Predicting Housing Prices in Delhi, India Using Neural Networks

House Price Dataset of Delhi, scraped from Magic Bricks between June 2021 and July 2021, containing 18 columns.

In [1]:
```
!kaggle datasets download -d goelyash/housing-price-dataset-of-delhiindia
```

```
Dataset URL: https://www.kaggle.com/datasets/goelyash/housing-price-dataset-of-delhiindia
License(s): CC0-1.0
housing-price-dataset-of-delhiindia.zip: Skipping, found more recently modified local copy (use --force to force download)
```

In [2]:
```
# Surpress warnings:
def warn(*args, **kwargs):
    pass
import warnings
warnings.warn = warn
```

In [3]:
```
import zipfile
zip_ref=zipfile.ZipFile("housing-price-dataset-of-delhiindia.zip","r")
zip_ref.extractall()
zip_ref.close()
```

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [5]:
```
df=pd.read_csv("Delhi_v2.csv")
df.head()
```

Out[5]:

	Unnamed: 0	price	Address	area	latitude	longitude	Bedrooms	Bathrooms	Balcony	Status	neworold	parking	Furnished_stat
0	0	5600000.0	Noida Extension, Noida, Delhi NCR	1350.0	28.608850	77.460560	3.0	3.0	NaN	Under Construction	New Property	NaN	N
1	1	8800000.0	Sector 79, Gurgaon, Delhi NCR	1490.0	28.374236	76.952416	3.0	3.0	NaN	Ready to Move	New Property	NaN	Semi-Furnish
2	2	16500000.0	Vaishali, Ghaziabad, Delhi NCR	2385.0	28.645769	77.385110	4.0	5.0	NaN	Ready to Move	New Property	1.0	Unfurnish
3	3	3810000.0	Link Road, F Block, Sector 50, Noida, Uttar Pr...	1050.0	28.566914	77.436434	2.0	2.0	3.0	NaN	New Property	1.0	Unfurnish
4	4	6200000.0	Jaypee Pavilion Court Sector 128, Noida, Secto...	1350.0	28.520732	77.356491	2.0	2.0	3.0	Ready to Move	Resale	1.0	N

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7738 entries, 0 to 7737
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Unnamed: 0        7738 non-null   int64
 1   price             7738 non-null   float64
 2   Address           7738 non-null   object
 3   area              7738 non-null   float64
 4   latitude          7738 non-null   float64
 5   longitude         7738 non-null   float64
 6   Bedrooms          7738 non-null   float64
 7   Bathrooms         7738 non-null   float64
 8   Balcony           5166 non-null   float64
 9   Status            7164 non-null   object
 10  neworold          7738 non-null   object
 11  parking           2612 non-null   float64
 12  Furnished_status  4124 non-null   object
 13  Lift              1733 non-null   float64
 14  Landmarks         2759 non-null   object
 15  type_of_building  7738 non-null   object
 16  desc              7738 non-null   object
 17  Price_sqft        7738 non-null   float64
dtypes: float64(10), int64(1), object(7)
memory usage: 1.1+ MB
```

In [7]:
```
df.describe()
```

Out[7]:

	Unnamed: 0	price	area	latitude	longitude	Bedrooms	Bathrooms	Balcony	parking	Lift	Price
count	7738.000000	7.738000e+03	7738.000000	7738.000000	7738.000000	7738.000000	7738.000000	5166.000000	2612.000000	1733.000000	7738.00
mean	3868.500000	8.320635e+06	1409.506591	28.552092	77.273476	2.708193	2.501163	2.426442	7.673047	1.829198	5543.66
std	2233.912524	7.223197e+06	718.929581	0.107420	0.180606	0.877026	0.867050	1.083677	60.417508	1.192607	2408.65
min	0.000000	1.700000e+06	501.000000	28.240023	76.884101	2.000000	2.000000	1.000000	1.000000	0.000000	2100.00
25%	1934.250000	4.200000e+06	990.000000	28.455539	77.078590	2.000000	2.000000	2.000000	1.000000	1.000000	3950.98
50%	3868.500000	6.000000e+06	1250.000000	28.574637	77.345320	3.000000	2.000000	2.000000	1.000000	2.000000	4972.67
75%	5802.750000	9.500000e+06	1650.000000	28.642520	77.421054	3.000000	3.000000	3.000000	2.000000	2.000000	6350.63
max	7737.000000	8.500000e+07	9500.000000	28.799748	77.688028	10.000000	10.000000	10.000000	1406.000000	10.000000	44378.69

In [8]:
```
df.nunique()
```

Out[8]:
```
Unnamed: 0          7738
price                584
Address             4145
area                1102
latitude            2942
longitude           2912
Bedrooms               9
Bathrooms              9
Balcony               10
Status                 2
neworold               2
parking               65
Furnished_status       3
Lift                  11
Landmarks           2612
type_of_building       2
desc                4181
Price_sqft          3946
dtype: int64
```

In [9]:
```
df.corr(numeric_only=True)
```

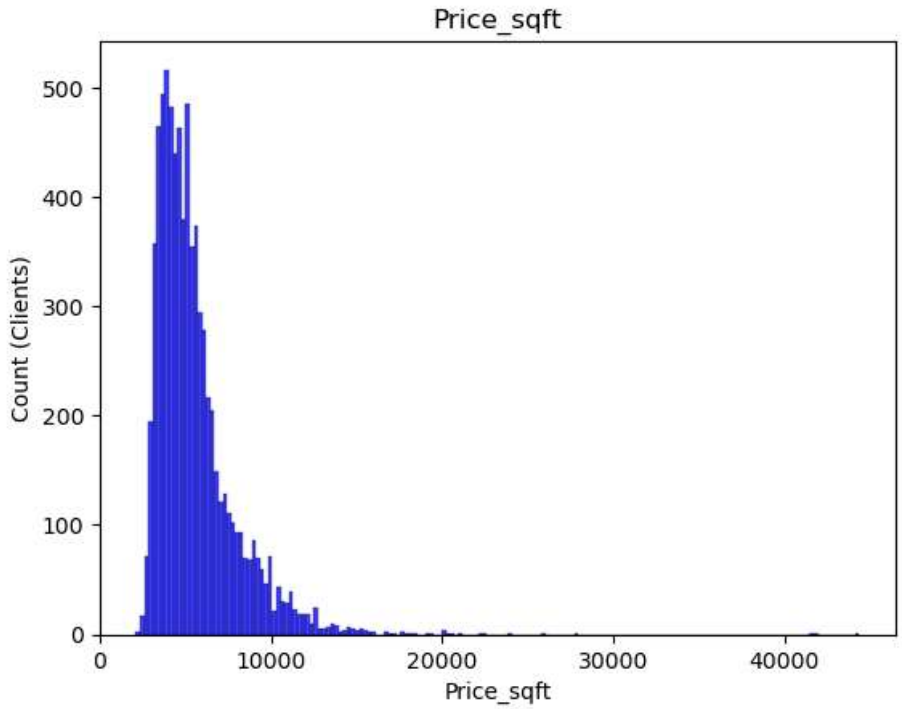
Out[9]:

	Unnamed: 0	price	area	latitude	longitude	Bedrooms	Bathrooms	Balcony	parking	Lift	Price_sqft
Unnamed: 0	1.000000	0.022589	0.002100	-0.030258	0.008796	-0.004658	0.008812	0.047535	-0.019743	0.006369	0.036812
price	0.022589	1.000000	0.849073	-0.227517	-0.331883	0.606914	0.691990	0.255096	-0.041640	0.037892	0.682768
area	0.002100	0.849073	1.000000	-0.279069	-0.184427	0.683479	0.763650	0.420476	-0.036780	0.128409	0.292711
latitude	-0.030258	-0.227517	-0.279069	1.000000	0.401701	-0.140817	-0.246663	-0.199374	-0.053874	-0.094808	-0.098981
longitude	0.008796	-0.331883	-0.184427	0.401701	1.000000	-0.166826	-0.205187	0.090932	0.019576	0.139778	-0.451146
Bedrooms	-0.004658	0.606914	0.683479	-0.140817	-0.166826	1.000000	0.765479	0.283880	-0.037920	-0.048828	0.348992
Bathrooms	0.008812	0.691990	0.763650	-0.246663	-0.205187	0.765479	1.000000	0.361291	-0.043036	0.068791	0.356413
Balcony	0.047535	0.255096	0.420476	-0.199374	0.090932	0.283880	0.361291	1.000000	0.000870	0.331883	-0.012863
parking	-0.019743	-0.041640	-0.036780	-0.053874	0.019576	-0.037920	-0.043036	0.000870	1.000000	0.037927	-0.045357
Lift	0.006369	0.037892	0.128409	-0.094808	0.139778	-0.048828	0.068791	0.331883	0.037927	1.000000	-0.133483
Price_sqft	0.036812	0.682768	0.292711	-0.098981	-0.451146	0.348992	0.356413	-0.012863	-0.045357	-0.133483	1.000000

In [10]:
```
dff=df.drop(["Address","Landmarks","price","Unnamed: 0","desc"],axis=1)
dff.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7738 entries, 0 to 7737
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   area              7738 non-null   float64
 1   latitude          7738 non-null   float64
 2   longitude         7738 non-null   float64
 3   Bedrooms          7738 non-null   float64
 4   Bathrooms         7738 non-null   float64
 5   Balcony           5166 non-null   float64
 6   Status            7164 non-null   object 
 7   neworold          7738 non-null   object 
 8   parking           2612 non-null   float64
 9   Furnished_status  4124 non-null   object 
 10  Lift              1733 non-null   float64
 11  type_of_building  7738 non-null   object 
 12  Price_sqft        7738 non-null   float64
dtypes: float64(9), object(4)
memory usage: 786.0+ KB
```

In [11]:
```
sns.histplot(data=dff,x="Price_sqft",color="b")
plt.xlabel("Price_sqft")
plt.ylabel("Count (Clients)")
plt.title("Price_sqft")
plt.show()
pd.DataFrame(dff["Price_sqft"].describe())
```



Out[11]:

	Price_sqft
count	7738.000000
mean	5543.660241
std	2408.659307
min	2100.000000
25%	3950.986915
50%	4972.674332
75%	6350.638693
max	44378.698225

In [12]:
```
out=dff["Price_sqft"].quantile(0.95)
out
```

Out[12]:
```
10000.0
```

Removing the outliers

In [13]:
```
datf=dff[dff["Price_sqft"]<=out]
datf.reset_index(inplace=True,drop=True)
datf.shape
```

Out[13]:
```
(7360, 13)
```

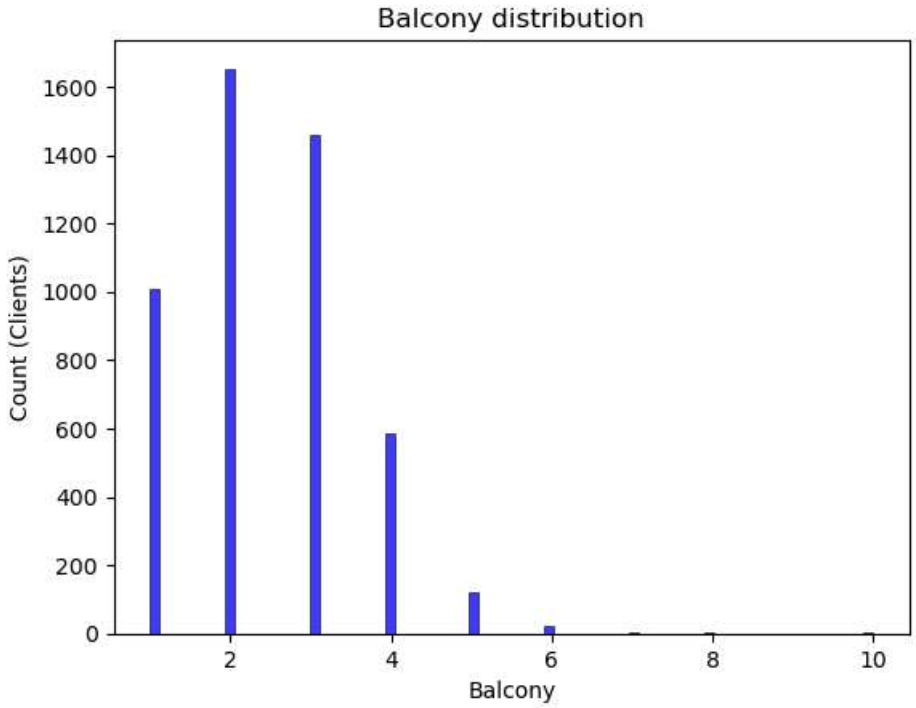
In [14]:
```
datf.head()
```

Out[14]:

	area	latitude	longitude	Bedrooms	Bathrooms	Balcony	Status	neworold	parking	Furnished_status	Lift	type_of_building	Price_
0	1350.0	28.608850	77.460560	3.0	3.0	NaN	Under Construction	New Property	NaN	NaN	2.0	Flat	4148.148
1	1490.0	28.374236	76.952416	3.0	3.0	NaN	Ready to Move	New Property	NaN	Semi-Furnished	2.0	Flat	5906.040
2	2385.0	28.645769	77.385110	4.0	5.0	NaN	Ready to Move	New Property	1.0	Unfurnished	NaN	Flat	6918.238
3	1050.0	28.566914	77.436434	2.0	2.0	3.0	NaN	New Property	1.0	Unfurnished	2.0	Flat	3628.571
4	1350.0	28.520732	77.356491	2.0	2.0	3.0	Ready to Move	Resale	1.0	NaN	3.0	Flat	4592.592

Replacing missing values

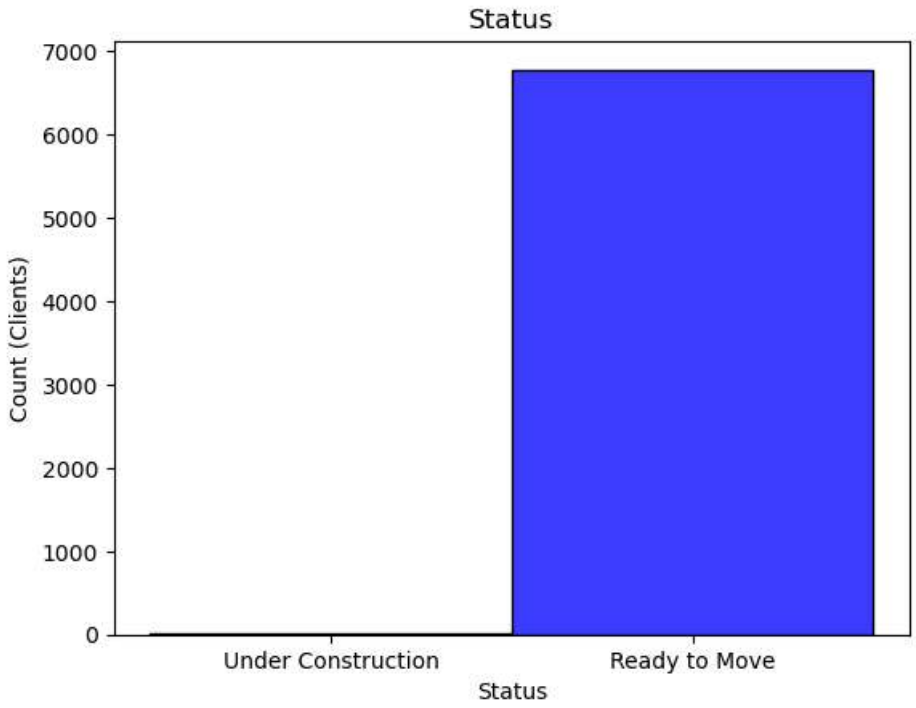
In [15]:
```
sns.histplot(data=datf,x="Balcony",color="b")
plt.xlabel("Balcony")
plt.ylabel("Count (Clients)")
plt.title("Balcony distribution")
plt.show()
print(pd.DataFrame(datf["Balcony"].value_counts()))
```




```
        count
Balcony
2.0      1653
3.0      1457
1.0      1007
4.0       588
5.0       121
6.0        20
10.0        3
7.0         3
8.0         3
9.0         1
```

In [16]:
```
datf["Balcony"].fillna(df["Balcony"].mode().iloc[0],inplace=True)
```

In [17]:
```
sns.histplot(data=datf,x="Status",color="b")
plt.xlabel("Status")
plt.ylabel("Count (Clients)")
plt.title("Status")
plt.show()
print(pd.DataFrame(datf["Status"].value_counts()))
```




```
                    count
Status
Ready to Move        6782
Under Construction     14
```

In [18]:
```
datf["Status"].fillna(df["Status"].mode().iloc[0],inplace=True)
```

In [19]:
```
pd.DataFrame(datf["parking"].value_counts())
```

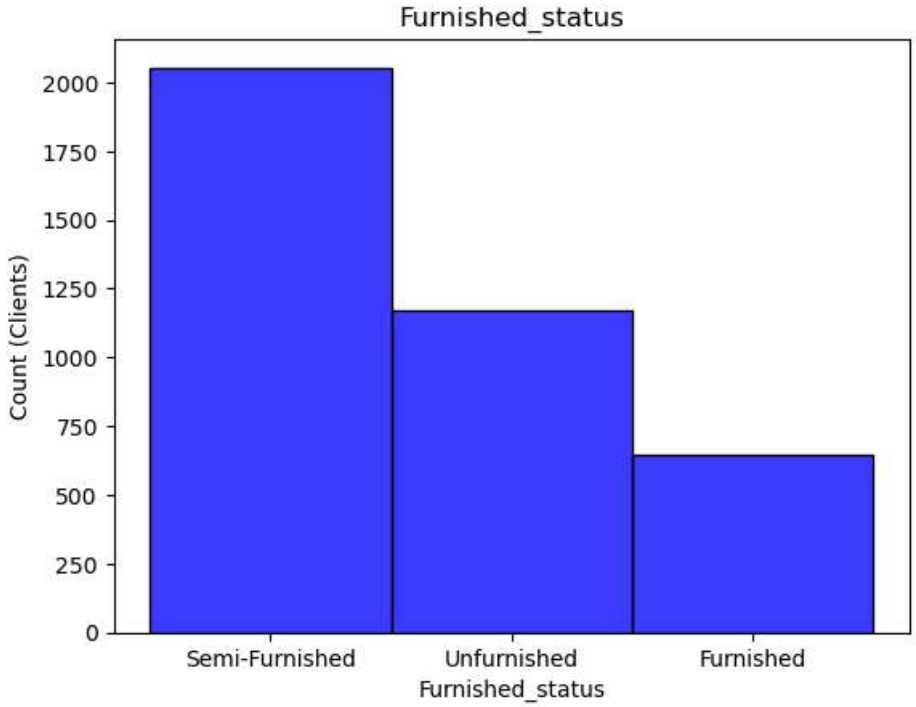
Out[19]:

parking	count
1.0	1651
2.0	574
3.0	84
4.0	29
6.0	10
...	...
18.0	1
602.0	1
16.0	1
624.0	1
179.0	1

63 rows × 1 columns

In [20]:
```
datf["parking"].fillna(df["parking"].mode().iloc[0],inplace=True)
```

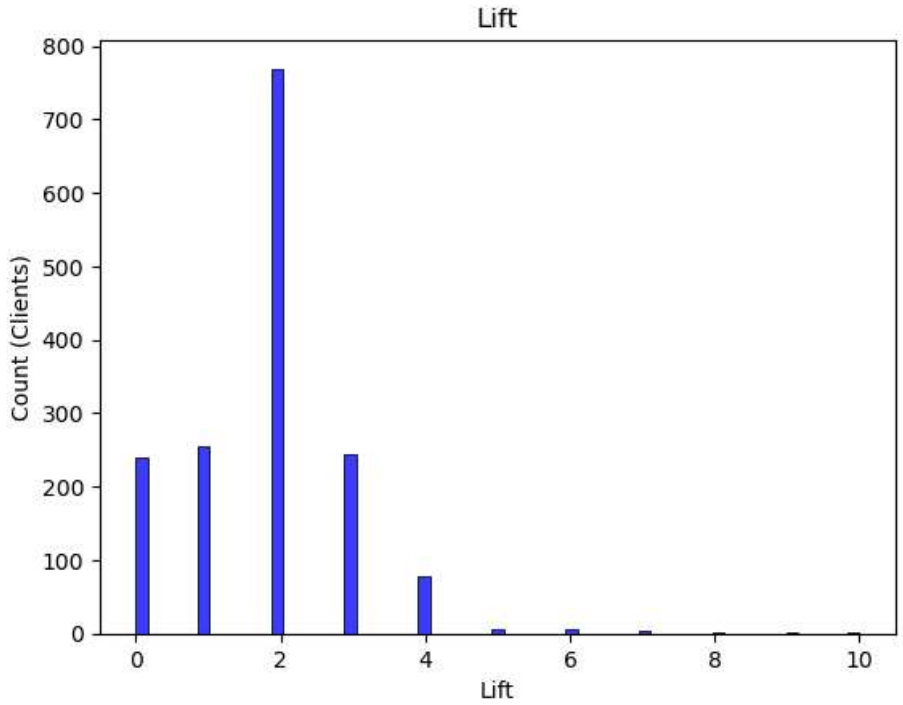
In [21]:
```
sns.histplot(data=datf,x="Furnished_status",color="b")
plt.xlabel("Furnished_status")
plt.ylabel("Count (Clients)")
plt.title("Furnished_status")
plt.show()
print(pd.DataFrame(datf["Furnished_status"].value_counts()))
```



Furnished_status	count
Semi-Furnished	2055
Unfurnished	1172
Furnished	644

In [22]:
```
datf["Furnished_status"].fillna(df["Furnished_status"].mode().iloc[0],inplace=True)
```

In [23]:
```
sns.histplot(data=datf,x="Lift",color="b")
plt.xlabel("Lift")
plt.ylabel("Count (Clients)")
plt.title("Lift")
plt.show()
print(pd.DataFrame(datf["Lift"].value_counts()))
```



```
      count
Lift
2.0     769
1.0     254
3.0     245
0.0     240
4.0      77
6.0       7
5.0       6
7.0       4
10.0      2
8.0       1
9.0       1
```

In [24]:
```
datf["Lift"].fillna(df["Lift"].mode().iloc[0],inplace=True)
```

In [25]:
```
datf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7360 entries, 0 to 7359
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   area              7360 non-null   float64
 1   latitude          7360 non-null   float64
 2   longitude         7360 non-null   float64
 3   Bedrooms          7360 non-null   float64
 4   Bathrooms         7360 non-null   float64
 5   Balcony           7360 non-null   float64
 6   Status            7360 non-null   object
 7   neworold          7360 non-null   object
 8   parking           7360 non-null   float64
 9   Furnished_status  7360 non-null   object
 10  Lift              7360 non-null   float64
 11  type_of_building  7360 non-null   object
 12  Price_sqft        7360 non-null   float64
dtypes: float64(9), object(4)
memory usage: 747.6+ KB
```

In [26]:
```
datf.nunique()
```

Out[26]:
```
area               1057
latitude           2719
longitude          2694
Bedrooms              9
Bathrooms             9
Balcony              10
Status                2
neworold              2
parking              63
Furnished_status      3
Lift                 11
type_of_building      2
Price_sqft         3715
dtype: int64
```

Converting the categorical entries into numerical ones

In [27]:
```
from sklearn.preprocessing import LabelEncoder
final_df=datf
for column in final_df.columns:
    if final_df[column].dtype == 'object':
        le = LabelEncoder()
        final_df[column] = le.fit_transform(final_df[column])
```

In [28]:
```
final_df.corr(numeric_only=True)
```

Out[28]:

	area	latitude	longitude	Bedrooms	Bathrooms	Balcony	Status	neworold	parking	Furnished_status	Lift	typ
area	1.000000	-0.276648	-0.171144	0.708508	0.773638	0.361521	0.024622	-0.067268	-0.013302	-0.014781	0.043350	
latitude	-0.276648	1.000000	0.422607	-0.144976	-0.248055	-0.151663	-0.005987	0.057831	-0.036681	-0.044814	-0.023581	
longitude	-0.171144	0.422607	1.000000	-0.156850	-0.194897	0.059638	0.004647	0.097625	0.003697	-0.008245	0.077498	
Bedrooms	0.708508	-0.144976	-0.156850	1.000000	0.753432	0.237567	0.005778	-0.042055	-0.016233	0.008842	-0.026126	
Bathrooms	0.773638	-0.248055	-0.194897	0.753432	1.000000	0.303258	0.024483	-0.052069	-0.018758	-0.010331	0.016043	
Balcony	0.361521	-0.151663	0.059638	0.237567	0.303258	1.000000	-0.013977	-0.035568	0.011083	0.001216	0.148764	
Status	0.024622	-0.005987	0.004647	0.005778	0.024483	-0.013977	1.000000	-0.127069	-0.002824	-0.006372	0.008236	
neworold	-0.067268	0.057831	0.097625	-0.042055	-0.052069	-0.035568	-0.127069	1.000000	0.016201	-0.004731	0.013361	
parking	-0.013302	-0.036681	0.003697	-0.016233	-0.018758	0.011083	-0.002824	0.016201	1.000000	-0.007023	0.025280	
Furnished_status	-0.014781	-0.044814	-0.008245	0.008842	-0.010331	0.001216	-0.006372	-0.004731	-0.007023	1.000000	0.043218	
Lift	0.043350	-0.023581	0.077498	-0.026126	0.016043	0.148764	0.008236	0.013361	0.025280	0.043218	1.000000	
type_of_building	0.017414	-0.008844	-0.005782	0.010986	0.010026	-0.002599	-0.005648	-0.006983	0.022445	-0.007999	0.018421	
Price_sqft	0.322863	-0.200779	-0.543093	0.313647	0.330614	0.028140	0.008838	-0.074156	-0.018500	-0.052717	-0.069917	

In [29]:
```
final_df.head()
```

Out[29]:

	area	latitude	longitude	Bedrooms	Bathrooms	Balcony	Status	neworold	parking	Furnished_status	Lift	type_of_building	Price_sqft
0	1350.0	28.608850	77.460560	3.0	3.0	2.0	1	0	1.0	1	2.0	0	4148.148148
1	1490.0	28.374236	76.952416	3.0	3.0	2.0	0	0	1.0	1	2.0	0	5906.040268
2	2385.0	28.645769	77.385110	4.0	5.0	2.0	0	0	1.0	2	2.0	0	6918.238994
3	1050.0	28.566914	77.436434	2.0	2.0	3.0	0	0	1.0	2	2.0	0	3628.571429
4	1350.0	28.520732	77.356491	2.0	2.0	3.0	0	1	1.0	1	3.0	0	4592.592593

In [30]:
```
final_df.drop(["Status"],axis=1,inplace=True)
```

In [31]:
```
final_df.shape
```

Out[31]:
```
(7360, 12)
```

In [32]:
```
x=final_df.drop("Price_sqft",axis=1)
y=final_df["Price_sqft"]
x=np.array(x)
y=np.array(y)
```

In [33]:
```
x_col=x.shape[1]
x_col
```

Out[33]:
```
11
```

Splitting the whole dataset into train and test datasets

In [34]:
```
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,random_state=42)
```

Scaling the features

In [35]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.transform(x_test)
```

In [36]:
```
import tensorflow as tf
from tensorflow import keras
from keras import Sequential
```

```
from keras.layers import Dense,BatchNormalization, Dropout
import keras_tuner as kt
```

```
WARNING:tensorflow:From C:\Users\mdsk5\anaconda3\Lib\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softm
ax_cross_entropy is deprecated. Please use tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

Hyperparameter Tuning using RandomSearchCV

In [37]:
```
def build_model(hp):
    model=Sequential()
    model.add(keras.Input(shape=(x_col,)))
    for i in range(hp.Int("layers",min_value=1,max_value=10)):
        model.add(
            Dense(
                hp.Int("unit"+str(i),min_value=5,max_value=300,step=60),
                activation=hp.Choice("activation"+str(i),values=["relu","tanh"])
                )
            )
    model.add(Dense(1,activation="linear"))
    model.compile(optimizer=tf.keras.optimizers.Adam(
                  hp.Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='LOG')),
                  loss="mse",metrics=["mae"])

    return model
```

In [38]:
```
tuner=kt.RandomSearch(build_model,
                      objective="mae",
                      max_trials=20,
                      directory='my_dir',
                      project_name='hp')
```

```
Reloading Tuner from my_dir\hp\tuner0.json
```

In [39]:
```
tuner.search(x_train,y_train,epochs=20,validation_data=(x_test,y_test))
```

```
Trial 20 Complete [00h 00m 09s]
mae: 2395.01318359375

Best mae So Far: 775.0404052734375
Total elapsed time: 00h 03m 51s
```

In [40]:
```
tuner.get_best_hyperparameters()[0].values
```

Out[40]:
```
{'layers': 5,
 'unit0': 245,
 'activation0': 'relu',
 'learning_rate': 0.0002662432681570655,
 'unit1': 5,
 'activation1': 'tanh',
 'unit2': 5,
 'activation2': 'relu',
 'unit3': 245,
 'activation3': 'relu',
 'unit4': 245,
 'activation4': 'relu',
 'unit5': 185,
 'activation5': 'relu',
 'unit6': 125,
 'activation6': 'relu',
 'unit7': 185,
 'activation7': 'tanh',
 'unit8': 125,
 'activation8': 'tanh',
 'unit9': 5,
 'activation9': 'tanh'}
```

In [41]:
```
model=tuner.get_best_models(num_models=1)[0]
model.summary()
```

```
WARNING:tensorflow:From C:\Users\mdsk5\anaconda3\Lib\site-packages\keras\src\saving\legacy\save.py:538: The name tf.train.Ne
wCheckpointReader is deprecated. Please use tf.compat.v1.train.NewCheckpointReader instead.

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 245)               2940

 dense_1 (Dense)             (None, 5)                 1230

 dense_2 (Dense)             (None, 5)                 30

 dense_3 (Dense)             (None, 245)               1470

 dense_4 (Dense)             (None, 245)               60270

 dense_5 (Dense)             (None, 1)                 246

=================================================================
Total params: 66186 (258.54 KB)
Trainable params: 66186 (258.54 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Using callbacks to prevent overfitting

In [42]:
```
callback=keras.callbacks.EarlyStopping(
    monitor="val_loss",
    min_delta=0,
    patience=5,
    verbose=1,
    mode="auto",
    baseline=None,
)
```

In [43]:
```
history=model.fit(x_train,y_train,epochs=200,validation_data=(x_test,y_test),callbacks=callback)
```

```
Epoch 1/200
184/184 [==============================] - 1s 3ms/step - loss: 1050349.7500 - mae: 771.1406 - val_loss: 1134551.2500 - val_m
ae: 805.5239
Epoch 2/200
184/184 [==============================] - 0s 2ms/step - loss: 1041084.1875 - mae: 766.4742 - val_loss: 1124809.7500 - val_m
ae: 806.0350
Epoch 3/200
184/184 [==============================] - 0s 2ms/step - loss: 1030343.5625 - mae: 762.7241 - val_loss: 1116075.7500 - val_m
ae: 801.4805
Epoch 4/200
184/184 [==============================] - 0s 2ms/step - loss: 1021626.1875 - mae: 759.6195 - val_loss: 1137453.5000 - val_m
ae: 801.6863
Epoch 5/200
184/184 [==============================] - 0s 2ms/step - loss: 1015045.3750 - mae: 755.0263 - val_loss: 1109939.8750 - val_m
ae: 798.3193
Epoch 6/200
184/184 [==============================] - 0s 2ms/step - loss: 1008032.6250 - mae: 752.6318 - val_loss: 1099815.5000 - val_m
ae: 793.0822
Epoch 7/200
184/184 [==============================] - 0s 2ms/step - loss: 997602.4375 - mae: 749.6944 - val_loss: 1103051.2500 - val_ma
e: 792.4496
Epoch 8/200
184/184 [==============================] - 0s 2ms/step - loss: 989874.0000 - mae: 747.2515 - val_loss: 1091946.1250 - val_ma
e: 783.2615
Epoch 9/200
184/184 [==============================] - 0s 2ms/step - loss: 987049.1250 - mae: 745.0770 - val_loss: 1085937.8750 - val_ma
e: 788.6705
Epoch 10/200
184/184 [==============================] - 1s 3ms/step - loss: 978434.8750 - mae: 742.0422 - val_loss: 1075823.7500 - val_ma
e: 780.5148
Epoch 11/200
184/184 [==============================] - 0s 2ms/step - loss: 974809.5625 - mae: 740.3794 - val_loss: 1077887.0000 - val_ma
e: 785.3599
Epoch 12/200
184/184 [==============================] - 0s 2ms/step - loss: 964707.1250 - mae: 734.7602 - val_loss: 1072209.8750 - val_ma
e: 783.3728
Epoch 13/200
184/184 [==============================] - 0s 2ms/step - loss: 956347.9375 - mae: 731.6196 - val_loss: 1059081.7500 - val_ma
e: 775.7266
Epoch 14/200
184/184 [==============================] - 0s 2ms/step - loss: 955677.8125 - mae: 733.4897 - val_loss: 1069719.6250 - val_ma
e: 769.1562
Epoch 15/200
184/184 [==============================] - 0s 2ms/step - loss: 948833.3750 - mae: 728.4099 - val_loss: 1052706.6250 - val_ma
e: 774.6198
Epoch 16/200
184/184 [==============================] - 0s 2ms/step - loss: 940407.5000 - mae: 726.6315 - val_loss: 1061406.1250 - val_ma
e: 767.3257
Epoch 17/200
184/184 [==============================] - 0s 2ms/step - loss: 940823.5000 - mae: 725.0844 - val_loss: 1054740.7500 - val_ma
e: 777.8772
Epoch 18/200
184/184 [==============================] - 0s 2ms/step - loss: 932829.5625 - mae: 724.0141 - val_loss: 1052434.6250 - val_ma
e: 777.4741
Epoch 19/200
184/184 [==============================] - 0s 2ms/step - loss: 932989.1875 - mae: 723.5446 - val_loss: 1040966.0625 - val_ma
e: 763.0253
Epoch 20/200
184/184 [==============================] - 0s 2ms/step - loss: 926398.0000 - mae: 718.0724 - val_loss: 1037669.7500 - val_ma
e: 764.5653
Epoch 21/200
184/184 [==============================] - 0s 2ms/step - loss: 917791.5000 - mae: 717.8456 - val_loss: 1036296.4375 - val_ma
e: 759.4383
Epoch 22/200
184/184 [==============================] - 0s 2ms/step - loss: 923847.5000 - mae: 719.1830 - val_loss: 1048330.9375 - val_ma
e: 765.0922
Epoch 23/200
184/184 [==============================] - 0s 2ms/step - loss: 914069.8125 - mae: 714.0080 - val_loss: 1031397.7500 - val_ma
e: 763.8140
Epoch 24/200
184/184 [==============================] - 0s 2ms/step - loss: 911961.1875 - mae: 713.8069 - val_loss: 1031482.6875 - val_ma
e: 756.2954
Epoch 25/200
184/184 [==============================] - 0s 2ms/step - loss: 908059.6250 - mae: 712.2388 - val_loss: 1026844.0625 - val_ma
e: 761.4702
Epoch 26/200
184/184 [==============================] - 0s 2ms/step - loss: 904484.1875 - mae: 710.7975 - val_loss: 1041968.0000 - val_ma
e: 764.5232
```

```
Epoch 27/200
184/184 [==============================] - 0s 2ms/step - loss: 900236.6875 - mae: 709.2963 - val_loss: 1025207.7500 - val_ma
e: 761.3053
Epoch 28/200
184/184 [==============================] - 0s 3ms/step - loss: 898880.9375 - mae: 709.0389 - val_loss: 1024822.1875 - val_ma
e: 762.2409
Epoch 29/200
184/184 [==============================] - 0s 2ms/step - loss: 897594.4375 - mae: 708.5884 - val_loss: 1017260.8125 - val_ma
e: 758.2079
Epoch 30/200
184/184 [==============================] - 0s 2ms/step - loss: 896890.9375 - mae: 706.1305 - val_loss: 1015632.0625 - val_ma
e: 752.6676
Epoch 31/200
184/184 [==============================] - 0s 2ms/step - loss: 891738.1875 - mae: 706.9269 - val_loss: 1018317.5000 - val_ma
e: 753.8192
Epoch 32/200
184/184 [==============================] - 0s 2ms/step - loss: 888681.9375 - mae: 706.4627 - val_loss: 1020068.0625 - val_ma
e: 759.7234
Epoch 33/200
184/184 [==============================] - 0s 2ms/step - loss: 885374.9375 - mae: 704.3605 - val_loss: 1023940.6250 - val_ma
e: 761.7509
Epoch 34/200
184/184 [==============================] - 0s 2ms/step - loss: 882950.8750 - mae: 702.7349 - val_loss: 1030001.6250 - val_ma
e: 757.2977
Epoch 35/200
184/184 [==============================] - 0s 2ms/step - loss: 879903.6250 - mae: 702.5853 - val_loss: 1006441.6250 - val_ma
e: 748.2228
Epoch 36/200
184/184 [==============================] - 0s 2ms/step - loss: 879767.5625 - mae: 701.7951 - val_loss: 1004853.6250 - val_ma
e: 747.8186
Epoch 37/200
184/184 [==============================] - 0s 2ms/step - loss: 874734.0625 - mae: 700.2505 - val_loss: 1021284.2500 - val_ma
e: 753.0834
Epoch 38/200
184/184 [==============================] - 0s 2ms/step - loss: 874325.3750 - mae: 699.5425 - val_loss: 1011568.4375 - val_ma
e: 756.8805
Epoch 39/200
184/184 [==============================] - 0s 2ms/step - loss: 867895.0625 - mae: 697.3554 - val_loss: 1021232.5000 - val_ma
e: 752.7552
Epoch 40/200
184/184 [==============================] - 0s 2ms/step - loss: 869066.8750 - mae: 698.2853 - val_loss: 1009981.7500 - val_ma
e: 745.3506
Epoch 41/200
184/184 [==============================] - 0s 2ms/step - loss: 867708.4375 - mae: 696.8190 - val_loss: 1008312.6875 - val_ma
e: 753.9169
Epoch 41: early stopping
```

Model evaluation

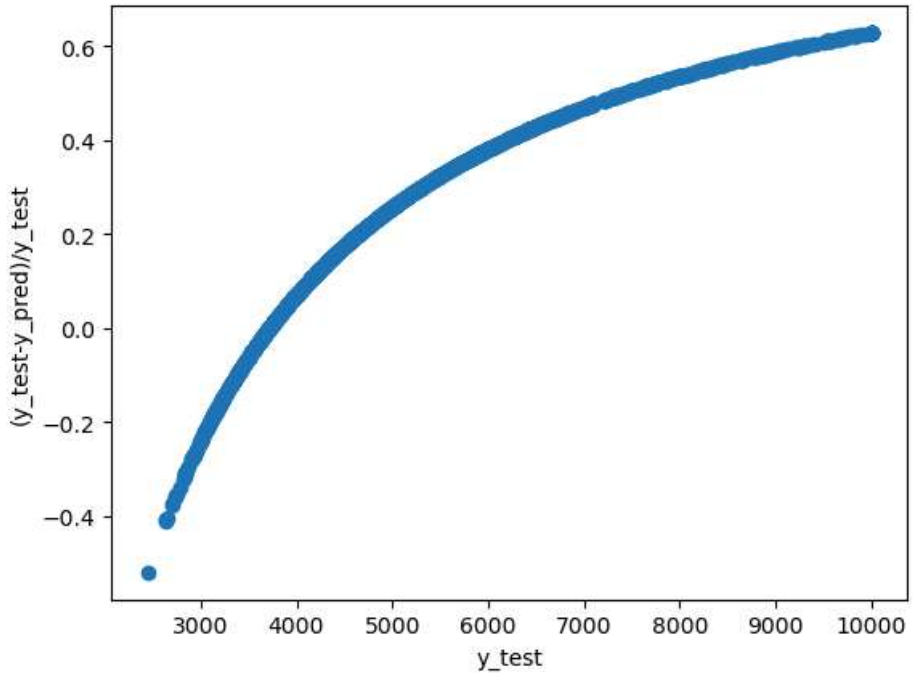
In [44]:
```
from sklearn.metrics import mean_absolute_error,r2_score,accuracy_score

# Compute MAE
y_pred=model.predict(x_test)
mae = mean_absolute_error(y_test,y_pred )
r2=r2_score(y_test,y_pred)
print(f"Mean Absolute Error (MAE): {mae}")
print(f"r2 score: {r2}")
```

```
46/46 [==============================] - 0s 1ms/step
Mean Absolute Error (MAE): 753.916823335624
r2 score: 0.6421548497867977
```

Plotting relative differences in output

In [45]:
```
res=y_test-y_pred[0]
plt.scatter(y_test,res/y_test)
plt.xlabel("y_test")
plt.ylabel("(y_test-y_pred)/y_test")
plt.show()
```



Comparison the performance between train and validation datasets

In [46]:
```
plt.plot(history.history["mae"],color="red",label="train")
plt.plot(history.history["val_mae"],color="blue",label="validation")
plt.title('mae')
plt.ylabel('mae')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```