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Deep Learning Employ for Low-Light Image Enhancement

Huda Dhari[1], Prof. Dr. Jameelah Harbi[2]

[1]College of Computer Sciences, Informatics Institute for Postgraduate Studies, Baghdad, Iraq
huda_on_off[at]ymail.com

[2]College of Computer Sciences, Al-Mustansiriyah University, Baghdad, Iraq
dr.jameelahharbi[at]gmail.com

Abstract: ***Images captured under low light situations suffer from low contrast and low visibility which can effect in bad manner on computer tasks to overcome this problem, enhancing low light image needed as pre-processing. This paper is presented a trainable model for low light image enhancing. It is based on multi scale Retinex by using deep learning and convolutional neural network (CNN) algorithm. Public (LOL) dataset has been used to train this model, consisted from 500 colored, low light images. Convolutional neural network bullied-up from eleven layers. SSIM and PSNR has been used to evaluate this model showing that average value of SSIM is (o.8) and average value of PSNR is and (21).***

Keywords: Deep Leaning, Convolutional Neural Network, Low-light image, Retinex

1. Introduction

These days, capturing images become part of our life by using different digital devices, such as smart phones or professional cameras. Images with good quality play main role in computer tasks such as sense understanding and object detection. However, images captured under poor light conditions yield low-light images which suffer from low brightness and noise. Low-light image can effect in bad manner on high-level computer tasks [1]. Therefore, many of method have been developed to deal and enhance such images. Low–light image enhancement process can be considered as pre-processing for high-level computer tasks.

In general, image enhancement can be divided into two types [2]: the first one based on histogram method and the second one on based on Retinex method. There many of versions of Retinex method have been developed such as single-scale-multi-scale and color restoration Retinex. The main short come of this method is that the kernels parameters are depend on artificial setting making this type of method inflexible. Therefore, deep learning and convolution neural network have been used in image processing field [3].

2. Related Work

Numerous methods have been proposed to processing and enhance images by using deep learning and convolution neural network algorithm to enhance images. However, less of them can get sufficient results [4]. For instance, VDSR [5] has been used 20 convolution layers with VGG filters in order to produce good images results. In the other hand, DnCNN [6] uses the same network of VDSR with little difference by adding layers of batch normalization followed the after convolutional layers, to get higher PSNR value, LLNet [7] has been proposed to be use low-light images enhancement, which learn to map between the low light/normal light regions of the input images, SRCNN[8] also, learns to map between end-to-end low/high-resolution images to carry out super-resolution process.

3. Retinex Theory

Retinex theory simulates the human color observation. It assumes that the images can be decomposed into reflectance and illumination components. Let M represent the source image, then it can be indicated by flowing equation:

$$M = R \times I \tag{1}$$

Where R indicates reflectance, I indicate illumination and $\times$ indicate element-wise multiplication. Reflectance represents the intrinsic of captured objects, which is consistent under any lightness circumstances.

The illumination represents the different lightness on objects. In the case of low-light images; it typically suffers from unbalanced illumination distributions and darkness [9]. Multi-scale Retinex proved that it is equivalent to CNN with feed forward propagation with residual structure [2].

4. Proposed Model

The proposed model is trainable model which trained to find the residual image when mapping between the low/normal light images, this known as residual structure. The mapping performed by using CNN with regression final layer to find the mean square error between the low/normal light input images, Then to compute the final enhanced image the residual image added to the original input low-light image. Figure (1) shows residual structure of the proposed model. The model made up of eleven layers each one of them play role in enhancement process. Network architecture of CNN can be is main phase of designing this model. This architecture made up of four main steps, these steps are features extraction, features enhancement, non-liner mapping, and reconstructed. Equation (2) expressed the four main steps of the proposed model.

$$g_4(g_3(g_2(g_1(x)))) \tag{2}$$

Where x is the input image, g_1 is the feature extraction step,

g_2 is feature enhancement step, $g_3$is the non-liner mapping step and g_4 is reconstruction step.

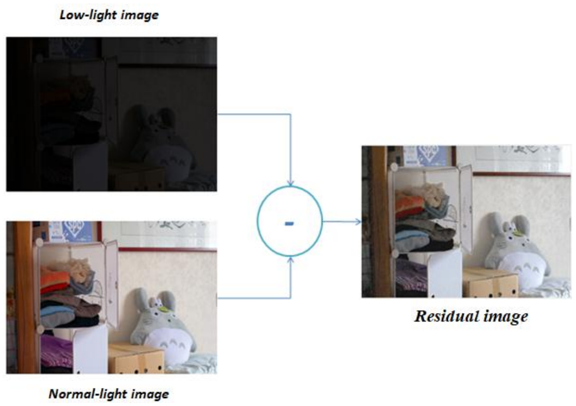

Figure 1: Residual structure of the proposed model.

4.1 Feature extraction

Usually, the first layer of the convolution neural network used for feature extraction from the input images this carry out by using convolution layer with 200 number of filters to get 200 different feature maps from one single input image and the size of the filter kernel is [3×3]. Convolution layer followed by (Relu) which refers to rectified linear unit.

The first step of the proposed model can be express as equation (3).

$$g_1\text{=max } (0,\, A_1 * \text{x} + b_1) \qquad (3)$$

Where max (0, -) is the Relu, A_1 is the weight of the first convolution layer, and $b_1$is bias of the first convolution layer.

4.2 Feature enhancement

After the feature extraction step, it is ready to map between the dark and normal light images. In this model 128 filters have been used in order to create 128 feature maps from the 200 feature maps of the previous layer. The size of the filter kernel is [3×3]. Convolution layer followed by (Relu) which refers to rectified linear unit.

The second step of the proposed model can be express as equation (4).

$$g_2\text{=max } (0,\, A_2 * \text{x} + b_2) \qquad (4)$$

Where A_2 is the weight of the second convolution layer, and b_2 is bias of the second convolution layer.

Then, batch normalization layer has been used to increase PSNR value.

4.3 Non-liner mapping

High dimensional vector from the previous layer has been mapped to anther high dimensional vector this performed by using convolution layer with 32 number of filters and the size of filter kernel is [3x3]. Afterward, convolutional layer followed by Relu. The third step of the proposed model can be express as equation (5).

$$g_3\text{=max } (0,\, A_3 * \text{x} + b_3) \qquad (5)$$

Where A_3 is the weight of the third convolution layer, and b_3 is bias of the third convolution layer.

Then, batch normalization layer has been used to increase PSNR value.

4.4 Reconstruction

Vector with high dimensional generated by the previous layer reconstructed into smaller dimensional vectors with three (channels), this performed by convolution layer with 3 number of filters and with kernel size [3x3]. Afterward, this convolutional layer followed by Relu. The forth step of the proposed model can be express as equation (6).

$$g_4\text{=max } (0,\, A_4 * \text{x} + b_4) \qquad (5)$$

Where $A_4$is the weight of the forth convolution layer, and b_4 is bias of the forth convolution layer.

Figure (2) shows the network architecture of this model with the four steps and Table1 is shows the network parameters.

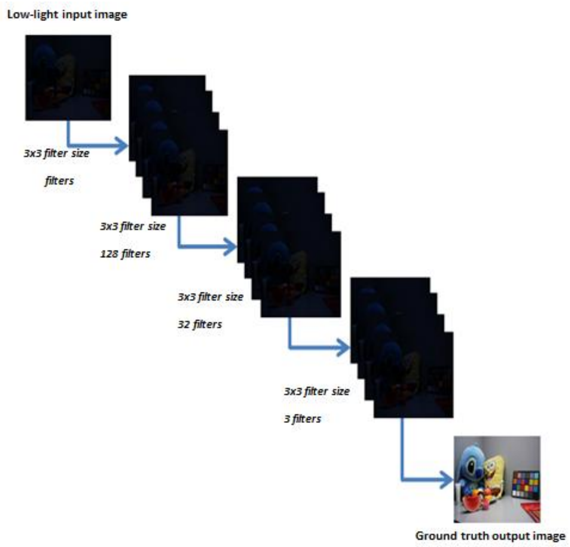

Figure 2: Network architecture.

Table 1: Network parameters

Layer number	Filter size	Number of filter	Bias value
Features Extraction	3x3	200	1
Features Enhancement	3x3	128	1
Non Liner Mapping	3x3	32	1
Reconstruction	3x3	3	1

5. Training

This model network has been trained by utilize the network architecture and parameters, as well using the training dataset. Adam optimizer has been used as optimization algorithm.

Training epoch number of regulate to 400. More number of epochs means longer training time. Training, took nearly two day and half to be train and learn from the input data. The learning rate regulates to 0.01 and it is dropped by value of 0.1rate for each 60 epochs. While, mini Batch Size specified is 128.The training carried by using CPU with and Intel® core_i5 and RAM capacity is 6GB and the operating system is Windows 10 using Matlab program version 2018. Table2 shows few values of training process results.

Table 2: Training process results

No. of Epoch	No. of Iteration	Base Learning	Time elapsed hh:mm:ss	Mini-Batch RMSE
1	1	0.01	00:00:01	2295.21
70	32600	0.001	09:09:26	321.38
120	56200	1.0000e-04	16:19:48	256.31
180	84500	1.0000e-05	25:26:18	327.16
250	117600	1.0000e-06	s35:38:32	203.72
310	146000	1.0000e-07	45:05:29	216.96
400	20000	1.0000e-08	59:09:45	150.69

6. Dataset

Public (LOL) dataset has been used for training and testing processes [3]. This dataset consisted from 500 low/normal pair's images with different senses with image format (PNG). Figure 3 shows public (LOL) dataset some samples and Figure 4 shows how this dataset is dividing.

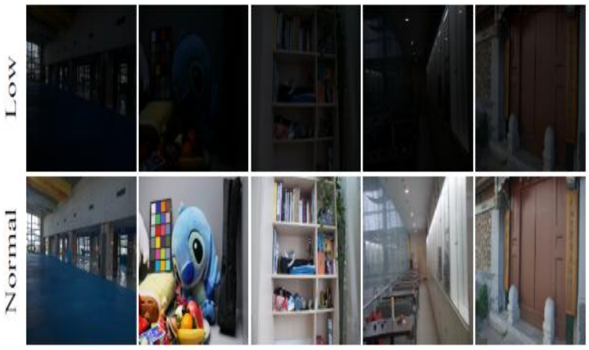

Figure 3: Public (LOL) dataset some samples.

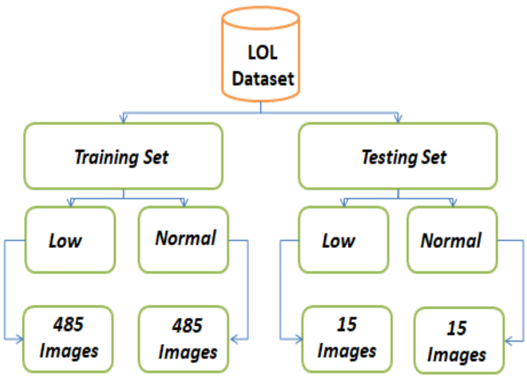

Figure 4: Dataset splitting.

7. Testing

Testing process of the proposed model performed by using testing (LOL) testing dataset which consisted from 15 images to evaluate and progress the trained network performance and compute PSNR and SSIM values for testing images. Figure 5 shows testing results in the testing dataset, and Table 3 shows PSNR/SSIM values results of the images shown in the Figure 5.

Table 3: PSNR/SSIM values results.

	PSNR(dB)	SSIM
Figure 4 (a)	27.29	0.81
Figure 4 (b)	24.7	0.84
Figure 4 (c)	21.8	0.85
Figure 4 (d)	28.75	0.81
Figure 4 (e)	23.8	0.76
Figure 4 (f)	18.4	0.83

Figure 6 shows histograms results of low light, enhanced, and reference images.

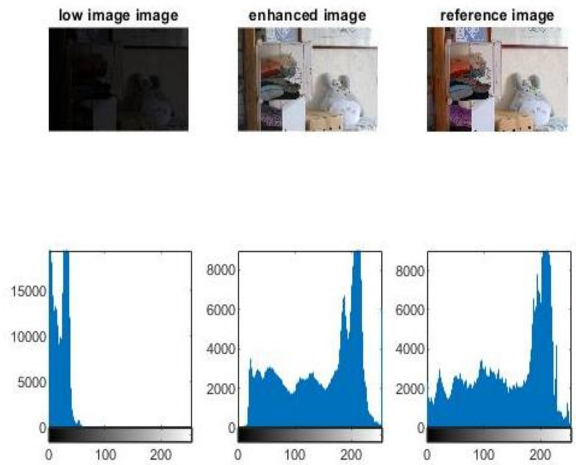

Figure 6: Histograms results of low light, enhanced, and reference images

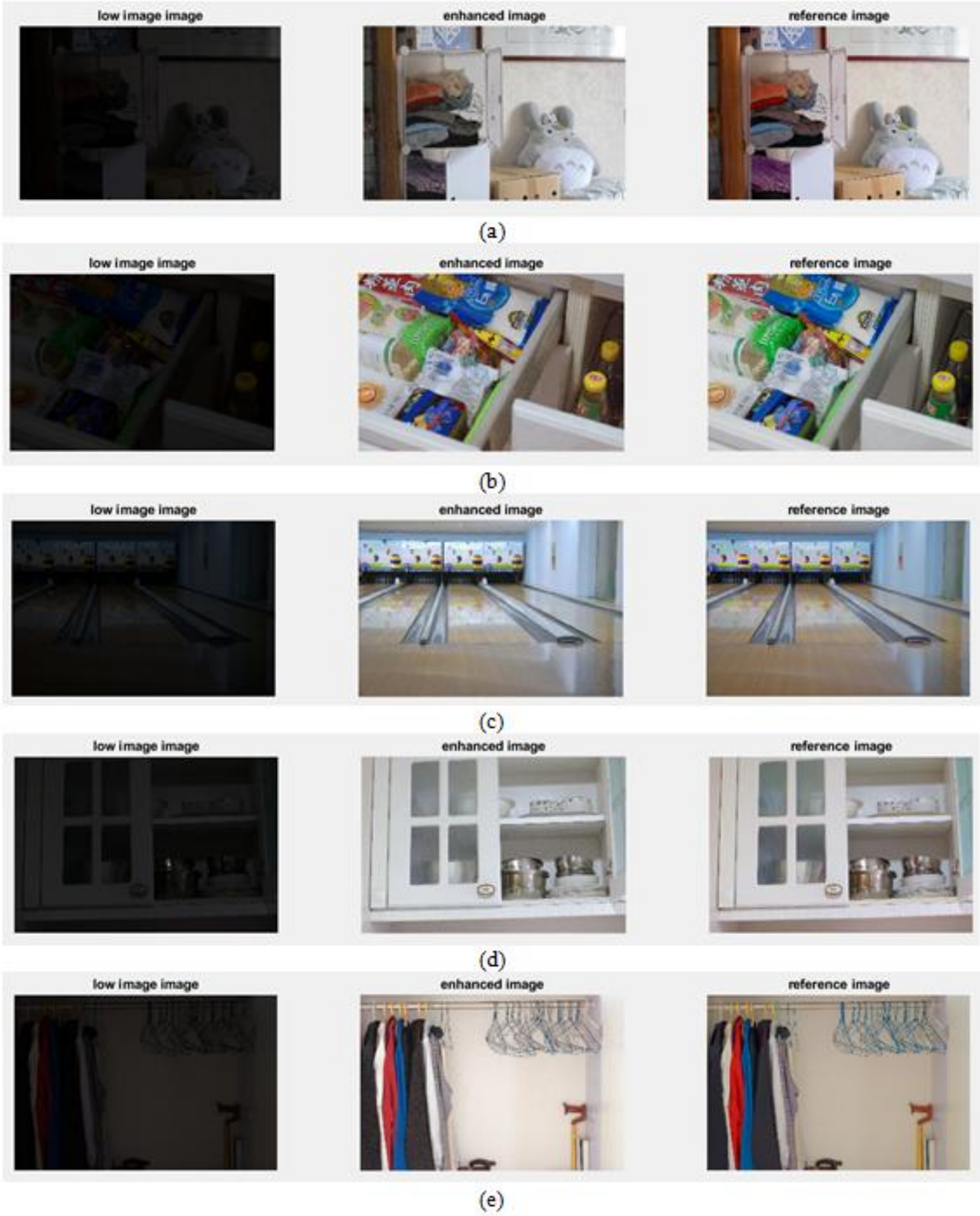

Figure 5: Results of testing process

8. Efficiency Testing

For ensuring proposed model performance, Ex Dark x dataset [10] has been used for efficacy testing. As well, by using images from Google search and reality life images. The results of efficacy test showing in Figure 7.

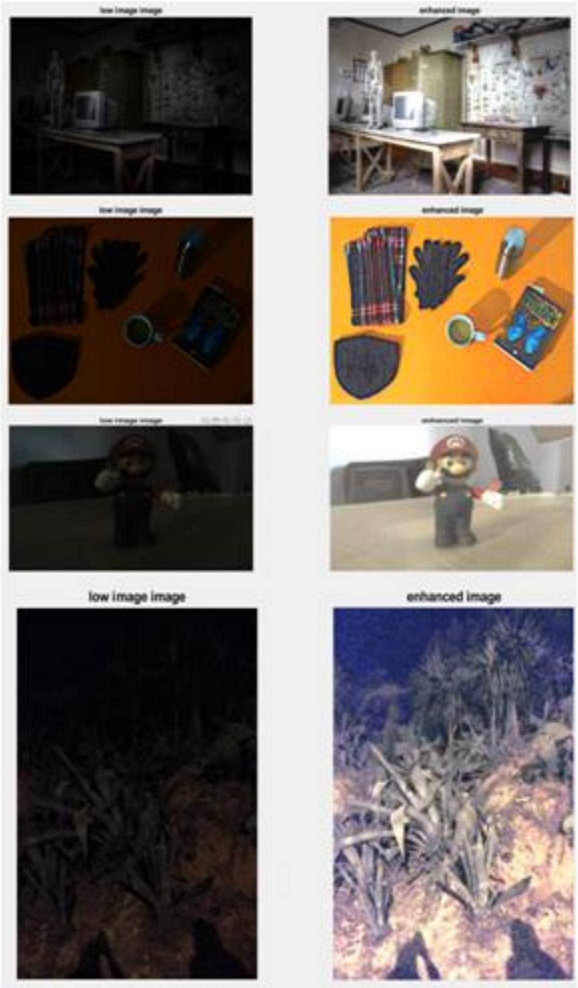

Figure 7: Results of efficacy testing

9. Results Discussion

Comprehensively, the process of the model training and testing is shown in Figure 8. From given testing results of the proposed model, they show that the average value of SSIM is 0.8.While, the average value for PSNR is 21(dB).This model designed and worked without any pre/post processing, meaning that the proposed model worked well.

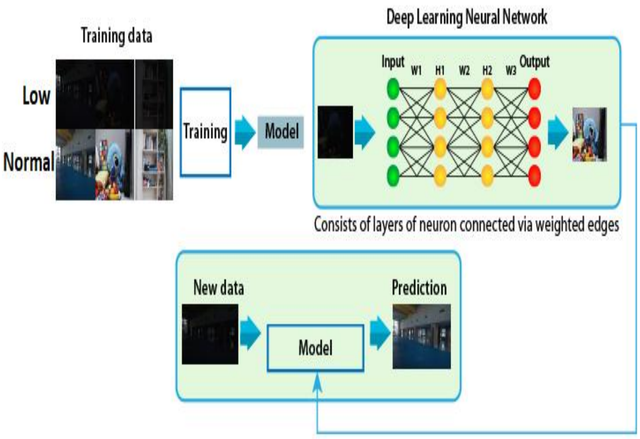

Figure 8: Overall process of the proposed model

10. Convolutions

CNN basically depends on the size of the dataset, also the quality of the dataset is an important issues to have good results .As well as, the performance of the proposed model depend on the depth and the architecture of CNN network**.**

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Author Profile

Huda Dhari was born in Baghdad, Iraq in 1992. She received B.S. degree in Network engineering from Al-Nahrieen University, Baghdad, in 2014. And Higher Diploma in Information Technology / Website Technology from IIPS, Baghdad, Iraq 2016. Where she is currently preparing for the M.S. degree in computer sciences. Her research interests in image processing and deep learning. She is working as Assistant Lecturer at Al-Israa University, Baghdad since 2014.

Prof. Dr. Jameelah H. Saud was born at 1966 in Baghdad. She was graduated from Baghdad Uni. Ph.D. in 2001, from Al-Mustansiriyah Uni. M.Sc. in 1996 and B.Sc. in1989. Her interested in theoretical fields and analysis of; image processing, data compression, digital signal processing, Pattern Recognition, and Multimedia systems. https://scholar.google.com/citations