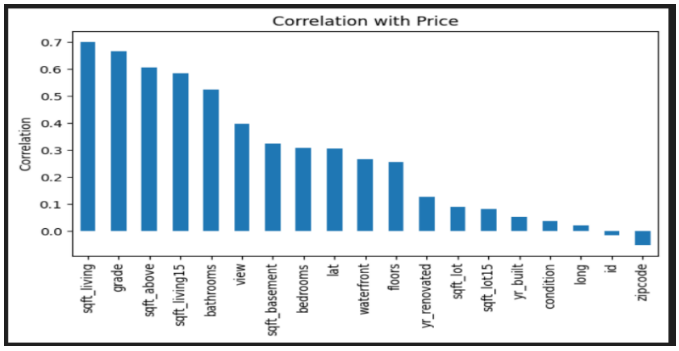
1. Introduction

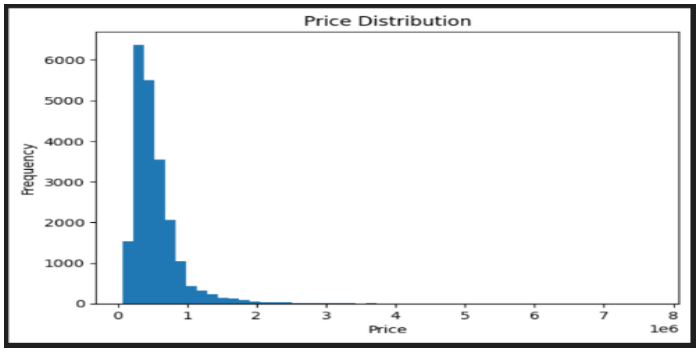
Property valuation is a complex task influenced by both **internal house attributes** and **external environmental factors**. Traditional machine learning models rely heavily on structured numerical features such as square footage, number of bedrooms, and location coordinates. However, these features alone often fail to capture neighbourhood characteristics like road layout, greenery, and urban density.

This project presents a **multimodal deep learning framework** that combines **tabular property data** with **satellite imagery** to predict house prices more accurately. By integrating visual context with numerical attributes, the model achieves improved performance and better real-world interpretability.

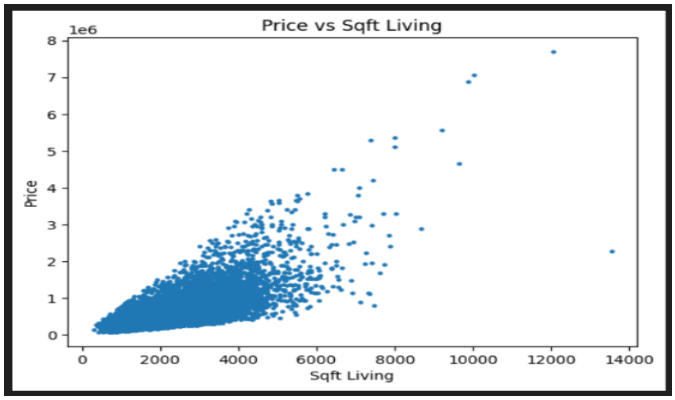
2. Exploratory Data Analysis (EDA)



This chart shows that features like sqft_living, grade, and bathrooms have the strongest positive influence on house prices.

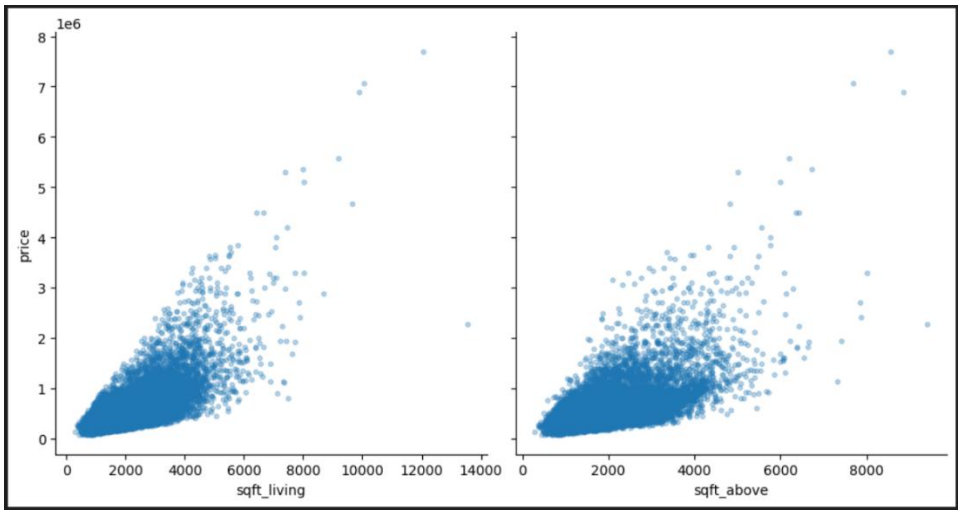


House prices are highly right-skewed, indicating the presence of a few very high-value properties.

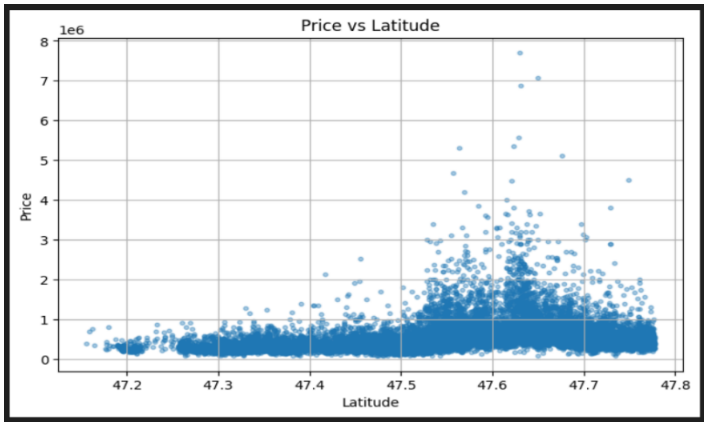


House prices generally increase with larger living area, though variability rises for bigger homes.

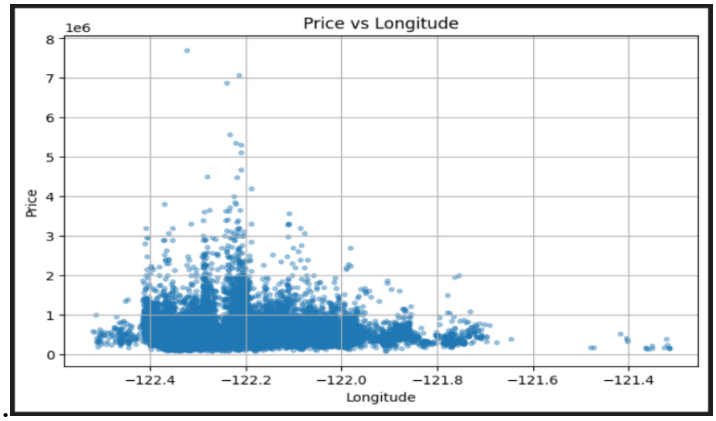
Predicted prices closely follow actual prices, indicating good overall model performance.



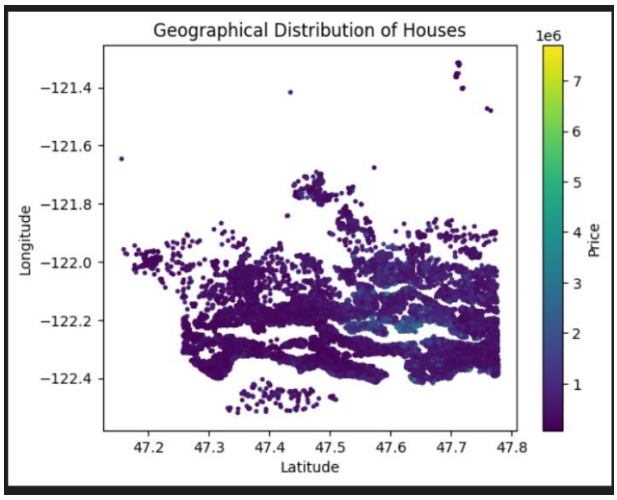
Above-ground living space shows a strong positive relationship with property price.



Certain latitude ranges correspond to higher house prices, highlighting location-based price variation

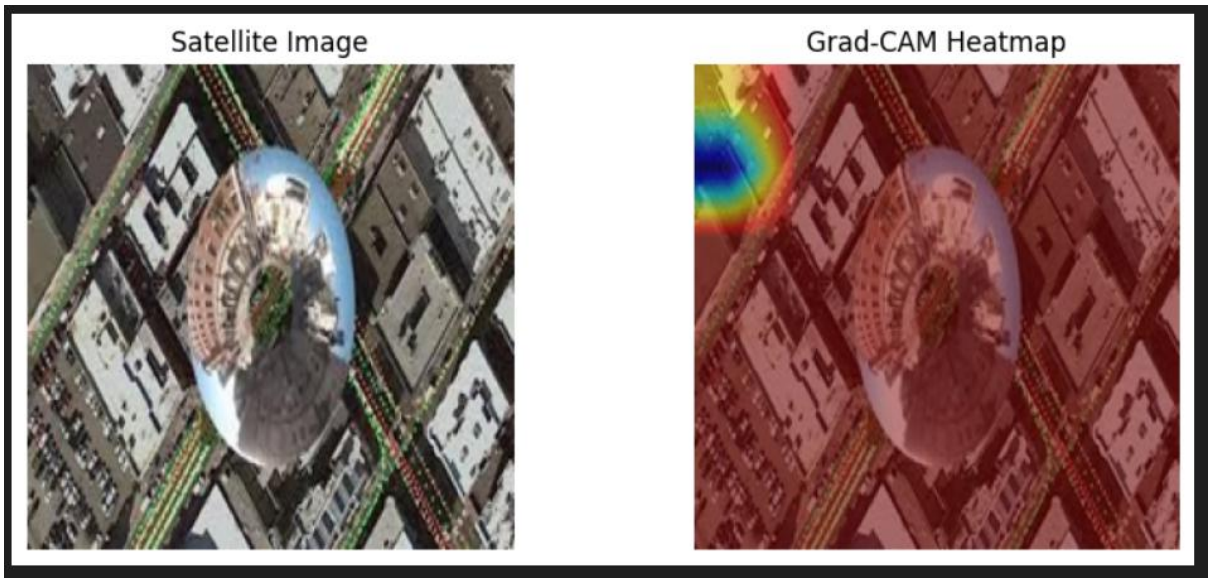


Price clustering across longitudes confirms the strong influence of geographical location on property value.



This plot shows the spatial distribution of houses, with higher-priced properties concentrated in specific latitude–longitude regions, highlighting strong location-based price patterns.

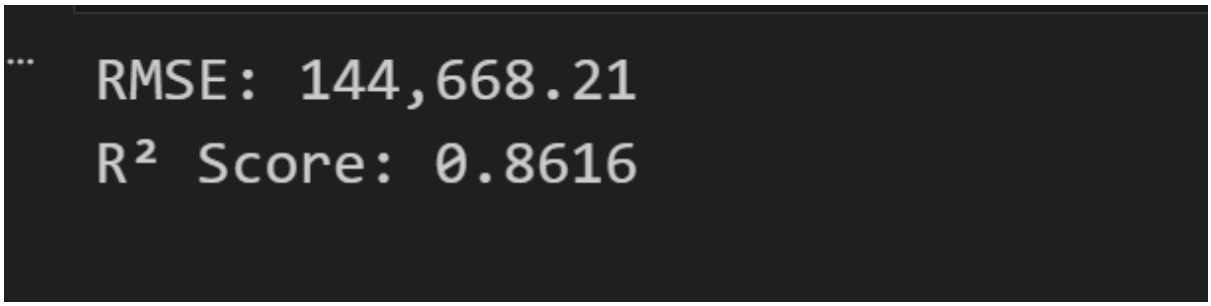
3. Grad-CAM Output



The Grad-CAM heatmap highlights surrounding roads, building density, and neighbourhood structure as the most influential regions affecting the model's price prediction.

4. **R^2 and RMSE :**

- **RMSE: 144,668.21**
- **R^2 Score: 0.8616**



Overall, the results demonstrate that combining tabular features with spatial visual information enables more interpretable and location-aware property price prediction.