[link for Housing Dataset]

In [1]:

```
#  upload file
from google.colab import files
uploaded = files.upload()
```

Choose File **No file selected**

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving Housing.csv to Housing.csv
```

In [2]:

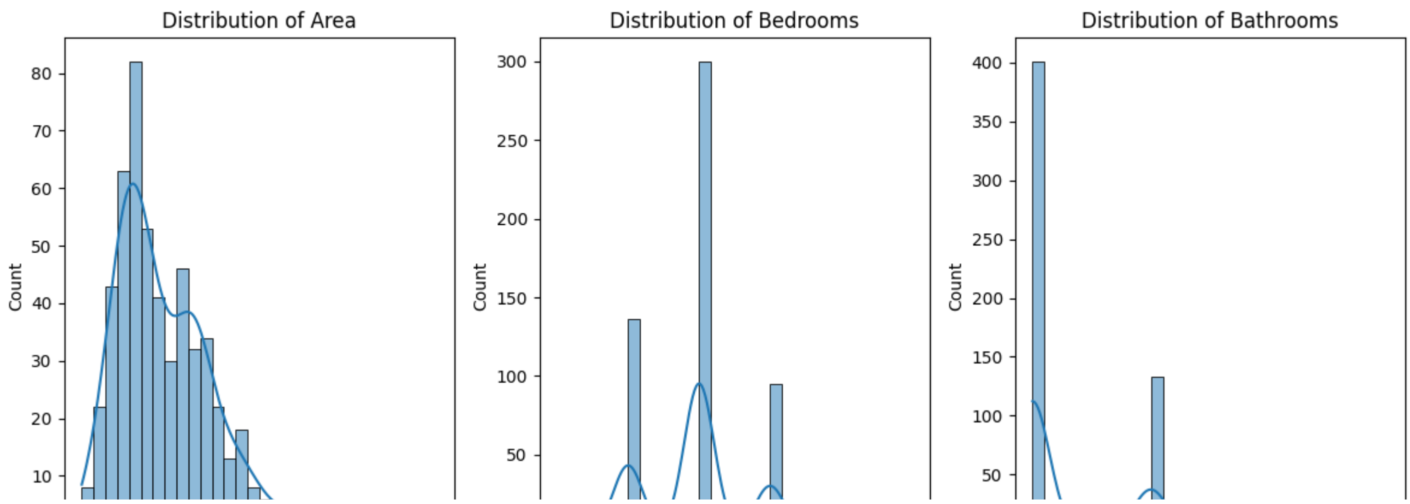
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error, r2_score

from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, AdaBoostRe
gressor
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor

# Load the dataset
data = pd.read_csv("Housing.csv")

# Display the first few rows
print(data.head())

# Data Preprocessing
# Convert categorical columns to numerical
categorical_columns = ['mainroad', 'guestroom', 'basement', 'hotwaterheating',
                       'airconditioning', 'prefarea', 'furnishingstatus']

numerical_columns = ['area', 'bedrooms', 'bathrooms', 'stories', 'parking']
target_column = 'price'
```

```
      price  area  bedrooms  bathrooms  stories mainroad guestroom basement  \
0  13300000  7420         4          2        3      yes        no       no
1  12250000  8960         4          4        4      yes        no       no
2  12250000  9960         3          2        2      yes        no      yes
3  12215000  7500         4          2        2      yes        no      yes
4  11410000  7420         4          1        2      yes       yes      yes

  hotwaterheating airconditioning  parking prefarea furnishingstatus
0              no             yes        2      yes        furnished
1              no             yes        3       no        furnished
2              no              no        2      yes   semi-furnished
3              no             yes        3      yes        furnished
4              no             yes        2       no        furnished
```

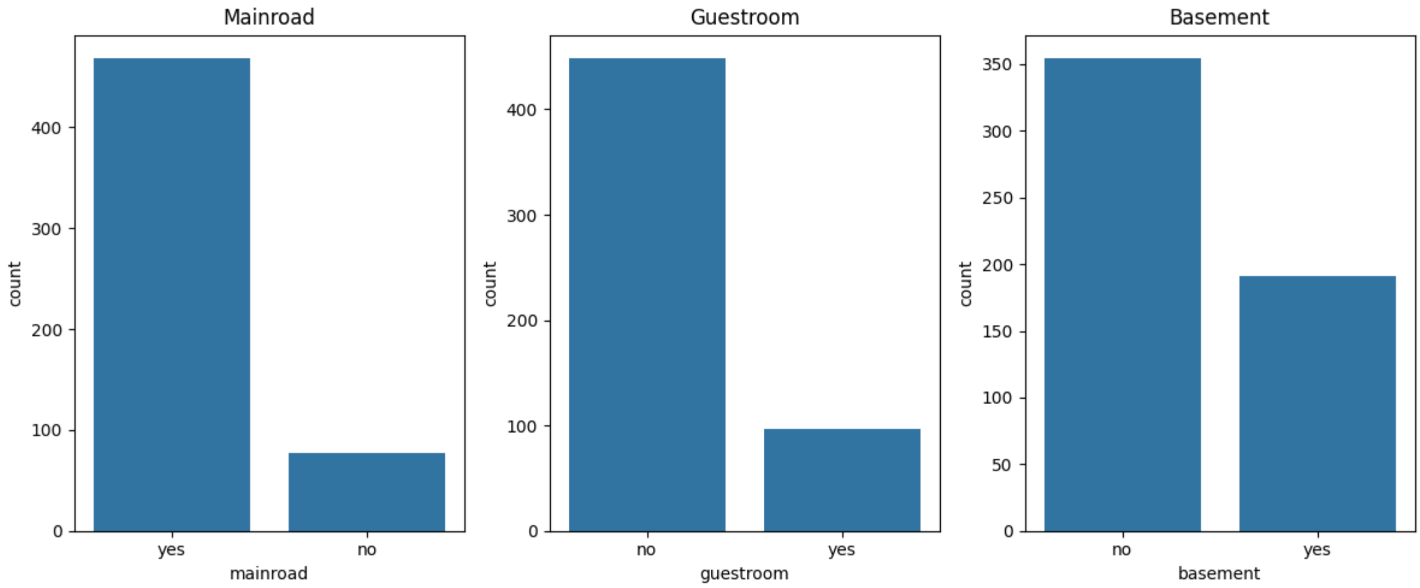
In [3]:

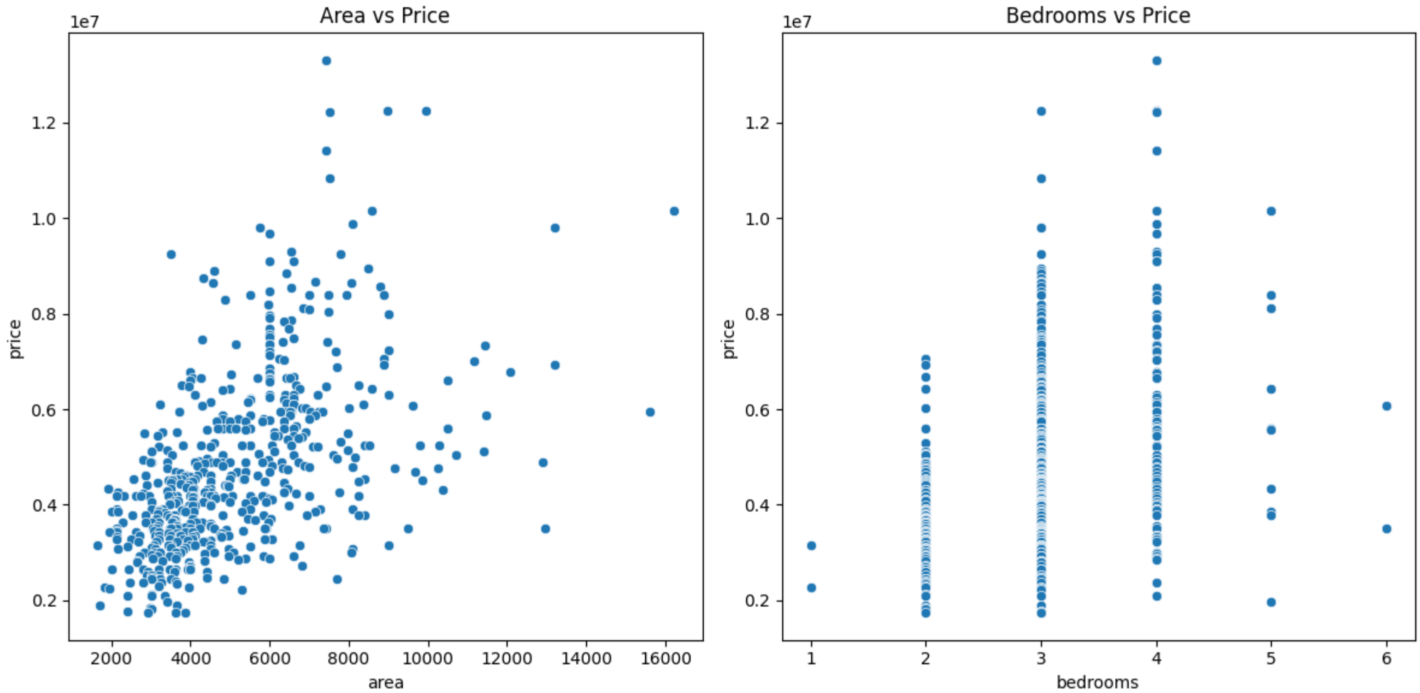
```
import matplotlib.pyplot as plt
import seaborn as sns
# Set up the visualizations
plt.figure(figsize=(12, 10))
```

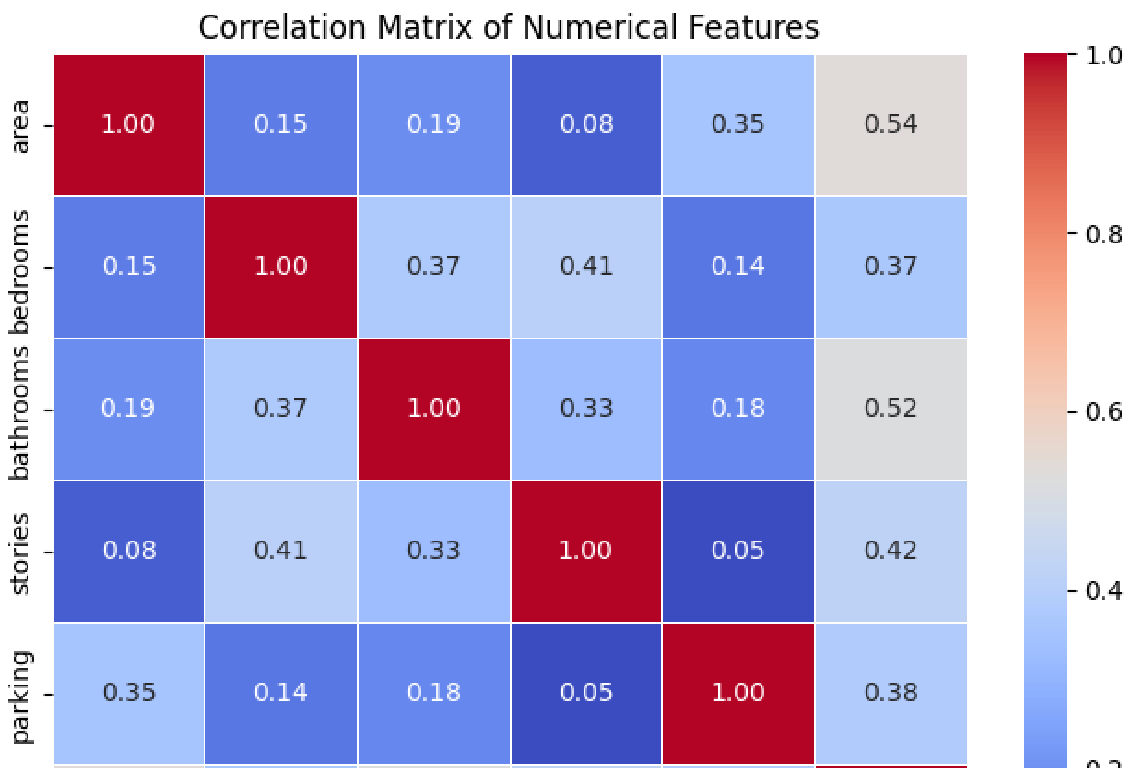
```
# 1. Histograms for numerical features (Area, Bedrooms, Bathrooms)
plt.subplot(2, 3, 1)
sns.histplot(data['area'], kde=True, bins=30)
plt.title('Distribution of Area')

plt.subplot(2, 3, 2)
sns.histplot(data['bedrooms'], kde=True, bins=30)
plt.title('Distribution of Bedrooms')

plt.subplot(2, 3, 3)
sns.histplot(data['bathrooms'], kde=True, bins=30)
plt.title('Distribution of Bathrooms')

# 2. Bar charts for categorical features
plt.subplot(2, 3, 4)
sns.countplot(x='mainroad', data=data)
plt.title('Mainroad')

plt.subplot(2, 3, 5)
sns.countplot(x='guestroom', data=data)
plt.title('Guestroom')

plt.subplot(2, 3, 6)
sns.countplot(x='basement', data=data)
plt.title('Basement')

plt.tight_layout()
plt.show()

# 3. Scatter plots for correlation between numerical features and target variable (price)
plt.figure(figsize=(12, 6))

# Scatter plot for Area vs Price
plt.subplot(1, 2, 1)
sns.scatterplot(x='area', y='price', data=data)
plt.title('Area vs Price')

# Scatter plot for Bedrooms vs Price
plt.subplot(1, 2, 2)
sns.scatterplot(x='bedrooms', y='price', data=data)
plt.title('Bedrooms vs Price')

plt.tight_layout()
plt.show()

# 4. Correlation matrix heatmap for numerical features
correlation_matrix = data[['area', 'bedrooms', 'bathrooms', 'stories', 'parking', 'price
']].corr()

plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', cbar=True, linewi
dths=0.5)
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```

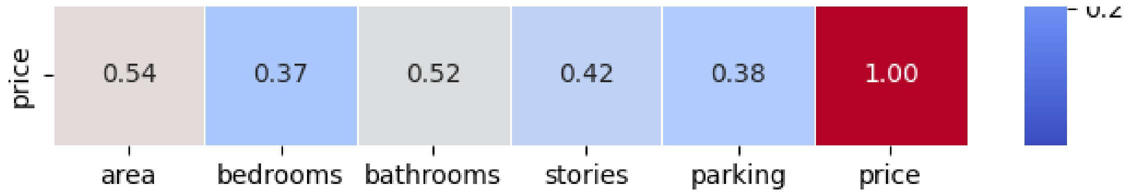



area
bedrooms
bathrooms


Mainroad
Guestroom
Basement
count
mainroad
guestroom
basement
yes
no


Area vs Price
Bedrooms vs Price
1e7
price
area
bedrooms


Correlation Matrix of Numerical Features
area
bedrooms
bathrooms
stories
parking
1.00 0.15 0.19 0.08 0.35 0.54
0.15 1.00 0.37 0.41 0.14 0.37
0.19 0.37 1.00 0.33 0.18 0.52
0.08 0.41 0.33 1.00 0.05 0.42
0.35 0.14 0.18 0.05 1.00 0.38



In [4]:

```
# Separating features and target
X = data[categorical_columns + numerical_columns]
y = data[target_column]

# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)

# OneHotEncoding for categorical columns
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_columns),
        ('cat', OneHotEncoder(drop='first'), categorical_columns)
    ])

# Building pipelines for models
models = {
    "Linear Regression": Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', LinearRegression())
    ]),
    "Random Forest": Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', RandomForestRegressor(random_state=42))
    ]),
    "Gradient Boosting": Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', GradientBoostingRegressor(random_state=42))
    ]),
    "AdaBoost": Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', AdaBoostRegressor(random_state=42))
    ]),
    "Support Vector Regressor (SVR)": Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', SVR())
    ]),
    "Decision Tree": Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', DecisionTreeRegressor(random_state=42))
    ])
}

# Training and evaluating models
results = {}
for model_name, pipeline in models.items():
    pipeline.fit(X_train, y_train)
    predictions = pipeline.predict(X_test)
    mse = mean_squared_error(y_test, predictions)
    r2 = r2_score(y_test, predictions)
    results[model_name] = {"MSE": mse, "R2": r2}

# Display results
print("Model Evaluation:")
for model_name, metrics in results.items():
    print(f"{model_name}: MSE = {metrics['MSE']:.2f}, R2 = {metrics['R2']:.2f}")

# Hyperparameter tuning for Random Forest
param_grid = {
    'model__n_estimators': [100, 200, 300],   # Number of trees
    'model__max_depth': [10, 20, 30, None],   # Maximum depth of the trees
    'model__min_samples_split': [2, 5, 10],   # Minimum samples to split an internal node
```

```python
    'model__min_samples_leaf': [1, 2, 4]      # Minimum samples at a leaf node
}

# Create the GridSearchCV object
grid_search = GridSearchCV(
    estimator=models["Random Forest"],  # Random Forest pipeline
    param_grid=param_grid,
    cv=5,  # 5-fold cross-validation
    scoring='neg_mean_squared_error',  # Minimize MSE
    n_jobs=-1,  # Use all available cores
    verbose=2
)

# Perform grid search on the training data
grid_search.fit(X_train, y_train)

# Best parameters and best score
print("\nBest Parameters:", grid_search.best_params_)
print("Best Score (negative MSE):", grid_search.best_score_)

# Use the best estimator for predictions
best_rf_model = grid_search.best_estimator_
tuned_predictions = best_rf_model.predict(X_test)

# Evaluate the tuned model
tuned_mse = mean_squared_error(y_test, tuned_predictions)
tuned_r2 = r2_score(y_test, tuned_predictions)

print(f"\nAfter Tuning: MSE = {tuned_mse:.2f}, R² = {tuned_r2:.2f}")
```

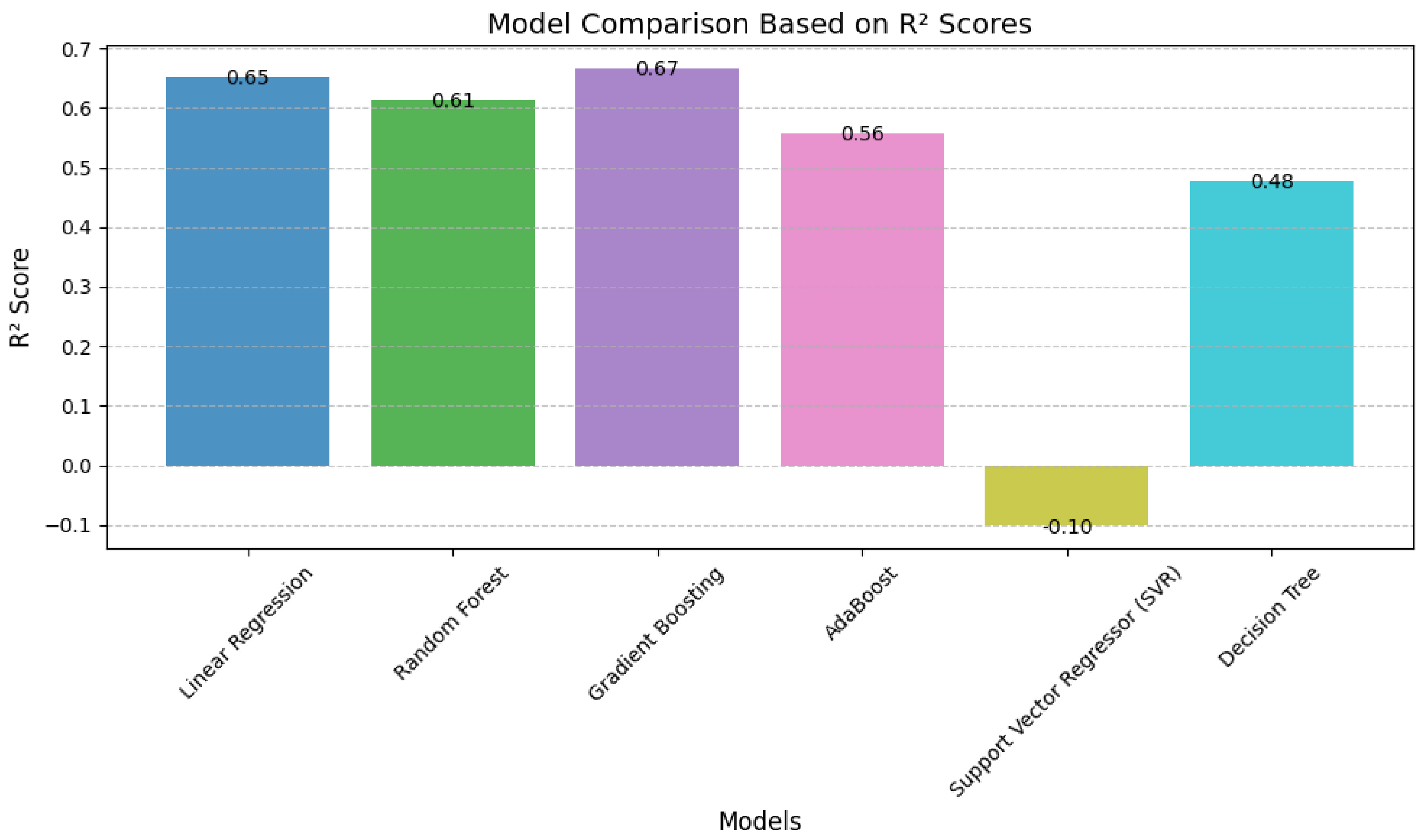
```
Model Evaluation:
Linear Regression: MSE = 1754318687330.67, R2 = 0.65
Random Forest: MSE = 1959323004717.27, R2 = 0.61
Gradient Boosting: MSE = 1688403924777.51, R2 = 0.67
AdaBoost: MSE = 2237444322297.88, R2 = 0.56
Support Vector Regressor (SVR): MSE = 5567929077615.07, R2 = -0.10
Decision Tree: MSE = 2642802637614.68, R2 = 0.48
Fitting 5 folds for each of 108 candidates, totalling 540 fits

Best Parameters: {'model__max_depth': 10, 'model__min_samples_leaf': 2, 'model__min_sampl
es_split': 10, 'model__n_estimators': 300}
Best Score (negative MSE): -1169287169970.3613

After Tuning: MSE = 2066175698215.50, R² = 0.59
```

In [8]:

```python
# Find the best model based on R2 score
best_model_name = max(results, key=lambda x: results[x]["R2"])
best_model_metrics = results[best_model_name]

# Print the best model
print(f"Best Model: {best_model_name} with R² = {best_model_metrics['R2']:.2f} and MSE =
{best_model_metrics['MSE']:.2f}")

# Visualization of results
model_names = list(results.keys())
r2_scores = [results[model]["R2"] for model in model_names]
mse_scores = [results[model]["MSE"] for model in model_names]

# Set colors for each bar
colors = plt.cm.tab10(np.linspace(0, 1, len(model_names)))

# Create a bar chart
plt.figure(figsize=(10, 6))
bars = plt.bar(model_names, r2_scores, color=colors, alpha=0.8)

# Annotate bars with their R2 scores
for bar, r2 in zip(bars, r2_scores):
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        bar.get_height() - 0.02,  # Position slightly below top of the bar
```

```
        f"{r2:.2f}",
        ha='center', va='bottom', fontsize=10, color="black"
    )

# Add titles and labels
plt.title("Model Comparison Based on R² Scores", fontsize=14)
plt.xlabel("Models", fontsize=12)
plt.ylabel("R² Score", fontsize=12)
plt.xticks(rotation=45, fontsize=10)
plt.grid(axis="y", linestyle="--", alpha=0.7)

# Show the chart
plt.tight_layout()
plt.show()
```

```
Best Model: Gradient Boosting with R² = 0.67 and MSE = 1688403924777.51
```

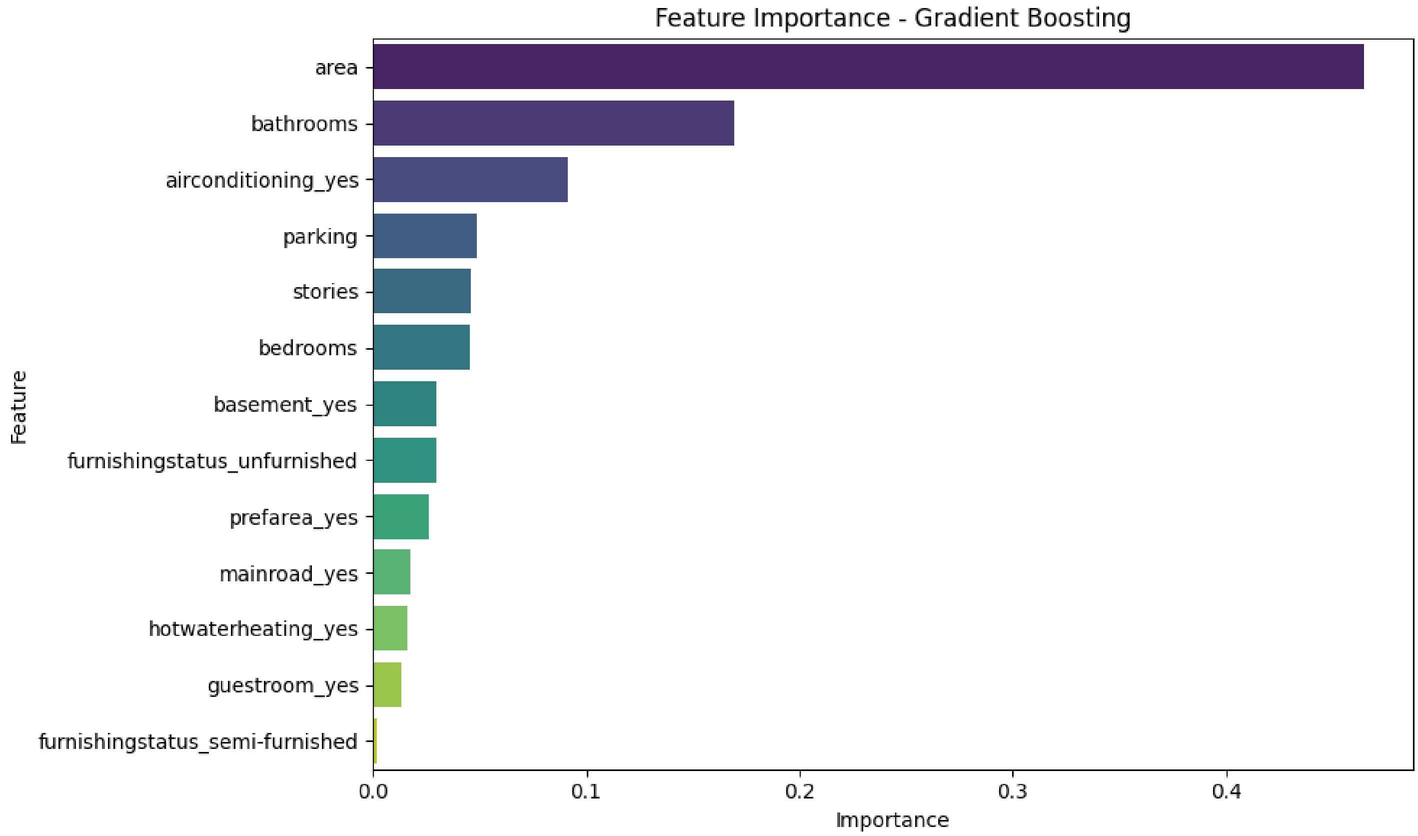


In [9]:

```
# Feature importance for Gradient Boosting
best_model = models["Gradient Boosting"]
gb_model = best_model.named_steps['model']

# Extracting feature importance
encoded_feature_names = numerical_columns + list(
    best_model.named_steps['preprocessor'].transformers_[1][1].get_feature_names_out(cat
egorical_columns)
)
feature_importances = pd.DataFrame({
    'Feature': encoded_feature_names,
    'Importance': gb_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# Plotting feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=feature_importances, palette="viridis")
plt.title('Feature Importance - Gradient Boosting')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```

```
<ipython-input-9-bcd625d243a6>:16: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='Importance', y='Feature', data=feature_importances, palette="viridis")
```



In [10]:

```
feature_importances
```

Out[10]:

	Feature	Importance
0	area	0.464321
2	bathrooms	0.169201
9	airconditioning_yes	0.091497
4	parking	0.048649
3	stories	0.045925
1	bedrooms	0.045333
7	basement_yes	0.029761
12	furnishingstatus_unfurnished	0.029653
10	prefarea_yes	0.026430
5	mainroad_yes	0.017484
8	hotwaterheating_yes	0.016257
6	guestroom_yes	0.013607
11	furnishingstatus_semi-furnished	0.001883

In [11]:

```
def predict_house_price(model_pipeline):
    """
    we define a function to predict house price based on user inputs.
    """
    print("\nEnter the house details for prediction:")
    try:
```

```
        # User inputs
        area = float(input("Enter area in square feet: "))
        bedrooms = int(input("Enter number of bedrooms: "))
        bathrooms = int(input("Enter number of bathrooms: "))
        stories = int(input("Enter number of stories: "))
        mainroad = input("Is the house on a main road? (yes/no): ").strip().lower()
        guestroom = input("Does the house have a guest room? (yes/no): ").strip().lower(
)
        basement = input("Does the house have a basement? (yes/no): ").strip().lower()
        hotwaterheating = input("Does the house have hot water heating? (yes/no): ").str
ip().lower()
        airconditioning = input("Does the house have air conditioning? (yes/no): ").stri
p().lower()
        parking = int(input("Enter the number of parking spaces: "))
        prefarea = input("Is the house in a preferred area? (yes/no): ").strip().lower()
        furnishingstatus = input("Enter furnishing status (furnished/semi-furnished/unfu
rnished): ").strip().lower()

        # Creating a dataframe for user input
        user_data = pd.DataFrame({
            'area': [area],
            'bedrooms': [bedrooms],
            'bathrooms': [bathrooms],
            'stories': [stories],
            'mainroad': [mainroad],
            'guestroom': [guestroom],
            'basement': [basement],
            'hotwaterheating': [hotwaterheating],
            'airconditioning': [airconditioning],
            'parking': [parking],
            'prefarea': [prefarea],
            'furnishingstatus': [furnishingstatus]
        })

        # Predicting house price
        predicted_price = model_pipeline.predict(user_data)[0]
        print(f"\nThe predicted house price is: ${predicted_price:,.2f}")
    except Exception as e:
        print(f"Error in input or prediction: {e}")


# Train the best model (Gradient Boosting)
final_model = models["Gradient Boosting"]
final_model.fit(X_train, y_train)

# Allow user input for prediction
predict_house_price(final_model)
```

```
Enter the house details for prediction:
Enter area in square feet: 1500
Enter number of bedrooms: 5
Enter number of bathrooms: 3
Enter number of stories: 3
Is the house on a main road? (yes/no): yes
Does the house have a guest room? (yes/no): yes
Does the house have a basement? (yes/no): no
Does the house have hot water heating? (yes/no): no
Does the house have air conditioning? (yes/no): yes
Enter the number of parking spaces: 3
Is the house in a preferred area? (yes/no): yes
Enter furnishing status (furnished/semi-furnished/unfurnished): furnished

The predicted house price is: $6,763,750.63
```

In [7]: