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0.1 Final Phase 4 Project Submission

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Click here to get the github repository

1 Overview

When we build a batiment, we have someting that very important. To be carefull about this thing, we are going to make a predictive model that estimates the heating load and the cooling load of a building based on its physical and structural features.

2 Business Understanding

The energy of a building is as really important as others parts of a building construction. For that we are going to make an accurate load predictions can support energy-efficient building design, reduce energy costs, and help meet sustainability standards.

3 Data Understanding

We use the **Energy Efficiency Dataset** (commonly available on the UCI Machine Learning Repository), which contains **768 building samples** with the following input features:

- **Relative Compactness(X1)**: A ratio that measures how compact a building's shape is.
- **Surface Area(X2)**: The total external area of the building's envelope (walls, roof, etc.).
- **Wall Area(X3)**: The total area of all external walls of the building.
- **Roof Area(X4)**: The horizontal external surface area of the building's roof.
- **Overall Height(X5)**: The vertical height of the building.
- **Orientation(X6)**: The building's facing direction (North, South, East, West).
- **Glazing Area(X7)**: The proportion of the building's exterior covered by windows (glass).
- **Glazing Area Distribution(X8)**: Definition: How the glazing (windows) is distributed across building facades (all on one side, evenly distributed, etc.).

Targets (Outputs):

- Heating Load(Y1) (kWh/m²): The amount of energy needed to maintain comfortable indoor temperature in cold conditions.
- Cooling Load(Y2) (kWh/m²): The amount of energy needed to keep indoor temperature comfortable in hot conditions.

3.1 importing module and package

[1]:
```
# data manipulation
import pandas as pd
import numpy as np

# vizualisation
import seaborn as sns
import matplotlib.pyplot as plt

# prepocessing
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler

# model
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor

# metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.metrics import roc_auc_score, roc_curve

# Filtering future warnings
import warnings
warnings.filterwarnings('ignore')
```

4 Data Preparation

[2]:
```
# load the dataset
df = pd.read_excel('data/ENB2012_data.xlsx')
df.head()
```

[2]:

	X1	X2	X3	X4	X5	X6	X7	X8	Y1	Y2
0	0.98	514.5	294.0	110.25	7.0	2	0.0	0	15.55	21.33
1	0.98	514.5	294.0	110.25	7.0	3	0.0	0	15.55	21.33
2	0.98	514.5	294.0	110.25	7.0	4	0.0	0	15.55	21.33
3	0.98	514.5	294.0	110.25	7.0	5	0.0	0	15.55	21.33

```
4  0.90  563.5  318.5  122.50  7.0   2  0.0   0  20.84  28.28
```

[3]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   X1      768 non-null    float64
 1   X2      768 non-null    float64
 2   X3      768 non-null    float64
 3   X4      768 non-null    float64
 4   X5      768 non-null    float64
 5   X6      768 non-null    int64
 6   X7      768 non-null    float64
 7   X8      768 non-null    int64
 8   Y1      768 non-null    float64
 9   Y2      768 non-null    float64
dtypes: float64(8), int64(2)
memory usage: 60.1 KB
```

[4]:

```python
df.describe()
```

[4]:

```
               X1          X2          X3          X4         X5          X6  \
count  768.000000  768.000000  768.000000  768.000000  768.00000  768.000000
mean     0.764167  671.708333  318.500000  176.604167    5.25000    3.500000
std      0.105777   88.086116   43.626481   45.165950    1.75114    1.118763
min      0.620000  514.500000  245.000000  110.250000    3.50000    2.000000
25%      0.682500  606.375000  294.000000  140.875000    3.50000    2.750000
50%      0.750000  673.750000  318.500000  183.750000    5.25000    3.500000
75%      0.830000  741.125000  343.000000  220.500000    7.00000    4.250000
max      0.980000  808.500000  416.500000  220.500000    7.00000    5.000000

               X7         X8          Y1          Y2
count  768.000000  768.00000  768.000000  768.000000
mean     0.234375    2.81250   22.307195   24.587760
std      0.133221    1.55096   10.090204    9.513306
min      0.000000    0.00000    6.010000   10.900000
25%      0.100000    1.75000   12.992500   15.620000
50%      0.250000    3.00000   18.950000   22.080000
75%      0.400000    4.00000   31.667500   33.132500
max      0.400000    5.00000   43.100000   48.030000
```

[5]:

```python
df.isna().sum() # check on null value
```

[5]:

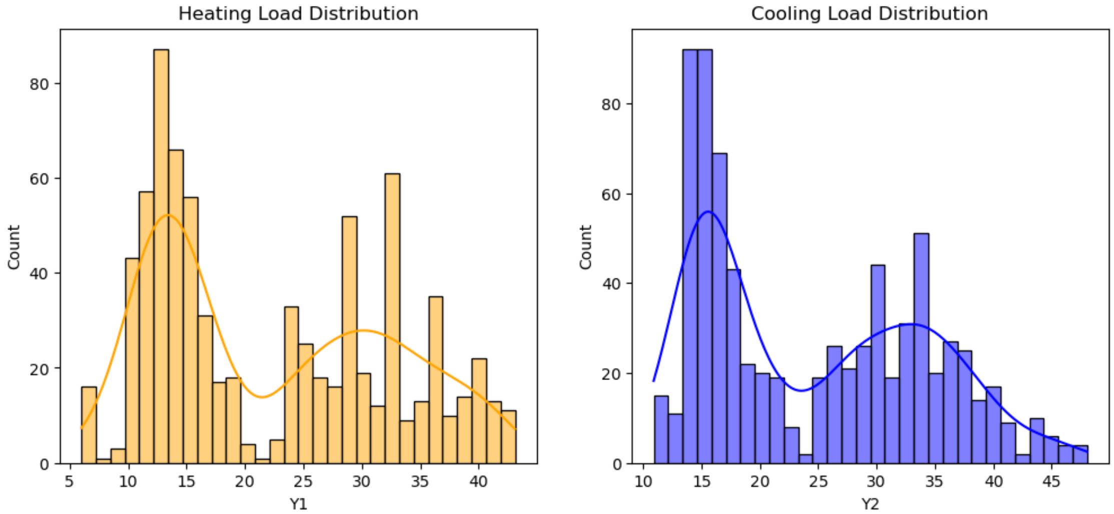
```
X1    0
X2    0
```

```
X3    0
X4    0
X5    0
X6    0
X7    0
X8    0
Y1    0
Y2    0
dtype: int64
```

[6]:
```python
# check on numeric and categorical
df.nunique()
```

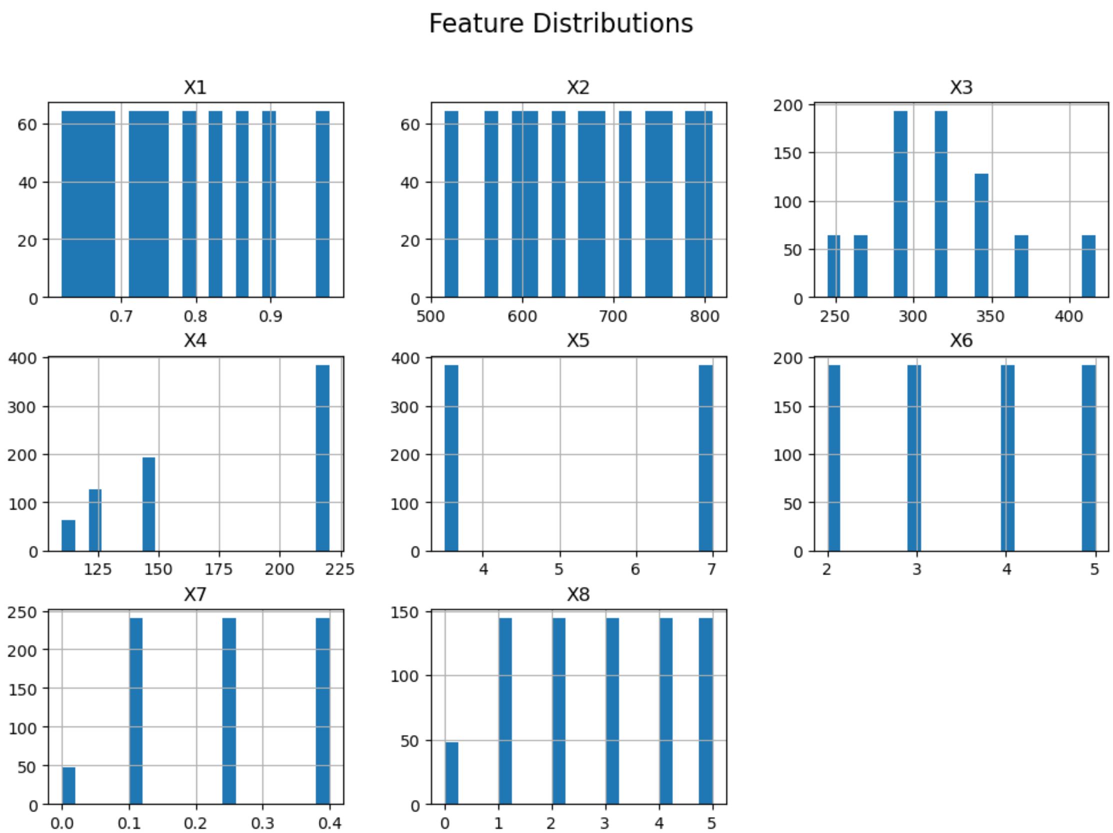
[6]:
```
X1     12
X2     12
X3      7
X4      4
X5      2
X6      4
X7      4
X8      6
Y1    587
Y2    636
dtype: int64
```

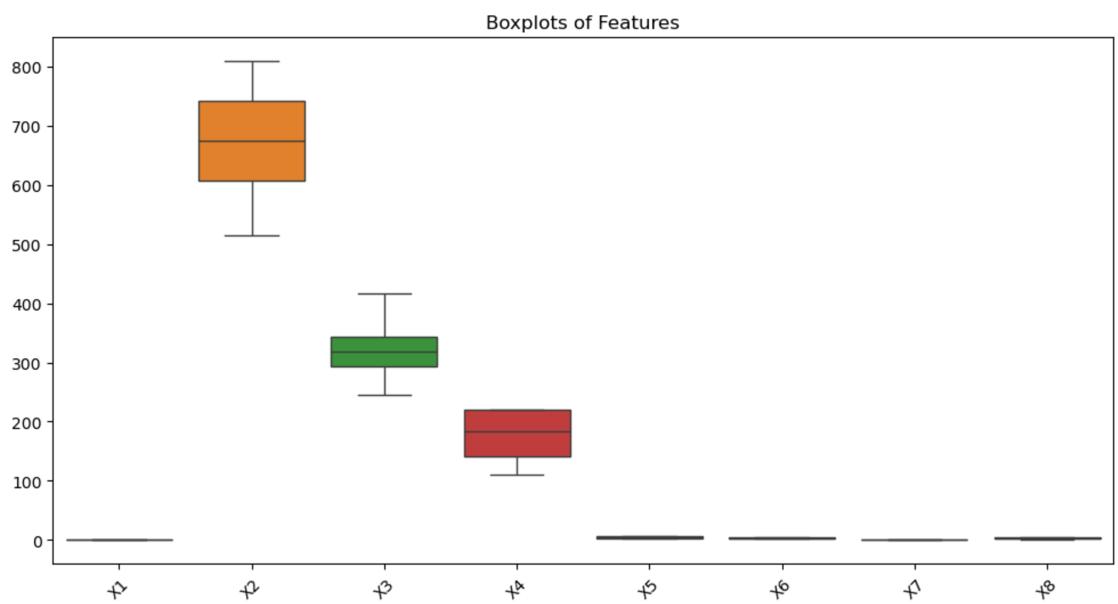
[7]:
```python
fig, axes = plt.subplots(1, 2, figsize=(12,5))
sns.histplot(df["Y1"], bins=30, kde=True, ax=axes[0], color="orange")
axes[0].set_title("Heating Load Distribution")

sns.histplot(df["Y2"], bins=30, kde=True, ax=axes[1], color="blue")
axes[1].set_title("Cooling Load Distribution")

plt.show()
```



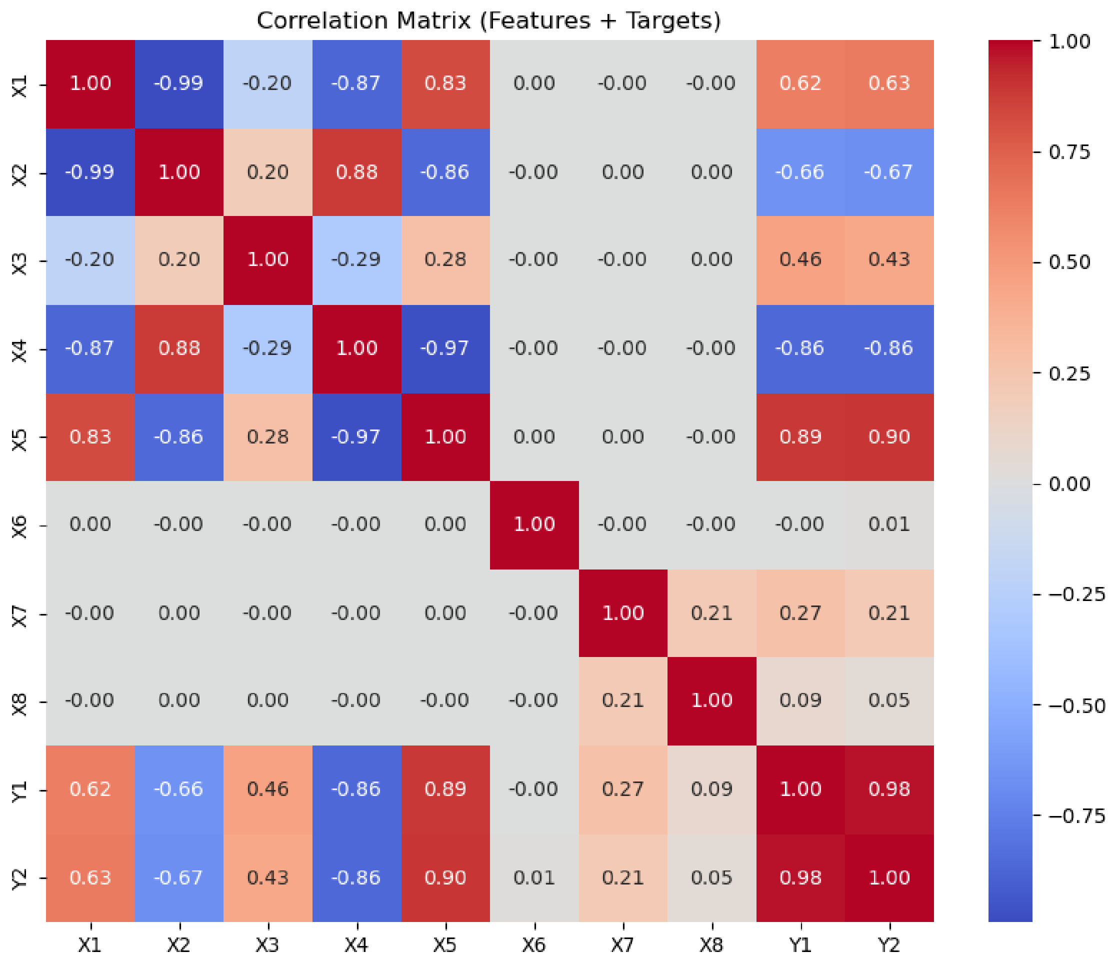
[8]:
```
FEATURES = ["X1","X2","X3", "X4", "X5", "X6", "X7","X8"]

TARGETS = ["Y1", "Y2"]
```

[9]:
```
df[FEATURES].hist(bins=20, figsize=(12,8))
plt.suptitle("Feature Distributions", fontsize=16)
plt.show()

# Boxplots
plt.figure(figsize=(12,6))
sns.boxplot(data=df[FEATURES])
plt.title("Boxplots of Features")
plt.xticks(rotation=45)
plt.show()
```


Feature Distributions
X1
X2
X3
X4
X5
X6
X7
X8


Boxplots of Features
X1
X2
X3
X4
X5
X6
X7
X8

```
[10]: corr = df[FEATURES + TARGETS].corr()

      plt.figure(figsize=(10,8))
      sns.heatmap(corr, annot=True, fmt=".2f", cmap="coolwarm", cbar=True)
      plt.title("Correlation Matrix (Features + Targets)")
      plt.show()
```



EDA Summary

- The dataset shows strong multicollinearity among several features (X1/X2, X4/X5).
- The most predictive features are X4 and X5, both strongly correlated with the targets.
- Y1 and Y2 are almost perfectly correlated (0.98), meaning they can be modeled jointly.
- X6 and X8 seem to have no significant relationship with the outputs possibly categorical or low impact.

4.1 Data prepocessing

Here we are going to make sure that our data is clean, consistent, and ready for modeling. - Let's drop redundant features to reduces multicollinearity. - X1 and X2 is hightly correlated, so we'll drop X2 - X4 and X5 , the same case, we'll drop X5 - in X8, it is almost no correlation, so we'll drop it

[11]:
```
df_reduced = df.drop(columns=['X2','X5','X8'])
df_reduced.head()
```

[11]:

	X1	X3	X4	X6	X7	Y1	Y2
0	0.98	294.0	110.25	2	0.0	15.55	21.33
1	0.98	294.0	110.25	3	0.0	15.55	21.33
2	0.98	294.0	110.25	4	0.0	15.55	21.33
3	0.98	294.0	110.25	5	0.0	15.55	21.33
4	0.90	318.5	122.50	2	0.0	20.84	28.28

[12]:
```
df_reduced.describe()
```

[12]:

	X1	X3	X4	X6	X7	Y1	\
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	
mean	0.764167	318.500000	176.604167	3.500000	0.234375	22.307195	
std	0.105777	43.626481	45.165950	1.118763	0.133221	10.090204	
min	0.620000	245.000000	110.250000	2.000000	0.000000	6.010000	
25%	0.682500	294.000000	140.875000	2.750000	0.100000	12.992500	
50%	0.750000	318.500000	183.750000	3.500000	0.250000	18.950000	
75%	0.830000	343.000000	220.500000	4.250000	0.400000	31.667500	
max	0.980000	416.500000	220.500000	5.000000	0.400000	43.100000	

	Y2
count	768.000000
mean	24.587760
std	9.513306
min	10.900000
25%	15.620000
50%	22.080000
75%	33.132500
max	48.030000

[13]:
```
df_reduced['X6'].nunique() # let's see how many distinct values
```

[13]: 4

We can see that X6(building orientation) is a categorical feature. It has only 4 distinct values. We are going to make an one-hot encoding .

[14]:
```
df_reduced = pd.get_dummies(df_reduced, columns=['X6'], prefix='X6',␣
↪drop_first=True).astype(int)
```

[15]:
```python
df_reduced.head()
```

[15]:

	X1	X3	X4	X7	Y1	Y2	X6_3	X6_4	X6_5
0	0	294	110	0	15	21	0	0	0
1	0	294	110	0	15	21	1	0	0
2	0	294	110	0	15	21	0	1	0
3	0	294	110	0	15	21	0	0	1
4	0	318	122	0	20	28	0	0	0

4.2 Modeling

[16]:
```python
X = df_reduced[['X1', 'X3', 'X4', 'X7', 'X6_3', 'X6_4', 'X6_5']]
y1 = df_reduced['Y1']  # Heating load
y2 = df_reduced['Y2']  # Cooling load
```

[17]:
```python
X_train, X_test, y1_train, y1_test = train_test_split(X, y1, test_size=0.2,␣
 ↪random_state=42)
_, _, y2_train, y2_test = train_test_split(X, y2, test_size=0.2,␣
 ↪random_state=42)
```

[18]:
```python
# linear regression model

model_y1 = LinearRegression()
model_y2 = LinearRegression()

model_y1.fit(X_train, y1_train)
model_y2.fit(X_train, y2_train)
```

[18]: LinearRegression()

[19]:
```python
# Predictions
y1_pred = model_y1.predict(X_test)
y2_pred = model_y2.predict(X_test)

# Metrics
print("Heating Load (Y1):")
print("MSE:", mean_squared_error(y1_test, y1_pred))
print("R²:", r2_score(y1_test, y1_pred))

print("\nCooling Load (Y2):")
print("MSE:", mean_squared_error(y2_test, y2_pred))
print("R²:", r2_score(y2_test, y2_pred))
```

```
Heating Load (Y1):
MSE: 21.973172477698295
R²: 0.7881295308330747

Cooling Load (Y2):
```

MSE: 21.19970682421335
R²: 0.7712300716000929

[20]:
```python
coeff_df_y1 = pd.DataFrame({'Feature': X.columns, 'Coefficient': model_y1.
    ↪coef_})
coeff_df_y2 = pd.DataFrame({'Feature': X.columns, 'Coefficient': model_y2.
    ↪coef_})

print("\nCoefficients for Heating Load (Y1):")
print(coeff_df_y1)

print("\nCoefficients for Cooling Load (Y2):")
print(coeff_df_y2)
```

```
Coefficients for Heating Load (Y1):
  Feature  Coefficient
0      X1     0.000000
1      X3     0.048954
2      X4    -0.179804
3      X7     0.000000
4    X6_3     0.318751
5    X6_4     0.192900
6    X6_5    -0.014860

Coefficients for Cooling Load (Y2):
  Feature  Coefficient
0      X1     0.000000
1      X3     0.040360
2      X4    -0.171403
3      X7     0.000000
4    X6_3    -0.267372
5    X6_4    -0.218451
6    X6_5     0.122052
```

4.3 Decision tree

[21]:
```python
# decision tree model
tree_y1 = DecisionTreeRegressor(random_state=42)
tree_y2 = DecisionTreeRegressor(random_state=42)

tree_y1.fit(X_train, y1_train)
tree_y2.fit(X_train, y2_train)
```

[21]:
```
DecisionTreeRegressor(random_state=42)
```

[22]:
```python
# Predictions
y1_pred = tree_y1.predict(X_test)
```

```
y2_pred = tree_y2.predict(X_test)

# Metrics
mse_y1 = mean_squared_error(y1_test, y1_pred)
mse_y2 = mean_squared_error(y2_test, y2_pred)

r2_y1 = r2_score(y1_test, y1_pred)
r2_y2 = r2_score(y2_test, y2_pred)

print("Heating Load (Y1):")
print("MSE =", mse_y1)
print("R² =", r2_y1)

print("\nCooling Load (Y2):")
print("MSE =", mse_y2)
print("R² =", r2_y2)
```

```
Heating Load (Y1):
MSE = 11.37836604869241
R² = 0.8902871328418207

Cooling Load (Y2):
MSE = 8.741029898401292
R² = 0.905673941598345
```

[23]:
```
importance_y1 = pd.DataFrame({'Feature': X.columns, 'Importance': tree_y1.
 ↪feature_importances_})
importance_y2 = pd.DataFrame({'Feature': X.columns, 'Importance': tree_y2.
 ↪feature_importances_})

print("\nFeature Importance for Heating Load (Y1):")
print(importance_y1.sort_values(by='Importance', ascending=False))

print("\nFeature Importance for Cooling Load (Y2):")
print(importance_y2.sort_values(by='Importance', ascending=False))
```

```
Feature Importance for Heating Load (Y1):
  Feature  Importance
2      X4    0.882722
1      X3    0.114560
6    X6_5    0.001073
5    X6_4    0.000980
4    X6_3    0.000665
0      X1    0.000000
3      X7    0.000000

Feature Importance for Cooling Load (Y2):
```

```
  Feature  Importance
2      X4    0.879893
1      X3    0.115696
6    X6_5    0.002177
4    X6_3    0.001277
5    X6_4    0.000958
0      X1    0.000000
3      X7    0.000000
```

4.4 Random forest

[24]:
```
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```

[33]:
```
rf_y1 = RandomForestRegressor(random_state=42)
grid_y1 = GridSearchCV(estimator=rf_y1, param_grid=param_grid,
                       cv=5, scoring='r2', n_jobs=-1, verbose=1)
grid_y1.fit(X_train, y1_train)
grid_y1.best_estimator_
#print("Best Parameters for Heating Load (Y1):")
#print()
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
```

[33]:
```
RandomForestRegressor(min_samples_leaf=4, min_samples_split=10,
                      n_estimators=200, random_state=42)
```

[34]:
```
rf_y2 = RandomForestRegressor(random_state=42)
grid_y2 = GridSearchCV(estimator=rf_y2, param_grid=param_grid,
                       cv=5, scoring='r2', n_jobs=-1, verbose=1)
grid_y2.fit(X_train, y2_train)
grid_y2.best_estimator_
#print("Best Parameters for Cooling Load (Y2):")
#print(best_params_)
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
```

[34]:
```
RandomForestRegressor(min_samples_leaf=4, min_samples_split=10,
                      n_estimators=200, random_state=42)
```

[35]:
```
# Predict with best models
y1_pred = grid_y1.best_estimator_.predict(X_test)
y2_pred = grid_y2.best_estimator_.predict(X_test)

# Metrics
```

```
print("\nHeating Load (Y1):")
print("MSE =", mean_squared_error(y1_test, y1_pred))
print("R² =", r2_score(y1_test, y1_pred))

print("\nCooling Load (Y2):")
print("MSE =", mean_squared_error(y2_test, y2_pred))
print("R² =", r2_score(y2_test, y2_pred))
```

```
Heating Load (Y1):
MSE = 11.293551097709443
R² = 0.8911049384397774

Cooling Load (Y2):
MSE = 8.72317150953825
R² = 0.9058666547511925
```

4.5 Evaluation

We have got complete results for all three models: linear regression, Decision tree and Random forest. Let analyse and visualize them. Let's create a dataframe for the results.

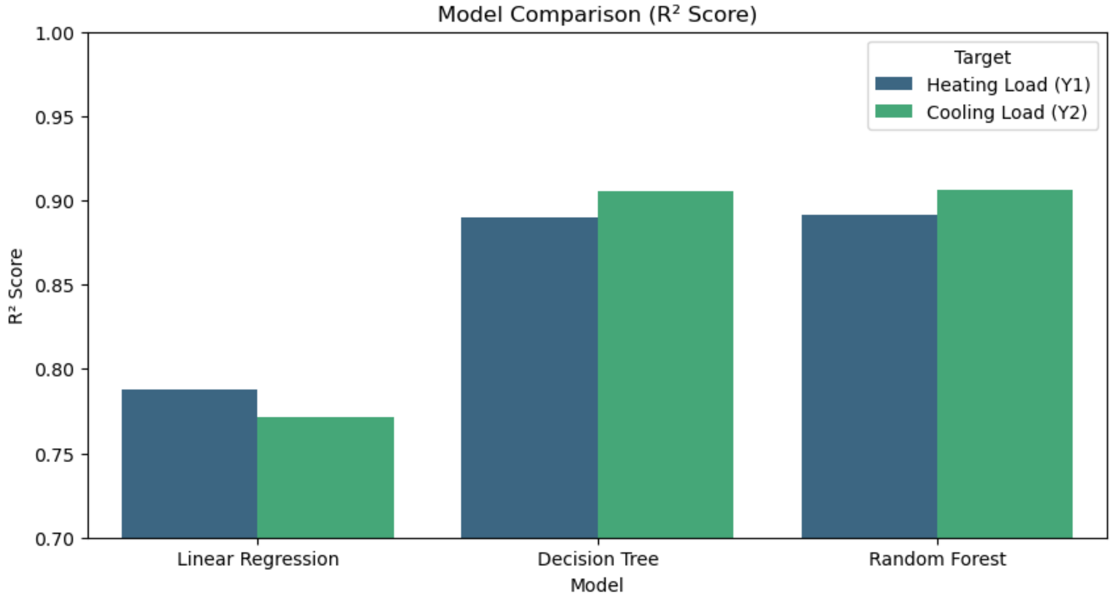
[28]:
```
# Create the results DataFrame
data = {
    "Model": ["Linear Regression", "Linear Regression", "Decision Tree",␣
 ↪"Decision Tree", "Random Forest", "Random Forest"],
    "Target": ["Heating Load (Y1)", "Cooling Load (Y2)", "Heating Load (Y1)",␣
 ↪"Cooling Load (Y2)", "Heating Load (Y1)", "Cooling Load (Y2)"],
    "MSE": [21.97, 21.20, 11.38, 8.74, 11.29, 8.72],
    "R2": [0.7881, 0.7712, 0.8903, 0.9057, 0.8911, 0.9059]
}

df_results = pd.DataFrame(data)
df_results
```

[28]:

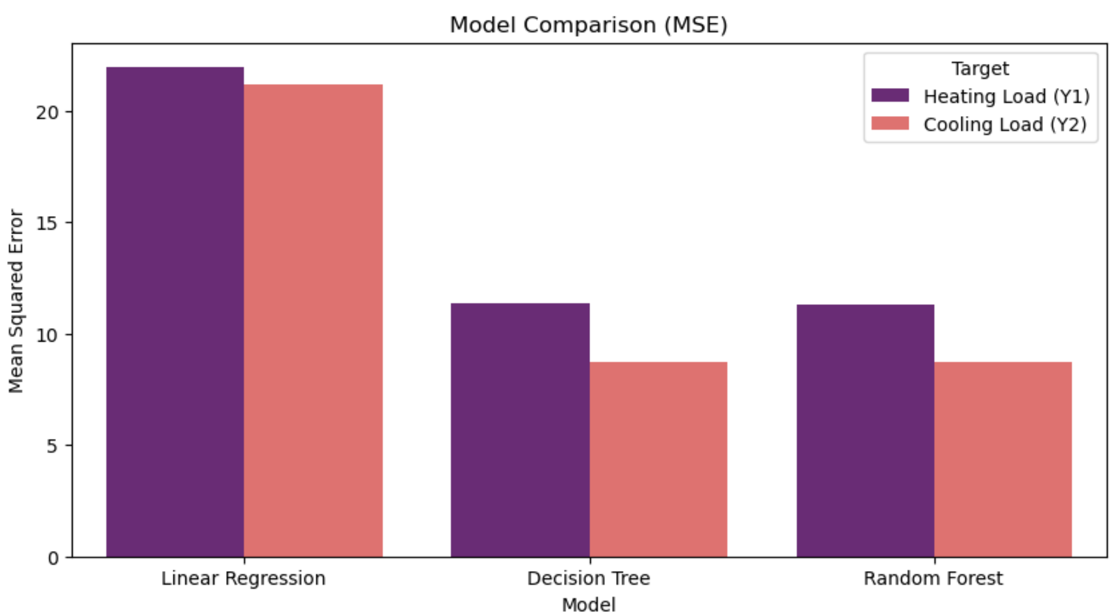
	Model	Target	MSE	R2
0	Linear Regression	Heating Load (Y1)	21.97	0.7881
1	Linear Regression	Cooling Load (Y2)	21.20	0.7712
2	Decision Tree	Heating Load (Y1)	11.38	0.8903
3	Decision Tree	Cooling Load (Y2)	8.74	0.9057
4	Random Forest	Heating Load (Y1)	11.29	0.8911
5	Random Forest	Cooling Load (Y2)	8.72	0.9059

[29]:
```
# Plot R² Comparison
plt.figure(figsize=(10,5))
sns.barplot(data=df_results, x="Model", y="R2", hue="Target", palette="viridis")
plt.title("Model Comparison (R² Score)")
plt.ylabel("R² Score")
```

```
plt.ylim(0.7, 1)
plt.show()
```

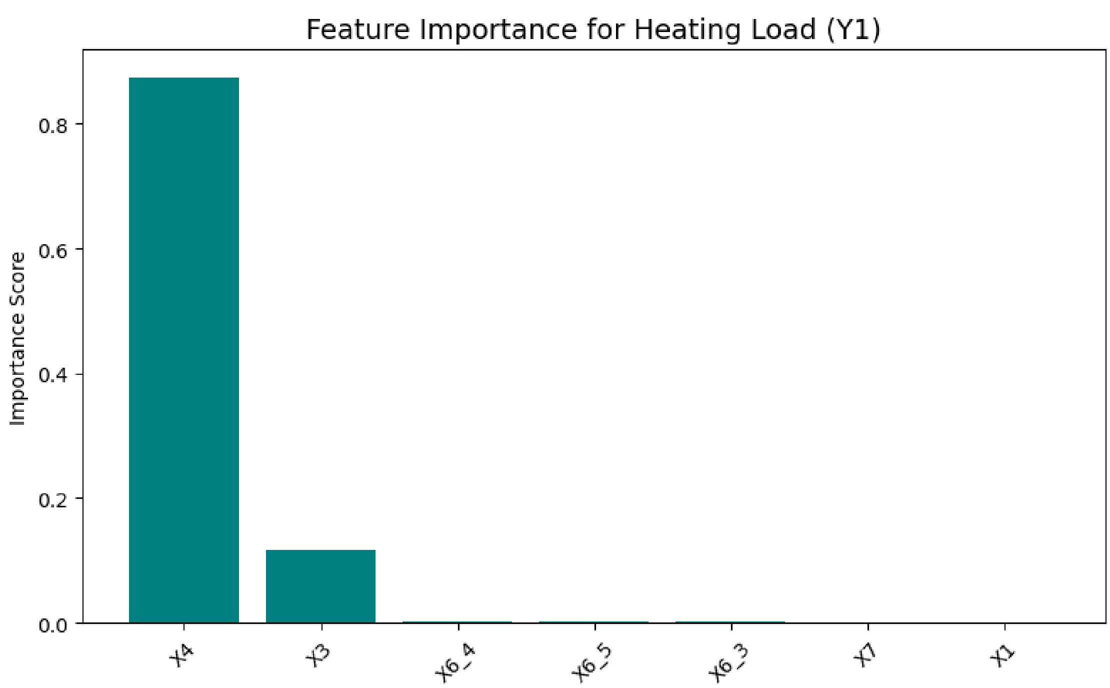


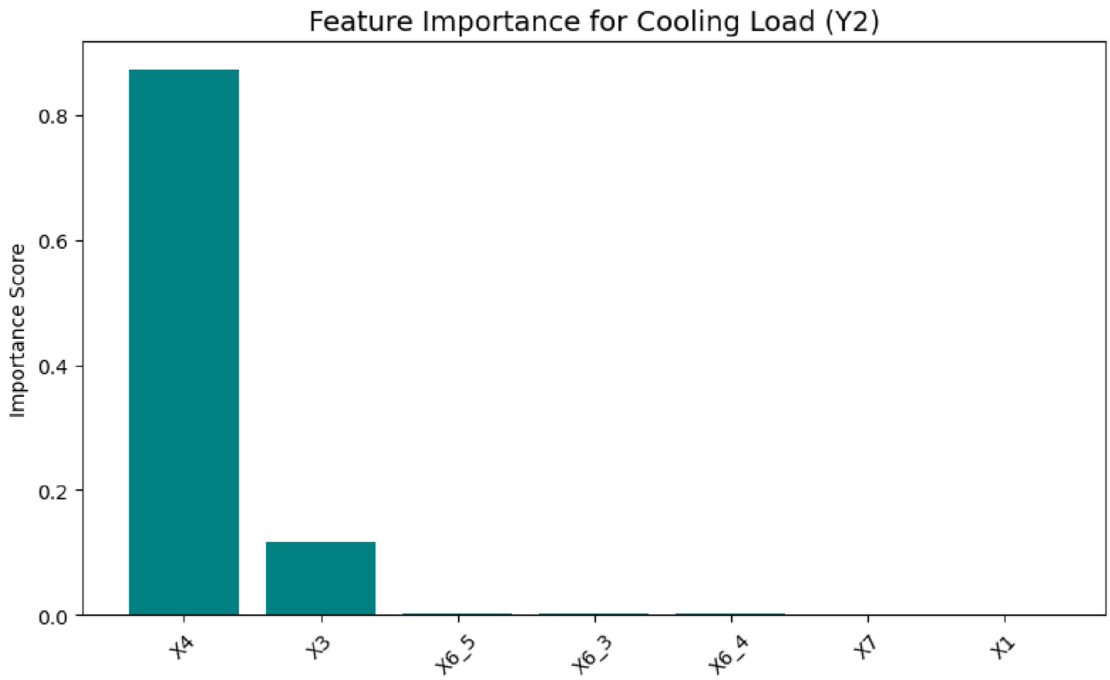
[30]:
```
# Plot MSE Comparison
plt.figure(figsize=(10,5))
sns.barplot(data=df_results, x="Model", y="MSE", hue="Target", palette="magma")
plt.title("Model Comparison (MSE)")
plt.ylabel("Mean Squared Error")
plt.show()
```



The linear regression is simple, interpretable, good baseline but limited accuracy. Decision tree is stronger, good for insight but may be overfit. The random forest model is highest accuracy , stable , handles nonlinearity. It is a recommended model.

[38]:
```python
#  Feature Importance Plot Function
def plot_feature_importance(model, features, title):
    importances = model.feature_importances_
    indices = np.argsort(importances)[::-1]
    sorted_features = [features[i] for i in indices]

    plt.figure(figsize=(8, 5))
    plt.title(title, fontsize=14)
    plt.bar(range(len(importances)), importances[indices], align='center',␣
 ↪color='teal')
    plt.xticks(range(len(importances)), sorted_features, rotation=45)
    plt.ylabel("Importance Score")
    plt.tight_layout()
    plt.show()

#  Plot feature importance for both models
plot_feature_importance(grid_y1.best_estimator_, X.columns, "Feature Importance␣
 ↪for Heating Load (Y1)")
plot_feature_importance(grid_y2.best_estimator_, X.columns, "Feature Importance␣
 ↪for Cooling Load (Y2)")
```





- X4 is clearly the dominant feature for both heating and cooling predictions,it contributes about 88%-89% of the model's predictive power.
- X3 is the second most important (around 11-12%) still relevant but far less dominant. All other features (X6_3, X6_4, X6_5, X1, X7) have negligible influence, meaning the model relies mostly on X4 and X3 to make predictions.

4.6 Conclusion

After evaluating three models, **Linear Regression, Decision Tree, and Random Forest,** we found that the Random Forest Regressor consistently produced the best results for predicting both heating (Y1) and cooling (Y2) loads. The R^2 values (0.89–0.91) indicate strong predictive accuracy, while the low MSE confirms minimal error. Feature importance analysis revealed that X4 and X3 are the most influential predictors in both targets. Therefore, the Random Forest model is selected as the optimal model due to its robustness, generalization ability, and ability to handle nonlinear patterns that linear regression cannot capture.

```
[ ]:
```