House Price Prediction using Supervised Learning

Problem Statement:

Predict the price of houses based on features like area, number of rooms, and amenities.

Dataset Description:

The dataset consists of 13 columns including:

- Numerical Features: area, bedrooms, bathrooms, stories, parking
- Categorical/Binary Features: mainroad, guestroom, basement, hotwaterheating, airconditioning, prefarea, furnishingstatus

No missing or duplicated values.

Importing Libraries

```
# Import libraries
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
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
```

Data Loading and Exploration

```
df = pd.read_csv('/content/Housing.csv')
df.head()
#df.isnull().sum()
#df.duplicated().sum()
```

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hot
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	

Data Preprocessing:

- Encode categorical columns using Label Encoding.
- Split dataset into features (X) and target (y).
- Train-Test Split (80-20).

```
# Encode Categorical Variables
categorical_cols = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditionin
le = LabelEncoder()
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])

# Features and Target
X = df.drop('price', axis=1)
y = df['price']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Model Building and Training

```
# Model Training
model = LinearRegression()
model.fit(X_train, y_train)

# Prediction
y_pred = model.predict(X_test)
```

Model Evaluation:

Evaluate model performance using MAE, MSE, RMSE, and R^2 Score.

```
# Evaluation
print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error (RMSE):", np.sqrt(mean_squared_error(y_test, y_pred)))
print("R2 Score:", r2_score(y_test, y_pred))
```

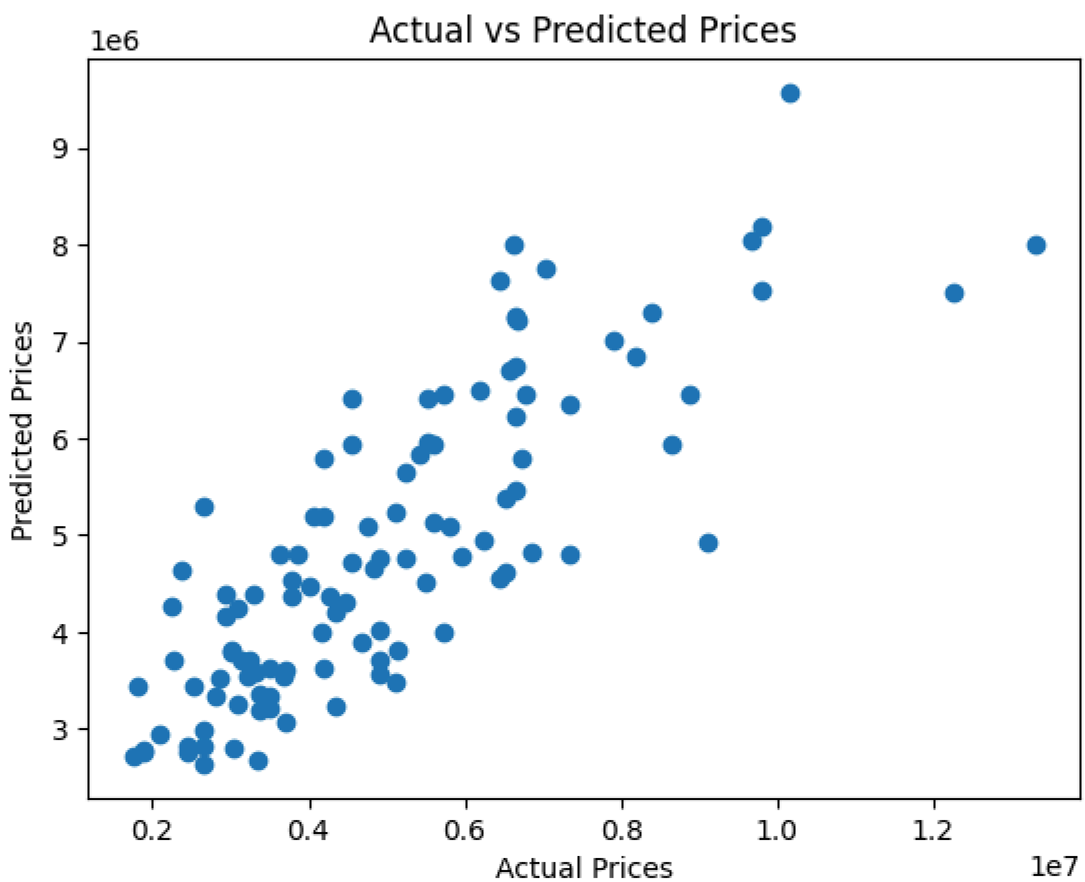
```
Mean Absolute Error (MAE): 979679.6912959901
Mean Squared Error (MSE): 1771751116594.0352
Root Mean Squared Error (RMSE): 1331071.4167895108
R2 Score: 0.6494754192267803
```

Visualizations:

- Scatter plot of Actual vs Predicted Prices
- Residual Distribution Plot

```
# Visualization: Actual vs Predicted Prices
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs Predicted Prices')
plt.show()

# Residual Plot
residuals = y_test - y_pred
sns.histplot(residuals, kde=True)
plt.title('Residuals Distribution')
plt.show()
```



Model Evaluation Summary

Mean Absolute Error (MAE): ₦979,680

→ On average, the model's predictions are off by approximately ₦980K.

Root Mean Squared Error (RMSE): ₦1,331,071

→ Larger deviations (outliers) have a stronger impact. So, predictions can be off by around ₦1.33M in worst cases.

R^2 Score: 0.649

→ About 64.9% of the variance in house prices is explained by the model. This is decent for a simple Linear Regression model, but there's room for improvement with more advanced algorithms or feature engineering.

Conclusion:

The Linear Regression model achieved an R^2 score of 64.9%, indicating it can explain
approximately two-thirds of the variance in house prices based on the selected features. While the