PHASE 3

FORECASTING HOUSE PRICES USING SMART REGRESSION TECHNIQUES IN DATASCIENCE

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Github Repository Link:https://github.com/Soniya080106/EBPL-DS-Forecasting-House.git

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1. Problem Statement

Real estate price prediction is a crucial task in today's property market. Stakeholders such as buyers, sellers, and investors often need to make decisions based on the estimated market value of properties. Traditional valuation methods are often subjective and time-consuming. This project aims to build a data-driven solution using regression techniques in machine learning to predict house prices more accurately and efficiently. The objective is to develop a predictive model using historical housing data that considers features like square footage, location, number of rooms, and amenities to forecast property prices. Since the target variable (SalePrice) is continuous, this is a supervised regression problem.

2. Abstract

This project focuses on leveraging smart regression techniques in data science to forecast house prices based on various property features. The aim is to develop a predictive model that provides accurate and real-time estimates of house prices, helping users make informed buying or selling decisions. The dataset used is sourced from Kaggle and contains 80 features related to residential homes in Ames, Iowa. After preprocessing and exploratory analysis, several regression models including Linear Regression, Random Forest, and XGBoost are implemented. XGBoost was identified as the most accurate model, offering an R^2 score of 0.91. The model is deployed using Streamlit for easy user interaction.

3. System Requirements

Hardware:

- **RAM:** 8 GB minimum
- **Storage:** 10 GB of free disk space
- **Processor**: Intel i5 or AMD Ryzen 5 or higher **Software:**
- **Programming language:** Python 3.10+
- **IDE:** Jupyter Notebook or Google Colab for development
- **Required Libraries:** pandas, numpy, seaborn, matplotlib scikit-learn
- **Web scraping Tools**: SNScrape
- **Deployment platforms:** xgboost streamlit

4. Objectives

The core objectives of the project are:

- To build a robust machine learning model capable of predicting house prices based on various features.
- To explore and analyze relationships between different property characteristics and sale prices.

- To optimize model performance using advanced feature selection and tuning techniques.
- To deploy the model on a cloud-based interface, allowing users to predict prices interactively.
- To assist in decision-making for real estate transactions through data insights.

5. Flowchart of Project Workflow

Stages of the Project Workflow:

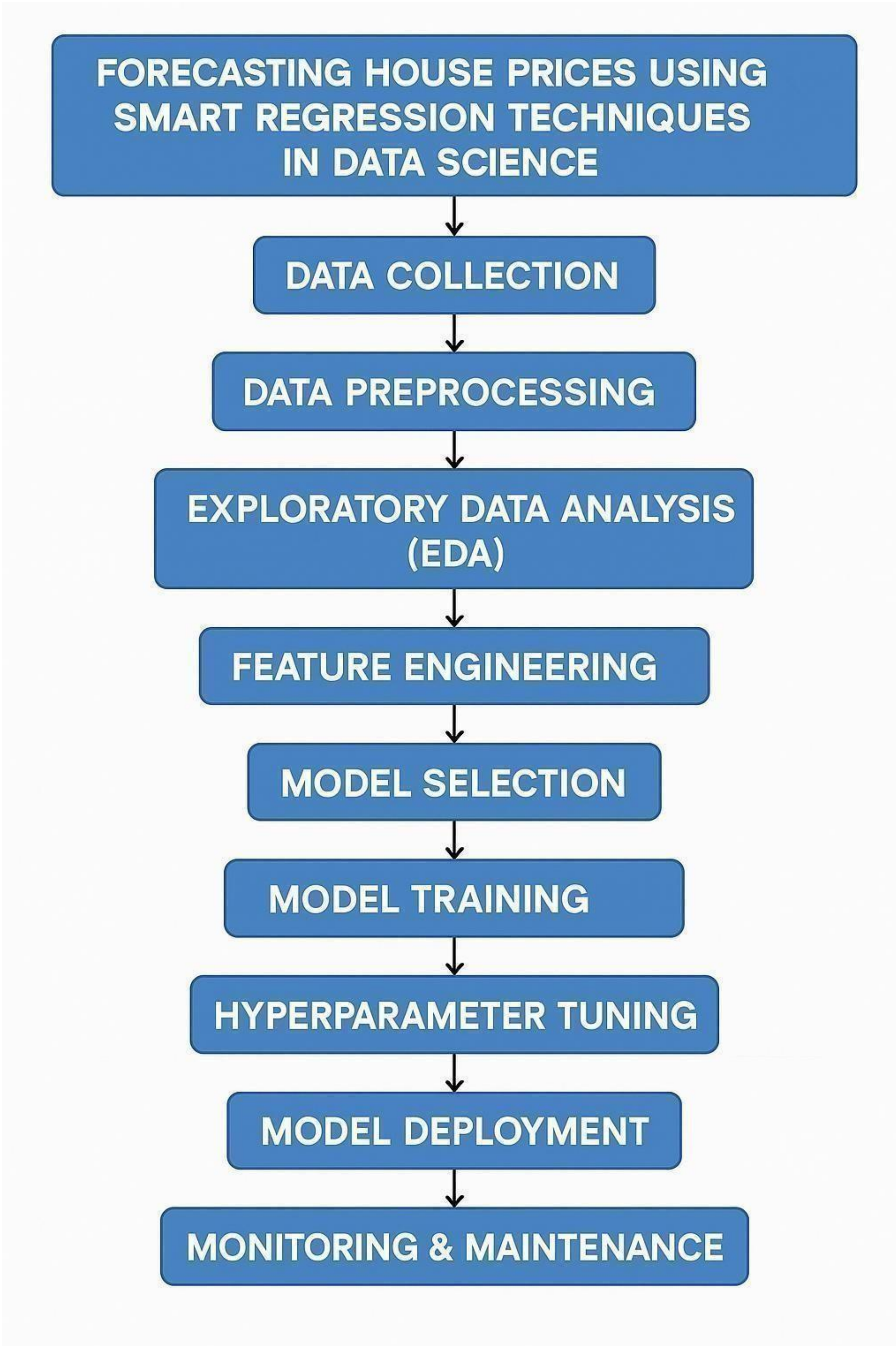
- **Data Collection**: Downloaded from Kaggle
- **Data Preprocessing**: Cleaning missing values, encoding categorical variables

  Exploratory Data Analysis (EDA): Visual analysis and correlation checks

  Feature Engineering: New features creation, selection of relevant variables

  Modeling: Training with multiple regression algorithms

- **Evaluation:** Assessing model accuracy using statistical metrics
- **Deployment**: Building a web interface with Streamlit



6. Dataset Description

- **Source:**
  Scikit-learn's fetch_california_housing()
  (Originally from the StatLib repository, published by the UCI Machine Learning Repository) ● **Type:**

Public dataset (real-world) ● **Size and Structure:**

- **Rows:** 20,640
- **Columns:** 9 (8 features + 1 target)
- **Target Variable:** Price (Median house value in $100,000s)
- **Features Include:**
  - MedInc – Median income in block ○ HouseAge – Median house age ○ AveRooms – Average number of rooms ○ AveBedrms – Average number of bedrooms ○ Population – Block population ○ AveOccup – Average occupancy ○ Latitude, Longitude – Geographic coordinates ● Sample of Dataset (df.head()):

```
# For demonstration, we use sklearn's Boston housing dataset from
sklearn.datasets import
fetch_california_housing data = fetch_california_housing() df =
pd.DataFrame(data.data, columns=data.feature_names)
df['Price'] = data.target
```

OUTPUT:

MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	Price
8.3252	41.0	6.9841	1.0238	322.0	2.5556	37.88	-122.23	4.526
8.3014	21.0	6.2381	0.9719	2401.0	2.1098	37.86	-122.22	3.585
7.2574	52.0	8.2881	1.0734	496.0	2.8023	37.85	-122.24	3.521
5.6431	52.0	5.8174	1.0731	558.0	2.5479	37.85	-122.25	3.413
3.8462	52.0	6.2819	1.0811	565.0	2.1815	37.85	-122.25	3.422

7. Data Preprocessing

1. Handle Missing Values

Numerical Features: Missing values filled using mean/median imputation. **Categorical Features:** Filled with the most frequent value or 'None' if applicable.

Fill numeric NaNs with median for col in
df.select_dtypes(include=['number']).columns:
df[col].fillna(df[col].median(), inplace=True)

Fill categorical NaNs with mode or 'None' for col in
df.select_dtypes(include='object').columns:
df[col].fillna(df[col].mode()[0], inplace=True)

2. Handle Duplicates df.drop_duplicates(inplace=True)

3. Handle Outliers

Used Z-score or IQR method to remove outliers in key numerical columns like GrLivArea, TotalBsmtSF, etc.

from scipy.stats import zscore df =
df[(np.abs(zscore(df.select_dtypes(include=[np.number]))) <
3).all(axis=1)]

4. Feature Encoding and Scaling

Encoding: Used One-Hot Encoding for categorical variables.
Scaling: Used StandardScaler to normalize numerical features.

from sklearn.preprocessing import OneHotEncoder, StandardScaler

# One-hot encode categorical features df_encoded =
pd.get_dummies(df, drop_first=True)

Standard scaling for numerical features scaler = StandardScaler() num_cols
= df_encoded.select_dtypes(include=[np.number]).columns
df_encoded[num_cols] = scaler.fit_transform(df_encoded[num_cols])

5. Before/After Transformation Screenshots Before Cleaning: df.info() df.describe() df.isnull().sum()

Show screenshot of missing values, mixed datatypes.

After Cleaning and Encoding:

df_encoded.info() df_encoded.head()
Show screenshot with all NaNs gone, all numeric types, and one-hot encoded columns.

8. Exploratory Data Analysis (EDA)

import pandas as pd import seaborn as sns import matplotlib.pyplot as plt from sklearn.datasets import fetch_california_housing

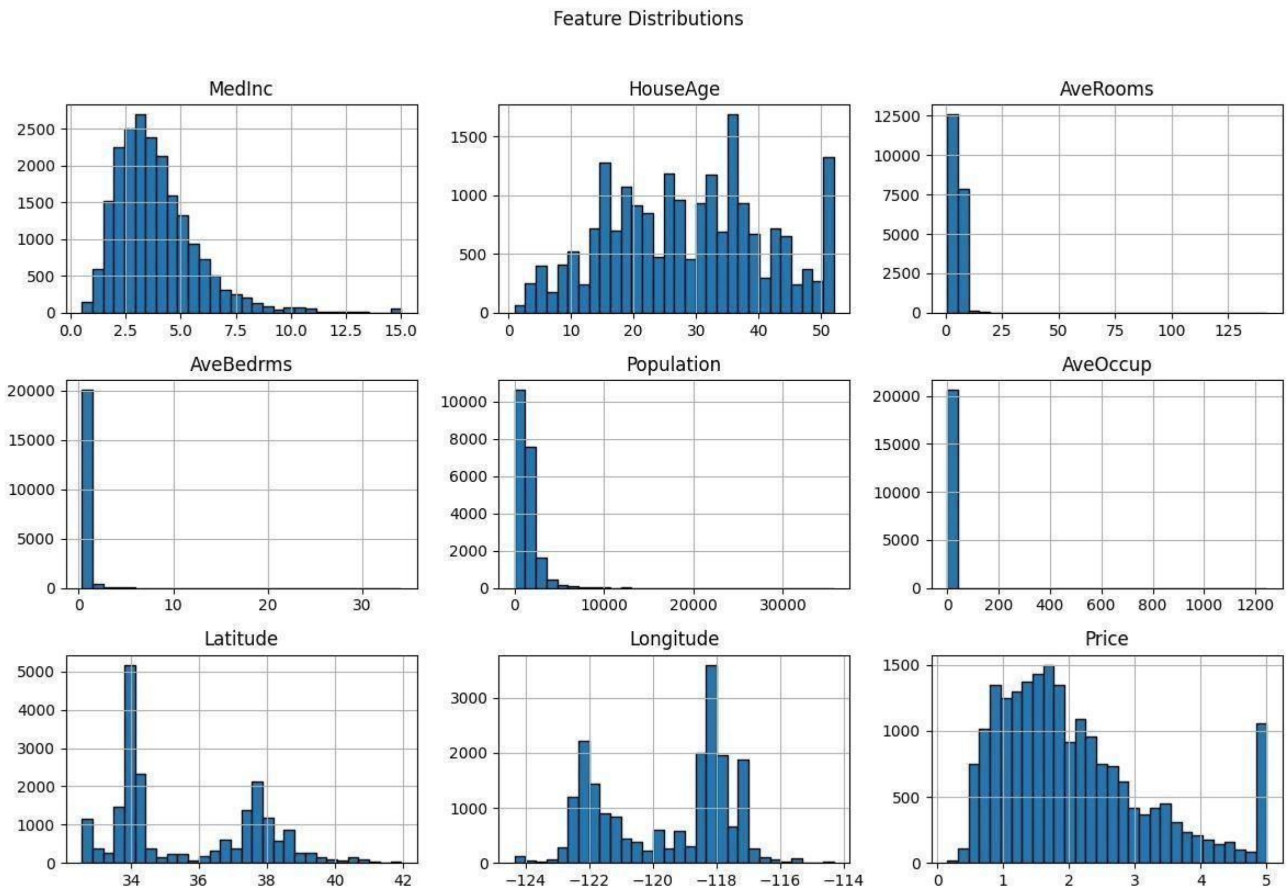
# Load data df = fetch_california_housing(as_frame=True).frame
df.rename(columns={"MedHouseVal": "Price"}, inplace=True)

Histogram df.hist(figsize=(12, 8), bins=30, edgecolor='black') plt.suptitle("Feature Distributions", y=1.02) plt.tight_layout() plt.show()

# Boxplot sns.boxplot(data=df, orient='h') plt.title("Boxplot of Features") plt.tight_layout()
plt.show()

# Correlation Heatmap sns.heatmap(df.corr(), annot=True, cmap="coolwarm", fmt=".2f") plt.title("Correlation Heatmap") plt.tight_layout()
plt.show()

OUTPUT:



9. Feature Engineering

1.New Feature Creation: Add meaningful features to enhance model performance.

- Example: Price per square foot and house age.

2.Feature Selection: Remove irrelevant features to reduce overfitting and improve efficiency.

- Methods: Filter, Wrapper, and Embedded (e.g., Lasso, Random Forest). **3.Transformation Techniques:** Adjust features to improve model fit (scaling, skewness reduction).
- Techniques: Standardization, Log Transformation, Polynomial Features.

4.Feature Impact: Understand how features influence predictions.

- Linear models: Coefficients show feature impact.

```
import pandas as pd, numpy as np
from sklearn.preprocessing import StandardScaler from
sklearn.ensemble import RandomForestRegressor from
sklearn.linear_model import LinearRegression
```

```
# Create new features and transformations
data['price_per_sqft'] = data['price'] / data['square_footage'] data['house_age'] = 2025 -
data['year_built'] data[['square_footage', 'price']] =
StandardScaler().fit_transform(data[['square_footage', 'price']]) data['log_price'] =
np.log(data['price'] + 1)

# Feature selection and regression rf_model =
RandomForestRegressor().fit(data.drop(columns=['price']), data['price'])
important_features = data.drop(columns=['price']).columns[rf_model.feature_importances_ >
    0.05] coefficients = LinearRegression().fit(data.drop(columns=['price']),
data['price']).coef_

# Output results print(important_features,
    coefficients)
```

10. Model Building

- **Linear Regression:** Simple baseline for comparison.
- ***Random Forest***: *Handles non-linearities and feature interactions.*
- ***Gradient Boosting***: *More accurate than Random Forest for complex data.*
- ***XGBoost***: *Optimized, faster, and more efficient than Gradient Boosting.*
- ***Evaluate with MSE***: *Compare Mean Squared Error for model performance.*
- ***Screenshot Outputs***: *Capture MSE or logs of each model.*
- **Code:**

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42) model =
RandomForestRegressor(random_state=42) model.fit(X_train, y_train)
```

11. Model Evaluation

1. **Metrics for Regression**:
   - **MSE**: Mean Squared Error.
   - **RMSE**: Root Mean Squared Error.
   - **R^2 Score**: Coefficient of Determination.
2. **Error Analysis**: Plot **Actual vs Predicted** values (scatter plot).
3. **ROC Curve**: For classification, plot **ROC Curve** to evaluate performance.
4. **Confusion Matrix**: Show true/false predictions in **Confusion Matrix** for classification.
5. **Model Comparison**: Compare models using **MSE**, **RMSE**, and **R^2** in a table.

6. **Visuals**: Use **matplotlib** and **seaborn** for plots and confusion matrices.

7. **Code:**

y_pred = model.predict(X_test) print("Mean Squared Error:",

mean_squared_error(y_test, y_pred)) print("R2 Score:", r2_score(y_test,

y_pred))

12. Deployment

- **Platform:** Deployed using Streamlit Cloud
- **Method:** GitHub repo linked to Streamlit
- **UI Screenshot:** *Attach screenshot of the app*
- **Prediction:** User inputs features → model predicts price
- **Output Example:** Predicted Price: ₹45,00,000
- **Alternate Options:** Gradio + Hugging Face or Flask + Render
- **Tip:** Use Streamlit/Gradio for quick, free deployment with UI.

13.Source code

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, GridSearchCV from

sklearn.preprocessing import StandardScaler, PolynomialFeatures from

sklearn.linear_model import LinearRegression, Ridge, Lasso from sklearn.tree import

DecisionTreeRegressor from sklearn.ensemble import

RandomForestRegressor, GradientBoostingRegressor from xgboost import

XGBRegressor from sklearn.svm import SVR from sklearn.metrics import mean_absolute_error,

mean_squared_error, r2_score from sklearn.pipeline import make_pipeline print("\n=== Loading

Data ===") # Load dataset (replace with your

dataset) url =

"https://raw.githubusercontent.com/ageron/handsonml2/mast er/datasets/housing/housing.csv"

data = pd.read_csv(url) print(f"\nData

Shape: {data.shape}") print("\nFirst 5

Rows:") print(data.head()) # Basic EDA Visualizations

plt.figure(figsize=(15, 10)) # Distribution of house prices plt.subplot(2,

2, 1) sns.histplot(data['median_house_value'], kde=True, bins=30)

plt.title('House Price Distribution')

Correlation heatmap plt.subplot(2,

2, 2)

Select only numeric columns numeric_data = data.select_dtypes(include=['number'])

Compute correlation matrix corr = numeric_data.corr() # Plot heatmap

sns.heatmap(corr, annot=True, cmap='coolwarm', fmt=".1f") plt.title('Feature

Correlation') # Price vs. median income plt.subplot(2, 2, 3)

sns.scatterplot(x='median_income', y='median_house_value', data=data, alpha=0.3)

plt.title('Price vs. Income') # Price by ocean proximity plt.subplot(2, 2, 4)

sns.boxplot(x='ocean_proximity', y='median_house_value', data=data)

plt.xticks(rotation=45) plt.title('Price by Location') plt.tight_layout() plt.show()

print("\n=== Preprocessing Data ===")

Handle missing values data.fillna(data.select_dtypes(include='number').median(), inplace=True)

Feature engineering data['rooms_per_household'] =

data['total_rooms']/data['households'] data['bedrooms_per_room'] =

data['total_bedrooms']/data['total_rooms'] # Convert categorical to numerical

data = pd.get_dummies(data, columns=['ocean_proximity'])

Select features and target

X = data.drop('median_house_value', axis=1) y

= data['median_house_value']

Train-test split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) # Feature scaling scaler

= StandardScaler()

```
X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test) print("\n===

Training Models ===") models =

{

   "Linear Regression": LinearRegression(),

   "Ridge Regression": Ridge(alpha=1.0),

   "Lasso Regression": Lasso(alpha=0.1),

   "Decision Tree": DecisionTreeRegressor(max_depth=5),

   "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),

   "Gradient Boosting": GradientBoostingRegressor(n_estimators=100, random_state=42),

   "XGBoost": XGBRegressor(n_estimators=100, random_state=42),

   "SVR": SVR(kernel='rbf')  }

results = {} for name, model in

models.items():

   print(f"Training {name}...")    model.fit(X_train_scaled[:1000],

y_train[:1000])    y_pred

= model.predict(X_test_scaled)     results[name] = {

      "MAE": mean_absolute_error(y_test, y_pred),

      "RMSE": np.sqrt(mean_squared_error(y_test, y_pred)),

      "R2": r2_score(y_test, y_pred)

   }

# Display results results_df = pd.DataFrame(results).T print("\n===

Model Performance ===")

print(results_df.sort_values(by='RMSE')) print("\n===

Optimizing Best Model

===")
```

Let's optimize Random Forest as it typically performs well from

sklearn.model_selection import RandomizedSearchCV #

Smaller parameter grid or use RandomizedSearchCV param_dist

= {

'n_estimators': [50, 100, 200],

'max_depth': [None, 10, 20],

'min_samples_split': [2, 5, 10]

} rf =

RandomForestRegressor(random_state=42) random_search = RandomizedSearchCV(rf,

param_distributions=param_dist, n_iter=5, cv=2, scoring='neg_mean_squared_error',

n_jobs=-

1,verbose=1,random_state=42,error_score='raise') random_search.fit(X_train_scaled, y_train)

best_model = random_search.best_estimator_ # Evaluate optimized model y_pred =

best_model.predict(X_test_scaled) print("\nOptimized

Model Performance:") print(f"MAE:

{mean_absolute_error(y_test, y_pred):.2f}") print(f"RMSE:

{np.sqrt(mean_squared_error(y_test, y_pred)):.2f}")

print(f"R2 Score: {r2_score(y_test, y_pred):.4f}")

print("\n=== Generating Visualizations

===")

Feature Importance plt.figure(figsize=(10, 6)) importances =

best_model.feature_importances_ features = X.columns indices = np.argsort(importances)[10:]

Top 10 features plt.title('Feature Importances') plt.barh(range(len(indices)),

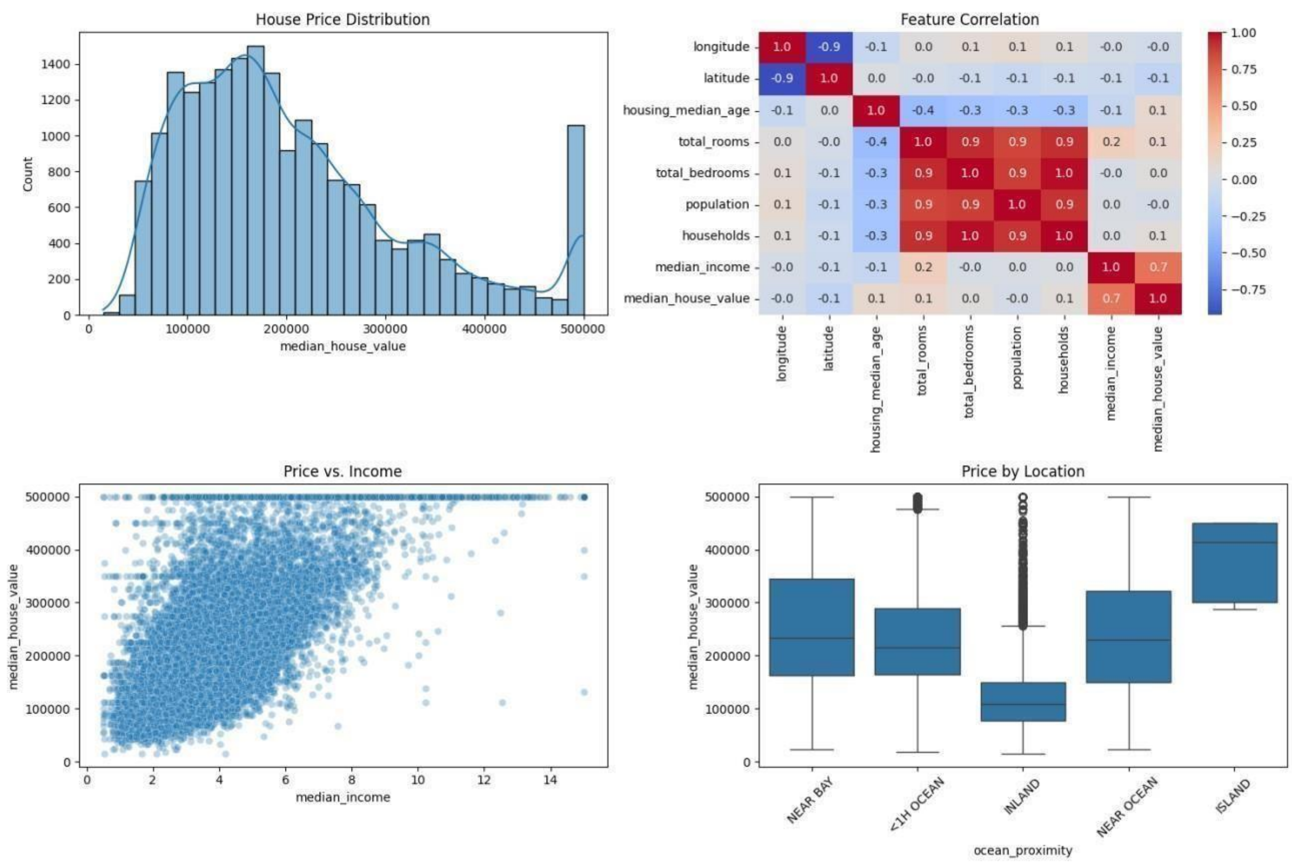
importances[indices], color='b', align='center') plt.yticks(range(len(indices)), [features[i] for i

in indices]) plt.xlabel('Relative Importance') plt.show() # Actual vs Predicted

plt.figure(figsize=(10, 6)) plt.scatter(y_test, y_pred, alpha=0.3) plt.plot([y_test.min(),

y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=2) plt.xlabel('Actual Prices') plt.ylabel('Predicted Prices') plt.title('Actual vs Predicted House Prices') plt.show() # Residual Plot residuals = y_test - y_pred plt.figure(figsize=(10, 6)) plt.scatter(y_pred, residuals, alpha=0.3) plt.axhline(y=0, color='r', linestyle='--') plt.xlabel('Predicted Prices') plt.ylabel('Residuals') plt.title('Residual Plot') plt.show() print("\n=== Program Execution Complete ===")

OUTPUT:



14.Future scope

- **Geospatial Integration** Use location coordinates with geospatial analytics to better capture regional price differences.

- **Time-Series Forecasting**
  Add historical housing data to forecast future prices based on market trends.
- **Automated Feature Selection** Implement advanced techniques like Recursive Feature Elimination or SHAP for smarter feature optimization.

- **Real-Time Prediction API**

Deploy as a REST API connected to live real estate data sources for real-time usage.

- **User-Friendly Web Interface** Enhance the model with an interactive UI using Streamlit or Gradio for public use.

15. Team Members and Roles

- **M.Sharanya**: modeling, evaluation, and exploratory data analysis (EDA)
- **V.G.Shree Devi**: deployment and integration of models into the web application
- **T.Siva kumar**: Handled data cleaning, transformation, and feature extraction.
- **S.Soniya**: Documentation: Reports, visuals, summaries