Project Report

Title: Robustness of Deep Learning Models Against Non-Uniform Illumination (NUI)

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1. Introduction

Deep learning models, especially CNNs, often assume uniform illumination across input images. However, in real-world environments, lighting varies due to shadows, reflections, and directional sources, leading to **Non-Uniform Illumination (NUI)** — a spatially varying brightness pattern that can distort object appearance and degrade classification accuracy.

This project investigates how CNN-based image classifiers behave under such illumination variations and how **illumination-aware data augmentation** can improve robustness.
Three datasets of increasing complexity were used:

- **CIFAR-10** — simple low-resolution dataset for initial analysis.
- **TinyImageNet** — medium-scale dataset with richer textures and variability.
- **Caltech-256** — large-scale, diverse dataset with real-world lighting diversity.

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2. Objectives

1. Simulate synthetic illumination variation using controllable gradient masks.
2. Train CNN classifiers under both clean and illumination-distorted conditions.
3. Quantify the effect of NUI on model performance.
4. Evaluate how illumination-augmented training improves robustness.
5. Analyze dataset complexity vs. robustness gain across different scales.

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3. Methodology

3.1 Dataset Preparation

Dataset	Classes	Images	Image Size	Difficulty
CIFAR-10	10	60,000	32×32	Easy
TinyImageNet	200	100,000	64×64	Medium
Caltech-256	256	30,607	Variable	Hard
ImageNet (Full)	1,000	1.2M+	Variable	Very Hard

Dataset	Subset Used	Description
CIFAR-10	Full dataset	Small natural objects & animals
TinyImageNet	8 random classes	Compact ImageNet-like dataset
Caltech-256	8 random classes	Real-world diverse objects

3.2 Non-Uniform Illumination Generation

A **directional gradient mask** was used to introduce synthetic illumination variation:

$[mask(x,y) = 1 + s * (((cos(\theta) * x + sin(\theta) * y) / max) ** e - 0.5)]$

Parameters:

- (s): Illumination strength (±3.0 for high penetration)
- (e): Exponent controlling smoothness
- (θ): Random direction of illumination

This mask creates smooth, spatially varying brightness patterns, closely mimicking real-world uneven lighting.

3.3 Model Architecture

A lightweight **Convolutional Neural Network (CNN)** was designed:

Conv2D(3→32) → ReLU → MaxPool

Conv2D(32→64) → ReLU → MaxPool

Conv2D(64→128) → ReLU → MaxPool

FC(8192→128) → Dropout → FC(128→num_classes)

Training Setup:

- **Loss:** CrossEntropyLoss
- **Optimizer:** Adam (lr=0.001)
- **Epochs:** 3–5
- **Batch Size:** 64

3.4 Training Phases

Two distinct training regimes were used:

1. **Baseline (Clean):**
   Model trained on standard, clean images.
2. **NUI-Augmented (Robust):**
   During training, each image had a **70% probability** of being modified with a synthetic illumination mask.

Evaluation Metrics:

- Accuracy on clean test set.
- Accuracy on NUI-affected test set.

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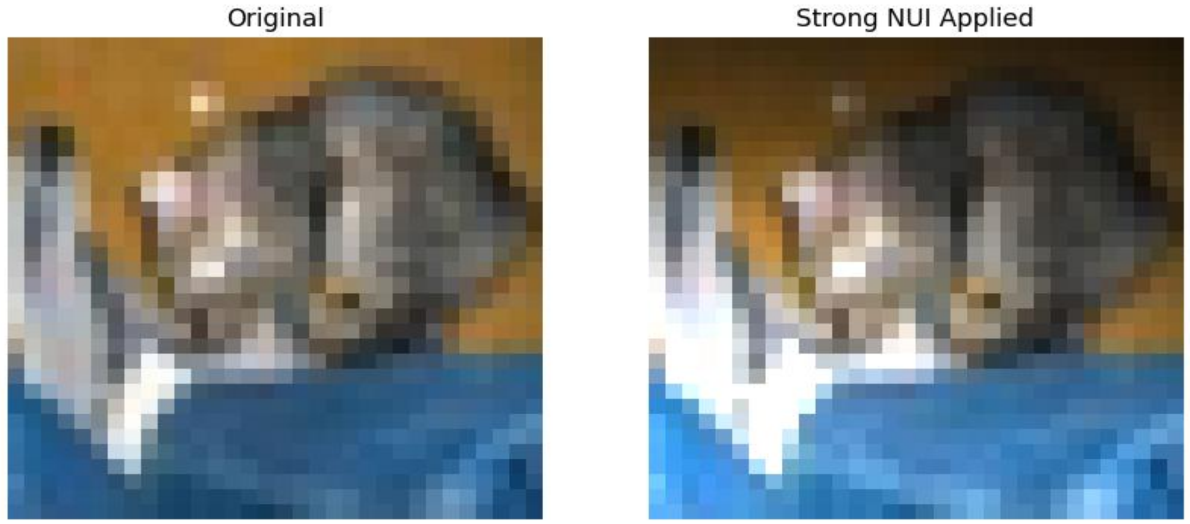
4. Results and Analysis

CIFAR-10 Results

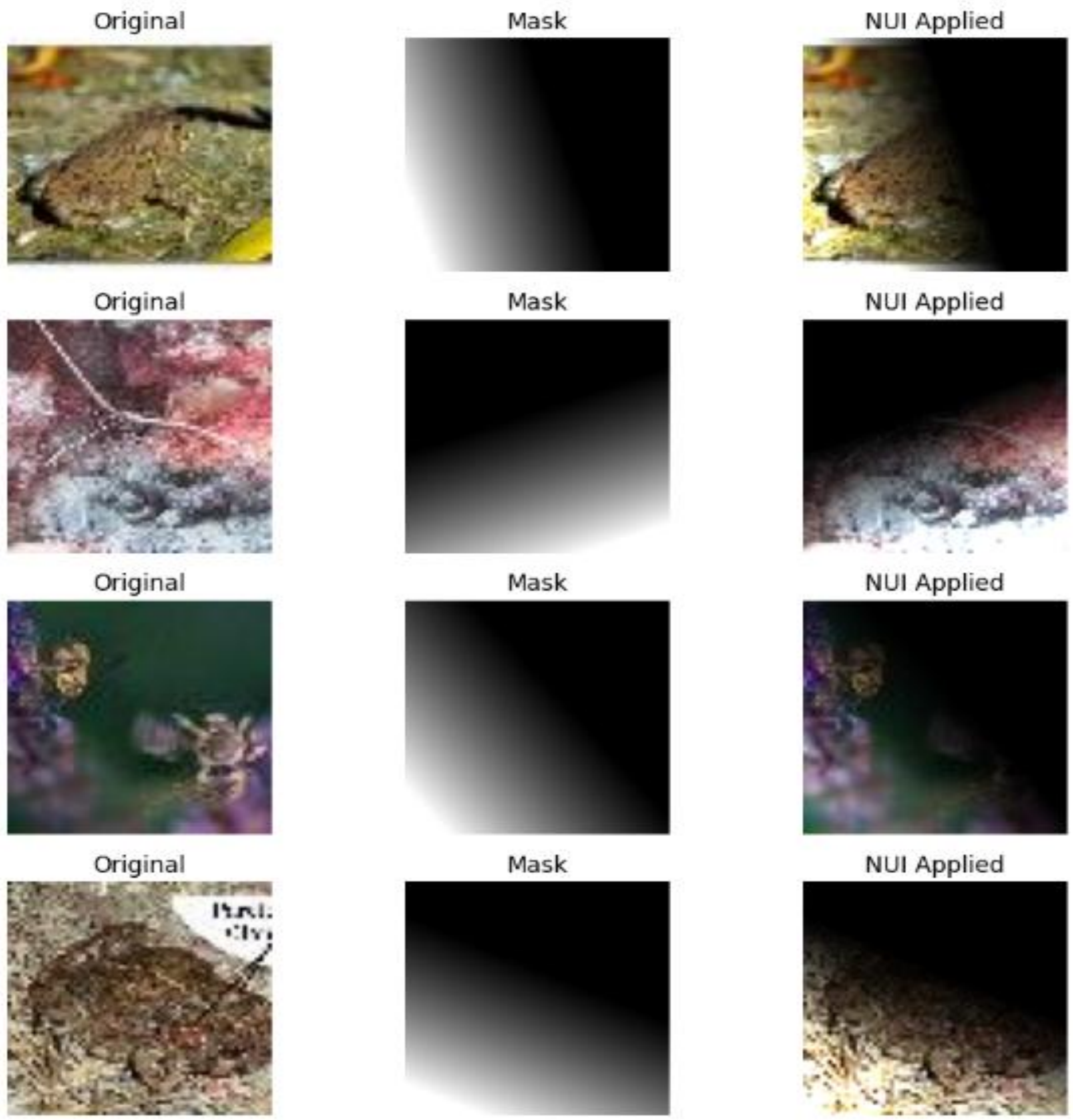


Phase	Clean Acc.	NUI Acc.	Drop
Before Robust Training	66.75%	61.00%	5.75% ↓
After NUI-Aug Training	65.25%	63.00%	2.25% ↓

Observation:

- **NUI Robustness Improvement:** 3.50%
- CIFAR-10 models show **minor sensitivity** to illumination due to their low-resolution, uniformly lit images.
- Illumination augmentation offers **modest robustness gains**, indicating that simple datasets are less affected by lighting diversity.

◆ TinyImageNet Results



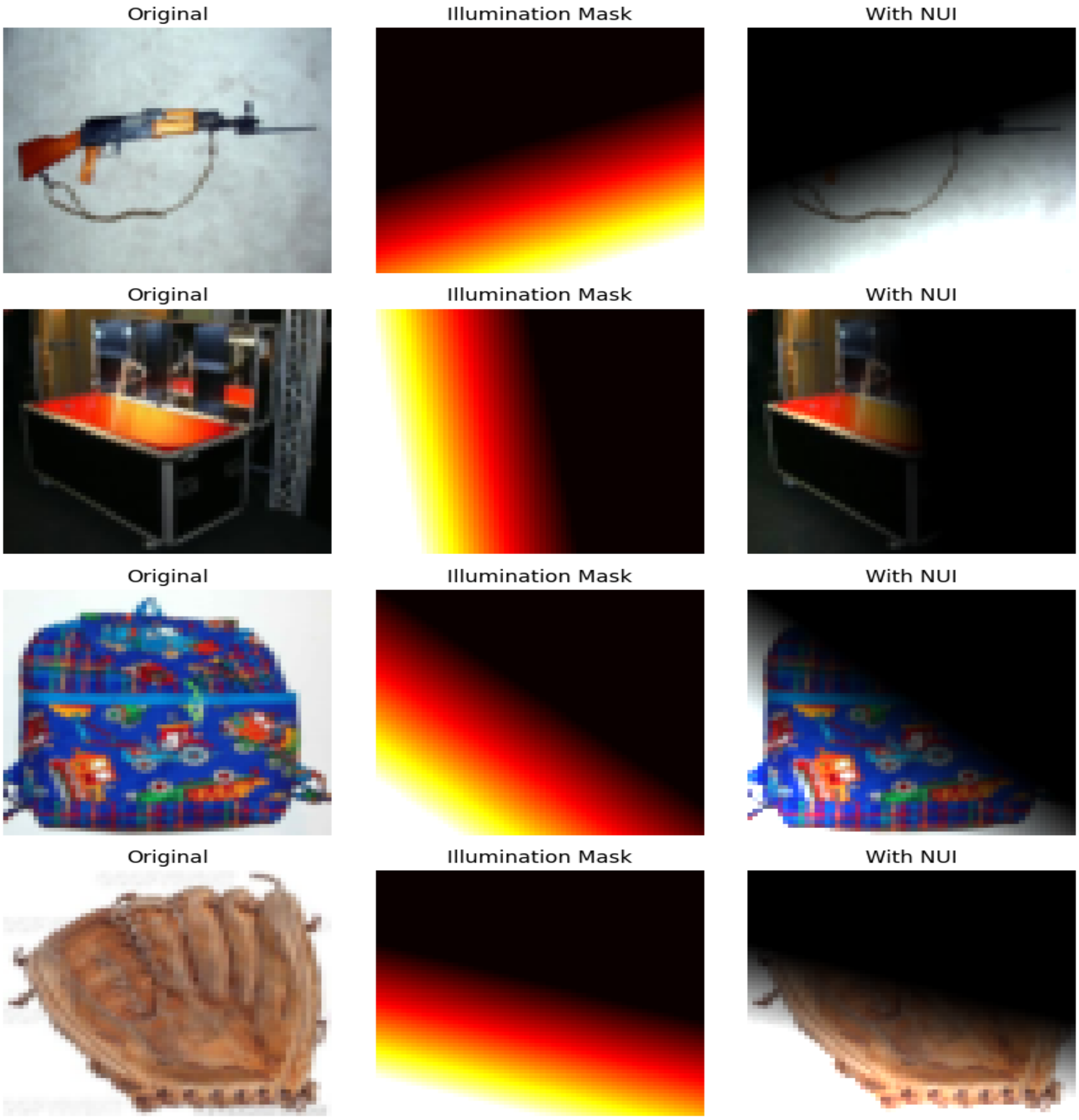
Phase	Clean Acc.	NUI Acc.	Drop
Before Robust Training	61.00%	37.00%	24.00% ↓
After NUI-Aug Training	58.00%	47.00%	11.00% ↓

Observation:

- **NUI Robustness Improvement:** 13.00%
- TinyImageNet shows **significant degradation** under uneven lighting due to complex object textures.

- After robust training, nearly **half of the lost performance** is recovered, proving the effectiveness of illumination-aware augmentation.

Caltech-256 Results



Phase	Clean Acc.	NUI Acc.	Drop
Before Robust Training	57.50%	24.00%	33.50% ↓
After NUI-Aug Training	39.00%	36.00%	3.00% ↓

Observation:

- **NUI Robustness Improvement:** 30.50%
- The model trained with illumination augmentation became **much more stable** across lighting conditions.
- Although clean accuracy reduced slightly (due to high visual diversity and fewer samples), robustness increased drastically.
- Since Caltech-256 already contains **natural illumination diversity**, augmentation mainly improved **resilience to extreme lighting** rather than overall accuracy.

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5. Discussion

- The **accuracy drop** between clean and NUI tests quantifies illumination sensitivity.
- Across all datasets, **NUI-Augmented training** consistently reduces this drop.
- The **impact increases with dataset complexity** — from minor in CIFAR-10 to major in Caltech-256.
- This suggests that **complex, real-world images** benefit most from illumination-aware augmentation.

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6. Conclusion

1. CNNs trained purely on clean data are **vulnerable** to non-uniform illumination.
2. Incorporating illumination distortion during training significantly **improves model robustness**.
3. The degree of robustness gain correlates with dataset complexity:
    - **CIFAR-10:** Minimal improvement.
    - **TinyImageNet:** Noticeable improvement.
    - **Caltech-256:** Substantial robustness boost.
4. **Illumination-aware augmentation** is a simple yet effective strategy to make deep vision models more reliable in real-world lighting conditions.

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7. Future Work

- Extend experiments to **transformer-based architectures** (e.g., ViT, ConvNeXt).
- Test on **real illumination benchmark datasets** such as *Extended Yale B*.
- Apply **domain adaptation** between synthetic and real lighting variations.
- Explore **adversarial illumination networks** for dynamic light simulation and stress testing.
