

Satellite Imagery-Based Property Valuation

1. Overview

Accurate property valuation is critical for real estate analytics. traditional valuation models rely heavily on tabular attributes such as size, no of rooms and construction quality. However, these models often fail to capture backgrounds and neighbourhood factors such as greenery, road connectivity and surrounding infrastructure.

In this project, I developed a multimodel regression model that integrates both tabular data and unstructured satellite images.

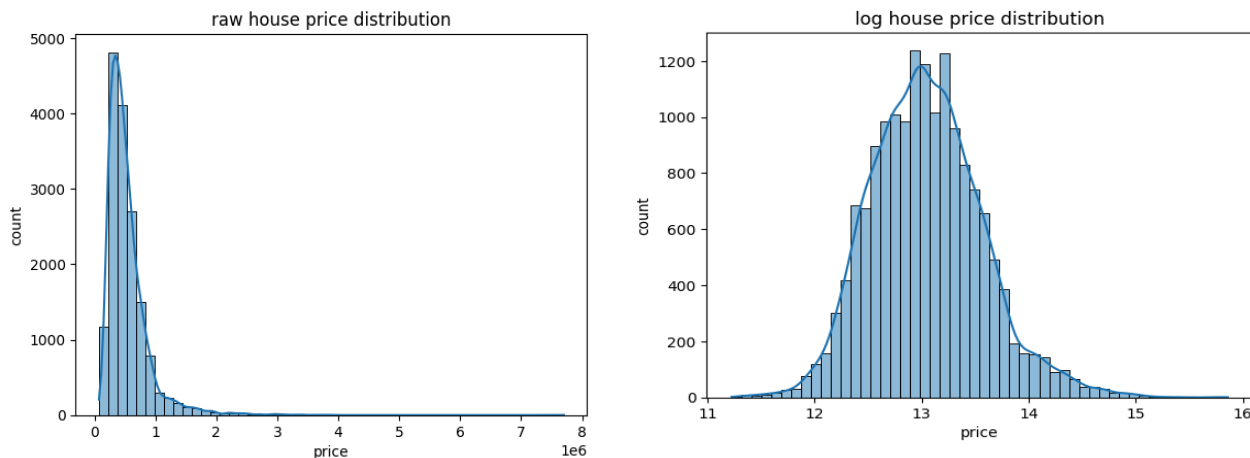
The primary objective was to evaluate whether incorporating visual context from satellite images improves house price prediction accuracy compared to tabular only models.

2. Exploratory Data Analysis(EDA)

2.1 Price Distribution

The target variable(price) exhibits a right-skewed distribution, with a small no of extremely expensive properties.

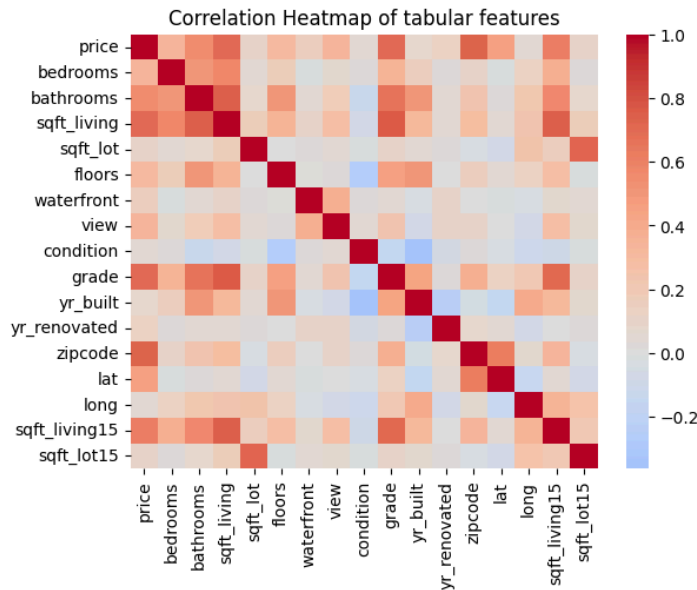
- To stabilize variance and reduce the influence of outliers, a $\log(\text{price})$ transformation was applied.
- This transformation significantly improved the model convergence and stability



2.2 Key Tabular Features

- Sqft_living, grade, bathrooms show strong positive correlation with price

- Waterfront is highly imbalanced but strongly associated with higher prices
- Zipcode was dropped to avoid high-cardinality noise



2.3 Satellite Image inspection

High resolution satellite images were fetched using ArcGIS world imagery based on latitude and longitude.

-High-Value properties often appear in areas with:

Dense greenery

Water bodies

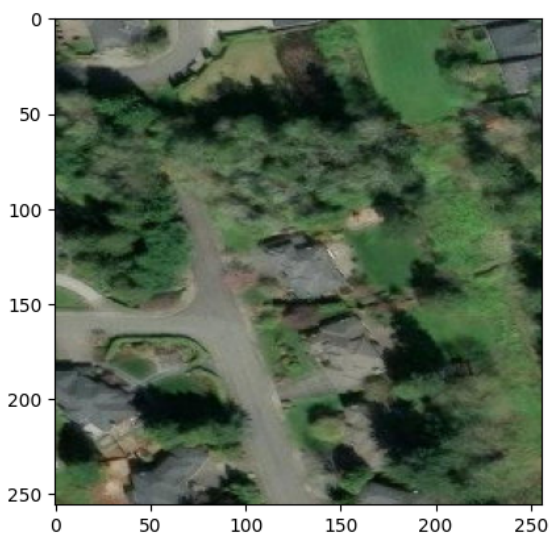
Larger plots and well organised roads

- Lower-Priced houses are typically located in:

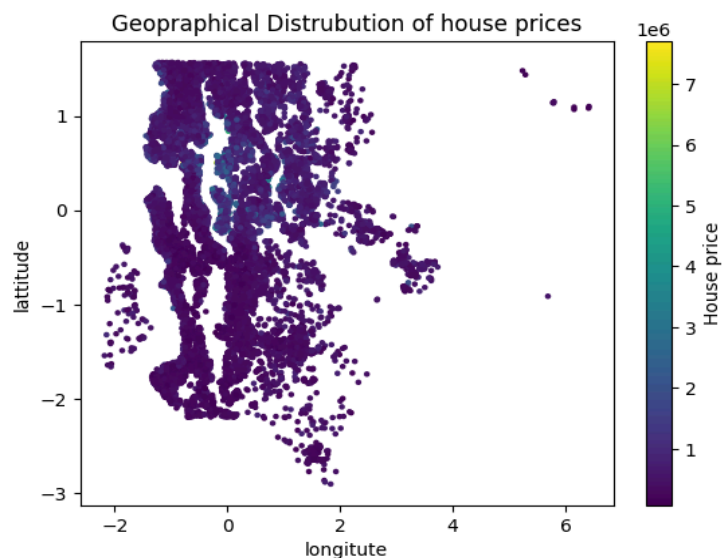
Densely packed regions

Areas dominated by concrete structures

Sample Satellite Images



Geographical Distribution of house prices



3. Final and visual insights

Satellite imagery adds contextual information that is not present in tabular data alone.

Key visual Drivers of property Value:

- Green Cover:presence of trees and parks is associated with higher valuation
- Water Proximity: waterfront and near-water regions show consistent price premiums
- Urban Density: Sparse layouts with larger plots are generally valued higher than dense housing clusters

These observations align with real-world real estate valuation.

4. Model Architecture

4.1 Tabular Model

- Baseline model includes XGBoost and Ridge Regression
- Features were standardized and the target was modeled in log-space

4.2 Image model

- Pretrained ResNet-18 model was used as a fixed feature extractor
- The classification head was removed and the network output a 512 dim embedding per image
- The cnn weights were frozen to prevent overfitting and reduce training cost

4.3 Multimodal Fusion

- Then using PCA it was reduced to 64 dimension



- Tabular features and images embeddings are concatenated.
- The fused representation was passed to a regression model for prediction

5.Results

5.1 Quantitative Performance

Model	RSME	R^2
Tabular Only(XGBoost)	111k	~0.90
Tabular+Satellite Images	116k	~0.89

5.2 Interpretation

The tabular only model slightly outperformed the multimodal model in terms of RSME.Satellite imagery did not significantly improve predictive accuracy

But added valuable interpretation,enabled qualitative neighbourhood-level insights,Improved model understanding rather than raw performance

6.Conclusion

The project demonstrates a complete multimodal ml pipeline for real estate valuation,integrating structured data with unstructured visual information.

Key takeaways:

- Tabular Features remain the strongest predictors of house prices.
- Satellite imagery provides meaningful contextual and explainability benefits.
- Multimodal systems are valuable even when they do not strictly outperform baseline models.