Senior Design Project



House Price Prediction Using Ensemble Learning Techniques

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AGENDA

PROBLEM DEFINITION

ABOUT DATASET

METHODOLOGY

SUMMARY

REFERENCE

THANK YOU NOTE





PROBLEM DEFINITION

To design an Machine Learning Algorithm for the accurate prediction of House Price using Random Forest, Support Vector Regression, Boosting algorithm and Ensemble models.

ABOUT DATASET

The dataset has been taken from Kaggle.

It has following features:-

ID: Unique identifier for each house listing.

Date: Date of the house listing.

Number of bedrooms: The count of bedrooms in the house. **Number of bathrooms**: The count of bathrooms in the house.

Living area: Total living area of the house in square feet.

Lot area: Total area of the lot in square feet.

Number of floors: Number of floors in the house.

Waterfront present: Indicates whether the house has a waterfront view (binary: 0 for no, 1 for yes).

Number of schools nearby: Number of schools located near the house.

Distance from the airport: Distance of the house from the nearest airport in miles.

Price: Price of the house.

ABOUT DATASET

Number of views: Number of views the house has received.

Condition of the house: Condition rating of the house.

Grade of the house: Grade rating of the house.

Area of the house (excluding basement): Total area of the house excluding the basement in square feet.

Area of the basement: Area of the basement in square feet.

Built Year: Year the house was originally built.

Renovation Year: Year of the last renovation, if any.

Postal Code: Postal code of the house location.

Latitude: Latitude coordinate of the house location.

Longitude: Longitude coordinate of the house location.

Living area after renovation: Total living area of the house after renovation in square feet.

Lot area after renovation: Total area of the lot after renovation in square feet.

Kaggle Link:- https://www.kaggle.com/datasets/mohamedafsal007/house-price-dataset-of-india

Methodology

Step 1: Data Exploration:

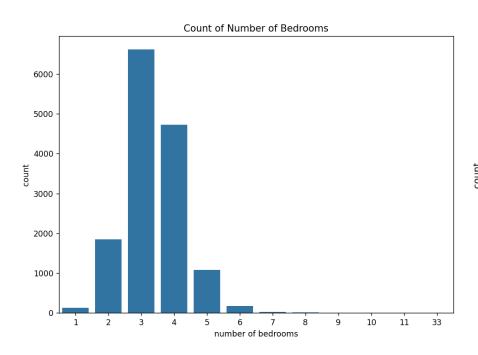
- Loaded the dataset and checked for missing values.
- Explored data types and basic statistics.
- We are not having any null value in our dataset.

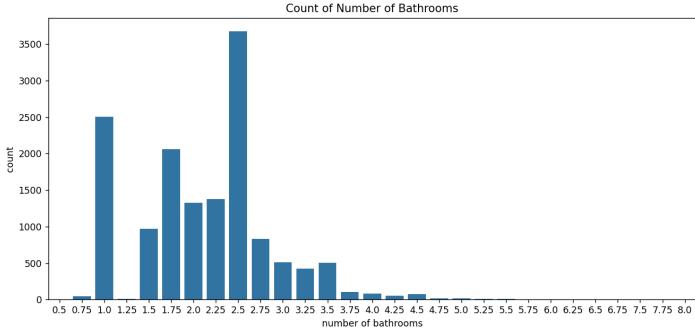
Out[4]:	number of bathrooms	living area	lot area	number of floors	waterfront present	number of views	condition of the house	 Built Year	Renovation Year	Postal Code	Lattitude	Longitude	living_area_renov	lot_area_renov	Number of schools nearby
	False	False	False	False	False	False	False	 False	False	False	False	False	False	False	False
	False	False	False	False	False	False	False	 False	False	False	False	False	False	False	False
	False	False	False	False	False	False	False	 False	False	False	False	False	False	False	False
	False	False	False	False	False	False	False	 False	False	False	False	False	False	False	False
	False	False	False	False	False	False	False	 False	False	False	False	False	False	False	False
	1														
n [5]:	df.isna()	.sum()												
ut[5]:	id					0									
	Date					0									
	number of					0									
	number of		rooms			0									
	living a	rea				0									
	lot area					0									
	number of floors waterfront present					0									
	number of views					0									
	condition of the house				0										
	grade of the house					0									
	Area of the house(excluding basement)														
	Area of the basement) 0									
	Built Year														
	Bullt Yea	ar				0									

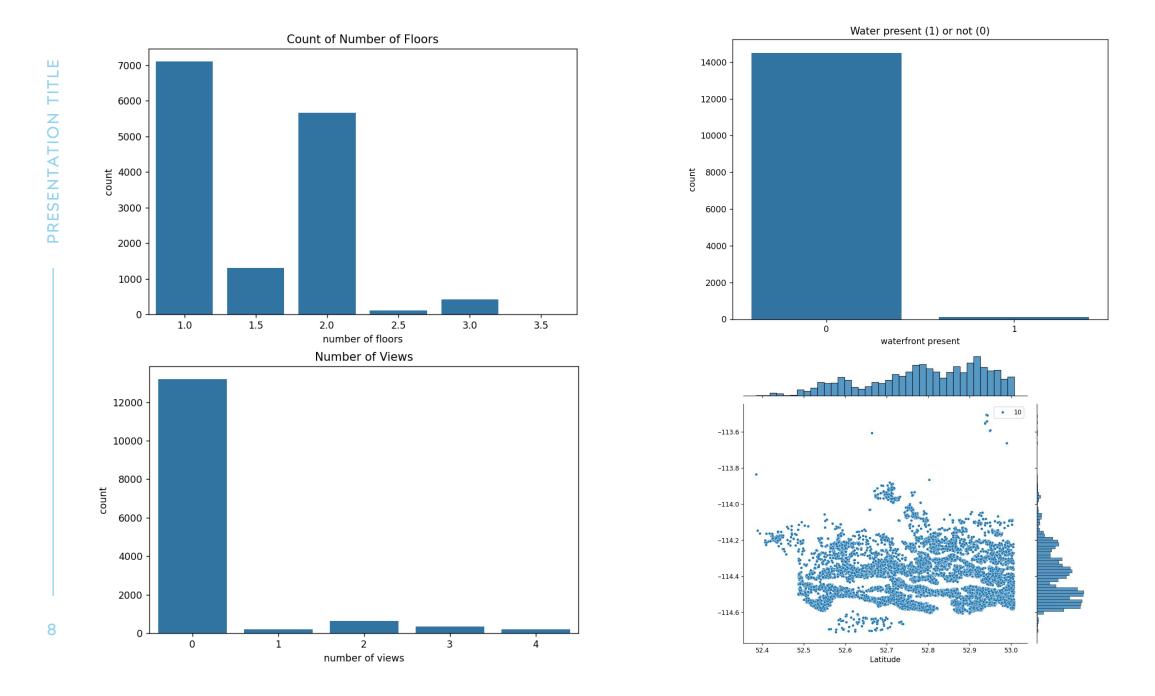
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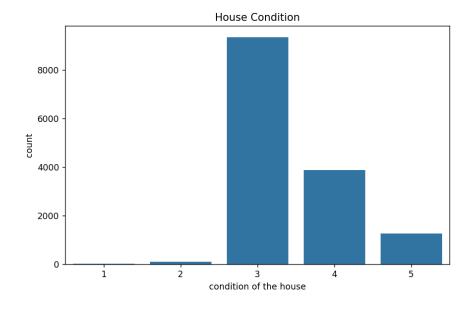
Step 2: Visualization:

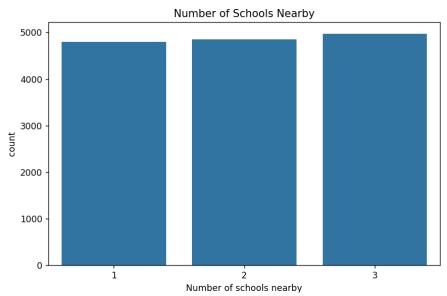
- Plotted count distributions for various features.
- Visualized geographical data and price distributions.
- Examined correlations and relationships between variables.

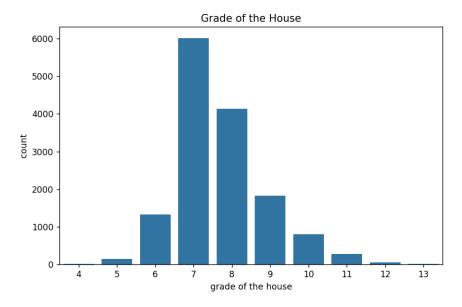


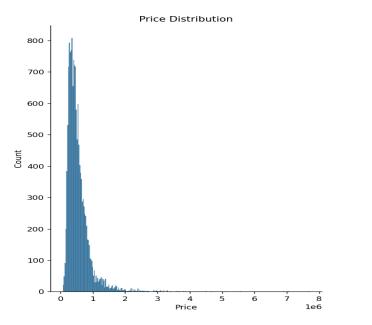


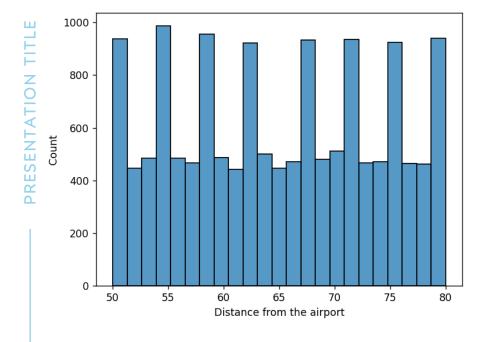


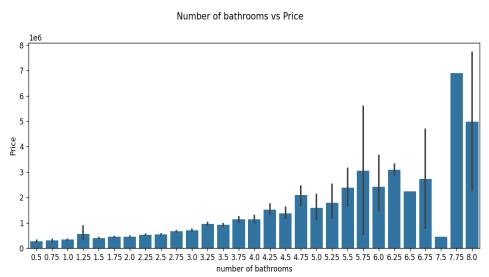


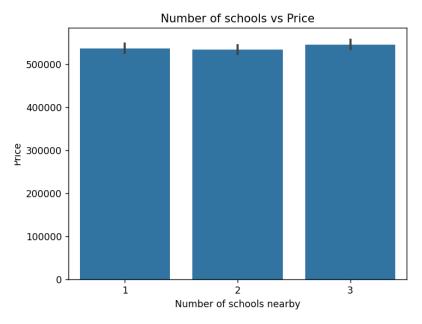


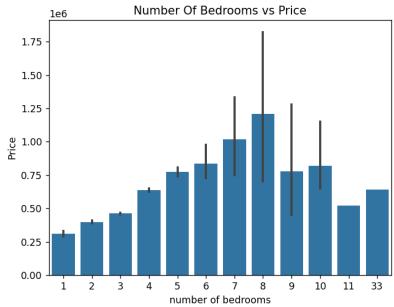


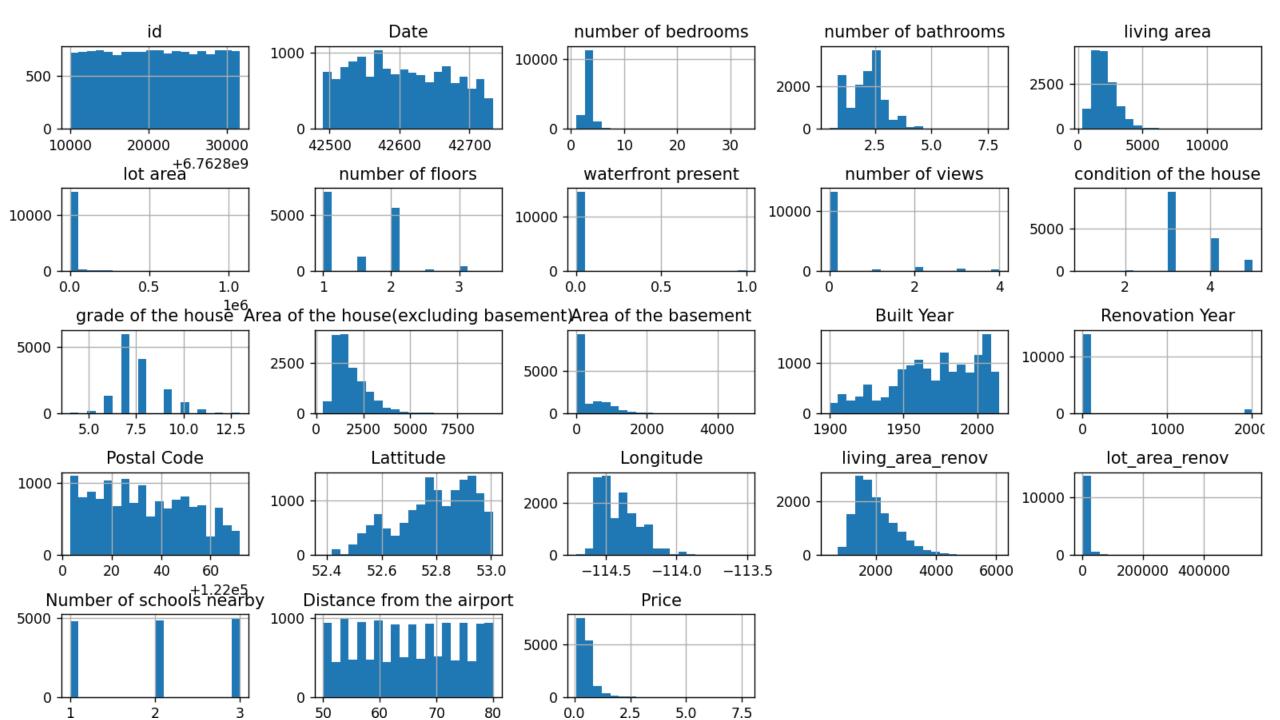


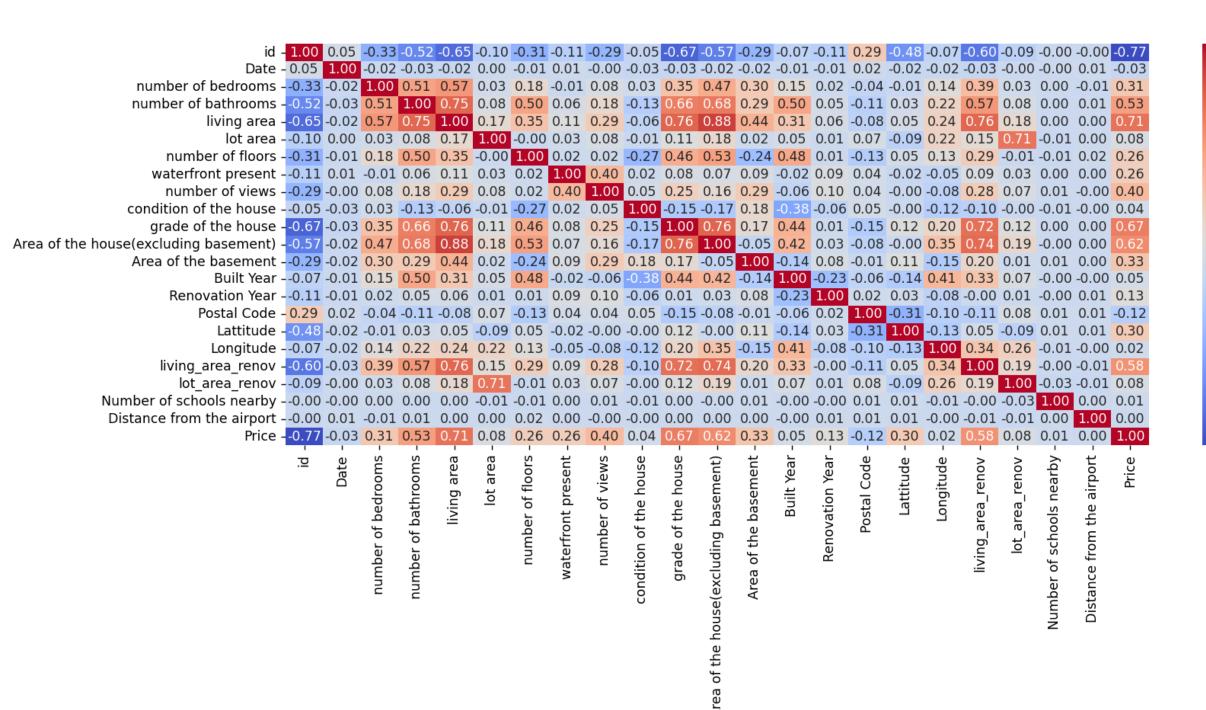




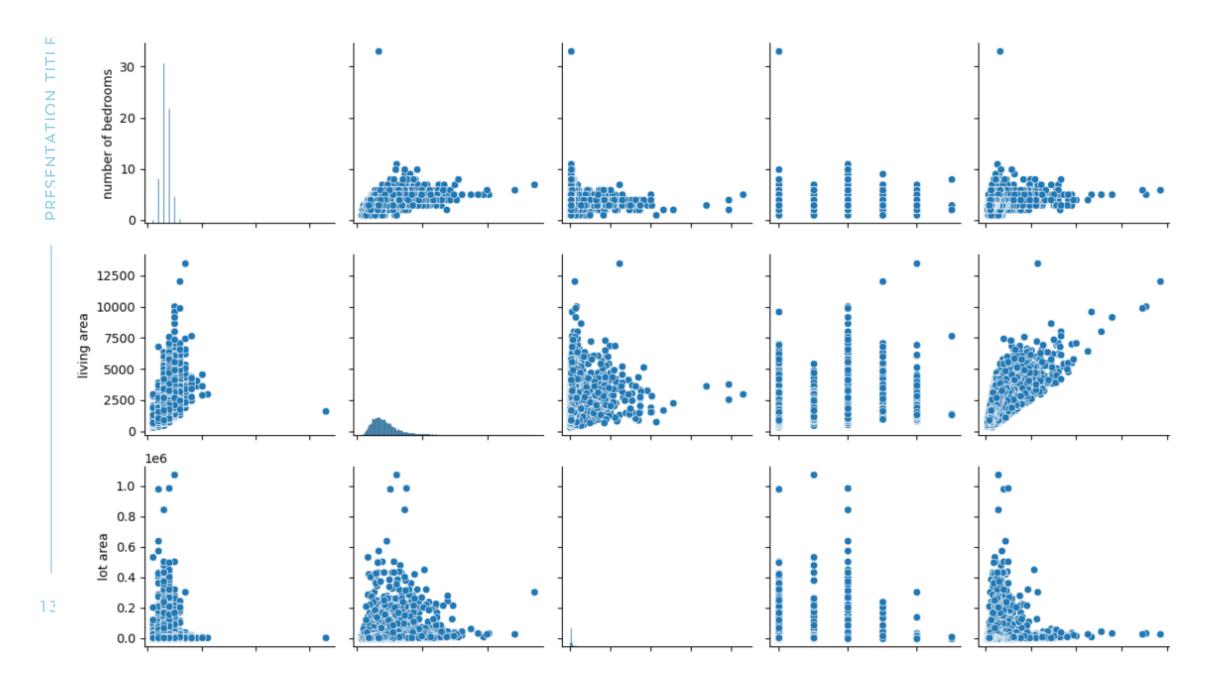


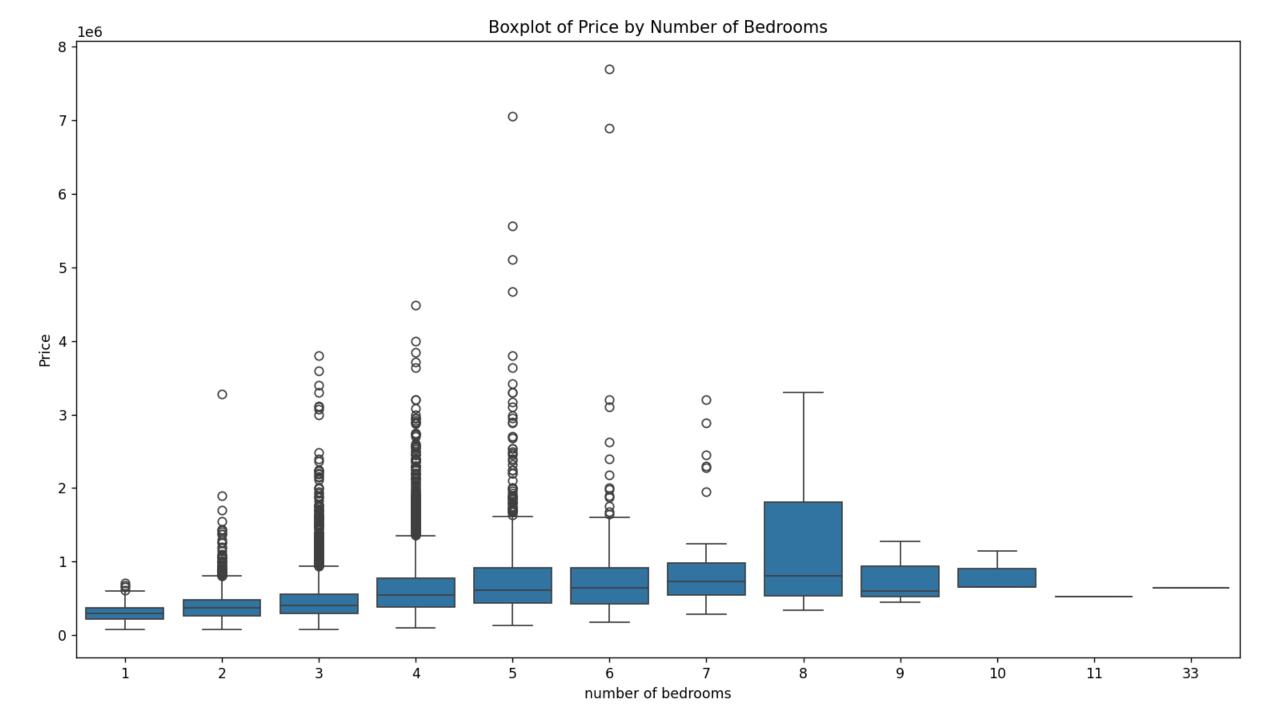






- 0.8 - 0.6 - 0.4 - 0.2 - 0.0 - -0.2 -0.4-0.6





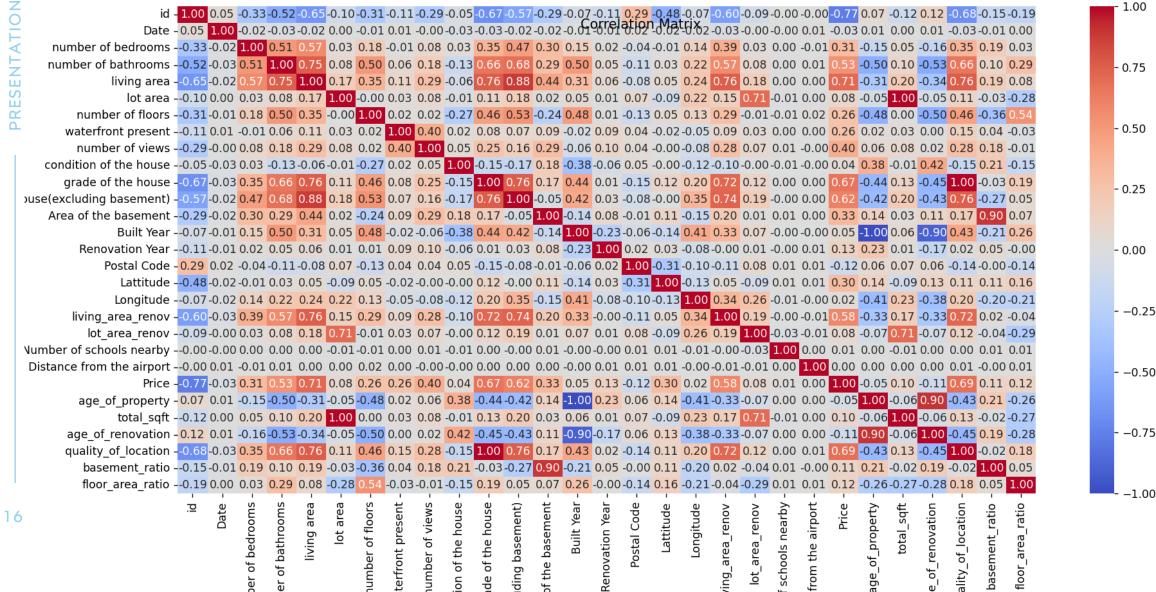
Step 3: Feature Engineering:

Created new features like property age and total square footage

```
1.00
       number of bedrooms - 1 0.46 0.57 0.034 0.16 0.006 0.079 0.027 0.35 0.47 0.3 0.15 0.016 0.044 0.013 0.14 0.39 0.02 9 0.03 4.006 20.31 -0.15 0.048 -0.16 0.35 0.058 -0.11
       number of bathrooms -0.46 1 0.7 0.0780.49 0.0550.17 -0.13 0.61 0.64 0.25 0.43 0.06-0.08 0.0360.18 0.51 0.07 0.02 0.012 0.51 -0.43 0.094-0.46 0.6 -0.030.078
                living area -0.57 0.7 1 0.17 0.35 0.11 0.29-0.0630.76 0.88 0.44 0.310.059-0.080.0550.24 0.76 0.180.0020400250.71 -0.31 0.2 -0.34 0.76 0.045 -0.1
                   lot area -0.0340.0780.17 1 -0.0092.0260.0780.00850.11 0.18 0.020.0520.00680.07-0.0910.22 0.15 0.71-0.0103.00380.0820.052 1 -0.0510.11-0.0130.07
                                                                                                                                                                - 0.75
           number of floors -0.16 0.49 0.350.0092 1 0.0130.017 -0.3 0.48 0.52 -0.24 0.57-0.0070.12 0.03 0.16 0.3 -0.012.0049.011 0.24 -0.50.00050.58 0.47 -0.14 0.33
         waterfront present -).0063.0550.110.0260.013 1 0.4 0.0190.080.0720.0850.0240.0860.0380.0220.0480.0860.0310.0016500140.260.0240.0290.0010.150.001130008
           - 0.50
      condition of the house -0.027-0.130.068.00850.3 0.0190.053 1 -0.15-0.17 0.18 -0.380.0620.0450.0030.12 -0.10.0047.00620.021.041 0.38 -0.01 0.42 -0.15 0.11 -0.11
         grade of the house -0.35 0.61 0.76 0.11 0.48 0.08 0.25 -0.15 1 0.76 0.17 0.440.015-0.15 0.12 0.2 0.72 0.12.000990490.67 -0.44 0.13 -0.45 1 -0.066.044
   ouse(excluding basement) -0.47 0.64 0.88 0.18 0.52 0.072 0.16 -0.17 0.76 1 -0.0460.42 0.0260.088.8e-06.35 0.74 0.190.002900120.62 -0.42 0.2 -0.43 0.76 -0.130.093
                                                                                                                                                                - 0.25
       Area of the basement - 0.3 0.25 0.44 0.02 -0.240.0850.29 0.18 0.17-0.046 1 -0.140.0750.0110.11 -0.15 0.2 0.0110.010.00290.33 0.14 0.03 0.11 0.17 0.34 -0.04
                  Built Year -0.15 0.43 0.310.0520.57-0.0240.0550.38 0.44 0.42 -0.14 1 -0.230.0620.14 0.41 0.330.07-30.001-6.0040.05 -1 0.059 -0.9 0.43 -0.12 0.2
           Renovation Year -0.0160.060.059.006-0.0070.086 0.1 -0.0620.0150.0260.075-0.23 1 0.0180.029-0.090.0026005390008890530.13 0.230.00830.170.0210.03-0.032
               Postal Code -0.0440.0830.080.07 -0.120.0380.0390.045-0.150.0840.0140.0620.018 1 -0.310.0990.110.0770.0110.012-0.120.0620.0680.058-0.140.0190.046
                                                                                                                                                                - 0.00
                  Lattitude -0.01 \( \textit{D}.0360.05 \( \textit{5}0.09 \) 10.03-0.02 \( \textit{D}.0046.00 \) 30.128.8e-06.11 -0.140.029-0.31 1 -0.130.0460.09 \( \textit{D}.007 \) 20.3 0.14-0.08 \( \textit{D}.008 \) 90.13 0.110.03 \( \textit{D}.008 \) 30.089
                 Longitude -0.14 0.18 0.24 0.22 0.16-0.0480.08-0.12 0.2 0.35 -0.15 0.41 -0.080.0990.13 1 0.34 0.26 -0.010.0031.024-0.41 0.23 -0.38 0.2 -0.0710.13
          living area renov -0.39 0.51 0.76 0.15 0.3 0.0860.28 -0.1 0.72 0.74 0.2 0.330.002@.110.0460.34 1 0.190.001200570.58 -0.33 0.17 -0.33 0.72-0.0290.13
                                                                                                                                                                 -0.25
             lot_area_renov -0.0290.0710.18 0.71-0.0120.0320.0720.00470.12 0.190.0110.0780.0059.0770.0920.26 0.19 1 -0.0250.0150.0760.0730.71-0.0710.12-0.0120.079
   Number of schools nearby -.0034002900240.018.00490016.0080.006.900990029.010.008000830110.015-0.010.00140.025 1 0.004.009900160.010.002400101.00590049
   Price -0.31 0.51 0.710.0820.24 0.26 0.4 0.0410.67 0.62 0.33 0.05 0.13 -0.12 0.3 0.0240.580.076.00990038 1 -0.050.099-0.11 0.690.00690.024
                                                                                                                                                                 -0.50
           age of property -0.15-0.43-0.310.0520.570.0240.0550.38-0.44-0.420.14 -1 0.230.0620.14-0.41-0.330.070.0016.004-0.05 1 -0.0590.9 -0.430.12 -0.2
                  total sqft -0.0480.094 0.2 1-0.0005090290.085-0.01 0.13 0.2 0.030.059.0085.0680.0890.23 0.17 0.71-0.010.0035.0990.059 1 -0.0590.13-0.0120.072
         age of renovation -0.16-0.46-0.340.0510.580.0010.0210.42-0.45-0.43 0.11 -0.9 -0.170.0580.13 -0.38-0.330.070.0020.002-0.11 0.9 -0.059 1
                                                                                                                                                                - -0.75
         quality_of_location -0.35 0.6 0.76 0.11 0.47 0.15 0.28 -0.15 1 0.76 0.17 0.430.021-0.14 0.11 0.2 0.72 0.120.0010.005 0.69 -0.43 0.13 -0.45
            floor area ratio -0.110.078-0.1 -0.07 0.330.0088.0280.110.0440.0930.04 0.2 -0.0320.0460.089-0.13-0.130.079.004500880.024-0.2-0.072-0.2 0.0430.029
15
                                                                                                                                                                - -1.00
```

Step 4: Feature Selection:

Identified and removed highly correlated features



Step 5: Modeling:

Split data for training and testing.

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

Trained RandomForest, XGBoost, and CatBoost models.

```
random forest model = RandomForestRegressor()
xgboost model = XGBRegressor()
 Train individual base models
random forest model.fit(X train scaled, y train)
xgboost_model.fit(X_train_scaled, y_train)
# Make predictions using individual base models
y pred rf = random forest model.predict(X test scaled)
y pred xgb = xgboost model.predict(X test scaled)
y pred rf
```

Evaluated models using R-squared scores.

Random Forest Model:

R-squared: 0.6591513191729483

XGBoost Model:

R-squared: 0.6487248781534409

R-squared: 0.6720537148567195

catboost:

R-Squared: 0.6681556299940523

Combined predictions to create an ensemble model.

Ensemble Model:

R-squared: 0.6772239409590448

Precision: 0.7687861271676301

Recall: 0.7287671232876712

Step 6: Model Selection:

Selected the best-performing model based on R-squared scores.

Best Model: CatBoost

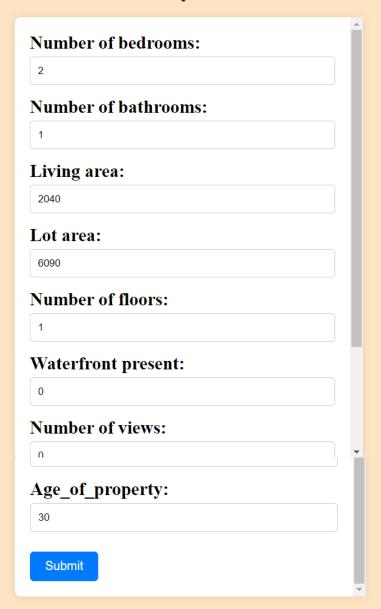
R-squared: 0.6681556299940523

Step 7: Frontend Integeration:

- Saved the selected model for future use.
- Integrated the Machine learning model with the website using flask and saving the executed model file as pickle file.
- Pickel file is used for reusing the compiled model again and again without compiling everytime.
- It increases the speed of website.

20

Find the Price of your Dream House



Predicted House price is: ₹587796



SUMMARY

The project involved analyzing housing data to predict prices in India. After data preprocessing and exploratory data analysis, redundant features were removed, leaving 8 informative features. Three machine learning models (Random Forest, XGBoost, CatBoost) were trained individually and combined using averaging to create an ensemble model. The best model, a combination of the three, achieved high accuracy. A Flask backend was implemented to serve predictions based on user inputs from a frontend interface.



Reference

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THANK YOU