7157
Epoch 135/500
10/10 0s 2ms/step - loss: 14.0033 - mae: 2.5776
Epoch 136/500
10/10 0s 2ms/step - loss: 14.7156 - mae: 2.6401
Epoch 137/500
10/10 0s 2ms/step - loss: 12.5318 - mae: 2.4864
Epoch 138/500
10/10 0s 2ms/step - loss: 12.9124 - mae: 2.5416
Epoch 139/500
10/10 0s 2ms/step - loss: 13.7044 - mae: 2.5440
Epoch 140/500
10/10 0s 2ms/step - loss: 13.0762 - mae: 2.5628
Epoch 141/500
10/10 0s 2ms/step - loss: 11.2069 - mae: 2.3918
Epoch 142/500
10/10 0s 2ms/step - loss: 15.0423 - mae: 2.5190
Epoch 143/500
10/10 0s 2ms/step - loss: 13.3621 - mae: 2.4933
Epoch 144/500
10/10 0s 2ms/step - loss: 14.5408 - mae: 2.6112
Epoch 145/500
10/10 0s 2ms/step - loss: 13.4501 - mae: 2.5153
Epoch 146/500
10/10 0s 2ms/step - loss: 14.4330 - mae: 2.5991
Epoch 147/500
10/10 0s 2ms/step - loss: 15.7644 - mae: 2.6010
Epoch 148/500
10/10 0s 2ms/step - loss: 17.3841 - mae: 2.7626
Epoch 149/500
10/10 0s 2ms/step - loss: 15.6525 - mae: 2.6328
Epoch 150/500
10/10 0s 2ms/step - loss: 12.1399 - mae: 2.4120
Epoch 151/500
10/10 0s 2ms/step - loss: 13.3692 - mae: 2.5149
Epoch 152/500
10/10 0s 2ms/step - loss: 13.7281 - mae: 2.5431
Epoch 153/500
10/10 0s 2ms/step - loss: 14.6275 - mae: 2.5051
Epoch 154/500
10/10 0s 2ms/step - loss: 12.4432 - mae: 2.2807
Epoch 155/500
10/10 0s 2ms/step - loss: 11.9748 - mae: 2.3453
Epoch 156/500
10/10 0s 2ms/step - loss: 13.0870 - mae: 2.4460
Epoch 157/500
10/10 0s 2ms/step - loss: 11.8200 - mae: 2.4027
Epoch 158/500
10/10 0s 2ms/step - loss: 16.0411 - mae: 2.6307
Epoch 159/500
10/10 0s 2ms/step - loss: 11.3464 - mae: 2.3642
Epoch 160/500
10/10 0s 2ms/step - loss: 12.6200 - mae: 2.4659

Epoch 161/500
10/10 0s 2ms/step - loss: 13.4703 - mae: 2.4894
Epoch 162/500
10/10 0s 2ms/step - loss: 12.5924 - mae: 2.4790
Epoch 163/500
10/10 0s 2ms/step - loss: 11.8639 - mae: 2.2974
Epoch 164/500
10/10 0s 2ms/step - loss: 10.4208 - mae: 2.1181
Epoch 165/500
10/10 0s 2ms/step - loss: 14.0252 - mae: 2.4600
Epoch 166/500
10/10 0s 2ms/step - loss: 10.9212 - mae: 2.1351
Epoch 167/500
10/10 0s 2ms/step - loss: 11.3777 - mae: 2.3104
Epoch 168/500
10/10 0s 2ms/step - loss: 12.3606 - mae: 2.3175
Epoch 169/500
10/10 0s 2ms/step - loss: 12.8797 - mae: 2.4185
Epoch 170/500
10/10 0s 2ms/step - loss: 11.9267 - mae: 2.3343
Epoch 171/500
10/10 0s 2ms/step - loss: 11.4147 - mae: 2.2555
Epoch 172/500
10/10 0s 2ms/step - loss: 11.4776 - mae: 2.2484
Epoch 173/500
10/10 0s 2ms/step - loss: 11.1689 - mae: 2.2583
Epoch 174/500
10/10 0s 2ms/step - loss: 10.5471 - mae: 2.1853
Epoch 175/500
10/10 0s 2ms/step - loss: 12.5190 - mae: 2.2610
Epoch 176/500
10/10 0s 2ms/step - loss: 10.3570 - mae: 2.2011
Epoch 177/500
10/10 0s 2ms/step - loss: 10.9849 - mae: 2.1909
Epoch 178/500
10/10 0s 2ms/step - loss: 13.0885 - mae: 2.4585
Epoch 179/500
10/10 0s 2ms/step - loss: 10.8020 - mae: 2.2282
Epoch 180/500
10/10 0s 2ms/step - loss: 9.2670 - mae: 2.0816
Epoch 181/500
10/10 0s 2ms/step - loss: 12.3236 - mae: 2.3666
Epoch 182/500
10/10 0s 2ms/step - loss: 9.7998 - mae: 2.1369
Epoch 183/500
10/10 0s 2ms/step - loss: 11.5325 - mae: 2.2095
Epoch 184/500
10/10 0s 2ms/step - loss: 11.1959 - mae: 2.2341
Epoch 185/500
10/10 0s 2ms/step - loss: 8.3149 - mae: 1.9905
Epoch 186/500
10/10 0s 2ms/step - loss: 9.9661 - mae: 2.1494
Epoch 187/500
10/10 0s 2ms/step - loss: 9.4774 - mae: 2.0671
Epoch 188/500
10/10 0s 2ms/step - loss: 11.7935 - mae: 2.1519
Epoch 189/500
10/10 0s 2ms/step - loss: 9.0832 - mae: 2.0469
Epoch 190/500
10/10 0s 2ms/step - loss: 12.5842 - mae: 2.2187
Epoch 191/500
10/10 0s 2ms/step - loss: 11.2557 - mae: 2.2303
Epoch 192/500
10/10 0s 2ms/step - loss: 14.4438 - mae: 2.4122

Epoch 193/500
10/10 0s 2ms/step - loss: 9.6123 - mae: 2.1208
Epoch 194/500
10/10 0s 2ms/step - loss: 9.2835 - mae: 2.0863
Epoch 195/500
10/10 0s 2ms/step - loss: 9.1685 - mae: 2.0193
Epoch 196/500
10/10 0s 2ms/step - loss: 9.4882 - mae: 2.0940
Epoch 197/500
10/10 0s 2ms/step - loss: 9.7595 - mae: 2.2450
Epoch 198/500
10/10 0s 2ms/step - loss: 9.4376 - mae: 2.1344
Epoch 199/500
10/10 0s 2ms/step - loss: 9.4817 - mae: 2.0300
Epoch 200/500
10/10 0s 2ms/step - loss: 9.4764 - mae: 2.1004
Epoch 201/500
10/10 0s 2ms/step - loss: 8.1801 - mae: 1.9625
Epoch 202/500
10/10 0s 2ms/step - loss: 8.5892 - mae: 1.9196
Epoch 203/500
10/10 0s 2ms/step - loss: 9.8965 - mae: 2.0705
Epoch 204/500
10/10 0s 2ms/step - loss: 9.9008 - mae: 2.0782
Epoch 205/500
10/10 0s 2ms/step - loss: 9.6559 - mae: 2.1069
Epoch 206/500
10/10 0s 2ms/step - loss: 13.3891 - mae: 2.3166
Epoch 207/500
10/10 0s 2ms/step - loss: 9.1082 - mae: 2.0022
Epoch 208/500
10/10 0s 2ms/step - loss: 9.9871 - mae: 2.0825
Epoch 209/500
10/10 0s 2ms/step - loss: 8.3529 - mae: 1.9391
Epoch 210/500
10/10 0s 2ms/step - loss: 12.1020 - mae: 2.2488
Epoch 211/500
10/10 0s 2ms/step - loss: 9.3521 - mae: 1.9769
Epoch 212/500
10/10 0s 2ms/step - loss: 10.4487 - mae: 2.0370
Epoch 213/500
10/10 0s 2ms/step - loss: 8.5481 - mae: 1.9807
Epoch 214/500
10/10 0s 2ms/step - loss: 8.7472 - mae: 2.0314
Epoch 215/500
10/10 0s 2ms/step - loss: 9.6581 - mae: 2.0228
Epoch 216/500
10/10 0s 2ms/step - loss: 10.5184 - mae: 2.1394
Epoch 217/500
10/10 0s 2ms/step - loss: 9.8058 - mae: 2.0452
Epoch 218/500
10/10 0s 2ms/step - loss: 10.0009 - mae: 2.0898
Epoch 219/500
10/10 0s 2ms/step - loss: 8.0937 - mae: 1.9801
Epoch 220/500
10/10 0s 2ms/step - loss: 8.2267 - mae: 1.9356
Epoch 221/500
10/10 0s 2ms/step - loss: 8.5747 - mae: 1.9111
Epoch 222/500
10/10 0s 2ms/step - loss: 8.4456 - mae: 1.9373
Epoch 223/500
10/10 0s 2ms/step - loss: 10.2775 - mae: 2.0597
Epoch 224/500
10/10 0s 2ms/step - loss: 8.8541 - mae: 1.9812

Epoch 225/500
10/10 0s 2ms/step - loss: 10.2441 - mae: 2.0272
Epoch 226/500
10/10 0s 2ms/step - loss: 8.5037 - mae: 1.9547
Epoch 227/500
10/10 0s 2ms/step - loss: 8.4962 - mae: 1.8930
Epoch 228/500
10/10 0s 2ms/step - loss: 10.2874 - mae: 2.1212
Epoch 229/500
10/10 0s 2ms/step - loss: 7.4717 - mae: 1.8514
Epoch 230/500
10/10 0s 2ms/step - loss: 7.8355 - mae: 1.8915
Epoch 231/500
10/10 0s 2ms/step - loss: 10.3750 - mae: 2.0916
Epoch 232/500
10/10 0s 2ms/step - loss: 8.1490 - mae: 1.8906
Epoch 233/500
10/10 0s 2ms/step - loss: 9.3002 - mae: 1.9579
Epoch 234/500
10/10 0s 2ms/step - loss: 9.7984 - mae: 2.0958
Epoch 235/500
10/10 0s 2ms/step - loss: 8.1692 - mae: 1.9182
Epoch 236/500
10/10 0s 2ms/step - loss: 7.9161 - mae: 1.8850
Epoch 237/500
10/10 0s 2ms/step - loss: 7.0815 - mae: 1.7902
Epoch 238/500
10/10 0s 2ms/step - loss: 8.9475 - mae: 1.8997
Epoch 239/500
10/10 0s 2ms/step - loss: 8.1444 - mae: 1.8783
Epoch 240/500
10/10 0s 2ms/step - loss: 7.5430 - mae: 1.7544
Epoch 241/500
10/10 0s 2ms/step - loss: 9.2055 - mae: 1.9481
Epoch 242/500
10/10 0s 2ms/step - loss: 8.3015 - mae: 1.8329
Epoch 243/500
10/10 0s 2ms/step - loss: 8.6849 - mae: 1.8838
Epoch 244/500
10/10 0s 2ms/step - loss: 8.4790 - mae: 1.8495
Epoch 245/500
10/10 0s 2ms/step - loss: 6.7190 - mae: 1.7190
Epoch 246/500
10/10 0s 2ms/step - loss: 7.8855 - mae: 1.7971
Epoch 247/500
10/10 0s 2ms/step - loss: 7.3038 - mae: 1.8482
Epoch 248/500
10/10 0s 2ms/step - loss: 7.7046 - mae: 1.8109
Epoch 249/500
10/10 0s 2ms/step - loss: 10.4530 - mae: 2.0775
Epoch 250/500
10/10 0s 2ms/step - loss: 7.8558 - mae: 1.8351
Epoch 251/500
10/10 0s 2ms/step - loss: 8.9916 - mae: 1.8844
Epoch 252/500
10/10 0s 2ms/step - loss: 6.4748 - mae: 1.7468
Epoch 253/500
10/10 0s 2ms/step - loss: 7.2290 - mae: 1.7803
Epoch 254/500
10/10 0s 2ms/step - loss: 8.4913 - mae: 1.9282
Epoch 255/500
10/10 0s 2ms/step - loss: 7.8452 - mae: 1.7730
Epoch 256/500
10/10 0s 2ms/step - loss: 10.0628 - mae: 2.0318

Epoch 257/500
10/10 0s 2ms/step - loss: 6.4110 - mae: 1.7346
Epoch 258/500
10/10 0s 2ms/step - loss: 7.6398 - mae: 1.7761
Epoch 259/500
10/10 0s 2ms/step - loss: 8.6387 - mae: 1.8866
Epoch 260/500
10/10 0s 2ms/step - loss: 6.6706 - mae: 1.7465
Epoch 261/500
10/10 0s 2ms/step - loss: 6.8878 - mae: 1.7770
Epoch 262/500
10/10 0s 2ms/step - loss: 6.0254 - mae: 1.6201
Epoch 263/500
10/10 0s 2ms/step - loss: 6.8832 - mae: 1.7164
Epoch 264/500
10/10 0s 2ms/step - loss: 6.2701 - mae: 1.6343
Epoch 265/500
10/10 0s 2ms/step - loss: 6.8577 - mae: 1.6951
Epoch 266/500
10/10 0s 2ms/step - loss: 6.3830 - mae: 1.6601
Epoch 267/500
10/10 0s 2ms/step - loss: 7.4352 - mae: 1.8036
Epoch 268/500
10/10 0s 2ms/step - loss: 5.6837 - mae: 1.5982
Epoch 269/500
10/10 0s 2ms/step - loss: 7.6979 - mae: 1.8353
Epoch 270/500
10/10 0s 2ms/step - loss: 7.5122 - mae: 1.8066
Epoch 271/500
10/10 0s 2ms/step - loss: 8.5986 - mae: 1.9211
Epoch 272/500
10/10 0s 2ms/step - loss: 6.8995 - mae: 1.6526
Epoch 273/500
10/10 0s 2ms/step - loss: 5.9973 - mae: 1.6490
Epoch 274/500
10/10 0s 2ms/step - loss: 7.4369 - mae: 1.8217
Epoch 275/500
10/10 0s 2ms/step - loss: 6.9303 - mae: 1.7830
Epoch 276/500
10/10 0s 2ms/step - loss: 5.5646 - mae: 1.5765
Epoch 277/500
10/10 0s 2ms/step - loss: 7.2120 - mae: 1.7956
Epoch 278/500
10/10 0s 2ms/step - loss: 6.3433 - mae: 1.6544
Epoch 279/500
10/10 0s 2ms/step - loss: 6.2514 - mae: 1.7489
Epoch 280/500
10/10 0s 2ms/step - loss: 5.5568 - mae: 1.5493
Epoch 281/500
10/10 0s 2ms/step - loss: 7.0587 - mae: 1.7983
Epoch 282/500
10/10 0s 2ms/step - loss: 6.0866 - mae: 1.6224
Epoch 283/500
10/10 0s 2ms/step - loss: 6.4047 - mae: 1.6550
Epoch 284/500
10/10 0s 2ms/step - loss: 5.4559 - mae: 1.5546
Epoch 285/500
10/10 0s 2ms/step - loss: 7.5079 - mae: 1.7009
Epoch 286/500
10/10 0s 2ms/step - loss: 6.3476 - mae: 1.6061
Epoch 287/500
10/10 0s 2ms/step - loss: 7.7504 - mae: 1.7274
Epoch 288/500
10/10 0s 2ms/step - loss: 5.5816 - mae: 1.5574

Epoch 289/500
10/10 0s 2ms/step - loss: 4.9951 - mae: 1.4785
Epoch 290/500
10/10 0s 2ms/step - loss: 7.1414 - mae: 1.7702
Epoch 291/500
10/10 0s 2ms/step - loss: 6.3082 - mae: 1.6775
Epoch 292/500
10/10 0s 2ms/step - loss: 6.0973 - mae: 1.6481
Epoch 293/500
10/10 0s 2ms/step - loss: 6.4175 - mae: 1.6994
Epoch 294/500
10/10 0s 2ms/step - loss: 5.1808 - mae: 1.5151
Epoch 295/500
10/10 0s 2ms/step - loss: 7.1450 - mae: 1.6905
Epoch 296/500
10/10 0s 2ms/step - loss: 6.5129 - mae: 1.6516
Epoch 297/500
10/10 0s 2ms/step - loss: 5.2998 - mae: 1.5275
Epoch 298/500
10/10 0s 2ms/step - loss: 5.7479 - mae: 1.6161
Epoch 299/500
10/10 0s 2ms/step - loss: 7.9996 - mae: 1.7880
Epoch 300/500
10/10 0s 2ms/step - loss: 7.3400 - mae: 1.7190
Epoch 301/500
10/10 0s 2ms/step - loss: 5.9777 - mae: 1.5937
Epoch 302/500
10/10 0s 2ms/step - loss: 5.6385 - mae: 1.5787
Epoch 303/500
10/10 0s 2ms/step - loss: 5.9573 - mae: 1.5735
Epoch 304/500
10/10 0s 2ms/step - loss: 6.2948 - mae: 1.6373
Epoch 305/500
10/10 0s 2ms/step - loss: 7.1615 - mae: 1.6629
Epoch 306/500
10/10 0s 2ms/step - loss: 5.7874 - mae: 1.5453
Epoch 307/500
10/10 0s 2ms/step - loss: 5.8065 - mae: 1.5868
Epoch 308/500
10/10 0s 2ms/step - loss: 6.2587 - mae: 1.6026
Epoch 309/500
10/10 0s 2ms/step - loss: 5.9954 - mae: 1.5823
Epoch 310/500
10/10 0s 2ms/step - loss: 5.6083 - mae: 1.5630
Epoch 311/500
10/10 0s 2ms/step - loss: 5.7552 - mae: 1.5777
Epoch 312/500
10/10 0s 2ms/step - loss: 6.4293 - mae: 1.6808
Epoch 313/500
10/10 0s 2ms/step - loss: 5.5544 - mae: 1.5292
Epoch 314/500
10/10 0s 2ms/step - loss: 6.4557 - mae: 1.6062
Epoch 315/500
10/10 0s 2ms/step - loss: 6.9868 - mae: 1.6614
Epoch 316/500
10/10 0s 2ms/step - loss: 6.8995 - mae: 1.6366
Epoch 317/500
10/10 0s 2ms/step - loss: 6.6834 - mae: 1.7046
Epoch 318/500
10/10 0s 2ms/step - loss: 5.1383 - mae: 1.4794
Epoch 319/500
10/10 0s 2ms/step - loss: 7.2462 - mae: 1.7361
Epoch 320/500
10/10 0s 2ms/step - loss: 5.3038 - mae: 1.5985

Epoch 321/500
10/10 0s 2ms/step - loss: 5.3879 - mae: 1.6180
Epoch 322/500
10/10 0s 2ms/step - loss: 4.8458 - mae: 1.4285
Epoch 323/500
10/10 0s 2ms/step - loss: 5.5357 - mae: 1.5509
Epoch 324/500
10/10 0s 2ms/step - loss: 5.1007 - mae: 1.4541
Epoch 325/500
10/10 0s 2ms/step - loss: 6.1960 - mae: 1.6208
Epoch 326/500
10/10 0s 2ms/step - loss: 5.4680 - mae: 1.6208
Epoch 327/500
10/10 0s 2ms/step - loss: 6.2393 - mae: 1.5900
Epoch 328/500
10/10 0s 2ms/step - loss: 6.6625 - mae: 1.6448
Epoch 329/500
10/10 0s 2ms/step - loss: 5.1893 - mae: 1.4869
Epoch 330/500
10/10 0s 2ms/step - loss: 6.4496 - mae: 1.6037
Epoch 331/500
10/10 0s 2ms/step - loss: 5.5337 - mae: 1.5596
Epoch 332/500
10/10 0s 2ms/step - loss: 4.7843 - mae: 1.4812
Epoch 333/500
10/10 0s 2ms/step - loss: 4.4153 - mae: 1.4262
Epoch 334/500
10/10 0s 2ms/step - loss: 5.5445 - mae: 1.5814
Epoch 335/500
10/10 0s 2ms/step - loss: 4.8357 - mae: 1.4996
Epoch 336/500
10/10 0s 2ms/step - loss: 4.6801 - mae: 1.4415
Epoch 337/500
10/10 0s 2ms/step - loss: 5.1378 - mae: 1.4871
Epoch 338/500
10/10 0s 2ms/step - loss: 4.6847 - mae: 1.4104
Epoch 339/500
10/10 0s 2ms/step - loss: 5.9131 - mae: 1.5580
Epoch 340/500
10/10 0s 2ms/step - loss: 4.9565 - mae: 1.4353
Epoch 341/500
10/10 0s 2ms/step - loss: 5.8498 - mae: 1.5372
Epoch 342/500
10/10 0s 2ms/step - loss: 4.0900 - mae: 1.3510
Epoch 343/500
10/10 0s 2ms/step - loss: 4.1917 - mae: 1.3814
Epoch 344/500
10/10 0s 2ms/step - loss: 6.5951 - mae: 1.6742
Epoch 345/500
10/10 0s 2ms/step - loss: 5.3282 - mae: 1.5771
Epoch 346/500
10/10 0s 2ms/step - loss: 5.1270 - mae: 1.5676
Epoch 347/500
10/10 0s 2ms/step - loss: 4.8063 - mae: 1.4751
Epoch 348/500
10/10 0s 2ms/step - loss: 5.1419 - mae: 1.4780
Epoch 349/500
10/10 0s 2ms/step - loss: 4.6075 - mae: 1.4363
Epoch 350/500
10/10 0s 2ms/step - loss: 5.9445 - mae: 1.6153
Epoch 351/500
10/10 0s 2ms/step - loss: 4.9041 - mae: 1.4446
Epoch 352/500
10/10 0s 2ms/step - loss: 4.3984 - mae: 1.4507

Epoch 353/500
10/10 0s 2ms/step - loss: 4.5721 - mae: 1.3950
Epoch 354/500
10/10 0s 2ms/step - loss: 5.5171 - mae: 1.4611
Epoch 355/500
10/10 0s 2ms/step - loss: 4.4113 - mae: 1.4118
Epoch 356/500
10/10 0s 2ms/step - loss: 4.3245 - mae: 1.4215
Epoch 357/500
10/10 0s 2ms/step - loss: 4.5887 - mae: 1.4132
Epoch 358/500
10/10 0s 2ms/step - loss: 4.3381 - mae: 1.3816
Epoch 359/500
10/10 0s 2ms/step - loss: 5.0401 - mae: 1.4428
Epoch 360/500
10/10 0s 2ms/step - loss: 4.0631 - mae: 1.3788
Epoch 361/500
10/10 0s 2ms/step - loss: 3.8212 - mae: 1.3277
Epoch 362/500
10/10 0s 2ms/step - loss: 4.0555 - mae: 1.3261
Epoch 363/500
10/10 0s 2ms/step - loss: 5.5322 - mae: 1.5030
Epoch 364/500
10/10 0s 2ms/step - loss: 4.6724 - mae: 1.4122
Epoch 365/500
10/10 0s 2ms/step - loss: 3.6798 - mae: 1.2705
Epoch 366/500
10/10 0s 2ms/step - loss: 4.4965 - mae: 1.4465
Epoch 367/500
10/10 0s 2ms/step - loss: 4.9848 - mae: 1.5121
Epoch 368/500
10/10 0s 2ms/step - loss: 4.3719 - mae: 1.3907
Epoch 369/500
10/10 0s 2ms/step - loss: 5.2816 - mae: 1.5213
Epoch 370/500
10/10 0s 2ms/step - loss: 4.9949 - mae: 1.4026
Epoch 371/500
10/10 0s 2ms/step - loss: 3.9851 - mae: 1.3146
Epoch 372/500
10/10 0s 2ms/step - loss: 4.3247 - mae: 1.3346
Epoch 373/500
10/10 0s 2ms/step - loss: 4.9048 - mae: 1.4235
Epoch 374/500
10/10 0s 2ms/step - loss: 4.6048 - mae: 1.3795
Epoch 375/500
10/10 0s 2ms/step - loss: 4.4579 - mae: 1.3860
Epoch 376/500
10/10 0s 2ms/step - loss: 4.8634 - mae: 1.4452
Epoch 377/500
10/10 0s 2ms/step - loss: 4.1517 - mae: 1.3574
Epoch 378/500
10/10 0s 2ms/step - loss: 4.2342 - mae: 1.3538
Epoch 379/500
10/10 0s 2ms/step - loss: 3.6875 - mae: 1.2499
Epoch 380/500
10/10 0s 2ms/step - loss: 4.7139 - mae: 1.4557
Epoch 381/500
10/10 0s 2ms/step - loss: 4.2517 - mae: 1.3641
Epoch 382/500
10/10 0s 2ms/step - loss: 3.7263 - mae: 1.3114
Epoch 383/500
10/10 0s 2ms/step - loss: 3.9610 - mae: 1.3465
Epoch 384/500
10/10 0s 2ms/step - loss: 4.2614 - mae: 1.3837

Epoch 385/500
10/10 0s 2ms/step - loss: 3.6555 - mae: 1.3245
Epoch 386/500
10/10 0s 2ms/step - loss: 3.5731 - mae: 1.2716
Epoch 387/500
10/10 0s 2ms/step - loss: 3.6035 - mae: 1.2559
Epoch 388/500
10/10 0s 2ms/step - loss: 3.9466 - mae: 1.3130
Epoch 389/500
10/10 0s 2ms/step - loss: 3.7162 - mae: 1.3086
Epoch 390/500
10/10 0s 2ms/step - loss: 4.2872 - mae: 1.3825
Epoch 391/500
10/10 0s 2ms/step - loss: 3.8216 - mae: 1.3094
Epoch 392/500
10/10 0s 2ms/step - loss: 4.0992 - mae: 1.3243
Epoch 393/500
10/10 0s 2ms/step - loss: 4.1449 - mae: 1.3785
Epoch 394/500
10/10 0s 2ms/step - loss: 3.4618 - mae: 1.2883
Epoch 395/500
10/10 0s 2ms/step - loss: 4.2395 - mae: 1.3246
Epoch 396/500
10/10 0s 2ms/step - loss: 5.0993 - mae: 1.4730
Epoch 397/500
10/10 0s 2ms/step - loss: 3.6924 - mae: 1.3545
Epoch 398/500
10/10 0s 2ms/step - loss: 3.3691 - mae: 1.2995
Epoch 399/500
10/10 0s 2ms/step - loss: 4.3088 - mae: 1.4101
Epoch 400/500
10/10 0s 2ms/step - loss: 4.3511 - mae: 1.3670
Epoch 401/500
10/10 0s 2ms/step - loss: 3.0112 - mae: 1.1808
Epoch 402/500
10/10 0s 2ms/step - loss: 3.9660 - mae: 1.3799
Epoch 403/500
10/10 0s 2ms/step - loss: 4.3204 - mae: 1.3924
Epoch 404/500
10/10 0s 2ms/step - loss: 4.7151 - mae: 1.4387
Epoch 405/500
10/10 0s 2ms/step - loss: 3.5842 - mae: 1.3089
Epoch 406/500
10/10 0s 2ms/step - loss: 3.5408 - mae: 1.2232
Epoch 407/500
10/10 0s 2ms/step - loss: 3.8837 - mae: 1.3776
Epoch 408/500
10/10 0s 2ms/step - loss: 3.3237 - mae: 1.2180
Epoch 409/500
10/10 0s 2ms/step - loss: 3.5438 - mae: 1.2280
Epoch 410/500
10/10 0s 2ms/step - loss: 3.4568 - mae: 1.2425
Epoch 411/500
10/10 0s 2ms/step - loss: 3.1387 - mae: 1.2141
Epoch 412/500
10/10 0s 2ms/step - loss: 3.5948 - mae: 1.2478
Epoch 413/500
10/10 0s 2ms/step - loss: 3.7701 - mae: 1.2903
Epoch 414/500
10/10 0s 2ms/step - loss: 3.5363 - mae: 1.2619
Epoch 415/500
10/10 0s 2ms/step - loss: 4.4231 - mae: 1.3960
Epoch 416/500
10/10 0s 2ms/step - loss: 3.7197 - mae: 1.2733

Epoch 417/500
10/10 0s 2ms/step - loss: 3.5718 - mae: 1.2698
Epoch 418/500
10/10 0s 2ms/step - loss: 4.0565 - mae: 1.3469
Epoch 419/500
10/10 0s 2ms/step - loss: 3.8988 - mae: 1.3756
Epoch 420/500
10/10 0s 2ms/step - loss: 3.3467 - mae: 1.2158
Epoch 421/500
10/10 0s 2ms/step - loss: 3.0864 - mae: 1.1702
Epoch 422/500
10/10 0s 2ms/step - loss: 3.5471 - mae: 1.2711
Epoch 423/500
10/10 0s 2ms/step - loss: 3.3762 - mae: 1.2385
Epoch 424/500
10/10 0s 2ms/step - loss: 2.9435 - mae: 1.1619
Epoch 425/500
10/10 0s 2ms/step - loss: 3.5551 - mae: 1.2723
Epoch 426/500
10/10 0s 2ms/step - loss: 3.3297 - mae: 1.2077
Epoch 427/500
10/10 0s 2ms/step - loss: 3.4316 - mae: 1.2040
Epoch 428/500
10/10 0s 2ms/step - loss: 3.5978 - mae: 1.2283
Epoch 429/500
10/10 0s 2ms/step - loss: 4.0620 - mae: 1.3176
Epoch 430/500
10/10 0s 2ms/step - loss: 3.6120 - mae: 1.2527
Epoch 431/500
10/10 0s 2ms/step - loss: 2.9489 - mae: 1.1274
Epoch 432/500
10/10 0s 2ms/step - loss: 3.0323 - mae: 1.1358
Epoch 433/500
10/10 0s 2ms/step - loss: 3.6807 - mae: 1.2623
Epoch 434/500
10/10 0s 2ms/step - loss: 3.3513 - mae: 1.2409
Epoch 435/500
10/10 0s 2ms/step - loss: 3.1069 - mae: 1.1686
Epoch 436/500
10/10 0s 2ms/step - loss: 3.4444 - mae: 1.2657
Epoch 437/500
10/10 0s 2ms/step - loss: 3.4500 - mae: 1.2091
Epoch 438/500
10/10 0s 2ms/step - loss: 3.4079 - mae: 1.2678
Epoch 439/500
10/10 0s 2ms/step - loss: 3.7399 - mae: 1.3023
Epoch 440/500
10/10 0s 2ms/step - loss: 3.0229 - mae: 1.1778
Epoch 441/500
10/10 0s 2ms/step - loss: 3.3274 - mae: 1.3039
Epoch 442/500
10/10 0s 2ms/step - loss: 4.2591 - mae: 1.4310
Epoch 443/500
10/10 0s 2ms/step - loss: 2.9415 - mae: 1.1745
Epoch 444/500
10/10 0s 2ms/step - loss: 3.1815 - mae: 1.1642
Epoch 445/500
10/10 0s 2ms/step - loss: 3.4405 - mae: 1.2523
Epoch 446/500
10/10 0s 2ms/step - loss: 3.2674 - mae: 1.2074
Epoch 447/500
10/10 0s 2ms/step - loss: 3.3782 - mae: 1.2488
Epoch 448/500
10/10 0s 2ms/step - loss: 3.4201 - mae: 1.2361

Epoch 449/500
10/10 0s 2ms/step - loss: 3.2412 - mae: 1.1798
Epoch 450/500
10/10 0s 2ms/step - loss: 3.4753 - mae: 1.2491
Epoch 451/500
10/10 0s 2ms/step - loss: 3.1766 - mae: 1.2141
Epoch 452/500
10/10 0s 2ms/step - loss: 2.6090 - mae: 1.1063
Epoch 453/500
10/10 0s 2ms/step - loss: 3.6247 - mae: 1.2676
Epoch 454/500
10/10 0s 2ms/step - loss: 3.0500 - mae: 1.1991
Epoch 455/500
10/10 0s 2ms/step - loss: 3.2092 - mae: 1.2090
Epoch 456/500
10/10 0s 2ms/step - loss: 2.9525 - mae: 1.1511
Epoch 457/500
10/10 0s 2ms/step - loss: 2.8282 - mae: 1.1367
Epoch 458/500
10/10 0s 2ms/step - loss: 3.4477 - mae: 1.2370
Epoch 459/500
10/10 0s 2ms/step - loss: 3.1320 - mae: 1.1776
Epoch 460/500
10/10 0s 2ms/step - loss: 2.7906 - mae: 1.1366
Epoch 461/500
10/10 0s 2ms/step - loss: 3.3138 - mae: 1.1546
Epoch 462/500
10/10 0s 2ms/step - loss: 2.8742 - mae: 1.1510
Epoch 463/500
10/10 0s 2ms/step - loss: 3.8489 - mae: 1.3753
Epoch 464/500
10/10 0s 2ms/step - loss: 3.9239 - mae: 1.3710
Epoch 465/500
10/10 0s 2ms/step - loss: 3.8718 - mae: 1.2453
Epoch 466/500
10/10 0s 2ms/step - loss: 3.0790 - mae: 1.2103
Epoch 467/500
10/10 0s 2ms/step - loss: 3.1677 - mae: 1.2274
Epoch 468/500
10/10 0s 2ms/step - loss: 2.8808 - mae: 1.1586
Epoch 469/500
10/10 0s 2ms/step - loss: 3.0288 - mae: 1.2021
Epoch 470/500
10/10 0s 2ms/step - loss: 3.3804 - mae: 1.2241
Epoch 471/500
10/10 0s 2ms/step - loss: 2.9097 - mae: 1.1423
Epoch 472/500
10/10 0s 2ms/step - loss: 2.9170 - mae: 1.1410
Epoch 473/500
10/10 0s 2ms/step - loss: 3.1063 - mae: 1.1809
Epoch 474/500
10/10 0s 2ms/step - loss: 3.2666 - mae: 1.1760
Epoch 475/500
10/10 0s 2ms/step - loss: 2.6668 - mae: 1.0715
Epoch 476/500
10/10 0s 2ms/step - loss: 2.6267 - mae: 1.0357
Epoch 477/500
10/10 0s 2ms/step - loss: 2.4852 - mae: 1.0771
Epoch 478/500
10/10 0s 2ms/step - loss: 3.0723 - mae: 1.1679
Epoch 479/500
10/10 0s 2ms/step - loss: 3.3036 - mae: 1.1940
Epoch 480/500
10/10 0s 2ms/step - loss: 3.2356 - mae: 1.1699

```
Epoch 481/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.4397 - mae: 1.0586
Epoch 482/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.7236 - mae: 1.0969
Epoch 483/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 3.6191 - mae: 1.1835
Epoch 484/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.7650 - mae: 1.1274
Epoch 485/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.5562 - mae: 1.1299
Epoch 486/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 3.3966 - mae: 1.2353
Epoch 487/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.7169 - mae: 1.1179
Epoch 488/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 3.0049 - mae: 1.1680
Epoch 489/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.7635 - mae: 1.1568
Epoch 490/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 3.4976 - mae: 1.2230
Epoch 491/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.8286 - mae: 1.1429
Epoch 492/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.9666 - mae: 1.1641
Epoch 493/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.9247 - mae: 1.1599
Epoch 494/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 3.0517 - mae: 1.1892
Epoch 495/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.8571 - mae: 1.1246
Epoch 496/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.7137 - mae: 1.0738
Epoch 497/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.6394 - mae: 1.0976
Epoch 498/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.5173 - mae: 1.0678
Epoch 499/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.4467 - mae: 1.0275
Epoch 500/500
10/10 ━━━━━━━━ 0s 2ms/step - loss: 2.7683 - mae: 1.1479
```

Model evaluation:

Loss (MSE): 2.60, MAE: 1.06

```
In [53]: models = {
    "Linear Regression": LinearRegression(),
    "Lasso": Lasso(),
    "K-Neighbors Regressor": KNeighborsRegressor(),
    "Decision Tree": DecisionTreeRegressor(),
    "Random Forest Regressor": RandomForestRegressor(),
    "Gradient Boosting": GradientBoostingRegressor(),
    "XGBRegressor": XGBRegressor(),
    "CatBoosting Regressor": CatBoostRegressor(verbose=0, iterations = 100),
    "AdaBoost Regressor": AdaBoostRegressor(),
    "ExtraTreesRegressor": ExtraTreesRegressor(),
    "Support Vector Regressor(RBF)": SVR(kernel="rbf"),
    "Support Vector Regressor(linear)": SVR(kernel="linear"),
    "Nu SVR(rbf)": NuSVR(kernel="rbf"),
    "ANN": ANN_model
}
```

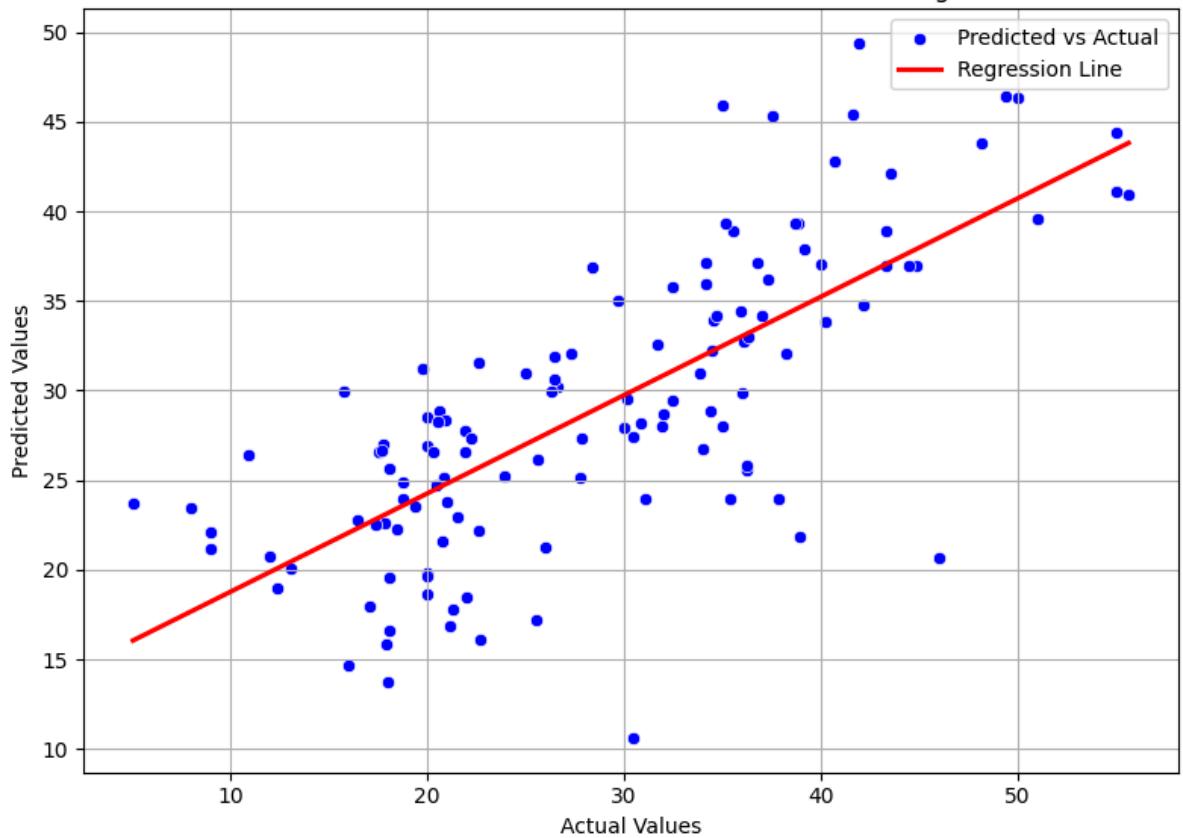
```
In [54]: def safe_flatten(y_pred):
    """
    Flattens the array if it's a 2D array with shape (n, 1).
    """
```

```
    Useful for ANN predictions.  
    """  
    if isinstance(y_pred, (np.ndarray, list)) and len(np.shape(y_pred)) == 2 and y_  
        return y_pred.flatten()  
    return y_pred
```

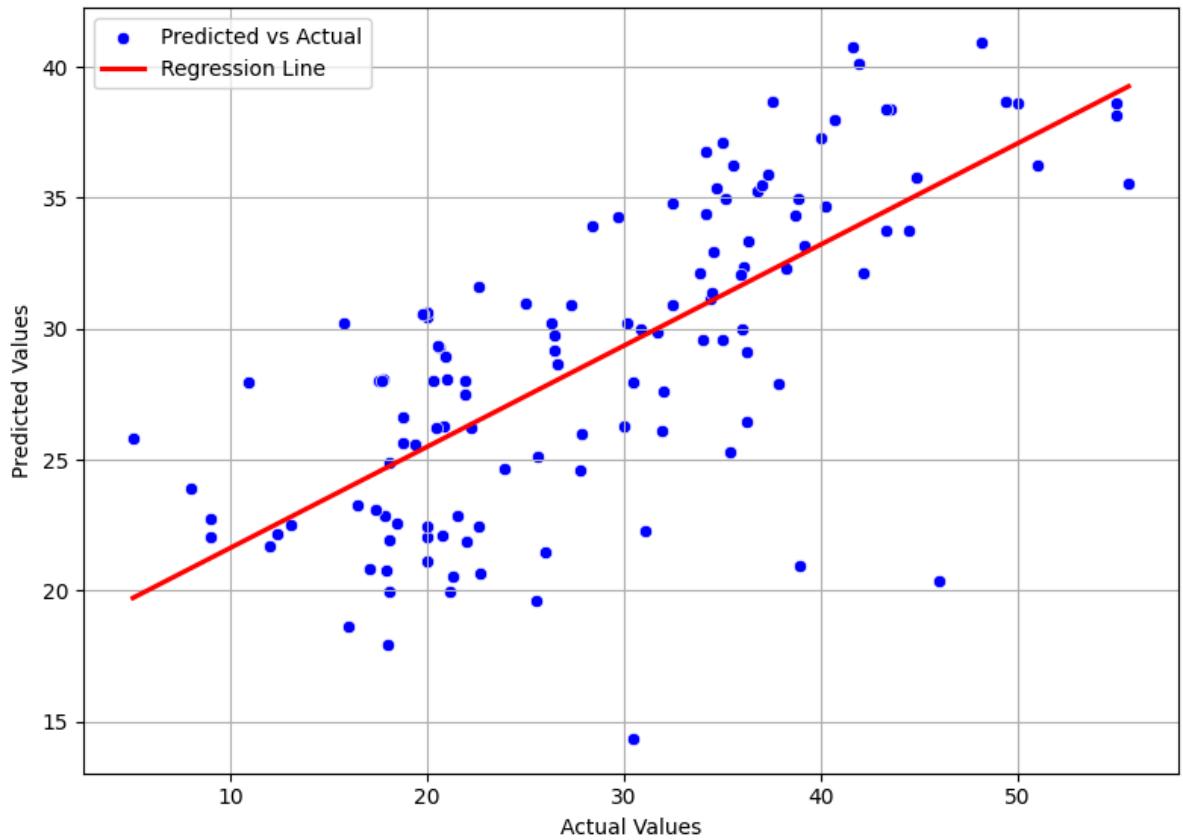
```
In [55]: r2_train_score = {}  
r2_test_score = {}  
def evaluate_model(models, X_train, y_train, X_val, y_val):  
    for model_name, model in models.items():  
        model.fit(X_train, y_train)  
  
        y_train_pred = model.predict(X_train)  
        y_test_pred = model.predict(X_val)  
  
        y = y_val  
        y_pred = safe_flatten(y_test_pred)  
  
        plt.figure(figsize=(8, 6))  
        r2 = r2_score(y, y_pred)  
  
        sns.scatterplot(x=y, y=y_pred, label='Predicted vs Actual', color='blue')  
        sns.regplot(x=y, y=y_pred, scatter=False, label='Regression Line', color='red')  
  
        plt.xlabel('Actual Values')  
        plt.ylabel('Predicted Values')  
        plt.title(f'CO2 Actual vs Predicted Values (R2 Score: {r2:.4f}) for {model_name}')  
        plt.legend()  
        plt.grid(True)  
        plt.tight_layout()  
        plt.savefig(f'CO2 Actual vs Predicted Values (R2 Score: {r2:.4f}) for {model_name}.png')  
        plt.show()  
  
    r2_train_score[model_name] = r2_score(y_train, y_train_pred)  
    r2_test_score[model_name] = r2_score(y_val, y_test_pred)
```

```
In [56]: evaluate_model(models, X_train_scaled, y_train.CO2, X_val_scaled, y_val.CO2)
```

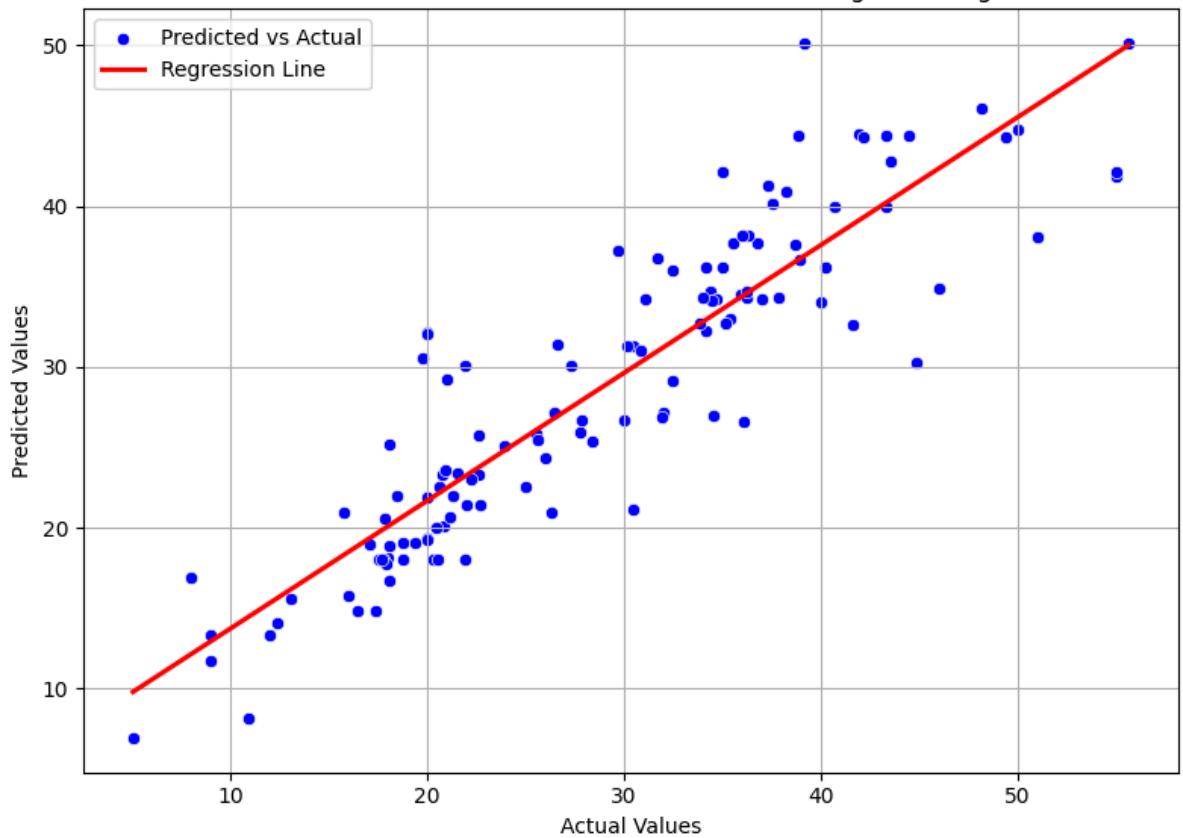
CO2 Actual vs Predicted Values (R^2 Score: 0.5424) for Linear Regression model



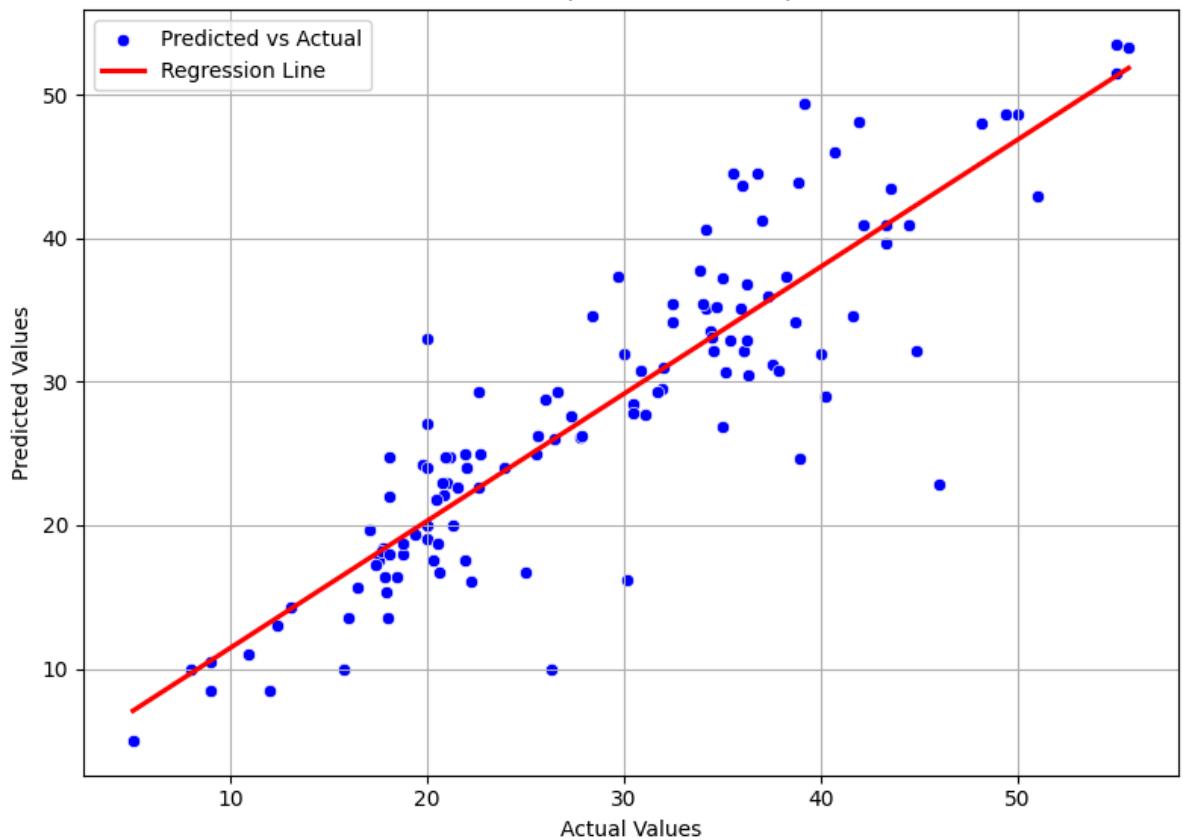
CO2 Actual vs Predicted Values (R^2 Score: 0.4774) for Lasso model



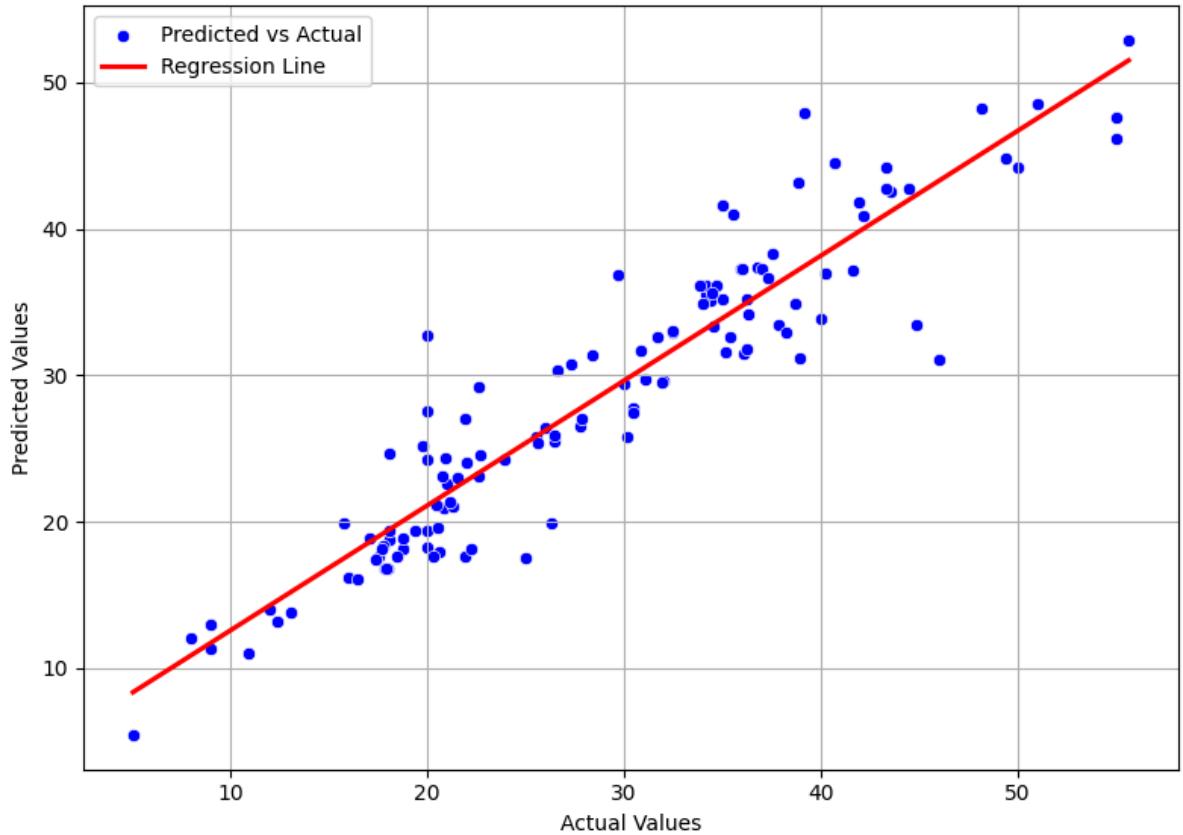
CO2 Actual vs Predicted Values (R^2 Score: 0.8124) for K-Neighbors Regressor model



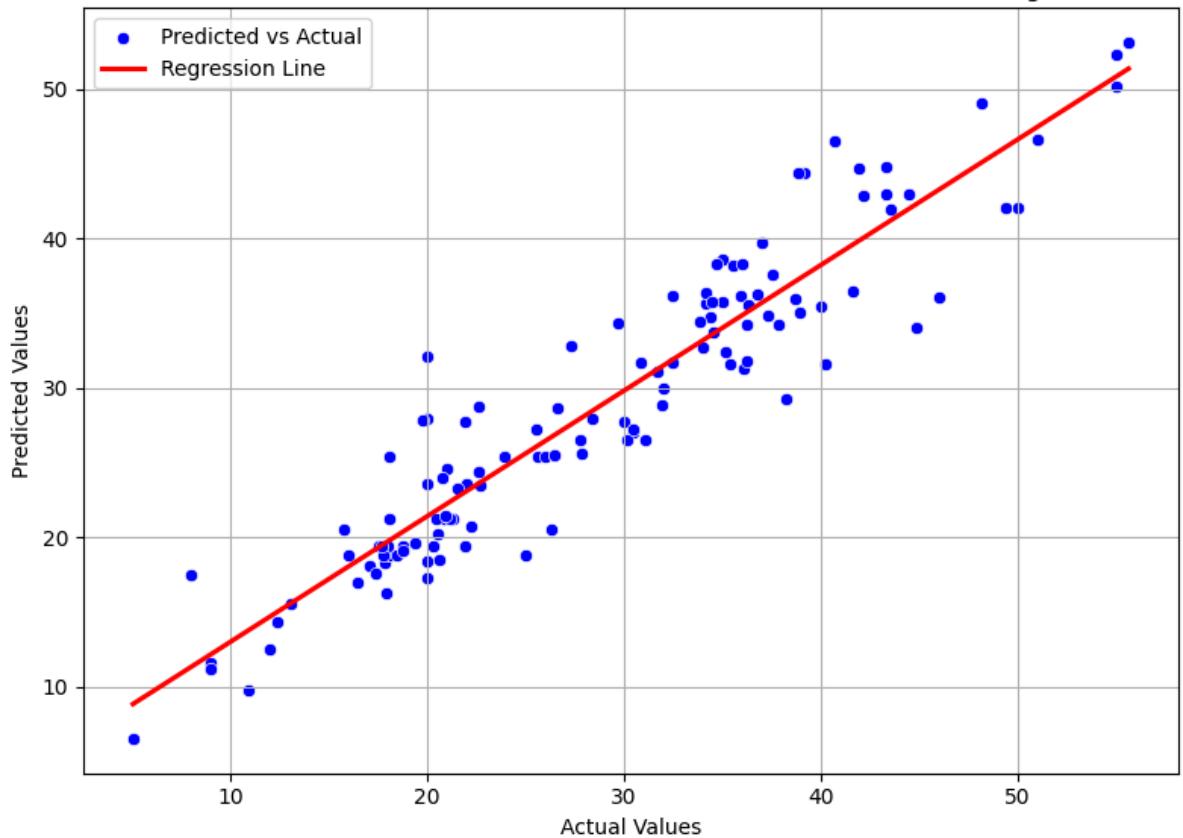
CO2 Actual vs Predicted Values (R^2 Score: 0.7719) for Decision Tree model



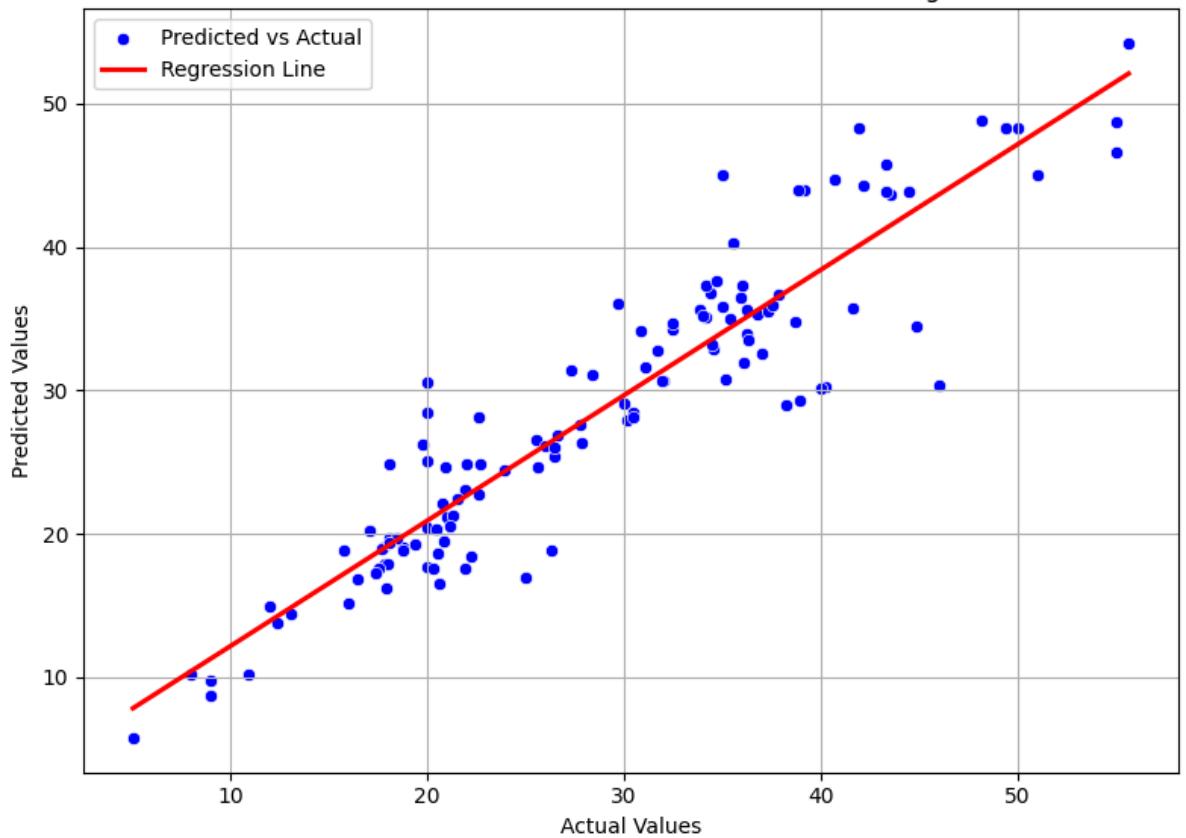
CO2 Actual vs Predicted Values (R^2 Score: 0.8769) for Random Forest Regressor model



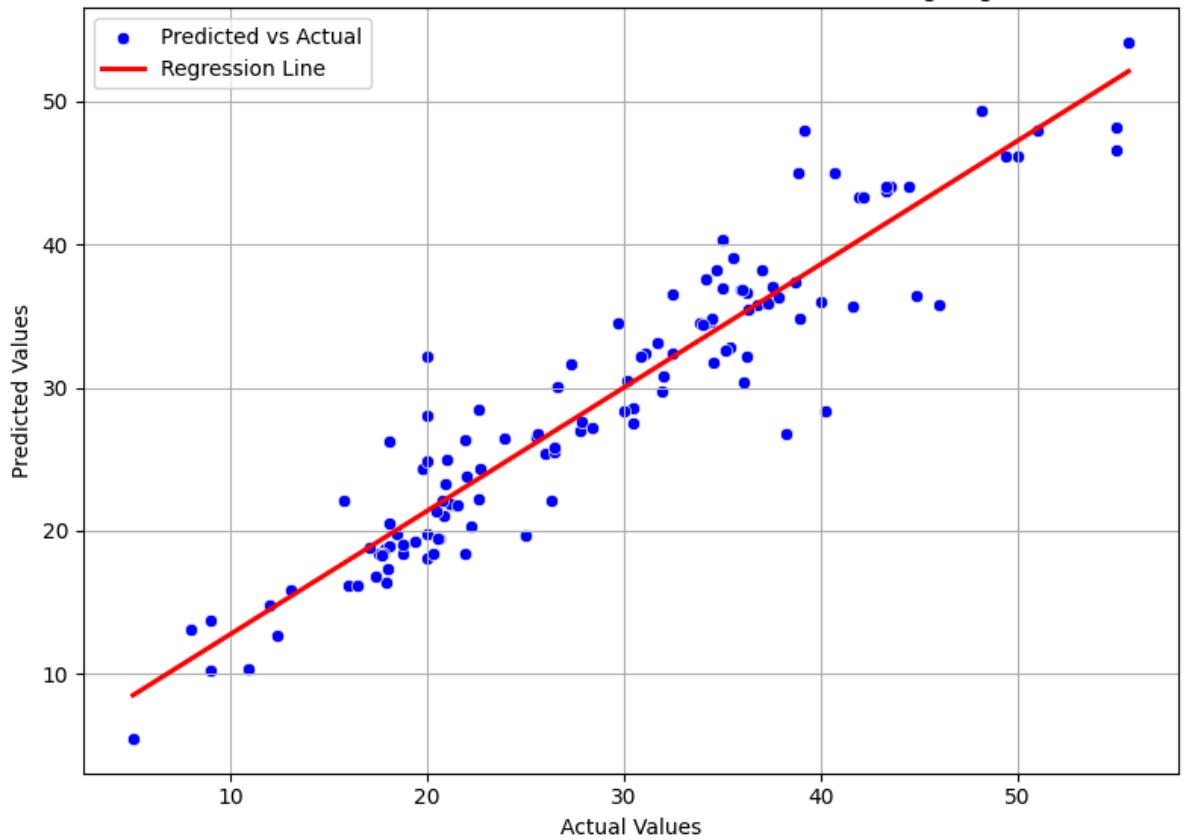
CO2 Actual vs Predicted Values (R^2 Score: 0.8804) for Gradient Boosting model



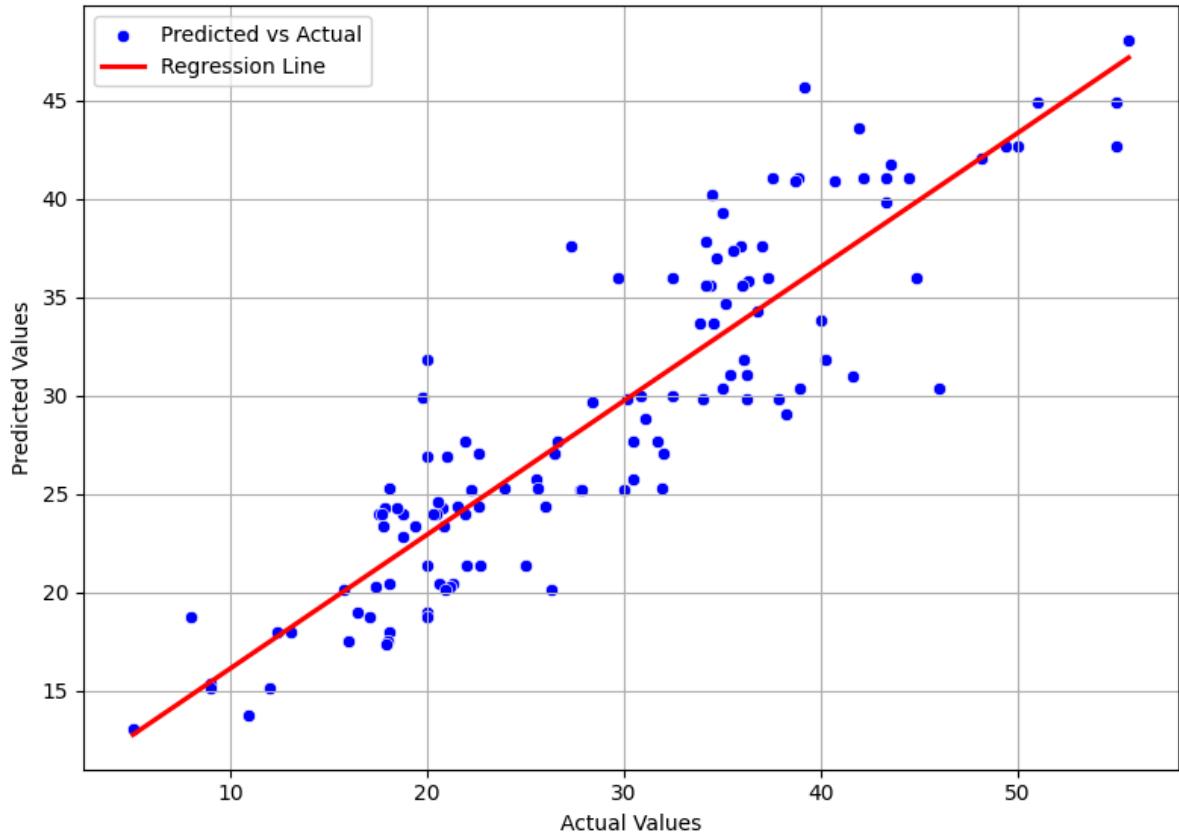
CO2 Actual vs Predicted Values (R^2 Score: 0.8631) for XGBRegressor model



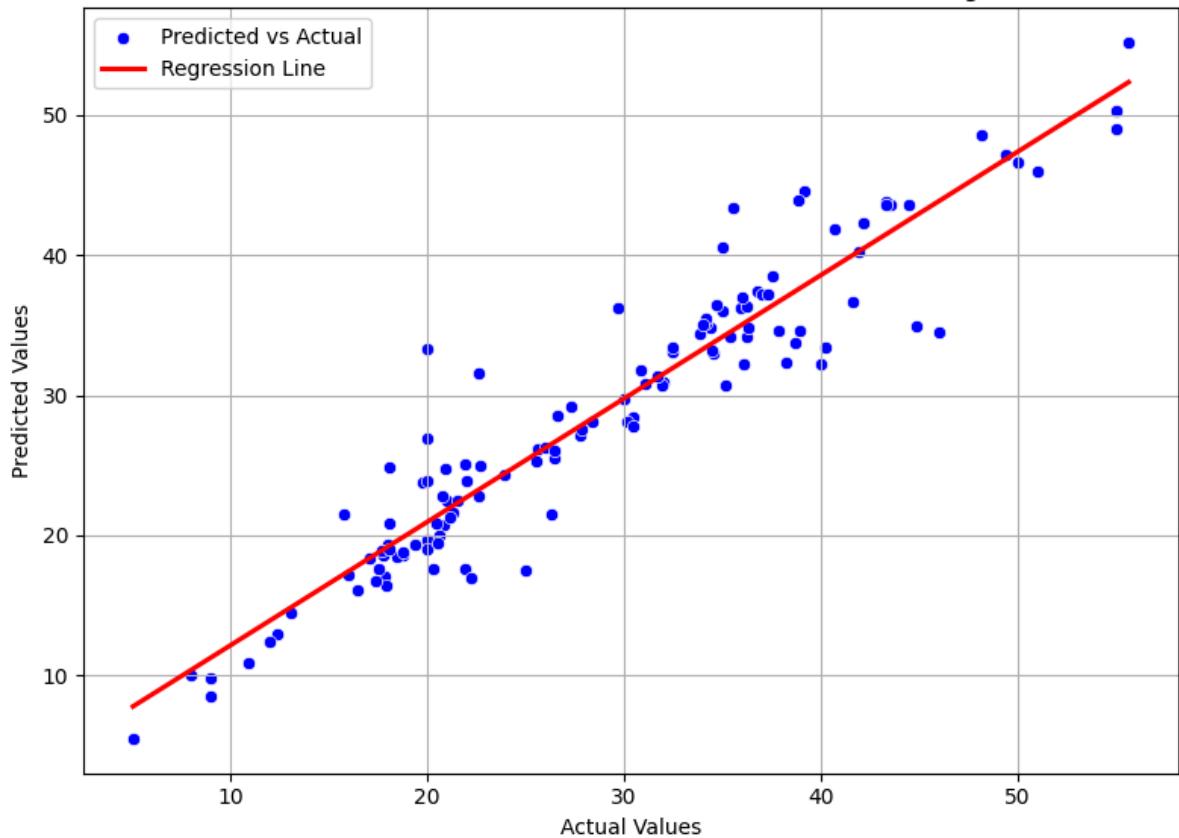
CO2 Actual vs Predicted Values (R^2 Score: 0.8853) for CatBoosting Regressor model

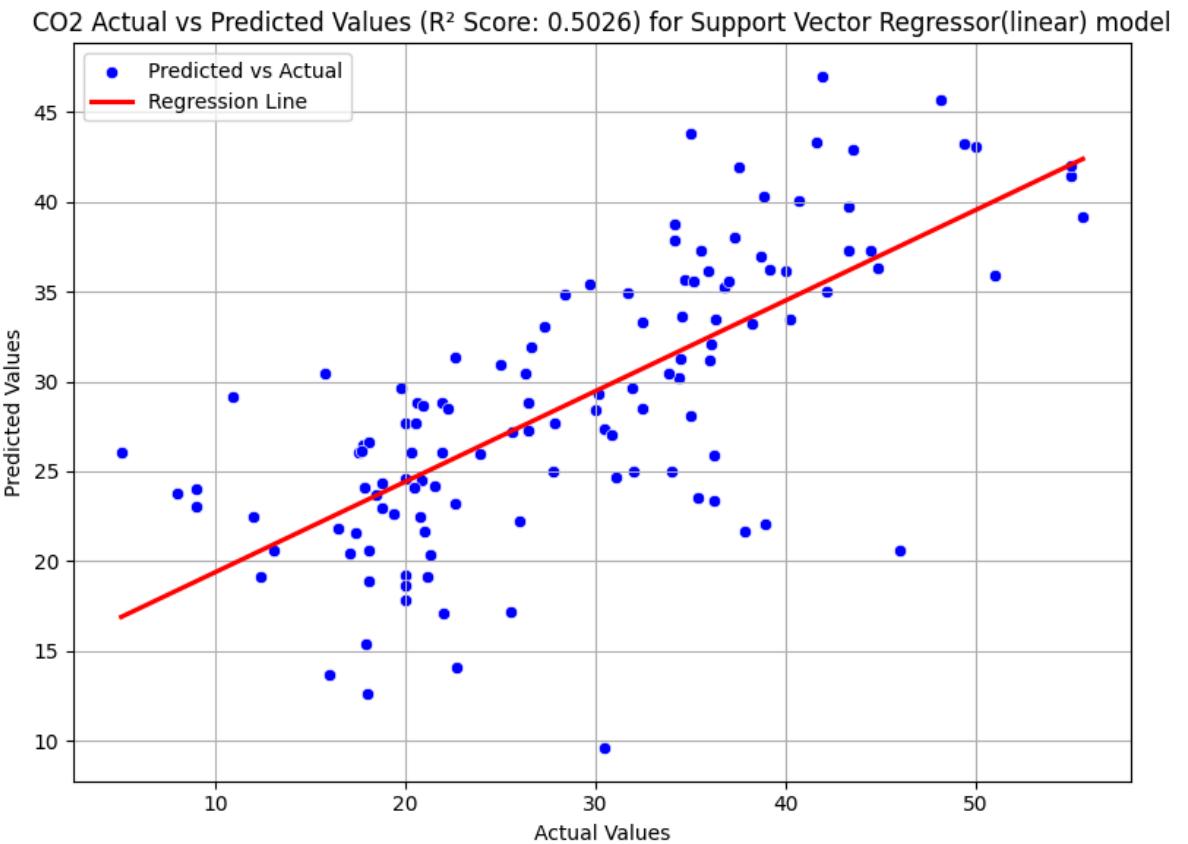
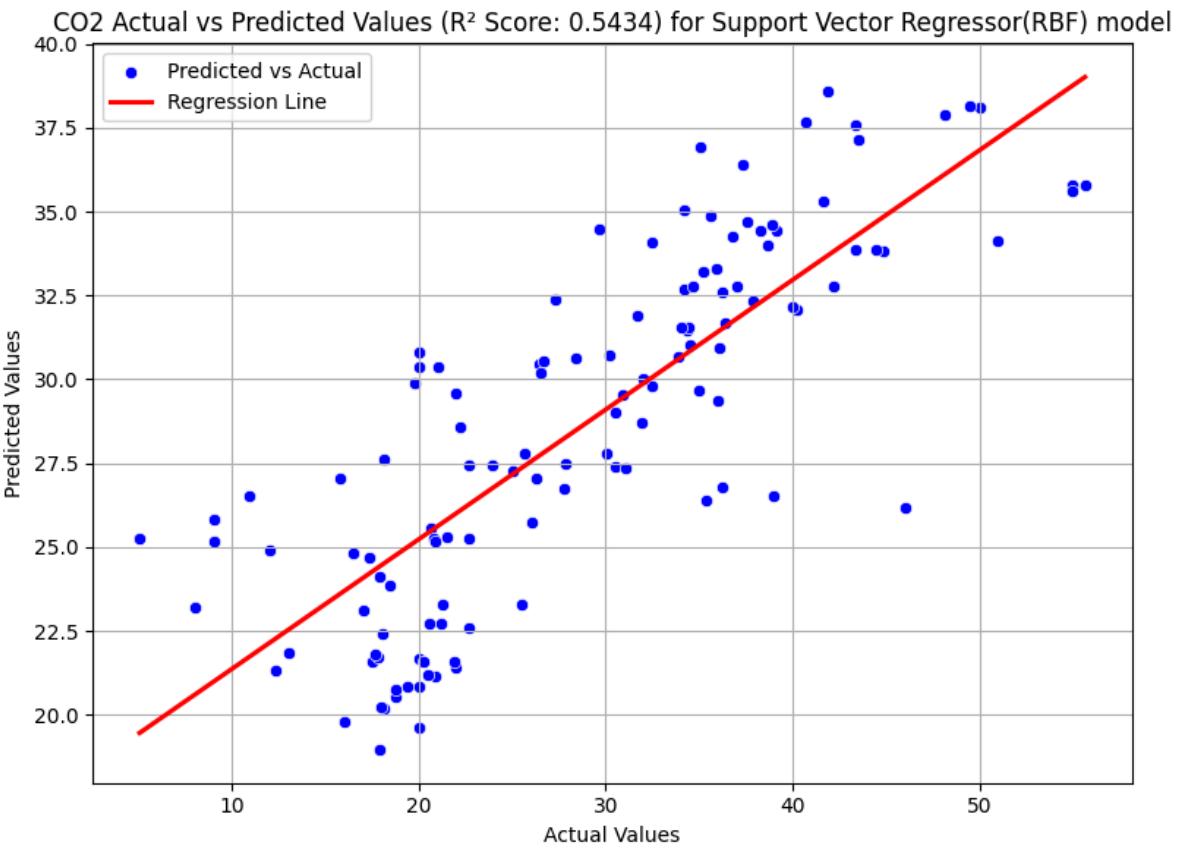


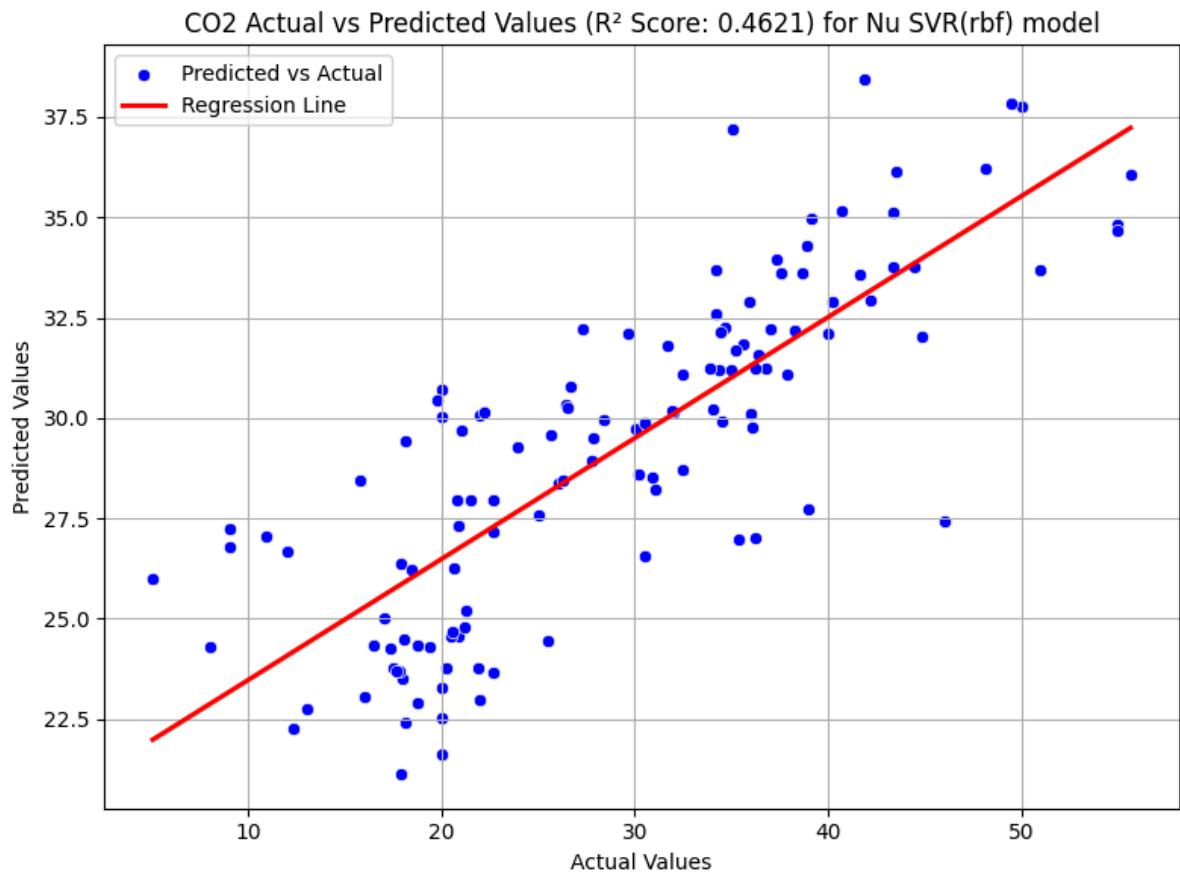
CO2 Actual vs Predicted Values (R^2 Score: 0.7860) for AdaBoost Regressor model



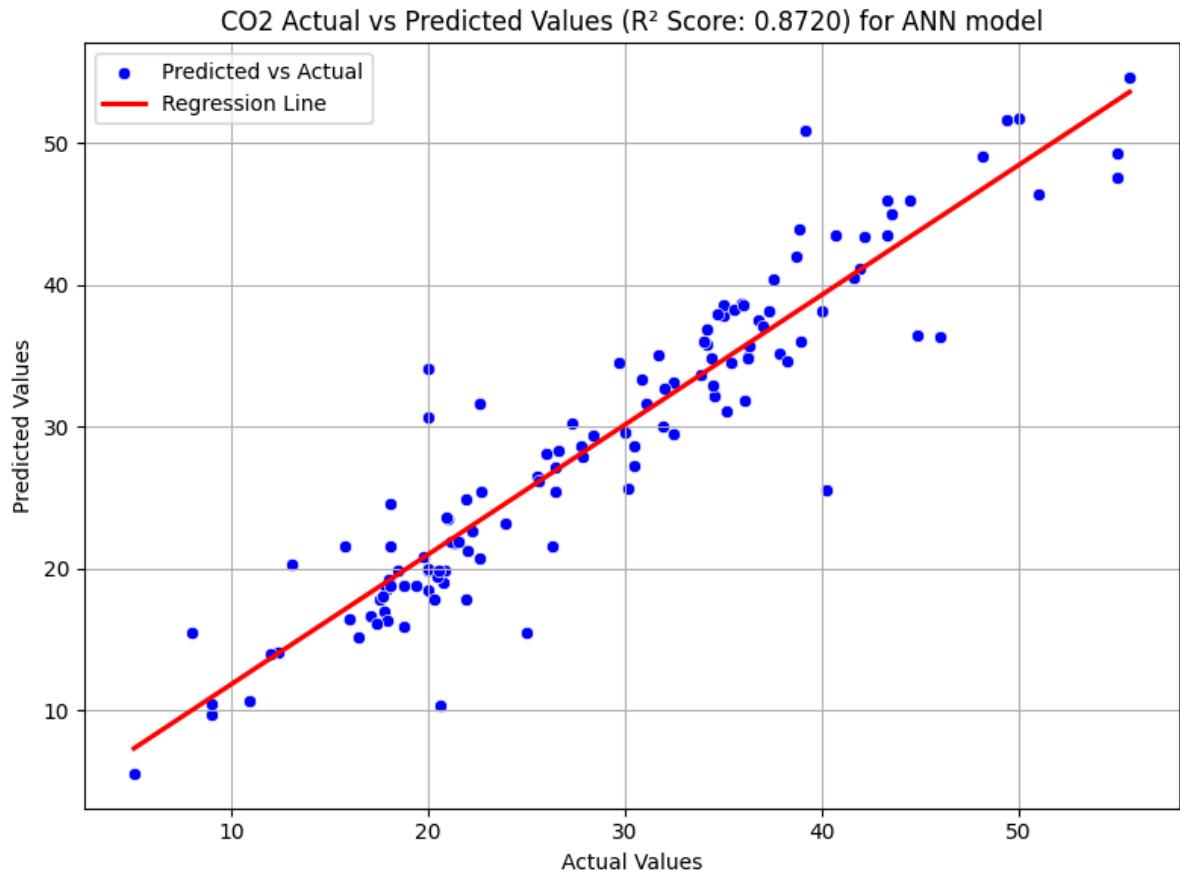
CO2 Actual vs Predicted Values (R^2 Score: 0.9002) for ExtraTreesRegressor model







```
10/10 ━━━━━━ 0s 2ms/step - loss: 2.3402 - mae: 1.0227
10/10 ━━━━━━ 0s 12ms/step
4/4 ━━━━━━ 0s 20ms/step
```



```
In [57]: score = pd.DataFrame(list(zip(models.keys(), r2_train_score.values(), r2_test_score
score
```

Out[57]:

	Model	r2_train_score	r2_test_score
0	Linear Regression	0.509402	0.542437
1	Lasso	0.452207	0.477392
2	K-Neighbors Regressor	0.838501	0.812381
3	Decision Tree	0.997671	0.771861
4	Random Forest Regressor	0.976996	0.876897
5	Gradient Boosting	0.941975	0.880438
6	XGBRegressor	0.997604	0.863107
7	CatBoosting Regressor	0.981642	0.885309
8	AdaBoost Regressor	0.833152	0.786018
9	ExtraTreesRegressor	0.997670	0.900201
10	Support Vector Regressor(RBF)	0.514539	0.543360
11	Support Vector Regressor(linear)	0.485929	0.502646
12	Nu SVR(rbf)	0.448582	0.462060
13	ANN	0.977113	0.871994

In [58]:

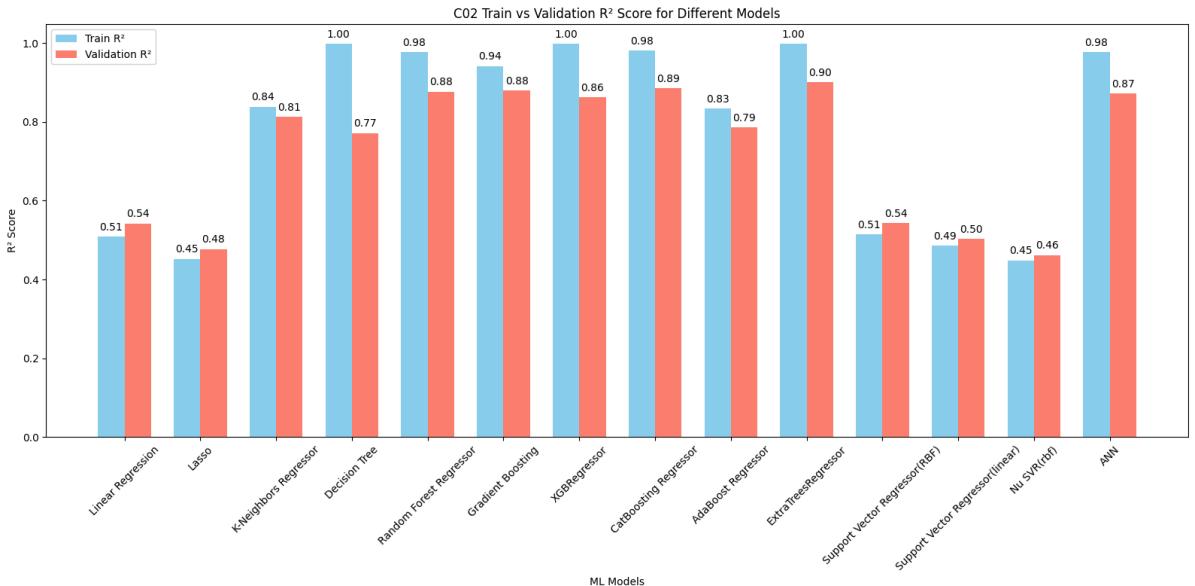
```
# Set positions
x = np.arange(len(score['Model']))
width = 0.35 # Width of the bars

# Create plot
fig, ax = plt.subplots(figsize=(16, 8))
bars1 = ax.bar(x - width/2, score['r2_train_score'], width, label='Train R2', color='blue')
bars2 = ax.bar(x + width/2, score['r2_test_score'], width, label='Validation R2', color='red')

# Add labels and title
ax.set_xlabel('ML Models')
ax.set_ylabel('R2 Score')
ax.set_title('CO2 Train vs Validation R2 Score for Different Models')
ax.set_xticks(x)
ax.set_xticklabels(score['Model'], rotation=45)
ax.legend()

# Add R2 score text on top of bars
for bar in bars1 + bars2:
    yval = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2.0, yval + 0.01, f'{yval:.2f}', ha='center')

plt.tight_layout()
plt.savefig("CO2 Train vs Validation R2 Score for Different Models")
plt.show()
```



Prediction for H2

```
In [59]: ANN_model = Sequential([
    Dense(32, input_dim=13),
    LeakyReLU(alpha=0.1),
    Dense(32, activation='tanh'),
    Dense(16, activation='relu'),
    Dense(1, activation='linear')
])

# Compile the model
ANN_model.compile(optimizer='adam',
                   loss='mean_squared_error',
                   metrics=['mae'])

# Train the model
ANN_model.fit(X_train_scaled, y_train.H2, epochs=500, verbose=1)

# Evaluate the model
loss, mae = ANN_model.evaluate(X_train_scaled, y_train.H2, verbose=0)
print(f"\nModel evaluation:\nLoss (MSE): {loss:.2f}, MAE: {mae:.2f}")
```

Epoch 1/500
10/10 2s 35ms/step - loss: 1114.5948 - mae: 30.6551
Epoch 2/500
10/10 0s 2ms/step - loss: 1092.6293 - mae: 30.3200
Epoch 3/500
10/10 0s 2ms/step - loss: 1016.1355 - mae: 29.1121
Epoch 4/500
10/10 0s 2ms/step - loss: 950.2632 - mae: 27.9327
Epoch 5/500
10/10 0s 2ms/step - loss: 925.0381 - mae: 27.6578
Epoch 6/500
10/10 0s 2ms/step - loss: 782.8148 - mae: 25.2815
Epoch 7/500
10/10 0s 2ms/step - loss: 713.4860 - mae: 23.5926
Epoch 8/500
10/10 0s 2ms/step - loss: 617.4475 - mae: 21.3423
Epoch 9/500
10/10 0s 2ms/step - loss: 466.7102 - mae: 17.8205
Epoch 10/500
10/10 0s 2ms/step - loss: 379.0529 - mae: 15.9844
Epoch 11/500
10/10 0s 2ms/step - loss: 279.0497 - mae: 13.2619
Epoch 12/500
10/10 0s 2ms/step - loss: 233.6953 - mae: 11.6012
Epoch 13/500
10/10 0s 2ms/step - loss: 185.0137 - mae: 10.2930
Epoch 14/500
10/10 0s 2ms/step - loss: 171.2313 - mae: 9.7690
Epoch 15/500
10/10 0s 2ms/step - loss: 135.7586 - mae: 8.6040
Epoch 16/500
10/10 0s 2ms/step - loss: 126.1504 - mae: 8.6905
Epoch 17/500
10/10 0s 2ms/step - loss: 110.9560 - mae: 7.9227
Epoch 18/500
10/10 0s 2ms/step - loss: 100.4794 - mae: 7.7887
Epoch 19/500
10/10 0s 2ms/step - loss: 94.4140 - mae: 7.5600
Epoch 20/500
10/10 0s 2ms/step - loss: 89.3403 - mae: 7.3504
Epoch 21/500
10/10 0s 2ms/step - loss: 84.1876 - mae: 7.1113
Epoch 22/500
10/10 0s 2ms/step - loss: 77.9369 - mae: 6.9014
Epoch 23/500
10/10 0s 2ms/step - loss: 70.5678 - mae: 6.6286
Epoch 24/500
10/10 0s 2ms/step - loss: 70.5308 - mae: 6.5333
Epoch 25/500
10/10 0s 2ms/step - loss: 68.7351 - mae: 6.5970
Epoch 26/500
10/10 0s 2ms/step - loss: 66.9746 - mae: 6.4009
Epoch 27/500
10/10 0s 2ms/step - loss: 59.5299 - mae: 6.0411
Epoch 28/500
10/10 0s 2ms/step - loss: 63.8065 - mae: 6.2055
Epoch 29/500
10/10 0s 2ms/step - loss: 64.7406 - mae: 6.3353
Epoch 30/500
10/10 0s 2ms/step - loss: 58.8110 - mae: 6.0271
Epoch 31/500
10/10 0s 2ms/step - loss: 56.1725 - mae: 5.9506
Epoch 32/500
10/10 0s 2ms/step - loss: 51.9402 - mae: 5.6167

Epoch 33/500
10/10 0s 2ms/step - loss: 51.1221 - mae: 5.6004
Epoch 34/500
10/10 0s 2ms/step - loss: 56.9818 - mae: 5.9647
Epoch 35/500
10/10 0s 2ms/step - loss: 53.5437 - mae: 5.8061
Epoch 36/500
10/10 0s 2ms/step - loss: 45.4872 - mae: 5.2557
Epoch 37/500
10/10 0s 2ms/step - loss: 50.6648 - mae: 5.5402
Epoch 38/500
10/10 0s 2ms/step - loss: 50.1591 - mae: 5.5287
Epoch 39/500
10/10 0s 2ms/step - loss: 49.0068 - mae: 5.4025
Epoch 40/500
10/10 0s 2ms/step - loss: 40.5049 - mae: 4.8911
Epoch 41/500
10/10 0s 2ms/step - loss: 47.4356 - mae: 5.3942
Epoch 42/500
10/10 0s 2ms/step - loss: 39.6630 - mae: 4.9123
Epoch 43/500
10/10 0s 2ms/step - loss: 38.3502 - mae: 4.8363
Epoch 44/500
10/10 0s 2ms/step - loss: 42.1500 - mae: 4.9903
Epoch 45/500
10/10 0s 2ms/step - loss: 35.0358 - mae: 4.6555
Epoch 46/500
10/10 0s 2ms/step - loss: 35.1659 - mae: 4.7034
Epoch 47/500
10/10 0s 2ms/step - loss: 38.4428 - mae: 4.7524
Epoch 48/500
10/10 0s 2ms/step - loss: 34.3109 - mae: 4.4980
Epoch 49/500
10/10 0s 2ms/step - loss: 37.6402 - mae: 4.6525
Epoch 50/500
10/10 0s 2ms/step - loss: 39.7448 - mae: 4.8190
Epoch 51/500
10/10 0s 2ms/step - loss: 32.8882 - mae: 4.2895
Epoch 52/500
10/10 0s 2ms/step - loss: 31.5809 - mae: 4.3003
Epoch 53/500
10/10 0s 2ms/step - loss: 30.1885 - mae: 4.1537
Epoch 54/500
10/10 0s 2ms/step - loss: 34.3234 - mae: 4.3767
Epoch 55/500
10/10 0s 2ms/step - loss: 32.0350 - mae: 4.1690
Epoch 56/500
10/10 0s 2ms/step - loss: 34.1826 - mae: 4.2859
Epoch 57/500
10/10 0s 2ms/step - loss: 28.0954 - mae: 3.9268
Epoch 58/500
10/10 0s 2ms/step - loss: 29.0354 - mae: 4.0484
Epoch 59/500
10/10 0s 2ms/step - loss: 28.5883 - mae: 3.9239
Epoch 60/500
10/10 0s 2ms/step - loss: 25.4623 - mae: 3.7134
Epoch 61/500
10/10 0s 2ms/step - loss: 29.6323 - mae: 4.0048
Epoch 62/500
10/10 0s 2ms/step - loss: 27.1073 - mae: 3.8058
Epoch 63/500
10/10 0s 2ms/step - loss: 25.8526 - mae: 3.5992
Epoch 64/500
10/10 0s 2ms/step - loss: 22.4837 - mae: 3.5261

Epoch 65/500
10/10 0s 2ms/step - loss: 24.3290 - mae: 3.5894
Epoch 66/500
10/10 0s 2ms/step - loss: 22.3423 - mae: 3.4705
Epoch 67/500
10/10 0s 2ms/step - loss: 24.8294 - mae: 3.6171
Epoch 68/500
10/10 0s 2ms/step - loss: 22.2324 - mae: 3.4568
Epoch 69/500
10/10 0s 2ms/step - loss: 21.4214 - mae: 3.3360
Epoch 70/500
10/10 0s 2ms/step - loss: 23.1652 - mae: 3.4849
Epoch 71/500
10/10 0s 2ms/step - loss: 21.0867 - mae: 3.3631
Epoch 72/500
10/10 0s 2ms/step - loss: 21.4526 - mae: 3.2845
Epoch 73/500
10/10 0s 2ms/step - loss: 20.9731 - mae: 3.3159
Epoch 74/500
10/10 0s 2ms/step - loss: 18.9955 - mae: 3.1295
Epoch 75/500
10/10 0s 2ms/step - loss: 19.0359 - mae: 3.1859
Epoch 76/500
10/10 0s 2ms/step - loss: 20.7746 - mae: 3.3432
Epoch 77/500
10/10 0s 2ms/step - loss: 19.9059 - mae: 3.1181
Epoch 78/500
10/10 0s 2ms/step - loss: 23.8073 - mae: 3.4327
Epoch 79/500
10/10 0s 2ms/step - loss: 19.2646 - mae: 3.1973
Epoch 80/500
10/10 0s 2ms/step - loss: 17.6540 - mae: 3.0792
Epoch 81/500
10/10 0s 2ms/step - loss: 17.8386 - mae: 3.1069
Epoch 82/500
10/10 0s 2ms/step - loss: 17.4348 - mae: 2.9877
Epoch 83/500
10/10 0s 2ms/step - loss: 18.3110 - mae: 2.9578
Epoch 84/500
10/10 0s 2ms/step - loss: 16.7106 - mae: 2.8899
Epoch 85/500
10/10 0s 2ms/step - loss: 19.1399 - mae: 3.1721
Epoch 86/500
10/10 0s 2ms/step - loss: 18.6142 - mae: 3.1050
Epoch 87/500
10/10 0s 2ms/step - loss: 16.1353 - mae: 2.8624
Epoch 88/500
10/10 0s 2ms/step - loss: 17.5072 - mae: 2.9965
Epoch 89/500
10/10 0s 2ms/step - loss: 18.2345 - mae: 2.9513
Epoch 90/500
10/10 0s 2ms/step - loss: 15.4015 - mae: 2.8102
Epoch 91/500
10/10 0s 2ms/step - loss: 15.4113 - mae: 2.8092
Epoch 92/500
10/10 0s 2ms/step - loss: 17.2828 - mae: 2.9984
Epoch 93/500
10/10 0s 2ms/step - loss: 12.9517 - mae: 2.5741
Epoch 94/500
10/10 0s 2ms/step - loss: 15.4109 - mae: 2.7929
Epoch 95/500
10/10 0s 2ms/step - loss: 15.1049 - mae: 2.7245
Epoch 96/500
10/10 0s 2ms/step - loss: 16.1652 - mae: 2.8040

Epoch 97/500
10/10 0s 2ms/step - loss: 11.9413 - mae: 2.5375
Epoch 98/500
10/10 0s 2ms/step - loss: 11.2699 - mae: 2.4382
Epoch 99/500
10/10 0s 2ms/step - loss: 16.3297 - mae: 2.6747
Epoch 100/500
10/10 0s 2ms/step - loss: 13.9504 - mae: 2.6735
Epoch 101/500
10/10 0s 2ms/step - loss: 14.0888 - mae: 2.6060
Epoch 102/500
10/10 0s 2ms/step - loss: 17.1756 - mae: 2.8884
Epoch 103/500
10/10 0s 2ms/step - loss: 12.7709 - mae: 2.5452
Epoch 104/500
10/10 0s 2ms/step - loss: 12.8165 - mae: 2.5843
Epoch 105/500
10/10 0s 2ms/step - loss: 10.8161 - mae: 2.4115
Epoch 106/500
10/10 0s 2ms/step - loss: 13.2415 - mae: 2.5811
Epoch 107/500
10/10 0s 2ms/step - loss: 12.4562 - mae: 2.3810
Epoch 108/500
10/10 0s 2ms/step - loss: 12.0395 - mae: 2.5435
Epoch 109/500
10/10 0s 2ms/step - loss: 14.2404 - mae: 2.6316
Epoch 110/500
10/10 0s 2ms/step - loss: 12.0284 - mae: 2.4667
Epoch 111/500
10/10 0s 2ms/step - loss: 12.0550 - mae: 2.5302
Epoch 112/500
10/10 0s 2ms/step - loss: 10.7273 - mae: 2.2651
Epoch 113/500
10/10 0s 2ms/step - loss: 11.3233 - mae: 2.3046
Epoch 114/500
10/10 0s 2ms/step - loss: 12.1697 - mae: 2.5089
Epoch 115/500
10/10 0s 2ms/step - loss: 11.9296 - mae: 2.3336
Epoch 116/500
10/10 0s 2ms/step - loss: 10.5377 - mae: 2.3086
Epoch 117/500
10/10 0s 2ms/step - loss: 10.8539 - mae: 2.3688
Epoch 118/500
10/10 0s 2ms/step - loss: 11.2646 - mae: 2.3152
Epoch 119/500
10/10 0s 2ms/step - loss: 10.2454 - mae: 2.2108
Epoch 120/500
10/10 0s 2ms/step - loss: 11.7935 - mae: 2.4377
Epoch 121/500
10/10 0s 2ms/step - loss: 11.8773 - mae: 2.3480
Epoch 122/500
10/10 0s 2ms/step - loss: 11.5365 - mae: 2.3916
Epoch 123/500
10/10 0s 2ms/step - loss: 11.1099 - mae: 2.2963
Epoch 124/500
10/10 0s 2ms/step - loss: 9.0959 - mae: 2.1998
Epoch 125/500
10/10 0s 2ms/step - loss: 14.5071 - mae: 2.5400
Epoch 126/500
10/10 0s 2ms/step - loss: 9.4520 - mae: 2.2113
Epoch 127/500
10/10 0s 2ms/step - loss: 14.5461 - mae: 2.5842
Epoch 128/500
10/10 0s 2ms/step - loss: 9.7880 - mae: 2.1922

Epoch 129/500
10/10 0s 2ms/step - loss: 12.1188 - mae: 2.2976
Epoch 130/500
10/10 0s 2ms/step - loss: 9.5429 - mae: 2.1590
Epoch 131/500
10/10 0s 2ms/step - loss: 10.5511 - mae: 2.2351
Epoch 132/500
10/10 0s 2ms/step - loss: 9.1897 - mae: 2.2316
Epoch 133/500
10/10 0s 2ms/step - loss: 9.6210 - mae: 2.2059
Epoch 134/500
10/10 0s 2ms/step - loss: 12.8312 - mae: 2.3434
Epoch 135/500
10/10 0s 2ms/step - loss: 8.5395 - mae: 2.0961
Epoch 136/500
10/10 0s 2ms/step - loss: 11.9462 - mae: 2.2693
Epoch 137/500
10/10 0s 2ms/step - loss: 10.3222 - mae: 2.2488
Epoch 138/500
10/10 0s 2ms/step - loss: 8.8143 - mae: 2.0755
Epoch 139/500
10/10 0s 2ms/step - loss: 10.3606 - mae: 2.2161
Epoch 140/500
10/10 0s 2ms/step - loss: 10.6472 - mae: 2.2352
Epoch 141/500
10/10 0s 2ms/step - loss: 9.0597 - mae: 2.1483
Epoch 142/500
10/10 0s 2ms/step - loss: 7.7616 - mae: 2.0117
Epoch 143/500
10/10 0s 2ms/step - loss: 9.9447 - mae: 2.2432
Epoch 144/500
10/10 0s 2ms/step - loss: 11.2080 - mae: 2.2716
Epoch 145/500
10/10 0s 2ms/step - loss: 8.5173 - mae: 2.0969
Epoch 146/500
10/10 0s 2ms/step - loss: 10.8170 - mae: 2.1970
Epoch 147/500
10/10 0s 2ms/step - loss: 8.6614 - mae: 2.0495
Epoch 148/500
10/10 0s 2ms/step - loss: 10.8627 - mae: 2.1863
Epoch 149/500
10/10 0s 2ms/step - loss: 8.6663 - mae: 2.0223
Epoch 150/500
10/10 0s 2ms/step - loss: 10.3985 - mae: 2.1448
Epoch 151/500
10/10 0s 2ms/step - loss: 7.1086 - mae: 1.8983
Epoch 152/500
10/10 0s 2ms/step - loss: 10.5836 - mae: 2.2107
Epoch 153/500
10/10 0s 2ms/step - loss: 10.7922 - mae: 2.1377
Epoch 154/500
10/10 0s 2ms/step - loss: 8.6874 - mae: 2.0690
Epoch 155/500
10/10 0s 2ms/step - loss: 8.1593 - mae: 2.0107
Epoch 156/500
10/10 0s 2ms/step - loss: 9.0320 - mae: 1.9707
Epoch 157/500
10/10 0s 2ms/step - loss: 9.3945 - mae: 2.1413
Epoch 158/500
10/10 0s 2ms/step - loss: 8.8443 - mae: 2.1230
Epoch 159/500
10/10 0s 2ms/step - loss: 7.6169 - mae: 1.9797
Epoch 160/500
10/10 0s 2ms/step - loss: 10.5259 - mae: 2.0268

Epoch 161/500
10/10 0s 2ms/step - loss: 10.4618 - mae: 2.0676
Epoch 162/500
10/10 0s 2ms/step - loss: 11.5185 - mae: 2.1594
Epoch 163/500
10/10 0s 2ms/step - loss: 9.6301 - mae: 2.1115
Epoch 164/500
10/10 0s 2ms/step - loss: 11.0644 - mae: 2.0734
Epoch 165/500
10/10 0s 2ms/step - loss: 10.6315 - mae: 2.0954
Epoch 166/500
10/10 0s 2ms/step - loss: 8.4702 - mae: 1.8991
Epoch 167/500
10/10 0s 2ms/step - loss: 10.9594 - mae: 2.2178
Epoch 168/500
10/10 0s 2ms/step - loss: 9.3868 - mae: 2.0571
Epoch 169/500
10/10 0s 2ms/step - loss: 10.3466 - mae: 2.1073
Epoch 170/500
10/10 0s 2ms/step - loss: 7.1306 - mae: 1.8311
Epoch 171/500
10/10 0s 2ms/step - loss: 9.4727 - mae: 2.0563
Epoch 172/500
10/10 0s 2ms/step - loss: 8.3707 - mae: 1.9968
Epoch 173/500
10/10 0s 2ms/step - loss: 6.5698 - mae: 1.8581
Epoch 174/500
10/10 0s 2ms/step - loss: 8.0879 - mae: 1.9908
Epoch 175/500
10/10 0s 2ms/step - loss: 7.5890 - mae: 1.9101
Epoch 176/500
10/10 0s 2ms/step - loss: 9.0711 - mae: 2.0736
Epoch 177/500
10/10 0s 2ms/step - loss: 7.1819 - mae: 1.9321
Epoch 178/500
10/10 0s 2ms/step - loss: 7.7444 - mae: 1.8828
Epoch 179/500
10/10 0s 2ms/step - loss: 7.8824 - mae: 1.8847
Epoch 180/500
10/10 0s 2ms/step - loss: 8.1463 - mae: 1.9676
Epoch 181/500
10/10 0s 2ms/step - loss: 7.6734 - mae: 1.9029
Epoch 182/500
10/10 0s 2ms/step - loss: 11.2891 - mae: 2.0640
Epoch 183/500
10/10 0s 2ms/step - loss: 9.0317 - mae: 1.9968
Epoch 184/500
10/10 0s 2ms/step - loss: 7.5230 - mae: 1.7912
Epoch 185/500
10/10 0s 2ms/step - loss: 10.7749 - mae: 2.1145
Epoch 186/500
10/10 0s 2ms/step - loss: 7.9760 - mae: 1.9564
Epoch 187/500
10/10 0s 2ms/step - loss: 7.2445 - mae: 1.8696
Epoch 188/500
10/10 0s 2ms/step - loss: 10.7488 - mae: 2.0677
Epoch 189/500
10/10 0s 2ms/step - loss: 11.8752 - mae: 2.1372
Epoch 190/500
10/10 0s 2ms/step - loss: 11.0457 - mae: 2.1318
Epoch 191/500
10/10 0s 2ms/step - loss: 9.7947 - mae: 1.9966
Epoch 192/500
10/10 0s 2ms/step - loss: 6.4591 - mae: 1.8224

Epoch 193/500
10/10 0s 2ms/step - loss: 7.3937 - mae: 1.8791
Epoch 194/500
10/10 0s 2ms/step - loss: 7.3974 - mae: 1.9366
Epoch 195/500
10/10 0s 2ms/step - loss: 9.8741 - mae: 1.9335
Epoch 196/500
10/10 0s 2ms/step - loss: 6.4772 - mae: 1.7487
Epoch 197/500
10/10 0s 2ms/step - loss: 8.8496 - mae: 1.8726
Epoch 198/500
10/10 0s 2ms/step - loss: 7.9928 - mae: 1.8353
Epoch 199/500
10/10 0s 2ms/step - loss: 7.2892 - mae: 1.7971
Epoch 200/500
10/10 0s 2ms/step - loss: 9.5112 - mae: 2.0260
Epoch 201/500
10/10 0s 2ms/step - loss: 7.6729 - mae: 1.8387
Epoch 202/500
10/10 0s 2ms/step - loss: 6.7752 - mae: 1.8458
Epoch 203/500
10/10 0s 2ms/step - loss: 7.4857 - mae: 1.7732
Epoch 204/500
10/10 0s 2ms/step - loss: 7.1225 - mae: 1.8155
Epoch 205/500
10/10 0s 2ms/step - loss: 7.7576 - mae: 1.7890
Epoch 206/500
10/10 0s 2ms/step - loss: 8.3094 - mae: 1.8439
Epoch 207/500
10/10 0s 2ms/step - loss: 7.1064 - mae: 1.8149
Epoch 208/500
10/10 0s 2ms/step - loss: 7.2610 - mae: 1.8466
Epoch 209/500
10/10 0s 2ms/step - loss: 7.8052 - mae: 1.8042
Epoch 210/500
10/10 0s 2ms/step - loss: 7.3714 - mae: 1.8327
Epoch 211/500
10/10 0s 2ms/step - loss: 8.8378 - mae: 1.8575
Epoch 212/500
10/10 0s 2ms/step - loss: 6.9301 - mae: 1.7717
Epoch 213/500
10/10 0s 2ms/step - loss: 10.3973 - mae: 1.9402
Epoch 214/500
10/10 0s 2ms/step - loss: 6.6419 - mae: 1.7870
Epoch 215/500
10/10 0s 2ms/step - loss: 7.5429 - mae: 1.8089
Epoch 216/500
10/10 0s 2ms/step - loss: 6.4012 - mae: 1.7884
Epoch 217/500
10/10 0s 2ms/step - loss: 6.8683 - mae: 1.8049
Epoch 218/500
10/10 0s 2ms/step - loss: 8.3755 - mae: 1.9024
Epoch 219/500
10/10 0s 2ms/step - loss: 6.7541 - mae: 1.7697
Epoch 220/500
10/10 0s 2ms/step - loss: 10.5222 - mae: 1.9829
Epoch 221/500
10/10 0s 2ms/step - loss: 5.4539 - mae: 1.6469
Epoch 222/500
10/10 0s 2ms/step - loss: 6.8794 - mae: 1.8283
Epoch 223/500
10/10 0s 2ms/step - loss: 8.5230 - mae: 1.8031
Epoch 224/500
10/10 0s 2ms/step - loss: 5.6973 - mae: 1.7187

Epoch 225/500
10/10 0s 2ms/step - loss: 6.2125 - mae: 1.6877
Epoch 226/500
10/10 0s 2ms/step - loss: 6.8679 - mae: 1.7486
Epoch 227/500
10/10 0s 2ms/step - loss: 6.6433 - mae: 1.7514
Epoch 228/500
10/10 0s 2ms/step - loss: 7.6813 - mae: 1.7963
Epoch 229/500
10/10 0s 2ms/step - loss: 8.2982 - mae: 1.8168
Epoch 230/500
10/10 0s 2ms/step - loss: 8.3549 - mae: 1.8734
Epoch 231/500
10/10 0s 2ms/step - loss: 5.7668 - mae: 1.6078
Epoch 232/500
10/10 0s 2ms/step - loss: 5.3217 - mae: 1.6369
Epoch 233/500
10/10 0s 2ms/step - loss: 8.9218 - mae: 1.8939
Epoch 234/500
10/10 0s 2ms/step - loss: 8.4267 - mae: 1.8587
Epoch 235/500
10/10 0s 2ms/step - loss: 6.5288 - mae: 1.7924
Epoch 236/500
10/10 0s 2ms/step - loss: 7.2114 - mae: 1.6976
Epoch 237/500
10/10 0s 2ms/step - loss: 8.7009 - mae: 1.9002
Epoch 238/500
10/10 0s 2ms/step - loss: 11.8370 - mae: 2.2791
Epoch 239/500
10/10 0s 2ms/step - loss: 9.3312 - mae: 2.0411
Epoch 240/500
10/10 0s 2ms/step - loss: 6.9957 - mae: 1.7641
Epoch 241/500
10/10 0s 2ms/step - loss: 6.6234 - mae: 1.7176
Epoch 242/500
10/10 0s 2ms/step - loss: 8.8208 - mae: 1.8211
Epoch 243/500
10/10 0s 2ms/step - loss: 7.1348 - mae: 1.6715
Epoch 244/500
10/10 0s 2ms/step - loss: 5.4715 - mae: 1.5996
Epoch 245/500
10/10 0s 2ms/step - loss: 6.3844 - mae: 1.5969
Epoch 246/500
10/10 0s 2ms/step - loss: 5.4936 - mae: 1.5854
Epoch 247/500
10/10 0s 2ms/step - loss: 7.1469 - mae: 1.7919
Epoch 248/500
10/10 0s 2ms/step - loss: 9.1041 - mae: 1.9110
Epoch 249/500
10/10 0s 2ms/step - loss: 7.4767 - mae: 1.7406
Epoch 250/500
10/10 0s 2ms/step - loss: 6.9387 - mae: 1.7127
Epoch 251/500
10/10 0s 2ms/step - loss: 8.9079 - mae: 1.8278
Epoch 252/500
10/10 0s 2ms/step - loss: 8.0146 - mae: 1.6697
Epoch 253/500
10/10 0s 2ms/step - loss: 5.3141 - mae: 1.5889
Epoch 254/500
10/10 0s 2ms/step - loss: 5.9803 - mae: 1.6378
Epoch 255/500
10/10 0s 2ms/step - loss: 6.1679 - mae: 1.6577
Epoch 256/500
10/10 0s 2ms/step - loss: 9.1172 - mae: 1.8403

Epoch 257/500
10/10 0s 2ms/step - loss: 8.7389 - mae: 1.7300
Epoch 258/500
10/10 0s 2ms/step - loss: 4.9727 - mae: 1.5645
Epoch 259/500
10/10 0s 2ms/step - loss: 8.1053 - mae: 1.7054
Epoch 260/500
10/10 0s 2ms/step - loss: 5.7324 - mae: 1.5636
Epoch 261/500
10/10 0s 2ms/step - loss: 5.7702 - mae: 1.6606
Epoch 262/500
10/10 0s 2ms/step - loss: 5.1102 - mae: 1.5558
Epoch 263/500
10/10 0s 2ms/step - loss: 8.2187 - mae: 1.7529
Epoch 264/500
10/10 0s 2ms/step - loss: 5.6487 - mae: 1.5869
Epoch 265/500
10/10 0s 2ms/step - loss: 7.0549 - mae: 1.6875
Epoch 266/500
10/10 0s 2ms/step - loss: 6.7540 - mae: 1.6745
Epoch 267/500
10/10 0s 2ms/step - loss: 5.4513 - mae: 1.5995
Epoch 268/500
10/10 0s 2ms/step - loss: 4.9412 - mae: 1.4961
Epoch 269/500
10/10 0s 2ms/step - loss: 5.8305 - mae: 1.5548
Epoch 270/500
10/10 0s 2ms/step - loss: 5.1986 - mae: 1.5340
Epoch 271/500
10/10 0s 2ms/step - loss: 6.2205 - mae: 1.6794
Epoch 272/500
10/10 0s 2ms/step - loss: 7.1818 - mae: 1.7159
Epoch 273/500
10/10 0s 2ms/step - loss: 6.7046 - mae: 1.6881
Epoch 274/500
10/10 0s 2ms/step - loss: 7.1028 - mae: 1.6782
Epoch 275/500
10/10 0s 2ms/step - loss: 5.2425 - mae: 1.5443
Epoch 276/500
10/10 0s 2ms/step - loss: 7.9231 - mae: 1.7119
Epoch 277/500
10/10 0s 2ms/step - loss: 6.4070 - mae: 1.6104
Epoch 278/500
10/10 0s 2ms/step - loss: 6.1086 - mae: 1.5280
Epoch 279/500
10/10 0s 2ms/step - loss: 6.2192 - mae: 1.5742
Epoch 280/500
10/10 0s 2ms/step - loss: 5.3833 - mae: 1.5374
Epoch 281/500
10/10 0s 2ms/step - loss: 5.3732 - mae: 1.5216
Epoch 282/500
10/10 0s 2ms/step - loss: 8.2961 - mae: 1.7057
Epoch 283/500
10/10 0s 2ms/step - loss: 5.7185 - mae: 1.5384
Epoch 284/500
10/10 0s 2ms/step - loss: 5.4435 - mae: 1.5106
Epoch 285/500
10/10 0s 2ms/step - loss: 4.6901 - mae: 1.4351
Epoch 286/500
10/10 0s 2ms/step - loss: 5.6154 - mae: 1.5610
Epoch 287/500
10/10 0s 2ms/step - loss: 8.0514 - mae: 1.6623
Epoch 288/500
10/10 0s 2ms/step - loss: 5.6747 - mae: 1.5369

Epoch 289/500
10/10 0s 2ms/step - loss: 7.1263 - mae: 1.6442
Epoch 290/500
10/10 0s 2ms/step - loss: 4.9073 - mae: 1.4977
Epoch 291/500
10/10 0s 2ms/step - loss: 5.6469 - mae: 1.5811
Epoch 292/500
10/10 0s 2ms/step - loss: 5.7845 - mae: 1.5949
Epoch 293/500
10/10 0s 2ms/step - loss: 5.6975 - mae: 1.5618
Epoch 294/500
10/10 0s 2ms/step - loss: 7.5297 - mae: 1.5875
Epoch 295/500
10/10 0s 2ms/step - loss: 7.1302 - mae: 1.6390
Epoch 296/500
10/10 0s 2ms/step - loss: 7.7524 - mae: 1.8223
Epoch 297/500
10/10 0s 2ms/step - loss: 6.0430 - mae: 1.6175
Epoch 298/500
10/10 0s 2ms/step - loss: 5.6257 - mae: 1.5270
Epoch 299/500
10/10 0s 2ms/step - loss: 6.8363 - mae: 1.6281
Epoch 300/500
10/10 0s 2ms/step - loss: 5.5411 - mae: 1.5706
Epoch 301/500
10/10 0s 2ms/step - loss: 6.9502 - mae: 1.6140
Epoch 302/500
10/10 0s 2ms/step - loss: 7.2920 - mae: 1.6932
Epoch 303/500
10/10 0s 2ms/step - loss: 4.6756 - mae: 1.4297
Epoch 304/500
10/10 0s 2ms/step - loss: 5.1857 - mae: 1.5748
Epoch 305/500
10/10 0s 2ms/step - loss: 5.2728 - mae: 1.4679
Epoch 306/500
10/10 0s 2ms/step - loss: 6.3675 - mae: 1.5771
Epoch 307/500
10/10 0s 2ms/step - loss: 6.1718 - mae: 1.5318
Epoch 308/500
10/10 0s 2ms/step - loss: 6.5667 - mae: 1.5377
Epoch 309/500
10/10 0s 2ms/step - loss: 5.3551 - mae: 1.4952
Epoch 310/500
10/10 0s 2ms/step - loss: 6.1853 - mae: 1.5391
Epoch 311/500
10/10 0s 2ms/step - loss: 6.4520 - mae: 1.5916
Epoch 312/500
10/10 0s 2ms/step - loss: 5.7195 - mae: 1.4803
Epoch 313/500
10/10 0s 2ms/step - loss: 5.1946 - mae: 1.4137
Epoch 314/500
10/10 0s 2ms/step - loss: 6.3695 - mae: 1.5332
Epoch 315/500
10/10 0s 2ms/step - loss: 5.7926 - mae: 1.5264
Epoch 316/500
10/10 0s 2ms/step - loss: 5.0271 - mae: 1.3905
Epoch 317/500
10/10 0s 2ms/step - loss: 6.1730 - mae: 1.5210
Epoch 318/500
10/10 0s 2ms/step - loss: 6.4764 - mae: 1.5540
Epoch 319/500
10/10 0s 2ms/step - loss: 7.4406 - mae: 1.6227
Epoch 320/500
10/10 0s 2ms/step - loss: 4.9613 - mae: 1.4559

Epoch 321/500
10/10 0s 2ms/step - loss: 6.2503 - mae: 1.5618
Epoch 322/500
10/10 0s 2ms/step - loss: 5.1739 - mae: 1.4555
Epoch 323/500
10/10 0s 2ms/step - loss: 6.0741 - mae: 1.5143
Epoch 324/500
10/10 0s 2ms/step - loss: 5.5198 - mae: 1.4028
Epoch 325/500
10/10 0s 2ms/step - loss: 6.2027 - mae: 1.5279
Epoch 326/500
10/10 0s 2ms/step - loss: 5.5669 - mae: 1.4459
Epoch 327/500
10/10 0s 2ms/step - loss: 5.7476 - mae: 1.4717
Epoch 328/500
10/10 0s 2ms/step - loss: 7.2202 - mae: 1.5584
Epoch 329/500
10/10 0s 2ms/step - loss: 4.3472 - mae: 1.3975
Epoch 330/500
10/10 0s 2ms/step - loss: 7.8109 - mae: 1.8309
Epoch 331/500
10/10 0s 2ms/step - loss: 6.8744 - mae: 1.8462
Epoch 332/500
10/10 0s 2ms/step - loss: 7.4220 - mae: 1.7634
Epoch 333/500
10/10 0s 2ms/step - loss: 5.1903 - mae: 1.5614
Epoch 334/500
10/10 0s 2ms/step - loss: 4.4283 - mae: 1.3985
Epoch 335/500
10/10 0s 2ms/step - loss: 6.3649 - mae: 1.5678
Epoch 336/500
10/10 0s 2ms/step - loss: 5.6595 - mae: 1.5216
Epoch 337/500
10/10 0s 2ms/step - loss: 6.0358 - mae: 1.5551
Epoch 338/500
10/10 0s 2ms/step - loss: 5.2973 - mae: 1.4561
Epoch 339/500
10/10 0s 2ms/step - loss: 4.9381 - mae: 1.4748
Epoch 340/500
10/10 0s 2ms/step - loss: 5.9186 - mae: 1.4710
Epoch 341/500
10/10 0s 2ms/step - loss: 6.5329 - mae: 1.5103
Epoch 342/500
10/10 0s 2ms/step - loss: 4.9771 - mae: 1.4264
Epoch 343/500
10/10 0s 2ms/step - loss: 5.9666 - mae: 1.4862
Epoch 344/500
10/10 0s 2ms/step - loss: 6.9080 - mae: 1.5821
Epoch 345/500
10/10 0s 2ms/step - loss: 4.7900 - mae: 1.4248
Epoch 346/500
10/10 0s 2ms/step - loss: 5.7387 - mae: 1.3954
Epoch 347/500
10/10 0s 2ms/step - loss: 4.0994 - mae: 1.3406
Epoch 348/500
10/10 0s 2ms/step - loss: 4.3751 - mae: 1.3677
Epoch 349/500
10/10 0s 2ms/step - loss: 6.8856 - mae: 1.5536
Epoch 350/500
10/10 0s 2ms/step - loss: 7.1493 - mae: 1.6020
Epoch 351/500
10/10 0s 2ms/step - loss: 6.0260 - mae: 1.4050
Epoch 352/500
10/10 0s 2ms/step - loss: 6.3759 - mae: 1.4909

Epoch 353/500
10/10 0s 2ms/step - loss: 7.1827 - mae: 1.5589
Epoch 354/500
10/10 0s 2ms/step - loss: 4.5492 - mae: 1.3603
Epoch 355/500
10/10 0s 2ms/step - loss: 4.6190 - mae: 1.4044
Epoch 356/500
10/10 0s 2ms/step - loss: 6.0925 - mae: 1.4800
Epoch 357/500
10/10 0s 2ms/step - loss: 5.5991 - mae: 1.5280
Epoch 358/500
10/10 0s 2ms/step - loss: 4.7222 - mae: 1.3377
Epoch 359/500
10/10 0s 2ms/step - loss: 4.8758 - mae: 1.3881
Epoch 360/500
10/10 0s 2ms/step - loss: 5.4003 - mae: 1.6245
Epoch 361/500
10/10 0s 2ms/step - loss: 6.0127 - mae: 1.6308
Epoch 362/500
10/10 0s 2ms/step - loss: 6.0645 - mae: 1.4797
Epoch 363/500
10/10 0s 2ms/step - loss: 4.5713 - mae: 1.3531
Epoch 364/500
10/10 0s 2ms/step - loss: 7.1943 - mae: 1.5619
Epoch 365/500
10/10 0s 2ms/step - loss: 4.1317 - mae: 1.3168
Epoch 366/500
10/10 0s 2ms/step - loss: 4.1440 - mae: 1.3329
Epoch 367/500
10/10 0s 2ms/step - loss: 3.6511 - mae: 1.2521
Epoch 368/500
10/10 0s 2ms/step - loss: 4.7178 - mae: 1.3649
Epoch 369/500
10/10 0s 2ms/step - loss: 5.3575 - mae: 1.4443
Epoch 370/500
10/10 0s 2ms/step - loss: 5.1984 - mae: 1.4837
Epoch 371/500
10/10 0s 2ms/step - loss: 4.3674 - mae: 1.3125
Epoch 372/500
10/10 0s 2ms/step - loss: 6.0808 - mae: 1.5719
Epoch 373/500
10/10 0s 2ms/step - loss: 6.3937 - mae: 1.4843
Epoch 374/500
10/10 0s 2ms/step - loss: 5.2546 - mae: 1.3394
Epoch 375/500
10/10 0s 2ms/step - loss: 4.8873 - mae: 1.3570
Epoch 376/500
10/10 0s 2ms/step - loss: 5.1401 - mae: 1.4841
Epoch 377/500
10/10 0s 2ms/step - loss: 3.9568 - mae: 1.3475
Epoch 378/500
10/10 0s 2ms/step - loss: 5.5639 - mae: 1.4754
Epoch 379/500
10/10 0s 2ms/step - loss: 5.5112 - mae: 1.3391
Epoch 380/500
10/10 0s 2ms/step - loss: 6.8268 - mae: 1.5052
Epoch 381/500
10/10 0s 2ms/step - loss: 4.4189 - mae: 1.3697
Epoch 382/500
10/10 0s 2ms/step - loss: 5.5878 - mae: 1.4552
Epoch 383/500
10/10 0s 2ms/step - loss: 6.2602 - mae: 1.4629
Epoch 384/500
10/10 0s 2ms/step - loss: 5.9859 - mae: 1.5162

Epoch 385/500
10/10 0s 2ms/step - loss: 4.9017 - mae: 1.4421
Epoch 386/500
10/10 0s 2ms/step - loss: 4.3737 - mae: 1.3324
Epoch 387/500
10/10 0s 2ms/step - loss: 5.1579 - mae: 1.4341
Epoch 388/500
10/10 0s 2ms/step - loss: 4.8381 - mae: 1.3956
Epoch 389/500
10/10 0s 2ms/step - loss: 4.6068 - mae: 1.3392
Epoch 390/500
10/10 0s 2ms/step - loss: 6.0883 - mae: 1.5154
Epoch 391/500
10/10 0s 2ms/step - loss: 5.0760 - mae: 1.4329
Epoch 392/500
10/10 0s 2ms/step - loss: 5.4054 - mae: 1.3992
Epoch 393/500
10/10 0s 2ms/step - loss: 4.6088 - mae: 1.3354
Epoch 394/500
10/10 0s 2ms/step - loss: 5.1086 - mae: 1.4613
Epoch 395/500
10/10 0s 2ms/step - loss: 4.2313 - mae: 1.3339
Epoch 396/500
10/10 0s 2ms/step - loss: 5.6489 - mae: 1.4291
Epoch 397/500
10/10 0s 2ms/step - loss: 5.3589 - mae: 1.4099
Epoch 398/500
10/10 0s 2ms/step - loss: 4.7635 - mae: 1.4131
Epoch 399/500
10/10 0s 2ms/step - loss: 5.1867 - mae: 1.3617
Epoch 400/500
10/10 0s 2ms/step - loss: 6.7598 - mae: 1.4851
Epoch 401/500
10/10 0s 2ms/step - loss: 5.2988 - mae: 1.3671
Epoch 402/500
10/10 0s 2ms/step - loss: 6.1980 - mae: 1.4217
Epoch 403/500
10/10 0s 2ms/step - loss: 5.5735 - mae: 1.4791
Epoch 404/500
10/10 0s 2ms/step - loss: 3.7590 - mae: 1.2944
Epoch 405/500
10/10 0s 2ms/step - loss: 5.4735 - mae: 1.4001
Epoch 406/500
10/10 0s 2ms/step - loss: 4.4777 - mae: 1.3710
Epoch 407/500
10/10 0s 2ms/step - loss: 6.3769 - mae: 1.4488
Epoch 408/500
10/10 0s 2ms/step - loss: 5.2930 - mae: 1.4899
Epoch 409/500
10/10 0s 2ms/step - loss: 5.7755 - mae: 1.4520
Epoch 410/500
10/10 0s 2ms/step - loss: 8.2348 - mae: 1.7018
Epoch 411/500
10/10 0s 2ms/step - loss: 5.6904 - mae: 1.5195
Epoch 412/500
10/10 0s 2ms/step - loss: 6.2407 - mae: 1.4353
Epoch 413/500
10/10 0s 2ms/step - loss: 5.6604 - mae: 1.4202
Epoch 414/500
10/10 0s 2ms/step - loss: 5.3496 - mae: 1.3409
Epoch 415/500
10/10 0s 2ms/step - loss: 5.7143 - mae: 1.4181
Epoch 416/500
10/10 0s 2ms/step - loss: 4.6167 - mae: 1.4812

Epoch 417/500
10/10 0s 2ms/step - loss: 4.3187 - mae: 1.4134
Epoch 418/500
10/10 0s 2ms/step - loss: 5.6760 - mae: 1.3625
Epoch 419/500
10/10 0s 2ms/step - loss: 4.5245 - mae: 1.3557
Epoch 420/500
10/10 0s 2ms/step - loss: 4.6400 - mae: 1.3385
Epoch 421/500
10/10 0s 2ms/step - loss: 4.8596 - mae: 1.3417
Epoch 422/500
10/10 0s 2ms/step - loss: 5.8839 - mae: 1.4252
Epoch 423/500
10/10 0s 2ms/step - loss: 4.6442 - mae: 1.3479
Epoch 424/500
10/10 0s 2ms/step - loss: 5.0663 - mae: 1.3204
Epoch 425/500
10/10 0s 2ms/step - loss: 4.2858 - mae: 1.3499
Epoch 426/500
10/10 0s 2ms/step - loss: 5.6484 - mae: 1.4001
Epoch 427/500
10/10 0s 2ms/step - loss: 3.8568 - mae: 1.2545
Epoch 428/500
10/10 0s 2ms/step - loss: 6.9560 - mae: 1.7138
Epoch 429/500
10/10 0s 2ms/step - loss: 6.3823 - mae: 1.7760
Epoch 430/500
10/10 0s 2ms/step - loss: 5.4932 - mae: 1.5845
Epoch 431/500
10/10 0s 2ms/step - loss: 4.9750 - mae: 1.4019
Epoch 432/500
10/10 0s 2ms/step - loss: 3.9146 - mae: 1.2470
Epoch 433/500
10/10 0s 2ms/step - loss: 4.5846 - mae: 1.3640
Epoch 434/500
10/10 0s 2ms/step - loss: 4.1352 - mae: 1.3496
Epoch 435/500
10/10 0s 2ms/step - loss: 4.2317 - mae: 1.3433
Epoch 436/500
10/10 0s 2ms/step - loss: 4.2104 - mae: 1.3218
Epoch 437/500
10/10 0s 2ms/step - loss: 6.5484 - mae: 1.4964
Epoch 438/500
10/10 0s 2ms/step - loss: 5.3031 - mae: 1.2997
Epoch 439/500
10/10 0s 2ms/step - loss: 4.4299 - mae: 1.3499
Epoch 440/500
10/10 0s 2ms/step - loss: 6.1646 - mae: 1.7112
Epoch 441/500
10/10 0s 2ms/step - loss: 8.4181 - mae: 2.0311
Epoch 442/500
10/10 0s 2ms/step - loss: 5.9539 - mae: 1.6273
Epoch 443/500
10/10 0s 2ms/step - loss: 6.8833 - mae: 1.6443
Epoch 444/500
10/10 0s 2ms/step - loss: 5.1876 - mae: 1.5861
Epoch 445/500
10/10 0s 2ms/step - loss: 3.9827 - mae: 1.2888
Epoch 446/500
10/10 0s 2ms/step - loss: 4.5678 - mae: 1.3328
Epoch 447/500
10/10 0s 2ms/step - loss: 3.8111 - mae: 1.2426
Epoch 448/500
10/10 0s 2ms/step - loss: 6.6780 - mae: 1.4879

Epoch 449/500
10/10 0s 2ms/step - loss: 4.4567 - mae: 1.2718
Epoch 450/500
10/10 0s 2ms/step - loss: 4.9940 - mae: 1.3376
Epoch 451/500
10/10 0s 2ms/step - loss: 3.5870 - mae: 1.2043
Epoch 452/500
10/10 0s 2ms/step - loss: 4.8427 - mae: 1.3439
Epoch 453/500
10/10 0s 2ms/step - loss: 4.7806 - mae: 1.3244
Epoch 454/500
10/10 0s 2ms/step - loss: 4.1371 - mae: 1.3259
Epoch 455/500
10/10 0s 2ms/step - loss: 4.7375 - mae: 1.2873
Epoch 456/500
10/10 0s 2ms/step - loss: 3.7486 - mae: 1.2529
Epoch 457/500
10/10 0s 2ms/step - loss: 3.0368 - mae: 1.1581
Epoch 458/500
10/10 0s 2ms/step - loss: 3.1106 - mae: 1.1513
Epoch 459/500
10/10 0s 2ms/step - loss: 4.3723 - mae: 1.3469
Epoch 460/500
10/10 0s 2ms/step - loss: 5.6502 - mae: 1.4341
Epoch 461/500
10/10 0s 2ms/step - loss: 3.5956 - mae: 1.2854
Epoch 462/500
10/10 0s 2ms/step - loss: 5.0966 - mae: 1.3140
Epoch 463/500
10/10 0s 2ms/step - loss: 3.9249 - mae: 1.2941
Epoch 464/500
10/10 0s 2ms/step - loss: 4.1178 - mae: 1.2350
Epoch 465/500
10/10 0s 2ms/step - loss: 5.1492 - mae: 1.3006
Epoch 466/500
10/10 0s 2ms/step - loss: 4.5485 - mae: 1.3094
Epoch 467/500
10/10 0s 2ms/step - loss: 4.7805 - mae: 1.3461
Epoch 468/500
10/10 0s 2ms/step - loss: 4.3751 - mae: 1.3163
Epoch 469/500
10/10 0s 2ms/step - loss: 3.2850 - mae: 1.2175
Epoch 470/500
10/10 0s 2ms/step - loss: 3.9013 - mae: 1.2812
Epoch 471/500
10/10 0s 2ms/step - loss: 5.8036 - mae: 1.3916
Epoch 472/500
10/10 0s 2ms/step - loss: 4.9086 - mae: 1.3535
Epoch 473/500
10/10 0s 2ms/step - loss: 5.6836 - mae: 1.4228
Epoch 474/500
10/10 0s 2ms/step - loss: 5.2234 - mae: 1.3286
Epoch 475/500
10/10 0s 2ms/step - loss: 3.2839 - mae: 1.2185
Epoch 476/500
10/10 0s 2ms/step - loss: 5.2718 - mae: 1.2781
Epoch 477/500
10/10 0s 2ms/step - loss: 4.2997 - mae: 1.2415
Epoch 478/500
10/10 0s 2ms/step - loss: 4.3531 - mae: 1.2744
Epoch 479/500
10/10 0s 2ms/step - loss: 4.9929 - mae: 1.3104
Epoch 480/500
10/10 0s 2ms/step - loss: 4.4795 - mae: 1.3177

```
Epoch 481/500
10/10 0s 2ms/step - loss: 4.2462 - mae: 1.3406
Epoch 482/500
10/10 0s 2ms/step - loss: 5.0282 - mae: 1.3370
Epoch 483/500
10/10 0s 2ms/step - loss: 3.7476 - mae: 1.2154
Epoch 484/500
10/10 0s 2ms/step - loss: 3.8581 - mae: 1.2283
Epoch 485/500
10/10 0s 2ms/step - loss: 4.9911 - mae: 1.2803
Epoch 486/500
10/10 0s 2ms/step - loss: 4.3683 - mae: 1.2385
Epoch 487/500
10/10 0s 2ms/step - loss: 4.6179 - mae: 1.2705
Epoch 488/500
10/10 0s 2ms/step - loss: 4.5909 - mae: 1.3205
Epoch 489/500
10/10 0s 2ms/step - loss: 3.2040 - mae: 1.1651
Epoch 490/500
10/10 0s 2ms/step - loss: 4.6336 - mae: 1.2532
Epoch 491/500
10/10 0s 2ms/step - loss: 4.5880 - mae: 1.2729
Epoch 492/500
10/10 0s 2ms/step - loss: 4.1006 - mae: 1.2435
Epoch 493/500
10/10 0s 2ms/step - loss: 3.5694 - mae: 1.1555
Epoch 494/500
10/10 0s 2ms/step - loss: 4.1799 - mae: 1.2588
Epoch 495/500
10/10 0s 2ms/step - loss: 4.7182 - mae: 1.2703
Epoch 496/500
10/10 0s 2ms/step - loss: 4.7736 - mae: 1.2977
Epoch 497/500
10/10 0s 2ms/step - loss: 4.7881 - mae: 1.2506
Epoch 498/500
10/10 0s 2ms/step - loss: 4.7631 - mae: 1.2596
Epoch 499/500
10/10 0s 2ms/step - loss: 3.2382 - mae: 1.1648
Epoch 500/500
10/10 0s 2ms/step - loss: 4.4652 - mae: 1.2477
```

Model evaluation:

Loss (MSE): 4.13, MAE: 1.23

```
In [60]: models = {
    "Linear Regression": LinearRegression(),
    "Lasso": Lasso(),
    "K-Neighbors Regressor": KNeighborsRegressor(),
    "Decision Tree": DecisionTreeRegressor(),
    "Random Forest Regressor": RandomForestRegressor(),
    "Gradient Boosting": GradientBoostingRegressor(),
    "XGBRegressor": XGBRegressor(),
    "CatBoosting Regressor": CatBoostRegressor(verbose=0, iterations = 100),
    "AdaBoost Regressor": AdaBoostRegressor(),
    "ExtraTreesRegressor": ExtraTreesRegressor(),
    "Support Vector Regressor(RBF)": SVR(kernel="rbf"),
    "Support Vector Regressor(linear)": SVR(kernel="linear"),
    "Nu SVR(rbf)": NuSVR(kernel="rbf"),
    "ANN": ANN_model
}
```

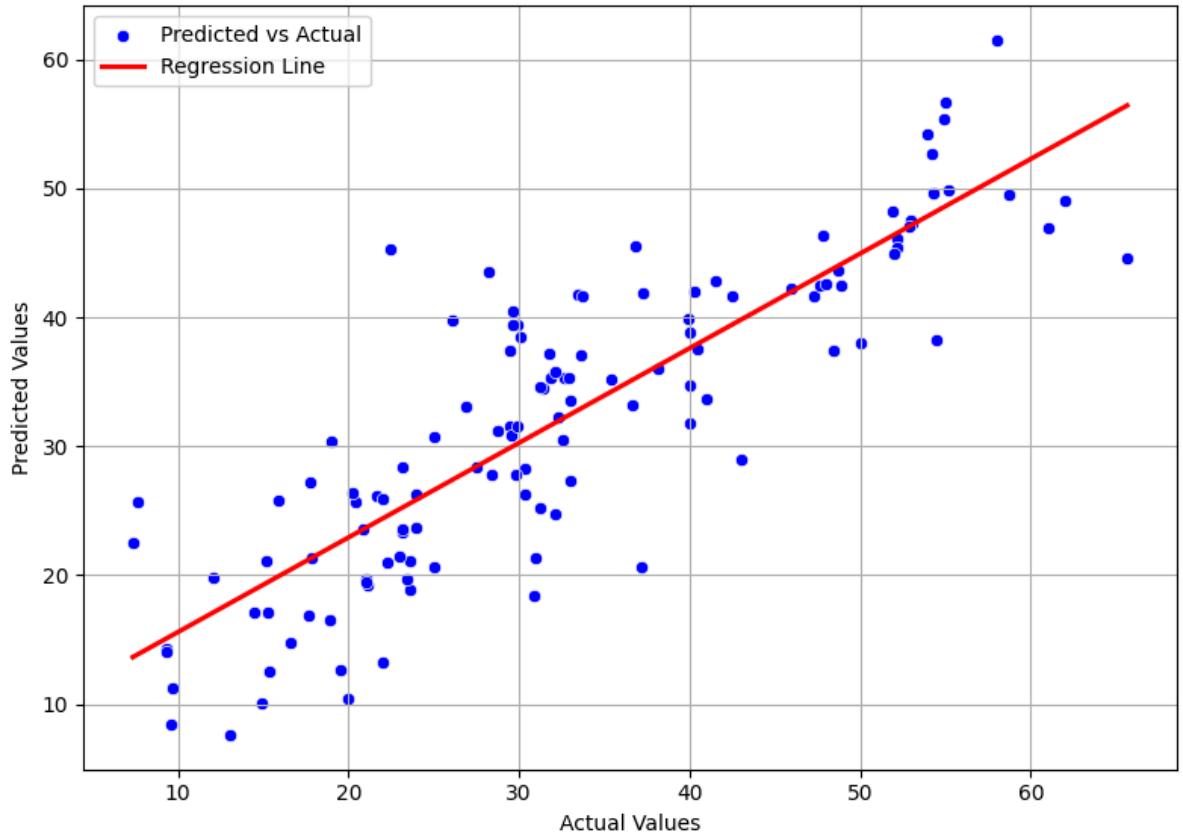
```
In [61]: def safe_flatten(y_pred):
    """
    Flattens the array if it's a 2D array with shape (n, 1).
    """
```

```
    Useful for ANN predictions.  
    """  
    if isinstance(y_pred, (np.ndarray, list)) and len(np.shape(y_pred)) == 2 and y_  
        return y_pred.flatten()  
    return y_pred
```

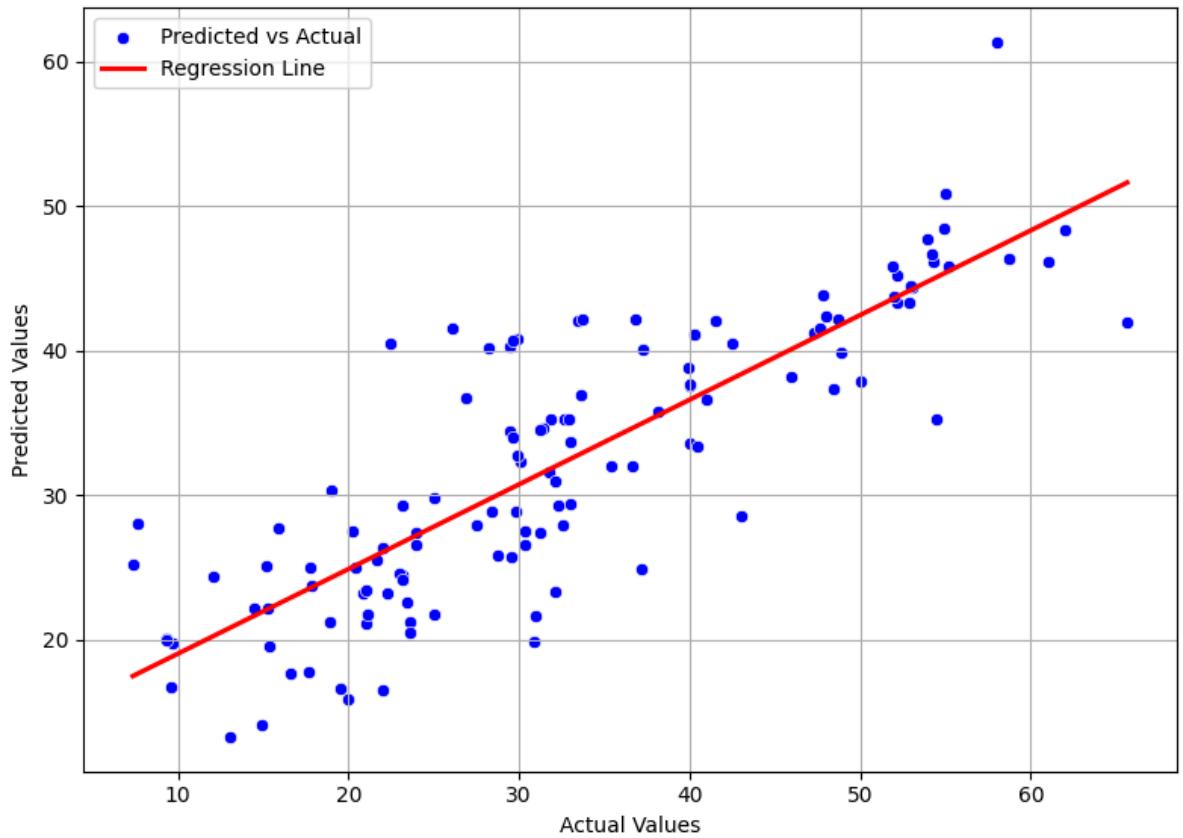
```
In [62]: r2_train_score = {}  
r2_test_score = {}  
def evaluate_model(models, X_train, y_train, X_val, y_val):  
    for model_name, model in models.items():  
        model.fit(X_train, y_train)  
  
        y_train_pred = model.predict(X_train)  
        y_test_pred = model.predict(X_val)  
  
        y = y_val  
        y_pred = safe_flatten(y_test_pred)  
  
        plt.figure(figsize=(8, 6))  
        r2 = r2_score(y, y_pred)  
  
        sns.scatterplot(x=y, y=y_pred, label='Predicted vs Actual', color='blue')  
        sns.regplot(x=y, y=y_pred, scatter=False, label='Regression Line', color='red')  
  
        plt.xlabel('Actual Values')  
        plt.ylabel('Predicted Values')  
        plt.title(f'H2 Actual vs Predicted Values (R2 Score: {r2:.4f}) for {model_name}')  
        plt.legend()  
        plt.grid(True)  
        plt.tight_layout()  
        plt.savefig(f'H2 Actual vs Predicted Values (R2 Score: {r2:.4f}) for {model_name}.png')  
        plt.show()  
  
    r2_train_score[model_name] = r2_score(y_train, y_train_pred)  
    r2_test_score[model_name] = r2_score(y_val, y_test_pred)
```

```
In [63]: evaluate_model(models, X_train_scaled, y_train.H2, X_val_scaled, y_val.H2)
```

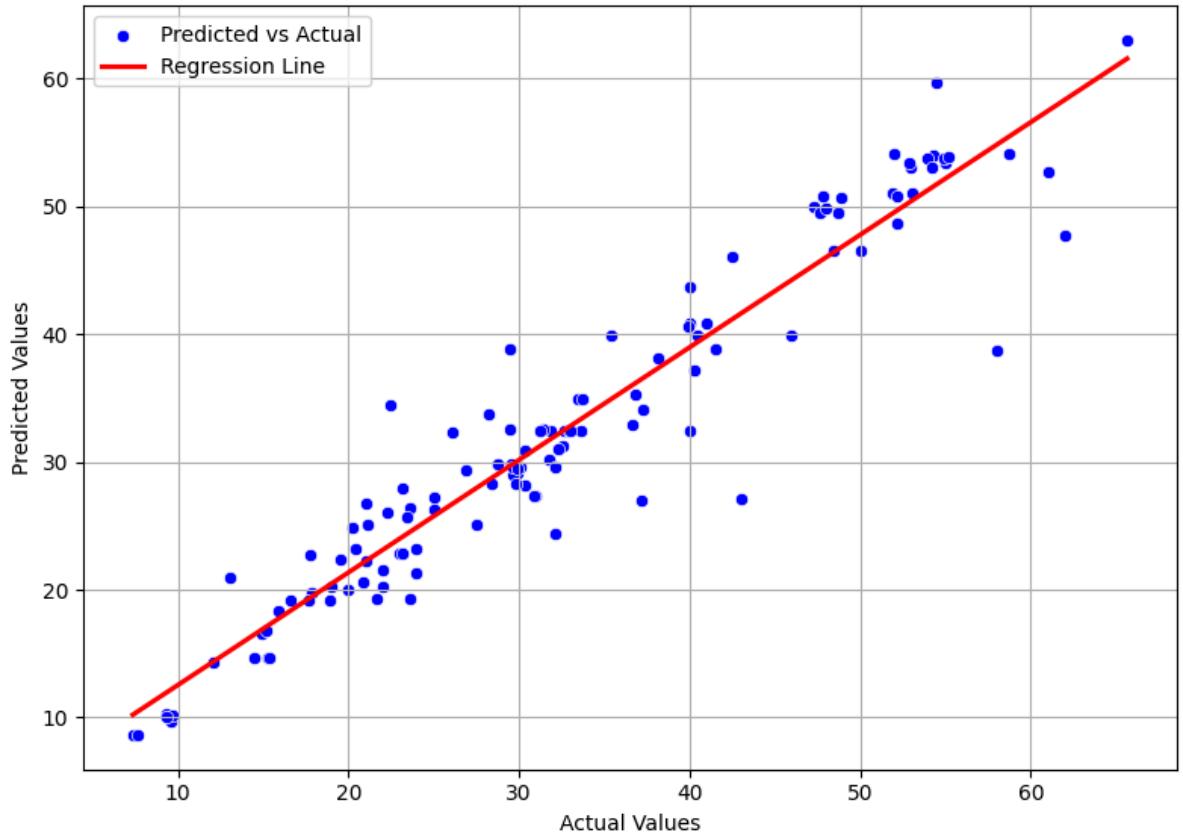
H2 Actual vs Predicted Values (R^2 Score: 0.7306) for Linear Regression model



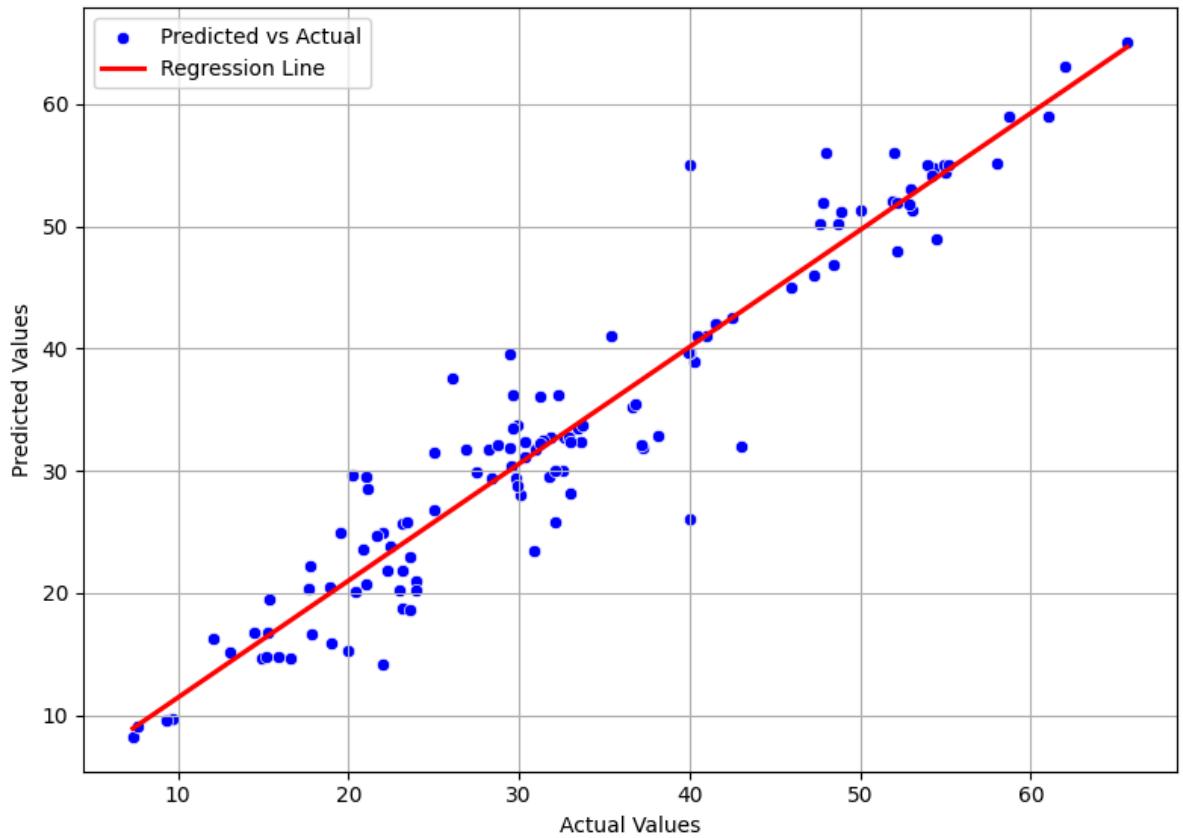
H2 Actual vs Predicted Values (R^2 Score: 0.6849) for Lasso model



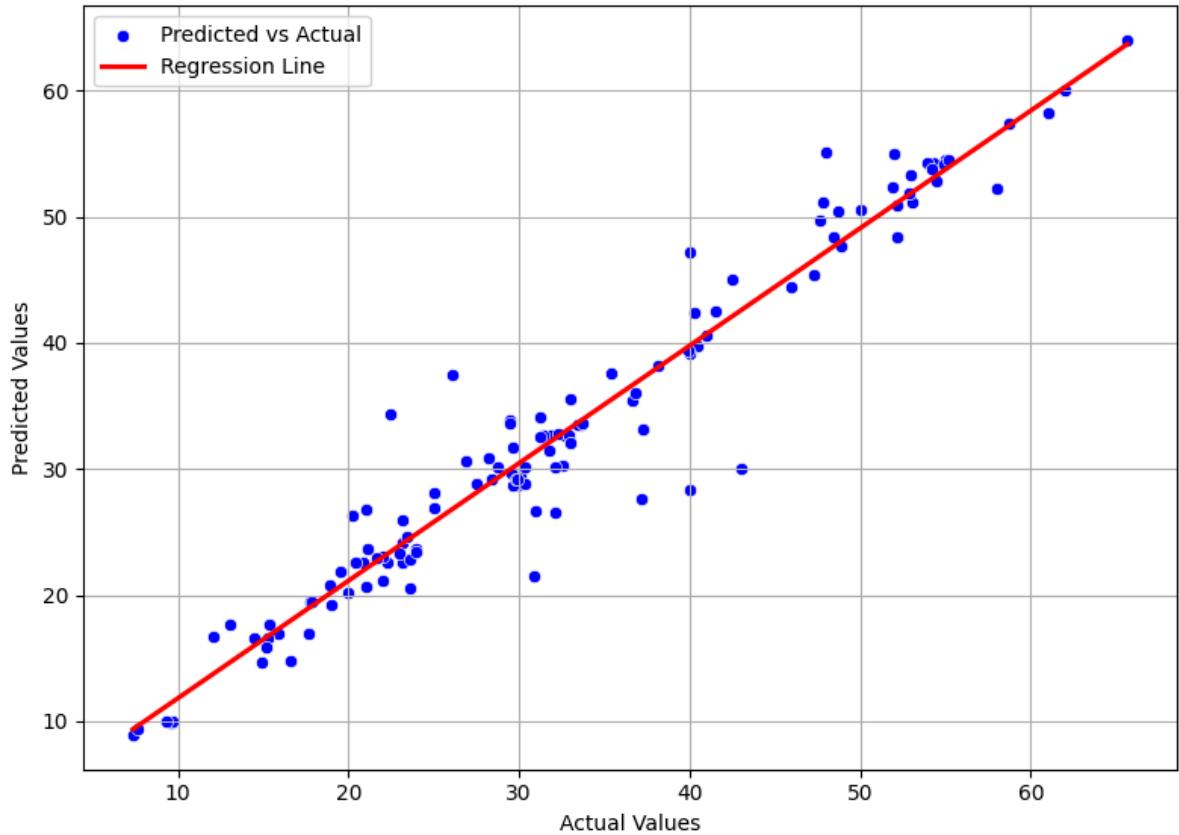
H2 Actual vs Predicted Values (R^2 Score: 0.9117) for K-Neighbors Regressor model



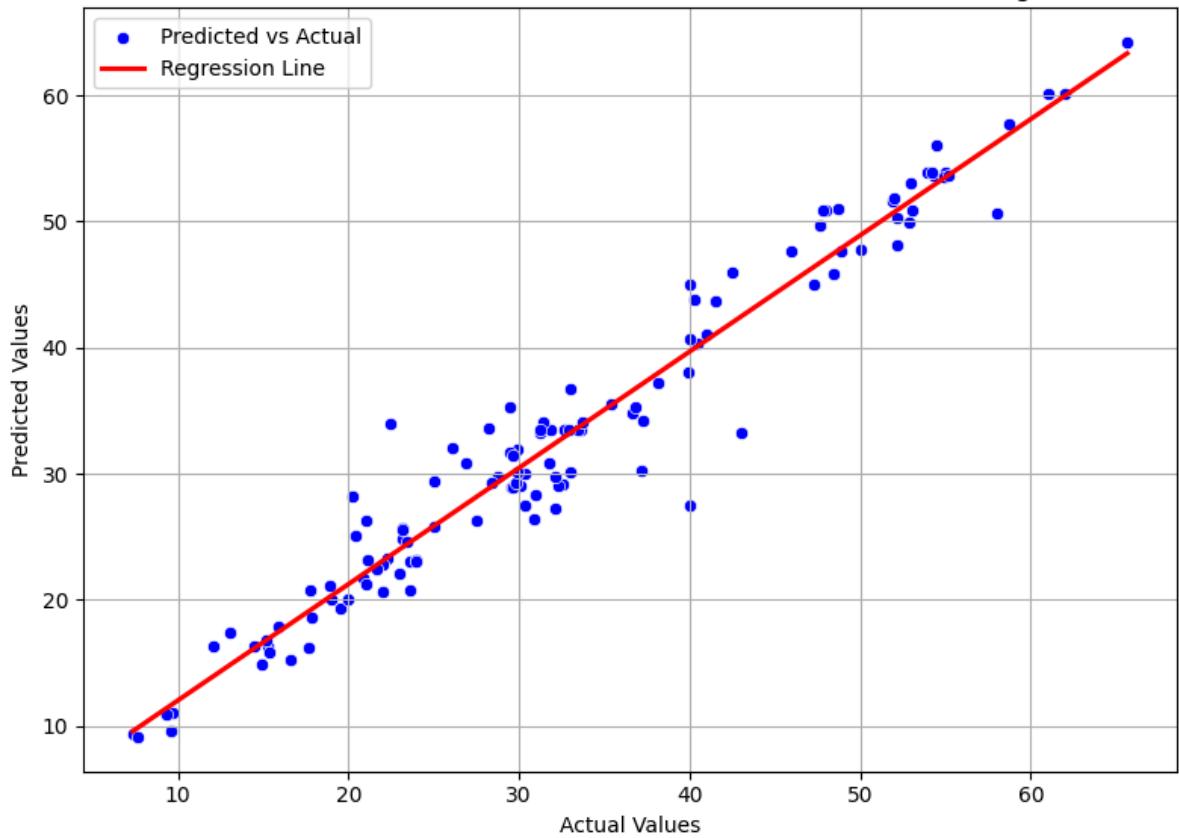
H2 Actual vs Predicted Values (R^2 Score: 0.9150) for Decision Tree model



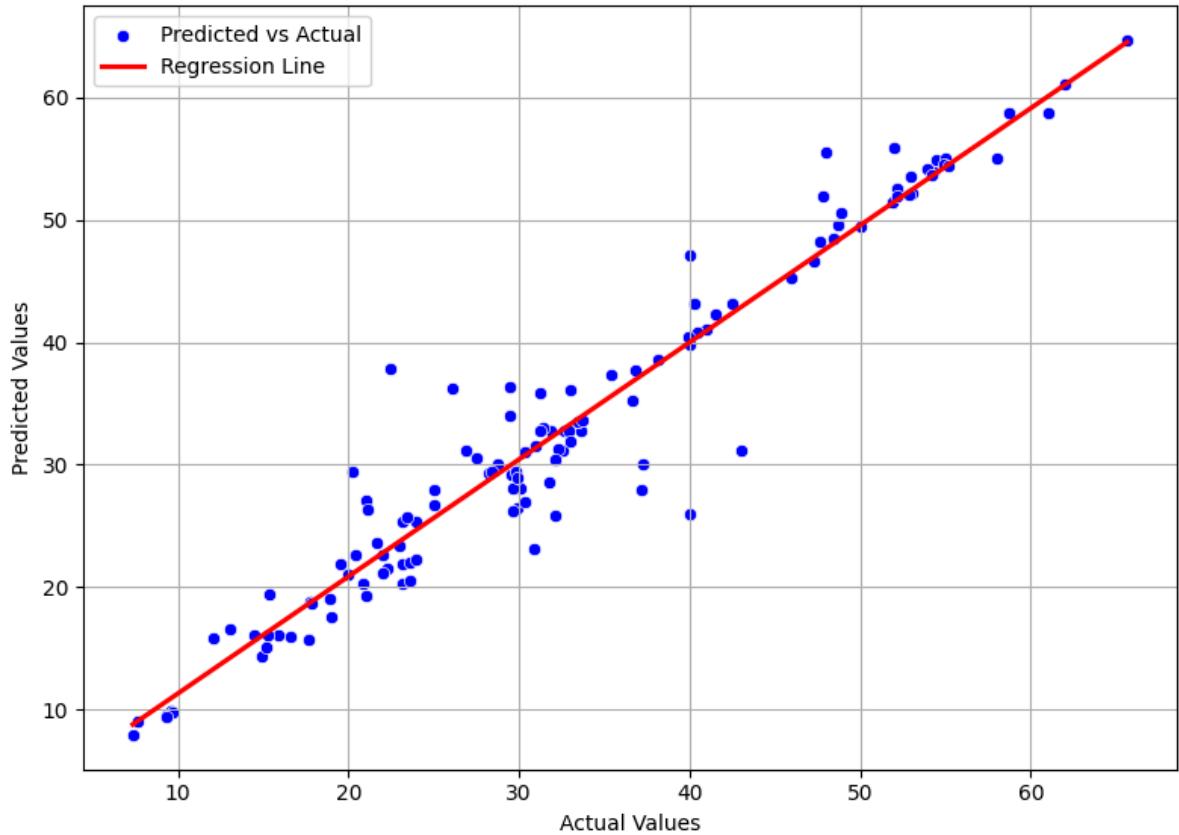
H2 Actual vs Predicted Values (R^2 Score: 0.9421) for Random Forest Regressor model



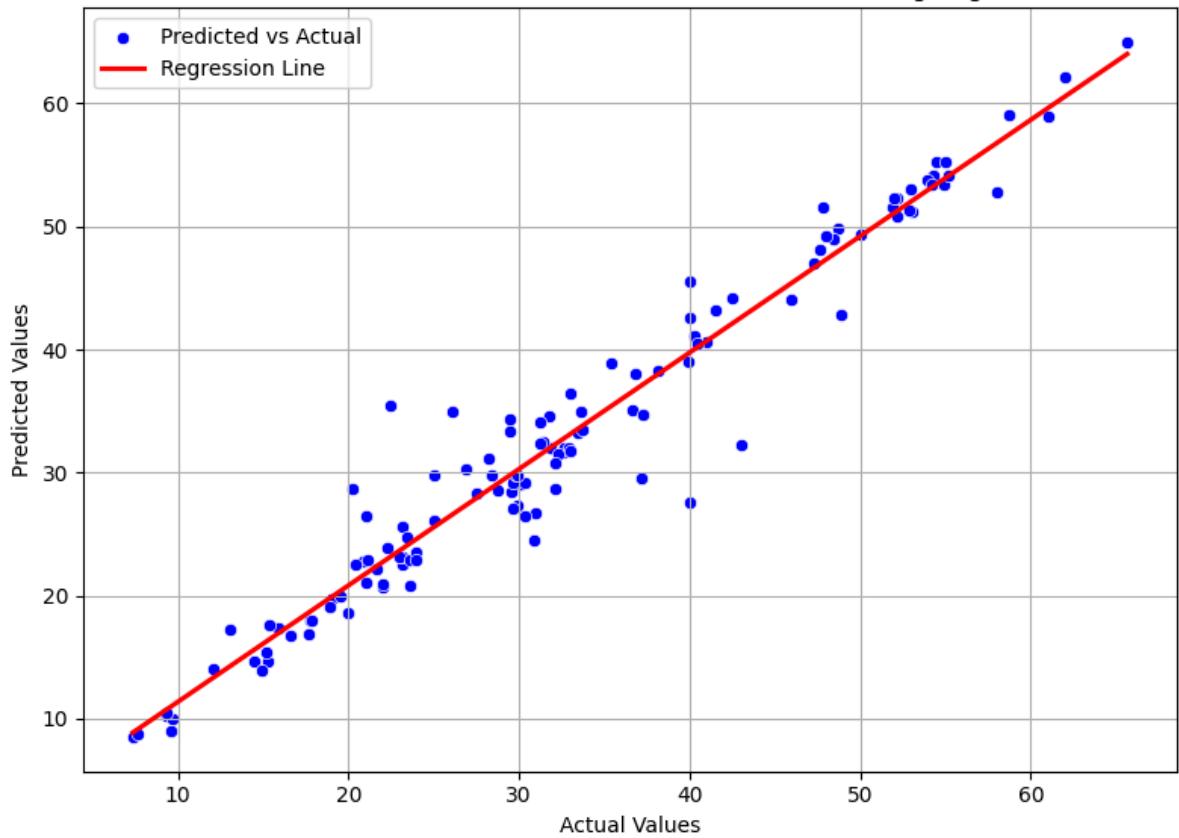
H2 Actual vs Predicted Values (R^2 Score: 0.9502) for Gradient Boosting model

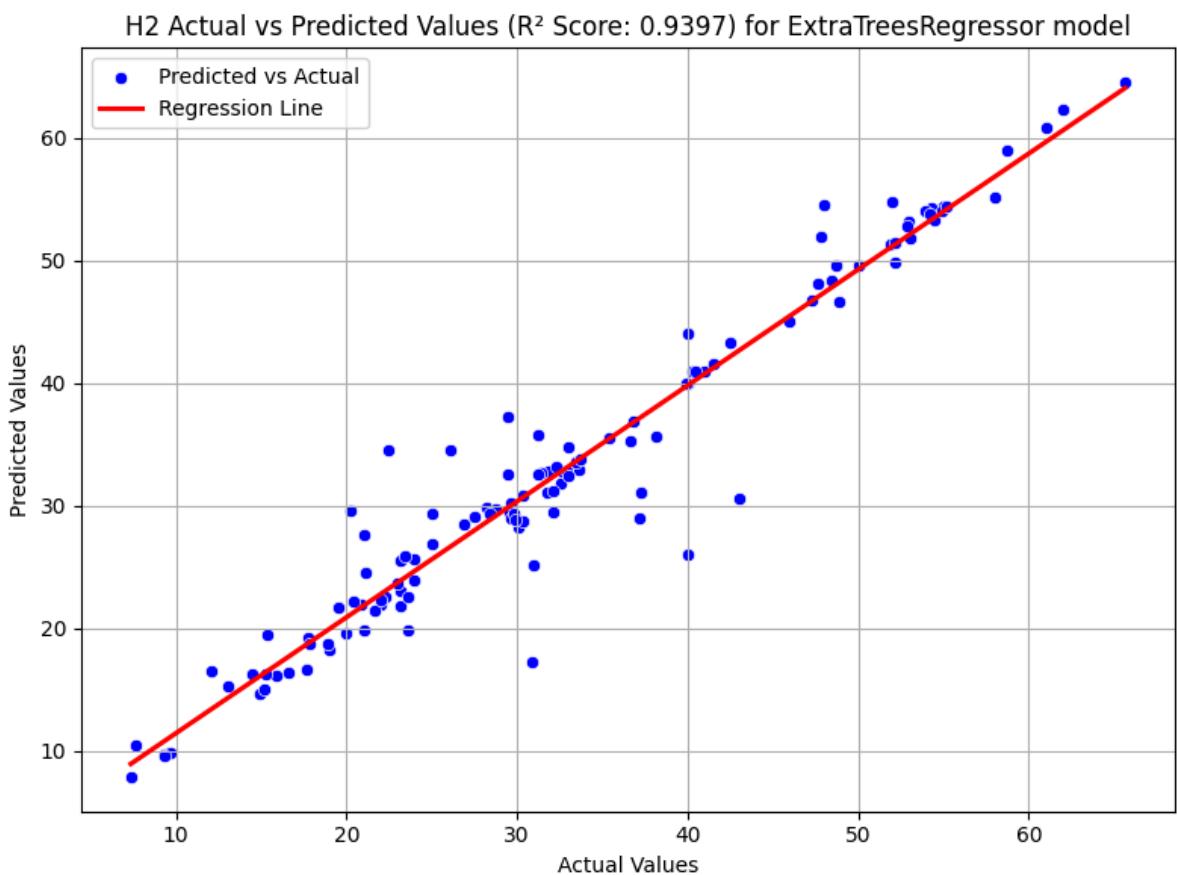
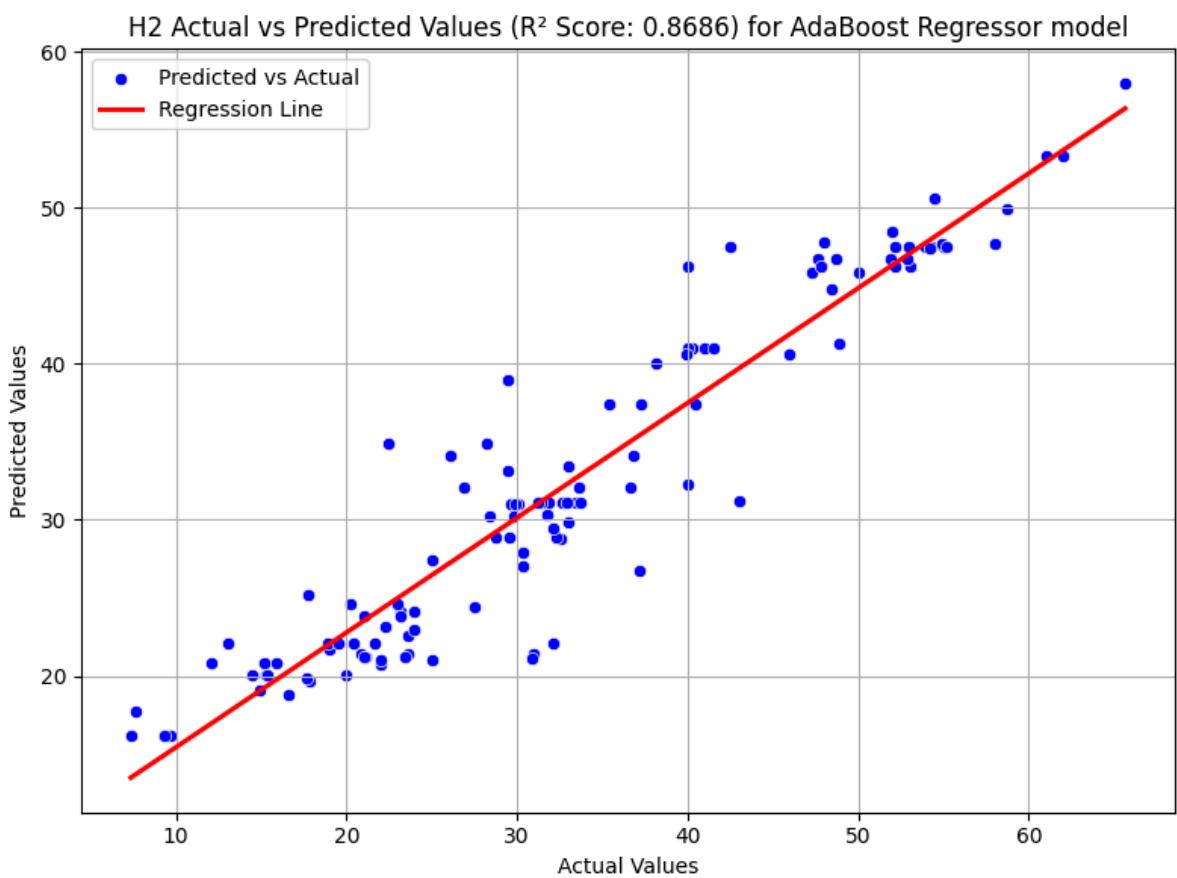


H2 Actual vs Predicted Values (R^2 Score: 0.9329) for XGBRegressor model

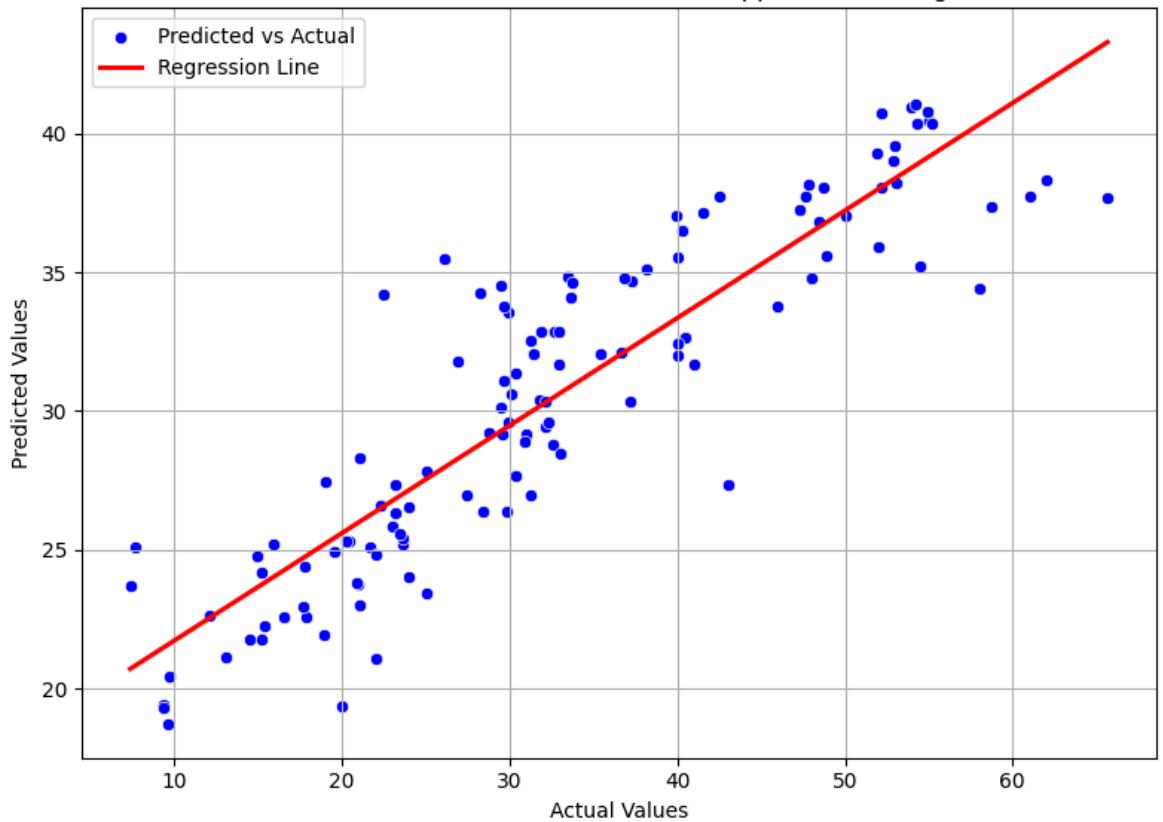


H2 Actual vs Predicted Values (R^2 Score: 0.9510) for CatBoosting Regressor model

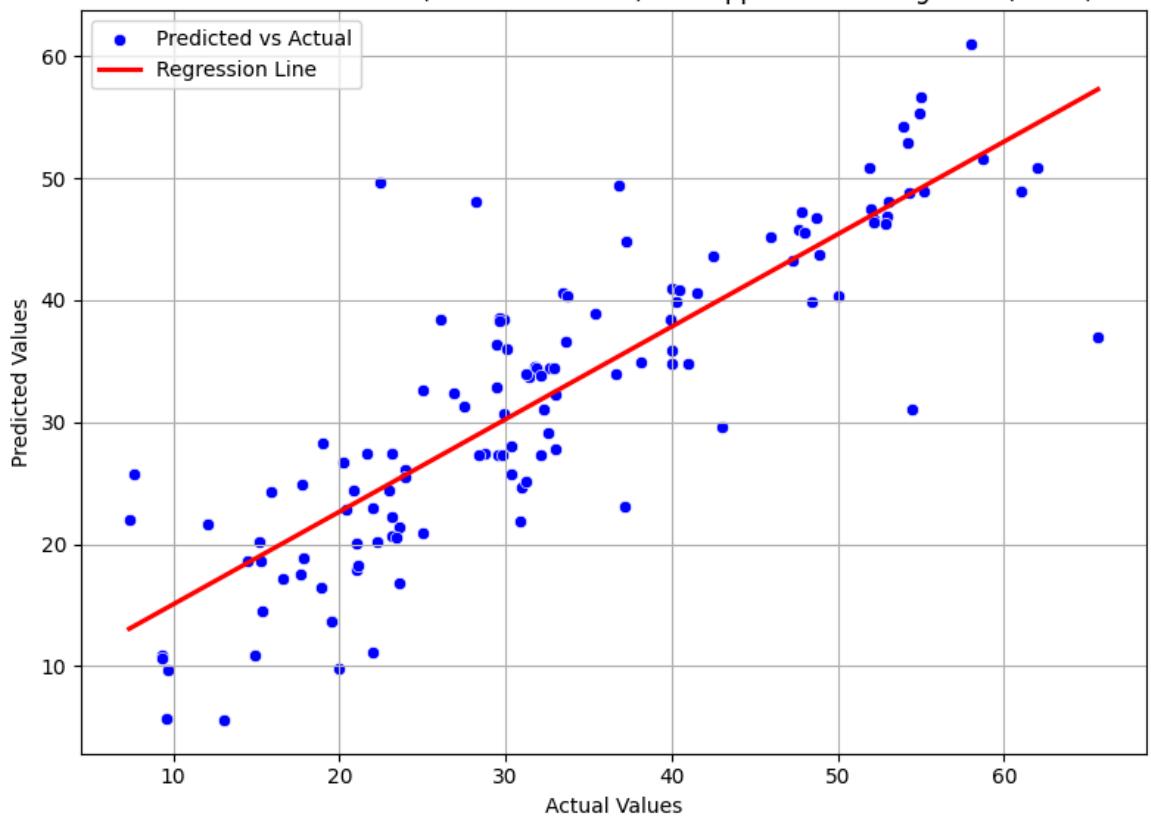




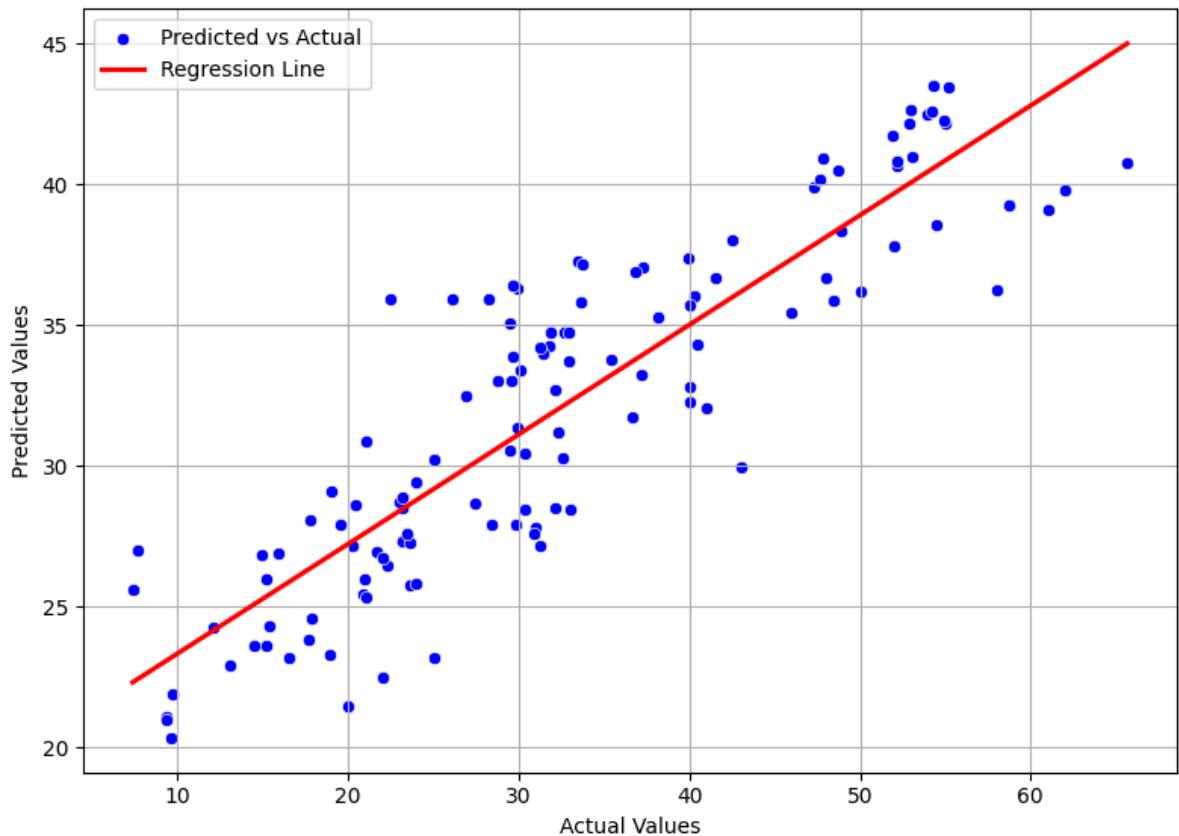
H2 Actual vs Predicted Values (R^2 Score: 0.5649) for Support Vector Regressor(RBF) model



H2 Actual vs Predicted Values (R^2 Score: 0.7220) for Support Vector Regressor(linear) model

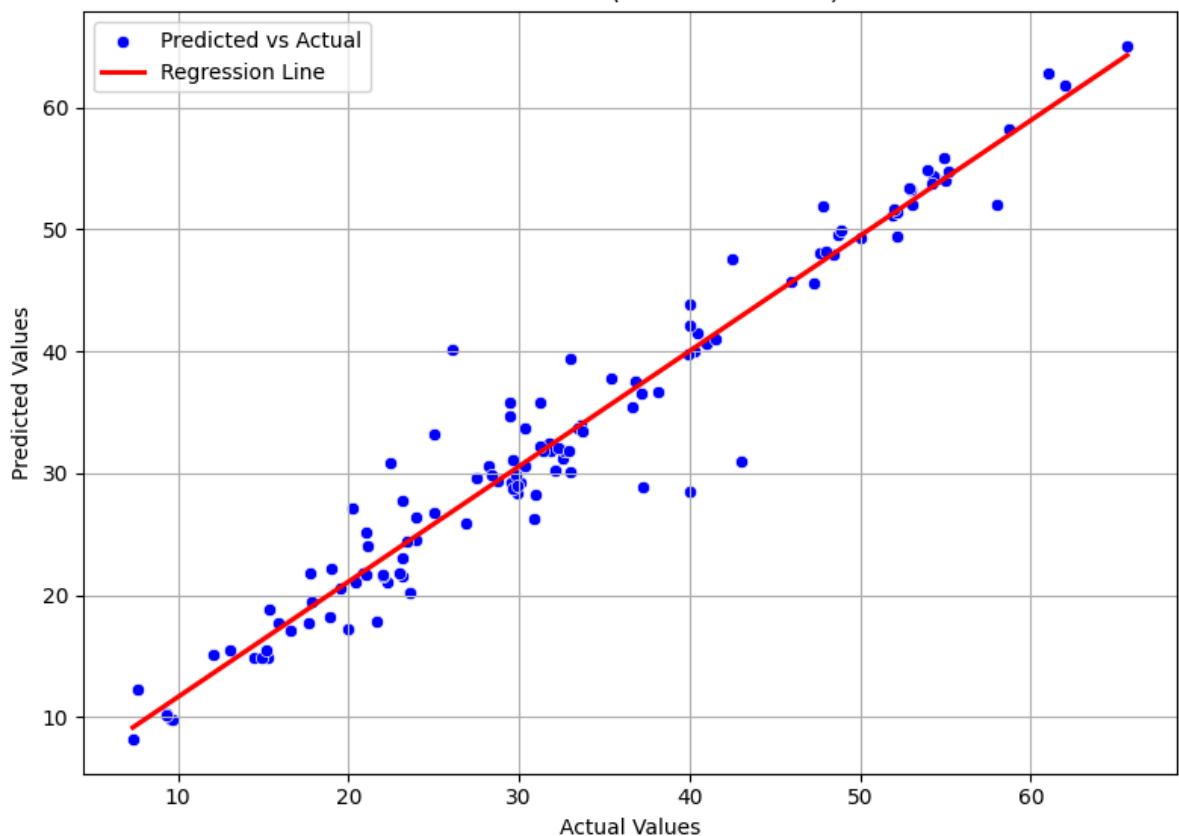


H2 Actual vs Predicted Values (R^2 Score: 0.5842) for Nu SVR(rbf) model



10/10 ————— 0s 2ms/step - loss: 4.4085 - mae: 1.2107
10/10 ————— 0s 12ms/step
4/4 ————— 0s 19ms/step

H2 Actual vs Predicted Values (R^2 Score: 0.9457) for ANN model



```
In [64]: score = pd.DataFrame(list(zip(models.keys(), r2_train_score.values(), r2_test_score
```

Out[64]:

	Model	r2_train_score	r2_test_score
0	Linear Regression	0.701773	0.730645
1	Lasso	0.650434	0.684888
2	K-Neighbors Regressor	0.896657	0.911715
3	Decision Tree	0.998124	0.914972
4	Random Forest Regressor	0.983950	0.942061
5	Gradient Boosting	0.966199	0.950161
6	XGBRegressor	0.998037	0.932889
7	CatBoosting Regressor	0.986135	0.951031
8	AdaBoost Regressor	0.856201	0.868602
9	ExtraTreesRegressor	0.998123	0.939666
10	Support Vector Regressor(RBF)	0.568170	0.564914
11	Support Vector Regressor(linear)	0.670485	0.721979
12	Nu SVR(rbf)	0.580037	0.584159
13	ANN	0.975372	0.945724

In [65]:

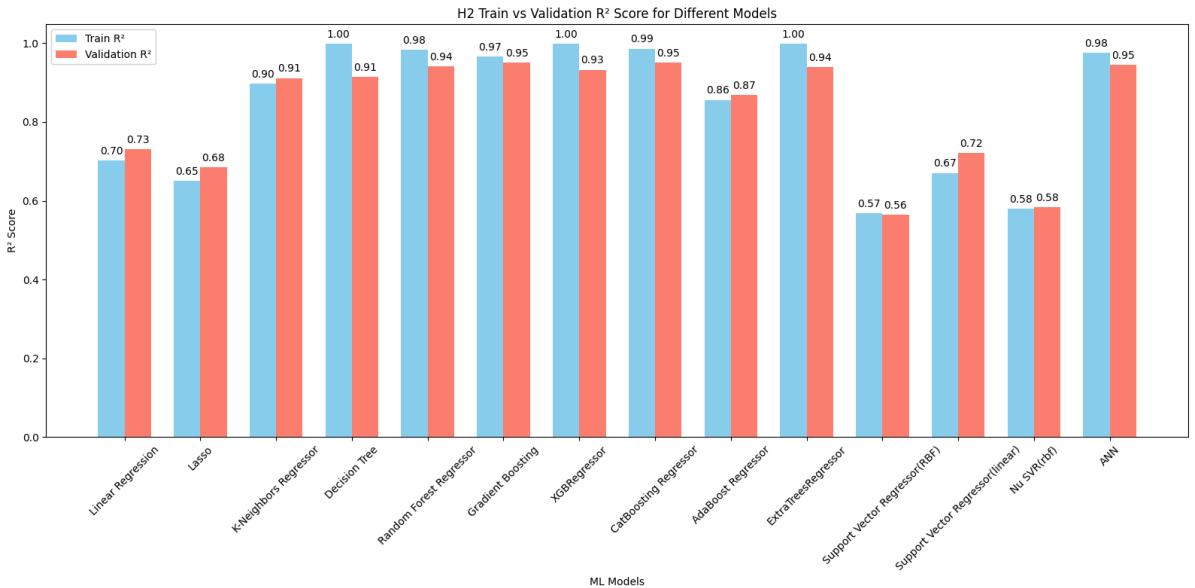
```
# Set positions
x = np.arange(len(score['Model']))
width = 0.35 # Width of the bars

# Create plot
fig, ax = plt.subplots(figsize=(16, 8))
bars1 = ax.bar(x - width/2, score['r2_train_score'], width, label='Train R2', color='blue')
bars2 = ax.bar(x + width/2, score['r2_test_score'], width, label='Validation R2', color='red')

# Add labels and title
ax.set_xlabel('ML Models')
ax.set_ylabel('R2 Score')
ax.set_title('H2 Train vs Validation R2 Score for Different Models')
ax.set_xticks(x)
ax.set_xticklabels(score['Model'], rotation=45)
ax.legend()

# Add R2 score text on top of bars
for bar in bars1 + bars2:
    yval = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2.0, yval + 0.01, f'{yval:.2f}', ha='center')

plt.tight_layout()
plt.savefig("H2 Train vs Validation R2 Score for Different Models")
plt.show()
```



Predicting CH4 values

```
In [66]: ANN_model = Sequential([
    Dense(32, input_dim=13),
    LeakyReLU(alpha=0.1),
    Dense(32, activation='tanh'),
    Dense(16, activation='relu'),
    Dense(1, activation='linear')
])

# Compile the model
ANN_model.compile(optimizer='adam',
                   loss='mean_squared_error',
                   metrics=['mae'])

# Train the model
ANN_model.fit(X_train_scaled, y_train.CH4, epochs=500, verbose=1)

# Evaluate the model
loss, mae = ANN_model.evaluate(X_train_scaled, y_train.CH4, verbose=0)
print(f"\nModel evaluation:\nLoss (MSE): {loss:.2f}, MAE: {mae:.2f}")
```

Epoch 1/500
10/10 2s 33ms/step - loss: 70.6160 - mae: 7.6613
Epoch 2/500
10/10 0s 2ms/step - loss: 67.3477 - mae: 7.4664
Epoch 3/500
10/10 0s 2ms/step - loss: 64.4833 - mae: 7.1564
Epoch 4/500
10/10 0s 2ms/step - loss: 53.4934 - mae: 6.4522
Epoch 5/500
10/10 0s 2ms/step - loss: 42.2167 - mae: 5.4767
Epoch 6/500
10/10 0s 2ms/step - loss: 31.6310 - mae: 4.5404
Epoch 7/500
10/10 0s 2ms/step - loss: 23.5081 - mae: 3.8119
Epoch 8/500
10/10 0s 2ms/step - loss: 16.0438 - mae: 3.1950
Epoch 9/500
10/10 0s 2ms/step - loss: 12.8049 - mae: 2.8408
Epoch 10/500
10/10 0s 2ms/step - loss: 12.6834 - mae: 2.8292
Epoch 11/500
10/10 0s 2ms/step - loss: 12.3268 - mae: 2.7783
Epoch 12/500
10/10 0s 2ms/step - loss: 10.5295 - mae: 2.5724
Epoch 13/500
10/10 0s 2ms/step - loss: 10.8168 - mae: 2.6067
Epoch 14/500
10/10 0s 2ms/step - loss: 10.1576 - mae: 2.5383
Epoch 15/500
10/10 0s 2ms/step - loss: 8.8011 - mae: 2.3645
Epoch 16/500
10/10 0s 2ms/step - loss: 10.1528 - mae: 2.4611
Epoch 17/500
10/10 0s 2ms/step - loss: 9.6955 - mae: 2.4197
Epoch 18/500
10/10 0s 2ms/step - loss: 8.7866 - mae: 2.2507
Epoch 19/500
10/10 0s 2ms/step - loss: 9.3735 - mae: 2.3614
Epoch 20/500
10/10 0s 2ms/step - loss: 8.3820 - mae: 2.2502
Epoch 21/500
10/10 0s 2ms/step - loss: 8.3800 - mae: 2.2129
Epoch 22/500
10/10 0s 2ms/step - loss: 7.9988 - mae: 2.1659
Epoch 23/500
10/10 0s 2ms/step - loss: 8.4071 - mae: 2.1871
Epoch 24/500
10/10 0s 2ms/step - loss: 8.6412 - mae: 2.2654
Epoch 25/500
10/10 0s 2ms/step - loss: 7.0446 - mae: 1.9809
Epoch 26/500
10/10 0s 2ms/step - loss: 7.4494 - mae: 2.0710
Epoch 27/500
10/10 0s 2ms/step - loss: 8.0073 - mae: 2.2071
Epoch 28/500
10/10 0s 2ms/step - loss: 7.6046 - mae: 2.1474
Epoch 29/500
10/10 0s 2ms/step - loss: 6.3849 - mae: 1.9433
Epoch 30/500
10/10 0s 2ms/step - loss: 7.7095 - mae: 2.1149
Epoch 31/500
10/10 0s 2ms/step - loss: 7.1924 - mae: 2.0663
Epoch 32/500
10/10 0s 2ms/step - loss: 5.3011 - mae: 1.7482

Epoch 33/500
10/10 0s 2ms/step - loss: 6.4545 - mae: 1.9535
Epoch 34/500
10/10 0s 2ms/step - loss: 5.6591 - mae: 1.8567
Epoch 35/500
10/10 0s 2ms/step - loss: 6.1660 - mae: 1.8697
Epoch 36/500
10/10 0s 2ms/step - loss: 5.4235 - mae: 1.7936
Epoch 37/500
10/10 0s 2ms/step - loss: 5.3126 - mae: 1.7244
Epoch 38/500
10/10 0s 2ms/step - loss: 5.3850 - mae: 1.7079
Epoch 39/500
10/10 0s 2ms/step - loss: 5.7843 - mae: 1.7979
Epoch 40/500
10/10 0s 2ms/step - loss: 5.6026 - mae: 1.8008
Epoch 41/500
10/10 0s 2ms/step - loss: 5.2041 - mae: 1.7255
Epoch 42/500
10/10 0s 2ms/step - loss: 5.6470 - mae: 1.7086
Epoch 43/500
10/10 0s 2ms/step - loss: 4.9662 - mae: 1.7107
Epoch 44/500
10/10 0s 2ms/step - loss: 4.5097 - mae: 1.6028
Epoch 45/500
10/10 0s 2ms/step - loss: 5.2323 - mae: 1.6789
Epoch 46/500
10/10 0s 2ms/step - loss: 4.8807 - mae: 1.6514
Epoch 47/500
10/10 0s 2ms/step - loss: 5.1146 - mae: 1.6787
Epoch 48/500
10/10 0s 2ms/step - loss: 4.1518 - mae: 1.5293
Epoch 49/500
10/10 0s 2ms/step - loss: 5.1279 - mae: 1.6591
Epoch 50/500
10/10 0s 2ms/step - loss: 4.5148 - mae: 1.5401
Epoch 51/500
10/10 0s 2ms/step - loss: 3.8827 - mae: 1.4627
Epoch 52/500
10/10 0s 2ms/step - loss: 4.5812 - mae: 1.5410
Epoch 53/500
10/10 0s 2ms/step - loss: 4.7875 - mae: 1.6548
Epoch 54/500
10/10 0s 2ms/step - loss: 4.0076 - mae: 1.4573
Epoch 55/500
10/10 0s 2ms/step - loss: 3.2892 - mae: 1.3714
Epoch 56/500
10/10 0s 2ms/step - loss: 4.4445 - mae: 1.5346
Epoch 57/500
10/10 0s 2ms/step - loss: 4.3629 - mae: 1.4796
Epoch 58/500
10/10 0s 2ms/step - loss: 4.1060 - mae: 1.4810
Epoch 59/500
10/10 0s 2ms/step - loss: 3.5897 - mae: 1.4172
Epoch 60/500
10/10 0s 2ms/step - loss: 4.2000 - mae: 1.4724
Epoch 61/500
10/10 0s 2ms/step - loss: 4.2431 - mae: 1.5309
Epoch 62/500
10/10 0s 2ms/step - loss: 3.5536 - mae: 1.4022
Epoch 63/500
10/10 0s 2ms/step - loss: 3.3941 - mae: 1.3886
Epoch 64/500
10/10 0s 2ms/step - loss: 3.2493 - mae: 1.2816

Epoch 65/500
10/10 0s 2ms/step - loss: 3.7941 - mae: 1.4107
Epoch 66/500
10/10 0s 2ms/step - loss: 4.4055 - mae: 1.4253
Epoch 67/500
10/10 0s 2ms/step - loss: 3.4501 - mae: 1.3525
Epoch 68/500
10/10 0s 2ms/step - loss: 2.8482 - mae: 1.2273
Epoch 69/500
10/10 0s 2ms/step - loss: 3.0341 - mae: 1.2827
Epoch 70/500
10/10 0s 2ms/step - loss: 3.2336 - mae: 1.2588
Epoch 71/500
10/10 0s 2ms/step - loss: 2.9249 - mae: 1.2445
Epoch 72/500
10/10 0s 2ms/step - loss: 3.3735 - mae: 1.2980
Epoch 73/500
10/10 0s 2ms/step - loss: 3.4526 - mae: 1.3387
Epoch 74/500
10/10 0s 2ms/step - loss: 2.8986 - mae: 1.2358
Epoch 75/500
10/10 0s 2ms/step - loss: 3.5092 - mae: 1.3499
Epoch 76/500
10/10 0s 2ms/step - loss: 3.9582 - mae: 1.3936
Epoch 77/500
10/10 0s 2ms/step - loss: 3.2539 - mae: 1.3001
Epoch 78/500
10/10 0s 2ms/step - loss: 3.6417 - mae: 1.3712
Epoch 79/500
10/10 0s 2ms/step - loss: 2.9017 - mae: 1.2169
Epoch 80/500
10/10 0s 2ms/step - loss: 2.6269 - mae: 1.1965
Epoch 81/500
10/10 0s 2ms/step - loss: 3.0454 - mae: 1.3247
Epoch 82/500
10/10 0s 2ms/step - loss: 2.7071 - mae: 1.1964
Epoch 83/500
10/10 0s 2ms/step - loss: 2.7534 - mae: 1.2072
Epoch 84/500
10/10 0s 2ms/step - loss: 3.2172 - mae: 1.2585
Epoch 85/500
10/10 0s 2ms/step - loss: 2.8604 - mae: 1.2009
Epoch 86/500
10/10 0s 2ms/step - loss: 2.3693 - mae: 1.1330
Epoch 87/500
10/10 0s 2ms/step - loss: 3.4616 - mae: 1.3586
Epoch 88/500
10/10 0s 2ms/step - loss: 2.7562 - mae: 1.1518
Epoch 89/500
10/10 0s 2ms/step - loss: 2.6645 - mae: 1.1766
Epoch 90/500
10/10 0s 2ms/step - loss: 2.1838 - mae: 1.0551
Epoch 91/500
10/10 0s 2ms/step - loss: 2.6251 - mae: 1.1505
Epoch 92/500
10/10 0s 2ms/step - loss: 2.0481 - mae: 1.0387
Epoch 93/500
10/10 0s 2ms/step - loss: 3.0150 - mae: 1.1822
Epoch 94/500
10/10 0s 2ms/step - loss: 2.3989 - mae: 1.0590
Epoch 95/500
10/10 0s 2ms/step - loss: 2.4187 - mae: 1.1082
Epoch 96/500
10/10 0s 2ms/step - loss: 2.4059 - mae: 1.1114

Epoch 97/500
10/10 0s 2ms/step - loss: 2.7873 - mae: 1.1642
Epoch 98/500
10/10 0s 2ms/step - loss: 2.1881 - mae: 1.0860
Epoch 99/500
10/10 0s 2ms/step - loss: 2.6421 - mae: 1.1545
Epoch 100/500
10/10 0s 2ms/step - loss: 2.5668 - mae: 1.1148
Epoch 101/500
10/10 0s 2ms/step - loss: 2.3790 - mae: 1.1245
Epoch 102/500
10/10 0s 2ms/step - loss: 2.6308 - mae: 1.1344
Epoch 103/500
10/10 0s 2ms/step - loss: 1.9022 - mae: 0.9783
Epoch 104/500
10/10 0s 2ms/step - loss: 2.0725 - mae: 1.0139
Epoch 105/500
10/10 0s 2ms/step - loss: 2.1113 - mae: 1.0321
Epoch 106/500
10/10 0s 2ms/step - loss: 2.2606 - mae: 1.0680
Epoch 107/500
10/10 0s 2ms/step - loss: 2.3831 - mae: 1.0577
Epoch 108/500
10/10 0s 2ms/step - loss: 1.8270 - mae: 0.9506
Epoch 109/500
10/10 0s 2ms/step - loss: 2.3821 - mae: 1.0660
Epoch 110/500
10/10 0s 2ms/step - loss: 1.8893 - mae: 0.9990
Epoch 111/500
10/10 0s 2ms/step - loss: 2.4212 - mae: 1.0995
Epoch 112/500
10/10 0s 2ms/step - loss: 2.2983 - mae: 1.0525
Epoch 113/500
10/10 0s 2ms/step - loss: 1.7501 - mae: 0.9437
Epoch 114/500
10/10 0s 2ms/step - loss: 2.2655 - mae: 1.0439
Epoch 115/500
10/10 0s 2ms/step - loss: 1.8413 - mae: 0.9441
Epoch 116/500
10/10 0s 2ms/step - loss: 1.5750 - mae: 0.9140
Epoch 117/500
10/10 0s 2ms/step - loss: 1.8818 - mae: 0.9506
Epoch 118/500
10/10 0s 2ms/step - loss: 1.9090 - mae: 0.9527
Epoch 119/500
10/10 0s 2ms/step - loss: 1.7036 - mae: 0.9043
Epoch 120/500
10/10 0s 2ms/step - loss: 1.8442 - mae: 0.9417
Epoch 121/500
10/10 0s 2ms/step - loss: 1.9014 - mae: 0.9426
Epoch 122/500
10/10 0s 2ms/step - loss: 1.9455 - mae: 0.9591
Epoch 123/500
10/10 0s 2ms/step - loss: 1.9879 - mae: 0.9574
Epoch 124/500
10/10 0s 2ms/step - loss: 1.6484 - mae: 0.9014
Epoch 125/500
10/10 0s 2ms/step - loss: 1.6820 - mae: 0.9016
Epoch 126/500
10/10 0s 2ms/step - loss: 1.9723 - mae: 0.9020
Epoch 127/500
10/10 0s 2ms/step - loss: 1.7140 - mae: 0.9240
Epoch 128/500
10/10 0s 2ms/step - loss: 1.9237 - mae: 0.9434

Epoch 129/500
10/10 0s 2ms/step - loss: 1.6188 - mae: 0.8930
Epoch 130/500
10/10 0s 2ms/step - loss: 1.8393 - mae: 0.9466
Epoch 131/500
10/10 0s 2ms/step - loss: 2.1072 - mae: 0.9716
Epoch 132/500
10/10 0s 2ms/step - loss: 2.1454 - mae: 0.9995
Epoch 133/500
10/10 0s 2ms/step - loss: 1.6137 - mae: 0.9135
Epoch 134/500
10/10 0s 2ms/step - loss: 1.9466 - mae: 0.9061
Epoch 135/500
10/10 0s 2ms/step - loss: 1.9614 - mae: 0.9459
Epoch 136/500
10/10 0s 2ms/step - loss: 2.0597 - mae: 0.9739
Epoch 137/500
10/10 0s 2ms/step - loss: 1.7268 - mae: 0.9127
Epoch 138/500
10/10 0s 2ms/step - loss: 1.8693 - mae: 0.9604
Epoch 139/500
10/10 0s 2ms/step - loss: 1.5961 - mae: 0.8997
Epoch 140/500
10/10 0s 2ms/step - loss: 1.9315 - mae: 0.9334
Epoch 141/500
10/10 0s 2ms/step - loss: 1.8167 - mae: 0.9400
Epoch 142/500
10/10 0s 2ms/step - loss: 1.5974 - mae: 0.8776
Epoch 143/500
10/10 0s 2ms/step - loss: 1.6477 - mae: 0.8815
Epoch 144/500
10/10 0s 2ms/step - loss: 1.8099 - mae: 0.9410
Epoch 145/500
10/10 0s 2ms/step - loss: 1.3409 - mae: 0.8179
Epoch 146/500
10/10 0s 2ms/step - loss: 2.0140 - mae: 0.9336
Epoch 147/500
10/10 0s 2ms/step - loss: 1.5765 - mae: 0.8702
Epoch 148/500
10/10 0s 2ms/step - loss: 1.4413 - mae: 0.8122
Epoch 149/500
10/10 0s 2ms/step - loss: 1.5498 - mae: 0.8641
Epoch 150/500
10/10 0s 2ms/step - loss: 1.6094 - mae: 0.9048
Epoch 151/500
10/10 0s 2ms/step - loss: 1.5682 - mae: 0.8713
Epoch 152/500
10/10 0s 2ms/step - loss: 1.7679 - mae: 0.8995
Epoch 153/500
10/10 0s 2ms/step - loss: 1.6262 - mae: 0.8826
Epoch 154/500
10/10 0s 2ms/step - loss: 1.2974 - mae: 0.7609
Epoch 155/500
10/10 0s 2ms/step - loss: 1.3416 - mae: 0.8277
Epoch 156/500
10/10 0s 2ms/step - loss: 1.3980 - mae: 0.8240
Epoch 157/500
10/10 0s 2ms/step - loss: 1.7966 - mae: 0.9172
Epoch 158/500
10/10 0s 2ms/step - loss: 1.6192 - mae: 0.8875
Epoch 159/500
10/10 0s 2ms/step - loss: 1.6593 - mae: 0.8809
Epoch 160/500
10/10 0s 2ms/step - loss: 1.4676 - mae: 0.8496

Epoch 161/500
10/10 0s 2ms/step - loss: 1.4575 - mae: 0.8376
Epoch 162/500
10/10 0s 2ms/step - loss: 1.4609 - mae: 0.8701
Epoch 163/500
10/10 0s 2ms/step - loss: 1.4645 - mae: 0.7702
Epoch 164/500
10/10 0s 2ms/step - loss: 1.2141 - mae: 0.7704
Epoch 165/500
10/10 0s 2ms/step - loss: 1.6663 - mae: 0.8837
Epoch 166/500
10/10 0s 2ms/step - loss: 1.3792 - mae: 0.8075
Epoch 167/500
10/10 0s 2ms/step - loss: 1.3996 - mae: 0.8480
Epoch 168/500
10/10 0s 2ms/step - loss: 1.2760 - mae: 0.8140
Epoch 169/500
10/10 0s 2ms/step - loss: 1.9824 - mae: 0.9692
Epoch 170/500
10/10 0s 2ms/step - loss: 1.4997 - mae: 0.8673
Epoch 171/500
10/10 0s 2ms/step - loss: 1.5659 - mae: 0.8470
Epoch 172/500
10/10 0s 2ms/step - loss: 1.4187 - mae: 0.8239
Epoch 173/500
10/10 0s 2ms/step - loss: 1.2377 - mae: 0.7494
Epoch 174/500
10/10 0s 2ms/step - loss: 1.6629 - mae: 0.8757
Epoch 175/500
10/10 0s 2ms/step - loss: 1.5143 - mae: 0.8550
Epoch 176/500
10/10 0s 2ms/step - loss: 1.4326 - mae: 0.8327
Epoch 177/500
10/10 0s 2ms/step - loss: 1.5989 - mae: 0.8583
Epoch 178/500
10/10 0s 2ms/step - loss: 1.5699 - mae: 0.8404
Epoch 179/500
10/10 0s 2ms/step - loss: 1.5473 - mae: 0.8285
Epoch 180/500
10/10 0s 2ms/step - loss: 1.3454 - mae: 0.8266
Epoch 181/500
10/10 0s 2ms/step - loss: 1.3735 - mae: 0.8323
Epoch 182/500
10/10 0s 2ms/step - loss: 1.1374 - mae: 0.7315
Epoch 183/500
10/10 0s 2ms/step - loss: 1.3483 - mae: 0.7927
Epoch 184/500
10/10 0s 2ms/step - loss: 1.1501 - mae: 0.7668
Epoch 185/500
10/10 0s 2ms/step - loss: 1.6541 - mae: 0.8575
Epoch 186/500
10/10 0s 2ms/step - loss: 1.5430 - mae: 0.8465
Epoch 187/500
10/10 0s 2ms/step - loss: 1.5626 - mae: 0.8491
Epoch 188/500
10/10 0s 2ms/step - loss: 1.4042 - mae: 0.8058
Epoch 189/500
10/10 0s 2ms/step - loss: 1.6736 - mae: 0.8591
Epoch 190/500
10/10 0s 2ms/step - loss: 1.2800 - mae: 0.7956
Epoch 191/500
10/10 0s 2ms/step - loss: 1.4494 - mae: 0.8154
Epoch 192/500
10/10 0s 2ms/step - loss: 1.2680 - mae: 0.7744

Epoch 193/500
10/10 0s 2ms/step - loss: 1.4634 - mae: 0.7994
Epoch 194/500
10/10 0s 2ms/step - loss: 1.2423 - mae: 0.7584
Epoch 195/500
10/10 0s 2ms/step - loss: 1.5262 - mae: 0.8349
Epoch 196/500
10/10 0s 2ms/step - loss: 1.3783 - mae: 0.8160
Epoch 197/500
10/10 0s 2ms/step - loss: 1.3314 - mae: 0.7922
Epoch 198/500
10/10 0s 2ms/step - loss: 1.5603 - mae: 0.8174
Epoch 199/500
10/10 0s 2ms/step - loss: 1.3356 - mae: 0.7514
Epoch 200/500
10/10 0s 2ms/step - loss: 1.2577 - mae: 0.7678
Epoch 201/500
10/10 0s 2ms/step - loss: 1.3354 - mae: 0.8149
Epoch 202/500
10/10 0s 2ms/step - loss: 1.3238 - mae: 0.7848
Epoch 203/500
10/10 0s 2ms/step - loss: 1.3904 - mae: 0.8046
Epoch 204/500
10/10 0s 2ms/step - loss: 1.0952 - mae: 0.7654
Epoch 205/500
10/10 0s 2ms/step - loss: 1.1305 - mae: 0.7352
Epoch 206/500
10/10 0s 2ms/step - loss: 1.1891 - mae: 0.7615
Epoch 207/500
10/10 0s 2ms/step - loss: 1.4054 - mae: 0.8069
Epoch 208/500
10/10 0s 2ms/step - loss: 1.2488 - mae: 0.7582
Epoch 209/500
10/10 0s 2ms/step - loss: 1.4230 - mae: 0.8258
Epoch 210/500
10/10 0s 2ms/step - loss: 1.2159 - mae: 0.7742
Epoch 211/500
10/10 0s 2ms/step - loss: 1.1850 - mae: 0.7596
Epoch 212/500
10/10 0s 2ms/step - loss: 1.1784 - mae: 0.7351
Epoch 213/500
10/10 0s 2ms/step - loss: 1.0477 - mae: 0.7052
Epoch 214/500
10/10 0s 2ms/step - loss: 1.5931 - mae: 0.8128
Epoch 215/500
10/10 0s 2ms/step - loss: 1.2815 - mae: 0.7677
Epoch 216/500
10/10 0s 2ms/step - loss: 1.2788 - mae: 0.7630
Epoch 217/500
10/10 0s 2ms/step - loss: 0.9537 - mae: 0.6925
Epoch 218/500
10/10 0s 2ms/step - loss: 1.0886 - mae: 0.7243
Epoch 219/500
10/10 0s 2ms/step - loss: 1.3045 - mae: 0.7542
Epoch 220/500
10/10 0s 2ms/step - loss: 1.0693 - mae: 0.7230
Epoch 221/500
10/10 0s 2ms/step - loss: 1.5097 - mae: 0.8097
Epoch 222/500
10/10 0s 2ms/step - loss: 1.1612 - mae: 0.7460
Epoch 223/500
10/10 0s 2ms/step - loss: 0.9942 - mae: 0.6677
Epoch 224/500
10/10 0s 2ms/step - loss: 1.1223 - mae: 0.7157

Epoch 225/500
10/10 0s 2ms/step - loss: 1.1008 - mae: 0.7213
Epoch 226/500
10/10 0s 2ms/step - loss: 1.4091 - mae: 0.7587
Epoch 227/500
10/10 0s 2ms/step - loss: 1.0882 - mae: 0.7121
Epoch 228/500
10/10 0s 2ms/step - loss: 0.9510 - mae: 0.6831
Epoch 229/500
10/10 0s 2ms/step - loss: 1.2222 - mae: 0.7332
Epoch 230/500
10/10 0s 2ms/step - loss: 1.4082 - mae: 0.7727
Epoch 231/500
10/10 0s 2ms/step - loss: 1.3565 - mae: 0.7392
Epoch 232/500
10/10 0s 2ms/step - loss: 0.9561 - mae: 0.6831
Epoch 233/500
10/10 0s 2ms/step - loss: 1.2139 - mae: 0.7154
Epoch 234/500
10/10 0s 2ms/step - loss: 1.0600 - mae: 0.7202
Epoch 235/500
10/10 0s 2ms/step - loss: 1.0548 - mae: 0.6985
Epoch 236/500
10/10 0s 2ms/step - loss: 1.1280 - mae: 0.7217
Epoch 237/500
10/10 0s 2ms/step - loss: 1.1638 - mae: 0.7333
Epoch 238/500
10/10 0s 2ms/step - loss: 0.9602 - mae: 0.6779
Epoch 239/500
10/10 0s 2ms/step - loss: 1.1121 - mae: 0.7170
Epoch 240/500
10/10 0s 2ms/step - loss: 1.1837 - mae: 0.7256
Epoch 241/500
10/10 0s 2ms/step - loss: 1.0395 - mae: 0.7047
Epoch 242/500
10/10 0s 2ms/step - loss: 1.2669 - mae: 0.7388
Epoch 243/500
10/10 0s 2ms/step - loss: 1.1946 - mae: 0.7203
Epoch 244/500
10/10 0s 2ms/step - loss: 1.1240 - mae: 0.7401
Epoch 245/500
10/10 0s 2ms/step - loss: 1.1183 - mae: 0.7217
Epoch 246/500
10/10 0s 2ms/step - loss: 1.2161 - mae: 0.7351
Epoch 247/500
10/10 0s 2ms/step - loss: 1.1895 - mae: 0.7459
Epoch 248/500
10/10 0s 2ms/step - loss: 1.3629 - mae: 0.7579
Epoch 249/500
10/10 0s 2ms/step - loss: 1.0308 - mae: 0.6975
Epoch 250/500
10/10 0s 2ms/step - loss: 1.2433 - mae: 0.7711
Epoch 251/500
10/10 0s 2ms/step - loss: 1.0634 - mae: 0.6841
Epoch 252/500
10/10 0s 2ms/step - loss: 1.1000 - mae: 0.7133
Epoch 253/500
10/10 0s 2ms/step - loss: 1.3446 - mae: 0.7421
Epoch 254/500
10/10 0s 2ms/step - loss: 1.2156 - mae: 0.7310
Epoch 255/500
10/10 0s 2ms/step - loss: 1.0830 - mae: 0.7280
Epoch 256/500
10/10 0s 2ms/step - loss: 1.2456 - mae: 0.7582

Epoch 257/500
10/10 0s 2ms/step - loss: 0.9643 - mae: 0.6617
Epoch 258/500
10/10 0s 2ms/step - loss: 1.3321 - mae: 0.7617
Epoch 259/500
10/10 0s 2ms/step - loss: 1.2529 - mae: 0.7236
Epoch 260/500
10/10 0s 2ms/step - loss: 0.9092 - mae: 0.6477
Epoch 261/500
10/10 0s 2ms/step - loss: 1.1769 - mae: 0.7254
Epoch 262/500
10/10 0s 2ms/step - loss: 1.3940 - mae: 0.7260
Epoch 263/500
10/10 0s 2ms/step - loss: 1.2523 - mae: 0.7200
Epoch 264/500
10/10 0s 2ms/step - loss: 1.3162 - mae: 0.7442
Epoch 265/500
10/10 0s 2ms/step - loss: 1.2829 - mae: 0.7513
Epoch 266/500
10/10 0s 2ms/step - loss: 1.0449 - mae: 0.7030
Epoch 267/500
10/10 0s 2ms/step - loss: 0.9424 - mae: 0.6881
Epoch 268/500
10/10 0s 2ms/step - loss: 1.3093 - mae: 0.7178
Epoch 269/500
10/10 0s 2ms/step - loss: 1.0206 - mae: 0.6624
Epoch 270/500
10/10 0s 2ms/step - loss: 0.9399 - mae: 0.6543
Epoch 271/500
10/10 0s 2ms/step - loss: 1.3514 - mae: 0.7346
Epoch 272/500
10/10 0s 2ms/step - loss: 1.2914 - mae: 0.7249
Epoch 273/500
10/10 0s 2ms/step - loss: 1.1557 - mae: 0.7589
Epoch 274/500
10/10 0s 2ms/step - loss: 1.2652 - mae: 0.7585
Epoch 275/500
10/10 0s 2ms/step - loss: 1.0496 - mae: 0.6791
Epoch 276/500
10/10 0s 2ms/step - loss: 1.4373 - mae: 0.7408
Epoch 277/500
10/10 0s 2ms/step - loss: 1.1234 - mae: 0.7037
Epoch 278/500
10/10 0s 2ms/step - loss: 1.0827 - mae: 0.7222
Epoch 279/500
10/10 0s 2ms/step - loss: 1.0610 - mae: 0.7003
Epoch 280/500
10/10 0s 2ms/step - loss: 0.9371 - mae: 0.6900
Epoch 281/500
10/10 0s 2ms/step - loss: 1.0118 - mae: 0.6881
Epoch 282/500
10/10 0s 2ms/step - loss: 0.9556 - mae: 0.6381
Epoch 283/500
10/10 0s 2ms/step - loss: 1.1929 - mae: 0.7074
Epoch 284/500
10/10 0s 2ms/step - loss: 1.0423 - mae: 0.7081
Epoch 285/500
10/10 0s 2ms/step - loss: 0.9400 - mae: 0.6582
Epoch 286/500
10/10 0s 2ms/step - loss: 1.0895 - mae: 0.6892
Epoch 287/500
10/10 0s 2ms/step - loss: 1.0601 - mae: 0.6677
Epoch 288/500
10/10 0s 2ms/step - loss: 1.0374 - mae: 0.6920

Epoch 289/500
10/10 0s 2ms/step - loss: 0.9185 - mae: 0.6640
Epoch 290/500
10/10 0s 2ms/step - loss: 0.9431 - mae: 0.6692
Epoch 291/500
10/10 0s 2ms/step - loss: 0.9391 - mae: 0.6216
Epoch 292/500
10/10 0s 2ms/step - loss: 0.9167 - mae: 0.6531
Epoch 293/500
10/10 0s 2ms/step - loss: 1.0084 - mae: 0.6657
Epoch 294/500
10/10 0s 2ms/step - loss: 1.0180 - mae: 0.6322
Epoch 295/500
10/10 0s 2ms/step - loss: 0.8524 - mae: 0.6094
Epoch 296/500
10/10 0s 2ms/step - loss: 0.9020 - mae: 0.6025
Epoch 297/500
10/10 0s 2ms/step - loss: 1.1155 - mae: 0.7014
Epoch 298/500
10/10 0s 2ms/step - loss: 1.0438 - mae: 0.6529
Epoch 299/500
10/10 0s 2ms/step - loss: 0.9610 - mae: 0.6119
Epoch 300/500
10/10 0s 2ms/step - loss: 1.2405 - mae: 0.7017
Epoch 301/500
10/10 0s 2ms/step - loss: 0.8934 - mae: 0.6289
Epoch 302/500
10/10 0s 2ms/step - loss: 1.0901 - mae: 0.6500
Epoch 303/500
10/10 0s 2ms/step - loss: 1.0268 - mae: 0.6503
Epoch 304/500
10/10 0s 2ms/step - loss: 1.0612 - mae: 0.6857
Epoch 305/500
10/10 0s 2ms/step - loss: 1.0559 - mae: 0.6749
Epoch 306/500
10/10 0s 2ms/step - loss: 0.8302 - mae: 0.6018
Epoch 307/500
10/10 0s 2ms/step - loss: 0.8969 - mae: 0.6315
Epoch 308/500
10/10 0s 2ms/step - loss: 1.3418 - mae: 0.6979
Epoch 309/500
10/10 0s 2ms/step - loss: 1.3480 - mae: 0.7236
Epoch 310/500
10/10 0s 2ms/step - loss: 0.9808 - mae: 0.7189
Epoch 311/500
10/10 0s 2ms/step - loss: 1.4512 - mae: 0.7422
Epoch 312/500
10/10 0s 2ms/step - loss: 0.9400 - mae: 0.6373
Epoch 313/500
10/10 0s 2ms/step - loss: 0.7427 - mae: 0.5689
Epoch 314/500
10/10 0s 2ms/step - loss: 0.9100 - mae: 0.6423
Epoch 315/500
10/10 0s 2ms/step - loss: 0.9477 - mae: 0.6236
Epoch 316/500
10/10 0s 2ms/step - loss: 0.9293 - mae: 0.6710
Epoch 317/500
10/10 0s 2ms/step - loss: 1.0562 - mae: 0.6867
Epoch 318/500
10/10 0s 2ms/step - loss: 0.8793 - mae: 0.6276
Epoch 319/500
10/10 0s 2ms/step - loss: 0.8735 - mae: 0.6431
Epoch 320/500
10/10 0s 2ms/step - loss: 0.9449 - mae: 0.6421

Epoch 321/500
10/10 0s 2ms/step - loss: 1.1383 - mae: 0.6810
Epoch 322/500
10/10 0s 2ms/step - loss: 0.7286 - mae: 0.5520
Epoch 323/500
10/10 0s 2ms/step - loss: 1.1844 - mae: 0.6646
Epoch 324/500
10/10 0s 2ms/step - loss: 0.8820 - mae: 0.6155
Epoch 325/500
10/10 0s 2ms/step - loss: 1.0783 - mae: 0.7087
Epoch 326/500
10/10 0s 2ms/step - loss: 0.9130 - mae: 0.6459
Epoch 327/500
10/10 0s 2ms/step - loss: 1.0431 - mae: 0.6538
Epoch 328/500
10/10 0s 2ms/step - loss: 0.9947 - mae: 0.6803
Epoch 329/500
10/10 0s 2ms/step - loss: 0.9793 - mae: 0.6437
Epoch 330/500
10/10 0s 2ms/step - loss: 0.8686 - mae: 0.6176
Epoch 331/500
10/10 0s 2ms/step - loss: 0.8304 - mae: 0.5991
Epoch 332/500
10/10 0s 2ms/step - loss: 1.0270 - mae: 0.6865
Epoch 333/500
10/10 0s 2ms/step - loss: 1.0400 - mae: 0.6838
Epoch 334/500
10/10 0s 2ms/step - loss: 1.3456 - mae: 0.7638
Epoch 335/500
10/10 0s 2ms/step - loss: 0.9271 - mae: 0.6914
Epoch 336/500
10/10 0s 2ms/step - loss: 1.1495 - mae: 0.7154
Epoch 337/500
10/10 0s 2ms/step - loss: 1.4542 - mae: 0.7570
Epoch 338/500
10/10 0s 2ms/step - loss: 1.1514 - mae: 0.6707
Epoch 339/500
10/10 0s 2ms/step - loss: 0.9134 - mae: 0.6118
Epoch 340/500
10/10 0s 2ms/step - loss: 1.3325 - mae: 0.7508
Epoch 341/500
10/10 0s 2ms/step - loss: 0.9095 - mae: 0.6332
Epoch 342/500
10/10 0s 2ms/step - loss: 0.9739 - mae: 0.6055
Epoch 343/500
10/10 0s 2ms/step - loss: 0.7662 - mae: 0.6054
Epoch 344/500
10/10 0s 2ms/step - loss: 1.2827 - mae: 0.7390
Epoch 345/500
10/10 0s 2ms/step - loss: 1.2914 - mae: 0.7563
Epoch 346/500
10/10 0s 2ms/step - loss: 1.2493 - mae: 0.7758
Epoch 347/500
10/10 0s 2ms/step - loss: 1.0907 - mae: 0.7114
Epoch 348/500
10/10 0s 2ms/step - loss: 1.3786 - mae: 0.7123
Epoch 349/500
10/10 0s 2ms/step - loss: 0.8551 - mae: 0.6055
Epoch 350/500
10/10 0s 2ms/step - loss: 1.1469 - mae: 0.6521
Epoch 351/500
10/10 0s 2ms/step - loss: 0.7097 - mae: 0.5409
Epoch 352/500
10/10 0s 2ms/step - loss: 0.8808 - mae: 0.6047

Epoch 353/500
10/10 0s 2ms/step - loss: 0.9680 - mae: 0.6306
Epoch 354/500
10/10 0s 2ms/step - loss: 0.7024 - mae: 0.5464
Epoch 355/500
10/10 0s 2ms/step - loss: 0.9843 - mae: 0.6309
Epoch 356/500
10/10 0s 2ms/step - loss: 0.7761 - mae: 0.5934
Epoch 357/500
10/10 0s 2ms/step - loss: 0.9253 - mae: 0.6418
Epoch 358/500
10/10 0s 2ms/step - loss: 1.5671 - mae: 0.8066
Epoch 359/500
10/10 0s 2ms/step - loss: 1.0630 - mae: 0.6956
Epoch 360/500
10/10 0s 2ms/step - loss: 1.0088 - mae: 0.6227
Epoch 361/500
10/10 0s 2ms/step - loss: 0.8778 - mae: 0.6120
Epoch 362/500
10/10 0s 2ms/step - loss: 0.9498 - mae: 0.6263
Epoch 363/500
10/10 0s 2ms/step - loss: 0.7678 - mae: 0.6044
Epoch 364/500
10/10 0s 2ms/step - loss: 0.9597 - mae: 0.6340
Epoch 365/500
10/10 0s 2ms/step - loss: 1.0817 - mae: 0.6192
Epoch 366/500
10/10 0s 2ms/step - loss: 0.8348 - mae: 0.5877
Epoch 367/500
10/10 0s 2ms/step - loss: 0.7662 - mae: 0.5881
Epoch 368/500
10/10 0s 2ms/step - loss: 0.9664 - mae: 0.5928
Epoch 369/500
10/10 0s 2ms/step - loss: 0.9573 - mae: 0.6290
Epoch 370/500
10/10 0s 2ms/step - loss: 0.6304 - mae: 0.5278
Epoch 371/500
10/10 0s 2ms/step - loss: 0.8430 - mae: 0.5789
Epoch 372/500
10/10 0s 2ms/step - loss: 0.8640 - mae: 0.5843
Epoch 373/500
10/10 0s 2ms/step - loss: 0.9841 - mae: 0.6142
Epoch 374/500
10/10 0s 2ms/step - loss: 0.9159 - mae: 0.6012
Epoch 375/500
10/10 0s 2ms/step - loss: 0.9002 - mae: 0.5914
Epoch 376/500
10/10 0s 2ms/step - loss: 0.8551 - mae: 0.6036
Epoch 377/500
10/10 0s 2ms/step - loss: 0.8661 - mae: 0.6111
Epoch 378/500
10/10 0s 2ms/step - loss: 0.9698 - mae: 0.6380
Epoch 379/500
10/10 0s 2ms/step - loss: 0.9427 - mae: 0.6315
Epoch 380/500
10/10 0s 2ms/step - loss: 0.8365 - mae: 0.5955
Epoch 381/500
10/10 0s 2ms/step - loss: 0.9933 - mae: 0.6244
Epoch 382/500
10/10 0s 2ms/step - loss: 0.9553 - mae: 0.6306
Epoch 383/500
10/10 0s 2ms/step - loss: 0.7316 - mae: 0.5657
Epoch 384/500
10/10 0s 2ms/step - loss: 0.8707 - mae: 0.6479

Epoch 385/500
10/10 0s 2ms/step - loss: 0.9535 - mae: 0.6645
Epoch 386/500
10/10 0s 2ms/step - loss: 0.9664 - mae: 0.6005
Epoch 387/500
10/10 0s 2ms/step - loss: 0.9679 - mae: 0.6214
Epoch 388/500
10/10 0s 2ms/step - loss: 0.7908 - mae: 0.5946
Epoch 389/500
10/10 0s 2ms/step - loss: 0.9552 - mae: 0.6455
Epoch 390/500
10/10 0s 2ms/step - loss: 0.7900 - mae: 0.5956
Epoch 391/500
10/10 0s 2ms/step - loss: 1.0715 - mae: 0.6283
Epoch 392/500
10/10 0s 2ms/step - loss: 0.8858 - mae: 0.6079
Epoch 393/500
10/10 0s 2ms/step - loss: 0.7583 - mae: 0.5670
Epoch 394/500
10/10 0s 2ms/step - loss: 0.8169 - mae: 0.5899
Epoch 395/500
10/10 0s 2ms/step - loss: 0.7155 - mae: 0.5847
Epoch 396/500
10/10 0s 2ms/step - loss: 0.8196 - mae: 0.5901
Epoch 397/500
10/10 0s 2ms/step - loss: 1.0240 - mae: 0.6588
Epoch 398/500
10/10 0s 2ms/step - loss: 0.9131 - mae: 0.6484
Epoch 399/500
10/10 0s 2ms/step - loss: 0.9884 - mae: 0.6736
Epoch 400/500
10/10 0s 2ms/step - loss: 0.8741 - mae: 0.5910
Epoch 401/500
10/10 0s 2ms/step - loss: 0.9638 - mae: 0.6140
Epoch 402/500
10/10 0s 2ms/step - loss: 0.8647 - mae: 0.5982
Epoch 403/500
10/10 0s 2ms/step - loss: 0.8738 - mae: 0.6082
Epoch 404/500
10/10 0s 2ms/step - loss: 0.7383 - mae: 0.5566
Epoch 405/500
10/10 0s 2ms/step - loss: 0.9866 - mae: 0.6301
Epoch 406/500
10/10 0s 2ms/step - loss: 0.7982 - mae: 0.5523
Epoch 407/500
10/10 0s 2ms/step - loss: 0.7243 - mae: 0.5301
Epoch 408/500
10/10 0s 2ms/step - loss: 0.8406 - mae: 0.5778
Epoch 409/500
10/10 0s 2ms/step - loss: 0.9663 - mae: 0.5669
Epoch 410/500
10/10 0s 2ms/step - loss: 0.7309 - mae: 0.5620
Epoch 411/500
10/10 0s 2ms/step - loss: 0.9836 - mae: 0.5986
Epoch 412/500
10/10 0s 2ms/step - loss: 0.6865 - mae: 0.5378
Epoch 413/500
10/10 0s 2ms/step - loss: 0.8375 - mae: 0.5795
Epoch 414/500
10/10 0s 2ms/step - loss: 0.8379 - mae: 0.5352
Epoch 415/500
10/10 0s 2ms/step - loss: 0.8321 - mae: 0.5724
Epoch 416/500
10/10 0s 2ms/step - loss: 0.6896 - mae: 0.5526

Epoch 417/500
10/10 0s 2ms/step - loss: 0.8542 - mae: 0.6395
Epoch 418/500
10/10 0s 2ms/step - loss: 1.1877 - mae: 0.6802
Epoch 419/500
10/10 0s 2ms/step - loss: 1.0857 - mae: 0.6420
Epoch 420/500
10/10 0s 2ms/step - loss: 0.8049 - mae: 0.5627
Epoch 421/500
10/10 0s 2ms/step - loss: 0.7135 - mae: 0.5287
Epoch 422/500
10/10 0s 2ms/step - loss: 0.7744 - mae: 0.5833
Epoch 423/500
10/10 0s 2ms/step - loss: 0.7775 - mae: 0.5693
Epoch 424/500
10/10 0s 2ms/step - loss: 0.7600 - mae: 0.5784
Epoch 425/500
10/10 0s 2ms/step - loss: 0.9504 - mae: 0.5906
Epoch 426/500
10/10 0s 2ms/step - loss: 0.8685 - mae: 0.5775
Epoch 427/500
10/10 0s 2ms/step - loss: 0.8219 - mae: 0.5566
Epoch 428/500
10/10 0s 2ms/step - loss: 0.7985 - mae: 0.5378
Epoch 429/500
10/10 0s 2ms/step - loss: 0.7892 - mae: 0.5556
Epoch 430/500
10/10 0s 2ms/step - loss: 0.7033 - mae: 0.5366
Epoch 431/500
10/10 0s 2ms/step - loss: 0.8739 - mae: 0.5788
Epoch 432/500
10/10 0s 2ms/step - loss: 0.7354 - mae: 0.5097
Epoch 433/500
10/10 0s 2ms/step - loss: 0.7075 - mae: 0.5305
Epoch 434/500
10/10 0s 2ms/step - loss: 0.7664 - mae: 0.5638
Epoch 435/500
10/10 0s 2ms/step - loss: 0.7571 - mae: 0.5417
Epoch 436/500
10/10 0s 2ms/step - loss: 0.7440 - mae: 0.5285
Epoch 437/500
10/10 0s 2ms/step - loss: 1.0028 - mae: 0.5797
Epoch 438/500
10/10 0s 2ms/step - loss: 0.6854 - mae: 0.5285
Epoch 439/500
10/10 0s 2ms/step - loss: 1.0163 - mae: 0.6007
Epoch 440/500
10/10 0s 2ms/step - loss: 0.9600 - mae: 0.5539
Epoch 441/500
10/10 0s 2ms/step - loss: 1.0031 - mae: 0.6130
Epoch 442/500
10/10 0s 2ms/step - loss: 0.9660 - mae: 0.5758
Epoch 443/500
10/10 0s 2ms/step - loss: 0.9638 - mae: 0.5868
Epoch 444/500
10/10 0s 2ms/step - loss: 0.8775 - mae: 0.5990
Epoch 445/500
10/10 0s 2ms/step - loss: 0.8684 - mae: 0.5577
Epoch 446/500
10/10 0s 2ms/step - loss: 0.9240 - mae: 0.5830
Epoch 447/500
10/10 0s 2ms/step - loss: 1.0143 - mae: 0.6310
Epoch 448/500
10/10 0s 2ms/step - loss: 1.0097 - mae: 0.6363

Epoch 449/500
10/10 0s 2ms/step - loss: 0.8631 - mae: 0.6690
Epoch 450/500
10/10 0s 2ms/step - loss: 0.7302 - mae: 0.5755
Epoch 451/500
10/10 0s 2ms/step - loss: 0.8937 - mae: 0.6261
Epoch 452/500
10/10 0s 2ms/step - loss: 1.1362 - mae: 0.6669
Epoch 453/500
10/10 0s 2ms/step - loss: 0.7067 - mae: 0.5592
Epoch 454/500
10/10 0s 2ms/step - loss: 0.7850 - mae: 0.5588
Epoch 455/500
10/10 0s 2ms/step - loss: 0.6798 - mae: 0.5574
Epoch 456/500
10/10 0s 2ms/step - loss: 1.0039 - mae: 0.6136
Epoch 457/500
10/10 0s 2ms/step - loss: 0.6463 - mae: 0.5145
Epoch 458/500
10/10 0s 2ms/step - loss: 0.8742 - mae: 0.5631
Epoch 459/500
10/10 0s 2ms/step - loss: 0.8664 - mae: 0.5443
Epoch 460/500
10/10 0s 2ms/step - loss: 0.8504 - mae: 0.5641
Epoch 461/500
10/10 0s 2ms/step - loss: 0.7152 - mae: 0.5247
Epoch 462/500
10/10 0s 2ms/step - loss: 0.7752 - mae: 0.5572
Epoch 463/500
10/10 0s 2ms/step - loss: 0.9584 - mae: 0.6286
Epoch 464/500
10/10 0s 2ms/step - loss: 0.8388 - mae: 0.6013
Epoch 465/500
10/10 0s 2ms/step - loss: 0.7425 - mae: 0.5554
Epoch 466/500
10/10 0s 2ms/step - loss: 0.8407 - mae: 0.5942
Epoch 467/500
10/10 0s 2ms/step - loss: 0.9818 - mae: 0.6339
Epoch 468/500
10/10 0s 2ms/step - loss: 0.8249 - mae: 0.5704
Epoch 469/500
10/10 0s 2ms/step - loss: 0.8735 - mae: 0.5803
Epoch 470/500
10/10 0s 2ms/step - loss: 0.8964 - mae: 0.6094
Epoch 471/500
10/10 0s 2ms/step - loss: 0.8151 - mae: 0.5787
Epoch 472/500
10/10 0s 2ms/step - loss: 0.9678 - mae: 0.6135
Epoch 473/500
10/10 0s 2ms/step - loss: 0.7901 - mae: 0.5616
Epoch 474/500
10/10 0s 2ms/step - loss: 0.6552 - mae: 0.4934
Epoch 475/500
10/10 0s 2ms/step - loss: 0.7844 - mae: 0.5473
Epoch 476/500
10/10 0s 2ms/step - loss: 0.7156 - mae: 0.5509
Epoch 477/500
10/10 0s 2ms/step - loss: 0.8273 - mae: 0.5840
Epoch 478/500
10/10 0s 2ms/step - loss: 0.9484 - mae: 0.5992
Epoch 479/500
10/10 0s 2ms/step - loss: 0.8047 - mae: 0.5694
Epoch 480/500
10/10 0s 2ms/step - loss: 0.7201 - mae: 0.5543

```
Epoch 481/500
10/10 0s 2ms/step - loss: 0.7042 - mae: 0.5518
Epoch 482/500
10/10 0s 2ms/step - loss: 0.8715 - mae: 0.5846
Epoch 483/500
10/10 0s 2ms/step - loss: 0.8387 - mae: 0.5530
Epoch 484/500
10/10 0s 2ms/step - loss: 0.6872 - mae: 0.5267
Epoch 485/500
10/10 0s 2ms/step - loss: 0.8135 - mae: 0.5773
Epoch 486/500
10/10 0s 2ms/step - loss: 0.8834 - mae: 0.5813
Epoch 487/500
10/10 0s 2ms/step - loss: 0.7122 - mae: 0.5464
Epoch 488/500
10/10 0s 2ms/step - loss: 0.5971 - mae: 0.4974
Epoch 489/500
10/10 0s 2ms/step - loss: 0.7398 - mae: 0.5271
Epoch 490/500
10/10 0s 2ms/step - loss: 0.8097 - mae: 0.5532
Epoch 491/500
10/10 0s 2ms/step - loss: 0.5899 - mae: 0.5076
Epoch 492/500
10/10 0s 2ms/step - loss: 0.7646 - mae: 0.5289
Epoch 493/500
10/10 0s 2ms/step - loss: 0.9578 - mae: 0.5835
Epoch 494/500
10/10 0s 2ms/step - loss: 0.6186 - mae: 0.5065
Epoch 495/500
10/10 0s 2ms/step - loss: 0.6257 - mae: 0.5189
Epoch 496/500
10/10 0s 2ms/step - loss: 0.8987 - mae: 0.5490
Epoch 497/500
10/10 0s 2ms/step - loss: 0.5790 - mae: 0.4977
Epoch 498/500
10/10 0s 2ms/step - loss: 0.8591 - mae: 0.5642
Epoch 499/500
10/10 0s 2ms/step - loss: 0.8338 - mae: 0.5641
Epoch 500/500
10/10 0s 2ms/step - loss: 1.0352 - mae: 0.5944
```

Model evaluation:

Loss (MSE): 0.74, MAE: 0.53

```
In [67]: models = {
    "Linear Regression": LinearRegression(),
    "Lasso": Lasso(),
    "K-Neighbors Regressor": KNeighborsRegressor(),
    "Decision Tree": DecisionTreeRegressor(),
    "Random Forest Regressor": RandomForestRegressor(),
    "Gradient Boosting": GradientBoostingRegressor(),
    "XGBRegressor": XGBRegressor(),
    "CatBoosting Regressor": CatBoostRegressor(verbose=0, iterations = 100),
    "AdaBoost Regressor": AdaBoostRegressor(),
    "ExtraTreesRegressor": ExtraTreesRegressor(),
    "Support Vector Regressor(RBF)": SVR(kernel="rbf"),
    "Support Vector Regressor(linear)": SVR(kernel="linear"),
    "Nu SVR(rbf)": NuSVR(kernel="rbf"),
    "ANN": ANN_model
}
```

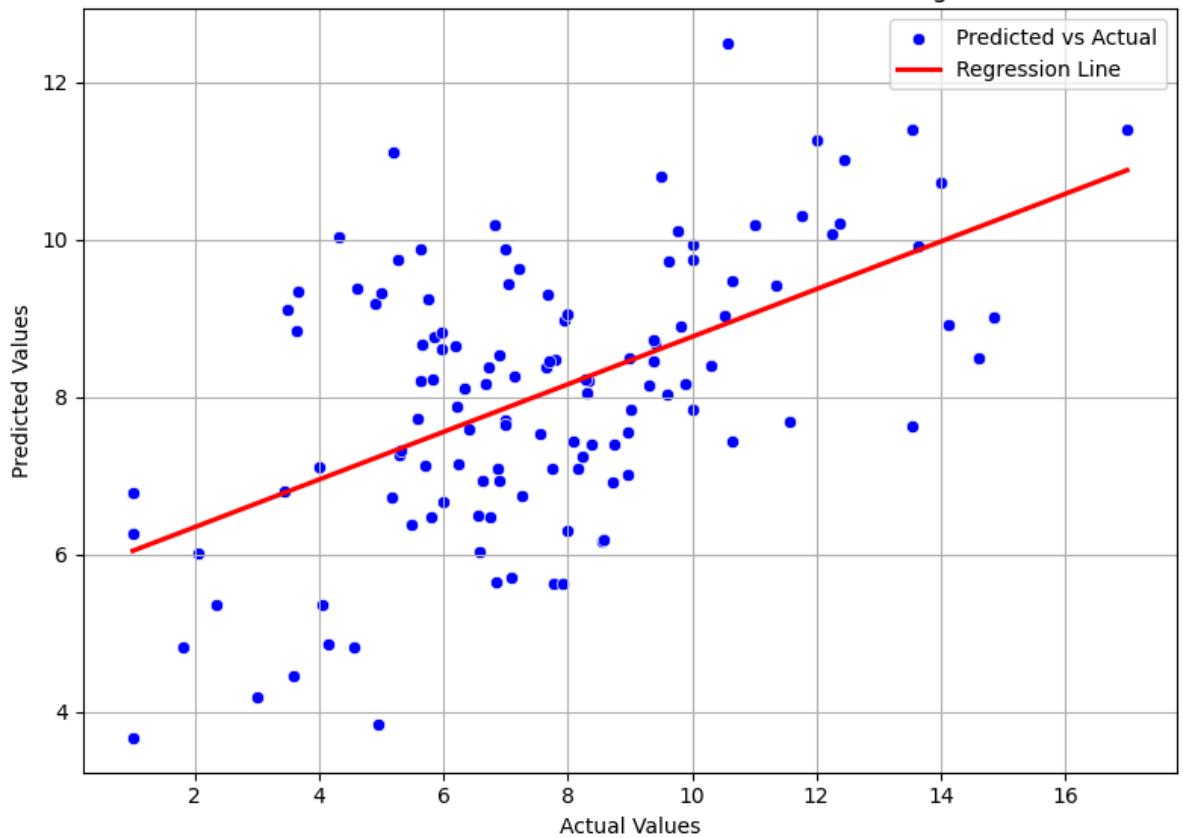
```
In [68]: def safe_flatten(y_pred):
    """
    Flattens the array if it's a 2D array with shape (n, 1).
    """
```

```
    Useful for ANN predictions.  
    """  
    if isinstance(y_pred, (np.ndarray, list)) and len(np.shape(y_pred)) == 2 and y_  
        return y_pred.flatten()  
    return y_pred
```

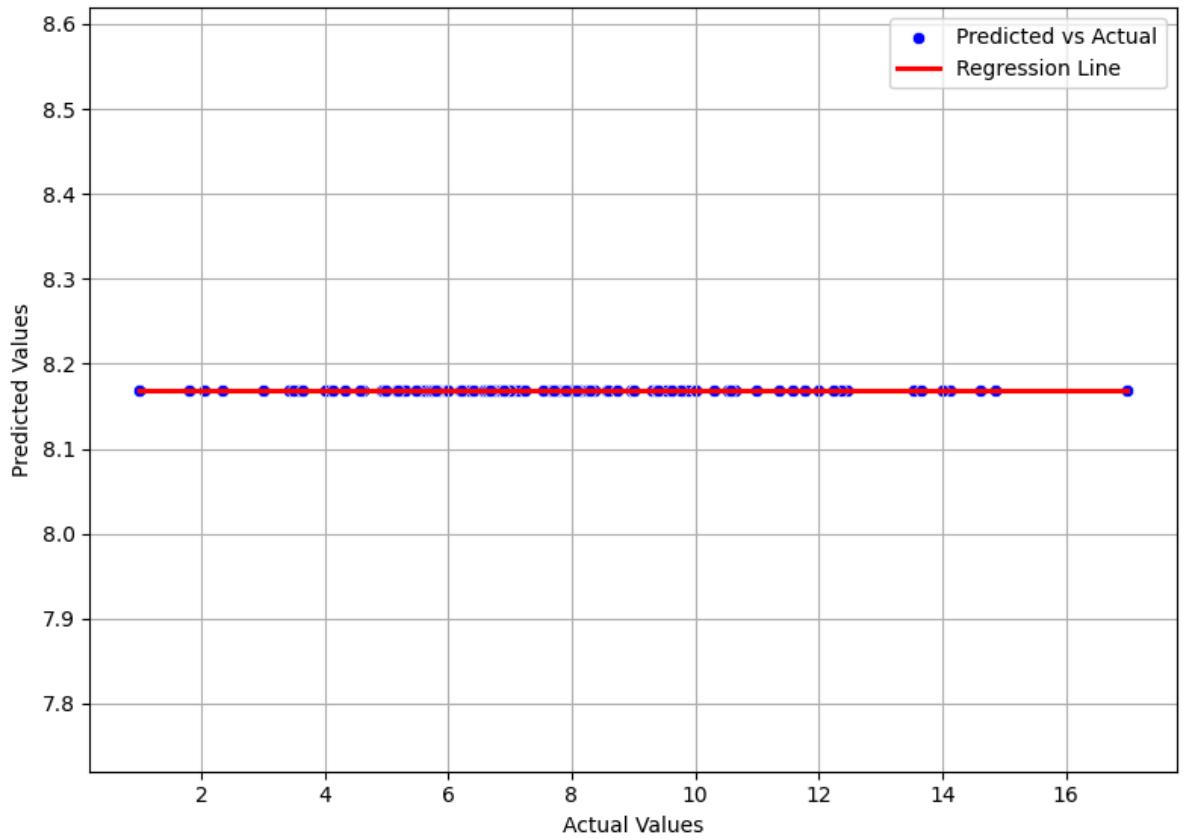
```
In [69]: r2_train_score = {}  
r2_test_score = {}  
def evaluate_model(models, X_train, y_train, X_val, y_val):  
    for model_name, model in models.items():  
        model.fit(X_train, y_train)  
  
        y_train_pred = model.predict(X_train)  
        y_test_pred = model.predict(X_val)  
  
        y = y_val  
        y_pred = safe_flatten(y_test_pred)  
  
        plt.figure(figsize=(8, 6))  
        r2 = r2_score(y, y_pred)  
  
        sns.scatterplot(x=y, y=y_pred, label='Predicted vs Actual', color='blue')  
        sns.regplot(x=y, y=y_pred, scatter=False, label='Regression Line', color='red')  
  
        plt.xlabel('Actual Values')  
        plt.ylabel('Predicted Values')  
        plt.title(f'CH4 Actual vs Predicted Values (R² Score: {r2:.4f}) for {model_name}')  
        plt.legend()  
        plt.grid(True)  
        plt.tight_layout()  
        plt.savefig(f'CH4 Actual vs Predicted Values (R² Score: {r2:.4f}) for {model_name}.png')  
        plt.show()  
  
    r2_train_score[model_name] = r2_score(y_train, y_train_pred)  
    r2_test_score[model_name] = r2_score(y_val, y_test_pred)
```

```
In [70]: evaluate_model(models, X_train_scaled, y_train.CH4, X_val_scaled, y_val.CH4)
```

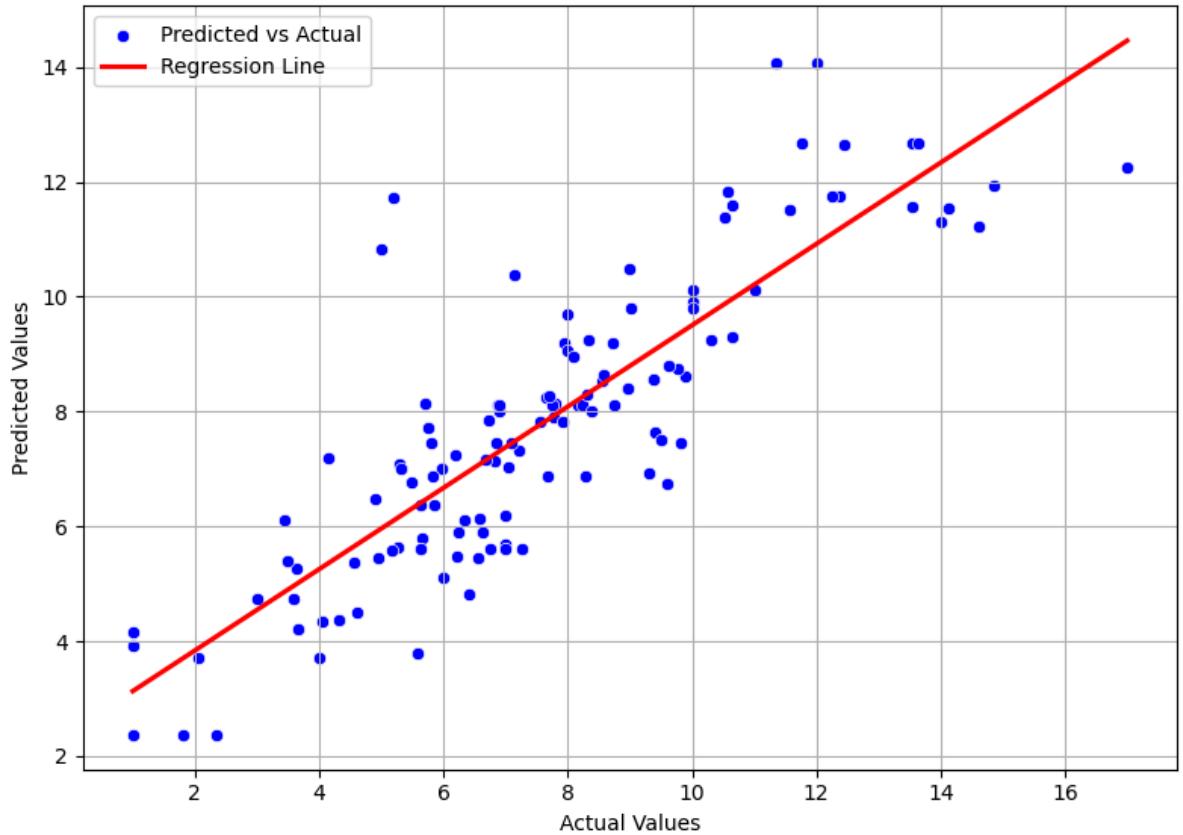
CH4 Actual vs Predicted Values (R^2 Score: 0.2737) for Linear Regression model



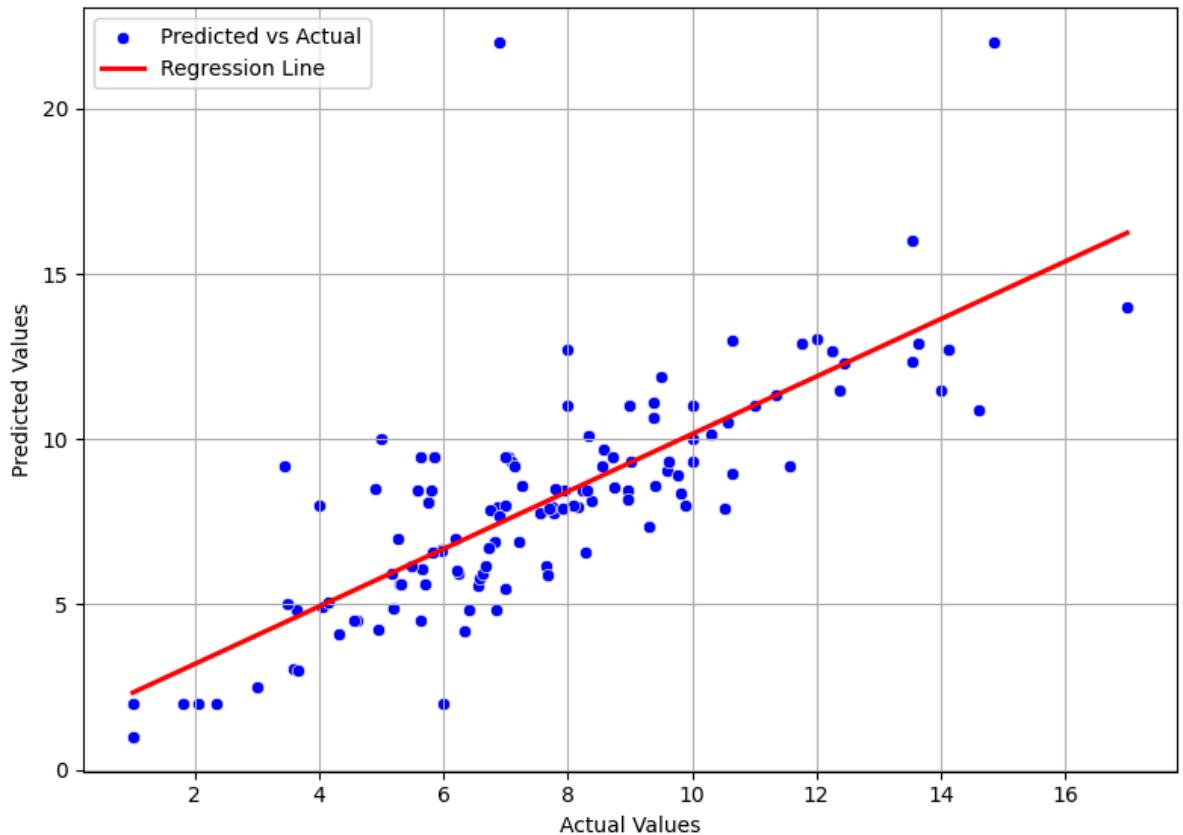
CH4 Actual vs Predicted Values (R^2 Score: -0.0331) for Lasso model

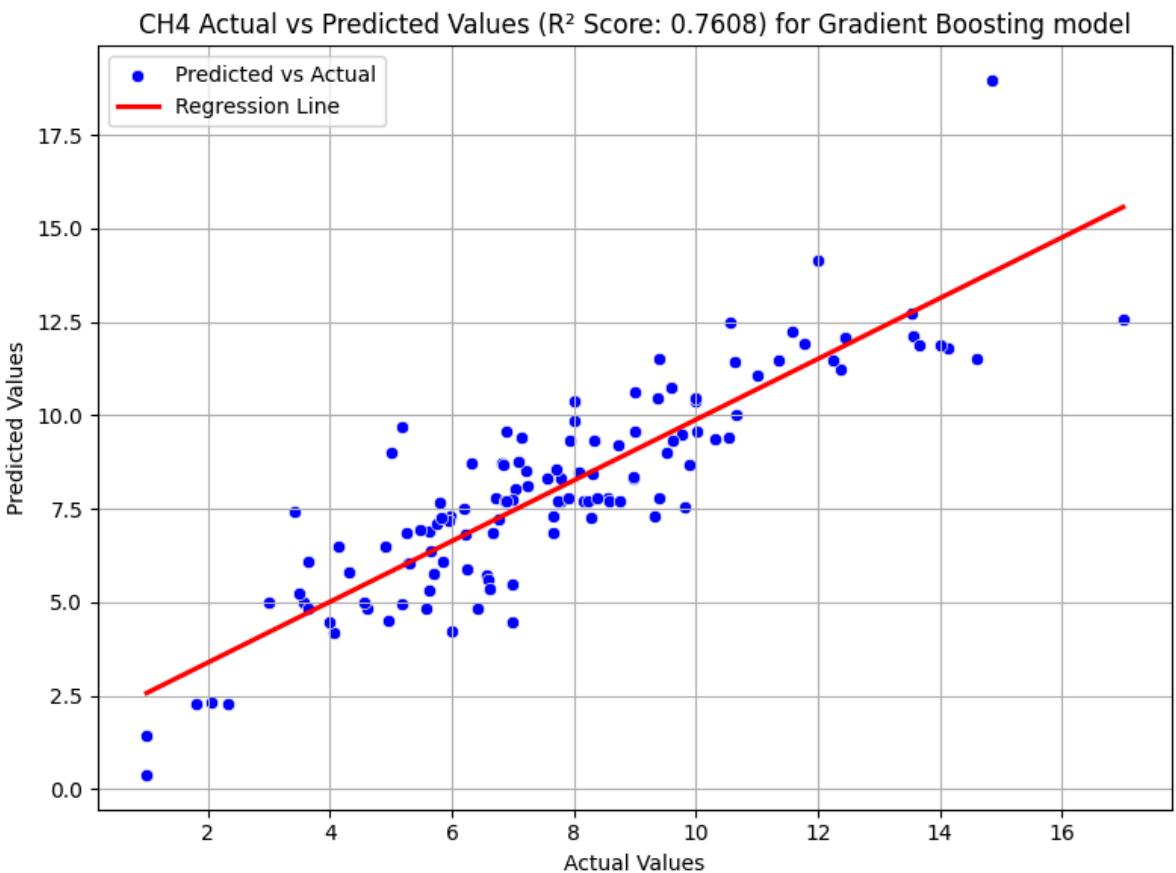
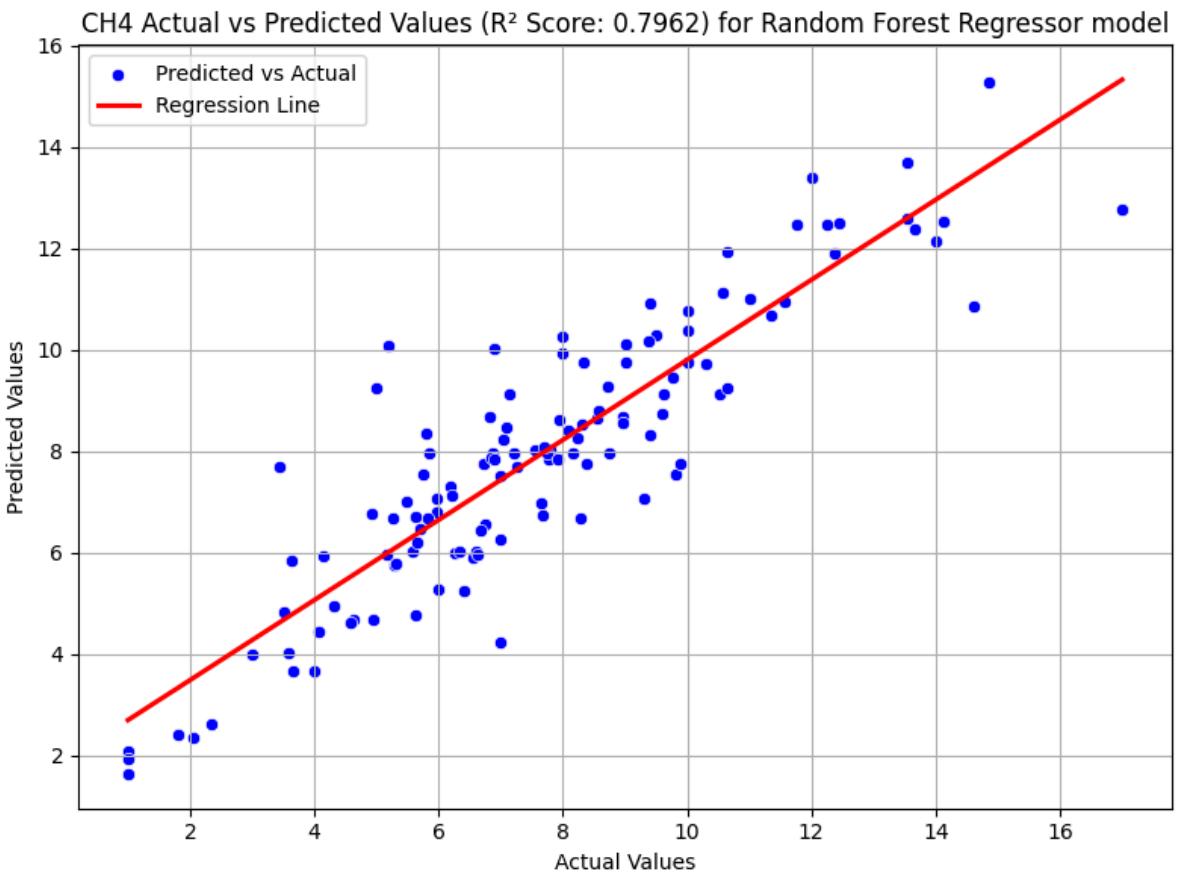


CH4 Actual vs Predicted Values (R^2 Score: 0.7210) for K-Neighbors Regressor model

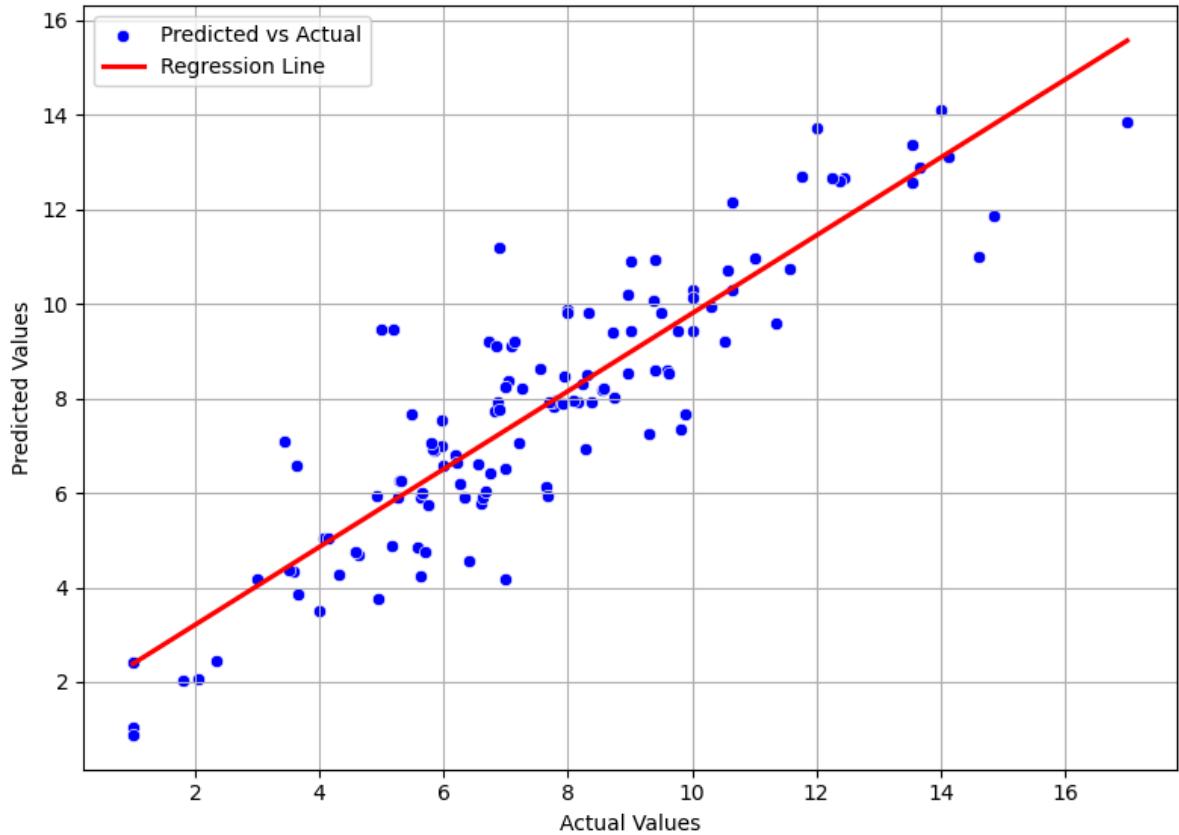


CH4 Actual vs Predicted Values (R^2 Score: 0.4528) for Decision Tree model

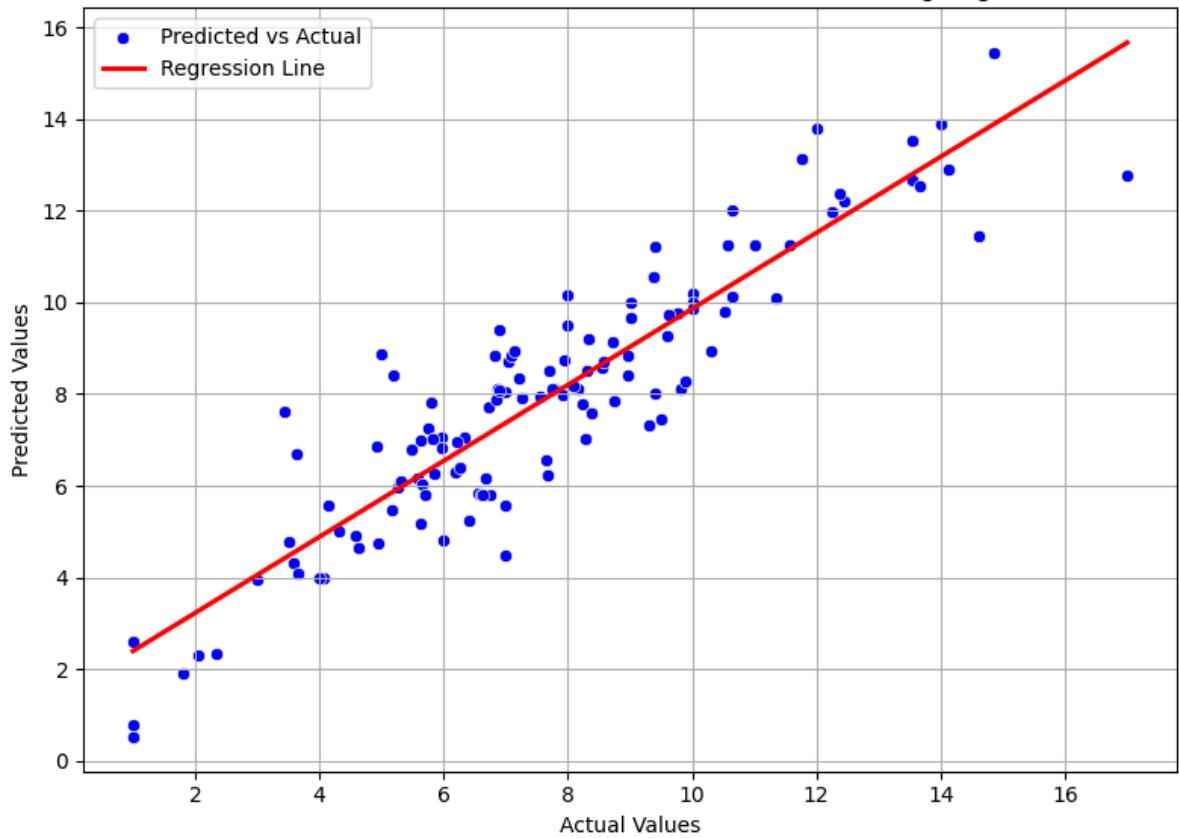




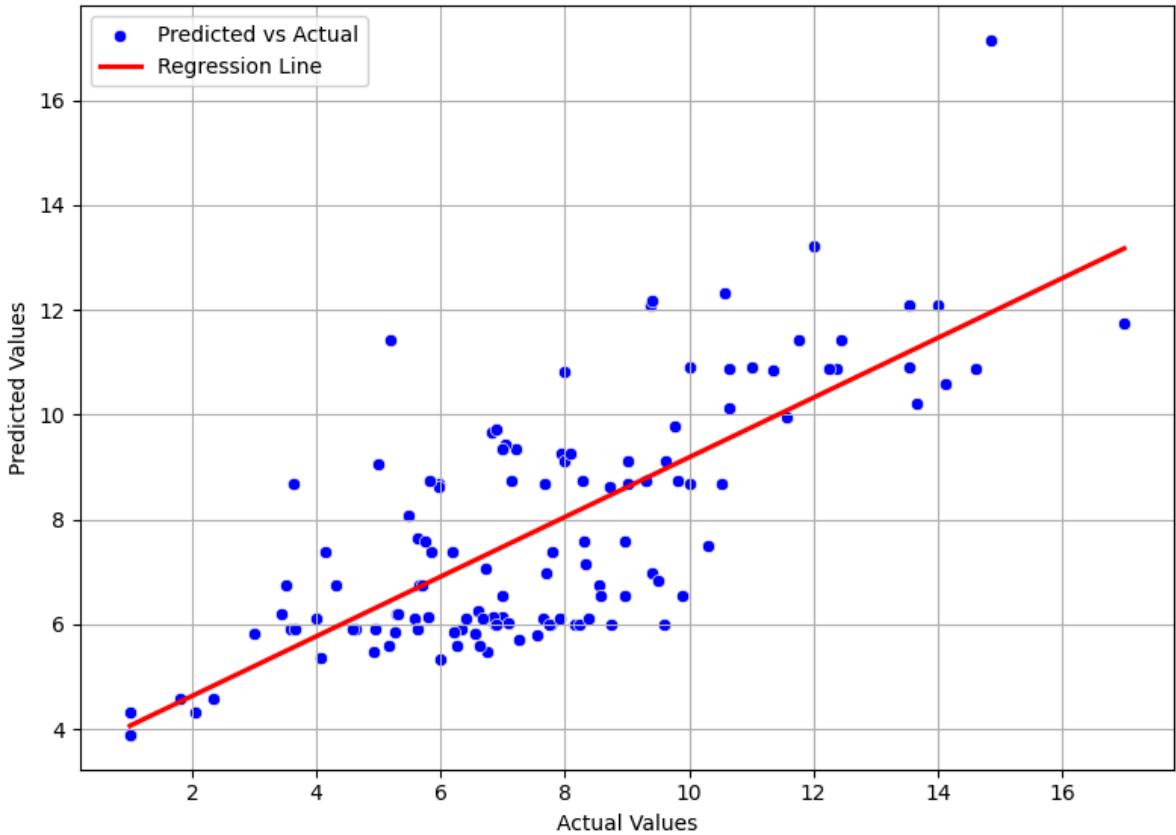
CH4 Actual vs Predicted Values (R^2 Score: 0.7903) for XGBRegressor model



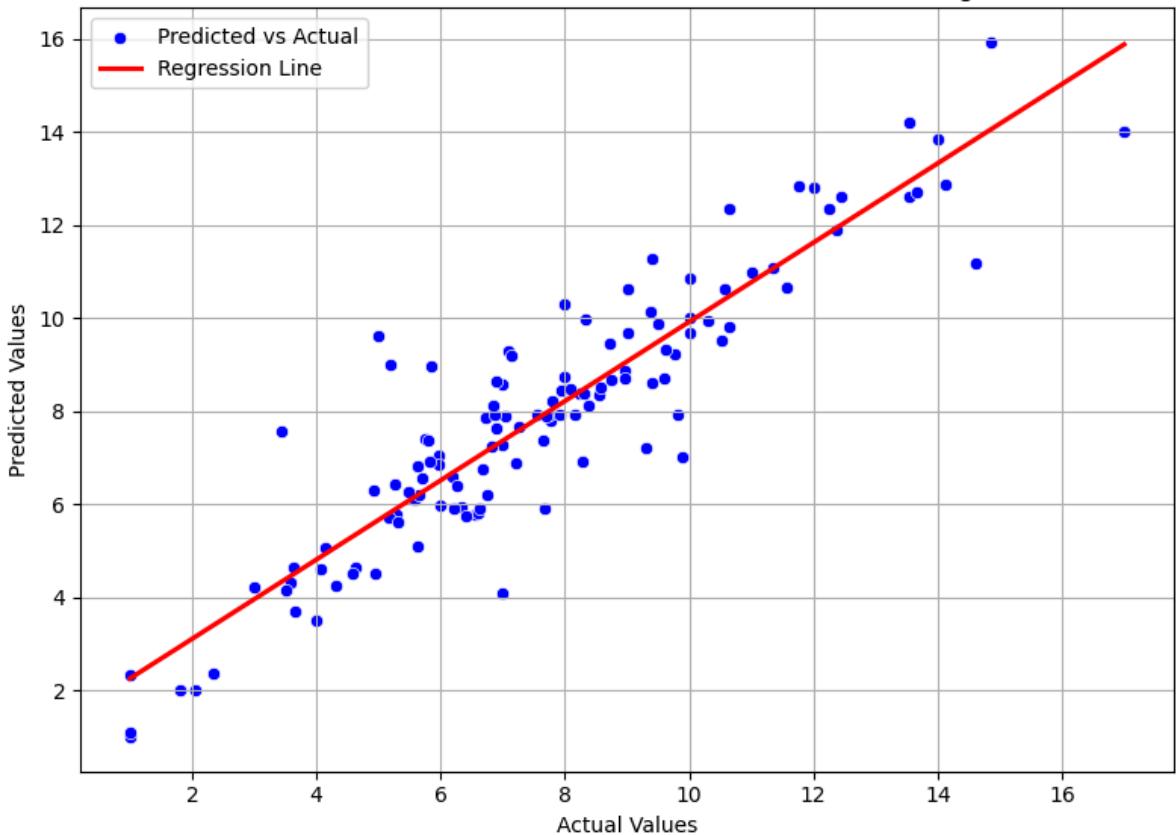
CH4 Actual vs Predicted Values (R^2 Score: 0.8210) for CatBoosting Regressor model



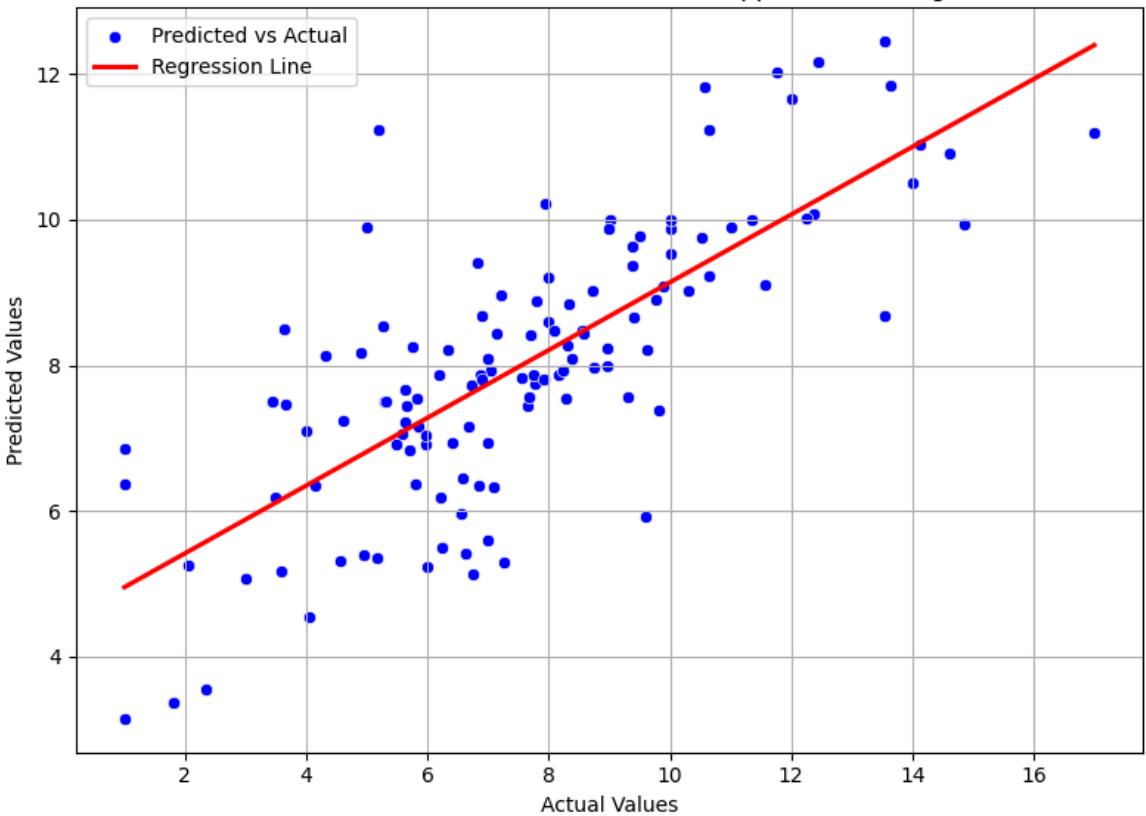
CH4 Actual vs Predicted Values (R^2 Score: 0.5490) for AdaBoost Regressor model



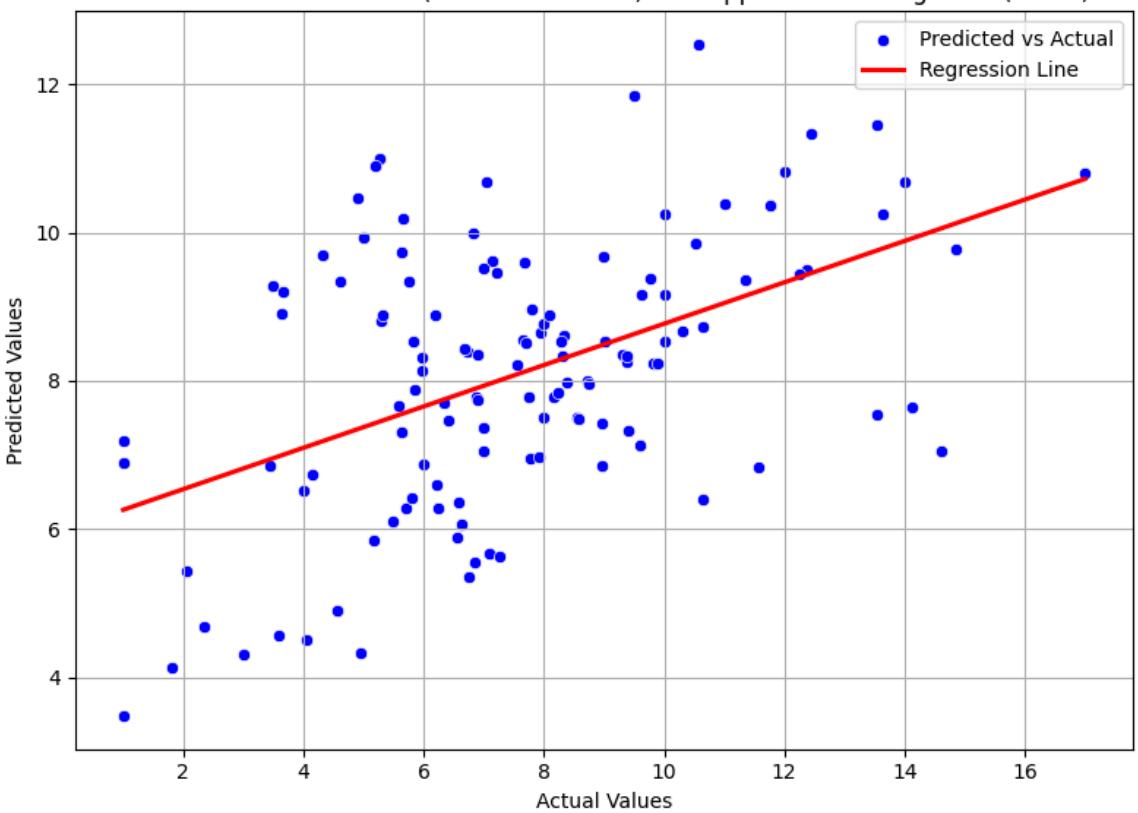
CH4 Actual vs Predicted Values (R^2 Score: 0.8326) for ExtraTreesRegressor model

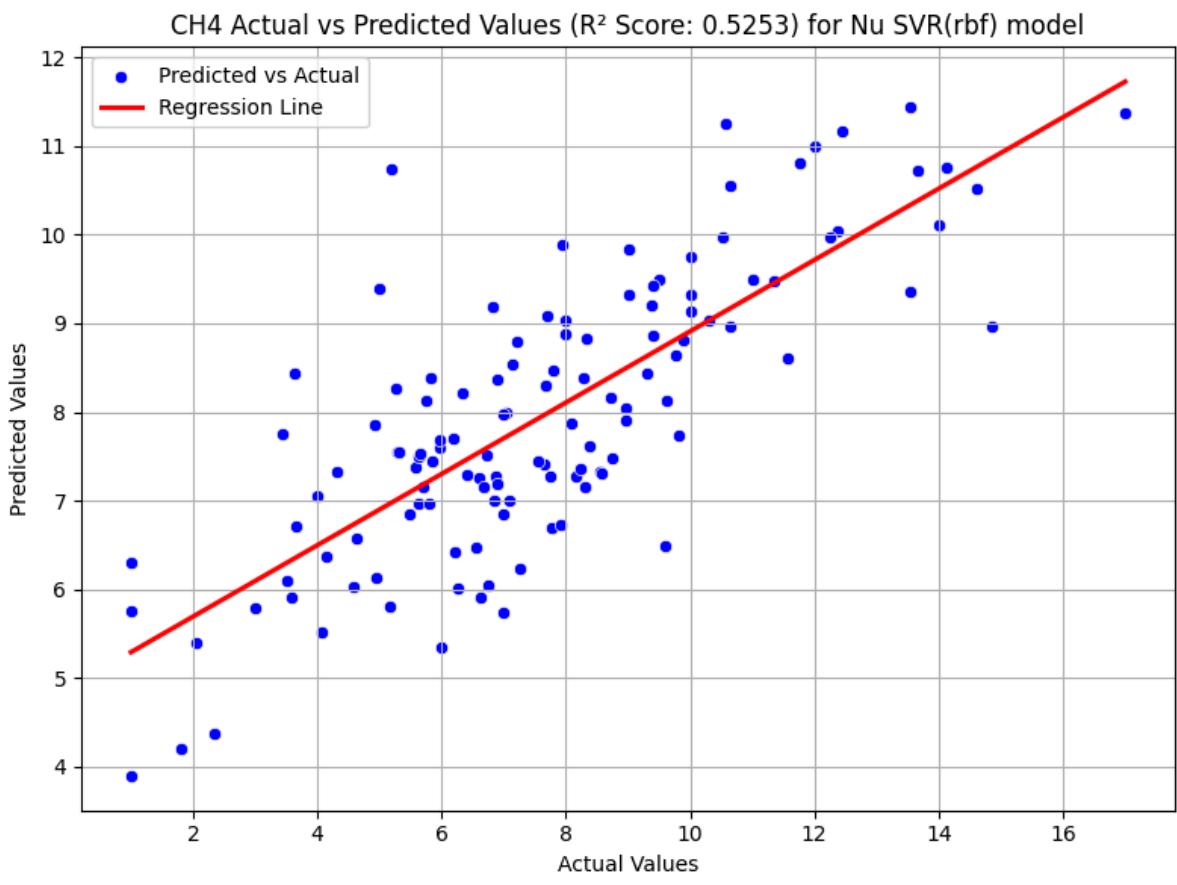


CH4 Actual vs Predicted Values (R^2 Score: 0.5336) for Support Vector Regressor(RBF) model

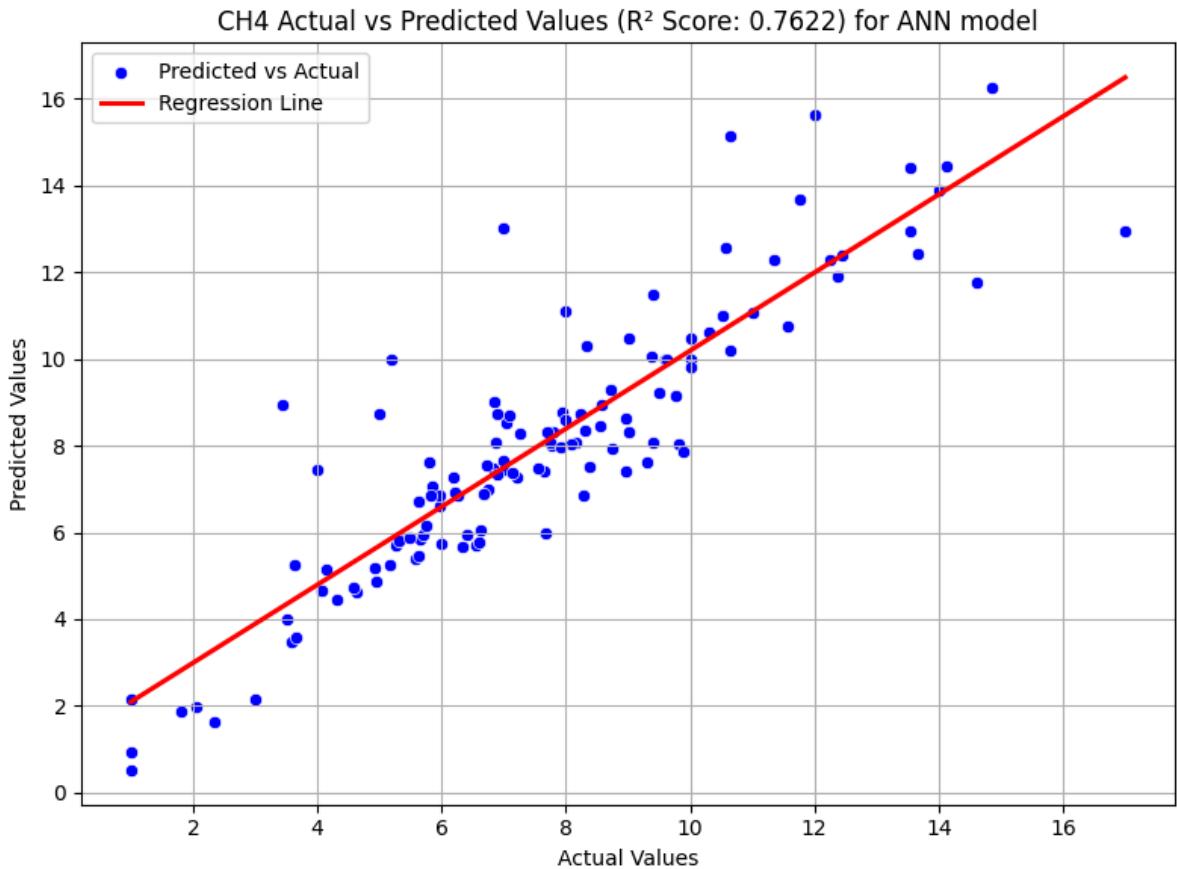


CH4 Actual vs Predicted Values (R^2 Score: 0.1957) for Support Vector Regressor(linear) model





10/10 ————— 0s 2ms/step - loss: 0.7597 - mae: 0.5493
 10/10 ————— 0s 12ms/step
 4/4 ————— 0s 19ms/step



```
In [71]: score = pd.DataFrame(list(zip(models.keys(), r2_train_score.values(), r2_test_score
score
```

Out[71]:

	Model	r2_train_score	r2_test_score
0	Linear Regression	0.257236	0.273732
1	Lasso	0.000000	-0.033079
2	K-Neighbors Regressor	0.746015	0.721042
3	Decision Tree	0.995971	0.452798
4	Random Forest Regressor	0.950031	0.796166
5	Gradient Boosting	0.915502	0.760806
6	XGBRegressor	0.995611	0.790316
7	CatBoosting Regressor	0.959128	0.821011
8	AdaBoost Regressor	0.708777	0.549022
9	ExtraTreesRegressor	0.995971	0.832564
10	Support Vector Regressor(RBF)	0.518792	0.533648
11	Support Vector Regressor(linear)	0.213773	0.195725
12	Nu SVR(rbf)	0.491429	0.525306
13	ANN	0.938276	0.762182

In [72]:

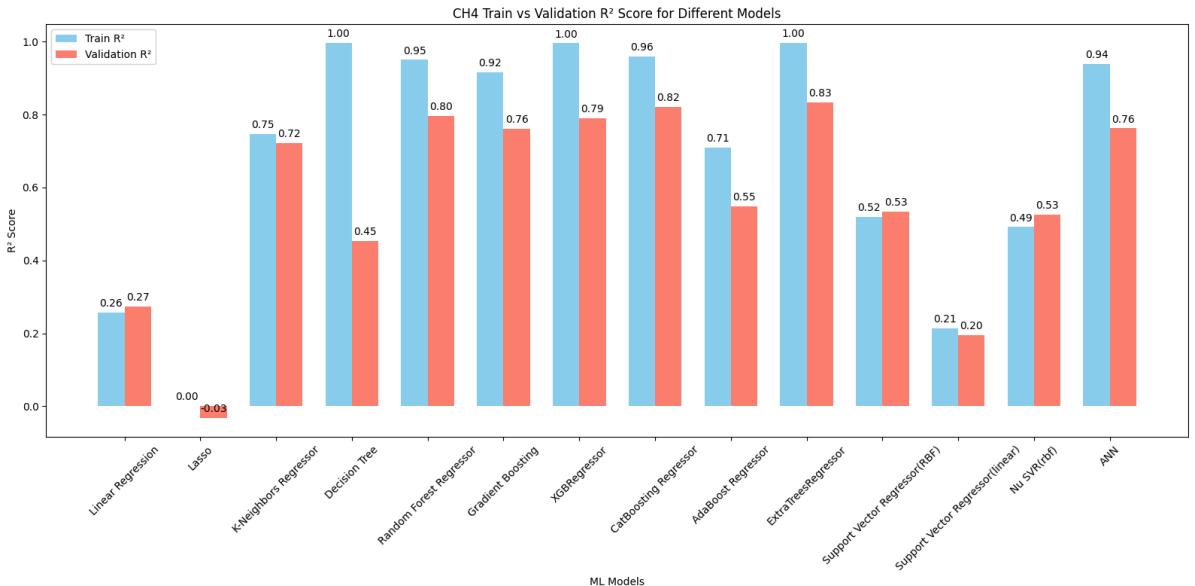
```
# Set positions
x = np.arange(len(score['Model']))
width = 0.35 # Width of the bars

# Create plot
fig, ax = plt.subplots(figsize=(16, 8))
bars1 = ax.bar(x - width/2, score['r2_train_score'], width, label='Train R2', color='blue')
bars2 = ax.bar(x + width/2, score['r2_test_score'], width, label='Validation R2', color='red')

# Add labels and title
ax.set_xlabel('ML Models')
ax.set_ylabel('R2 Score')
ax.set_title('CH4 Train vs Validation R2 Score for Different Models')
ax.set_xticks(x)
ax.set_xticklabels(score['Model'], rotation=45)
ax.legend()

# Add R2 score text on top of bars
for bar in bars1 + bars2:
    yval = bar.get_height()
    ax.text(bar.get_x() + bar.get_width()/2.0, yval + 0.01, f'{yval:.2f}', ha='center')

plt.tight_layout()
plt.savefig("CH4 Train vs Validation R2 Score for Different Models")
plt.show()
```



```
In [73]: import zipfile
import os

with zipfile.ZipFile('kaggle_output.zip', 'w') as zipf:
    for file in os.listdir():
        if file.endswith('.png'):
            zipf.write(file)
```

In []: