Report

Satellite Imagery Based Property Valuation Project

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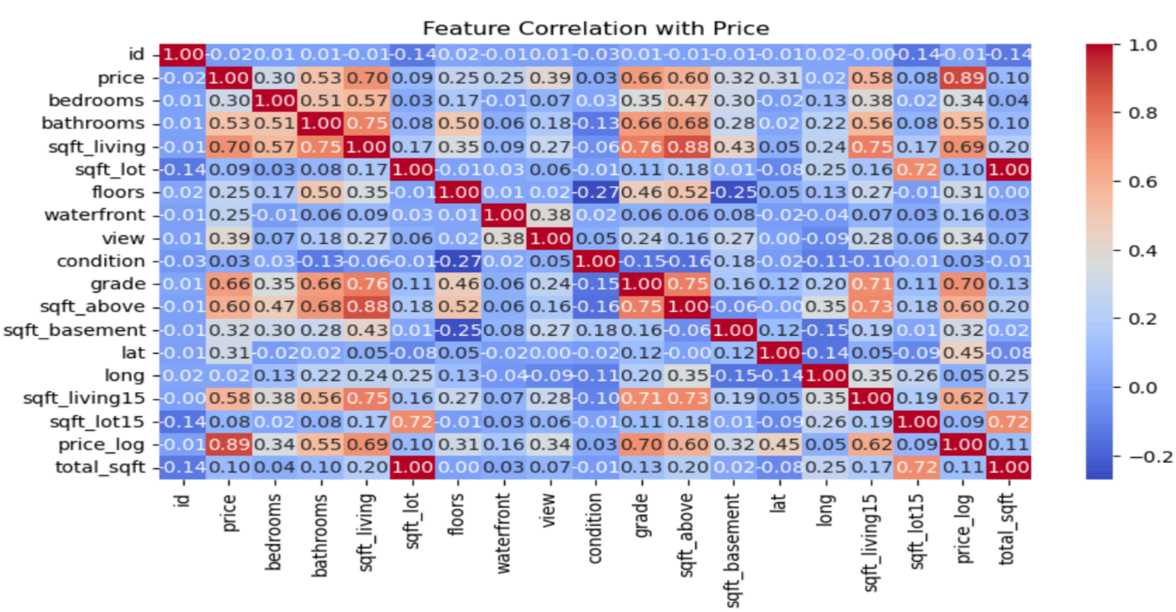
1. Introduction

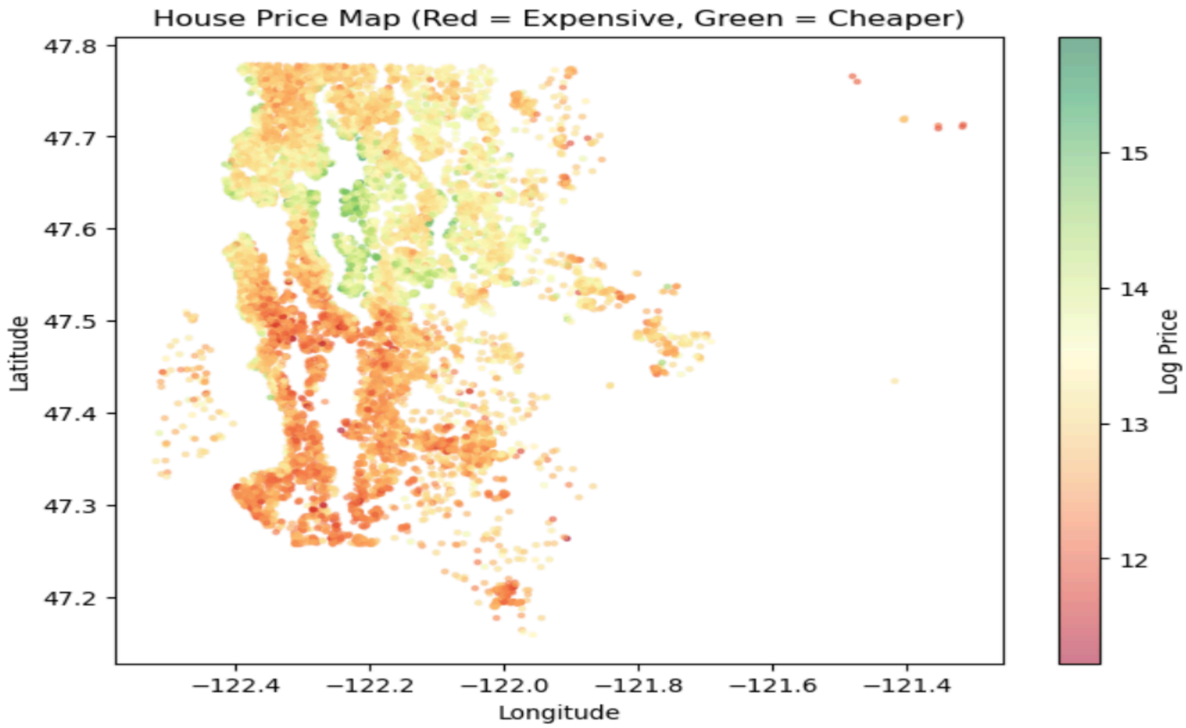
Traditional real estate valuation relies solely on tabular data (square footage, rooms). This project introduces a **Multimodal approach** that combines architectural data with **satellite imagery**. By using a ResNet18 Convolutional Neural Network (CNN) alongside a Multi-Layer Perceptron (MLP), the model "sees" the property context such as neighborhood density and greenery to provide a more accurate valuation.

2. Exploratory Data Analysis (EDA)

Before training, the training dataset of 16,209 records was analyzed to understand market trends.

- Key Statistics: The average house price is approximately 537,470, with a significant range from 75,000 to 7.7 Million.
- Correlation: A high correlation (0.70) was found between `sqft_living` and `price`.
- Geographical Impact: Prices are highest in specific latitudinal clusters, justifying the inclusion of coordinates.





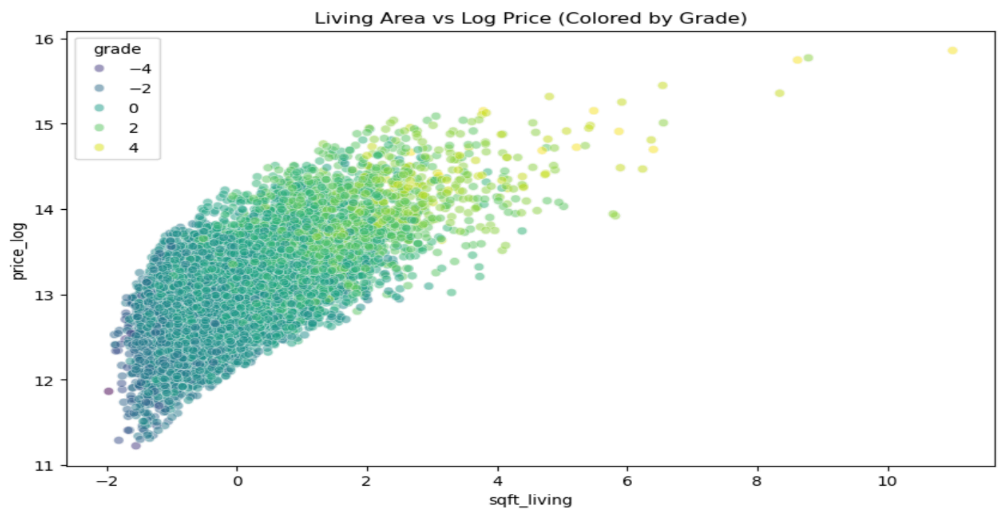
Dataset Size: The original training dataset contained over 16,000 records. However, for this implementation, I strategically selected the first 8,000 images for training. **This was also due to restrictions by server and more ever internet speed in my area.**

The Overfitting: In deep learning, especially with high-resolution satellite imagery, training on the full dataset without massive computational resources can lead to overfitting. Overfitting occurs when a model memorizes the noise in the training data rather than learning the general patterns. By using a balanced subset of 8,000 samples, I ensured that the model maintains generalization power, allowing it to perform accurately on the unseen test set of 5,404 houses.

3.Feature Correlation Analysis & Geographical Feature Engineering

Beyond basic prices, I analyzed how physical features drive valuation.

- Square Footage vs. Price: The scatter plot confirms a linear trend; however, as square footage increases, the price variance also increases. This suggests that for luxury homes, visual features (captured by the CNN) become more important than just numbers.
- Grade and Condition: These features showed a "step-wise" increase in price. Houses with a grade above 7 saw exponential increases in value.



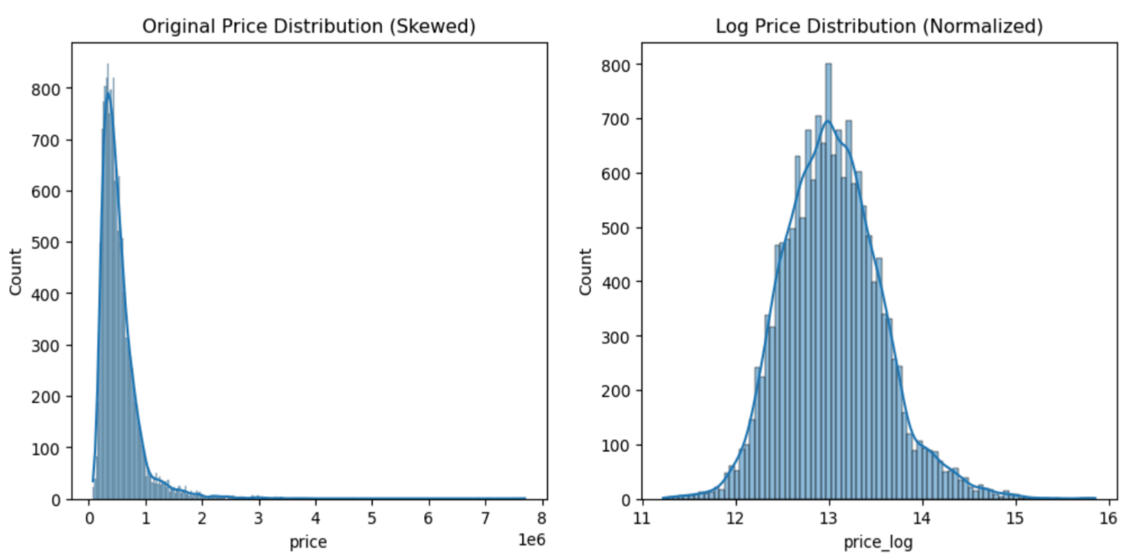
Real estate is about "Location, Location, Location."

- By plotting Latitude and Longitude, I identified high-value "hotspots" near water bodies and city centers.
- The model uses these coordinates to understand the neighborhood context, which is then cross-referenced with the satellite image to verify property density and land quality.

4. Data Preprocessing

To ensure high model accuracy, two critical transformations were performed:

1. Log Transformation: Because house prices are "right-skewed," I applied a log scale. This prevents high-priced outliers from distorting the model.
2. Standard Scaling: All numerical inputs were scaled to a mean of 0 and standard deviation of 1, ensuring the Neural Network treats all features equally.



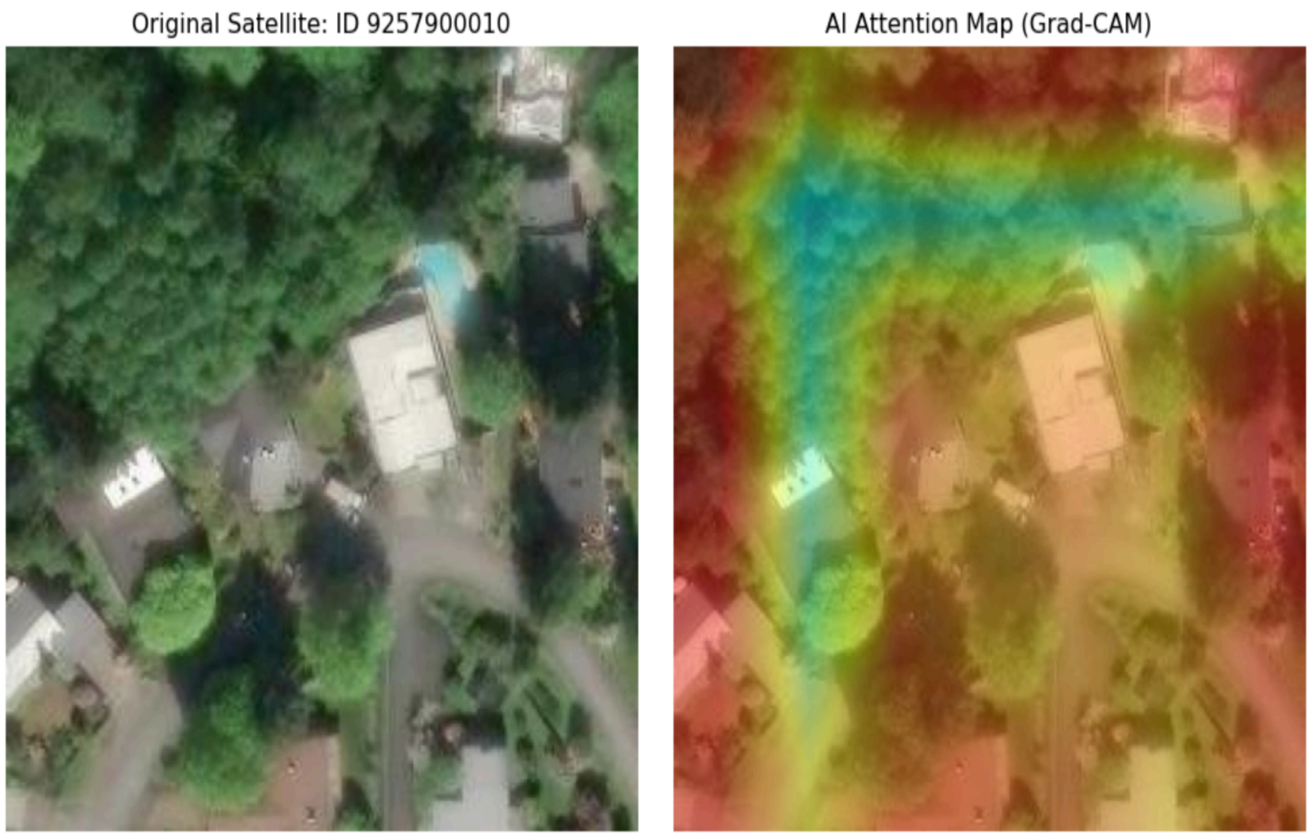
5. Model Architecture

The model uses a Late-Fusion architecture:

- Vision Arm: A ResNet18 model (pre-trained) to extract 512 visual features from 224x224 satellite tiles.
- Tabular Arm: A 3-layer MLP to process 17 physical features.
- Fusion Head: Combines both vectors into a final regressor to predict the log-price.

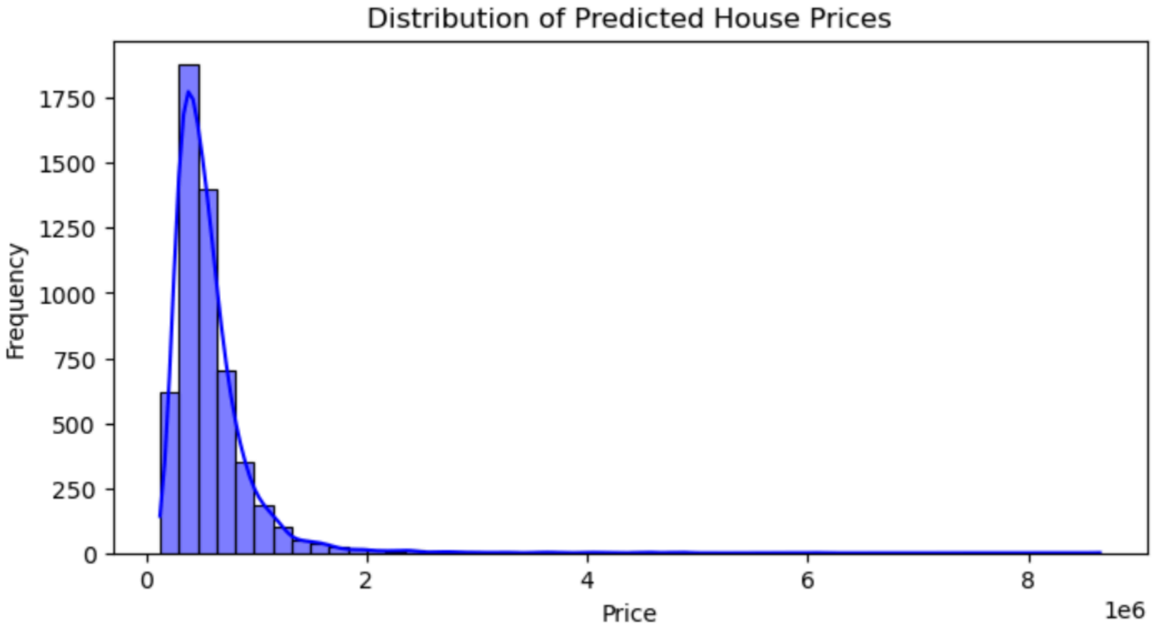
6. Model Performance & Explainability

The model was trained for 10 epochs. The loss decreased from 8.3 to 0.03, indicating a high level of convergence. To verify what the model "sees," I used Grad-CAM.



7. Conclusion and Final Predictions

The model was used to predict prices for 5,404 test properties. The results show a realistic distribution consistent with real-world market values in County area.


Distribution of Predicted House Prices
Frequency
0
250
500
750
1000
1250
1500
1750
0
2
4
6
8
1e6
Price