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DEEP LEARNING-POWERED ENHANCEMENT OF LOW-LIGHT VIDEO TO AUGMENT VISIBILITY

Dr. J. Srikanth[1], M. Vaishnavi[2], S. Sai Kumar Yadav[2], MOHD Kamran[2]

[1]Associate Professor, [2]UG Scholar, [1,2]Department of CSE (AI & ML)

[1,2]Kommuri Pratap Reddy Institute of Technology, Ghatkesar, Hyderabad, Telangana.

ABSTRACT

Low-light conditions can severely limit visibility in surveillance, security, and various other applications. Traditional methods of enhancing low-light videos often rely on filters and post-processing techniques. Recent advances in deep learning and computer vision have opened up new possibilities for significantly improving visibility in low-light scenarios. Traditional methods for enhancing low-light videos may involve using filters and post-processing techniques. While effective to some extent, these methods may not always produce satisfactory results and may not be suitable for real-time applications. The primary challenge is to develop a deep learning-based system capable of enhancing the visibility of low-light videos. This involves training a model to recognize and correct for low-light conditions, while preserving important details and reducing noise. Improving visibility in low-light conditions is crucial for a wide range of applications, including security, surveillance, and outdoor activities. The ability to enhance video quality in real-time can lead to better decision-making, improved safety, and increased effectiveness in a variety of settings. The project, "Deep Learning-Powered Enhancement of Low-Light Video to Augment Visibility," aims to leverage the power of advanced deep learning algorithms to significantly improve the visibility of low-light videos. By training models on extensive datasets of low-light video samples, this research endeavors to develop a system capable of autonomously and accurately enhancing video quality in real-time. Deep learning algorithms excel at learning complex relationships in data, making them well-suited for this task. This advancement holds great promise for enhancing visibility in low-light conditions, ultimately leading to improved safety and effectiveness in applications such as surveillance, security, and outdoor activities.

Keywords: Low Light image, Computer Vision, Noise Reduction, Video Augmentation

1. INTRODUCTION

The pursuit of enhancing visibility in low-light conditions through deep learning-powered methods represents a significant advancement in the realm of video processing and computer vision. Historically, addressing the challenges of low-light video has been a persistent concern, given the inherent limitations of conventional imaging systems in capturing clear and detailed information in conditions of reduced illumination. Over time, researchers and engineers have sought innovative solutions to overcome the limitations of traditional image enhancement techniques. The advent of deep learning, particularly convolutional neural networks (CNNs), has revolutionized the field by providing a powerful framework for extracting complex features and patterns from visual data. This shift marked a departure from conventional methods that often relied on handcrafted features and rule-based algorithms. The historical context of deep learning in image and video enhancement can be traced back to the mid-2010s when deep neural networks gained prominence in various computer vision tasks. Researchers began exploring their potential applications in low-light video enhancement to address challenges such as noise, blur, and lack of clarity associated with insufficient lighting conditions.

As deep learning algorithms evolved and became more sophisticated, they demonstrated the capacity to learn and adapt to intricate patterns within low-light video data. The training of neural networks on large datasets containing examples of both well-illuminated and low-light scenarios enabled the models to decipher and amplify relevant details even in challenging visual environments. The augmentation of visibility in low-light video through deep learning involves the development of specialized models that can effectively process and enhance the information present in dark or poorly lit scenes. These models learn to distinguish between noise and valuable visual content, employing complex network architectures to refine and amplify image features while minimizing artifacts.

2. LITERATURE SURVEY

Due to the development of technology and the continuous improvement of photographic equipment, we have higher and higher requirements for the quality of the images we capture, but we often have difficulty obtaining suitable images because of the interference of environmental factors. Uneven lighting, low lighting, and other factors like backlighting can result in imperfect image information, diminishing the overall quality of captured images an image under suboptimal lighting conditions. Consequently, these issues can have a cascading effect on advanced tasks such as object recognition, detection, and classification. As artificial intelligence technologies continue to evolve, the associated industries are also changing, and thus the requirements for related downstream tasks are increasing. The quality of tasks completed in the image processing area [1,2,3,4,5] can greatly affect the efficiency of upstream tasks. In daily life, we often encounter uncontrollable environmental or equipment factors that cause uneven lighting, darkness, backlighting, and blurring of captured images [6,7,8,9] However, we have demand for high-quality images. Superior image quality is crucial for everyday scenarios and holds significant importance across various sectors [10,11,12,13] including intelligent transportation and vision monitoring. Therefore, quality enhancement of images has become a subject worthy of further exploration.

3.PROPOSED METHODOLOGY

3.1 Overview

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.

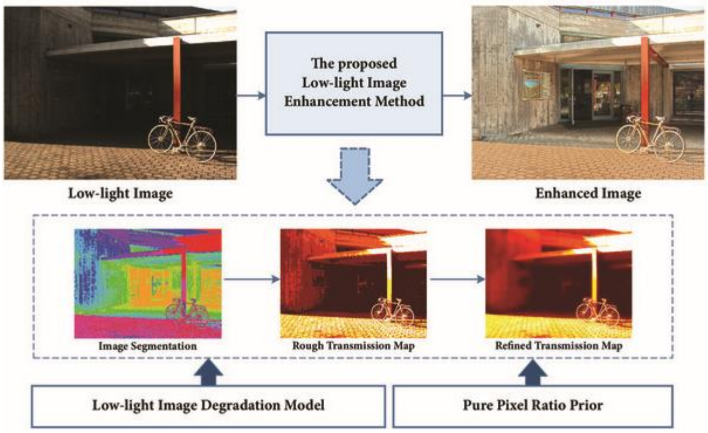

Figure 1: Proposed LIME system.

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

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.

Figure 2: Sample low-light images fed to the proposed model.

PSNR 10.171815771384654
SSIM 0.18386150146633054
MSE 1.0857190890301478

PSNR 13.747368386518946
SSIM 0.3436245339679396
MSE 0.9086185481481482

PSNR 11.031691901461375
SSIM 0.5199471454508887
MSE 1.0771644632584392

Fig. 3: Illustrating the obtained enhanced images using proposed model with quality metrics as PSNR, SSIM, and MSE.

Figure 3 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.

5. CONCLUSIONS

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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