Assignment 7: Energy Efficiency Dataset

Predicting Heating Load from Building Features

Q1: Load Dataset

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (10, 6)

# Read Excel file
df = pd.read_excel('ENB2012_data.xlsx')

# Rename columns
columns = ['Relative_Compactness', 'Surface_Area', 'Wall_Area', 'Roof_Area',
           'Overall_Height', 'Orientation', 'Glazing_Area', 'Glazing_Area_Distributio
           'Heating_Load', 'Cooling_Load']
df.columns = columns

df.head()
```

	Relative_Compactness	Surface_Area	Wall_Area	Roof_Area	Overall_Height	Orientation	Glaz
0	0.98	514.5	294.0	110.25	7.0	2	
1	0.98	514.5	294.0	110.25	7.0	3	
2	0.98	514.5	294.0	110.25	7.0	4	
3	0.98	514.5	294.0	110.25	7.0	5	
4	0.90	563.5	318.5	122.50	7.0	2	

Q2: Dataset Summary

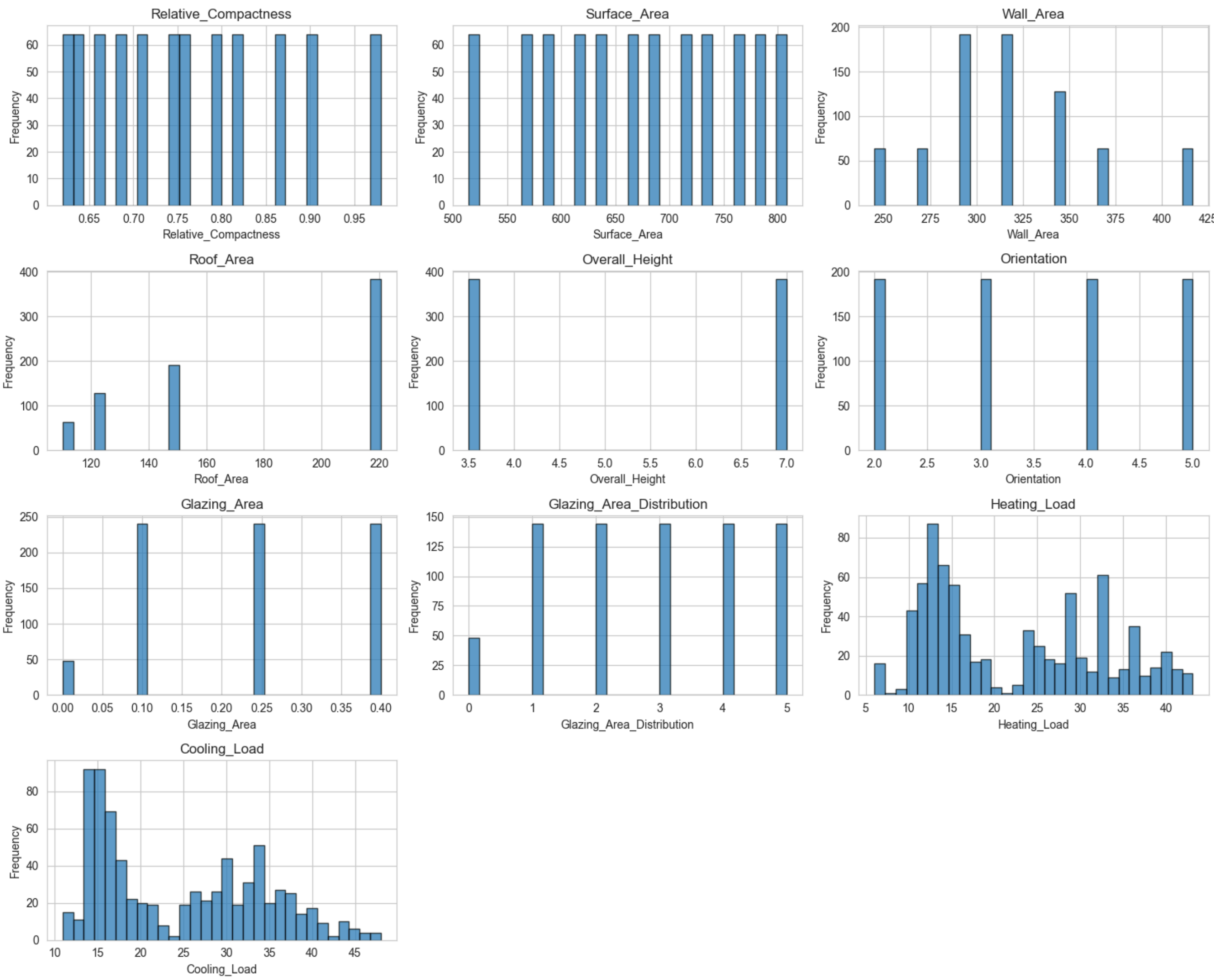
```
print("Dataset Info:")
print(f"Rows: {len(df)}")
print(f"Columns: {len(df.columns)}")
print(f"\nMissing values:\n{df.isnull().sum()}")
print(f"\nBasic statistics:")
df.describe()
```

```
Dataset Info:
Rows: 768
Columns: 10

Missing values:
Relative_Compactness         0
Surface_Area                 0
Wall_Area                    0
Roof_Area                    0
Overall_Height               0
Orientation                  0
Glazing_Area                 0
Glazing_Area_Distribution    0
Heating_Load                 0
Cooling_Load                 0
dtype: int64

Basic statistics:
```

	Relative_Compactness	Surface_Area	Wall_Area	Roof_Area	Overall_Height	Orientatio
count	768.000000	768.000000	768.000000	768.000000	768.00000	768.00000
mean	0.764167	671.708333	318.500000	176.604167	5.25000	3.50000
std	0.105777	88.086116	43.626481	45.165950	1.75114	1.11876
min	0.620000	514.500000	245.000000	110.250000	3.50000	2.00000
25%	0.682500	606.375000	294.000000	140.875000	3.50000	2.75000
50%	0.750000	673.750000	318.500000	183.750000	5.25000	3.50000
75%	0.830000	741.125000	343.000000	220.500000	7.00000	4.25000
max	0.980000	808.500000	416.500000	220.500000	7.00000	5.00000

Q3: Feature Distributions

```python
fig, axes = plt.subplots(4, 3, figsize=(15, 12))
axes = axes.ravel()

for idx, col in enumerate(df.columns):
    axes[idx].hist(df[col].dropna(), bins=30, edgecolor='black', alpha=0.7)
    axes[idx].set_title(f'{col}')
    axes[idx].set_xlabel(col)
    axes[idx].set_ylabel('Frequency')

for idx in range(len(df.columns), len(axes)):
    axes[idx].set_visible(False)

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



Observations:

- Orientation and Glazing_Area_Distribution are categorical
- Overall_Height has only 2 values
- Surface/Wall/Roof areas show multiple peaks

Q4: Unique Values

```
print("Unique values per feature:")
for col in df.columns:
    print(f"{col:30s}: {df[col].nunique():3d}")

print("\nCategorical features:")
for col in ['Orientation', 'Glazing_Area_Distribution', 'Overall_Height']:
    print(f"\n{col}:")
    print(df[col].value_counts().sort_index())
```

```
Unique values per feature:
Relative_Compactness          :  12
Surface_Area                  :  12
Wall_Area                     :   7
Roof_Area                     :   4
Overall_Height                :   2
Orientation                   :   4
Glazing_Area                  :   4
Glazing_Area_Distribution     :   6
Heating_Load                  : 587
Cooling_Load                  : 636

Categorical features:

Orientation:
Orientation
2    192
3    192
4    192
5    192
Name: count, dtype: int64

Glazing_Area_Distribution:
Glazing_Area_Distribution
0     48
1    144
2    144
3    144
4    144
5    144
Name: count, dtype: int64

Overall_Height:
Overall_Height
3.5    384
7.0    384
Name: count, dtype: int64
```

Q4.1: Duplicates

```
n_duplicates = df.duplicated().sum()
print(f"Duplicate rows: {n_duplicates}")
```

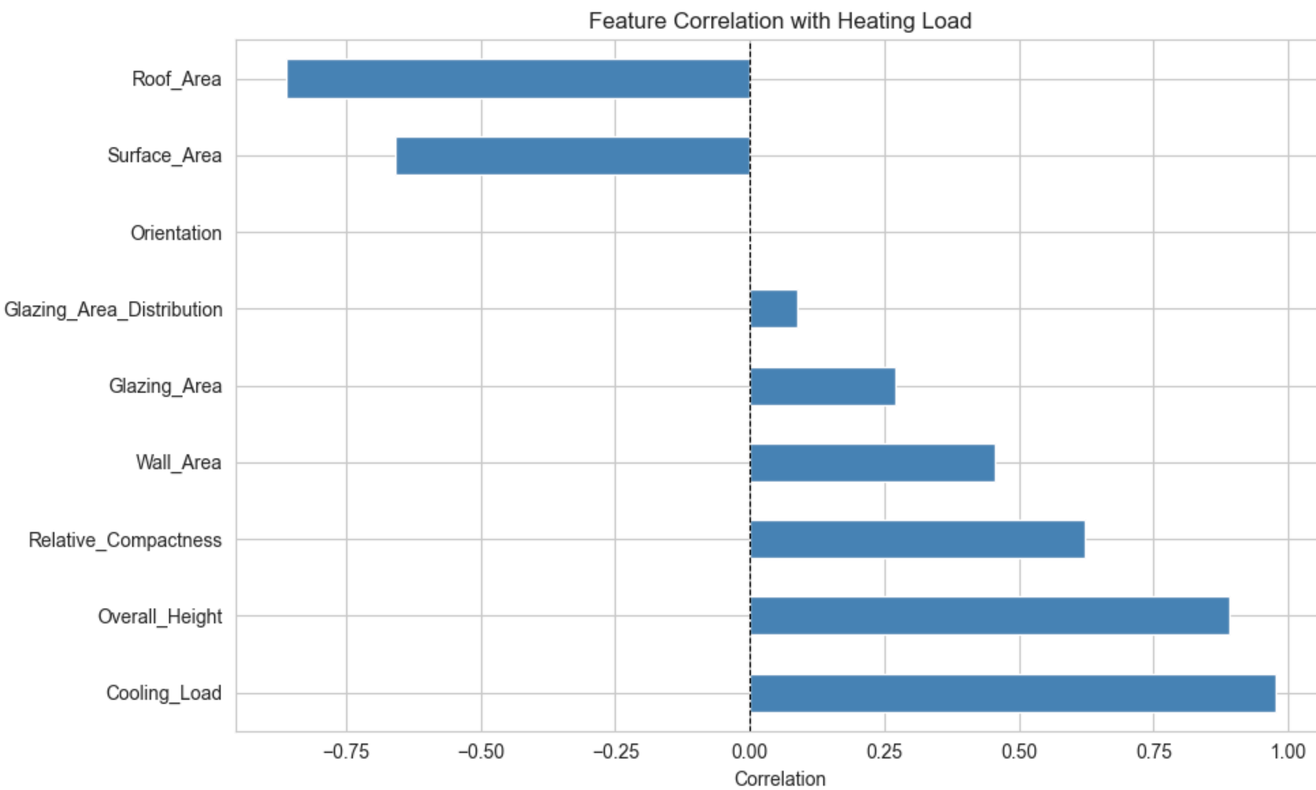
```
Duplicate rows: 0
```

Q5: Correlation with Target

```
correlations = df.corr()['Heating_Load'].drop('Heating_Load').sort_values(ascending=Fa

print("Correlations with Heating_Load:")
print(correlations)

plt.figure(figsize=(10, 6))
correlations.plot(kind='barh', color='steelblue')
```

```
plt.title('Feature Correlation with Heating Load')
plt.xlabel('Correlation')
plt.axvline(x=0, color='black', linestyle='--', linewidth=0.8)
plt.tight_layout()
plt.show()

print("\n⚠️ WARNING: Cooling_Load has high correlation (0.976)")
print("This is DATA LEAKAGE - must remove it!")
```

```
Correlations with Heating_Load:
Cooling_Load                   0.975862
Overall_Height                 0.889430
Relative_Compactness           0.622272
Wall_Area                      0.455671
Glazing_Area                   0.269842
Glazing_Area_Distribution      0.087368
Orientation                   -0.002587
Surface_Area                  -0.658120
Roof_Area                     -0.861828
Name: Heating_Load, dtype: float64
```



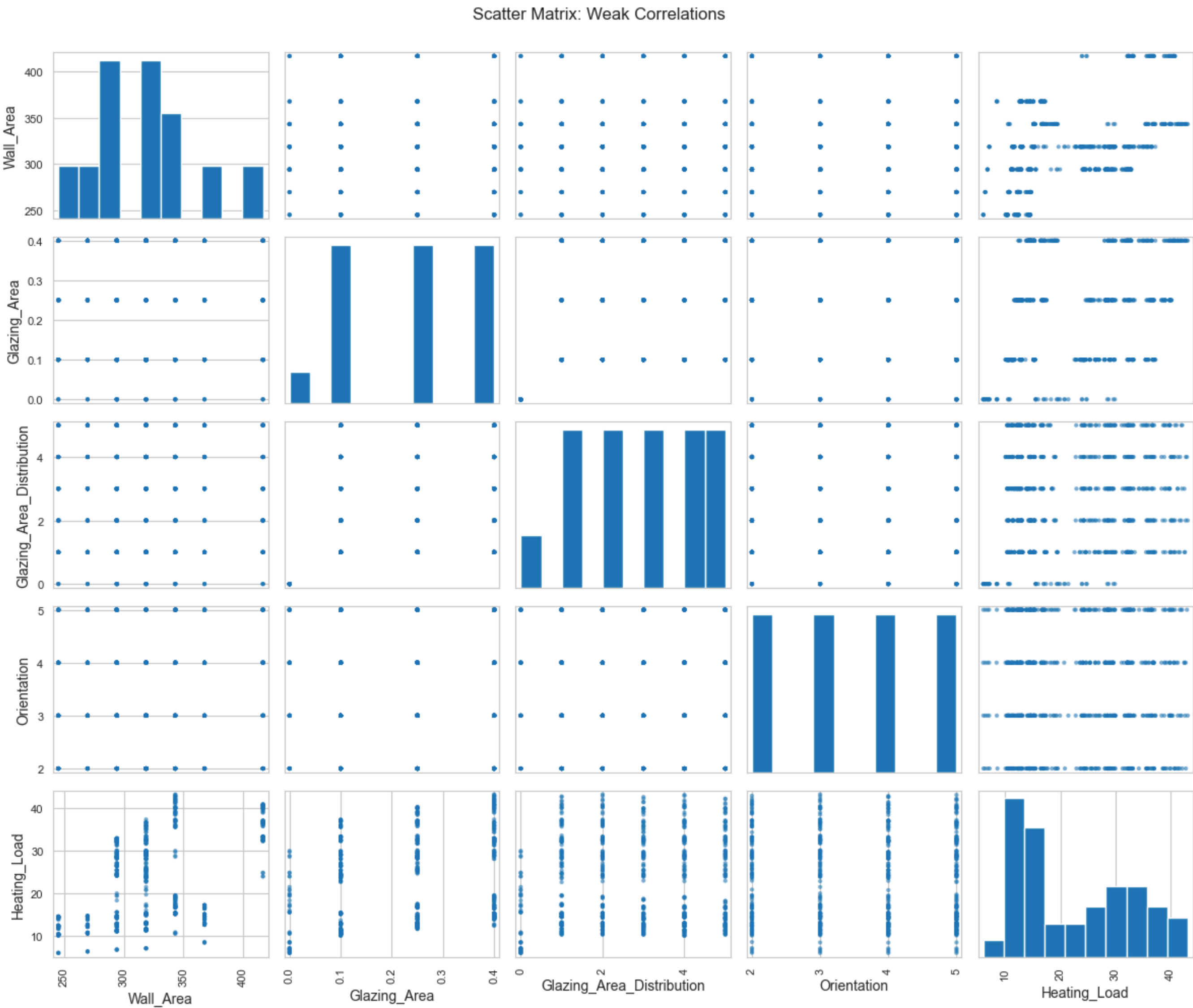

```
⚠️ WARNING: Cooling_Load has high correlation (0.976)
This is DATA LEAKAGE - must remove it!
```

Q6: Scatter Matrix

```
from pandas.plotting import scatter_matrix

# Select weak correlations
weak_features = correlations[abs(correlations) < 0.5].index.tolist()
features_to_plot = weak_features + ['Heating_Load']
```

```
print(f"Weak correlation features: {weak_features}")

scatter_matrix(df[features_to_plot], figsize=(12, 10), alpha=0.6, diagonal='hist')
plt.suptitle('Scatter Matrix: Weak Correlations', y=1.0)
plt.tight_layout()
plt.show()
```

```
Weak correlation features: ['Wall_Area', 'Glazing_Area', 'Glazing_Area_Distribution',
'Orientation']
```



Q7: Custom Transformer

```
from sklearn.base import BaseEstimator, TransformerMixin

class RatioTransformer(BaseEstimator, TransformerMixin):
    """Creates ratio features from column pairs"""

    def __init__(self, ratio_pairs):
        # ratio_pairs = [(num_col, denom_col, new_col_name), ...]
        self.ratio_pairs = ratio_pairs
```

```
    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X_copy = X.copy()
        for num_col, denom_col, new_col in self.ratio_pairs:
            # +1e-10 prevents division by zero
            X_copy[new_col] = X_copy[num_col] / (X_copy[denom_col] + 1e-10)
        return X_copy

# Test
ratio_transformer = RatioTransformer([('Wall_Area', 'Surface_Area', 'Wall_to_Surface_R
test_df = ratio_transformer.fit_transform(df.head())
print("New feature created:")
print(test_df[['Wall_Area', 'Surface_Area', 'Wall_to_Surface_Ratio']].head())
```

```
New feature created:
   Wall_Area  Surface_Area  Wall_to_Surface_Ratio
0      294.0         514.5               0.571429
1      294.0         514.5               0.571429
2      294.0         514.5               0.571429
3      294.0         514.5               0.571429
4      318.5         563.5               0.565217
```

Q8: Preprocessing Pipeline

```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder

# Define feature groups
categorical_features = ['Orientation', 'Glazing_Area_Distribution']
numerical_features = ['Relative_Compactness', 'Surface_Area', 'Wall_Area', 'Roof_Area
                      'Overall_Height', 'Glazing_Area']

# Create pipeline
preprocessor = ColumnTransformer([
    ('cat', OneHotEncoder(drop='first', sparse_output=False), categorical_features),
    ('num', StandardScaler(), numerical_features)  # Mean=0, Std=1
], remainder='drop')

print("Pipeline created!")
print(f"Categorical: {categorical_features}")
print(f"Numerical: {numerical_features}")
```

```
Pipeline created!
Categorical: ['Orientation', 'Glazing_Area_Distribution']
Numerical: ['Relative_Compactness', 'Surface_Area', 'Wall_Area', 'Roof_Area', 'Overal
l_Height', 'Glazing_Area']
```

Q9: Train/Test Split

```
from sklearn.model_selection import train_test_split
```

```python
# Remove both targets (avoid data leakage!)
X = df.drop(['Heating_Load', 'Cooling_Load'], axis=1)
y = df['Heating_Load']

# Split: 80% train, 20% test, random_state=42 for reproducibility
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=

print(f"Training: {len(X_train)} samples")
print(f"Test: {len(X_test)} samples")
```

```
Training: 614 samples
Test: 154 samples
```

Q10: Apply Preprocessing

```python
# Fit on train only (no data leakage!)
X_train_processed = preprocessor.fit_transform(X_train)
X_test_processed = preprocessor.transform(X_test)

print(f"Processed train shape: {X_train_processed.shape}")
print(f"Processed test shape: {X_test_processed.shape}")
print(f"Total features: {X_train_processed.shape[1]}")
```

```
Processed train shape: (614, 14)
Processed test shape: (154, 14)
Total features: 14
```

Q11: Linear Regression

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Train model
lr_model = LinearRegression()
lr_model.fit(X_train_processed, y_train)

# Predict
y_pred_lr = lr_model.predict(X_test_processed)

# Evaluate
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
r2_lr = r2_score(y_test, y_pred_lr)

print("Linear Regression Results:")
print(f"RMSE: {rmse_lr:.4f}")
print(f"R² Score: {r2_lr:.4f}")
```

```
Linear Regression Results:
RMSE: 2.8723
R² Score: 0.9209
```

Q12: Random Forest

```
from sklearn.ensemble import RandomForestRegressor

# n_estimators=200: number of trees
# random_state=42: reproducibility
# n_jobs=-1: use all CPU cores
rf_model = RandomForestRegressor(n_estimators=200, random_state=42, n_jobs=-1)
rf_model.fit(X_train_processed, y_train)

y_pred_rf = rf_model.predict(X_test_processed)

rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))
r2_rf = r2_score(y_test, y_pred_rf)

print("Random Forest Results:")
print(f"RMSE: {rmse_rf:.4f}")
print(f"R² Score: {r2_rf:.4f}")
```

```
Random Forest Results:
RMSE: 0.5285
R² Score: 0.9973
```

Q13: Gradient Boosting

```
from sklearn.ensemble import GradientBoostingRegressor

# n_estimators=200: number of boosting rounds
# learning_rate default=0.1: step size
gb_model = GradientBoostingRegressor(n_estimators=200, random_state=42)
gb_model.fit(X_train_processed, y_train)

y_pred_gb = gb_model.predict(X_test_processed)

rmse_gb = np.sqrt(mean_squared_error(y_test, y_pred_gb))
r2_gb = r2_score(y_test, y_pred_gb)

print("Gradient Boosting Results:")
print(f"RMSE: {rmse_gb:.4f}")
print(f"R² Score: {r2_gb:.4f}")
```

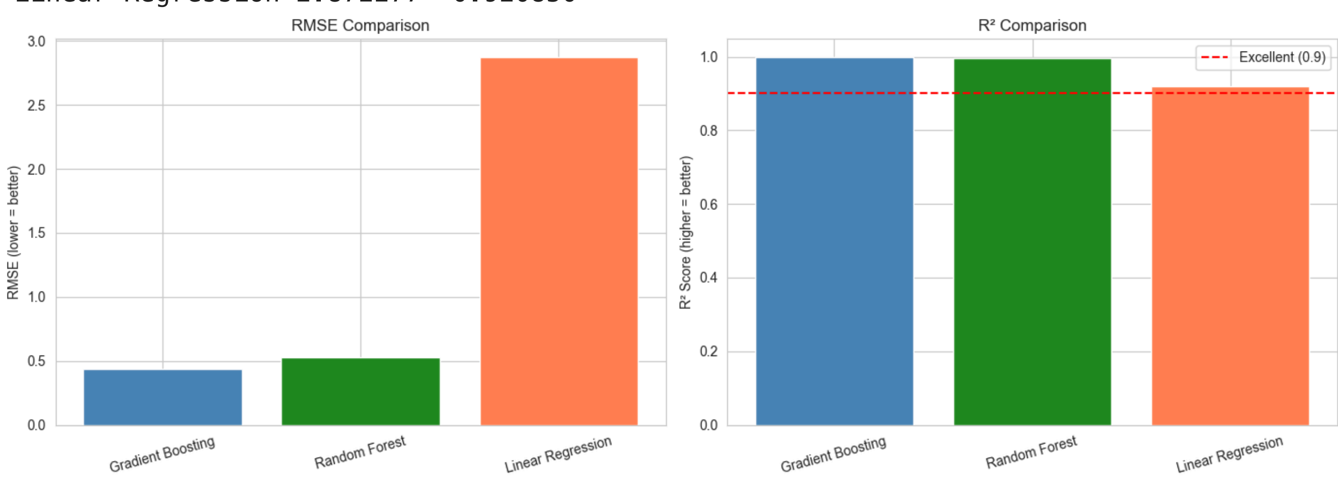
```
Gradient Boosting Results:
RMSE: 0.4403
R² Score: 0.9981
```

Q14: Model Comparison

```
# Create comparison table
results = pd.DataFrame({
    'Model': ['Linear Regression', 'Random Forest', 'Gradient Boosting'],
    'RMSE': [rmse_lr, rmse_rf, rmse_gb],
    'R² Score': [r2_lr, r2_rf, r2_gb]
})

results = results.sort_values('R² Score', ascending=False).reset_index(drop=True)
```

```python
print("Model Comparison:")
print(results.to_string(index=False))

# Visualize
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# RMSE (lower is better)
axes[0].bar(results['Model'], results['RMSE'], color=['steelblue', 'forestgreen', 'co
axes[0].set_ylabel('RMSE (lower = better)')
axes[0].set_title('RMSE Comparison')
axes[0].tick_params(axis='x', rotation=15)

# R² (higher is better)
axes[1].bar(results['Model'], results['R² Score'], color=['steelblue', 'forestgreen',
axes[1].set_ylabel('R² Score (higher = better)')
axes[1].set_title('R² Comparison')
axes[1].tick_params(axis='x', rotation=15)
axes[1].axhline(y=0.9, color='red', linestyle='--', label='Excellent (0.9)')
axes[1].legend()

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

```
Model Comparison:
            Model     RMSE  R² Score
Gradient Boosting 0.440269  0.998140
    Random Forest 0.528480  0.997321
Linear Regression 2.872277  0.920850
```



R^2 Metric Explanation

R^2 (Coefficient of Determination) measures how well the model explains data variance.

Range: 0 to 1 (can be negative for very bad models)

Interpretation:

- **R^2 = 1.0**: Perfect predictions (100% variance explained)
- **R^2 = 0.9**: Excellent (90% variance explained)
- **R^2 = 0.5**: Moderate (50% variance explained)

- **R^2 = 0.0**: No better than predicting the average

Why tree models win:

- Building features have **non-linear** relationships
- Complex interactions between shape, area, and glazing
- Linear Regression assumes straight-line relationships
- Random Forest and Gradient Boosting capture curves and interactions