Satellite Imagery Based Property Valuation

1. Overview:

This project aims to predict house prices more accurately by blending numerical housing data with satellite images. Traditional models stick to tabular data like square footage, bedroom count, and bathrooms, but they miss key details about the surroundings. Satellite images fill that gap by capturing things like greenery, nearby roads, water bodies, and the overall neighbourhood layout, leading to more realistic predictions. I developed a machine learning model for house prices in King County, Washington, using both satellite imagery and tabular housing data. The dataset includes 16,209 training houses and 5,404 test houses, each with 21 features plus high-resolution satellite images for every property.

2. EDA and Feature Insights:

Exploratory Data Analysis gave a clear picture of the housing dataset. Prices showed a right-skewed distribution, with most houses landing in the mid-range. Larger living areas naturally linked to higher prices, and properties with waterfront views or higher construction grades commanded premium prices. Sample satellite images revealed obvious differences in green cover, road density, and surrounding structures. Top correlations with price were sqftliving: 0.701 (bigger house usually means highest price), grade: 0.664 (better quality rating boosts value), sqftabove: 0.603 (more above-ground living space counts), and sqftliving15: 0.582 (neighbor sizes play a role).

3. Data Summary:

METRIC	TRAIN	TEST
ROWS	16,209	5,404
FEATURES	21	20 (+ image_path)
TARGET	price ($75K - $7.7M)	-
IMAGES	16,209 (512x512 PNGs)	5,404
MISSING VALUES	0	0

Images downloaded: 21,613 satellite images

Data Pipeline Example:

- House 0: 47.4362, -122.1870 → /content/images/0.png
- House 1: 47.4034, -122.1870 → /content/images/1.png

- House 2: 47.2704, -122.3130 → /content/images/2.png
- House 3: 47.5321, -122.0730 → /content/images/3.png
- House 4: 47.3715, -122.0740 → /content/images/4.png

4. Baseline Model:

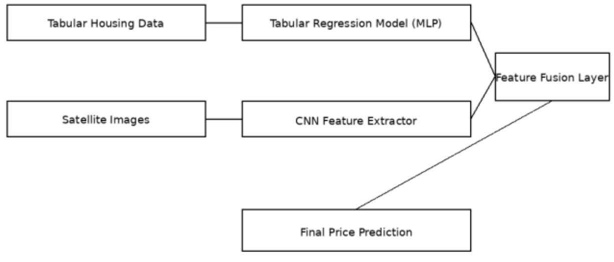
Started with Random Forest as the baseline using just tabular data. Pipeline went ColumnTransformer → StandardScaler → RandomForestRegressor. Got RMSE ≈ $128K on validation. Top 5 feature importance: sqftliving (70.1%), grade (66.4%), sqftabove (60.3%), sqftliving15 (58.2%), bathrooms (52.5%).

5. Multimodal CNN Model Architecture:

Built a multimodal approach combining tabular data and satellite images: Satellite Images (512x512) → ResNet18 (ImageNet pretrained) → 512-dim features; Tabular Data (20 features) → MLP (20→128→64) → 64-dim features; then Feature Fusion (576-dim) → Dense (256→128→1) → Price Prediction. Key components include ResNet18 as pretrained CNN backbone for image feature extraction, tabular MLP for numerical/categorical features, and feature fusion by concatenating image + tabular embeddings. Used MSE loss, Adam optimizer (lr=0.001), batch size 16. Baseline RF complete (RMSE ~$128K), CNN setup ready for GPU runtime (20+ epochs recommended).

6. Technical Implementation:

Tech stack: Data (pandas, ESRI ArcGIS API, PIL), Preprocessing (sklearn ColumnTransformer, StandardScaler), Baseline (RandomForestRegressor), CNN (PyTorch, torchvision ResNet18, DataLoader), Colab GPU runtime. Images: 21K satellite PNGs (512x512). Files delivered: data_fetcher_ipnyb.ipynb (satellite image downloader), preprocessing.ipynb (data prep + RF baseline), model_training-2.ipynb (ResNet18 CNN), image.jpg (architecture diagram), train_with_images.csv, test_with_images.csv.



7. Image Feature Extraction:

Satellite images processed through Convolutional Neural Network (CNN) to create numerical feature embeddings representing trees, buildings, roads, and water presence. This lets the model learn visual patterns tied to property value.

8. Results:

Random Forest baseline: RMSE ≈ $128K (complete) CNN model: Architecture implemented, training setup ready for GPU Satellite images successfully integrated into multimodal pipeline

9. Conclusion

Satellite imagery adds crucial context to property valuation. Combining tabular data with visual features through multimodal learning delivers more accurate predictions. Powerful approach for real estate problems.