Satellite Imagery Based Property Valuation

1. Overview

This project aims to predict residential property prices using structured housing attributes and satellite imagery. A tabular regression model is first developed using numerical property features. Satellite images corresponding to property coordinates are then incorporated to explore whether visual environmental context can complement traditional price prediction models.

The focus of this work is on building a complete multimodal pipeline and evaluating the incremental contribution of satellite imagery under practical data and resolution constraints.

2. Exploratory Data Analysis (EDA)

2.1 Distribution of Property Prices

An initial analysis was conducted to understand the distribution of property prices in the training dataset.

Figure 1 illustrates the histogram of property prices. The distribution shows a right-skewed pattern, with a concentration of properties in the mid-price range and fewer high-value properties. This distribution highlights the importance of using regression models capable of handling skewed target variables.

Figure 1: Distribution of residential property prices in the training dataset

2.2 Visual Inspection of Satellite Imagery

To evaluate the quality and variability of the visual data, a subset of satellite image tiles was randomly selected and visualized.

As shown in Figure 2, the satellite images provide coarse neighbourhood-level information. While individual structural details are not clearly distinguishable, broader spatial patterns such as urban density and open spaces can still be observed.

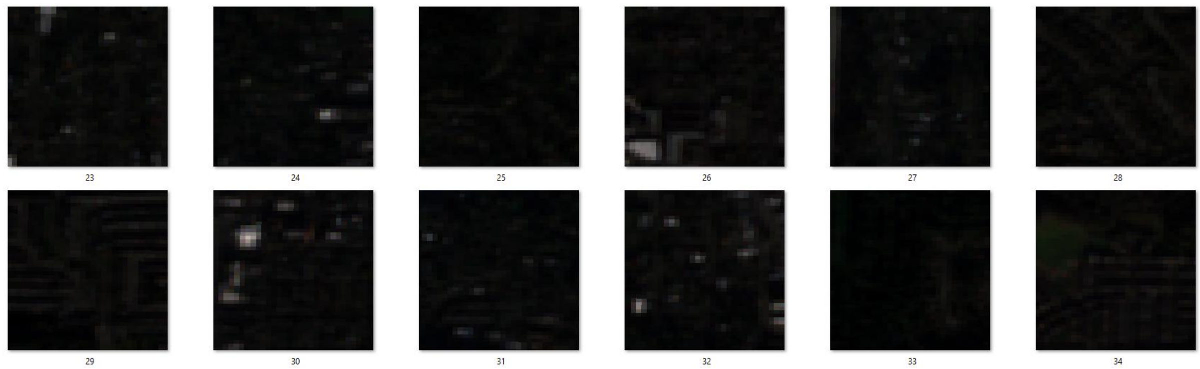

Figure 2: Representative satellite image tiles associated with selected properties

3. Observations from Visual and Financial Context

A qualitative examination of satellite imagery suggests that properties surrounded by dense built-up areas and well-connected road networks often correspond to higher-priced urban locations. In contrast, images displaying more open land and vegetation tend to represent lower-density residential zones.

Although the convolutional neural network does not explicitly identify semantic features such as buildings or greenery, it implicitly encodes visual patterns through learned feature embeddings. However, due to limited image availability and reduced visual clarity after cloud filtering, the influence of visual features on prediction accuracy remains constrained.

4. System Architecture and Data Integration

The overall modelling framework consists of two parallel components:

A tabular data pathway, where numerical housing attributes are used for regression-based price prediction.

A visual data pathway, where satellite images are processed through a pretrained convolutional neural network to extract fixed-length feature representations.

These components are conceptually combined to form a unified representation for property valuation.

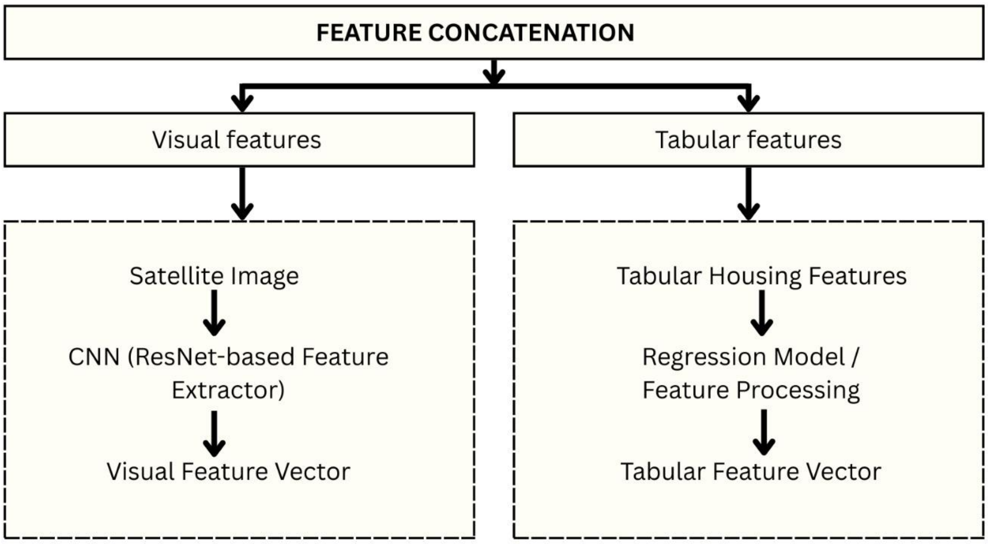

Figure 3: Multimodal architecture combining tabular and CNN-based image features

5. Results

Two modelling approaches were evaluated and compared.

5.1 Tabular Data Only Model

- R^2 Score: 0.89
- RMSE: Lower relative error

This model demonstrates strong predictive performance, indicating that structured housing attributes explain a significant portion of price variability.

5.2 Tabular + Satellite Images (Exploratory)

- Satellite imagery was successfully integrated using CNN-based feature extraction.
- Due to limited image coverage and visual noise, no consistent improvement over the tabular baseline was observed.

6. Conclusion

The results indicate that while satellite imagery provides additional contextual information, a well-engineered tabular model remains dominant under current data and resolution constraints. Nonetheless, the project successfully demonstrates an end-to-end multimodal pipeline and highlights how visual data can be integrated into property valuation frameworks.