PHASE 3 Submission

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Github repository link: https://github.com/Leelavathi-12/Forecasting-house-price-accurately-using-smart-regression-techniques-in-data-science.git

Forecasting house price accurately using smart regression techniques in data science

Problem Statement

Real estate price prediction is a crucial task in today's property market. Stakeholders such as buyers, sellers, and investors need to make informed decisions based on the accurate market value of properties. Traditional valuation methods are often subjective and time-consuming. This project aims to build a data-driven solution using machine learning techniques to predict house prices more accurately and efficiently. The objective is to develop a predictive model using regression techniques 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.

1.Abstract

This project focuses on developing a machine learning model to predict house prices based on historical data and various property features. This involves analyzing specific property details. It provides accurate and data-driven 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:** 8GB minimum
- **Storage:** 10GB 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 Tool:** BS4/Scrapy
- **Deployment platform:** Streamlit

2.Objectives

The main objectives of the project are:

- To build an accurate 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 via a web-based user interface, allowing users to predict prices interactively.
- To assist stakeholders in decision-making for real estate investments through data insights.

3.Flowchart of Project Workflow

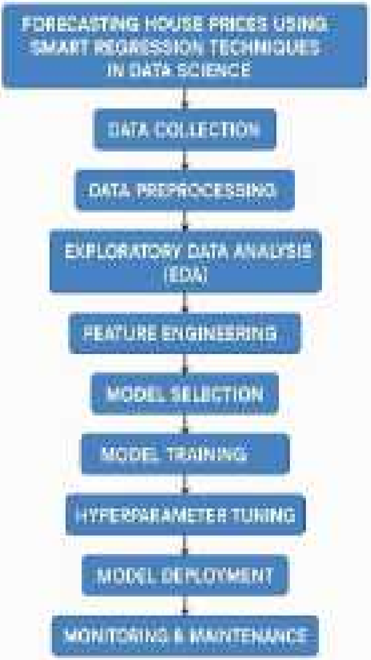
Stages of the Project Workflow:

- **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 web interface with Streamlit



FORECASTING HOUSE PRICES USING SMART REGRESSION TECHNIQUES IN DATA SCIENCE

DATA COLLECTION

DATA PREPROCESSING

EXPLORATORY DATA ANALYSIS (EDA)

FEATURE ENGINEERING

MODEL SELECTION

MODEL TRAINING

HYPERPARAMETER TUNING

MODEL DEPLOYMENT

MONITORING & MAINTENANCE

1.Dataset Description

https://www.kaggle.com/datasets/jordanin/llm-prompts-

- Source:

  Scikit-learn (fetch_california_housing)
  (Originally from the StatLib Repository, published by the UCI Machine Learning Repository)

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 Dataset (First 5 Rows)

```
# 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:

```
 MedIncHouseAgeAveRoomsAveBedrmsPopulationAveOccupLatitudeLongitudePrice
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
```

3. 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 / IQR method to remove outliers in key numeric 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 screenshots of missing values, outliers, data types.

AfterCleaningandEncoding

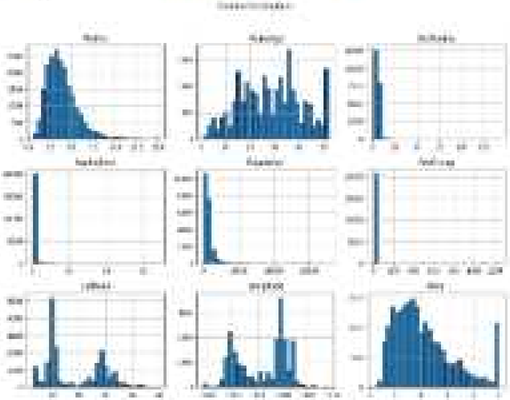
df_encoded.info(df_encoded.head())

ShowsencodeddatasetwithNaNs gone,allnumerictypes,andone-hotencoded columns.

6.Exploratory Data Analysis (EDA)

```
importpandasaspd importseaborn
as sns import matplotlib.pyplot as
plt
fromsklearn.datasetsimport fetch_california_housing

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

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

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

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

OUTPUT:



7.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

# [illegible]
```

```
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_

#important.display(important_features,
    coefficients)
```

8. Model Building

- **LinearRegression:** Simple baseline for comparison.
- **RandomForest:** Handles non-linear data and feature interactions.
- **GradientBoosting:** More accurate than RandomForest for complex data.
- **XGBoost:** Optimized, faster, and more efficient than GradientBoosting.
- **Evaluate with MSE:** Compares Mean Squared Error of models for performance.
- **Accuracy of Outputs:** Computed MSE for 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)
```

9. Model Evaluation

1. **Metrics for Regression:**
   - **MSE:** Mean Squared Error.
   - **RMSE:** Root Mean Squared Error.
   - **R² 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:** Shows correct/incorrect predictions in **Confusion Matrix** for classification.
5. **Model Comparison:** Compare models using **MSE, RMSE, and R²** in a table.
6. **Visualize:** Use **scatter plots**, **residual plots** and [illegible].

7. Code:

```
y_pred=model.predict(X_test)print("MeanSquaredError:",

mean_squared_error(y_test, y_pred))

print("R2Score:",r2_score(y_test,y_pred))
```

10. Deployment

- **Platform:** DeployedusingStreamlitCloud
- **Method:** GitHub repo linked to Streamlit
- **UIScreenshot:** Attachscreenshotsoftheapp
- **Prediction:** User inputs features→model predicts price
- **OutputExample:** PredictedPrice: ₹45,00,000
- **AlternateOptions:** Gradio+HuggingFaceorFlask+Render
- **Tip:** UseStreamlit/Gradioforquick,freedeploymentwithUI

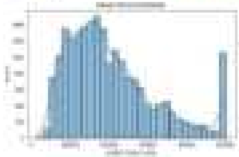
11. Source code

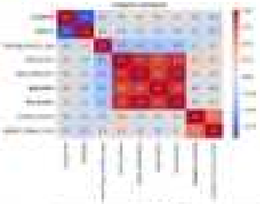
```
import pandas as pd import numpy as np import matplotlib.pyplot as plt import

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

dataset)

url =

"https://raw.githubusercontent.com/ageron/handson-ml2/

master/datasets/housing/housing.csv" data =

pd.read_csv(url) print("Data Shape:", data.shape)
```

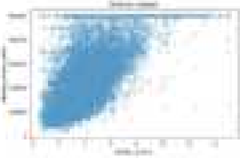
```
[illegible]
Visualization
plt.figure(figsize=(15, 10)) # Distribution of house prices
plt.subplot(2, 2, 1) sns.histplot(data['median_house_value'],
kde=True, bins=30) plt.title('House Price Distribution')

# Correlation heatmap
plt.subplot(2, 2, 2)
# Select only numeric columns numeric_data=
data.select_dtypes(include=[np.number])
# Compute correlation matrix corr = numeric_data.corr() sns.
heatmap(corr, annot=True, cmap='coolwarm',
fmt='.2f')
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['total_bedrooms'].fillna(data['total_bedrooms'].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'])
```

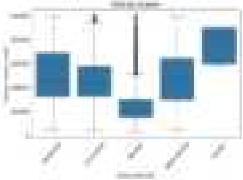
```
# Select features and target
X = data.drop(['median_house_value'], axis=1)y
= data['median_house_value']
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) #
Feature scaling scaler
= StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
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=200, random_state=42),
   "Gradient Boosting": GradientBoostingRegressor(n_estimators=200, random_state=42),
   "XGBoost": XGBRegressor(n_estimators=300, random_state=42),
   "SVR": SVR(kernel='rbf')
}results={}for name, model in
models.items():
   print(f"Training {name}...")
model.fit(X_train_scaled, y_train)    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
# Define parameter grid for 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=3,
scoring='neg_root_mean_squared_error', n_jobs=-
1,verbose=1,random_state=42) 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[:5]) 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=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', 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=0.5)
plt.axhline(y=0, color='r', linestyle='--') plt.xlabel('Predicted Prices')
plt.ylabel('Residuals') plt.title('Residual Plot')
plt.show() print("\n----Project Execution Complete
---")
```

OUTPUT:









14.Future scope

- **Geospatial Integration:** Incorporate external datasets like geospatial and POIs to better capture regional price differences.

- **Time-Series Forecasting:** Add historical housing price 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

1. [illegible] **– Data Collection and Integration:** Responsible for sourcing datasets, conducting EDA, and preparing the initial dataset for analysis.

2. B.RAMYA – *Data Cleaning and EDA: Cleans and preprocesses data, performs exploratory analysis, and generates initial insights.*
3. T.VAISHNAVI – *Feature Engineering and Modeling: Works on feature extraction and selection; develops and trains machine learning models.*
4. S.LEELAVATHI– *Evaluation and Optimization: Tunes hyperparameters, validates models, and documents performance metrics.*
5. B.BHARATHI – *Documentation and Presentation: Compiles reports, prepares visualizations, and leads the presentation and optional deployment.*