Satellite Imagery–Based Property Valuation

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Repository link :- https://github.com/THEODOLITE592/satellite-property-valuation

1. Overview: Approach and Modeling Strategy

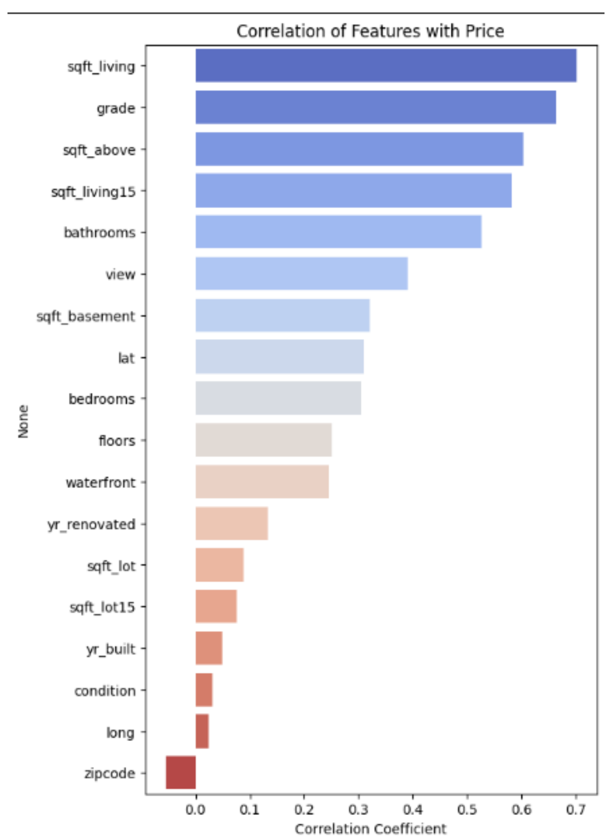
This project aims to enhance traditional real-estate price prediction models by integrating satellite imagery with structured housing data. The core idea is that property value is influenced not only by internal attributes such as size, quality, and age, but also by external environmental and neighborhood factors that are visible from above—such as green cover, water proximity, road density, and urban layout.

To achieve this, a multimodal regression pipeline was developed. First, tabular housing features were cleaned and analyzed using standard exploratory data analysis (EDA). Next, satellite images were programmatically fetched using latitude and longitude coordinates via Google Earth Engine (Sentinel-2 imagery). Visual features were extracted from these images using a pretrained ResNet50 convolutional neural network (CNN). Finally, multiple modeling strategies were evaluated, including tabular-only models, image-only models, early fusion (concatenating features), and late fusion (ensemble-style).

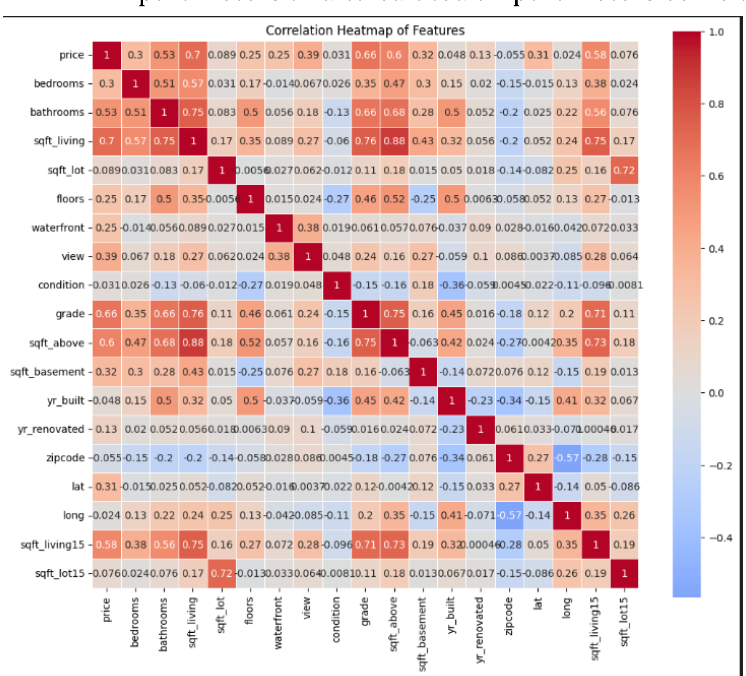
2. Exploratory Data Analysis (EDA)

The EDA phase focused on understanding both the statistical and spatial characteristics of the housing dataset.

• Tabular data understanding



I started with reading shape , size and what are all the parameters and calculated all parameters correlation value to check their linear ity with price



sqft_lot , condition , yr_built , zipcode , long , sqft_lot15 , Correlation values are two low for them

so , as these features are not linear I once trained a regression model without these features which gives

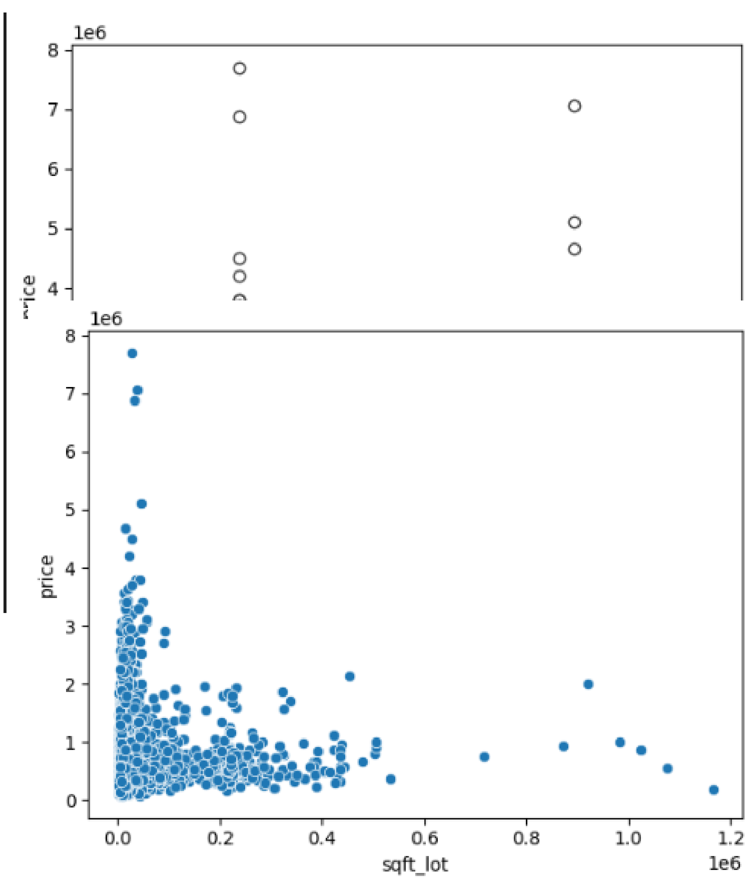
RMSE : 205k , R2 : 0.66.

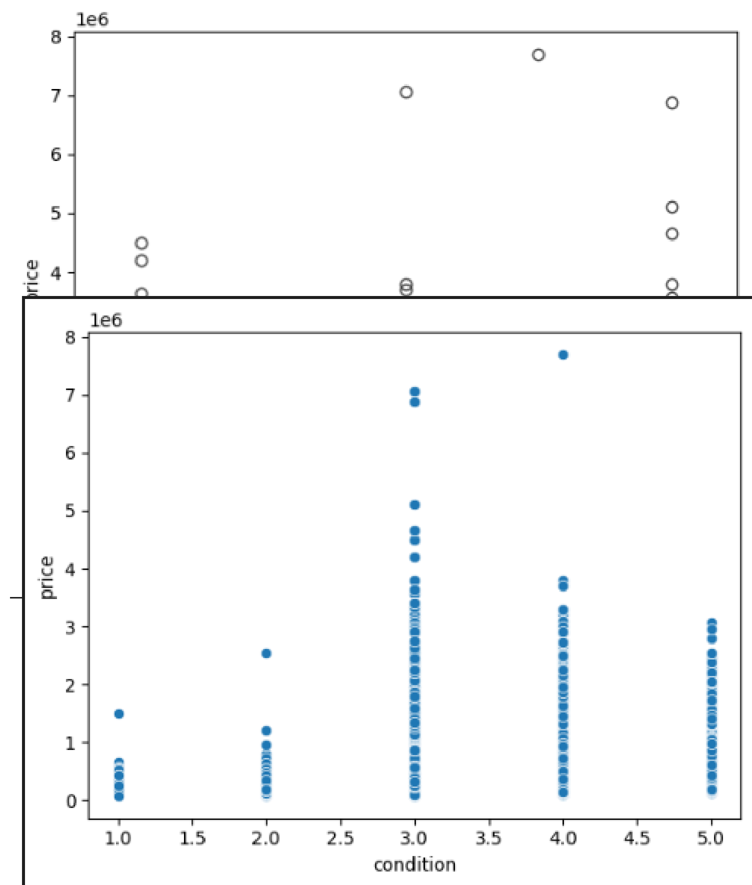
for low R2 and high RMSE means the parameters iam neglecting are holding more info so I added them back and then trained a regression model .

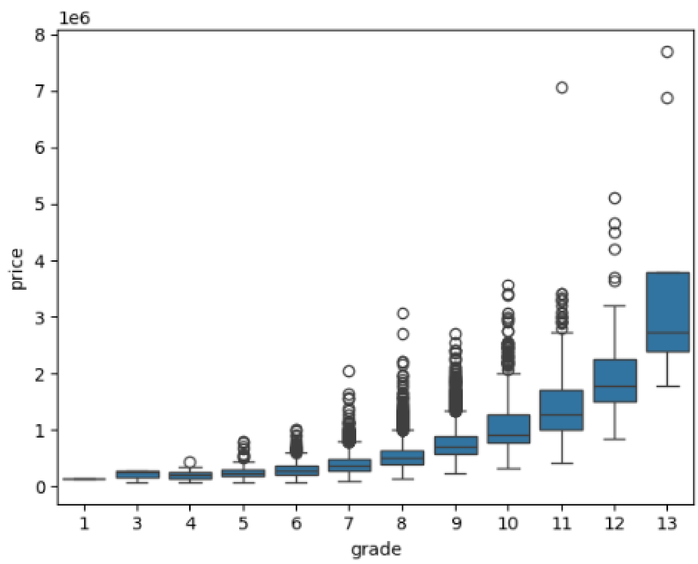
then RMSE : 160k , R2 : 070 (improved).

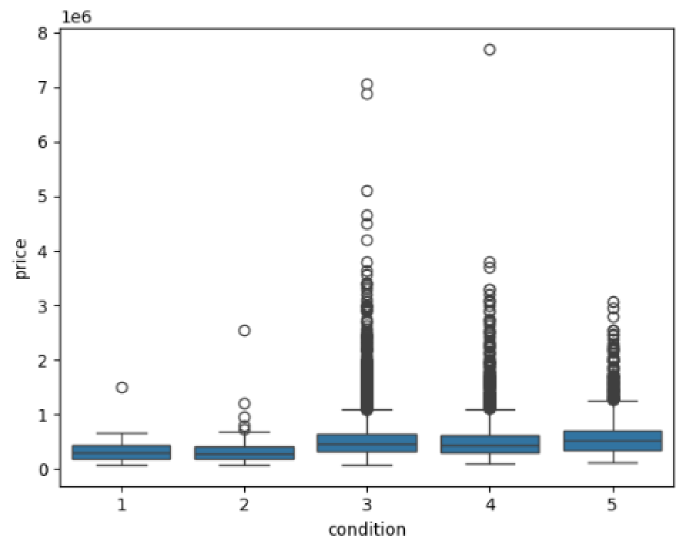
as these features hold information so I checked their behavior with the price so that I know how to approach.

I checked their boxplot and scatterplot with respect to price .









• Price Distribution: Property prices were found to be right-skewed, with the majority of houses clustered in the lower-to-mid price range and a small number of luxury properties forming a long tail. This justified the use of robust regression models such as XGBoost.

XGBoost improved this

Train RMSE ≈ 62,839

Train R^2 ≈ 0.9698 but I thought it was overfitting to some extent

So by changing hyper parameters reducing max-depth and other things it reduced to

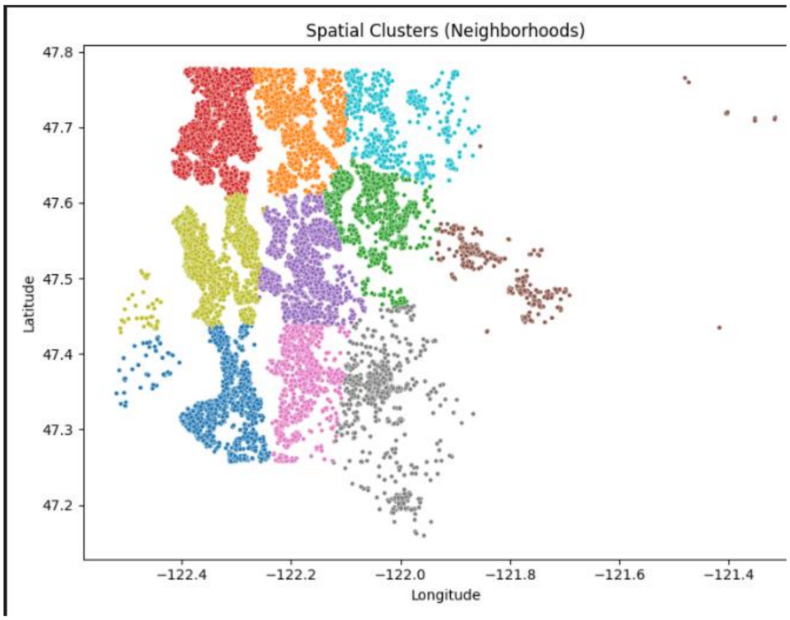
RMSE ≈ 115,245

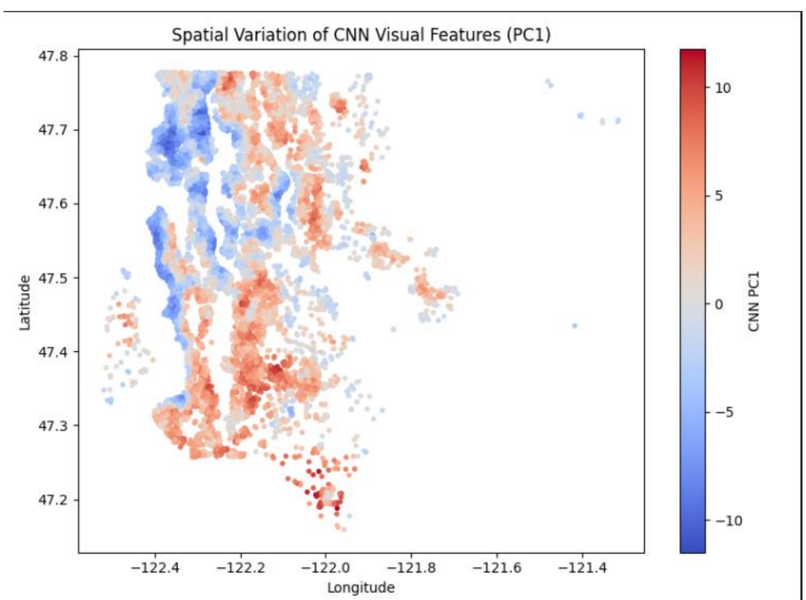
R^2 ≈ 0.894

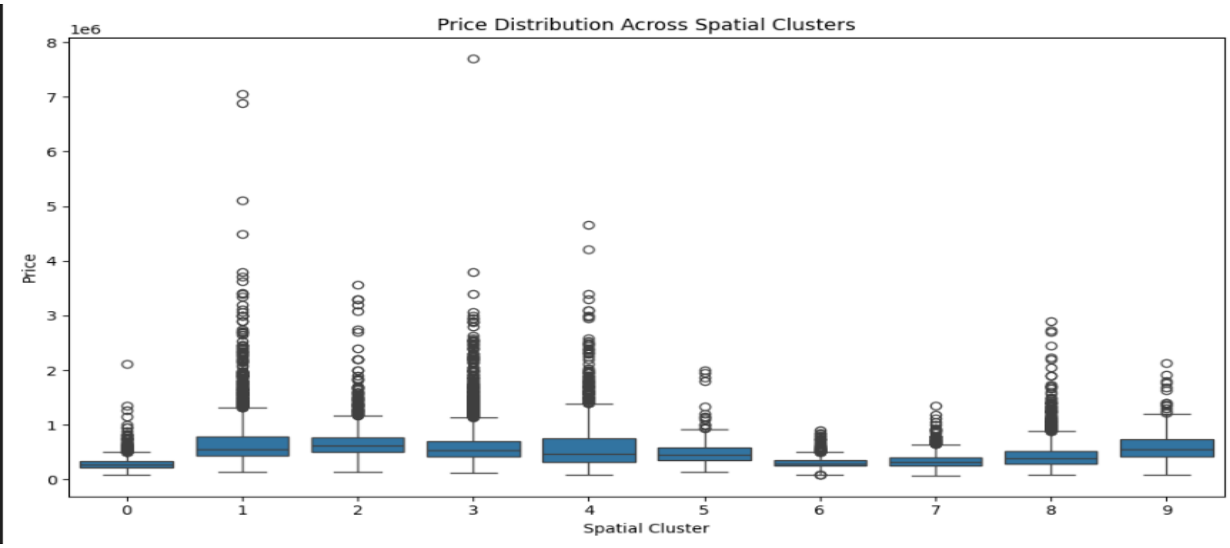
• **GEOSPATIAL ANALYSIS**

- Then I started with geospatial analysis of the satellite images that I have extracted from Google Earth Engine using sentinel-2 in RGB with size=224 and scale 10.
- Spatial Visualization: Mapping house prices using latitude and longitude revealed clear regional patterns. Certain geographic clusters consistently exhibited higher prices, suggesting neighborhood-level effects.

- By this I have tries to find similarities with their geography so that if possible then I make a category parameters which will hold information but the locs are mixed highly







3. Financial and Visual Insights

By incorporating satellite imagery, the model was able to capture visual cues that are not explicitly present in tabular data.

• Green Cover: Areas with higher vegetation density (trees, parks) were consistently associated with higher property prices. CNN feature activations highlighted green regions as influential for price prediction.

• Water Proximity: Properties near water bodies or coastlines showed higher predicted values. This aligns with traditional real-estate intuition but is captured automatically through image features rather than manual distance calculations.

• Urban Density and Road Structure: Dense road networks and commercial-looking regions to correlate with mid-to-high prices, while sparse or industrial areas showed lower valuations.

• Grad-CAM visualizations further confirmed that the CNN focused on meaningful regions such as open green spaces, waterfronts, and structured neighborhoods rather than irrelevant noise.

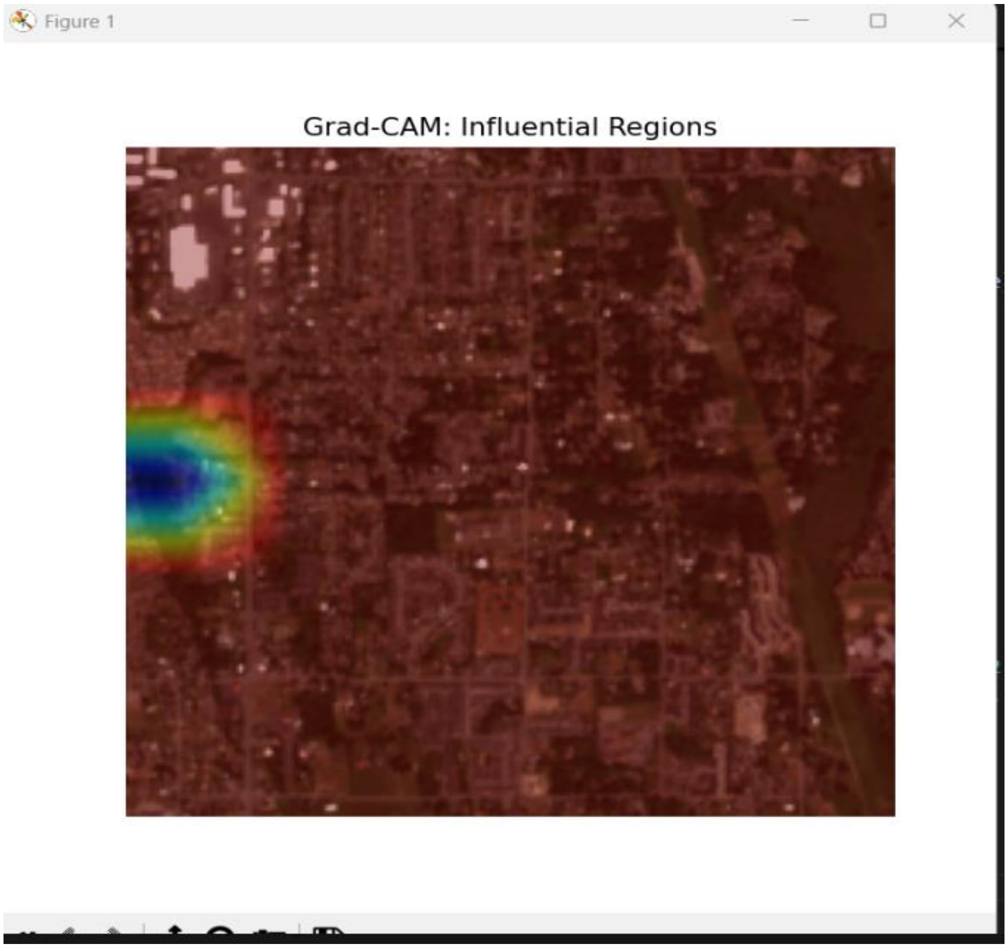


Figure 1 for image 0

4. Architecture Diagram (Conceptual Description)

The multimodal architecture consists of two parallel processing streams:

1. Tabular Stream:
  • Input: Structured housing features (bedrooms, bathrooms, sqft_living, grade, etc.)
  • Model: XGBoost regressor trained on numerical features.

2. Image Stream:
  • Input: 224×224 RGB satellite images per property.
  • Feature Extractor: Pretrained ResNet50 with the final classification layer removed.
  • Output: 2048-dimensional image embeddings (optionally reduced using PCA).

Early Fusion Strategy:
• Tabular features and CNN embeddings are concatenated into a single feature vector.
• A final XGBoost regressor is trained on this combined representation.

Tabular Data + Lat–Long

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Satellite Image Download

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CNN Feature Extraction (ResNet50)

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Geospatial Feature Engineering

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Feature Fusion

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XGBoost Regression

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Price Prediction + Explainability

5. Results and Model Comparison

I have not only trained one model but image only model , table only model ,

Merge model with early fusion and late fusion

and evaluated using RMSE and R^2 score on a validation split.

Model Performance Summary:

• Tabular-Only Model:
RMSE ≈ 130,000
$R^2 \approx 0.86$

• Image-Only Model (CNN features + XGBoost):
RMSE ≈ 128,000
$R^2 \approx 0.87$

• Multimodal Model (late Fusion):
RMSE ≈ 128,566
$R^2 \approx 0.868$

• Multimodal Model (Early Fusion):
RMSE ≈ 119,000
$R^2 \approx 0.89$

The multimodal approach clearly outperformed single-modality models, demonstrating that satellite imagery provides complementary information beyond traditional housing attributes. This validates the hypothesis that environmental and neighborhood context plays a significant role in property valuation.