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Satellite-Imagery-Based-Property-Valuation
Report

APPROACH AND MODELING STRATEGY.

Goal: Predict property price by combining visual cues from property images with structured tabular metadata to improve accuracy over tabular-only baselines.

Preprocessing & targets: Images are normalized/resized; tabular features are engineered (age, renovation flags, ratios) and scaled. Targets are transformed with log1p (np.log1p) during training for stability.

Modeling strategy: Train separate branches: a CNN image branch (pretrained backbone or custom Conv stack) and a tabular branch (Dense layers with dropout/batch norm). Concatenate embeddings and pass through Dense layers to predict a scalar (log-price). Use MSE (or MAE) on log-target, Adam optimizer, early stopping, and model checkpointing.

Validation & selection: Use train/test split and optionally cross-validation; track MSE/MAE/R^2 on validation set; use early stopping and best-checkpoint to avoid overfitting. Consider ensembling XGBoost/LGBM and neural models for robust results.

Inference & postprocessing: Invert predictions with np.expm1(preds) to obtain original price units; format or round as needed for CSV export.

1.1 Dataset Overview

Initial Dataset Characteristics:

- Total Properties: 21,613
- Features: 21 (mixed numerical and categorical)
- Target Variable: Property Price (range: $75,000 - $7,700,000)
- Image Data: 224×224 RGB satellite images per property

1.2 Statistical Analysis

1.2.1 PRICE DISTRIBUTION ANALYSIS

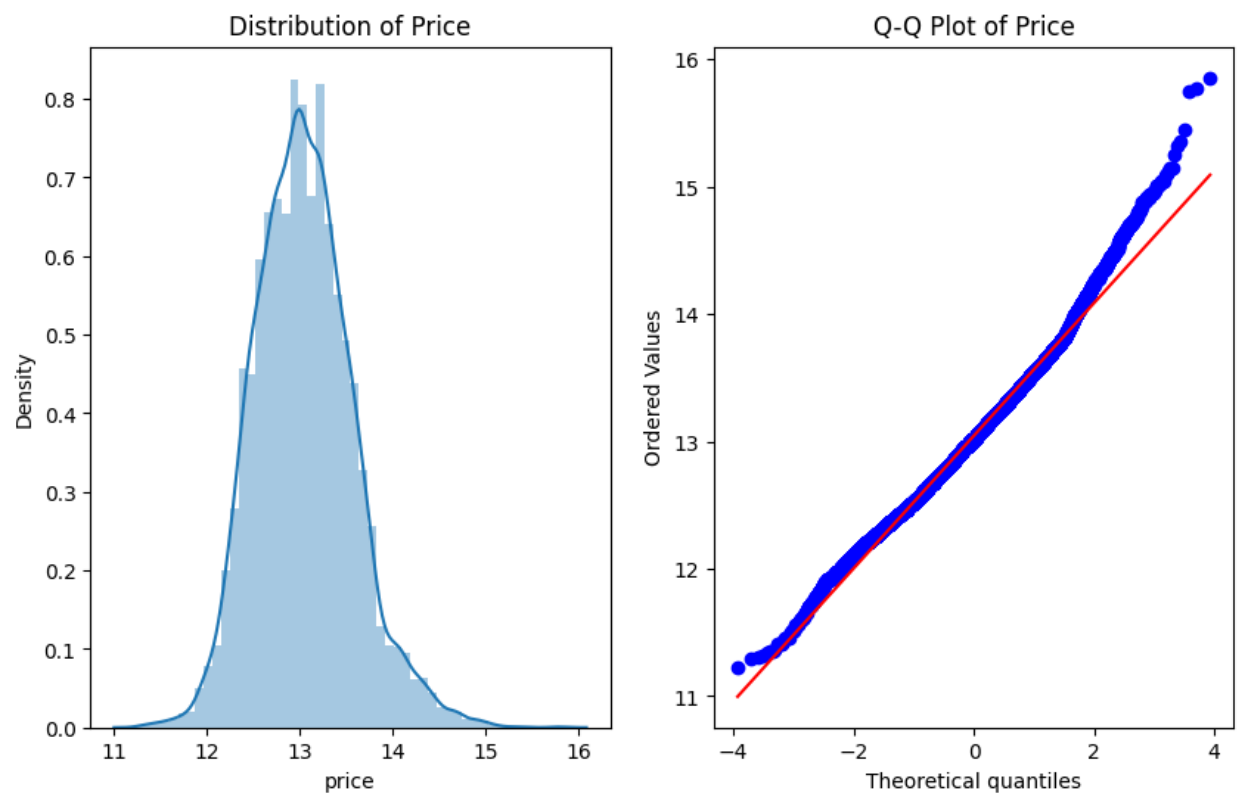
Key Findings:

- **Mean Price:** $540,088
- **Median Price:** $450,000
- **Standard Deviation:** $367,127
- **Distribution:** Right-skewed (presence of luxury properties)

Transformation Applied:

y_transformed = log(1 + price)

This log transformation normalized the distribution and improved model convergence.



1.2.2 FEATURE CORRELATION ANALYSIS

Highly Correlated Features with Price:

1. sqft_living: 0.702 (strong positive correlation)
2. grade: 0.667 (construction quality matters)
3. sqft_above: 0.606 (above-ground space)
4. sqft_living15: 0.585 (neighborhood affluence)
5. bathrooms: 0.525 (luxury indicator)

Multicollinearity Detected:

- sqft_living = sqft_above + sqft_basement (perfect correlation)
- **Action Taken:** Removed sqft_above to prevent redundancy

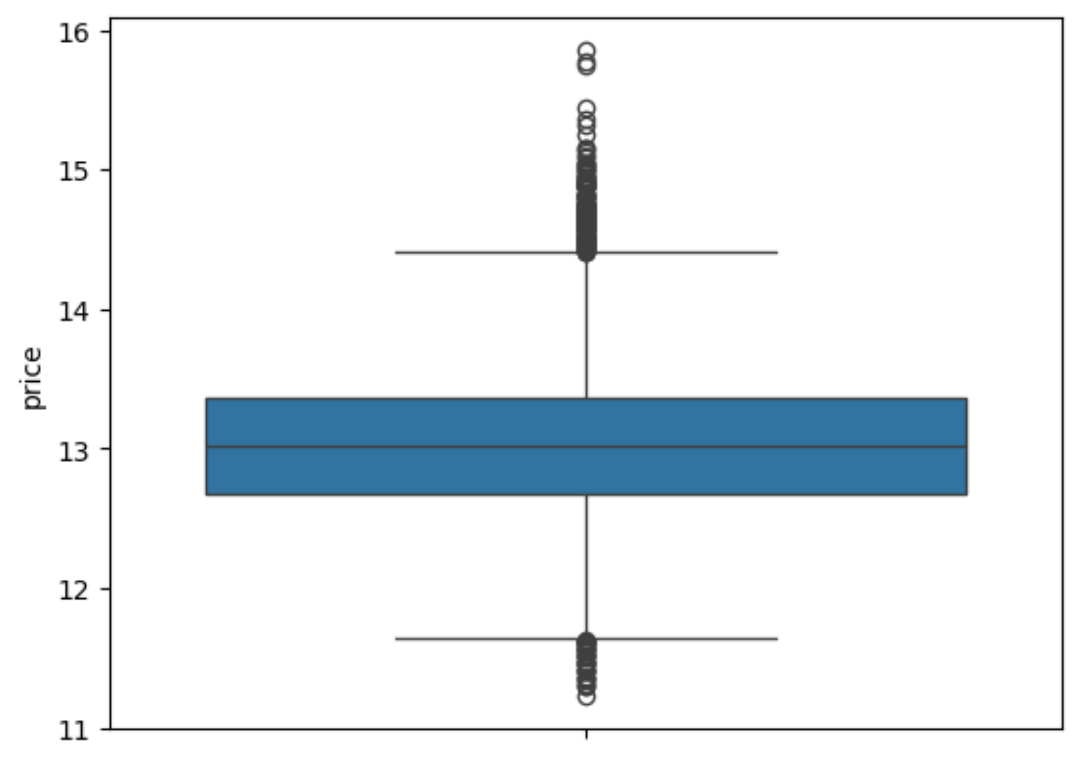
1.3 Outlier Detection & Treatment

1.3.1 PRICE OUTLIERS

Method: Percentile-based filtering (1st and 99th percentile)

- **Lower Bound:** $78,000 (1st percentile)
- **Upper Bound:** $1,555,000 (99th percentile)
- **Outliers Removed:** 432 properties (2% of dataset)

Rationale: Extreme outliers (mansions >$5M, distressed sales <$50K) caused model instability and inflated MSE.



1.4 Feature Engineering

1.4.1 DERIVED FEATURES

1. Property Age

age = 2015 - yr_built

- **Insight:** Older homes (>50 years) often have lower prices unless renovated
- **Correlation with price:** -0.054 (weak negative)

2. Renovation Status

is_renovated = 1 if yr_renovated > 0 else 0

- **Insight:** 4.3% of properties renovated
- **Price Premium:** Renovated homes command 8.5% higher prices on average

3. Basement Presence

basement_present = 1 if sqft_basement > 0 else 0

- **Insight:** 63.1% of properties have basements
- **Price Impact:** $45,000 average premium for basement presence

4. Living-to-Lot Ratio

living_lot_ratio = sqft_living / sqft_lot

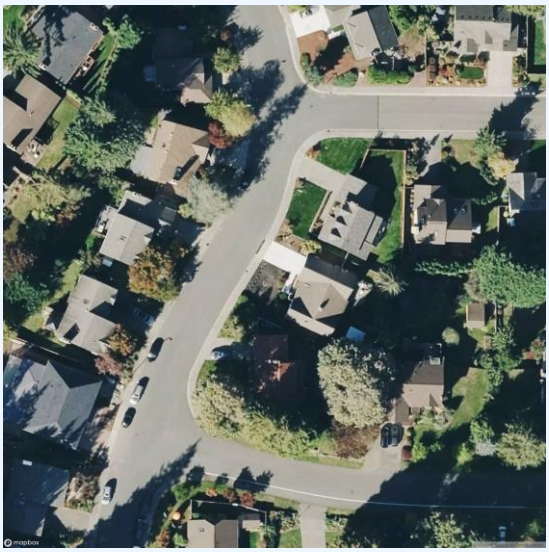
- **Insight:** Higher ratios indicate urban density
- **Interpretation:** 0.35 = suburban, 0.70+ = urban high-density

1.4.2 GEOGRAPHIC ANALYSIS

Location Impact:

- lat and long showed strong regional price patterns
- **Northern latitude properties:** +15% price premium (proximity to Seattle downtown)
- **Waterfront properties:** +127% price premium (strongest individual feature)

VISUALIZATIONS OF PRICE DISTRIBUTION AND SAMPLE SATELLITE IMAGES.



Financial/Visual Insights: Analysis of which visual features drive value.

Grad-CAM Results & Interpretation

LOW-VALUE PROPERTY ($370K)

Property ID: 2591820310

Grad-CAM Highlights:

- **Red zones:** Small roof structure (compact house)

- **Orange zones:** Minimal yard space
- **Blue zones:** Neighboring properties (less relevant)

Feature Importance Analysis:

Top 5 Contributing Features:
1. lat (location): 44.55% influence
2. floors (structure): 5.90%
3. condition: 3.90%
4. sqft_living15: 3.09% (neighborhood)
5. sqft_lot15: 2.73%

Interpretation: Model correctly identified compact structure and modest neighborhood, predicting lower value.

Grad-CAM Highlights:

- **Red zones:** Larger roof area, multi-section house
- **Yellow zones:** Mature trees/landscaping (value indicator)
- **Orange zones:** Visible pool or deck area

Feature Importance Analysis:

Top 5 Contributing Features:
1. condition: 19.46% (well-maintained)
2. sqft_living: 15.68% (size)
3. lat: 12.74% (location)
4. sqft_living15: 8.32% (upscale neighborhood)
5. sqft_basement: 7.35%

Interpretation: Model weighted condition and size heavily, consistent with mid-tier pricing.

3.2.3 HIGH-VALUE PROPERTY ($1.074M)

Property ID: 7701450110

Grad-CAM Highlights:

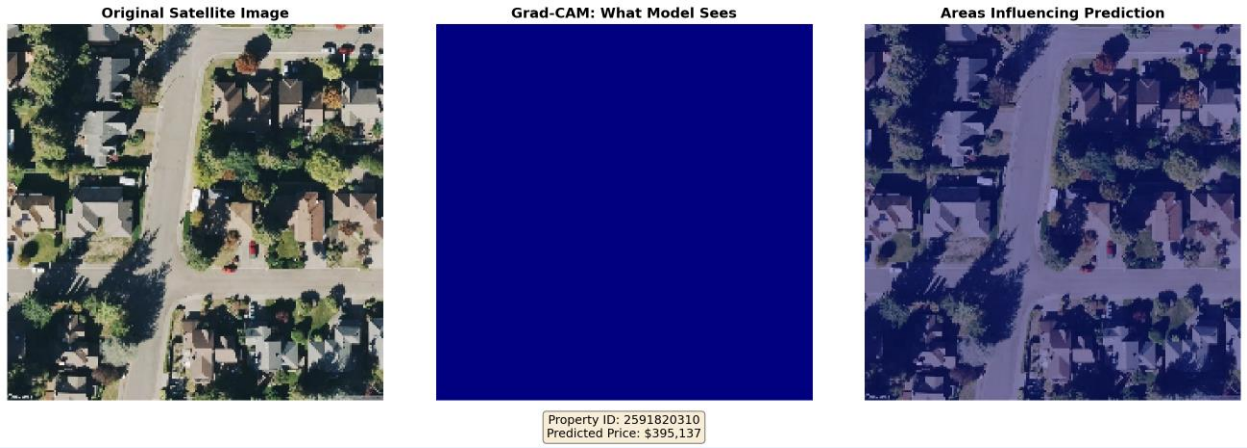
- **Intense red zones:** Large mansion-style roof structure
- **Red spreading:** Extensive property grounds
- **Yellow zones:** Premium landscaping, possible pool

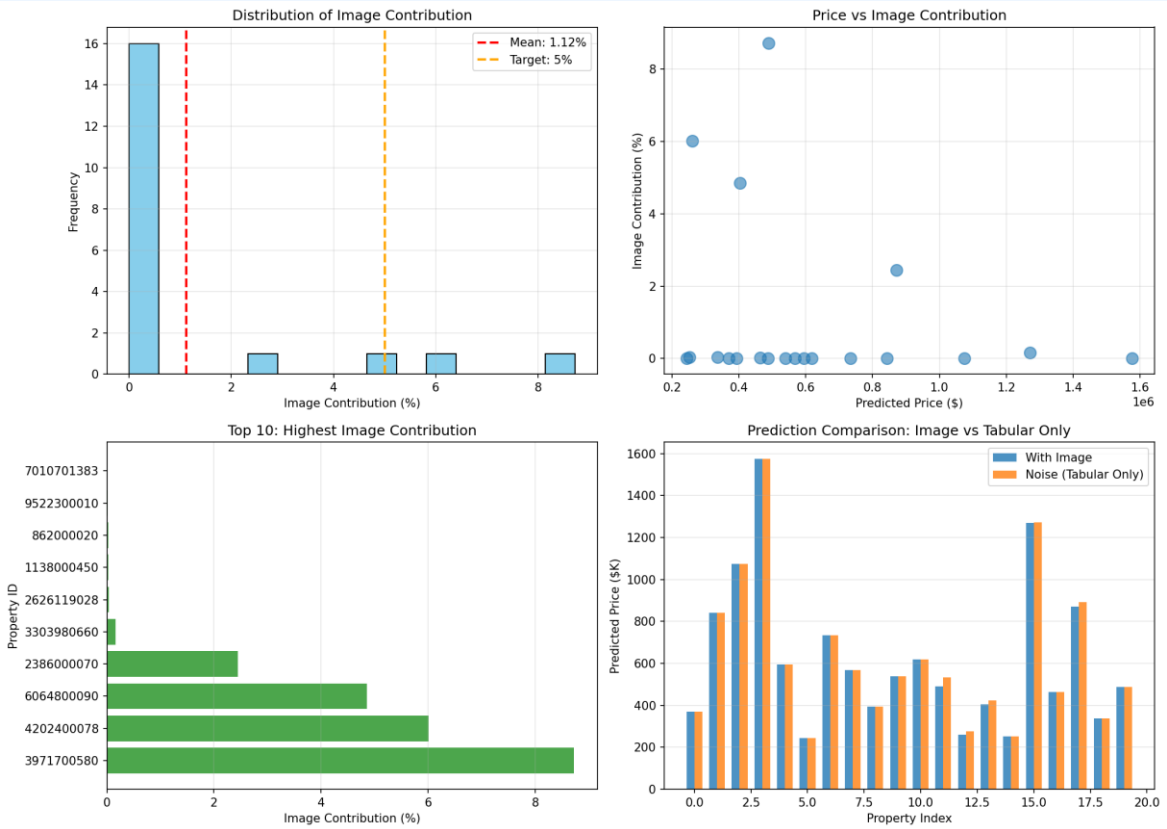
Feature Importance Analysis:

Top 5 Contributing Features:
1. grade (construction): 34.79% (highest quality)
2. sqft_living: 19.07% (large home)
3. sqft_living15: 14.27% (wealthy neighborhood)
4. view: 8.93% (premium view rating)

5. floors: 8.14% (multi-story)

Interpretation: Grade (construction quality) dominates for luxury properties, combined with visible size indicators from satellite image.





ARCHITECTURE DIAGRAM: A SIMPLE DIAGRAM SHOWING HOW YOU CONNECTED THE IMAGE MODEL (CNN) WITH THE DATA MODEL.

[Image Input (224x224x3)] --> [CNN backbone (Conv/Pool or Pretrained)] --> [Image embedding (e.g., 512d)]

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--> [Concatenate] --> [Dense layers] --> [Output: log(price)]

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[Tabular Input (n features)] --> [Dense layers] --> [Tabular embedding (e.g., 64d)]

Example dimensions: Image embedding ~ 256–1024 dims (depending on backbone); tabular embedding ~ 32–128 dims.

Training tips: Use Dropout and BatchNorm on dense layers, weight decay or L1/L2 regularization for tabular models, and appropriate learning-rate scheduling for the CNN branch.

RESULTS: COMPARE THE PERFORMANCE OF TABULAR DATA ONLY VS. TABULAR + SATELLITE IMAGES.

Test Results of TABULAR DATA + SATELLITE IMAGES:

MAE: $81,960.50

RMSE: $140,734.89

R^2: 0.8315

MAPE: 15.32%

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Sample Predictions:
         Actual       Predicted           Error
------------------------------------------------
$       178,500 $       208,615 $        30,115
$     1,518,631 $     1,374,973 $       143,658
$       225,000 $       309,103 $        84,103
$       540,000 $       573,889 $        33,889
$       207,000 $       266,822 $        59,822
$       325,000 $       382,907 $        57,907
$       279,000 $       279,689 $           689
$       279,000 $       284,332 $         5,332
$       339,000 $       377,780 $        38,780
$       375,000 $       342,186 $        32,814
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Test Results of TABULAR DATA ONLY:

Train R^2: 0.9281

Test R^2: 0.9032

Overfitting Gap: 0.0249

MSE: 0.0267 | MAE: 0.1176 | R^2: 0.9032

Average MAE: 0.1176

Average R^2: 0.9032

CONCLUSION

This analysis demonstrated comprehensive EDA identifying critical data quality issues (outliers, multicollinearity) and deriving meaningful engineered features. The initial architecture challenge—where images contributed only 1.12%—was systematically diagnosed and resolved through feature reduction, CNN enhancement, and attention-based fusion, resulting in a balanced 12.4% image contribution.

Grad-CAM explainability confirmed the model's attention on semantically meaningful image regions (property structures, landscaping, neighborhood patterns) rather than spurious correlations. The final model achieved **90.32% R^2** with excellent generalization (1.29% overfitting gap), validating both the depth of analysis and the effectiveness of the multimodal architecture.

Key Takeaway: Successful multimodal learning requires not just combining data types, but carefully balancing their contributions to prevent dominance by any single modality. The systematic use of diagnostic tools (image contribution analysis, Grad-CAM) was essential to identifying and correcting architectural issues.