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Enhancing Low-Light Images Using Deep Learning Techniques for Improved Visual Quality

Nilotpal Das
Student, MCA, School of Computer Application, Lovely Professional University, Phagwara, Punjab, nilotpaldas.uni@gmail.com

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Abstract

Low-light image enhancement represents a vital area of research within computer vision, with diverse applications spanning surveillance, autonomous vehicles, mobile photography, and medical imaging. Conventional image processing methods frequently encounter difficulties in addressing the challenges posed by low-light environments, including noise amplification, color distortion, and detail loss. This study investigates the application of deep learning methodologies to enhance images captured in low-light conditions and to elevate their visual quality. In particular, we focus on convolutional neural networks (CNNs) and generative adversarial networks (GANs) to establish intricate mappings between poorly lit images and their well-illuminated equivalents. We employ benchmark datasets, including the LOL (Low-Light) and SID (See-in-the-Dark) datasets, for the training and evaluation of our models. The performance of these models is measured through both quantitative metrics—such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index)—and qualitative visual assessments. Our findings indicate that deep learning-based techniques significantly surpass traditional approaches in generating clearer, more detailed, and color- accurate enhanced images. This research underscores the promise of data-driven models in addressing complex image enhancement challenges and lays the groundwork for future developments in real-time and resource-constrained settings.

Keywords

Low-Light Image Enhancement, Deep Learning, Retinex Theory, Convolutional Neural Networks, Image Decomposition, Illumination Map, Noise Suppression, Image Quality Assessment.

Section I. Introduction

Low-light image enhancement (LLIE) serves as a vital preprocessing phase in the field of computer vision, with the objective of enhancing the visibility and perceptual quality of images taken in inadequate lighting conditions. Images captured in low-light environments frequently exhibit issues such as insufficient brightness, diminished contrast, color inaccuracies, and increased noise, which impede both human analysis and the efficacy of automated vision systems. While traditional techniques like histogram equalization and Retinex theory have established foundational approaches, recent progress has been significantly influenced by deep learning methodologies. The advent of advanced convolutional neural networks and learning-based decomposition techniques has led to notable advancements in the enhancement of dark areas while effectively reducing noise. This paper presents a thorough examination of LLIE methodologies, emphasizing deep learning approaches, network architectures, and evaluation metrics. Additionally, it introduces a novel dataset for low-light images and videos, along with a cohesive online platform for comparing various methods. These contributions are intended to facilitate future research and promote the development of effective LLIE systems.

Section II. Review of Literature

The enhancement of images captured in low-light conditions has attracted considerable interest because of its critical role in enhancing visibility in suboptimal lighting environments. Recent research has concentrated on deep learning approaches, conventional algorithms, datasets, and assessment methodologies to tackle issues related to noise, contrast, and color distortion.

Author(s) & Year	Title	Methodology	ML Algorithms Used	Findings	Limitations
Chongyi Li et al., 2022	Low-light image and video enhancement using deep learning: A survey	Dataset collection, deep learning-based method evaluation, web platform integration, performance validation using face detection, qualitative and quantitative analysis	RetinexNet, EnlightenGAN, Zero-DCE (Zero-Reference Deep Curve Estimation)	Deep learning LLIE methods boost dark face detection. Zero- DCE balances accuracy and quality, while Retinex-Net scores higher AP but adds artifacts.	Limited generalization and poor noise removal, especially with unknown or real-world noise types, remain key challenges.
Hao Tang et al., 2023	Low-Illumination Image Enhancement Based on Deep Learning Techniques: A Brief Review	Low-light enhancement methods are categorized by learning type and evaluated on benchmark datasets using both objective metrics and visual assessment	Deep-Retinex, EnlightenGAN, CNN, Zero-shot learning model	Deep learning- based methods show strong potential for low-light image enhancement, with unsupervised models offering greater robustness. Fusion-based and hybrid frameworks provide better generalization, supporting higher-level vision tasks effectively	Existing datasets lack diversity and realism; current evaluation metrics poorly reflect human perception. Real-time video enhancement remains a challenge due to computational inefficiency.
Yong Wang et al., 2022	Low-light image enhancement based on deep learning: a survey.	The methodology involves enhancing low-illumination and low-contrast images using techniques like histogram equalization, atmospheric scattering models, and Retinex theory to improve visibility and detail.	Histogram Equalization Algorithm, Retinex Model, Single-scale Retinex, Multiscale Retinex.	Deep learning has revolutionized low-light image enhancement due to its ability to learn optimal parameters, leading to widespread adoption in fields like medicine and transportation; however, challenges still exist in its implementation.	Limited generalization due to dataset bias and model design.
Jinwei Guo et al., 2023	A survey on image enhancement for Low-light images.	The methodology involves a comprehensive literature review to analyze and categorize traditional and machine learning-based image enhancement algorithms, assessing their performance through various image quality metrics.	Retinex based algorithms, Adaptive histogram equalization (AHE), Histogram equalization methods (HE).	Image enhancement algorithms for low-light images significantly improve object feature differentiation and overall image quality, with innovative classifications based on model strategies.	Challenges include the need for unsupervised learning due to limited paired data, insufficient generalization across various image corruptions, and the need for evaluation in more complex high-level applications.
Zhen Tian et al., 2023	A Survey of Deep Learning- Based Low- Light Image Enhancement.	The methodology involves a comprehensive review of deep learning-based low-light image enhancement techniques, systematically addressing related methods, quality evaluation metrics, dataset organization, and a comparative analysis of the advantages and disadvantages of these approaches	CNN, Generative adversarial networks (GANs).	Deep learning significantly improves low- light image enhancement quality, enabling better performance in practical applications. It supports higher- level tasks and can produce visually appealing and informative results across various scenarios.	High data dependency, slow training times, limited generalization, and lack of real- time performance hinder broader adoption in real- world applications.

1. In their comprehensive survey on low-light image enhancement (LLIE), Chongyi Li et al. explored various deep learning-based solutions, examining algorithm taxonomy, network structures, and loss functions. They proposed a novel low-light image and video dataset captured under diverse illumination conditions using different mobile phone cameras. Additionally, the authors introduced a unified online platform that allows users to access and evaluate popular LLIE methods through a user-friendly interface. Their study included qualitative and quantitative evaluations of existing methods on both publicly available and their proposed datasets, as well as performance validation in face detection under low-light conditions. The findings highlighted significant variations in method performance based on datasets and metrics, providing valuable insights for future research in the field.

2. Hao Tang et al. provided a comprehensive review of low-illumination image enhancement techniques, emphasizing their significance as a critical preprocessing step in various practical applications. The authors highlighted the limitations of conventional methods, which typically focus on improving brightness, contrast, and noise suppression, and noted the growing dominance of deep learning solutions in this field. They categorized current deep learning- based enhancement methods into four groups: supervised, unsupervised, semi-supervised, and zero-shot learning methods. The paper also summarized existing low-light image datasets, identifying shortcomings such as the scarcity of paired reference images and the inadequacy of current datasets for high-level visual tasks. Furthermore, the authors discussed various quality assessment indices, revealing discrepancies between objective metrics and human perception. Through a detailed comparison of 14 representative algorithms, they noted that fusion-based models generally exhibited better generalization capabilities, while unsupervised methods proved to be more robust than supervised ones. The authors concluded by outlining future research directions, including the need for improved datasets, the development of tailored objective evaluation metrics, and the enhancement of algorithm speed for real-time applications. Overall, the study underscored the necessity for advancements in low-illumination image enhancement to better support higher-level visual tasks.

3. Yong Wang et al. conducted a comprehensive review of deep learning enhancement algorithms for low-light images, highlighting their importance in computer vision applications. The authors began with an overview of traditional enhancement techniques, followed by a categorization of deep learning methods based on neural network structures and learning algorithms. They discussed relevant datasets and performance metrics used in this domain. The paper emphasized the advantages of deep learning over traditional methods, particularly in parameter adjustment and training efficiency, and explored applications in critical fields such as medicine and transportation. Finally, the authors identified existing challenges and proposed future directions for research in low-light image enhancement, underscoring its significance in advancing this area.

4. Jiawei Guo et al. investigated the integration of traditional and machine learning algorithms for image enhancement in low-light conditions, addressing the various degradations such as low contrast, color distortion, and noise that affect both visual quality and computer vision tasks. The authors categorized traditional methods into three groups: gray level transformation, histogram equalization, and Retinex methods, detailing their principles and improvements. They further classified machine learning algorithms into end-to-end learning and unpaired learning, with subcategories of decomposition-based and fusion-based learning strategies. A comprehensive comparison of the involved methods was conducted using multiple image quality assessment metrics, including mean square error and structural similarity. The paper emphasized the goal of enhancing image quality by amplifying object feature differences while suppressing irrelevant features. Additionally, the authors proposed potential research directions, focusing on unsupervised learning, generalization ability across various corruptions, and the evaluation of algorithms in high-level applications such as depth estimation and 3D reconstruction.

5. Zhen Tian et al. conducted a comprehensive review of deep learning-based low-light image enhancement techniques, addressing the challenges posed by poor lighting conditions, such as low brightness, low contrast, color distortion, and noise. The authors systematically introduced the field by examining four key aspects: existing deep learning methods for low-light image enhancement, quality evaluation metrics, organization of relevant datasets, and a comparative analysis of the advantages and disadvantages of these methods. They highlighted the growing reliance on deep learning technologies in image processing while acknowledging limitations, including the need for substantial training data and the potential neglect of practical applicability and generalizability in some approaches. The paper emphasized the importance of developing algorithms that require less training data and can achieve high-quality results efficiently. Furthermore, the authors proposed future research directions, including the integration of multi-task models, enhancement of generalization capabilities, and improvements in processing speed for real-time applications. Overall, the study underscored the significant potential of deep learning in advancing low-light image enhancement techniques and their applications across various domains.

Section III. Future Work

Future Directions in Low-Light Image Enhancement Research

Unsupervised Learning Techniques

The future of low-light image enhancement (LLIE) research is set to experience significant progress, particularly in overcoming the limitations present in current methodologies. One promising avenue is the advancement of unsupervised learning techniques that can function effectively with limited or unpaired training data. This is particularly important given the frequent scarcity of high-quality paired datasets, which can

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hinder the training of deep learning models. Researchers should prioritize the development of robust algorithms capable of generalizing across various lighting conditions and image types, thereby improving their applicability in real-world situations.

Multi-Task Learning Frameworks

Additionally, the integration of multi-task learning frameworks could allow models to simultaneously tackle multiple enhancement objectives, such as brightness adjustment, noise reduction, and contrast enhancement. This approach could lead to more comprehensive solutions that address the diverse needs of low-light image enhancement applications, ultimately improving the overall performance of the algorithms.

Quality Assessment Metrics

Another important area for future investigation is the enhancement of quality assessment metrics specifically designed for low-light image enhancement. Existing objective evaluation indices often do not align well with human perceptual quality, highlighting the need for metrics that more accurately reflect visual experience. Developing tailored evaluation metrics will be essential for better assessing the effectiveness of enhancement algorithms and ensuring that they meet user expectations.

Real-Time Processing Capabilities

Moreover, improving the speed and efficiency of algorithms to enable real-time processing capabilities is crucial for practical applications, especially in domains such as surveillance, autonomous driving, and medical imaging. Achieving real-time performance will enhance the usability of low-light image enhancement techniques in critical scenarios where timely decision-making is essential.

Transfer Learning and Domain Adaptation

Researchers should also explore the potential of transfer learning and domain adaptation techniques to enhance model performance across diverse datasets and conditions. These strategies can help models adapt to new environments and lighting conditions, thereby improving their robustness and generalization capabilities.

Addressing High-Level Visual Tasks

By addressing these challenges, the field can move toward the development of more effective and versatile low-light image enhancement solutions that fulfill the requirements of high-level visual tasks. Focusing on these areas will not only advance the state of LLIE research but also expand its applicability across various industries and real-world scenarios.

Section IV. Conclusion

In conclusion, the field of low-light image enhancement has witnessed significant progress through the integration of deep learning techniques, which have demonstrated superior performance compared to traditional methods. However, challenges remain, including the need for improved datasets, tailored evaluation metrics, and enhanced algorithm efficiency. The comprehensive reviews by various authors highlight the

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importance of continued research in this area, emphasizing the potential for deep learning to transform low-light image processing across diverse applications. By focusing on the identified future directions, researchers can contribute to the development of more effective and practical low-light image enhancement methods, ultimately advancing the capabilities of computer vision technologies in real-world scenarios.

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