ISSN 2616-5775 Vol. 6, Issue 2: 104-108, DOI: 10.25236/AJCIS.2023.060214

Research on Low-Light Enhancement of Eye Image Dataset Based on DLN

Dengjie Deng[1,*], Jiahui Yang[2]

[1]Chongqing Metropolitan College of Science and Technology, Chongqing, 402160, China
[2]College of Information Science and Engineering, Shandong Agricultural University, Taian, China, 271001
[*]Corresponding author: Pariston1952@163.com

Abstract: *Image acquisition system in the process of image acquisition, due to the influence of various uncontrollable factors, especially under adverse conditions such as indoor lighting and individual cases, image acquisition system often has a low contrast ratio, low dynamic range intensity, dark and bright areas of the image details disappear and other defects. Therefore, it has become a problem to obtain a clear image under the condition of finding the function. In this paper, Deep Lightening Network technology is used to analyze eye images under low-light conditions. Different from traditional methods, this method introduces machine learning method to generate enhanced images using learning models. Through experimental verification and comparison, the proposed algorithm can improve the overall brightness and contrast of the image. Based on 485 eye images, compared with two conventional lighten methods, the average PSNR score was 18.2420dB, and the SSIM score was 0.8011. Compared with the second best method, the PSNR and SSIM are improved by 2.02 and 0.01 respectively. Reduce the influence of uneven illumination, improve image quality and sharpness.*

Keywords: *Image processing; Low-light image enhancement; Convolutional neural network; Deep learning*

1. Introduction

In recent years, the processing of image data sets characterized by large capacity such as graphics, images and videos has been widely used in medicine, transportation, industrial automation and other fields. Image acquisition system In the process of image acquisition, due to the influence of various uncontrollable factors, especially under adverse conditions such as indoor lighting and individual conditions, image acquisition system often has defects such as low contrast, low dynamic range intensity, and the disappearance of details in light and dark areas of the image. Therefore, how to obtain a clear image under the condition of finding the function becomes a difficult problem.

In order to improve the fundus image to achieve better identification and clarity, so that ophthalmol doctors can better judge the patient's specific eye physiological conditions. Common methods include linear enhancement, mask enhancement technology, histogram equalization method and its improved method, Retinex model-based enhancement method, bilateral filtering algorithm based enhancement method and dark channel prior theory based enhancement method, etc.

In this paper,Deep Lightening Network technology is used to analyze fundus images under low light conditions. Different from traditional methods, this method introduces machine learning methods and uses the learning model to generate enhanced images. Through experimental verification and comparison, the proposed algorithm can improve the overall brightness and contrast of the image, reduce the influence of uneven illumination, and improve the quality and clarity of the image. Information extracted from shallow layers has detailed local information (such as edges and textures), while depth has a large sensory field and more global features (such as complex textures and shapes) can be obtained [1].However, cnn has more convolutions and complex structures to obtain more powerful learning capabilities[2][3][4].

2. Related Work

Histogram equalization method was proposed in 1987, which can change the gray value of the input image point by point. The mainstream method used in the early stage of low noise image enhancement

ISSN 2616-5775 Vol. 6, Issue 2: 104-108, DOI: 10.25236/AJCIS.2023.060214

is histogram equalization, but the enhanced image has serious details loss, color distortion, noise increase and other problems.

Image masking technology uses selected images, graphics or objects to block the processed image to control the area of image processing or processing. The mask operation recalculates the value of each pixel in the image according to the mask matrix to improve the image contrast and brightness.

Linear enhancement does not consider the reasons for the degradation of image quality, only the features of interest in the image are selected to highlight, and the attenuation of unwanted features, its purpose is mainly to improve the image intelligibility. The disadvantage is that there will be different requirements in different scenes, and it is necessary to manually adjust the contrast and brightness of the image.

Convolution Neural Networks (CNNS) have achieved impressive results on many tasks such as image classification[5], semantic segmentation[6], super-resolution[7], object detection[8] and more.In this paper, a novel CNN structure (i.e., Deep Lightening Network (DLN)) is used in the iterative processing of images.

3. Method

In this paper, a novel CNN structure (i.e., Deep Lightening Network (DLN)) is used in the iterative processing of images.

3.1 The interactive low-light enhancement

We solve the low-light enhancement problem by estimating the residual between low-light and normal-light images through a residual learning model. The model has an interactive element that controls the power of weak light enhancement.

3.2 Deep Lightening Network (DLN)

Figure 1 illustrates that our proposed method consists of three parts: shallow feature extraction, illumination backprojection (LBP) block, and illumination process. The DLN takes the low-brightness image as input. Enter the shallow feature extraction part consisting of two convolutional layers (Conv.*2 on the left of Figure 1), where each layer has 64 3 × 3 filters with a step size of 1 and padding of 1. Then, multiple LBP (with Feature Aggregation (FA) module) algorithms start to perform cumulative enhancement on the low-brightness image. The bright-up process then receives the result of LBP and estimates the residual of the common brightness image (Conv.*2 on the right of Figure 1) through two convolutional layers. Filter size 3*3, step size 1, padding 1). Finally, the residual was enhanced by adding the interaction factor. Comprehensive experiments are conducted to compare our DLN with several state of the art methods. The results show that our proposed DLN outperforms all other methods in terms of both subjective and objective measures.

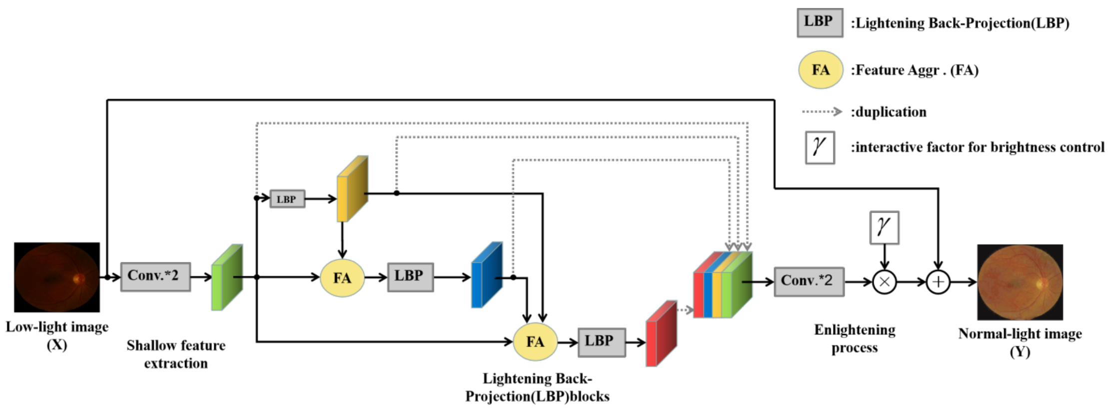

Figure 1: Architecture of Deep Lightening Network (DLN).

3.3 Lighten the BP

Based on the back-projection theory (as shown in Figure 2), a low-light (LL) image (D, see left green

ISSN 2616-5775 Vol. 6, Issue 2: 104-108, DOI: 10.25236/AJCIS.2023.060214

arrow in Figure 2) can be obtained from its normal-light (NL) version (Y) by performing a darkening operation (X). The purpose of LL augmentation is to find a lightning operation (L_1) that predicts the NL image ($Y \in R$ H×W×3) from the observed LL image (X) (see the red arrow at the top in Figure 2). If brightening (L_1) and dimming (D) were operated in an ideal situation, the ground truth (X) and estimated ($\tilde{X}$)LL images would be the same. In the real case, their difference ($R_{LL} \in R$ a residual term H×W×3, for $R_{LL} = X + \tilde{X}$) indicates the weakness of the bright (L_1) and dark (D) operations. Based on the residual information (R_{LL}), it is possible to estimate the residual ($\tilde{R}_{NL} \in \mathrm{R}$ H×W×3), as $\tilde{R}_{LL} = Y + \tilde{Y}$) in the NL domain by a brightening operation (L_2). Finally, the residual $\tilde{R}_{NL}$ is added to the $\tilde{Y}$ mid-refined intermediate NL estimate ($\tilde{Y}$), that is $\hat{Y} = \tilde{Y} + \tilde{R}_{NL}$, where $\hat{Y} \in \mathrm{R}$ H×W×3 is the refined NL estimate.

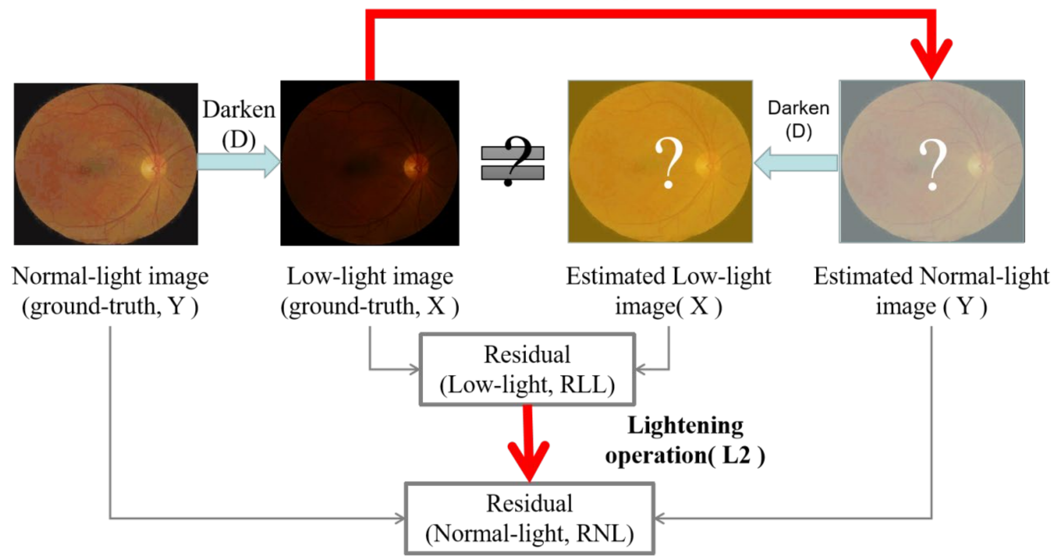

Figure 2: Relation between the low- and normal-light images.

3.4 Feature aggregation (FA)

As shown in FIG. 1, DLN has multiple short connections between LBPS that can propagate features from the former to the latter. To use features more effectively, we propose a Feature aggregation (FA) block to enhance feature representation based on multiple intermediate results. Figure 1 to the left of the first FA block has two inputs that fuse information from the two feature maps, and the second FA block to the right fuses the three input feature maps.

4. Result

In order to improve the performance of fundus images, in the experimental test data set of this paper, there are 485 images in the test set and 15 in the validation set, which mainly contain fundus image data under various conditions and lighting conditions.

The hardware environment of this paper is model i7-11370, frequency 3.30GHz processor, 16GB memory. Due to the GPU acceleration of image processing, the experiment uses the GPU model RTX 3050, and the comparison experiments are completed on pycharm2021 and matlab2020a. The lack of objective evaluation methods for light condition measurement makes it difficult to evaluate the performance of different low light enhancement methods. We believe that the enhanced LL image should be close to the real NL image. Therefore, we adopt Peak Signal-to-Noise Ratio (PSNR) and Structure Similarity (SSIM), which are widely used in the field of image restoration, to measure the quality of the estimation.

The experiment is mainly divided into two parts. One is batch brightening the fundus image data set with depth illumination network, and other methods (binary Mask and linear enhancements) are used to brighten the fundus image data set. Second, the results of the brightened images obtained by different methods are compared with the original images, and the corresponding PSNR and SSIM data are obtained(as shown in Figure 3).

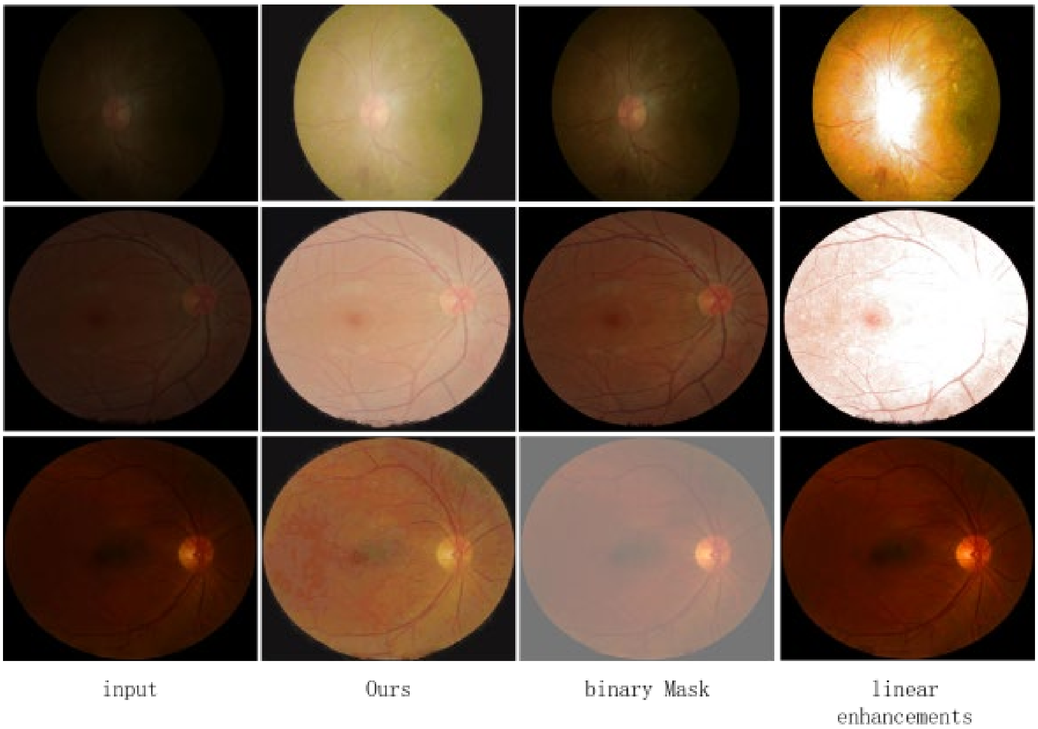

Figure 3: Comparison of experimental results of different lightening methods

The evaluation on real datasets compares DLN with existing methods and the results are shown in the table(as shown in Table 1). It can be concluded from the table that the DLN method achieves the best performance in both PSNR and SSIM, with an average PSNR score of 18.2420dB and a SSIM score of 0.8011, which is 2.02 and 0.01 higher than the second best method linear enhancements in PSNR and SSIM. The results show that the proposed DLN method has good brightness enhancement ability and achieves the best low-illumination enhancement results among all the comparison methods.

Table 1: PSNR and SSIM values of the results of different brightening methods

Method	Ours	binary mask	linear enhancements
PSNR	**18.24201367**	**12.19104719**	**16.20143892**
SSIM	**0.801189141**	**0.562260878**	**0.794978372**

5. Conclusions

In this paper, we introduce our proposed Deep Lightening Network (DLN) for low-light image enhancement. Instead of directly learning the mapping relationship between low-light images and normal-light images in the past, a new Lightening Back Projection (LBP) block was proposed to iteratively learn the difference between low-light images and normal-light images. We compare the performance of the proposed DLN with other methods from both subjective and objective aspects. The numerical results and performance are more accurate and clear.The research will play an important role in eye medical diagnosis, greatly improving the doctor's judgment of the patient's condition. In the following, based on the method used in this paper, we will deeply investigate how to judge the eye health of patients only by relying on AI, especially some details that are not obvious to the naked eye.

Acknowledgements

For the writing of this graduation practice report, I need to thank Mr. Gu most, who has given me full help and support throughout the whole process. Teacher Gu not only patiently gave me the shortcomings of the practice report and valuable suggestions for the improvement of the practice report, but also gave

ISSN 2616-5775 Vol. 6, Issue 2: 104-108, DOI: 10.25236/AJCIS.2023.060214

me Pointers and answers when I met difficulties. On the occasion of the completion of this paper, I would like to express my heartfelt thanks and respect.

References

[1] Lu Deng. Research on Image Recognition Algorithm Based on Deep Convolution Neural Network [J]. Academic Journal of Computing & Information Science, 2020, 3(2).
[2] Shafiq Muhammad, Gu Zhaoquan. Deep Residual Learning for Image Recognition: A Survey [J]. Applied Sciences, 2022, 12(18).
[3] Gao Huang, Zhuang Liu, Laurens Van Der Maaten and Kilian Q Weinberger, "Densely connected convolutional networks," Proceedings, IEEE conference on computer vision and pattern recognition (CVPR), pp. 4700-4708, 2017, Hawaii, United States.
[4] Meihua Wang, Lunbao Chen, Yun Liang, Yuexing Hao, Haijun He, Chao Li. Single image rain removal with reusing original input squeeze-and-excitation network[J]. IET Image Processing, 2020, 14(8).
[5] Convolutional Neural Networks; New Convolutional Neural Networks Findings Has Been Reported by Investigators at Google (ImageNet Classification with Deep Convolutional Neural Networks) [J]. Journal of Engineering, 2017.
[6] Spyros Gidaris and Nikos Komodakis, "Object detection via a multiregion & semantic segmentation-aware CNN model," Proceedings, ICCV, 2015.
[7] Zhisong Liu, Liwen Wang, Chu-Tak Li and Wan-Chi Siu, "Hierarchical Back Projection Network for Image Super-Resolution," Proceedings, IEEE conference on computer vision and pattern recognition workshops (CVPRW), pp. 0-0, 2019, California, United States.
[8] Li Wenze. Analysis of Object Detection Performance Based on Faster R-CNN [J]. Journal of Physics: Conference Series, 2021, 1827(1).