An Attention-Enhanced ResNet50 Framework for Multi-Class Outdoor Image Classification

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***Abstract*—The task of outdoor scene image classification involves recognizing different object categories within complex real-world environments. This is a fundamental challenge in computer vision with critical applications in smart cities, autonomous systems, and visual surveillance. In this project, the goal is to classify outdoor images into five categories: Trees, Cars, Buildings, Laboratories, and People. This task is particularly difficult due to background noise, significant class imbalance, and the visual similarity between certain categories. To address these challenges, we propose an attention-enhanced deep learning framework based on ResNet50. The proposed system introduces a spatial attention mechanism to focus on discriminative regions and applies a dynamic class reweighting strategy to handle imbalanced data adaptively. Furthermore, the system incorporates explainable artificial intelligence (XAI) using Grad-CAM to highlight regions influencing the model's predictions. Experimental results on a dataset of 2,160 images show that the enhanced architecture improves accuracy from a baseline of 87% to approximately 89.81%, offering a more reliable and interpretable solution for outdoor scene understanding.**

***Index Terms*—ResNet50, Attention Mechanism, Dynamic Reweighting, Grad-CAM, Outdoor Scene Classification.**

I. Introduction

Outdoor scene understanding is a fundamental challenge in computer vision, where the primary goal is to recognize objects and environments from images captured in real-world conditions [**?**]. This capability is essential for numerous fields, playing an important role in smart cities for monitoring public spaces and traffic, as well as in autonomous vehicles where high accuracy in classifying objects like people and cars is required for safety.

In this project, we aim to build a deep learning model capable of classifying outdoor images into five main categories: Trees, Persons, Labs, Cars, and Buildings. These categories represent common elements in urban and campus-like environments. However, real-world data collection presents significant hurdles. The images in our dataset were collected using mobile devices, resulting in variations in lighting, camera angles, resolution, and background clutter. Such noise can harm model performance; for instance, if a class is consistently captured from a specific angle, the model may memorize the angle rather than the object features.

A major challenge in this domain is class imbalance. Our dataset consists of 2,160 images, but the distribution is uneven (see Fig. 1). For example, the Tree class contains 833 images, whereas the Lab class contains only 220. Standard deep learning models often become biased toward dominant classes in such scenarios.

To overcome these issues, this paper proposes:

- A ResNet50-based model optimized for outdoor classification.
- A spatial attention mechanism to focus on informative regions and reduce background noise impact.
- A dynamic class reweighting strategy that updates loss weights based on validation performance to mitigate class imbalance.
- Integration of Grad-CAM for explainability, allowing visual verification of the model's decision-making process.

II. Related Work

Deep learning has established itself as a powerful approach for image classification, capable of learning hierarchical features from raw pixels. Early architectures such as LeNet, AlexNet, and VGGNet laid the groundwork for modern computer vision [1], [2].

A. Residual Networks (ResNet)

A significant breakthrough occurred with the introduction of ResNet (Residual Network) by He et al. [3], which addressed the vanishing gradient problem in deep networks using skip connections. ResNet50, a 50-layer variant, is widely used as a backbone for transfer learning due to its stable training behavior and high performance, achieving a Top-5 ImageNet accuracy of approximately 92.9%.

B. Handling Class Imbalance

Class imbalance is traditionally addressed via static weighting. However, static weights do not adapt to the model's learning progress. Recent research suggests dynamic reweighting strategies, where class importance is adjusted during training [4]. For example, adaptive reweighting in medical imaging has been shown to outperform static models by balancing network influences dynamically.

C. Explainable AI (XAI)

Modern deep learning systems require interpretability. Grad-CAM (Gradient-weighted Class Activation Mapping) is a prominent technique that visualizes regions contributing to predictions. It has been successfully applied in various domains, such as nanoparticle classification, to verify that models focus on meaningful structures rather than artifacts [5].

III. Methodology

The proposed framework consists of five main stages: data preprocessing, feature extraction, attention-based refinement, classification, and explainability.

A. Dataset and Preprocessing

The dataset comprises 2,160 outdoor images collected via mobile devices. The class distribution is shown in Fig. 1. The data was split into 80% for training and 20% for validation.

IV. Model Pipeline

This section summarizes the end-to-end pipeline implemented in our notebook (data handling, training loop, and explainability) to ensure reproducibility and clarity.

A. Pipeline Overview

Given an input RGB image, the processing and prediction flow is:

1) **Input acquisition:** Read image paths and labels from the dataset folders.
2) **Split strategy:** Perform a stratified split into training (80%) and validation (20%) using a fixed seed for reproducibility.
3) **Validation balancing (downsampling):** To reduce dominance of the majority class in validation, we downsample each validation class to match the smallest class count. This makes validation feedback more balanced and prevents the model from appearing artificially strong on the dominant class.
4) **Preprocessing:** Decode JPEG → resize to 224×224 → apply ImageNet preprocessing using `preprocess_input`.
5) **Efficient input pipeline:** Build a `tf.data` pipeline with shuffling (train only), batching (batch size $= 32$), and prefetching for faster GPU training.
6) **Training-time augmentation:** Apply random horizontal flipping, small rotations, and zooming during training to improve generalization.
7) **Feature extraction (backbone):** Use a pretrained ResNet50 (ImageNet) with `include_top=False` as the feature extractor [3]. The backbone is frozen initially to preserve general visual features.
8) **Attention refinement:** Reshape the last convolutional feature map and apply a learnable attention weighting across spatial tokens (details in Sec. IV-D2).
9) **Classification head:** Global average pooling → dropout → dense softmax over 5 classes.
10) **Dynamic reweighting:** After each epoch, update class weights based on per-class validation accuracy so harder classes receive stronger emphasis in the next epoch.
11) **Explainability (Grad-CAM):** Generate Grad-CAM heatmaps on validation samples to verify the model attends to semantically relevant regions [6].

B. Input Pipeline and Preprocessing

To ensure stable training and consistent input distribution, each image is processed as:

$$\text{JPEG decode} \rightarrow \text{Resize}(224, 224) \rightarrow \text{ImageNet preprocess}$$

We implemented this using a `tf.data.Dataset` with:

- **Shuffle:** enabled only for training (to break ordering bias),
- **Batching:** batch size $= 32$,
- **Prefetch:** `AUTOTUNE` for better GPU utilization.

C. Augmentation Module

We apply augmentation only during training using:

- Random horizontal flip,
- Random rotation (small range),
- Random zoom (small range).

This targets real-world variability (mobile capture angles, scale changes, and framing) and reduces overfitting to background artifacts.

D. Backbone + Attention + Head

1) ResNet50 Feature Extractor: We use ResNet50 pretrained on ImageNet as a frozen backbone to extract robust features [3]. The final classification layers are removed (`include_top=False`).

2) Attention Block: Let $F \in \mathbb{R}^{7\times7\times2048}$ be the final convolutional feature map output by ResNet50. We reshape it into a token sequence:

$$X \in \mathbb{R}^{49\times2048}$$

Then we compute a learnable attention score per token using a trainable vector $W \in \mathbb{R}^{2048\times1}$:

$$S = XW, \quad \alpha = \text{softmax}(S)$$

and reweight the tokens:

$$X' = X \odot \alpha$$

Finally, we apply average pooling across tokens, followed by dropout and a softmax classifier.

E. Dynamic Class Reweighting During Training

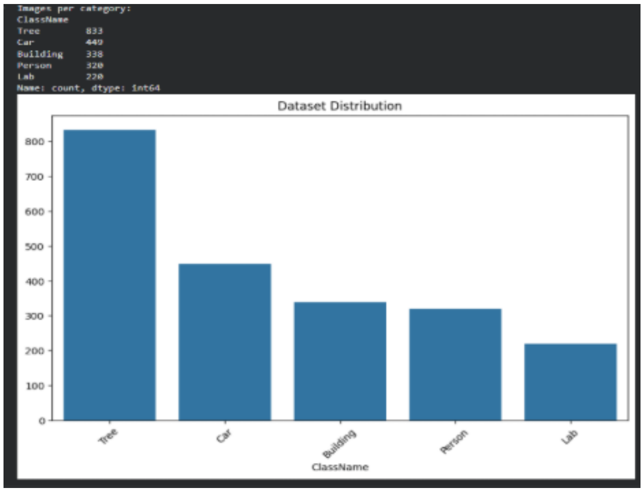
To mitigate class imbalance in a learning-aware way, we update class weights at the end of each epoch. Concretely:

- Predict on the validation dataset,
- Compute per-class validation accuracy,
- Assign higher weights to classes with lower accuracy for the next epoch (inverse-accuracy weighting with smoothing).

This forces the loss to focus more on underperforming classes instead of keeping static weights throughout training.

F. Grad-CAM Explainability

We use Grad-CAM to produce heatmaps from the last convolutional block of ResNet50 (e.g., `conv5_block3_out`) [6]. This visual inspection helps validate that the model relies on meaningful regions (e.g., car body, building edges, tree canopy) rather than irrelevant background patterns.



```
Images per category:
ClassName
Tree         833
Car          449
Building     338
Person       320
Lab          220
Name: count, dtype: int64
```

Fig. 1. Dataset Distribution showing significant class imbalance.

Preprocessing steps included:

- **Resizing:** Images were resized to 224 × 224 pixels to match ResNet50 input requirements.
- **Normalization:** Pixel values were scaled and aligned with ImageNet statistics.
- **Augmentation:** To improve generalization, we applied random horizontal flipping, small rotations, and zooming.

G. Architecture Design

We utilize ResNet50 pretrained on ImageNet as the feature extractor. The final classification layer was removed, and the backbone was frozen to preserve learned features. The dynamic weighting mechanism is illustrated in Fig. 2.

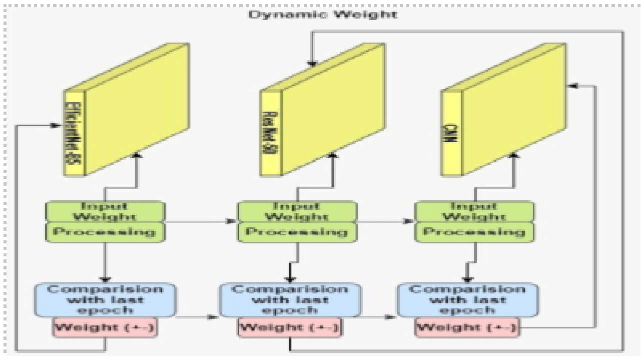


Fig. 2. Proposed Dynamic Weighting Strategy applied during training.

1) Dynamic Class Reweighting: To address imbalance, we implement a dynamic reweighting strategy. After each epoch, validation metrics are computed. Classes with higher loss or lower accuracy are assigned higher weights for the subsequent epoch. This ensures the network allocates more capacity to difficult or underrepresented categories.

V. Experiments and Results

A. Training Configuration

The model was trained for 15 epochs using the Adam optimizer and sparse categorical cross-entropy loss. Training utilized a mini-batch strategy optimized via a `tf.data` pipeline.

B. Quantitative Results

The baseline ResNet50 achieved a validation accuracy of 87–88%. The proposed attention-enhanced model with dynamic reweighting achieved an accuracy of **89.81%**. Fig. 3 shows the convergence of accuracy and loss during training.

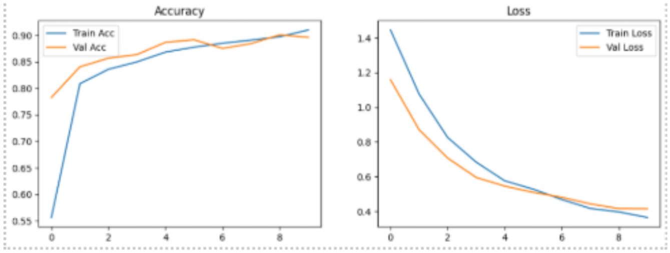


Fig. 3. Training and Validation Accuracy (left) and Loss (right) curves.

Table I presents the detailed performance metrics. The model shows high precision and recall even for the minority 'Lab' class.

TABLE I
CLASS-WISE PERFORMANCE METRICS

Class	Precision	Recall	F1-Score	Support
Tree	0.8429	0.8676	0.8551	68
Car	0.8776	0.9556	0.9149	90
Building	0.9070	0.8864	0.8966	44
Person	0.8955	0.9375	0.9160	64
Lab	0.9351	0.8675	0.9000	166
Accuracy			**0.8981**	432

C. Confusion Matrix Analysis

The confusion matrix (Fig. 4) highlights the model's ability to distinguish visually similar classes. There is a clear reduction in misclassifications for minority classes compared to standard baselines.

VI. Explainability

To ensure the model is not a "black box," we utilized Grad-CAM to visualize decisions. As seen in Fig. 5, the heatmaps focus on relevant features:

- **Tree:** Focuses on branches and leaves.
- **Building:** Focuses on structural edges and windows.
- **Car:** Focuses on the chassis and wheels.

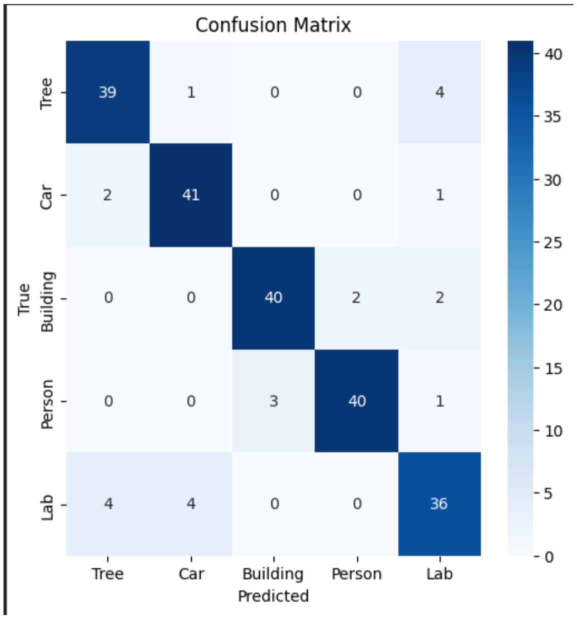


Fig. 4. Confusion Matrix showing strong diagonal performance.

This confirms the model is learning semantic features rather than memorizing background artifacts.

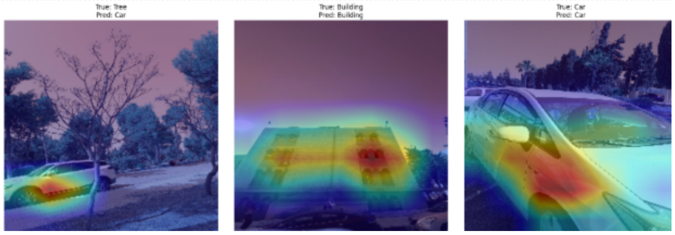


Fig. 5. Grad-CAM visualizations for Tree, Building, and Car classes.

VII. Conclusion

This paper presented an attention-enhanced ResNet50 framework for outdoor image classification. By integrating spatial attention and dynamic class reweighting, we improved classification performance on a challenging, imbalanced dataset from 87% to 89.81%. The integration of Grad-CAM provided interpretability, ensuring trust in the model's predictions. Future work will focus on expanding the dataset to include diverse environmental conditions and exploring multi-head attention mechanisms.

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