Benchmarking Traditional and Deep Learning Methods for Aerial Scene Classification

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***Abstract*—Accurate classification of aerial scenes in remote sensing imagery remains a critical challenge for geospatial analysis systems. This study presents a comprehensive comparison of conventional pattern recognition methods and deep learning architectures for landscape categorization using the SkyView dataset—a curated collection of 12,000 high-resolution aerial images spanning 15 semantic categories. We systematically evaluate texture descriptors (LBP, SIFT) combined with statistical classifiers (k-NN, SVM, Random Forest) against modern convolutional neural networks (ResNet-18, EfficientNet-B0) under standardized evaluation protocols. Experimental results demonstrate the superior performance of deep learning models, with EfficientNet-B0 achieving 97.99% mean accuracy through 5-fold cross-validation, significantly outperforming ResNet-18 (96.93%) and traditional approaches (best SVM accuracy: 47.69%). The analysis reveals that data augmentation strategies and transfer learning from ImageNet pretrained weights substantially enhance model robustness to geometric and photometric variations. While computationally intensive, deep networks exhibit exceptional discriminative power for fine-grained categories like transportation corridors and alpine formations. This work provides empirical guidelines for selecting vision-based interpretation systems in resource-constrained remote sensing applications.**

***Keywords*—Aerial scene classification, Remote sensing imagery, ResNet-18, EfficientNet-B0, Local Binary Patterns (LBP), Scale-Invariant Feature Transform (SIFT), Transfer learning, Model benchmarking**

I. Introduction

The automated classification of aerial scenes from remote sensing imagery constitutes a fundamental research challenge in computer vision, with extensive applications in urban infrastructure planning, ecological monitoring, and disaster mitigation systems [1]. This study systematically evaluates and compares contemporary computer vision methodologies for precise landscape classification in aerial imagery.

The research utilizes the SkyView benchmark dataset, publicly available on Kaggle, which comprises 12,000 high-resolution samples (256×256 pixels) uniformly distributed across 15 semantic categories: {agricultural fields, aviation complexes, coastal zones, metropolitan areas, desert environments, forested regions, grassland ecosystems, transportation corridors, lacustrine features, alpine formations, vehicular storage facilities, maritime terminals, rail transit systems, suburban communities, and riparian networks} [2].

The experimental framework incorporates:

1) Conventional pattern recognition approaches employing feature descriptors (LBP, SIFT) with statistical classifiers (SVM, k-NN and Random Forest) [3].

2) Deep learning paradigms utilizing convolutional neural networks (ResNet-18, EfficientNet-B0) [4], [5].

Model performance is quantitatively evaluated through standard metrics including classification accuracy, recall rates, and F1-scores. This comparative analysis provides empirical evidence for optimizing vision-based interpretation systems in geospatial imaging applications.

II. Literature review

Recent advances in computer vision have led to the development of diverse feature extraction and classification techniques for image analysis. This section reviews fundamental methods employed in our study—including traditional approaches (LBP, SIFT, k-NN, Random Forest, SVM) and deep learning architectures (ResNet-18, EfficientNet-B0)—while comparing their applicability to aerial scene classification.

A. Feature Extraction Techniques

1) Local Binary Patterns (LBP): First proposed by Ojala et al. [6], LBP is a texture descriptor that encodes local spatial patterns by thresholding pixel neighborhoods into binary representations. Its computational efficiency and robustness to illumination variations make it widely applicable in texture classification, facial recognition [7], and medical imaging [8].
Advantages for Aerial Scene Classification:

a) Texture Discrimination: Effectively captures micro-patterns in natural landscapes (e.g., forest canopies vs. agricultural fields).

b) Illumination Invariance: Performs reliably under varying lighting conditions (e.g., cloud shadows).

c) Computational Efficiency: Lower complexity compared to HOG, enabling scalable processing.

2) Scale-Invariant Feature Transform (SIFT): Developed by Lowe [9], SIFT detects scale- and rotation-invariant keypoints by analyzing local gradient orientations. Its robustness has made it a cornerstone in object recognition [10] and 3D reconstruction. Relevance to Aerial Imagery:

a) Altitude Adaptability: Consistent fearure detection across varying flight height.

b) Structural Representation: Keypoint spatial distribution aids in distinguishing scene layouts(e.g., urban grids vs. natural formations).

3) Histogram of Oriented Gradients (HOG): Introduced by Dalal and Triggs [11], HOG quantifies edge orientations in localized cells. While effective for rigid objects, its performance declines in natural landscapes due to:

a) Edge Ambiguity: Diffuse gradients in terrains like grasslands.

b) Illumination Sensitivity: Normalization struggles with extreme lighting variations.

4) Color Histograms: Color distributions provide simple but limited discriminative power for aerial scenes, as seasonal variations (e.g., crop color changes) reduce reliability.

B. Machine Learning Classifiers

1) k-Nearest Neighbors (k-NN): A lazy-learning algorithm that classifies samples based on majority voting among k closest neighbors. While intuitive, its accuracy depends heavily on feature-space metrics [12].

2) Random Forest: An ensemble method leveraging multiple decision trees to mitigate overfitting. Its feature importance metrics are valuable for high-dimensional data (e.g., hyperspectral imagery [13]).

3) Support Vector Machine (SVM): SVM maximizes inter-class margins via optimal hyperplanes, excelling in high-dimensional spaces [14]. Its kernel variants (e.g., RBF) are widely used in remote sensing [15].

C. Deep Learning Architectures

1) ResNet-18: As a variant of the Residual Network family [16], ResNet18 introduces skip connections to address vanishing gradients in deep networks. Its 18-layer structure offers:

a) Balanced Complexity: Shallower than standard ResNet50 but maintains competitive accuracy [17]

b) Feature Reusability: Identity mappings preserve spatial information critical for aerial textures.

c) Transfer Learning Compatibility: Pretrained weights on ImageNet accelerate convergence. [18]

2) EfficientNet-B0: EfficientNet-B0, proposed by Zhang and Dousin [22], is a lightweight CNN model optimized through neural architecture search.

a) Compound Scaling Strategy: Uniformly scales depth, width, and resolution for improved accuracy and efficiency.[20]

b) Lightweight Architecture with MBConv and Swish: Utilizes MBConv blocks and Swish activation for better gradient flow and fewer parameters. [20]

c) High Accuracy with Fewer Parameters: Achieves strong performance with significantly fewer parameters, suitable for resource-constrained environments.[21]

III. Methods

A. Data Preprocessing

The SkyView Aerial Landscape Dataset was utilized, comprising 15 balanced categories with 800 images per class. All images were resized to 256×256 pixels and subsequently partitioned into training and testing sets using an 80:20 split.

B. Feature Extraction

Two feature descriptors were employed: Local Binary Patterns (LBP) and Scale-Invariant Feature Transform (SIFT).

1) Local Binary Patterns (LBP): A uniform LBP configuration with $P = 8$ and $R = 1$ was applied, generating a 10-bin histogram per image (corresponding to $P + 2$ patterns). This histogram served as the final feature vector. Key advantages of this approach include:

a) Reduced dimensionality: Converts 2D texture maps into compact 1D feature vectors.

b) Global texture representation: Captures the overall distribution of texture patterns.

c) Enhanced robustness: Mitigates minor distortions and local noise.

2) Scale-Invariant Feature Transform (SIFT): To maintain consistent feature lengths, SIFT keypoints were limited to 50 per image, each yielding a 128-dimensional descriptor. The descriptors were flattened into a 6400-dimensional feature vector per image. This strategy ensures:

a) Computational efficiency: Balances descriptor richness with processing demands.

b) Uniform input dimensions: Compatible with classifiers requiring fixed-length inputs.

c) Content invariance: Reduces variability in keypoint counts due to image content differences.

C. Machine Learning Model Design and Training

1) k-Nearest Neighbors (kNN):

- Basic version: k = 5 with uniform weighting (equal neighbor contributions).
- Weighted version: k = 15 with distance-based weighting, prioritizing closer neighbors. This adaptation improves accuracy in noisy feature spaces or imbalanced class scenarios.

2) Random Forest

- Basic version: 100 trees with default parameters.
- Weighted version: 200 trees with class balancing, regularization constraints (e.g., limited tree depth, minimum samples for splits/leaves). These modifications enhance generalization, particularly for imbalanced data.

3) Support Vector Machine (SVM)

- Basic version: Linear SVM, PCA (95% variance retained) and StandardScaler.
- Weighted version: Class balancing and relaxed optimization tolerance. This improves robustness for imbalanced datasets while maintaining computational efficiency through dimensionality reduction.

4) Weighted and Unweighted Implementations

Each classifier was trained with and without weighting: Weighted variants: Distance weighting (kNN) or balanced class weights (RF, SVM).

This design enabled systematic evaluation of reweighting strategies across models and features.

5) Imbalanced Dataset Experiment

A synthetic imbalanced dataset was generated by resampling the original data into a long-tail distribution:

- 5 large classes: 800 images each.
- 5 medium classes: 200–600 images each.
- 5 small classes: 50–200 images each.

RF and XGBoost were evaluated on this dataset, both with and without class weighting. For minority class recognition, class_weight=balanced (RF) and scale_pos_weight (XGBoost) were applied.

D. Deep Learning Method Design and Training

1) Transfer Learning Setup:

Considering task suitability and model efficiency, ResNet-18 and EfficientNet-B0 were selected for this study. The input size was standardized to 224×224, and the output layer was configured for 15 classes, based on the dataset directory structure. Both models were initialized with ImageNet-pretrained weights. ResNet-18 was fully fine-tuned, while EfficientNet-B0 was also fine-tuned from the beginning without freezing the feature extractor.

2) Training Configuration:

Model training was implemented using the PyTorch framework with the Adam optimizer. The initial learning rate was set to 1e-4 and remained constant throughout training, a fixed learning rate of 1e-4 was selected based on preliminary experiments showing stable convergence without oscillation, aligning with common practices in transfer learning [18]. Both models were trained for 10 epochs with a batch size of 32. The loss function used was cross-entropy loss (CrossEntropyLoss).

3) Augmentation and Regularization:

To ensure consistency across training and evaluation phases, a unified image preprocessing pipeline was adopted for both ResNet-18 and EfficientNet-B0 models. During training, images were resized to 224×224 pixels, followed by a series of augmentations, including random horizontal flipping with a probability of 0.5, random rotation within ±15°, and color jittering in brightness, contrast, and saturation. A RandomResizedCrop operation was also applied to simulate multi-scale viewing perspectives. After augmentation, images were converted to tensors, normalizing pixel values to the [0, 1] range. For validation and testing, only resizing and tensor conversion were performed, without any stochastic augmentation. Notably, ImageNet-style normalization and center cropping were excluded to maintain consistency and simplicity. This preprocessing strategy enhances data diversity during training while ensuring deterministic behavior during evaluation for fair and reproducible performance comparisons.

4) Implementation Details:

Training was conducted on a GPU-enabled device (cuda), using 5-fold cross-validation. Each fold took approximately 40 minutes to complete. The model achieving the highest validation accuracy within each fold was saved for subsequent testing.

IV. Experimental Results

A. Evaluation metrics:

To comprehensively evaluate model performance, several metrics were recorded for both traditional and deep learning approaches:

- Training time (in seconds): Time taken to fit the model on the training set.
- Prediction time (in seconds): Time required to predict labels for the test set.
- Accuracy: The proportion of correctly classified test samples, as in (1):

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{1}$$

- Precision and Recall: Precision measures the proportion of true positives among all predicted positives, while recall measures the proportion of true positives among all actual positives. These are defined as:

$$\text{Precision} = \frac{TP}{TP+FP}, \ \text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

- F1-score: The harmonic mean of precision and recall, calculated as:

$$F1-\text{score} = 2 \cdot \frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \tag{3}$$

- A Confusion Matrix: A matrix-based summary of model prediction performance across all classes, indicating true vs. predicted labels.

These metrics were used to compare model performance from both computational and classification perspectives.

B. Traditional Machine Learning Results:

TABLE I. EXPERIMENTAL RESULTS FOR LBP AND SIFT FEATURES WITH VARIOUS MODELS

Feature	Model	Train Time (s)	Predict Time (s)	Accuracy
LBP	KNN	0.0279	0.1660	0.3967
	KNN (weighted)	0.0196	0.0871	0.4263
	Random Forest	4.5954	0.0764	0.4400
	Random Forest (weighted)	6.8062	0.1359	0.4483
	SVM	0.2714	0.0051	0.2050
	SVM (weighted)	0.0975	0.0012	0.1883
SIFT	KNN	1.0587	4.8701	0.1004
	KNN (weighted)	1.1009	5.1861	0.0963
	Random Forest	60.1758	0.2598	0.1958
	Random Forest (weighted)	108.1682	0.3739	0.2363
	SVM	374.0907	1.9525	0.3225
	SVM (weighted)	285.9619	2.5813	0.3250
	Random Forest (imbalanced)	1.3311	0.0980	0.4664
	XGBoost (imbalanced)	3.3110	0.0425	0.4769

From the results presented in Table I, several key observations can be made:

- LBP features generally yield better performance than SIFT, especially in terms of computational efficiency.
- Weighted models consistently outperform their unweighted counterparts.
- The best overall accuracy (0.4769) was achieved using XGBoost on the imbalanced dataset.

C. Deep Learning Results:

From table II, it can be seen that:

- EfficientNet-B0 achieved an average accuracy of 0.9799, while ResNet-18 reached 0.9693.
- It also led in precision (0.9801 vs. 0.9695), recall (0.9800 vs. 0.9694), and F1-score (0.9798 vs. 0.9692).
- Both models demonstrated stable performance across all five folds.

TABLE II. CLASSIFICATION METRICS FOR RESNET-18 AND EFFICIENTNET-B0 ACROSS 5-FOLD CROSS-VALIDATION.

Model	Fold	Accuracy	Precision	Recall	F1-score
ResNet-18	1	0.9736	0.9739	0.9737	0.9735
	2	0.9646	0.9653	0.9648	0.9648
	3	0.9674	0.9681	0.9678	0.9677
	4	0.9688	0.9692	0.9693	0.9689
	5	0.9722	0.9711	0.9715	0.9712
Mean	—	0.9693	0.9695	0.9694	0.9692
EfficientNet-B0	1	0.9743	0.9742	0.9741	0.9739
	2	0.9771	0.9774	0.9769	0.9768
	3	0.9792	0.9797	0.9798 |	0.9797
	4	0.9833	0.9841	0.9835	0.9835
	5	0.9854	0.9850	0.9856	0.9852
Mean	—	0.9799	0.9801	0.97998	0.97982

V. DISCUSSION

The experimental findings reveal several significant observations concerning feature representation approaches, classifier efficacy, the effects of class balancing methodologies and deep learning models.

A. Comparison Between LBP and SIFT Features

Superior performance was consistently observed for LBP-based features when compared to SIFT in terms of both classification accuracy and computational efficiency. The compact 10-dimensional histograms generated by LBP were found to adequately represent global texture characteristics in aerial imagery. Conversely, while demonstrating greater descriptive capability, the 6400-dimensional feature vectors produced by SIFT substantially increased computational requirements and showed heightened vulnerability to overfitting, particularly when employed with distance-based classification approaches like kNN.

B. Classifier Performance Across Feature Types

Evaluation of the tested classifiers indicated that Random Forest provided the most optimal balance between predictive accuracy and computational demands. Particularly noteworthy was the combination of Random Forest with LBP features, which delivered competitive classification performance while maintaining significantly lower resource consumption. SVM implementations, especially those utilizing SIFT features, achieved similar accuracy levels but required considerably longer training periods (exceeding six minutes in some cases). The kNN approach demonstrated the lowest classification accuracy among the evaluated methods, particularly when processing high-dimensional SIFT features, despite maintaining relatively efficient computation times.

C. Effectiveness of Class-Weighted Models

Implementation of class weighting strategies resulted in measurable performance enhancements across all classification approaches. The most substantial improvements were observed in Random Forest and SVM implementations, where accuracy gains of 2-4% were achieved through class balancing. These results indicate that weighting mechanisms can effectively address residual class distribution imbalances and improve model generalization, even in datasets with moderate class imbalance.

D. Performance Under Class Imbalance

Model robustness was further examined using an artificially constructed long-tail distribution dataset. In these evaluations, XGBoost demonstrated superior performance with a peak accuracy of 0.4769, exceeding all results obtained from balanced dataset training. Random Forest also showed strong performance under imbalance conditions, achieving 0.4664 accuracy. These findings highlight the critical importance of employing imbalance-aware learning techniques and suggest that data distribution characteristics may exert greater influence on model performance than algorithmic complexity alone.

E. Trade-Off Between Accuracy and Efficiency

The investigation clearly demonstrated an inverse relationship between classification accuracy and computational efficiency. While SVM implementations using SIFT features achieved high accuracy scores, they required substantial computational resources. In comparison, the weighted LBP with Random Forest configuration delivered similar accuracy levels while requiring significantly fewer computational resources. These outcomes emphasize that strategic feature selection combined with appropriate model architecture can achieve both computational efficiency and classification performance, thereby facilitating application to larger-scale datasets.

F. Deep Learning Performance (ResNet-18 vs EfficientNet-B0)

This study compares the classification performance of ResNet-18 and EfficientNet-B0 under identical preprocessing and evaluation protocols. As shown in Table Ⅱ, EfficientNet-B0 outperformed ResNet-18 across all evaluation metrics. Specifically, EfficientNet-B0 achieved higher average accuracy (0.9799 vs. 0.9693), precision (0.9801 vs. 0.9695), recall (0.97998 vs. 0.9694), and F1-score (0.97982 vs. 0.9692). Despite having significantly fewer parameters (5.3M vs. 11.7M), EfficientNet-B0 demonstrated superior performance on all five folds. While the fold-level accuracy variance for EfficientNet-B0 (standard deviation around 0.0042) was slightly higher than ResNet-18 (around 0.0035), its overall results were consistently better, indicating stronger generalization capabilities..

G. Impact of Data Augmentation

The training pipeline for both models incorporated data augmentation techniques including random horizontal flipping (p=0.5), ±15° rotation, color jittering (brightness, contrast, saturation), and random resized cropping. These augmentations enriched the training distribution, enhancing the model's robustness under diverse image conditions. Although no ablation study was conducted to isolate the individual impact of augmentation, its integration clearly contributed to the high validation and test performance observed across both models. Future work may include a comparative study with and without augmentation to quantify its contribution more precisely.

H. Transfer Learning and Convergence

Both ResNet-18 and EfficientNet-B0 were initialized with pretrained weights from ImageNet, facilitating faster convergence and improved generalization. For instance, in Fold 1, ResNet-18 achieved a validation accuracy of 0.9632 by epoch 3 and reached 0.9736 by epoch 6. Similarly, EfficientNet-B0 improved from 0.9278 at epoch 1 to 0.9743 by epoch 4. These early-stage gains demonstrate the effectiveness of transfer learning in accelerating feature extraction from limited training data.

I. Fold Stability and Generalization

In 5-fold cross-validation, both models exhibited low variance in performance across folds. ResNet-18's accuracy ranged from 0.9646 to 0.9736 with a standard deviation of approximately 0.0035. EfficientNet-B0 ranged from 0.9743 to 0.9854 with a standard deviation of 0.0042. Although the latter displayed slightly higher variation, its overall results were more favorable, indicating better cross-fold generalization and stability.

J. Class-Wise Performance via Confusion Matrices

The confusion matrices revealed strong per-class performance for both models, particularly in categories such as Beach, Forest, Parking, and Residential, where EfficientNet-B0 achieved near-perfect precision and recall. Minor misclassifications were observed between visually similar classes, such as Airport vs. Highway and Desert vs. Mountain. Compared to ResNet-18, EfficientNet-B0 demonstrated reduced inter-class confusion across most categories, suggesting improved discriminative feature learning.

VI. CONCLUSION

This study provides a systematic evaluation of traditional feature-based methods and deep learning architectures for aerial scene classification using the SkyView benchmark dataset. The experimental results demonstrate that modern convolutional neural networks, particularly EfficientNet-B0, significantly outperform conventional approaches based on handcrafted features (LBP, SIFT) and statistical classifiers. With a mean accuracy of 97.99% achieved through rigorous 5-fold cross-validation, EfficientNet-B0 establishes itself as the superior architecture, surpassing ResNet-18 (96.93%) while utilizing 54.7% fewer parameters. Key technical insights include:

- Data Augmentation Efficacy: The integration of geometric transformations (±15° rotation, random flipping) and photometric adjustments (color jittering) improved model robustness, reducing inter-class confusion by 22% compared to baseline training protocols.
- Transfer Learning Necessity: ImageNet-pretrained weights enabled rapid convergence, with both deep models achieving over 90% validation accuracy within 4 epochs, underscoring the value of domain adaptation in limited-data scenarios.
- Computational Trade-Offs: While traditional methods (best SVM accuracy: 47.69%) showed lower computational costs, their limited discriminative capability for fine-grained categories (e.g., coastal zones vs. riparian networks) renders them impractical for precision-critical applications.

For practical deployment in resource-constrained environments, EfficientNet-B0 emerges as the optimal choice, balancing 98% classification accuracy with real-time inference capabilities. Future work should investigate hybrid architectures combining CNNs and vision transformers, expand category granularity for complex landscapes, and explore unsupervised domain adaptation techniques to address seasonal variations in aerial imagery.

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