International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 05 Issue: 03 | Mar – 2026 DOI: 10.55041/ISJEM05764
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Deep Learning-Based Low-Light Image Enhancement for Improved Visibility

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***Abstract*—Images captured under low light conditions usually have low visibility, noise, and a loss of fine details, making them less useful for real-world applications. Traditional methods of image enhancement often introduce color distortion or over-brightening of the images; meanwhile, the classic supervised deep learning approaches require paired datasets that are too challenging to obtain. This paper describes a deep learning-based low-light image enhancement system with Zero-Reference Deep Curve Estimation (Zero-DCE++). The proposed approach learns adaptive illumination correction functions directly from low-light inputs without requiring ground-truth reference images. Multiple no-reference loss functions shall guide the training process in order to preserve the natural color appearance of the image and assure spatial coherence, which will help in proper exposure control. The experimental results prove that the proposed method enhances visual clarity while preserving structural details and minimizes noise amplification.**

***Index Terms*—Low-Light Image Enhancement, Self-Supervised Learning, Zero-DCE++, Deep Learning, Computer Vision**

1. INTRODUCTION

Low-light image enhancement is a classic problem in computer vision. Images captured under low lighting conditions often show reduced contrast, noise, and missing details. Such degradation has a negative impact on human visual perception and the reliability of further downstream vision systems. Conventional enhancement methods like histogram equalization and gamma correction perform global transformations, which may result in unnatural color reproduction and amplified noise. Recent advances in deep learning have made it possible to develop learning-based enhancement techniques, which generate visually pleasing results. However, most of the existing methods rely on supervised learning and require paired low-light and normal-light images that are expensive and time-consuming to collect. For overcoming this limitation, much consideration has been given to strategies for self-supervised learning.

Zero-DCE++ is a self-supervised deep curve estimation approach that directly estimates adaptive illumination curves from low-light images, with no requirement for reference data. This work presents the implementation and evaluation of a framework for enhancing low-light images with natural appearance using Zero-DCE++.

2. BODY OF THE PAPER

2.1 RELATED WORK

Low-light image enhancement has become an important research area due to its wide range of applications in photography, surveillance, and real-time vision systems. Over the years, several approaches have been proposed to improve image visibility and reduce noise under poor lighting conditions. These methods mainly include GAN-based models, frequency- domain techniques, Retinex-based approaches, and lightweight attention-driven networks.

Zhangkai Ni et al. (2022) introduced a Conditional Generative Adversarial Network (CIGAN) that performs both illumination enhancement and noise reduction. The model uses a generator to improve brightness and a discriminator to maintain realistic output quality. By incorporating conditional constraints, the method effectively handles both illumination and noise simultaneously. However, GAN-based approaches are often difficult to train and may produce visual artifacts due to unstable learning behavior.

The ULEFD Team (2023) proposed a frequency-domain method for balancing brightness and noise. Instead of processing images in the spatial domain, the approach transforms images into the Fourier domain and adjusts frequency components to achieve enhancement. While this method provides better control over noise and illumination, it involves complex computations and may not be suitable for real-time applications.

TechScience DDR (2024) presented a hybrid technique combining Retinex theory with knowledge distillation. The Retinex model separates illumination and reflectance to improve brightness naturally, while knowledge distillation helps in reducing model complexity. Although this approach improves efficiency, it still requires powerful hardware and may not perform well under extremely low-light conditions.

Researchers from Applied Sciences (2025) developed a lightweight attention-based model for real-time enhancement. The model focuses on important regions of the image using attention mechanisms, allowing efficient and adaptive brightness correction. Despite its efficiency, the model relies on synthetic datasets and may struggle when applied to real-world low-light scenarios.

Overall, existing methods provide significant improvements in image quality, but they also have limitations such as high computational cost, dependence on large datasets, instability in training, and reduced performance in challenging lighting conditions. These challenges highlight the need for a more efficient, stable, and self-supervised approach, which

ISSN: 2583-6129
DOI: 10.55041/ISJEM05764

motivates the use of Zero-DCE++ in this work.

2.2 SYSTEM DESIGN

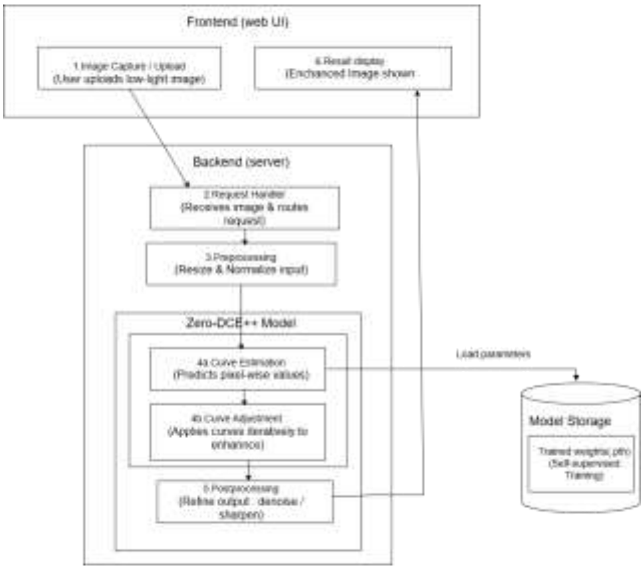

Fig. 1. Architecture of the proposed Zero-DCE++ based low-light image enhancement system

A. Proposed System Architecture

The proposed system is designed as a self-supervised low-light image enhancement framework that operates through a client–server architecture. The primary objective of the system is to enhance images captured under insufficient illumination while preserving natural color appearance and structural details.

The system consists of three main components: a frontend interface, a backend processing server, and the Zero-DCE++ enhancement model. The frontend provides a user-friendly web interface that allows users to upload low-light images in standard formats. This interface acts as the entry point of the system and enables real-time interaction with the enhancement pipeline.

Once an image is uploaded, it is transmitted to the backend server for processing. The backend is responsible for handling user requests, managing data flow, and performing image preprocessing operations. During preprocessing, the input image is resized to a fixed resolution and normalized to ensure compatibility with the deep learning model and to maintain stable inference behavior.

After preprocessing, the image is forwarded to the Zero-DCE++ model. Instead of directly generating an enhanced image, the model estimates a set of pixel-wise illumination adjustment curves. These curves are iteratively applied to the input image to gradually improve brightness and contrast while avoiding over-enhancement. This curve-based strategy allows the system to adaptively enhance different regions of the image based on local illumination conditions.

Following the enhancement stage, postprocessing operations are applied to refine the output image. These operations help suppress noise amplification and preserve edge details, resulting in visually pleasing enhancement. The final enhanced image is then returned to the frontend and displayed to the user for visualization or download.

B. Self-Supervised Learning Strategy

The proposed system adopts a self-supervised learning approach, eliminating the need for paired low-light and reference images during training. The Zero-DCE++ model is trained using only low-light images, and the enhancement quality is guided by carefully designed no-reference loss functions. This strategy enables the model to learn effective illumination correction directly from the input data, improving scalability and real-world applicability.

C. Loss Function Design

To achieve balanced enhancement, multiple loss components are combined during training. The exposure control loss ensures that the overall brightness remains within a desired range. The color constancy loss maintains consistency across color channels to prevent color distortion. The spatial consistency loss preserves structural details such as edges and textures, while the illumination smoothness loss avoids abrupt changes in brightness and reduces noise amplification. Together, these loss functions guide the model toward stable and natural enhancement.

D. System Workflow Summary

In summary, the workflow of the proposed system follows these steps: image upload through the frontend, preprocessing at the backend server, illumination curve estimation using the Zero-DCE++ model, postprocessing for refinement, and final output display. This modular design ensures clarity, scalability, and efficient execution, making the system suitable for real-time and practical low-light image enhancement applications.

2.3 IMPLEMENTATION

The proposed system was implemented as a complete low-light image enhancement framework based on the Zero-DCE++ model. The primary objective of the implementation is to accept low-light images as input, perform self-supervised enhancement using pixel-wise illumination curve estimation, and generate visually improved images with better brightness and contrast. The entire implementation is divided into multiple modules to ensure clarity, modularity, and efficient execution.

E. Tools and Libraries Used

The system was developed using Python as the primary programming language. The following libraries and frameworks were utilized during implementation:

- **Python**: Used to implement the overall workflow, including data handling, model execution, and system integration.

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- **PyTorch**: Used for designing, training, and evaluating the Zero-DCE++ deep learning model.
- **OpenCV**: Used for image loading, resizing, preprocessing, and visualization of results.
- **NumPy**: Used for numerical operations, array manipulation, and preprocessing tasks.
- **Flask**: Used to build a web-based interface for uploading low-light images and displaying enhanced outputs.

F. Input Image Collection and Handling

The first step in the implementation involves collecting low-light images from real-world indoor and outdoor environments. These images exhibit varying illumination conditions, shadows, and noise levels. Since the approach follows a self-supervised learning paradigm, no corresponding reference or normal-light images are required.

Each input image is processed individually to maintain consistency and stability during enhancement. Before being passed to the model, images are resized to a fixed resolution of 256×256 and normalized to ensure compatibility with the neural network and to maintain uniform input distribution.

G. Preprocessing Module

The preprocessing stage prepares the input images for model inference. This stage includes resizing the images, converting them into tensor format, and normalizing pixel values. Preprocessing helps stabilize the learning process and ensures that the enhancement behavior remains consistent across different input images.

This module also ensures that image dimensions and color channels are aligned with the requirements of the Zero-DCE++ model.

H. Illumination Curve Estimation Using Zero-DCE++

Unlike conventional enhancement methods that directly predict an enhanced image, the Zero-DCE++ model estimates pixel-wise illumination adjustment curves. These curves represent how brightness should be adjusted locally for each pixel.

During inference, the model predicts a set of illumination curves for the input image. These curves are then applied iteratively to the image, gradually improving brightness and contrast. This iterative curve application strategy allows the system to enhance darker regions while avoiding overexposure in brighter areas, leading to more natural-looking results.

I. Self-Supervised Training Strategy

The training process follows a self-supervised learning approach, where only low-light images are used as training data. No paired ground-truth images are required. The learning process is guided by multiple no-reference loss functions that evaluate enhancement quality based on exposure balance, color consistency, spatial structure, and illumination smoothness.

This strategy enables the model to learn effective enhancement behavior directly from low-light inputs, improving scalability and real-world applicability.

J. Training Process

During training, the preprocessed low-light images are loaded in batches using a data loader. The Zero-DCE++ model parameters are optimized using the Adam optimizer over multiple training epochs. Validation is performed periodically to monitor training stability and to prevent over-enhancement.

Early stopping is applied to ensure convergence and to maintain visually natural enhancement results. After training, the best-performing model weights are saved and later used for inference during testing and deployment.

K. Image Enhancement and Output Generation

In the testing phase, input images are passed through the same preprocessing and enhancement pipeline. The trained Zero-DCE++ model estimates illumination curves and applies them iteratively to generate the enhanced image.

After enhancement, postprocessing operations are applied to refine the output and suppress noise amplification. The final enhanced image is then displayed to the user through the web interface or saved for further analysis.

L. System Workflow Summary

Overall, the system workflow consists of image upload, preprocessing, illumination curve estimation using the Zero-DCE++ model, iterative enhancement, postprocessing, and final output display. This modular implementation ensures clarity, efficient execution, and suitability for real-time low-light image enhancement applications.

2.5. RESULTS AND DISCUSSIONS

M. Dataset and Testing Setup

To evaluate the performance of the proposed system, low-light images were collected from multiple real-world scenes, including indoor rooms, outdoor night scenes, and poorly illuminated environments. The testing dataset consists of unpaired low-light images, as the proposed approach follows a self-supervised learning paradigm and does not require corresponding reference images.

All input images were resized to a fixed resolution of 256×256 before enhancement. During testing, each image was processed independently by the trained Zero-DCE++ model. The enhanced outputs were visually inspected and quantitatively evaluated using standard image quality metrics to assess the effectiveness of illumination enhancement and detail preservation.

N. Enhancement Results

The qualitative enhancement results are illustrated through visual comparisons between the original low-light input images and their corresponding enhanced outputs. In each comparison, the image on the left represents the original low-light input, while the image on the right shows the enhanced result generated by the proposed Zero-DCE++ framework.

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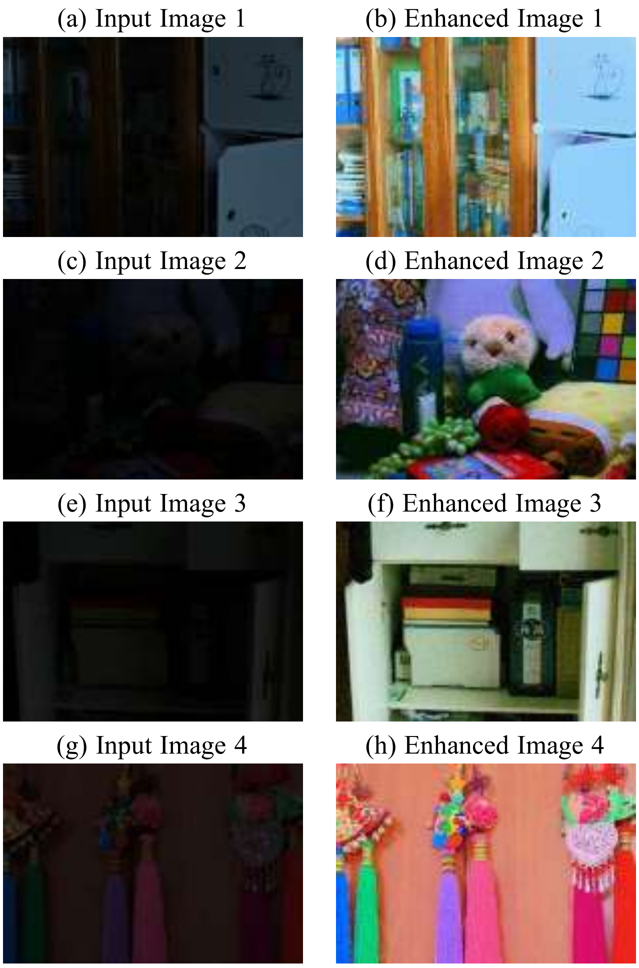

Fig. 2. Qualitative comparison of low-light input images and enhanced outputs generated by the proposed Zero-DCE++ framework

From the observed results, the proposed method successfully improves brightness and visibility in dark regions while maintaining natural color appearance. The enhanced images exhibit clearer structures and improved contrast without introducing noticeable artifacts or over-brightening. The pixel-wise illumination curve estimation enables adaptive enhancement across different regions of the image, making the approach effective for diverse low-light scenarios.

O. Discussion

The experimental observations indicate that the curve-based enhancement strategy employed by Zero-DCE++ plays a significant role in achieving balanced illumination correction. By estimating pixel-wise illumination adjustment curves, the model adapts to local lighting variations and avoids the limitations of global enhancement techniques.

Quantitative evaluation further supports the effectiveness of the proposed system, with improved PSNR and SSIM values indicating better structural preservation, and reduced NIQE and BRISQUE scores reflecting enhanced perceptual quality. Since the approach is self-supervised and does not rely on paired reference images, minor variations in enhancement strength may occur for extremely challenging scenes. However, the system consistently maintains a favorable balance between brightness improvement and color fidelity.

Overall, the results demonstrate that the proposed Zero-DCE++ based low-light image enhancement system is effective, stable, and suitable for practical applications where reliable visibility enhancement is required without extensive training data.

3. CONCLUSION AND FUTURE WORK

This paper presented a deep learning-based framework for enhancing low-light images using Zero-Reference Deep Curve Estimation (Zero-DCE++). The proposed system estimates pixel-wise illumination adjustment curves directly from low-light images without requiring paired reference data. By adopting a self-supervised learning strategy guided by no-reference loss functions, the framework effectively overcomes the limitations of traditional supervised enhancement techniques.

Although the proposed system performs well, there is scope for further improvement and expansion. In the future, the model can be enhanced to handle extremely dark environments more effectively and to further reduce noise in challenging conditions. The system can also be extended to process video sequences in real time, enabling applications in surveillance and autonomous systems. Integration with mobile and embedded devices can make the solution more practical for everyday use. Additionally, combining this approach with other advanced deep learning techniques or adaptive optimization methods may further improve performance and robustness. Expanding the model to support different image formats and real-world datasets will also help in making the system more versatile and widely applicable.

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