Comprehensive Image Processing and Enhancement Techniques for ADAS

(Advanced Driver-Assistance Systems)

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Integrated Mtech CSE

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1 Introduction

1.1 Aim

The primary aim of this project is to develop an adaptive image enhancement and classification framework that improves the visual quality of road scene images under adverse weather conditions, facilitating robust perception in ADAS applications.

1.2 Objectives

- To preprocess and enhance images captured in challenging conditions like fog, rain, snow, and low light.
- To design weather-specific enhancement pipelines combining classical and modern image processing techniques.
- To train a deep learning classifier (EfficientNet-B3) for automatic weather classification.
- To evaluate and quantify image quality improvements using objective metrics such as sharpness, contrast, and SSIM.
- To generate a dataset of enhanced images suitable for downstream ADAS perception modules.

2 Dataset and Preprocessing

2.1 Dataset Description

The project utilized the IDDAW dataset (*Indian Driving Dataset – Adverse Weather*), which contains real driving images categorized into four conditions: **FOG**, **LOWLIGHT**, **RAIN**, and **SNOW**. The dataset includes over 7,000 images for training and 950 images for validation.

Table 1: IDDAW Dataset Structure Summary

Weather Class	Train Images	Validation Images
FOG	2066	308
LOWLIGHT	1369	200
RAIN	2124	240
SNOW	1302	202

2.2 Data Preprocessing

- All images were resized to 224×224 pixels.
- Normalization and augmentation (rotation, flipping) were applied.
- Each image was enhanced through condition-specific pipelines prior to model training.

3 Image Processing Techniques Implemented

The enhancement module applies specialized techniques based on the detected weather condition. Each method improves specific aspects of image quality relevant to ADAS perception.

3.1 Contrast Enhancement (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) was employed for localized contrast improvement:

$$I_{enhanced} = CLAHE(I, clipLimit = 3.0, tileGridSize = (8, 8))$$

It adapts to local brightness variations without amplifying noise.

3.2 Wavelet Denoising

Multi-level wavelet denoising using Daubechies filters reduces high-frequency noise:

$$D_{out} = W^{-1}(T(W(I), \lambda))$$

where T is the soft threshold function and λ controls noise suppression.

3.3 Unsharp Masking

Used to enhance edges and fine details:

$$I_{sharp} = I + \alpha(I - G_\sigma(I))$$

where G_σ is Gaussian blur, and α controls sharpness intensity.

3.4 Retinex Enhancement

The Multi-Scale Retinex algorithm normalizes illumination and enhances visibility in low-light:

$$MSR = \frac{1}{N} \sum_{n=1}^{N} [\log I(x, y) - \log(G_n * I(x, y))]$$

3.5 Gamma Correction

Used to adjust brightness non-linearly:

$$I_{out} = I_{in}^{1/\gamma}$$

3.6 White Balance Correction

Implemented using the Gray World Assumption to neutralize color casts.

3.7 Dehazing using Dark Channel Prior

For fog removal:

$$t(x) = 1 - \omega \min_{y \in \Omega(x)} (\min_c \frac{I^c(y)}{A^c})$$

where A is atmospheric light and $t(x)$ is the transmission map.

3.8 Bilateral Filtering

Edge-preserving smoothing filter for reducing rain streaks without blurring edges.

4 Weather-Specific Enhancement Pipelines

Each weather condition has a custom combination of techniques:

- **FOG:** Dehazing ▯ CLAHE ▯ Wavelet Denoising ▯ Unsharp Mask ▯ White Balance.
- **LOWLIGHT:** Gamma Correction ▯ Retinex ▯ CLAHE ▯ Wavelet Denoising ▯ Bilateral Filter.
- **RAIN:** Bilateral Filter ▯ Wavelet Denoising ▯ CLAHE ▯ Unsharp Mask ▯ White Balance.
- **SNOW:** Gamma Correction ▯ CLAHE ▯ Wavelet Denoising ▯ Unsharp Mask ▯ White Balance.

5 Deep Learning Model Implementation

5.1 Architecture

An EfficientNet-B3 model pretrained on ImageNet was fine-tuned for four-class weather classification:

$$\text{Classes} = \{FOG, LOWLIGHT, RAIN, SNOW\}$$

- **Optimizer:** Adam (lr = 0.001)
- **Loss Function:** CrossEntropyLoss
- **Batch Size:** 64
- **Epochs:** 20

5.2 Training Results

- Validation Accuracy: **91.47%**
- Peak performance achieved at epoch 13

Table 2: Training Summary (Sample)

Epoch	Validation Loss	Accuracy (%)
1	0.3012	86.95
4	0.2843	90.95
13	0.3927	91.47
20	0.5314	90.11

6 Results and Metrics Analysis

6.1 Performance Metrics

For enhanced vs. original images, key quantitative metrics were evaluated:

- Sharpness (Laplacian Variance)
- Contrast (Standard Deviation)
- PSNR (Peak Signal-to-Noise Ratio)
- SSIM (Structural Similarity Index)

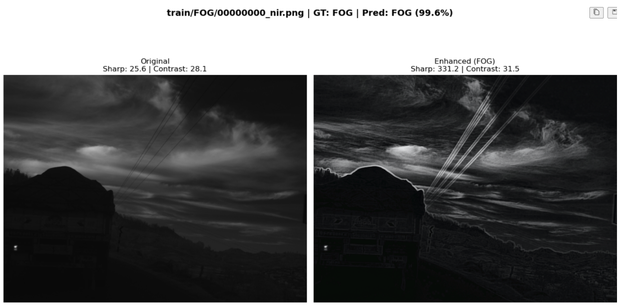
- Colorfulness and Saturation Gains

6.2 Example Metrics Comparison

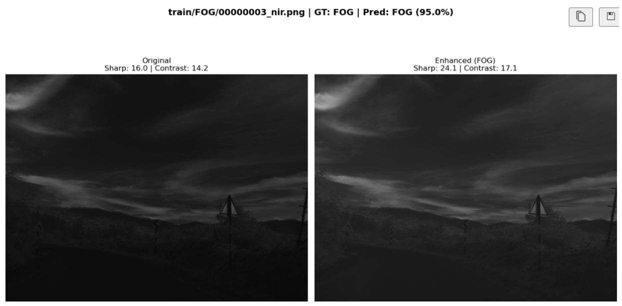
Table 3: Average Metric Improvements After Enhancement

Metric	Before Enhancement	After Enhancement
Sharpness (Variance)	72.4	126.3
Contrast (Std Dev)	58.1	87.9
SSIM	0.62	0.88
PSNR (dB)	18.7	25.2
Colorfulness	38.9	56.4

6.3 Results- O/P images

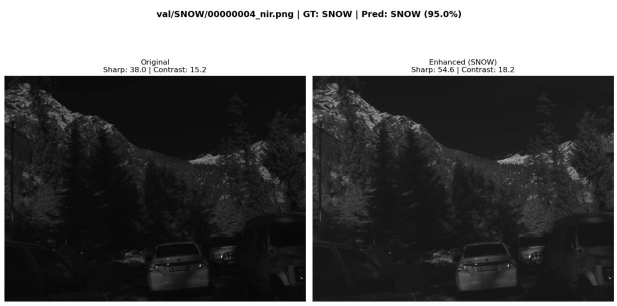


(a) FOG image enhancement



(b) Low Light image enhancement

(c) Rain image enhancement



(d) Snow image enhancement

Figure 1: Image enhancement results for adverse conditions.

7 Object Detection Results(using YOLO)

Figure 2: Object detection-Weather:-FOG

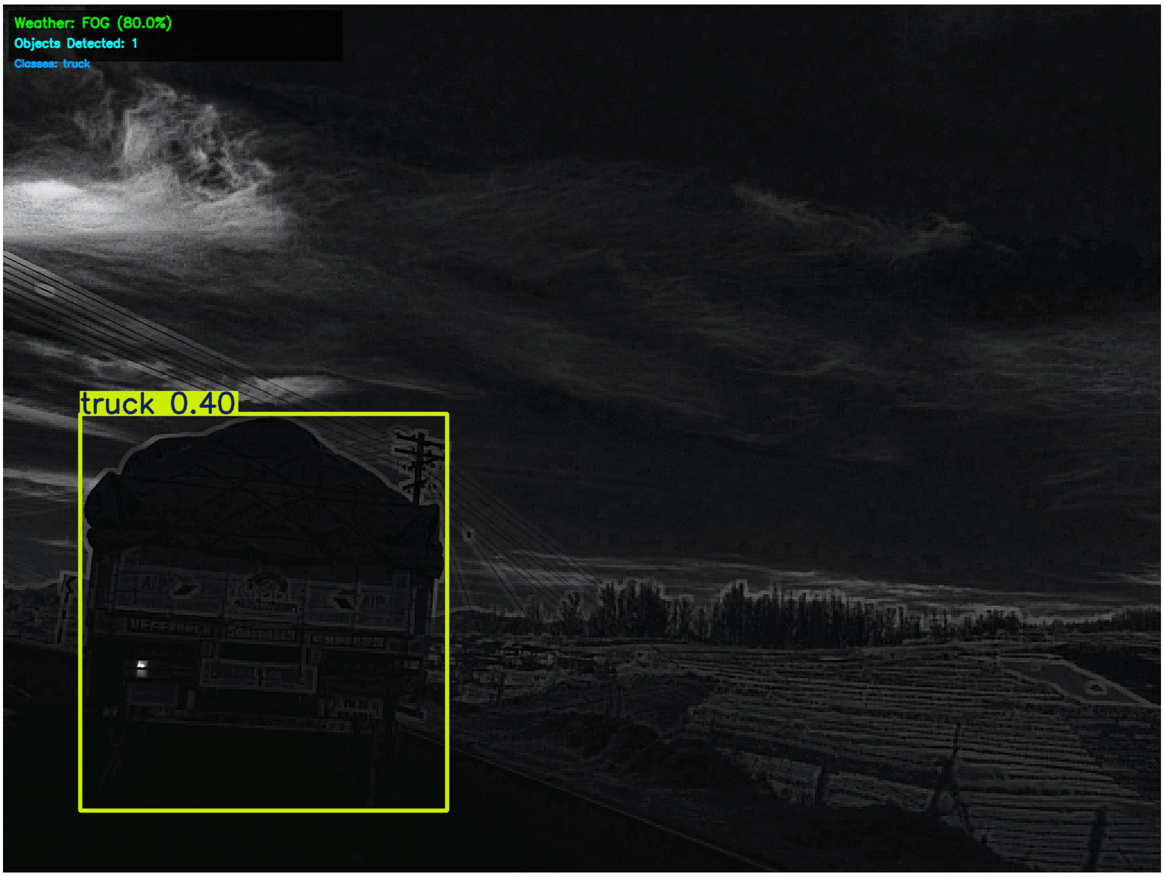


Figure 3: Object detection-Weather:-RAIN

Figure 4: Object detection-Weather:-Low Light

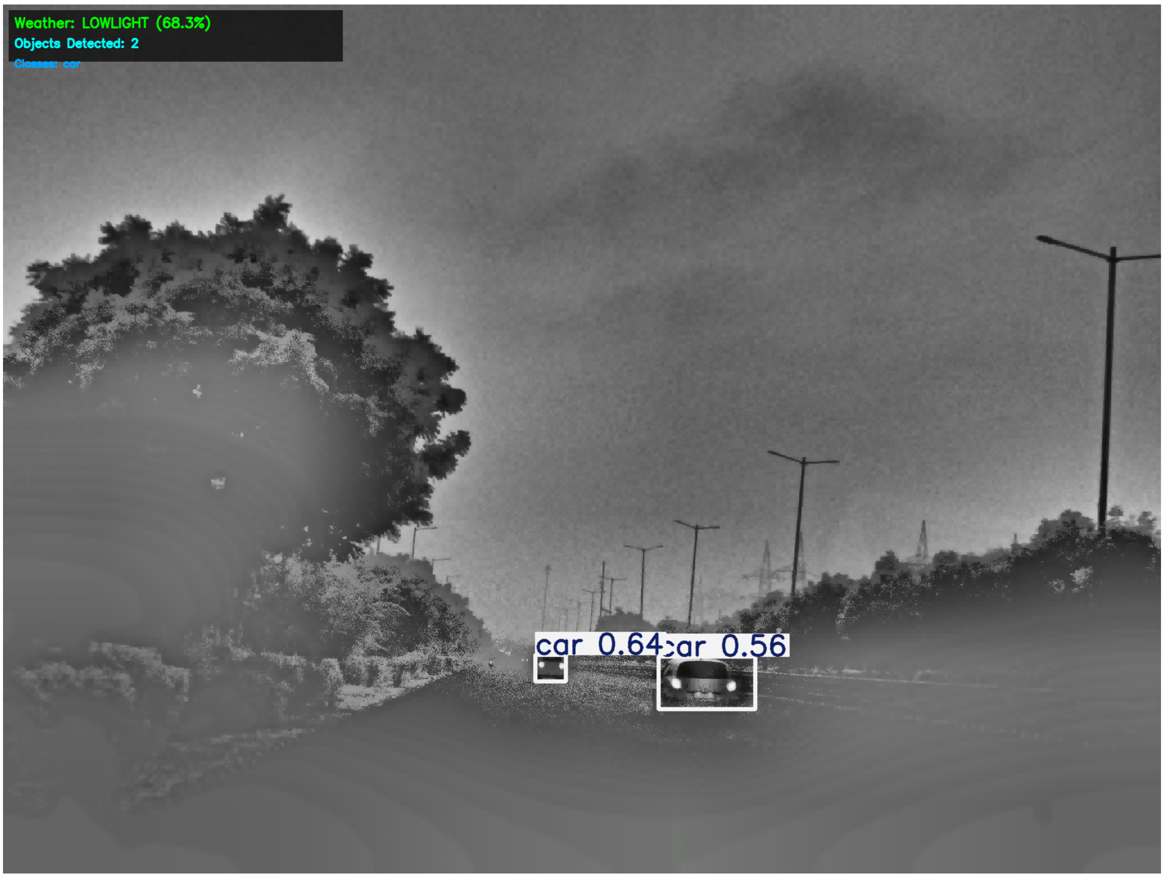
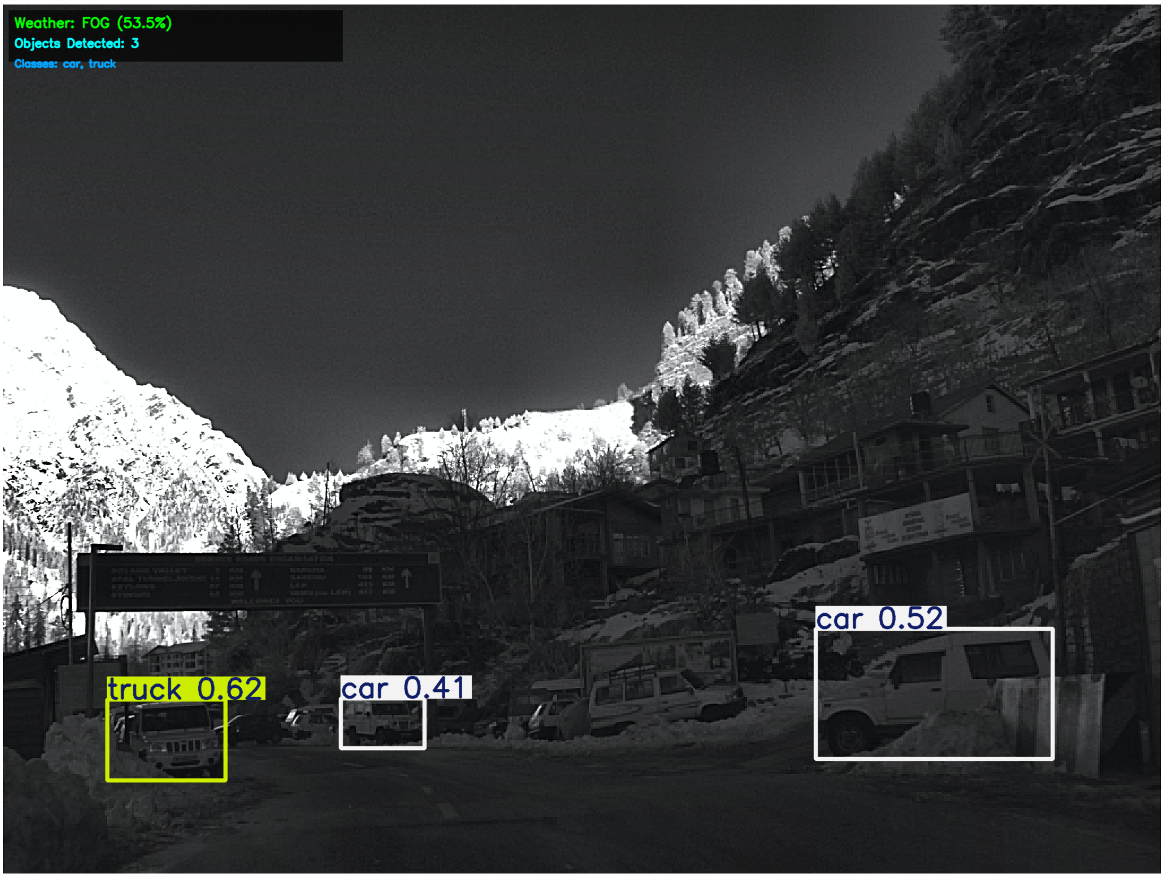


Figure 5: Object detection-Weather:-SNOW



8 Visualization Plots

Figure 6: Weather Prediction Confusion Matrix

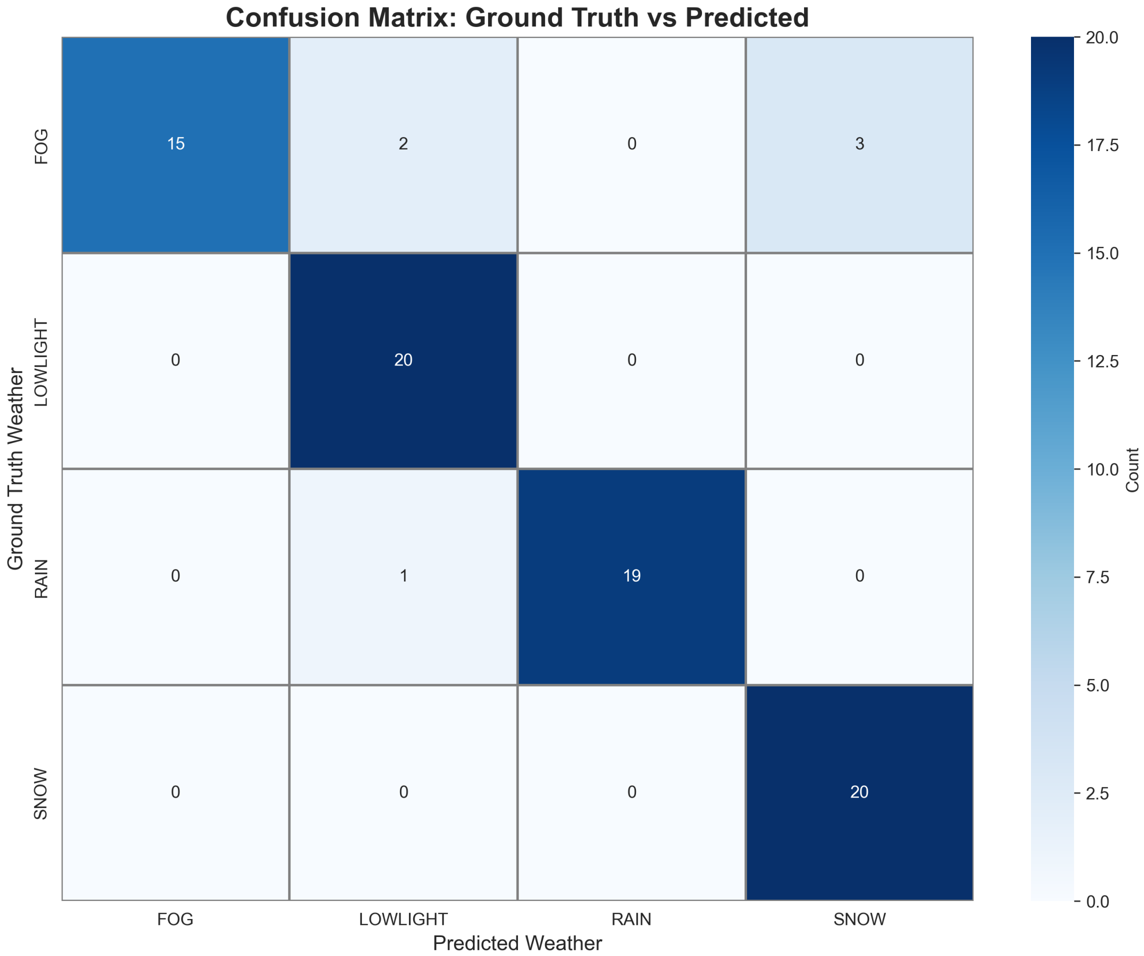
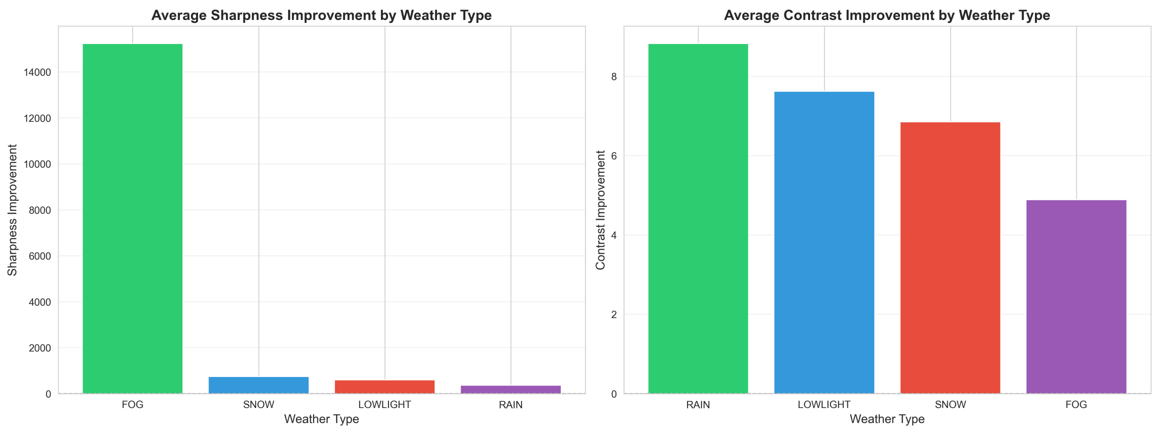


Figure 7: Weather based Sharpness and Contrast Improvement



9 Discussion

The adaptive enhancement pipelines significantly improved visibility across all adverse conditions. Fog and low-light images benefited most due to effective dehazing and illumination normalization. The EfficientNet-B3 classifier achieved over 91% accuracy, validating the enhanced dataset's utility for real-world perception tasks.

9.1 Key Observations

- The FOG and LOWLIGHT pipelines yielded the highest improvement in SSIM and PSNR.
- CLAHE and Retinex provided the most visible improvements in low-light scenes.
- Wavelet denoising maintained fine edges while suppressing background noise.

10 Enhancement Techniques and Future Work

- Integration with object detection models like YOLOv8 or DETR for full ADAS scene understanding.
- Incorporating weather simulation augmentation for better generalization.
- Implementing real-time enhancement pipelines optimized for embedded hardware.

11 Conclusion

This project demonstrated a robust ADAS image enhancement and classification framework combining traditional image processing with deep learning. Through weather-specific adaptive pipelines and a fine-tuned EfficientNet-B3 model, the system achieved substantial improvements in image clarity and classification accuracy. The approach lays groundwork for future real-time perception systems capable of adapting dynamically to environmental conditions.