Edge Boosted Global Awared Low-light Image Enhancement Network

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ARTICLE INFO	ABSTRACT
	Low-light images are captured in situations where the environment lighting is poor or the camera hardware is not capable of producing good quality images. These types of images tend to have low contrast, blurry details, noise, and color distortion. In computer vision applications, image brightness plays a crucial role, and therefore, low-light image enhancement is used as a preprocessing step. In this study, we have improved the Low-Light Enhancement Network with Global Awareness (GLADNet) method by adding a U-Net based edge information extraction unit. The channel attention mechanism was also incorporated into the edge information extraction unit to achieve color preservation. Our experiments show that our proposed method has achieved higher PSNR, SSIM, and FSIM metrics compared to reference images. Additionally, it has produced lower NIQE and BRISQUE values for non-reference performance evaluation. Moreover, our proposed method removes noise better and produces visual results that are closer to the target images.

Introduction

Low-light images can result from poor camera settings or from camera sensors that are not exposed to enough light. It is important to have good image quality both for human visual pleasing and for the performance of computer vision algorithms. A number of studies [1]-[4] have been conducted in the field of low-light image enhancement, which includes techniques such as illuminating insufficient brightness, preventing color distortion, removing noise, and preserving texture and detail. Previous work in this area has been based on various methods such as histogram equalization [5]-[9], gamma correction [10]-[12], Retinex theory [13]-[16], and deep learning [17]-[19], among others.

Histogram equalization is a method used to enhance the contrast of an image by adjusting the distribution of its gray levels [20]. This technique works by spreading the distribution of gray levels over a wider range, which makes unclear details in the image more clear. However, applying this method to the entire image can lead to undesirable outcomes, such as bright regions reaching saturation values. To overcome this problem, an adaptive histogram equalization (AHE) [5] technique is used, which computes local histograms from different regions of the image and performs histogram equalization with respect to these regions. However,

AHE can be slow and produce noise in homogeneous regions. To avoid oversaturation and noise, the Contrast Limited Adaptive Histogram Equalization (CLAHE) [6] technique applies a threshold to each local histogram equalization. Another extension of histogram equalization, the Brightness Preserving Dynamic Histogram Equalization (BPDHE) [7], aims to improve contrast while preserving the average brightness of the image.

The enhancement of low-light images by gamma correction is inspired by the interaction between humans and nature. The sensitivity of the human eye to brightness is thought to be exponentially proportional to the amount of light entering from the outside [21]. In dimly lit environments, the human eye is more sensitive to differences in brightness, but as the amount of light increases, the eye's ability to detect differences in brightness decreases. To avoid this, the image is exponentiated with the gamma value. Because gamma correction is applied to the entire image, it can create unwanted saturation or dark areas depending on the exponentiation value. To avoid these situations, adaptive gamma correction (AGC) [10] has been proposed. This method uses statistical information about the images to determine the parameters needed to improve contrast.

Retinex theory is an approach that assumes that an image can be decomposed into two components: illumination and reflection [22]. The idea of Retinex theory led to the development of the Single Scale Retinex (SSR) algorithm [13], which uses a single Gaussian filter to estimate the illumination map of the image after decomposing it. However, SSR may not be able to capture all the details in dark images while estimating the illumination map. To address this, researchers have developed the Multiscale Retinex (MSR) architecture [14], which applies Gaussian filters at different scales to the image and combines the filtered results. However, this can cause color distortion and halo effects in the image. To improve this situation, the Multiscale Retinex with Color Restoration (MSRCR) approach [15] approach adds a color factor that processes the R, G, and B channels of the image to restore its color and prevent halos and color distortion.

Deep learning is a type of neural network that consists of multiple layers and different architectures [23]. Research in low-light image enhancement has benefited greatly from the development of deep learning. One of the first deep learning models for low-light image enhancement is the Low-light Net (LLNet) [17]. LLNet uses deep autoencoders, known as Stacked Sparse Denoising Autoencoders (SSDA), to learn the basic characteristics of low-light images and enhance image contrast while reducing noise. Another study, the Multi-Branch Low-Light Enhancement Network (MBLLEN) [18], developed a branched model consisting of three subnetworks designed to extract features at different levels. The Feature Extraction Network (FEM) is the first subnetwork that extracts features at different levels. The Enhancement Module (EM) is the second subnetwork that enhances the extracted features, and the third subnetwork, the Fusion Module (FM), performs multi-branch fusion.

Edge detection is used to detect significant changes in brightness within an image [24]. The information about edges in an image is one of the important features and therefore a topic of research [25]. The importance of edge detection can be observed in its use in various studies such as image segmentation [26] and image recognition [27]. In this study, we aimed to improve the quality of images by enhancing the detail information, which would reduce the loss of content due to lack of detail in low-light images. To achieve this, we conducted experiments by adding edge information to the detail reconstruction block in the GLAD-Net [28] architecture.

The main contributions of our study can be summarized as follows:

- Adding edge information increases the detail of the image, resulting in better visual and numerical results.

- Adding a channel attention mechanism to the edge extraction block preserves the color information.

- The proposed method reduces noise and improves en-hancement on images with higher edge complexity.

Related Work

Low-light images are characterized by low contrast, blur, and high ISO noise [29]. These types of images are often difficult to recognize, and various methods have been developed to improve contrast and brightness while removing noise. One of the earlier approaches was based on histogram equalization. Dynamic Histogram Equalization (DHE) [30] divides the histogram of the input image according to local minima and applies histogram equalization to each image segment. This provides both local and global contrast enhancement in the image, and the result of histogram equalization is with good detail preservation. However, DHE does not preserve the average brightness of the image, which can lead to saturation. To overcome this shortcoming, a method called Brightness Preserving Dynamic Histogram Equalization (BPDHE) [7] was proposed. First, a Gaussian filter is applied to the image histogram. Then, the image is divided into local maxima. This approach preserves the average brightness of the image better. Histogram equalization is applied to each subdivision, and finally, the output image is normalized with respect to the input image to compensate for the effects of the operations on the average brightness. This preserves the average brightness of the image, and results in a contrast-enhanced image. The Contextual and Variational Contrast (CVC) algorithm has been developed by Celik and Tjahjadi [31]. This algorithm uses a histogram-based approach to enhance the contrast of an input image. It creates a 2D histogram of the input image by using the relationship between each pixel and its neighbors. The CVC algorithm works effectively on both gray and color images. It preserves the detail information of the input image while enhancing the contrast of images taken under different lighting conditions. However, it does not fully exploit the relationship between input and output gray level differences. To solve this problem, Lee et al [32] proposed a new contrast enhancement method that uses LDR to control the output gray level differences. They extract 2D histograms with a different approach than CVC. They exploit the statistical information of gray level differences between neighboring pixels of the input image, and use optimization for enhancement at each layer.

Guo et al. proposed the Retinex-based LIME method [33] for low-light image enhancement. This method focuses only on estimating the illumination factor of an image. It estimates an illumination map using the maximum values in the R, G, and B color channels of an image. They propose an algorithm based on the Lagrangian Multiplier (ALM) to enhance this estimated illumination map. Although it has a good performance on image enhancement in low light conditions, the enhanced image has a noise problem. To reduce the noise in the image, Ren et al. proposed Robust Low-Light Enhancement via Low-Rank Regularized Retinex Model (LR3M) [34], which estimates the illumination and reflectance map in the image in a sequential manner. This ranking is done to remove noise from the reflectance map according to the low-rank priority. Xu et al. developed a method that also considers the color of the image, the structure and texture aware retinex model (STAR) [35] generates

structure and texture maps using the exponentiated mean local variance (EMLV) filter. This allows for more accurate estimation of reflectance and illumination components. The unsupervised low-light image enhancement network ZERRIN-Net [36], which focuses on low-light noise removal, consists of the noise estimation subnetwork N-net, the reflection component estimation subnetwork RI-Net. The network DMT-Net [37] consists of several networks: Decoupled-Net to separate the luminance channel into reflectance and illumination, Denoising-Net to remove noise in reflectance, Boosting-Net to improve illumination and reduce halo effects, and Chrominance-Net to reduce chromatic distortion of Cb and Cr channels. The Self-Reference Deep Adaptive Curve Estimation (Self-DACE) network [38] is a two-part architecture consisting of an adaptive curve to improve the brightness of low-light images and a noise removal method to estimate and remove hidden noise in images. Real-low to Real-normal Network (R2RNet) [39] is a Retinex-based network consisting of Decom-Net to decompose the input image into illumination and reflectance components, Denoise-Net to remove noise from the reflectance map and Relight-Net to improve contrast.

The Edge-Enhanced Multi-Exposure Fusion Network (EEMEFN) [40], designed to reduce image noise, correct color distortion, and enhance edge information lost at low illumination levels, consists of two basic networks. It includes a Multi-Exposure Fusion (MEF) module specifically designed to deal with high contrast and color distortion, and an Edge Enhancement (EE) module to enhance and sharpen edge information. This proposed dual network structure aims to provide effective image processing solutions to achieve cleaner and higher quality image results. Zero-Reference Deep Curve Estimation [19], a deep learning-based method, has been developed to enhance low-light images. It finds a Deep Curve Estimation Network (DCE-Net) that estimates an image-specific curve. The estimated curves are used to create an enhanced image by adjusting the dynamic range of the input image on a pixel-by-pixel basis. Fu et al [41] propose Low-light Enhancement Generative Adversarial Network (LE-GAN), an unsupervised method based on Generative Adversarial Network (GAN), which aims to enhance image brightness, remove image noise, and improve color distortion using attention mechanisms. Convolutional Dense Attention Guided Network (CDAN) [42] aims to improve the performance of the architecture by adding convolutional blocks, dense blocks, attention modules, and jump links to autoencoders that aim to enhance low-brightness images while preserving natural colors. Fast and Light-Weight Network (FLW-Net) [43] consists of two relative loss functions with Global Feature Extraction (GFE) and Local Enhancement Network (LEN) subnetworks to remove network noise and preserve structural information.

Edge detection is the process of identifying the boundaries or edges of objects in an image. In image processing, edge detection is a critical preprocessing step because edges provide valuable information for determining the shape, size, and position of objects. Edge detection plays an important role in several computer vision applications, including image segmentation, object recognition, medical imaging, and visual saliency generation [44]. The Canny edge detection algorithm [45] is an efficient method that has been widely used to detect edges in images. Various methods are used to extract edge information, such as Roberts [46], Prewitt [47], and Sobel [48]. These methods are used in object recognition and other image processing tasks to emphasize structure in images and to highlight edge information.

With the rapid advancements in deep learning, many new deep learning networks have emerged to solve problems in computer vision. One such architecture is U-Net, which has gained prominence due to its unique design that caters to medical image segmentation. The U-Net architecture is characterized by its U-shaped structure and the inclusion of contextual information, which makes it fast and efficient [49]. It is designed to work with limited data usage, which is a significant advantage. The architecture comprises network convolution and inverse convolution layers arranged symmetrically. Each convolution layer is followed by a ReLU activation function and a maximum pooling process. The inward shrinking structure inside this symmetric structure creates a bottleneck that contains all the essential features of the image. This particular design ensures that efficient results can be achieved even with less data [50].

There are several studies that use the U-Net architecture for low-light image enhancement. One of these studies, the Kindling the Darkness (KinD) network [51], aims to both remove noise and accurately enhance the color information of the image while illuminating an image taken under low light levels. It performs the training process with three networks: a decomposition network, a reflectance restoration network, and an illumination adjustment network. The reflectance restoration network, based on the U-Net, consists of 10 convolutional layers. Each double convolution is followed by maximum pooling. Another study by Jiang et al. [52] developed a self-regulated low-light image enhancement architecture that aims to prevent image chromatic aberration. This architecture includes a reflectance estimation network. This network is based on the U-Net. It consists of 19 convolutional layers, four subsampling steps, and four upsampling layers. This work includes several network models that focus on low-light image enhancement using the U-Net architecture and achieve impressive results.

The LAU-Net [53] is an advanced network that is integrated with the U-Net and consists of three main components: the Parallel Attention Unit (PAU), the Internal Resizing Module (IRM), and external convolutional layers. The PAU uses attention mechanisms at the end of the encoder blocks to extract important features from both spatial and channel dimensions. The IRM facilitates the flow of information by creating long jump connections within the network, while the external convolutional layers help reduce noise in the input image. On the other hand, the AFDNet [54] is based on the U-Net architecture and has an Adaptive Frequency Decomposition (AFD) module that adaptively extracts low frequency information for contrast enhancement and noise reduction, and low and high frequency information for detail recovery. The Laplacian pyramid in the
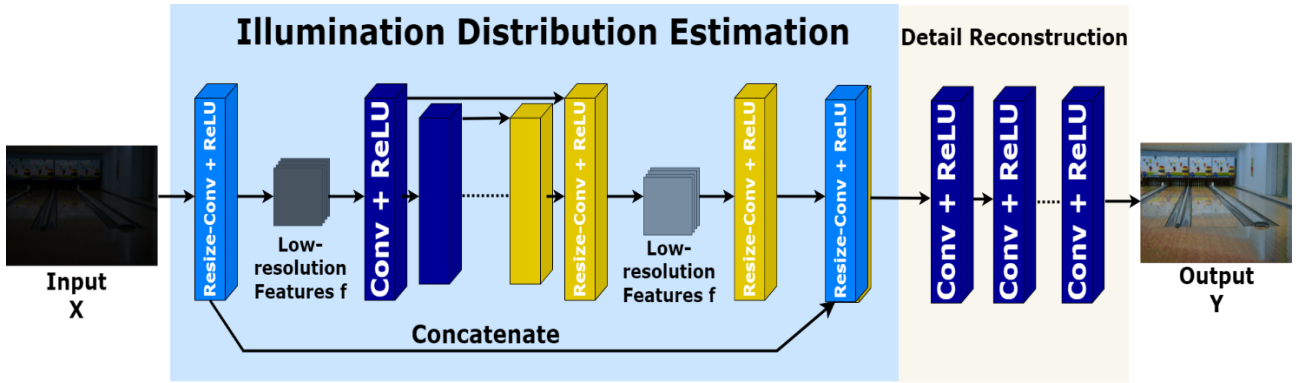
Figure 1. GLADNet architecture [28].

network increases the width of the feature, which strengthens the connection between the encoder and decoder and guides the recovery of image details.

Proposed Method

The GLADNet [28] architecture is an image enhancement method that first uses a global illumination distribution estimation network and attempts to estimate the illumination map of the image. It then combines this estimated map with the input image. This combined image is the input image to the detail reconstruction network. The network is designed to extract the details from the dark image content. The architecture of GLADNet is shown in Figure 1. The edge information of the components in an image is the detail information of the image. It is a very difficult task to extract the edge information of objects in a dark image while illuminating it. While the GLADNet architecture illuminates the content of an image, we propose an additional integrated network to further sharpen the fine details in the texture of the image and the edge information it contains. This specialized network, shown in Figure 2, learns the edge infor-

low-light image enhancement. The model adapted from GLADNet is shown in Figure 3.

The architecture of GLADNet [28] consists of two main parts. The first part, Global Illumination Distribution Estimation, contains the network that performs the illumination estimation of the image. The second part, Detail Reconstruction, is used to recover detail information. First, the input image is resized to 96x96 using nearest neighbor interpolation. This is followed by a ReLU activation function and a downsampling layer. The image is then passed through a network of encoders and decoders. This network consists of 5 downsampling and 5 upsampling networks. Each convolution layer has two steps with a kernel size of 3x3. The ReLU activation function is used in each layer. The resizing size and receptive area of each layer are adjusted to ensure full coverage of the bottleneck layer.

Each downsampling layer is connected to the corresponding upsampling layers by jump links. During the reconstruction phase, the focus is on recovering details. The details may be lost during the illumination estimation of the
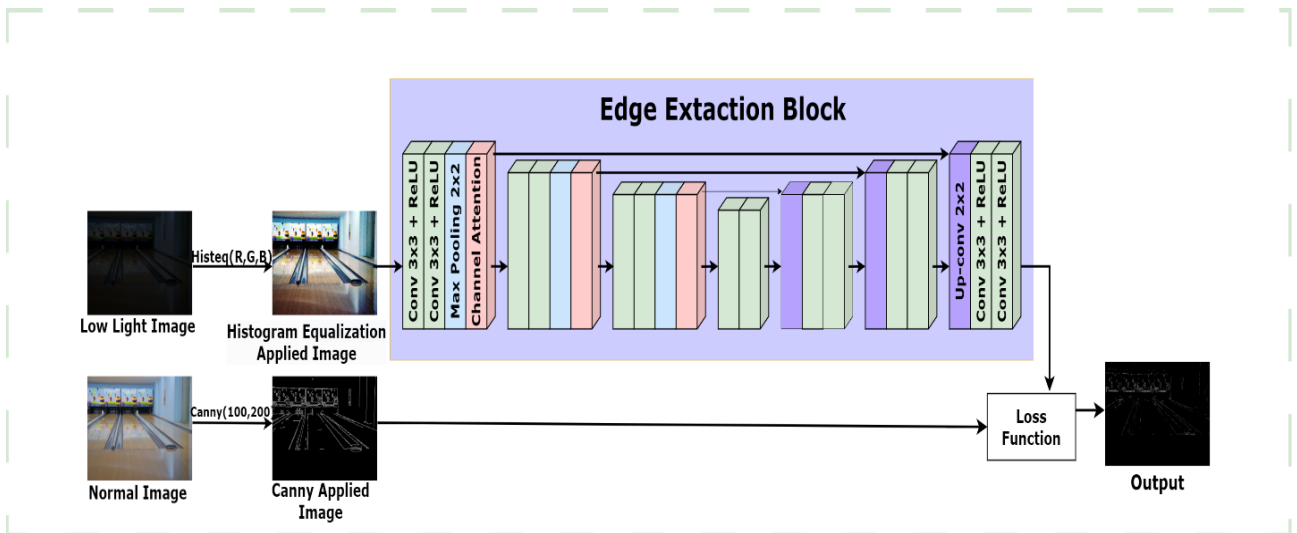

Figure 2. The proposed Edge Extraction Block.

mation within the image itself. The results of this network are fed into the detail reconstruction network and combined with the results of the GLADNet network. This integration increases the strength of GLADNet and its effectiveness in

reconstructed image. Therefore, the original image is considered to have more detail information than the generated prediction result. Both the estimated image result and the
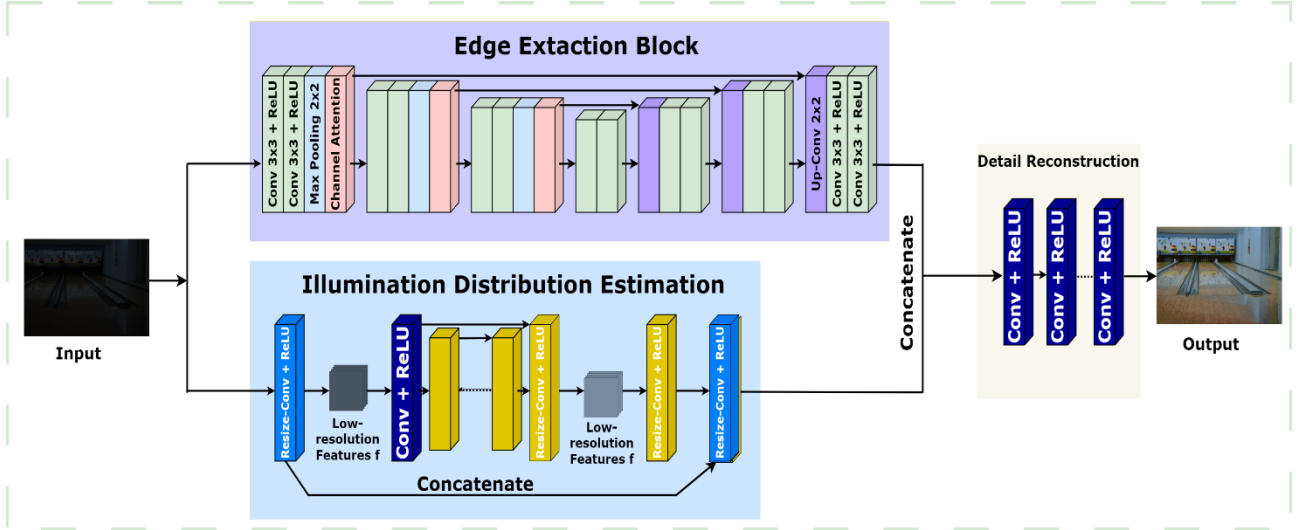
Figure 3. The proposed approach modified from GLADNet [28].

original image are merged. Then, three successive convolution layers are applied to the merged image. In the proposed method, we applied 5 convolutional layers. In these layers, the ReLU activation function and the number of steps are set to 2, and the L1 norm is used as the loss function.

Our Approach

The proposed method is designed to increase the detail information in the reconstruction phase by focusing on the edge information of objects in the image. The proposed Edge Extraction Block (EEB) is shown in Figure 2. The EEB unit consists of encoders and decoders, gets a histogram equalized low light image as input, and the decoder side compares the results with the Canny [45] edge information of the ground truth image. This network consists of 8 convolution layers to focus on learning the object edge information of the low-resolution image. Each pair of convolution layers is connected to the corresponding upsampling layers by skip connections. In addition, after the first three double convolution layers, the channel attention module (CA), one of the attention mechanisms used in the work of Zamir et al. [55], is employed. The CA mechanism generates more salient edge information by making the network focus on more important channels.

The edge information obtained as a result of the encoder and decoder was used as input for the reconstruction stage by combining the detailed original image with the predicted edges. The Binary Cross Entropy Loss function was used for this network. The proposed approach ensured the preservation of details.

Experiments

The proposed model is trained using two different datasets, low-light matched (LOL) dataset [60] and RAISE [61]. The LOL dataset consists of 500 images with 585 for training and 15 for testing. The RAISE dataset is a synthetic dataset of 1000 image pairs, and the exposure value is adjusted using the Adobe Lightroom photo editing program by modifying Highlights, Shadows, Vibrance, Whites.

These settings are adjusted so that the histogram of the Y channel of the image matches the result.

In this study, to assess the effectiveness of the proposed approach, we utilized five metrics. Three of these metrics used reference images: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Feature Similarity Index (FSIM). The remaining two metrics were used for non-reference images, namely Natural Image Quality Evaluator (NIQE) and Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE).

PSNR (Peak Signal to Noise Ratio) [56] is a commonly used metric for assessing the quality of an image. This metric measures the similarity between the original image and the reconstructed or compressed image in terms of pixel values. It evaluates how well the reconstructed image preserves the details and characteristics of the original image.

$$PSNR = 10.log_{10}(\frac{MAX^2}{MSE}) \qquad (1)$$

Where MAX is the maximum signal level and MSE is the mean squared error. A mean squared error (MSE) is the average square of the difference between the processed image and the reference image. It is computed by the following formula.

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(f_{ij} - g_{ij})^2 \qquad (2)$$

Here, i and j are the pixel positions of image M multiplied by image N.

The SSIM (Structural Similarity Index) [56] is a metric that measures structural similarity by taking subsections from an image to compare the similarity between two images. This metric evaluates the similarity between images by considering factors such as color and contrast. It is computed by the following formula.

$$SSIM (f,g) = [l(f,g)]^\alpha. [c(f,g)]^\beta. [s(f,g)]^\lambda \qquad (3)$$

Here, f and g represent the input and target images, respectively. I(f,g), c(f,g) and s(f,g) respectively represent the

Figure 4. Visual results. The abbreviations of EEB, CA, and GT namely stands for Edge Extraction Block, Channel Attention, and Ground Truth.

illumination of the image, the contrast of the image and the structural difference of the image, and α, β, λ are positive constants. Each component is calculated by the formulas given below.

$$l(f,g) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} \tag{4}$$

$$c(f,g) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} \tag{5}$$

$$s(f,g) = \frac{2\sigma_{xy}\sigma_y + C_3}{\sigma_x\sigma_y + C_3} \tag{6}$$

Here, $\mu_x\mu_y$ is the average brightness of the target image with the input image. $\sigma_x\sigma_y$ is the standard deviation of the brightness between the input image and the target image. σ_{xy} is the covariance between the input image and the target image, and C1, C2, C3 are constants.

The Feature Similarity Index Matrix (FSIM) [57] takes out two attributes, Phase Congruency (PC) and Gradient Magnitude (GM), to evaluate the image quality, and makes an evaluation according to these properties. The formula is given below.

$$S_L(x) = [S_{PC}(x)]^\alpha \cdot [S_G(x)]^\beta \tag{7}$$

Where PC is the phase compatibility and GM is the gradient magnitude. The α and β parameters determine the relative importance of the PC and GM properties. The PC and GM formulations are given below.

$$GM(x) = \sqrt{Gx^2 + Gy^2} \tag{8}$$

Here Gx refers to the horizontal gradient of the image, Gy to the vertical gradient of the image.

$$S_{PC} = \frac{2PC_1PC_2 + T_1}{PC_1^2 + PC_2^2 + T_1} \tag{9}$$

Here, T1 is a positive constant that increases the stability of the S_{PC}. The S_{PC} range is from 0 to 1.

The Natural Image Quality Evaluator (NIQE) [58] is used as a completely blind, non-reference evaluation measure for properties derived from the statistical properties of undistorted natural images. The Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) [59] is a blind, non-reference image quality evaluation metric based on natural scene statistics. BRISQUE is an index that measures the quality of an image close to the image quality perceived by the human eye. This index uses a feature-based approach to assess image quality and can operate without the need for a reference image.

Table 1. The quantitative experiments.

Base	EEB	CA	PSNR (↑)	SSIM (↑)	FSIM (↑)
✓			16.5925	0.6503	0.8184
✓	✓		16.7298	0.6619	0.8190
✓	✓	✓	**16.9710**	**0.6629**	**0.8267**

Table 1 shows that the results with the Edge Extraction Block added to the proposed architecture perform well when compared to the GLADNet results. With the addition of the Channel Attention (CA) block to the proposed Edge Extraction block, it is found that the color matching in the image is further improved. In Figure 4, a low-light image was given to different architectures and specific regions were cropped to show the visual results. When the cropped images were examined, it was found that the visual result produced by the inspired architecture was not very similar to the target image. However, when an edge extraction block was added to the architecture, the detail in the cropped image increased. By further adding channel attention to the proposed edge extraction block, the produced image color became even closer to the target image.
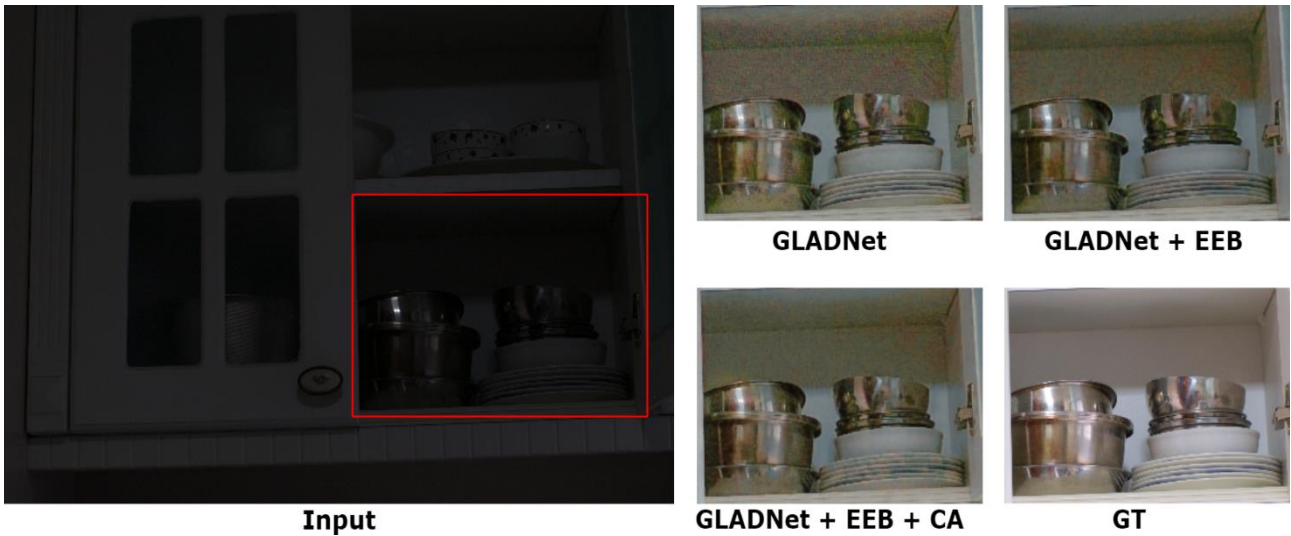
Figure 5. Visual results. The abbreviations of EEB, CA, and GT namely stands for Edge Extraction Block, Channel Attention, and Ground Truth.

In Figure 5, the base model shows noise, while the proposed architecture with edge extraction block shows less noise. By adding channel attention, even better noise removal is achieved.

We compared our proposed method with state-of-the-art methods on the LOL dataset and presented the results in Table 2. Our method outperformed the compared methods.

Two test images were used to measure the effectiveness of a proposed model. The aim was to determine whether the proposed model performed better on complex or flat images. This was done by calculating the number of edge pixels in both images. The image with the higher number of edge pixels was considered complex, while the image with a lower sum of edge pixels was considered flat. To calculate the edge pixels, the Canny algorithm was applied to both images. The normal bright image, represented by

Figure 6. Complexity of images based on edge information.

"a" in Figure 6, had 16.228 edge pixels. The image containing "c" had 10.424 edge pixels. When the proposed models were tested using the PSNR metric, the GLADNet architecture produced a result of 18.8204 on the complex image. The proposed edge block resulted in a score of 21.1139, and when the channel attention mechanism was added to the edge blocks, the result was 21.2802. This represents a 13.1% increase in performance for the proposed architecture.

Table 2. The performance comparison of the proposed method with state-of-the-art methods.

Method/Metric	PSNR (↑)	SSIM (↑)
Histogram Equalization	14.5414	0.4664
RetinexNET [60]	14.9281	0.4896
SSIENet [62]	15.4248	0.6562
Kind [51]	16.1909	**0.7090**
Ours	**16.9710**	0.6629

Two photos were taken in the evening, when it was getting dark, and in a room with artificial light. The proposed architectures were successively applied to these photographs. The images were compared numerically with the NIQE and BRISQUE metrics since they did not correspond to the reference image with normal lighting. Looking at the numerical results of the images taken in Figure (7) Indoor and Figure (8) Outdoor in Table (3), the BRISQUE value is good when the EEB is added to the proposed interior architecture. Both the NIQE and BRISQUE values were better when the proposed architecture was added to EEB with CA, while in the outdoor environment, the value was better when EEB and CA were added. When the visual results are

examined, we can see that the color and edge information are preserved both in the indoor and outdoor environments.

Table 3. Numerical comparison of indoor and outdoor images captured from real-world environments.

	Method/ Metric	NIQE (↓)	BRISQUE (↓)
Outdoor Scenes	GLADNet	3.9537	25.9353
	GLADNet+ EEB	4.1320	**19.2600**
	GLADNet+ EEB + CA	**3.8555**	22.8995
Indoor Scenes	GLADNet	6.4291	33.4529
	GLADNet + EEB	5.5562	39.7556
	GLADNet + EEB + CA	**5.3216**	**32.5379**

Figure 7. Effects of the proposed method on real-world indoor scenes.

Running Time Comparison

In order to determine the running time of the proposed method, we ran each model ten times and calculated the average running time. The average running times for both the based and the proposed models are presented in Table 4. It is worth noting that the inclusion of EEB and channel attention resulted in a slight increase in the running time.

Table 4. The comparison of running times.

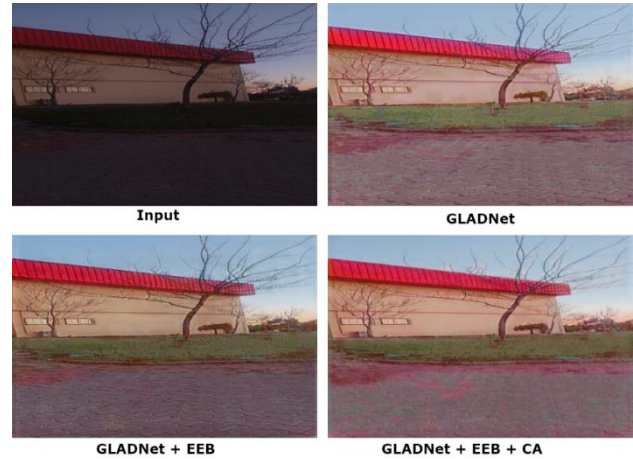| Method	Average Working Time
GLADNet	**0.1552**
GLADNet + EEB	0.1570
GLADNet + EEB + CA	0.1574

Figure 8. Effects of the proposed method on real-world outdoor scenes.

Configurations

We used the same Adam optimization method as in the original study. As set up, each mini-group contains 8 image pairs. It starts training with a learning rate of 1e-3 and is adjusted every 100 mini-group passes by multiplying this rate by 0.96. The model was trained for exactly 50 epochs. For the edge information extraction network, we used the Adam optimization method. This network was trained for 250 epochs. We used TÜBİTAK TRUBA infrastructure to train the proposed method.

Conclusion

Edge information improves the image. It organizes the image away from blurring, extracts the edge information of objects in the image, and increases the saliency of objects in the image. In this regard, it has been the subject of interest in many studies. In this study, we have developed a network that captures the edge information of the image, which we believe will be effective in increasing the image detail. This improves the original model and makes it easier to increase the detail information of the image while brightening it. Due to inadequate camera equipment and environmental conditions, images may have been taken in low-light conditions. Inadequate lighting can have the effect of obscuring some areas of the image content or the entire image. In this study, an edge information extraction network is added to an architecture that has been developed for image enhancement in low light conditions. The goal of this network is to capture the fine texture and sharp edge information of objects in the image in detail while the image is illuminated. Since we have a limited image dataset to train this network, we used the U-Net architecture, which gives good results on small datasets. Histogram equalization was applied to the low-light image to reveal the details in the image. The edge information of the target image was detected using the Canny detector. In the U-Net architecture, the edge information of the low-light image with histogram equalization is learned by targeting the edge information of the target image. This network, called the edge information extraction

network, aims to illuminate the image by preserving more detailed information. The detail reconstruction network of the GLADNet architecture is combined with the result of the edge information extraction network. This result is added to the reconstruction detail information recovery network. The experiments show that we achieved high PNSR, SSIM, and FSIM metrics, and the results are close in color to the target images. Similarly, lower results were obtained for NIQE and BRISQUE values in the non-reference metric measurements. The complexity test we applied and there is less runtime difference by adding the EEB block. Conducted experiments also showed that the added edge information improves more on complex images. When we model the low-light image from everyday life, we see a visual and numerical improvement. As a future work we plan to use attention mechanisms to improve illumination of the low-light images.

Acknowledgement

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