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Fusion Deep Learning with Adaptive Gamma Correction (DLAGC) to Enhance Images in Low Light

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ABSTRACT

Object detection in dark areas or poor light images represents a big challenge in computer vision. The poor light images suffer from intensive noise, low contrast, and reduced visibility. Based on the affirmation, this paper proposes a fusion model based on deep learning with adaptive gamma correction (DLAGC). It enhances the low-light image Based on the combination of the images that outcome from deep learning and adaptive gamma correction in pixel-level image fusion. The deep learning estimated pixel-level adjustment curves of RGB channels. Moreover, the adaptive gamma correction value is calculated based on the value of the image Luminance factor and the average color factor, resulting in a locally adaptive value with each pixel. The proposed model DLAGC has demonstrated the ability to improve image quality by enhancing lighting, highlighting fine details, and reducing noise while maintaining natural color balance. To evaluate the proposed model, two reference datasets (LOL and Brightening Train) and three non-reference datasets (DICM, LIME, UCID_V2). The Experimental results show that the proposed model outperforms the state of the art of low light methods. The proposed model gets an average PSNR is 17.386, SSIM is 0.788, and FSIM is 0.92 for reference datasets. Meanwhile, the achieved average NIQE is 3.684 for nan-reference datasets. Therefore, the model provides a real-world solution for image enhancement under different lighting conditions.

Keywords: Low light image enhancement, deep learning, adaptive gamma correction, contrast enhancement, color correction.

INTRODUCTION

Many fields in computer vision need clear and high-quality images [1], such as object detection in the dark area[2], self-driving[3], security monitoring, military[4], biomedicine, and aerospace[1]. Many factors affect the image, such as clarity and quality [5]. One of the most important factors is the low light, which causes the image to suffer from blurry and has low brightness, loss of detail, high noise[6], and poor visual quality[7]. These issues affect the identifies the object and texture in images [8]. The Low-light image technique enhancement is utilized to overcome these issues. Where these techniques aim to improve the dynamic range and contrast of low-light images to restore color details, remove noise, and recover lost information [9]. Figure 1 shows the distribution of intensity color to low light and enhanced image.

Over the past decade, many technical solutions have emerged to enhance low-light images, including traditional methods and modern techniques. Traditional methods, such as Histogram equalization (HE), use rearranged values of the pixels to follow a uniform distribution[10]. Moreover, the Retinex theory model considers an image combination of reflectance and illumination[11]. Additionally, Gamma correction (GC) promotes the brightness in the dark pixels[12]. However, these methods may result in excessive enhancement and strong noise of the enhanced image.

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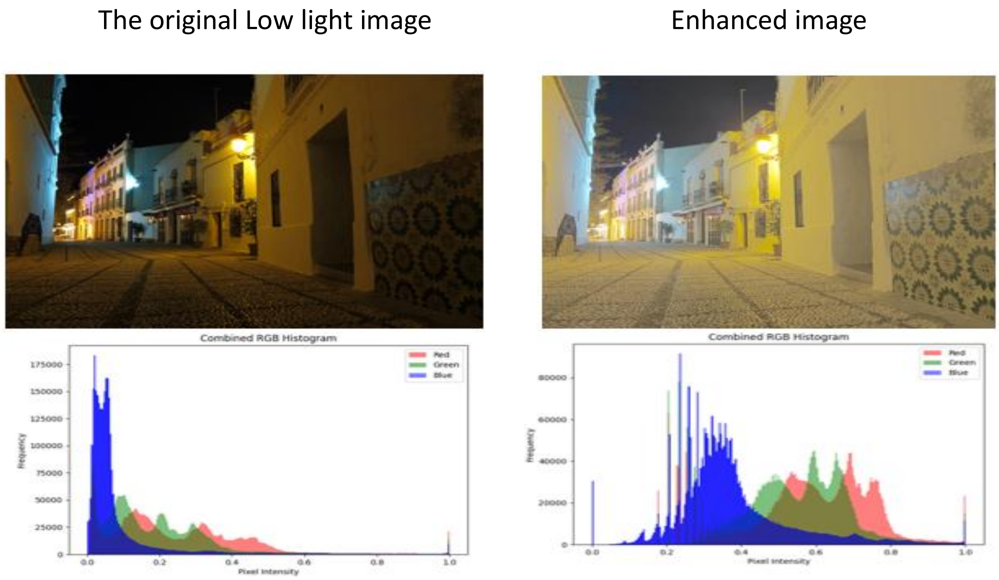

Figure. 1 distributed intensity color to the low light image and enhanced image.

Modern techniques depend on deep learning [13], which works by extracting and analyzing features to improve lighting and image quality and restore lost details [14]. However, a solution based on deep learning can be challenging in terms of losing real fine details due to unrealistic features generated. In addition, deep learning may fail to improve images with certain types of noise or distortion.

To overcome these challenges, this paper proposes a fusion model (DLAGC) to enhance low-light images by merging deep learning with Adaptive Gamma correction.

This merging process aims to achieve a balance between restoring fine details and the image's visual quality while preserving natural colors and making the enhanced image closer to the real image. Image enhancement uses adaptive gamma to restore real fine details and enhance contrast. At the same time, deep learning works to enhance image lighting and restore lost colors.

The proposed model (DLAGC) focuses on achieving the following contributions.

1. Designing a deep learning (DL) algorithm can estimate the pixel-wise curve and improve images in different light conditions without needing to reference images by using non-reference loss functions to avoid the risk of overfitting.
2. Proposing adaptive gamma correction (AGC) method depends on the illuminance factor and average color rate of each pixel in the image to adjust the enhancement of adaptation dynamic characteristics of the scene, which results in ensuring the improvement of lighting, preserving details, and natural contrast of the image.
3. The Proposed fusion image model results from combining the DL and AGC to achieve a balanced enhancement capability of restoring lost details from DL and the contrast by AGC to enhance the quality and realism of the resulting image.

In this paper, the evaluation of the proposed solution (DLAGC) is based on the benchmark datasets, reference datasets (LOL, Brightening Train) non-reference datasets (DICM, LIME, UCID_V2). The results gained through the benchmark datasets delineate that the proposed DLAGC can enhance different image light conditions, such as completely dark, partially dark, and Backlight. Additionally, the results exhibit that, in the quantitative evaluation, the solution presents high results in (PSNR, SSIM, and FSIM) and the best result in NIQE. Additionally, the qualitative evaluation of (DLAGC) results in a clear image with high fine details for object recognition and very close to the original image. Moreover, this work represents a good step towards developing more efficient techniques for enhancing low-light images, which can be useful in many applications such as medical image processing, security surveillance, and night photography.

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The rest of the paper is organized as follows: Section 2 reviews some research on improving low-light images using traditional and modern methods. Section 3 presents the effect of gamma correction on image brightness. Section 4 describes the model and proposed solution. Section 5 provides a discussion of the results. Finally, Section 6 ends with a conclusion.

RELATED WORKS

Generally, the background literature solutions for low-light images, divided into two branches for enhancing image low-light, include traditional and deep learning methods. The following sections will discuss these models.

1- Traditional methods

The histogram equation (HE) is used for enhancing the contrast in images by distributing the color more evenly gradations. The image in adaptive histogram equalization (AHE) [15] splits into multiple small blocks. That can lead to better enhancement results and increase the local contrast of the image. Contrast-limited adaptive histogram equalization (CLAHE) [16]establishes a threshold. It takes averages of the regions above the determined threshold for every gray level in order to prevent the possible blocky effect caused by AHE. Although these methods are simple, they often fail to preserve natural colors and increase noise.

Retinex theory [17] assumes that an image could be decomposed into reflectance and illumination to restore natural lighting. Jobson et al. presented two Retinex variations: single-scale Retinex (SSR) [18] and multi-scale Retinex (MSR) [19]. SSR employs a Gaussian filter to smooth the illumination map initially; MSR develops on SSR by adding color restoration and multi-scale Gaussian filters. Xiu Ji et al. [20] presented a method based on the Retinex theory, enhancing illumination and improving image details. In this method, an adaptive color balance technique was used to handle the color variations in low-light images. The acquired image was converted from RGB space to HSV space, and the illumination and reflection components were precisely extracted using the multi-scale Gaussian function in combination with Retinex theory. The light components separated into zones with high and low light levels and enhanced the low light levels. They tried weighting and fusing the image's block areas, and after that they applied the detail enhancement algorithm for further improve the image's details. These methods suffer from unwanted colors (artifacts), and poor handling of high noise or fine details.

Gamma correction is used to improve low-light images by adjusting brightness and contrast levels to match the image details. Jeon et al. [21] proposed an atmospheric scattering model to enhance low-light images using gamma correction prior depending on combined color spaces. The model is based on a transition map derived from the saturation of the original image in two color spaces. Because of estimating saturation is challenging, gamma correction converts the map into a function based on the original image's average and maximum values. An algorithm was also proposed to determine pixel-adaptive gamma values to avoid over- or under-enhancement. The model suffers from complications due to using more than one color space, and the restored images suffer from noise that reduces their quality when dealing with high opacity and low-efficiency cases.

2- Deep learning methods

Deep learning has led to the development of numerous innovative methods for improving low-light images.

Zhang et al. [22] presented a simple network inspired by Retinex theory that splits images into two components: illumination to adjust the light and reflection to remove distortions. This approach relied on the principle of segmentation to improve the learning and regularization process. The network has trained using double-exposed images without a need for real reflection or illumination information. However, this approach does not solve the problem of poor contrast and tends to sacrifice the naturalness of the enhanced image.

Guo et al. [23] proposed zero-reference deep curve estimation (Zero-DCE) to enhance low-light images. A deep network has been trained to estimate pixel-level adjustment curves without a need for reference images. The model has trained to learn how to adjust the dynamic range of the input image by estimating the parameters of the curves that enhance the image during the forward pass. The unsupervised training used loss functions, including spatial consistency, correct exposure, color Constancy, and Luminance smoothness. The model suffers from the difficulty of

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handling very low-light images where details are lost and the possibility of distortions and artifacts in complex-light images due to the general nature of the adjustments.

Xiaoqian et al. [24] introduced a deep enhancement model called Degradation-Aware Deep Retinex Network (DADRN) to enhance low-light images. The model is based on the Retinex theory using a decomposition network, which divides low-light images into reflectance and illumination maps and treats the deterioration in reflectance during the decomposition stage. A module called the Degradation-Aware Module (DA Module) was introduced, which helps train the decomposition network acting as a restorer during training without any additional cost during testing. Although the technique aims to improve illumination and reflectance, images may need additional enhancement on an aesthetic level, such as contrast, color saturation, and fine detail clarity.

EFFECT GAMMA CORRECTION ON IMAGE BRIGHTNESS

Gamma Correction (GC) is a nonlinear mapping function used to improve the brightness of an image [25]. The primary purpose of GC in image processing is to enhance low-light images by controlling the parameter γ, and the basic form of GC is depicted in Equation 2.

$$Ix' = A \times (Ix)\gamma \tag{2}$$

Where: Ix' is the output image value, Ix is the input image, γ is the gamma value, A constant that is often set to 1 for simplicity in many applications.

PROPOSED FUSION DEEP LEARNING WITH ADAPTIVE GAMMA CORRECTION (DLAGC) MODEL

This model aims to reduce noise, avoid artificial colors, and restore fine details, such as object edges or fine textures, by restoring color balance to make the objects well-lit and close the enhanced image to the natural image. The steps of the proposed model for enhancing low-light images are shown in Figure 2.

Step1. (Image preprocessing)

1. Images are resized to 256x256.
2. Values are normalized to be between 0 and 1 to facilitate mathematical processing.

Step 2. (Image enhancing): Image enhancement is done in three stages

1. Low-light image enhancement uses deep learning (DL).
2. Low-light image enhancement uses adaptive gamma correction (AGC).
3. Fusion of Enhanced Images

The two outputs of the enhanced image from deep learning (DL) and adaptive gamma correction (AGC) are fused using a linear equation.

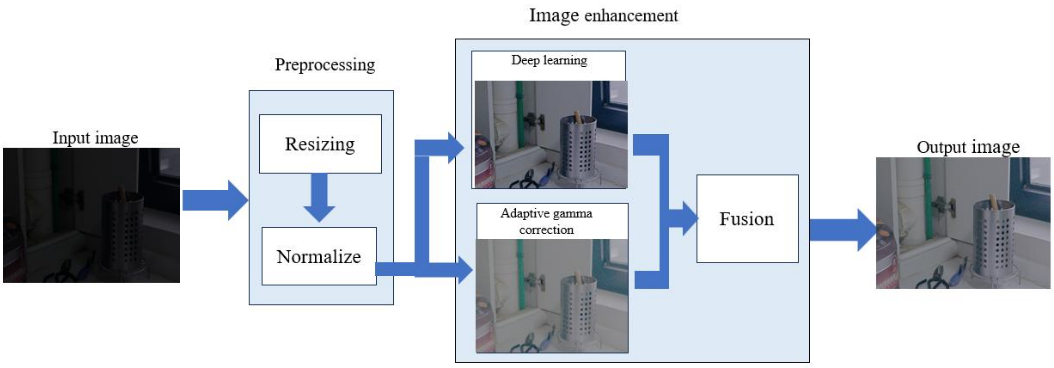

Figure 2: Steps of the proposed model DLAGC for enhancing low-light images

A- Image preprocessing

Low-light image data are prepared and processed for use in training deep learning or an image enhancement model using adaptive gamma correction.

Resizing Images to 256×256 ensures that all images are consistent in size, making them feedable to the model.

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Normalize the pixel value to be between 0 and 1 to prevent data loss due to overflow truncation and facilitate mathematical processing

B- Image Enhancing

1. Train model

Deep learning was trained using 3028 images from the SICE [26] part1 dataset. The dataset includes 589 sequences from indoor and outdoor scenes, containing 4,413 multi-exposure images. The resolution of most images is between 3000×2000 and 6k×4k. The dataset is available on https://github.com/csjcai/SICE. Deep learning was trained with a total training epoch of 75, a learning rate of 0.0001, and a batch size for the training dataset of 14.

2. Deep learning (DL)

A simple and lightweight deep learning with six convolutional layers is used. The first three layers extract features from the original image. The fourth layer merges the extracted features from the second and third layers. The fifth layer merges the outputs of the fourth layer with the outputs of the first layer. The sixth layer generates alpha maps, which are utilized for image enhancement, producing 18 channels divided into six maps ($\alpha 1$, ..., $\alpha 6$), each one containing three RGB channels, as shown in Figure 3. The deep learning outputs pixel-specific parameter maps to apply LE curves. This paper applies the LE curve [23] as shown in Equation (2). We repeat the equation in six iterations to enhance images with better illumination and deeper color clarity.

$$LE\text{n}(x)= LE\text{n-1}(x)+\alpha\text{n}\ LE\text{n-1}(x)\ (1- LE\text{n-1}\ (x)) \tag{2}$$

Where x denotes the image pixel coordinates, LEn enhanced versions of the given input (x), αn are trainable curve parameters.

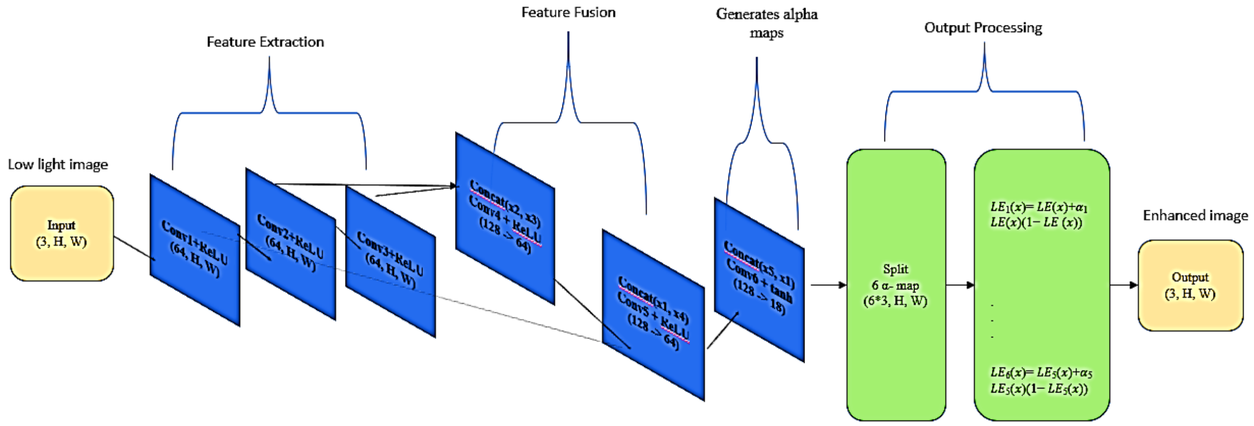

Figure. 3: Proposed deep learning (DL)

Several non-reference losses, including as spatial consistency loss, exposure control loss, color constancy loss, and luminance smoothing loss, are utilized to allow the network to complete training with zero reference data.

1. spatial consistency loss

The error Lspa is adjusted as Eq. (3) to avoid a significant variation in the value of a pixel's neighboring pixels between the original image and the enhanced version.

$$L_{spa} = \frac{1}{K}\sum_{i=1}^{k}\sum_{j\in\Omega(i)}(|(Y_i - Y_j)| - |(I_i - I_j)|)^2 \tag{3}$$

Where (i) is the four adjacent regions (top, down, left, and right) centered at the region's center(i), and K is the local region's number, Y and I represent the average intensity value of the local region in the enhanced image and input image.

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2. Exposure Control Loss

It is referred to the distance between the average intensity value [23] as shown in Eq. (4).

$$L_{exp} = \frac{1}{M}\sum_{k=1}^{M}|y_k - E| \tag{4}$$

Where M is the number of local regions, where the regions are nonoverlapping, Y is the value of average intensity in a local region of the enhanced image, and E is the gray level of the ideal RGB color space.

3. Color Constancy Loss

According to the grayscale color constancy model [27], the color average of each sensor channel is calculated across the entire image, and the color constancy loss principle is used to correct any color deviations that may appear in the enhanced image. An adjustment relationship is built between the three RGB channels to ensure that their average values are as close as possible to the enhanced average values after the enhancement process, as shown in Eq. (5).

$$L_{col} = \sum_{\forall(p,q)\in\varepsilon}(J^p - J^q)^2, \varepsilon = \{(R,G),(R,B),(G,B)\} \tag{5}$$

Where (p,q) refers to the set of channels belonging to top Ɛ, and Jp and Jq refer to the average intensity values of channels p and q.

4. Luminance Smoothing Loss

To maintain a consistent relationship between surrounding pixels or to reduce the influence of brightness changes between neighboring pixels, a lightness smoothing loss is added to each curve mapping equation [28], as shown in Eq. (6).

$$L_{tvA} = \frac{1}{N}\sum_{n=1}^{N}\sum_{c\in\zeta}(|\nabla_x A_n^c| + |\nabla_y A_n^c|)^2, \zeta = \{R,G,B\} \tag{6}$$

Where N refers to the number of iterations, A_n^c refer to the curve parameter map of each channel, ∇_x refer to the horizontal gradient of the image, ∇_y refer to the vertical gradient
of the image, and ζ refer to the RGB three-channel color.

The Eq. (7) refers to the total loss of the functions

$$L_{total} = w_1 L_{spa} + w_2 L_{exp} + w_3 L_{col} + w_4 L_{tvA} \tag{7}$$

where w1, w2, w3, and w4 refer to the weight of the loss value, which in this model is set to 250, 1.5, 9, and 12, respectively.

3. Adaptive gamma correlation (AGC)

The adaptive gamma correction (AGC) value is calculated from the calculation of the image brightness factor (L) and the average color factor ($\check{I}$), which is calculated from the average of the RGB color channels.

Luminance factor (L)

This represents the brightness level of the image ,as shown in Eq. (8)[5].

$$L=0.2126 I_R^c+0.7152 I_G^c+0.0722 I_B^c \tag{8}$$

Where I_R^c, I_G^c, and I_B^c are the mean channels of red, green, and blue, respectively.

Average colors factor ($\check{I}$)

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It is the sum of the average three colors (μ^R, μ^G, and μ^B). as shown in Eq. (8) [5].

$$\check{I} = \frac{\mu^R+\mu^G+\mu^B}{3} \tag{8}$$

To calculate the adaptive gamma value, the average color ($\check{I}$) and Luminance factor (L) value for each pixel in the low-light image was used, as shown in Eq. (9).

$$\gamma = \gamma_c + \left[(0.5 - L) \times \left(1 - \check{I}\right)\right] - [(3 \times L) + \check{I}] \tag{9}$$

Where γ_c is the control parameter in this model equal to 3.5.
To obtain adaptive gamma, use Eq. 10 [5].

$$I_{x'} = \mathrm{A} \times (I_x)^{\frac{1}{\gamma}} \tag{10}$$

Where Ix is the input image, Ix' is the enhanced image by adaptive gamma correction.

4. Fusion

To obtain high quality, high contrast, and clear details in this model's enhanced image, the enhanced image produced by deep learning is fusion with the enhanced image produced by adaptive gamma correction, as shown in Eq. (11).

$$\text{Fusion} = \mathcal{E}D\,Di + \mathcal{E}G\,Gi \tag{11}$$

where ƐD + ƐG = 1, Di is the Enhanced image from deep learning, Gi is the Enhanced image from adaptive gamma correction, and ƐD is the adjustment parameters of the enhanced image by deep learning and adaptive gamma correction, respectively. According to the experiment, the optimal result is ƐD= 0.5, ƐG= 0.5.

DISCUSSION DISCUSSION

1. Testing dataset

The proposed model DLAGC uses five datasets to validate the performance of the model divided into two categories: reference and non-reference datasets.

- **Full reference dataset**
  - ✓ The Low-Light dataset (LOL) contains 500 low/normal-light image pairs divided into 485 pairs for training and 15 pairs for evaluation. All images have a resolution of 400 × 600 pixels.
  - ✓ The low-light images contain noise produced during the photo capture process. The dataset consists of two categories: real photography pairs and synthetic pairs from raw images [29].
  - ✓ The Brightening Train dataset includes 1000 images[29].
- **Non-reference dataset**
  - ✓ DICM Contains 69 images collected with commercial digital cameras of variable dimensions[30].
  - ✓ The LIME dataset includes 10 low-light images [11].
  - ✓ UCID_V2 dataset includes 886 images [29].

2. Quantitative Evaluation

Three reference metrics, PSNR [31] (Peak to Signal to Noise), SSIM [31] (structural similarity index), and FSIM [32](Feature Similarity Index), calculate the difference between the enhancement result and the ground truth pixel-by-pixel for full reference images, have been used to assess the effectiveness of low-light image enhancement quantitatively. Nonreference metrics, which compute the quality score without the ground truth, have been accepted for non-reference datasets. representative measure, the Natural Image Quality Evaluator (NIQE) [33].
Table 1 compares the proposed model's results with those of the set of methods on two benchmark datasets, LOL and Brightening Train, using PSNR, SSIM, and FSIM metrics. The proposed model significantly outperforms the other methods.

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On the benchmark dataset LOL, the proposed model DLAGC achieved the highest values of PSNR (16.193), SSIM (0.688), and FSIM (0.905), demonstrating a high ability to improve low-light images while preserving structural and visual details. Methods such as LGMS [34] showed acceptable results in some metrics but were significantly lower than the proposed model in overall performance. The proposed model shows high efficiency in image improvement while balancing all metrics. On the Bright datasets, the proposed model DLAGC also outperforms PSNR (18.580), SSIM (0.889), and FSIM (0.936), demonstrating good image enhancement in diverse lighting conditions while preserving visual features. The proposed model DLAGC is a superior solution for image enhancement under complex lighting conditions, making it suitable for practical applications that require quality enhancement while preserving visual details.

Table 1: Compares the proposed model's results with the set of methods on two benchmark datasets, LOL and Brightening Train, using PSNR, SSIM, and FSIM metrics.

Algorithm	Dataset								
	LOL			Brightening Train			Average		
	PSNR↑	SSIM↑	FSIM↑	PSNR↑	SSIM↑	FSIM↑	PSNR↑	SSIM↑	FSIM↑
IAGC [35]	11.260	0.468	0.864	14.056	0.663	0.861	12.658	0.565	0.862
LGMS [34]	15.834	0.475	0.847	16.943	0.747	0.902	16.388	0.611	0.874
LIEW [36]	12.678	0.638	0.880	16.943	0.747	0.902	14.810	0.692	0.891
LLEI [21]	15.502	0.463	0.827	16.921	0.764	0.892	16.211	0.613	0.859
Proposed model (DLAGC)	16.193	0.688	0.905	18.580	0.889	0.936	17.386	0.788	0.92

Table 2 shows the values measured using the non-reference NIQE metric, where the decrease in the value indicates an improvement in the visual quality and an increase in the naturalness of the image on three non-reference datasets (DICM, LIME, UCID_V2). According to the results, the proposed model DLAGC achieved the best result among the studied methods with an average of 3.684, followed by LLEI [21] with an average of 3.737, then IAGC [35] with an average of 3.832, followed by LIEW [36-37-38] with an average of 3.877, and the least LGMS [34] with an average of 3.994. These numbers indicate that the proposed model DLAGC performed well compared to other methods in the non-reference standard and outperformed the methods in the reference metrics.

Table 2 compares the proposed model's results with the set of methods on three nan reference datasets, DCIM, LIME, and UCID_V2, using the NIQE↓ metric.

Algorithm	Dataset			Average
	DICM	LIME	UCID_V2	
IAGC [35]	4.007	3.948	3.542	3.832
LGMS [34]	3.941	4.384	3.659	3.994
LIEW [36]	3.804	4.096	3.733	3.877
LLEI [21]	3.596	3.964	3.653	3.737
Proposed model (DLAGC)	3.666	3.883	3.505	3.684

3. Qualitative evaluation

The optical performance of the proposed model DLAGC was examined and analyzed on a set of low-light images. The images used to test the proposed model were characterized by very low, mixed, or medium illumination, as shown in Figures 4 and 5. The proposed model proved its efficiency in detail clarity, color quality, and enhanced illumination quality. The proposed model produces more natural illumination than the original images, and fine details (such as sharp edges of the subject or repetitive patterns in the background) became more transparent and less visual noise. While in the IAGC model, the resulting images suffered from dark areas and there was a clear deviation in colors, which led to the lack of clarity of some details and poor visual quality. When looking at the color balance, there are no unwanted color tones (such as green or purple shades) in the images generated by the proposed model, which

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often appear in traditional enhancement techniques when trying to increase the illumination level. Instead, the model succeeded in maintaining the correct and realistic colors of the subjects in the images while improving the dark and light tones in a balanced manner. This contributed to producing clearer and smoother images while maintaining natural color saturation. While in the LGMS model, the resulting images suffered from unwanted colors (artifacts), image blur, noise, and excessive lighting. In addition, the proposed model DLAGC can restore shadows and enhance bright areas (bright spots) without excessively smoothing details or amplifying noise, resulting in a clean and visually balanced scene. Compared to the LIEWS model, which produced images with low contrast and excessive smoothing, the LLEI model produced images with chromatic aberration, where the colors in the images were far from natural colors, in addition to the presence of noise and the lack of improvement in dark areas in the images. The integrated optical performance demonstrates the effectiveness of the proposed model DLAGC, which simultaneously improved lighting, removed noise, adjusted color, and preserved details. As a result, the resulting images have natural lighting and good visual quality, with more accurate and vivid details that avoid any chromatic aberration or noise in the highlights.

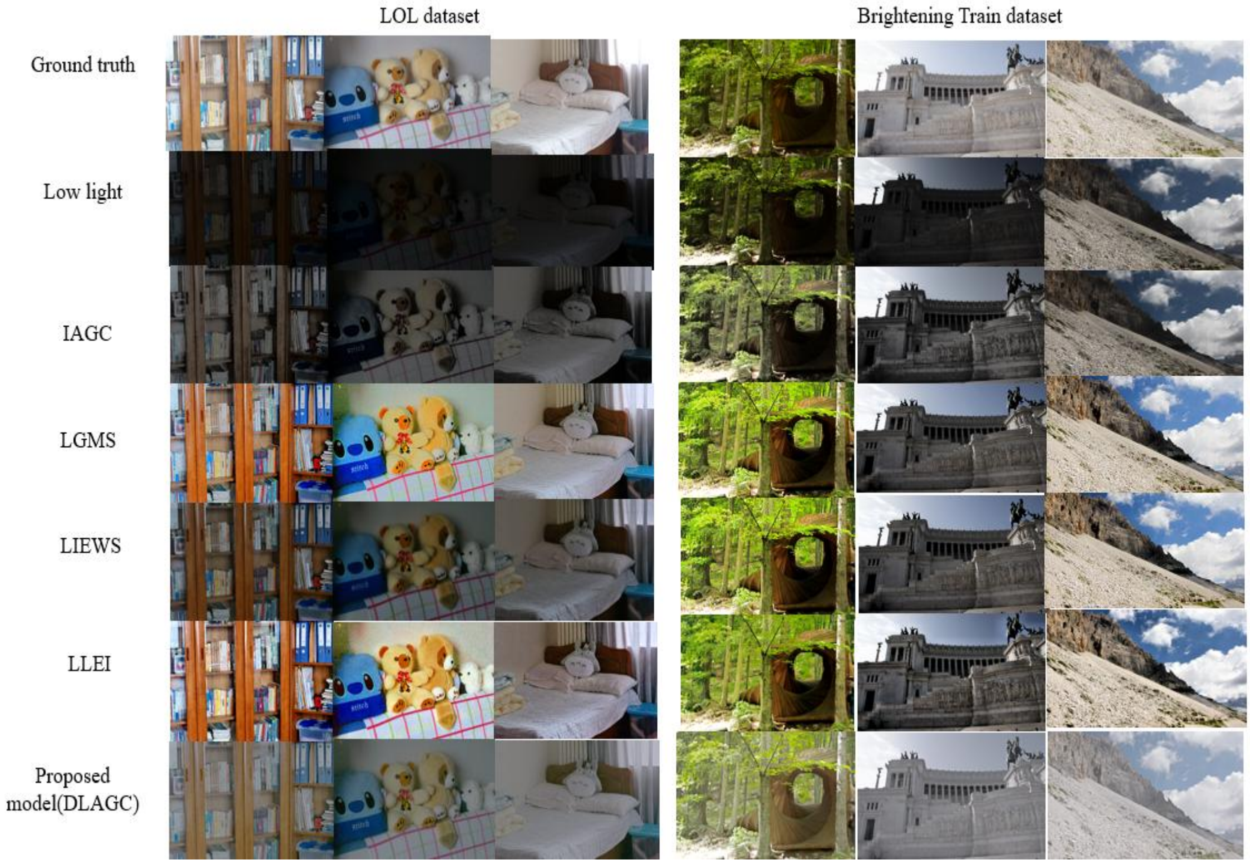

Figure 4: Compares the result images of the proposed model DLAGC with the set images of methods on reference datasets LOL and Brightening Train

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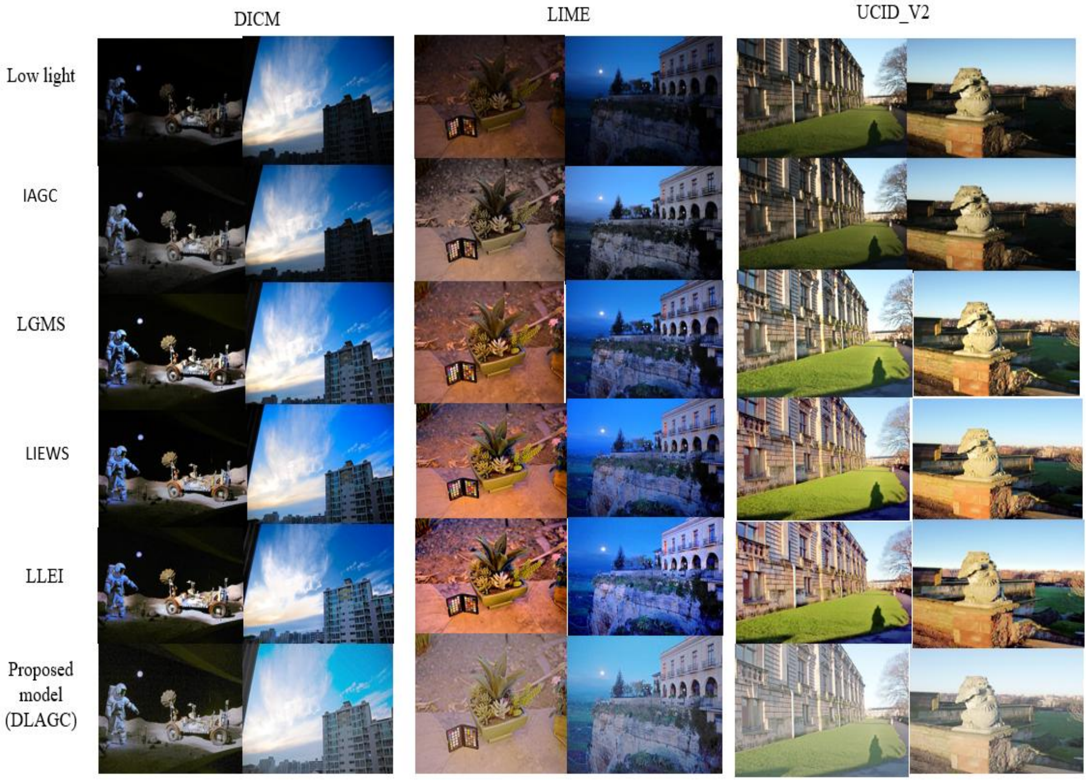

Figure 5: Compare the result images of the proposed model DLAGC with the set images of methods on non-reference datasets DICM, LIME, and UCID_V2.

CONCLUSION

This paper introduces a fusion model based on combining deep learning and adaptive gamma correction to enhance low-light images. The proposed model DLAGC shows the ability to enhance image illuminations and restore fine details while reducing noise and maintaining color balance. The fusion model outperforms many related solutions in terms of qualitative and quantitative evaluation. The results obtained are based on different datasets highlighting the model impact, including high-efficiency low-light images while balancing all other metrics (such as complex illumination conditions). This model provides a practical solution to many challenges in low-light image processing fields. For example, critical medical image applications, security surveillance, computer vision systems, night photography, and autonomous driving.

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