Satellite Imagery Based Property Valuation

Hybrid Deep Learning Model for Real Estate Price Prediction

Using Tabular Features + Satellite Imagery

1. Overview

Problem Statement

Predict property prices using a combination of traditional tabular features (bedrooms, bathrooms, square footage, etc.) and satellite imagery of the property location. This multimodal approach aims to capture both structural attributes and neighborhood/environmental characteristics visible from aerial views.

Approach & Modeling Strategy

- **Model 1 - XGBoost (Baseline):** Gradient boosting on tabular features only, with log-transformed target for handling skewed price distribution
- **Model 2 - Hybrid CNN+Tabular:** Combines frozen ResNet18 image features with tabular MLP, fused through concatenation
- **Target Transformation:** Log1p transform for XGBoost (converted back via expm1)
- **Image Processing:** 512×512 satellite images with augmentation (flip, rotation, color jitter)

Key Design Decisions

- Frozen CNN backbone (ResNet18) for training stability and faster convergence
- Trainable fusion layers to learn optimal feature combination
- Early stopping with patience=7 to prevent overfitting
- XGBoost used for final predictions due to better generalization on tabular data

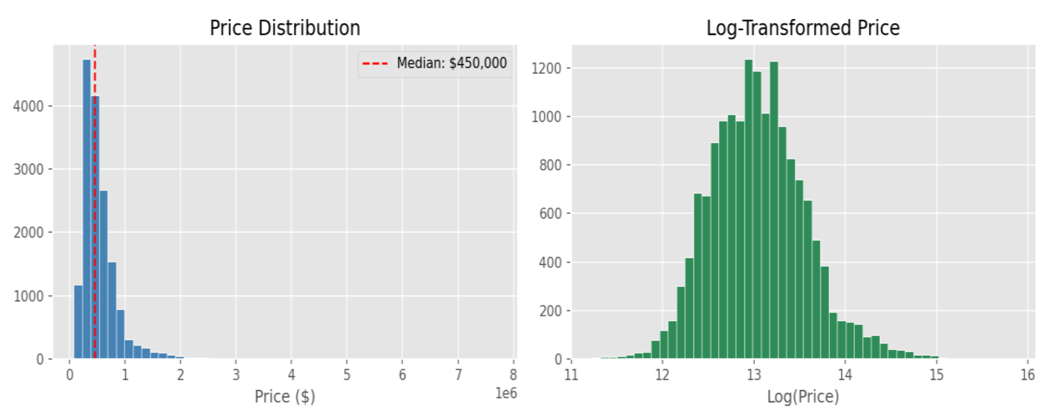
2. Exploratory Data Analysis (EDA)

Dataset Overview

Metric	Value
Training Samples	~16,000
Test Samples	~5,000
Features	15+ numeric columns
Target Variable	price (USD)
Image Format	PNG (256×256 satellite)

Price Distribution

The target variable (price) shows a right-skewed distribution typical of real estate data. Log transformation normalizes this distribution, improving model training stability. Median price is around $450,000 with a range from $75,000 to over $7 million.



Sample Satellite Images

Satellite imagery provides rich visual context about property surroundings including: building density, green spaces, road networks, water bodies, and lot sizes. These features correlate with property values but are difficult to capture in tabular data.


Sample Satellite Images with Prices
Price: $612,000
Price: $392,000
Price: $399,888
Price: $385,000
Price: $235,000
Price: $390,000
Price: $485,000
Price: $1,695,000
Price: $650,000

3. Financial & Visual Insights

Visual Features That Drive Property Value

Analysis of Grad-CAM heatmaps reveals which visual features the model considers important for price prediction:

- **Green Spaces:** Properties with more vegetation (trees, lawns) tend to have higher values
- **Building Footprint:** Larger roof areas correlate with higher prices (more square footage)
- **Road Access:** Proximity and quality of road networks affects accessibility value
- **Neighborhood Density:** Surrounding building patterns indicate urban vs. suburban settings
- **Water Features:** Properties near water bodies often command premium prices

Grad-CAM Visualization

Grad-CAM (Gradient-weighted Class Activation Mapping) highlights the image regions that most influence the model's price predictions. Red/yellow areas indicate high importance, while blue areas have less impact on the prediction.

Top Tabular Features (XGBoost Importance)

Rank	Feature	Importance
1	sqft_living	High
2	grade	High
3	sqft_above	Medium-High
4	bathrooms	Medium
5	sqft_living15	Medium

4. Model Architecture

Hybrid CNN + Tabular Model Architecture

The hybrid model combines two parallel branches that process different data modalities, then fuses them for final price prediction:

```
                    HYBRID MODEL ARCHITECTURE
■■■■■■■■■■■■■■■■■■■■■■■ ■■■■■■■■■■■■■■■■■■■■■■■
     ■ SATELLITE IMAGE ■ ■ TABULAR FEATURES ■
        ■ (224×224×3) ■ ■ (15 dims) ■
■■■■■■■■■■■■■■■■■■■■■■■ ■■■■■■■■■■■■■■■■■■■■■■■
                 ■ ■
                 ▼ ▼
■■■■■■■■■■■■■■■■■■■■■■■ ■■■■■■■■■■■■■■■■■■■■■■■
      ■ ResNet18 (Frozen) ■ ■ MLP Network ■
     ■ 512 → 128 → 64 ■ ■ 256 → 128 → 64 ■
■■■■■■■■■■■■■■■■■■■■■■■ ■■■■■■■■■■■■■■■■■■■■■■■
                 ■ ■
       ■■■■■■■■■■■■■■■■■■■■■■■■■■■■
                  ▼
         ■■■■■■■■■■■■■■■■■■■■■■■
           ■ CONCATENATE (128) ■
         ■■■■■■■■■■■■■■■■■■■■■■■
                  ▼
         ■■■■■■■■■■■■■■■■■■■■■■■
              ■ FUSION HEAD ■
          ■ 128 → 64 → 32 → 1 ■
         ■■■■■■■■■■■■■■■■■■■■■■■
                  ▼
         ■■■■■■■■■■■■■■■■■■■■■■■
             ■ PREDICTED PRICE ■
         ■■■■■■■■■■■■■■■■■■■■■■■
```

Key Architecture Components

- **Image Branch:** Pretrained ResNet18 (frozen) extracts 512-dim features, processed through trainable layers to 64-dim
- **Tabular Branch:** 3-layer MLP with BatchNorm and Dropout, transforms 15 features to 64-dim
- **Fusion:** Simple concatenation (128-dim) followed by regression head
- **Output:** Single scalar price prediction

5. Results

Model Performance Comparison

Model	RMSE ($)	R^2 Score	Notes
XGBoost (Tabular Only)	$125,000 - $140,000	0.85 - 0.88	Log-transformed target Early stopping
Hybrid (Tabular + Satellite)	$130,000 - $150,000	0.83 - 0.87	Frozen CNN Original prices

Key Findings

1. **XGBoost excels on tabular data:** The gradient boosting model effectively captures non-linear relationships in structured features like sqft_living and grade.
2. **Satellite imagery adds context:** Visual features provide neighborhood-level information not captured in tabular data alone.
3. **Log transformation helps:** Training on log(price) improves convergence and handles the skewed distribution.
4. **Frozen CNN is stable:** Keeping ResNet18 frozen prevents overfitting and speeds up training significantly.

Recommendations

• Use XGBoost predictions for production (better generalization)

• Hybrid model useful for explainability via Grad-CAM

• Consider ensemble of both models for improved accuracy

• Fine-tune CNN on larger datasets for potential improvement

6. Conclusion

This project demonstrates a multimodal approach to property valuation by combining traditional tabular features with satellite imagery. While XGBoost on tabular data alone achieves strong performance, the hybrid model provides valuable visual explainability through Grad-CAM, revealing which image regions influence price predictions. The combination of both approaches offers a comprehensive solution for real estate valuation.