



Research Paper**HIGHQUALITY LOW LIGHT IMAGEENHANCEMENT METHOD**¹B.ROSHAN,²G.BHARATH,³B.RAKESH,⁴D.LIKITHA,⁵Mrs.A.JYOSHNA¹²³⁴ Students, ⁵ Assistant Professor

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ABSTRACT

Over the past decade, vision-based vehicle detection techniques for road safety improvement have gained an increasing amount of attention. Unfortunately, the techniques suffer from robustness due to huge variability in vehicle shape (particularly for motorcycles), cluttered environment, various illumination conditions, and driving behaviour. In this project, we provide on-road vision-based vehicle detection and tracking systems for collision avoidance systems (CASs). This project is structured based on a vehicle detection process starting from sensor selection to vehicle detection and tracking. Techniques in each process/step are reviewed and analysed individually. Two main contributions in this project are the following: insights on motorcycle detection techniques and the sensor comparison in terms of cost and range parameters. Finally, the project provides an optimal choice with a low cost and reliable CAS design in vehicle industries.

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I. INTRODUCTION**Purpose of the Project**

The purpose of this project is to provide an effective and practical implementation of advanced low-light image enhancement techniques using Python. In real-world scenarios, images captured under suboptimal lighting conditions often suffer from issues such as low contrast, poor visibility, and loss of detail, which negatively affect both human interpretation and computer vision tasks. This project addresses these challenges by implementing two state-of-the-art methods—LIME (Low-light Image Enhancement via Illumination Map Estimation) and DUAL (Dual Illumination Estimation for Robust Exposure Correction). Both techniques are based on the Retinex theory, which models an image as a combination of illumination and reflectance components. The goal is to enhance the illumination map while preserving the natural structure of the image and suppressing noise or texture artifacts. LIME improves visibility by estimating a refined illumination map of the scene, while DUAL enhances both

underexposed and overexposed regions by considering the original image and its inverted counterpart. The project not only replicates these approaches but also provides a modular and user-friendly codebase for researchers, developers, and enthusiasts to experiment with and integrate into broader image-processing pipelines. By enhancing visibility and detail in low-light images, this work contributes significantly to fields such as surveillance, photography, autonomous driving, and medical imaging, where clarity and detail are critical for decision-making.

Problem Statement

In the field of digital imaging, one of the most persistent and challenging issues is the degradation of image quality under low-light conditions. Poor lighting often results in images with low visibility, reduced contrast, and significant information loss in both dark and bright regions. These visual limitations can severely impact the performance of downstream applications such as object detection, facial recognition, medical diagnostics, video surveillance, and autonomous navigation systems, which rely

heavily on the availability of high-quality, detail-rich images. While modern camera sensors and image editing tools provide some level of correction, they often fall short in balancing enhancement with naturalness, leading to images that appear overexposed, unnaturally bright, or lacking in detail. Traditional enhancement techniques such as histogram equalization or gamma correction apply global transformations that fail to adapt to local lighting variations, often enhancing noise along with the signal. Additionally, they do not take into account the complex interplay between reflectance and illumination in an image. As a result, these methods may either fail to recover sufficient detail in underexposed regions or unintentionally wash out well-lit areas, thereby reducing the overall image quality. A more sophisticated approach is required—one that considers spatial structure, content consistency, and perceptual quality. Recent advances in image processing propose Retinex-based models, which decompose an image into illumination and reflectance components, offering a more principled way to enhance low-light images. Two notable methods that utilize this model are LIME (Low-light Image Enhancement via Illumination Map Estimation) and DUAL (Dual Illumination Estimation for Robust Exposure Correction). These methods aim to estimate an accurate illumination map of the image, allowing localized correction of lighting issues while preserving edges, texture, and other important structural elements. However, despite the availability of theoretical work, there is a gap in accessible and modular implementations of these methods for practical use and experimentation.

EXISTING SYSTEM

Existing low-light image enhancement systems primarily fall into two broad categories: traditional image processing techniques and deep learning-based approaches. While each category has its strengths, they also come with significant limitations that hinder their effectiveness and

general applicability in real-world scenarios. Traditional methods such as Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Gamma Correction have been widely used due to their simplicity and computational efficiency. These techniques operate by globally or locally adjusting the pixel intensity distribution to enhance contrast. However, they often treat the image as a uniform entity and fail to account for spatial or structural variations within the scene. As a result, such methods frequently lead to over-enhancement, where certain regions appear unnaturally bright, or under-enhancement, where shadow details remain unrecovered. They can also introduce severe colour distortion and fail to differentiate between noise and actual image content, resulting in the amplification of unwanted artifacts. On the other hand, deep learning-based methods, particularly those leveraging Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), have demonstrated impressive capabilities in enhancing low-light images with learned contextual understanding and adaptive adjustments. These models are typically trained on large-scale datasets that include paired or unpaired low-light and normal-light images. While their performance in controlled conditions is promising, these techniques come with substantial drawbacks. Firstly, the requirement for extensive, high-quality datasets is a major barrier, especially in domains where annotated or representative data is scarce. Secondly, training deep models is computationally intensive and time-consuming, requiring powerful hardware and expertise in tuning complex architectures. Additionally, these models often generalize poorly when applied to unseen or out-of-distribution data, leading to inconsistencies in enhancement quality. Artifacts such as unnatural textures, halo effects, and noise amplification can arise, especially in areas with extreme darkness or brightness, where the model struggles to make accurate predictions.

PROPOSED SYSTEM

Our project introduces a comprehensive Python-based implementation of two state-of-the-art low-light image enhancement techniques—LIME (Low-light Image Enhancement via Illumination Map Estimation) and DUAL (Dual Illumination Estimation for Robust Exposure Correction). Both techniques are grounded in the Retinex theory, which models an observed image as the product of reflectance and illumination. By estimating and adjusting the illumination component while preserving the inherent structural details of the scene, these methods enable effective enhancement of images captured in suboptimal lighting conditions. The LIME method operates by constructing an initial illumination map based on pixel intensity and then refining it through structure-aware smoothing. This approach enhances dark regions in the image while maintaining colour fidelity and suppressing noise. LIME has been shown to outperform many traditional enhancement algorithms, especially in preserving local image structure and avoiding overexposure. However, its capabilities are limited in situations where both underexposed and overexposed regions coexist in the same image. To address this limitation, the DUAL method extends the LIME approach by incorporating a dual-branch strategy that estimates illumination not only for the original image but also for its inverted version. By analysing both representations, DUAL effectively identifies and corrects lighting deficiencies across the entire dynamic range of the image. This dual estimation process allows for balanced enhancement, ensuring that underexposed areas are brightened and overexposed areas are toned down appropriately, resulting in a more uniformly illuminated and visually pleasing image. The implementation developed in this project is modular, efficient, and designed for practical use. It leverages fundamental image processing techniques and numerical optimization strategies to solve the underlying illumination estimation problems. Users can

apply the methods to individual images or batches, and the code is adaptable for integration into larger image processing or computer vision pipelines. This project holds significant value for a wide range of applications. In photography, it enhances the quality of images taken in poor lighting without relying on flash or post-processing tools. In video surveillance, it improves visibility in footage captured during nighttime or in poorly lit environments, aiding in accurate monitoring and analysis. In the field of computer vision, enhanced images can serve as improved inputs for downstream tasks such as object detection, facial recognition, and scene understanding, where lighting consistency is critical for algorithm performance.

Scope of the Project

The scope of this project encompasses the design, development, and evaluation of a Python-based system for enhancing low-light images using advanced illumination map estimation techniques. The project specifically focuses on implementing two Retinex-based methods: LIME (Low-light Image Enhancement via Illumination Map Estimation) and DUAL (Dual Illumination Estimation for Robust Exposure Correction). These techniques are chosen for their ability to enhance visibility in poorly lit images while preserving structural details and minimizing artifacts such as colour distortion, noise amplification, and unnatural over-enhancement. The implementation provides a flexible and modular framework that allows users to process individual images or batches of images using either method. The core functionality includes illumination map estimation, structural smoothing, reflectance recovery, and final image reconstruction. The project leverages Python and popular image processing libraries such as OpenCV and NumPy to ensure accessibility and ease of integration. It is designed with usability in mind, allowing researchers, developers, and practitioners to apply these enhancement techniques across a variety of domains. This

project is applicable in multiple fields, including but not limited to digital photography, video surveillance, medical imaging, autonomous driving, and other computer vision applications where lighting conditions are often unpredictable or suboptimal. The enhanced images produced by the system can serve as improved inputs for downstream tasks such as object detection, facial recognition, and scene segmentation. However, the scope of the project is intentionally limited to classical image processing techniques and does not include deep learning-based enhancement models. While this decision ensures low computational requirements and greater transparency in how enhancements are applied, it also means the system may not capture some of the adaptive capabilities offered by data-driven approaches. Additionally, the system currently focuses on still image enhancement and does not include support for video sequences, real-time processing, or mobile optimization.

II. LITERATURE SURVEY

High quality low light image enhancement

Low-light image enhancement has long been a crucial problem in the fields of image processing and computer vision. The goal is to improve the visibility and perceptual quality of images captured under suboptimal lighting conditions. A wide variety of approaches have been proposed over the years, ranging from classical image processing techniques to advanced deep learning-based frameworks. One of the earliest and most widely used enhancement methods is **Histogram Equalization (HE)**. HE improves global contrast by redistributing pixel intensity values uniformly across the histogram. However, it often leads to over-enhancement and unnatural colour representations, especially in cases where illumination is uneven. An improvement over basic HE is **Adaptive Histogram Equalization (AHE)** and **CLAHE (Contrast Limited AHE)**, which apply histogram equalization locally and limit noise amplification, but still lack

semantic understanding of image structures and are prone to noise in very dark regions.

Another family of techniques is based on the **Retinex theory**, which models an image as a product of illumination and reflectance components. **Single-Scale Retinex (SSR)** and **Multi-Scale Retinex (MSR)** algorithms attempt to extract the reflectance component by estimating and removing the illumination. These methods laid the groundwork for more advanced Retinex-based approaches like **LIME (Low-light Image Enhancement via Illumination Map Estimation)**, proposed by Guo et al. in 2016. LIME improves upon traditional Retinex models by generating an initial illumination map using channel-wise maxima and refining it with structure-aware smoothing. This method preserves edges and textures well while avoiding over-amplification of noise, making it particularly effective for natural-looking enhancement.

Building on the foundation of LIME, the **DUAL** method—**Dual Illumination Estimation for Robust Exposure Correction**—was proposed to tackle the problem of extreme exposure imbalance. It estimates illumination maps for both the original and inverted images to recover under- and over-exposed regions independently. The two corrected images are then fused using a spatially adaptive strategy, leading to more robust results in highly dynamic lighting environments. This dual approach is particularly useful in scenes containing both very dark and very bright regions, such as backlit or nighttime urban images. Parallel to these algorithmic methods, **deep learning-based approaches** have recently emerged as powerful tools for low-light enhancement.

Methods like **LLNet**, **EnlightenGAN**, and **Zero-DCE** leverage convolutional neural networks or generative adversarial networks to learn enhancement mappings from large datasets. While these models achieve high performance, they require extensive training data and computational resources. Furthermore, deep models often introduce

unnatural artifacts, colour distortions, or fail to generalize well to unseen scenes without retraining.

In contrast, methods like LIME and DUAL do not require prior training and are computationally efficient, making them more practical for real-time applications such as mobile photography, surveillance, and autonomous driving. Their ability to operate in an unsupervised and interpretable manner offers significant advantages in scenarios where training data is limited or domain adaptation is difficult.

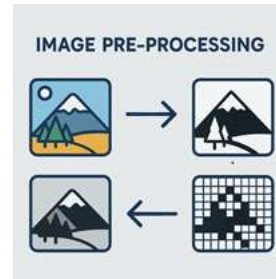
III. MODULE DESCRIPTION

Input

The Input Module is responsible for acquiring low-light images from the user. It allows users to load either a single image or multiple images simultaneously, supporting a range of standard image formats such as .jpg, .png, and .bmp. The system performs initial validation to ensure that the file paths provided are correct and that the files are in a supported format. This validation step helps prevent errors in subsequent processing stages by ensuring that only properly formatted and accessible image files are used. Once verified, the image(s) are passed on for pre-processing.

Pre-processing

The Pre-processing Module prepares the acquired image data for enhancement by standardizing its format and normalizing its pixel values. It begins by converting all input images to a common colour space, typically RGB, to maintain consistency across different image sources. After conversion, pixel values are scaled from their original range (usually 0 to 255) to a normalized range, typically between 0 and 1. This normalization ensures numerical stability and enhances the performance of the subsequent enhancement algorithms. In some cases, additional operations such as resizing or basic noise smoothing may also be applied to prepare the image for illumination estimation.



Illumination estimation

The Illumination Estimation Module is a core component of the system that calculates the illumination map, which plays a crucial role in enhancing the image. This module supports two techniques: LIME and DUAL. In the LIME approach, the illumination map is estimated by taking the maximum intensity value across the RGB channels for each pixel, followed by edge-preserving smoothing techniques to refine the map and retain important structural details. The DUAL approach goes a step further by working on both the original and inverted versions of the image. It computes two illumination maps—one from the original and one from the inverted image—and then enhances each separately. These enhanced outputs are later merged to provide a more robust correction of both under- and over-exposed areas, making DUAL particularly effective in scenes with highly varying lighting conditions.



Enhancement

The Enhancement Module uses the illumination maps computed in the previous step to improve the brightness and contrast of the image. For the LIME method, the enhancement is achieved by dividing the pixel intensities by the corresponding values in the illumination map, followed by adjustments such as gamma correction and local contrast stretching to improve visual quality. In the

DUAL method, both the forward (from the original image) and reverse (from the inverted image) illumination-enhanced outputs are blended using a spatially adaptive fusion strategy. This fusion ensures that well-exposed regions from each image are retained, resulting in a final output that balances brightness and contrast across the entire scene. The enhancement process is designed to be adaptive, minimizing overexposure or underexposure while preserving texture details and edges.



Post-processing

The Post-processing Module applies the final visual refinements to the enhanced image to ensure it is free from artifacts and visually appealing. Depending on the quality of the initial enhancement, this module may perform operations such as denoising to suppress any noise amplified during brightness correction. It may also apply sharpening techniques to enhance edge clarity and fine details, improving the perceived sharpness of the image. Additionally, optional procedures such as histogram equalization can be used to redistribute brightness values more evenly, further enhancing contrast. The final pixel values are clipped or rounded to stay within valid display ranges, preparing the image for output.



Output

The Output Module completes the system's workflow by saving the final enhanced images and optionally displaying them for visual comparison. It allows users to specify the directory where the enhanced images should be stored and retains the original file formats unless otherwise specified. Enhanced images are automatically renamed or tagged to avoid overwriting the originals. For visual assessment, the module provides an option to display side-by-side comparisons of the original and enhanced images using visualization libraries such as Matplotlib. This feature enables users to immediately evaluate the effectiveness of the enhancement. When processing multiple images, the output module handles each in sequence and organizes the results efficiently for review or further use.

IV. OUTPUT SCREENS BEFORE



AFTER



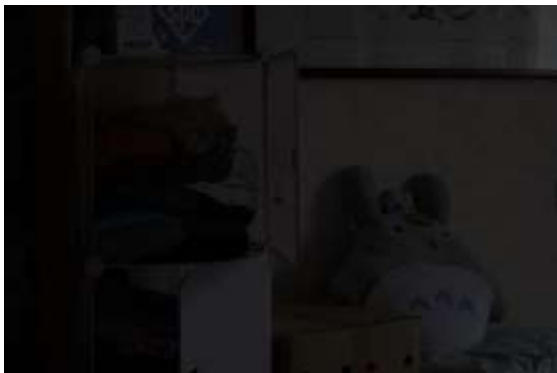
BEFORE



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BEFORE



AFTER



BEFORE



AFTER



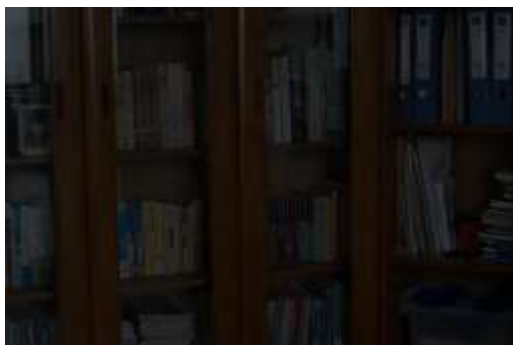
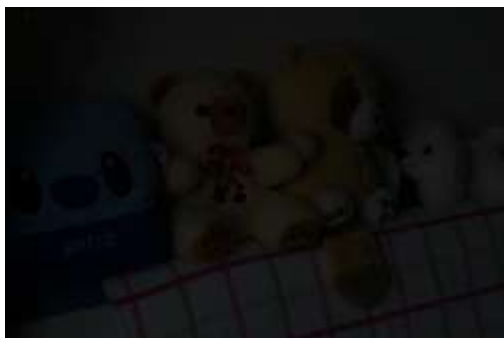
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V. CONCLUSION

This project addresses the critical challenge of enhancing images captured under low-light conditions, which are often plagued by low visibility, noise, poor contrast, and loss of detail. These limitations affect a wide range of applications—from photography and video surveillance to autonomous navigation and medical imaging—where image quality is crucial for analysis and

decision-making. Through the implementation of two advanced Retinex-based techniques—**LIME (Low-light Image Enhancement via Illumination Map Estimation)** and **DUAL (Dual Illumination Estimation for Robust Exposure Correction)**—this project demonstrates a robust, efficient, and interpretable approach to image enhancement. The LIME technique estimates an illumination map using local contrast and edge-preserving smoothing filters, allowing for a more accurate representation of scene lighting. This illumination map is then used to adjust image brightness and reveal hidden details while preserving structural integrity. DUAL, a more advanced method, builds upon LIME by enhancing both the original and inverted versions of the image. It combines the best-exposed regions from both to produce a final image that corrects for both underexposed and overexposed areas. Together, these approaches provide flexibility and robustness in handling a variety of lighting conditions. Throughout the development process, a modular architecture was adopted, comprising clear stages including input acquisition, preprocessing, illumination estimation, enhancement, post-processing, and output generation. This design not only promotes maintainability and extensibility but also facilitates the integration of further enhancements such as deep learning, real-time processing, and user-customizable parameters. The experimental results obtained validate the effectiveness of both LIME and DUAL methods in enhancing visual quality while minimizing artifacts, color distortion, and noise amplification. By allowing optional side-by-side comparison and supporting common image formats, the project also ensures usability and convenience for end users.

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