Comprehensive Predictive Modeling of Ames House Prices

1. Introduction (200 words) • Overview of Real Estate Price Prediction (100 words): Discuss the significance of predicting real estate prices, its impact on industries like marketing, business intelligence, and urban planning. • Scope and Objectives (50 words): Outline the aims of the research, including developing predictive models and evaluating their effectiveness. • Structure of the Report (50 words): Briefly describe the structure of the report, summarizing the main sections.

2. Exploratory Data Analysis

2.1 Dataset Description

• Description of the Dataset (100 words): Explain the key attributes (e.g., zoning, lot size, building characteristics, neighborhood factors). • Source (25 words): Cite the dataset source (e.g., Kaggle, UCI Machine Learning Repository).

Import libraries

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from scipy.stats import skew

%matplotlib inline
sns.set_style('darkgrid')
```

Load data

In [4]:
```python
dataset = pd.read_csv("house-price-data-apr2024.csv")
dataset.describe()
```

Out[4]:

	LotFrontage	LotArea	OverallQual	OverallCond	MasVnrArea	BsmtFinSF1	Bsm
count	1201.000000	1460.000000	1460.000000	1460.000000	1452.000000	1460.000000	146(
mean	70.049958	10516.828082	6.099315	5.575342	103.685262	443.639726	4(
std	24.284752	9981.264932	1.382997	1.112799	181.066207	456.098091	161
min	21.000000	1300.000000	1.000000	1.000000	0.000000	0.000000	(
25%	59.000000	7553.500000	5.000000	5.000000	0.000000	0.000000	(
50%	69.000000	9478.500000	6.000000	5.000000	0.000000	383.500000	(
75%	80.000000	11601.500000	7.000000	6.000000	166.000000	712.250000	(
max	313.000000	215245.000000	10.000000	9.000000	1600.000000	5644.000000	1474

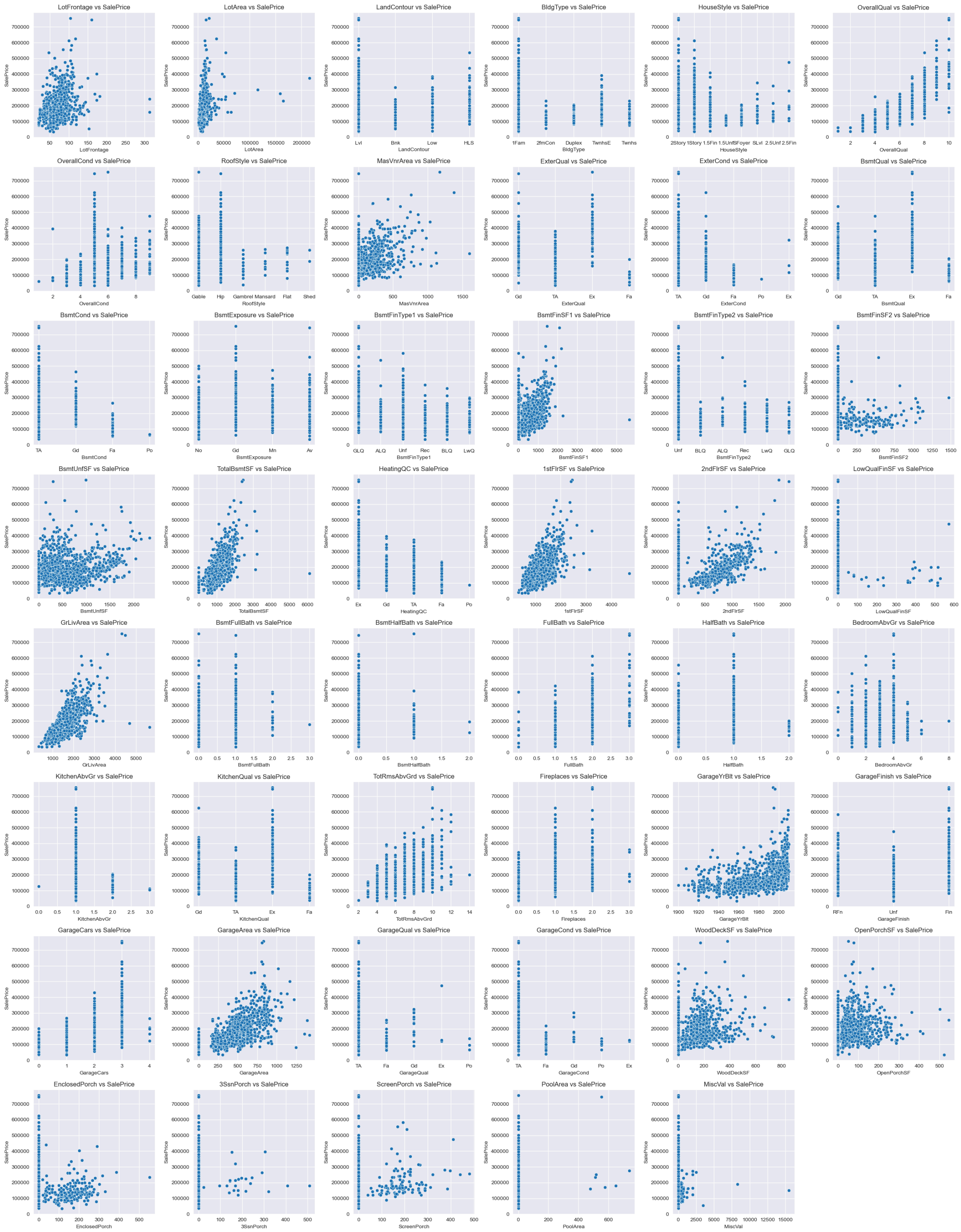
8 rows × 32 columns

2.1 Feature Distributions Relative to target

A comprehensive initial assessment of how each of the 46 features is distributed relative to the target variable `SalePrice` is visualized.

In [5]:

```
# Assuming 'dataset' is your DataFrame
df = dataset.copy()  # Make a copy to avoid modifying the original dataset

# List of features to visualize
features = df.columns.tolist()
features.remove('SalePrice')
target = 'SalePrice'

# Number of rows and columns for subplots
num_rows = 8
num_cols = 6

# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(25, 4*num_rows))
axes = axes.flatten()

# Plot each feature and calculate skewness
for i, feature in enumerate(features):
    # Plotting scatterplot
    sns.scatterplot(x=df[feature], y=df[target], ax=axes[i])
    axes[i].set_title(f'{feature} vs {target}')
    axes[i].set_xlabel(feature)
    axes[i].set_ylabel(target)

# Remove any unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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



2.2 Sale Price

In [6]:
```
saleprice = dataset["SalePrice"]
sns.displot(saleprice,kde = True)
plt.title("House Price Distribution")
plt.show()
```

From the plot the distribution of `SalePrice` data is apparently right skewed. Its Skewness and Kurtosis statistics are checked.This was expected as few people can afford very expensive houses.

In [7]:
```
print(f"""Skewness: {saleprice.skew()}
Kurtosis: {saleprice.kurt()}""")
```

```
Skewness: 1.8828757597682129
Kurtosis: 6.536281860064529
```

2.3 Numerical Features

There are total 31 numercial features.

In [8]:
```
numerical_data = df.select_dtypes(include="number")
numerical_list = numerical_data.columns.tolist()
numerical_list.remove("SalePrice")
print("Number of numerical variables: " , len(numerical_list))
```

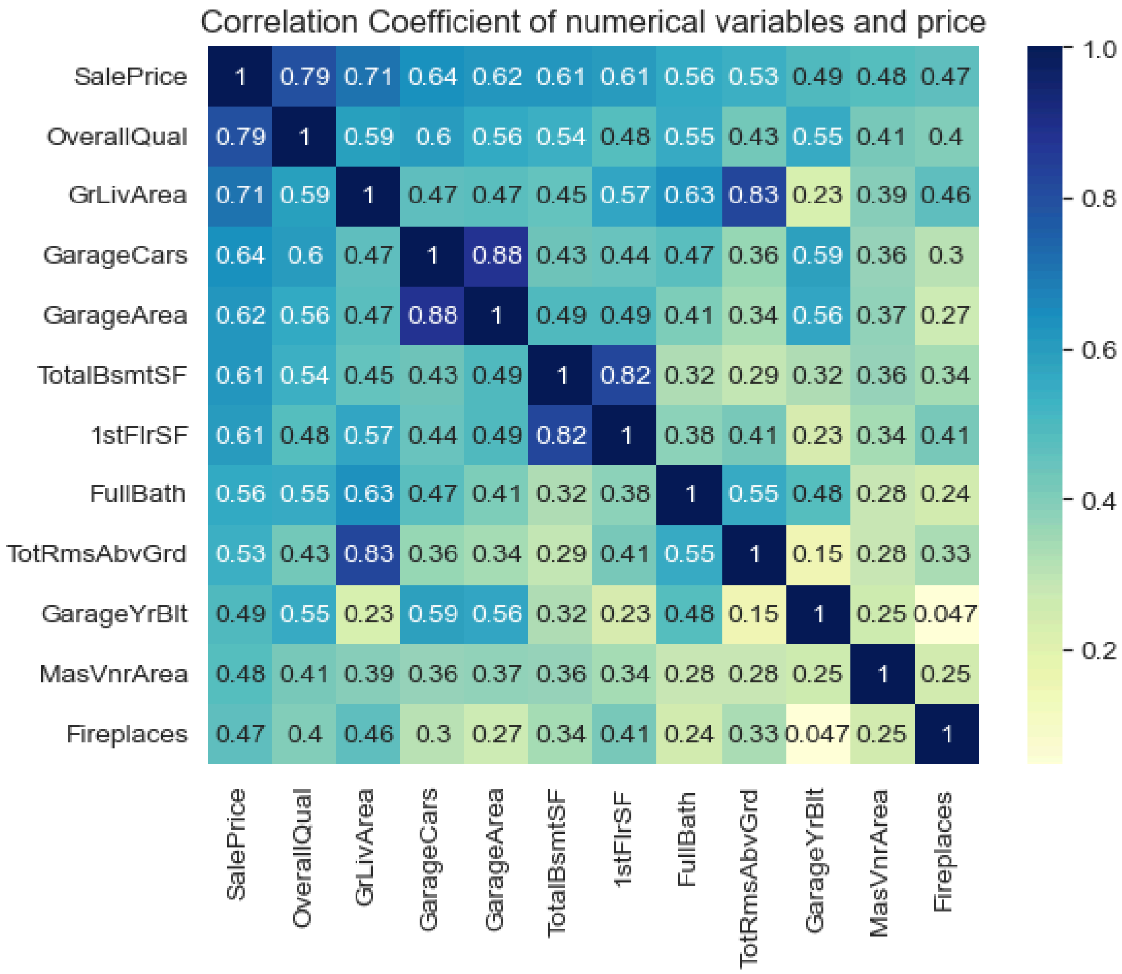
```
Number of numerical variables:  31
```

Correlation coefficient with target variable

To have a first glance of which numeric variables have a high correlation with the `SalePrice`. The correlation coefficient is computed. All coefficient>0.4 is initially defined as a relative strong linear relationship and visualized. However, it is clear that the multicollinearity is an issue. For example: the correlation between `GarageCars` and `GarageArea` is very high (0.89), while both have relatively high correlations with `SalePrice`.

Pearson Correlation Range	Strength of Correlation	Interpretation
0.7 to 1.0 (positive or negative)	Strong	Indicates a strong linear relationship where one variable tends to increase (or decrease) as the other variable increases.
0.5 to 0.7 (positive or negative)	Moderate to Strong	Suggests a meaningful linear relationship between the variables, though not as strong as the highest range.
0.3 to 0.5 (positive or negative)	Weak to Moderate	The relationship exists but is less pronounced and may not be as influential in linear models.
0 to 0.3 (positive or negative)	Weak or No Correlation	Indicates a weak linear relationship or no linear relationship between the variables.

```
In [9]: corr = numerical_data.corr()

        corr_sorted = corr["SalePrice"].sort_values(ascending=False)
        corr_high = corr_sorted[abs(corr_sorted)>0.4].index.tolist()
        corr_numVar = corr.loc[corr_high,corr_high]

        sns.heatmap(corr_numVar, cmap="YlGnBu", annot=True)
        plt.title("Correlation Coefficient of numerical variables and price")
        plt.show()
```



Skewness

Skewness Range	Description
Near Zero (0)	Data is symmetric, with skewness between -0.5 and 0.5.
Moderate Skewness	Data is moderately asymmetric, with skewness between -1 to -0.5 or 0.5 to 1.
High Skewness	Data is highly skewed, with skewness greater than 1 or less than -1. Transformations needed.

In [10]:

```
# Make a copy of numerical_data to avoid modifying the original dataset
numerical = numerical_data.drop(columns=["SalePrice"]).copy()
features = numerical.columns.tolist()
skewed_features = []

num_rows = 8
num_cols = 6

# Create subplots for visualization
fig, axes = plt.subplots(num_rows, num_cols, figsize=(25, 4*num_rows))
axes = axes.flatten()

# Iterate over each feature
for i, feature in enumerate(features):
    # Plot histogram with KDE (Kernel Density Estimate)
    sns.histplot(numerical[feature], kde=True, ax=axes[i])

    # Calculate skewness for the current feature
    skewness = skew(numerical[feature].dropna())

    # Identify and store features with skewness greater than 1
    if skewness > 1:
        skewed_features.append(feature)

    axes[i].set_title(f'{feature} - Skewness: {skewness:.2f}')
    axes[i].set_xlabel(feature)
    axes[i].set_ylabel('')

print("Skewed Features:", skewed_features)
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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

```
Skewed Features: ['LotFrontage', 'LotArea', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF
2', 'TotalBsmtSF', '1stFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtHalfBath', 'Kitch
enAbvGr', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorc
h', 'PoolArea', 'MiscVal']
```

Characteristics summary of numercial variable derived from EDA

Numercial Variable	Characteristics summary derived from EDA
LotFrontage	Skewed data, initially had outliers, strong correlation with SalePrice.
LotArea	Skewed data, initially had outliers, moderate correlation with SalePrice.
OverallQual	Strong positive correlation with SalePrice.
OverallCond	Weak negative correlation with SalePrice.
MasVnrArea	Skewed data, moderate correlation with SalePrice.
BsmtFinSF1	Skewed data, moderate correlation with SalePrice.
BsmtFinSF2	Skewed data, low correlation with SalePrice.
BsmtUnfSF	Low correlation with SalePrice.
TotalBsmtSF	Skewed data, initially had outliers, strong correlation with SalePrice.
1stFlrSF	Skewed data, moderate correlation with SalePrice.
2ndFlrSF	Low correlation with SalePrice.
LowQualFinSF	Low correlation with SalePrice.
GrLivArea	Skewed data, strong correlation with SalePrice.

Numercial Variable	Characteristics summary derived from EDA
BsmtFullBath	Low correlation with SalePrice.
BsmtHalfBath	Skewed data, low correlation with SalePrice.
FullBath	Moderate correlation with SalePrice.
HalfBath	Low correlation with SalePrice.
BedroomAbvGr	Low correlation with SalePrice.
KitchenAbvGr	Skewed data, weak negative correlation with SalePrice.
TotRmsAbvGrd	Moderate correlation with SalePrice.
Fireplaces	Moderate correlation with SalePrice.
GarageYrBlt	Low correlation with SalePrice.
GarageCars	Moderate correlation with SalePrice.
GarageArea	Moderate correlation with SalePrice.
WoodDeckSF	Skewed data, moderate correlation with SalePrice.
OpenPorchSF	Skewed data, moderate correlation with SalePrice.
EnclosedPorch	Low correlation with SalePrice.
3SsnPorch	Low correlation with SalePrice.
ScreenPorch	Low correlation with SalePrice.
PoolArea	Low correlation with SalePrice.

2.4 Categorical Features

There are total 16 categorical features.

In [11]:
```
categorical_data = df.select_dtypes(exclude="number")
categorical_list = categorical_data.columns.tolist()
print("Number of categorical variables: " , len(categorical_list))
```

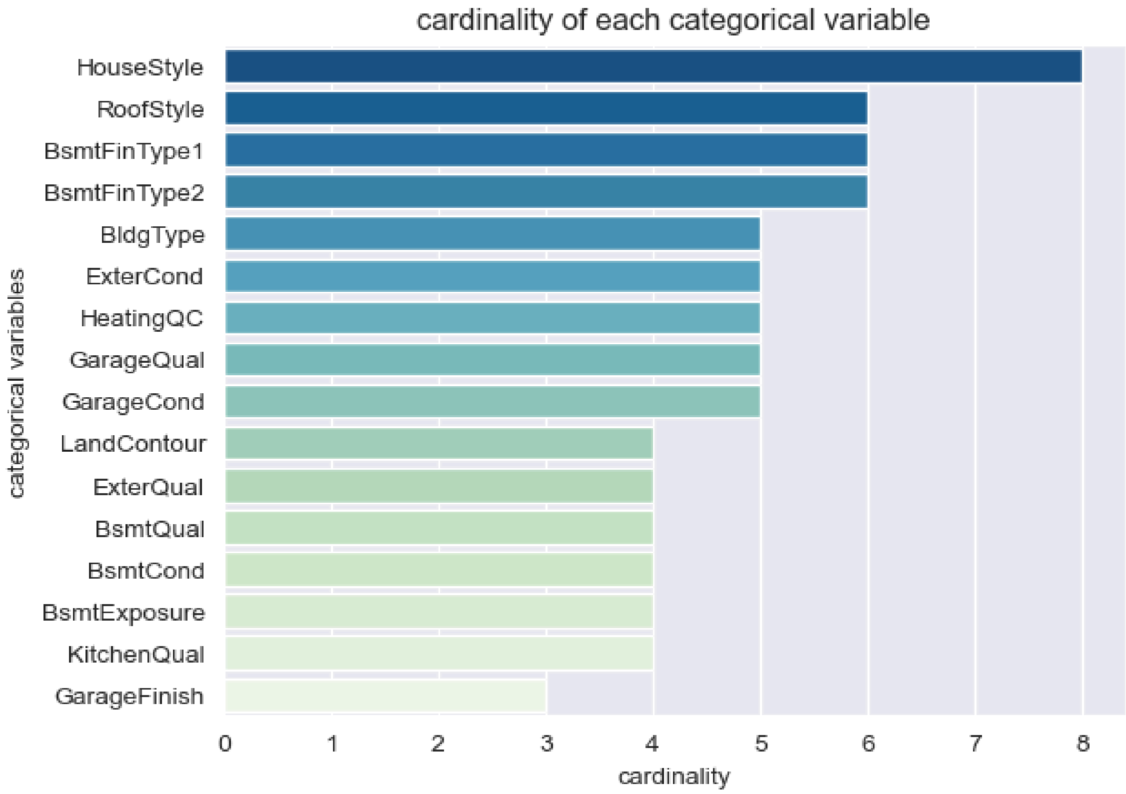
```
Number of categorical variables:  16
```

In [12]:
```
print(categorical_list)
```

```
['LandContour', 'BldgType', 'HouseStyle', 'RoofStyle', 'ExterQual', 'ExterCond',
'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'HeatingQ
C', 'KitchenQual', 'GarageFinish', 'GarageQual', 'GarageCond']
```

To have an initial feel of categorical variables 's characteristics. The cardinality of categorical variables is visualized. Categorical variables with high cardinality (i.e. `HouseStyle` , `RoofSytle` , `BsmtFinType1` , and `BsmtFinType2`) may have a significant impact on the analysis or modeling process.

In [13]:
```
cardinality = {var: df[var].nunique() for var in categorical_list}
cardinality_df = pd.DataFrame(cardinality.items(), columns=["Variable", "Cardinality
cardinality_df=cardinality_df.sort_values(by="Cardinality",ascending=False)

sns.barplot(y=cardinality_df["Variable"],x=cardinality_df["Cardinality"],data=cardin
plt.ylabel("categorical variables")
plt.xlabel("cardinality")
plt.title("cardinality of each categorical variable")
plt.show()
```



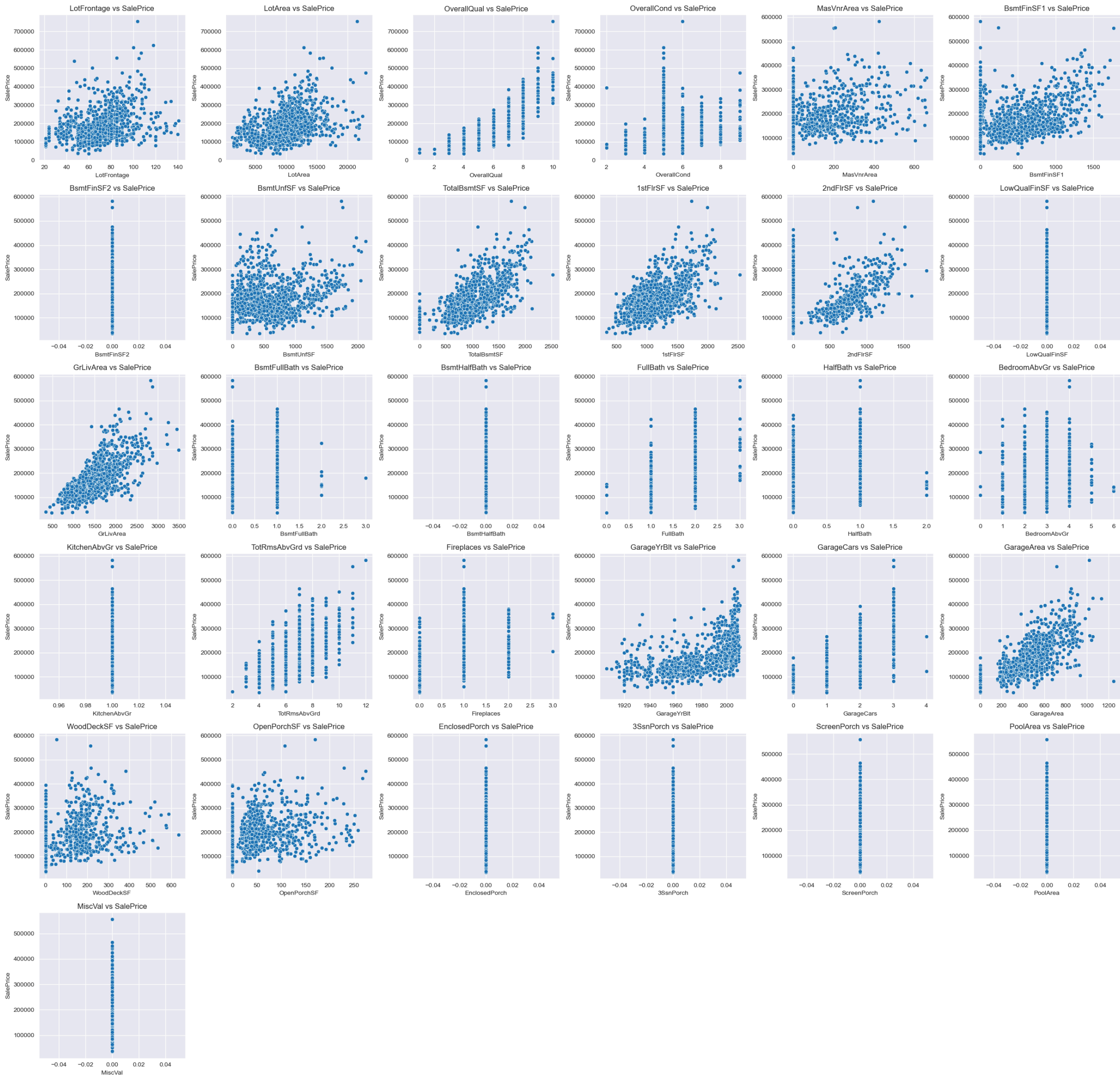
3. Data Preprocessing

3.1 Missing Value

For numerical variables, given that the missing percentage for `LotFrontage` and `GarageYrBlt` is relatively high (17.7% and 5.5% respectively), creating missing value indicators is more suitable compared to other approaches such as mean imputation. Each of these variables are replaced by a new variable that works as a missing value indicator. If the value in the original variable is missing then the corresponding value in the new variable should be 1, otherwise it should be 0.

In [14]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# List of numerical columns to process
# Remove outliers and plot
n_cols = 6  # Number of plots per row
n_rows = (len(numerical_list) + n_cols - 1) // n_cols  # Calculate number of rows ne

fig, axes = plt.subplots(n_rows, n_cols, figsize=(25, 4 * n_rows))
axes = axes.flatten()  # Flatten the 2D array of axes for easy iteration
num_outlier=0
for i, column in enumerate(numerical_list):
    if column in df.columns:
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 3 * IQR
        upper_bound = Q3 + 3 * IQR

        # Identify outliers
        outliers = df[(df[column] > upper_bound) | (df[column] < lower_bound)].index
        df.drop(outliers, inplace=True)

        # Plot each column in the subplot
        sns.scatterplot(x=df[column], y=df['SalePrice'], ax=axes[i])
        axes[i].set_title(f'{column} vs SalePrice')
        num_outlier+=1

print(num_outlier)
# Remove any unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

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

```
31
```



In [15]:

```
numerical_missing = numerical_data.isna().sum().sort_values(ascending=False)
numerical_missing_percent = numerical_missing/len(numerical_data) * 100
numerical_missing_data = pd.DataFrame({
                                    "Percent": numerical_missing_percent,
                                    "Count": numerical_missing})
numerical_missing_data.head(10)
```

Out[15]:

	Percent	Count
LotFrontage	17.739726	259
GarageYrBlt	5.547945	81
MasVnrArea	0.547945	8
BedroomAbvGr	0.000000	0
MiscVal	0.000000	0
PoolArea	0.000000	0
ScreenPorch	0.000000	0
3SsnPorch	0.000000	0
EnclosedPorch	0.000000	0
OpenPorchSF	0.000000	0

In [16]:
```
vars_with_missing = []
for var in df.select_dtypes(include="number").columns:
    if df[var].isnull().any():
        vars_with_missing.append(var)
for var in vars_with_missing:
    df[var+"_missing"] = df[var].isnull().astype(int)
    df.drop(columns=[var],inplace=True)

sum(df.select_dtypes(include="number").isna().sum())
```

Out[16]: 0

For categorical variables, the proportion of missing values is relatively low (`GarageFinish` , `GarageQual` , and ```BsmtExposure`` range between 2.5% and 5.5%, this is considered low) and unlikely to skew the data. Mode imputation for categorical variables replaces missing values with the most frequent category.

In [17]:
```
categorical_missing = categorical_data.isna().sum().sort_values(ascending=False)
categorical_missing_percent = categorical_missing/len(categorical_data) * 100
categorical_missing_data = pd.DataFrame({
                                     "Percent": categorical_missing_percent,
                                     "Count": categorical_missing})
categorical_missing_data.head(10)
```

Out[17]:

	Percent	Count
GarageFinish	5.547945	81
GarageQual	5.547945	81
GarageCond	5.547945	81
BsmtExposure	2.602740	38
BsmtFinType2	2.602740	38
BsmtQual	2.534247	37
BsmtCond	2.534247	37
BsmtFinType1	2.534247	37
LandContour	0.000000	0
BldgType	0.000000	0

In [18]:
```
for column in categorical_data.columns:
    mode_value = df[column].mode()[0]
    df[column].fillna(mode_value,inplace=True)
sum(df.select_dtypes(exclude="number").isna().sum())
```

Out[18]: 0

All missing values have been handled!

3.2 Label Encoding

Many machine learning algorithms require numerical input. Label encoding is necessary to transform these categories into numerical values. All ordinal categorical variables are encoded into numbers based on the mean value of the target variable (`SalePrice`). The smaller value corresponds to the category that has the smaller mean house sale price. That is. the category that has the smallest mean house sale price can be replaced with 0, the next category with 1,

In [19]:
```
cat_vars = df.select_dtypes(exclude=['number']).columns

for var in cat_vars:
    # Calculate mean sale price for each category in the training set
    mean_sale_price = df.groupby(var)['SalePrice'].mean().sort_values()

    # Create a mapping dictionary for encoding
    encoding_map = {category: i for i, category in enumerate(mean_sale_price.index)}

    # Apply encoding to both training and testing datasets
    # Define the default value to assign to missing values in the test dataset
    # This value represents the encoding for missing categories that were not present
    df["encoded_" + var] = df[var].map(encoding_map)
    df["encoded_" + var] = df[var].map(encoding_map)

    # Drop original categorical variables
    df.drop(columns=[var], inplace=True)
```

3.3 Remove outliers

Exploratory data analysis (EDA) has identified outliers in the GrLivArea variable. Since regression models are sensitive to outliers, these outliers need to be removed to improve model accuracy.

In [20]:
```
# sns.scatterplot(x=df['GrLivArea'], y=df['SalePrice'],data=df)
# plt.show()
```

In [21]:
```
# outlier=df[df['GrLivArea']>4000].index
# print(outlier)
# df.drop(outlier,inplace=True,axis=0)
```

4. Feature Engineering

4.1 Split Data into Training and Testing Sets

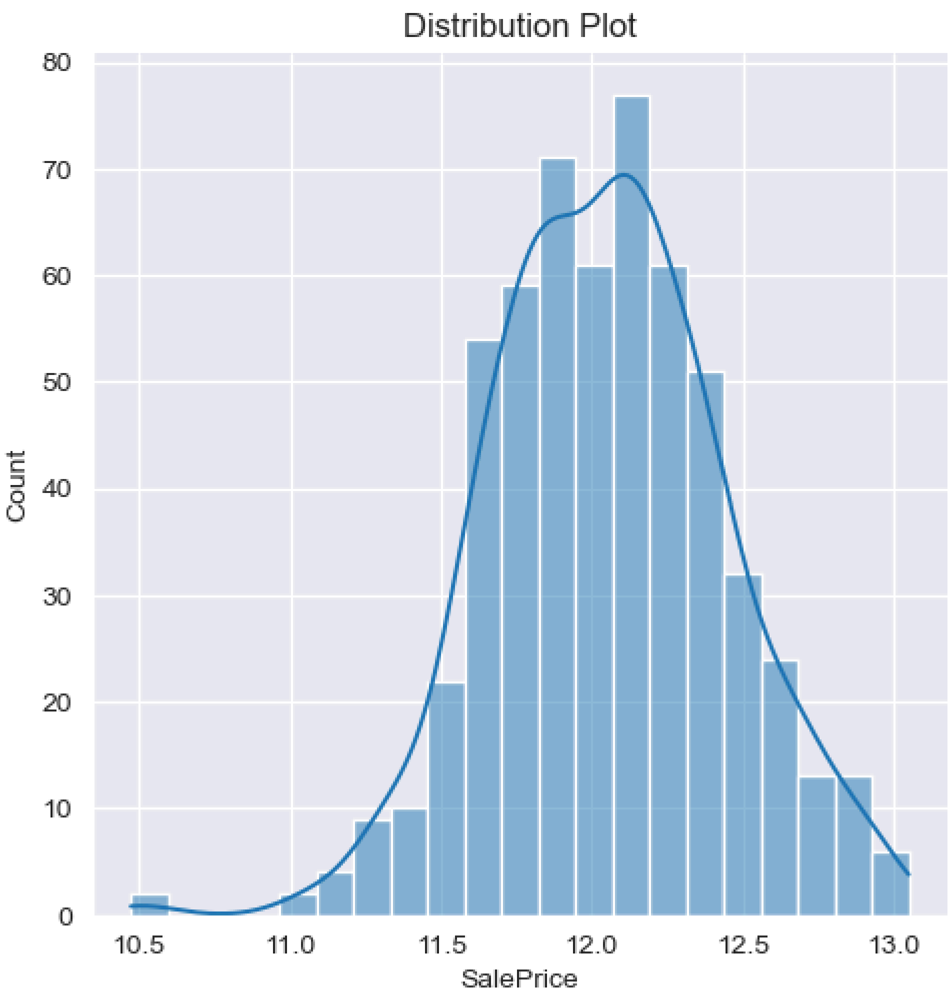
Split the data into training and test sets, with 70% for training and 30% for testing. This step is done after data preprocessing but before transformation and standardization to prevent data leakage.

In [22]:
```
from sklearn.model_selection import train_test_split

train_df, test_df = train_test_split(df, test_size=0.3, random_state=10)
```

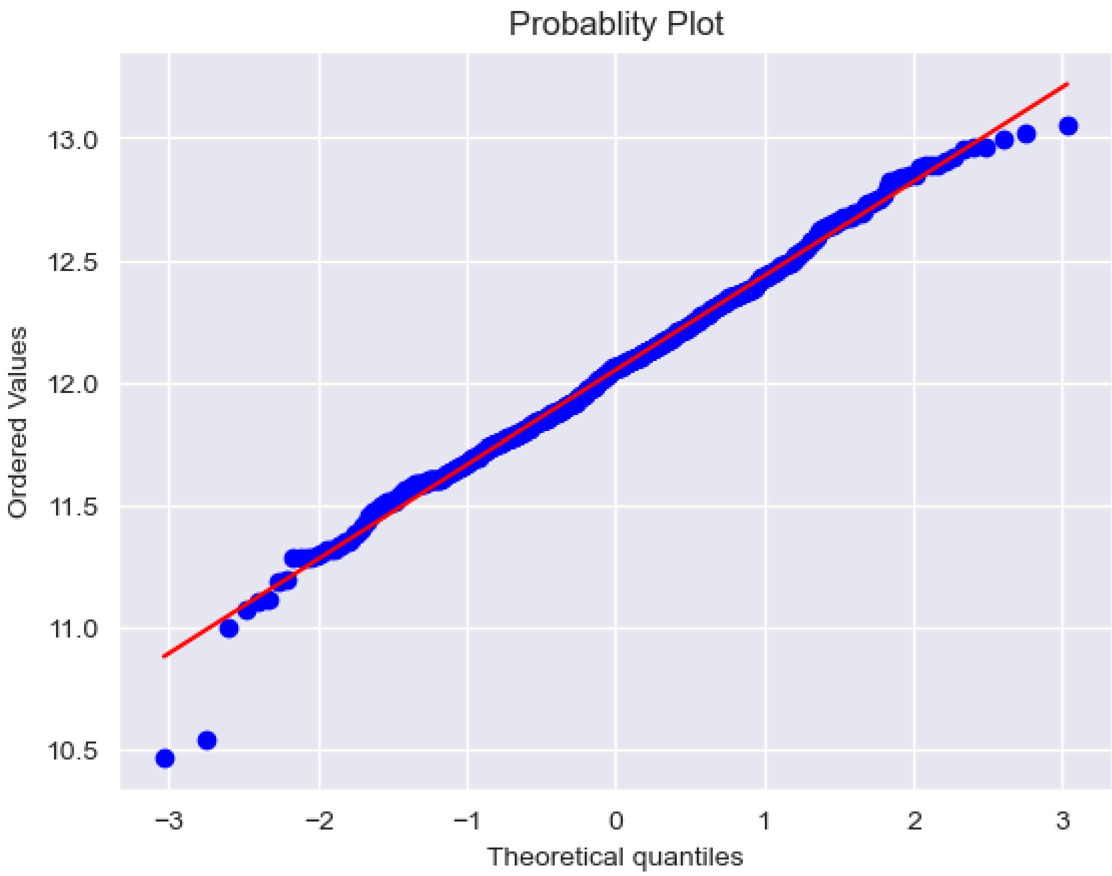
4.2 Fixing skewness with Log Transformation

The target variable(`SalePrice`) is right skewed as shown before. Since normal distribution is crucial for linear regression, a log transformation is performed on skewed data to approximate a normal distribution. From distribution plot and QQ plot, the transformed data is approximately normally distributed.

In [23]:
```
train_df['SalePrice'] = np.log(train_df['SalePrice'])
test_df['SalePrice'] = np.log(test_df['SalePrice'])

sns.displot(train_df["SalePrice"], kde=True)
plt.title("Distribution Plot")
plt.show()
```



In [24]:
```
stats.probplot(train_df["SalePrice"], dist="norm", plot=plt)
plt.title("Probablity Plot")
plt.show()
```



4.3 Filter and Wrapper

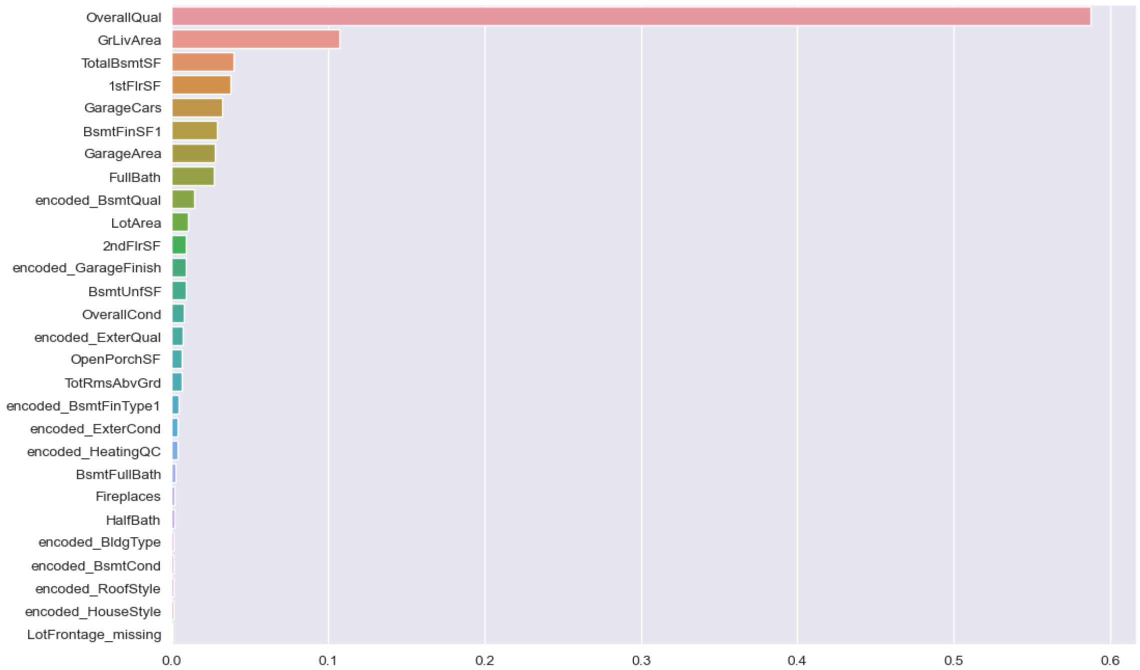
In [25]:

```
from sklearn.feature_selection import VarianceThreshold

y_train= train_df['SalePrice']
y_test= test_df['SalePrice']

X_train = train_df.drop('SalePrice', axis=1)
X_test = test_df.drop('SalePrice', axis=1)

variances = X_train.var(axis=0)
threshold_n=0.95

sel = VarianceThreshold(threshold=threshold_n*(1-threshold_n))
X_train_filtered = sel.fit_transform(X_train)
X_test_filtered = sel.transform(X_test)

idx = np.where(sel.variances_>threshold_n)[0]
mask = X_train.columns[sel.get_support(indices=True)]
X_train_filtered = pd.DataFrame(X_train_filtered,columns=mask)
X_test_filtered = pd.DataFrame(X_test_filtered,columns=mask)

print(idx)
print(mask)
```

```
[ 0  1  3  5  6  7  8 10 17 20 21 22 33 39 40]
Index(['LotArea', 'OverallQual', 'OverallCond', 'BsmtFinSF1', 'BsmtUnfSF',
       'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'GrLivArea', 'BsmtFullBath',
       'FullBath', 'HalfBath', 'BedroomAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'LotFrontage_missing', 'encoded_LandContour', 'encoded_BldgType',
       'encoded_HouseStyle', 'encoded_RoofStyle', 'encoded_ExterQual',
       'encoded_ExterCond', 'encoded_BsmtQual', 'encoded_BsmtCond',
       'encoded_BsmtExposure', 'encoded_BsmtFinType1', 'encoded_HeatingQC',
       'encoded_KitchenQual', 'encoded_GarageFinish'],
      dtype='object')
```

In [26]:
```
from sklearn.ensemble import RandomForestRegressor

model = RandomForestRegressor(random_state=7)
wrap = model.fit(X_train_filtered, y_train)
importances=model.feature_importances_
indices = np.argsort(importances)[::-1]

threshold_r = 0.001
filtered_importance = np.where(importances>threshold_r)[0]
sorted_indices = indices[filtered_importance]

selected_feature = X_train_filtered.columns[sorted_indices]

print("Number of selected features: ",len(sorted_indices))
print(indices)

plt.figure(figsize=(12,8))
sns.barplot(x=importances[sorted_indices],y=np.array(X_train_filtered.columns)[sorte
plt.show()
```

```
Number of selected features:  28
[ 1  8  5  6 15  3 16 10 26  0  7 32  4  2 24 18 13 29 25 17 30 12 28 31
  9 14 11 20 21 27 23 22 19]
```



In [27]:
```
from sklearn.feature_selection import RFE

model_rfe = RandomForestRegressor(random_state=7)

rfe = RFE(estimator=model_rfe, n_features_to_select=len(sorted_indices))
fit = rfe.fit(X_train_filtered, y_train)

X_train_wrapper = pd.DataFrame(fit.transform(X_train_filtered),columns=selected_featu
X_test_wrapper = pd.DataFrame(fit.transform(X_test_filtered),columns=selected_featur
```

4.3 Standardization and transformation

Standardization (or z-score normalization) is necessary to ensure all variables have the same scale for comparisons. It transforms the data to have a mean of 0 and a standard deviation of 1.

$$x_i' = \frac{x_i - \mu}{\sigma}$$

In [28]:
```
from sklearn.preprocessing import StandardScaler

# Standardize the features to have mean=0 and variance=1
# StandardScaler can help mitigate overflow issues by scaling the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_wrapper)
X_test_scaled = scaler.transform(X_test_wrapper)
```

To mitigate skewness observed during EDA, Yeo-Johnson transformation is implemented to address skewed data distributions by applying a power transformation after z-score normalization. This method adjusts the data distribution to approximate normality, thereby improving the suitability of the data for robust and accurate predictions.

$$\begin{cases} \frac{(y+1)^{\lambda}-1}{\lambda} & \text{if } y \geq 0, \lambda \neq 0 \\ \ln(y+1) & \text{if } y \geq 0, \lambda = 0 \\ \frac{-(|y|+1)^{2-\lambda}-1}{2-\lambda} & \text{if } y < 0, \lambda \neq 2 \\ -\ln(|y|+1) & \text{if } y < 0, \lambda = 2 \end{cases}$$

In [29]:
```
from sklearn.preprocessing import PowerTransformer

# Apply the Yeo-Johnson transformation to the standardized features
# PowerTransformer with 'yeo-johnson' method handles non-positive data, but overflow
pt = PowerTransformer(method='yeo-johnson')
X_train_transformed = pt.fit_transform(X_train_scaled)
X_test_transformed = pt.transform(X_test_scaled)

# Convert transformed arrays back to DataFrame
X_train_transformed_df = pd.DataFrame(X_train_transformed, columns=X_train_wrapper.co
X_test_transformed_df = pd.DataFrame(X_test_transformed, columns=X_test_wrapper.colu
```

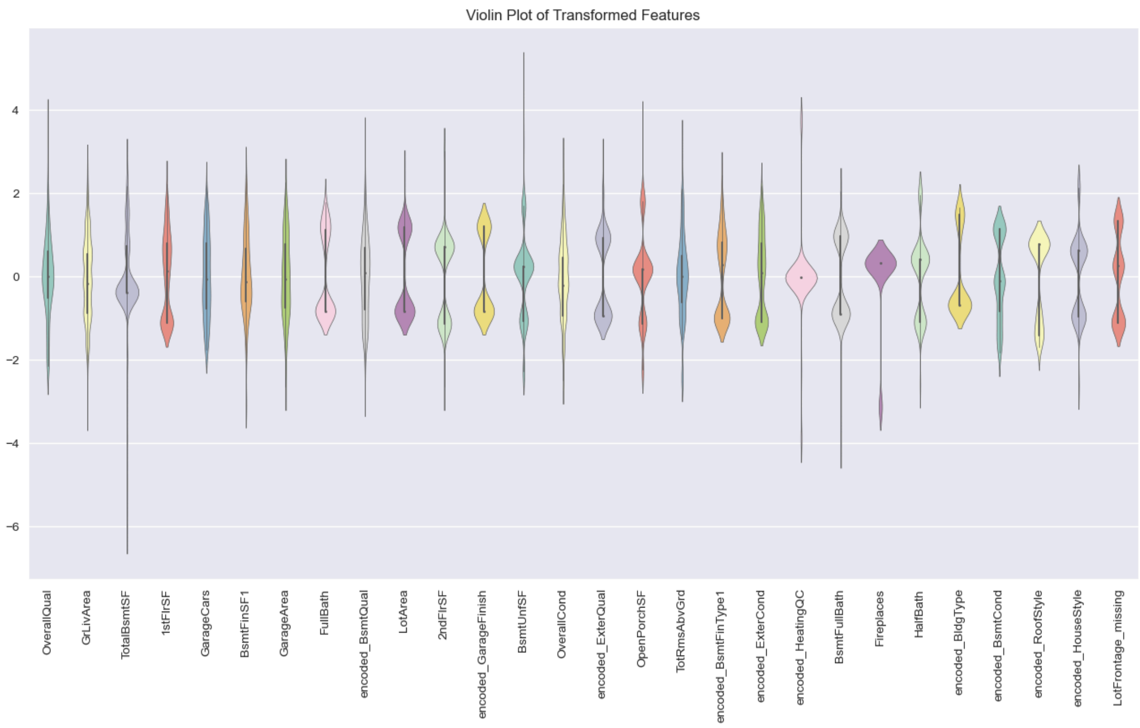
In [30]:

```
mean_before = X_train_wrapper.mean()
std_before = X_train_wrapper.std()

mean_after = X_train_transformed_df.mean()
std_after = X_train_transformed_df.std()

summary_df = pd.DataFrame(
    {'Feature': X_train_wrapper.columns,
    'Mean Before': mean_before.values,
    'Std Before': std_before.values,
    'Mean After standardalization and transformation': mean_after,
    'Std After standardalization and transformation': std_after}
)

summary_df.head(10)
```

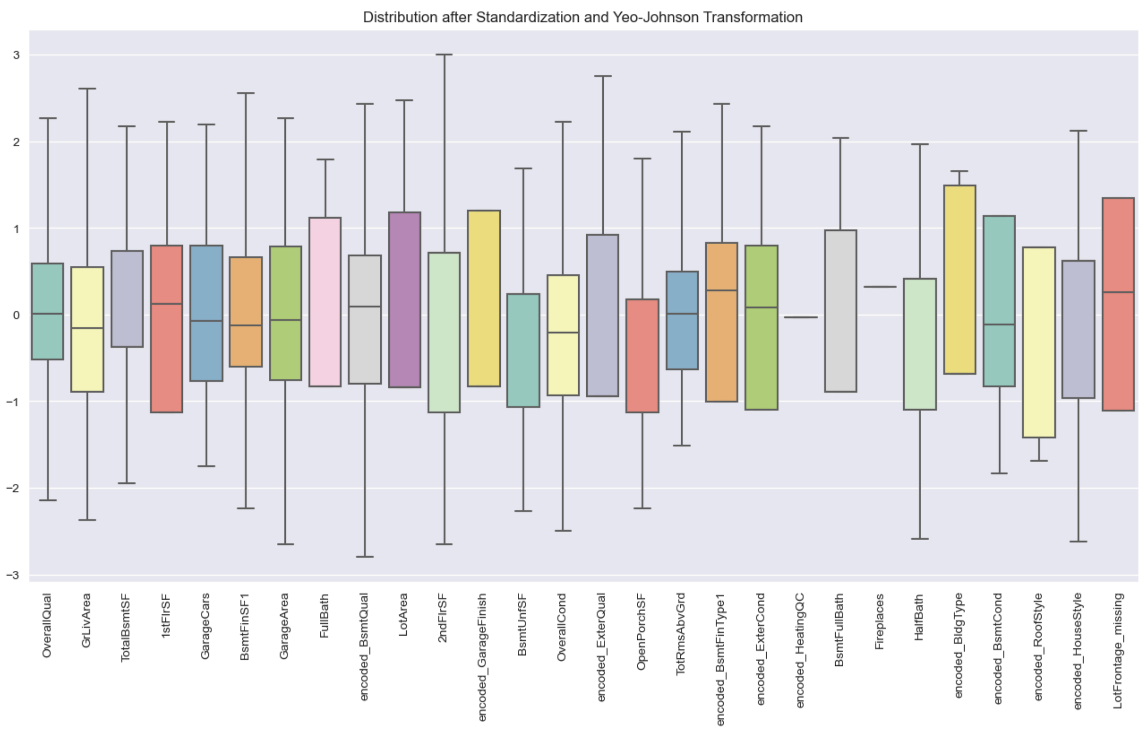
Out[30]:

	Feature	Mean Before	Std Before	Mean After standardalization and transformation	St standarda transfor
OverallQual	OverallQual	9114.345009	3459.971449	3.947028e-17	1.
GrLivArea	GrLivArea	6.246935	1.403118	-4.024802e-17	1.
TotalBsmtSF	TotalBsmtSF	5.430823	0.944065	2.469323e-17	1.
1stFlrSF	1stFlrSF	438.176883	428.568820	1.102446e-16	1.
GarageCars	GarageCars	619.644483	452.785835	3.499827e-17	1.
BsmtFinSF1	BsmtFinSF1	1057.821366	384.437716	3.110958e-18	1.
GarageArea	GarageArea	1129.656743	344.544425	-1.011061e-17	1.
FullBath	FullBath	336.751313	427.798462	-8.671795e-17	1.
encoded_BsmtQual	encoded_BsmtQual	1466.408056	460.363670	2.333218e-18	1.
LotArea	LotArea	0.418564	0.507770	-9.297875e-16	1.

In [31]:
```python
plt.figure(figsize=(16, 8))
sns.violinplot(data=X_train_transformed_df, palette='Set3',orient='v', linewidth=0.5
plt.title('Violin Plot of Transformed Features')
plt.xticks(rotation=90)
plt.show()
```



In [32]:
```python
# Box plot comparing original, standardized, and transformed distributions
plt.figure(figsize=(16, 8))
sns.boxplot(data=X_train_transformed_df, orient="v", palette='Set3', showfliers=Fals
plt.title('Distribution after Standardization and Yeo-Johnson Transformation')
plt.xticks(rotation = 90)
plt.show()
```



Apparently from the boxplot some featuress including `ScreenPorch` , `LotFrontage` have low variance, indicating these features do not provide siginicant information and can be filtered.

In [33]:
```
X_test_transformed_df
```

Out[33]:

	OverallQual	GrLivArea	TotalBsmtSF	1stFlrSF	GarageCars	BsmtFinSF1	GarageArea
0	-1.496152	0.547739	-0.377372	-1.128162	0.231945	-1.153801	-1.766537
1	2.152842	1.925553	-0.377372	1.888093	0.005598	2.215691	2.007323
2	0.040778	1.241577	-0.377372	1.241648	-0.125201	1.066230	1.025292
3	0.270990	1.241577	-0.377372	1.383493	-1.220879	0.464281	0.418732
4	0.229423	-0.161042	-0.377372	-1.128162	1.562162	0.986242	1.477448
...	...	...	...	...	...	...	...
241	-0.403726	-0.887997	-0.377372	0.494244	-1.000851	-0.727116	-1.125564
242	1.412629	0.547739	-0.377372	-1.128162	0.743466	-0.429914	-0.702068
243	-0.258428	-0.887997	1.525320	-0.566567	0.391539	-0.471499	-0.760075
244	0.457130	0.547739	-0.377372	-1.128162	1.633533	1.122385	1.077753
245	-0.081014	-0.887997	-0.377372	0.607204	-0.983510	-0.557949	-0.881999

246 rows × 28 columns

5. Modeling

5.1 KFold and Cross-validation

In machine learning, evaluating the performance of a model is crucial to ensure its effectiveness on unseen data. Cross-validation is a technique used to achieve this by splitting the data into multiple subsets, training the model on some subsets, and evaluating it on others.

In [34]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

num_folds = 10
seed = 7

kfold = KFold(n_splits=10, shuffle=True, random_state=seed)
```

5.2 Evaluate Function

To streamline the evaluation process for multiple models, a evaluate function is defined. It fits the model, performs cross-validation, calculates metrics (RMSE and R-squared), and plots

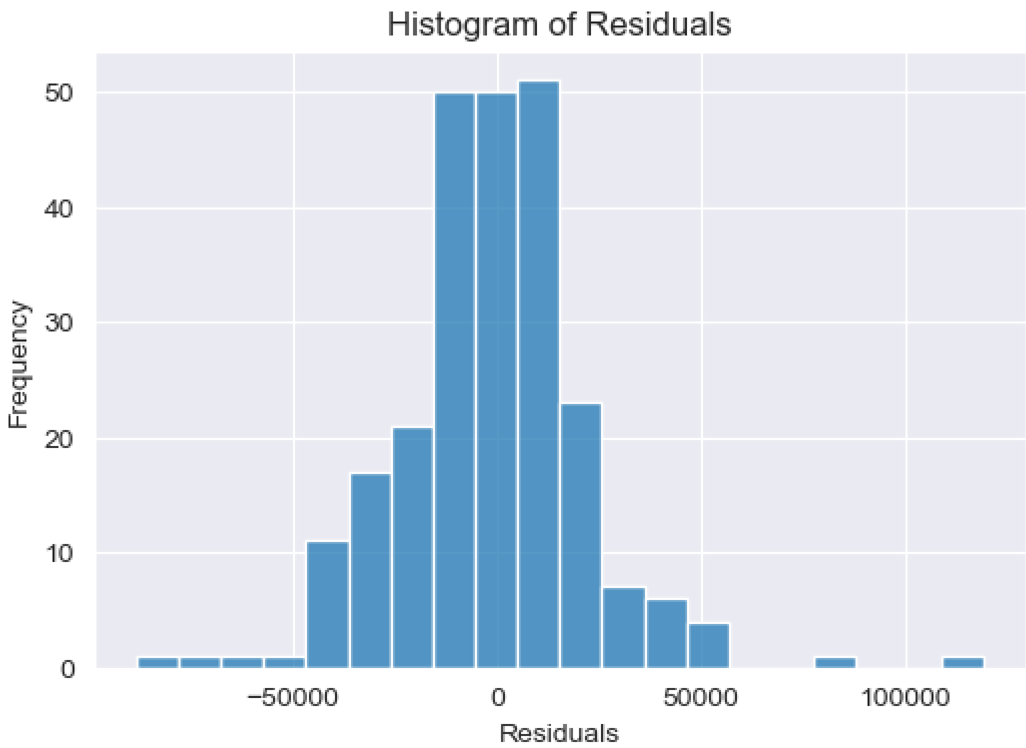
In [36]:
```
def evaluate_model(model, X_train_transformed_df, y_train, X_test_transformed_df, y_
    model.fit(X_train_transformed_df,y_train)

    scores = cross_val_score(model,X_train_transformed_df,y_train,cv=kfold,scoring='
    rmse_scores = np.sqrt(-scores)
    print("RMSE Scores for each fold:", rmse_scores)

    y_predict = model.predict(X_test_transformed_df)
    mse = mean_squared_error(y_test, y_predict)
    r_squared = r2_score(y_test,y_predict)
    print("R-squared:", r_squared)
    print("Mean Squared Error:", mse)

    y_test_rescaled = np.exp(y_test)
    y_pred_rescaled = np.exp(y_predict)
    residuals = y_test_rescaled - y_pred_rescaled

    plt.figure(figsize=(6, 4))
    sns.histplot(residuals, bins=20)
    plt.xlabel("Residuals")
    plt.ylabel("Frequency")
    plt.title('Histogram of Residuals')
    plt.show()
```

5.3 Candidate models

5.3.1 LinearRegression

In [37]:
```
from sklearn.linear_model import LinearRegression

model = LinearRegression(
    fit_intercept=True,    # Whether to calculate the intercept for this model
    n_jobs=None            # The number of jobs to use for the computation. -1 means
)

evaluate_model(model, X_train_transformed_df, y_train, X_test_transformed_df, y_test)
```

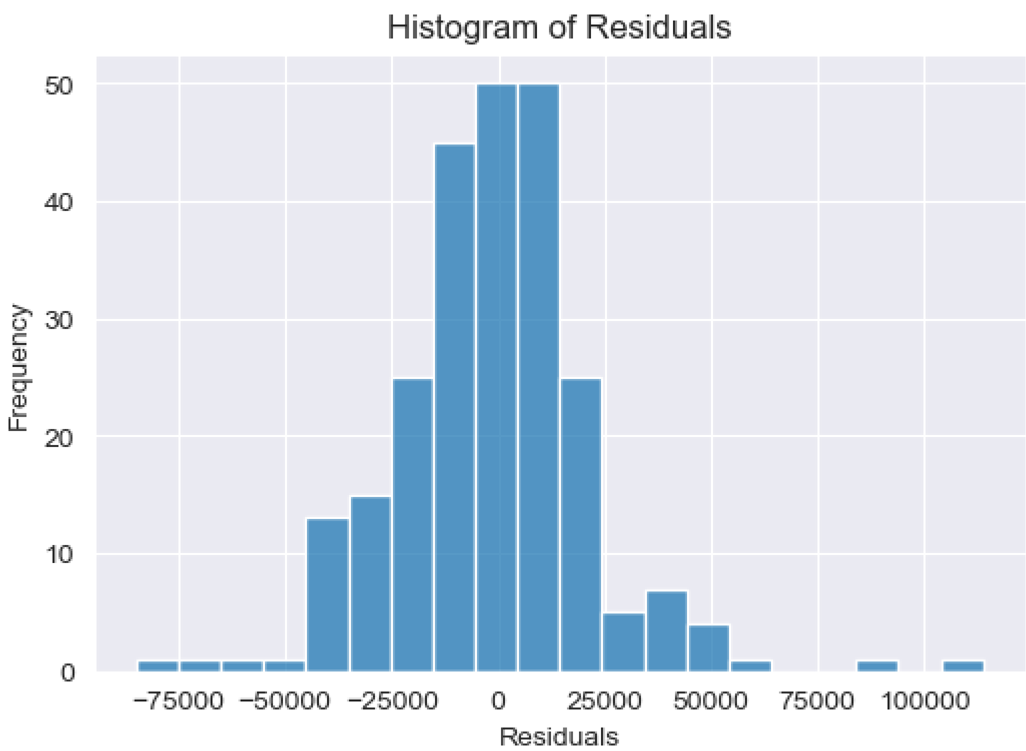
```
RMSE Scores for each fold: [0.11909885 0.09570957 0.15256688 0.11230547 0.14502937
0.10969366
 0.09856047 0.14465786 0.11715607 0.1060386 ]
R-squared: 0.9062370438904005
Mean Squared Error: 0.01430928131863001
```



5.3.2 RidgeRegression

In [65]:
```
from sklearn.linear_model import Ridge
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform,randint

#  Set up the RandomizedSearchCV with appropriate distributions and ranges and find
model = Ridge(random_state=seed)
param_grid = {'alpha': uniform(0,10),'tol':uniform(0.01,0.000001),'max_iter':randint
rsearch = RandomizedSearchCV(estimator=model, param_distributions=param_grid, n_iter
rsearch.fit(X_train_transformed_df, y_train)

print("Recommended alpha ", rsearch.best_estimator_.alpha)
print("Recommended tol ", rsearch.best_estimator_.tol)
print("Recommended max_iter ", rsearch.best_estimator_.max_iter)

# Define Ridge model
model = Ridge(
    alpha=rsearch.best_estimator_.alpha,            # Regularization strength (highe
    fit_intercept=True,                              # Whether to calculate the inte
    max_iter=rsearch.best_estimator_.max_iter,      # Maximum number of iterations f
    tol=rsearch.best_estimator_.tol,                # Precision of the solution
    solver='auto',                                  # Algorithm to use in the optimi
    random_state=seed                               # Seed used by the random number
)

evaluate_model(model, X_train_transformed_df, y_train, X_test_transformed_df, y_test)
```

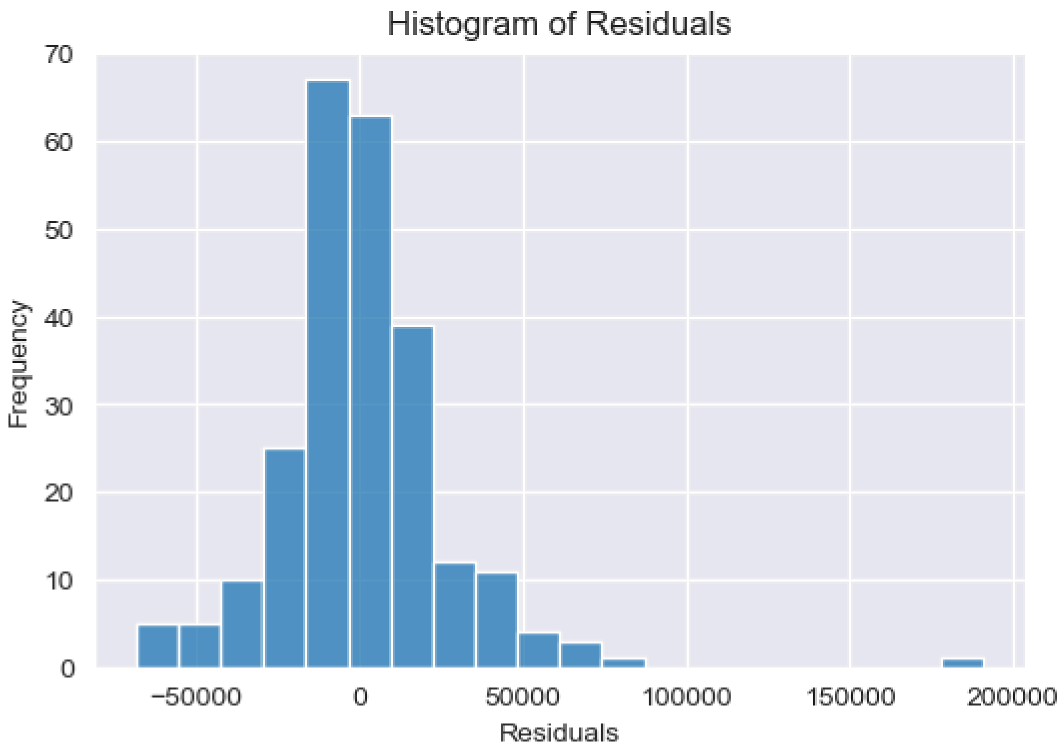
```
Recommended alpha  9.782228970785825
Recommended tol  0.010000977989511996
Recommended max_iter  625
RMSE Scores for each fold: [0.12007371 0.09442221 0.15352298 0.11062168 0.14301735
0.10976461
 0.09997454 0.14468644 0.11603621 0.10601213]
R-squared: 0.9076109876624214
Mean Squared Error: 0.014099602051192603
```



5.3.3 RandomForestRegression

In [46]:
```
from sklearn.ensemble import RandomForestRegressor

# Define Random Forest model
model = RandomForestRegressor(
    n_estimators=100,       # Number of trees in the forest
    criterion='squared_error',       # Function to measure the quality of a split ('r
    max_depth=None,         # Maximum depth of the trees. None means nodes are expand
    min_samples_split=2,    # Minimum number of samples required to split an internal
    min_samples_leaf=1,     # Minimum number of samples required to be at a leaf node
    bootstrap=True,         # Whether bootstrap samples are used when building trees
    random_state=seed,      # Seed used by the random number generator for reproducib
    n_jobs=None             # The number of jobs to run in parallel for both fit and
)

evaluate_model(model, X_train_transformed_df, y_train, X_test_transformed_df, y_test)
```

```
RMSE Scores for each fold: [0.09893152 0.09475912 0.18370296 0.15826665 0.15682039
0.09370734
 0.13532155 0.15019337 0.10260196 0.13731984]
R-squared: 0.8831525003433816
Mean Squared Error: 0.017832242213125963
```



In [1]:
```
import xgboost
from xgboost import XGBRegressor
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[1], line 1
----> 1 import xgboost
      2 from xgboost import XGBRegressor
      4 model = LinearRegression(
      5     fit_intercept=True,   # Whether to calculate the intercept for this m
odel
      6     copy_X=True,          # If True, X will be copied; else, it may be ov
erwritten
      7     n_jobs=None           # The number of jobs to use for the computatio
n. -1 means using all processors
      8 )

ModuleNotFoundError: No module named 'xgboost'
```