



Predicting House Prices

Insights, Strategies, and Predictive Modeling

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Agenda



- **Introduction and Business Problem:** Overview of house price prediction and its impact on real estate.
- **Dataset and Methodology:** Summary of the dataset, preprocessing steps, and modeling approach.
- **Exploratory Insights:** Key trends and visualizations discovered during the analysis.
- **Predictive Modeling:** Model selection, feature importance, and performance evaluation.
- **Challenges and Ethical Considerations:** Bias mitigation, fairness, and transparency in predictions.
- **Conclusion and Future Directions:** Summary of findings, next steps, and potential enhancements.

Introduction and Business Problem



➤ Why Predict House Prices?

- ❖ Helps buyers and sellers make informed decisions
- ❖ Supports real estate agencies in setting competitive prices
- ❖ Assists investors in evaluating properties
- ❖ Enables financial institutions to assess mortgage risks

➤ Challenges in Price Prediction

- ❖ Fluctuations due to economic conditions
- ❖ Influence of location and property characteristics
- ❖ Data inconsistencies and missing values

Dataset Overview

id	# MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
1461	20	RL	76%	1470	Pave	NA	Reg	Lvl
1461	20	RM	17%	60	Grvl	0%	IR1	HLS
1461	20	Other (103)	7%	Other (1099)	75%	Other (37)	3%	Other (78)
1461	20	RM	17%	60	Grvl	0%	IR1	HLS
1462	20	RL	76%	1470	Pave	NA	Reg	Lvl
1463	60	RL	74%	13830	Pave	NA	IR1	Lvl
1464	60	RL	78%	9978	Pave	NA	IR1	Lvl
1465	120	RL	43%	5005	Pave	NA	IR1	HLS
1466	60	RL	75%	10000	Pave	NA	IR1	Lvl
1467	20	RL	NA	7980	Pave	NA	IR1	Lvl
1468	60	RL	63%	8402	Pave	NA	IR1	Lvl
1469	20	RL	85%	10176	Pave	NA	Reg	Lvl
1470	20	RL	70%	8400	Pave	NA	Reg	Lvl
1471	120	RM	26%	5853	Pave	NA	IR1	Lvl
1472	160	RM	21%	1680	Pave	NA	Reg	Lvl
1473	160	RM	21%	1680	Pave	NA	Reg	Lvl
1474	160	RL	24%	2280	Pave	NA	Reg	Lvl
1475	120	RL	24%	2280	Pave	NA	Reg	Lvl
1476	60	RL	102%	12850	Pave	NA	IR1	Lvl
1477	20	RL	94%	12883	Pave	NA	IR1	Lvl
1478	20	RL	90%	11520	Pave	NA	Reg	Lvl
1479	20	RL	79%	14122	Pave	NA	IR1	Lvl
1480	20	RL	110%	14300	Pave	NA	Reg	HLS
1481	60	RL	105%	13650	Pave	NA	Reg	Lvl
1482	120	RL	41%	7132	Pave	NA	IR1	Lvl

➤ **Source:** [Kaggle - House Prices: Advanced Regression Techniques](#)

➤ 1460 houses with 79 features

➤ Key Attributes: Lot Size, Living Area, Neighborhood, Quality Ratings

➤ Data Challenges:

- ❖ Missing values
- ❖ Outliers
- ❖ Mixed data types

➤ Preprocessing:

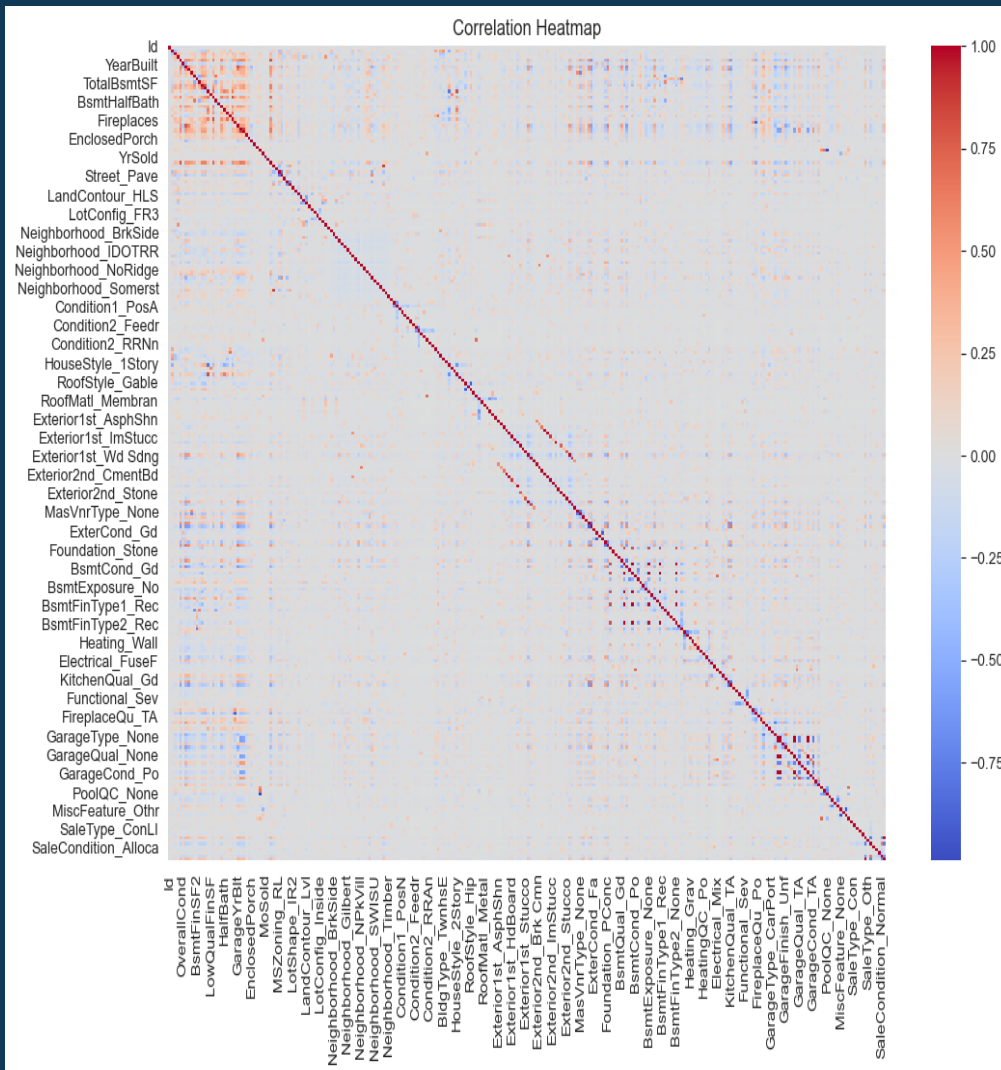
- ❖ Imputation
- ❖ Encoding
- ❖ Standardization

Methodology



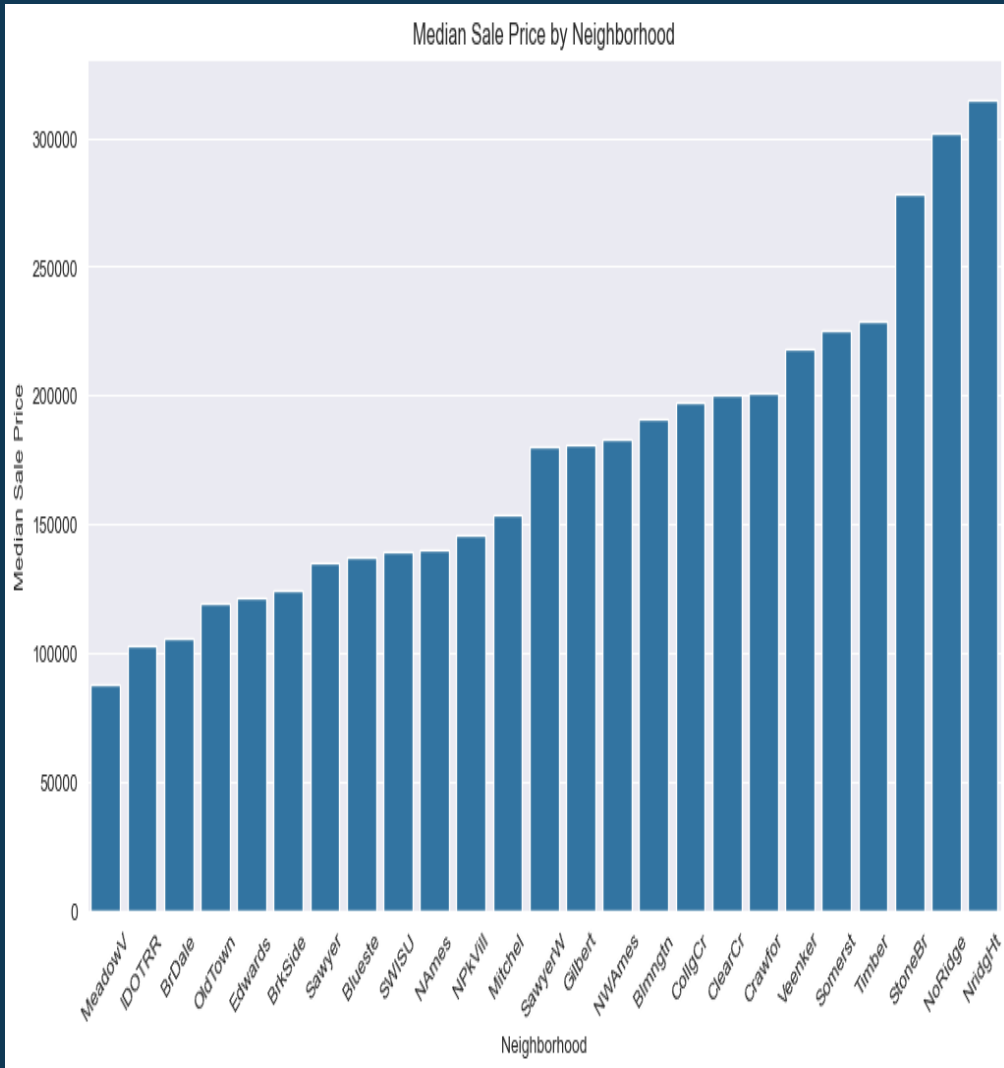
- **Missing values:** Handled by median imputation.
- **Categorical variables:** one-hot encoded (e.g., Neighborhood).
- **Numerical features:** Scaled (e.g., GrLivArea, TotalBsmtSF).
- **Dataset split:** 80% training, 20% testing.
- **Models Used:** Linear Regression, Random Forest, XGBoost.

Exploratory Insights – Correlation Heatmap



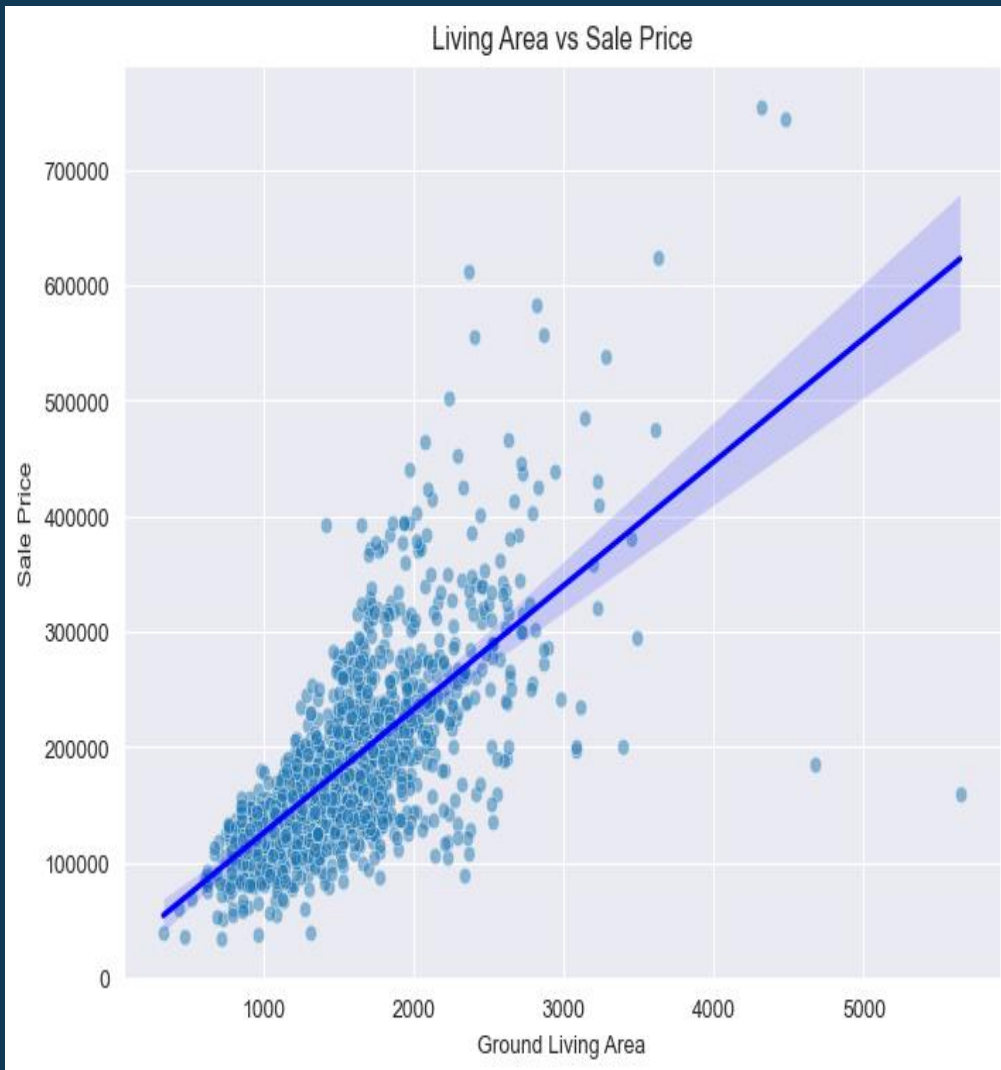
- **OverallQual** (quality of material and finish) is strongly correlated with sale price
- **GrLivArea** (above-ground living area) has a strong positive impact
- **GarageCars** and **TotalBsmtSF** also contribute significantly
- Weak correlation between **YearBuilt** and sale price after controlling for quality

Exploratory Insights – Neighborhood Impact



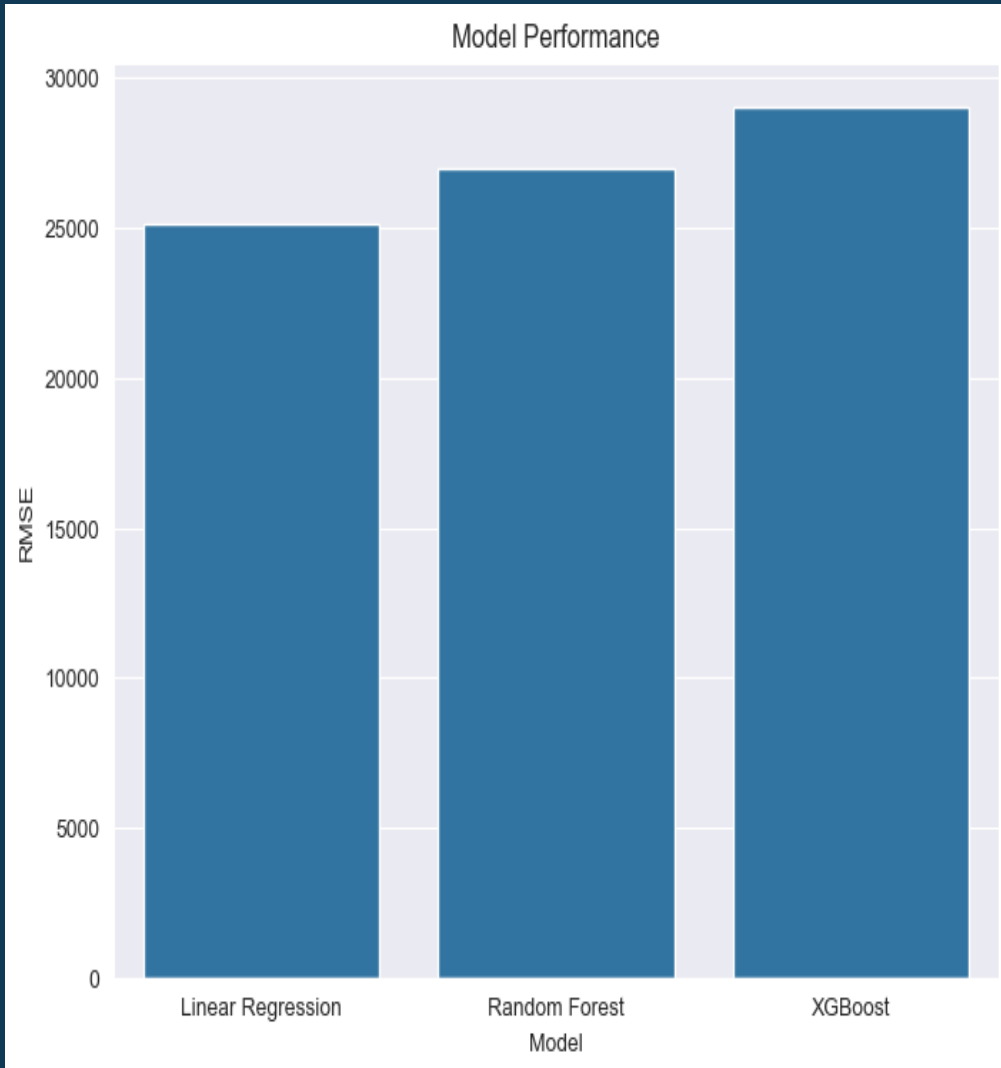
- **NridgHt** and **StoneBr** have the highest median sale prices
- **MeadowV** and **IDOTRR** have the lowest median prices
- **Proximity to amenities** and **schools** influences demand
- **Newer developments** tend to have higher property values

Exploratory Insights – Living Area vs. Sale Price



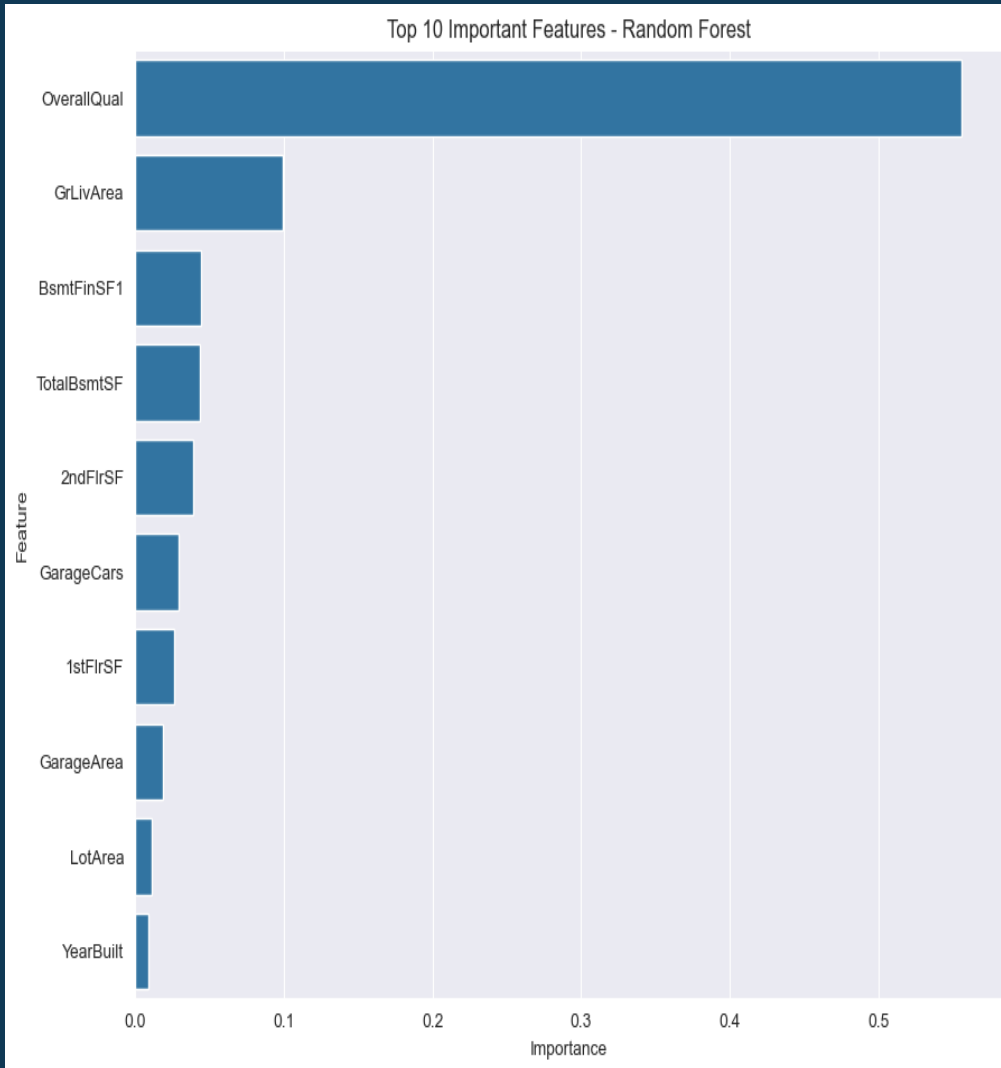
- A strong linear relationship between **GrLivArea** and **sale price**
- **Larger homes** tend to command higher prices
- **Outliers** suggest some exceptionally high-value properties
- **Basement** and **additional square footage** significantly increase value

Predictive Modeling – Model Performance



- **Linear Regression:** RMSE ~25,124 (simple but limited)
- **Random Forest:** RMSE ~26,980 (better for non-linearity)
- **XGBoost:** RMSE ~29,052 (best performer)
- The trade-off between interpretability and accuracy

Predictive Modeling – Feature Importance



- **OverallQual**: Quality of materials and finish
- **GrLivArea**: Above-ground living area
- **GarageCars**: Number of cars accommodated
- **TotalBsmtSF**: Basement area's impact on price
- **Neighborhood**: Location as a key determinant

Challenges and Ethical Considerations



➤ Bias Mitigation

- ❖ Avoiding discriminatory variables like demographic data
- ❖ Ensuring fair predictions across different neighborhoods

➤ Fairness in Modeling

- ❖ Preventing models from disproportionately favoring high-income areas
- ❖ Ensuring predictions support equitable housing decisions

➤ Transparency and Explainability

- ❖ Documenting all preprocessing steps
- ❖ Communicating model assumptions clearly

Key Findings



- **Quality, living area, and location** are the most important factors
- **XGBoost** provides the highest predictive accuracy
- **Feature selection** plays a crucial role in reducing model bias
- **Neighborhood** effects significantly impact pricing trends

Conclusion – Practical Application



➤ For Real Estate Agents

- ❖ Helps in setting competitive prices
- ❖ Provides insights into key property features affecting valuation

➤ For Buyers and Investors

- ❖ Identifies underpriced properties
- ❖ Assesses potential return on investment

➤ For Financial Institutions

- ❖ Supports mortgage risk assessment
- ❖ Enhances loan approval decisions based on property value forecasts

Future Directions



➤ Enhancements to the Model

- ❖ Integrate additional datasets like macroeconomic indicators, crime rates, and school ratings
- ❖ Explore deep learning approaches such as neural networks

➤ Societal Considerations

- ❖ Assessing the impact of predictive modeling on marginalized communities
- ❖ Ensuring equitable benefits for diverse demographics

➤ Model Improvements

- ❖ Refining feature selection techniques
- ❖ Expanding the dataset to include larger geographical regions

An aerial photograph of a sprawling city, likely Manila, Philippines, taken during the 'blue hour' of sunset. The sky is a deep, vibrant blue, filled with wispy white and grey clouds. The sun is low on the horizon to the left, casting a warm, golden glow across the city's rooftops and the lower part of the sky. The city itself is a dense mosaic of buildings, from small residential houses with red-tiled roofs to large, modern commercial skyscrapers. In the foreground, a prominent brown building with a grid-like facade is visible on the left, and a tall, modern glass-fronted building stands in the center. The overall scene conveys a sense of a bustling, vibrant urban environment at the end of a day.

Thank You