House Price Prediction 🏡

About the Dataset

Importing the Essential Libraries, Metrics

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
import pickle

from sklearn.model_selection import train_test_split, cross_val_score,GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.ensemble import RandomForestRegressor,StackingRegressor
from sklearn.svm import SVR
```

```
from xgboost import XGBRegressor
from sklearn.preprocessing import PolynomialFeatures
```

Loading the Data

In [2]:
```
df = pd.read_csv("D:\Data_Science\Machine_Learning\House_Prices\Real Estate Data V2
```

Exploratory Data Analysis

Taking a look at the first 5 rows of the dataset

In [3]:
```
df.head()
```

Out[3]:

	property_title	location	total_area	price_per_sqft	baths	balcony
0	4 BHK Flat for sale in Kanathur Reddikuppam, C...	Kanathur Reddikuppam, Chennai	2583	7700	4	Yes
1	10 BHK Independent House for sale in Pozhichal...	Ramanathan Nagar, Pozhichalur,Chennai	7000	3210	6	Yes
2	3 BHK Flat for sale in West Tambaram, Chennai	Kasthuribai Nagar, West Tambaram,Chennai	1320	7580	3	No
3	7 BHK Independent House for sale in Triplicane...	Naveenilaya,Chepauk, Triplicane,Chennai	4250	7840	5	Yes
4	2 BHK Flat for sale in Avadi, Chennai	Avadi, Chennai	960	5000	3	Yes

Checking the shape—i.e. size—of the data

In [4]:
```
df.shape
```

Out[4]:
```
(14521, 6)
```

Learning the dtypes of columns' and how many non-null values are there in those columns

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14521 entries, 0 to 14520
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   property_title  14521 non-null  object
 1   location        14521 non-null  object
 2   total_area      14521 non-null  int64 
 3   price_per_sqft  14521 non-null  int64 
 4   baths           14521 non-null  int64 
 5   balcony         14521 non-null  object
dtypes: int64(3), object(3)
memory usage: 680.8+ KB
```

Getting the statistical summary of dataset

In [6]:
```
df.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
total_area	14521.0	1296.410302	1239.278021	70.0	650.0	1000.0	1438.0	35000.0
price_per_sqft	14521.0	11667.392053	48723.970262	0.0	4480.0	6050.0	9310.0	999000.0
baths	14521.0	2.751188	0.897810	1.0	2.0	3.0	3.0	6.0

Visualizing the correlations between numerical variables

In [7]:
```
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(numeric_only=True), cmap="RdBu")
plt.title("Correlations Between Variables", size=15)
plt.show()
```

Feature Selection

In [8]:
```
df['price']=df['total_area']*df['price_per_sqft']
```

In [9]:
```
df.drop('price_per_sqft',axis=1,inplace=True)
```

Checking for the missing values

In [10]:
```
print("Missing Values by Column")
print("-"*30)
print(df.isna().sum())
print("-"*30)
print("TOTAL MISSING VALUES:",df.isna().sum().sum())
```

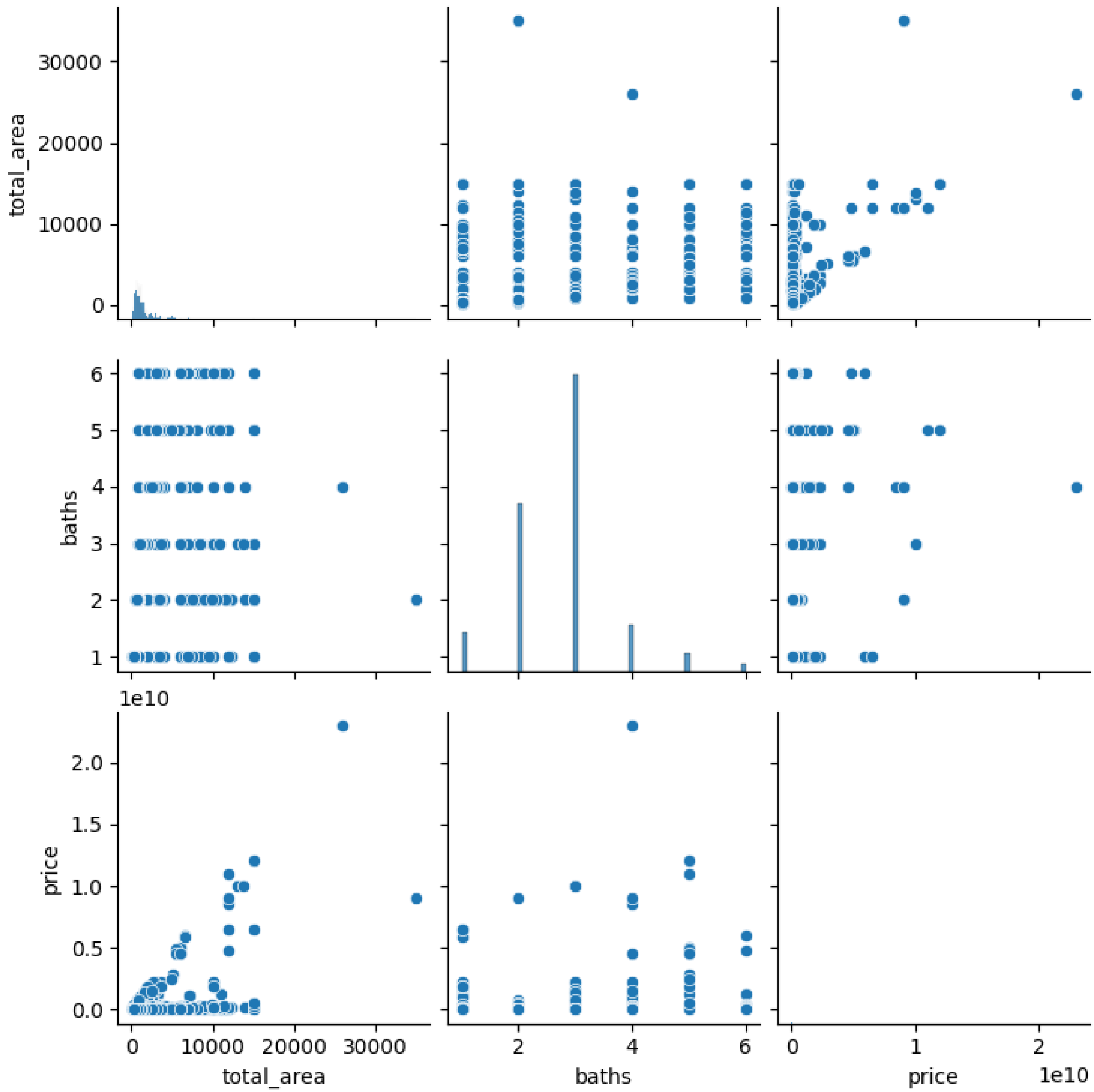
```
Missing Values by Column
------------------------------
property_title    0
location          0
total_area        0
baths             0
balcony           0
price             0
dtype: int64
------------------------------
TOTAL MISSING VALUES: 0
```

Data Visualization

Visualizing the Correlation between the numerical variables using pairplot visualization

In [11]:
```
sns.pairplot(df)
```

Out[11]:
```
<seaborn.axisgrid.PairGrid at 0x29c3c604a10>
```



Data Pre-Processing

Making Data Ready for Training

In [12]:
```
df['no_of_rooms'] = df['property_title'].str.split(" ").str[0]
df['flat_type'] = df['property_title'].str.split(" ").str[1]
df['city'] = df['location'].str.split(",").str[-1]
df['city'] = df['city'].str.strip(" ")
```

In [13]:
```
df['city'].replace("New Delhi","Delhi",inplace=True)
```

In [14]:
```
df.drop('property_title',axis=1,inplace=True)
df.drop('location',axis=1,inplace=True)
```

One-Hot Encoding

Encoding the categorical features in X dataset manually to better use in Streamlit App

In [15]:
```
df['balcony'].replace('Yes',1,inplace=True)
df['balcony'].replace('No',0,inplace=True)
```

In [16]:
```
df.replace('Chennai',0,inplace=True)
df.replace('Bangalore',1,inplace=True)
df.replace('Hyderabad',2,inplace=True)
df.replace('Mumbai',3,inplace=True)
df.replace('Thane',4,inplace=True)
df.replace('Kolkata',5,inplace=True)
df.replace('Pune',6,inplace=True)
df.replace('Delhi',7,inplace=True)
```

In [17]:
```
df['flat_type'].replace('Independent','RK',inplace=True)
df['flat_type'].replace('Flat','BHK',inplace=True)
```

In [18]:
```
df.replace('BHK',0,inplace=True)
df.replace('RK',1,inplace=True)
df.replace('R',2,inplace=True)
df.replace('BH',3,inplace=True)
```

Standardizing the Data

Standardizing the numerical columns in dataset. Adjusts the minimum of the features as 0 and maximum features as 1 for better prediction manually:

In [19]:
```
Q1 = df.total_area.quantile(0.25)
Q3 = df.total_area.quantile(0.75)
IQR = Q3-Q1
lower_limit=Q1-1.5*IQR
upper_limit=Q3+1.5*IQR
df = df[(df.total_area>lower_limit)&(df.total_area<upper_limit)]
df['total_area_scaled'] = df['total_area']/df['total_area'].max()
```

In [20]:
```
Q1 = df.price.quantile(0.25)
Q3 = df.price.quantile(0.75)
IQR = Q3-Q1
lower_limit=Q1-1.5*IQR
upper_limit=Q3+1.5*IQR
df = df[(df.price>lower_limit)&(df.price<upper_limit)]
df['price_scaled'] = df['price']/df['price'].max()
```

In [21]:
```
df.drop('total_area',axis=1,inplace=True)
df.drop('price',axis=1,inplace=True)
```

In [22]:
```
df['no_of_rooms'] = df['no_of_rooms'].astype('int')
Q1 = df.no_of_rooms.quantile(0.25)
Q3 = df.no_of_rooms.quantile(0.75)
IQR = Q3-Q1
lower_limit=Q1-1.5*IQR
upper_limit=Q3+1.5*IQR
df = df[(df.no_of_rooms>lower_limit)&(df.no_of_rooms<upper_limit)]
```

In [23]:
```
Q1 = df.baths.quantile(0.25)
Q3 = df.baths.quantile(0.75)
IQR = Q3-Q1
lower_limit=Q1-1.5*IQR
upper_limit=Q3+1.5*IQR
df = df[(df.baths>lower_limit)&(df.baths<upper_limit)]
```

X, y Split

Splitting the data into X and y chunks

In [24]:
```
X = df.drop('price_scaled',axis=1)
y = df['price_scaled']
```

Splitting the data into Train and Test chunks for better evaluation

In [25]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [26]:
```
print(f"X: {X.shape}")
print(f"y: {y.shape}")
print(f"X_Train: {X_train.shape}")
print(f"X_Test: {X_test.shape}")
print(f"y_Train: {y_train.shape}")
print(f"y_Train: {y_test.shape}")
```

```
X: (11947, 6)
y: (11947,)
X_Train: (9557, 6)
X_Test: (2390, 6)
y_Train: (9557,)
y_Train: (2390,)
```

Defining several evaluation functions for convenience

In [27]:
```
def evaluate(model, predictions):
    rmse_cross_val = np.sqrt(-cross_val_score(model, X, y, scoring="neg_mean_square
    mae = mean_absolute_error(y_test, predictions)
    mse = mean_squared_error(y_test, predictions)
    rmse = np.sqrt(mean_squared_error(y_test, predictions))
    r_squared = r2_score(y_test, predictions)

    print("Accuracy:", model.score(X_test, y_test).mean())
    print("Cross Val Score:", cross_val_score(model, X_test, y_test).mean())
    print("MAE:", mae)
```

```python
    print("MSE:", mse)
    print("RMSE:", rmse)
    print("R2 Score:", rmse_cross_val)
    print("-" * 30)
    print("RMSE Cross-Validation:", rmse_cross_val)

    new_row = pd.DataFrame({
        "Model": [str(model)],
        "MAE": [mae],
        "MSE": [mse],
        "RMSE": [rmse],
        "R2 Score": [r_squared],
        "RMSE (Cross-Validation)": [rmse_cross_val]
    })
    return new_row

models = pd.DataFrame(columns=["Model", "MAE", "MSE", "RMSE", "R2 Score", "RMSE (Cr
```

Machine Learning Models

Linear Regression

In [28]:

```python
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
predictions = lin_reg.predict(X_test)
evaluation = evaluate(lin_reg, predictions)
models = pd.concat([models, evaluation], ignore_index=True)
```

```
Accuracy: 0.3382968203463056
Cross Val Score: 0.3271753795240433
MAE: 0.1263938475286214
MSE: 0.029074034469124647
RMSE: 0.17051109778874995
R2 Score: 0.17156683389310376
------------------------------
RMSE Cross-Validation: 0.17156683389310376
```

Ridge Regression

In [29]:

```python
ridge = Ridge()
ridge.fit(X_train, y_train)
predictions = ridge.predict(X_test)
df = pd.concat([models, evaluate(ridge,predictions)], ignore_index=True)
```

```
Accuracy: 0.3382786856777934
Cross Val Score: 0.3271394139313299
MAE: 0.12642698416091075
MSE: 0.02907483127348289
RMSE: 0.1705134342903306
R2 Score: 0.17156351626791447
------------------------------
RMSE Cross-Validation: 0.17156351626791447
```

Lasso Regression

In [30]:
```
lasso = Lasso()
lasso.fit(X_train, y_train)
predictions = lasso.predict(X_test)
evaluation = evaluate(lasso, predictions)
models = pd.concat([models, evaluation], ignore_index=True)
```

```
Accuracy: -6.068457059971166e-06
Cross Val Score: -0.006646608422507816
MAE: 0.1655638424424565
MSE: 0.04393844823123038
RMSE: 0.2096150000148615
R2 Score: 0.21124836151191878
------------------------------
RMSE Cross-Validation: 0.21124836151191878
```

Elastic Net

In [31]:
```
elastic_net = ElasticNet()
elastic_net.fit(X_train, y_train)
predictions = elastic_net.predict(X_test)
evaluation = evaluate(elastic_net, predictions)
models = pd.concat([models, evaluation], ignore_index=True)
```

```
Accuracy: -6.068457059971166e-06
Cross Val Score: -0.006646608422507816
MAE: 0.1655638424424565
MSE: 0.04393844823123038
RMSE: 0.2096150000148615
R2 Score: 0.21124836151191878
------------------------------
RMSE Cross-Validation: 0.21124836151191878
```

Support Vector Machines

In [32]:
```
svr = SVR(C=10, kernel='poly', gamma='scale', epsilon=0.1)
svr.fit(X_train, y_train)
predictions = svr.predict(X_test)
evaluation = evaluate(svr, predictions)
models = pd.concat([models, evaluation], ignore_index=True)
```

```
Accuracy: 0.33798171308730596
Cross Val Score: 0.3051635083217683
MAE: 0.1224396794753583
MSE: 0.029087879709092244
RMSE: 0.1705516921906442
R2 Score: 0.18016913811821758
------------------------------
RMSE Cross-Validation: 0.18016913811821758
```

Random Forest Regressor

In [33]:
```
random_forest = RandomForestRegressor(n_estimators=100)
random_forest.fit(X_train, y_train)
predictions = random_forest.predict(X_test)
df = pd.concat([models, evaluate(random_forest,predictions)], ignore_index=True)
```

```
Accuracy: 0.4150305084562622
Cross Val Score: 0.3789544049720475
MAE: 0.11425486668554749
MSE: 0.02570249574655191
RMSE: 0.16031997924947441
R2 Score: 0.17566330697584998
------------------------------
RMSE Cross-Validation: 0.17566330697584998
```

XGBoost Regressor

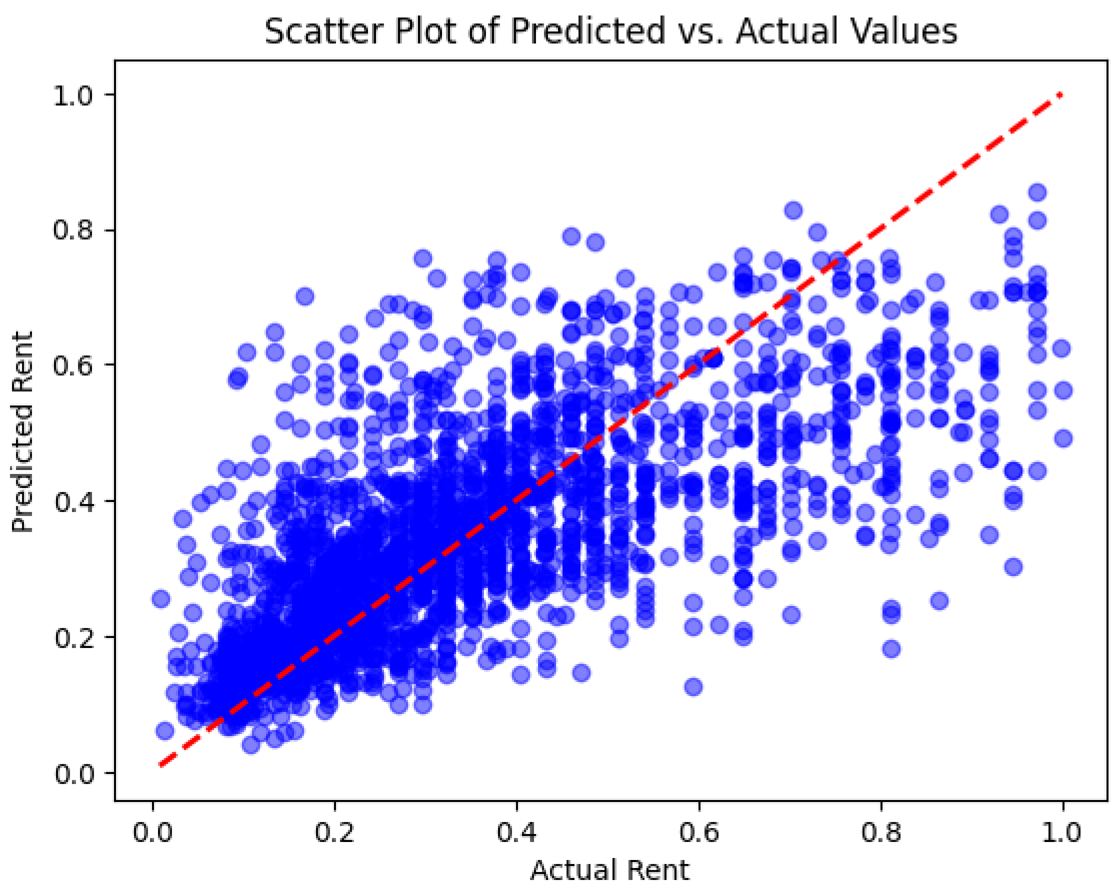
Hyper Parameter Tunning Using Grid Search

In [34]:
```
xgbr = XGBRegressor()
parameters = {'nthread':[1],
              'objective':['reg:linear'],
              'learning_rate': [0.01], #so called `eta` value
              'max_depth': [5],
              'min_child_weight': [5],
              'silent': [0.1],
              'subsample': [0.5],
              'colsample_bytree': [0.5],
              'n_estimators': [1000]}

xgbr.fit(X_train,y_train)
predictions = xgbr.predict(X_test)
evaluation = evaluate(xgbr, predictions)
models = pd.concat([models, evaluation], ignore_index=True)
```

```
Accuracy: 0.47113643961784357
Cross Val Score: 0.35870541300592657
MAE: 0.1104750948015856
MSE: 0.02323730315465918
RMSE: 0.1524378665380068
R2 Score: 0.16946648522643284
------------------------------
RMSE Cross-Validation: 0.16946648522643284
```

```
In [35]: y_pred = xgbr.predict(X_test)
bin = np.arange(0,y_pred.max()+10000,100000)
plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
#plt.scatter(y_pred, bins, color='red', alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', co
plt.xticks=bin
plt.xlabel('Actual Rent')
plt.ylabel('Predicted Rent')
plt.title('Scatter Plot of Predicted vs. Actual Values')
plt.show()
```



Model Comparison

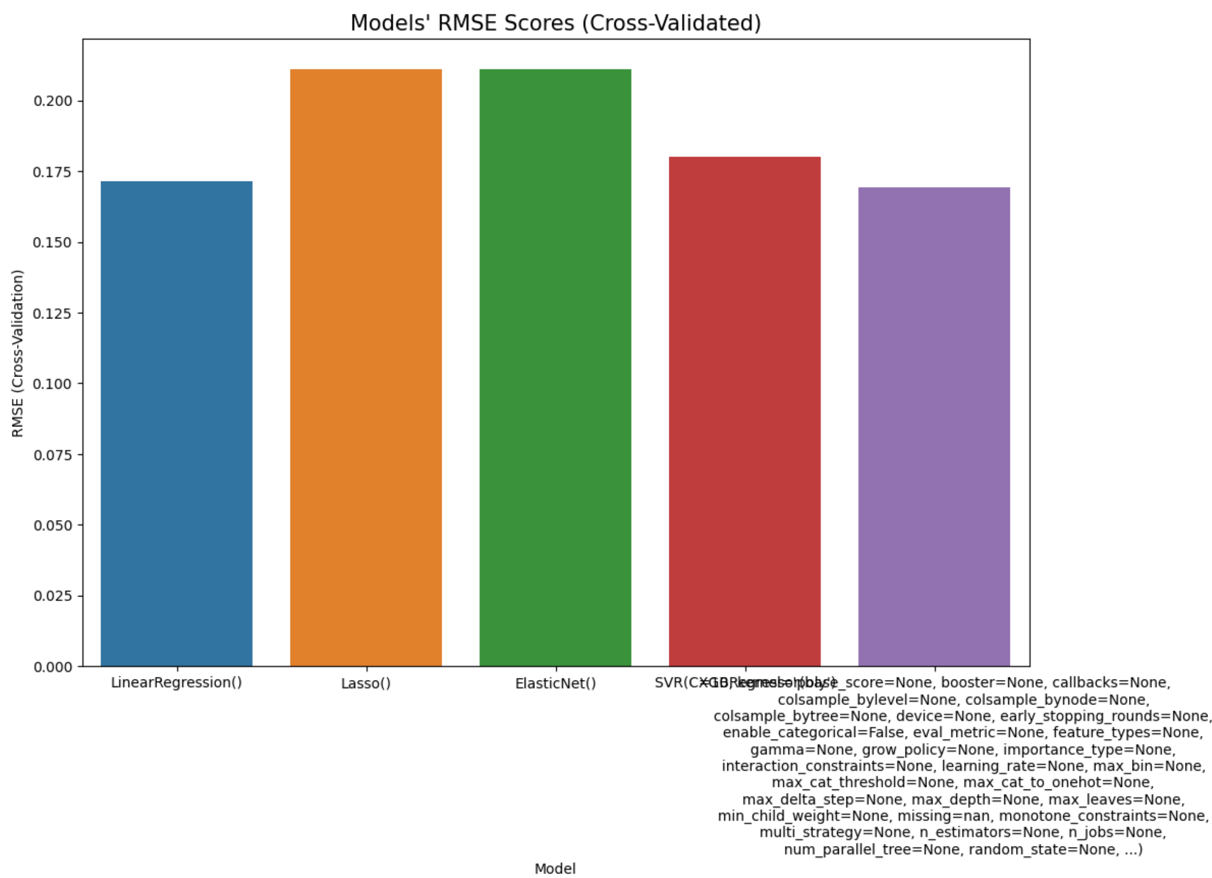
The less the Root Mean Squared Error (RMSE), The better the model is.

```
In [36]: models
```

Out[36]:

	Model	MAE	MSE	RMSE	R2 Score	RMSE (Cross-Validation)
0	LinearRegression()	0.126394	0.029074	0.170511	0.338297	0.171567
1	Lasso()	0.165564	0.043938	0.209615	-0.000006	0.211248
2	ElasticNet()	0.165564	0.043938	0.209615	-0.000006	0.211248
3	SVR(C=10, kernel='poly')	0.122440	0.029088	0.170552	0.337982	0.180169
4	XGBRegressor(base_score=None, booster=None, ca...	0.110475	0.023237	0.152438	0.471136	0.169466

In [37]:
```python
plt.figure(figsize=(12,8))
sns.barplot(x=models["Model"], y=models["RMSE (Cross-Validation)"])
plt.title("Models' RMSE Scores (Cross-Validated)", size=15)
plt.show()
```



In [38]:
```python
with open('xgboost_regressor_model.pkl', 'wb') as file:
    pickle.dump(xgbr, file)
```