A Review of Modern Low Light Image Enhancement Techniques

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Abstract: Enhancing low-light images is a major challenge in computer vision. It suffersfrom modest contrast, unclear details, and intensive noise. Low-w light image enhancement aimsed to enhance the quality of the image that is captured under imperfect lighting and restore the image with a high-accuracy colour distributioned with standard lighting. This paper discusses the evolution of techniques used to improve image quality, starting from traditional methods such as dehazingg, histogram equalisation (HE), gamma correction (GC), and Retinex theory methods to modern techniques that rely on deep learning networks based on specially trained models for low- light image enhancement.t Dynamic and restoring lost details, for example, CNNs, GANs, and U-Net.

Keywords: Low light image enhancement (LLIE), Datasets, traditional techniques, deep learning methods.

1. Introduction

The fast growth in digital devices and imaging tools, for example, pads, tablets, and smartphones, has made taking digital photos a simple and common practice worldwide [1]. Many factors influence the image capture.

The atmospheric effect is an important factor, which includes fog, haze, sand, dust, and high and low lighting [2]. Low light levels during image capture result in various image degradations, such as reduced visibility, color casts, intensive noise, and low contrast [3]. That makes it challenging to recognize the scene or object [4]. Low-light enhancement techniques aim to raise the contrast and dynamic range in the low light images during

the attempt to recover lost information, eliminate noise, and restore color details [5].
Low light image enhancement (LLIE) is a crucial task in computer vision, that is basically used in fields including surveillance, military applications [6], image classification, object detection, face recognition, autonomous driving[7], and night photography [8].
Many algorithms have been proposed in the last few decades in low light image enhancement (LLIE), including deep learning-based methods and traditional algorithms [9]. Traditional techniques involve histogram equalization(HE), Ritnex theory [10], Dehazing, and gamma correction(GC) methods. For histogram equalization(HE) redistributes luminance results across the histogram by increase the contrast in image [7], the Retinex model approaches divide low-illumination images in illuminance and reflection images [11]. Dehazing techniques are used to enhance the contrast of hazy imagse [12]. The deep learning-based enhancing low light images method targets for using the deep learning-based algorithm for converting invisible information into visible information [11]. Deep learning-based algorithms that use algorithms to improve low-light images by leveraging image features learned in natural lighting conditions require a large amount of data for training. [13]. The motivation to write this review is that not all the methods in previous reviews to enhance low light images in deep view are covered. There are main real-life applications that suffer from significant lowlight effects on target images, such as medical approaches, real-time surveillance systems, object tracking, and so on.

The objectives and scope of this survey are

1- This survey introduces studying of the traditional low light image enhancement (LLIE) algorithms, which will help to understand the advantages and limitation of LLIE methods based on traditional methods including histogram equalization (HE), Retinex theory, Dehazing, and gamma correction (GC) methods.

2- This survey introduces studying for deep learning-based algorithms for enhancing low-light images and quantitatively analyze and compare these algorithms based on the image quality assessment methods.

2. Traditional Low Light Image Enhancement (LLIE) Methods

There are many traditional low-light image enhancement (LLIE) methods involving histogram equalization, Retinex theory, dehazing, and gamma correction.

2.1. Histogram Equalization (HE)

Using the histogram equation in low-contrast images leads to an increase in the image contrast by distributing the pixel values in the image more evenly across the range of allowed values [14], as shown in Figure 1 [15].

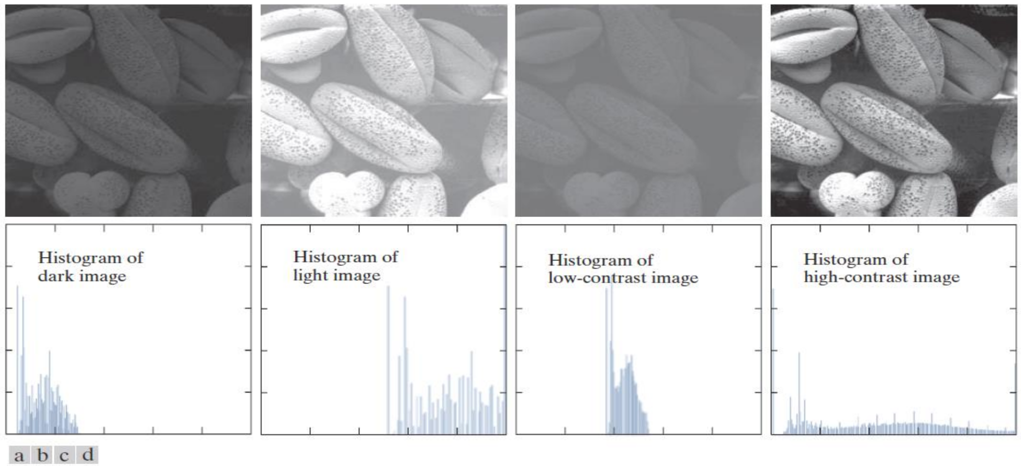

Figure 1. Histograms of four images, a is dark, b is light, c is low contrast, d is high contrast [15]

The HE method is a technique that enhances contrast and uniformly distributes the grey range of an image. The purpose of histogram algorithms based on histogram equalisation has been to produce dynamic histogram equalisation (DHE) [16], adaptive histogram equalisation (AHE) [17], and contrast-limited adaptive histogram equalisation (CLAHE) [18]. In order to perform histogram equalisation processing, AHE splits the image into multiple small blocks. This leads to improvingage's local contrast and producing enhancement outcomes. To avoid the potential blocky effect created by AHE, CLAHE groups thend average values fort exceed the threshold at each grayscale level. Figure 2 [13] shows images that have been processed with the three different HE algorithms.

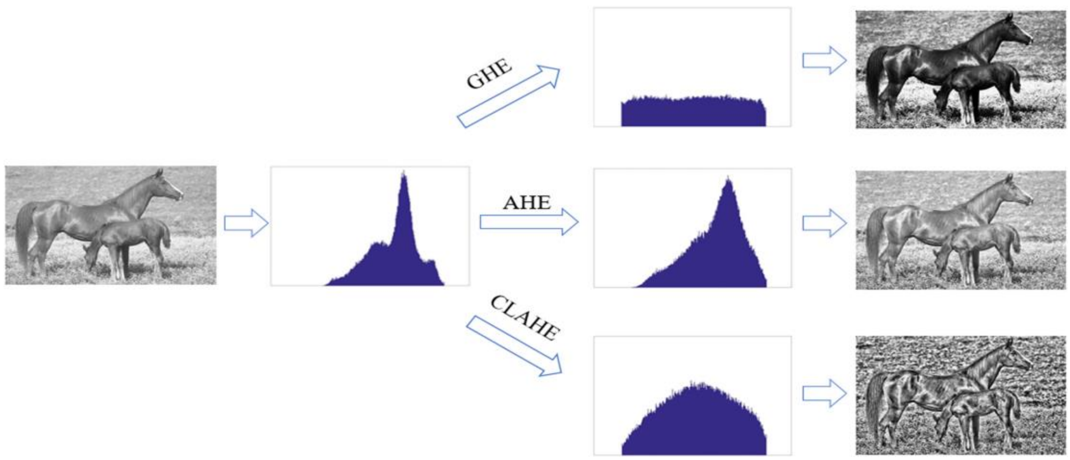

Figure 2. images that have been processed with the three different HE algorithms [13]

Banik *et al.* [19] suggested a technique for improving the contrast in low-light images by utilising histogram equation (HE) and luminance adjustment. The colour space was converted from RGB (red, green, blue) to HSV (hue, saturation, value). Then, the V (valuehannel was changed by histogram equation (HE). In this method, enhancing the contrast through HE leads to reducing quality of the enhanced image as well as the noise and computational complexity.***The challenges of histogram equalization***

Histogram equalisation methods fail to take into account the image's structural information, leading to insufficient enhancement and noise amplification problems. HE is prone to chromatic aberration, and details are lost when grayscale merging.These methods often yield unrealistic and unnatural outcomes since several priors or presumptions were notliable enough to hold under various illumination circumstances.**2.2. Retinex theory**

It assumes that a captured colour image is divided into two components involving luminance and reflection [20]. The final improved image combines the reflectance map and the enhanced illumination map [21],own in Figure 3 [21].

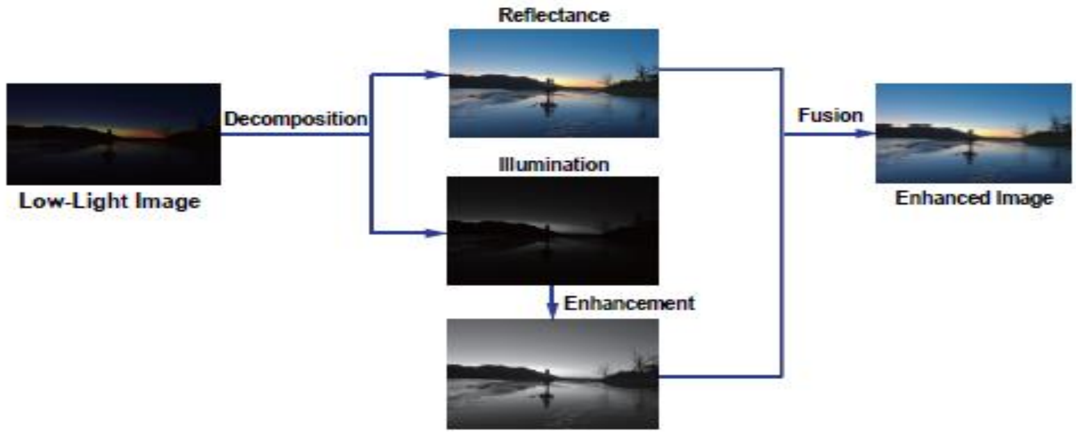

Figure 3. Retinex [21]

Single-scale Retinex (SSR) [22] and multi-scale Retinex (MSR) [23] are two Retinex variations that were proposed by Jobson *et al.* For smoothing the illumination map, SSR first uses a Gaussian filter; MSR expands on SSR by adding multi-scale Gaussian filters and colour restoration. In order to enhance images, Pan *et al.* [24] sted an algorithm based on Retinex theory. The suggested technique consists of three phases to improve the bright and dark areas to differing degrees. In the first phase, the lighting and reflection components are estimated from the raw image. In the second phase, two input images are blended using BEF (brightness enhancement function) as well as IACE (improved adaptive contrast enhancement) to enhance the illumination component using a Gaussian Laplacian pyramid.In the third phase, the final enhanced image is derived using Retinex theory. Working with the illumination map and the parameters used requires fine-tuning, which can be challenging in some cases.***The challenges of Retinex theory-based methods***

Retinex theory approaches often produce unnatural-looking images and suffer from excessive enhancement as a result of treating reflectance as the ultimate result of enhancement. These methods suffer from issues like colour deviation, artifacts, and noise that is preserved or increased.**2.3. Dehazing**

Blurry images and low-light images are similar in their poor contrast. Since dehazing techniques are used to improve the contrast of blurry images, this approach has also been adopted to improve low-light images [12]. The dehazing process adjusts the pixel values to conform to the normal distribution [25]. Accordingly, low-light techniques can improve by using dehazing-based images, where the inverted low-light images are treated as blurry images. Then, dehazing algorithms are applied to improve their quality [21], as shown in Figure 4 [21]. Figure 4. Dehazing [21] Pei and Lee [26] proposed a technique for nighttime haze image enhancement. This technique alters the airtight hue from a "blue shift" to a "grayish" while dealing with the input nighttime haze image. Following the first nighttime haze images' colour transfer pre-processing, the output images are gradually transformed into the final haze-free images by applying the refined Dark Channel Prior (DCP) approach and the bilateral filter in local contrast correction (BFLCC).In this technique, colour processing can result in unnatural changes in the original colors, especially in cases where the original colours are complex or overlapping.**The challenges of Dehanzing methods**

1-Removing haze from an image can distort colors, making the image look unnatural or unrealistic. 2. Increasing the brightness of images can introduce noise, which negatively affects the image's accuracy. 3. Someehazing techniques can be slow, especially in high-resolution images. 4. Theuration of enhanced images is typically exaggerated, and the images are typically over-enhanced.**2.4. Gamma Correction**

Gamma correction (GC) is achieved for each individual pixel in a non-linear way. GC has the ability to increase brightness, particularly in dark pixels [27]. Where a large gamma value ise useds to increase visibility and a small gamma value to avoid over-brightening [2],] as shown in Figure 5 [2].

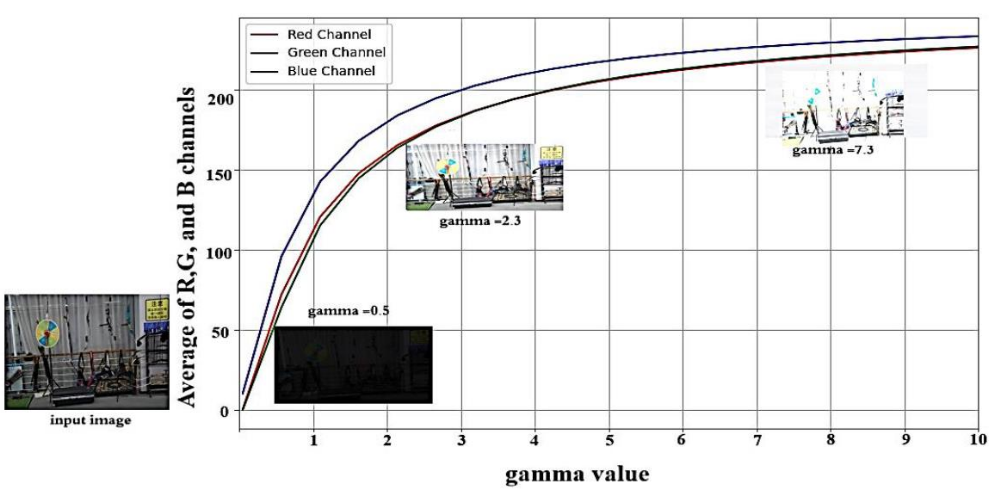

Figure 5. Effect gamma value on brightness and average R, G, and B channel [2]

Alsaeedi *et al.* [2] suggested adaptive gamma and color correction (AGCC) to enhance images taken in low light. For bring back original color of image, the suggested model seeks to improve the color rates and balance of the image. The proposed method consists of three stages. Adaptive gamma correlation, Color correcting uses the high channel's mean value (R, G, and B), and Normalizes contrast color. The effectiveness of the AGCC model depends on an accurate estimate of the appropriate gamma value for the current lighting. When the estimates are incorrect, that may lead to unsatisfactory improvements. The model also requires fine-tuning of the parameters, which may require additional expertise from the users to achieve optimal performance.

The challenges of Gamma Correction methods

Determining the optimal gamma value can be challenging, as inappropriate values may lead to undesirable results. Increasing brightness may lead to a loss of detail in bright areas or shadows, which affects the image quality. When applying gamma correction, noise may increase in low-light areas, making the image appear blurry.**3. Deep learning methods**

The field of deep learning approaches has seen enormous growth in recent years [28]. Deep learning approaches have the advantages of reducing hyperparameters and good generalisation under different lighting conditions.s Compared to traditional methods [9]. Figure 6 [13] shows the flowchart for the EnlightenGANalgorithm.

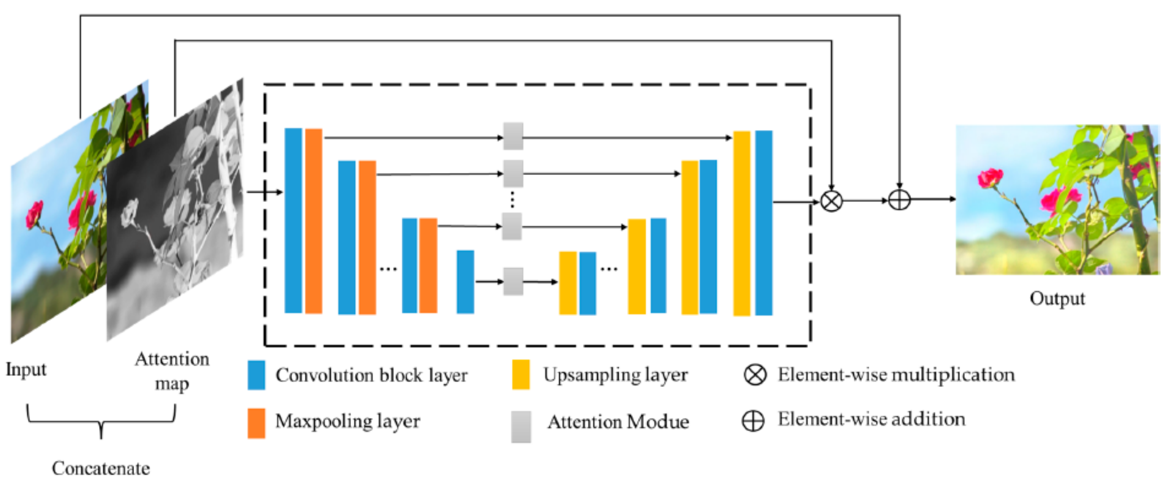

Figure 6. Flowchart for Enlighten GAN algorithm [13]

Batziou *et al.* [29] suggested a low-light image enhancement method. Where a modified U-Net-based architecture was created in a way that includes dense blocks that contain dense, convolutional, and Haar wavelet pooling layers to preserve texture regions and increase their quality. There is a chance in this method of loss of detail because it uses Haar wavelet pooling. That is designed to reduce dimensionality but may inadvertently lead to losingthe fine details in the images, which can be crucial for some applications. Tao *et al.* [30] built an innovative LEGAN (Low-Light Imageancement Generative Adversarial Network) enhancement model for the industrial internet of smart cameras. In this model, the input is split into two branches by the Haar waveletod decomposition procedure. To effectively suppress noise, these branches are then independently encodedsequence of compact residual blocks. After a feature selection module is painstakingly created to uncover correlations between image foreground–background and low–high frequency signals, finally reconstructing an extensive feature map ance detail recovery. This makes it possible to use a multi-scale stepwise upsampling technique to restore images using the feature maps that have been reconstructed. This model faces limitations related to computational complexity, the need for diverse training data, the difficulty of training GANs, and the challenges associated with dealing with noise.Researchers [31] introduced a model based on a deep learning approach for enhancing low-light images (LLIE). They have used a wavelet-based neural network and multi-scale attention (WMANet), where the model combines the benefits of wavelet technology and multi-scale attention to achieve excellent results. Wavelet transform helps in analysing the image accurately, while the attention network enhances detail enhancement and noise reduction. In this model,odel increasing the number of decomposition levels increases the running time, which poses a limitation in using higher decomposition levels due to their impact on processing time. Hai *et al.* [32] suggested a deepeep convolutional neural network k, called R2RNet (Retinex-based Real Lowow to Real Normalmal Network) to enhance low-ow light images.ge. It consists of three subnets (Decom-Net, Denoise-Net, and Relight-Net). Decom-Net is used for decomposing, Denoise-Net is used for denoising, and Relight-Net is used for contrast improvement and detail preservation. R2RNet employs frequency information to maintain details.

Implementing this model requires significant computational resources, which may make it difficult to implement in real time on devices with limited capabilities.Yan *et al.* [33] put a technique to increase low-light images named CIDNet (Color and Intensity Decoupling Network) using HVI colour space under trainable parameters for adjusting different image illumination scales, decoupling the image brightness and color. Built on top of the HVI colour space, the dual-branch network processes colour and brightness simultaneously with the help of a symmetric HVI Transform module and plug-and-play LCA (Lighten Cross-Attention) module.This method increases computational complexity, which leads to increased training time or the need for powerful computational capabilities.Liu *et al.* [34] presented a framework that mixed the principled optimization unrolling method with the cooperative prior architectural search strategy. They named it Retinex-inspired unrolling with architecture search (RUAS); it enhances the low light inspired by Retinex and is lightweight and efficient. Initially, they developed optimization models using the Retinex rule. After that, they developed a collaborative, reference-free method to identify specific architectures inside a compact search space. Although the strategy effectively enhances low light, there are specific scenarios where RUAS may not perform optimally, such as environments with mixed lighting, high noise, or complex details. Yang *et al.* [35] suggested an approach known as NeRCo for collaborative image enhancement in low-light conditions. This approach enables the recovery of perceptually friendly images reliably and without external supervision. A neural representation was used to normalise the levels of degradation in the input images. The method relied on leveraging pre-trained visual-language models to provide prior information and added a high-frequency feature extractor to guide the image enhancement process toward results more compatible with human perception. In this approach, complex operations such as collaborative constraints may require careful design and advanced technical skills, making the model difficult for non-specialist users. Image enhancement operations may result in the loss of some important details or increase noise, affecting the quality of the final image. Xu *et al.* [36] presented a signal-to-noise-ratio-aware (SNR-aware) framework for low-light image enhancement. The framework combines a transformer architecture and a convolutional model to produce spatially variable low-light enhancement with SNR priority.They also developed a signal-to-noise-ratio-aware transformer with a novel self-attention module to improve image enhancement performance in low-light conditions. The model relies on SNR estimates. The accuracy of the SNR estimates may affect the model's effectiveness, which may lead to unexpected performance in images with high noise.In order to create a monochrome raw image from a colourful raw image, Dong *et al.* [37] developed a simulator based on deep neural networks to simulate the operation of the De Bayer Filter. Low-light image enhancement is proposed by combining coloured raw data with synthetic monochrome data using a fully convolutional network. In order to produce a complementaryomplimentary interaction between features from colourful and monochrome raw images, channel-wise attention is also added to the fusion process. The simulation accuracy provided by the De-Bayer-Filter tool may not be perfect, which may affect the quality of the resulting images. Combining colour data with monochrome data may result in losing some important details or colors. Yi *et al.* [38] designed Diff-Retinex, a generative and physically explicable approach to the image in low-ow light conditions. They aim to combine the advantages of the generative network and the physical model. The image enhancement problem in low light is reformulated by Retinex analysis and conditional image synthesis using Diff-Retinex. To increase the application of the Retinex decomposition. They create generative diffusion-based networks to address the different degradations in each component, such as intensive noise, colour shift, scene degradation, and dark illumination. Using a diffusion-based generative framework can be complicated to implement and modify and requires advanced technical knowledge.Wu *et al.* [39] presented a deep optimization network called URetinex-Net, which is based on the Retinex model for low-light image enhancement (LLIE). This network partitions low-light images into two layers of illumination and reflection by formulating the optimization problem as a learnable network. Three learning modules are designed to perform the following tasks: data-driven initialization, highly efficient decomposition optimization, and illumination adjustment based on user inputs. The decomposition problem is formulated as an implicit pre-structured model, where achieving optimal performance requires fine-tuning the parameters used in different modules. However, the network may face challenges when dealing with images with very low illumination or high noise. Jiang *et al.* [9] suggested a new self-regularized low-light image-enhancing technique that reduces colour deviation and adapts to a wider range of illumination circumstances. This technique, which takes its cues from the HSV colour space, solely incorporates Retinex theory into brightness (value while maintaining the other colours (hue saturation. Additionally, a brand-new random brightness disturbance technique is intended to produce another abnormal brightness in the same scene. It is used in conjunction with the original brightness form, which is accomplished by a CNN, to estimate the same reflectance. The Retinex theory treats the reflectance,hich is presumably unrelated to any illumination,s the enhanced brightness. Although colour preservation is improved with this approach, there may still be colour drift issues in some cases, which affects the final image quality. In some cases, colour and brightness separations may result in a loss of fine detail, especially in bright areas. Table 1 shows a summaryquantitatively analysingcomparing learning-based techniques according to the image quality assessment criteri

Table 1. Summary for Quantitatively analyze and compare deep learning-based according to the image quality assessment criteria.

Ref.	Year	Methods	Datasets	evaluation metrics	Limitations
[29]	2023	U-Net &Haar wavelet pooling	LOL	PSNR↑=21.266	Loss of fine details in the images
				SSIM↑=0.784	
			SYN	PSNR↑=19.212	
				SSIM↑=0.716	
[31]	2024	WMANet	WMANet dataset	PSNR↑=30.0850	Increases the running time
				SSIM↑=0.9437	
				LPIPS↓=0.0252	
				ΔE↓=2.8494	

			LOL	PSNR↑=23.8892	
				SSIM↑=0.8366	
				LPIPS↓=0.0547	
				ΔE↓=6.9615	
[32]	2023	R2RNet	LOL	PSNR↑=20.207	Difficult to implement in real time on devices with limited capabilities.
				SSIM↑=0.816	
				FSIM↑=0.933	
				MAE↓=0.036	
				GMSD↓=0.076	
[33]	2024	CIDNet	LOL -Blur	PSNR↑=26.572	Increases computational complexity
				SSIM↑=0.890	
				LPIPS↓=0.120	
				FLOPs↓=7.57	
[34]	2021	RUAS	MIT	PSNR↑=20.830	There are certain scenarios where RUAS may not perform optimally, such as environments with mixed lighting, high noise, or complex details.
				SSIM↑=0.854	
				LPIPS↓=0.141	
			LOL	PSNR↑=18.226	
				SSIM↑=0.717	
				LPIPS↓=0.354	
[30]	2024	LEGAN	LOL	PSNR↑=23.637	computational complexity, the need for diverse training data, the difficulty of training GANs, and the challenges associated with dealing with noise.
				SSIM↑=0.824	
			Yarn	PSNR↑=41.165	
				SSIM↑=0.965	
[35]	2023	NeRCo	LOL	PSNR↑=19.84	Difficult to use for non-specialist users. the loss of some important details or increase noise.
				SSIM↑=0.7713	
				NIQE ↓=11.26	

				LOE ↓=117.7	
			LSRW	PSNR↑=19.00	
				SSIM↑=0.5360	
				NIQE ↓=9.23	
				LOE ↓=189.5	
			LIME	NIQE ↓=11.01	
				LOE ↓=187.2	
[36]	2022	Xu *et al.*	SID	PSNR↑=22.87	The effectiveness of the model may be affected by the accuracy of the SNR estimates, which may lead to unexpected performance in images with high noise.
				SSIM↑=0.625	
			SMID	PSNR↑=28.49	
				SSIM↑=0.805	
			SDSD-indoor	PSNR↑=29.44	
				SSIM↑=0.894	
			SDSD-outdoor	PSNR↑=28.66	
				SSIM↑=0.866	
[37]	2022	Dong *et al.*	MCR Dataset	PSNR↑=31.69	The loss of some important details or colors, which may affect the quality of the final image.
				SSIM↑=0.908	
[38]	2023	Diff-Retinex	LOL	PSNR↑=21.98	The different degradations in each of these components, such as noise, color deviation, loss of scene, dark illumination
				SSIM↑=0.863	
				FID↓=47.85	
				LPIPS↓=0.048	
				BIQI↓=19.97	
				LOE↓=191.56	
			VE-LOL-L	FID↓=47.75	
				LPIPS↓=0.050	
				BIQI↓=26.54	

				LOE ↓=149.60	
[39]	2022	URetinex-Net	LOL	MAE↓=0.0832	Need for fine-tuning of the parameters and network may have difficulty processing images with very low illumination or high noise.
				PSNR↑=21.3282	
				SSIM↑=0.8348	
				LPIPS↓=1.2234	
			LSRW	MAE↓=0.1068	
				PSNR↑=18.9467	
				SSIM↑=0.7808	
				LPIPS↓=1.2744	
[9]	2021	Jiang *et al.*	SICE	PSNR↑=17.06	Color drift issues in some cases, which affects the final image
				SSIM↑=0.530	
			DICM	NIQE↓=2.5392	
			LIME	NIQE↓=3.6910	
			MEF	NIQE↓=3.8238	
			NPE	NIQE↓=3.3379	
			SICE	NIQE↓=4.4703	

4. Conclusion

The purpose of low light image enhancement algorithms is to continue to innovate in this field. Images captured in low-light environments can be improved by enhancing images while preserving details, suppressing uninteresting features, improving image quality, and enriching information. That led to enhancing the performance of various computer vision applications and contributing to advancements in many areas, such as surveillance, photography, and autonomous driving. This paper summarizes and describes a set of widely used categories of low-light image enhancement techniques, including traditional and deep learning-based techniques. The quality of the enhanced images in low light is evaluated, and the limitations and drawbacks of each technique used are identified, such as loss of detail, poor illumination, high noise, unwanted colors (artifacts) or color distortion, or high computational complexity. Learning-based techniques are more suitable for considering the diverse conditions in real-world scenarios for low-quality image enhancement than manual feature-based methods (traditional methods).

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