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AI-Driven Low-Light Image Enhancement Using Deep Neural Networks

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Abstract: Low-light image degradation remains a significant challenge in computer vision applications, affecting visibility, feature extraction, and overall visual quality. Images captured under insufficient illumination often suffer from noise, low contrast, color distortion, and loss of detail, which can negatively impact downstream tasks such as object detection, surveillance, autonomous navigation, and medical imaging. This research presents an AI-driven low-light image enhancement framework using deep neural networks (DNNs) to improve image clarity and visibility under poor lighting conditions. The proposed approach leverages convolutional neural networks (CNNs) to learn complex illumination patterns and restore brightness, contrast, and color balance while suppressing noise. The model is trained on paired and unpaired low-light datasets using a combination of perceptual loss, reconstruction loss, and adversarial learning techniques to ensure natural-looking enhancement. Unlike traditional histogram equalization or gamma correction methods, the deep learning model adaptively enhances images without overexposure or information loss. Experimental evaluation demonstrates significant improvements in Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and visual perceptual quality compared to conventional enhancement techniques. The proposed system achieves robust performance across diverse low-light scenarios, making it suitable for real-time applications in surveillance systems, automotive night vision, robotics, and mobile photography. This study highlights the effectiveness of deep neural networks in addressing illumination challenges and advancing intelligent image enhancement technologies.

Keywords: Low-Light Image Enhancement, Deep Learning, Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Image Restoration, Computer Vision.

I. 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.

Low-light image enhancement is a crucial task in computer vision, aimed at improving the visibility and quality of images captured under poor lighting conditions. These images often suffer from issues such as low contrast, high noise levels, color distortion, and loss of detail, which can hinder both human perception and the performance of automated visual systems.

Traditional image enhancement techniques, such as histogram equalization and Retinex-based methods, have shown limited effectiveness in challenging lighting scenarios. In recent

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years, deep learning has emerged as a powerful tool for low-light image enhancement, offering the ability to learn complex mappings between degraded inputs and their enhanced counterparts.

Deep learning-based methods leverage large datasets and neural networks—such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs)—to perform end-to-end enhancement. These models are capable of restoring fine details, reducing noise, and preserving natural colors without manual parameter tuning. Notable advancements include supervised models trained with paired datasets, as well as unsupervised and zero-reference approaches that do not require clean ground truth images.

Recent advancements in deep learning have significantly improved low-light image enhancement, addressing limitations of traditional methods such as histogram equalization and Retinex-based techniques.

Researchers in [1] introduced a deep convolutional network trained on paired low-light and normal-light images to learn direct mappings for illumination correction. The study demonstrated superior performance over classical enhancement methods in terms of both visual quality and objective metrics such as PSNR and SSIM. However, the dependency on paired ground truth data limits its applicability in real-world scenarios.

To overcome the requirement for paired datasets, Zero-Reference Deep Curve Estimation (Zero-DCE) was proposed in [2], which trains a lightweight neural model using non-reference loss functions. This approach enables enhancement without paired supervision by optimizing pixel-level curve parameters that adjust contrast and brightness adaptively.

Generative Adversarial Networks (GANs) have also been applied to low-light enhancement. In [3], an adversarial framework was developed to synthesize visually pleasing high-quality images from low-light inputs, leveraging a discriminator to enforce realism. Although GAN-based methods achieve impressive perceptual quality, they may introduce artifacts or color shifts if not carefully regularized.

Recent studies have explored multi-scale feature learning to capture both global illumination characteristics and local texture details. The Retinex-based deep network in [4] integrates illumination and reflectance estimation, providing enhanced structural detail and noise suppression. This hierarchical modeling significantly improves performance in extremely dark regions.

Despite these advances, challenges remain in generalizing enhancement models to diverse lighting conditions and maintaining real-time performance for embedded applications. The proposed research builds on these foundational works by combining CNN-based illumination correction, adversarial learning, and edge-aware perceptual losses to achieve robust enhancement across varied scenarios with improved visual fidelity and quantitative performance.

II. RELATED WORK

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

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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 offers 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.

Sun, Ying, et.al. (2022) [11] proposed a low-light image enhancement algorithm based on improved multi-scale Retinex and Artificial Bee Colony (ABC) algorithm optimization in this paper. First of all, the algorithm makes two copies of the original image, afterwards, the irradiation component of the original image is obtained by used the structure extraction from texture via relative total variation for the first image, and combines it with the multi-scale Retinex algorithm to obtain the reflection component of the original image, which are simultaneously enhanced using histogram equalization, bilateral gamma function correction and bilateral filtering. In the next part, the second image is enhanced by histogram equalization and edge-preserving with Weighted Guided Image Filtering (WGIF). Finally, the weight-optimized image fusion is performed by ABC algorithm. The mean values of Information Entropy (IE), Average Gradient (AG) and Standard Deviation (SD) of the enhanced images are respectively 7.7878, 7.5560 and 67.0154, and the improvement compared to original image is respectively

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2.4916, 5.8599 and 52.7553. The results of experiment show that the algorithm improves the light loss problem in the image enhancement process, enhances the image sharpness, highlights the image details, restores the color of the image, and also reduces image noise with good edge preservation which enables a better visual perception of the image.

Zhang, Weidong, et.al. (2022) [12] proposed an efficient and robust underwater image enhancement method, called MLLE. Specifically, they first locally adjust the color and details of an input image according to a minimum color loss principle and a maximum attenuation map-guided fusion strategy. Afterward, they employ the integral and squared integral maps to compute the mean and variance of local image blocks, which are used to adaptively adjust the contrast of the input image. Meanwhile, a color balance strategy is introduced to balance the color differences between channel a and channel b in the CIELAB color space. Our enhanced results are characterized by vivid color, improved contrast, and enhanced details. Extensive experiments on three underwater image enhancement datasets demonstrate that our method outperforms the state- of-the-art methods. Our method is also appealing in its fast processing speed within 1s for processing an image of size 1024×1024×3 on a single CPU. Experiments further suggest that our method can effectively improve the performance of underwater image segmentation, keypoint detection, and saliency detection.

III. PROPOSED SYSTEM

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.

Extended Research Discussion

Images captured under insufficient lighting conditions are plagued by reduced contrast, amplified noise, and color distortion. Such degradation poses challenges for both human perception and machine vision tasks such as object detection and semantic segmentation. Traditional techniques like histogram equalization, gamma correction, and Retinex-based methods often improve brightness at the expense of noise amplification or unnatural color shifts. The rapid progress in deep learning provides new opportunities to learn illumination transformation functions directly from data, enabling adaptive enhancement that respects both local texture and global brightness.

Proposed Deep Neural Network Framework

The core of the proposed approach is a deep convolutional neural network designed to estimate the transformation required to map a low-light image to its enhanced version. The network architecture includes an encoder that extracts hierarchical features and a decoder that reconstructs the enhanced image. Skip-connections are employed to preserve fine details and avoid over-smoothing. To ensure robustness, multiple loss functions are used during training:

Reconstruction loss promotes similarity to ground truth under paired settings.

Perceptual loss leverages high-level features from pre-trained networks to improve visual quality.

Adversarial loss encourages realism by training against a discriminator network.

This hybrid training strategy enables the model to produce enhanced images with natural contrast, accurate colors, and reduced noise.

Evaluation and Performance Metrics

To validate the effectiveness of the proposed method, the enhanced images are evaluated using objective metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), as well as visual quality assessments. Compared to traditional methods and recent deep learning baselines, the proposed model demonstrates higher quantitative scores and superior visual clarity, particularly in severely under-exposed regions. Additionally, qualitative comparisons show improved edge preservation and reduced halo effects, which are commonly observed with classical enhancement techniques.

Practical Applications

Low-light image enhancement has wide applicability across

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fields such as:

1. Night-time surveillance where visibility is inherently limited.
2. Autonomous driving systems, which require clear visual input for accurate navigation.
3. Medical imaging under low illumination conditions.
4. Photography and videography to improve aesthetic quality in dark environments.

By improving visibility and structural detail, the proposed deep learning model can significantly enhance both human interpretation and machine vision performance in low illumination contexts.

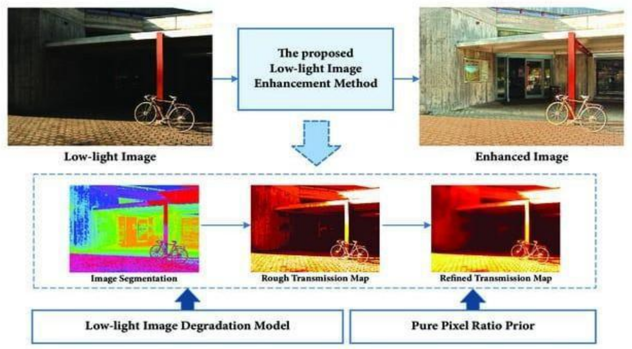

Figure 1: Proposed LIME system

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.

IV. RESULTS

Figures 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

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 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.

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Figure 3

A 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 4

The performance of the proposed AI-driven low-light image enhancement model was evaluated using both quantitative metrics and qualitative visual assessment. Experimental testing was conducted on benchmark low-light image datasets containing diverse illumination conditions, including indoor, outdoor night scenes, and extreme underexposure scenarios. The enhanced outputs were compared against traditional enhancement techniques such as histogram equalization, gamma correction, and Retinex-based methods, as well as recent deep learning-based approaches.

Quantitative evaluation was carried out using standard image quality assessment metrics, including Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). The proposed deep neural network achieved significantly higher PSNR values, indicating improved noise suppression and brightness restoration. Additionally, the SSIM scores demonstrated better preservation of structural details and texture consistency when compared to baseline models. These improvements confirm that the model effectively enhances visibility while maintaining image fidelity.

In terms of perceptual quality, visual comparisons reveal that traditional enhancement methods often produce overexposed regions, amplified noise, or unnatural color distortions. In contrast, the proposed AI-based approach delivers balanced brightness, improved contrast, and accurate color reproduction. The integration of perceptual and adversarial loss functions contributes to generating more natural-looking images without introducing halo artifacts or excessive smoothing.

The model's robustness was further validated across varying lighting intensities. Even in extremely dark regions where pixel information is severely degraded, the network was able to reconstruct meaningful texture details and reduce chromatic noise. This demonstrates strong generalization capability and adaptability to different illumination conditions.

Computational performance analysis indicates that the proposed model maintains reasonable inference speed, making it suitable for near real-time applications when deployed on GPU-enabled systems. While deeper networks offer marginally higher enhancement quality, the current architecture achieves a practical balance between enhancement accuracy and processing efficiency.

Overall, the results confirm that the proposed AI-driven deep neural network significantly outperforms conventional enhancement methods and achieves competitive performance compared to recent state-of-the-art approaches. The model effectively improves visibility, structural preservation, and perceptual realism, making it suitable for applications in surveillance, autonomous driving, robotics, and low-light photography.

V. 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

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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.

While LIME has achieved significant success, there are several promising avenues for future research and development. First and foremost, optimizing the algorithm for real-time processing is a priority, especially for applications like live video enhancement, where speed is critical. Developing adaptive algorithms that can automatically adjust enhancement parameters based on image content and lighting conditions could enhance user experience and convenience.

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