HOUSE PRICE PREDICTION

The real estate industry is a significant sector of the economy, and accurately predicting house prices is crucial for various stakeholders, including homebuyers, sellers, and real estate investors. Machine learning models can play a pivotal role in providing more precise and data-driven predictions of house prices.

1.PROBELM STATEMENT

The aim of this project is to develop a machine learning model that predicts house prices based on a set of features related to the properties. Specifically, the goal is to create a model that can accurately estimate the selling price of houses, taking into account factors such as location, size, number of bedrooms and bathrooms, neighborhood characteristics, and other relevant attributes.

2.DATA

Data is collected from kaggle

In [41]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [42]:
```python
!pip install seaborn
```

```
Requirement already satisfied: seaborn in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (0.12.2)
Requirement already satisfied: numpy!=1.24.0,>=1.17 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from seaborn) (1.24.4)
Requirement already satisfied: pandas>=0.25 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from seaborn) (2.0.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from seaborn) (3.7.2)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (1.0.5)
Requirement already satisfied: cycler>=0.10 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (9.4.0)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from pandas>=0.25->seaborn) (2022.7)
Requirement already satisfied: tzdata>=2022.1 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from pandas>=0.25->seaborn) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\dinesh\desktop\jio_ml\env\lib\site-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.1->seaborn) (1.16.0)
```

In [43]:
```python
import seaborn as sns
```

In [44]:
```python
df = pd.read_csv("house-prices - ML Dataset.csv")
```

In [45]:
```python
df.head()
df
```

Out[45]:

	Home	Price	SqFt	Bedrooms	Bathrooms	Offers	Brick	Neighborhood
0	1	114300	1790	2	2	2	No	East
1	2	114200	2030	4	2	3	No	East
2	3	114800	1740	3	2	1	No	East
3	4	94700	1980	3	2	3	No	East
4	5	119800	2130	3	3	3	No	East
...	...	...	...	...	...	...	...	...
123	124	119700	1900	3	3	3	Yes	East
124	125	147900	2160	4	3	3	Yes	East
125	126	113500	2070	2	2	2	No	North
126	127	149900	2020	3	3	1	No	West
127	128	124600	2250	3	3	4	No	North

128 rows × 8 columns

In [46]:
```python
df.isna().sum()
```

Out[46]:
```
Home            0
Price           0
SqFt            0
Bedrooms        0
Bathrooms       0
Offers          0
Brick           0
Neighborhood    0
dtype: int64
```

In [47]:
```python
df.duplicated().sum()
```

Out[47]:
```
0
```

In [48]:
```python
df.shape
```

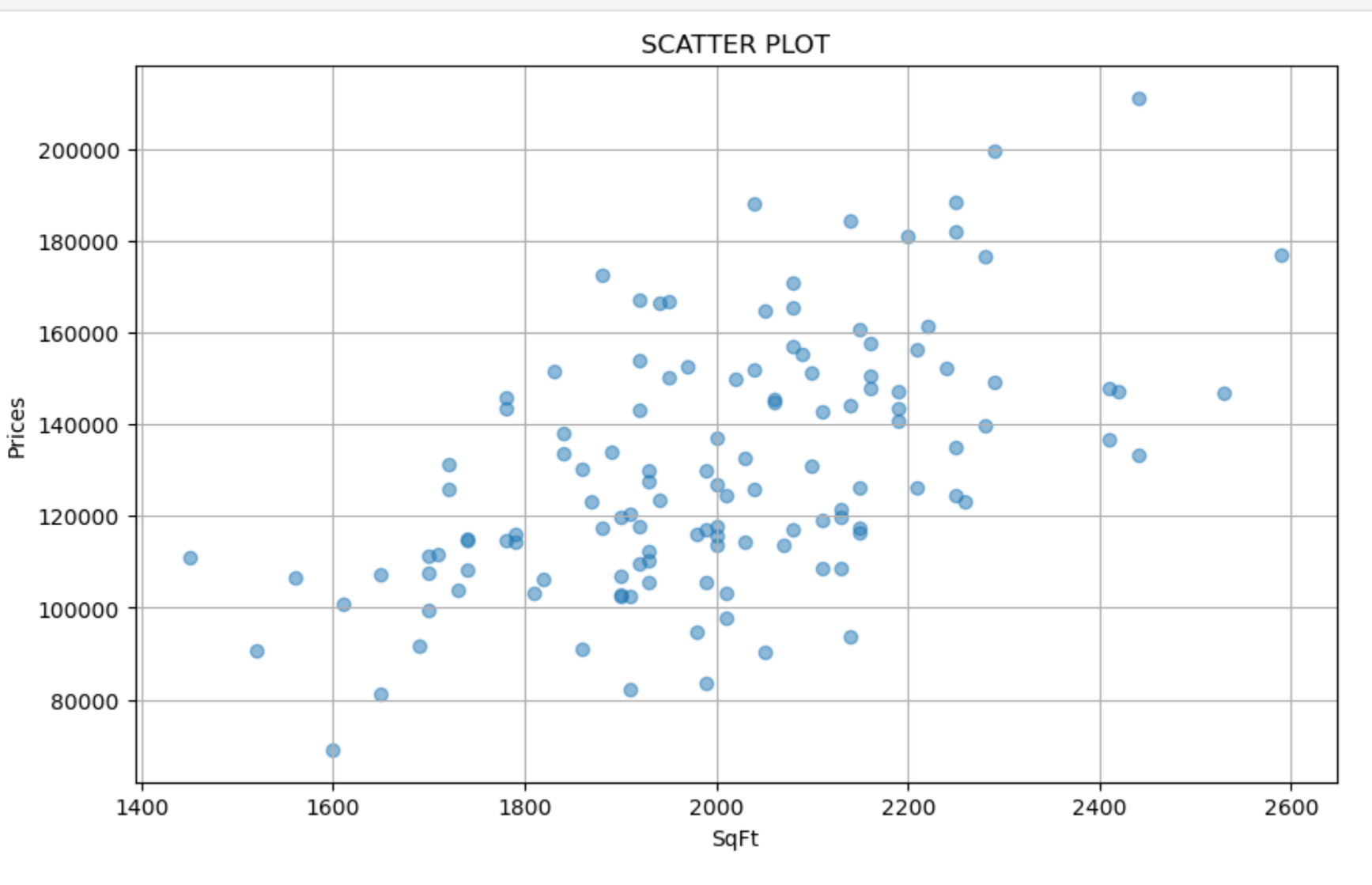
Out[48]:
```
(128, 8)
```

In [49]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 128 entries, 0 to 127
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Home          128 non-null    int64
 1   Price         128 non-null    int64
 2   SqFt          128 non-null    int64
 3   Bedrooms      128 non-null    int64
 4   Bathrooms     128 non-null    int64
 5   Offers        128 non-null    int64
 6   Brick         128 non-null    object
 7   Neighborhood  128 non-null    object
dtypes: int64(6), object(2)
memory usage: 8.1+ KB
```

Plotting a scatter plot for finiding outliers

In [50]:
```python
plt.figure(figsize=(10,6))
plt.scatter(df['SqFt'],df['Price'], alpha = 0.5)
plt.grid(True)
plt.title("SCATTER PLOT")
plt.xlabel("SqFt")
plt.ylabel("Prices")
plt.show()
```



Finding outliers using IQR and dropping them.

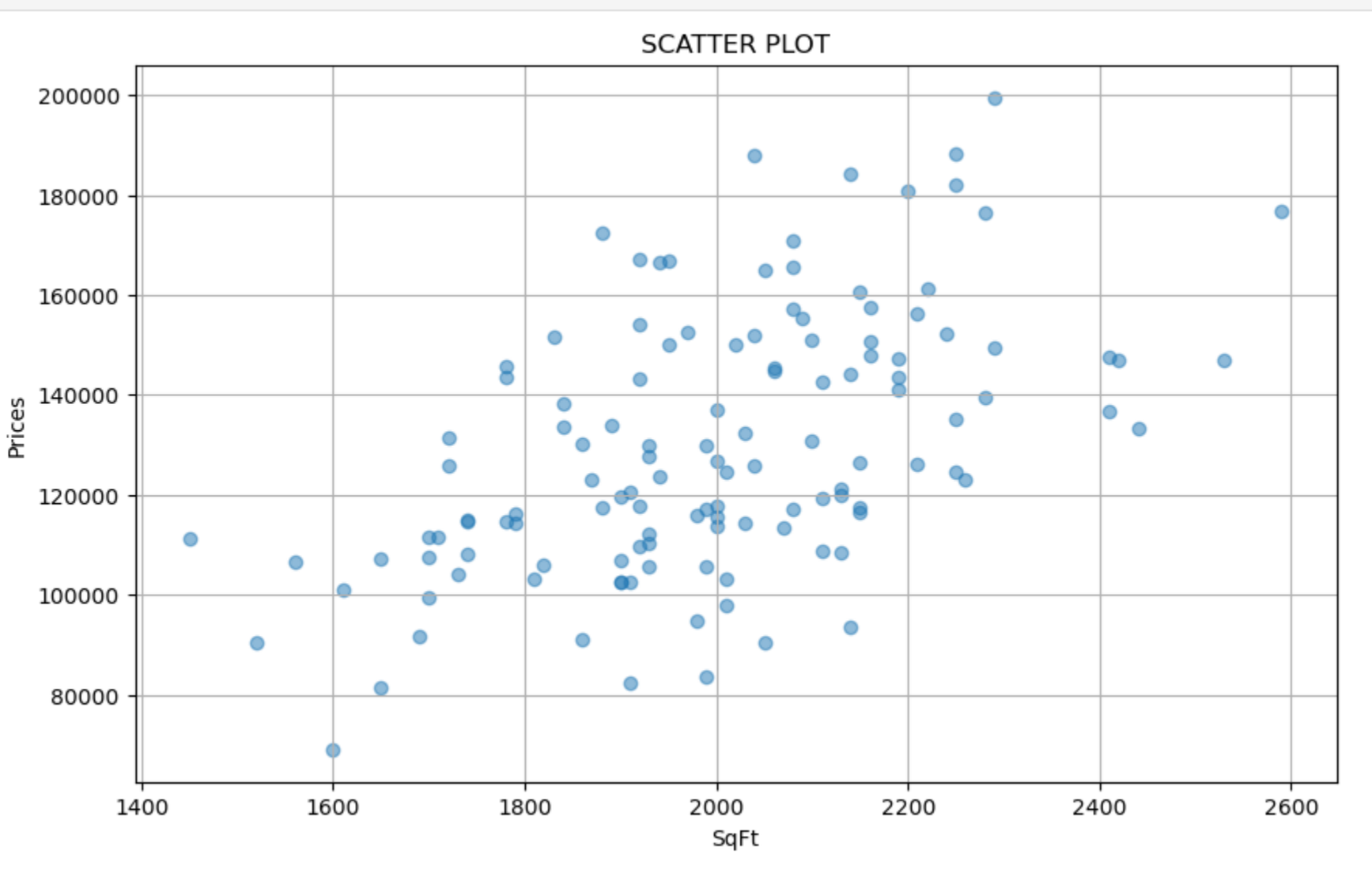
In [51]:
```python
Q1 = df['Price'].quantile(0.25)
Q3 = df['Price'].quantile(0.75)
IQR = Q3-Q1

lower_bound = Q1 - 1.5*IQR
upper_bound = Q3 + 1.5*IQR
dfo = df[(df['Price']>= lower_bound)& (df['Price']<=upper_bound)]
dfo
```

Out[51]:

	Home	Price	SqFt	Bedrooms	Bathrooms	Offers	Brick	Neighborhood
0	1	114300	1790	2	2	2	No	East
1	2	114200	2030	4	2	3	No	East
2	3	114800	1740	3	2	1	No	East
3	4	94700	1980	3	2	3	No	East
4	5	119800	2130	3	3	3	No	East
...	...	...	...	...	...	...	...	...
123	124	119700	1900	3	3	3	Yes	East
124	125	147900	2160	4	3	3	Yes	East
125	126	113500	2070	2	2	2	No	North
126	127	149900	2020	3	3	1	No	West
127	128	124600	2250	3	3	4	No	North

127 rows × 8 columns

In [52]:
```python
plt.figure(figsize=(10,6))
plt.scatter(dfo['SqFt'],dfo['Price'], alpha = 0.5)
plt.grid(True)
plt.title("SCATTER PLOT")
plt.xlabel("SqFt")
plt.ylabel("Prices")
plt.show()
```



Changing Categorical values to numerical values

In [53]:
```python
dfe = pd.get_dummies(dfo,columns=['Brick','Neighborhood'])
```

In [54]:
```python
dfed=dfe.astype(int)
dfed
```

Out[54]:

	Home	Price	SqFt	Bedrooms	Bathrooms	Offers	Brick_No	Brick_Yes	Neighborhood_East	Neighborhood_North	Neighborhood_West
0	1	114300	1790	2	2	2	1	0	1	0	0
1	2	114200	2030	4	2	3	1	0	1	0	0
2	3	114800	1740	3	2	1	1	0	1	0	0
3	4	94700	1980	3	2	3	1	0	1	0	0
4	5	119800	2130	3	3	3	1	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...
123	124	119700	1900	3	3	3	0	1	1	0	0
124	125	147900	2160	4	3	3	0	1	1	0	0
125	126	113500	2070	2	2	2	1	0	0	1	0
126	127	149900	2020	3	3	1	1	0	0	0	1
127	128	124600	2250	3	3	4	1	0	0	1	0

127 rows × 11 columns

Applying "SCALING" on numerical values

In [55]:
```python
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaled_features = scaler.fit_transform(dfed)

scaled_df = pd.DataFrame(scaled_features, columns=dfed.columns)
```

In [56]:
```python
scaled_df
```

Out[56]:

	Home	Price	SqFt	Bedrooms	Bathrooms	Offers	Brick_No	Brick_Yes	Neighborhood_East	Neighborhood_North	Neighborhood_West
0	0.000000	0.346626	0.298246	0.000000	0.0	0.2	1.0	0.0	1.0	0.0	0.0
1	0.007874	0.345859	0.508772	0.666667	0.0	0.4	1.0	0.0	1.0	0.0	0.0
2	0.015748	0.350460	0.254386	0.333333	0.0	0.0	1.0	0.0	1.0	0.0	0.0
3	0.023622	0.196319	0.464912	0.333333	0.0	0.4	1.0	0.0	1.0	0.0	0.0
4	0.031496	0.388804	0.596491	0.333333	0.5	0.4	1.0	0.0	1.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...
122	0.968504	0.388037	0.394737	0.333333	0.5	0.4	0.0	1.0	1.0	0.0	0.0
123	0.976378	0.604294	0.622807	0.666667	0.5	0.4	0.0	1.0	1.0	0.0	0.0
124	0.984252	0.340491	0.543860	0.000000	0.0	0.2	1.0	0.0	0.0	1.0	0.0
125	0.992126	0.619632	0.500000	0.333333	0.5	0.0	1.0	0.0	0.0	0.0	1.0
126	1.000000	0.425613	0.701754	0.333333	0.5	0.6	1.0	0.0	0.0	1.0	0.0

127 rows × 11 columns

Splitting data into training and testing sets

In [57]:
```python
x = scaled_df.drop('Price',axis = 1)
y = scaled_df['Price']
```

In [58]:
```python
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2)
```

In [59]:
```python
scaled_df.describe()
```

Out[59]:

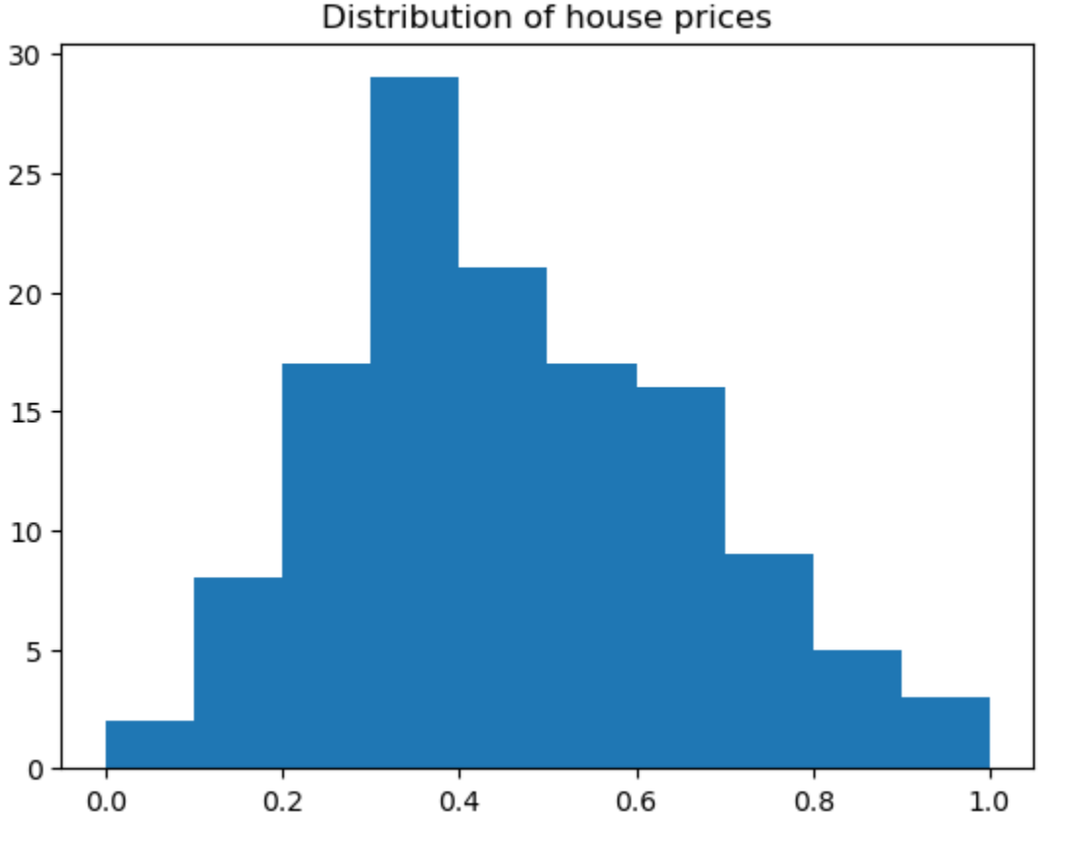
	Home	Price	SqFt	Bedrooms	Bathrooms	Offers	Brick_No	Brick_Yes	Neighborhood_East	Neighborhood_North	Neighborhood_West
count	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000	127.000000
mean	0.497551	0.465424	0.480246	0.338583	0.220472	0.314961	0.677165	0.322835	0.354331	0.346457	0.299213
std	0.291917	0.199309	0.183113	0.241191	0.257071	0.214579	0.469412	0.469412	0.480204	0.477725	0.459727
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.248031	0.323236	0.377193	0.333333	0.000000	0.200000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	0.496063	0.434049	0.482456	0.333333	0.000000	0.400000	1.000000	0.000000	0.000000	0.000000	0.000000
75%	0.744094	0.603528	0.605263	0.333333	0.500000	0.400000	1.000000	1.000000	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

In [60]:
```python
scaled_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 127 entries, 0 to 126
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Home                127 non-null    float64
 1   Price               127 non-null    float64
 2   SqFt                127 non-null    float64
 3   Bedrooms            127 non-null    float64
 4   Bathrooms           127 non-null    float64
 5   Offers              127 non-null    float64
 6   Brick_No            127 non-null    float64
 7   Brick_Yes           127 non-null    float64
 8   Neighborhood_East   127 non-null    float64
 9   Neighborhood_North  127 non-null    float64
 10  Neighborhood_West   127 non-null    float64
dtypes: float64(11)
memory usage: 11.0 KB
```

In [77]:
```python
plt.hist(scaled_df['Price'])
plt.title('Distribution of house prices')
```

Out[77]:
```
Text(0.5, 1.0, 'Distribution of house prices')
```



Dropping Home column as there is no use with Home field.

In [79]:
```python
scaled_df_ = scaled_df.drop('Home',axis=1)
scaled_df_
```

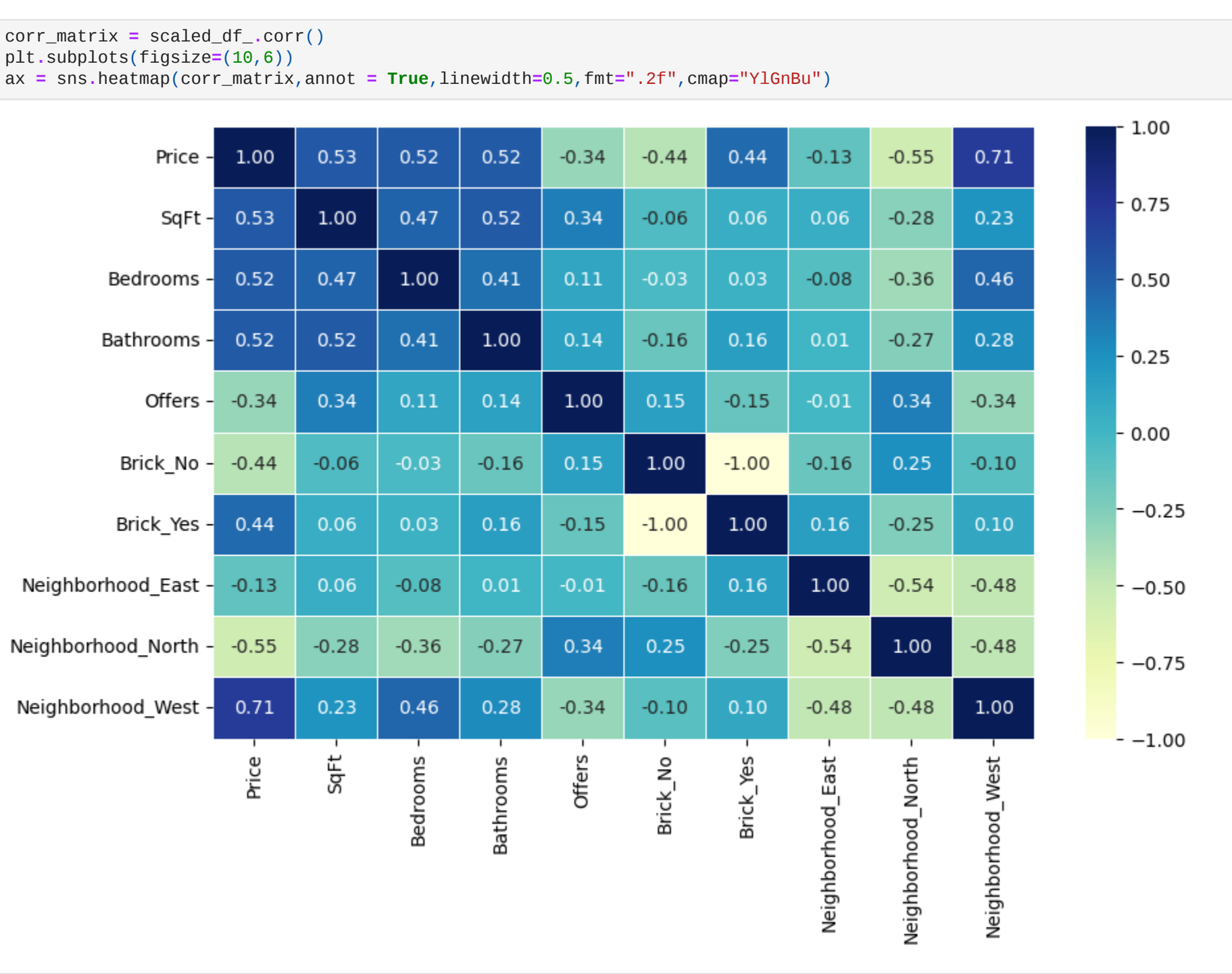
Out[79]:

	Price	SqFt	Bedrooms	Bathrooms	Offers	Brick_No	Brick_Yes	Neighborhood_East	Neighborhood_North	Neighborhood_West
0	0.346626	0.298246	0.000000	0.0	0.2	1.0	0.0	1.0	0.0	0.0
1	0.345859	0.508772	0.666667	0.0	0.4	1.0	0.0	1.0	0.0	0.0
2	0.350460	0.254386	0.333333	0.0	0.0	1.0	0.0	1.0	0.0	0.0
3	0.196319	0.464912	0.333333	0.0	0.4	1.0	0.0	1.0	0.0	0.0
4	0.388804	0.596491	0.333333	0.5	0.4	1.0	0.0	1.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...
122	0.388037	0.394737	0.333333	0.5	0.4	0.0	1.0	1.0	0.0	0.0
123	0.604294	0.622807	0.666667	0.5	0.4	0.0	1.0	1.0	0.0	0.0
124	0.340491	0.543860	0.000000	0.0	0.2	1.0	0.0	0.0	1.0	0.0
125	0.619632	0.500000	0.333333	0.5	0.0	1.0	0.0	0.0	0.0	1.0
126	0.425613	0.701754	0.333333	0.5	0.6	1.0	0.0	0.0	1.0	0.0

127 rows × 10 columns

Identifying correlations between features and the target variable

In [80]:
```python
corr_matrix = scaled_df_.corr()
plt.subplots(figsize=(10,6))
ax = sns.heatmap(corr_matrix,annot = True,linewidth=0.5,fmt=".2f",cmap="YlGnBu")
```



In [81]:
```python
target_correlation = corr_matrix['Price']
target_correlation
```

Out[81]:
```
Price                 1.000000
SqFt                  0.531726
Bedrooms              0.516275
Bathrooms             0.518797
Offers               -0.335503
Brick_No             -0.438237
Brick_Yes             0.438237
Neighborhood_East    -0.130496
Neighborhood_North   -0.552294
Neighborhood_West     0.710226
Name: Price, dtype: float64
```

Importing ML models

In [64]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
```

In [65]:
```python
models = {"Linear Regression":LinearRegression(),
         "DecisionTreeRegressor":DecisionTreeRegressor(),
         "Random Forest": RandomForestRegressor()}



def fit_and_score(models,x_train,x_test,y_train,y_test):

    np.random.seed(42)
    model_scores = {}
    for name,model in models.items():
        model.fit(x_train,y_train)
        model_scores[name]=model.score(x_test,y_test)
    return model_scores
```

In [66]:
```python
fit_and_score(models,x_train,x_test,y_train,y_test)
```

Out[66]:
```
{'Linear Regression': 0.8174006931391103,
 'DecisionTreeRegressor': 0.6151472513561919,
 'Random Forest': 0.7355506823067638}
```

EVALUATION METRICS

In [67]:
```python
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
```

In [68]:
```python
def fit_and_score(models,x_train,x_test,y_train,y_test):

    np.random.seed(77)
    model_scores = {}
    for name,model in models.items():
        model.fit(x_train,y_train)
        score =model.score(x_test,y_test)
        y_pred = model.predict(x_test)
        mae = mean_absolute_error(y_test, y_pred)
        r2 = r2_score(y_test, y_pred)
        rmse = np.sqrt(mean_squared_error(y_test, y_pred))

        print("Mean Absolute Errorr of ", name , ":"  , mae)
        print("R-squared:",name,':', r2)
        print("Root Mean Squared Error:",name,":", rmse)
```

In [69]:
```python
fit_and_score(models,x_train,x_test,y_train,y_test)
```

```
Mean Absolute Errorr of  Linear Regression : 0.06851883258612554
R-squared: Linear Regression : 0.8174006931391103
Root Mean Squared Error: Linear Regression : 0.08536664977561825
Mean Absolute Errorr of  DecisionTreeRegressor : 0.11432279377064652
R-squared: DecisionTreeRegressor : 0.5371415832556464
Root Mean Squared Error: DecisionTreeRegressor : 0.13591355063753352
Mean Absolute Errorr of  Random Forest : 0.08651191599811232
R-squared: Random Forest : 0.7406051514874015
Root Mean Squared Error: Random Forest : 0.10174646958715704
```

Considering Random Forest Regressor model

Applying hypertuning on Random Forest Regressor model, even though Linear regression has highest accuracy.Because there are no hyper parameters for Linear regression model, so it can't be tuned.

In [70]:
```python
from sklearn.model_selection import GridSearchCV
model = RandomForestRegressor()
model.fit(x_train,y_train)
y_preds = model.predict(x_test)
np.random.seed(42)
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5, 10]
}
scoring = 'neg_mean_squared_error'
grid_search = GridSearchCV(model, param_grid, scoring=scoring, cv=5)
grid_search.fit(x_train, y_train)
best_params = grid_search.best_params_
best_model = grid_search.best_estimator_
test_predictions = best_model.predict(x_test)
test_mse = mean_squared_error(y_test,test_predictions)
test_R2 = r2_score(y_test,test_predictions)
```

In [71]:
```python
test_mse
```

Out[71]:
```
0.010429350216960682
```

In [72]:
```python
test_R2
```

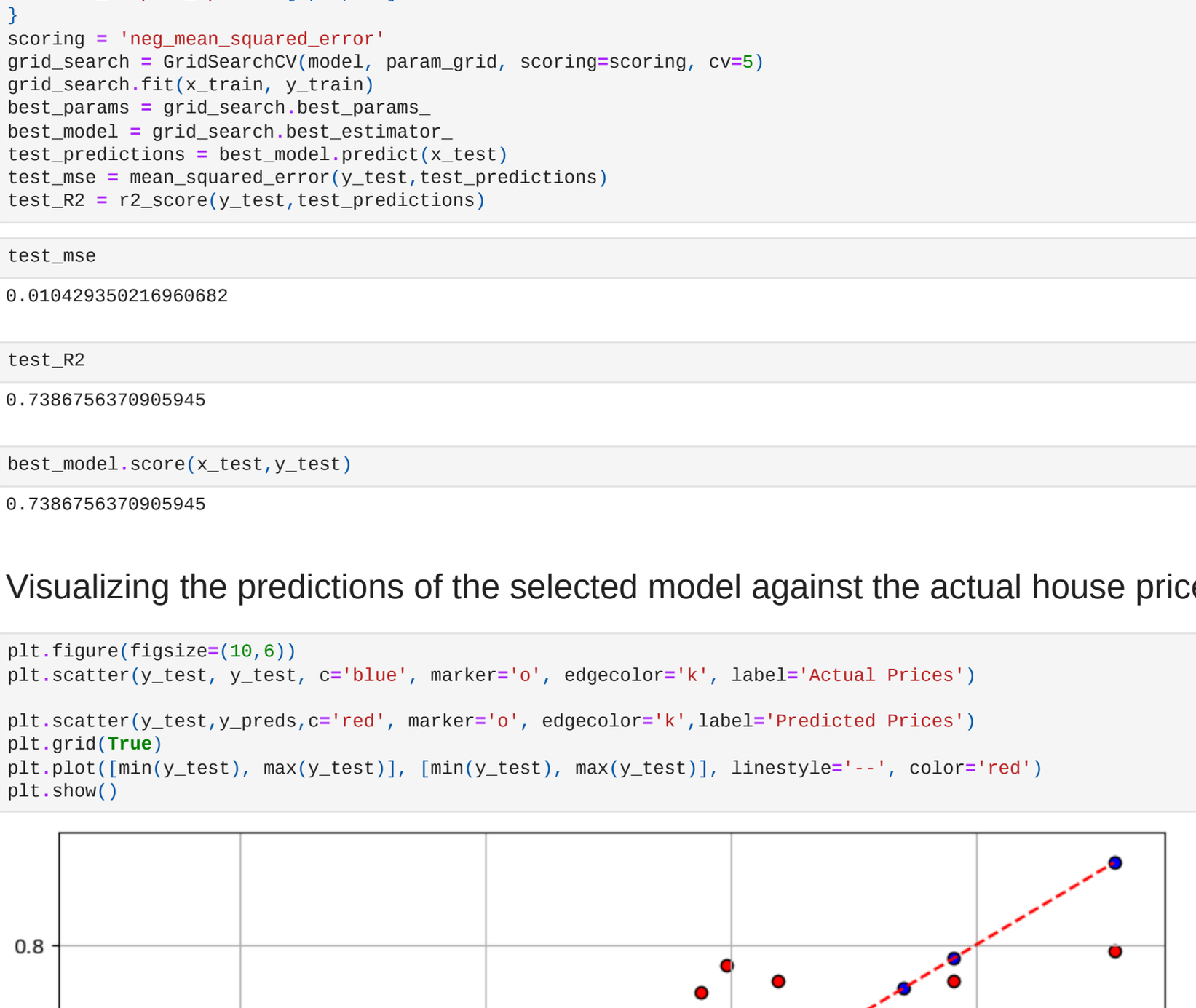
Out[72]:
```
0.7386756370905945
```

In [73]:
```python
best_model.score(x_test,y_test)
```

Out[73]:
```
0.7386756370905945
```

Visualizing the predictions of the selected model against the actual house prices.

In [74]:
```python
plt.figure(figsize=(10,6))
plt.scatter(y_test, y_test, c='blue', marker='o', edgecolor='k', label='Actual Prices')

plt.scatter(y_test,y_preds,c='red', marker='o', edgecolor='k',label='Predicted Prices')
plt.grid(True)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], linestyle='--', color='red')
plt.show()
```



Finding feature importance scores

In [75]:
```python
importances = best_model.feature_importances_
feature_names = x.columns
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)
```

In [76]:
```python
feature_importance_df
```

Out[76]:

	Feature	Importance
9	Neighborhood_West	0.546551
1	SqFt	0.225615
4	Offers	0.053680
3	Bathrooms	0.046732
0	Home	0.045082
5	Brick_No	0.030381
6	Brick_Yes	0.027341
2	Bedrooms	0.016619
8	Neighborhood_North	0.005523
7	Neighborhood_East	0.002476

Neighborhood_West has the highest feature importance

In [ ]:

In [ ]: