In [2]:
```
import numpy as np
import pandas as pd
```

In [3]:
```
housing= pd.read_csv("train (1).csv")
```

In [1]:
```
#print(housing.to_string())
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     588 non-null    object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
 39  Heating        1460 non-null   object 
 40  HeatingQC      1460 non-null   object 
 41  CentralAir     1460 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1460 non-null   int64  
 44  2ndFlrSF       1460 non-null   int64  
 45  LowQualFinSF   1460 non-null   int64  
 46  GrLivArea      1460 non-null   int64  
 47  BsmtFullBath   1460 non-null   int64  
 48  BsmtHalfBath   1460 non-null   int64  
 49  FullBath       1460 non-null   int64  
 50  HalfBath       1460 non-null   int64  
 51  BedroomAbvGr   1460 non-null   int64  
 52  KitchenAbvGr   1460 non-null   int64  
 53  KitchenQual    1460 non-null   object 
 54  TotRmsAbvGrd   1460 non-null   int64  
 55  Functional     1460 non-null   object 
```

```
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

In [6]:
```
housing.describe()
```

Out[6]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	
count	1460.000000	1460.000000	1201.000000	1460.000000	1460.000000	1460.000000	146
mean	730.500000	56.897260	70.049958	10516.828082	6.099315	5.575342	197
std	421.610009	42.300571	24.284752	9981.264932	1.382997	1.112799	3
min	1.000000	20.000000	21.000000	1300.000000	1.000000	1.000000	187
25%	365.750000	20.000000	59.000000	7553.500000	5.000000	5.000000	195
50%	730.500000	50.000000	69.000000	9478.500000	6.000000	5.000000	197
75%	1095.250000	70.000000	80.000000	11601.500000	7.000000	6.000000	200
max	1460.000000	190.000000	313.000000	215245.000000	10.000000	9.000000	201

8 rows × 38 columns

In [10]:
```
# Calculate the percentage of missing values in each column
missing_percentage = housing.isna().mean() * 100

# Filter columns with missing values
missing_columns = missing_percentage[missing_percentage > 0]

# Output the filtered columns and the count of them
missing_columns, len(missing_columns)
```

Out[10]:
```
(LotFrontage     17.739726
 Alley           93.767123
 MasVnrType      59.726027
 MasVnrArea       0.547945
 BsmtQual         2.534247
 BsmtCond         2.534247
 BsmtExposure     2.602740
 BsmtFinType1     2.534247
 BsmtFinType2     2.602740
 Electrical       0.068493
 FireplaceQu     47.260274
 GarageType       5.547945
 GarageYrBlt      5.547945
 GarageFinish     5.547945
 GarageQual       5.547945
 GarageCond       5.547945
 PoolQC          99.520548
 Fence           80.753425
 MiscFeature     96.301370
 dtype: float64,
 19)
```

In [11]:
```
# Forward fill missing values for object-type columns with missing data
housing.loc[:, missing_columns.reset_index()['index']].select_dtypes(includ

# Backward fill missing values for object-type columns with missing data
housing.loc[:, missing_columns.reset_index()['index']].select_dtypes(includ
```

Out[11]:

	Alley	MasVnrType	BsmtQual	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinType:
0	Grvl	BrkFace	Gd	TA	No	GLQ	Un
1	Grvl	BrkFace	Gd	TA	Gd	ALQ	Un
2	Grvl	BrkFace	Gd	TA	Mn	GLQ	Un
3	Grvl	BrkFace	TA	Gd	No	ALQ	Un
4	Grvl	BrkFace	Gd	TA	Av	GLQ	Un
...	...	...	...	...	...	...	..
1455	NaN	Stone	Gd	TA	No	Unf	Un
1456	NaN	Stone	Gd	TA	No	ALQ	Re
1457	NaN	NaN	TA	Gd	No	GLQ	Un
1458	NaN	NaN	TA	TA	Mn	GLQ	Re
1459	NaN	NaN	TA	TA	No	BLQ	Lw(

1460 rows × 16 columns

In [12]:
```
# Count the missing values in each column
missing_values = housing.isna().sum()

# Output the missing values count for each column
print(missing_values)
```

```
Id                 0
MSSubClass         0
MSZoning           0
LotFrontage      259
LotArea            0
                ...
MoSold             0
YrSold             0
SaleType           0
SaleCondition      0
SalePrice          0
Length: 81, dtype: int64
```

In [13]:
```
# Calculate the mean of float64-type columns with missing data
housing.loc[:, missing_columns.reset_index()['index']].select_dtypes(includ
```

Out[13]:
```
LotFrontage      70.049958
MasVnrArea      103.685262
GarageYrBlt    1978.506164
dtype: float64
```

In [14]:
```
# Impute missing values in 'LotFrontage' with a default value of 70.04
housing['LotFrontage'] = np.where(housing['LotFrontage'].isna(), 70.04, hou

# Impute missing values in 'MasVnrArea' with a default value of 103.685262
housing['MasVnrArea'] = np.where(housing['MasVnrArea'].isna(), 103.685262,

# Impute missing values in 'GarageYrBlt' with a default value of 1978.50616
housing['GarageYrBlt'] = np.where(housing['GarageYrBlt'].isna(), 1978.50616
```

In [15]:
```
housing
```

Out[15]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandCo
0	1	60	RL	65.0	8450	Pave	NaN	Reg	
1	2	20	RL	80.0	9600	Pave	NaN	Reg	
2	3	60	RL	68.0	11250	Pave	NaN	IR1	
3	4	70	RL	60.0	9550	Pave	NaN	IR1	
4	5	60	RL	84.0	14260	Pave	NaN	IR1	
...	...	...	...	...	...	...	...	...	
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	

1460 rows × 81 columns

In [16]:
```
# Count the missing values in each column
missing_values = housing.isna().sum()

# Drop columns with more than 50% missing values
housing.drop(missing_values[missing_values > 50].reset_index()['index'], ax

# Output the shape of the dataframe after column removal
housing.shape
```

Out[16]: (1460, 71)

Converting cat cols into numerical cols

In [17]:
```
# Get the column names with 'object' data type (categorical columns)
df_cat=housing.select_dtypes(include=['object']).columns
```

In [18]:
```
df_cat
```

Out[18]:
```
Index(['MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition
2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual',
       'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'Heatin
g',
       'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functiona
l',
       'PavedDrive', 'SaleType', 'SaleCondition'],
      dtype='object')
```

In [21]:
```
# Importing necessary libraries for preprocessing and metrics
from sklearn import preprocessing, metrics
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
```

In [22]:
```
# Initialize the OneHotEncoder for categorical data encoding
ohe = OneHotEncoder()
```

In [23]:
```
# Reset the index of the DataFrame without keeping the old index
housing.reset_index(drop=True, inplace=True)

# List of categorical columns in the housing dataset
df_cat_cols = ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'U
               'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Con
               'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior
               'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foun
               'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'Bsm
               'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'Kitchen
               'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', '
               'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature'
               'SaleCondition']
```

In [24]:
```
# Apply OneHotEncoder to the categorical columns in housing dataset
ohe_var = ohe.fit_transform(housing[['MSZoning', 'Street', 'LotShape', 'Lan
                                     'LotConfig', 'LandSlope', 'Neighborhoo
                                     'BldgType', 'HouseStyle', 'RoofStyle',
                                     'Exterior2nd', 'ExterQual', 'ExterCond
                                     'BsmtCond', 'BsmtExposure', 'BsmtFinTy
                                     'HeatingQC', 'CentralAir', 'Electrical
                                     'PavedDrive', 'SaleType', 'SaleConditi
```

In [25]:
```
# Convert the OneHotEncoded array into a DataFrame with appropriate column
ohe_var = pd.DataFrame(ohe_var.toarray(), columns=ohe.get_feature_names_out
```

In [26]:
```
# Concatenate the original housing DataFrame with the OneHotEncoded columns
housing_new = pd.concat([housing, ohe_var], axis=1)
```

In [2]:
```
#housing_new
```

In [28]:
```
# Drop the original categorical columns after OneHotEncoding
housing_new.drop(columns=['MSZoning', 'Street', 'LotShape', 'LandContour',
                          'LotConfig', 'LandSlope', 'Neighborhood', 'Condit
                          'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl'
                          'Exterior2nd', 'ExterQual', 'ExterCond', 'Foundat
                          'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'Bsmt
                          'HeatingQC', 'CentralAir', 'Electrical', 'Kitchen
                          'PavedDrive', 'SaleType', 'SaleCondition'], inpla
```

In [3]:
```
#housing_new
```

Type *Markdown* and LaTeX: α^2

In [36]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant

# Add a constant term to the DataFrame to account for the intercept in VIF
df_constant = add_constant(housing_new)

# Calculate VIF for each variable
vif_data = pd.DataFrame()
vif_data["Feature"] = df_constant.columns
vif_data["VIF"] = [variance_inflation_factor(df_constant.values, i) for i i

# Display the VIF values for each feature
print(vif_data)
```

```
C:\ProgramData\anaconda3\Lib\site-packages\statsmodels\regression\linea
r_model.py:1781: RuntimeWarning: divide by zero encountered in scalar d
ivide
  return 1 - self.ssr/self.centered_tss
C:\ProgramData\anaconda3\Lib\site-packages\statsmodels\stats\outliers_i
nfluence.py:198: RuntimeWarning: divide by zero encountered in scalar d
ivide
  vif = 1. / (1. - r_squared_i)

                   Feature        VIF
0                    const   0.000000
1                       Id   1.192539
2               MSSubClass  33.805402
3              LotFrontage   2.505810
4                  LotArea   3.417143
..                     ...        ...
251   SaleCondition_AdjLand        inf
252    SaleCondition_Alloca        inf
253    SaleCondition_Family        inf
254    SaleCondition_Normal        inf
```

In [37]:
```
# Select columns with VIF values greater than or equal to 20
reqcols = vif_data.loc[vif_data['VIF'] >= 20, 'Feature']

# Access the corresponding columns in the housing_new DataFrame
housing_new.loc[:, reqcols]
```

Out[37]:

	MSSubClass	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stFlrSF	2ndFlrSF
0	60	706	0	150	856	856	854
1	20	978	0	284	1262	1262	0
2	60	486	0	434	920	920	866
3	70	216	0	540	756	961	756
4	60	655	0	490	1145	1145	1053
...	...	...	...	...	...	...	...
1455	60	0	0	953	953	953	694
1456	20	790	163	589	1542	2073	0
1457	70	275	0	877	1152	1188	1152
1458	20	49	1029	0	1078	1078	0
1459	20	830	290	136	1256	1256	0

1460 rows × 226 columns

In [38]:
```
def correlation(df, threshold):
    correlated_cols = set()
    corre_matrix = df.corr()
    for i in range(len(corre_matrix.columns)):
        for j in range(i):
            if abs(corre_matrix.iloc[i, j]) > threshold:
                correlated_cols.add(corre_matrix.columns[i])
    return correlated_cols
```

In [39]:
```
# Function to remove highly correlated features (multicollinearity)
def remove_multicollinearity(df, threshold):
    correlated_cols = correlation(df, threshold)

    # Drop highly correlated columns
    df_cleaned = df.drop(columns=correlated_cols)

    return df_cleaned

# Apply the function with a threshold (e.g., 0.9 for high correlation)
threshold = 0.9
housing_cleaned = remove_multicollinearity(housing_new, threshold)

# Check the shape of the new DataFrame after removing correlated features
print(housing_cleaned.shape)
```

```
(1460, 239)
```

In [40]:
```
# Remove multicollinearity using correlation before training the model
threshold = 0.9
housing_cleaned = remove_multicollinearity(housing_new, threshold)

# Now, split the data into training and test sets
X = housing_cleaned.loc[:, housing_cleaned.columns != 'SalePrice'].values
y = housing_cleaned.loc[:, housing_cleaned.columns == 'SalePrice'].values

# Train/Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra

# Model Training
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[40]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [41]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_sco

# Predict on the test set
y_pred = regressor.predict(X_test)

# Evaluate performance
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
r2 = r2_score(y_test, y_pred)

# Print evaluation metrics
print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("Root Mean Squared Error:", rmse)
print("R² Score:", r2)
```

```
Mean Absolute Error: 22259.56716756969
Mean Squared Error: 3096707469.952557
Root Mean Squared Error: 55648.067980412015
R² Score: 0.5515819940928334
```

In [42]:
```
# Predict on the training set
y_train_pred = regressor.predict(X_train)

# Compare training vs test performance
train_mae = mean_absolute_error(y_train, y_train_pred)
test_mae = mean_absolute_error(y_test, y_pred)

train_r2 = r2_score(y_train, y_train_pred)
test_r2 = r2_score(y_test, y_pred)

# Print comparison
print("Training MAE:", train_mae)
print("Test MAE:", test_mae)
print("Training R²:", train_r2)
print("Test R²:", test_r2)
```

```
Training MAE: 12548.10328137777
Test MAE: 22259.56716756969
Training R²: 0.94058573886167
Test R²: 0.5515819940928334
```

In [43]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge

# Hyperparameter tuning for Ridge regression (example)
ridge = Ridge()
param_grid = {'alpha': [0.1, 1, 10, 100]}  # Tuning the regularization para
grid_search = GridSearchCV(ridge, param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Best hyperparameters
print("Best alpha:", grid_search.best_params_)

# Train and evaluate with the best model
best_ridge = grid_search.best_estimator_
y_pred_best = best_ridge.predict(X_test)
print("Best Model R²:", r2_score(y_test, y_pred_best))
```

```
Best alpha: {'alpha': 10}
Best Model R²: 0.7093565606475368
```

In [44]:
```
#adjusted R2
# Function to compute adjusted R²
def adjusted_r2_score(X, y, model):
    n = len(y)  # Number of observations
    p = X.shape[1]  # Number of features
    r2 = r2_score(y, model.predict(X))  # R² Score
    adj_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)
    return adj_r2

# Calculate Adjusted R² for both models
train_adj_r2 = adjusted_r2_score(X_train, y_train, regressor)
test_adj_r2 = adjusted_r2_score(X_test, y_test, regressor)

print("Training Adjusted R²:", train_adj_r2)
print("Test Adjusted R²:", test_adj_r2)
```

```
Training Adjusted R²: 0.9253644319177274
Test Adjusted R²: -1.4620686739431226
```

In [45]:
```
from sklearn.linear_model import Ridge

ridge = Ridge(alpha=10)  # You can start with alpha=10, but we can tune it
ridge.fit(X_train, y_train)
y_pred_ridge = ridge.predict(X_test)
print("R² (Ridge):", r2_score(y_test, y_pred_ridge))
```

```
R² (Ridge): 0.7093565606475368
```

In [46]:
```
from sklearn.preprocessing import StandardScaler

# Scaling the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Fit Ridge on scaled data
ridge.fit(X_train_scaled, y_train)
y_pred_ridge_scaled = ridge.predict(X_test_scaled)
print("R² (Ridge with Scaling):", r2_score(y_test, y_pred_ridge_scaled))
```

```
R² (Ridge with Scaling): 0.5878693901662428
```

In [47]:
```
from sklearn.model_selection import cross_val_score

# Use Ridge with cross-validation
cv_scores = cross_val_score(ridge, X_train_scaled, y_train, cv=5, scoring='
print(f"Cross-Validation MSE (negative): {cv_scores}")
```

```
Cross-Validation MSE (negative): [-7.23414763e+08 -1.48384541e+09 -5.58768
417e+08 -8.23647330e+08
 -4.14967786e+08]
```

In [48]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {'alpha': [0.1, 1, 10, 100, 1000]}
grid_search = GridSearchCV(ridge, param_grid, cv=5, scoring='neg_mean_squar
grid_search.fit(X_train_scaled, y_train)

print(f"Best parameters: {grid_search.best_params_}")
```

```
Best parameters: {'alpha': 100}
```

In [49]:
```
# Train with the best alpha found from GridSearchCV
best_ridge = Ridge(alpha=100)
best_ridge.fit(X_train_scaled, y_train)
y_pred_best_ridge = best_ridge.predict(X_test_scaled)

print("R² (Ridge with alpha=100):", r2_score(y_test, y_pred_best_ridge))
```

```
R² (Ridge with alpha=100): 0.6307215979489333
```

In [50]:
```
from sklearn.linear_model import Lasso

lasso = Lasso(alpha=100)
lasso.fit(X_train_scaled, y_train)
y_pred_lasso = lasso.predict(X_test_scaled)

print("R² (Lasso with alpha=100):", r2_score(y_test, y_pred_lasso))
```

```
R² (Lasso with alpha=100): 0.5968935100449475
```

In [58]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_sco

# Make predictions using the trained Random Forest model
y_pred = rf_model.predict(X_train)

# Evaluate performance
mse = mean_squared_error(y_train, y_pred)
mae = mean_absolute_error(y_train, y_pred)
r2 = r2_score(y_train, y_pred)

# Print evaluation metrics
print(f"Mean Squared Error (MSE): {mse}")
print(f"Mean Absolute Error (MAE): {mae}")
print(f"R² (Coefficient of Determination): {r2}")
```

```
Mean Squared Error (MSE): 127450989.59156996
Mean Absolute Error (MAE): 6522.615590753425
R² (Coefficient of Determination): 0.97929968918002
```

In [59]:
```
# Predicting on the test set
y_test_pred = rf_model.predict(X_test)

# Evaluating the model performance on the test set
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_sco

# Mean Squared Error
mse_test = mean_squared_error(y_test, y_test_pred)
# Mean Absolute Error
mae_test = mean_absolute_error(y_test, y_test_pred)
# R²
r2_test = r2_score(y_test, y_test_pred)

print("Test Mean Squared Error (MSE):", mse_test)
print("Test Mean Absolute Error (MAE):", mae_test)
print("Test R²:", r2_test)
```

```
Test Mean Squared Error (MSE): 1196368366.8795376
Test Mean Absolute Error (MAE): 17709.577739726028
Test R²: 0.8267601565172202
```

In [60]:
```
def adjusted_r2(R2, n, p):
    return 1 - (1 - R2) * (n - 1) / (n - p - 1)

# Calculate Adjusted R² for the training set
n_train = X_train.shape[0]  # Number of samples in the training set
p_train = X_train.shape[1]  # Number of features in the training set
adj_r2_train = adjusted_r2(rf_model.score(X_train, y_train), n_train, p_tra

# Calculate Adjusted R² for the test set
n_test = X_test.shape[0]  # Number of samples in the test set
p_test = X_test.shape[1]  # Number of features in the test set
adj_r2_test = adjusted_r2(rf_model.score(X_test, y_test), n_test, p_test)

# Display the Adjusted R² values
print("Adjusted R² (Train):", adj_r2_train)
print("Adjusted R² (Test):", adj_r2_test)
```

```
Adjusted R² (Train): 0.973996487915052
Adjusted R² (Test): 0.048815198990775244
```

In [61]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_train)  # Scale the train data
X_test_scaled = scaler.transform(X_test)  # Use the same scaling for test d
```

In [62]:
```
from sklearn.decomposition import PCA

# Initialize PCA and fit it to the scaled data
pca = PCA(n_components=0.95)  # Keep 95% of variance
X_train_pca = pca.fit_transform(X_scaled)
X_test_pca = pca.transform(X_test_scaled)

print(f"Original number of features: {X_scaled.shape[1]}")
print(f"Reduced number of features after PCA: {X_train_pca.shape[1]}")
```

```
Original number of features: 238
Reduced number of features after PCA: 153
```

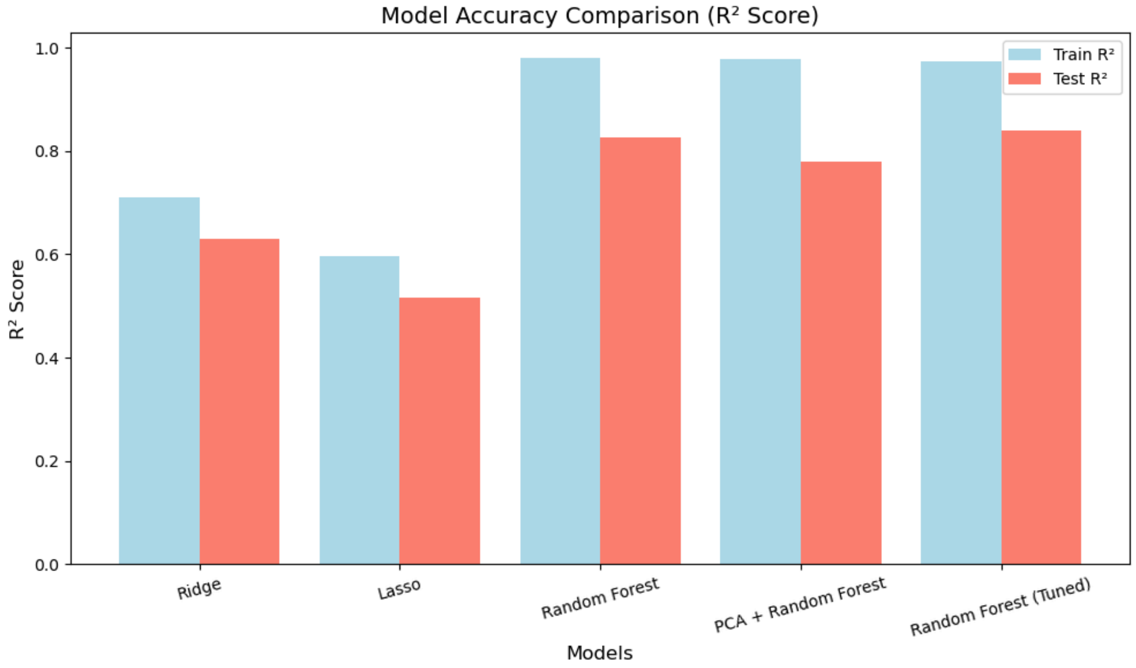
In [63]:
```
from sklearn.ensemble import RandomForestRegressor

# Initialize and train the Random Forest model
rf_pca = RandomForestRegressor(random_state=42)
rf_pca.fit(X_train_pca, y_train)

# Evaluate the model
train_pred_pca = rf_pca.predict(X_train_pca)
test_pred_pca = rf_pca.predict(X_test_pca)

# Calculate the performance metrics
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_sco

# Train metrics
train_mse = mean_squared_error(y_train, train_pred_pca)
train_mae = mean_absolute_error(y_train, train_pred_pca)
train_r2 = r2_score(y_train, train_pred_pca)

# Test metrics
test_mse = mean_squared_error(y_test, test_pred_pca)
test_mae = mean_absolute_error(y_test, test_pred_pca)
test_r2 = r2_score(y_test, test_pred_pca)

# Print results
print(f"Train MSE: {train_mse}")
print(f"Train MAE: {train_mae}")
print(f"Train R²: {train_r2}")

print(f"Test MSE: {test_mse}")
print(f"Test MAE: {test_mae}")
print(f"Test R²: {test_r2}")
```

```
C:\ProgramData\anaconda3\Lib\site-packages\sklearn\base.py:1151: DataConve
rsionWarning: A column-vector y was passed when a 1d array was expected. P
lease change the shape of y to (n_samples,), for example using ravel().
  return fit_method(estimator, *args, **kwargs)

Train MSE: 135271553.29757774
Train MAE: 7101.626917808219
Train R²: 0.9780294903371503
Test MSE: 1520675043.5950634
Test MAE: 20648.582226027396
Test R²: 0.7797990035228807
```

In [64]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor

# Define the Random Forest model
rf = RandomForestRegressor(random_state=42)

# Set up the parameter grid to search through
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}

# Set up the grid search with cross-validation
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                           cv=5, n_jobs=-1, verbose=2, scoring='neg_mean_sq

# Fit the grid search to the training data
grid_search.fit(X_train, y_train)

# Get the best parameters from the grid search
best_params = grid_search.best_params_

# Get the best model from the grid search
best_rf_model = grid_search.best_estimator_

# Evaluate the best model on the test data
y_test_pred = best_rf_model.predict(X_test)

# Print best parameters and evaluation metrics
print("Best parameters:", best_params)

from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_sco

test_mse = mean_squared_error(y_test, y_test_pred)
test_mae = mean_absolute_error(y_test, y_test_pred)
test_r2 = r2_score(y_test, y_test_pred)

print(f'Test MSE: {test_mse}')
print(f'Test MAE: {test_mae}')
print(f'Test R²: {test_r2}')
```

```
Fitting 5 folds for each of 216 candidates, totalling 1080 fits

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\base.py:1151: DataConve
rsionWarning: A column-vector y was passed when a 1d array was expected. P
lease change the shape of y to (n_samples,), for example using ravel().
  return fit_method(estimator, *args, **kwargs)

Best parameters: {'bootstrap': True, 'max_depth': 20, 'min_samples_leaf':
1, 'min_samples_split': 2, 'n_estimators': 200}
Test MSE: 1115900026.6556997
Test MAE: 17525.504969436388
Test R²: 0.8384123558327681
```

In [4]:
```
import matplotlib.pyplot as plt

# Define models and their R² scores (replace these values with actual resul
models = ['Ridge', 'Lasso', 'Random Forest', 'PCA + Random Forest', 'Random
train_r2_scores = [0.7094, 0.5969, 0.9793, 0.9780, 0.9740]  # Add Train R²
test_r2_scores = [0.6307, 0.5169, 0.8268, 0.7798, 0.8384]   # Add Test R² h

# Create bar width and positions
x_pos = range(len(models))
width = 0.4

# Plot
plt.figure(figsize=(10, 6))
plt.bar(x=[p - width/2 for p in x_pos], height=train_r2_scores, width=width
plt.bar(x=[p + width/2 for p in x_pos], height=test_r2_scores, width=width,

# Add labels and title
plt.xlabel('Models', fontsize=12)
plt.ylabel('R² Score', fontsize=12)
plt.title('Model Accuracy Comparison (R² Score)', fontsize=14)
plt.xticks(x_pos, models, rotation=15)
plt.legend()
plt.tight_layout()

# Show Plot
plt.show()
```



In [ ]: