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Low-Light Image Enhancement Techniques: A Review

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ABSTRACT

Low-light images from low-quality environments suffer from noise, contrast, and visibility problems, and occur in both computer vision and human perception. Conventional image enhancement methods, including Retinex-based algorithms and histogram equalization, are insufficient for suppressing noise and preserving enhancement in low-light conditions. In recent years, many deep learning-based methods (both hybrids, GANs, and CNNs) have been proposed and have exhibited promising results in enhancing the quality of low-light images. And finally, in the frame of this work, a detailed description of well-known low-light image enhancement algorithms is presented. Their advantages, disadvantages, and applications are discussed. The paper also examines how well these techniques generalize to other domains such as autonomy, surveillance, and medical imaging, and outlines several future directions for research on low-light enhancement.

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1. Introduction

In computer vision and image processing, low-light image enhancement is a fundamental problem that focuses on enhancing the visibility and quality of photographs taken in poorly illuminated conditions. Images captured in low light frequently have several problems, including noise, low contrast, blurred details, and poor visibility. Due to these problems, it may be very challenging for both human viewers and computer vision systems to interpret these images. Several applications, such as industrial production, driverless vehicles, medical imaging, security surveillance, and surveillance in low light or at night, depend on improving low-light images. Enhancing image quality can aid in critical tasks like tracking, identifying, and locating objects. It can also help with facial recognition, which is crucial for security systems [1].

For decades, conventional image-enhancing techniques have been employed to increase visibility in low-light images. These approaches include contrast modification, histogram equalization, and Retinex-based procedures. Retinex techniques separate image reflectance and illumination components to ensure color stability and improved light management, while histogram equalization, for instance, expands the range of pixel values to increase contrast. But these techniques frequently result in some distortions that take away from the image's natural look, like noise

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amplification, over-enhancement, and strange color shifts. Furthermore, they might not work well in all low-light situations, particularly when there is complicated noise or uneven lighting distribution [2].

As deep learning has become more popular, researchers are using more advanced techniques that use neural networks—specifically, convolutional neural networks to improve low-light images. Deep learning methods offer the advantage of not depending on manually created rules, but rather on data to learn intricate, hierarchical image attributes. Adaptive brightness improvement, detail preservation, and noise reduction are just a few of the issues that these approaches can successfully solve that traditional methods have. Deep learning algorithms can learn from enormous datasets, improve image quality, and generalize effectively to new images that closely mimic human vision [3].

Some of the most well-known deep learning-based techniques for improving low light levels are Retinex-net, dual illumination networks, GANs, and U-Net designs. U-Net was first created for medical picture segmentation, but because of its encoder-decoder structure, which allows it to collect both local and global information, it has been modified for low-light image augmentation. Another promising approach is the generator-discriminator architecture of generative adversarial networks, which generates enhanced images that are nearly identical to normal-light images. It has been shown that the Retinex-Net and dual illumination networks, which combine deep learning with the Retinex decomposition model, are more successful in differentiating between illumination and reflectance and altering each independently for better enhancement results [4].

In addition to CNNs, hybrid models—which combine traditional methods and deep learning techniques—have recently been introduced. In order to enhance details while reducing noise, these models usually incorporate multi-scale processing, adaptive loss functions, and attention strategies. Attention techniques allow the network to focus on specific areas of the image that require more improvement, for example, and preserve important features even in low light. Additionally, some networks, like Zero-DCE, are exceptionally effective for real-time applications because they are made to function lightly and without requiring a lot of training data [5].

Enhancing low-light images presents both technical and contextual difficulties. Various applications frequently call for varying degrees of improvement depending on the kinds of objects being detected, noise levels, and lighting. For example, within the scope of surveillance, improving overall visibility while eliminating ‘noise’ could be of greater value than in medical imaging, where the target could be adding focus on smaller objects while suppressing noise variables.
In order to empower users with some degree of control over the enhancement process, marketers developed interactive enhancement algorithms. These algorithms enable users to adjust brightness, contrast, and other parameters within specific boundaries. In addition, many systems in diverse domains of the real world need to process information within critical time limits. New work in model optimization, such as shallow models, and fast methods of processing try to address this issue by making sure that an improvement can be made quickly without the reduction of output quality. Technologies like self-driving cars, where real-time image augmentation greatly improves object recognition and navigation under darkness, rely on such Augmented Reality systems [6].

This study aims to provide a comprehensive analysis of the various approaches to enhancing low-light images, with a focus on deep learning strategies. We will examine the pros and cons of different strategies, evaluate their application in practical settings, and discuss ongoing challenges in the field. The review will also focus on recent advancements in enhancing the effectiveness and efficiency of deep learning models.

2. Traditional Low–light Enhancement methods

2.1 Histogram Equalization

Histogram Equalization is a widely used method to enhance a bad image. While it is comparable to a histogram stretch, this method frequently yields more aesthetically acceptable results for a variety of photos. Using the technique of histogram equalization, the resulting image's histogram is as flat as feasible (when the histogram is stretched, its overall shape stays the same). A histogram with mountains clustered tightly together is the outcome. A spreading or flatting histogram makes the dark pixels appear darker and the light pixels appear lighter [7].

2.2 Gamma Correction

Another popular method for changing an image's brightness is gamma correction. It functions based on the nonlinear relationship between the pixel values and the human eye's perception of intensity. Gamma correction is a straightforward and user-friendly technique that can be used to attain the desired brightness in images, particularly those taken in poorly lit conditions. It is frequently utilized in display systems to modify display contrast to better suit the properties of human vision. It has certain drawbacks, such as limited control over noise. Gamma correction enhances the visibility of dark areas but does not automatically eliminate noise that may be present in low-light images. It is unable to process images with a lot of illumination variation [8].

2.3 Retinex-Based Methods

A technique that divides an image into two primary parts: illumination and reflectance. Because it divides the image into its intrinsic reflectance, which represents the object's inherent qualities, like texture and color, and illumination, which represents the light sources and surroundings, this model has been widely utilized in low-light image improvement. Enhancing the reflectance component while modifying the light for improved visibility is the aim of Retinex-based techniques. Retinex-based techniques, including single-scale or multi-scale methods, use different algorithms to break down an image into its light and reflectance components. Usually, methods like bilateral or logarithmic filtering are used to estimate the lighting, and the original image is divided by the estimated illumination to determine the reflectance [9].

2.4 Wavelet Transform and Denoising

A wavelet is a small wave that needs to oscillate to distinguish between various frequencies. Because it divides the image into distinct frequency components, it is especially helpful for sharply enhancing high-frequency elements and low-frequency elements. Wavelet transformation works by breaking down a signal into a variety of small waves with varying frequencies and durations. After that, the original signal will be completely recreated based on the wavelet transform coefficients by using the Inverse Wavelet Transformation technique on the constituted signal. The wavelet transform adds information without boosting noise by selectively boosting the high-frequency components and reducing the low-frequency noise [10].

2.5 Image Fusion Techniques

It is a technique aimed at creating a single improved image by combining several images taken in various lighting or exposure settings. The concept is to create a single image with improved visibility by combining data from several low-light images. Before integrating the input images using weighted averaging or other statistical methods, these methods usually entail registering the images. Combining the best aspects of each image is the aim, maintaining tiny details while improving contrast and brightness [11]. The comparison of conventional low-light image-enhancing techniques is shown in Table 1 below.

Table 1: A Comparison of Traditional Low-Light Image Enhancement Methods

Method	Advantage	Disadvantage	Typical Use Cases
Histogram Equalization	Simple, inexpensive	Increases noise, can distort color, and can erase small details in places with strong contrast.	Satellite imagery, contrast enhancement, and medical imaging
Gamma Correction	Brightness adjustment is a simple, intuitive, and commonly used feature in display systems.	Ignores noise and may result in areas of excessive or insufficient exposure.	Basic contrast enhancement, photography, and display adjusting
Retinex-	Enhances color balance,	Problems with extreme low-	Recognizing objects,

Based Methods	works well with color images, and better maintains lighting characteristics.	light circumstances, sensitivity to parameter selection, and halo effects	maintaining image color, and improving images at night
Wavelet Transform	Ideal for multi-scale images, it effectively reduces noise and enhances small details.	Computationally costly and could cause blackness in areas that are smooth.	Denoising, edge preservation, and multi-resolution improvement
Image Fusion	Combines details from several pictures, improving contrast and brightness.	Requires several pictures, has alignment problems, and, if improperly registered, may result in artifacts.	Remote sensing, image registration, and low-light surveillance

3. Deep Learning Low-light Image Enhancement Techniques

3.1 Convolution Neural Networks

CNNs have been proven to be the backbone of the latest image enhancement techniques, and as a result, low-light image enhancement is no exception. CNNs have an inherent architecture to learn different levels of spatial abstractions of various features in images, such as edges, textures, and objects, after presenting them to the network as convolutional layers and by pooling operations. These networks have been demonstrated to improve image quality by capturing non-linear mapping between low-light and enhanced images with an abundance of training data. CNN-Based Methods for Low-Light Image Enhancement [12].

3.2 Generative adversarial networks

Generative adversarial networks, as a potent model to generate realistic samples, can learn the distribution of a dataset with only unpaired training data. GAN contains two neural networks: a generator and a discriminator. The generated images are more realistic, and the discriminator judges the quality of the generated images. The two networks are trained simultaneously, with the generator in order to create increasingly realistic images to fool the discriminator. The generator takes an input low-light image and generates an output enhanced image. The enhanced image is then compared against real high-quality images by the discriminator, which provides this error to the generator as feedback to adjust its output [13].

3.3. Zero-Reference Deep Curve Estimation

Zero-DCE is a data-driven low-light image enhancement method with deep learning in the absence of paired data. However, the GAN-based methods have the drawback of depending on ground-truth images for training and are not able to directly handle the enhancement curve higher than first-order, for which Zero-DCE predicts the higher-order enhancement curves for an input image to learn how to adjust overall brightness and contrast. Zero-DCE uses a deep neural network to directly learn high-order enhancement curves from the low-light image to simulate the transformation. It is suitable because this method does not rely on reference images [14]. Table 2 below illustrates a comparison of deep learning-based low-light image enhancement methods.

Table 2. Comparison table of deep learning-based low-light image enhancement Methods

Method	Advantage	Disadvantage	Typical Use Cases

Convolutional Neural Networks	Flexible and effective for extracting spatial features, automatic feature learning	Requires substantial training datasets and is computationally costly.	Face recognition, object detection, and real-time improvement
Generative Adversarial Networks	unsupervised learning, high-quality images,	Large datasets are needed for training instability, and it is computationally costly.	Video and image enhancement
Zero-Reference Deep Curve Estimation	Effective on low-resolution images, computationally efficient	Inadequate fine-tuning may be ineffective on really noisy images	computational efficiency, Real-time enhancement

4. Hybrid Techniques
4.1 Combining Retinex with Deep Learning

Among the most relevant hybrid methods is the fusion of the Retinex theory and deep learning. For the separation of the low-light image into the illumination and reflectance, the retinex-based methods are well known [9]. These hybrid models would be able to better learn how to enhance both components by using two strategies: Retinex theory and deep learning. The image is decomposed into its illumination and reflectance components, according to the classical Retinex model. Then, deep learning methods, such as GANs or CNNs [12, 13], are utilized to enhance both the lighting and reflectance elements. This two-step approach allows for better separation and enhancement of features, improving the quality of the output image.

4.2 Multi-Scale Networks

Multi-scale networks were designed for boosting performance in low-light images by applying operations at different scales of the same image resolution. These networks are very useful for enabling the model to learn from both global and local features on different scales, resulting in enhancing the images more robustly. The input image is propagated through several scales, which enables the network to perceive important local details as well as coarse structural features. The multiplex-level features are then gathered to produce the final enhanced image [15].

5- Related work

Authors in [16] presented a pipeline to enhance object detection in low-light scenarios by optimizing the detected object and its resolution in two cascaded stages. In the first step of their proposed approach, three heterogeneous supervised deep learning algorithms, namely ZeroDCE++, Gladnet, and TBEFN, process low-illuminated images for contrast enhancement, noise suppression, and detail restoration. Then, in the second stage, these enhanced images are passed to YOLOv7. The model is tested on the ExDark dataset, and its performance is measured in terms of no-reference image quality metrics (BRISQUE, PIQE, NIQE, and information entropy) and detection metrics (recall, precision, mean average precision, and F1 score). Experiments show that in terms of the overall detection performance, the TBEFN-based variant of the system outperforms YOLOv7 without enhancement by increasing the mean average precision from 0.49 to 0.574. TBEFN also delivered the best NIQE and BRISQUE scores and more significant image quality enhancement, while Gladnet achieved the best in PIQE and entropy. The two-stage system, however, has disadvantages: it is computationally more intensive and has a relatively higher training time, particularly on low hardware configurations. Furthermore, the separation of enhancement and detection phases may constrain real-time deployment. Results show that deep learning-based enhancement, especially TBEFN, can significantly improve object detection in low illumination and suggest that the enhancement can be embedded into detection frames for efficient enhancement.

In [17], a training-data-free DL method for low-light image enhancement based on untrained NN priors was proposed. The method is developed based on the Retinex decomposition model, where an image is decomposed into reflectance and illumination parts, each represented by an individually initialized and untrained NN. To avoid this inherent ambiguity between the two layers, the authors introduced architectural and capacity discrepancies between the NNs, where a low-capacity network is used for smooth illumination and a high-capacity one is used for detailed reflectance. There is an end-to-end differentiable histogram balancing for adaptive illumination correction. Experiments on five well-known benchmark databases (LOL, LIME, NPE, MEF, and DICM) demonstrate that their method can effectively compete with and even outperform most supervised and unsupervised methods and obtain the best overall performance in terms of no-reference and full-reference image quality assessment. Their method has never accessed training samples. They visually compare their proposed method with existing methods and demonstrate that it can enhance contrast, mitigate noise, and preserve fine details better than existing methods. However, their approach has limitations, and one of them is the high computational cost, as it performs an iterative optimization (with up to 100,000 iterations) and is much slower than pre-trained models, which hinders its use in real-time applications. However, their approach shows good generalization and robustness, which is especially important in applications such as clinical imaging or forensics, where it is very difficult to have a good annotated training dataset.

In [18], a deep learning-based technique is proposed for the enhancement of low-light-captured images by using the CNN architecture. The method is developed to suppress noise, improve contrasts, and optimize the retention of details by making full use of the deep feature extraction ability through many CNN-based layers with residual connections. A core element of the approach is a bespoke loss that jointly measures pixel-wise and perceptual differences between the input and ground truth images to obtain visually pleasing and high-fidelity enhanced results. One of the appealing features of their proposed model is its generalization to test images not seen during training, which would allow practical applications such as surveillance, medical imaging, and underwater photography. But their approach requires a large labeled dataset to train, which is unfavorable for domains with few annotated data. In addition, the high computational complexity of deep CNN may also prevent its real-time implementation.

Authors in [19] present a new gamma curve-based low-light image enhancement algorithm that focuses on the instructiveness, speed, and preferences. Unlike typical deep learning models, which provide fixed outputs, their proposed approach gives users direct control over the brightness and the visual quality of the intensity-enhanced image within a single tunable optimization parameter. The algorithm is computationally efficient, requiring only one-time training without reference images, and capable of real-time implementation for various platforms. Experiments conducted on five benchmark datasets show that their proposed method is slightly better than the state-of-the-art Zero-DCE++ in terms of the image quality of the object. Their method is advantageous due to its instructiveness, user-friendliness, and fast response. However, it might miss more complex semantic information that is present in deeper deep learning architectures and is mostly biased towards brightness, and as such, may be less effective at detailed texture and color enhancement in some cases.

In [20], a U-Net-based supervised deep learning framework is introduced to improve low-light images. Their proposed framework combines basic pre-processing operators and some advanced modules to enhance brightness, eliminate noise, and keep textures. Their model was tested on the LOL dataset and obtained a PSNR of 24.31 and an SSIM of 0.854, outperforming the state of the art, including Retinex and HSL, etc. The main benefits of the method are end-to-end effective processing, simultaneous good structure preservation, and reduced computational complexity, which make it applicable in real-time scenarios. Nevertheless, their proposed model is not capable of dealing with challenging illumination conditions and illumination non-homogeneity of backlit images, and integrating spatial-angular feature blocks in spatial and semantic enhancement can be further explored.

Authors in [21] investigate deep learning-based face detection under low-light conditions, using four low-light image enhancement models (MirNet, AGC, RetinexNet, and Retinex) based on the LOL dataset as evaluation criteria, using PSNR and SSIM metrics. These models are also fused in their study with a face detection model, namely RetinaFace, and evaluated on the dark face dataset. Modeling of Retinex used on RetinaFace achieved the mean average precision of 0.43%, which significantly improved face detection over the RetinaFace model (0.27% mAP) with no enhancement. Their study concludes that low-light image enhancement improves the performance of face detection, especially under challenging lighting conditions, such as a real low-light environment. But the advantages are small, although they need more optimization for wider application. Although the technique appears to have potential for improving the accuracy of detection, it is unclear how effective it will be in all low-light conditions or for images that were significantly degraded.

In [22] a new method was presented based on Multi-Level Network Fusion. Relevant features were extracted using structural, perceptual, and color loss. Their approach exceeded traditional strategies. The major advantage of MFIE-Net is that it can effectively suppress noise and does not introduce color distortion, yielding sharper images.

However, the drawback is that such a method may incur high computational costs due to its complexity compared to simpler methods. Experimental results showed that the accuracy of their proposed method has dramatic improvements in low-light image quality enhancement.

In [23], a new strategy based on normalizing flow is introduced to enhance low-light images by correcting the downside of the conventional deep learning methods with pixel-wise reconstruction loss. However, these techniques tend to be sensitive to wrong brightness, residual noise, and artifacts. They introduce a conditional normalizing flow, which more closely models the complex distribution of normally exposed images while boosting the brightness and reducing the noise. Additionally, their proposed method enhanced saturation and reduced color deviation. Their approach shows excellent results in terms of SSIM, PSNR, and LPIPS

In [24], the Pyramid Diffusion Model for low-light image enhancement is presented, which exploits an innovative pyramid resolution approach to process the results faster while stably obtaining the results without loss to fine-grained image information. By gradually reducing the resolution during the reverse pass, their work obtained up to two times faster run-time compared to classical diffusion models, but with equivalent accuracy. It also contained a global corrector to compensate for the common problems in regular diffusion models, such as RGB shift and global deterioration. Their work outperformed other approaches by large margins in terms of both image quality and processing time. In particular, the accuracy of their work was a PSNR of 27.09, an SSIM of 0.93, and an LPIPS of 0.10 (which is over the winning entry with a 10-point improvement in SSIM and a 21-point improvement on LPIPS over all other participants on the LOLV2 dataset). Their work is more powerful than simpler methods, but it does require proper tuning of the parameters and is more computationally demanding.

Authors in [25] presented a deep lightning network, which utilized residual learning to predict residues between low-light and normal-light images to boost visibility and details of the image. The network consisted of several LBP (Lightening Back-Projection) units, which gradually refine the image by lightning and darkening the image in such a way that the residuals of restoring a better image are learned. Furthermore, their work also contained a Feature Aggregation block, which aggregated features from different intermediate stages to enhance the local and global feature representation ability. This led to a superior gain in both objective metrics (PSNR, SSIM) and subjective visual quality, which is confirmed by quantitative comparison with other existing methods such as Retinex-Net and LightenNet. Higher PSNR and SSIM indicate that their model works well for low-light image enhancement. Unfortunately, its deep learning architecture is computationally intensive and may be computationally expensive, particularly if the image resolution is high. It also heavily depends on large-scale paired low-light and normal-light training data, which may not always be sufficient in some scenarios.

Authors in [26] used a simple convolutional network architecture specifically designed for improving low-light images. Their proposed strategy combined classical techniques with deep learning for brightness and contrast improvement of low-light images.. Accuracy rate, evaluated with PSNR and SSIM, had strong improvements, which indicated that EnhanceGAN could effectively be applied to enhancing the quality of images in the underexposure situation. Although the method was very efficient and simple to use, it also had some limitations. The simplicity of their model may limit its flexibility by not supporting sophisticated iterative feedback mechanisms and feature combination strategies that can be found in more sophisticated models. Additionally, their model may be more likely to be overfit to the data if trained with a smaller amount of data, which again may not be suitable for different low-light-inspired conditions. So, even if the method provides a faster and less costly option, it might not be as detail-enhancing compared to more sophisticated models. Table 3 below illustrates a comparison of previous works.

Table 3. A comparison table of previous works

Study	**Enhancement Approach**	**Methodology**	**Performance Metrics**	**Advantage**	**Limitations**
Al-refai et al. (2025)	Two steps for object detection in low-light environments	Deep learning-based image enhancement with YOLOv7	MAP, NIQE	Significant improvement in object detection after enhancement	Limited to object detection applications
Liang et al. (2022)	Self-supervised low-light image	Untrained NNs with the Retinex decomposition	No direct comparison to traditional	No need for training samples, effective for	Complexity in noise handling

	enhancement	model	methods	extreme conditions	
Brahmaji et al. (2023)	Deep learning with modified CNN	CNNs with noise reduction	Objective metrics, Visual quality	High performance in removing noise, preserves textures	Long processing time requires large datasets
Yangming Shi et al. (2022)	Interactive low-light image enhancement	Lightweight network	Visual quality, Speed	User-adjustable, fast processing	Not designed for all lighting conditions
Chandini et al. (2023)	Deep learning with U-Net	CNN	Objective performance, Noise reduction	Good texture, edge preservation	Real-time performance limitations
Panchal et al. (2024)	Multi-level network fusion	Image fusion, CNN	PSNR, SSIM	Improved color and detail preservation	Potential overfitting in certain scenarios
Wang et al. (2022)	Low-light image enhancement with normalizing flow	Normalizing flow model	PSNR, SSIM, and LPIPS	Better exposure, reduced noise/artifacts	High complexity and may not handle global properties well
Xin et al. (2023)	Multispectral reconstruction-based enhancement	Using a multispectral reconstruction algorithm	LOL dataset comparison	Better enhancement for both synthetic and real-world images	Requires careful calibration of spectral response
Li-Wen et al. (2020)	Deep Lightning Network	Several Lightning Back-Projection blocks.	PSNR and SSIM	Easy to implement, end-to-end network works	Computationally expensive
Riyas et al. (2024)	CNN	classical techniques with deep learning	PSNR and SSIM	Faster and less costly option	Not supporting sophisticated iterative feedback mechanisms

6. Challenges

Many low-light image enhancement algorithms and particularly those that utilize large networks, can be computationally slow and demanding. This restricts their use for real-time applications or on constrained devices like mobile phones, etc.

Images taken under extremely low light conditions or degraded conditions also come with a specific set of problems. In low-light conditions, images can be very noisy, blurry, and lack details, and so it may be challenging to enhance low-light images without over-smoothing or modifying critical characteristics. This is of particular concern when the lighting levels are too low for obtaining an image with any useful information.

It is a challenge to enable the users to experience the image enhancement interactively in real time with good quality and less computational overhead. These standard techniques often fail to be personalized. Low-light image enhancement is usually used as a preprocessing stage for other computer vision tasks, including object detection, semantic segmentation, face recognition, etc. Yet, the improvement of low-light images may influence the performance of the downstream tasks in a negative way if not done well, in particular one introduces artifacts or removes important details during enhancement.

7. Conclusion

An image enhancement method for low-light images aims to enhance the information, improve image quality, suppress uninteresting features, and increase the difference between the features of various objects in the image. This essay explores the concept, goal, methods of execution, benefits, and drawbacks of image enhancement from the perspectives of conventional procedures and algorithms based on machine learning in depth. To examine machine learning-based image enhancement algorithms from the perspective of digital image theory, it is categorized based on the model strategy and conventional techniques in conjunction with the algorithm. Several algorithms are examined to determine how well they perform in image quality assessment techniques in order to compare other algorithms.

This paper classifies traditional low-light image enhancement algorithms, summarizes the process of improvement of the traditional methods, introduces the deep learning-based image enhancement methods, and discusses hybrid techniques. Based on the discussion of the aforementioned scenario and the real-world scenario, this paper also identifies the limitations of the current technology and forecasts its future direction.

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