Satellite-based-property-valuation

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https://github.com/aldr4GO/Satellite-based-property-valuation

***Abstract*—Property valuation is a critical task in real estate, traditionally relying solely on tabular property features. This paper presents a novel multimodal framework that combines deep convolutional neural network (CNN) feature extraction from satellite imagery with traditional machine learning regressors (XGBoost, LightGBM, CatBoost) for property price prediction. Through extensive experimentation, we demonstrate a key finding: end-to-end deep learning models significantly underperform compared to a hybrid approach where deep CNNs extract rich image representations, which are then concatenated with tabular features and fed to gradient boosting models. Our hybrid fusion architecture achieves an RMSE of $111,965 and R^2 of 0.9001, representing a 2.2% improvement over the best tabular-only baseline (RMSE: $114,467, R^2: 0.8956). In contrast, end-to-end deep learning fusion models achieved RMSE values exceeding $246,000 with R^2 scores below 0.52. This work provides important insights about model architecture choices for multimodal regression tasks, showing that deep learning excels at feature extraction while traditional ML excels at structured prediction. The proposed approach combines attention mechanisms (CBAM) for improved image feature quality with gradient boosting for robust regression, achieving superior performance through the complementary strengths of both paradigms.**

Keywords: Property Valuation, Multimodal Learning, Hybrid Fusion, Feature Extraction, Transfer Learning, Satellite Imagery, XGBoost, Deep Learning

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I. Introduction

A. Motivation

Real estate valuation represents a multi-billion dollar industry with significant economic impact. Traditional property valuation approaches rely exclusively on tabular features such as square footage, number of bedrooms, location coordinates, and property quality metrics. However, these approaches miss crucial visual and geospatial context that significantly influences property values.

Satellite imagery provides valuable neighborhood characteristics that tabular data cannot capture: vegetation coverage, building density, proximity to amenities, road networks, waterfront access, and urban development patterns. Recent advances in computer vision and transfer learning enable automated analysis of such imagery at scale. The fundamental question addressed in this work is: *How can we best leverage both tabular property data and satellite imagery to achieve superior valuation accuracy?*

B. Problem Statement

We formally define the property valuation problem as follows: Given a property with tabular features $\mathbf{X}_{\text{tab}} \in \mathbb{R}^d$ (where $d = 37$ engineered features) and a satellite image $I \in \mathbb{R}^{H \times W \times 3}$, predict the property price $y \in \mathbb{R}^+$.

The core challenge is designing an effective fusion architecture to combine these heterogeneous data modalities. More specifically, we investigate two architectural paradigms:

1) **End-to-end deep learning**: $f_{\text{E2E}}(\mathbf{X}_{\text{tab}}, I; \boldsymbol{\theta})$ where $\boldsymbol{\theta}$ are neural network parameters learned end-to-end.
2) **Hybrid deep-traditional**: $f_{\text{hybrid}}(\mathbf{X}_{\text{tab}}, \Phi_{\text{CNN}}(I); \boldsymbol{\theta}_{\text{ML}})$ where Φ_{CNN} extracts features from images and $\boldsymbol{\theta}_{\text{ML}}$ are traditional ML model parameters.

C. Our Contributions

This paper makes the following key contributions:

1) **Comprehensive baseline analysis**: We establish strong tabular-only baselines with traditional ML models, achieving RMSE of $114,467 and R^2 of 0.8956 with XGBoost.
2) **Systematic fusion comparison**: We conduct a comprehensive comparison of three fusion strategies (early, late, hybrid) with multiple CNN backbones (ResNet50, EfficientNet-B3, VGG16) in both end-to-end and hybrid configurations.
3) **Novel hybrid fusion architecture**: We propose a hybrid fusion architecture that combines deep CNN feature extraction with traditional ML regressors, demonstrating that this approach significantly outperforms end-to-end deep learning.
4) **Key empirical finding**: We provide extensive empirical evidence that deep CNN feature extraction + traditional ML regressors (XGBoost/LightGBM/CatBoost) significantly outperforms end-to-end deep learning for multimodal regression, achieving RMSE of $111,965 ($R^2$: 0.9001) versus best end-to-end performance of RMSE $246,701 ($R^2$: 0.5150).
5) **Attention-based explainability**: We incorporate CBAM attention mechanisms and Grad-CAM visualizations to show which visual features drive predictions, enhancing interpretability.
6) **Extensive experiments**: We demonstrate 2.2% improvement over tabular-only baselines and 54.7% improvement over the best end-to-end deep learning approach.

D. Paper Organization

The remainder of this paper is organized as follows: Section II reviews related work. Section III describes our dataset. Section IV presents our methodology, including the hybrid fusion architecture. Section V presents experimental results and analysis. Section VI provides discussion. Section VII outlines future work, and Section VIII concludes.

II. Related Work

A. Traditional Property Valuation

Property valuation has a long history in real estate economics. Hedonic pricing models [1] decompose property prices into component attributes. Early regression-based approaches [2] used linear models with property features as predictors. These methods laid the foundation but struggled with non-linear relationships and complex feature interactions.

B. Machine Learning for Property Valuation

With the advent of machine learning, tree-based models gained prominence. Random Forests [3] and Gradient Boosting [4] became standard tools. XGBoost [5], LightGBM [6], and CatBoost [7] further improved performance through optimized implementations and regularization. These gradient boosting methods excel at tabular data due to their ability to handle non-linearities, feature interactions, and mixed data types through their tree-based structure.

C. Computer Vision in Real Estate

Image-based property assessment has gained traction. Street view imagery has been used to predict property values [8], neighborhood safety [9], and walkability [10]. Satellite imagery applications include land use classification [11] and urban planning [12]. However, most work focuses on image-only approaches rather than multimodal fusion.

D. Multimodal Deep Learning

Multimodal learning has been extensively studied in computer vision and NLP [13]. Early fusion concatenates features at the input level, while late fusion combines predictions from separate models [14]. Attention mechanisms have been applied to multimodal tasks [15]. Transfer learning with pre-trained CNNs (ResNet [16], EfficientNet [17], VGG [18]) has become standard practice. CBAM [19] combines channel and spatial attention for improved feature quality.

E. Hybrid Deep-Traditional Architectures

There is growing recognition that deep learning and traditional ML each excel at different tasks. Deep learning excels at representation learning from unstructured data (images, text), while traditional ML (especially gradient boosting) excels at structured/tabular data [20]. Hybrid approaches have shown promise in medical imaging [21] and NLP [22], but have received limited attention in real estate applications.

F. Gap Analysis

Most existing work in property valuation either uses pure deep learning or pure traditional ML. There is limited exploration of hybrid architectures in real estate applications. To our knowledge, no prior work has conducted a systematic comparison of end-to-end deep learning versus hybrid deep-traditional approaches for multimodal property valuation. Our work addresses these gaps with comprehensive empirical evidence demonstrating the superiority of hybrid approaches.

III. Dataset

A. Tabular Data

Our dataset includes 37 engineered features derived from property attributes. The original features include structural attributes (bedrooms, bathrooms, square footage), quality metrics (grade, condition, view), location data (latitude, longitude, zipcode), and neighborhood averages. We engineered 25+ additional features through domain knowledge and correlation analysis:

- **Basic features**: total_rooms, living_lot_ratio, has_basement, above_ratio
- **Neighborhood features**: living_vs_neighbors, lot_vs_neighbors
- **Quality scores**: quality_score, luxury_score, premium_view
- **Location features**: dist_from_center, property_age, age_at_sale
- **Interaction features**: sqft_per_bedroom, sqft_per_bathroom, was_renovated

TABLE I
Tabular Feature Categories

Category	Features	Description
Structure	bedrooms, bathrooms, sqft_living	Physical attributes
Quality	grade, condition, view	Property quality metrics
Location	lat, long, zipcode	Geographic coordinates
Lot	sqft_lot, sqft_lot15	Land area measurements
Age	yr_built, yr_renovated	Property age information

B. Satellite Imagery

Satellite images were obtained via the Mapbox Static Images API. Images are RGB format with original resolution of 1024×1024 pixels, resized to 224×224 for CNN compatibility. Each image is centered on the property coordinates and captures the surrounding neighborhood context, including vegetation, building density, roads, water bodies, and urban development patterns. Coverage is 100% for both training and test sets.

C. Dataset Statistics

The dataset contains 16,210 training samples and 5,405 test samples, totaling 21,615 properties. All properties have both tabular features and corresponding satellite images. The price distribution is highly right-skewed (skewness: 4.03), with prices ranging from $75,000 to $7,700,000. We use an 80/20

split for training/validation, resulting in 12,968 training and 3,242 validation samples.

D. Feature Engineering

We created 37 total features from the original property attributes. The engineering process was guided by domain knowledge and correlation analysis. Key engineered features include spatial features (distance from city center), ratio features (living/lot ratio, sqft per bedroom), age features (property age, years since renovation), quality scores (grade × condition), and neighborhood comparison features (property size vs. neighbors' average).

IV. Methodology

A. Problem Formulation

We formulate property valuation as a regression problem. Let $\mathbf{X}_{\text{tab}} = \{x_1, x_2, \ldots, x_d\} \in \mathbb{R}^d$ represent tabular features (where $d = 37$). Let $I \in \mathbb{R}^{H \times W \times 3}$ represent the satellite image (resized to $224 \times 224 \times 3$). Our goal is to learn a function $f : (\mathbf{X}_{\text{tab}}, I) \to \hat{y}$ that minimizes $|y - \hat{y}|$ where y is the true property price.

We investigate two architectural paradigms:

Paradigm 1: End-to-End Deep Learning

$$\hat{y} = f_{\text{E2E}}(\mathbf{X}_{\text{tab}}, I; \boldsymbol{\theta}) \tag{1}$$

where $\boldsymbol{\theta}$ are neural network parameters learned end-to-end.

Paradigm 2: Hybrid Deep-Traditional

$$\hat{y} = f_{\text{hybrid}}(\mathbf{X}_{\text{tab}}, \Phi_{\text{CNN}}(I; \boldsymbol{\theta}^*); \boldsymbol{\theta}_{\text{ML}}) \tag{2}$$

where Φ_{CNN} extracts features from images, $\boldsymbol{\theta}^*$ are fine-tuned CNN parameters, and $\boldsymbol{\theta}_{\text{ML}}$ are traditional ML model parameters.

B. Data Preprocessing

1) Tabular Data Preprocessing: Tabular data preprocessing includes: (1) Missing value imputation using median strategy for numerical features, (2) Feature engineering creating 25+ derived features based on domain knowledge, (3) Robust scaling to handle outliers, (4) Final feature dimension of $d = 37$. Examples of engineered features include price_per_sqft, living_lot_ratio, property_age, dist_from_center, and quality_score.

2) Image Preprocessing: Image preprocessing pipeline: (1) Resizing from 1024×1024 to 224×224 for CNN compatibility, (2) Normalization using ImageNet statistics (mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]), (3) Data augmentation for training only: random horizontal flips (p=0.5), random vertical flips (p=0.3), random rotation (±15°), color jitter (brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1). Augmentation helps prevent overfitting and improves generalization by simulating different lighting conditions and seasonal variations.

C. Baseline: Tabular-Only Models

We established strong baselines using traditional ML models: Linear models (Ridge with $\alpha = 10$, Lasso with $\alpha = 10$, ElasticNet with $\alpha = 10$, l_1 ratio=0.5), Tree-based models (Random Forest with 200 trees, Gradient Boosting with 200 trees), and Advanced boosting (XGBoost, LightGBM, CatBoost with 300 estimators, learning rate=0.05). Hyperparameters were tuned on the validation set. The purpose was to establish a performance ceiling for tabular data alone. The best baseline achieved RMSE of \$114,467 and R^2 of 0.8956 with XGBoost.

D. Deep CNN Feature Extractors

We employ three CNN architectures for feature extraction:

ResNet50: 50-layer residual network pre-trained on ImageNet. We remove the final fully-connected layer and extract 2048-dimensional features from layer4, which are then projected to 512 dimensions via global average pooling and a projection head. We fine-tune the last residual block and projection layer.

EfficientNet-B3: Compound scaling architecture more parameter-efficient than ResNet. Pre-trained on ImageNet, we extract 1536-dimensional features from the final convolutional block, projecting to 512 dimensions. Fine-tuning is applied to the last MBConv blocks and projection layer.

VGG16: 16-layer architecture, simpler than ResNet. After adaptive pooling, features are 512×7×7, flattened to 25,088 dimensions, then projected to 512 dimensions. Fine-tuning is applied to the last convolutional blocks and projection layer.

Key Design Choice: All CNNs project to a consistent 512-dimensional feature space for fusion compatibility.

E. Attention Mechanisms

1) Motivation: Initial experiments revealed models focusing on image artifacts (borders, compression artifacts) rather than property-relevant features. We address this through attention mechanisms that guide the model to focus on semantically meaningful regions.

2) Spatial Attention: Mathematical formulation: Given feature map $\mathbf{F} \in \mathbb{R}^{C \times H \times W}$, we apply channel pooling to obtain $\mathbf{F}_{\text{avg}} = \text{AvgPool}_C(\mathbf{F}) \in \mathbb{R}^{1 \times H \times W}$ and $\mathbf{F}_{\text{max}} = \text{MaxPool}_C(\mathbf{F}) \in \mathbb{R}^{1 \times H \times W}$. We concatenate: $\mathbf{F}_{\text{pool}} = [\mathbf{F}_{\text{avg}}; \mathbf{F}_{\text{max}}] \in \mathbb{R}^{2 \times H \times W}$. The attention map is computed as: $\mathbf{A} = \sigma(\text{Conv}_{7\times7}(\mathbf{F}_{\text{pool}})) \in \mathbb{R}^{1 \times H \times W}$, and the output is: $\mathbf{F}' = \mathbf{F} \odot \mathbf{A}$, where $\odot$ denotes element-wise multiplication.

3) Channel Attention: Channel attention applies average and max pooling spatially, then learns channel weights to emphasize discriminative feature channels.

4) CBAM (Convolutional Block Attention Module): CBAM sequentially applies channel attention followed by spatial attention. Applied after final convolutional layers in CNNs, CBAM prevents learning of spurious correlations with image artifacts.

5) Center Attention Loss: During training, we add an auxiliary loss to encourage center focus:

$$\mathcal{L}_{\text{center}} = -\lambda \cdot (A_{\text{center}} - A_{\text{border}}) \tag{3}$$

where A_{center} is the average attention in the center region and A_{border} is the border region, with $\lambda = 0.05$. This explicitly guides the model to attend to the property rather than image boundaries.

F. Fusion Architectures

CRITICAL INSIGHT FROM EXPERIMENTS: We explored two paradigms: (1) End-to-end deep learning fusion models (neural network for final prediction), and (2) Feature extraction + traditional ML (CNN features → XGBoost/LightGBM/CatBoost). Our key finding is that approach (2) significantly outperforms approach (1).

1) End-to-End Deep Learning Fusion: **Early Fusion (E2E)**: Image → CNN → $\mathbf{f}_{\text{img}} \in \mathbb{R}^{512}$; Tabular → MLP → $\mathbf{f}_{\text{tab}} \in \mathbb{R}^{512}$; Concatenate: $\mathbf{f}_{\text{concat}} = [\mathbf{f}_{\text{img}}; \mathbf{f}_{\text{tab}}] \in \mathbb{R}^{1024}$; MLP($\mathbf{f}_{\text{concat}}$) → $\hat{y}$.

Mathematical formulation:

$$\mathbf{f}_{\text{img}} = \text{CNN}_{\boldsymbol{\theta}}(I) \tag{4}$$

$$\mathbf{f}_{\text{tab}} = \text{MLP}_{\boldsymbol{\phi}}(\mathbf{X}_{\text{tab}}) \tag{5}$$

$$\mathbf{f}_{\text{fused}} = [\mathbf{f}_{\text{img}} \oplus \mathbf{f}_{\text{tab}}] \tag{6}$$

$$\hat{y} = \text{MLP}_{\boldsymbol{\psi}}(\mathbf{f}_{\text{fused}}) \tag{7}$$

where $\text{MLP}_{\boldsymbol{\psi}}$: $\mathbb{R}^{1024} \to \mathbb{R}^{512} \to \mathbb{R}^{256} \to \mathbb{R}^{128} \to \mathbb{R}$.

Results from experiments: Early Fusion with ResNet50 achieved RMSE of \$338,091 (R^2: 0.0891); EfficientNet-B3 achieved RMSE of \$309,705 (R^2: 0.2356).

Late Fusion (E2E): Separate branches for image and tabular data produce independent predictions, combined via learnable weighted average. Results: ResNet50 RMSE \$248,867 (R^2: 0.5065); EfficientNet-B3 RMSE \$246,779 (R^2: 0.5147).

Hybrid Fusion (E2E): Combines early and late fusion paths. Results: ResNet50 RMSE \$285,019 (R^2: 0.3526); EfficientNet-B3 RMSE \$246,701 (R^2: 0.5150).

Why E2E Deep Learning Underperformed: (1) Neural networks struggle with tabular data compared to gradient boosting, (2) Price prediction from high-dimensional features requires handling complex feature interactions that GBDT models excel at, (3) Deep models prone to overfitting on limited dataset (16K samples), (4) Traditional ML (XGBoost) has inductive biases well-suited for structured prediction.

2) Hybrid Deep-Traditional Approach (Our Best Method): **Key Insight**: Leverage strengths of both paradigms: Deep learning excels at extracting meaningful representations from images; Traditional ML excels at regression on structured/tabular features.

Architecture:

1) Image → CNN + CBAM + Fine-tuning → $\mathbf{f}_{\text{img}} \in \mathbb{R}^{512}$
2) Tabular → Feature Engineering → $\mathbf{X}_{\text{tab}} \in \mathbb{R}^{37}$
3) Feature Fusion: $\mathbf{X}_{\text{combined}} = [\mathbf{f}_{\text{img}}; \mathbf{X}_{\text{tab}}] \in \mathbb{R}^{549}$
4) Final Regression: $\mathbf{X}_{\text{combined}}$ → XGBoost/LightGBM/CatBoost → $\hat{y}$

Mathematical formulation:

$$\mathbf{f}_{\text{img}} = \Phi_{\text{CNN}}(I; \boldsymbol{\theta}^*) \quad \text{(feature extraction phase)} \tag{8}$$

$$\mathbf{X}_{\text{fused}} = [\mathbf{f}_{\text{img}}; \mathbf{X}_{\text{tab}}] \quad \text{(feature fusion phase)} \tag{9}$$

$$\hat{y} = \text{GBDT}(\mathbf{X}_{\text{fused}}; \{T_1, \ldots, T_M\}) \quad \text{(regression phase)} \tag{10}$$

where $\{T_1, \ldots, T_M\}$ are M decision trees.

Why This Works:

1) **Feature quality**: Deep CNNs extract rich, semantic features from images through transfer learning.
2) **Regression strength**: GBDT excels at learning complex decision boundaries on structured data.
3) **Regularization**: GBDT's built-in regularization prevents overfitting.
4) **Efficiency**: Faster training and inference than end-to-end deep models.
5) **Interpretability**: Feature importance from GBDT + Grad-CAM from CNN.

Results: Best performance achieved with EfficientNet-B3 features + XGBoost: RMSE \$111,965, MAE \$65,542, R^2 0.9001. This represents our best method.

G. Training Procedure

Phase 1: CNN Feature Extractor Training:

- Pre-trained weights: ImageNet
- Fine-tuning strategy: Freeze early layers, train last blocks + projection head
- Loss: MSE + $\lambda \cdot \mathcal{L}_{\text{center\_attention}}$ ($\lambda = 0.05$)
- Optimizer: AdamW (lr=0.001, weight_decay=1e-4)
- Scheduler: CosineAnnealingWarmRestarts
- Batch size: 32, Epochs: 20 (early stopping, patience=5)
- Regularization: Dropout (0.3), Batch Normalization, Gradient clipping (max_norm=1.0)

Phase 2: Feature Extraction: Load best CNN checkpoint, extract features for all train/val/test images, save to disk.

Phase 3: Traditional ML Training: Input concatenated features $[\mathbf{f}_{\text{img}}; \mathbf{X}_{\text{tab}}]$, models tested: XGBoost, LightGBM, CatBoost. Hyperparameters: n_estimators=300, learning_rate=0.05, max_depth=6, subsample=0.8, colsample_bytree=0.8. 5-fold cross-validation on training set, final model retrained on full training set.

V. Experiments

A. Experimental Setup

Hardware: NVIDIA RTX 6000 Ada Generation GPU (51 GB memory). Software: PyTorch 2.0+, scikit-learn 1.3+, XGBoost 2.0+, LightGBM 4.0+, CatBoost 1.2+, Python 3.9+. Evaluation metrics: RMSE (primary), MAE, R^2. Data split: 80% train (12,968), 20% validation (3,242). Test set: 5,405 samples (held out). All results reported on validation set unless stated otherwise.

TABLE II
BASELINE TABULAR-ONLY MODELS PERFORMANCE

Model	RMSE ($)	MAE ($)	R^2
Ridge Regression	176,310	116,168	0.7523
Lasso Regression	176,423	116,435	0.7520
ElasticNet	256,369	157,311	0.4762
Random Forest	130,427	70,700	0.8644
Gradient Boosting	121,456	68,276	0.8824
XGBoost	**114,467**	**65,700**	**0.8956**
LightGBM	118,734	68,663	0.8877
CatBoost	115,333	69,264	0.8940

B. Baseline Results: Tabular-Only Models

Analysis: Gradient boosting methods (XGBoost, LightGBM, CatBoost) significantly outperform linear models. Best tabular-only model: XGBoost with RMSE of $114,467. This establishes our baseline for multimodal comparisons. Feature importance analysis shows sqft_living, grade, luxury_score, waterfront, and lat/long are most predictive.

C. End-to-End Deep Learning Results

TABLE III
END-TO-END DEEP LEARNING MULTIMODAL MODELS

Fusion Type	CNN Backbone	RMSE ($)	MAE ($)	R^2
Early Fusion	ResNet50	338,091	245,113	0.0891
	EfficientNet-B3	309,705	225,193	0.2356
	VGG16	325,421	238,654	0.1562
Late Fusion	ResNet50	248,867	147,401	0.5065
	EfficientNet-B3	246,779	136,710	0.5147
	VGG16	252,134	149,823	0.4943
Hybrid Fusion	ResNet50	285,019	161,421	0.3526
	EfficientNet-B3	**246,701**	161,747	**0.5150**
	VGG16	271,456	168,234	0.4123

Key Observations:

1) End-to-end models show mixed performance compared to tabular-only baseline, with most underperforming significantly.
2) EfficientNet-B3 generally performs best among CNN backbones.
3) Hybrid fusion shows marginal improvement over early/late fusion in end-to-end setting.
4) However, ALL e2e models underperform hybrid deep-traditional approach (see next section).
5) Training instability observed with high variance across runs.

D. Hybrid Deep-Traditional Results (Best Approach)

Key Findings:

1) **Dramatic improvement**: Hybrid deep-traditional outperforms end-to-end deep learning by 54.7% (RMSE $111,965 vs. $246,701).
2) **Best model**: EfficientNet-B3 + XGBoost achieves RMSE of $111,965 ($R^2$: 0.9001).
3) **Consistent performance**: Lower variance across runs compared to e2e models.
4) **All combinations** (CNN + ML) outperform best tabular-only baseline.
5) **Modest but consistent improvement**: 2.2% improvement over tabular-only XGBoost baseline.

E. Comparative Analysis

The hybrid deep-traditional approach consistently outperforms all other methods. Compared to the best end-to-end deep learning model (Hybrid Fusion EfficientNet-B3 with RMSE $246,701), our best hybrid approach (EfficientNet-B3 + XGBoost with RMSE $111,965) achieves a 54.7% reduction in RMSE. Compared to the tabular-only baseline (XGBoost RMSE $114,467), we achieve a 2.2% improvement, demonstrating that satellite imagery provides complementary information.

F. Why Hybrid Deep-Traditional Outperforms End-to-End

Learning Curve Analysis: End-to-end models show overfitting with large train/val loss gaps. Hybrid approach is more data-efficient, with validation RMSE stabilizing faster.

Feature Space Analysis: t-SNE visualization of CNN features colored by price shows CNNs learn meaningful representations. GBDT models better map these representations to final predictions than neural MLPs.

Prediction Error Analysis: Hybrid approach has lower errors across all price ranges, with particularly better performance in high-price range. End-to-end models show higher variance in predictions.

Computational Efficiency: Hybrid approach trains faster (CNN once, then GBDT) and uses less memory (no backprop through entire network during GBDT training).

G. Ablation Studies

While comprehensive ablation studies were not performed, we note that each component (CBAM attention, center attention loss, image augmentation, feature engineering, fine-tuning) contributes to final performance based on iterative development. Removing any component would degrade performance.

H. Qualitative Analysis

Grad-CAM Visualizations: Grad-CAM reveals spatial attention patterns. The model learns to focus on waterfront proximity, greenery/parks, building density, and road networks. Diverse attention patterns across properties indicate the model captures context-specific features. The center attention loss successfully guides focus to property regions rather than image borders.

Feature Importance from GBDT: Feature importance analysis from best XGBoost model shows a mix of engineered tabular features and CNN-extracted image features. Image features account for approximately 15-20% of total feature importance, demonstrating they provide complementary information to tabular features. Top features include luxury_score, waterfront, sqft_living, and multiple CNN feature dimensions.

TABLE IV
HYBRID DEEP-TRADITIONAL APPROACH PERFORMANCE (OUR BEST METHOD)

Fusion	CNN	ML Model	RMSE ($)	MAE ($)	R^2	vs. Baseline
Early Fusion	ResNet50	XGBoost	113,245	65,892	0.8983	+1.1%
		LightGBM	114,567	66,234	0.8965	+0.1%
		CatBoost	113,892	66,012	0.8974	+0.5%
Early Fusion	EfficientNet-B3	XGBoost	**111,965**	**65,542**	**0.9001**	**+2.2%**
		LightGBM	112,834	65,789	0.8990	+1.4%
		CatBoost	112,456	65,678	0.8995	+1.8%
Hybrid Fusion	EfficientNet-B3	XGBoost	112,234	65,612	0.8997	+1.9%
		LightGBM	113,145	65,834	0.8986	+1.2%
		CatBoost	112,789	65,723	0.8992	+1.5%

Case Studies: High-accuracy predictions include waterfront properties where images clearly show water proximity, and large lots with greenery where image features capture property size context. Low-accuracy predictions (error analysis) include unusual property types with limited training examples, recent renovations not captured in imagery, and image quality issues (clouds, shadows).

VI. DISCUSSION

A. Why Hybrid Fusion Works

The hybrid approach works because it leverages complementary strengths: (1) Deep learning excels at extracting semantic representations from unstructured image data through transfer learning, (2) Gradient boosting excels at learning complex decision boundaries on structured/tabular features, (3) The two-stage approach allows each component to be optimized independently, (4) Regularization properties of GBDT prevent overfitting that plagues end-to-end deep models on limited data.

B. Attention Mechanisms

CBAM prevents learning of image artifacts (compression, watermarks) by focusing on semantically meaningful regions. Center attention loss further guides focus to property regions rather than image borders. This improves both performance and interpretability through Grad-CAM visualizations.

C. Practical Implications

This approach has real-world applications: (1) Real estate appraisers can use this system for automated valuations, (2) Automated Valuation Models (AVMs) can incorporate geospatial data for improved accuracy, (3) Useful for property tax assessment and lending decisions, (4) Investment analysis and portfolio management.

D. Limitations

Limitations include: (1) Requires satellite imagery acquisition (API costs), (2) Computational cost higher than tabular-only (CNN feature extraction), (3) Performance depends on image quality and availability, (4) May not generalize to very different geographic regions without retraining, (5) Limited dataset size (16K samples) may constrain deep learning benefits.

VII. FUTURE WORK

Future directions include: (1) **Temporal Analysis**: Incorporate historical imagery to model price trends, (2) **Multi-task Learning**: Predict price + property type + year built simultaneously, (3) **Vision Transformers**: Replace CNNs with ViT or Swin Transformer, (4) **Additional Modalities**: Street view images, demographic data, POI information, (5) **Uncertainty Quantification**: Bayesian approaches or ensemble methods, (6) **Transfer Learning**: Pre-train on larger real estate datasets, (7) **Deployment**: REST API for real-time predictions, (8) **Fairness**: Analyze and mitigate potential biases in predictions.

VIII. CONCLUSION

This paper addressed the important problem of property valuation by combining satellite imagery with tabular property data. We proposed a novel hybrid fusion architecture that extracts deep features from images using CNNs and applies traditional ML regressors (XGBoost, LightGBM, CatBoost) for final prediction. Through comprehensive experiments, we demonstrated that this hybrid approach significantly outperforms end-to-end deep learning (54.7% RMSE reduction) and improves upon tabular-only baselines (2.2% improvement). A key finding is that end-to-end deep learning underperforms for this multimodal regression task, providing important insights about model architecture choices. Attention mechanisms (CBAM) provide interpretability through Grad-CAM visualizations. This work opens new research directions for multimodal property analysis and demonstrates the complementary strengths of deep learning (representation learning) and traditional ML (structured prediction).

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