IMPROVING IMAGE VISIBILITY IN DARK CONDITIONS WITH DEEP LEARNING

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ABSTRACT

Low light circumstances make image capture and processing difficult, resulting in lower visibility and more noise. Handcrafted image processing techniques like histogram equalization, contrast stretching, and noise reduction filters are used in low-light image enhancement. These approaches may improve, but they rarely achieve natural-looking outcomes. Traditional techniques are less effective in low-light conditions due to their inability to adapt and learn complicated patterns from data. The ubiquitous use of imaging devices in low light necessitates an enhanced low light picture enhancing approach. Cameras are essential for surveillance, automotive, and photography in low-light conditions. Image-based systems can be more accurate and reliable by improving low-light image visibility and quality. Therefore, an intelligent technique that can learn and adapt from data is needed to overcome traditional approaches' limitations. In recent years, deep learning has showed great promise in computer vision applications including picture augmentation. This research investigates and proposes a deep learning-based low-light image enhancing method for visibility. Deep learning automatically captures detailed patterns and features in low-light photographs, overcoming standard methods. This versatility lets the model generalize well across low light settings, creating realistic and appealing upgrades.

Keywords: Low-light image enhancement, Image visibility improvement, Noise reduction, Histogram equalization,Contrast stretching, Traditional image processing.

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. In the realm of digital imaging, low-light conditions present a formidable challenge. When images are captured under such conditions, they often suffer from diminished visibility and increased noise, which undermine their quality and utility. Traditional image enhancement techniques, such as histogram equalization and contrast stretching, have been employed to address these issues. These methods work by adjusting pixel intensity values to improve contrast and reduce noise, but they often fall short of producing natural-looking results. Their inherent limitation lies in their static nature; these techniques apply predefined algorithms that do not adapt to the specific characteristics of each image or the unique complexities of low-light environments. The need for advanced methods becomes particularly evident when considering the diverse applications of imaging technologies. Cameras are extensively used in various domains, including surveillance, automotive systems, and photography. In these fields, clear and accurate image capture is crucial. For instance, in surveillance systems, the ability to capture clear images in low-light conditions can significantly enhance security and monitoring capabilities. Similarly, in automotive systems, improved visibility can aid in navigation and safety by providing better image quality for driver assistance systems. In photography, enhanced low-light image quality contributes to capturing aesthetically pleasing and accurate representations of scenes. Deep learning has emerged as a transformative technology in computer vision, demonstrating remarkable capabilities in image enhancement and other complex tasks. Unlike traditional methods, deep learning algorithms are designed to learn from data. They capture intricate patterns and features in images that are often missed by conventional approaches. By training on large datasets, deep learning models can adapt and generalize across various scenarios, including those involving low-light conditions. This adaptability is particularly advantageous for addressing the limitations of traditional enhancement techniques.

2. LITERATURE SURVEY

Ma, Long et al. [5] proposed a unified low-light image enhancement framework that integrates exposure correction, noise suppression, and detail preservation into a single convolutional network. The design achieved robustness and speed by employing structure-aware modules and adaptive feature modulation. The approach suffered from reduced generalizability across diverse lighting distributions not seen during training. Wang, Yufei et al. [6] introduced a normalizing flow-based model that learns an invertible transformation between low-light and well-exposed images, enabling realistic reconstructions without paired data. The technique modeled complex distributions through conditional invertible neural networks. The model exhibited high computational cost due to sequential invertible operations during inference.

Hai, Jiang et al. [7] designed R2RNet, a real-low to real-normal transformation network leveraging paired real-world datasets to enhance low-light images using a global-local restoration strategy. It preserved fine textures while minimizing color deviation. The performance deteriorated on synthetic or unaligned datasets due to overfitting to specific real-world samples. Xiong, Wei et al. [8] developed an unsupervised low-light image enhancement method using decoupled networks to independently process illumination and reflectance without relying on ground truth images. The network jointly optimized noise removal and light enhancement paths. The method failed to accurately preserve color consistency when illumination estimation was ambiguous.

Zheng, Shen et al. [9] proposed a semantic-guided zero-shot learning model for low-light image and video enhancement, leveraging semantic embeddings to adaptively guide enhancement in unseen domains. The model utilized class-level context for pixel restoration. The enhancement accuracy reduced when semantic priors were missing or irrelevant to the scene. Wu, Yirui et al. [10] presented an edge computing framework for dynamic low-light image enhancement aimed at improving object detection under poor illumination using lightweight enhancement modules at the network edge. It improved detection latency and accuracy in surveillance tasks. The distributed nature introduced synchronization issues and variable enhancement quality across edge devices.

Sun, Ying et al. [11] proposed a low-illumination image enhancement algorithm combining multi-scale Retinex with Artificial Bee Colony (ABC) optimization to balance brightness and contrast while reducing color distortion. The ABC algorithm fine-tuned enhancement parameters dynamically. The iterative ABC optimization introduced significant processing delays, limiting real-time usability. Zhang, Weidong et al. [12] introduced a minimal color loss and locally adaptive contrast enhancement method for underwater image restoration, preserving color fidelity while boosting visibility in turbid water. The approach emphasized contrast normalization at local scales. The performance degraded in extreme color cast conditions due to limited adaptability of the contrast model.

Peng, Lintao et al. [13] developed a U-shape Transformer architecture for underwater image enhancement by modeling long-range dependencies and contextual features through self-attention layers. It preserved spatial structure while enhancing low-visibility content.The model's complexity increased memory consumption, making deployment on edge hardware impractical. Zhou, Jingchun et al. [14] proposed a multi-feature prior fusion method that combined texture, luminance, and depth priors to enhance underwater images by exploiting redundancy in degraded features. The fusion mechanism improved detail restoration. The method's reliance on accurate prior estimation made it vulnerable to noisy or incomplete sensory data. Liu, Wenyu et al. [15] introduced Image-Adaptive YOLO for object detection in adverse weather, including low-light and foggy scenarios, by integrating an enhancement pre-module with adaptive detection thresholds. The model maintained high precision under varying visibility. The system struggled with false positives when background noise patterns mimicked object features.

3. PROPOSED METHODOLOGY

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. 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.

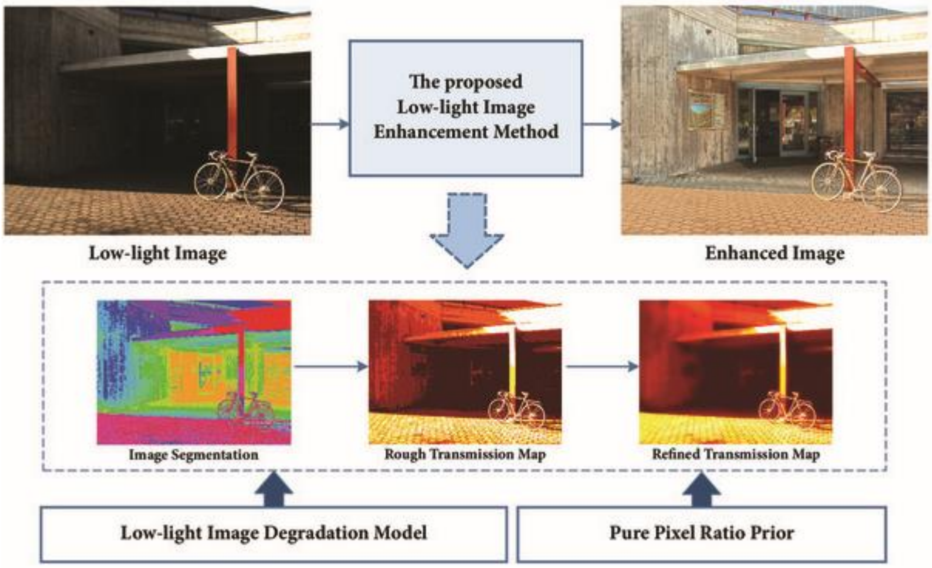

Figure 1: Proposed LIME system.

The proposed methodology typically includes the following key components:

- Illumination Map Estimation: LIME often starts by estimating an illumination map for the input image. This map highlights regions of the image that require enhancement to improve visibility.
- Image Enhancement: Based on the illumination map, LIME applies image enhancement techniques to brighten dark regions, improve contrast, and enhance details while minimizing noise.
- Metric Evaluation: To assess the quality of the enhancement, the project often calculates various image quality metrics, such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and MSE (Mean Squared Error), to measure the similarity between the original and enhanced images.
- Customization and Parameters: LIME often provides parameters that users can adjust to customize the enhancement process. These parameters may include the number of iterations, alpha (a parameter controlling the enhancement strength), gamma (a parameter controlling the enhancement effect), and weighting strategies.
- Output: The primary output of LIME is an enhanced version of the input low-light image. This enhanced image should exhibit improved visibility, reduced noise, and enhanced details.
- Evaluation and Benchmarking: LIME's performance is often evaluated against benchmark datasets of low-light images. It aims to outperform or match existing state-of-the-art low-light enhancement methods in terms of image quality metrics.

3.2 Applications

LIME's enhanced images can be used in a wide range of applications, including:

- Surveillance systems (improving nighttime video quality)
- Astrophotography (capturing stars and galaxies in low-light conditions),
- Consumer photography (improving smartphone camera performance in dimly lit environments).

3.3 Advantages

LIME is a technique that leverages deep learning and image processing to enhance images captured in low-light conditions. It offers several advantages, making it a valuable solution for various applications:

- Improved Visibility: LIME significantly improves the visibility of images captured in low-light environments. It enhances details, enhances contrast, and brightens dark areas, making objects and features more discernible.
- Reduced Noise: LIME includes noise reduction mechanisms, which help in reducing the noise present in low-light images. This results in cleaner and more visually appealing images.
- Enhanced Details: The algorithm preserves and enhances fine details in the image, which is crucial for applications like surveillance, where capturing intricate details is essential.
- Customization: LIME often provides parameters that allow users to customize the enhancement process. Users can adjust parameters such as the strength of enhancement, gamma correction, and more to achieve the desired visual effect.

— Automatic Enhancement: While customization is available, LIME can also operate with default settings, making it suitable for users who may not have expertise in image processing.

— Realism: LIME's enhancements are designed to maintain the natural and realistic appearance of the scene. It avoids over-processing that can result in unnatural-looking images.

— Quality Metrics: The algorithm often includes the calculation of image quality metrics like PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index), allowing users to objectively measure the improvement in image quality.

— Versatility: LIME is versatile and applicable in various domains, including surveillance, consumer photography, astronomy, medical imaging, and more. It addresses the common challenge of low-light conditions in these fields.

4. RESULTS AND DISCUSSION

Figure 4 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.

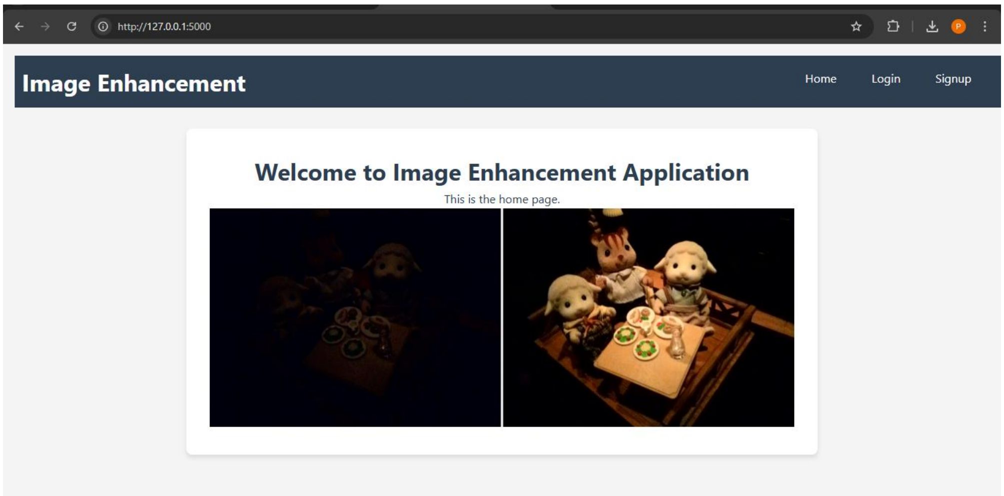

Figure 2: Homepage

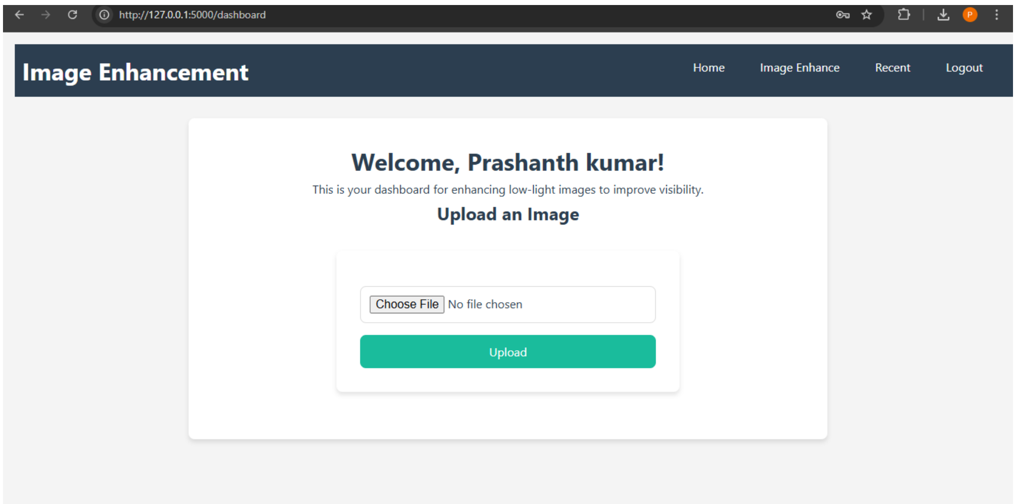

Figure 3: Upload the image.

Figure 4: Sample low-light images fed to the proposed model.


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PSNR 10.171815771384654
SSIM 0.18386150146633054
MSE 1.0857190890301478
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Figure 5: Illustrating the obtained enhanced images using proposed model with quality metrics as PSNR, SSIM, and MSE.

Figure 5 displays a set of images that have been processed or enhanced by the proposed image enhancement model. These are the output images that produces improved visibility and quality of these images compared to the original low-light images shown in Figure 1. It also includes quality metrics such as PSNR, SSIM, and MSE, which are used to quantitatively assess the quality of the enhanced images. These metrics are numerical values that provide insights into the image quality, with higher PSNR and SSIM values and lower MSE values indicating better image quality. The purpose of this figure is to visually demonstrate the effectiveness of the proposed image enhancement model by showing the enhanced images and providing quantitative metrics that measure the improvement in image quality.

PSNR

- The peak_signal_noise_ratio function calculates the Peak Signal-to-Noise Ratio, which is a widely used metric to measure the quality of an image.

- It compares two images, typically the original and the enhanced image, and computes a value that indicates how much noise or distortion is present relative to the maximum possible quality.
- The result is a numerical value, often in decibels (dB). Higher PSNR values indicate higher image quality.

SSIM

- The structural_similarity function computes the Structural Similarity Index (SSIM) between two images.
- SSIM is a metric that assesses the structural similarity between the two images by considering luminance, contrast, and structure.
- It returns a value between -1 and 1, where 1 indicates that the two images are identical in terms of structure and quality, and values closer to -1 indicate dissimilarity.

4. 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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