

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```
fuel_data = pd.read_csv('fuel_consumption_dataset (2).csv')
fuel_data.head()
```

| | MODELYEAR | MAKE | MODEL | VEHICLECLASS | ENGINESIZE | CYLINDERS | TRANSMISSION | FUELTYPE | FUELCONSUMPTION_CITY | FUELCONSUM |
|---|-----------|-------|------------|--------------|------------|-----------|--------------|----------|----------------------|------------|
| 0 | 2014 | ACURA | ILX | COMPACT | 2.0 | 4 | AS5 | Z | 9.9 | |
| 1 | 2014 | ACURA | ILX | COMPACT | 2.4 | 4 | M6 | Z | 11.2 | |
| 2 | 2014 | ACURA | ILX HYBRID | COMPACT | 1.5 | 4 | AV7 | Z | 6.0 | |
| 3 | 2014 | ACURA | MDX 4WD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.7 | |
| 4 | 2014 | ACURA | RDX AWD | SUV - SMALL | 3.5 | 6 | AS6 | Z | 12.1 | |

```
fuel_data.isnull()
```

| | MODELYEAR | MAKE | MODEL | VEHICLECLASS | ENGINESIZE | CYLINDERS | TRANSMISSION | FUELTYPE | FUELCONSUMPTION_CITY | FUELCONSUMP |
|------|-----------|-------|-------|--------------|------------|-----------|--------------|----------|----------------------|-------------|
| 0 | False | False | False | False | False | False | False | False | False | False |
| 1 | False | False | False | False | False | False | False | False | False | False |
| 2 | False | False | False | False | False | False | False | False | False | False |
| 3 | False | False | False | False | False | False | False | False | False | False |
| 4 | False | False | False | False | False | False | False | False | False | False |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 1062 | False | False | False | False | False | False | False | False | False | False |
| 1063 | False | False | False | False | False | False | False | False | False | False |
| 1064 | False | False | False | False | False | False | False | False | False | False |
| 1065 | False | False | False | False | False | False | False | False | False | False |
| 1066 | False | False | False | False | False | False | False | False | False | False |

1067 rows × 13 columns

```
print("\n== UNIQUE VALUES PER COLUMN (FUEL) ==")
for col in fuel_data.columns:
    print(f"{col}: {fuel_data[col].nunique()} unique values")
```

```
== UNIQUE VALUES PER COLUMN (FUEL) ==
MODELYEAR: 1 unique values
MAKE: 39 unique values
MODEL: 663 unique values
VEHICLECLASS: 16 unique values
ENGINESIZE: 45 unique values
CYLINDERS: 7 unique values
TRANSMISSION: 22 unique values
FUELTYPE: 4 unique values
FUELCONSUMPTION_CITY: 167 unique values
FUELCONSUMPTION_HMY: 118 unique values
FUELCONSUMPTION_COMB: 148 unique values
FUELCONSUMPTION_COMB MPG: 43 unique values
CO2EMISSIONS: 159 unique values
```

```
print("\n== FUEL DATASET INFO ==")
print(fuel_data.info())
```

```
print("\n== FUEL DATASET DESCRIPTION ==")
print(fuel_data.describe())
```

```

print("\n==== MISSING VALUES (FUEL) ===")
print(fuel_data.isnull().sum())

print("\n==== UNIQUE VALUES PER COLUMN (FUEL) ===")
for col in fuel_data.columns:
    print(f"{col}: {fuel_data[col].nunique()} unique values")

mean      2014.0      3.346298      5.794752      13.296532
std       0.0        1.415895      1.797447      4.101253
min      2014.0      1.000000      3.000000      4.600000
25%     2014.0      2.000000      4.000000     10.250000
50%     2014.0      3.400000      6.000000     12.600000
75%     2014.0      4.300000      8.000000     15.550000
max      2014.0      8.400000     12.000000     30.200000

      FUELCONSUMPTION_HWY  FUELCONSUMPTION_COMB  FUELCONSUMPTION_COMB MPG \
count      1067.000000      1067.000000      1067.000000
mean      9.474602       11.580881      26.441425
std       2.794510       3.485595       7.468702
min      4.900000       4.700000      11.000000
25%     7.500000       9.000000      21.000000
50%     8.800000      10.900000      26.000000
75%    10.850000      13.350000      31.000000
max     20.500000      25.800000      60.000000

CO2EMISSIONS
count  1067.000000
mean   256.228679
std    63.372304
min    108.000000
25%   207.000000
50%   251.000000
75%   294.000000
max   488.000000

==== MISSING VALUES (FUEL) ===
MODELYEAR          0
MAKE               0
MODEL              0
VEHICLECLASS       0
ENGINESIZE         0
CYLINDERS          0
TRANSMISSION        0
FUELTYPE            0
FUELCONSUMPTION_CITY  0
FUELCONSUMPTION_HWY  0
FUELCONSUMPTION_COMB  0
FUELCONSUMPTION_COMB MPG  0
CO2EMISSIONS        0
dtype: int64

==== UNIQUE VALUES PER COLUMN (FUEL) ===
MODELYEAR: 1 unique values
MAKE: 39 unique values
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VEHICLECLASS: 16 unique values
ENGINESIZE: 45 unique values
CYLINDERS: 7 unique values
TRANSMISSION: 22 unique values
FUELTYPE: 4 unique values
FUELCONSUMPTION_CITY: 167 unique values
FUELCONSUMPTION_HWY: 118 unique values
FUELCONSUMPTION_COMB: 148 unique values
FUELCONSUMPTION_COMB MPG: 43 unique values
CO2EMISSIONS: 159 unique values

```

```

sns.pairplot(
    data=fuel_data,
    x_vars=['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTION_CITY', 'FUELCONSUMPTION_HWY',
            'FUELCONSUMPTION_COMB', 'FUELCONSUMPTION_COMB MPG', 'CO2EMISSIONS'],
    y_vars=['CO2EMISSIONS'],
    height=4,
    aspect=1
)

```

```
<seaborn.axisgrid.PairGrid at 0x7df96dbb7d90>

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

numeric_cols = ['ENGINESIZE', 'CYLINDERS', 'FUELCONSUMPTION_CITY',
                 'FUELCONSUMPTION_HWY', 'FUELCONSUMPTION_COMB', 'FUELCONSUMPTION_COMB_MP']
categorical_cols = ['MAKE', 'MODEL', 'VEHICLECLASS', 'FUELTYPE', 'TRANSMISSION']

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_cols),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
    ])
X = preprocessor.fit_transform(fuel_data)
y = fuel_data['CO2EMISSIONS']
```

```
X.shape
```

```
(1065, 750)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
from sklearn.tree import DecisionTreeRegressor
```

```
model_fuel = DecisionTreeRegressor(random_state=0)
```

```
model_fuel.fit(X_train, y_train)
```

```
▼ DecisionTreeRegressor ⓘ ?  
DecisionTreeRegressor(random_state=0)
```

```
y_pred = model_fuel.predict(X_test)
```

```
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"📊 Regression Evaluation Metrics:")
print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
print(f"R² Score: {r2:.4f}")
```

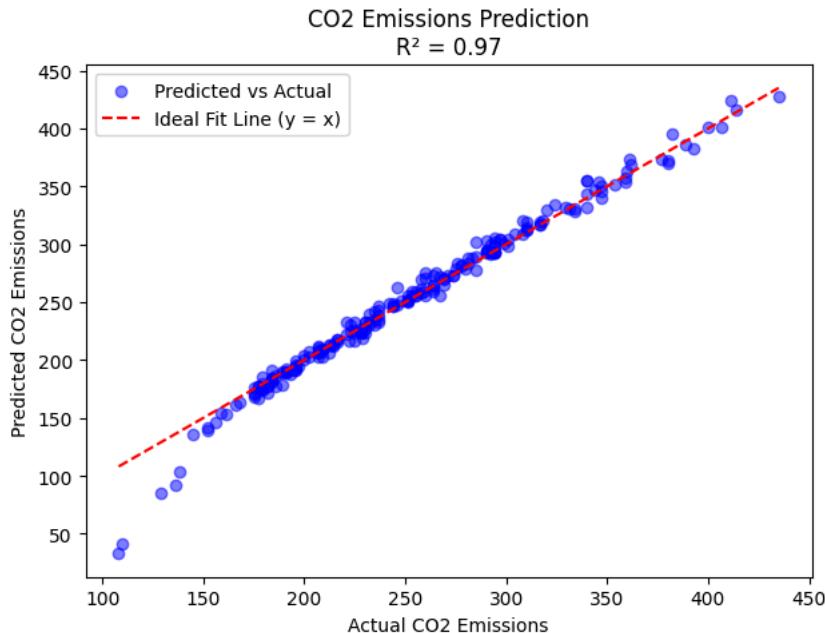
```
📊 Regression Evaluation Metrics:
Mean Absolute Error (MAE): 1.1127
Mean Squared Error (MSE): 23.2817
Root Mean Squared Error (RMSE): 4.8251
R² Score: 0.9942
```

```
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.scatter(y_test, y_pred, alpha=0.5, color='blue', label='Predicted vs Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', label='Ideal Fit Line (y = x)')
plt.xlabel('Actual CO2 Emissions')
plt.ylabel('Predicted CO2 Emissions')
plt.title(f'CO2 Emissions Prediction\nR² = {r2_fuel:.2f}')
plt.legend()

plt.tight_layout()
plt.show()
```



Start coding or generate with AI.