

# DEEP LEARNING-BASED LOW LIGHT IMAGE ENHANCEMENT FOR IMPROVED VISIBILITY

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## Abstract

Low light conditions pose significant challenges for image capture and processing, leading to degraded image quality with reduced visibility and increased noise. Traditional low light image enhancement methods typically involve hand-crafted image processing techniques, such as histogram equalization, contrast stretching, and noise reduction filters. While these methods may provide some improvement, they often fail to produce visually pleasing and natural-looking results. The lack of adaptability and limited ability to learn complex patterns from data makes traditional approaches less effective in handling various low light scenarios. The need for an advanced low light image enhancement technique arises from the widespread application of imaging devices in low light conditions. Industries such as surveillance, automotive, and photography heavily rely on cameras to capture images in challenging lighting situations. By enhancing the visibility and overall quality of low light images, the accuracy and reliability of image-based systems can be significantly improved. Therefore, an intelligent approach that can learn and adapt from data becomes essential to tackle the limitations of traditional methods. In recent years, deep learning has shown remarkable potential in various computer vision tasks, including image enhancement. This project aims to explore and propose a deep learning-based approach to address the issue of low light image enhancement for improved visibility. The deep learning-based approach overcomes the limitations of traditional techniques by automatically capturing intricate patterns and features in low light images. This adaptability allows the model to generalize well across various low light scenarios, leading to visually appealing and realistic enhancements.

## 1. Introduction

Insufficient illumination in the image capturing seriously affects the image quality from many aspects, such as low contrast and low visibility. Removing these degradations and transforming a low-light image into a high-quality sharp image is helpful to improve the performance of high-level visual tasks, such as image recognition [1], object detection [2], semantic segmentation [3], etc, and can also improve the performance of intelligent systems in some practical applications, such as autonomous driving, visual navigation [4], etc. Low-light image enhancement, therefore, is highly desired. Over the past few decades, there have been a large number of methods employed to enhance degraded images captured under insufficient illumination conditions. These methods have made great progress in improving image contrast and can obtain enhanced images with better visual quality. In addition to contrast, another special degradation of low-light images is noise. Many methods utilized additional denoising methods as pre-processing or post-processing. However, using denoising methods as pre-processing will cause blurring, while applying denoising as post-processing will result in noise amplification. Recently, some methods have designed effective models to perform denoising and contrast enhancement simultaneously and obtain satisfactory results. It is noteworthy that many previous methods focused on using the spatial domain information of the image for enhancement, and

image processing in frequency domain is also one of the important methods in the image enhancement field.

## 2. Literature Survey

Ma, Long, et.al. (2022) [5] They develop a new Self-Calibrated Illumination (SCI) learning framework for fast, flexible, and robust brightening images in real-world low-light scenarios. To be specific, they establish a cascaded illumination learning process with weight sharing to handle this task. Considering the computational burden of the cascaded pattern, they construct the self-calibrated module which realizes the convergence between results of each stage, producing the gains that only use the single basic block for inference (yet has not been exploited in previous works), which drastically diminishes computation cost. They then define the unsupervised training loss to elevate the model capability that can adapt general scenes. Further, they make comprehensive explorations to excavate SCI's inherent properties (lacking in existing works) including operation-insensitive adaptability (acquiring stable performance under the settings of different simple operations) and model-irrelevant generality (can be applied to illumination-based existing works to improve performance). Finally, plenty of experiments and ablation studies fully indicate our superiority in both quality and efficiency. Applications on low-light face detection and nighttime semantic segmentation fully reveal the latent practical values for SCI. Wang, Yufei, et.al. (2022) [6] They investigate to model this one-to-many relationship via a proposed normalizing flow model. An invertible network that takes the low-light images/features as the condition and learns to map the distribution of normally exposed images into a Gaussian distribution. In this way, the conditional distribution of the normally exposed images can be well modelled, and the enhancement process, i.e., the other inference direction of the invertible network, is equivalent to being constrained by a loss function that better describes the manifold structure of natural images during the training. The experimental results on the existing benchmark datasets show our method achieves better quantitative and qualitative results, obtaining better-exposed illumination, less noise and artifact, and richer colors. Hai, Jiang, et.al. (2023) [7] A novel Retinex-based Real-low to Real-normal Network (R2RNet) is proposed for low-light image enhancement, which includes three subnets: a Decom-Net, a Denoise-Net, and a Relight-Net. These three subnets are used for decomposing, denoising, contrast enhancement and detail preservation, respectively. Our R2RNet not only uses the spatial information of the image to improve the contrast but also uses the frequency information to preserve the details. Therefore, our model achieved more robust results for all degraded images. Unlike most previous methods that were trained on synthetic images, they collected the first Large-Scale Real-World paired low/normal-light images dataset (LSRW dataset) to satisfy the training requirements and make our model have better generalization performance in real-world scenes. Extensive experiments on publicly available datasets demonstrated that our method outperforms the existing state-of-the-art methods both quantitatively and visually. In addition, our results showed that the performance of the high-level visual task (i.e., face detection) can be effectively improved by using the enhanced results obtained by our method in low-light conditions.

Xiong, Wei, et.al. (2022) [8] tackle the problem of enhancing real-world low-light images with significant noise in an unsupervised fashion. Conventional unsupervised approaches focus primarily on illumination or contrast enhancement but fail to suppress the noise in real-world low-light images. To address this issue, they decoupled this task into two sub-tasks: illumination enhancement and noise suppression. They proposed a two-stage, fully unsupervised model to handle these tasks separately. In the noise suppression stage, they propose an illumination-aware denoising model so that real noise at different locations is removed with the guidance of the illumination conditions. To facilitate the unsupervised training, they constructed pseudo triplet samples and propose an adaptive content loss correspondingly to preserve contextual details. To thoroughly evaluate the performance of the

enhancement models, they build a new unpaired real-world low-light enhancement dataset. Extensive experiments show that our proposed method outperforms the state-of-the-art unsupervised methods concerning both illumination enhancement and noise reduction.

Zheng, Shen, et.al. (2022) [9] proposed a semantic-guided zero-shot low-light enhancement network (SGZ) which is trained in the absence of paired images, unpaired datasets, and segmentation annotation. Firstly, they design an enhancement factor extraction network using depthwise separable convolution for an efficient estimate of the pixel-wise light deficiency of a low-light image. Secondly, we propose a recurrent image enhancement network to progressively enhance the low-light image with affordable model size. Finally, we introduce an unsupervised semantic segmentation network for preserving the semantic information during intensive enhancement. Extensive experiments on benchmark datasets and a low-light video demonstrate that our model outperforms the previous state-of-the-art. They further discuss the benefits of the proposed method for low-light detection and segmentation. Wu, Yirui, et.al. (2022) [10] proposed an edge computing and multi-task driven framework to complete tasks of image enhancement and object detection with fast response. The proposed framework consists of two stages, namely cloud-based enhancement stage and edge-based detection stage. In cloud-based enhancement stage, they establish connection between mobile users and cloud servers to input rescaled and small-size illumination parts of lowlight images, where enhancement subnetworks are dynamically combined to output several enhanced illumination parts and corresponding weights based on low-light context of input images. During edge-based detection stage, cloud-computed weights offer informativeness information on extracted feature maps to enhance their representation abilities, which results in accurate predictions on labels and positions for objects. By applying the proposed framework in cloud computing system, experimental results show it significantly improves detection performance in mobile multimedia and low-light environment.

### 3. Proposed System Model

This proposed methodology focused on improving the visibility and quality of images captured under low-light or challenging lighting conditions. The primary goal of the proposed model is to enhance the details and visual appeal of such images, making them clearer and more visually appealing. It employs a deep learning-based approach to enhance low-light images. It utilizes techniques from computer vision, image processing, and deep neural networks to achieve its objectives as shown in Figure 1.

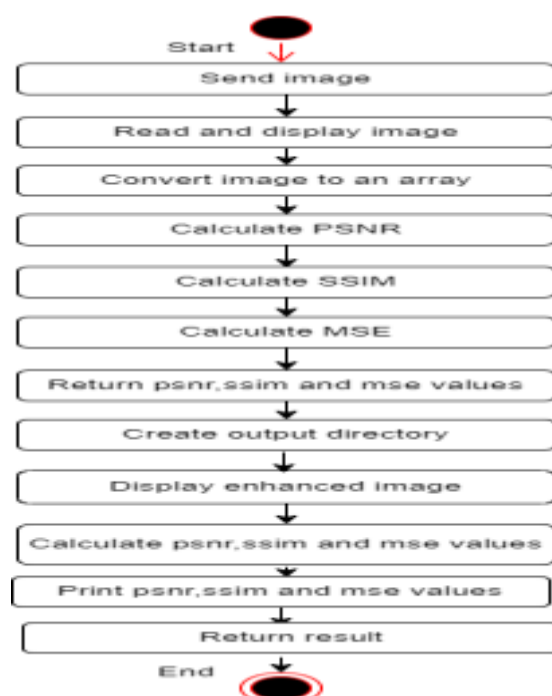


Figure 1: Proposed LIME system.

Overall, this research is designed to address the challenges posed by low-light images by applying deep learning-based techniques to enhance image quality, improve visibility, and provide visually appealing results. It finds applications in a variety of fields where low-light image enhancement is critical for obtaining meaningful and usable visual data. UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML. The Unified Modeling Language Is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

#### 4. Results description

Figure 2 shows a collection of original images that are taken in low-light conditions or have poor lighting quality. These images serve as the input to the proposed image enhancement model. These images are the input images that the model will process in order to improve their visibility and quality. The purpose of this figure is to provide a visual representation of the types of images that the model is designed to enhance.



## 5. Conclusion

This work represents a significant advancement in the domain of image processing and computer vision. By focusing on the challenge of enhancing images captured in low-light conditions, LIME offers a robust solution that improves image quality and visibility. Leveraging deep learning techniques, this project effectively addresses common issues encountered in low-light images, including noise, inadequate contrast, and the loss of critical details. One of the notable strengths is its versatility and adaptability. LIME provides users with the flexibility to fine-tune enhancement parameters, ensuring that the output aligns with specific requirements and preferences. Moreover, the integration of quality metrics such as PSNR, SSIM, and MSE enables a quantitative assessment of the success of the enhancement process. This ensures that the enhanced images not only look visually appealing but also maintain or exceed the quality of the original images. The impact of the LIME project extends across diverse domains. It finds application in fields like surveillance, where enhancing nighttime video quality is essential for security purposes. In astronomy, LIME aids in capturing the intricate details of stars and galaxies under challenging lighting conditions. Additionally, in consumer photography, the project enhances smartphone camera performance, particularly in dimly lit environments, offering users the capability to take high-quality photos even in adverse lighting conditions.

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