In [30]:
```python
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.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from xgboost import XGBRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error


import warnings
warnings.filterwarnings('ignore')
```

DATA LOADING AND EXPLORATION

In [2]:
```python
data = pd.read_csv("mobile_prices_2023.csv")
```

In [3]:
```python
data.head()
```

Out[3]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Price in INR	Date of Scraping
0	POCO C50 (Royal Blue, 32 GB)	4.2	33,561	2 GB RAM	32 GB ROM	8MP Dual Camera	5MP Front Camera	5000 mAh	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro...	₹5,649	2023-06-17
1	POCO M4 5G (Cool Blue, 64 GB)	4.2	77,128	4 GB RAM	64 GB ROM	50MP + 2MP	8MP Front Camera	5000 mAh	Mediatek Dimensity 700 Processor	₹11,999	2023-06-17
2	POCO C51 (Royal Blue, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6,999	2023-06-17
3	POCO C55 (Cool Blue, 64 GB)	4.2	22,621	4 GB RAM	64 GB ROM	50MP Dual Rear Camera	5MP Front Camera	5000 mAh	Mediatek Helio G85 Processor	₹7,749	2023-06-17
4	POCO C51 (Power Black, 64 GB)	4.3	15,175	4 GB RAM	64 GB ROM	8MP Dual Rear Camera	5MP Front Camera	5000 mAh	Helio G36 Processor	₹6,999	2023-06-17

In [4]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1836 entries, 0 to 1835
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Phone Name         1836 non-null   object
 1   Rating ?/5         1836 non-null   float64
 2   Number of Ratings  1836 non-null   object
```

```
 3   RAM                  1836 non-null   object
 4   ROM/Storage          1662 non-null   object
 5   Back/Rare Camera     1827 non-null   object
 6   Front Camera         1435 non-null   object
 7   Battery              1826 non-null   object
 8   Processor            1781 non-null   object
 9   Price in INR         1836 non-null   object
 10  Date of Scraping     1836 non-null   object
dtypes: float64(1), object(10)
memory usage: 157.9+ KB
```

DATA CLEANING AND PREPARATION

In [5]:
```
data.isnull().sum()
```

Out[5]:
```
Phone Name             0
Rating ?/5             0
Number of Ratings      0
RAM                    0
ROM/Storage          174
Back/Rare Camera       9
Front Camera         401
Battery               10
Processor             55
Price in INR           0
Date of Scraping       0
dtype: int64
```

In [6]:
```
data_cleaned = data.copy()
data_cleaned.dropna(thresh=len(data.columns)*0.7, inplace=True)
```

In [7]:
```
data_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1826 entries, 0 to 1835
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Phone Name           1826 non-null   object
 1   Rating ?/5           1826 non-null   float64
 2   Number of Ratings    1826 non-null   object
 3   RAM                  1826 non-null   object
 4   ROM/Storage          1662 non-null   object
 5   Back/Rare Camera     1826 non-null   object
 6   Front Camera         1435 non-null   object
 7   Battery              1826 non-null   object
 8   Processor            1781 non-null   object
 9   Price in INR         1826 non-null   object
 10  Date of Scraping     1826 non-null   object
dtypes: float64(1), object(10)
memory usage: 171.2+ KB
```

In [8]:
```
data_cleaned.isnull().sum()
```

Out[8]:
```
Phone Name             0
Rating ?/5             0
Number of Ratings      0
RAM                    0
ROM/Storage          164
Back/Rare Camera       0
Front Camera         391
Battery                0
Processor             45
Price in INR           0
```

```
Date of Scraping        0
dtype: int64
```

In [9]:
```
# Removing , and $ from the values
data_cleaned['Number of Ratings'] = data_cleaned['Number of Ratings'].astype(str).str.re
data_cleaned['Price in INR'] = data_cleaned['Price in INR'].astype(str).str.replace('₹',

# Text Parsing - Extract numeric values from 'RAM', 'ROM/Storage', 'Battery'
data_cleaned['RAM'] = data_cleaned['RAM'].str.extract('(\d+)').astype(float)
data_cleaned['ROM/Storage'] = data_cleaned['ROM/Storage'].str.extract('(\d+)').astype(fl
data_cleaned['Battery'] = data_cleaned['Battery'].str.extract('(\d+)').astype(float)
```

Replacing null values with mode

In [10]:
```
mode_value = data_cleaned['ROM/Storage'].mode()[0]
data_cleaned['ROM/Storage'].fillna(mode_value, inplace=True)

mode_value = data_cleaned['Front Camera'].mode()[0]
data_cleaned['Front Camera'].fillna(mode_value, inplace=True)

mode_value = data_cleaned['Processor'].mode()[0]
data_cleaned['Processor'].fillna(mode_value, inplace=True)

mode_value = data_cleaned['RAM'].mode()[0]
data_cleaned['RAM'].fillna(mode_value, inplace=True)

mode_value = data_cleaned['Battery'].mode()[0]
data_cleaned['Battery'].fillna(mode_value, inplace=True)
```

In [11]:
```
# Date format changing
data_cleaned['Date of Scraping'] = pd.to_datetime(data_cleaned['Date of Scraping'])
```

In [12]:
```
data_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1826 entries, 0 to 1835
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Phone Name         1826 non-null   object
 1   Rating ?/5         1826 non-null   float64
 2   Number of Ratings  1826 non-null   float64
 3   RAM                1826 non-null   float64
 4   ROM/Storage        1826 non-null   float64
 5   Back/Rare Camera   1826 non-null   object
 6   Front Camera       1826 non-null   object
 7   Battery            1826 non-null   float64
 8   Processor          1826 non-null   object
 9   Price in INR       1826 non-null   float64
 10  Date of Scraping   1826 non-null   datetime64[ns]
dtypes: datetime64[ns](1), float64(6), object(4)
memory usage: 171.2+ KB
```

In [13]:
```
data_cleaned.head()
```

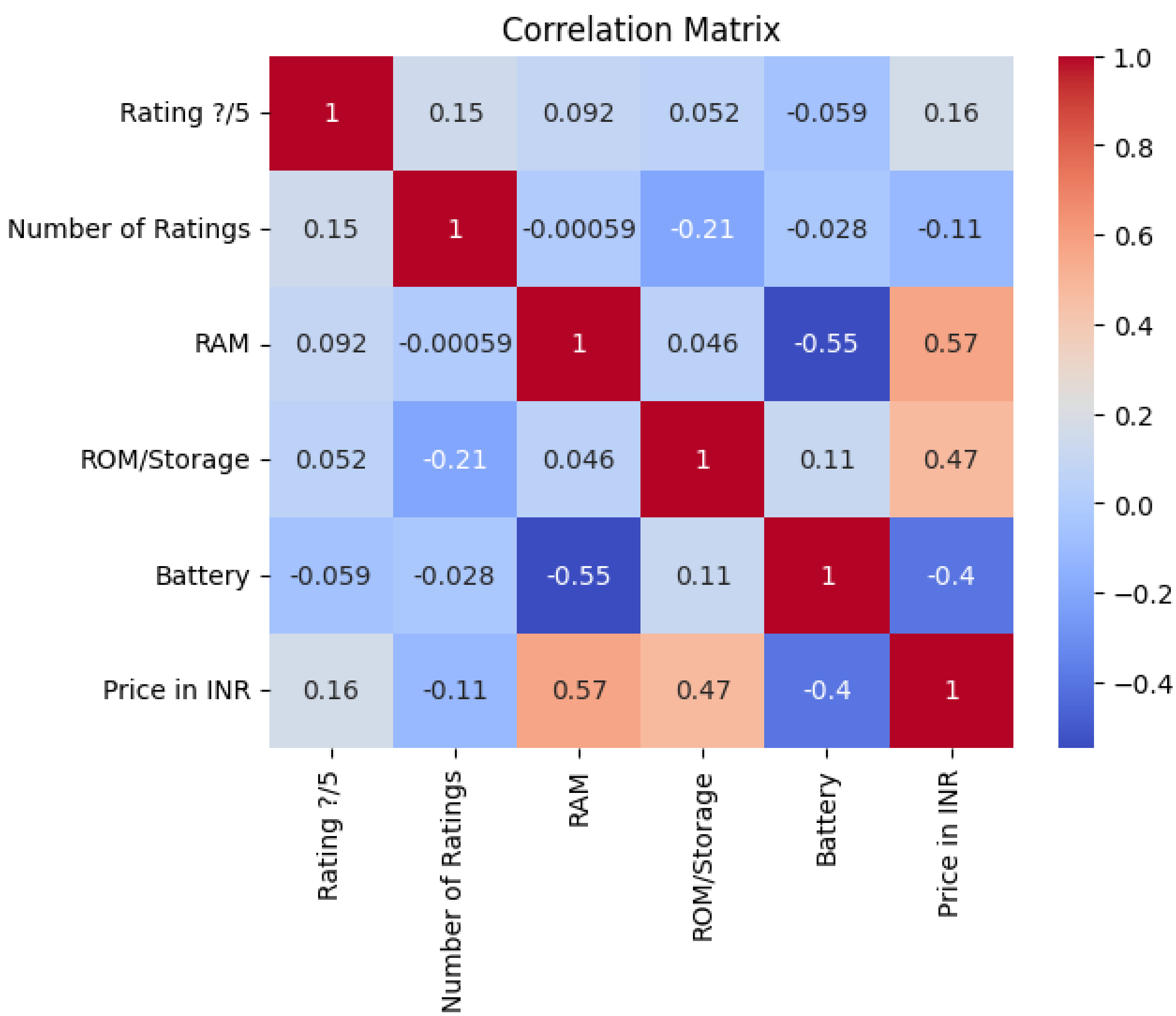
Out[13]:

	Phone Name	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Back/Rare Camera	Front Camera	Battery	Processor	Price in INR	Date of Scraping
0	POCO C50 (Royal Blue, 32 GB)	4.2	33561.0	2.0	32.0	8MP Dual Camera	5MP Front Camera	5000.0	Mediatek Helio A22 Processor, Upto 2.0 GHz Pro...	5649.0	2023-06-17
1	POCO	4.2	77128.0	4.0	64.0	50MP +	8MP	5000.0	Mediatek	11999.0	2023-06-

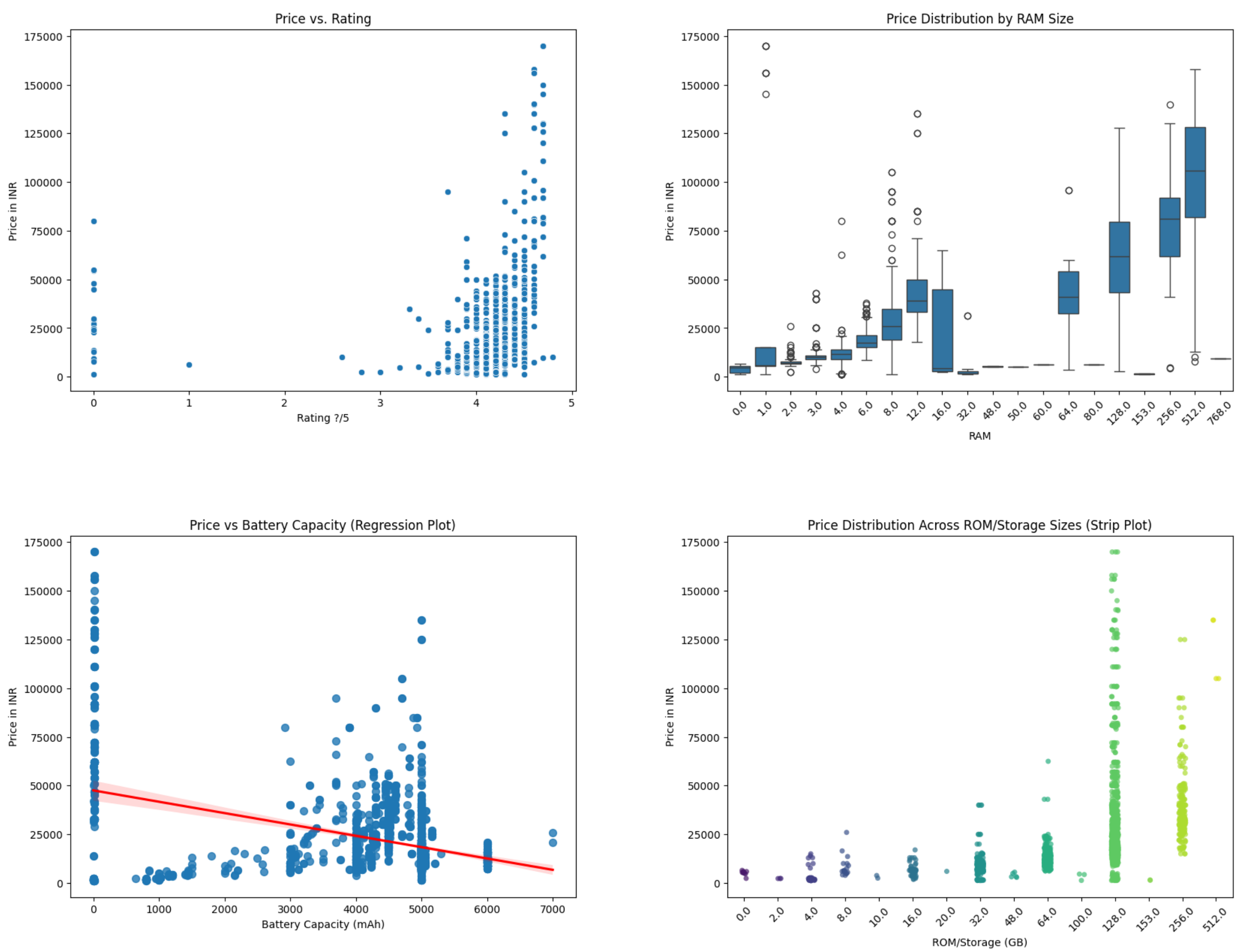
	M4 5G (Cool Blue, 64 GB)					2MP	Front Camera		Dimensity 700 Processor		17
2	POCO C51 (Royal Blue, 64 GB)	4.3	15175.0	4.0	64.0	8MP Dual Rear Camera	5MP Front Camera	5000.0	Helio G36 Processor	6999.0	2023-06-17
3	POCO C55 (Cool Blue, 64 GB)	4.2	22621.0	4.0	64.0	50MP Dual Rear Camera	5MP Front Camera	5000.0	Mediatek Helio G85 Processor	7749.0	2023-06-17
4	POCO C51 (Power Black, 64 GB)	4.3	15175.0	4.0	64.0	8MP Dual Rear Camera	5MP Front Camera	5000.0	Helio G36 Processor	6999.0	2023-06-17

EXPLORATORY DATA ANALYSIS

In [14]:
```
# a. Heatmap: Correlation Matrix
numeric_cols = data_cleaned.select_dtypes(include=[float, int]).columns
correlation_matrix = data_cleaned[numeric_cols].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



In [15]:
```python
fig, axs = plt.subplots(2, 2, figsize=(20, 15))

# Adjust the spacing between the plots
plt.subplots_adjust(hspace=0.4, wspace=0.3)

# Scatter Plot: Price vs. Rating
sns.scatterplot(x='Rating ?/5', y='Price in INR', data=data_cleaned, ax=axs[0, 0])
axs[0, 0].set_title('Price vs. Rating')

# Box Plot: Price distribution across different RAM sizes
sns.boxplot(x='RAM', y='Price in INR', data=data_cleaned, order=sorted(data_cleaned['RAM
axs[0, 1].set_title('Price Distribution by RAM Size')
axs[0, 1].tick_params(axis='x', rotation=45)

# Regression Plot: Price distribution vs Battery capacity
sns.regplot(x='Battery', y='Price in INR', data=data_cleaned, scatter_kws={'s':50}, line
axs[1, 0].set_title('Price vs Battery Capacity (Regression Plot)')
axs[1, 0].set_xlabel('Battery Capacity (mAh)')
axs[1, 0].set_ylabel('Price in INR')

# Strip Plot: Price distribution vs ROM size
sns.stripplot(x='ROM/Storage', y='Price in INR', data=data_cleaned, jitter=True, palette
axs[1, 1].set_title('Price Distribution Across ROM/Storage Sizes (Strip Plot)')
axs[1, 1].set_xlabel('ROM/Storage (GB)')
axs[1, 1].set_ylabel('Price in INR')
axs[1, 1].tick_params(axis='x', rotation=45)

# Show the main figure
plt.show()
```



In [16]:
```python
# Function to detect and remove outliers using IQR method
```

```python
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    # Return DataFrame without outliers
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

# Iterate over each numeric column to remove outliers
numeric_cols = data_cleaned.select_dtypes(include=['float64', 'int64']).columns

for col in numeric_cols:
    df = remove_outliers(data_cleaned, col)
```

DATA ANALYSIS

In [17]:
```python
data_cleaned.describe()
```

Out[17]:

	Rating ?/5	Number of Ratings	RAM	ROM/Storage	Battery	Price in INR	Date of Scraping
count	1826.000000	1.826000e+03	1826.000000	1826.000000	1826.000000	1826.000000	1826
mean	4.219058	4.693457e+04	25.012048	107.489595	4072.690581	23832.502738	2023-06-17 00:00:00
min	0.000000	0.000000e+00	0.000000	0.000000	0.000000	1199.000000	2023-06-17 00:00:00
25%	4.200000	1.353000e+03	4.000000	64.000000	4000.000000	10115.000000	2023-06-17 00:00:00
50%	4.300000	8.579000e+03	6.000000	128.000000	5000.000000	15999.000000	2023-06-17 00:00:00
75%	4.400000	4.149500e+04	8.000000	128.000000	5000.000000	27997.250000	2023-06-17 00:00:00
max	4.800000	1.342530e+06	768.000000	512.000000	7000.000000	169999.000000	2023-06-17 00:00:00
std	0.516233	9.777745e+04	79.184334	68.274877	1683.124981	24399.981785	NaN

In [18]:
```python
features = ['RAM', 'Battery', 'Rating ?/5','ROM/Storage']
target = 'Price in INR'
```

In [19]:
```python
X = data_cleaned[features] # Adjust features as needed
y = data_cleaned[target]
```

In [20]:
```python
#Encoding categorical columns into numerical using one hot encoding
X = pd.get_dummies(X)
```

In [21]:
```python
#splitting the dataset into 80% for training and 20% for testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

In [22]:
```python
#Satndardizing the features using standard scaler method
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [23]:
```python
#using regressor models as values are continous not discrete
models = {
    "DecisionTreeRegressor": DecisionTreeRegressor(),
    "RandomForest": RandomForestRegressor(),
```

```python
    "LinearRegression": LinearRegression(),
    "XGBoost": XGBRegressor()
}
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    predictions = model.predict(X_test)
    # Evaluate the model
    results[name] = {
        "R² Score": r2_score(y_test, predictions),
        "MAE": mean_absolute_error(y_test, predictions),
        "MSE": mean_squared_error(y_test, predictions)
    }
    if name == "LinearRegression":
        coefficients = pd.DataFrame(model.coef_, features, columns=['Coefficient'])
        intercept = model.intercept_
        predicted_prices = model.predict(X)

        print(f"{name} Model Coefficients:")
        print(coefficients)
        print(f"Intercept: {intercept}")
        print(f"Predicted Prices: {predicted_prices[:5]}")  # Display first 5 predicted
```

```
LinearRegression Model Coefficients:
              Coefficient
RAM           9891.210084
Battery      -5600.783410
Rating ?/5    2323.418242
ROM/Storage  11965.616793
Intercept: 23873.919863013696
Predicted Prices: [-27567602.61473175 -27164920.45718995 -27164688.11536575
 -27164920.45718995 -27164688.11536575]
```

In [24]:

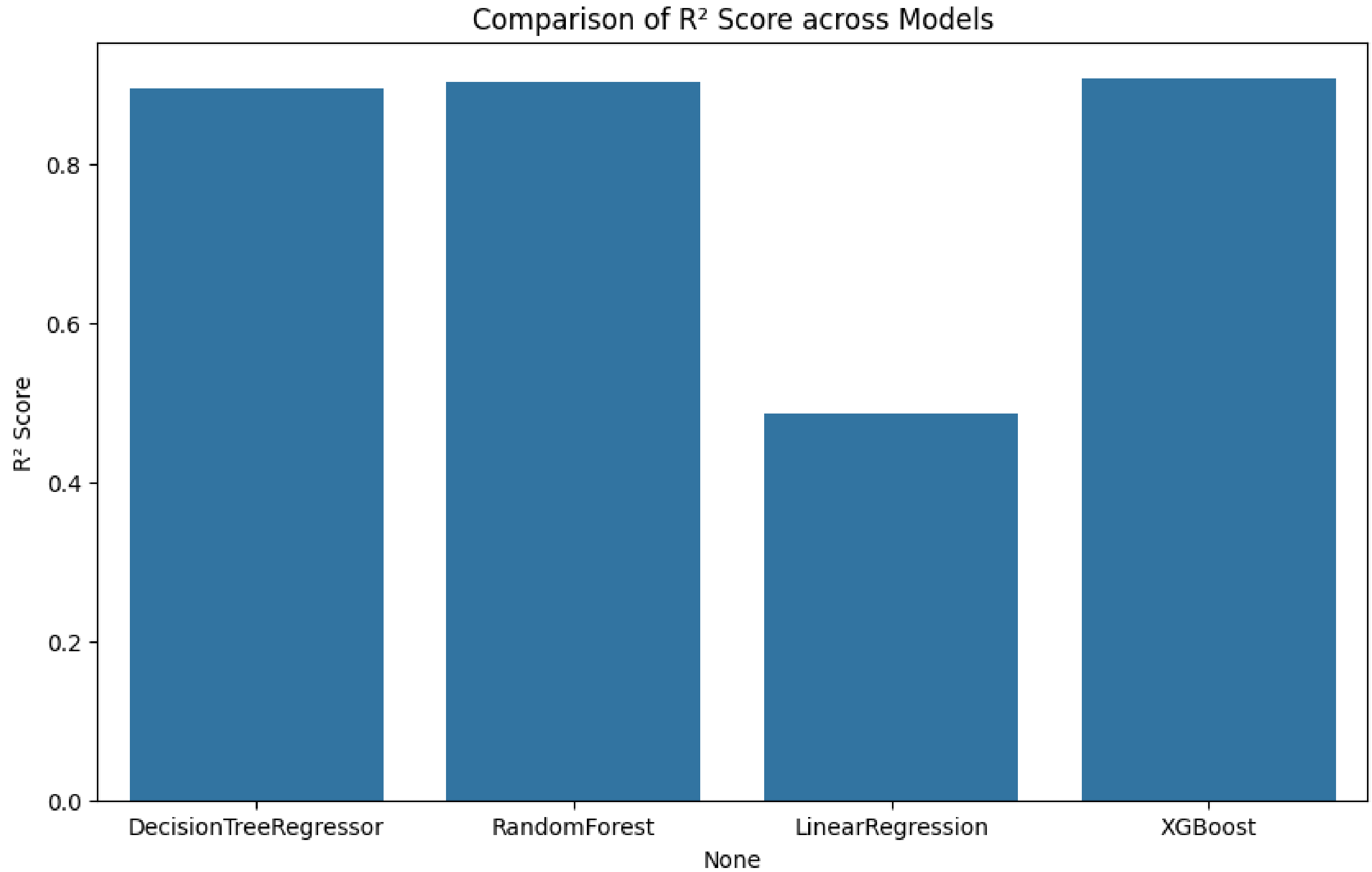
```python
# Display results
results_df = pd.DataFrame(results).T
print(results_df)
```

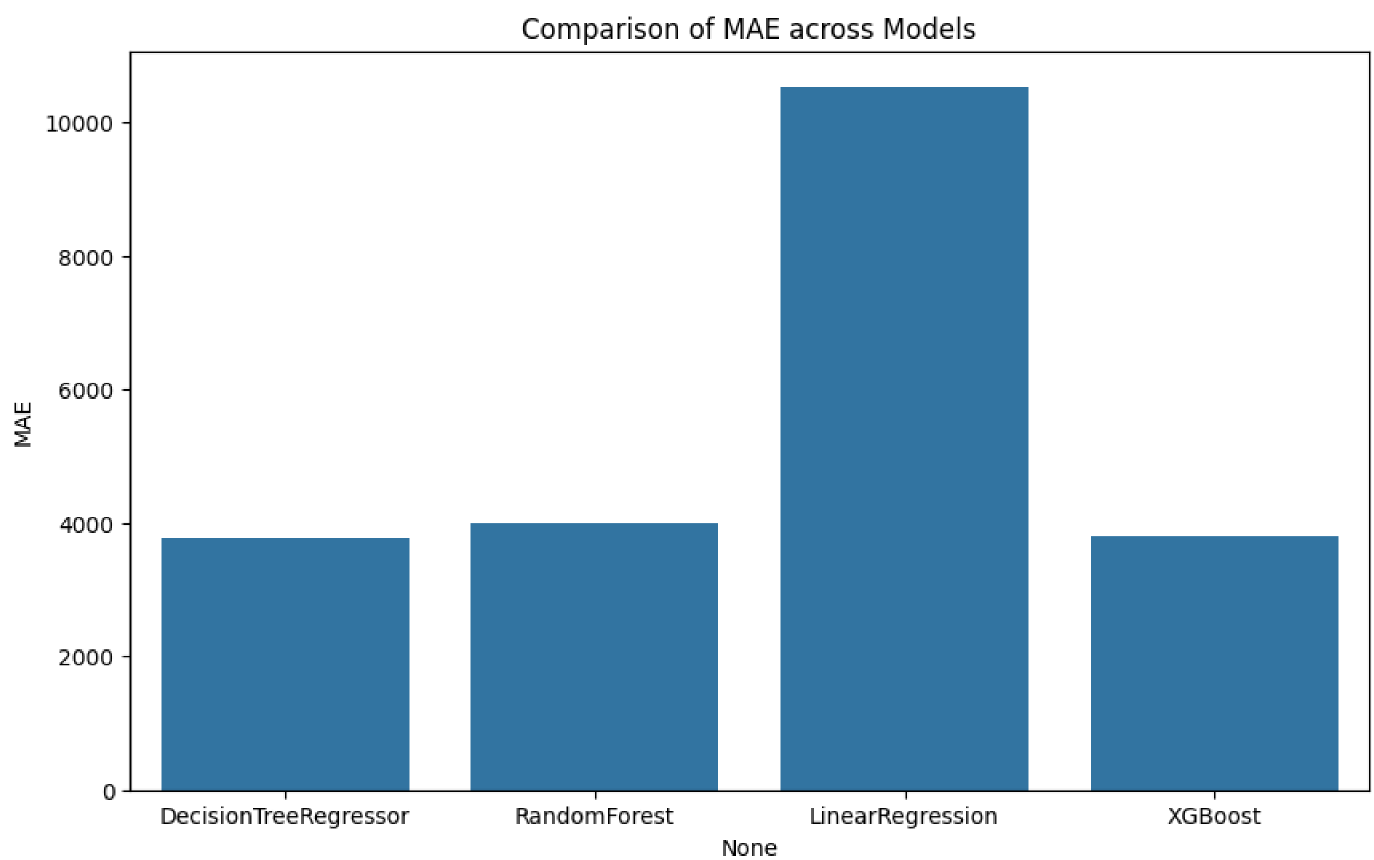
```
                       R² Score           MAE           MSE
DecisionTreeRegressor  0.893506   3787.609799  6.543456e+07
RandomForest           0.901237   4000.163397  6.068475e+07
LinearRegression       0.486400  10539.385427  3.155795e+08
XGBoost                0.906809   3801.054650  5.726077e+07
```

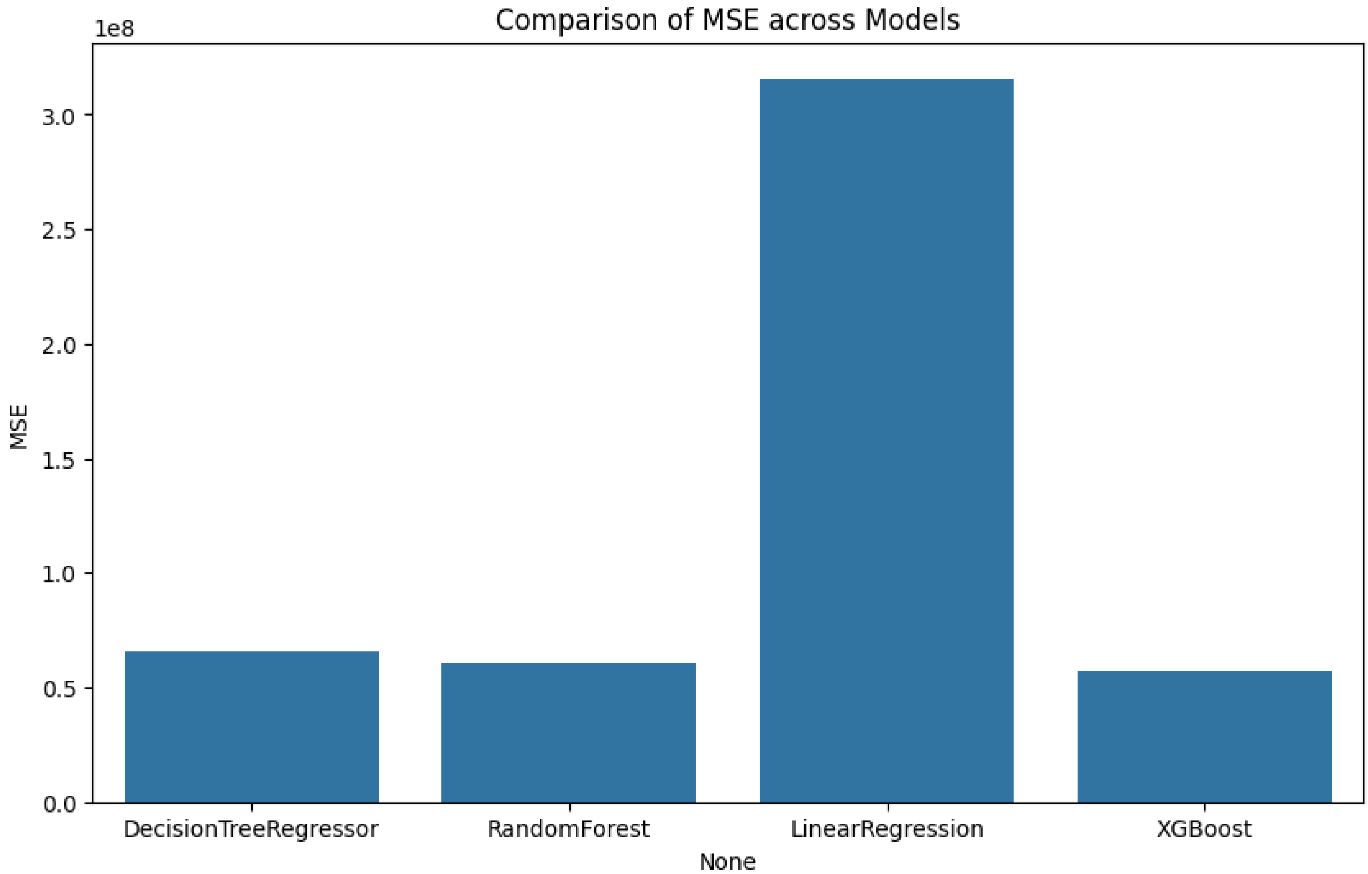
VISUALIZATION OF RESULT

In [25]:

```python
# Visualize model performance
metrics = ["R² Score", "MAE", "MSE"]
for metric in metrics:
    plt.figure(figsize=(10, 6))
    sns.barplot(x=results_df.index, y=results_df[metric])
    plt.title(f'Comparison of {metric} across Models')
    plt.ylabel(metric)
    plt.show()
```


Comparison of R² Score across Models
R² Score
0.0
0.2
0.4
0.6
0.8
DecisionTreeRegressor
RandomForest
LinearRegression
XGBoost
None


Comparison of MAE across Models
MAE
0
2000
4000
6000
8000
10000
DecisionTreeRegressor
RandomForest
LinearRegression
XGBoost
None



RECOMMENDATION

R2 value - Ranges from -1 to +1

```
1. +1 Best Fit<br>
2. 0 No Fit<br>
3. -1 Worst Fit <br>
```

MAE value - Mean Absolute Error

Lower MAE - Model's prediction are closer to actual values.

Higher MAE - Model's prediction deviate more from the actual values.

MSE value - Mean Squared Error

Lower MSE - Model's prediction are closer to actual values.

Higher MSE - Model's prediction deviate more from the actual values.

In [28]:

```
# Based on the results, recommend the best-performing model.
best_model1 = results_df['R² Score'].idxmax()
print(f"The best performing model is {best_model1} with an R² Score of {results_df.loc[b

best_model2 = results_df['MAE'].idxmin()
print(f"The best performing model is {best_model2} with MAE Score of {results_df.loc[bes

best_model3 = results_df['MSE'].idxmin()
print(f"The best performing model is {best_model3} with MSE Score of {results_df.loc[bes
```

```
The best performing model is XGBoost with an R² Score of 0.91.
The best performing model is DecisionTreeRegressor with MAE Score of 3787.61.
The best performing model is XGBoost with MSE Score of 57260765.20.
```