dlcuvasle

March 20, 2025

#Importing necessary libraries

1 Starting by importing necassary libraries for data handling, preprocessing, and evaluation.

[30]:
```
#Importing necessary libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
import torch
import torch.nn as nn
import torch.optim as optim
from sklearn.impute import SimpleImputer
from torch.utils.data import DataLoader, TensorDataset
```

#Loading the dataset

2 Loading the Ames Housing dataset into Pandas DataFrame to look into its structure.

[31]:
```
#Loading the dataset
df=pd.read_csv("/content/AmesHousing.csv")
df.head()
```

[31]:
```
   Order        PID  MS SubClass MS Zoning  Lot Frontage  Lot Area Street  \
0      1  526301100           20        RL         141.0     31770   Pave
1      2  526350040           20        RH          80.0     11622   Pave
2      3  526351010           20        RL          81.0     14267   Pave
3      4  526353030           20        RL          93.0     11160   Pave
4      5  527105010           60        RL          74.0     13830   Pave
```

```
  Alley Lot Shape Land Contour  … Pool Area Pool QC  Fence Misc Feature  \
0   NaN       IR1          Lvl  …         0     NaN    NaN          NaN
1   NaN       Reg          Lvl  …         0     NaN  MnPrv          NaN
2   NaN       IR1          Lvl  …         0     NaN    NaN         Gar2
3   NaN       Reg          Lvl  …         0     NaN    NaN          NaN
4   NaN       IR1          Lvl  …         0     NaN  MnPrv          NaN

  Misc Val Mo Sold Yr Sold Sale Type  Sale Condition  SalePrice
0        0       5    2010       WD           Normal     215000
1        0       6    2010       WD           Normal     105000
2    12500       6    2010       WD           Normal     172000
3        0       4    2010       WD           Normal     244000
4        0       3    2010       WD           Normal     189900

[5 rows x 82 columns]
```

[32]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2930 entries, 0 to 2929
Data columns (total 82 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Order            2930 non-null   int64
 1   PID              2930 non-null   int64
 2   MS SubClass      2930 non-null   int64
 3   MS Zoning        2930 non-null   object
 4   Lot Frontage     2440 non-null   float64
 5   Lot Area         2930 non-null   int64
 6   Street           2930 non-null   object
 7   Alley            198 non-null    object
 8   Lot Shape        2930 non-null   object
 9   Land Contour     2930 non-null   object
 10  Utilities        2930 non-null   object
 11  Lot Config       2930 non-null   object
 12  Land Slope       2930 non-null   object
 13  Neighborhood     2930 non-null   object
 14  Condition 1      2930 non-null   object
 15  Condition 2      2930 non-null   object
 16  Bldg Type        2930 non-null   object
 17  House Style      2930 non-null   object
 18  Overall Qual     2930 non-null   int64
 19  Overall Cond     2930 non-null   int64
 20  Year Built       2930 non-null   int64
 21  Year Remod/Add   2930 non-null   int64
 22  Roof Style       2930 non-null   object
```

```
23  Roof Matl        2930 non-null   object
24  Exterior 1st     2930 non-null   object
25  Exterior 2nd     2930 non-null   object
26  Mas Vnr Type     1155 non-null   object
27  Mas Vnr Area     2907 non-null   float64
28  Exter Qual       2930 non-null   object
29  Exter Cond       2930 non-null   object
30  Foundation       2930 non-null   object
31  Bsmt Qual        2850 non-null   object
32  Bsmt Cond        2850 non-null   object
33  Bsmt Exposure    2847 non-null   object
34  BsmtFin Type 1   2850 non-null   object
35  BsmtFin SF 1     2929 non-null   float64
36  BsmtFin Type 2   2849 non-null   object
37  BsmtFin SF 2     2929 non-null   float64
38  Bsmt Unf SF      2929 non-null   float64
39  Total Bsmt SF    2929 non-null   float64
40  Heating          2930 non-null   object
41  Heating QC       2930 non-null   object
42  Central Air      2930 non-null   object
43  Electrical       2929 non-null   object
44  1st Flr SF       2930 non-null   int64
45  2nd Flr SF       2930 non-null   int64
46  Low Qual Fin SF  2930 non-null   int64
47  Gr Liv Area      2930 non-null   int64
48  Bsmt Full Bath   2928 non-null   float64
49  Bsmt Half Bath   2928 non-null   float64
50  Full Bath        2930 non-null   int64
51  Half Bath        2930 non-null   int64
52  Bedroom AbvGr    2930 non-null   int64
53  Kitchen AbvGr    2930 non-null   int64
54  Kitchen Qual     2930 non-null   object
55  TotRms AbvGrd    2930 non-null   int64
56  Functional       2930 non-null   object
57  Fireplaces       2930 non-null   int64
58  Fireplace Qu     1508 non-null   object
59  Garage Type      2773 non-null   object
60  Garage Yr Blt    2771 non-null   float64
61  Garage Finish    2771 non-null   object
62  Garage Cars      2929 non-null   float64
63  Garage Area      2929 non-null   float64
64  Garage Qual      2771 non-null   object
65  Garage Cond      2771 non-null   object
66  Paved Drive      2930 non-null   object
67  Wood Deck SF     2930 non-null   int64
68  Open Porch SF    2930 non-null   int64
69  Enclosed Porch   2930 non-null   int64
70  3Ssn Porch       2930 non-null   int64
```

```
 71  Screen Porch     2930 non-null   int64
 72  Pool Area        2930 non-null   int64
 73  Pool QC          13 non-null     object
 74  Fence            572 non-null    object
 75  Misc Feature     106 non-null    object
 76  Misc Val         2930 non-null   int64
 77  Mo Sold          2930 non-null   int64
 78  Yr Sold          2930 non-null   int64
 79  Sale Type        2930 non-null   object
 80  Sale Condition   2930 non-null   object
 81  SalePrice        2930 non-null   int64
dtypes: float64(11), int64(28), object(43)
memory usage: 1.8+ MB
```

#Kept only important features and dropped others

[33]:
```python
# Selecting relevant features and dropping remaining
col= ['Lot Area', 'Gr Liv Area', 'Total Bsmt SF', 'Garage Cars',
                   'Overall Qual','Year Built', 'Year Remod/Add',
                   'Full Bath','Bsmt Qual','Neighborhood','Kitchen Qual',
                   'Garage Type','Overall Cond', 'SalePrice']

df = df[col]
print(df.head())
```

```
   Lot Area  Gr Liv Area  Total Bsmt SF  Garage Cars  Overall Qual  \
0     31770         1656         1080.0          2.0             6
1     11622          896          882.0          1.0             5
2     14267         1329         1329.0          1.0             6
3     11160         2110         2110.0          2.0             7
4     13830         1629          928.0          2.0             5

   Year Built  Year Remod/Add  Full Bath Bsmt Qual Neighborhood Kitchen Qual  \
0        1960            1960          1        TA        NAmes           TA
1        1961            1961          1        TA        NAmes           TA
2        1958            1958          1        TA        NAmes           Gd
3        1968            1968          2        TA        NAmes           Ex
4        1997            1998          2        Gd      Gilbert           TA

  Garage Type  Overall Cond  SalePrice
0      Attchd             5     215000
1      Attchd             6     105000
2      Attchd             6     172000
3      Attchd             5     244000
4      Attchd             5     189900
```

[34]:
```python
# Summary statistics
df.describe()
```

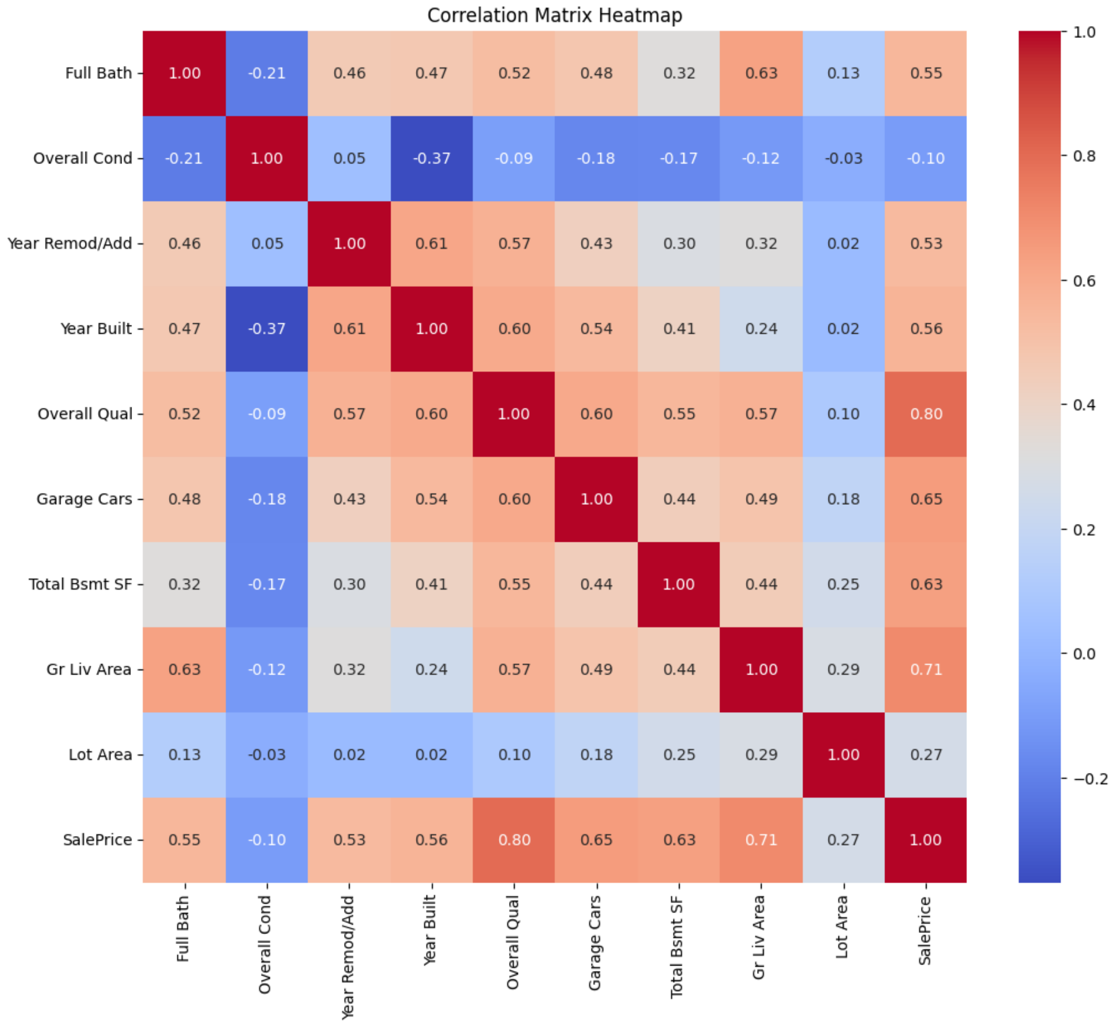
[34]:

```
              Lot Area   Gr Liv Area  Total Bsmt SF  Garage Cars  Overall Qual  \
count    2930.000000  2930.000000    2929.000000  2929.000000   2930.000000   
mean    10147.921843  1499.690444    1051.614544     1.766815      6.094881   
std      7880.017759   505.508887     440.615067     0.760566      1.411026   
min      1300.000000   334.000000       0.000000     0.000000      1.000000   
25%      7440.250000  1126.000000     793.000000     1.000000      5.000000   
50%      9436.500000  1442.000000     990.000000     2.000000      6.000000   
75%     11555.250000  1742.750000    1302.000000     2.000000      7.000000   
max    215245.000000  5642.000000    6110.000000     5.000000     10.000000   

        Year Built  Year Remod/Add    Full Bath  Overall Cond      SalePrice  
count  2930.000000     2930.000000  2930.000000   2930.000000    2930.000000  
mean   1971.356314     1984.266553     1.566553      5.563140  180796.060068  
std      30.245361       20.860286     0.552941      1.111537   79886.692357  
min    1872.000000     1950.000000     0.000000      1.000000   12789.000000  
25%    1954.000000     1965.000000     1.000000      5.000000  129500.000000  
50%    1973.000000     1993.000000     2.000000      5.000000  160000.000000  
75%    2001.000000     2004.000000     2.000000      6.000000  213500.000000  
max    2010.000000     2010.000000     4.000000      9.000000  755000.000000  
```

3 Generating a heatmap to visualize the correlation between numerical features and Sale Price.

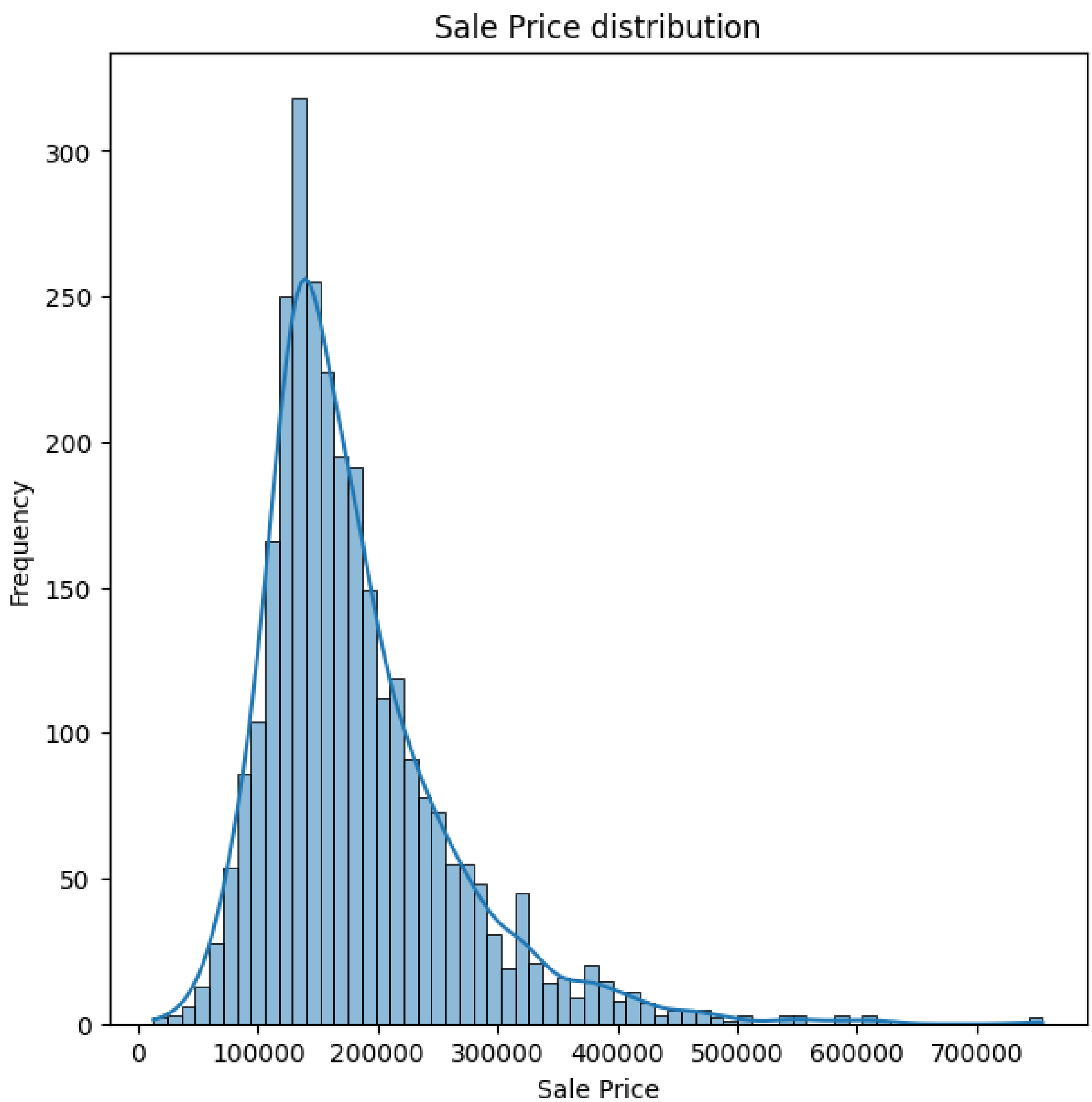
[35]:

```python
#Data Visualization
# Correlation Heatmap for numerical features

columns_for_heatmap = ['Full Bath', 'Overall Cond', 'Year Remod/Add',
                        'Year Built', 'Overall Qual', 'Garage Cars',
                        'Total Bsmt SF', 'Gr Liv Area', 'Lot Area', 'SalePrice']

heatmap_df = df[columns_for_heatmap]

correlation_matrix = heatmap_df.corr()

plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix Heatmap')
plt.show()
```



4 The histogram shows the distribution of Sale Prices in the dataset.

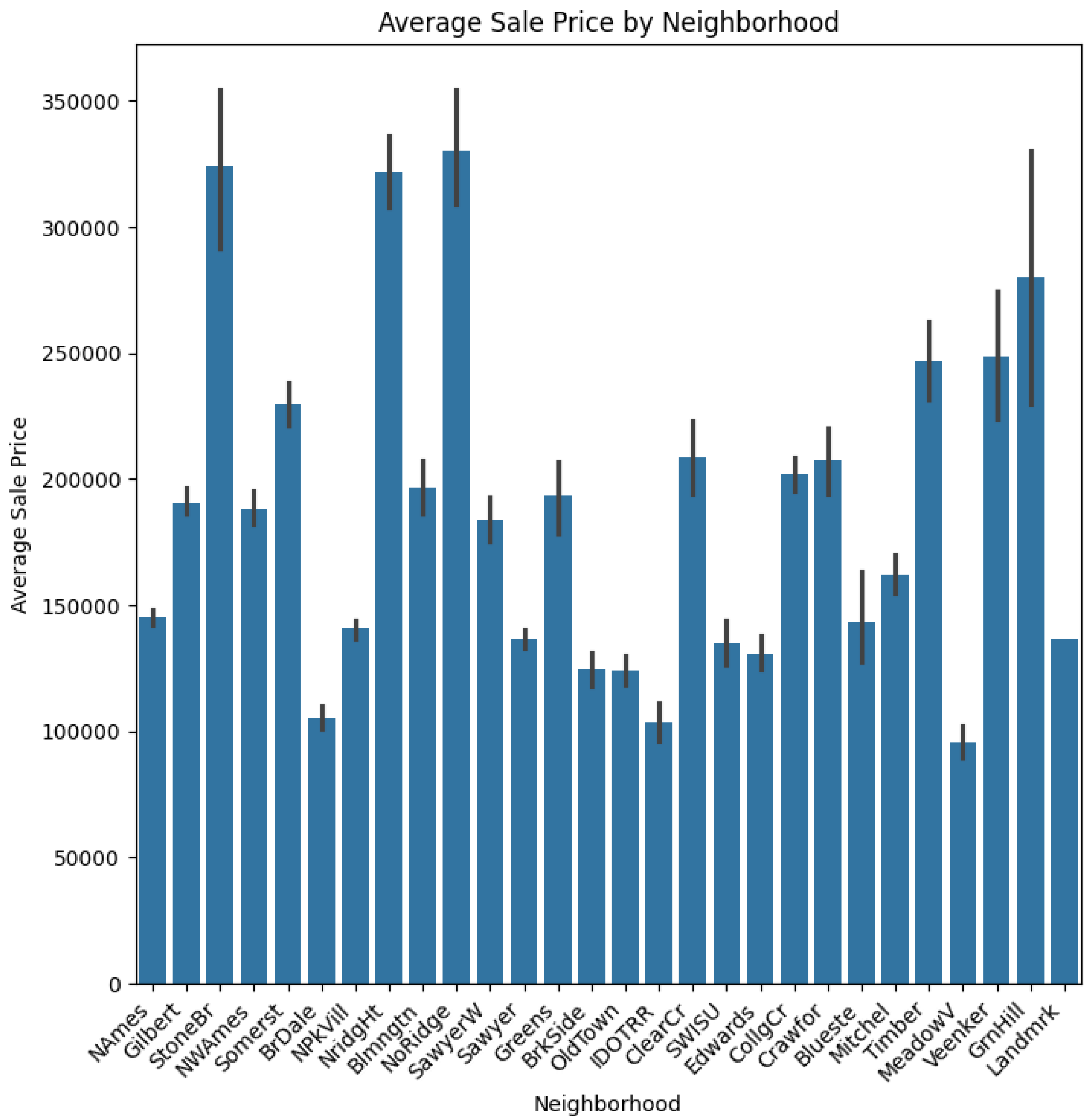
[36]:
```
#Sale Price distribution
plt.figure(figsize=(7,7))
sns.histplot(df['SalePrice'], kde=True)
plt.title('Sale Price distribution')
plt.xlabel('Sale Price')
plt.ylabel('Frequency')
plt.show()
```

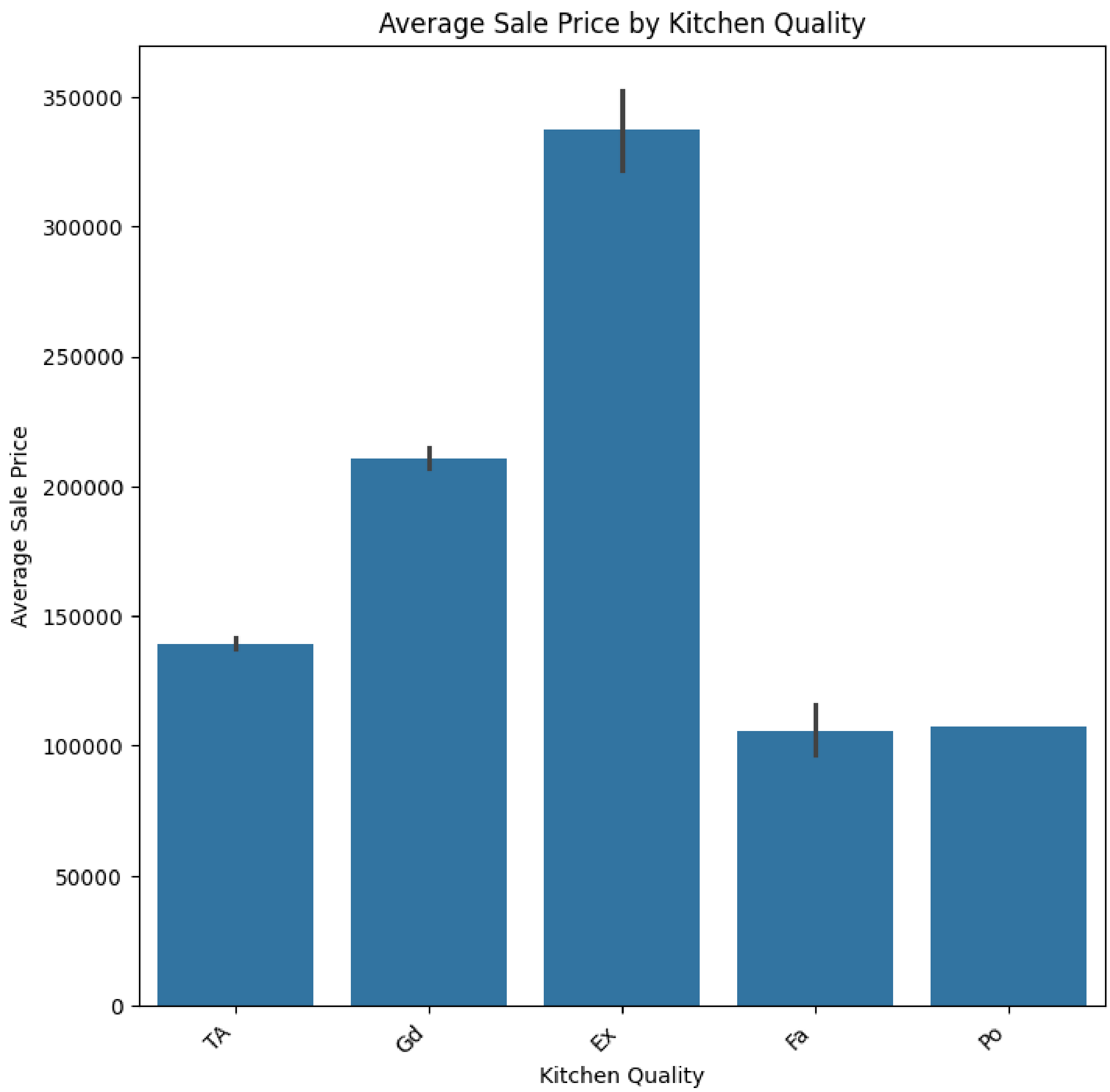


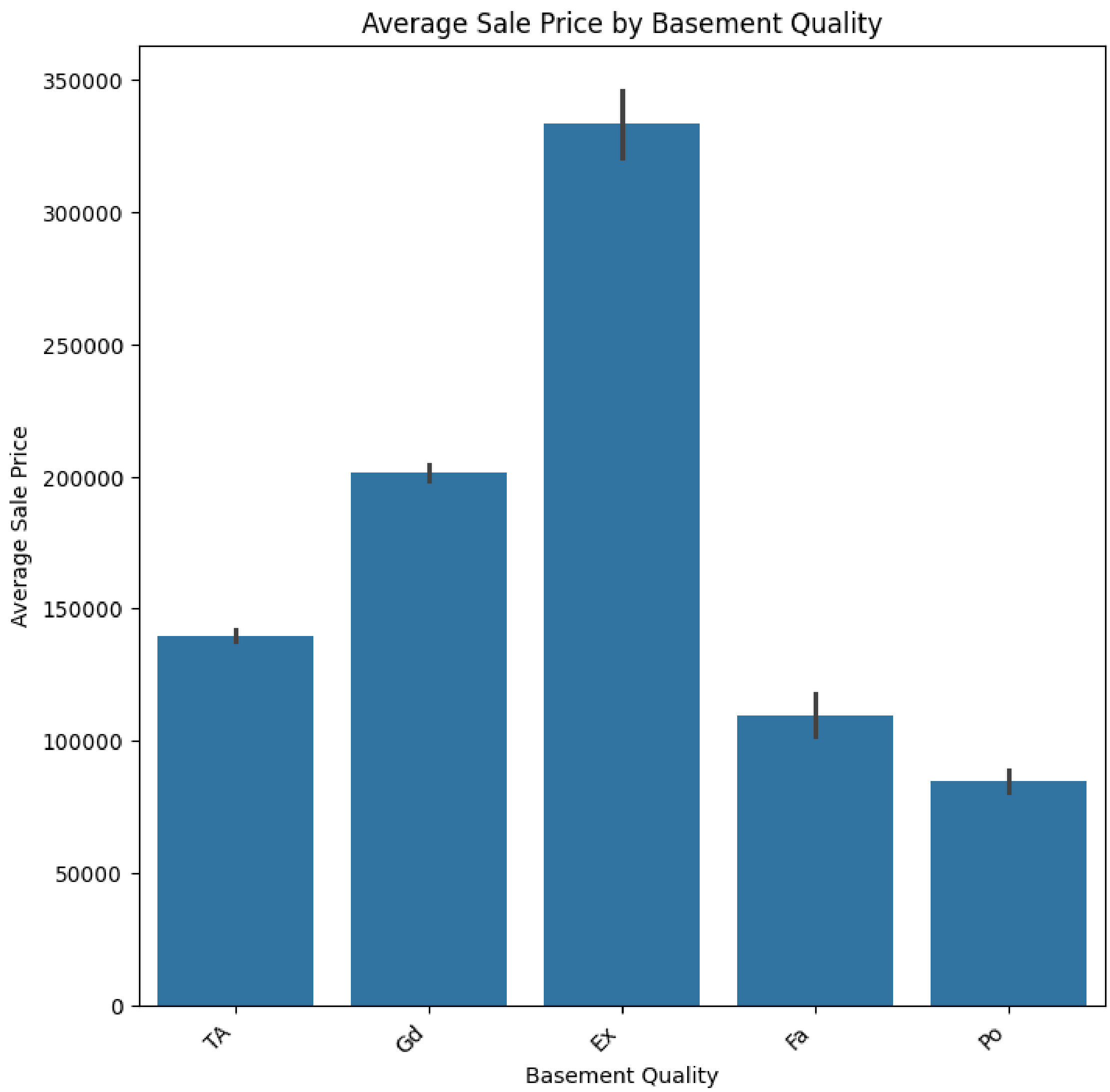
5 Used bar plots to analyze the effect of categorical variables on Sale Price.

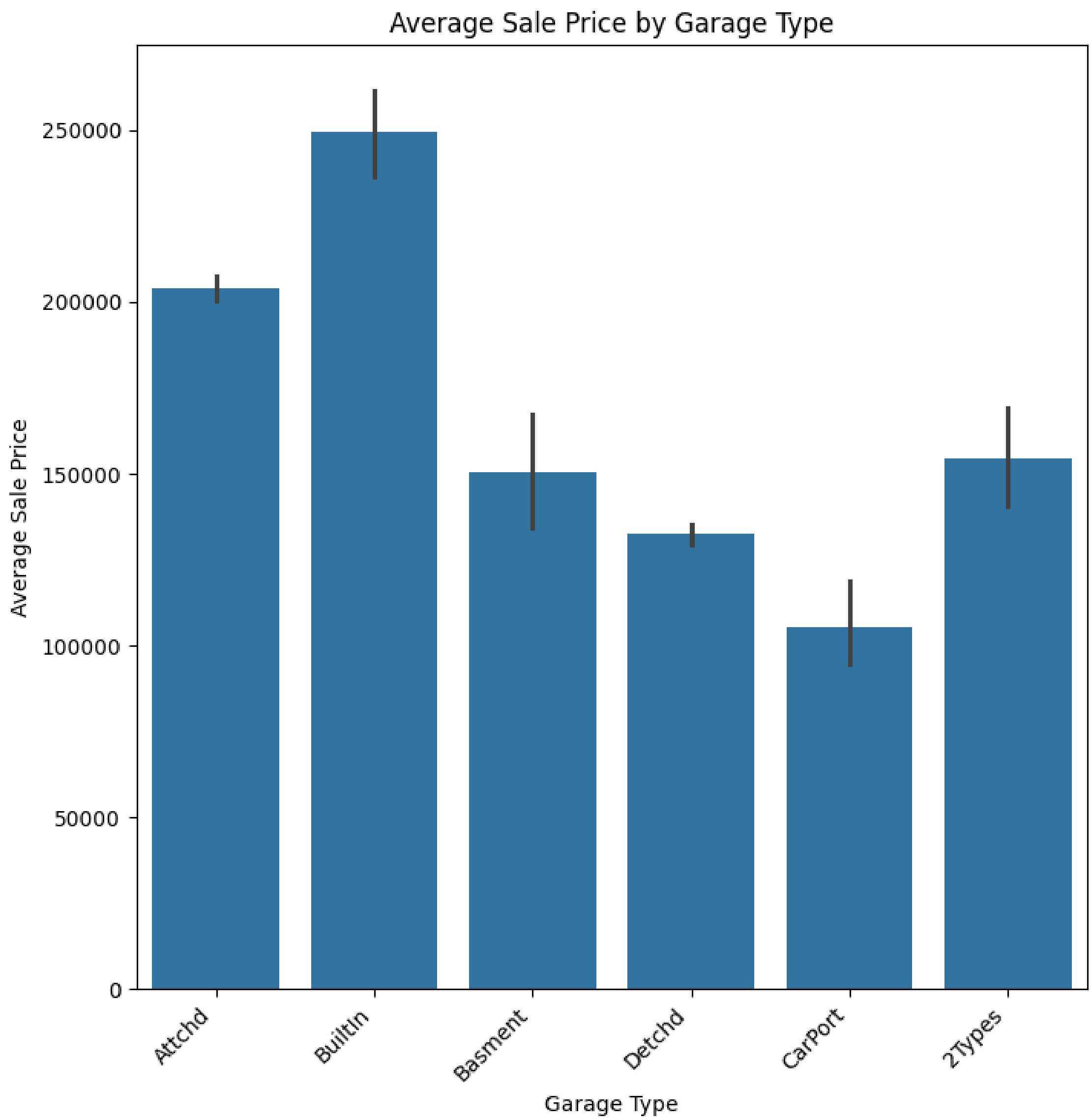
[37]:
```
# Feature Analysis for Categorical features
# Sale Price by Neighborhood
plt.figure(figsize=(8,8))
sns.barplot(x='Neighborhood', y='SalePrice', data=df, estimator=np.mean)
plt.title('Average Sale Price by Neighborhood')
plt.xlabel('Neighborhood')
plt.ylabel('Average Sale Price')
plt.xticks(rotation=45, ha='right')
```

```
plt.show()

# Sale Price by Kitchen Qual
plt.figure(figsize=(8,8))
sns.barplot(x='Kitchen Qual', y='SalePrice', data=df, estimator=np.mean)
plt.title('Average Sale Price by Kitchen Quality')
plt.xlabel('Kitchen Quality')
plt.ylabel('Average Sale Price')
plt.xticks(rotation=45, ha='right')
plt.show()

# Sale Price by Bsmt Qual
plt.figure(figsize=(8,8))
sns.barplot(x='Bsmt Qual', y='SalePrice', data=df, estimator=np.mean)
plt.title('Average Sale Price by Basement Quality')
plt.xlabel('Basement Quality')
plt.ylabel('Average Sale Price')
plt.xticks(rotation=45, ha='right')
plt.show()

# Sale Price by Garage Type
plt.figure(figsize=(8,8))
sns.barplot(x='Garage Type', y='SalePrice', data=df, estimator=np.mean)
plt.title('Average Sale Price by Garage Type')
plt.xlabel('Garage Type')
plt.ylabel('Average Sale Price')
plt.xticks(rotation=45, ha='right')
plt.show()
```


Average Sale Price by Neighborhood
Average Sale Price
350000
300000
250000
200000
150000
100000
50000
0
NAmes
Gilbert
StoneBr
NWAmes
Somerst
BrDale
NPkVill
NridgHt
Blmngtn
NoRidge
SawyerW
Sawyer
Greens
BrkSide
OldTown
IDOTRR
ClearCr
SWISU
Edwards
CollgCr
Crawfor
Blueste
Mitchel
Timber
MeadowV
Veenker
GrnHill
Landmrk
Neighborhood


Average Sale Price by Kitchen Quality
350000
300000
250000
200000
150000
100000
50000
0
Average Sale Price
TA
Gd
Ex
Fa
Po
Kitchen Quality

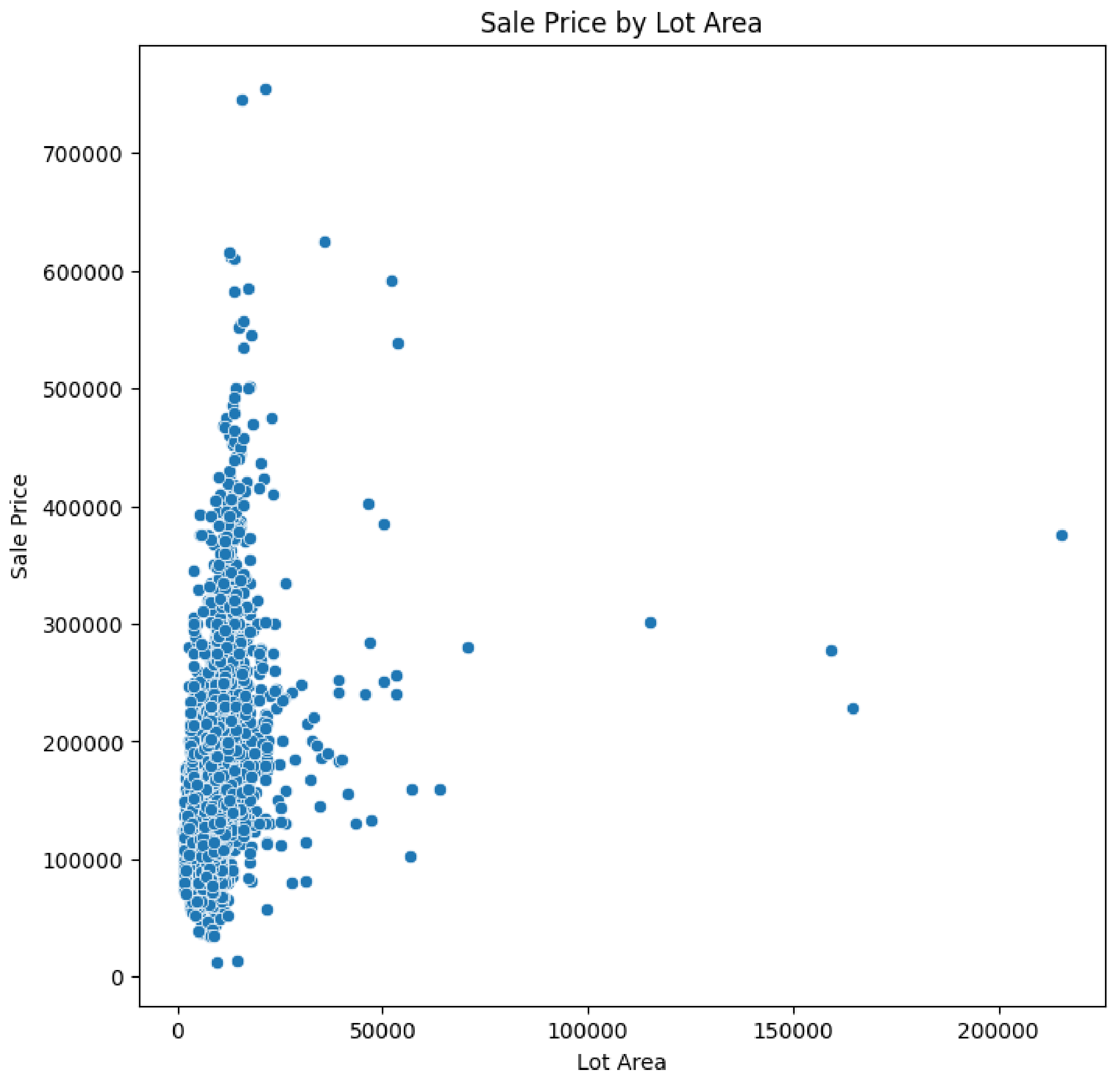

Average Sale Price by Basement Quality
Average Sale Price
350000
300000
250000
200000
150000
100000
50000
0
TA
Gd
Ex
Fa
Po
Basement Quality

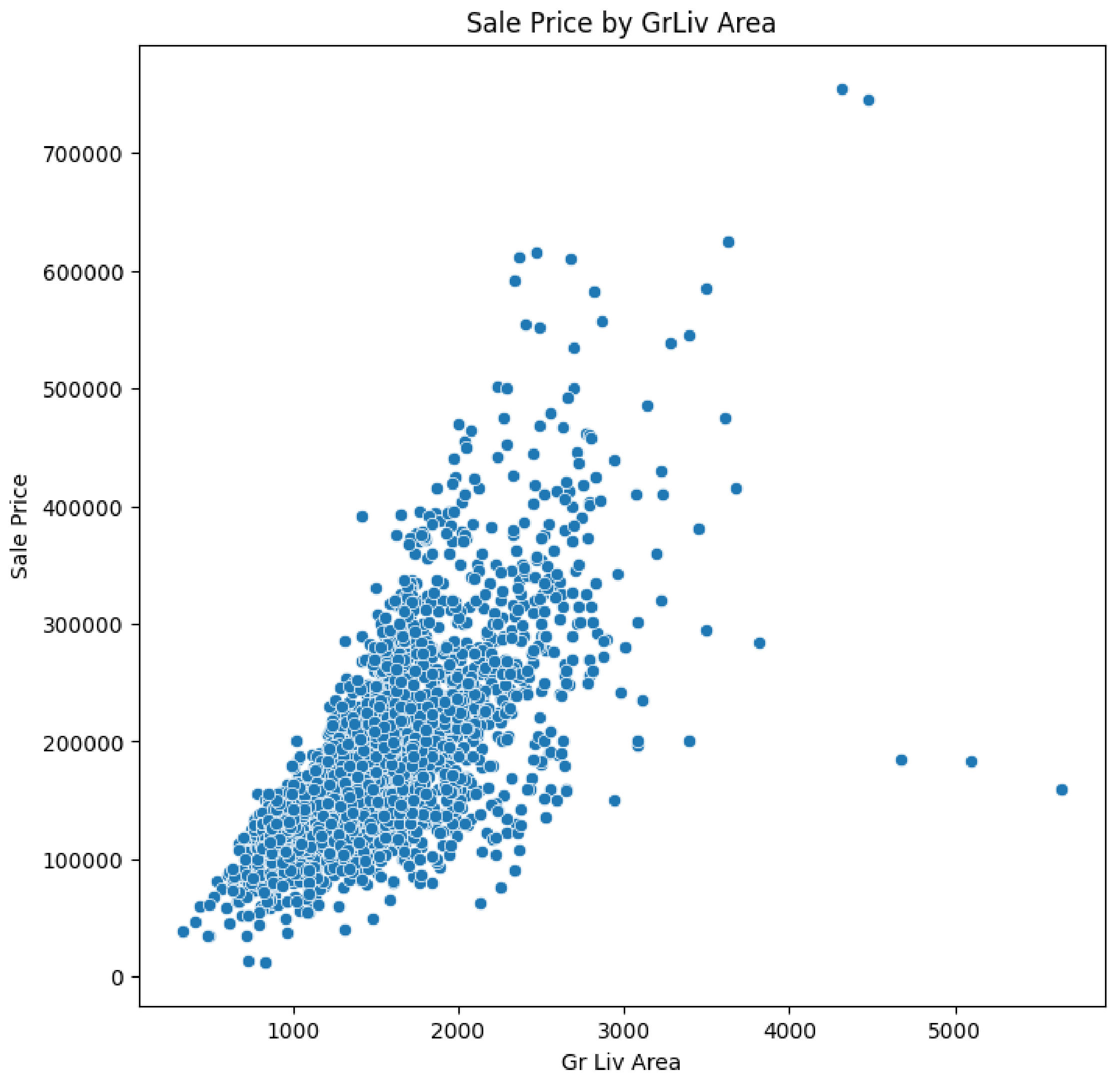


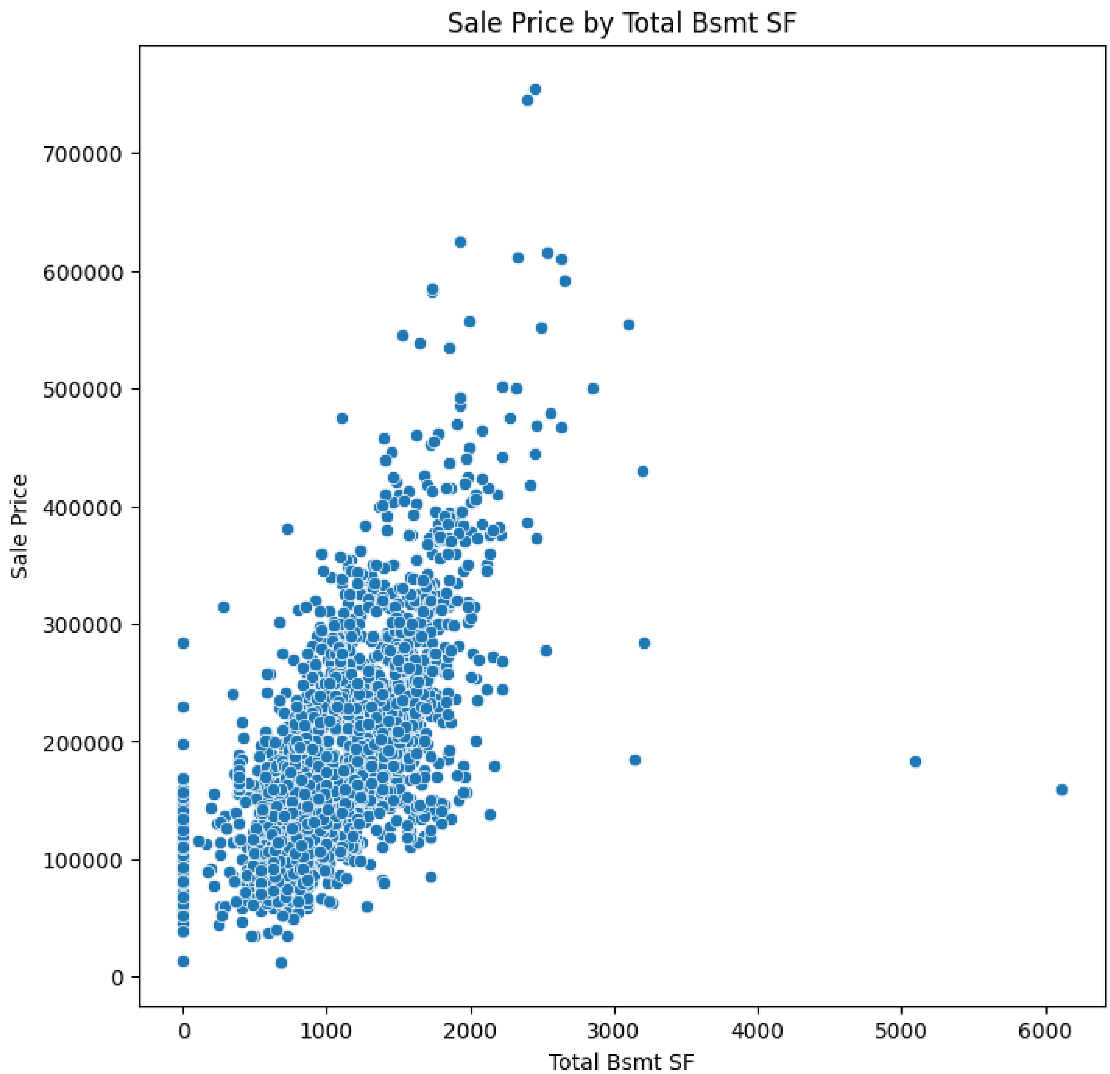
6 Used Scatter plots to identify patterns and trends with respect to Sales Price

[38]:
```
# Feature Analysis Numerical Features

# Sale Price by Lot Area
plt.figure(figsize=(8,8))
sns.scatterplot(x='Lot Area', y='SalePrice', data=df)
plt.title('Sale Price by Lot Area')
plt.xlabel('Lot Area')
plt.ylabel('Sale Price')
```

```python
plt.show()

# Sale Price by Gr Liv Area
plt.figure(figsize=(8,8))
sns.scatterplot(x='Gr Liv Area', y='SalePrice', data=df)
plt.title('Sale Price by GrLiv Area')
plt.xlabel('Gr Liv Area')
plt.ylabel('Sale Price')
plt.show()

# Sale Price by Total Bsmt SF
plt.figure(figsize=(8,8))
sns.scatterplot(x='Total Bsmt SF', y='SalePrice', data=df)
plt.title('Sale Price by Total Bsmt SF')
plt.xlabel('Total Bsmt SF')
plt.ylabel('Sale Price')
plt.show()
```


Sale Price by Lot Area
Sale Price
700000
600000
500000
400000
300000
200000
100000
0
0
50000
100000
150000
200000
Lot Area


Sale Price by GrLiv Area
Sale Price
Gr Liv Area
0
100000
200000
300000
400000
500000
600000
700000
1000
2000
3000
4000
5000



7 Counted the missing values and applied appropriate imputation strategies.

[39]:
```
# Missing Value Handling
# Counting missing value
missing_values = df.isnull().sum()
missing_values
```

[39]:
```
Lot Area          0
Gr Liv Area       0
Total Bsmt SF     1
Garage Cars       1
```

```
Overall Qual        0
Year Built          0
Year Remod/Add      0
Full Bath           0
Bsmt Qual          80
Neighborhood        0
Kitchen Qual        0
Garage Type       157
Overall Cond        0
SalePrice           0
dtype: int64
```

[40]:
```
from sklearn.impute import SimpleImputer
missing_val_col = [col for col in df.columns if df[col].isnull().any()]


for column in missing_val_col:
    if df[column].dtype == 'object':
        df[column] = df[column].fillna('Unknown')  # Replacing with unknow
    else:
        imputer = SimpleImputer(strategy='median')
        df[column] = imputer.fit_transform(df[[column]]) # Applying imputation
# Final
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2930 entries, 0 to 2929
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Lot Area        2930 non-null   int64
 1   Gr Liv Area     2930 non-null   int64
 2   Total Bsmt SF   2930 non-null   float64
 3   Garage Cars     2930 non-null   float64
 4   Overall Qual    2930 non-null   int64
 5   Year Built      2930 non-null   int64
 6   Year Remod/Add  2930 non-null   int64
 7   Full Bath       2930 non-null   int64
 8   Bsmt Qual       2930 non-null   object
 9   Neighborhood    2930 non-null   object
 10  Kitchen Qual    2930 non-null   object
 11  Garage Type     2930 non-null   object
 12  Overall Cond    2930 non-null   int64
 13  SalePrice       2930 non-null   int64
dtypes: float64(2), int64(8), object(4)
memory usage: 320.6+ KB
None
```

[41]:
```
#statistics for numerical features
df.describe()
```

[41]:
```
            Lot Area   Gr Liv Area  Total Bsmt SF  Garage Cars  Overall Qual  \
count    2930.000000  2930.000000    2930.000000  2930.000000   2930.000000
mean    10147.921843  1499.690444    1051.593515     1.766894      6.094881
std      7880.017759   505.508887     440.541315     0.760449      1.411026
min      1300.000000   334.000000       0.000000     0.000000      1.000000
25%      7440.250000  1126.000000     793.000000     1.000000      5.000000
50%      9436.500000  1442.000000     990.000000     2.000000      6.000000
75%     11555.250000  1742.750000    1301.500000     2.000000      7.000000
max    215245.000000  5642.000000    6110.000000     5.000000     10.000000

        Year Built  Year Remod/Add    Full Bath  Overall Cond      SalePrice
count  2930.000000     2930.000000  2930.000000   2930.000000    2930.000000
mean   1971.356314     1984.266553     1.566553      5.563140  180796.060068
std      30.245361       20.860286     0.552941      1.111537   79886.692357
min    1872.000000     1950.000000     0.000000      1.000000   12789.000000
25%    1954.000000     1965.000000     1.000000      5.000000  129500.000000
50%    1973.000000     1993.000000     2.000000      5.000000  160000.000000
75%    2001.000000     2004.000000     2.000000      6.000000  213500.000000
max    2010.000000     2010.000000     4.000000      9.000000  755000.000000
```

8 Now separating the target variable and applying scaling and encoding to the features.

[42]:
```
# Preprocessing

X = df.drop('SalePrice', axis=1)
y = df['SalePrice']

# Separating numerical and categorical features
num_features = X.select_dtypes(include=['int64', 'float64']).columns
categ_features = X.select_dtypes(include=['object']).columns

# Applying Standard Scaler and One Hot Encoder
scaler = StandardScaler()
encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore') #␣
 ↪sparse=False for array output

# Standardizing
X_num = scaler.fit_transform(X[num_features])

# One-hot encoding
X_cat = encoder.fit_transform(X[categ_features])
```

```
# Combining
X_final= np.concatenate([X_num, X_cat], axis=1)
```

[43]:
```
# Splitting the dataset into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X_final, y, test_size=0.2,␣
↪random_state=33)
```

9 Random Forest

[44]:
```
# Initializing and training the Random Forest model
rand_for = RandomForestRegressor(random_state=33)
rand_for.fit(X_train, y_train)

# Predicting
y_pred = rand_for.predict(X_test)

# Evaluating the model
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print(f"Mean Absolute Error: {mae}")
print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Mean Absolute Error: 17131.505895010567
Root Mean Squared Error: 29788.02723769507
R-squared: 0.8782274868558273
```

[44]:
```

```

10 Hyperparameter tuning for random forest..

[45]:
```
# Hyperparameter tuning

from sklearn.model_selection import GridSearchCV

# Defining the parameter grid
param_grid = { 'min_samples_leaf': [1,2,4,6], 'max_depth': [5,10,15],
    'n_estimators': [50,70,100,150],
    'min_samples_split': [2,5,7,10]}


grid_search = GridSearchCV(estimator=rand_for, param_grid=param_grid,
```

```
                             scoring='neg_mean_squared_error', cv=5, n_jobs=-1)

# Fitting the training data
grid_search.fit(X_train, y_train)

# Finding the best parameters
print("Best parameters: ", grid_search.best_params_)

# Evaluation of model with the best parameters
best_model = grid_search.best_estimator_
y_pred_best = best_model.predict(X_test)

best_mae = mean_absolute_error(y_test, y_pred_best)
best_rmse = np.sqrt(mean_squared_error(y_test, y_pred_best))
best_r2score= r2_score(y_test, y_pred_best)

print(f"Mean Absolute Error : {best_mae}")
print(f"Root Mean Squared Error : {best_rmse}")
print(f"R-squared: {best_r2score}")
```

```
Best parameters:  {'max_depth': 15, 'min_samples_leaf': 1, 'min_samples_split':
2, 'n_estimators': 150}
Mean Absolute Error : 17174.33645106686
Root Mean Squared Error : 29331.014611094266
R-squared: 0.8819353301444577
```

11 Now traing again the random forest with the best parameters obtained by hyperparameter tuning..

[46]:
```
# Retraining the random forest model with best parameters
rand_for_best = RandomForestRegressor(max_depth = 15, min_samples_leaf= 1,
                                      min_samples_split =2, n_estimators=150, ␣
 ↪random_state=33)
rand_for_best.fit(X_train, y_train)

# Predicting
y_pred1 = rand_for_best.predict(X_test)

# Evaluating the model
mae = mean_absolute_error(y_test, y_pred1)
rmse = np.sqrt(mean_squared_error(y_test, y_pred1))
r2 = r2_score(y_test, y_pred1)

print(f"Mean Absolute Error for best parameter: {mae}")
print(f"Root Mean Squared Error for best parameter: {rmse}")
print(f"R-squared for bestparameter: {r2}")
```

```
Mean Absolute Error for best parameter: 17174.33645106686
Root Mean Squared Error for best parameter: 29331.014611094266
R-squared for bestparameter: 0.8819353301444577
```

12 Neural Network

[47]:
```
# Changing train and test sets into tensor
X_train_tensor = torch.tensor(X_train, dtype=torch.float32)
y_train_tensor = torch.tensor(y_train.values, dtype=torch.float32)
X_test_tensor = torch.tensor(X_test, dtype=torch.float32)
y_test_tensor = torch.tensor(y_test.values, dtype=torch.float32)

train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)

# Defining the Neural Network
input_size = X_train_tensor.shape[1]

model = nn.Sequential(
    nn.Linear(input_size, 128),
    nn.ReLU(),
    nn.Dropout(0.2),
    nn.Linear(128, 64),
    nn.ReLU(),
    nn.Dropout(0.2),
    nn.Linear(64, 1)
)

# Training the model
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

num_epochs = 150
for epoch in range(num_epochs):
    for batch_X, batch_y in train_loader:
        # Forward pass
        outputs = model(batch_X)
        loss = criterion(outputs, batch_y.unsqueeze(1))

        # Backward
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

     # printing loss for every 10th epoch
    if (epoch + 1) % 10 == 0:
        print(f'Epoch [{epoch + 1}/{num_epochs}], Loss: {loss.item():10f}')
```

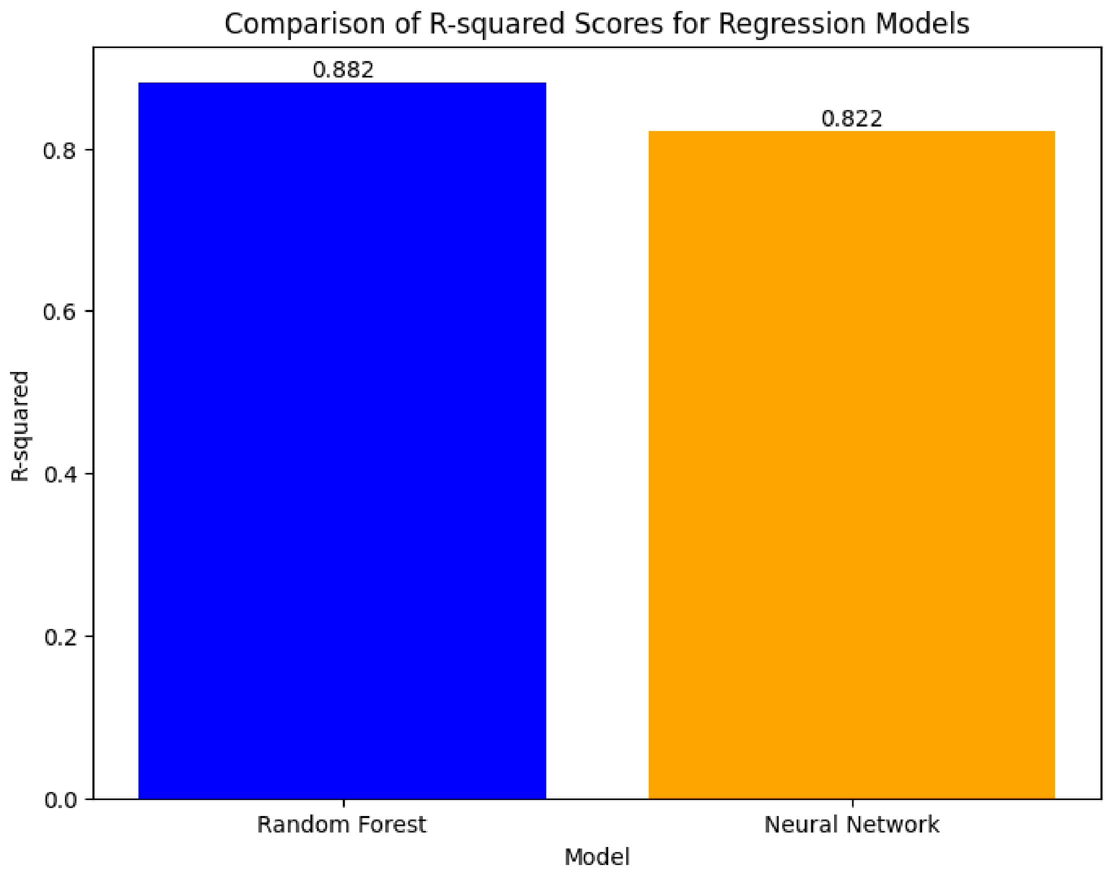
```
# Evaluating the model
with torch.no_grad():
    y_pred_tensor = model(X_test_tensor)
    y_pred = y_pred_tensor.numpy().flatten()

    mae = mean_absolute_error(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    r2 = r2_score(y_test, y_pred)

    print(f"Mean Absolute Error: {mae}")
    print(f"Root Mean Squared Error: {rmse}")
    print(f"R-squared: {r2}")
```

```
Epoch [10/150], Loss: 22240262144.000000
Epoch [20/150], Loss: 1364950144.000000
Epoch [30/150], Loss: 1547612928.000000
Epoch [40/150], Loss: 9466639360.000000
Epoch [50/150], Loss: 724118272.000000
Epoch [60/150], Loss: 2748892160.000000
Epoch [70/150], Loss: 462178080.000000
Epoch [80/150], Loss: 345691584.000000
Epoch [90/150], Loss: 996115072.000000
Epoch [100/150], Loss: 1447556480.000000
Epoch [110/150], Loss: 1400299520.000000
Epoch [120/150], Loss: 689396864.000000
Epoch [130/150], Loss: 765328768.000000
Epoch [140/150], Loss: 1092056320.000000
Epoch [150/150], Loss: 730307008.000000
Mean Absolute Error: 22852.669921875
Root Mean Squared Error: 35991.623914460986
R-squared: 0.82222580909729
```

13 Now comparing the two models - Random Forest and Neural Network

[48]:
```
# Model comparison
random_forest_r2score= r2_score(y_test, y_pred1)
neural_network_r2score = r2_score(y_test, y_pred)

models = ['Random Forest', 'Neural Network']
r2_scores = [random_forest_r2score, neural_network_r2score]

plt.figure(figsize=(8, 6))
plt.bar(models, r2_scores, color=['blue', 'orange'])
plt.xlabel('Model')
```

```
plt.ylabel('R-squared')
plt.title('Comparison of R-squared Scores for Regression Models')

# Add values on top of the bars
for i, score in enumerate(r2_scores):
    plt.text(i, score, str(round(score, 3)), ha='center', va='bottom')

plt.show()
```



The R2 score achieved by Random Forest model is more than that of Neural Network model. So, here the Random Forest model outperformed the Neural Network model.