An Exploration of State-of-Art Approaches on Low-Light Image Enhancement Techniques

V. S. Anila, G. Nagarajan, and T. Perarasi

1 Introduction

Computer vision is an area of artificial intelligence (AI) that enables computers and systems to extract useful information from digital images. The quality of the image will depend on a number of factors, including illumination, contrast and brightness. Images that are captured in an environment having low illumination or low light are categorized as low-light images. In many real-time applications, this low-light condition may occur. So, to overcome this, many low-light image enhancement methods are used. This survey paper's main goal is to investigate the various image improvement techniques for low-light images. Image enhancement is a technique that helps to improve the quality of an image. The parameters that define the image quality are color, contrast, brightness, illumination, etc. During the image acquisition, sufficient light intensity is needed. If the light intensity is low, the captured image will give less information than the original image. In many applications, there is a possibility of low-light conditions. It is necessary to create an enhancement method that is more suited for low-light images in order to get around this. The popular low-light image enhancement methods are Gamma transformation, Histogram equalization, Retinex methods, machine learning and deep learning methods. In recent years, the availability of various learning models introduces a large exploration of low-light image enhancement methods. This survey paper divides the algorithm into two classes, traditional methods and learning-based methods. This learning-based algorithms are again classified into machine learning-based and deep learning-based

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methods. Section 2 describes a few existing low-light applications. Section 3 explains the classification of enhancement methods.

2 Low-Light Images

Medical image processing has been widely used in research in recent years to diagnose a variety of disorders. When considering various medical imaging techniques, this low-light environment could affect the accuracy of the diagnosis. One of the most important methods for identifying abnormalities of the larynx is laryngeal endoscopy. Due to the anatomical structure of the human body, it is difficult to get illuminated images of this region. As a result, low-light images are obtained.

This enhancement scheme is also applicable for the enhancement of chest x-ray for the detailed analysis of Covid-19 cases. Figures 1, 2 show the larynx endoscopy image and chest x-ray image. Night traffic monitoring is a major challenge in today's world. These types of enhancement algorithms are useful for improving the analysis of monitoring systems. The other important areas where this low-light condition may exist are underwater images, foggy images, satellite images, etc. (Figs. 3, 4).

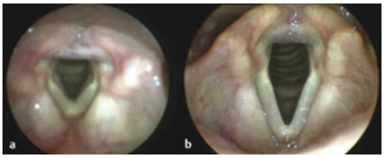

Fig. 1 Larynx endoscopy image

Fig. 2 Covid-19 chest x-ray image

Fig. 3 Underwater image

Fig. 4 Foggy image

3 Methodologies

This survey paper introduces a distinction between traditional and learning-based low-light image enhancement technique (Fig. 5).

The traditional methods are Gamma transformation, Histogram equalization and Retinex-based methods. The learning methods are machine learning (ML) and deep learning methods (DL). Methods based on machine learning have only recently become available. Machine learning is a subset of artificial intelligence. They are capable of learning by themselves without being explicitly programmed. The limitations of ML algorithms are, they require supervision for feature extraction and handle only thousands of data points. Commonly preferred ML algorithms are principal component analysis (PCA), regression, support vector machine (SVM), etc.

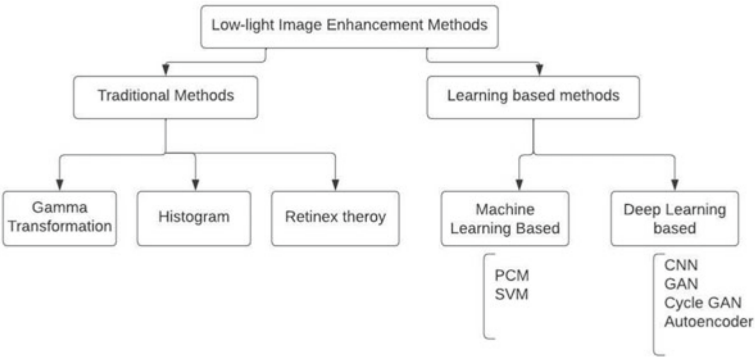

Fig. 5 Classification of low-light image enhancement techniques

Several deep learning-based image enhancement methods have also emerged since 2016. DL is a subset of the ML algorithm. Millions of data points are processed by DL algorithms. As a result, a large number of features are extracted without supervision. Convolution neural networks (CNNs) have been used as the foundation of deep learning frameworks in a variety of research papers. Deep learning-based methods can achieve excellent results in low-light image enhancement. Section 3.4 describes about deep learning algorithms.

3.1 Gamma Transformation

A Gamma function is a nonlinear transformation. Gamma correction is a technique used for image enhancement.

$$g(x, y) = f(x, y)^{\surd} \tag{1}$$

where '$\surd$' represents the gamma correction parameter. By varying the parameter, several different transformation curves can be obtained. When '$\surd$' > 1, the transformation will broaden the dynamic range of the low-gray value areas of the image and compress the range of the high-gray value areas. When '$\surd$' < 1 the transformation will have the low gray values and stretch the high gray values. When '$\surd$' = 1 output remains unchanged (Fig. 6).

A pair of complementary gamma functions by fusion is one of the methods used for low-light image enhancement (Li et al. 2020). The pair of complementary functions are as follows,

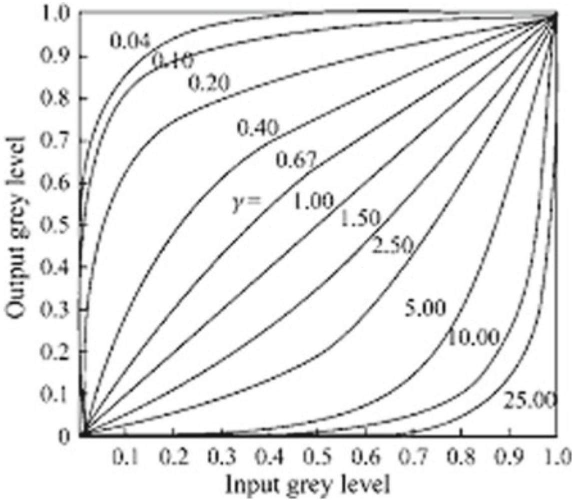

Fig. 6 Gamma transformation

$$y_1 = 1 - \left(1 - (x)^{\surd}\right) \tag{2}$$

$$y_2 = (1 - (1 - (x)))^{1/\surd} \tag{3}$$

where x—input pixel value, y_1 and y_2—transformed output pixels.

The input red, green, blue (RGB) image is transformed into a hue, saturation, value (HSV) image. The brightness of the image is determined by the value component (V), which depends on the amount of light intensity present in the environment. The value component is enhanced by the above transformation equations. Then two enhanced 'V' components are combined by,

$$I_1 = c_1 y_1 + c_2 y_2 \tag{4}$$

where $c_1 = V_i / \sum V_i$.

"I_1" is the first input for the fusion process. The identical value component is subjected to sharpening and histogram equalization to produce the second input for the fusion. The second input for fusion is,

$$I_2 = (V + 2H(V) - G * H(V))/2 \tag{5}$$

The value components I_1 and I_2 are fused by the image fusion process. This overall process improves the brightness of the low-light images by adjusting the dark region and compressing the bright region. The advantage of using this gamma function is that it generates even brightness.

3.2 Histogram Equalization

Histogram equalization (Narendra and Fitch 1981; Abdullah-Al-Wadud et al. 2007) is one of the traditional methods for low-light image enhancement. The pixels are the basic building blocks of an image. Each pixel holds a specific intensity value. The histogram is a plot that shows the number of pixels versus their intensity values. The histogram equalization algorithm uses the cumulative distribution function (CDF) to adjust the output gray level to have a uniform distribution (Fig. 7).

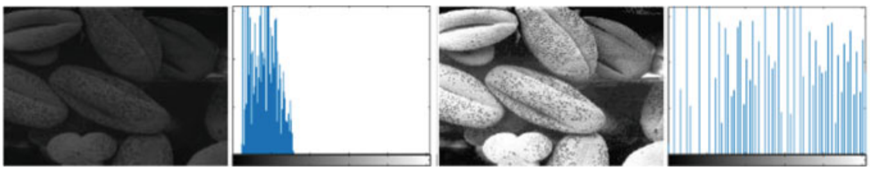

Fig. 7 Example of histogram equalization

'I_1' will serve as the input image, and 'L' will serve as the gray value. 'N' is for the overall number of pixels in a picture, '$I(i, j)$' stands for the gray value at the point with coordinates (i, j), and 'n_k' stands for the number of pixels at gray level k. The likelihood that a specific gray level 'k' will occur is,

$$P(k) = n_k/N; \quad \text{where } k = 0, 1, \ldots, L-1 \tag{6}$$

The cumulative distribution function (CDF) of the gray level of an image 'I' is given by,

$$C(k) = \sum_{0}^{k} p(r); \quad k = 0, 1, \ldots, L-1 \tag{7}$$

The histogram equalization algorithm maps the original image to an enhanced image with a uniform gray-level distribution based on CDF (Table 1). The enhanced output image is represented as follows:

$$f(k) = (L-1) * C(k) \tag{8}$$

3.3 Retinex Theory

Retinex theory (Land 1977) is one of the major strategies employed in low-light image enhancement. As per the Retinex theory, the observed image is represented as the product of reflectance and illumination component (Fig. 8).

As per Retinex theory,

$$S(X, Y) = R(X, Y) * L(X, Y) \tag{9}$$

where

$S(X, Y)$—Observed image,

$R(X, Y)$—Reflectance component,

$L(X, Y)$—Illumination component.

A low-light image is characterized as it is captured in a low illuminance region. Illuminance is the measure of how much incident light illuminates the surface. For images taken in dim lighting, illuminance is below the standard level. As per the Retinex theory, the reflectance component is considered as the enhanced image, $R = S/L$. By choosing the proper illumination map, the required enhanced image is obtained. Most of the research work is carried out based on this equation. By

Table 1 Different histogram methods

Histogram method	Findings
Equal area Dualistic Sub-image Histogram Equalization (DSIHE) (Wang et al. 1999)	The input images are decomposed into two equal area sub-images based on its original probability density functions
Minimum Mean Brightness Error Bi-histogram Equalization (MMBEBHE) (Chen and Ramli 2003)	This method preserves the maximum brightness of the image
Adaptive Histogram Equalization (AHE) (Megha et al. 2016)	It deals with contrast restoration for medical and other unclear images
Partially Overlapped Subblock Histogram Equalization (POSHE) (Ganesan and Rabbani 2019)	This method separates subblock images recursively into different sub-images with the cumulative density function (CDF)
Contrast Limited Adaptive Histogram Equalization (CLAHE) (Yadav et al. 2014)	This method partitions the images into contextual regions and applies the histogram equalization to each region. It is a specially developed algorithm for medical images
Recursive Mean Separate Histogram Equalization (RMSHE) (Chen and Ramli 2013)	This is a generalized model of Bi-histogram equalization. This method is used to provide better and scalable brightness preservation
A Recursive Sub-image Histogram Equalization (RSIHE) (Sim et al. 2007; Singh 2014)	It is developed to overcome the drawback of generic histogram equalization for grayscale images and it provides better image compensation
An Entropy-based Dynamic Sub-histogram Equalization (EDSHE) method (Parihar and Verma 2016)	Recursive division of the histogram based on the entropy of the sub histograms is performed. Each sub-histogram is divided recursively into two sub-histograms with equal entropy. A dynamic range is allocated to each sub-histogram based on entropy
A Dynamic Histogram Equalization (DHE) (Abdullah-Al-Wadud et al. 2007)	The image histogram is partitioned based on local minima and a unique gray value range is assigned to each partition
A Fuzzy-based Brightness Preserving Dynamic Histogram Equalization (BPDHE) (Sheet et al. 2010)	It is used to reduce computational complexity, in which execution time is dependent on image size and nature of the histogram
Bi-histogram Equalization with a Plateau Limit (BHEPL) (Ooi et al. 2009)	It is preferred for short processing time image enhancement. It divides the input histogram into two independent sub-histograms to maintain the mean brightness
A Median Mean-based Sub-image clipped Histogram Equalization (MMSICHE) (Singh and Kapoor 2014)	To improve the brightness level, information content (entropy) and better enhancement rate

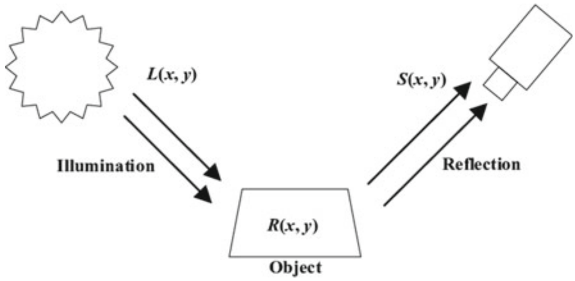

Fig. 8 Retinex model

using the illumination component, the enhanced outputs are obtained by performing division operations. To overcome the difficulty in this division operation an inverse term is used. The inverse term is expressed in the given equation,

$$R = S * L^{-1} \tag{10}$$

Using an inverse illumination map (L^{-1}), the enhanced image (R) is obtained. Many of the deep learning model uses this Retinex theory as the basic theory. As per the theory, illumination map is constructed by various CNN models. Current research works are carried out in deep learning without Retinex theory also. Deep learning models will play an important role in the enhancement of low-light images.

3.4 Deep Learning-Based Methods

Deep learning has been applied to computer vision tasks such as low-light image enhancement in recent years due to its excellent representation and generalization abilities. Many deep learning models use Retinex theory for their operation. A convolutional neural network (CNN) is a deep learning network architecture that learns directly from data. CNNs are especially useful for detecting patterns in images in order to recognize objects, classes and categories.

Figure 9 shows the basic architecture of convolutional neural network (CNN). The function of the convolution layer is to extract meaningful information by applying a sliding window on the input matrix. The pooling layer reduces the height and width while maintaining the depth information to conduct dimensionality reduction. Based on the application, different types of pooling are preferred. These are maximum pooling, average pooling and minimum pooling. Fully connected layer will perform the classification.

A generative adversarial network (GAN) (Goodfellow et al. 2014) is an unsupervised deep learning-based model. It uses unlabelled data for training. GAN contains two competing neural networks called generator and discriminator, which compete against one another and may evaluate, discover and follow variations within the

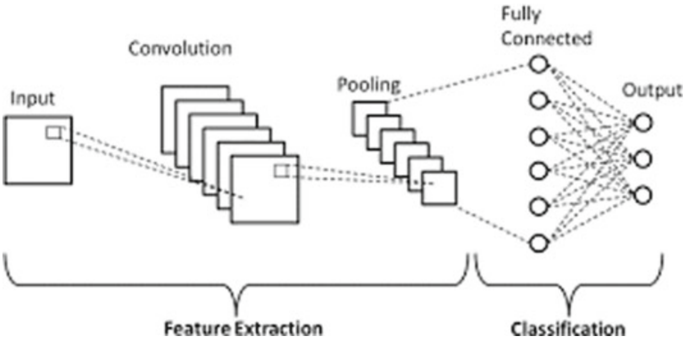

Fig. 9 Convolutional neural networks

dataset. The generator generates fake samples of images and tries to fool the discriminator. During the training phase, the generator and discriminator run in competition with each other. The model is trained to function more effectively during each epoch.

A Retinex-based attention network (Huang et al. 2020) uses Retinex as the basic theory for the learning of deep neural networks. This technique calculates an improved image from a reflectance map. Illumination extraction block is developed using an attention mechanism module, resulting in an illumination map prediction network. In order to gain more precise illumination information for the input image, this attention technique is inserted between the convolution layer and batch normalization. On both low illumination images with uniform light and uneven illumination, this model lessens the impact of noise and the augmented information that results.

A Multiscale Attention Retinex Network (MARN) (Zhang and Wang 2021) is designed to predict a detailed inverse illumination map of the input image. When compared with various CNN algorithms, the Multiscale Attention Retinex Network gives better feature extraction. This MARN improves the generalization capability of the network. Instead of using more image priors, an illumination attention map is used to learn the model. It improves the quality of the image in various lighting conditions. This utilizes reconstruction loss, structure similarity loss and detail loss. If the inverse illumination is predicted, the reflectance map is calculated by using Retinex theory and then this reflectance map is estimated as an enhanced image.

A simple generative adversarial network with a Retinex model (Ma et al. 2021), a decomposition network is used to decompose the low-light image into illuminance and reflection maps. For training the GAN structure unpaired datasets are used. This provides a better generalization to the model. By using this structure, reduced training complexity and reduced training time is achieved. This model is applied to mobile phones with small memory.

An enlighten GAN is a modified GAN structure (Jiang et al. 2021). It introduces Enlighten GAN structure that can be trained without image pairs. Even with unpaired datasets, this structure is generalized very well for various real-time images. This model introduces a global and local discriminator structure that handles spatially varying light conditions in the input image. The results of Enlighten GAN are compared with several state-of-art methods. All results show the superiority of Enlighten GAN.

Various approaches have been used to improve image segmentation (Long et al. 2015). Segmentation is the process of dividing an image into its various parts. These basic operations are performed in many computer vision tasks. Segmentation shows good performance during daytime or in bright light. In the case of low-light images, segmentation is not performed well because of the presence of noise, blurredness, etc. The process of segmentation can be divided into a single-class and multi-class segmentation. In single-class segmentation (Wang and Ren 2018), only one object or one feature is considered for segmentation. In multi-class segmentation (Dai and Gool 2018), multiple features are considered. In Cho et al. (2020), semantic segmentation of low-light images with modified Cycle GAN is introduced. The modified Cycle GAN is trained using paired dataset and the L_1 loss function is added to the existing Cycle GAN for improving the performance of the segmentation.

Table 2 summarizes the low-light image enhancement techniques.

4 Conclusion

Various state-of-art methods are discussed in this paper for low-light image enhancement. Many of the deep learning structures use Retinex as the basic theory of operation. The illumination map is modified by using various learning architectures, CNN, GAN, Cyclic GAN, etc., which are a few illustrations of deep learning models. This survey presents some works which are more suitable in a noisy environment also. In many real-time applications, low-light conditions may occur due to the unavailability of environmental light. Low-light image enhancement thus plays a crucial role in each of these scenarios. Low-light image enhancement can be extended to the enhancement of low-light video also.

Table 2 Low-light image enhancement techniques

References	Year	Design methodology	Inferences
Singh and Bhandari (2021)	2021	• It is a machine learning algorithm • The RGB input image is converted to hue, saturation, value (HSV) space • The reflection coefficient of the 'V' component is obtained • Image fusion is performed by principal component analysis (PCA) method • Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to fused image • The fused image is converted to RGB plane	The irregular brightness due to low illumination can be upgraded by this method
Liang et al. (2021)	2021	• It includes a two-stage CNN • Image Signal Processing pipeline (ISP) operations are grouped into the restoration group and the enhancement group • A CNN model called CAMERANET is designed with two sub-networks to perform the two groups of subtasks	It uses a framework for deep learning-based ISP pipeline design. The effect of noise is reduced
Zhu et al. (2021)	2021	• In the camera, a unit called an image signal processing pipeline (ISP) is used to generate JPEG format images • Denoising, demosaicing, detail enhancement and white balance of noises are all included in ISP • A two-stage network has modified the conventional ISP	The image-denoising module U net helps to reduce the effect of noises

(continued)

Table 2 (continued)

References	Year	Design methodology	Inferences
Cho et al. (2021)	2021	• Semantic segmentation is very difficult during the night-time due to the insufficient amount of external light • So, it is unable to detect the shape and color information of objects • The Cycle GAN structure is used for getting improved segmentation of low-light images	This architecture improves the segmentation performance by preserving the shape and color information of the images
Wang et al. (2020a)	2020	• It generates residual between low and normal images by using a deep neural network • A lightening backpropagation is used to lighten the dark images by predicting their illumination	By using the lightening backpropagation module better enhancement is achieved
Lu and Zhang (2021)	2021	• According to the Retinex theory, the illumination component is calculated • The two-branch exposure fusion network aimed to produce adaptable enhancement in various illuminations • SSIM, L_1 and L_2 losses are considered for better performance	It provides better enhancements in noisy environments
Lim and Kim (2021)	2021	• A Laplacian pyramid is a type of image representation in which the DSLR technique is used to adjust global illumination and restores the local details • These two tasks are performed with separate encoder-decoder architecture	This architecture produces better enhancement for local details without any color distortions

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Table 2 (continued)

References	Year	Design methodology	Inferences
Ravirathinam et al. (2021)	2021	• An encoder-decoder architecture is used for image enhancement • The function of the encoder is to extract the features from the images • The decoder enhances the input images with the help of extracted features	The multi-context feature extraction modules help to extract complex features Three loss functions are used here for better enhancement
Lu et al. (2020)	2020	• In the selfie image enhancement, background and foreground are separately enhanced and combined together • Modules, such as gain estimation and raw data processing are used • The gain estimation module separates the foreground and background of input images and predicts their gain	Effectiveness and robustness of the deep selfie images are obtained
Lamba et al. (2021)	2021	• The light fields are used for refocussing and depth estimation of images • For low-light images, it is difficult to get these light fields • L3FNet is a DNN architecture used for low-light field restoration	Better optimized results are achieved
Wang et al. (2022)	2022	• A mixed attention-guided generative adversarial network called MAGAN for low-light image enhancement is designed • It uses an unsupervised learning method • A mixed attention module called feature attention and pixel attention is used	Noise reduction is achieved

(continued)

Table 2 (continued)

References	Year	Design methodology	Inferences
Guo et al. (2017)	2017	• It is based on Retinex theory • The illumination map is calculated by finding the maximum intensity of each pixel in R, G and B components • From this an illumination map is constructed, where an augmented Lagrangian multiplier-based algorithm is used	A consistent illumination map is generated. Like traditional Retinex theory input image is not divided into reflection and illumination
Wang et al. (2020b)	2020	• It works well with low-light noisy images • It uses non-subsampled Shearlet Transform (NSST) to decompose the input image into low-pass subband and bandpass subband • For noise reduction, bandpass subband is suppressed	By this method, better noise reduction with good adaptability and good stability are achieved
Guo et al. (2020)	2020	• This model uses regularized illumination optimization and deep noise suppression • Gamma correction is used for obtaining an illumination map • A guided filter-based detail boosting is introduced to optimize the reflection map • These two images are combined to get enhanced images	It utilizes regularized illumination optimization and deep blind denoising. Maritime images are used in this method
Garg et al. (2022)	2022	• LiCENt—Light Channel Enhancement Network that uses a combination of an autoencoder and CNN • The RGB image is converted to HSL space and improves the 'L' value of the HSL image	The learnable parameter is reduced by a factor of 8.92. It avoids over-enhancement and color distortion. This is a lightweight and fast method

(continued)

Table 2 (continued)

References	Year	Design methodology	Inferences
Guo et al. (2019)	2019	• This architecture is based on Multiscale Retinex theory (MSR) which is considered as a CNN unit • Its output is given to perform a discrete wavelet transform to get better output • A pipeline neural network called LLIE-net is designed and it is trained using paired datasets	Better noise reduction. The pipeline network is designed such that in the prediction phase no artificial parameter is considered. Better results for real-time data
Park et al. (2018)	2018	• It is a Retinex-based model • Dual autoencoders are used • A low illumination component results in an enhanced reflectance component • The illumination component is blurred by using a stacked autoencoder unit • The improved reflectance component results an enhanced image • A convolutional autoencoder network is used to prevent noise amplification	This is applicable to robot vision and visual surveillance applications
Li et al. (2019)	2019	• An adaptive bright color channel-based enhancement method and a denoising method are formulated • A bright channel model and deep convolutional neural network are used for denoising and color correction	This scheme removes the electrical noise and modifies the color distortions of the radiometric compensation in water

(continued)

Table 2 (continued)

References	Year	Design methodology	Inferences
Ren et al. (2019)	2019	• A traditional Retinex model with a camera response model is combined • The exposure ratio for each pixel is estimated by the illumination estimation technique • As per the exposure ratio, the camera response model adjusts each pixel to the desired exposure • A less distorted enhanced image is obtained	Response characteristics of the camera is utilized to enhance the illumination. This model reduces color and lightness distortion
Ma et al. (2019)	2019	• This algorithm utilizes three stages, image reconstruction, image enhancement and color distortion • The RGB image is converted to an HSI image then low-light image enhancement via illumination map estimation (LIME) is used to enhance the reconstructed grayscale map. Retinex theory is used for illumination estimation	The effect of Halo and noise in the input image have been reduced. The modified color distortion method is designed. It is more applicable for edge detection, feature mapping, object recognition and tracking
Yang et al. (2021)	2021	• The sparse gradient minimization sub-network (SGM-Net) is designed, which extracts paired illumination maps. Two sub-networks namely enhance net and restore net are used for contrast enhancement and noise reduction	Reduces the effect of noise and preserves edge information
Wang et al. (2018)	2018	• The Global Illumination Aware and Detail Preserving Network (GLADNet) is formulated. An input image is rescaled to a certain size and using an encoder-decoder network a global illumination is generated	More vivid and natural results are obtained. GLADNet adjusts the whole image at the same time, so over exposure in brighter region and under exposure in darker regions can be avoided

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