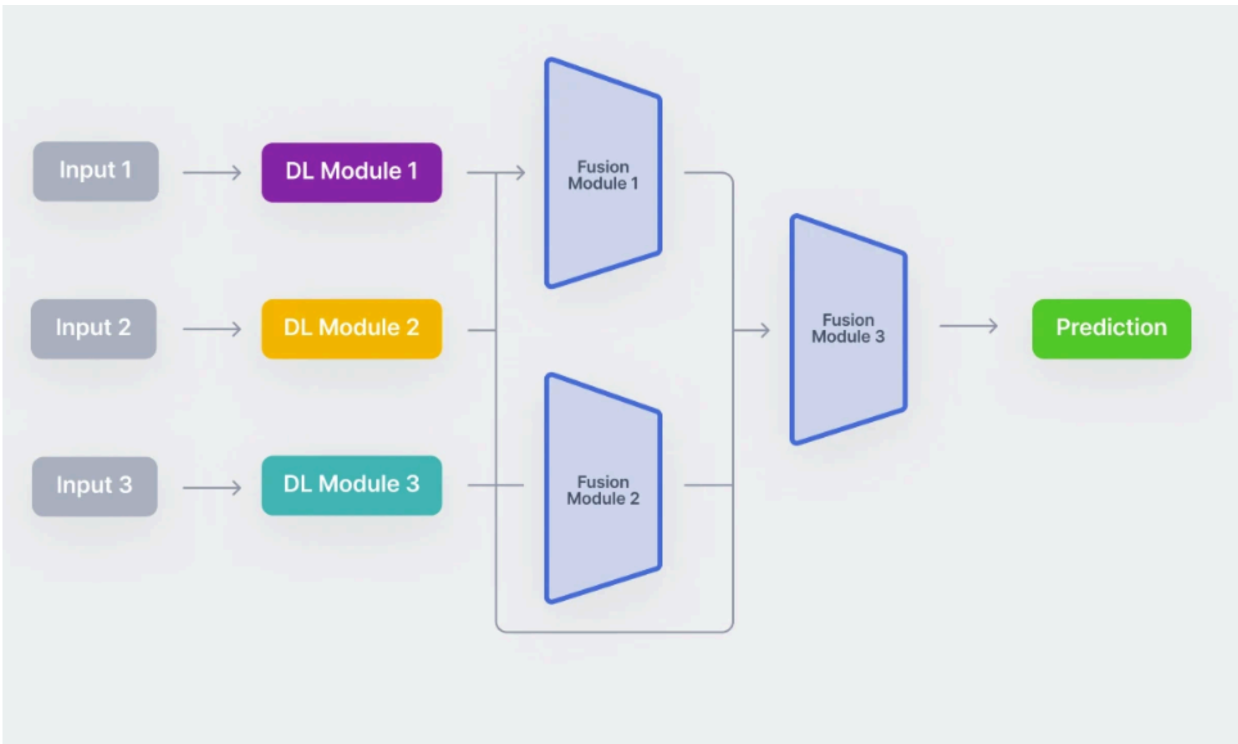
SATTELITE-Property Valuation



Introduction

Property price prediction is a key task in real estate analysis. Most traditional models rely only on structured data such as number of bedrooms, bathrooms, size of the house, and geographic coordinates. Although these features are important, they do not fully describe the surrounding environment of a property.

Recent advances in satellite imagery make it possible to capture visual information about neighborhoods, road patterns, greenery, and nearby infrastructure. Such visual cues can strongly influence property prices but are often ignored in tabular-only models.

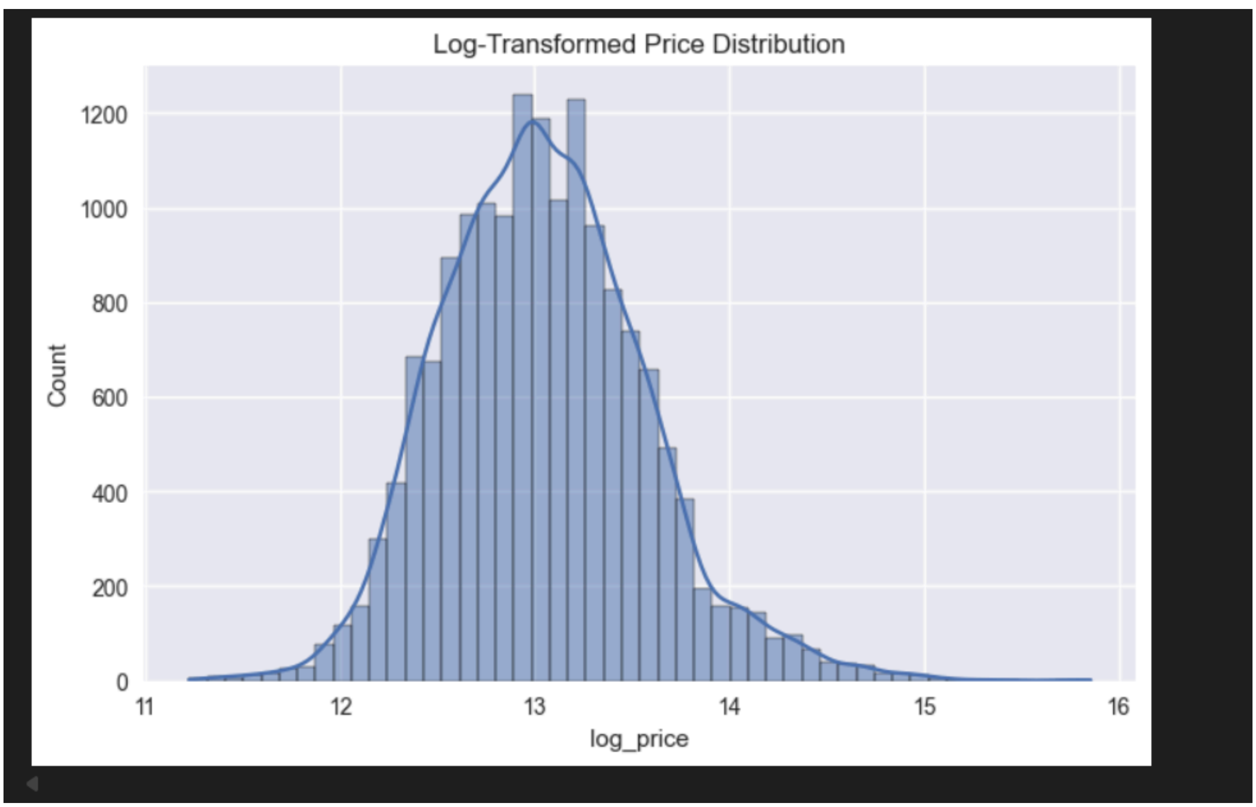
In this project, we propose a **multimodal learning approach** for property valuation by combining **tabular features** with **satellite image features**. A baseline regression model is trained using only tabular data. Later, satellite image features extracted using a deep learning model are fused with tabular features to build a multimodal prediction model.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to understand the distribution of property prices, geographical patterns, and the relationship between different features before building the prediction models. Visualizations were used to identify trends, variations, and potential anomalies in the dataset

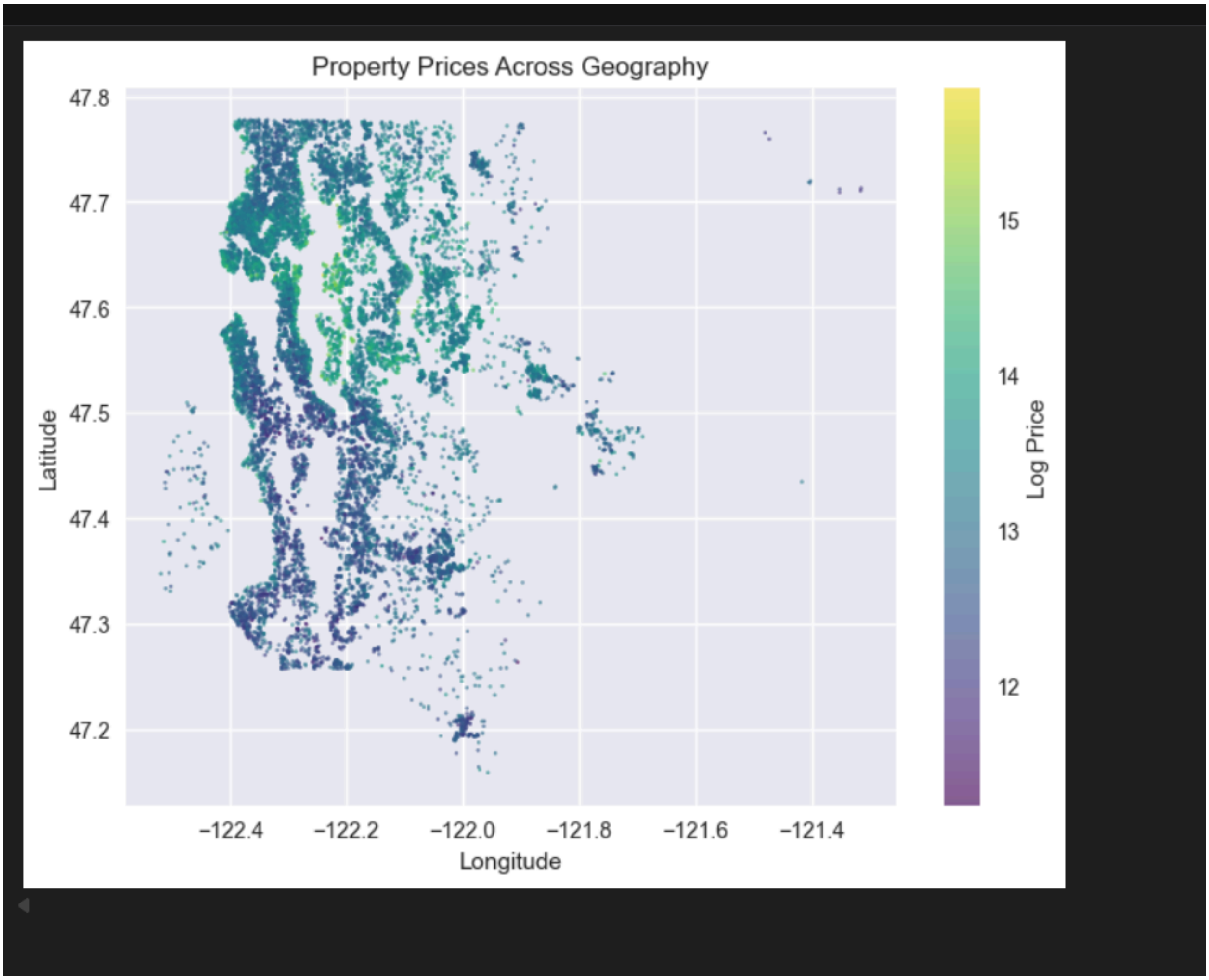
Price Distribution Analysis

The raw property prices showed a skewed distribution with a long tail for high-value properties. To reduce skewness and stabilize variance, a **log transformation** was applied to the price variable. This resulted in a more normalized distribution, making it suitable for regression modeling.



Geographic Distribution of Properties

To analyze spatial trends, property locations were plotted using latitude and longitude values. The color intensity represents the log-transformed property prices. This visualization highlights how property prices vary across different regions and clusters.

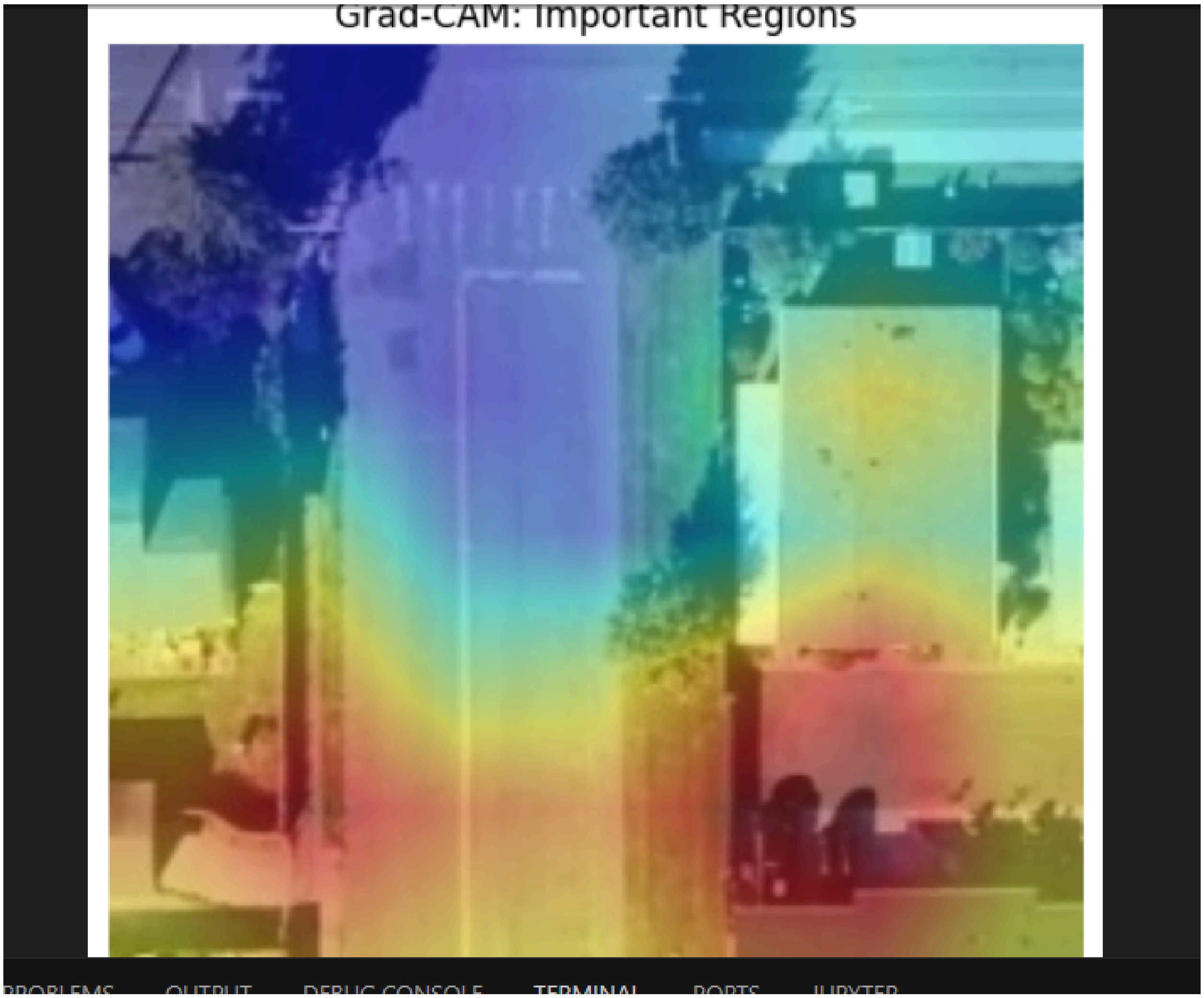


Satellite Image Samples

Sample satellite images were visualized to understand the visual diversity in the dataset. These images capture differences in neighborhood structure, building density, road layouts, and surrounding greenery, which can influence property prices.

Model Interpretability using Grad-CAM

To interpret the contribution of satellite images in price prediction, Grad-CAM visualizations were generated using a pretrained ResNet model. These heatmaps highlight regions in the satellite images that the model considers important while making predictions, such as buildings, roads, and surrounding areas.



Model Architecture

This project follows a **multimodal learning architecture** that combines information from two different data sources:

Tabular property features

Satellite imagery

Baseline Model (Tabular Only)

The baseline model uses only structured tabular data such as:

1. Number of bedrooms and bathrooms
2. Living area and lot size
3. Floors, condition, grade

4.Latitude and longitude

These features are first standardized using `StandardScaler`. A **Linear Regression** model is then trained to predict the **log-transformed property price**. This model serves as a reference to evaluate the impact of adding satellite image information.

Multimodal Model (Tabular + Satellite Images)

For the multimodal approach, satellite images corresponding to each property are processed using a **pretrained ResNet-18** convolutional neural network. Instead of training the CNN from scratch, it is used as a **feature extractor**, capturing high-level visual features such as building layout, surrounding roads, and neighborhood patterns.

The extracted image features are then concatenated with the tabular features to form a single combined feature vector. This fused feature set is standardized and passed to a **Linear Regression model** for final price prediction.

This architecture allows the model to learn from both **numerical attributes** and **visual context**, improving predictive performance.

Model Evaluation and Results

To evaluate model performance, the dataset was split into training and validation sets. The models were evaluated using **Root Mean Squared Error (RMSE)** and **R^2 score** on the validation set.

Baseline Model Performance

RMSE: 0.2621
R^2 Score: 0.7529

The baseline model captures general pricing trends using tabular features alone. However, it lacks information about the visual and environmental characteristics of properties.

Multimodal Model Performance

RMSE: 0.2404

R^2 Score: 0.7922

The multimodal model shows a clear improvement over the baseline. The lower RMSE indicates better prediction accuracy, and the higher R^2 score suggests that the model explains more variance in property prices.

This improvement demonstrates that **satellite imagery provides valuable additional information** beyond traditional tabular data.

Predicted vs Actual Analysis

A scatter plot of predicted versus actual log prices shows that most predictions lie close to the ideal diagonal line, indicating good model calibration. Some deviations are observed for extremely high-priced properties, which is expected due to market variability.

Interpretability using Grad-CAM

Grad-CAM visualizations were used to interpret the satellite image features learned by the CNN. The highlighted regions often correspond to buildings, roads, and surrounding infrastructure, confirming that the model focuses on meaningful visual patterns relevant to property valuation.

Conclusion

In this project, a multimodal learning framework was developed for satellite imagery–based property price prediction. A baseline regression model using only tabular data was first established, followed by an enhanced multimodal model that integrates satellite image features.

The results clearly show that incorporating satellite imagery improves prediction performance, as reflected by lower RMSE and higher R^2 values. Visual interpretability using Grad-CAM further supports the effectiveness of the image-based features.

Overall, this project demonstrates the potential of **combining structured data with visual information** for real-world regression tasks such as property valuation.

Submitted by

Pranshu Sharma(23118063)