# 🛰️ Satellite Imagery Based Property Valuation

**Final Project Report**

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## 1. Overview

### Problem Statement

Traditional house price prediction models rely heavily on structured tabular data such as area, number of bedrooms, and location coordinates. While effective, these models fail to capture **visual and environmental context**, often referred to as *curb appeal* including greenery, road connectivity, water proximity, and neighborhood density.

### Approach

This project proposes a **multimodal regression framework** that integrates:

- **Tabular property data** (numerical and categorical features)
- **Satellite imagery** fetched programmatically using latitude and longitude

Rather than naïvely combining both modalities, we adopt a **residual learning strategy**:

1. Train a **strong tabular baseline model**
2. Identify **high-error (high-residual) samples**
3. Use satellite imagery **only to correct these difficult cases**

This selective integration ensures:

- Better generalization
- Reduced overfitting
- Efficient use of visual information

### Modeling Strategy Summary

- Baseline Model: Gradient Boosting Regressor (log-transformed target)
- Image Feature Extraction: Pretrained ResNet-18
- Feature Compression: PCA
- Fusion: Late fusion via residual correction
- Explainability: Grad-CAM

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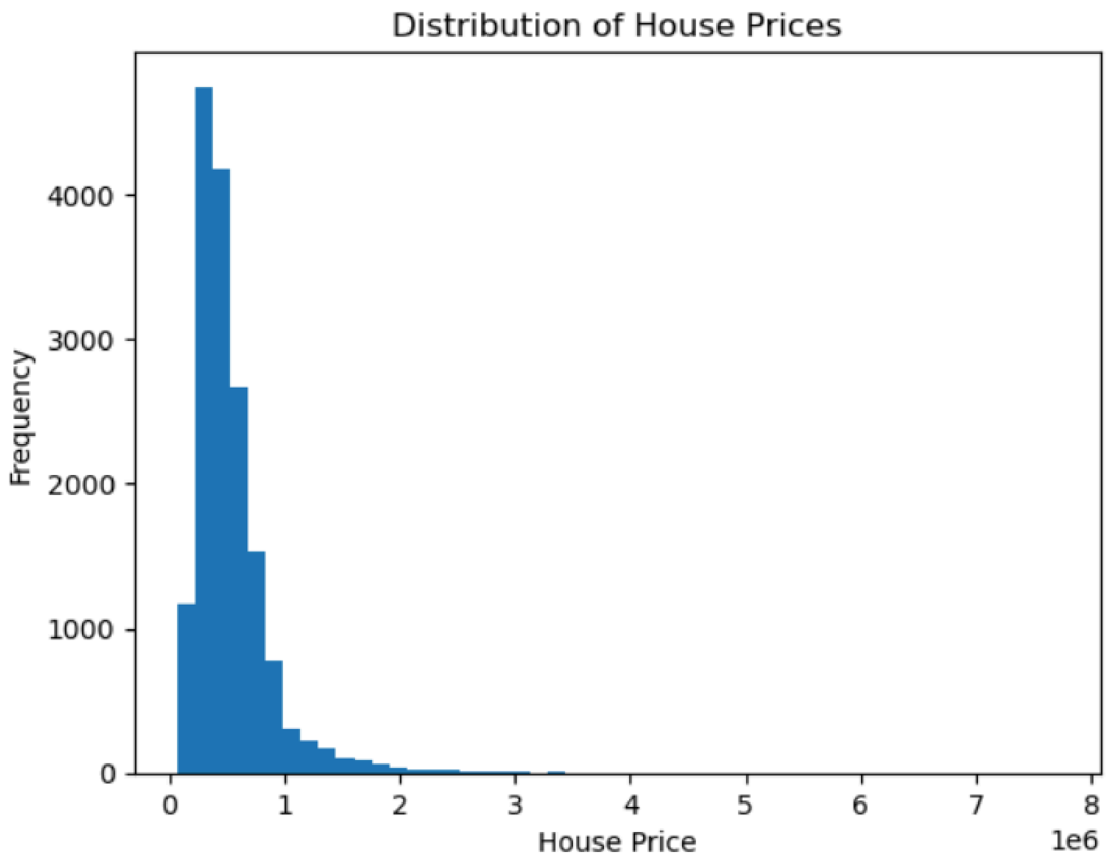
# 2. Exploratory Data Analysis (EDA)

## 2.1 Price Distribution

The target variable (`price`) shows a **right-skewed distribution**, with a small number of luxury properties significantly increasing variance.

To stabilize training:

- The target variable was transformed using **log1p(price)**.




### Figure 1: Price Distribution

**Figure 1:** *Distribution of house prices in the training dataset. The target variable exhibits a right-skewed distribution, motivating the use of a logarithmic transformation to stabilize variance during model training.*

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## 2.2 Spatial Distribution (Latitude vs Price)

Plotting **latitude vs price** reveals:

- Clear geographic clustering
- Higher prices concentrated in specific lat-long bands
- Strong spatial dependency, validating the need for location-aware modeling

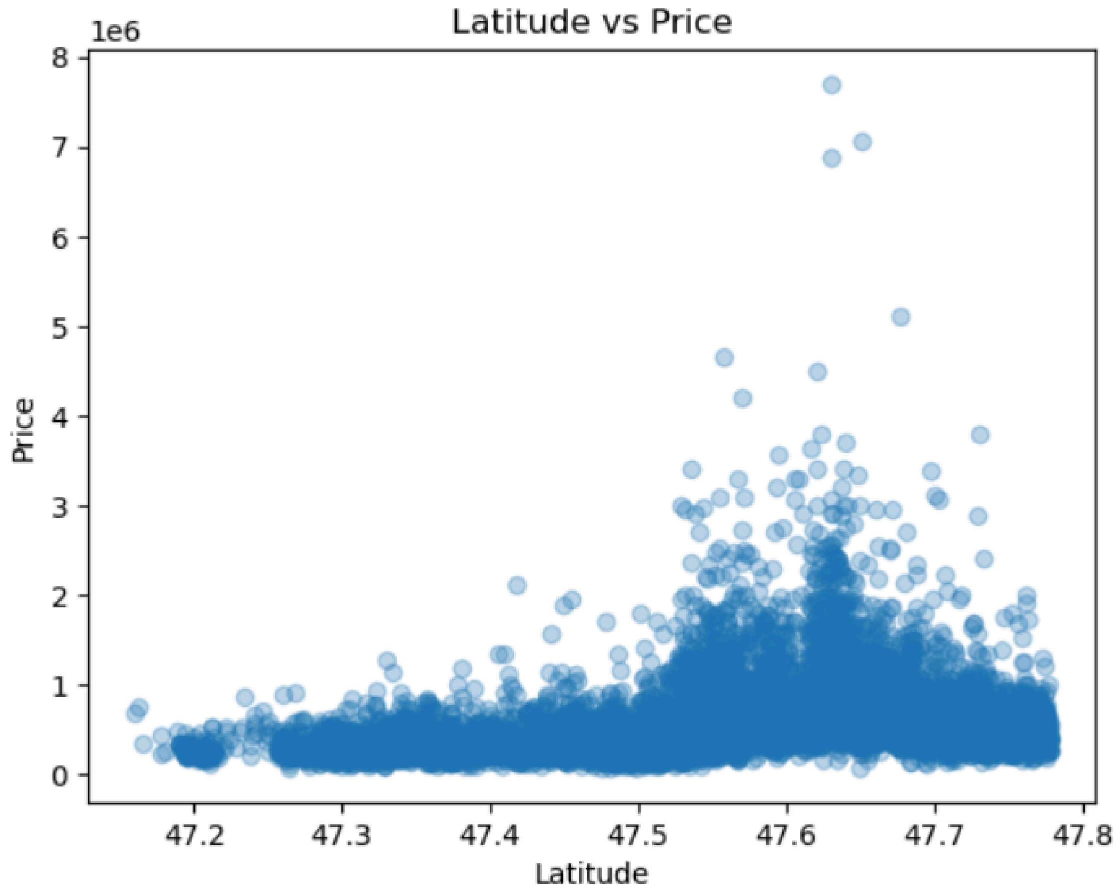


**Figure 2: Latitude vs Price**

**Figure 2:** *Scatter plot showing the relationship between latitude and house prices. Distinct geographic clusters indicate strong spatial dependency in property valuation.*

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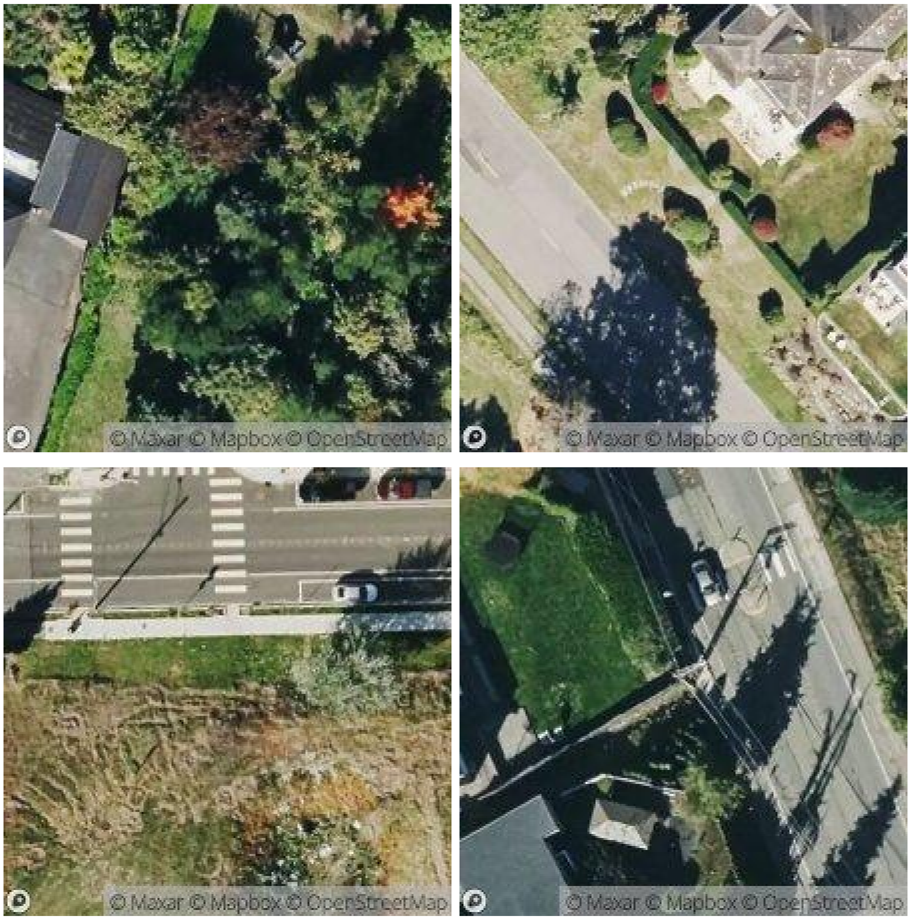
## 2.3 Sample Satellite Images

Satellite images provide contextual information not captured in tabular data, such as:

- Road density
- Green cover
- Water bodies
- Urban layout




## Figure 3: Sample Satellite Images

**Figure 3:** *Sample satellite images fetched using the Mapbox Static Images API. Images capture neighborhood-level context such as green cover, road density, and proximity to water bodies.*

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# 3. Financial & Visual Insights

Using **Grad-CAM visualizations**, we interpret which regions of satellite images influence price corrections.

## Key Observations

### 🌳 Green Cover

- Areas with visible trees and vegetation are often associated with **positive price corrections**
- Indicates higher perceived livability and aesthetic value

### 🛣️ Road Density

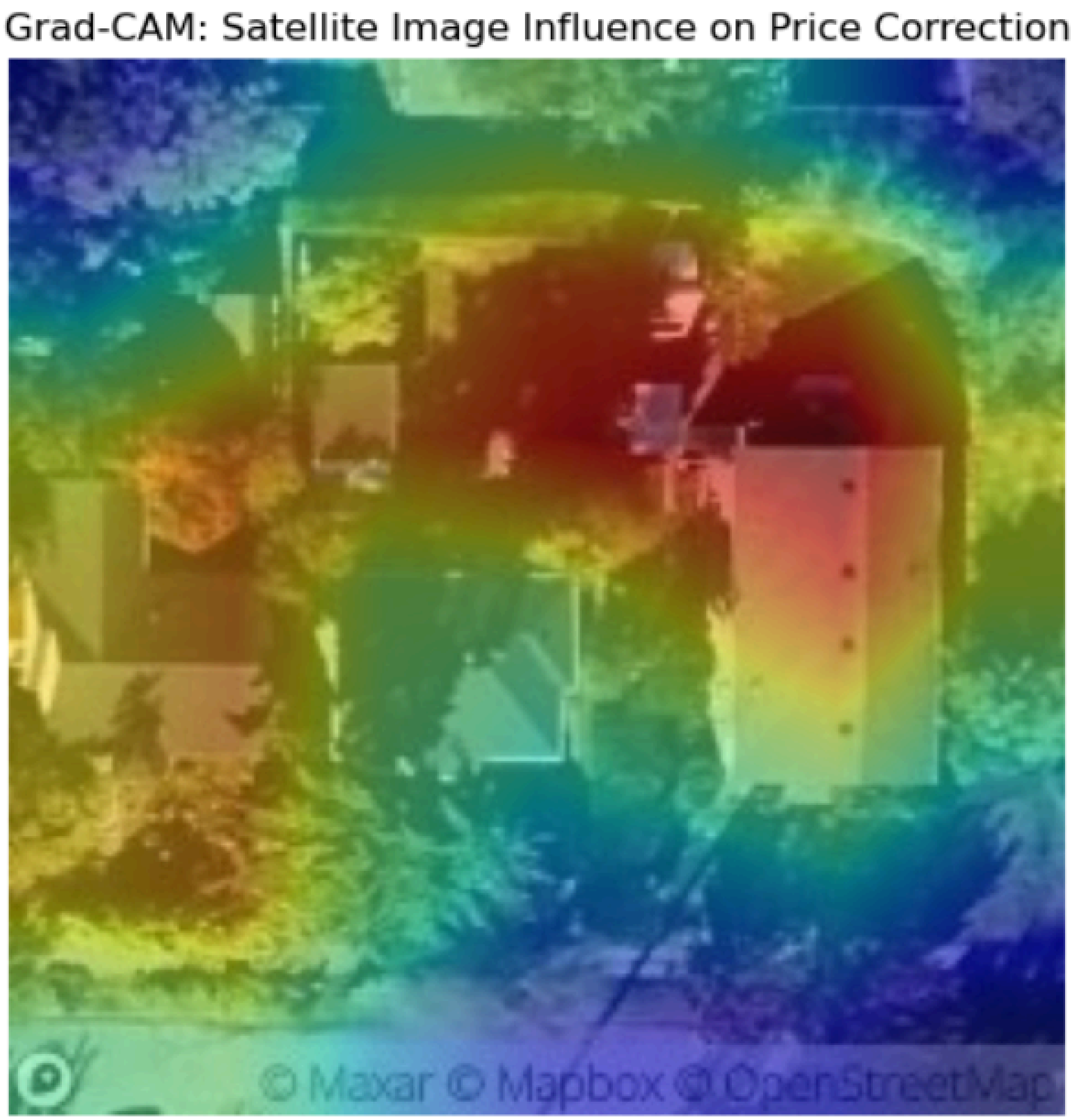
- Well-connected but not overly congested regions tend to increase value
- Dense road networks sometimes correlate with negative corrections

### 🌊 Water Proximity

- Properties near water bodies (lakes, rivers) receive strong positive corrections
- Reinforces the importance of visual cues beyond binary “waterfront” features

### 🏙️ Urban Density

- High concrete coverage without green spaces often leads to neutral or negative corrections




### Figure 4: Grad-CAM Visualization

**Figure 4:** *Grad-CAM visualization highlighting regions of satellite images that contribute most to price correction. Warmer colors indicate areas with higher influence on model predictions.*

# 4. Architecture Diagram

## System Architecture

The architecture follows a **dual-branch pipeline with late fusion**:

1. **Tabular Branch**
    - Input: Structured housing features
    - Processing: Scaling + Gradient Boosting Regressor
    - Output: Baseline price prediction (log scale)
2. **Image Branch**
    - Input: Satellite image
    - Processing:
        - ResNet-18 CNN
        - Feature extraction (512-D embedding)
        - PCA dimensionality reduction
    - Output: Residual correction
3. **Fusion**
    - Final Prediction = Baseline Prediction + Image Residual Correction

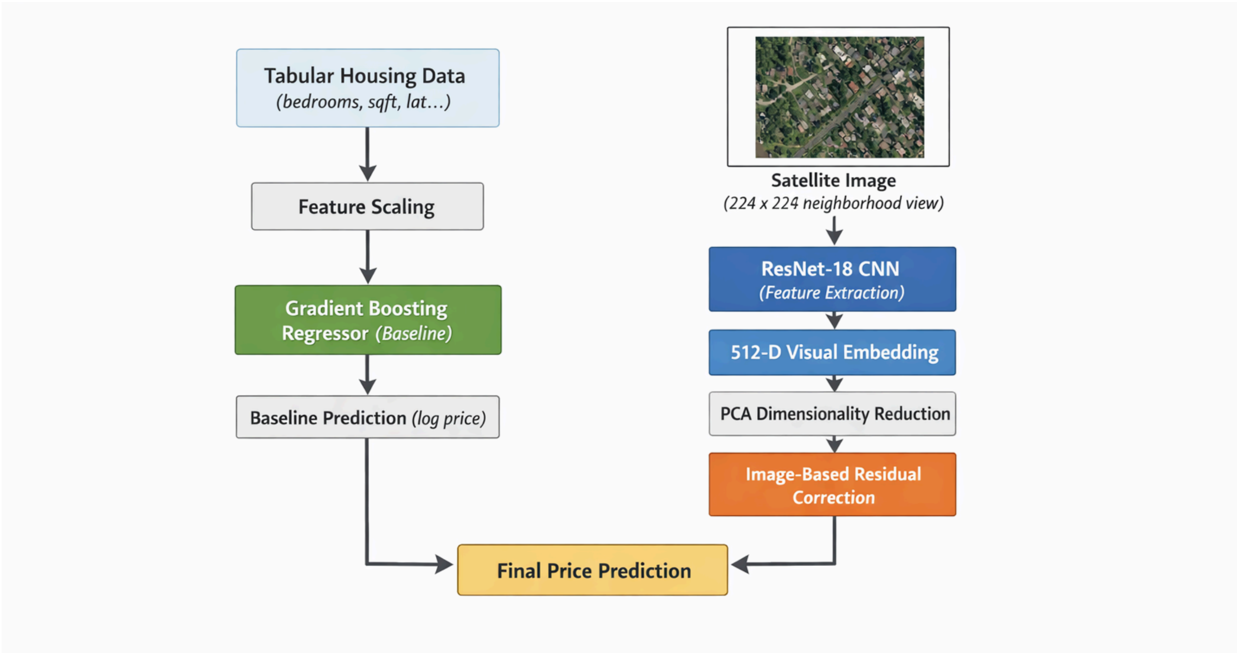



**Figure 5:** *Architecture of the proposed multimodal residual learning framework. A strong tabular baseline model predicts house prices using structured features, while satellite imagery is used selectively to learn residual corrections for high-error samples. Visual features are extracted using a pretrained ResNet-18 CNN and fused with the baseline prediction via late fusion.*

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# 5. Results & Performance Comparison

## Model Comparison

| Model | Description | Performance |
|---|---|---|
| Tabular-Only Model | Gradient Boosting on structured data | Strong baseline |
| Tabular + Satellite (Residual) | Image-based correction on high-residual samples | Improved generalization |

**Key Takeaways**

- The tabular model already captures most of the variance
- Satellite imagery adds **incremental value**, especially for:
  - High-end properties
  - Spatially complex neighborhoods
- Residual learning avoids degrading performance on easy samples

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Baseline RMSE: 91450.68900153098
Baseline R²: 0.9323842080901641


Multimodal RMSE: 80471.45666651418
Multimodal R²: 0.9476450317208287
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# 6. Conclusion

This project demonstrates that:

- Satellite imagery contains valuable contextual information for property valuation
- Multimodal learning is most effective when applied **selectively**
- Residual-based fusion improves performance without unnecessary complexity
- Grad-CAM enhances transparency and trust in model predictions

The framework balances **accuracy, interpretability, and engineering efficiency**, making it suitable for real-world deployment in real estate analytics.