House Price Prediction Dataset.

The dataset contains 2000 rows of house-related data, representing various features that could influence house prices. Below, we discuss key aspects of the dataset, which include its structure, the choice of features, and potential use cases for analysis.

I found this dataset in Kaggle.

1.This is a supervised regression problem in machine learning. :

Supervised Learning: The model is trained on labeled data, where each example has input features (e.g., area, number of bedrooms, bathrooms, etc.) and a corresponding target output (house price). The goal is to learn the mapping from input to output.

Regression: The task is to predict a continuous numerical value (the house price) based on the input features, which makes it a regression problem. Unlike classification, where the output is a category or class, regression predicts real-valued outputs.

Characteristics of this ML Problem: Features: Attributes such as area, bedrooms, bathrooms, floors, year built, location, condition, and garage. Target: House price (a continuous numeric value). Goal: Train a model that can predict the house price based on the given features.

We'll use supervised machine learning models to predict the house price. The steps involve:

1. Data preprocessing: Handle categorical variables, missing values, Label encoding and normalization.
2. Model selection: We can try several models, such as: Linear Regression, Decision Tree Regressor, Random Forest Regressor.
3. Model evaluation: Use metrics such as mean squared error (MSE) and R-squared to evaluate model performance.

```
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
#load data
data=pd.read_csv('/House_Price_Prediction_Dataset[1].csv')
```

```
data
```

	Id	Area	Bedrooms	Bathrooms	Floors	YearBuilt	Location	Condition	Garage	
0	1	1360	5	4	3	1970	Downtown	Excellent	No	1
1	2	4272	5	4	3	1958	Downtown	Excellent	No	4
2	3	3592	2	2	3	1938	Downtown	Good	No	2
3	4	966	4	2	2	1902	Suburban	Fair	Yes	2
4	5	4926	1	4	2	1975	Downtown	Fair	Yes	6
...	...	...	...	...	...	...	...	...	...	
1995	1996	4994	5	4	3	1923	Suburban	Poor	No	2
1996	1997	3046	5	2	1	2019	Suburban	Poor	Yes	5
1997	1998	1062	5	1	2	1903	Rural	Poor	No	4
1998	1999	4062	3	1	2	1936	Urban	Excellent	Yes	1
1999	2000	2989	5	1	3	1903	Suburban	Fair	No	4

2000 rows × 10 columns

```
#first five data
data.head()
```

	Id	Area	Bedrooms	Bathrooms	Floors	YearBuilt	Location	Condition	Garage	Price
0	1	1360	5	4	3	1970	Downtown	Excellent	No	149919
1	2	4272	5	4	3	1958	Downtown	Excellent	No	424998
2	3	3592	2	2	3	1938	Downtown	Good	No	266746
3	4	966	4	2	2	1902	Suburban	Fair	Yes	244020
4	5	4926	1	4	2	1975	Downtown	Fair	Yes	636056

```
#tail - last five data
data.tail()
```

	Id	Area	Bedrooms	Bathrooms	Floors	YearBuilt	Location	Condition	Garage	
1995	1996	4994	5	4	3	1923	Suburban	Poor	No	2
1996	1997	3046	5	2	1	2019	Suburban	Poor	Yes	5
1997	1998	1062	5	1	2	1903	Rural	Poor	No	4
1998	1999	4062	3	1	2	1936	Urban	Excellent	Yes	1
1999	2000	2989	5	1	3	1903	Suburban	Fair	No	4

```
#the main columns
data.columns
```

```
Index(['Id', 'Area', 'Bedrooms', 'Bathrooms', 'Floors', 'YearBuilt',
       'Location', 'Condition', 'Garage', 'Price'],
      dtype='object')
```

```
#the shape of the data
data.shape
```

```
(2000, 10)
```

```
#describe
data.describe()
```

	Id	Area	Bedrooms	Bathrooms	Floors	YearBuilt	
count	2000.000000	2000.000000	2000.000000	2000.00000	2000.000000	2000.000000	2000
mean	1000.500000	2786.209500	3.003500	2.55250	1.993500	1961.446000	537676
std	577.494589	1295.146799	1.424606	1.10899	0.809188	35.926695	276428
min	1.000000	501.000000	1.000000	1.00000	1.000000	1900.000000	50005
25%	500.750000	1653.000000	2.000000	2.00000	1.000000	1930.000000	300098
50%	1000.500000	2833.000000	3.000000	3.00000	2.000000	1961.000000	539254
75%	1500.250000	3887.500000	4.000000	4.00000	3.000000	1993.000000	780086
max	2000.000000	4999.000000	5.000000	4.00000	3.000000	2023.000000	999656

```
#finding null values
data.isnull().sum()
```

	0
Id	0
Area	0
Bedrooms	0
Bathrooms	0
Floors	0
YearBuilt	0
Location	0
Condition	0
Garage	0
Price	0

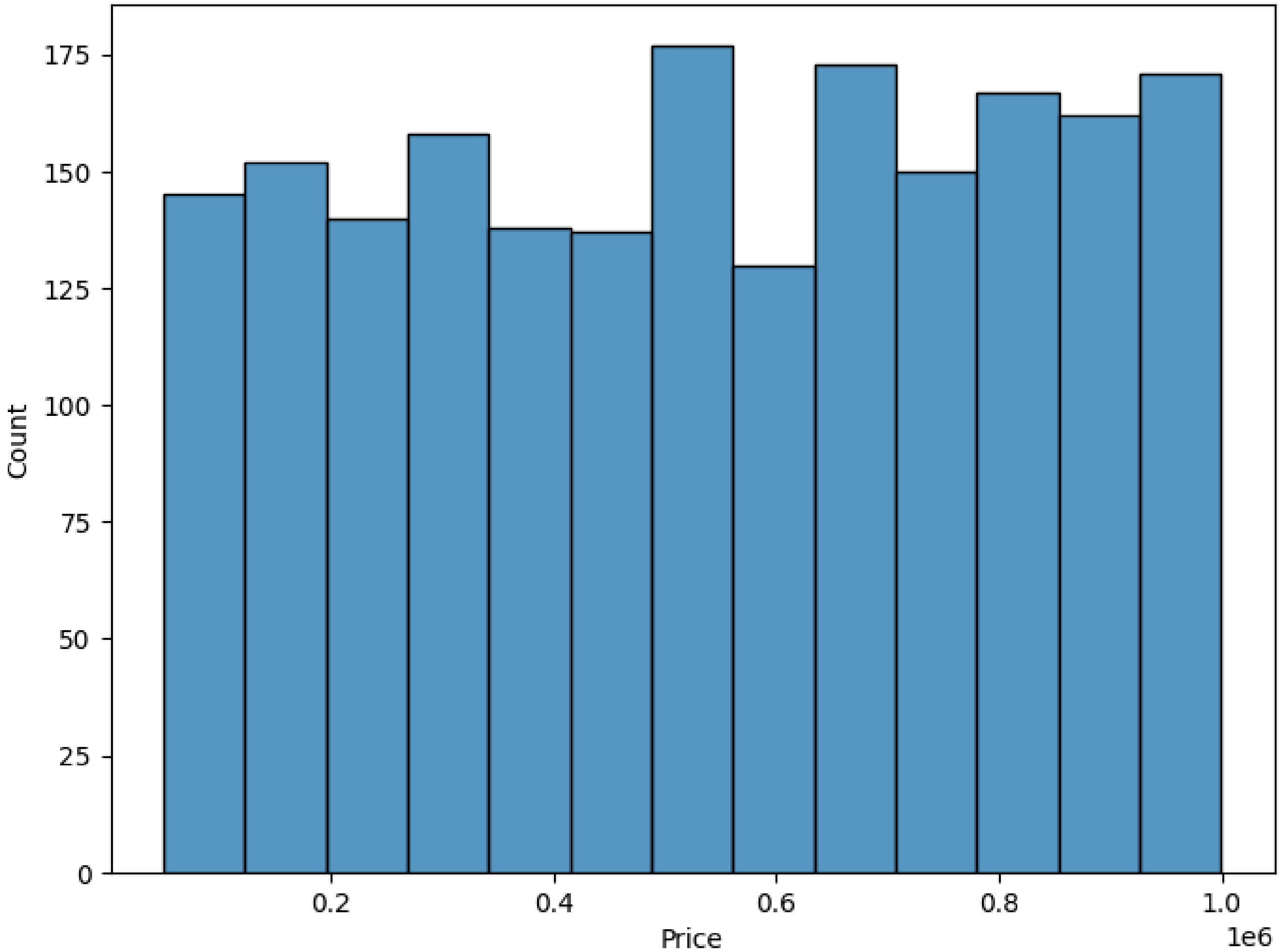
dtype: int64

```
#info
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 10 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Id         2000 non-null   int64
 1   Area       2000 non-null   int64
 2   Bedrooms   2000 non-null   int64
 3   Bathrooms  2000 non-null   int64
 4   Floors     2000 non-null   int64
 5   YearBuilt  2000 non-null   int64
 6   Location   2000 non-null   object
 7   Condition  2000 non-null   object
 8   Garage     2000 non-null   object
 9   Price      2000 non-null   int64
dtypes: int64(7), object(3)
memory usage: 156.4+ KB
```

```
plt.figure(figsize=(8, 6))
sns.histplot(data['Price'])
```

```
<Axes: xlabel='Price', ylabel='Count'>
```




```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
```

Pre Processing Techniques

1.Handling Missing values

```
#Check for missing values in the dataset
missing_values=data.isnull().sum()
```

2.Label Encoding

```
#Encode Categorical variables:Location,Condition,Garage
label_encoder = LabelEncoder()
data['Location'] = label_encoder.fit_transform(data['Location'])
```

```
data['Condition'] = label_encoder.fit_transform(data['Condition'])
data['Garage'] = label_encoder.fit_transform(data['Garage'])
```

```
data
```

	Id	Area	Bedrooms	Bathrooms	Floors	YearBuilt	Location	Condition	Garage
0	1	1360	5	4	3	1970	0	0	0
1	2	4272	5	4	3	1958	0	0	0
2	3	3592	2	2	3	1938	0	2	0
3	4	966	4	2	2	1902	2	1	1
4	5	4926	1	4	2	1975	0	1	1
...	...	...	...	...	...	...	...	...	...
1995	1996	4994	5	4	3	1923	2	3	0
1996	1997	3046	5	2	1	2019	2	3	1
1997	1998	1062	5	1	2	1903	1	3	0
1998	1999	4062	3	1	2	1936	3	0	1
1999	2000	2989	5	1	3	1903	2	1	0

2000 rows × 10 columns

3.Feature Scaling

```
# Separate features (X) and target (y)
X = data.drop(columns=['Id', 'Price'])
y = data['Price']
```

```
y
```

	Price
0	149919
1	424998
2	266746
3	244020
4	636056
...	...
1995	295620
1996	580929
1997	476925
1998	161119
1999	482525

2000 rows × 1 columns

dtype: int64

```
# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Standardize the feature data (normalize the scale)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)



# Output the shape of the datasets to ensure proper split
X_train_scaled.shape, X_test_scaled.shape, y_train.shape, y_test.shape
```

```
((1600, 8), (400, 8), (1600,), (400,))
```

The data has been successfully split into training and testing sets: Training data: 1600 samples with 8 features Testing data: 400 samples with 8 features

1.linear regression model

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
# Initialize and train the Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train_scaled, y_train)

# Predict on test data
y_pred_lr = lr_model.predict(X_test_scaled)

# Calculate performance metrics for Linear Regression
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)

mse_lr, r2_lr
```

```
(78729422262.6482, -0.011961539273188215)
```

2.Decision tree regression model

```
from sklearn.tree import DecisionTreeRegressor

# Initialize and train the Decision Tree Regressor
dt_model = DecisionTreeRegressor(random_state=42)
dt_model.fit(X_train_scaled, y_train)

# Predict on test data
y_pred_dt = dt_model.predict(X_test_scaled)

# Calculate performance metrics for Decision Tree Regressor
mse_dt = mean_squared_error(y_test, y_pred_dt)
r2_dt = r2_score(y_test, y_pred_dt)

mse_dt, r2_dt
```

```
(169190327830.495, -1.1747156229636482)
```

3. Randomforest Regressor

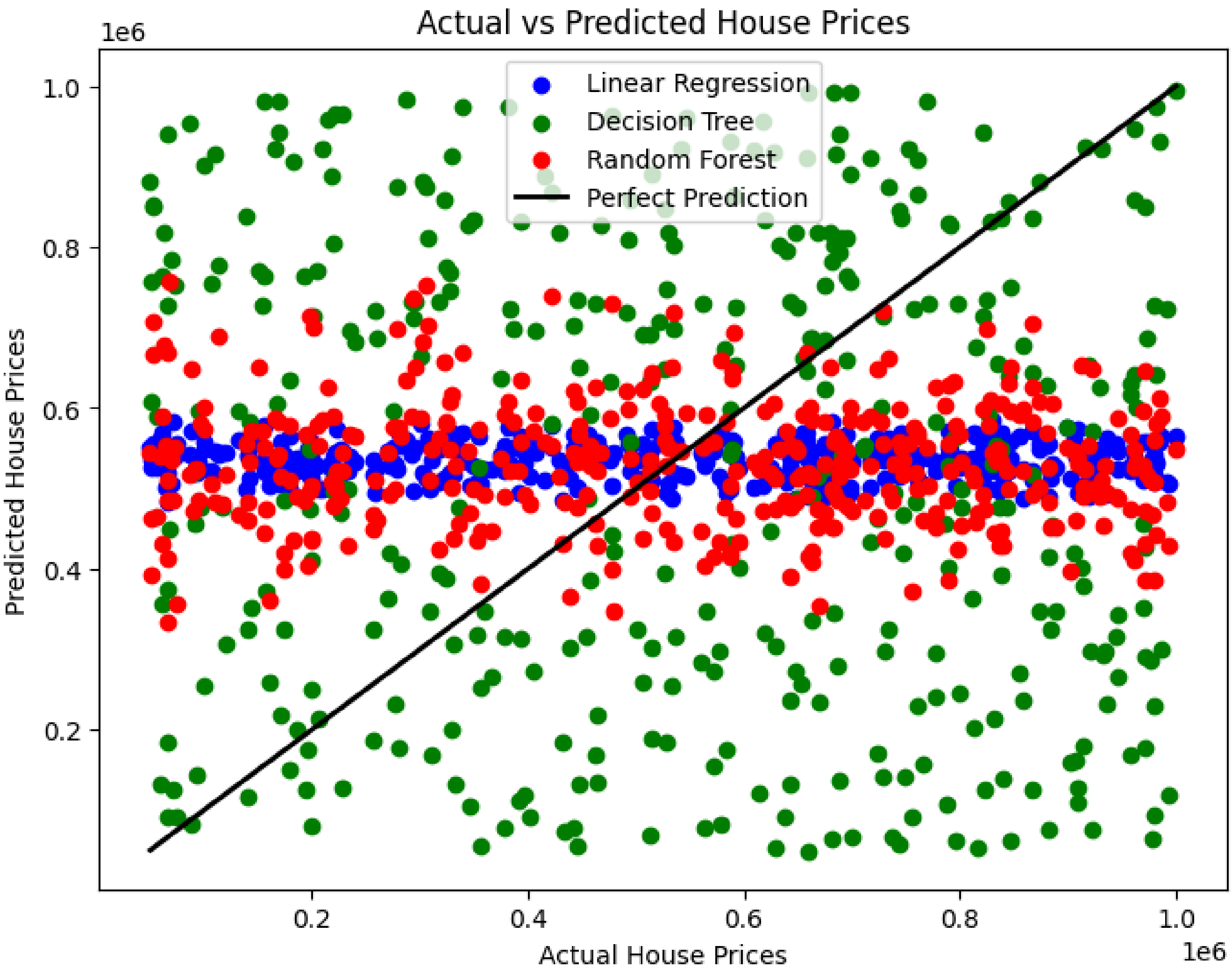
```
from sklearn.ensemble import RandomForestRegressor

# Initialize and train the Random Forest Regressor
rf_model = RandomForestRegressor(random_state=42)
rf_model.fit(X_train_scaled, y_train)

# Predict on test data
y_pred_rf = rf_model.predict(X_test_scaled)

# Calculate performance metrics for Random Forest Regressor
```

```
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

print(f'Random Forest MSE: {mse_rf}')
print(f'Random Forest R-squared: {r2_rf}')
```

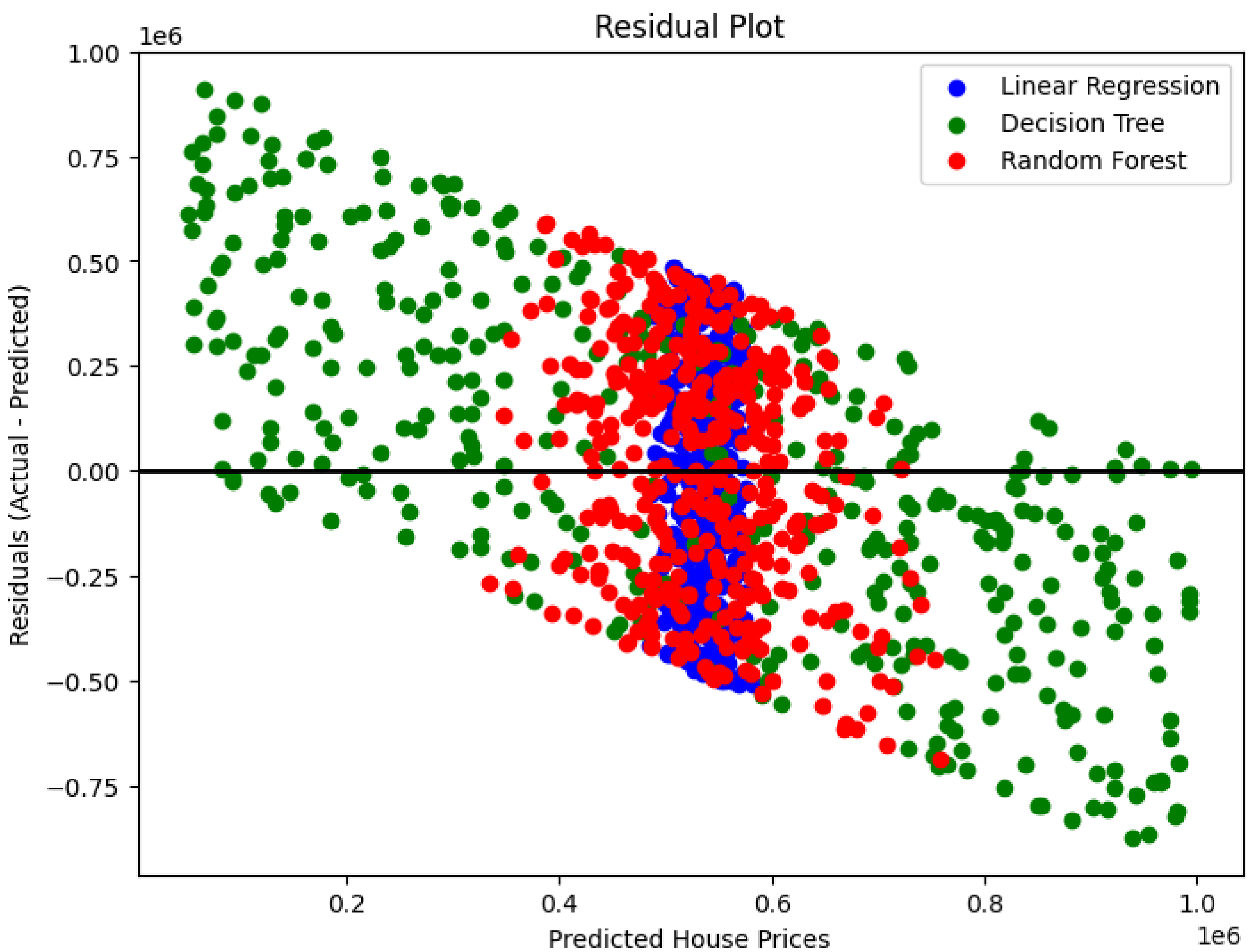
```
Random Forest MSE: 86258440081.58017
Random Forest R-squared: -0.1087370044333893
```

Double-click (or enter) to edit

```
#visualize chart for actual and predicted prices
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred_lr, color='blue', label='Linear Regression')
plt.scatter(y_test, y_pred_dt, color='green', label='Decision Tree')
plt.scatter(y_test, y_pred_rf, color='red', label='Random Forest')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='black', lw=2, label=
plt.xlabel('Actual House Prices')
plt.ylabel('Predicted House Prices')
plt.legend()
plt.title('Actual vs Predicted House Prices')
plt.show()
```

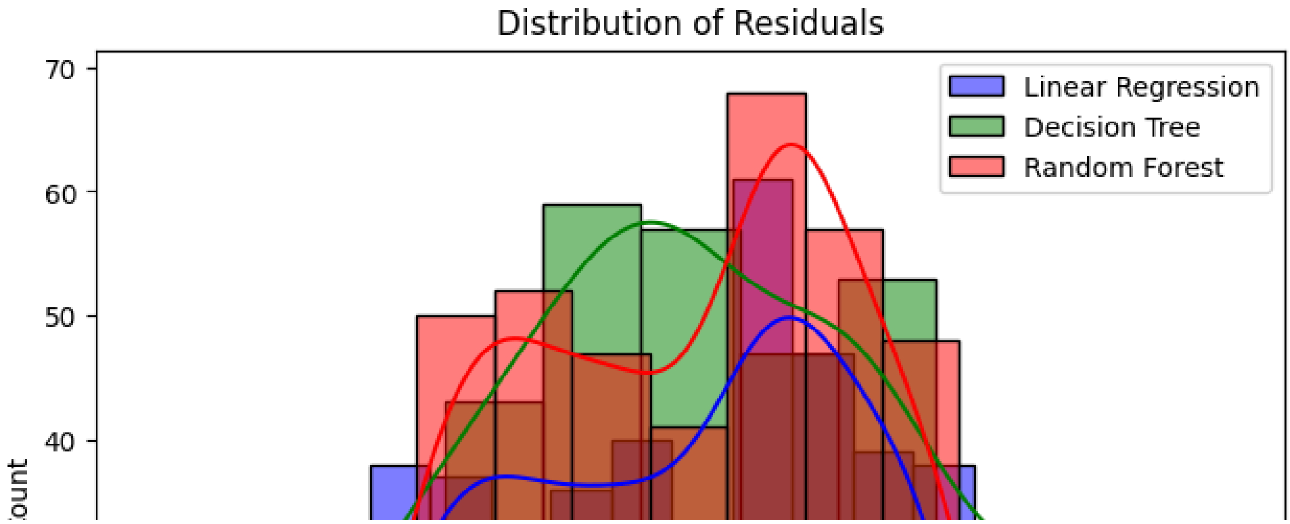



```
plt.figure(figsize=(8, 6))
plt.scatter(y_pred_lr, y_test - y_pred_lr, color='blue', label='Linear Regression')
plt.scatter(y_pred_dt, y_test - y_pred_dt, color='green', label='Decision Tree')
plt.scatter(y_pred_rf, y_test - y_pred_rf, color='red', label='Random Forest')
plt.axhline(y=0, color='black', lw=2)
plt.xlabel('Predicted House Prices')
plt.ylabel('Residuals (Actual - Predicted)')
plt.legend()
plt.title('Residual Plot')
plt.show()
```



Start coding or generate with AI.

```
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.histplot(y_test - y_pred_lr, color='blue', label='Linear Regression', kde=True)
sns.histplot(y_test - y_pred_dt, color='green', label='Decision Tree', kde=True)
sns.histplot(y_test - y_pred_rf, color='red', label='Random Forest', kde=True)
plt.xlabel('Residuals')
plt.legend()
plt.title('Distribution of Residuals')
plt.show()
```


Distribution of Residuals
70
60
50
40
Count
Linear Regression
Decision Tree
Random Forest