ReDI School of Digital Integration

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We use tech to connect human potential and opportunity with dignity & humility

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ML House Price Prediction

Predict residential house prices using machine learning models by leveraging historical property and feature data.

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Motivation: Why this project/ Idea / Dataset?

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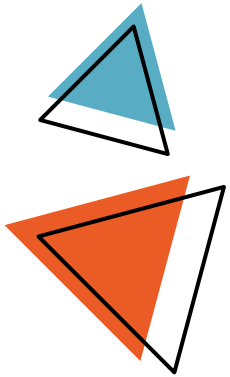
Topics Covered

The project encompassed the following major topics:

1. **Problem Definition and Dataset**
2. **Methodology**
    - Part 1 – Data Preparation
    - Part 2 – Modeling
3. **Exploratory Data Analysis (EDA)**
4. **Model Evaluation & Metrics**
5. **Model Comparison & Best Model Selection**
6. **Ethical Considerations and Limitations**
7. **Conclusion and Future Work**



1. Problem Definition and Dataset

Purpose

- Predict house prices from property features (size, location, condition)
- Support buyers, sellers, and investors with data-driven insights

Problem & Objectives

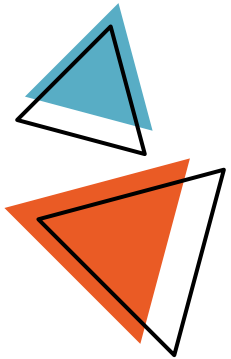
- Pricing influenced by multiple factors; traditional methods often miss patterns
- **Objectives:**
  - Preprocess and analyze dataset
  - Train & evaluate regression models (Linear, Decision Tree, Random Forest, Gradient Boosting, XGBoost)
  - Compare performance (MAE, RMSE, R^2) and select best model

Dataset

- **Source:** Kaggle House Price dataset (4600 rows)
- **Why:** Rich features, real-world data, suitable for regression

Key Features

price, bedrooms, bathrooms, sqft_living, sqft_lot, floors, waterfront, view, condition, yr_built, yr_renovated, city, statezip



1. Problem Definition and Dataset

Dataset Feature Overview

COLUMN NAME	DESCRIPTION
date	The date when the house was listed or sold.
price	The selling price of the house.
bedrooms	The number of bedrooms in the house.
bathrooms	The number of bathrooms in the house.
sqft_living	The total living area of the house (in square feet).
sqft_lot	The size of the lot on which the house is built (in square feet).
floors	The number of floors or stories in the house.
waterfront	A binary indicator (0 or 1) of whether the house has a waterfront view.
view	A rating (usually from 0 to 4) of the house's view quality.
condition	A rating of the house's condition, typically from 1 (poor) to 5 (excellent).
sqft_above	The living area above ground level (in square feet).
sqft_basement	The area of the basement (if any) in square feet.
yr_built	The year the house was built.
yr_renovated	The year the house was last renovated (if applicable).
street	The street name or identifier where the house is located.
city	The city where the house is located.
statezip	The state and ZIP code of the property location.
country	The country where the property is located.

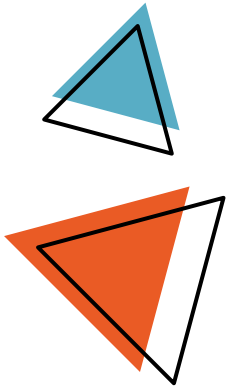
2. Methodology – Part 1 (Data Preparation)

Step 1: Data Cleaning & Preprocessing

- Checked for missing values and duplicates → none found
- Handled outliers using IQR method for *'price'* and *'sqft_lot'*
- Separated features *(X)* and target *(price)*

Step 2: Feature Engineering

- Created **new features**
  - House age = year_sold − yr_built
  - Has_been_renovated (0/1)
- Dropped irrelevant/redundant columns: *date, yr_renovated, yr_built, street, country*
- Kept *city* for location-based prediction



Step 3: Encoding & Scaling

- One-Hot Encoding and StandardScaler for categorical & numerical features
- Categorical features: *waterfront, view, condition, city, statezip, has_been_renovated*
- Numerical features: *'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'sqft_above', 'sqft_basement', 'house_age'*

2. Methodology – Part 2 (Modeling)

Step 4: Train-Test Split

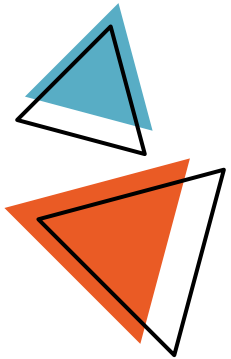
- 80% training, 20% testing
- Ensured reproducibility with *random_state=42*

Step 5: Model Development

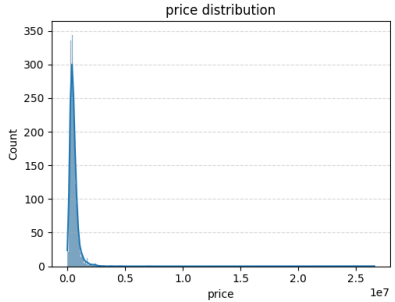
- Trained 5 regression models:
  - Linear Regression
  - Decision Tree
  - Random Forest
  - Gradient Boosting
  - XGBoost
- Used pipelines for consistent preprocessing

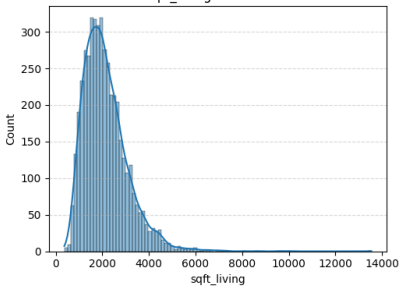
Step 6: Evaluation and Selection

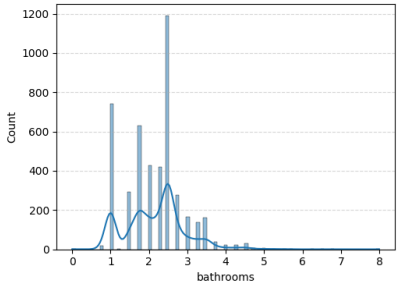
- Metrics: **MAE**, **RMSE**, **R^2**
- Compared models using evaluation metrics and R^2 scores
- XGBoost selected as **best-performing model**

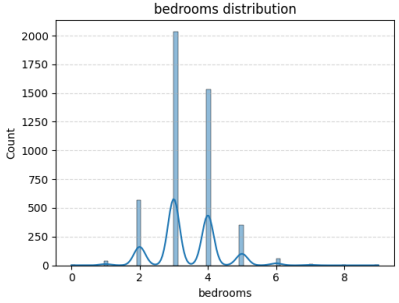


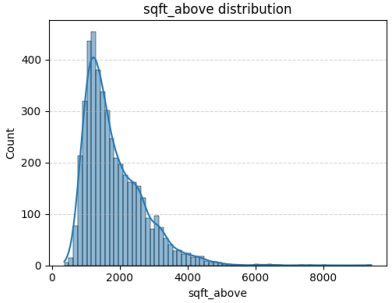
3. Exploratory Data Analysis *[Univariate Analysis]*

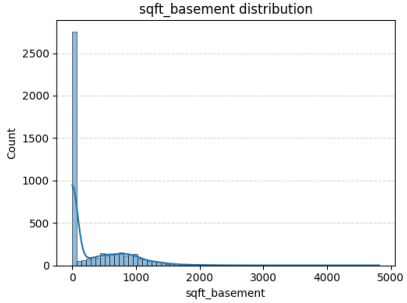


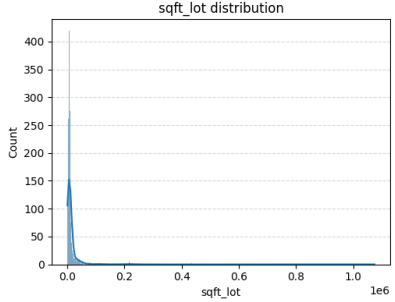




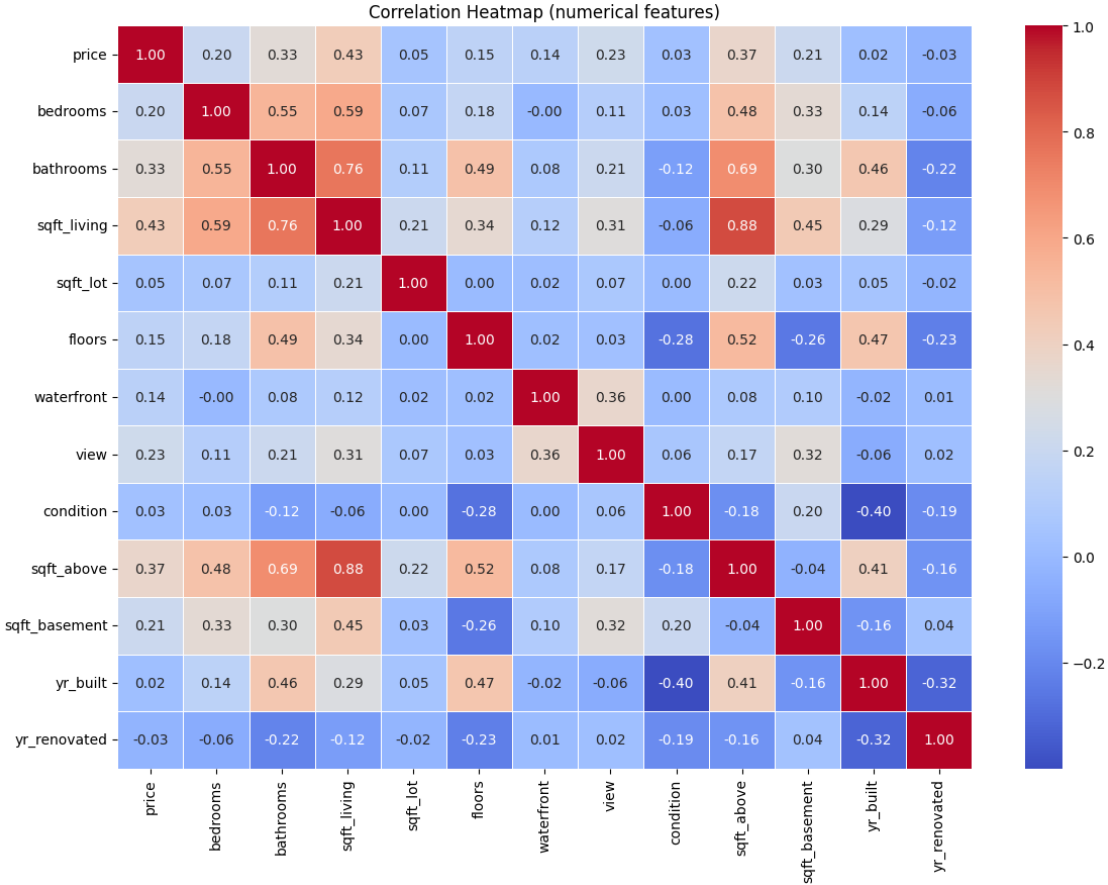








3. Exploratory Data Analysis *[Correlation Heatmap]*



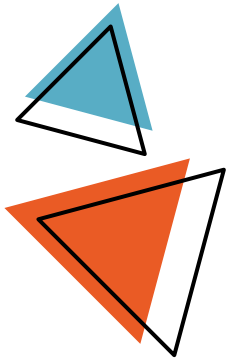
4. Model Evaluation & Metrics

Evaluation Metrics Used

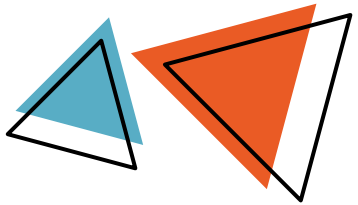
- **MAE (Mean Absolute Error):** Average absolute difference between predicted & actual prices
- **RMSE (Root Mean Squared Error):** Penalizes larger errors more than MAE
- **R^2 Score:** Explains variance captured by the model (closer to 1 → better)

Model Performance Overview

- Trained 5 regression models on pre-processed data
- Predicted prices on test set and evaluated metrics
- Recorded all results in a summary table for comparison

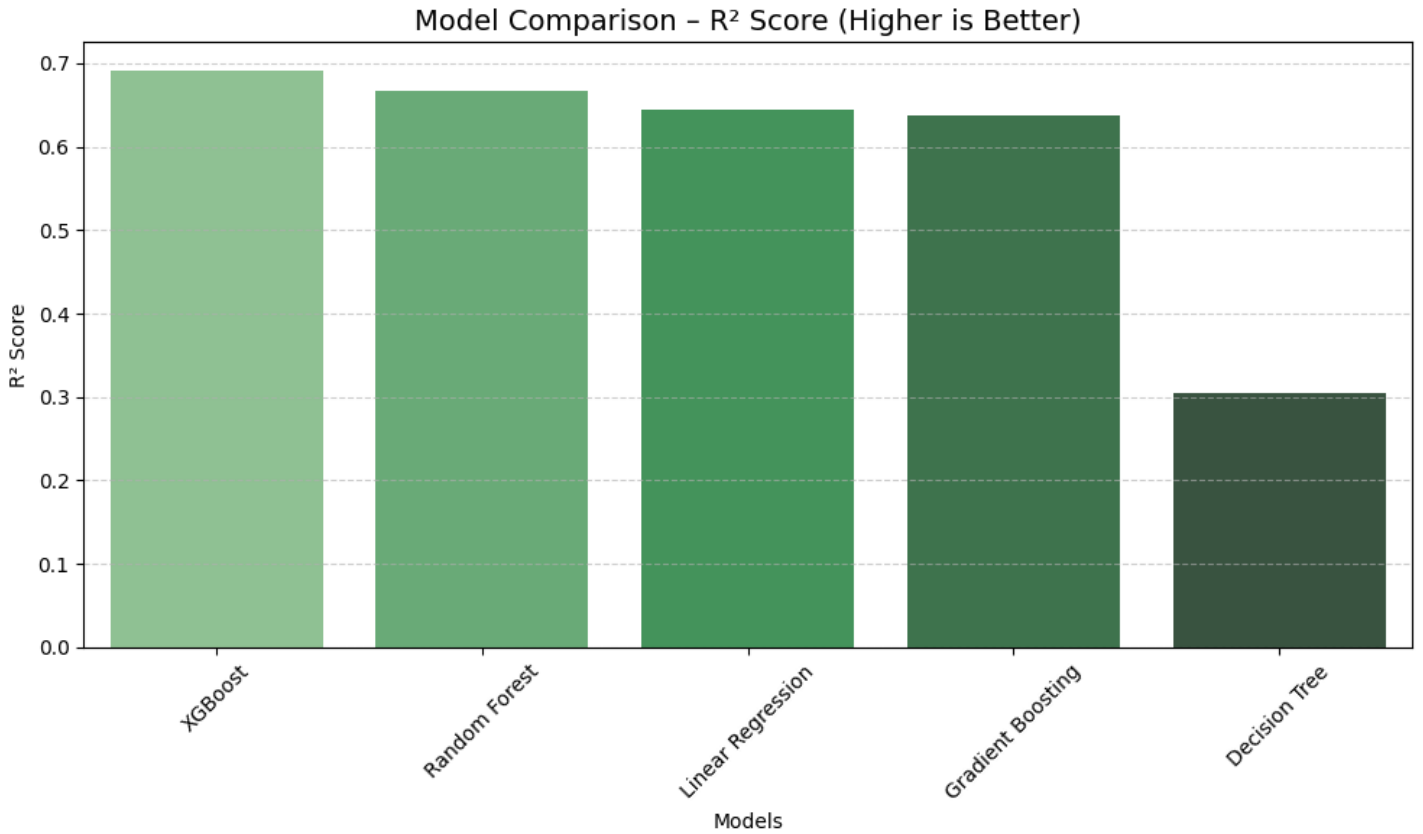


4. Model Evaluation & Metrics



MODEL	MAE	RMSE	R^2
XGBOOST	76622.215760	120005.577660	0.690844
RANDOM FOREST	80753.549907	124429.664012	0.667630
LINEAR REGRESSION	77733.731146	128540.436437	0.645306
GRADIENT BOOSTING	89127.342755	129807.674638	0.638278
DECISION TREE	110962.330760	180009.877922	0.304388

5. Model Comparison & Best Model Selection



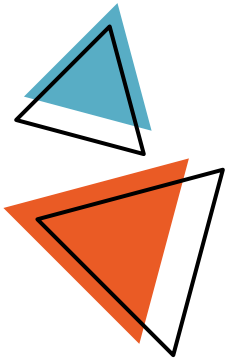
5. Model Comparison & Best Model Selection

Model Comparison Highlights

- XGBoost: **Best R^2 (0.69)**, lowest MAE & RMSE → most accurate predictions
- Random Forest: Good performance, slightly lower R^2
- Linear Regression & Gradient Boosting: Moderate performance
- Decision Tree: Lowest R^2 → underfitting observed

Best Model Selection

- **XGBoost chosen** as final model for predictions
- Reasons:
  - Handles numerical & categorical features efficiently
  - Robust to outliers and complex patterns
  - Consistently highest R^2 & lowest errors



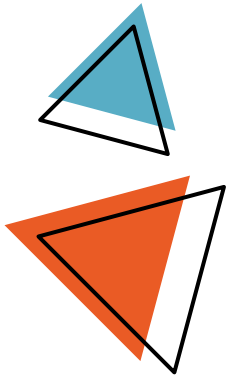
6. Ethical Considerations and Key Limitations

Ethical Considerations

- **Location Bias:** Model may favor high-income areas.
- **Historical Inequities:** Old building/renovation patterns influence prices.
- **Sampling Bias:** Data from one region only.
- **Transparent Processing:** No personal data; clear documentation.

Key Limitations

- **Limited Scope:** Single region, single time period.
- **Missing Factors:** School quality, crime, interior condition not included.
- **Market Variability:** Static data cannot capture rapid trends.



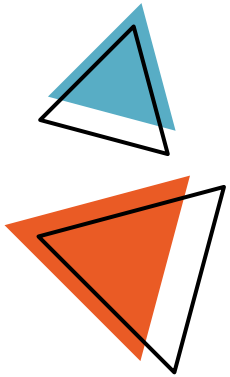
7. Conclusion & Future Work

Conclusion

- **Strong Workflow:** Completed full ML pipeline from cleaning to modeling.
- **Best Model:** XGBoost delivered highest accuracy and lowest errors.
- **Useful Features:** Engineered features improved prediction quality significantly.

Future Improvements

- **Tuning Models:** Apply grid/random search to boost performance.
- **More Features:** Add neighbourhood, school, or macroeconomic indicators.
- **Explainability:** Use SHAP to understand feature impact clearly.



Bibliography

- House Price Prediction Dataset
  https://www.kaggle.com/datasets/shree1992/housedata

- GitHub link to the project repository
https://github.com/SyedHussnainHaiderKazmi/ML-House-Price-Prediction

Thanks a lot!

Contact

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