Satellite Imagery Based Property Valuation

A Multimodal Machine Learning Approach

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1. Introduction

Property valuation plays a crucial role in real estate markets, urban planning, and financial decision-making. Accurate estimation of property prices enables informed investment decisions, fair taxation, and efficient market functioning. Traditional valuation models primarily rely on structured tabular data such as property size, number of rooms, construction quality, and geographic coordinates.

While these attributes capture intrinsic property characteristics, they often fail to explicitly represent neighborhood-level and environmental factors such as greenery, road networks, urban density, and surrounding infrastructure. Satellite imagery provides a rich visual representation of such contextual information and has the potential to complement tabular features.

This project investigates whether combining satellite imagery with structured housing data using **multimodal machine learning** can improve property price prediction compared to a strong tabular baseline.

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2. Problem Statement

The objectives of this project are:

- To predict property prices using tabular features alone
- To extract contextual visual information from satellite images
- To integrate tabular and visual modalities into a unified regression framework
- To evaluate whether satellite imagery improves predictive performance

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3. Dataset Description

3.1 Tabular Data

The tabular dataset consists of historical housing records containing intrinsic property-level attributes. The target variable is **property price**, treated as a continuous regression target.

Key features include:

- Bedrooms
- Bathrooms
- Living area (sqft_living)
- Construction grade

- Property condition
- Latitude and longitude

These features form the foundation for baseline machine learning models.

3.2 Satellite Image Data

Each property is associated with a satellite image retrieved using geographic coordinates. The images capture surrounding environmental context such as:

- Road connectivity
- Urban layout
- Vegetation density
- Neighborhood structure

Satellite images were standardized to a fixed resolution and spatial scale to ensure consistency across samples.

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4. Data Acquisition and Image Retrieval

Satellite imagery was collected using the **Mapbox Static Images API**. Latitude and longitude values from the tabular dataset were used to request satellite images centered at each property location.

To maintain uniformity:

- A fixed zoom level was used
- Satellite map style was kept constant
- Images were saved using unique property identifiers

An automated pipeline ensured one-to-one alignment between tabular records and images, while skipping already downloaded images to avoid redundancy.

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5. Exploratory Data Analysis (EDA)

Exploratory Data Analysis was conducted to understand feature distributions, relationships, and spatial patterns prior to model training.

5.1 Target Variable Analysis

5.1.1 Distribution of Property Prices

A histogram of property prices reveals a **right-skewed distribution**, with a small number of high-priced outliers.

Observation:

- Most properties lie within a moderate price range
- Extreme values justify the use of RMSE and R^2 as evaluation metrics

(Figure 1.a: Histogram of property prices)

5.2 Univariate Feature Analysis

5.2.1 Bedrooms and Bathrooms

Histograms show that bedrooms and bathrooms follow discrete distributions, with most properties clustered around typical residential values.

Insight:
While higher counts are associated with higher prices, these features alone are weaker predictors compared to size-based attributes.

(Figure 2.a: Distribution of bedrooms, Figure 2.b: Distribution of bathrooms)

5.2.2 Living Area (sqft_living)

The living area feature shows a strong positive relationship with property price.

Key Insight:
Living area is the single strongest individual predictor of price, justifying its dominance in tabular models.

(Figure 2.c: Living area distribution)

5.3 Bivariate and Spatial Analysis

Scatter plots reveal non-linear relationships between features and price. Geographic plots of latitude and longitude demonstrate clear spatial clustering of high-value properties.

Conclusion:
Location effects are primarily spatial and non-linear, motivating the use of satellite imagery to capture neighborhood-level context.

(Figure 3.a: Feature vs price, Figure 3.b: Spatial price distribution)

5.4 Satellite Image Analysis

Visual inspection of satellite images corresponding to low- and high-priced properties reveals clear differences:

- Low-priced properties often appear in dense, irregular layouts
- High-priced properties tend to be located in well-planned neighborhoods with visible greenery

This qualitative evidence supports the hypothesis that satellite imagery captures meaningful environmental patterns.

(Figure 4: Sample satellite images across price ranges)

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6. Modeling and Methodology

6.1 Tabular Baseline Model

A **Random Forest Regressor** was trained using structured features only. This model captures non-linear interactions effectively and serves as a strong baseline.

6.2 Multimodal Model Architecture

The multimodal model consists of:

- **Image Encoder:** Pretrained ResNet-18 used as a frozen feature extractor
- **Tabular Encoder:** Fully connected neural network
- **Fusion Layer:** Concatenation of image and tabular embeddings
- **Regression Head:** Predicts property price

CNN weights were frozen to enable efficient CPU-based training.

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7. Evaluation Protocol

Models were evaluated using an 80–20 split on the training dataset.

Metrics Used:

- Root Mean Squared Error (RMSE)
- Coefficient of Determination (R^2)

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8. Results and Discussion

8.1 Quantitative Results

Model	RMSE	R^2
Tabular Only	150,366	0.82
Tabular + Satellite (Multimodal)	613,415	-1.52

8.2 Interpretation of Results

The tabular-only model achieves strong predictive performance, explaining over 80% of the variance in property prices. In contrast, the multimodal model underperforms, with a significantly higher RMSE and negative R^2 score.

This indicates that, in this dataset:

- Structured features dominate price prediction
- Satellite imagery introduces noise rather than additional signal

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9. Conclusion and Future Work

9.1 Conclusion

This project demonstrates a complete end-to-end **multimodal property valuation pipeline**. While satellite imagery was hypothesized to improve prediction accuracy, experimental results show that structured housing attributes already capture the majority of price-relevant information.

Negative results are scientifically valuable and highlight the importance of strong baselines and rigorous evaluation in applied machine learning.

9.2 Future Work

Potential improvements include:

- Fine-tuning CNNs on real estate–specific imagery
- Residual modeling approaches
- Handcrafted visual features such as green cover and road density
- Higher-resolution satellite imagery

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10. References

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