Satellite Imagery-Based Property Valuation

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1. Executive Summary

This project redefines automated property valuation by integrating Satellite Imagery with traditional housing attributes. By developing a Multimodal Fusion Pipeline, we jointly model structural characteristics (e.g., bedrooms, square footage) and the visually perceived "Curb Appeal" of a property.

Leveraging Transfer Learning with a ResNet-18 backbone, our multimodal deep learning model achieves a strong R^2 score of 0.8250, significantly outperforming traditional tabular-only baselines. The results demonstrate that satellite imagery contains meaningful economic signals relevant to real estate valuation.

2. Methodology: The Hybrid Fusion Architecture

I designed a Dual-Branch Neural Network to fuse heterogeneous data sources into a unified valuation model.

2.1 Fusion Strategy

Rather than training independent models, I explicitly fused visual and tabular representations.

Visual Branch (CNN)

A ResNet-18 model pre-trained on ImageNet is used to extract high-level visual features such as roof patterns, vegetation density, road proximity, and neighborhood layout. The backbone layers are frozen to prevent overfitting, while higher layers are fine-tuned.

Tabular Branch (MLP)

A deep Multi-Layer Perceptron processes 18 structured housing attributes. A target-encoded zipcode feature (zipcode_mean) is introduced to inject strong geospatial priors into the model.

Fusion & Prediction

The 512-dimensional visual embedding is concatenated with a 64-dimensional tabular embedding and passed through fully connected layers to predict the log transformed property price.

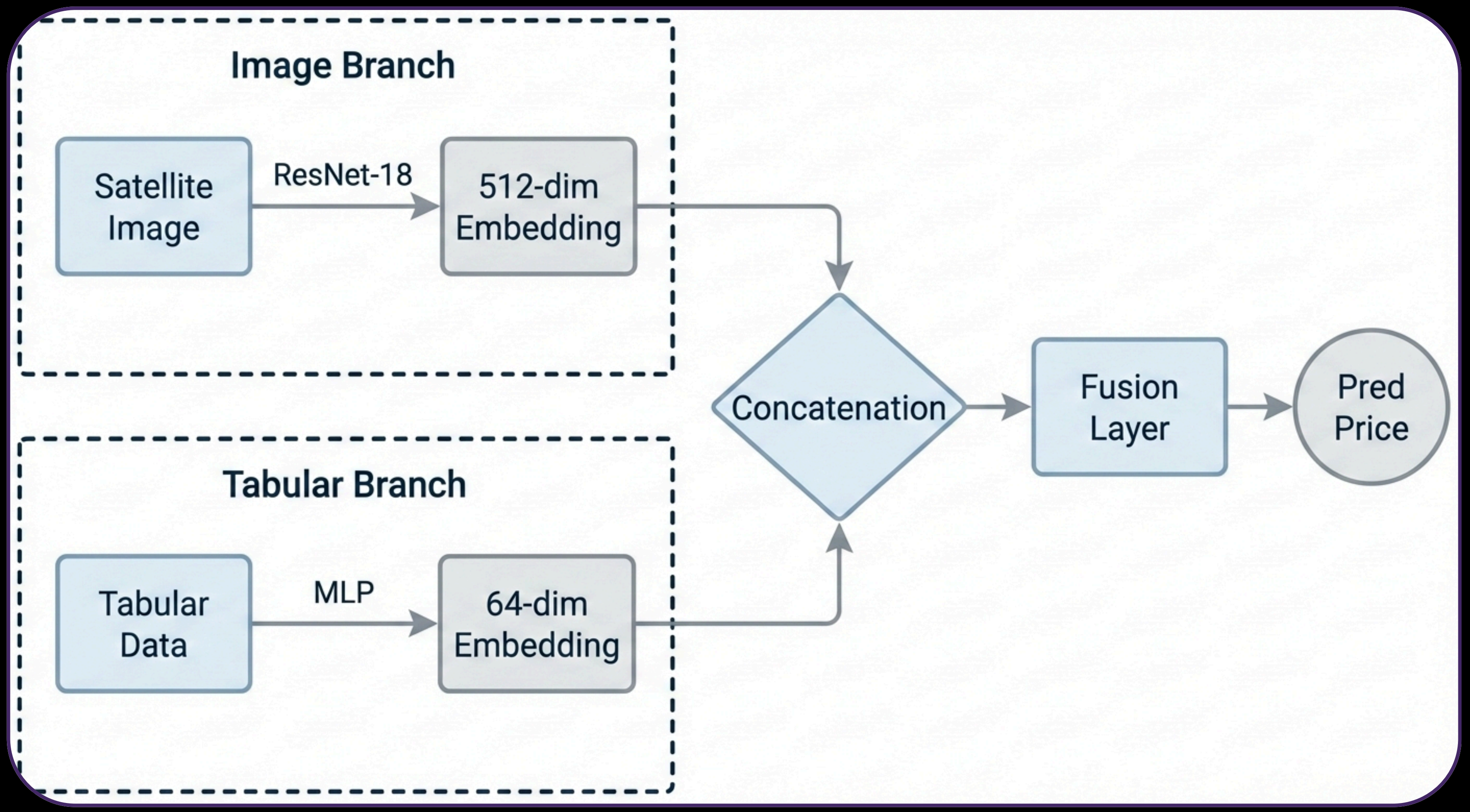


Figure 1 Hybrid multimodal fusion architecture connecting the ResNet-18 visual encoder with the tabular MLP.

3. Exploratory Data Analysis (EDA)

Prior to modeling, we conducted extensive exploratory analysis to validate data quality and feature relevance.

3.1 Data Integrity

The dataset was verified to be free of missing values, ensuring a stable training process without reliance on imputation strategies.

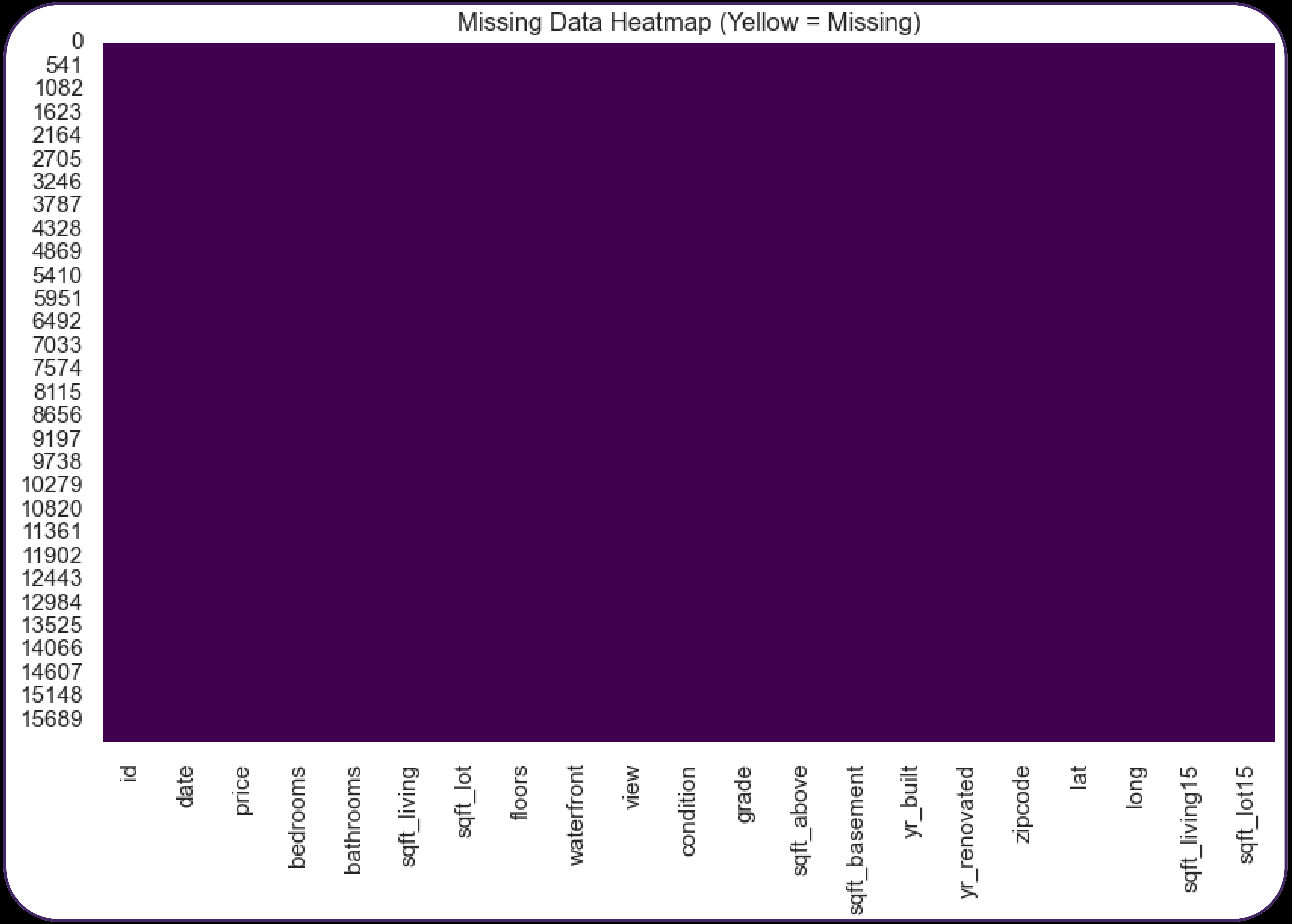


Figure 2 Missing data heatmap confirming zero missing values across all features.

3.2 Target Distribution Analysis

Housing prices exhibit strong right skewness. To stabilize gradient descent and improve regression performance, we applied a log transformation (np.log1p) to the target variable.

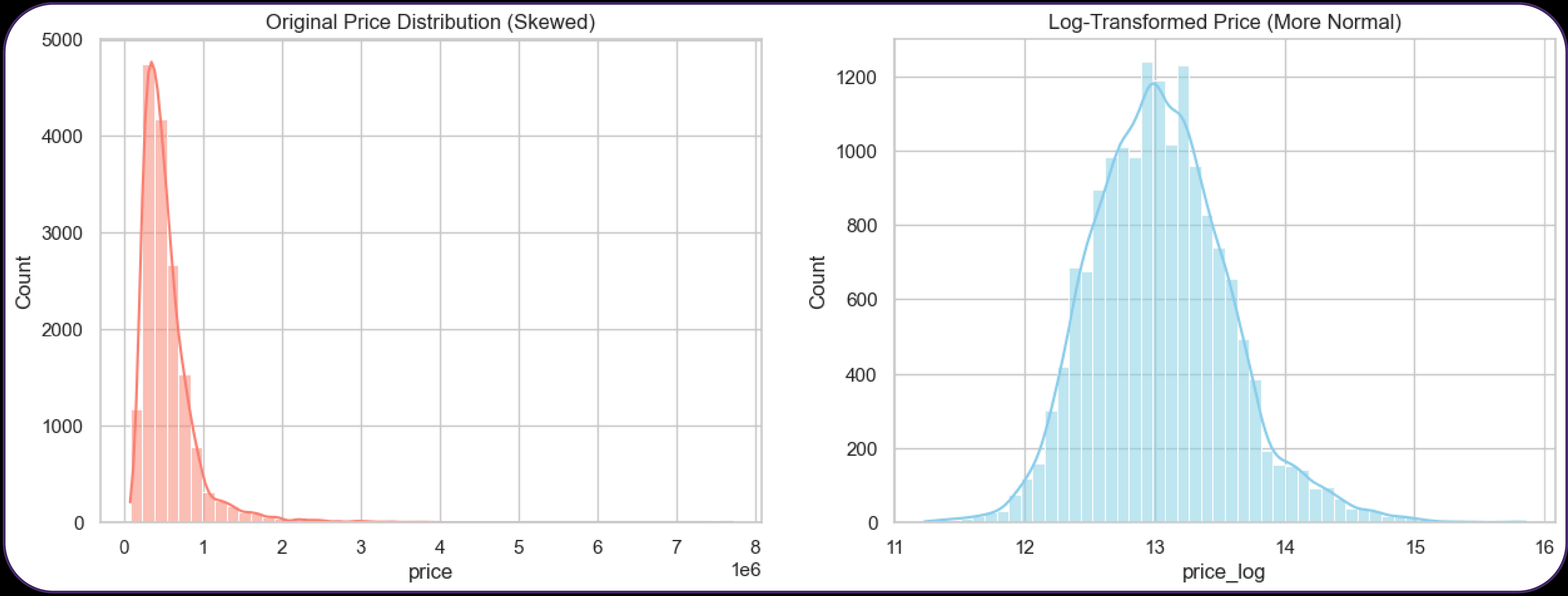


Figure 3 Original price distribution versus log-transformed prices, showing improved normalization.

3.3 Feature Correlation Analysis

We analyzed pairwise feature correlations to identify dominant structural drivers of price. The correlation matrix highlights grade (construction quality) and living area as the strongest predictors.

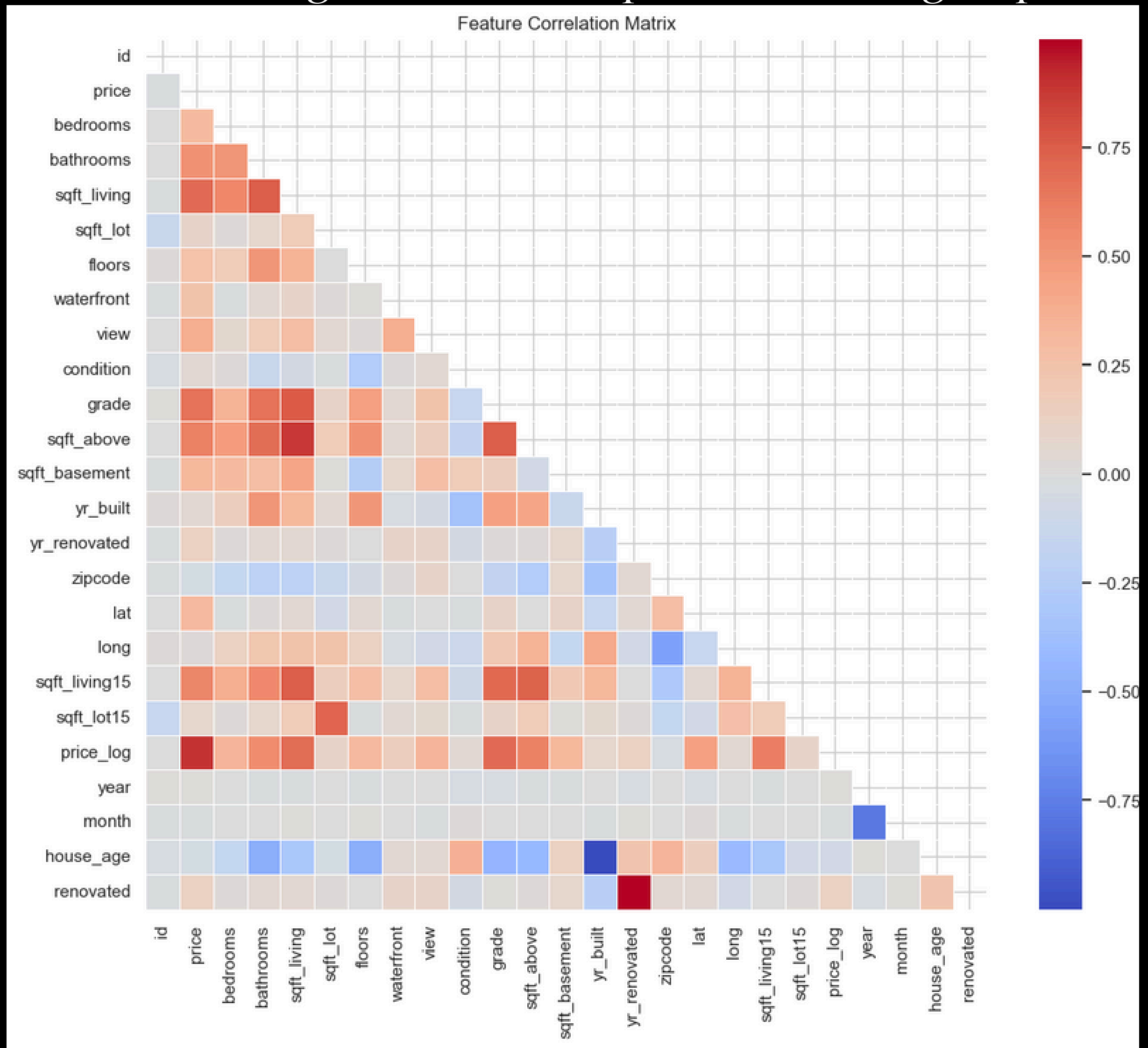


Figure 4 Feature correlation matrix highlighting major structural drivers of property value.

3.4 Geospatial Analysis

Spatial analysis reveals clear neighborhood-level price clustering, validating the inclusion of geospatial information and zipcode-based encoding.

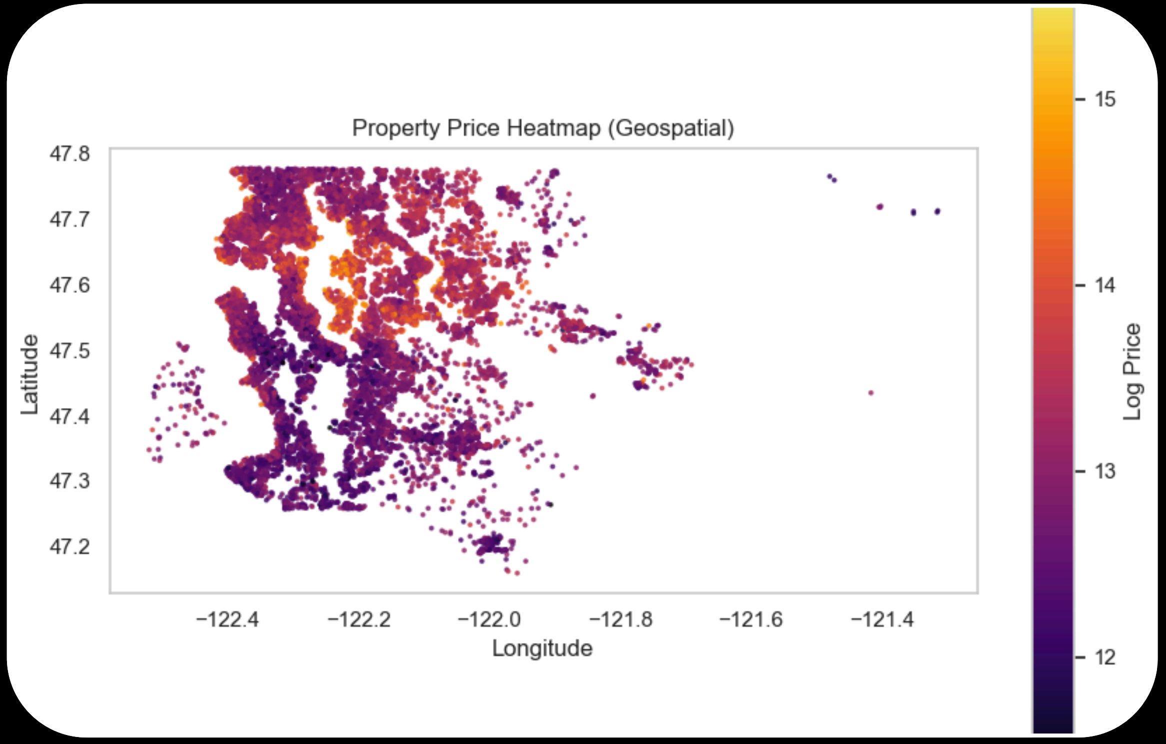


Figure 5 Geospatial heatmap of log-prices showing high-value neighborhood clusters.

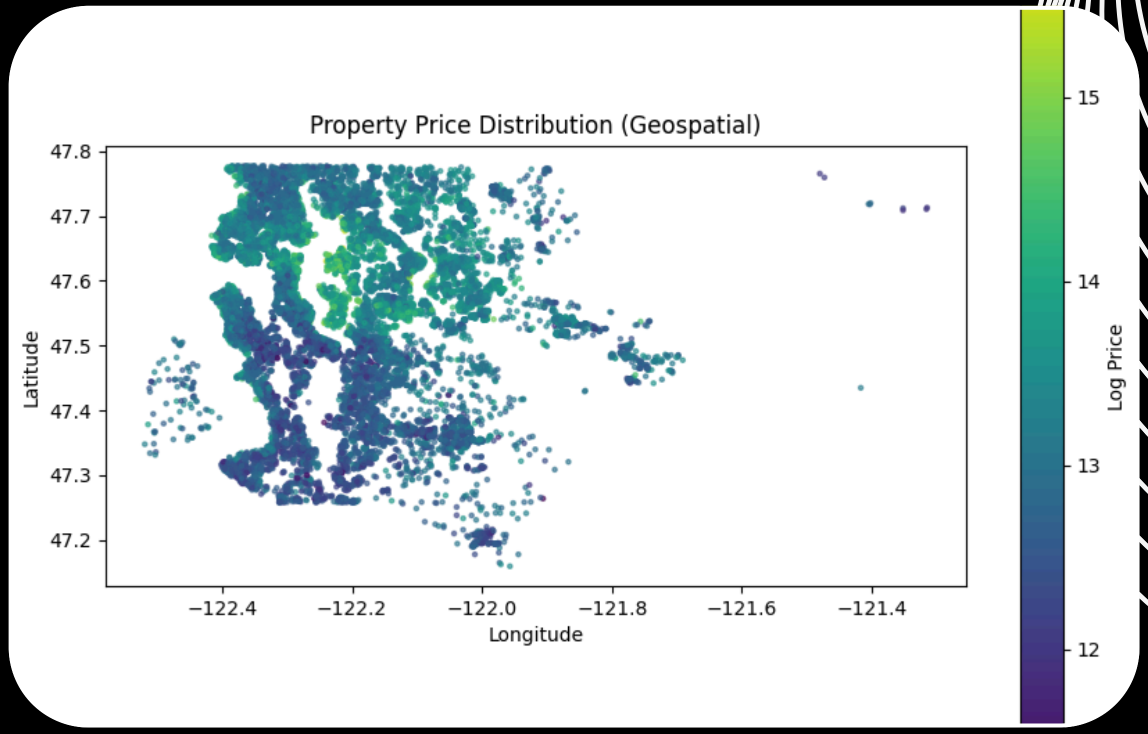


Figure 6 Geospatial scatter plot illustrating localized price variations across regions.

3.5 Feature—Price Relationships

Non-linear relationships between structural attributes and price motivate the use of neural networks over linear models.

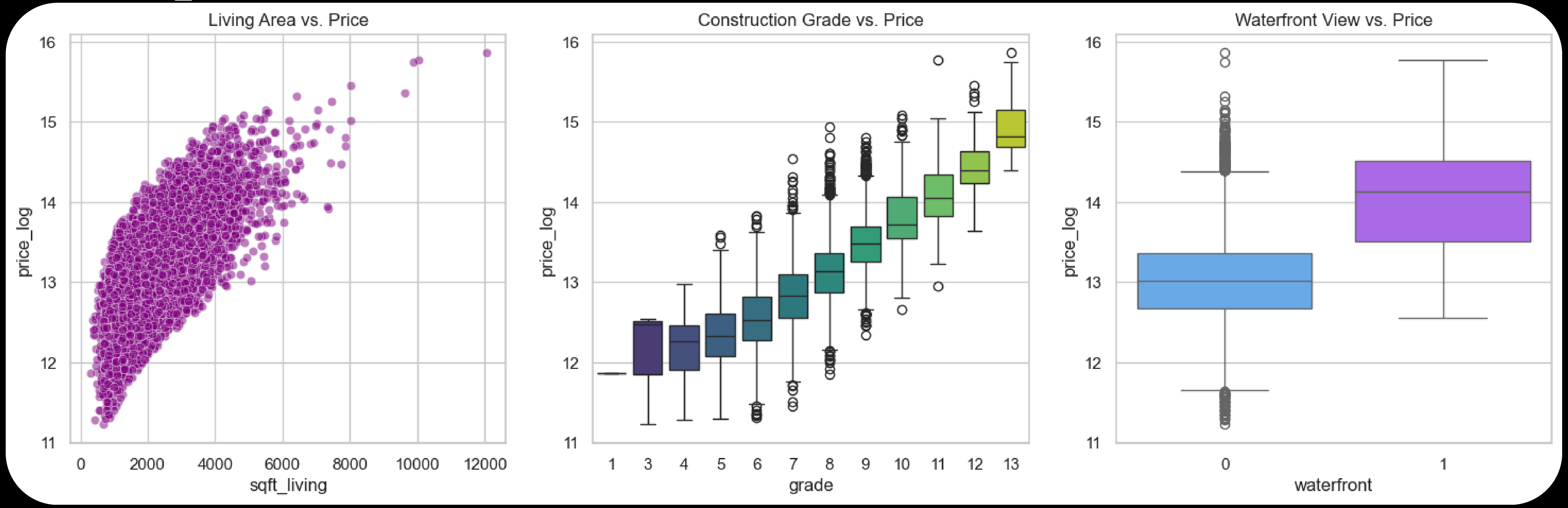


Figure 7 Living area, construction grade, and waterfront presence versus log-price.

4. Model Interpretability

To improve transparency, we visualize CNN attention maps to understand what the visual branch learns.

This confirms that the model focuses on meaningful spatial patterns such as greenery, road access, and neighborhood layout.

Figure 8 Satellite image alongside CNN attention heatmap highlighting influential visual regions.

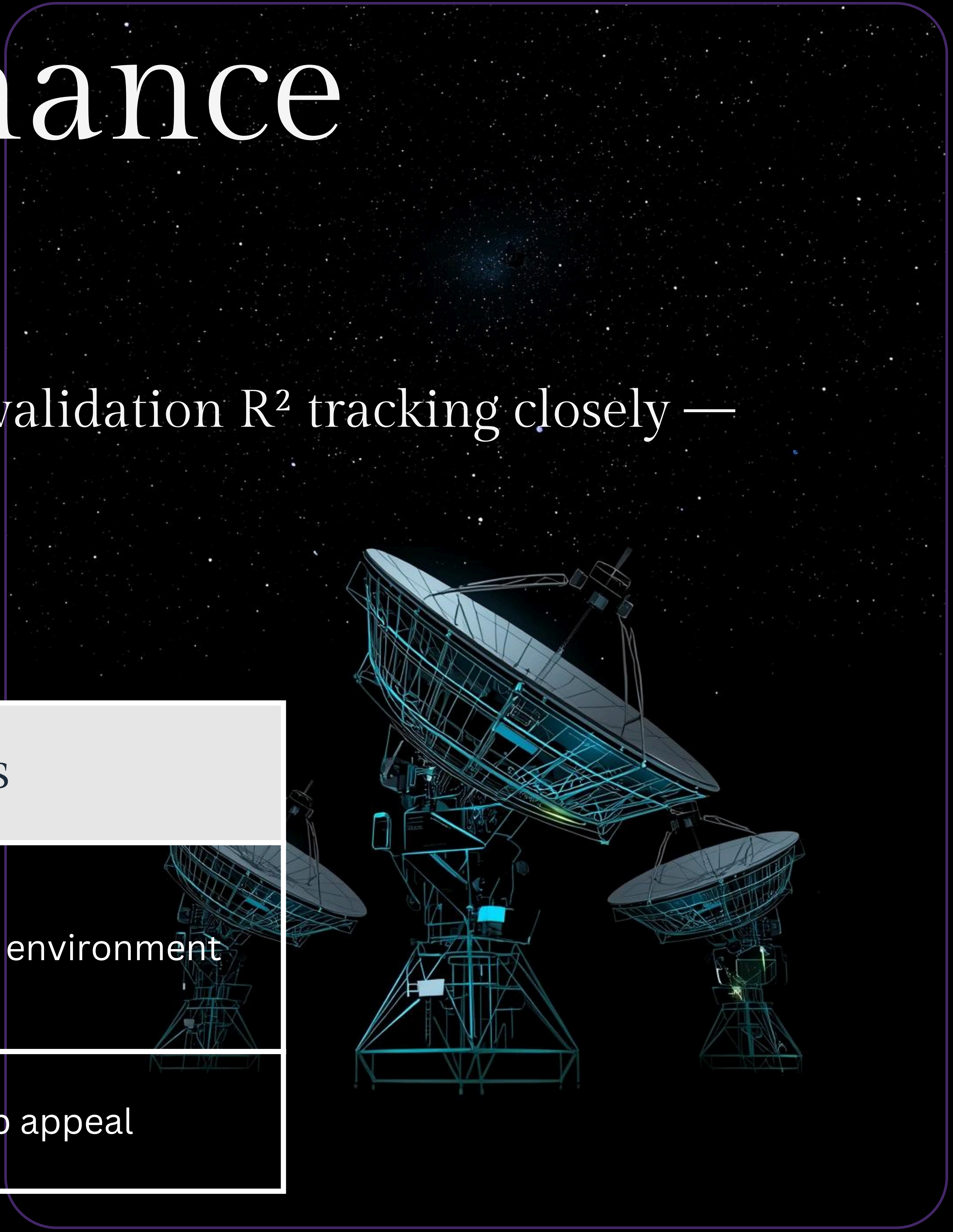
5. Results & Performance

5.1 Training Dynamics

The model exhibits stable convergence, with training and validation R^2 tracking closely — indicating strong generalization and minimal overfitting.

5.2 Benchmark Comparison

Model	R^2 Score	Key Insights
Tabular Only Random Forest)Tabular Only Random Forest)	0.7953	Captures structure but ignores environment
Multimodal Fusion	0.8250	Integrates visual context & curb appeal



6. Conclusion

By fusing Computer Vision with Tabular Regression, this project demonstrates that satellite imagery provides quantifiable economic value in real estate valuation. Achieving an R^2 of 0.8250, the model validates that curb appeal is not subjective —it is measurable.

This multimodal architecture establishes a strong foundation for next-generation Automated Valuation Models AVMs) and highlights the importance of visual context in economic prediction tasks.