In [1]:
```python
#import the libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.linear_model import LinearRegression,Lasso
from sklearn.metrics import mean_squared_error,mean_absolute_error
from sklearn.ensemble import RandomForestRegressor
```

In [2]:
```python
data = pd.read_csv('/Users/macbookproci9/Documents/HousePricePredection/HousePrices
```

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

Out[3]:

	POSTED_BY	UNDER_CONSTRUCTION	RERA	BHK_NO.	BHK_OR_RK	SQUARE_FT	READY_
0	Owner	0	0	2	BHK	1300.236407	
1	Dealer	0	0	2	BHK	1275.000000	
2	Owner	0	0	2	BHK	933.159722	
3	Owner	0	1	2	BHK	929.921143	
4	Dealer	1	0	2	BHK	999.009247	

In [4]:
```python
# Summary statistics
data.describe()
```

Out[4]:

	UNDER_CONSTRUCTION	RERA	BHK_NO.	SQUARE_FT	READY_TO_MOVE
count	29451.000000	29451.000000	29451.000000	2.945100e+04	29451.00000C
mean	0.179756	0.317918	2.392279	1.980217e+04	0.820244
std	0.383991	0.465675	0.879091	1.901335e+06	0.38399
min	0.000000	0.000000	1.000000	3.000000e+00	0.00000C
25%	0.000000	0.000000	2.000000	9.000211e+02	1.00000C
50%	0.000000	0.000000	2.000000	1.175057e+03	1.00000C
75%	0.000000	1.000000	3.000000	1.550688e+03	1.00000C
max	1.000000	1.000000	20.000000	2.545455e+08	1.00000C

In [5]:
```python
# Checking for missing values
data.isnull().sum()
```

Out[5]:
```
POSTED_BY                  0
UNDER_CONSTRUCTION         0
RERA                       0
BHK_NO.                    0
BHK_OR_RK                  0
SQUARE_FT                  0
READY_TO_MOVE              0
RESALE                     0
ADDRESS                    0
LONGITUDE                  0
LATITUDE                   0
TARGET(PRICE_IN_LACS)      0
dtype: int64
```

In [33]:

```
# Data Pre-processing
data['POSTED_BY'] = data['POSTED_BY'].astype('category')
data['BHK_OR_RK'] = data['BHK_OR_RK'].astype('category')
data['ADDRESS'] = data['ADDRESS'].astype('category')
```

In [39]:

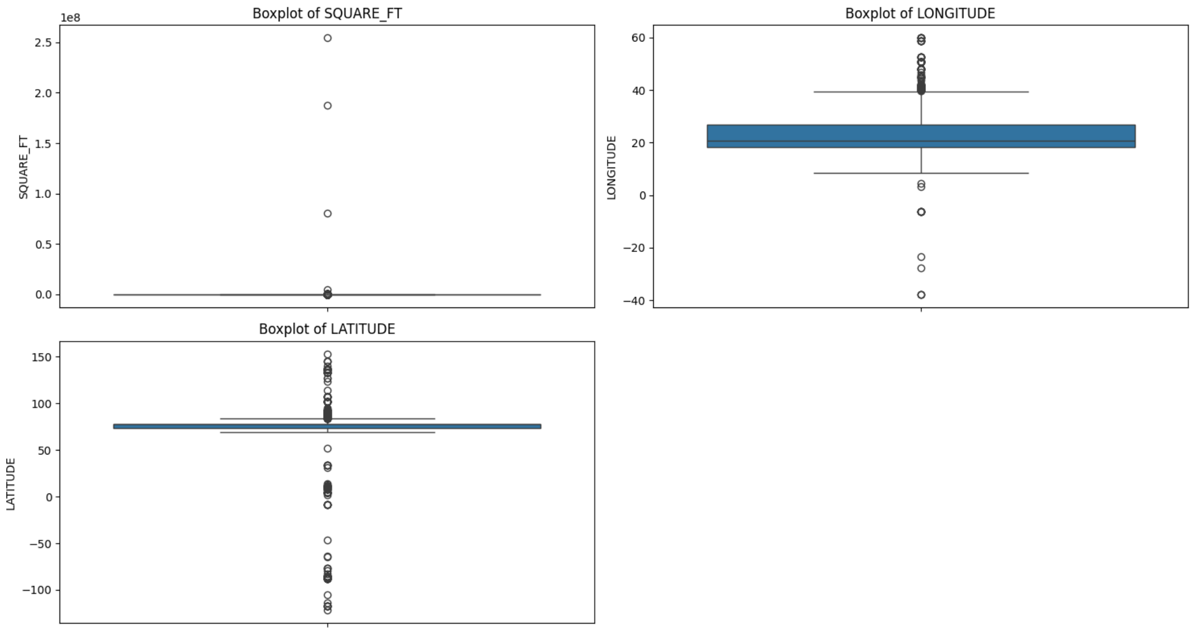
```
# Select key features to simplify the dataset
selected_features = [
    'UNDER_CONSTRUCTION', 'RERA', 'BHK_NO.', 'SQUARE_FT', 'READY_TO_MOVE',
    'RESALE', 'LONGITUDE', 'LATITUDE', 'TARGET(PRICE_IN_LACS)',
    'POSTED_BY', 'BHK_OR_RK'
]

# Create a subset of the data with selected features
data_subset = data[selected_features].copy()
```

In [40]:

```
# Separate numerical and categorical features
numerical_features = ['SQUARE_FT', 'LONGITUDE', 'LATITUDE']
categorical_features = ['POSTED_BY', 'BHK_OR_RK']
```

In [56]:

```
# Identify and visualize outliers
plt.figure(figsize=(15, 8))
for i, feature in enumerate(numerical_features, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(data[feature])
    plt.title(f'Boxplot of {feature}')
plt.tight_layout()
plt.show()
```



In [57]:

```
# Handling outliers using IQR method
def handle_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
    df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]
    return df

for feature in numerical_features:
    data_subset = handle_outliers(data_subset, feature)
```

In [58]:

```
# Scaling numerical features
scaler = StandardScaler()
```

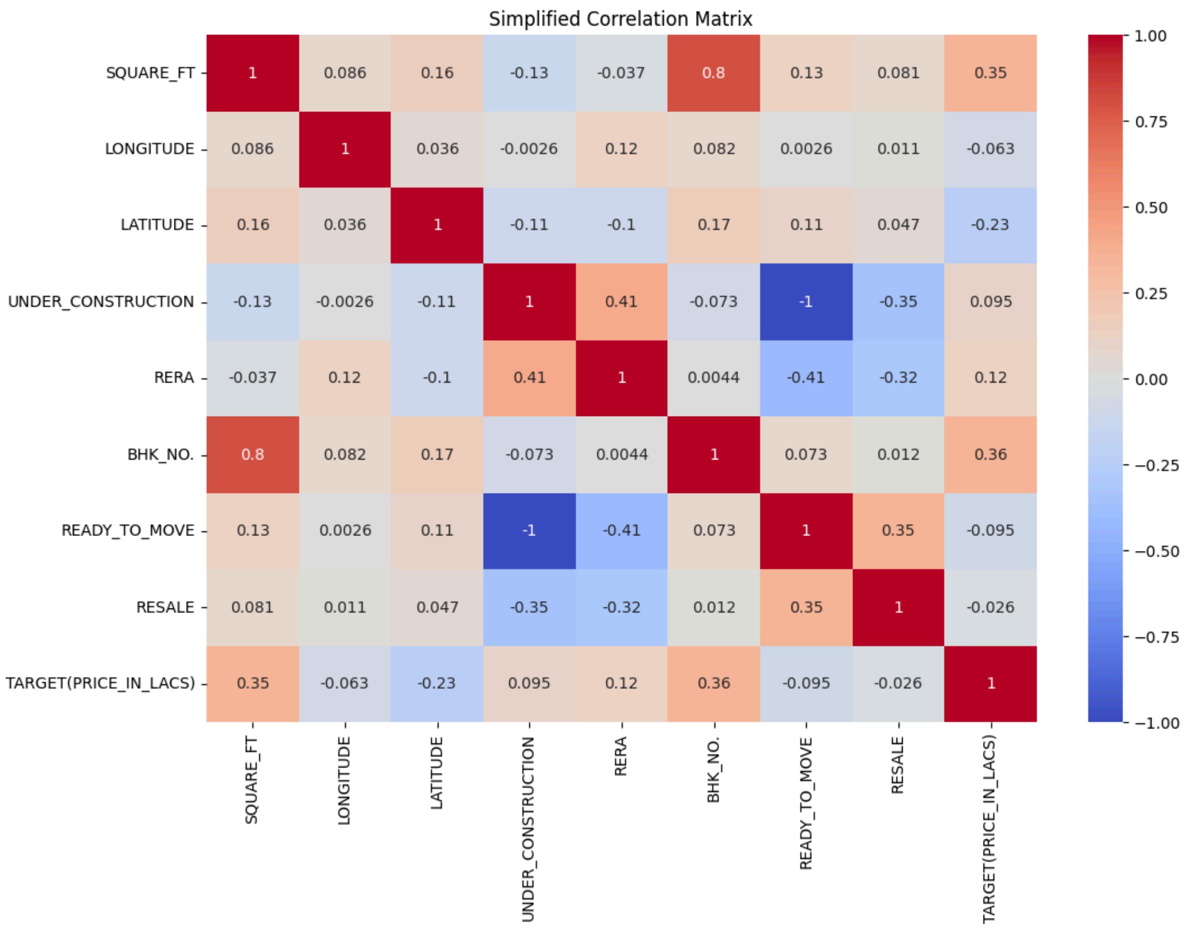
```
data_subset[numerical_features] = scaler.fit_transform(data_subset[numerical_featur
```

In [59]:
```
# Encoding categorical features
data_subset = pd.get_dummies(data_subset, drop_first=True)
```

In [60]:
```
# Split the data into features and target
X = data_subset.drop('TARGET(PRICE_IN_LACS)', axis=1)
y = data_subset['TARGET(PRICE_IN_LACS)']
```

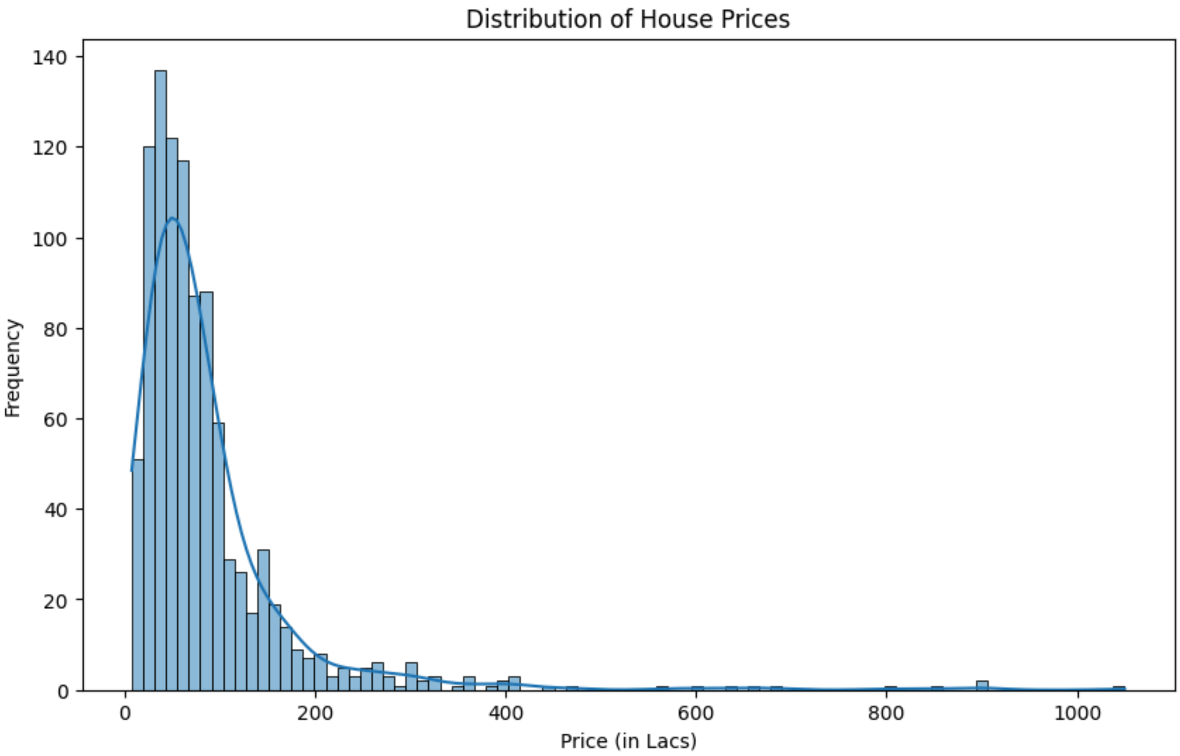
In [61]:
```
# Sample a smaller subset of the data for all visualizations
data_sample = data_subset.sample(n=1000, random_state=42)
```

In [62]:
```
# Visualization: Simplified Correlation Matrix (only for numerical features)
plt.figure(figsize=(12, 8))
simplified_correlation_matrix = data_sample[numerical_features + ['UNDER_CONSTRUCTI
sns.heatmap(simplified_correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Simplified Correlation Matrix')
plt.show()
```

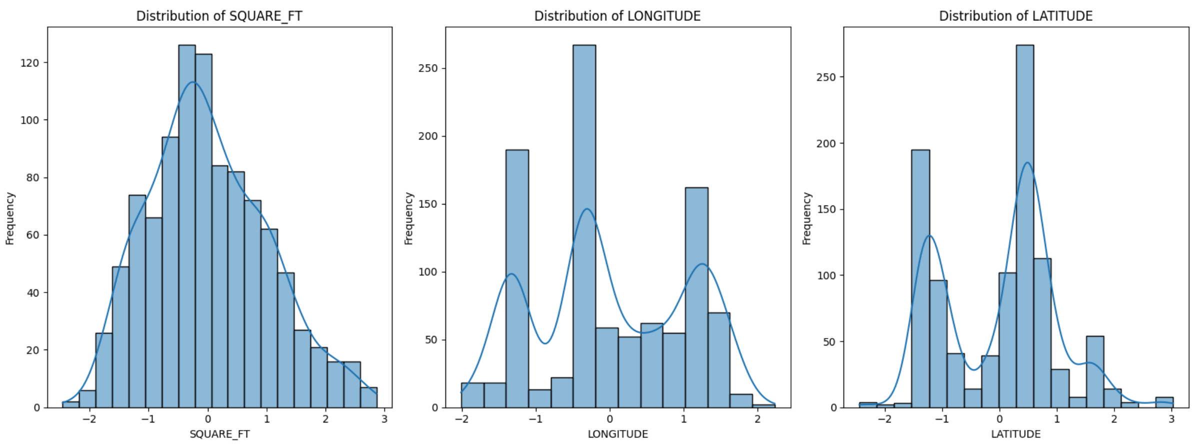


	SQUARE_FT	LONGITUDE	LATITUDE	UNDER_CONSTRUCTION	RERA	BHK_NO.	READY_TO_MOVE	RESALE	TARGET(PRICE_IN_LACS)
SQUARE_FT	1	0.086	0.16	-0.13	-0.037	0.8	0.13	0.081	0.35
LONGITUDE	0.086	1	0.036	-0.0026	0.12	0.082	0.0026	0.011	-0.063
LATITUDE	0.16	0.036	1	-0.11	-0.1	0.17	0.11	0.047	-0.23
UNDER_CONSTRUCTION	-0.13	-0.0026	-0.11	1	0.41	-0.073	-1	-0.35	0.095
RERA	-0.037	0.12	-0.1	0.41	1	0.0044	-0.41	-0.32	0.12
BHK_NO.	0.8	0.082	0.17	-0.073	0.0044	1	0.073	0.012	0.36
READY_TO_MOVE	0.13	0.0026	0.11	-1	-0.41	0.073	1	0.35	-0.095
RESALE	0.081	0.011	0.047	-0.35	-0.32	0.012	0.35	1	-0.026
TARGET(PRICE_IN_LACS)	0.35	-0.063	-0.23	0.095	0.12	0.36	-0.095	-0.026	1

In [63]:
```
# Visualization: Distribution of the Target Variable (House Prices)
plt.figure(figsize=(10, 6))
sns.histplot(data_sample['TARGET(PRICE_IN_LACS)'], kde=True)
plt.title('Distribution of House Prices')
plt.xlabel('Price (in Lacs)')
plt.ylabel('Frequency')
plt.show()
```




```
In [64]: # Visualization: Distribution of Numerical Features
plt.figure(figsize=(16, 6))

for i, feature in enumerate(numerical_features):
    plt.subplot(1, 3, i + 1)
    sns.histplot(data_sample[feature], kde=True)
    plt.title(f'Distribution of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Frequency')

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




```
In [66]: from sklearn.model_selection import train_test_split
# Split the data into features and target
X = data_subset.drop('TARGET(PRICE_IN_LACS)', axis=1)
y = data_subset['TARGET(PRICE_IN_LACS)']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

```
In [67]: # Train the regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[67]:

```
▾ LinearRegression
LinearRegression()
```

In [68]:

```
# Predict on the test set
y_pred = model.predict(X_test)
```

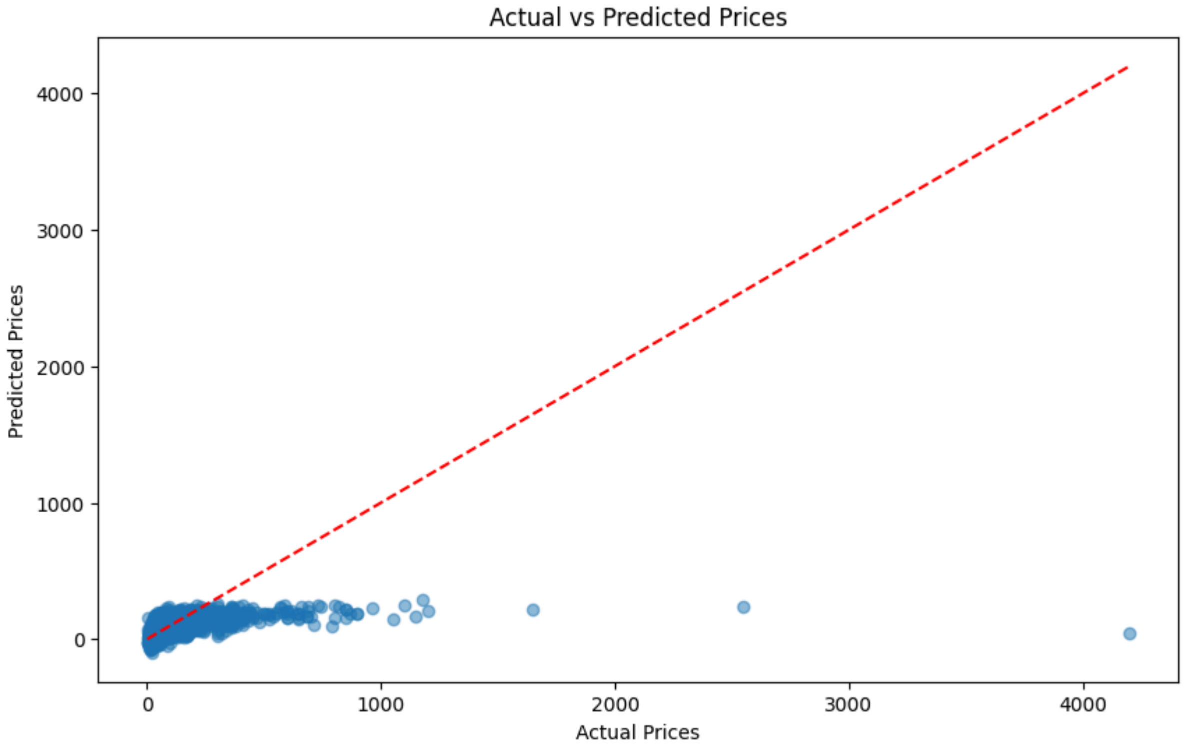
In [69]:

```
# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print evaluation metrics
print(f'Mean Absolute Error (MAE): {mae}')
print(f'Mean Squared Error (MSE): {mse}')
print(f'R-squared (R2): {r2}')
```

```
Mean Absolute Error (MAE): 48.463038458939955
Mean Squared Error (MSE): 11176.970511370722
R-squared (R2): 0.19055951714940644
```

In [70]:

```
# Plotting Actual vs Predicted values
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', color='red')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs Predicted Prices')
plt.show()
```



In [78]:

```
#using Lasso regression to regularize the model and see if it improves performance.
from sklearn.linear_model import Lasso

# Train the Lasso regression model with polynomial features
model_lasso = Lasso(alpha=1.0, max_iter=10000)
model_lasso.fit(X_train, y_train)

# Predict on the test set
y_pred_lasso = model_lasso.predict(X_test)
```

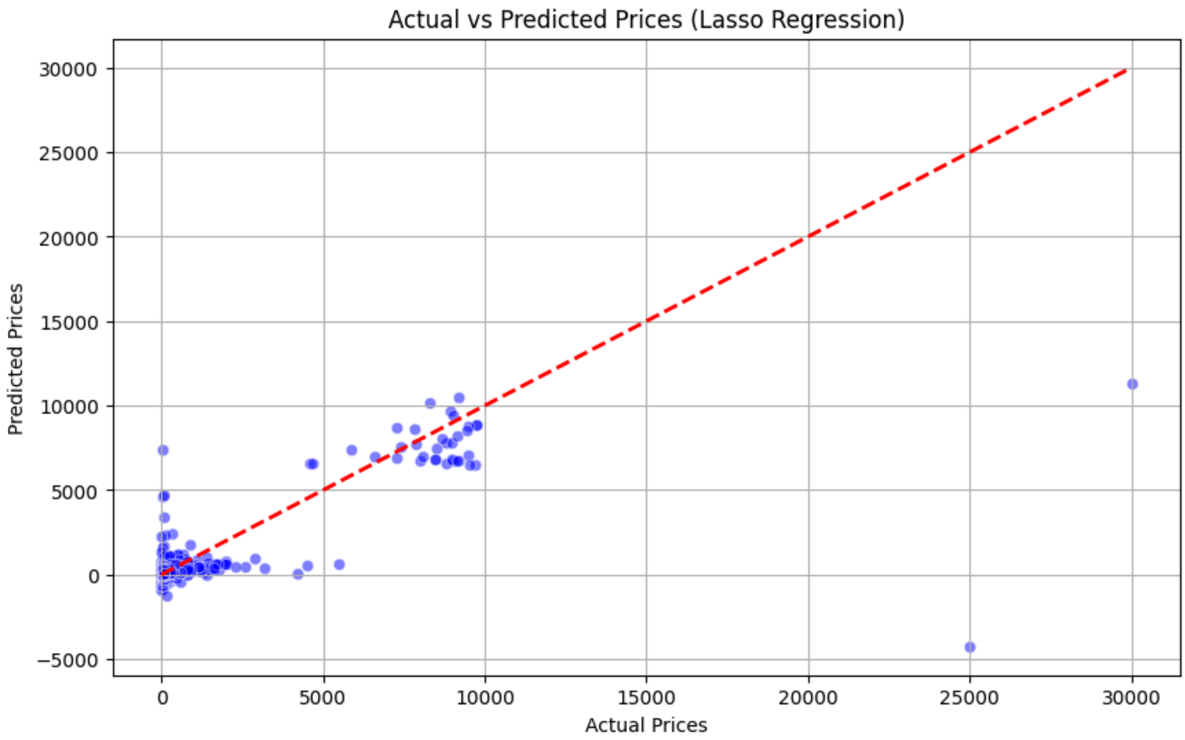
```
# Calculate evaluation metrics for the Lasso model
mse_lasso = mean_squared_error(y_test, y_pred_lasso)
mae_lasso = mean_absolute_error(y_test, y_pred_lasso)
r2_lasso = r2_score(y_test, y_pred_lasso)

# Print evaluation metrics
print(f'Mean Absolute Error (MAE) for lasso Model: {mae_lasso}')
print(f'Mean Squared Error (MSE) for lasso Model: {mse_lasso}')
print(f'R-squared (R2) for lasso Model: {r2_lasso}' )
```

```
Mean Absolute Error (MAE) for lasso Model: 91.01474734478398
Mean Squared Error (MSE) for lasso Model: 189036.35394077082
R-squared (R2) for lasso Model: 0.595976729163743
```

```
/usr/local/Cellar/jupyterlab/4.1.6_1/libexec/lib/python3.12/site-packages/sklearn/l
inear_model/_coordinate_descent.py:678: ConvergenceWarning: Objective did not conve
rge. You might want to increase the number of iterations, check the scale of the fe
atures or consider increasing regularisation. Duality gap: 6.839e+08, tolerance: 8.
573e+05
  model = cd_fast.enet_coordinate_descent(
```

In [79]:

```
# Plotting Actual vs Predicted values for Lasso Regression
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_lasso, alpha=0.5, color='blue', edgecolors='w', linewidt
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', color='red',
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs Predicted Prices (Lasso Regression)')
plt.grid(True)
plt.show()
```



In [80]:

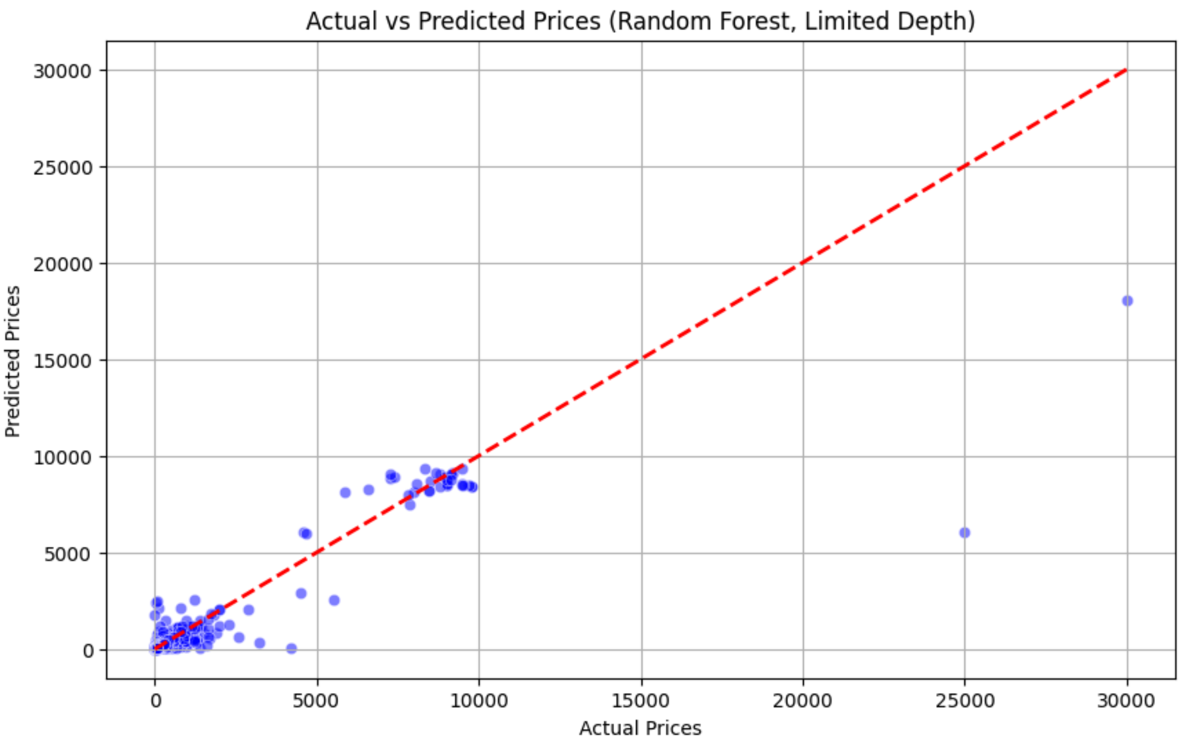
```
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor

# Train the Random Forest model with polynomial features
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Predict on the test set
y_pred_rf = rf_model.predict(X_test)

# Calculate evaluation metrics for the Random Forest model
```

```
mse_rf = mean_squared_error(y_test, y_pred_rf)
mae_rf = mean_absolute_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

# Print evaluation metrics
print(f'Mean Absolute Error (MAE) for Random Forest model: {mae_rf}')
print(f'Mean Squared Error (MSE) for Random Forest model: {mse_rf}')
print(f'R-squared (R2) for Random Forest model: {r2_rf}' )
```

```
Mean Absolute Error (MAE) for Random Forest model: 35.43424714765673
Mean Squared Error (MSE) for Random Forest model: 72563.81163230346
R-squared (R2) for Random Forest model: 0.8449109501486942
```

In [83]:

```
# Plotting Actual vs Predicted values for Random Forest
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_rf, alpha=0.5, color='blue', edgecolors='w', linewidths=
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', color='red',
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs Predicted Prices (Random Forest, Limited Depth)')
plt.grid(True)
plt.show()
```

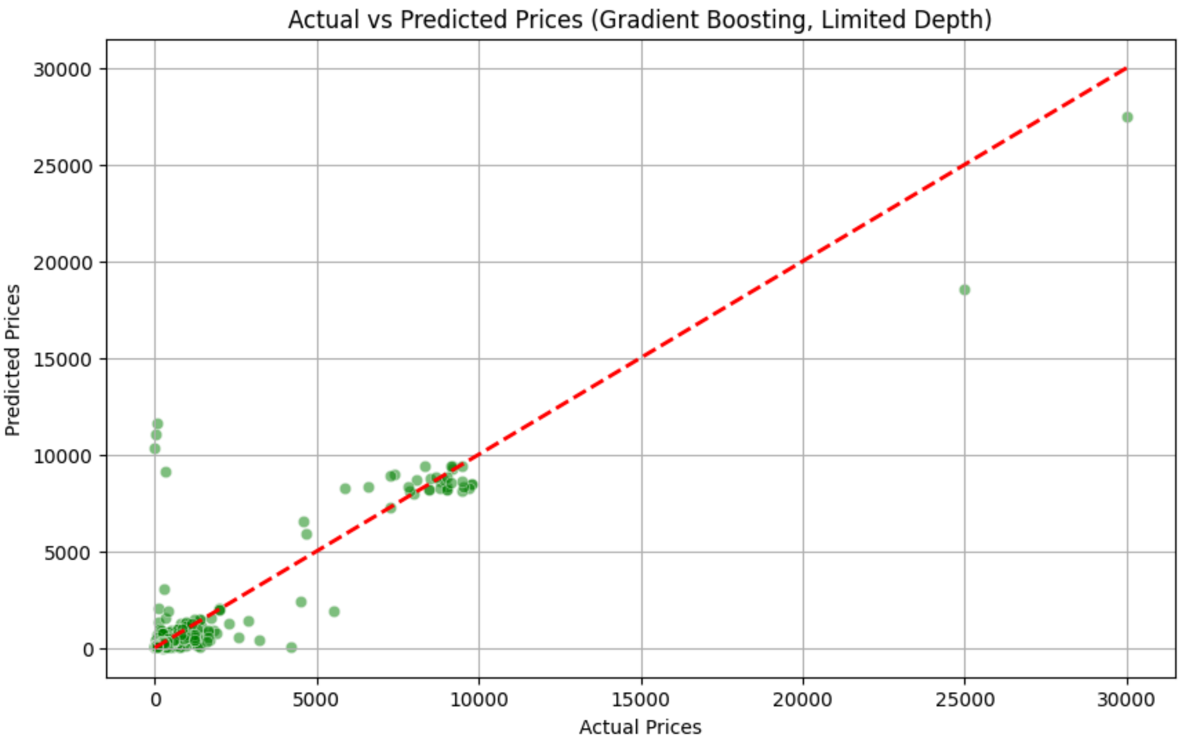


In [84]:

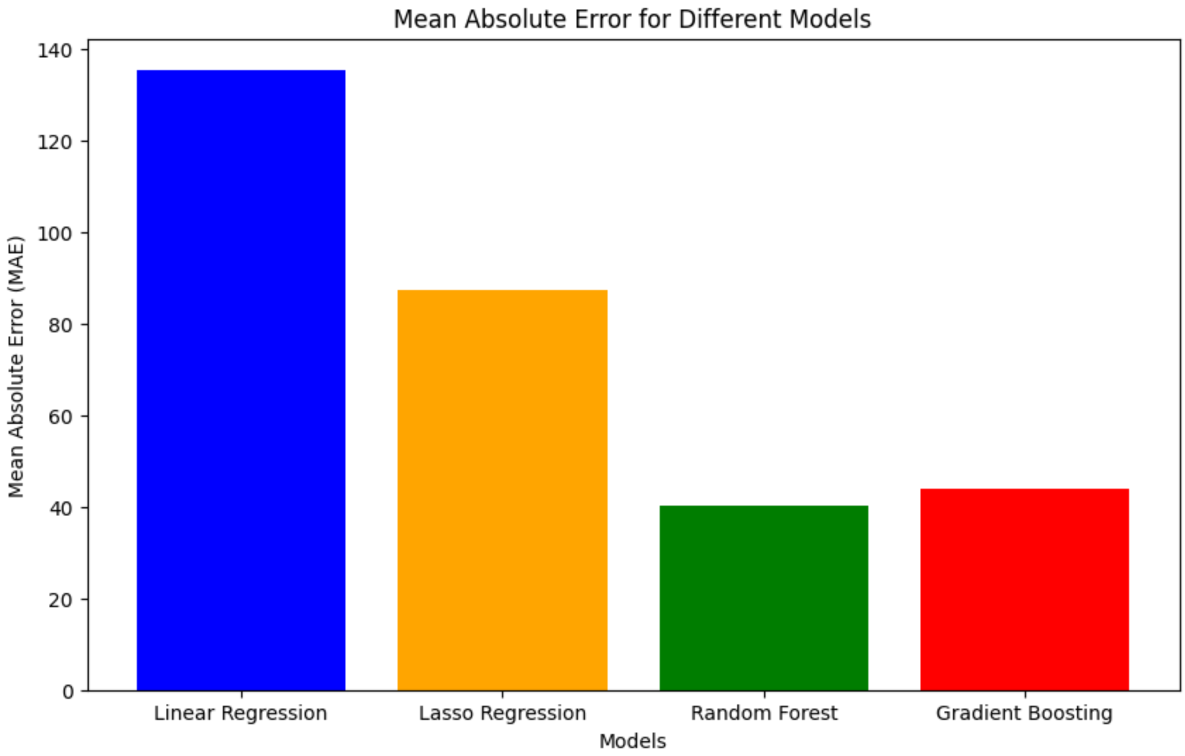
```
# Train the Gradient Boosting model with polynomial features
gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
gb_model.fit(X_train, y_train)

# Predict on the test set
y_pred_gb = gb_model.predict(X_test)

# Calculate evaluation metrics for the Gradient Boosting model
mse_gb = mean_squared_error(y_test, y_pred_gb)
mae_gb = mean_absolute_error(y_test, y_pred_gb)
r2_gb = r2_score(y_test, y_pred_gb)

# Print evaluation metrics
print(f'Mean Absolute Error (MAE) for Gradient Boosting model: {mae_gb}')
print(f'Mean Squared Error (MSE) for Gradient Boosting model: {mse_gb}')
print(f'R-squared (R2) for Gradient Boosting model: {r2_gb}' )
```

```
Mean Absolute Error (MAE) for Gradient Boosting model: 47.38070590991943
Mean Squared Error (MSE) for Gradient Boosting model: 72822.02737331315
R-squared (R2) for Gradient Boosting model: 0.8443590712847122
```

In [86]:
```
# Plotting Actual vs Predicted values for Gradient Boosting (Limited Depth)
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_gb, alpha=0.5, color='green', edgecolors='w', linewidths
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], '--', color='red',
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual vs Predicted Prices (Gradient Boosting, Limited Depth)')
plt.grid(True)
plt.show()
```



In [1]:
```
import matplotlib.pyplot as plt

# Mean Absolute Error values for all models
models = ['Linear Regression', 'Lasso Regression', 'Random Forest', 'Gradient Boost
mae_values = [135.44, 87.44, 40.17, 43.80]

# Plotting the Mean Absolute Error for all models
plt.figure(figsize=(10, 6))
plt.bar(models, mae_values, color=['blue', 'orange', 'green', 'red'])
plt.xlabel('Models')
plt.ylabel('Mean Absolute Error (MAE)')
plt.title('Mean Absolute Error for Different Models')
plt.show()
```


Mean Absolute Error for Different Models
Mean Absolute Error (MAE)
140
120
100
80
60
40
20
0
Linear Regression
Lasso Regression
Random Forest
Gradient Boosting
Models

In [ ]: