Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

MSDCE: Light-Enhancement Curve-based Algorithm for Improving Visual Quality of Images with Uneven Lightening

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Abstract

Enhancing low-light images under uneven illumination remains a challenging problem in computer vision. This study proposes an enhanced version of the Zero-Reference Deep Curve Estimation (Zero-DCE) model, named MS-DCE (Multi-Scale Deep Curve Estimation). The proposed model incorporates comprehensive architectural modifications and refined loss functions to improve performance. Specifically, multi-scale convolution is introduced to capture contextual information at varying scales, depth-wise separable convolutions are employed to reduce model parameters and computational cost, and traditional up-sampling is replaced with PixelShuffle to improve image resolution. Additionally, the loss functions are refined to mitigate overexposure while preserving natural colour consistency, thereby enhancing visual quality, particularly in regions with uneven lighting. Experimental results on the Part 2 subset of the SICE dataset demonstrate substantial improvements in image quality, with a 2% increase in PSNR and a 4% improvement in perceptual quality. These modifications not only enhance low-light image recovery but also provide a more efficient solution for handling complex illumination conditions.

Keywords: Image enhancement, Neural networks, Low-light enhancement, Uneven lightening

1. Introduction

The improvement of images taken at low and uneven lightening has consistently posed a significant challenge in the field of image processing, particularly under conditions of uneven

DOI: https://doi.org/10.36548/jiip.2024.4.003
Received: 03.11.2024, received in revised form: 29.11.2024, accepted: 08.12.2024, published: 17.12.2024

illumination [1, 8, 16, 25]. Such scenarios often result in poor image visibility, adversely affecting various applications, including surveillance, photography, and medical imaging [4, 5, 17, 28]. Specifically, images captured under low light conditions typically exhibit high noise levels, low contrast, and colour distortions, collectively leading to degraded visual quality, making the need for image enhancement particularly urgent.

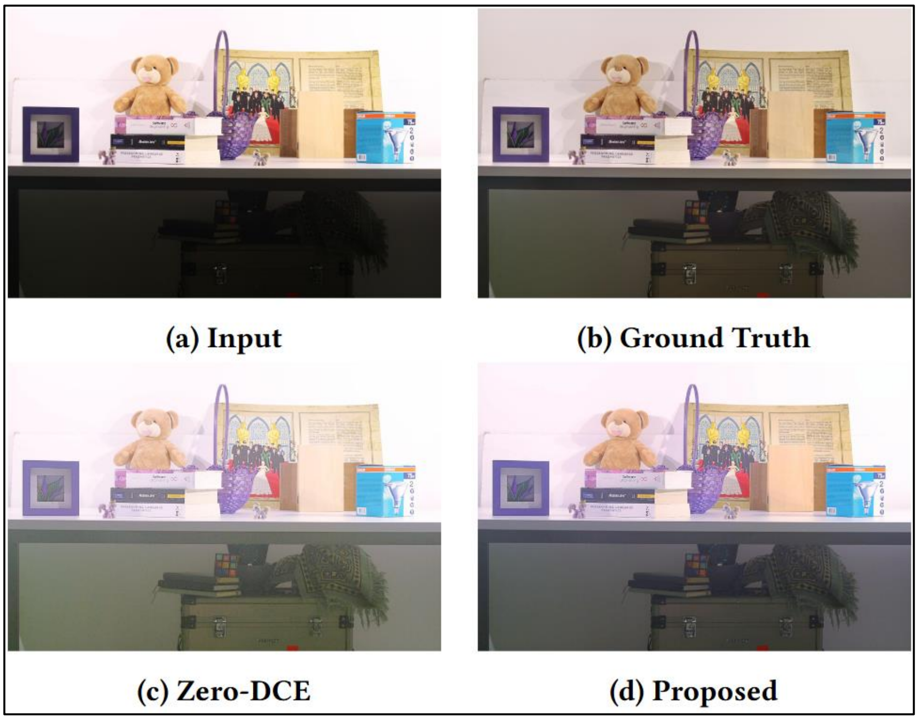

Figure 1. Visual Comparison of Performance of Proposed.

Figure 1 is a comparison of a representative of low-light image that demonstrates that the proposed method produces visually appealing results, excelling in brightness, colour accuracy, contrast, and overall naturalness.

Historically, a range of techniques has been employed to address the issue of low-light image enhancement, from traditional histogram equalization methods to more advanced deep-learning approaches. Among these, the Zero-DCE algorithm [7] has emerged as a notable method due to its ability to enhance images without relying on additional high-light images for reference. Zero-DCE dynamically adjusts the light map of an image by learning light-related curves, a process that has demonstrated considerable success in general low-light conditions.

However, the standard Zero-DCE method often encounters difficulties when illumination is unevenly distributed across the image. In this case, the enhancement process often causes areas with high exposure to become overexposed. This difference in the distribution of light in the image not only results in an enhanced image that is less visually appealing but also conceals important details, which is especially problematic in applications that require high accuracy.

To address this challenge, this research introduces several innovative modifications to the Zero-DCE model. Specifically, enhancing the model architecture by incorporating three key modifications: 1) The integration of Multi-Scale Convolution for better feature extraction across different scales. 2) Depth-wise separable convolutions are utilized to significantly reduce the model's parameter count while preserving its performance. 3) The adoption of PixelShuffle to replace traditional interpolation methods for more efficient up-sampling. In addition, the study proposes two novel loss functions, BrightPenaltyLoss (BPLoss) and ColorDynaLoss (CDLoss), designed to effectively handle the issue of uneven illumination in low-light images.

2. Related Work

The field of low-light image improvement has received substantial attention within computer vision, striving to mitigate the adverse effects of under or overexposure that frequently compromise image quality. Methodological evolution in this field has transitioned from conventional enhancement strategies to the implementation of advanced deep learning paradigms.

2.1 Conventional Methods

Historically, spatial domain manipulation has been central to image quality enhancement, with grey-level transformation playing a key role in improving dynamic range and contrast. By adjusting pixel intensity levels, this method enhances visibility, brightening dark regions and darkening bright ones. Histogram Equalization (HE) [21] is a commonly applied method for redistributing grayscale intensities, which results in a more uniform distribution and enhances the contrast. This technique is particularly effective in revealing hidden details in images with low contrast, often caused by factors such as glare or inadequate lighting.

Despite their effectiveness, conventional methods such as HE has limitations under complex lighting conditions. HE can lead to over-enhancement, causing some areas to become overly bright or dark, resulting in detail loss and unnatural visuals. Additionally, it may introduce noise and artifacts, especially in low signal-to-noise ratio images. Retinex-based methods [9, 11], while effective in certain contexts, can struggle with colour fidelity and balance in scenes with highly variable illumination, leading to colour distortion and exaggerated edges. Their computational complexity also limits their suitability for real-time applications.

2.2 Deep-learning Models

The integration of deep learning has significantly advanced low-light image enhancement, enabling adaptive, algorithm-driven solutions [2, 3, 6]. End-to-end learning frameworks [12, 13, 15], such as LLNet [15], that utilize encoder-decoder architectures for simultaneous parameter optimization [14, 22, 23, 27]. These frameworks learn complex mappings from low-light to enhanced images, ensuring coordinated enhancement across all stages and resulting in improved visual quality and consistency across diverse lighting conditions.

Fusion-based approaches combine images captured at different exposures, preserving key features from each source to restore details and correct colour imbalances. Techniques like Exposure Fusion and Multi-Exposure Image Fusion (MEF), aided by deep learning, merge exposures to maintain a natural appearance while enhancing visibility.

Emerging unpaired learning methods address the challenge of paired datasets by using Generative Adversarial Networks (GANs) and adversarial training to learn mappings from unpaired data. Models like EnlightenGAN [10] demonstrate impressive flexibility, improving unpaired low and normal-light images across various real-world scenarios [20]. Overall, these innovations enhance the potential of low-light image enhancement by providing effective and adaptable solutions.

The development in low-light image enhancement emphasizes a pivotal shift from dependence on traditional methodologies towards utilizing deep learning constructs, adeptly navigating the intricate challenges inherent to low-light imaging. While foundational methods established critical precedents, the advent of deep learning has broadened the horizons for adaptive, algorithmic image enhancement, indicating a new era of innovation within this field.

3. Proposed Work

3.1 MS-DCE

The MS-DCE model is built upon the Light-Enhancement Curves (LE-Curves) [7] foundation, enhancing feature extraction capabilities through the incorporation of Multi-Scale Convolutions. To mitigate the increased parameter complexity introduced by multi-scale convolutions, depth-wise separable convolutions are integrated, reducing computational cost while maintaining performance. Additionally, an efficient PixelShuffle up-sampling technique is adopted to improve sampling efficiency. The overall model architecture is shown in Figure. 2.

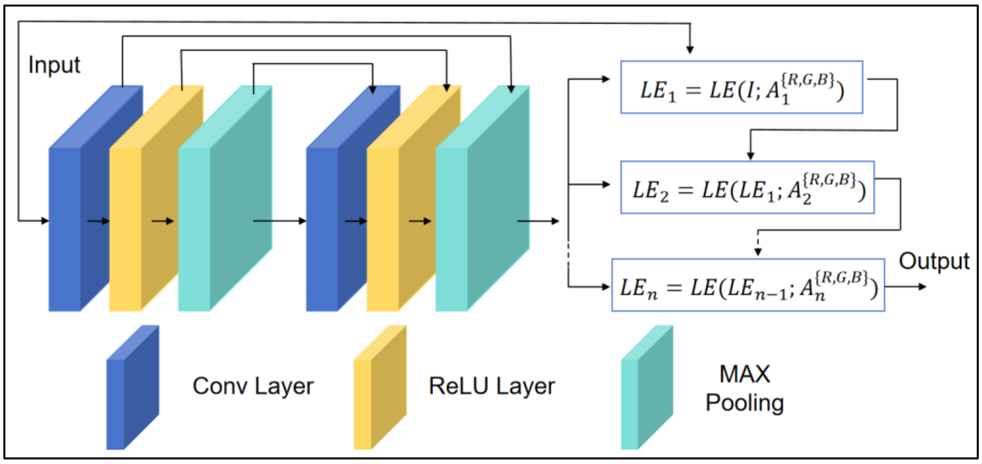

Figure 2. The Framework of MS-DCE

3.2 Improvements to the Model

Multi-Scale Convolutions: Multi-scale convolutions are introduced to improve the model's ability to capture contextual information at varying scales, enhancing feature extraction. This modification enables the model to learn from a broader set of features, improving its performance in handling low-light images with uneven illumination. For an input image I, the multi-scale convolution operation is represented as:

$$Y_s = \sum_{k \epsilon K} Conv_k(I) \tag{1}$$

where $Conv_k(I)$ denotes the convolution with kernels of different sizes $k\epsilon K = \{3 \times 3, 5 \times 5, 7 \times 7\}$ on the input image, and Y_s is the output feature map after multi-scale convolutions. This modification improves the ability to capture complex features in unevenly lit scenes, as opposed to using a single convolution kernel as in the original Zero-DCE model

Depth Convolution:

$$Y_d^c = Conv_d^c(I^c)\ for\ each\ channel \quad c = 1, \dots, C \tag{2}$$

where $Conv_d^c(I^c)$ represents the depth-wise convolution applied to each individual input channel.

Pointwise Convolution:

$$Y_p = Conv_1 x1(Y_d) \tag{3}$$

The total computational cost in terms of floating-point operations (FLOPs) is:

$$FLOP_{s_{depthwise}} = C \cdot H \cdot W \cdot k^2 + C' \cdot H \cdot W \tag{4}$$

Compared to the standard convolution in the original Zero-DCE, depth-wise separable convolutions greatly reduce the computational complexity while maintaining performance, making the model more efficient.

PixelShuffle for Up-sampling: Instead of traditional up-sampling methods, MS-DCE uses PixelShuffle, a technique that efficiently increases image resolution by rearranging the feature map’s channel information into spatial dimensions, improving sampling efficiency and reducing blurring artifacts.

3.3 Improvement of Loss Function

To control the underexposed and overexposed regions, Guo et al. [7] introduced an exposure control loss function L_{exp} to regulate the exposure level. The loss L_{exp} is defined as:

$$L_{exp} = \frac{1}{M}\sum_{k=1}^{M}|Y_k - E| \tag{5}$$

In this research, to enhance the capabilities of the ZERO-DCE framework in low-light image enhancement, introduces a novel loss function, BrightPenaltyLoss (BPLoss), designed to mitigate overexposure and underexposure issues [18, 19, 24]. The core innovation of BPLoss lies in its brightness penalty mechanism, which regulates the overall brightness of the image by penalizing pixels that exceed a predefined brightness threshold. First, BPLoss computes the average brightness of local regions through average pooling and compares it to a target brightness value, using the mean squared error (MSE) to minimize the difference. Second, it imposes a penalty on pixels whose brightness surpasses the specified threshold, thereby controlling overly bright regions. The final loss function is a weighted sum of the MSE and the penalty term, ensuring that the image brightness aligns with the desired value while preventing excessive brightness. The mathematical formulation of BPLoss is given by:

$$L_{bp} = \frac{1}{M}\sum_{k=1}^{M}|Y_k - E| + \omega * \frac{1}{M}\sum_{k=1}^{M}\max(0, Y_k - T)^2 \tag{6}$$

where Y_k denotes the pixel intensity of the enhanced image, E represents the target exposure level, and T signifies the predefined threshold to identify overexposed regions. M is the total number of pixels in the image, and ω is a weighting factor that controls the relative importance of penalizing overexposure compared to achieving the target exposure level. The second term introduces a quadratic penalty for pixels exceeding the overexposure threshold T. This penalty is activated only for pixels where the intensity Y_k surpasses T, effectively suppressing overexposure artifacts without affecting correctly exposed regions. The inclusion of ω allows for fine-tuning the sensitivity of the loss function to overexposure, offering flexibility in balancing exposure correction and overexposure mitigation.

Colour Constancy Loss: It is a correct potential color deviation in the enhanced image, building upon the Gray-World color constancy hypothesis. This loss also establishes relationships among the three adjusted channels. The color constancy loss L_{col} is defined as:

$$L_{col} = \sum_{\forall(p,q)\in\varepsilon}\left(J_p - J_q\right)^2, \varepsilon = \{(R,G),(R,B),(G,B)\} \tag{7}$$

To further improve the image enhancement process in the framework of ZERO-DCE, this research proposes an innovative loss function, the ColorDynaLoss (CDLoss), aimed at ensuring colour consistency across the enhanced image. By considering the dynamic range of the image and weighting the loss of colour consistency, a more effective method is provided for colour balance and contrast adjustment in enhancing the low-light images. This loss function occurs during the improvement of low-light images to ensure that the colour consistency of the scene is preserved. The formal definition of CDLoss is as follows:

$$L_{cd} = \sum_{\forall(p,q)\in\varepsilon} W_{dr} \cdot \left(J_p - J_q\right)^2, \varepsilon = \{(R,G),(R,B),(G,B)\}$$

$$W_{dr} = \frac{max(I) - min(I)}{max(max(I) - min(I))} \tag{8}$$

where J_p and J_q denote the colour intensity values of the two corresponding pixels in the enhanced image across the colour channels R, G and B. The set ε includes all possible pairs of these colour channels. W_{dr} denotes a dynamic range weight. Here, $max(I)$ and $min(I)$ refer to the maximum and minimum intensity values across the entire image I, respectively. The normalization by the maximum dynamic range across the image ensures that W_{dr} scales the loss according to the relative dynamic range of the image, thereby adapting the influence of colour consistency loss based on the image's overall exposure level.

The core objective of CDLoss is twofold. Firstly, it aims to minimize the squared difference in colour intensity between each pair of colour channels, ensuring that the colour balance is maintained post-enhancement. Secondly, by incorporating the dynamic range weight W_{dr}, CDLoss adapts the penalty for colour inconsistency based on the dynamic range of the image, thereby ensuring that the colour fidelity is preserved especially in images with a wide dynamic range.

4. Empirical Analysis

4.1 Implementation Details and Datasets

To minimize the influence of external factors, the same SICE training set [26] and hyperparameters as those in the original Zero-DCE paper are adopted. The MS-DCE model is trained using 360 multi-exposure sequences from the first part of the SICE dataset. This Part1 subset includes 3022 images with varying exposure levels, which are randomly divided into 2422 images for training and the rest for validation. All training images are resized to 512×512. The system is implemented in PyTorch and runs on NVIDIA 4080 GPUs with a batch size of 8. Filter weights in each layer are initialized using a Gaussian distribution (mean = 0, standard deviation = 0.02), and biases are set to a constant value. The ADAM optimizer with default parameters is employed for network optimization, maintaining a fixed learning rate of 1e-4. The weights W_{col} and W_{tv} are assigned values of 0.5 and 20, respectively, to ensure proper balance among the loss components.

4.2 Benchmark Evaluations

The MS-DCE model was evaluated against the original Zero-DCE model by reproducing its results using publicly available open-source code and the recommended parameters. Quantitative evaluations were performed on the Part2 subset of the SICE dataset [26], which consists of 229 multi-exposure sequences with corresponding reference images. For this evaluation, the first three low-light images from each sequence were selected, and all images were resized to 1200×900×3. This process resulted in a total of 687 pairs of low-light and normal-light images. The comparison results are summarized in Table 1

Table 1. Quantitative Comparisons of Low-Light Images are Conducted using Full-Reference Image Quality Assessment Metrics. The Best Results are Highlighted in Red, while the Second-Best Results are shown in Blue.

Methods	**PSNR↑**	**SSIM↑**	**MAE↓**
RetinexNet[11]	15.98527	0.547565	34.67509
LIME[27]	16.17153	0.575655	33.59297
EnlightenGan[17]	16.68133	0.593574	32.08510
Zero-DCE[7]	16.88485	0.593650	31.75830
Proposed	17.21068	0.596319	30.55651

4.3 Visual and Perceptual Comparisons

Considering the scarcity of datasets for complex lighting scenes, images with complex lighting conditions were selected from the LIME [7] and DICM [12] datasets for evaluation. The performance of the proposed method was compared with EnlightenGAN, the original Zero-DCE model, and the latest low-light enhancement models. A typical visual comparison scene is shown in Fig. 3 and 4. Compared with other methods, MS-DCE can better maintain the texture of the towel under the front irradiation of the room lamp. In an outdoor scene with sufficient light, the proposed model did not exhibit noticeable overexposure. MS-DCE effectively enhanced dark areas while preserving the colour of the input image and also produced favourable results in regions with adequate brightness.

Similar to the Zero-DCE experiment, a user study was conducted to quantitatively evaluate the individual visual quality of the traditional and proposed methods. Both approaches were tested on low-light images from the DICM, LIME and other datasets. For each enhanced image, the corresponding input image was provided as a reference. A total of 10 participants independently assessed the visual quality of the enhanced images. Furthermore, a new criterion was introduced to identify cases of excessive brightness enhancement. The training was performed by observing:

(1) whether the result contains overexposed/underexposed artifacts or overexposed/ under enhanced areas.

(2) Whether there is colour deviation in the results.

(3) Whether the resulting texture is unnatural and the noise is obvious.

(4) The result is whether there is an unnatural brightness caused by overexposure.

The visual quality ratings ranged from 1 to 5, with 1 indicating the worst quality and 5 representing the best quality. The average subjective scores for each image set are presented in Table 2, demonstrating that the results of this research were more favoured by the participants.

Table 2. User Study (US)↑ and Perceptual Index (PI)↓ Scores on the Image Sets (LIME, DICM) are REPORTED.

Methods	LIME	DICM	Average
RetinexNet[11]	4.135/3.203	4.201/3.146	4.168/3.175
LIME[27]	3.891/3.562	4.002/3.471	3.946/3.516
EnlightenGan[17]	4.256/2.995	4.309/2.890	4.283/2.942
Zero-DCE[7]	4.287/2.532	4.330/2.346	4.309/2.439
CIDNet[23]	4.452/2.815	4.498/2.476	4.475/2.646
Proposed	4.602/2.941	4.635/2.305	4.618/2.623

4.4 Quantitative Comparisons

For full-reference image quality assessment, Mean Absolute Error (MAE), Structural Similarity Index (SSIM) [26], and Peak Signal-to-Noise Ratio (PSNR dB) were utilized to quantitatively evaluate the performance of various methods on the Part2 subset of the SICE dataset [26]. The proposed MS-DCE model outperforms LIME, EnlightenGAN, the original Zero-DCE, and other competing methods, demonstrating superior capability in enhancing low-light image quality. As illustrated in Figure. 3 and 4, the proposed approach more effectively restores image details in high-exposure regions of images with uneven illumination. Additionally, the computational efficiency did not increase significantly, as shown in Table 3, with the added 0.001s of operation time on the GPU being negligible and substantially lower than that of other models.

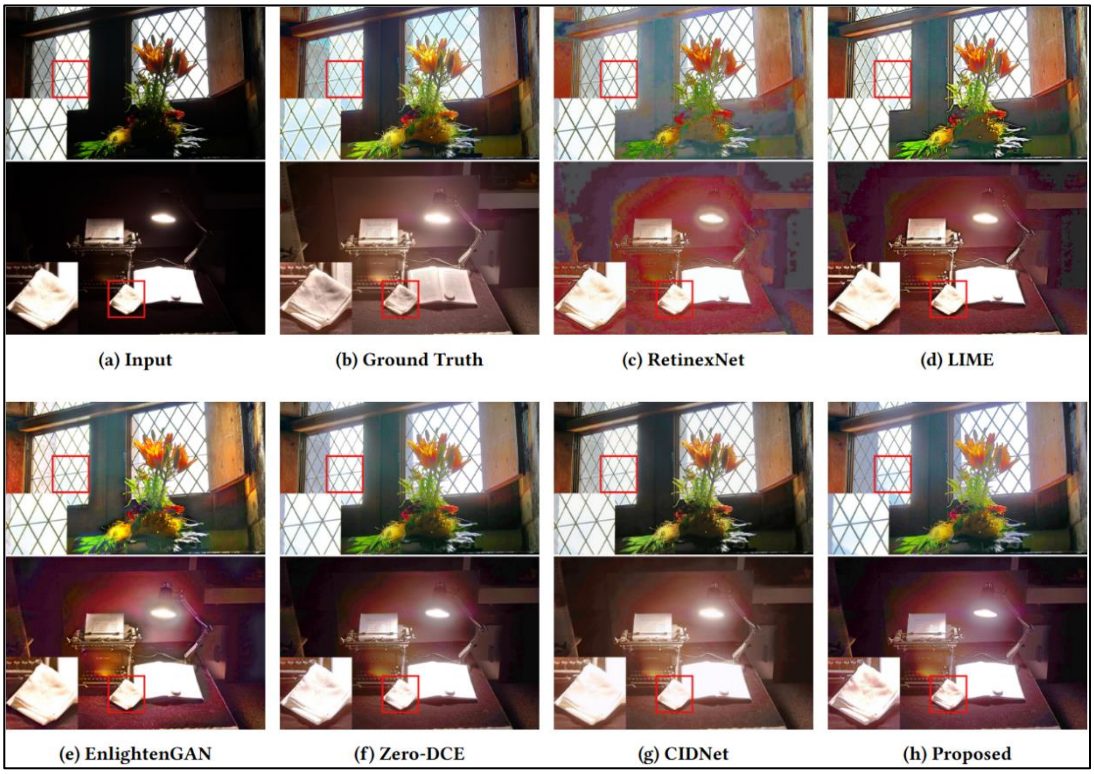

Figure 3. Visual Contrast of Non-Uniform Light Images of Typical Models. The Red Boxes Indicate Significant Differences.

Figure 4. Visual Comparisons on Representative Low-Light Images are Presented, with Red Boxes Highlighting the Noticeable Differences.

Table 3. Runtime (RT) Comparisons, Measured in Seconds, are Provided. The Best Results are Highlighted in Red, while the Second-best Results are Marked in Blue.

Methods	Times	Platform
RetinexNet[11]	2.2658	PyTorch (GPU)
LIME[27]	2.3954	PyTorch (GPU)
EnlightenGan[17]	0.5750	PyTorch (GPU)
Zero-DCE[7]	0.0113	PyTorch (GPU)
CIDNet[23]	0.0679	PyTorch (GPU)
Proposed	0.0086	PyTorch (GPU)

5. Conclusion

This research introduces the MS-DCE model, an enhanced version of the Zero-DCE framework for low-light image enhancement. The MS-DCE model incorporates key innovations, including multi-scale convolutions for improved feature extraction, depth-wise separable convolutions to reduce computational complexity, and PixelShuffle up-sampling for more efficient resolution enhancement. Additionally, two novel loss functions-BrightPenaltyLoss (BPLoss) and ColorDynaLoss (CDLoss)-are proposed to address overexposure, underexposure, and colour fidelity, ensuring more balanced enhancement across varying lighting conditions. Experimental results on the SICE Part2 dataset demonstrate the superiority of MS-DCE over the original Zero-DCE and other models, with notable improvements in handling both overexposed and underexposed regions, as well as in preserving colour consistency. These advancements highlight the MS-DCE model's potential for high-quality low-light image enhancement and provide a more effective solution for complex illumination conditions. Future work will focus on refining adaptive brightness and dynamic colour adjustment techniques to further optimize low-light enhancement in challenging scenarios.

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