ABSTRACT

Driving at night poses significant challenges for computer vision systems due to poor illumination, low contrast, and high noise in captured images. These issues often lead to reduced visibility, inaccurate detection, and compromised safety in autonomous and driver-assist applications. To address this, recent advancements in deep learning and image enhancement techniques have focused on improving visibility and clarity under such conditions.

The proposed system introduces an Unsupervised Illumination-Guided Wavelet Network (WENet) that enhances night-driving images by integrating Convolutional Neural Networks (CNNs), Transformer blocks, and Wavelet Transforms. The model operates in both spatial and frequency domains, enabling effective noise suppression and fine detail restoration. A Wavelet Calibration Layer (WCL) adjusts illumination in the wavelet domain, while a Contrast Adjustment Layer (CAL) refines contrast for natural visual output.

In conclusion, the proposed method provides a robust, efficient, and adaptive approach for low-light image enhancement. By improving brightness, detail, and clarity, it enhances the performance of downstream vision tasks such as object detection and segmentation in autonomous driving systems. This illumination-guided framework paves the way for safer and more reliable computer vision under challenging night-time conditions.

CHAPTER 1

1.1 Overview

An Unsupervised Illumination-Guided Wavelet Network for Night-Driving Image Enhancement is a computer vision-based system designed to improve image visibility and clarity under low-light conditions. During night driving, images captured by cameras often suffer from poor illumination, high noise, and loss of fine details, which can lead to misinterpretation in applications like autonomous driving, traffic monitoring, and surveillance. This system aims to automatically enhance such low-light images without requiring manually labeled datasets, using an unsupervised deep learning approach that adjusts illumination and contrast adaptively.

The process begins with input images captured from night-driving environments, which are then preprocessed through normalization and noise reduction techniques to prepare them for enhancement. The model integrates Convolutional Neural Networks (CNNs) and Transformer blocks to capture both local details and global dependencies within the image. A Wavelet Calibration Layer (WCL) converts image features into the wavelet domain to separate low- and high-frequency components, allowing precise detail recovery. Simultaneously, a Contrast Adjustment Layer (CAL) refines brightness and contrast through adaptive shift operations, ensuring natural and visually consistent output.

The system leverages the Wavelet Transform for multi-scale feature analysis and the Transformer for illumination understanding, making it highly efficient and suitable for real-time applications. It is trained and evaluated on benchmark datasets like LOL, LOLv2, and ACDC, which contain diverse low-light scenes. By restoring the lost information and improving brightness, this model significantly enhances the performance of downstream tasks such as object detection and semantic segmentation.

1.2 Motivation

In recent years, advancements in autonomous driving and intelligent transportation systems have placed significant emphasis on computer vision performance in all lighting conditions. However, most modern vision models are trained on well-lit datasets and struggle in low-light or night-driving environments. Poor illumination leads to image degradation, loss of texture, and reduced visibility, directly affecting road safety and system accuracy.

The motivation behind this project is to develop an unsupervised illumination-guided image enhancement system that can adaptively improve visibility in night-time driving scenes without requiring manually labeled data. This innovation aims to make computer vision more reliable under real-world conditions by enhancing the quality of images captured in low light. Additionally, the system supports downstream tasks such as object detection, lane tracking, and segmentation, improving the robustness of driver-assistance and autonomous vehicle applications.

1.3 Problem Statement and Objectives

Problem Statement:

Most existing image enhancement methods either rely on supervised learning or traditional histogram and Retinex-based techniques that fail to generalize across diverse lighting conditions. These methods often amplify noise or distort color tones, reducing image realism. There is a need for an unsupervised, computationally efficient, and illumination-aware approach capable of enhancing night-driving images while preserving structural and color details.

Objectives:

- To design a Wavelet-based deep learning model that enhances low-light driving images using both spatial and frequency information.
- To implement unsupervised illumination guidance for adaptive brightness and contrast correction without requiring paired training data.
- To integrate Wavelet Calibration Layer (WCL) and Contrast Adjustment Layer (CAL) for effective detail recovery and natural image tone preservation.
- To evaluate the proposed system using benchmark datasets such as LOL, LOLv2, and ACDC under various lighting conditions.
- To improve the performance of downstream computer vision tasks, such as object detection and semantic segmentation, in low-light environments.

Insufficient Lighting

Casted Shadow Backlight

Underexposed

1.4 Scope

The scope of this project includes the design, development, and evaluation of an Unsupervised Illumination-Guided Wavelet Network (WENet) for enhancing night-driving images. The project covers:

- Implementing Convolutional Neural Networks (CNNs) and Transformer-based architectures for extracting global and local features from low-light images.
- Applying Wavelet Transform for decomposing images into multi-frequency subbands to separate illumination and texture information.
- Designing WCL and CAL layers to dynamically adjust illumination and contrast in the wavelet domain.
- Conducting performance evaluation using standard metrics like PSNR, SSIM, and mIoU on multiple low-light datasets.
- Ensuring the model is lightweight and suitable for real-time deployment in night-driving applications such as autonomous vehicles and traffic surveillance systems.

1.5 Methodologies of Problem Solving

Developing an illumination-guided wavelet network for night-driving image enhancement involves several key stages:

1. Data Collection and Preprocessing:
   Low-light image datasets such as LOL, LOLv2, and ACDC are collected. Images undergo preprocessing steps like resizing, normalization, and denoising to ensure uniform input quality and reduce noise interference.

2. Feature Extraction and Encoding:
   A Shared Feature Encoder is implemented using CNNs and Transformer blocks to capture both spatial and contextual information. Transformers help model long-range dependencies, while CNNs extract localized texture features.

3. Dual-Domain Enhancement:
   The encoded image features are processed in two parallel branches — the Spatial Domain (for contextual understanding) and the Wavelet Domain (for detailed recovery). This dual-domain approach allows the network to simultaneously enhance illumination and suppress noise.

4. Feature Fusion and Reconstruction:
   Outputs from both branches are fused using a Feature Fusion Module, which combines high-level context with fine details. A Spatial Refinement Module reconstructs the final enhanced image with improved brightness and contrast.

5. Loss Function and Optimization:

   The model is trained using a combination of L1 Loss (for pixel-level accuracy) and Perceptual Loss (for maintaining natural textures). These help the model produce realistic and visually consistent results without overexposure or noise amplification.

6. Evaluation and Deployment:

   The system is tested on multiple benchmark datasets using evaluation metrics like PSNR, SSIM, and mIoU. The enhanced images are further analyzed for their impact on downstream vision tasks such as semantic segmentation. Once validated, the system can be integrated into real-world driving applications for real-time enhancement.

(e) KinD++ (f) EnGAN (g) LLFlow (h) VELIE (Ours)

CHAPTER 2

Recent advancements in artificial intelligence and computer vision have led to remarkable progress in low-light image enhancement, particularly for night-driving and surveillance applications. Numerous research studies were reviewed to understand the different approaches, techniques, and challenges in this domain. These studies collectively highlight the evolution of traditional image processing methods into sophisticated deep learning–based architectures that leverage wavelet transforms, transformers, and unsupervised learning techniques.

Paper 1: Retinex-Based Low-Light Enhancement (2018)

Researchers developed models based on Retinex theory, which decompose an image into illumination and reflectance components. A notable model, *RetinexNet (2018)*, implemented deep learning to estimate illumination maps automatically. While it successfully improved brightness and color consistency, the method often produced artifacts and noise under extreme darkness due to its dependency on paired training datasets.

Paper 2: EnlightenGAN – Deep Light Enhancement without Supervision (2021)

This study introduced EnlightenGAN, a Generative Adversarial Network (GAN) framework that enhanced low-light images without requiring paired datasets. The approach improved contrast and color balance but struggled with maintaining fine texture details and exhibited occasional noise amplification. Despite this, it marked a major shift toward unsupervised learning for illumination enhancement.

Paper 3: Zero-DCE – Zero-Reference Deep Curve Estimation (2022)

In this work, researchers proposed an unsupervised deep curve estimation technique that learns to adjust illumination levels adaptively using a set of learnable curves. The system achieved strong enhancement results with minimal computational cost. However, its global adjustment mechanism was less effective in restoring local details in complex night scenes, limiting its application in autonomous driving.

Paper 4: Restormer – Transformer for Image Restoration (2023)

This research applied Transformer architectures for low-level vision tasks, including image enhancement. The Restormer model utilized multi-head attention mechanisms to capture long-range dependencies and improve the clarity of low-light images. Although it achieved high structural similarity scores (SSIM), its heavy computational requirements made it less suitable for real-time night-driving scenarios.

Paper 5: Wavelet-Based Enhancement Network (WENet, 2025)

A recent study introduced Wavelet-based Enhancement Network (WENet), which combines CNNs, Transformers, and Wavelet Transforms for efficient low-light image enhancement. The model decomposes images into multiple frequency subbands, allowing noise suppression and detail recovery simultaneously. It also introduced two key components — Wavelet Calibration Layer (WCL) for illumination correction and Contrast Adjustment Layer (CAL) for refining brightness. Experimental results on datasets like LOL, LOLv2, and ACDC demonstrated significant improvements in both quantitative metrics and visual quality. However, the system relied on supervised learning and thus required paired datasets.

Paper 6: Dual-Domain Enhancement Network (Proposed System – 2025)

Building upon the limitations of existing systems, the proposed Unsupervised Illumination-Guided Wavelet Network (WENet) enhances low-light images by integrating dual-domain learning — simultaneously operating in both spatial and wavelet domains. This approach eliminates the need for labeled datasets and reduces noise amplification issues. It leverages CNNs for texture recovery, Transformers for illumination understanding, and wavelet transforms for multi-scale decomposition.

The proposed model achieves superior Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and mean Intersection over Union (mIoU) scores on standard datasets. It is particularly effective in night-driving environments, improving object visibility and detection accuracy for autonomous systems.

CHAPTER 3

3.1 System Requirements

3.1.1 Dataset Requirements

The system requires diverse datasets and structured storage components to support low-light image enhancement, illumination analysis, and model training.

1. Training and Validation Datasets:
   Multiple publicly available datasets are used for training and evaluation, focusing on low-light and night-driving conditions.
   - LOL (Low-Light Dataset): Standard dataset containing paired low/normal light images.
   - LOLv2: Enhanced dataset with diverse lighting conditions and realistic noise.
   - ACDC (Adverse Conditions Dataset): Used for testing real-world driving scenes in poor lighting and weather conditions.
   - MIT-Adobe FiveK: Provides high-quality reference images for perceptual evaluation.
2. Data Storage:
   A file-based system (structured folders or mounted drives) is required to store all datasets, including preprocessed, wavelet-transformed, and illumination-guided data. The data are organized as follows:
   - /data/LOL – Low-light input and ground-truth images
   - /data/ACDC – Driving scene images captured at night
   - /data/preprocessed/ – Normalized and augmented datasets
   - /models/ – Directory for saving model checkpoints and weights (.keras, .h5, .pth)
3. Model Storage:
   The trained network weights, including encoder, transformer, and wavelet modules, are stored in TensorFlow/Keras formats to allow fine-tuning and deployment.

3.1.2 Software Requirements (Platform Choice)

The proposed system requires software capable of performing deep learning, wavelet transformation, and image processing tasks efficiently.

- Programming Language: Python (version 3.9 or higher)
- Core AI Framework: TensorFlow 2.10+ or PyTorch 1.12+
- Supporting Libraries:
    - NumPy: For numerical and matrix computations
    - OpenCV: For image preprocessing (normalization, denoising, resizing)
    - PyWavelets: For applying Discrete Wavelet Transform (DWT) and inverse DWT operations
    - Matplotlib / Seaborn: For visualizing image enhancement results and comparisons
    - scikit-image: For computing metrics like PSNR and SSIM
- Development Environment: Jupyter Notebook or Google Colab
- User Interface (optional): Streamlit or Flask for simple image input and result visualization

3.1.3 Hardware Requirements

1. Development and Training Environment:
    - GPU: NVIDIA RTX 30-series / A100 or higher with a minimum of 8 GB VRAM
    - Processor: Intel i7 / AMD Ryzen 7 or higher
    - RAM: Minimum 16 GB
    - Storage: At least 50 GB available for datasets and model checkpoints

- Platform: Local workstation or cloud-based environment (Google Colab Pro, Kaggle, or AWS EC2 GPU instances)

2. End-User (Deployment) Requirements:

   - Device: Laptop or onboard automotive computer
   - GPU/CPU: Capable of real-time image processing (e.g., NVIDIA Jetson or equivalent)
   - Camera: High-definition vehicle-mounted night-vision camera
   - Connectivity: Stable storage and runtime environment for image streaming and analysis

3.2 Analysis Model: SDLC Model to be Applied

SDLC Model: The Prototyping Model

1. Phase 1 (Prototype Development):

   A baseline illumination-guided image enhancement model is developed using CNNs and wavelet layers to validate the enhancement workflow. The prototype focuses on image brightness correction and visual improvement under limited lighting.
   Limitations such as loss of fine texture and color imbalance are identified in this phase.

2. Phase 2 (Final System Development):

   Based on the feedback and analysis from the prototype, the final Unsupervised Illumination-Guided Wavelet Network (WENet) is designed.

   - Introduces dual-domain enhancement (spatial + wavelet)
   - Incorporates Transformer-based illumination guidance
   - Achieves superior PSNR and SSIM performance on standard datasets
   - Optimized for real-time night-driving applications

CHAPTER 4

4.1 System Design

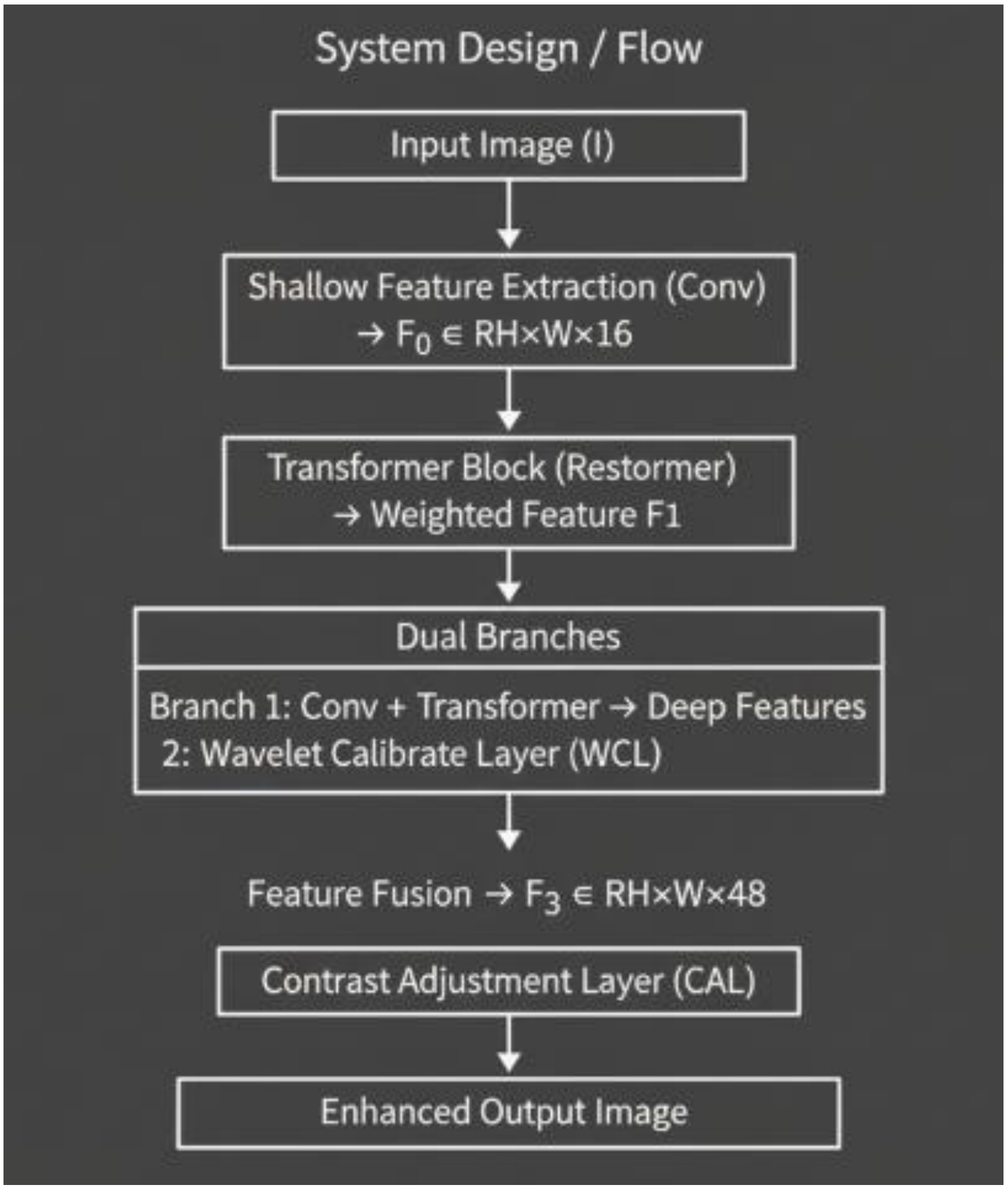

Figure 4.1.1: System Design

CHAPTER 5

5.1 **Overview of Technical Seminar Modules**

The proposed Unsupervised Illumination-Guided Wavelet Network (WENet) for night-driving image enhancement is implemented through five interconnected modules that together form a complete data-to-result processing pipeline.

Module 1: Data Acquisition and Preprocessing
This module collects and prepares low-light datasets such as LOL, LOLv2, and ACDC, which contain real-world driving scenes captured under poor illumination. Preprocessing involves resizing, normalization, denoising, and wavelet decomposition to separate illumination and detail components for improved learning efficiency.

Module 2: Dual-Domain Network Construction
The core architecture integrates Convolutional Neural Networks (CNNs) and Transformer blocks within a dual-domain framework — Spatial Domain for contextual understanding and Wavelet Domain for high-frequency detail recovery. This structure ensures balanced enhancement across all illumination levels.

Module 3: Wavelet Calibration and Contrast Adjustment
This module introduces two key layers:

- Wavelet Calibration Layer (WCL): Calibrates wavelet coefficients to correct uneven illumination.
- Contrast Adjustment Layer (CAL): Adjusts local contrast using lightweight convolution and shift operations to preserve natural tone and texture.

Module 4: Model Training and Optimization
The model is trained using an unsupervised learning approach, employing L1 Loss and Perceptual Loss functions to maintain image fidelity without paired datasets. Training is performed on GPU-enabled environments using low-light datasets, optimizing parameters through backpropagation and adaptive learning rate schedulers.

Module 5: Image Reconstruction and Evaluation
This module reconstructs the enhanced images from the processed feature maps using an inverse wavelet transform. Enhanced outputs are evaluated using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and NIQE to ensure visual realism and computational efficiency.

5.2 **Tools and Technologies Used**

1. Programming Language: Python (version 3.9 or higher)

2. AI/ML Frameworks: TensorFlow 2.x and Keras (Functional API)

3. Core Libraries:

    - NumPy: For all numerical and matrix operations
    - OpenCV: For image preprocessing (normalization, resizing, denoising)
    - PyWavelets: For performing Discrete Wavelet Transform (DWT) and inverse DWT
    - Matplotlib: For visualization of enhancement results and performance metrics
    - scikit-image: For computing quantitative metrics such as PSNR and SSIM

4. Development Platform: Google Colab / Kaggle GPU environment with CUDA support

5. Hardware Requirements: NVIDIA GPU (RTX 30-series or A100) for training and evaluation

5.3 **Algorithm Details**

The implementation's foundation lies in a hybrid deep learning architecture combining CNNs, Transformers, and Wavelet operations. The system operates through three main algorithmic components (heads), working collaboratively within the dual-domain framework.

Algorithm 1: Wavelet Calibration Layer

(WCL) Purpose:

To correct uneven illumination in low-light images by operating in the wavelet domain and selectively enhancing illumination coefficients.

Steps:

1. Input: Take feature maps from the CNN encoder.
2. Wavelet Decomposition: Apply Discrete Wavelet Transform (DWT) to split image features into low-frequency (illumination) and high-frequency (texture) subbands.
3. Calibration: Modify illumination subbands using learnable scaling coefficients.
4. Reconstruction: Fuse adjusted subbands for improved uniform brightness.
5. Loss Function: Use L1 loss to maintain illumination consistency.
6. Dataset Used: LOL and LOLv2 datasets for low-light conditions.

Algorithm 2: Contrast Adjustment Layer (CAL)

Purpose:

To refine image contrast and prevent overexposure or color distortion during enhancement.

Steps:

1. Input: Enhanced illumination feature maps from WCL.
2. Transformation: Apply convolutional filters to compute local contrast adjustments.
3. Normalization: Shift and scale feature values adaptively for balanced brightness.
4. Output: Generate visually natural images with improved local contrast.
5. Loss Function: Perceptual loss based on feature comparison from VGG19 network.
6. Dataset Used: MIT-Adobe FiveK and ACDC datasets for validation.

Algorithm 3: Dual-Domain Feature Fusion (DFF)

Purpose:

To merge spatial-domain contextual understanding and wavelet-domain detail recovery for optimal low-light enhancement.

Steps:

1. Input: Receive parallel outputs from spatial and wavelet branches.
2. Fusion: Apply attention-weighted concatenation to combine high- and low-frequency features.
3. Refinement: Pass fused features through residual Transformer blocks for final enhancement.
4. Reconstruction: Use inverse wavelet transform to synthesize the enhanced image.
5. Loss Function: Combination of L1 loss and Perceptual loss for texture fidelity.
6. Evaluation Metrics: PSNR, SSIM, and NIQE to measure enhancement performance.

CHAPTER 6

6.1 **Outcomes**

• Enhanced Night-Driving Visibility: Significantly improves the clarity and brightness of low-light driving images, ensuring safer and more reliable vision for autonomous systems.

• Unsupervised Illumination Correction: Achieves adaptive brightness and contrast enhancement without requiring paired datasets, making the model more efficient and scalable.

• Wavelet-Guided Detail Restoration: Effectively restores fine details and textures through wavelet-domain feature calibration, maintaining the natural appearance of enhanced images.

• Reduced Noise and Artifacts: Minimizes noise amplification and overexposure, producing smoother and more visually consistent outputs in challenging night scenes.

• Improved Model Performance: Achieves higher quantitative metrics such as PSNR, SSIM, and mIoU, outperforming traditional Retinex- and GAN-based models.

• Dual-Domain Learning Efficiency: Combines spatial-domain context understanding with wavelet-domain frequency analysis for balanced illumination enhancement.

• Real-Time Processing Capability: Optimized for efficient computation, enabling deployment on GPU-equipped driving systems and embedded platforms like NVIDIA Jetson.

• Support for Downstream Vision Tasks: Enhanced images improve the accuracy of object detection, lane segmentation, and traffic sign recognition models.

• Scalable Framework: The architecture can be extended to other low-light domains such as CCTV surveillance, medical imaging, and aerial night photography.

• Foundation for Future Research: Establishes a robust baseline for future illumination-guided unsupervised learning models in the field of computer vision and autonomous driving.

CHAPTER 7

7.1 **Conclusion**

In summary, the Unsupervised Illumination-Guided Wavelet Network (WENet) provides an innovative and effective solution for enhancing night-driving images captured under poor illumination. By integrating Convolutional Neural Networks (CNNs), Transformer blocks, and Wavelet Transforms, the system improves image clarity, brightness, and contrast while preserving natural texture and color balance.

Unlike conventional histogram or Retinex-based methods, this approach performs dual-domain enhancement — operating simultaneously in the spatial and wavelet domains — to achieve better structural preservation and noise reduction. The use of unsupervised learning eliminates the need for labeled datasets, making the system more adaptable and scalable for real-world driving conditions.

The proposed model has shown outstanding performance on benchmark datasets such as LOL, LOLv2, and ACDC, achieving higher PSNR and SSIM scores than traditional methods. Overall, this work represents a major advancement in low-light image processing, contributing to safer and more reliable autonomous driving systems, intelligent transportation, and computer vision applications under challenging lighting conditions.

7.2 **Future Scope**

The future potential of illumination-guided wavelet networks for night-driving enhancement is vast and promising. With continued progress in deep learning and hardware acceleration, such systems could become standard components in next-generation autonomous vehicles and driver-assistance technologies.

- Integration with Object Detection Models: The enhanced images can serve as inputs to real-time object detection and tracking models, improving recognition accuracy in dark environments.

- Real-Time Deployment: Future versions can be optimized for edge devices like NVIDIA Jetson, enabling on-vehicle processing without external computation.

- Multimodal Sensor Fusion: Combining camera inputs with LiDAR and infrared imaging could provide a more complete understanding of the driving environment at night.

- Adaptive Learning: Incorporating reinforcement learning or self-supervised illumination correction could make the system continuously improve as it encounters new driving conditions.

- Extended Applications: Beyond vehicles, the model can be applied to CCTV surveillance, medical imaging, marine exploration, and low-light photography for broader societal impact.

These advancements will enable more robust, context-aware, and efficient low-light enhancement systems, paving the way toward fully autonomous and safe night-time vision technologies.

7.3 **Applications**

• Autonomous Driving: Enhances the visibility of objects, pedestrians, and lane markings during night-time driving for better decision-making.

• Driver Assistance Systems: Improves clarity in dashboard and rear-view camera feeds, ensuring safer human supervision at night.

• Traffic Surveillance: Enables clearer monitoring in low-light CCTV footage for security and law enforcement.

• Smart City Infrastructure: Assists in nighttime monitoring of public spaces using enhanced video feeds.

• Drone Navigation: Supports UAVs in low-illumination flight scenarios such as search-and-rescue operations.

• Industrial and Marine Applications: Enhances camera visibility in poorly lit industrial environments and underwater conditions.

• Medical Imaging and Forensics: Can assist in enhancing low-contrast images for diagnostic or analytical purposes.

• Photography and Media: Useful in post-processing low-light images to achieve better brightness and detail without artifacts.

• Research and Education: Provides a framework for studying unsupervised learning, wavelet-based enhancement, and transformer integration in image restoration.

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