Ravinthiran_Partheepan_Housing_Prediction_using_KNN_Decision_Tree_

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1 Computational Intelligence and Decision Making - Lab Work 1

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1.1 KNN Problem Statement:

Problem: based on the given data of historical real estate transactions create the decision-making model (DMM) which aims to predict prices of new real estate objects.

Project workflow:

- P1. Perform given data analysis and preprocessing
- P2. Implement K-Nearest Neighbors (KNN), Decision tree (DT), and random forest (RF) algorithms (You cannot use library functions for these algorithms)
- P3. Use implemented algorithms to create DMM for the given problem and evaluate the results.
- P4. Use "scikit-learn" (or other) library functions for the same algorithms and evaluate the results.
- P5. Write conclusions.

1.2 Library Import

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error,␣
↪mean_absolute_percentage_error
from sklearn.impute import SimpleImputer
```

1.3 Data Import

[2]:
```
read_hist_csv = pd.read_csv("C:/Users/ravin/KTU/CI-DM/Task 1/Datasets/Task 1/
↪historicalData.tsv", sep="\t")
read_hist_csv.head()
```

[2]:
```
   Id  LotFrontage  LotArea Street Neighborhood  YearBuilt  YearRemodAdd  \
0   1         65.0     8450   Pave      CollgCr       2003          2003
1   2         80.0     9600   Pave      Veenker       1976          1976
2   3         68.0    11250   Pave      CollgCr       2001          2002
3   4         60.0     9550   Pave      Crawfor       1915          1970
4   5         84.0    14260   Pave      NoRidge       2000          2000

  CentralAir PavedDrive SaleCondition  SalePrice
0          Y          Y        Normal     208500
1          Y          Y        Normal     181500
2          Y          Y        Normal     223500
3          Y          Y       Abnorml     140000
4          Y          Y        Normal     250000
```

[3]:
```
read_new_csv = pd.read_csv("C:/Users/ravin/KTU/CI-DM/Task 1/Datasets/Task 1/
↪newData.tsv", sep="\t")
read_new_csv.head()
```

[3]:
```
     Id  LotFrontage  LotArea Street Neighborhood  YearBuilt  YearRemodAdd  \
0  1000         64.0     6762   Pave      CollgCr       2006          2006
1  1001         74.0    10206   Pave      Edwards       1952          1952
2  1002         60.0     5400   Pave      OldTown       1920          1950
3  1003         75.0    11957   Pave      Somerst       2006          2006
4  1004          NaN    11500   Pave       NWAmes       1976          1976

  CentralAir PavedDrive SaleCondition  SalePrice
0          Y          Y        Normal     206000
1          N          Y        Normal      82000
2          Y          N       Abnorml      86000
3          Y          Y        Normal     232000
4          Y          Y        Normal     136905
```

1.4 Data type of features: LotFrontage, LotArea, Street,...SalePrice

[4]:
```
print(read_hist_csv.dtypes)
```

```
Id                int64
LotFrontage     float64
LotArea           int64
Street           object
Neighborhood     object
YearBuilt         int64
```

```
YearRemodAdd       int64
CentralAir        object
PavedDrive        object
SaleCondition     object
SalePrice          int64
dtype: object
```

[5]:
```python
print(read_new_csv.dtypes)
```

```
Id                 int64
LotFrontage      float64
LotArea            int64
Street            object
Neighborhood      object
YearBuilt          int64
YearRemodAdd       int64
CentralAir        object
PavedDrive        object
SaleCondition     object
SalePrice          int64
dtype: object
```

1.5 Data Quality Test

[6]:
```python
# Checking for Missing values in HistoricalData
check_hist_dat_null = read_hist_csv.isnull().sum()
print(check_hist_dat_null)
```

```
Id                 0
LotFrontage      173
LotArea            0
Street             0
Neighborhood       0
YearBuilt          0
YearRemodAdd       0
CentralAir         0
PavedDrive         0
SaleCondition      0
SalePrice          0
dtype: int64
```

[7]:
```python
# Checking for missing values in NewData
check_new_dat = read_new_csv.isnull().sum()
print(check_new_dat)
```

```
Id               0
LotFrontage     86
LotArea          0
Street           0
```

```
Neighborhood      0
YearBuilt         0
YearRemodAdd      0
CentralAir        0
PavedDrive        0
SaleCondition     0
SalePrice         0
dtype: int64
```

1.6 Missing Value Imputation

[8]:
```python
# Historical Data NaN imputation
# Dropping the rows with NaN would eliminate large protions of data because␣
↪since there are 173 cells in the LotFrontage features has NaN
# So imputing those missing values with value 0

fill_na_hist = read_hist_csv.fillna(read_hist_csv.median()) #Median
check_Hist_NaN = fill_na_hist.isnull().sum()
print(check_Hist_NaN)
```

```
Id               0
LotFrontage      0
LotArea          0
Street           0
Neighborhood     0
YearBuilt        0
YearRemodAdd     0
CentralAir       0
PavedDrive       0
SaleCondition    0
SalePrice        0
dtype: int64
```

```
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\2933457410.py:5:
FutureWarning: The default value of numeric_only in DataFrame.median is
deprecated. In a future version, it will default to False. In addition,
specifying 'numeric_only=None' is deprecated. Select only valid columns or
specify the value of numeric_only to silence this warning.
  fill_na_hist = read_hist_csv.fillna(read_hist_csv.median()) #Median
```

[9]:
```python
# NewData NaN Imputation
fill_na_new = read_new_csv.fillna(0)
check_New_NaN = fill_na_new.isnull().sum()
print(check_New_NaN)
```

```
Id               0
LotFrontage      0
LotArea          0
Street           0
```

```
Neighborhood     0
YearBuilt        0
YearRemodAdd     0
CentralAir       0
PavedDrive       0
SaleCondition    0
SalePrice        0
dtype: int64
```

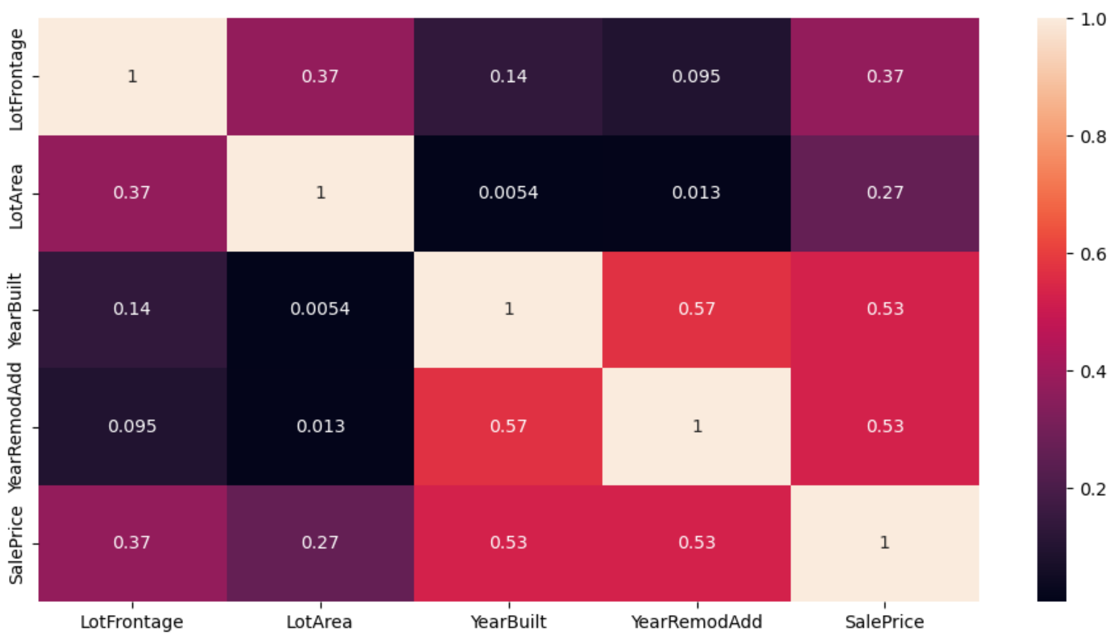
[10]:
```
# Dropping the ID field
read_hist_csv.drop(['Id'], axis=1, inplace=True)
```

1.7 Correlation Analysis

[11]:
```
# Implementing correlation to understand the dependency between each feaure␣
↪whether it is positively corrleated or negative correlated
plt.figure(figsize=(12,6))
sns.heatmap(read_hist_csv.corr(), annot=True)
```

```
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\1103431315.py:3:
FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(read_hist_csv.corr(), annot=True)
```

[11]: <Axes: >



1.8 Checking for Duplicates

[12]:
```
# Histroical Data Feature Duplication Check
duplicate_hist = read_hist_csv[read_hist_csv.duplicated()]
print(duplicate_hist)
```

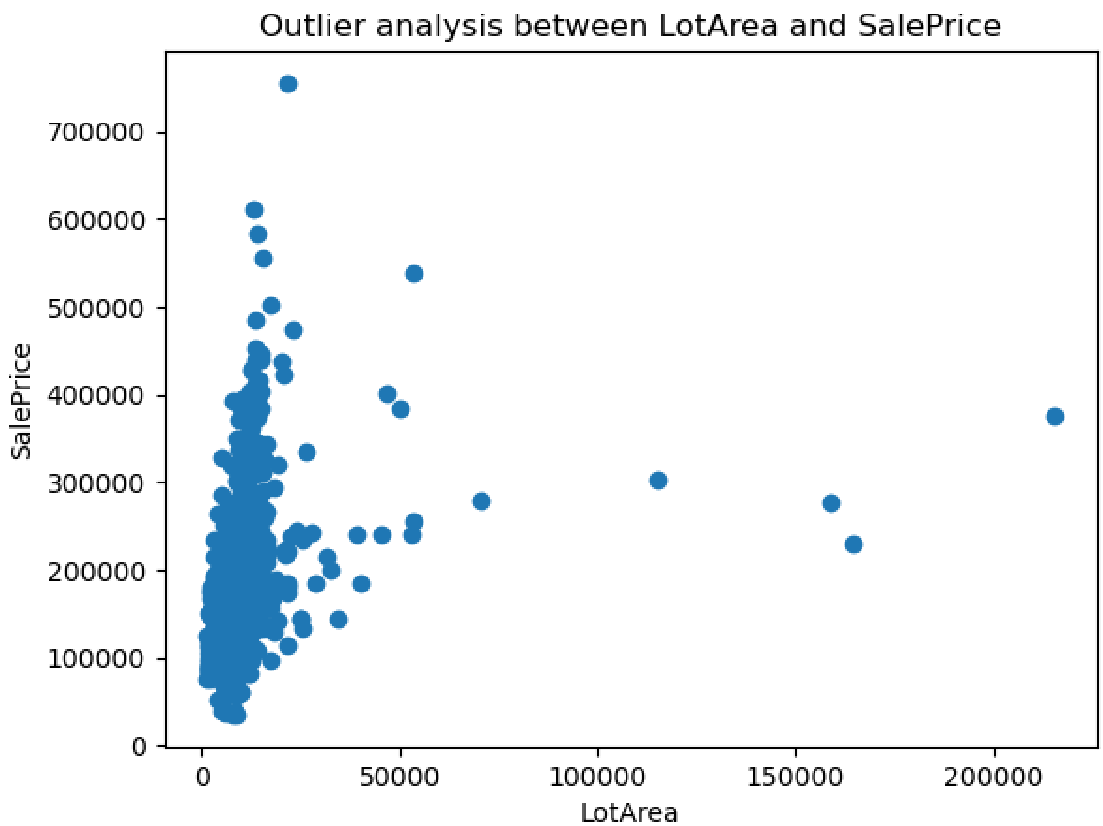
```
Empty DataFrame
Columns: [LotFrontage, LotArea, Street, Neighborhood, YearBuilt, YearRemodAdd,
CentralAir, PavedDrive, SaleCondition, SalePrice]
Index: []
```

[13]:
```
duplicate_new = read_new_csv[read_new_csv.duplicated()]
print(duplicate_new)
```

```
Empty DataFrame
Columns: [Id, LotFrontage, LotArea, Street, Neighborhood, YearBuilt,
YearRemodAdd, CentralAir, PavedDrive, SaleCondition, SalePrice]
Index: []
```

1.9 Outlier Analysis

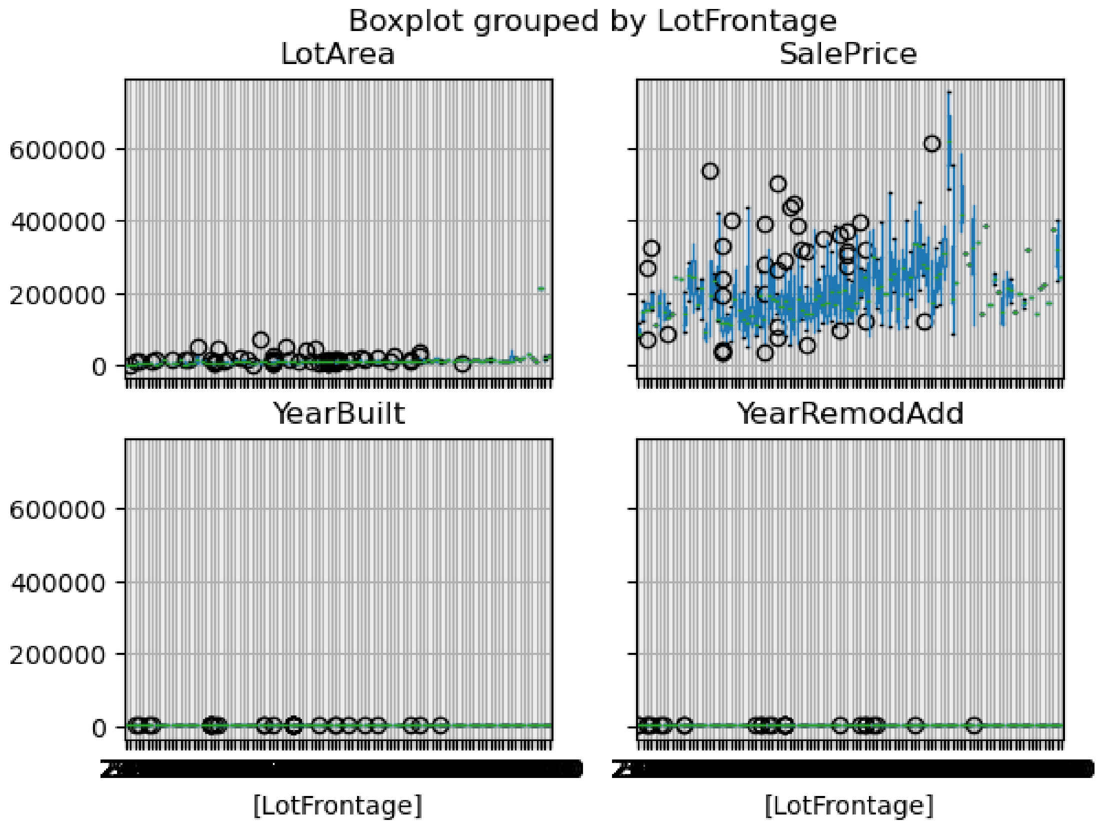
[14]:
```
scat_outlier = plt.scatter(read_hist_csv["LotArea"], read_hist_csv["SalePrice"])
plt.title("Outlier analysis between LotArea and SalePrice")
plt.xlabel("LotArea")
plt.ylabel("SalePrice")
plt.show()
```



[15]:
```
# Outlier analysis using Box-Plot
scale_fig = plt.figure(figsize=(10,7))
read_hist_csv.boxplot(by="LotFrontage")
```

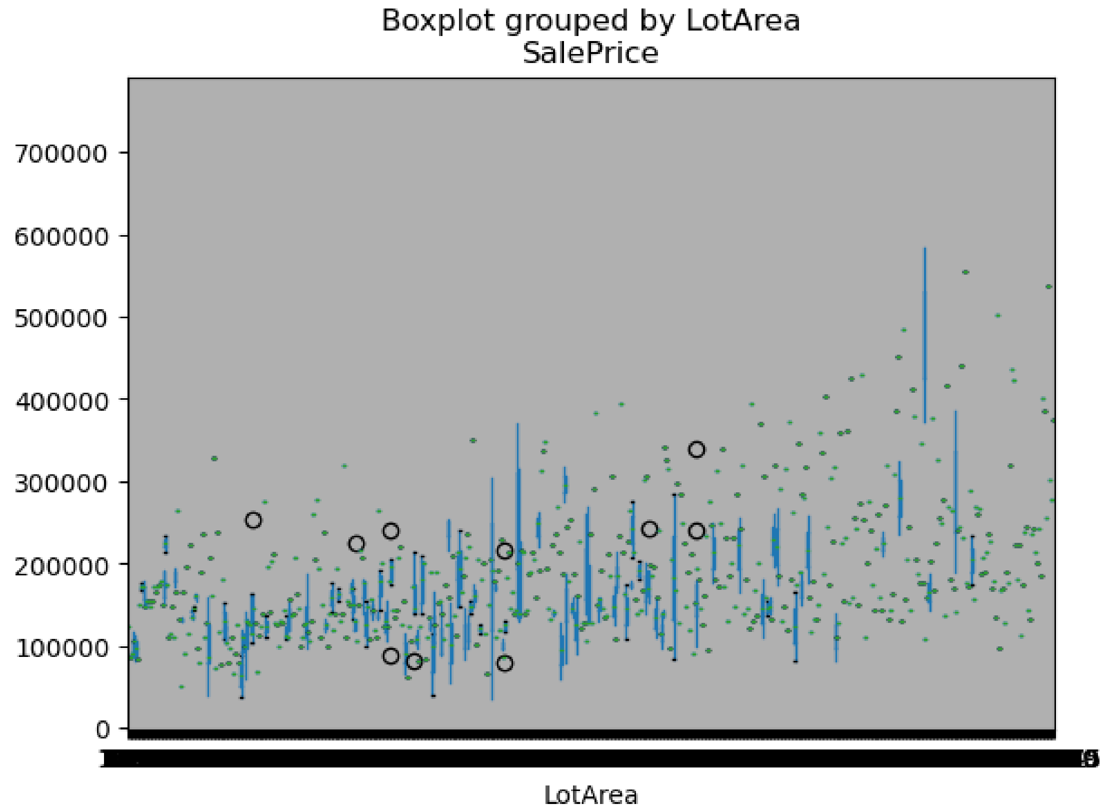
[15]:
```
array([[<Axes: title={'center': 'LotArea'}, xlabel='[LotFrontage]'>,
        <Axes: title={'center': 'SalePrice'}, xlabel='[LotFrontage]'>],
       [<Axes: title={'center': 'YearBuilt'}, xlabel='[LotFrontage]'>,
        <Axes: title={'center': 'YearRemodAdd'}, xlabel='[LotFrontage]'>]],
      dtype=object)
```

```
<Figure size 1000x700 with 0 Axes>
```




```
[16]: scale_fig = plt.figure(figsize=(10,7))
      read_hist_csv.boxplot(by="LotArea", widths= 1.0, column=["SalePrice"])
```

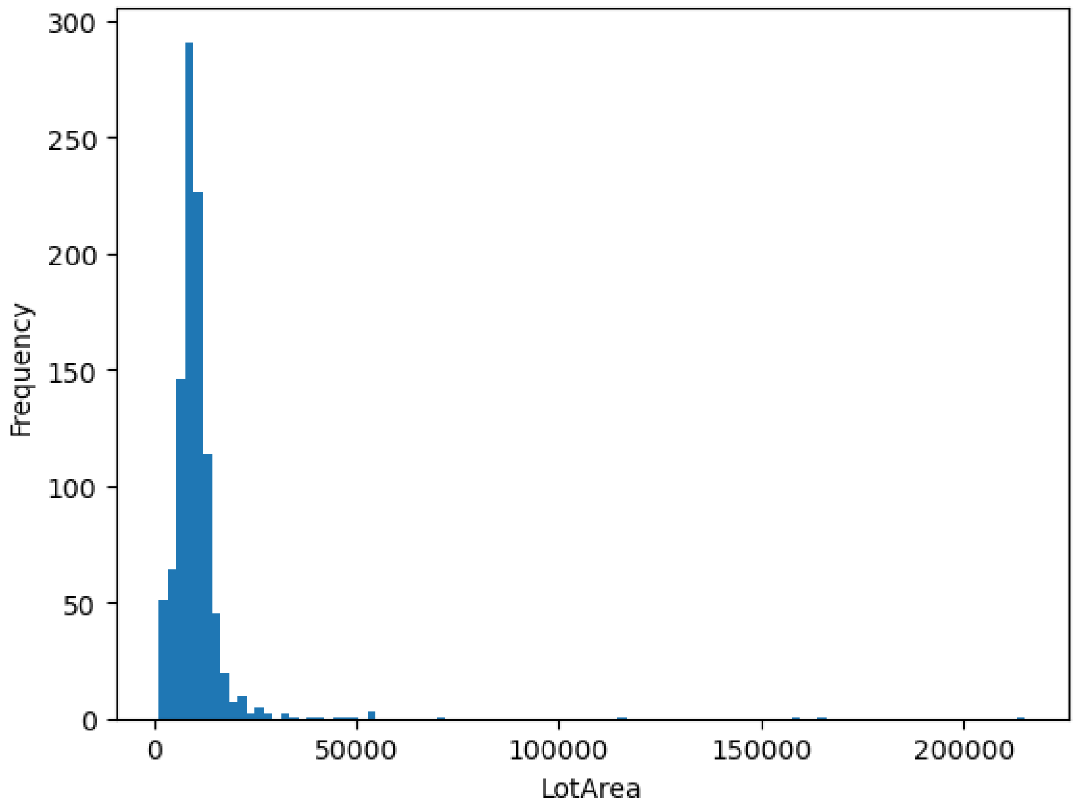
```
[16]: <Axes: title={'center': 'SalePrice'}, xlabel='LotArea'>

      <Figure size 1000x700 with 0 Axes>
```



1.10 Data Distribution

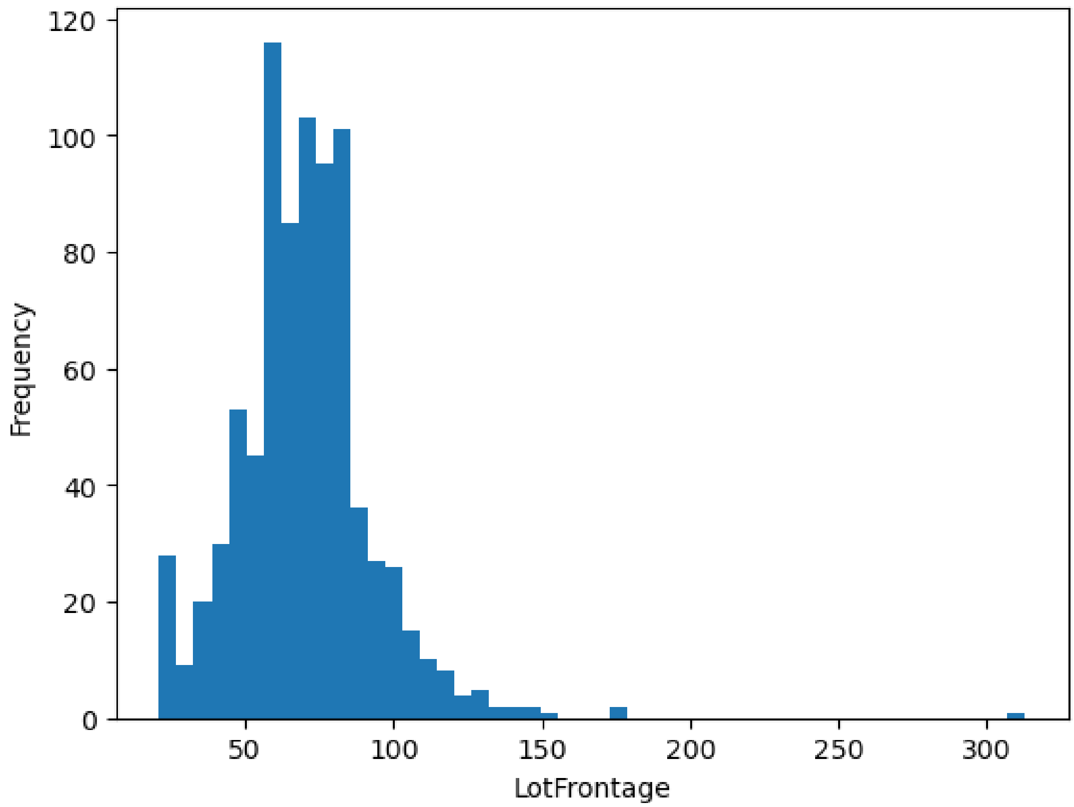
[17]:
```
plt.hist(read_hist_csv["LotArea"], bins=100)
plt.xlabel("LotArea")
plt.ylabel("Frequency")
```

[17]: Text(0, 0.5, 'Frequency')



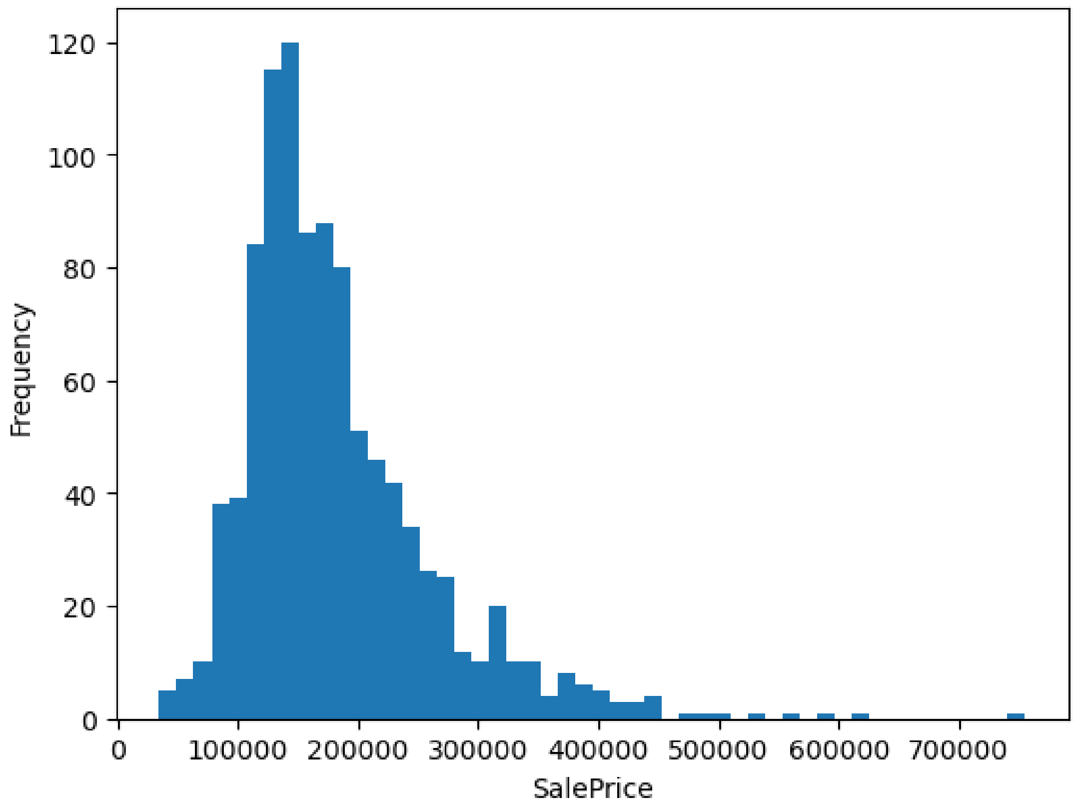
[18]:
```
plt.hist(read_hist_csv["LotFrontage"], bins=50)
plt.xlabel("LotFrontage")
plt.ylabel("Frequency")
```

[18]: `Text(0, 0.5, 'Frequency')`



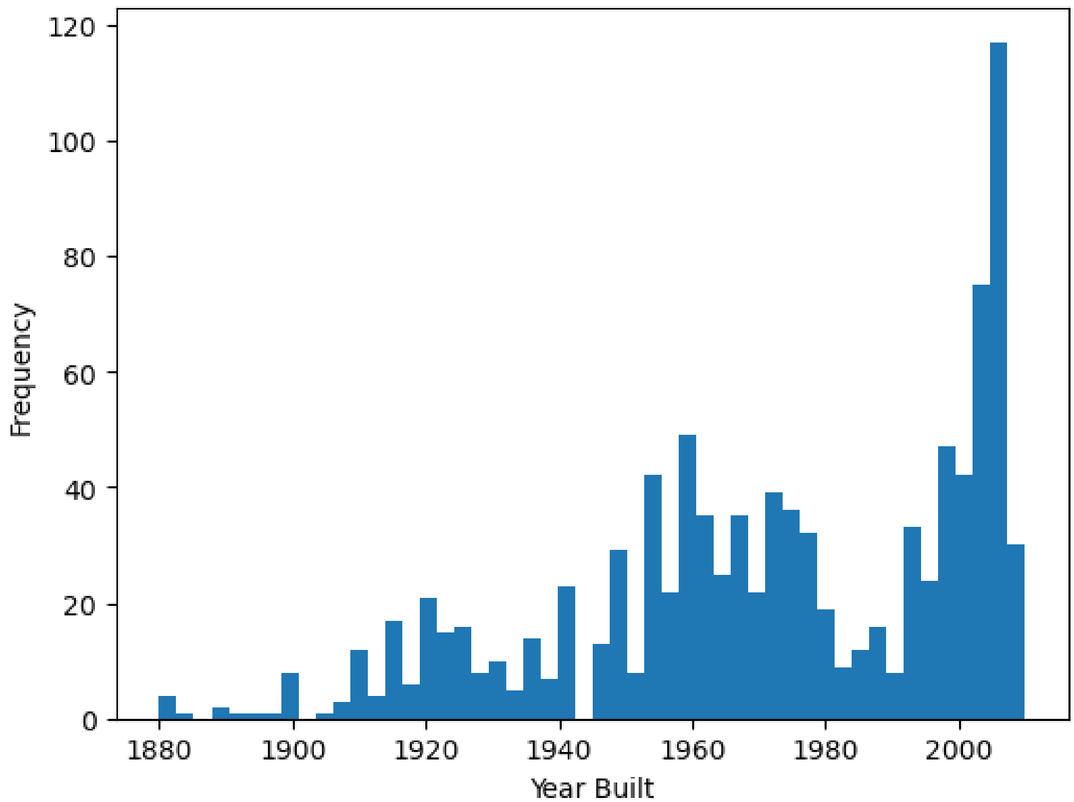
[19]:
```
plt.hist(read_hist_csv["SalePrice"], bins=50)
plt.xlabel("SalePrice")
plt.ylabel("Frequency")
```

[19]: Text(0, 0.5, 'Frequency')



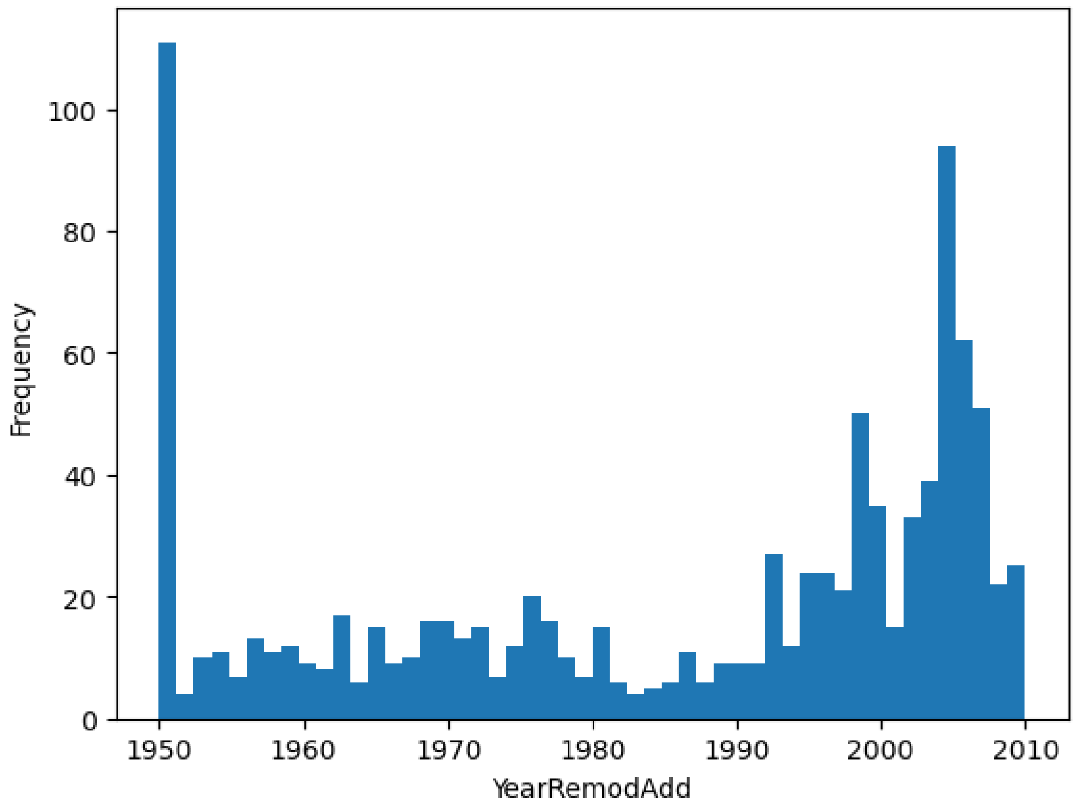
[20]:
```
plt.hist(read_hist_csv["YearBuilt"], bins=50)
plt.xlabel("Year Built")
plt.ylabel("Frequency")
```

[20]: Text(0, 0.5, 'Frequency')




```
[21]: plt.hist(read_hist_csv["YearRemodAdd"], bins=50)
      plt.xlabel("YearRemodAdd")
      plt.ylabel("Frequency")
```

```
[21]: Text(0, 0.5, 'Frequency')
```



1.10.1 Derived Feature between [YearBuilt - YearRemodAdd]

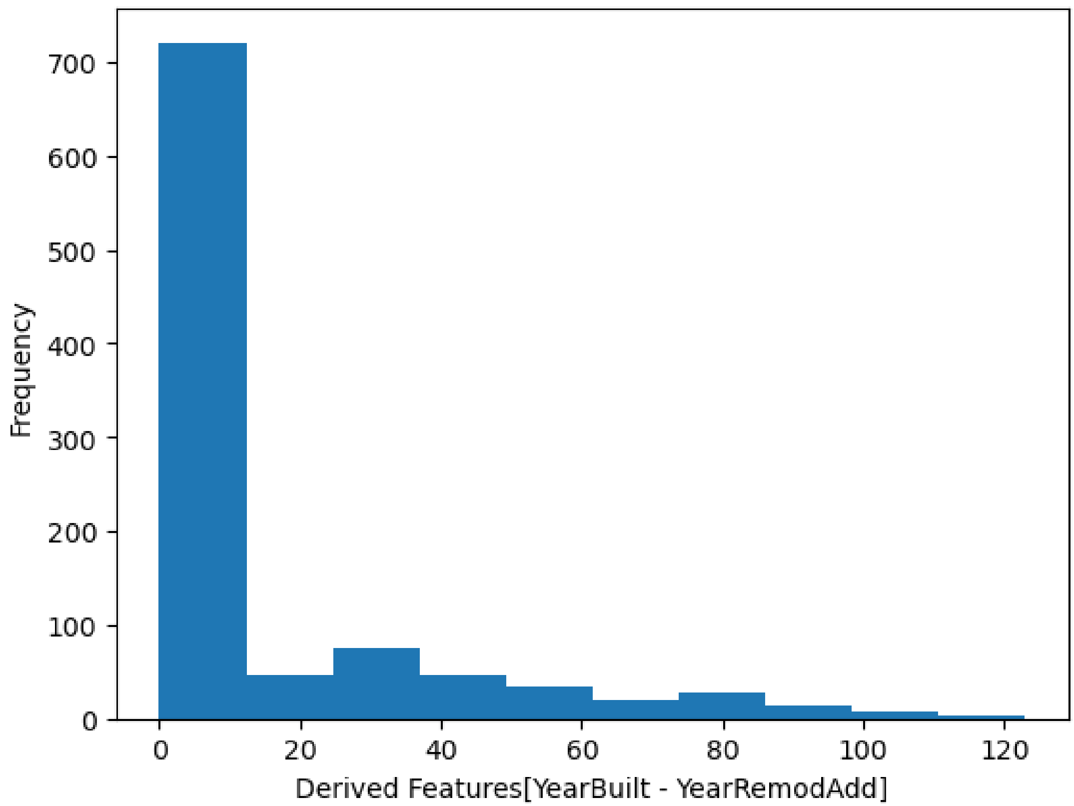
[22]:
```
# The features = [YearBuilt, YearRemoteAdd] share strong positive corrleation␣
↪with value 0.57
# We can create derived features for finding the difference between the two␣
↪features using [YearBuilt-YearRemoteAdd]
# Note: RemoteYearAdd feature states the year of rennovation / remodelling␣
↪performed

read_hist_csv["derived_features"] = read_hist_csv["YearRemodAdd"] -␣
↪read_hist_csv["YearBuilt"]
print(read_hist_csv["derived_features"])
```

```
0       0
1       0
2       1
3      55
4       0
       ..
994     1
995     4
```

```
996      0
997      0
998     28
Name: derived_features, Length: 999, dtype: int64
```

[23]:
```
plt.hist(read_hist_csv["derived_features"], bins=10)
plt.xlabel("Derived Features[YearBuilt - YearRemodAdd]")
plt.ylabel("Frequency")
```

[23]:
```
Text(0, 0.5, 'Frequency')
```



1.11 Train-Test Dataset Split

[24]:
```
features = ['LotFrontage', 'LotArea', 'Street', 'Neighborhood', 'YearBuilt',␣
 ↪'YearRemodAdd', 'CentralAir', 'PavedDrive', 'SaleCondition']
X = read_hist_csv[features]
y = read_hist_csv['SalePrice']
```

[25]:
```
# Missing values
feature_na = ['LotFrontage']
numeric_imputer = SimpleImputer(strategy='median')
```

```
for elements in feature_na:
    X[elements] = numeric_imputer.fit_transform(X[[elements]])

check_new_dat = X.isnull().sum()
print(check_new_dat)
```

```
LotFrontage      0
LotArea          0
Street           0
Neighborhood     0
YearBuilt        0
YearRemodAdd     0
CentralAir       0
PavedDrive       0
SaleCondition    0
dtype: int64
```

```
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\2595087311.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[elements] = numeric_imputer.fit_transform(X[[elements]])
```

1.11.1 Encoding categorical features

[26]:
```
label_encoders = {}
categorical_columns = ['Street', 'Neighborhood', 'CentralAir', 'PavedDrive',␣
 ↪'SaleCondition']
for col in categorical_columns:
    lab_encode = LabelEncoder()
    X[col] = lab_encode.fit_transform(X[col])
    label_encoders[col] = lab_encode
```

```
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\377571960.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[col] = lab_encode.fit_transform(X[col])
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\377571960.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[col] = lab_encode.fit_transform(X[col])
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\377571960.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[col] = lab_encode.fit_transform(X[col])
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\377571960.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[col] = lab_encode.fit_transform(X[col])
C:\Users\ravin\AppData\Local\Temp\ipykernel_11844\377571960.py:5:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X[col] = lab_encode.fit_transform(X[col])
```

[27]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

1.12 Normalization for Features = [LotArea, LotFrontage, SalesPrice,..]

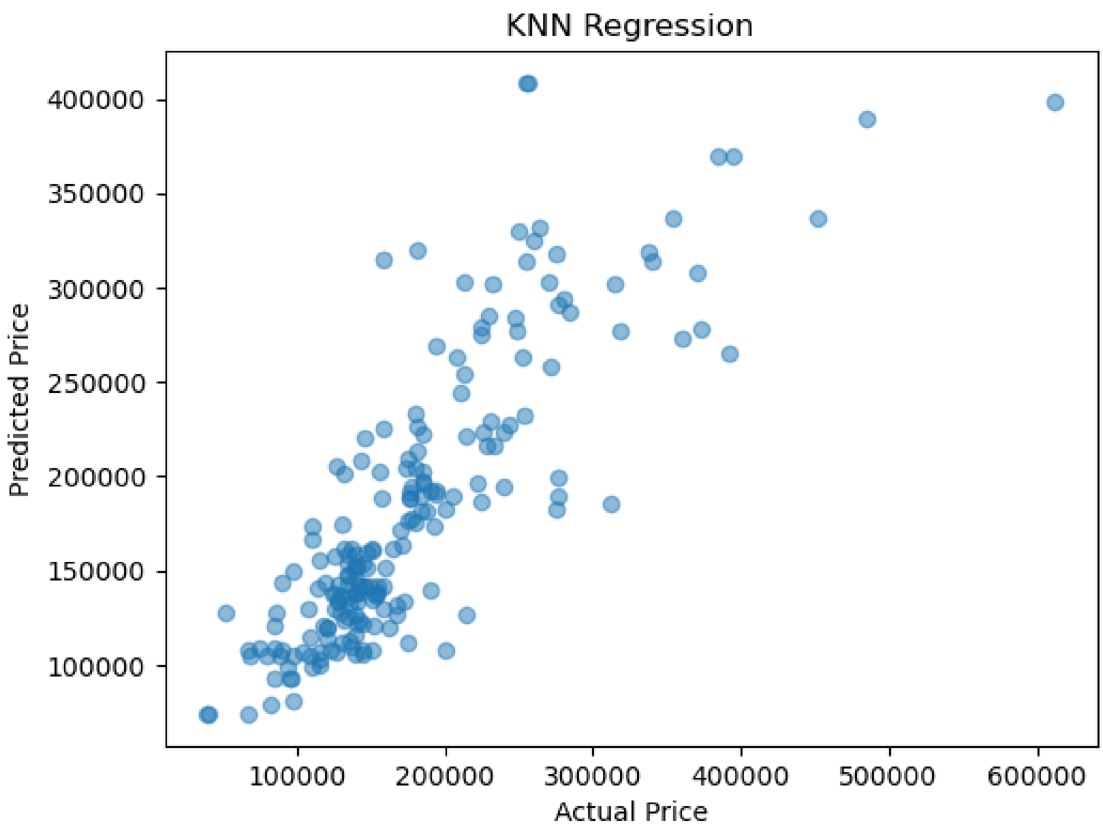
[28]:
```
# Using standard scaler to normalize kurtosis - Sales price
# LotArea and LotFrontage Follows Gaussian Distribution so there's no need to␣
↪perform normalization
# Since the Price feature follow kurtosis we use log-scaling

normalize = StandardScaler() # Z-Score Normalization
X_train = normalize.fit_transform(X_train)
X_test = normalize.transform(X_test)
```

1.13 P2. Implementation of KNN

[29]:
```
knn_regressor = KNeighborsRegressor(n_neighbors=5)
knn_regressor.fit(X_train, y_train)

# Making predictions on the test dataset
knn_predictions = knn_regressor.predict(X_test)
```

[30]:
```
plt.subplot()
plt.scatter(y_test, knn_predictions, alpha=0.5)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("KNN Regression")
```

[30]:
```
Text(0.5, 1.0, 'KNN Regression')
```

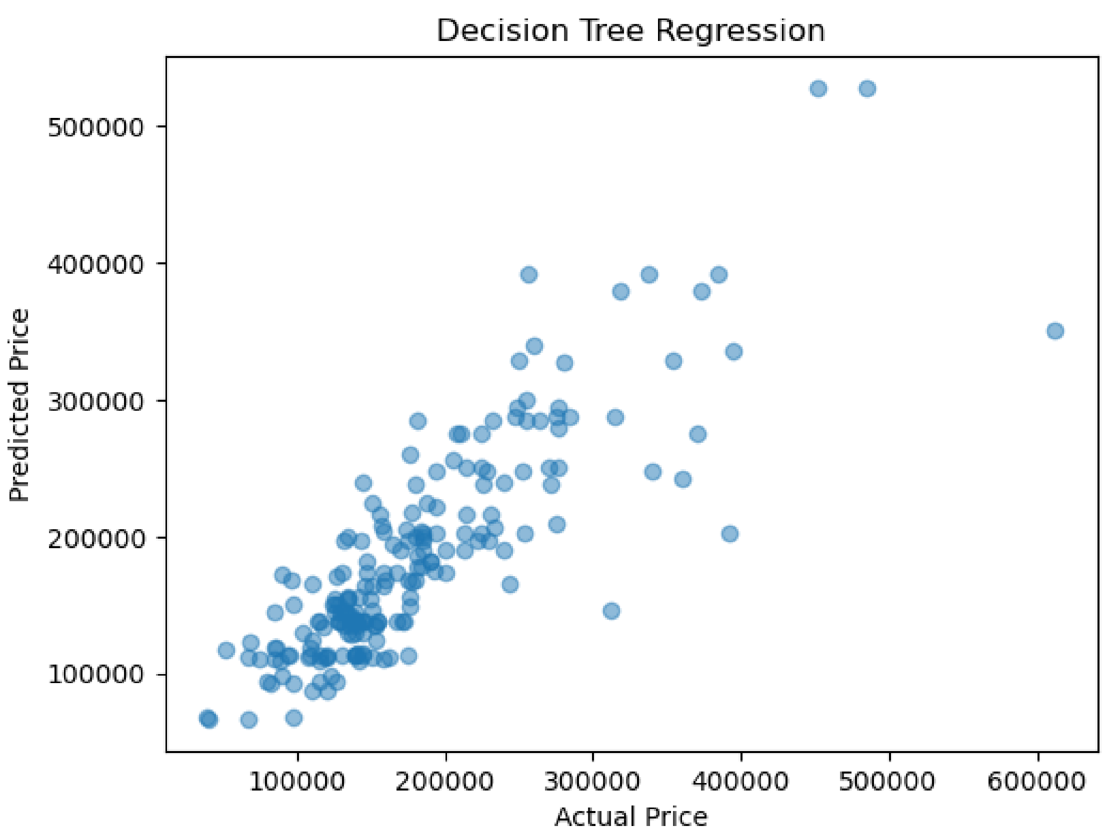


1.14 P2. Implementation of Decision Tree

[31]:
```
decision_tree_regressor = DecisionTreeRegressor(min_samples_leaf=3,␣
    ↪max_depth=10, random_state=42)
decision_tree_regressor.fit(X_train, y_train)

# Making predictions on the test set
dt_predictions = decision_tree_regressor.predict(X_test)
```

[32]:
```
plt.subplot()
plt.scatter(y_test, dt_predictions, alpha=0.5)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Decision Tree Regression")
```

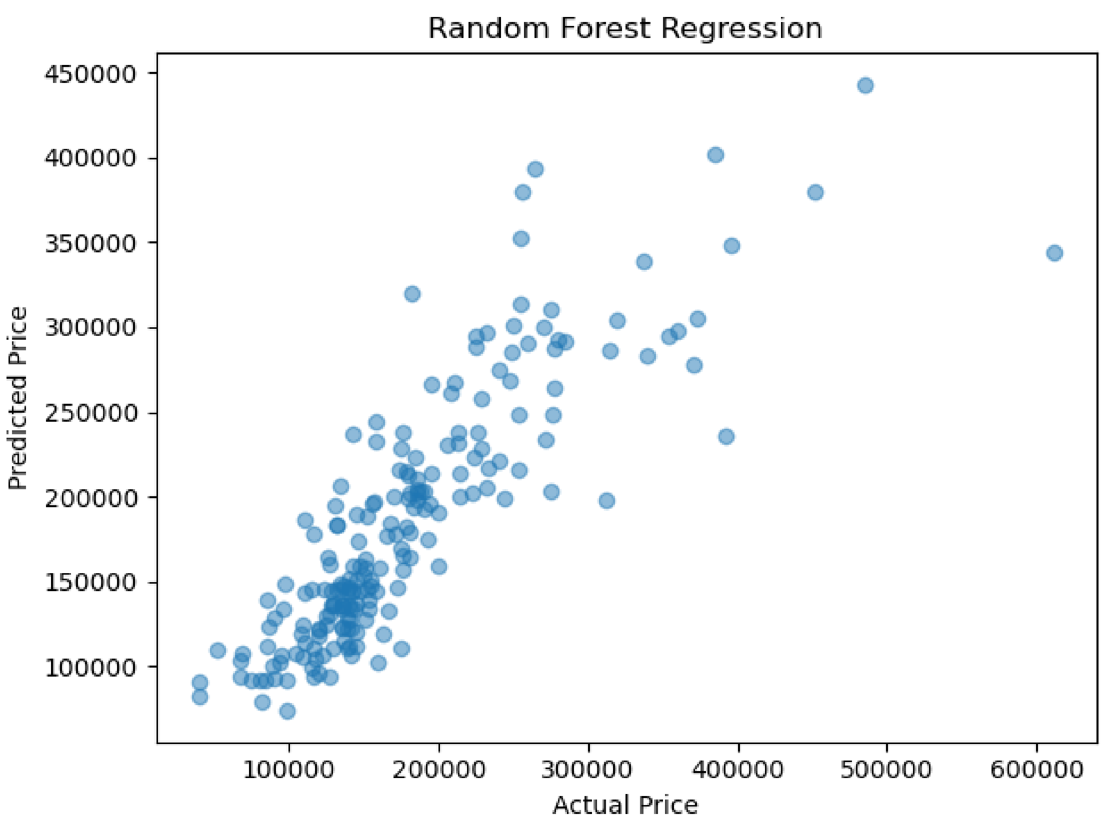
[32]: Text(0.5, 1.0, 'Decision Tree Regression')



1.15 P2. Implementation of Random Forest

[33]:
```
random_forest_regressor = RandomForestRegressor(n_estimators=100,␣
 ↪random_state=42)
random_forest_regressor.fit(X_train, y_train)

# Making predictions on the test set
rf_predictions = random_forest_regressor.predict(X_test)
```

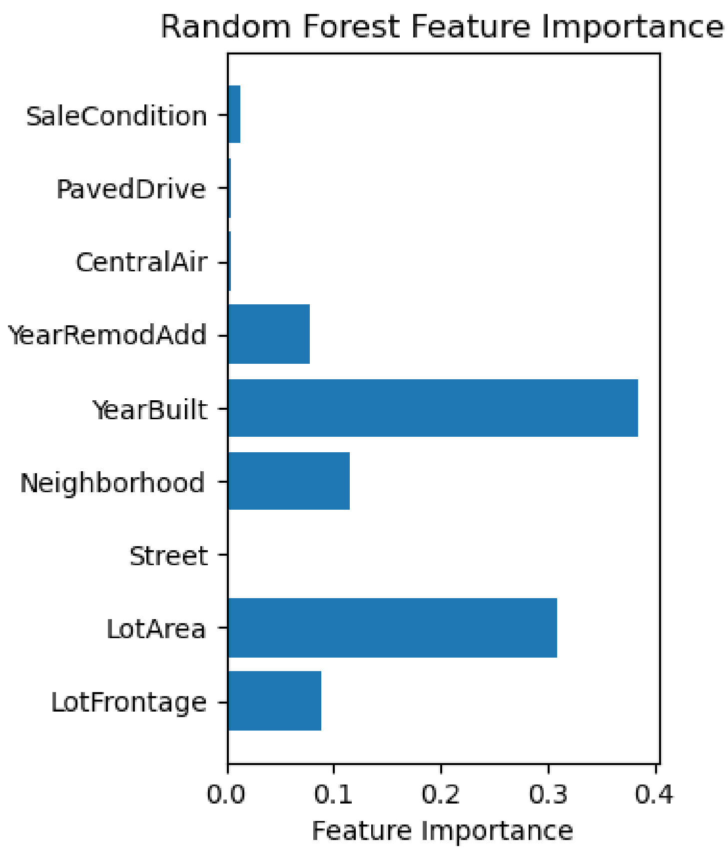
[34]:
```
plt.subplot()
plt.scatter(y_test, rf_predictions, alpha=0.5)
plt.xlabel("Actual Price")
plt.ylabel("Predicted Price")
plt.title("Random Forest Regression")
plt.tight_layout()
plt.show()
```



1.16 Feature Importance Analysis

[35]:
```
rf_feature_importance = random_forest_regressor.feature_importances_
plt.subplot(122)
plt.barh(features, rf_feature_importance)
plt.xlabel("Feature Importance")
plt.title("Random Forest Feature Importance")
```

[35]: Text(0.5, 1.0, 'Random Forest Feature Importance')



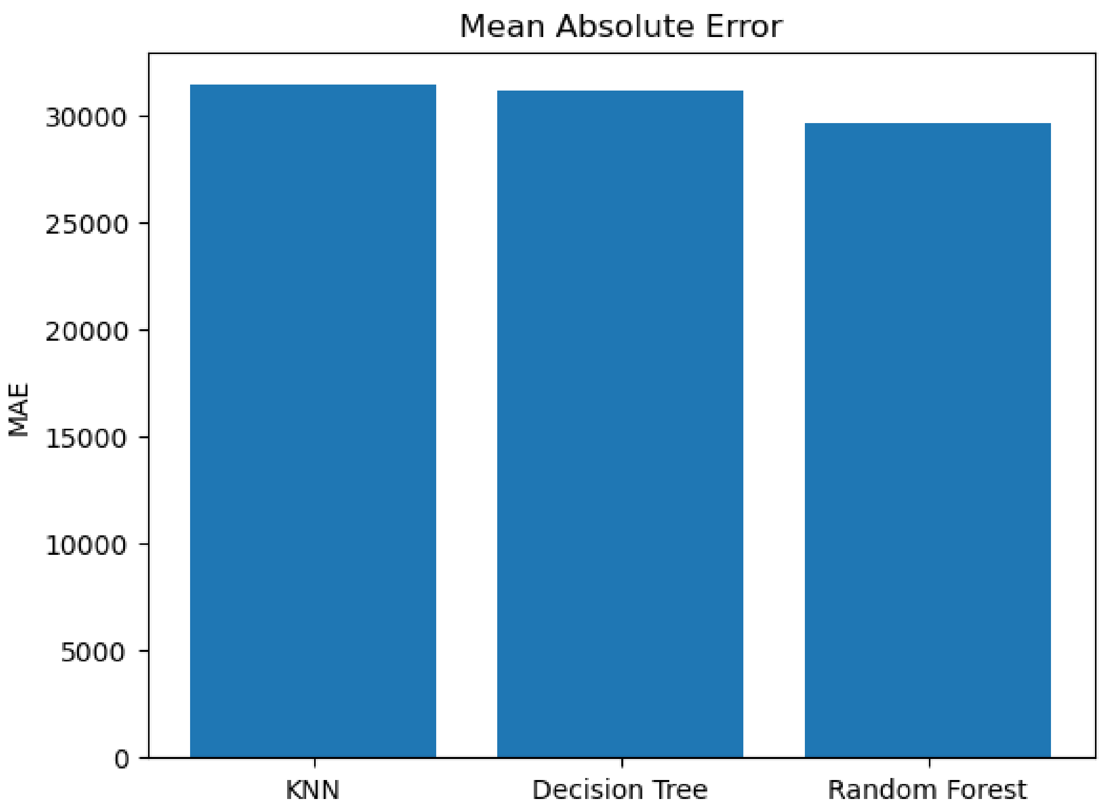
1.17 Evaluation models using MAE, MAPE metrics

[37]:
```
# MAE and MAPE evaluation of KNN Model
knn_mae = mean_absolute_error(y_test, knn_predictions)
knn_mape = mean_absolute_percentage_error(y_test, knn_predictions)

print("KNN Regressor MAE: ", knn_mae)
print("KNN Regressor MAPE", knn_mape)

# MAE and MAPE evaluation of Decision Tree Model
```

```
dt_mae = mean_absolute_error(y_test, dt_predictions)
dt_mape = mean_absolute_percentage_error(y_test, dt_predictions)

print("DT Regressor MAE: ", dt_mae)
print("DTRegressor MAPE", dt_mape)

# MAE and MAPE evaluation of Random Forest Model
rf_mae = mean_absolute_error(y_test, rf_predictions)
rf_mape = mean_absolute_percentage_error(y_test, rf_predictions)

print("RF Regressor MAE: ", rf_mae)
print("RF Regressor MAPE", rf_mape)

# Mean Absolute Error Visualization
trained_models = ["KNN", "Decision Tree", "Random Forest"]
mae_scores = [knn_mae, dt_mae, rf_mae]

plt.subplot()
plt.bar(trained_models, mae_scores)
plt.ylabel("MAE")
plt.title("Mean Absolute Error")
```

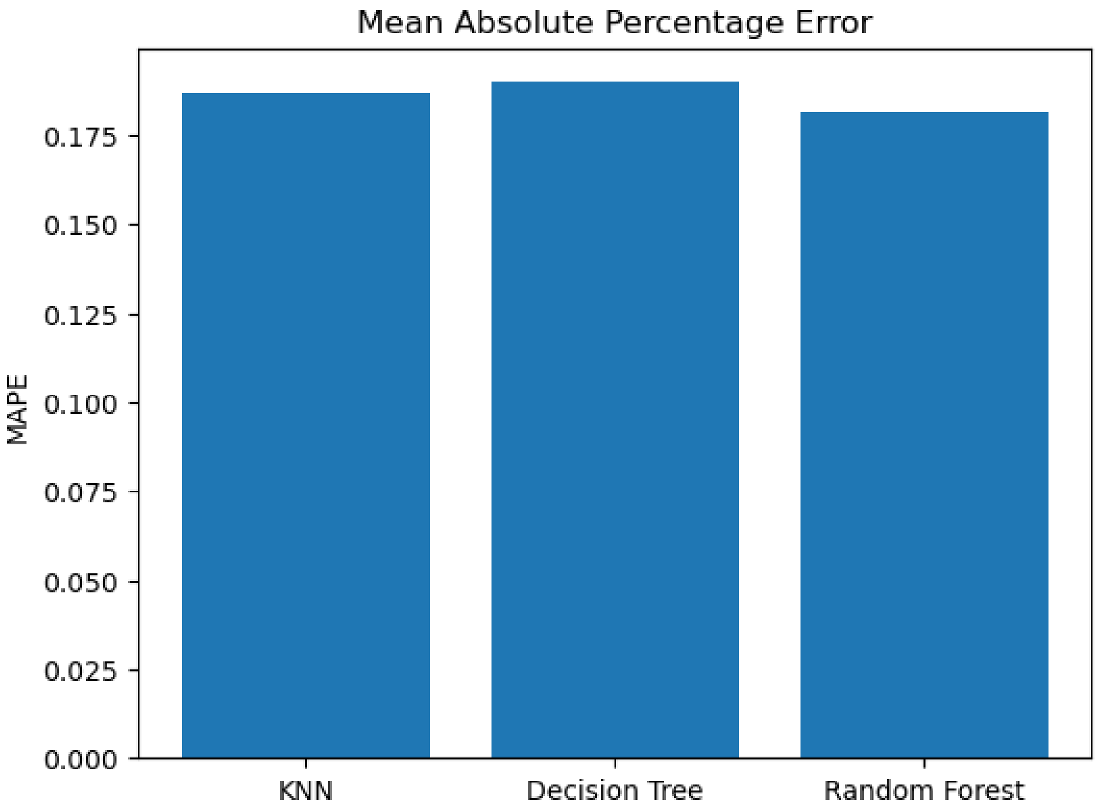
```
KNN Regressor MAE:  31419.286
KNN Regressor MAPE 0.1869290327180879
DT Regressor MAE:  31206.244614645097
DTRegressor MAPE 0.1899427934301395
RF Regressor MAE:  29650.54651095238
RF Regressor MAPE 0.1815675752904022
```

[37]:
```
Text(0.5, 1.0, 'Mean Absolute Error')
```



[38]:
```
# Mean Absolute Percentage Error Visualization
trained_model_for_MAPE = ["KNN", "Decision Tree", "Random Forest"]
mape_scores = [knn_mape, dt_mape, rf_mape]

plt.subplot()
plt.bar(trained_models, mape_scores)
plt.ylabel("MAPE")
plt.title("Mean Absolute Percentage Error")
```

[38]:
```
Text(0.5, 1.0, 'Mean Absolute Percentage Error')
```



1.18 Evaluate results using MSE, R^2 metrics

[39]:
```
# Evaluation of KNN model
knn_mse = mean_squared_error(y_test, knn_predictions)
knn_r2 = r2_score(y_test, knn_predictions)

print("KNN Regression MSE:", knn_mse)
print("KNN Regression R^2:", knn_r2)
```

```
KNN Regression MSE: 2125543174.6260002
KNN Regression R^2: 0.6796325091952962
```

[40]:
```
# Evaluation of Decision Tree model
dt_mse = mean_squared_error(y_test, dt_predictions)
dt_r2 = r2_score(y_test, dt_predictions)

print("Decision Tree Regression MSE:", dt_mse)
print("Decision Tree Regression R^2:", dt_r2)
```

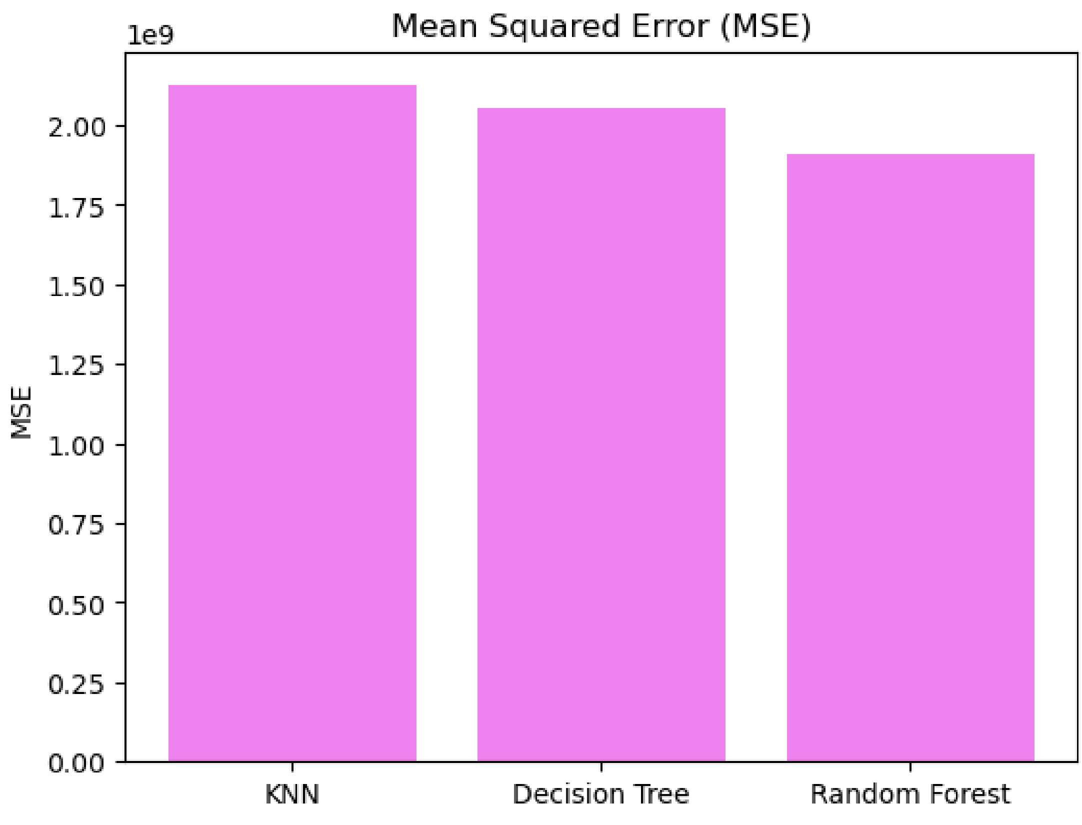
```
Decision Tree Regression MSE: 2053873667.1627307
Decision Tree Regression R^2: 0.6904347269753497
```

[41]:
```python
# Evaluation of Random Forest model
rf_mse = mean_squared_error(y_test, rf_predictions)
rf_r2 = r2_score(y_test, rf_predictions)

print("Random Forest Regression MSE:", rf_mse)
print("Random Forest Regression R^2:", rf_r2)
```

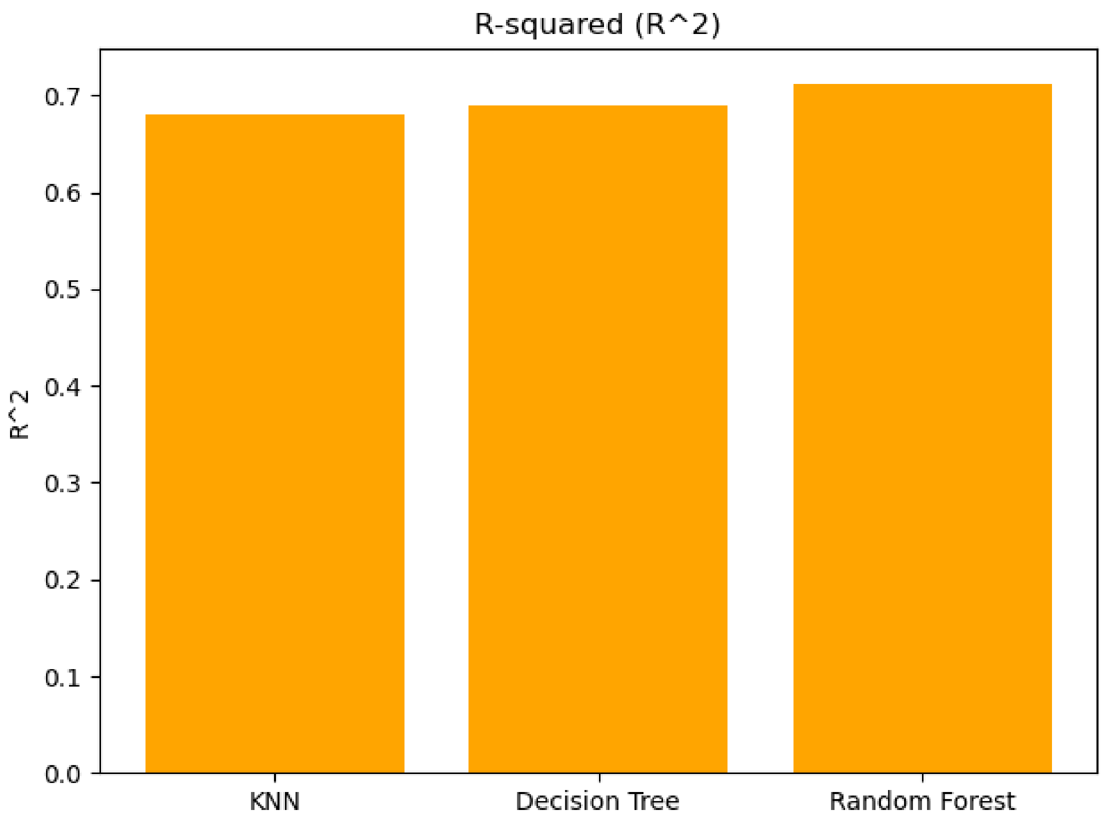
```
Random Forest Regression MSE: 1907485039.886032
Random Forest Regression R^2: 0.7124988081771974
```

[42]:
```python
trained_models = ['KNN', 'Decision Tree', 'Random Forest']
mse_scores = [knn_mse, dt_mse, rf_mse]
r2_scores = [knn_r2, dt_r2, rf_r2]
plt.subplot()
plt.bar(trained_models, mse_scores, color='violet')
plt.ylabel('MSE')
plt.title('Mean Squared Error (MSE)')
```

[42]:
```
Text(0.5, 1.0, 'Mean Squared Error (MSE)')
```



[43]:
```
plt.subplot()
plt.bar(trained_models, r2_scores, color='orange')
plt.ylabel('R^2')
plt.title('R-squared (R^2)')
plt.tight_layout()
plt.show()
```



1.19 House Price Prediction based on one-sample using Random Forest

[44]:
```
# The X_test represents the testing data
# The array or list takes the rows as the input
sample_data = X_test[[3,4,40]]
predict_price = random_forest_regressor.predict(sample_data)
print("The predicted price for the sample is:", predict_price)
```

```
The predicted price for the sample is: [297570.81 146016.69 119605.89]
```

1.20 Conclusion

- Based on the above results, Random Forest model has lower rate of Mean Squared Error (Sqaured difference between the actual value and the predicted value) with value 1.8 compared to Decision Tree and KNN Models.

- [1] From R-Squared evaluation metric perspective, Random Forest produced 0.7 units compared to KNN = 0.67, and Decision Tree = 0.41 which indicates Random Forest model analyzed there is a high correlation between features which explains there is small difference between the actual value and fitted value or predicted value.

Reference:

[1] https://statisticsbyjim.com/regression/interpret-r-squared-regression/