# PHASE II PROJECT SUBMISSION

## PREDICTING HOUSE PRICE USING MACHINE LEARNING.

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**PROJECT** : PREDICTING HOUSE PRICE

## INTRODUCTION

The housing market is a critical sector of the global economy, and accurately predicting house prices is paramount for homeowners,buyers, sellers, and investors. Machine learning has emerged as a powerful tool for this task, offering the potential to harness complex data and uncover valuable insights. In this abstract, we present a comprehensive modular framework for house price prediction using

machine learning, designed to enhance the flexibility, accuracy, and interpretability of predictive models.

- **Data Acquisition and Preprocessing**

The first module focuses on data collection and preprocessing, crucialsteps in building robust house price prediction models. Various data sources, such as property details, neighborhood characteristics, and historical transaction records, are collected. Data preprocessing techniques, including missing value handling, outlier detection, and data normalization, ensure the dataset's quality and readiness for model training.

- **Feature Selection and Engineering**

It is dedicated to feature selection and engineering, which play a pivotal role in shaping the predictive power of machine learning models. Feature selection methods like correlation analysis and mutual information are employed to identify the most influential variables. Feature engineering techniques, such as one-hot encoding,polynomial features, and spatial aggregation, are utilized to create new informative features and capture complex relationships within the data.

- **Model Selection and Training**

This module delves into the selection and training of machine learning models. A diverse set of algorithms, including linear regression, decision trees, support vector machines, and ensemble methods like random forests and gradient boosting, are explored.

Model hyperparameters are tuned using techniques like grid search orBayesian optimization. Cross-validation ensures robust model performance assessment.

- **Model Evaluation and Interpretability**

The evaluation of predictive models is a critical step in Module 4. Various metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared are used to assess model accuracy and generalization. Interpretability is addressed through techniques like feature importance analysis and SHAP (SHapley Additive exPlanations), shedding light on the factors that influencehouse price predictions.

- **Deployment and Scalability**

It focuses on deploying the trained model in a real-world setting.Considerations include API integration, containerization for scalability, and security measures to protect sensitive data. Deployment tools and cloud services are leveraged to ensure seamlessintegration into existing systems, providing users with access to accurate price predictions.

- **Ongoing Monitoring and Maintenance**

Continued model performance is crucial in the dynamic real estate market. Module 6 emphasizes continuous monitoring and maintenance. Monitoring tools track model drift and potential degradation in performance, while scheduled retraining and updates keep the model current with changing market conditions and emerging trends.

- **User Interface and Accessibility**

This module focuses on user experience and accessibility. A user-friendly interface is designed to make the model accessible to a wideraudience, allowing users to input property details and receive price predictions easily. Visualization tools may also be incorporated to help users understand the model's predictions and underlying data.

- **Regulatory Compliance and Ethics**

The ethical and regulatory considerations in housing prediction are addressed in this module. Fairness, transparency, and adherence to data privacy laws are paramount. Steps are taken to ensure that the model's predictions do not discriminate against any group and that user data is handled responsibly and securely.

- **Feedback Loop and Adaptation**

A feedback loop is established to incorporate user feedback and improve model performance continually. User feedback, as well as new data sources, are used to fine-tune the model and adapt it to evolving market dynamics.

**Data Source**

| Avg. Area Income | Avg. Area House Age | Avg. Area Number of Rooms | Avg. Area Number of Bedrooms | Area Population | Price | Address |
|---|---|---|---|---|---|---|
| 79545.45857 | 5.682861322 | 7.009188143 | 4.09 | 23086.8005 | 1059033.56 | 208 |
| 79248.64245 | 6.002899808 | 6.730821019 | 3.09 | 40173.07217 | 1505890.91 | 188 |
| 61287.06718 | 5.86588984 | 8.51272743 | 5.13 | 36882.1594 | 1058987.99 | 9127 |
| 63345.24005 | 7.188236095 | 5.586728665 | 3.26 | 34310.24283 | 1260616.81 | USS |
| 59982.19723 | 5.040554523 | 7.839387785 | 4.23 | 26354.10947 | 630943.489 | USNS |
| 80175.75416 | 4.988407758 | 6.104512439 | 4.04 | 26748.42842 | 1068138.07 | 06039 |
| 64698.46343 | 6.025335907 | 8.147759585 | 3.41 | 60828.24909 | 1502055.82 | 4759 |
| 78394.33928 | 6.989779748 | 6.620477995 | 2.42 | 36516.35897 | 1573936.56 | 972 Joyce |
| 59927.66081 | 5.36212557 | 6.393120981 | 2.3 | 29387.396 | 798869.533 | USS |
| 81885.92718 | 4.42367179 | 8.167688003 | 6.1 | 40149.96575 | 1545154.81 | Unit 9446 |
| 80527.47208 | 8.093512681 | 5.0427468 | 4.1 | 47224.35984 | 1707045.72 | 6368 |
| 50593.6955 | 4.496512793 | 7.467627404 | 4.49 | 34343.99189 | 663732.397 | 911 |
| 39033.80924 | 7.671755373 | 7.250029317 | 3.1 | 39220.36147 | 1042814.1 | 209 |
| 73163.66344 | 6.919534825 | 5.993187901 | 2.27 | 32326.12314 | 1291331.52 | 829 |
| 69391.38018 | 5.344776177 | 8.406417715 | 4.37 | 35521.29403 | 1402818.21 | PSC 5330, |
| 73091.86675 | 5.443156467 | 8.517512711 | 4.01 | 23929.52405 | 1306674.66 | 2278 |
| 79706.96306 | 5.067889591 | 8.219771123 | 3.12 | 39717.81358 | 1556786.6 | 064 |
| 61929.07702 | 4.788550242 | 5.097009554 | 4.3 | 24595.9015 | 528485.247 | 5498 |
| 63508.1943 | 5.94716514 | 7.187773835 | 5.12 | 35719.65305 | 1019425.94 | Unit 7424 |
| 62085.2764 | 5.739410844 | 7.091808104 | 5.49 | 44922.1067 | 1030591.43 | 19696 |
| 86294.99909 | 6.62745694 | 8.011897853 | 4.07 | 47560.77534 | 2146925.34 | 030 Larry |
| 60835.08998 | 5.551221592 | 6.517175038 | 2.1 | 45574.74166 | 929247.6 | USNS |
| 64490.65027 | 4.21032287 | 5.478087731 | 4.31 | 40358.96011 | 718887.232 | 95198 |
| 60697.35154 | 6.170484091 | 7.150536572 | 6.34 | 28140.96709 | 743999.819 | 9003 Jay |
| 59748.85549 | 5.339339881 | 7.748681606 | 4.23 | 27809.98654 | 895737.133 | 24282 |

## PROGRAM

```
Importing

Dependenciesimport

pandas as pd import

numpy as np import

seaborn as sns

import matplotlib.pyplot as plt

from sklearn.model_selection
importtrain_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import r2_score,
mean_absolute_error,mean_squared_error
```

```
from sklearn.linear_model import
LinearRegressionfrom sklearn.linear_model import
Lasso
from sklearn.ensemble import
RandomForestRegressorfrom sklearn.svm import SVR
import xgboost as xg

%matplotlib
inlineimport
warnings
warnings.filterwarnings("ignore")

/opt/conda/lib/python3.10/site-
packages/scipy/_init_.py:146: UserWarning: A
NumPy
version >=1.16.5 and <1.23.0 is required for
thisversion of SciPy (detected version
1.23.5
warnings.warn(f"A NumPy version
>={np_minversion}and <{np_maxversion}"
Loading Dataset
dataset = pd.read_csv('E:/USA_Housing.csv')
```

**Model 1 - Linear Regression In [1]:**

```
model_lr=LinearRegression()
```

**In [2]:**

```
model_lr.fit(X_train_scal, Y_train)
```

**Out[2]:**

```
▾ LinearRegression
LinearRegression()
```

**Predicting**

**PricesIn [3]:**

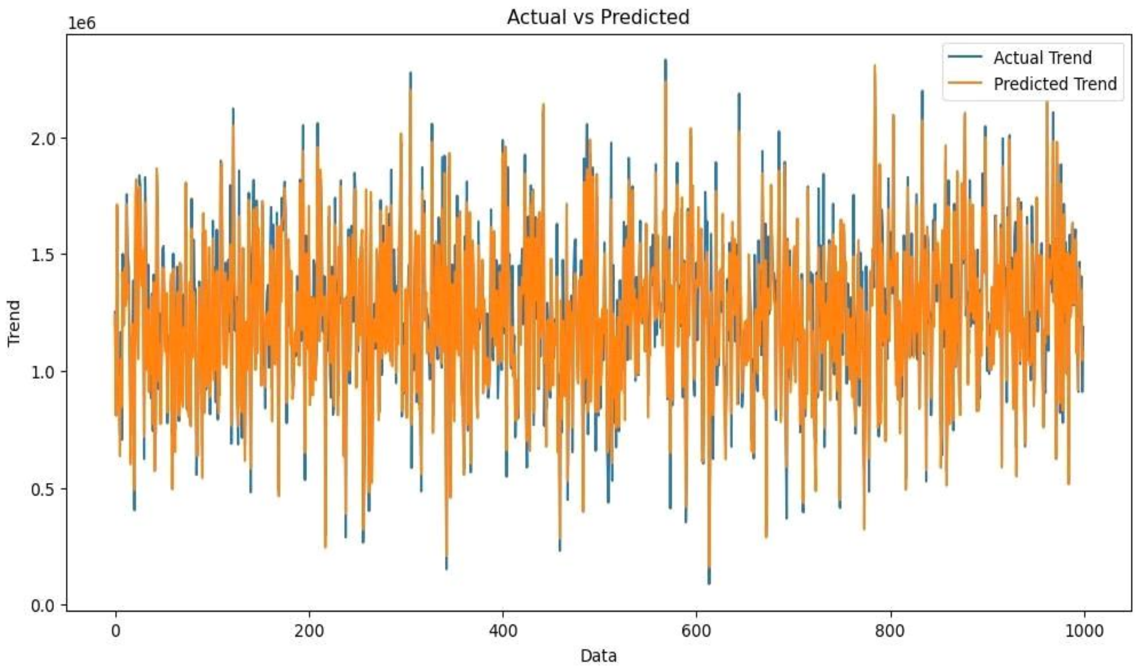
```
Prediction1 =
model_lr.predict(X_test_scal)Evaluation of
Predicted Data
```

**In [4]:**

```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)),
Y_test,label='Actual Trend')
plt.plot(np.arange(len(Y_test)),
Prediction1,label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend'
)plt.legend()
plt.title('Actual vs Predicted')
```

**Out[4]:**

Text(0.5, 1.0, 'Actual vs Predicted')

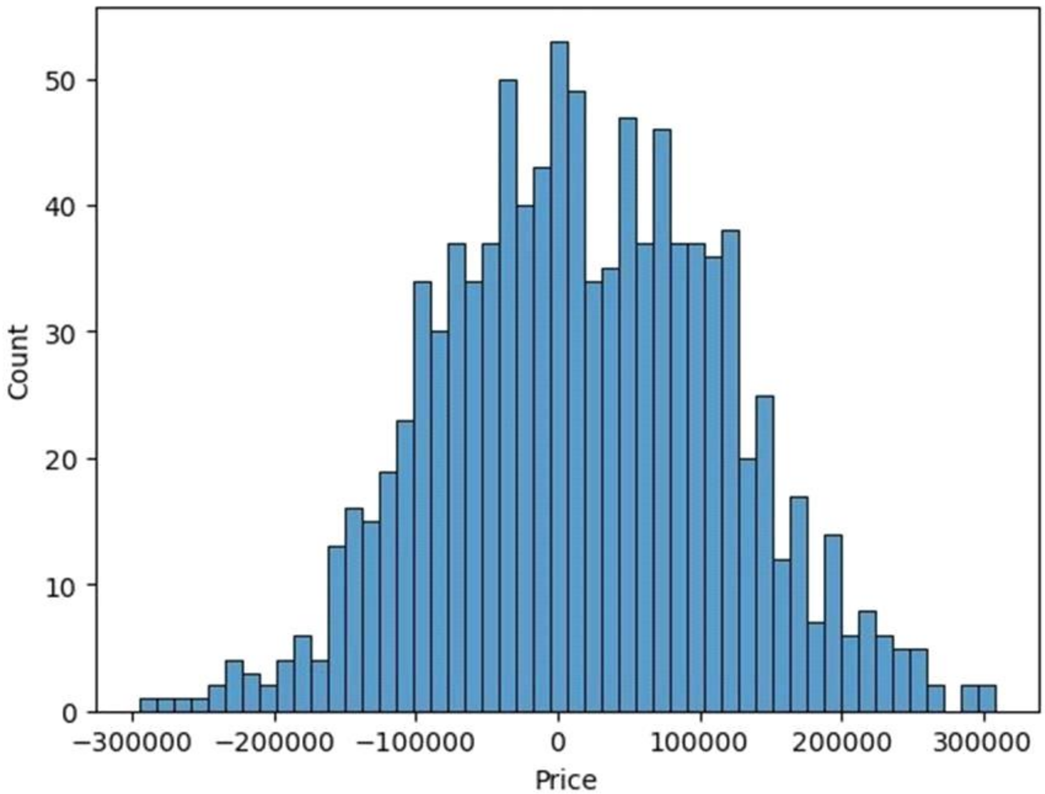



**In [5]:**

```
sns.histplot((Y_test-Prediction1), bins=50)
```

**Out[5]:**

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




**In [6]:**

```
print(r2_score(Y_test, Prediction1))
print(mean_absolute_error(Y_test,
Prediction1))print(mean_squared_error(Y_test,
Prediction1))
```

**Out[6]:**

0.9182928179392918

82295.49779231755

10469084772.975954

**Model 2 - Support Vector Regressor**

In [7]:

model_svr =

SVR()In [8]:

model_svr.fit(X_train_scal,

Y_train)Out[8]:

▾ SVR

SVR()

**Predicting**

**PricesIn [9]:**

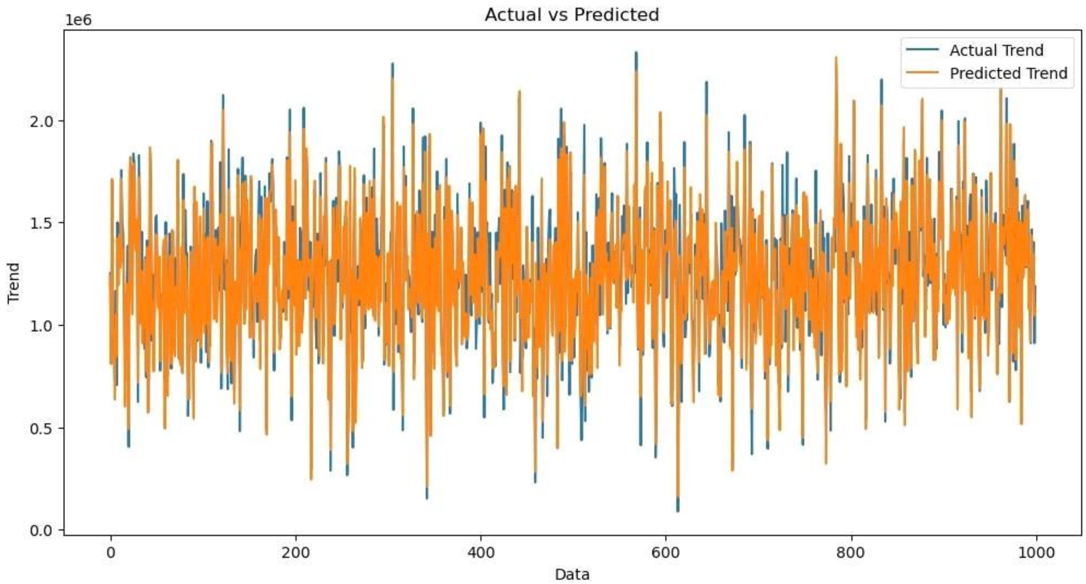
```
Prediction2 =

model_svr.predict(X_test_scal)Evaluation of

Predicted Data
```

**In [10]:**

```
plt.figure(figsize=(12,6))

plt.plot(np.arange(len(Y_test)),
Y_test,label='Actual Trend')

plt.plot(np.arange(len(Y_test)),
Prediction2,label='Predicted Trend')

plt.xlabel('Data')

plt.ylabel('Trend'

)plt.legend()

plt.title('Actual vs Predicted')
```

**Out[10]:**

```
Text(0.5, 1.0, 'Actual vs Predicted')
```

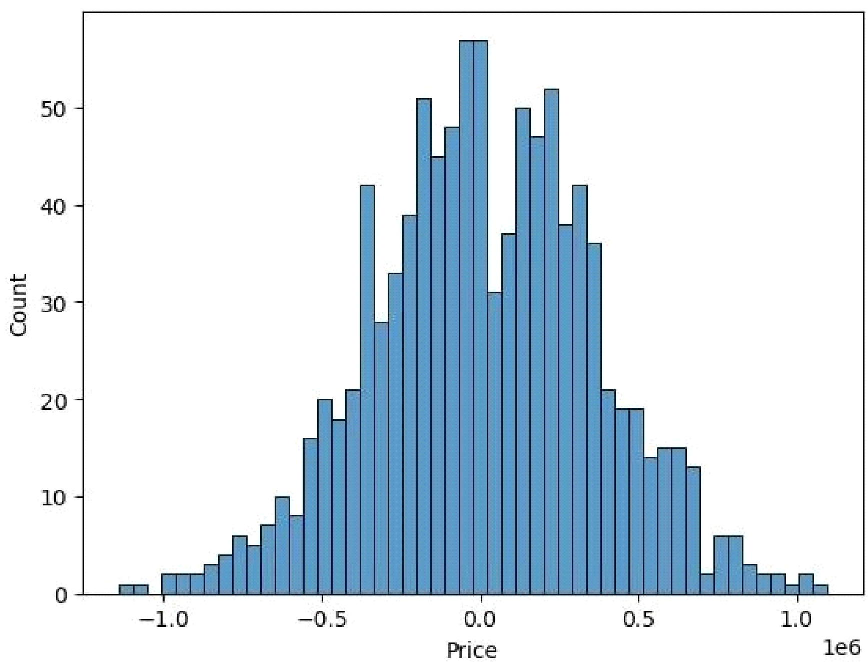



**In [11]:**

```
sns.histplot((Y_test-Prediction2), bins=50)
```

**Out[12]:**

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




**In [12]:**

```
print(r2_score(Y_test, Prediction2))
print(mean_absolute_error(Y_test,
Prediction2))print(mean_squared_error(Y_test,
Prediction2))
-0.0006222175925689744

286137.81086908665
128209033251.4034
```

**Model 3 - Lasso**

**RegressionIn [13]:**

```
model_lar = Lasso(alpha=1)
```

**In [14]:**

```
model_lar.fit(X_train_scal,Y_train)
```

Out[14]:

```
Lasso
Lasso(alpha=1)
```

**Predicting**

**PricesIn [15]:**

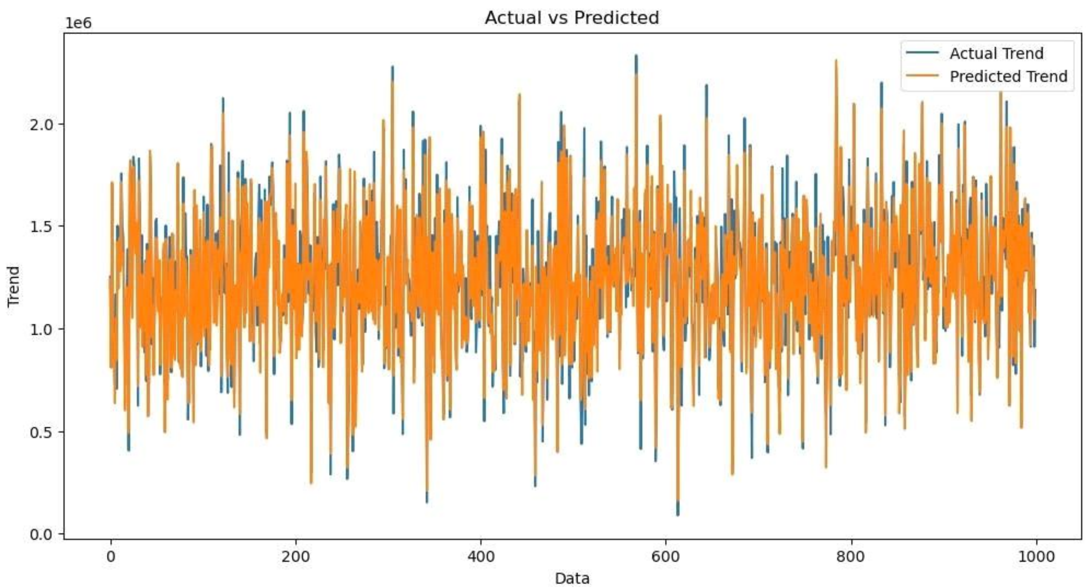
```
Prediction3 =
model_lar.predict(X_test_scal)Evaluation of
Predicted Data
```

**In [16]:**

```
plt.figure(figsize=(12,6))

plt.plot(np.arange(len(Y_test)),
Y_test,label='Actual Trend')

plt.plot(np.arange(len(Y_test)),
Prediction3,label='Predicted Trend')

plt.xlabel('Data')

plt.ylabel('Trend'

)plt.legend()

plt.title('Actual vs Predicted')
```

**Out[16]:**

Text(0.5, 1.0, 'Actual vs Predicted')

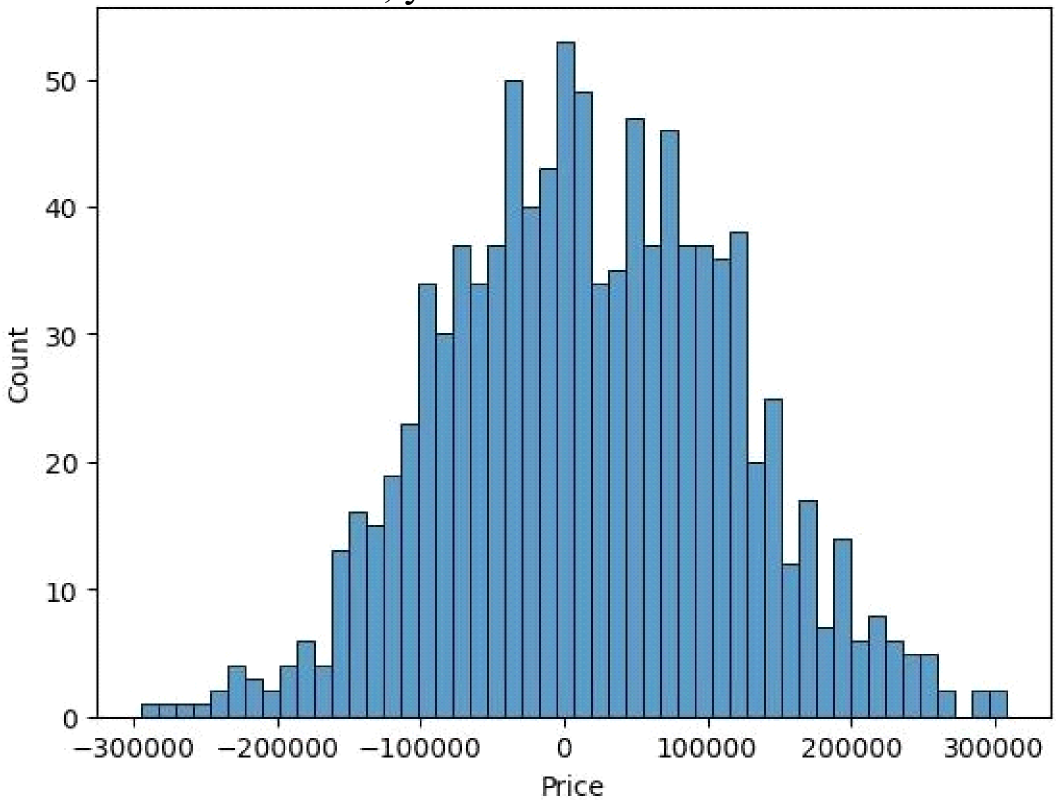



**In [17]:**

```
sns.histplot((Y_test-Prediction3), bins=50)
```

**Out[17]:**

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




**In [18]:**

```
print(r2_score(Y_test, Prediction2))
print(mean_absolute_error(Y_test,
Prediction2))print(mean_squared_error(Y_test,
Prediction2))
```

```
-0.0006222175925689744

286137.81086908665

128209033251.4034
```

**Model 4 - Random Forest**

**Regressor** **In [19]:**

```
model_rf = RandomForestRegressor(n_estimators=50)
```

**In [20]:**

```
model_rf.fit(X_train_scal, Y_train)
```

Out[20]:

```
RandomForestRegressor
RandomForestRegressor(n_estimators=50)
```

**Predicting**

**Prices****In [21]:**

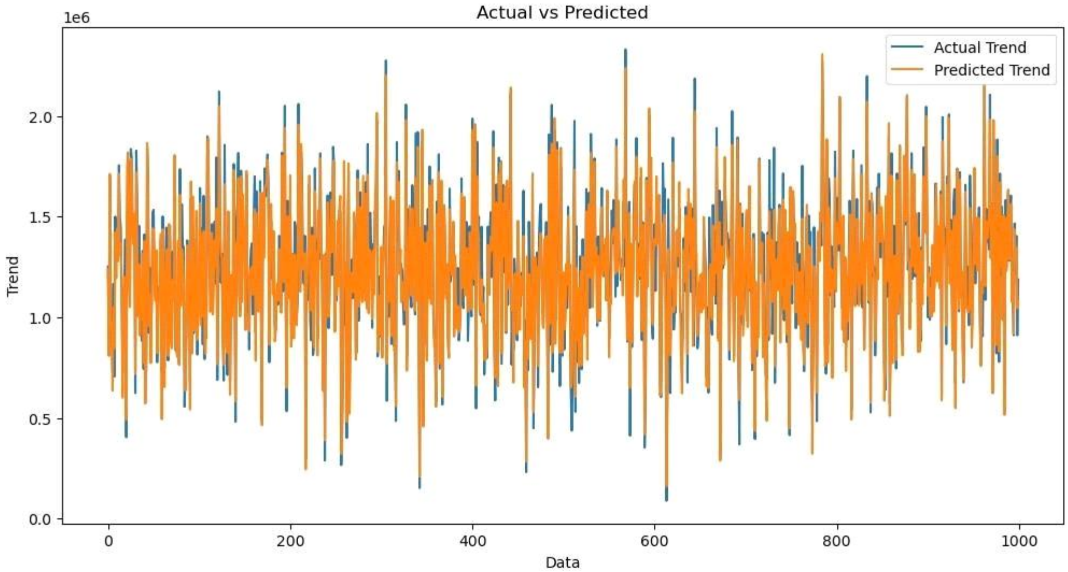
```
Prediction4 =
model_rf.predict(X_test_scal)Evaluation of
Predicted Data
```

**In [22]:**

```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)),
Y_test,label='Actual Trend')
plt.plot(np.arange(len(Y_test)),
Prediction4,label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend'
)plt.legend()
plt.title('Actual vs Predicted')
```

**Out[22]:**

Text(0.5, 1.0, 'Actual vs Predicted')




**In [23]:**

```
sns.histplot((Y_test-Prediction4), bins=50)
```

**Out[23]:**

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

**In [24]:**

```
print(r2_score(Y_test, Prediction2))
print(mean_absolute_error(Y_test,
Prediction2))print(mean_squared_error(Y_test,
Prediction2))
```

**Out [24] :**

-0.0006222175925689744

286137.81086908665

128209033251.4034

**Model 5 - XGboost**

**Regressor In [25]:**

```
model_xg = xg.XGBRegressor()
```

**In [26]:**

```
model_xg.fit(X_train_scal, Y_train)
```

**Out[26]**

XGBRegressor

XGBRegressor(base_score=None, booster=None,

callbacks=None,colsample_bylevel=None,

colsample_bynode=None, colsample_bytree=None,

early_stopping_rounds=None, enable_categorical=False,

eval_metric=None, feature_types=None,

gamma=None, gpu_id=None, grow_policy=None, importance_type=None,

interaction_constraints=None, learning_rate=None, max_bin=None,

max_cat_threshold=None, max_cat_to_onehot=None,

max_delta_step=None, max_depth=None, max_leaves=None,

min_child_weight=None, missing=nan, monotone_constraints=None,

n_estimators=100, n_jobs=None,

num_parallel_tree=None,predictor=None,

random_state=None, ...)

**Predicting**

**Prices In [27]:**

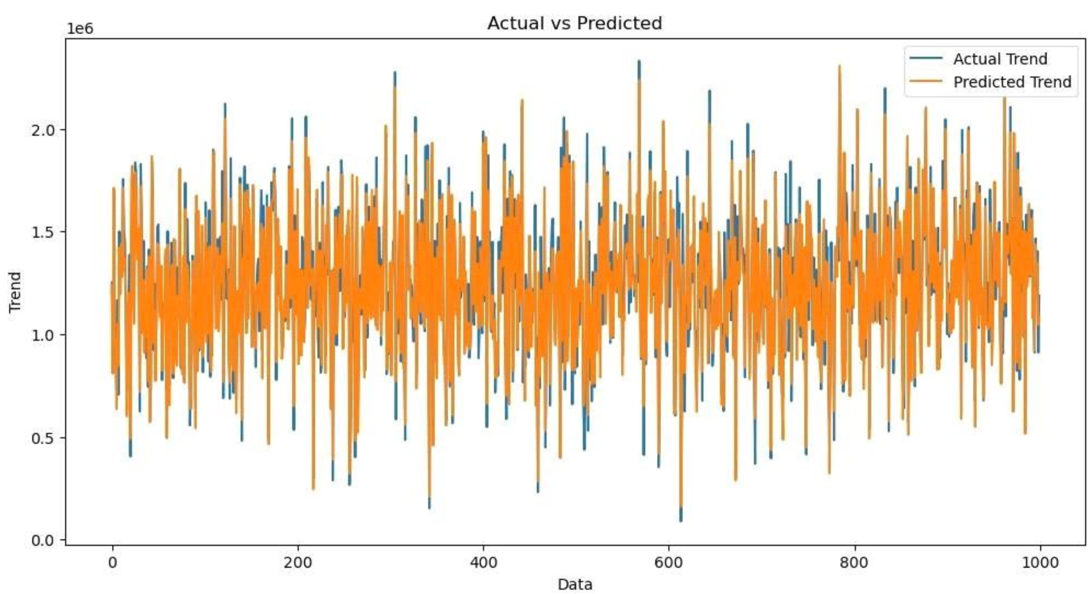
```
Prediction5 =
model_xg.predict(X_test_scal)Evaluation of
Predicted Data
```

**In [28]:**

```
plt.figure(figsize=(12,6))
plt.plot(np.arange(len(Y_test)),
Y_test,label='Actual Trend')
plt.plot(np.arange(len(Y_test)),
Prediction5,label='Predicted Trend')
plt.xlabel('Data')
plt.ylabel('Trend'
)plt.legend()
plt.title('Actual vs Predicted')
```

**Out[28]:**

Text(0.5, 1.0, 'Actual vs Predicted')

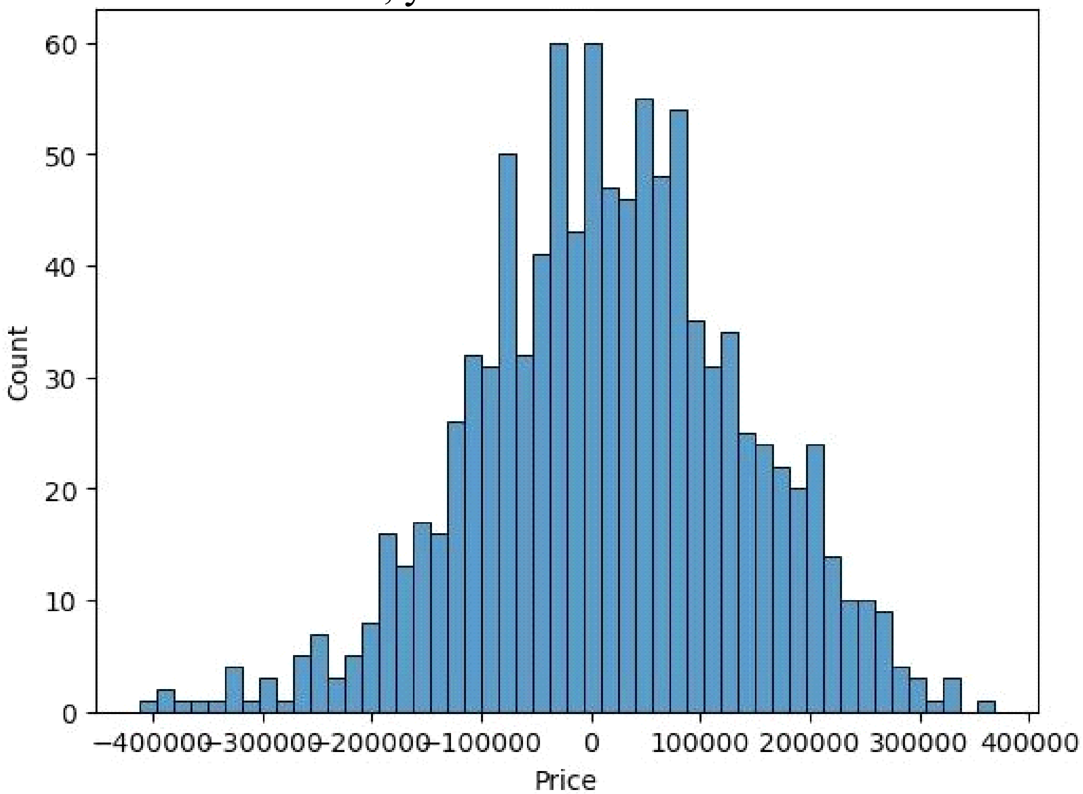


**In [29]:**

```
sns.histplot((Y_test-Prediction4), bins=50)
```

**Out[29]:**

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




**In [30]:**

```
print(r2_score(Y_test, Prediction2))
print(mean_absolute_error(Y_test,
Prediction2))print(mean_squared_error(Y_test,
Prediction2))
```

**Out [30] :**

-0.0006222175925689744

286137.81086908665

128209033251.4034

## CONCLUSION

In summary, this modular framework for house price prediction usingmachine learning offers a comprehensive and structured approach to building robust predictive models in the real estate industry. Each module addresses a critical aspect of the process, from data collectionand preprocessing to model deployment, interpretability, and ongoingmaintenance. By breaking down the workflow into discrete modules, this framework provides flexibility and adaptability, ensuring that house price prediction models remain accurate and valuable in an ever-changing real estate landscape.