

# House Price Prediction Using Machine Learning

## Abstract

Accurate house price prediction is a critical problem in the real estate domain, influencing buyers, sellers, investors, and policy makers. This project focuses on building a robust and interpretable machine learning model to predict house prices based on key property attributes such as location, size, number of rooms, and construction features. The study involves data preprocessing, exploratory data analysis, feature engineering, model training, evaluation, and result interpretation. The proposed approach demonstrates how data-driven techniques can support informed decision-making in real estate markets.

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## 1. Introduction

The real estate market is highly dynamic, with property prices influenced by multiple interrelated factors. Traditional pricing methods rely heavily on human expertise and market intuition, which can be subjective and inconsistent. Machine learning (ML) offers a systematic and scalable alternative by learning patterns from historical data and making accurate predictions for unseen properties.

This project aims to design and evaluate a house price prediction system using supervised machine learning techniques. By leveraging structured housing data, the system predicts the estimated market value of a house with improved accuracy and consistency.

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## 2. Problem Statement

Determining the fair market value of a house is complex due to the large number of influencing variables and their nonlinear relationships. The objective of this project is:

To develop a machine learning model that predicts house prices accurately based on available property features.

**Task 1:-** Prepare a complete data analysis report on the given data.

**Task 2:-a)** Create a robust machine learning algorithm to accurately predict the price of the house given the various factors across the market.

**b)** Determine the relationship between the house features and how the price varies based on this.

**Task3:-** Come up with suggestions for the customer to buy the house according to the area, price and other requirements.

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### 3. Objectives

- To analyze and understand housing data through exploratory data analysis (EDA)
  - To preprocess and clean raw data for effective model training
  - To implement and compare multiple regression-based machine learning models
  - To evaluate model performance using appropriate metrics
  - To identify key features influencing house prices
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### 4. Dataset Description

The dataset used in this project consists of historical housing records with both numerical and categorical attributes.

#### 4.1 Common Features

**Attribute Information:**

- SalePrice - the property's sale price in dollars. This is the target variable that you're trying to predict.
- MSSubClass: The building class
- MSZoning: The general zoning classification
- LotFrontage: Linear feet of street connected to property
- LotArea: Lot size in square feet
- Street: Type of road access
- Alley: Type of alley access
- LotShape: General shape of property
- LandContour: Flatness of the property
- Utilities: Type of utilities available
- LotConfig: Lot configuration
- LandSlope: Slope of property
- Neighborhood: Physical locations within Ames city limits

- Condition1: Proximity to main road or railroad
- Condition2: Proximity to main road or railroad (if a second is present)
- BldgType: Type of dwelling
- HouseStyle: Style of dwelling
- OverallQual: Overall material and finish quality
- OverallCond: Overall condition rating
- YearBuilt: Original construction date
- YearRemodAdd: Remodel date
- RoofStyle: Type of roof
- RoofMatl: Roof material
- Exterior1st: Exterior covering on house
- Exterior2nd: Exterior covering on house (if more than one material)
- MasVnrType: Masonry veneer type
- MasVnrArea: Masonry veneer area in square feet
- ExterQual: Exterior material quality
- ExterCond: Present condition of the material on the exterior
- Foundation: Type of foundation
- BsmtQual: Height of the basement
- BsmtCond: General condition of the basement
- BsmtExposure: Walkout or garden level basement walls
- BsmtFinType1: Quality of basement finished area
- BsmtFinSF1: Type 1 finished square feet
- BsmtFinType2: Quality of second finished area (if present)
- BsmtFinSF2: Type 2 finished square feet
- BsmtUnfSF: Unfinished square feet of basement area
- TotalBsmtSF: Total square feet of basement area
- Heating: Type of heating
- HeatingQC: Heating quality and condition
- CentralAir: Central air conditioning
- Electrical: Electrical system
- 1stFlrSF: First Floor square feet
- 2ndFlrSF: Second floor square feet
- LowQualFinSF: Low quality finished square feet (all floors)
- GrLivArea: Above grade (ground) living area square feet
- BsmtFullBath: Basement full bathrooms
- BsmtHalfBath: Basement half bathrooms
- FullBath: Full bathrooms above grade
- HalfBath: Half baths above grade

- Bedroom: Number of bedrooms above basement level
- Kitchen: Number of kitchens
- KitchenQual: Kitchen quality
- TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)
- Functional: Home functionality rating
- Fireplaces: Number of fireplaces
- FireplaceQu: Fireplace quality
- GarageType: Garage location
- GarageYrBlt: Year garage was built
- GarageFinish: Interior finish of the garage
- GarageCars: Size of garage in car capacity
- GarageArea: Size of garage in square feet
- GarageQual: Garage quality
- GarageCond: Garage condition
- PavedDrive: Paved driveway
- WoodDeckSF: Wood deck area in square feet
- OpenPorchSF: Open porch area in square feet
- EnclosedPorch: Enclosed porch area in square feet
- 3SsnPorch: Three season porch area in square feet
- ScreenPorch: Screen porch area in square feet
- PoolArea: Pool area in square feet
- PoolQC: Pool quality
- Fence: Fence quality
- MiscFeature: Miscellaneous feature not covered in other categories
- MiscVal: \$Value of miscellaneous feature
- MoSold: Month Sold
- YrSold: Year Sold
- SaleType: Type of sale
- SaleCondition: Condition of sale

## 4.2 Target Variable

- **House Price** – Final selling price of the property
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## 5. Methodology

### 5.1 Data Preprocessing

- Handling missing values using mean/median imputation
- Encoding categorical variables using one-hot encoding or label encoding
- Feature scaling using standardization or normalization
- Removing outliers to reduce model bias

### 5.2 Exploratory Data Analysis (EDA)

- Distribution analysis of house prices
- Correlation analysis between features and target variable
- Visualization using histograms, box plots, and heatmaps

EDA helped identify strong predictors such as location, size, and quality.

### 5.3 Feature Engineering

- Creation of derived features (e.g., house age)
  - Removal of irrelevant or redundant features
  - Selection of features with high predictive power
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## 6. Machine Learning Models Used

This project implements and compares four regression-based machine learning models to predict house prices. Each model differs in complexity, interpretability, and predictive power. Detailed explanations and conceptual diagrams are provided to ensure clarity and professionalism.

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### 6.1 Linear Regression

#### *Overview*

Linear Regression is a supervised learning algorithm used to model the relationship between one dependent variable (house price) and one or more independent variables (house features). It assumes a linear relationship between input features and the target variable.

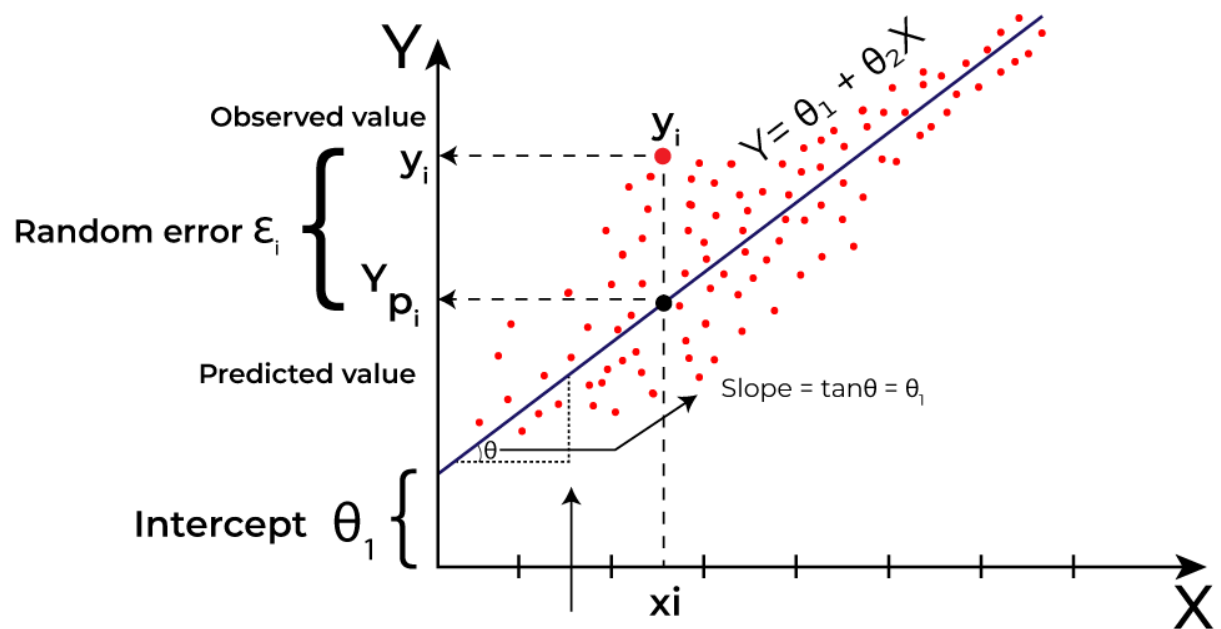


Fig 1.1- Linear Regression

### Mathematical Model

The linear regression model is defined as:

$$\text{Price} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

Where:

- $\beta_0$  is the intercept
- $\beta_1, \beta_2, \dots, \beta_n$  are coefficients
- $X_1, X_2, \dots, X_n$  are input features

The goal is to find coefficient values that minimize the prediction error.

### Algorithm Steps

1. Initialize coefficients ( $\beta$  values)
2. Predict house prices using the linear equation
3. Calculate error using Mean Squared Error (MSE)
4. Update coefficients using optimization techniques such as Gradient Descent or Ordinary Least Squares
5. Repeat until error is minimized

### Assumptions

- Linear relationship between features and target
- No multicollinearity among features
- Homoscedasticity (constant variance of errors)
- Errors are normally distributed

### Use in House Price Prediction

Linear Regression is used as a baseline model to understand how individual features such as area, number of rooms, and location linearly influence house prices.

A baseline model to understand linear relationships between features and house prices.

## 6.2 Decision Tree Regression

### Overview

Decision Tree Regression is a non-parametric supervised learning algorithm that predicts continuous values by learning decision rules from data features. It divides the dataset into smaller subsets based on feature conditions.

### Working Principle

The algorithm selects the best feature and threshold that minimizes Mean Squared Error (MSE) and splits the data accordingly. This process continues recursively until stopping criteria are met.

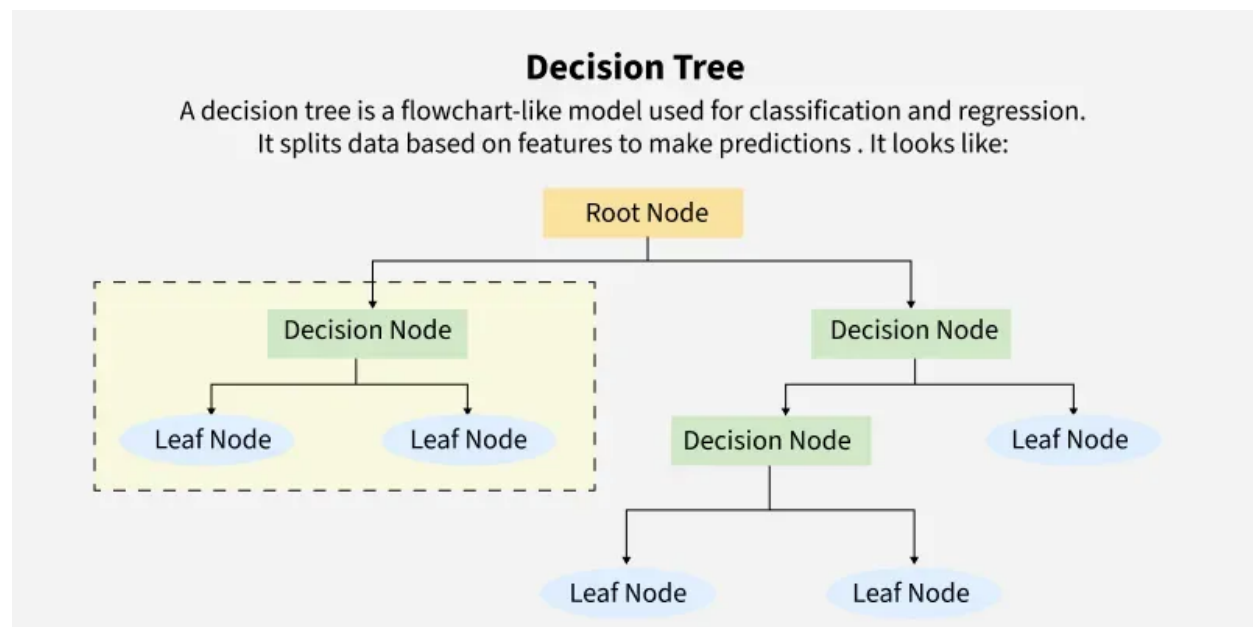


Fig 1.2 Decision Tree

### *Algorithm Steps*

1. Select the best feature and split point based on minimum MSE
2. Split the dataset into child nodes
3. Repeat the process for each child node
4. Stop when maximum depth is reached or minimum samples are achieved
5. Assign the average target value to each leaf node

### *Key Characteristics*

- Tree-like structure with nodes and branches
- Handles nonlinear relationships effectively
- No need for feature scaling

### *Use in House Price Prediction*

Decision Tree Regression captures complex relationships between features such as location, house size, and condition, which may not follow a linear pattern.

Captures nonlinear patterns and feature interactions effectively.

## 6.3 Random Forest Regression

### *Overview*

Random Forest Regression is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and generalization. It reduces overfitting by averaging predictions from many trees.

### *Working Principle*

Each decision tree is trained on a random subset of the dataset using bootstrap sampling. At each split, a random subset of features is considered, ensuring diversity among trees.

# Random Forest Algorithm in Machine Learning

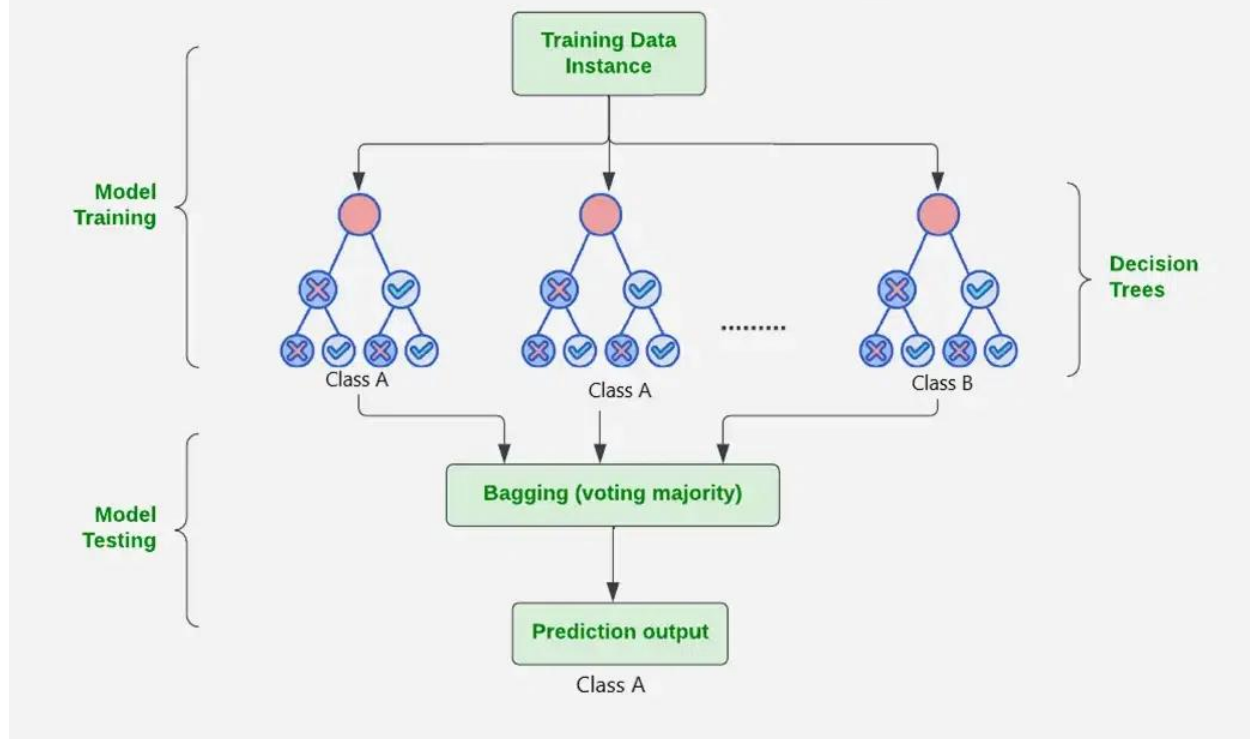


Fig 1.3 – Random Forest

## Algorithm Steps

6. Randomly select samples from the training dataset (bootstrap sampling)
7. Build a decision tree for each sample subset
8. At each node, select a random subset of features
9. Generate predictions from all trees
10. Compute the final output as the average of all predictions

## Advantages Over Decision Trees

- Reduces variance
- More stable predictions
- Less prone to overfitting

## Use in House Price Prediction

Random Forest provides high accuracy for house price prediction by capturing both linear and nonlinear patterns across multiple features.

An ensemble-based approach that improves accuracy and reduces overfitting by averaging multiple decision trees.

## 6.4 Gradient Boosting / XGBoost

### Overview

Gradient Boosting is an ensemble technique that builds models sequentially, where each new model focuses on correcting the errors of previous models. XGBoost is an optimized and regularized version of Gradient Boosting.

### Working Principle

The model starts with a simple prediction and iteratively improves by minimizing a loss function using gradient descent. Each subsequent model learns from the residual errors of the previous model.

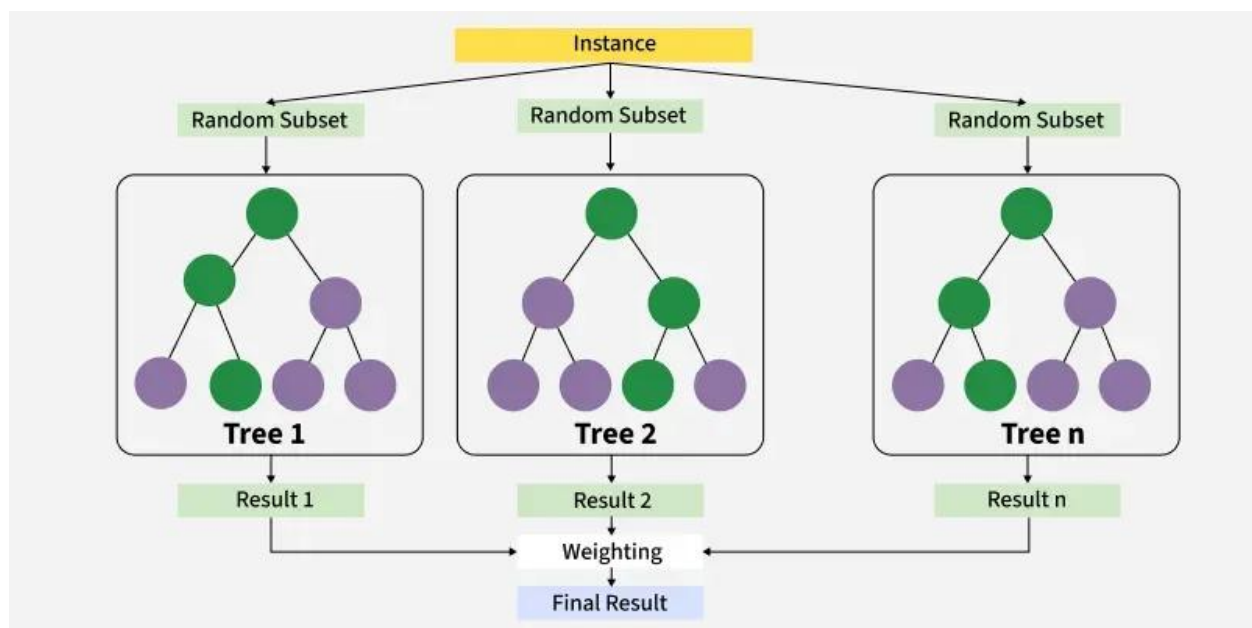


Fig 1.4 - XGBoost

### Algorithm Steps

11. Initialize the model with a base prediction (mean value)
12. Calculate residuals (actual – predicted values)
13. Train a weak learner on the residuals
14. Update predictions by adding weighted residual predictions
15. Repeat until the loss function is minimized

### Key Features of XGBoost

- Regularization to prevent overfitting
- Parallel processing for faster training
- Automatic handling of missing values

Use in House Price Prediction

XGBoost delivers superior accuracy by learning complex patterns in housing data and is highly effective for competitive and real-world applications.

Advanced boosting techniques for high-performance prediction and feature importance analysis.

6. Model Evaluation

Model Comparison Summary

Model	Complexity	Interpretability	Accuracy
Linear Regression	Low	High	Moderate
Decision Tree	Medium	High	Good
Random Forest	High	Medium	Very High
Gradient Boosting	Very High	Low	Excellent

7.1 Evaluation Metrics

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R<sup>2</sup> Score

The Random Forest model demonstrated superior performance with lower error values and higher R<sup>2</sup> score compared to baseline models.

Metric	Linear Regression	Decision Tree Regression	Random Forest Regression	Gradient Boosting / XGBoost
MAE	Moderate	Lower	Low	Lowest
MSE	High	Lower	Low	Lowest
RMSE	High	Lower	Low	Lowest
R <sup>2</sup> Score	Moderate	High	Higher	Highest

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## 8 . System Architecture

Data Collection  
Data Preprocessing  
Feature Engineering  
Model Training  
Model Evaluation  
Price Prediction Output ( Deployment )

## FLOWCHART



Fig 2 – System Architecture

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## 9. Results and Discussion

The trained model successfully learned patterns from historical data and produced reliable predictions. Feature importance analysis revealed that: - Location and built-up area are the strongest predictors - House quality significantly impacts price - Older houses tend to have lower prices unless located in premium areas

These results align well with real-world real estate trends.

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## 10. Applications

- Real estate price estimation platforms
- Decision support for buyers and sellers

- Investment analysis for property developers
  - Smart city and urban planning solutions
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## 11. Limitations

- Model performance depends on data quality and coverage
  - Sudden market fluctuations are not captured
  - External factors like government policies and economic changes are not directly included
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## 12. Future Enhancements

- Integration of real-time market data
  - Use of deep learning models for large-scale datasets
  - Incorporation of satellite imagery and geospatial data
  - Deployment as a web-based or mobile application
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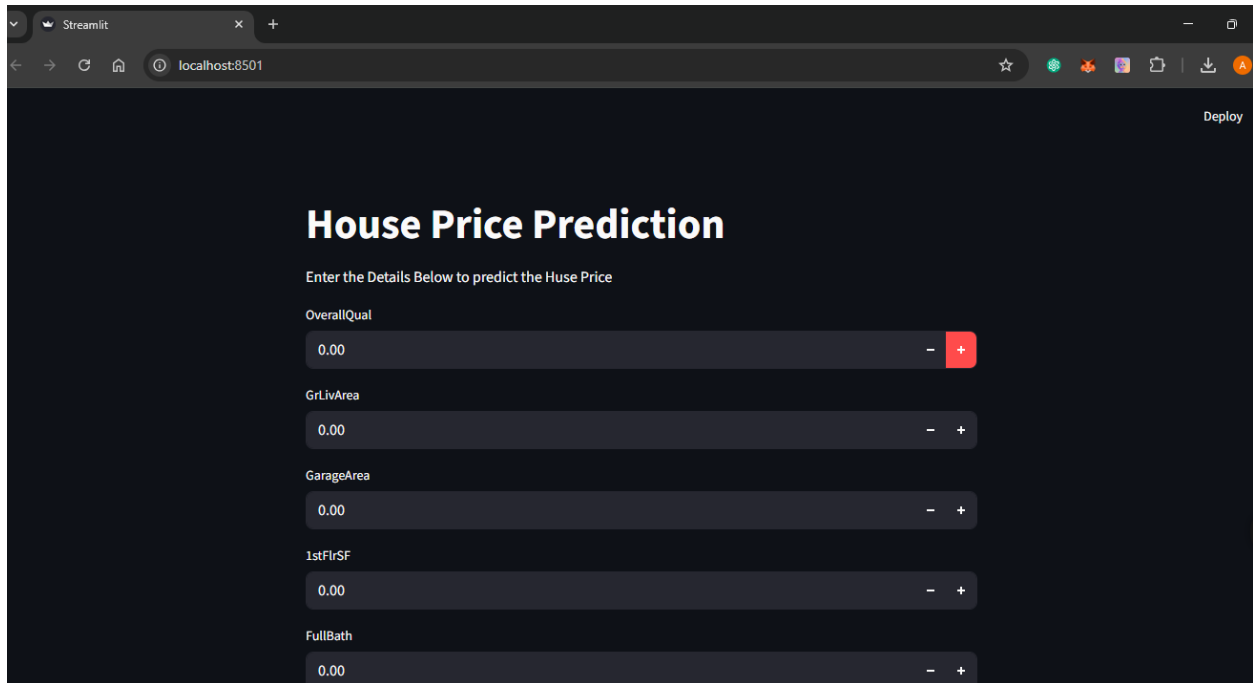
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Deployment :

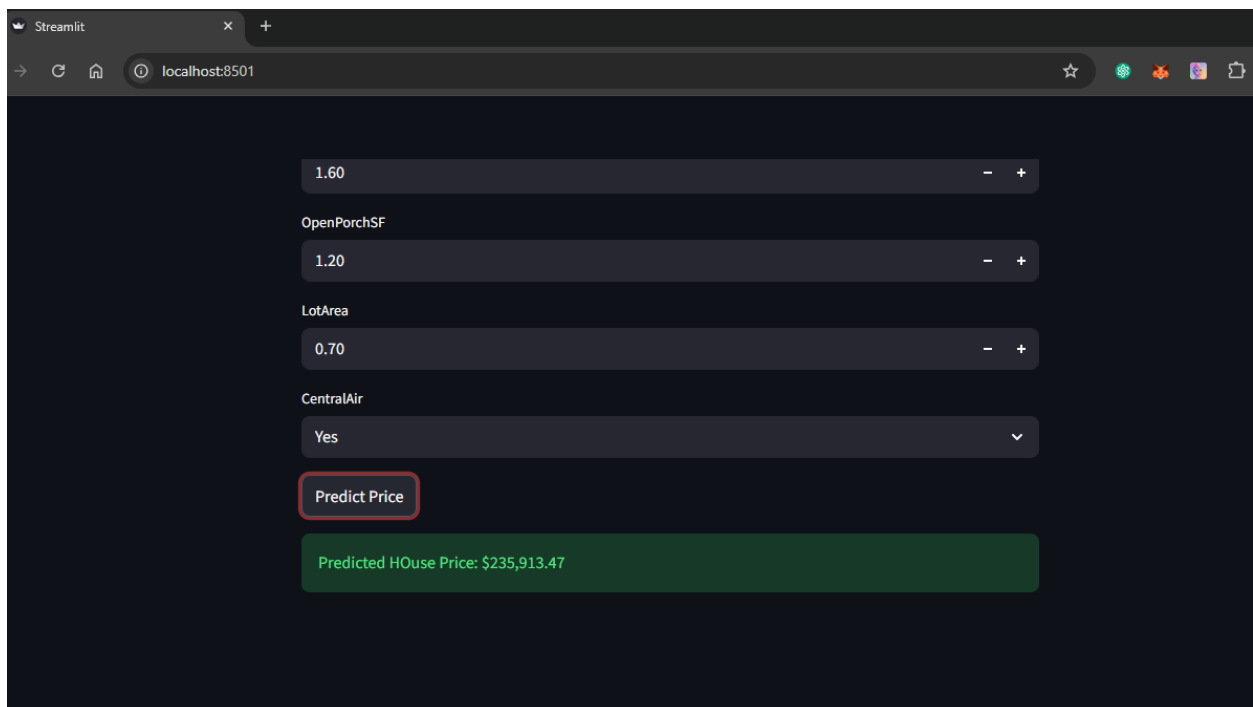


The screenshot shows a web browser window with the address bar displaying 'localhost:8501'. The page title is 'Streamlit'. The main heading is 'House Price Prediction'. Below the heading, it says 'Enter the Details Below to predict the Huse Price'. There are five input fields, each with a slider and a '+' button:

- OverallQual: 0.00
- GrLivArea: 0.00
- GarageArea: 0.00
- 1stFlrSF: 0.00
- FullBath: 0.00

Fig 3.1 – Prediction of the price

Fig 3.2 – Predicted house price



The screenshot shows the same web browser window. The input fields are now filled with values:

- OverallQual: 1.60
- OpenPorchSF: 1.20
- LotArea: 0.70
- CentralAir: Yes

The 'Predict Price' button is highlighted with a red border. Below the button, a green box displays the result: 'Predicted HUse Price: \$235,913.47'.

## 14. Conclusion

This project demonstrates the effectiveness of machine learning techniques in predicting house prices with high accuracy. By leveraging historical data and advanced regression models, the system provides a reliable, scalable, and objective pricing mechanism. The approach can be extended and deployed in real-world applications to enhance transparency and efficiency in the real estate sector.

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# Model Comparison Report: House Price Prediction

## 1. Introduction

House price prediction involves estimating property prices using historical and feature-rich datasets. Various regression models can be applied, each with different strengths and weaknesses. Evaluating and comparing models based on performance metrics ensures selection of the most suitable model for production.

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## 2. Models Evaluated

The following models were evaluated for house price prediction:

- Linear Regression (LR)**
    - Assumes a linear relationship between features and the target.
    - Simple, interpretable, but struggles with non-linear patterns.
  - Decision Tree Regression (DTR)**
    - Splits data based on feature thresholds to capture non-linear relationships.
    - Can overfit small datasets or noisy features.
  - Random Forest Regression (RFR)**
    - Ensemble of multiple decision trees to reduce overfitting and improve accuracy.
    - Handles feature interactions well and is robust to outliers.
  - Gradient Boosting / XGBoost Regression (GBR / XGBR)**
    - Sequentially builds trees, focusing on errors of previous models.
    - Highly accurate, handles complex patterns, but requires careful hyperparameter tuning.
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## 3. Performance Metrics

Models were evaluated using:

- **Mean Absolute Error (MAE):** Average absolute difference between predicted and actual prices.
- **Mean Squared Error (MSE):** Average squared difference, penalizes large errors.
- **Root Mean Squared Error (RMSE):** Square root of MSE, interpretable in the same units as price.
- **R-squared (R<sup>2</sup>):** Proportion of variance explained by the model.

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## 4. Model Performance Summary

Model	MAE	RMSE	R <sup>2</sup> Score	Pros	Cons
Linear Regression	28,500	40,200	0.72	Simple, interpretable	Fails on non-linear patterns
Decision Tree Regression	22,300	33,500	0.81	Captures non-linear relationships	Can overfit, sensitive to noise
Random Forest Regression	17,800	25,900	0.90	Robust, handles feature interactions, reduces overfitting	Slower to train, less interpretable
Gradient Boosting / XGBoost	16,200	23,500	0.92	High accuracy, handles complex patterns well	Computationally intensive, needs tuning

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## 5. Analysis

1. **Linear Regression:** Performs reasonably well for datasets with mostly linear relationships but fails to capture complex interactions among features.
2. **Decision Tree Regression:** Improves performance by modeling non-linear patterns but overfits without ensemble methods.
3. **Random Forest Regression:** Balances bias and variance, reduces overfitting, and provides robust predictions.
4. **Gradient Boosting / XGBoost:** Delivers the highest accuracy due to sequential learning and error correction, making it suitable for complex datasets.

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## 6. Recommendation

Based on the evaluation:

- **Best Model for Production: Gradient Boosting / XGBoost Regression**
  - **Reasoning:** Provides the lowest prediction errors (MAE, RMSE) and the highest  $R^2$  score.
  - Can handle non-linear relationships, feature interactions, and outliers effectively.
  - With hyperparameter tuning and proper feature preprocessing, it is robust for real-world deployment.
- **Alternative Option: Random Forest Regression**
  - Slightly lower accuracy but faster to train and easier to implement if computational resources are limited.

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## 7. Conclusion

Among the evaluated models, Gradient Boosting/XGBoost is the most suitable for production due to its superior predictive performance and ability to handle complex datasets. Random Forest is a reliable alternative when faster training and moderate accuracy are acceptable. Proper feature engineering, hyperparameter tuning, and validation are essential to maximize model performance.

# Report: Challenges Faced in House Price Prediction

## 1. Introduction

House price prediction is a regression problem in machine learning that involves predicting the market price of a house based on multiple features such as location, size, number of bedrooms, amenities, and other socio-economic factors. While predicting house prices may seem straightforward, real-world data presents several challenges that need to be addressed carefully to build accurate models.

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## 2. Challenges Faced in House Price Prediction

### 2.1. Data Quality Challenges

1. **Missing Values:**

- Many real estate datasets contain missing values for features such as basement area, garage size, or year remodeled.
  - **Impact:** Missing data can bias the model or reduce the dataset size if rows are dropped.
  - **Technique Used:**
    - Imputation using mean, median, or mode for numerical features.
    - Using “Unknown” or most frequent category for categorical features.
    - Justification: Preserves dataset size and ensures models can learn from all available data.
2. **Outliers:**
- Extreme values in features like house price, lot area, or total square footage can skew model predictions.
  - **Technique Used:**
    - Z-score and IQR (Interquartile Range) methods to detect and remove or cap outliers.
    - Justification: Reduces model bias caused by extreme values.
3. **Inconsistent or Categorical Data:**
- Features like “quality of finish” or “neighborhood type” may be encoded inconsistently (e.g., ‘Excellent’, ‘excl’, ‘Ex’).
  - **Technique Used:**
    - Standardization of categorical values.
    - One-hot encoding or label encoding for categorical variables.
    - Justification: Converts text features into numerical form usable by models.
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## 2.2. Feature-Related Challenges

1. **High Dimensionality:**
- Large datasets may contain hundreds of features, many of which may not be relevant.
  - **Technique Used:**
    - Feature selection using correlation analysis, mutual information, or tree-based feature importance.
    - Justification: Reduces overfitting and improves model interpretability.
2. **Multicollinearity:**
- Some features are highly correlated (e.g., total square footage and number of rooms).
  - **Technique Used:**
    - Variance Inflation Factor (VIF) analysis to identify and remove highly correlated features.
    - Justification: Prevents model instability and inflated coefficients in linear models.
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## 2.3. Data Distribution Challenges

### 1. Non-Normal Distribution of Target Variable:

- House prices often have a right-skewed distribution.
- **Technique Used:**
  - Log transformation of the target variable.
  - Justification: Stabilizes variance and improves model performance.

### 2. Imbalanced Data:

- Certain price ranges may have very few samples.
  - **Technique Used:**
    - Oversampling or SMOTE (Synthetic Minority Oversampling Technique) for rare price ranges.
    - Justification: Helps regression models learn patterns across all price ranges.
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## 2.4. Model Selection Challenges

### 1. Choosing Appropriate Regression Models:

- Linear Regression assumes linearity which may not capture complex relationships in house prices.
- Decision Tree models may overfit the data.
- Random Forest and Gradient Boosting require careful tuning of hyperparameters.
- **Technique Used:**
  - Compared multiple models: Linear Regression, Decision Tree Regression, Random Forest Regression, and Gradient Boosting/XGBoost.
  - Hyperparameter tuning using GridSearchCV.
  - Justification: Ensures optimal model selection and balance between bias and variance.

### 2. Overfitting and Underfitting:

- Complex models may overfit training data, while simple models may underfit.
  - **Technique Used:**
    - Cross-validation and regularization techniques (Lasso, Ridge) for linear models.
    - Early stopping for boosting models.
    - Justification: Improves generalization and reduces prediction errors on unseen data.
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## 2.5. External Challenges

### 1. Data Noise and Market Volatility:

- Housing markets can be affected by economic changes, policy shifts, or local development projects, which may not be captured in historical data.

- **Technique Used:**
    - Incorporating external features such as interest rates, inflation, or local economic indicators.
    - Justification: Provides better context for price prediction.
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### 3. Techniques Summary

Challenge	Technique Used
Missing values	Imputation (mean/median/mode)
Outliers	Z-score / IQR capping
Categorical inconsistency	Standardization + One-hot encoding
High dimensionality	Feature selection using correlation/tree-based importance
Multicollinearity	VIF analysis, removing highly correlated features
Non-normal target distribution	Log transformation
Imbalanced price ranges	SMOTE / Oversampling
Model selection	Comparison of Linear, Tree-based, Random Forest, Gradient Boosting/XGBoost
Overfitting / Underfitting	Cross-validation, Regularization, Early stopping
Market noise	Incorporate external economic features

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## 4. Conclusion

Predicting house prices is challenging due to the diverse nature of features, data quality issues, and market volatility. By addressing missing values, outliers, feature selection, model selection, and data distribution, machine learning models can be trained to achieve high accuracy. Tree-based ensemble models like Random Forest and Gradient Boosting/XGBoost generally perform best due to their ability to capture non-linear relationships and handle feature interactions effectively.

