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# Low-Light Image Enhancement by Using Convolutional Neural Network

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***Abstract*—*Capturing images in various lighting conditions, practically low-light , resulting in images suffer from many issues such as low-contrast, low-visibility and noise, this type of images known as low light image. Low light of images have unpleased feeling when looking at them also they effect badly in the further computer vision tasks. This paper is proposed a model to enhance such images. This model based on multi scale Retinex and deep learning using convolutional neural network (CNN). This trainable model has been trained by using (LOL) dataset which consisted from eleven layer used to enhanced and mapping between the dark and normal light regions in the image. The model has been tested and evaluated by using SSIM and PSNR values, the resulted showed that the average values for SSIM and PSNR are (o.8) and (21) respectively.***

***Index Terms:*** **Convolutional Neural Network, Deep Leaning, Low-light image and Retinex.**

## I. INTRODUCTION

Nowadays, almost every person is interests in capturing images in every single day using various digital devices. The quality and resolution of captured image is essential thing. Therefore, good digital device and lighting are needed. Unfortunately not in all cases of capturing image conditions be perfect to capture an image with high quality. For example, when capturing image under lack of illumination conditions resulted in an image suffer from low contrast, where everything in the image would be a single shade of gray ton with muted color. Low-light image can cause problems in the takes that based on computer vision [1]. So many low-light image enhancement methods have been developed to deal with such problems. In general low-light image methods can be divided into two groups [2]: the first one is Histogram methods, these types of methods resulted in images that look unnatural. The second methods are the Retinex methods. These types of methods decompose the input image into illumination and reflection. Image processing with this type of methods yield images with natural look and makes sure that the texture of the high-light region will be kept [3]. However, Retinex suffered from one problem which it is depend on the artificial setting of the kernels. This makes this method inflexible. In the other hand, because of the fast development of deep learning the researcher have been use deep leaning in the image processing felid by using convolution neural network [4].

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## II. RELATED WORK

Many methods have been proposed using deep learning to enhance images. However, fewer of them can generate ideal results [5].For example, VDSR [6] used VGG filters and 20 convolutional layers to get good results. When DnCNN [7] uses similar VDSR network but they adds batch normalization layers after convolutional layers, to achieves higher PSNR, LLNet [8] is used to enhance low-light images, this method mapped between the low light/high light images, SRCNN[9] this method learns end-to-end mapping between low/high-resolution images mapping to perform super-resolution operations.

## III. RETINEX THEORY

Retinex theory is simulates human color perception by assuming the images can be decomposed into two parts: reflectance and illumination. Let H represent the image, then it can be indicated by:

$$H = R \times I \qquad (1)$$

Where R represents reflectance, I represent illumination and × represents element-wise multiplication.

Reflectance represents the basic of captured objects, which is steady under any lightness situations; while the illumination is represent various light conditions on objects of the images. A low-light image suffers from darkness and unbalanced illumination distributions [4].

Multi-scale Retinex method proved that it is equivalent to feed forward CNN with residual structure [2]

## IV. PROPOSED MODEL

The proposed model is based on multi-scale Retinex. This network designed to find the residual image by finding the mean square error between low/normal-light images using CNN. The final enhanced image can be compute by adding the residual image, which obtained from the convolution neural network, to the original input low-light image. Fig (1) illustrates the proposed model residual structure.

This model consisted from eleven layers connected to each other, As much as the network deeper means that proper perceiving of edges and texture of the input image. Consequently, results of good output image, every layer of them perform its own function in enhancement process. These layers will describe in the next sections. Network architecture can be considered as the main phase of designing the proposed model. The architecture of the proposed model made up of four steps, these can be

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expressed as following equation:

$$F_4(F_3(F_2(F_1(I)))) \qquad (2)$$

Where:

I is the input image, $F_1$ represents the features extraction first step, $F_2$ represents the features enhancement second step, $F_3$ is a non-liner mapping third step, and $F_4$ is reconstructed fourth step.

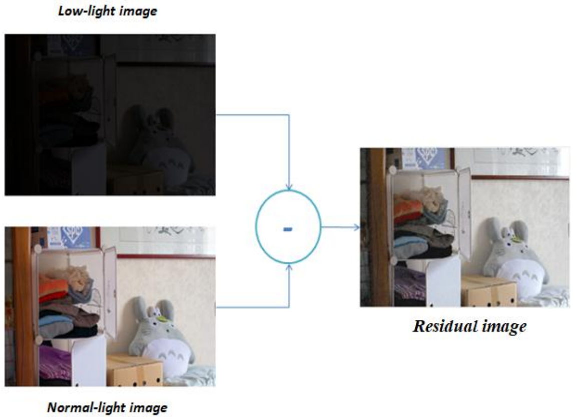


**Fig.1: The proposed model of the residual structure.**

### A. Features Extraction

It is the first step of proposed model architecture, to extract the features from input images. This carried out by using convolutional layer with filter kernel size of [3x3],and filters number are 200 filters , which resulting of 200 various features maps for a single input image. Then following convolutional layer by rectified linear unit (Relu), this can be express by next equation:

$$F_1(I) = Max\ (0, W_1 * I + b_1), \qquad (3)$$

Where Max (0,-) is rectified linear unit, $W_1$ is a weight of first convolutional layer, * is means convolution operation, and $b_1$ is a bias of first convolution layer.

### B. Features Enhancement

By using convolutional layer with kernel size of [3x3] and the numbers of filters are 128, to map the low-light image to normal-light image. Then following convolution layer by rectified linear unit (Relu), this can be express by next equation:

$$F_2(I) = Max\ (0, W_2 * F_1(I) + b_2) \qquad (4)$$

Where $W_2$ a weight of second convolutional layer is, $b_2$ is a bias of second convolutional layer.

To increase PSNR value, we will use batch normalization layer used.

### C. Non Liner Mapping

Mapping between high dimensional and high dimensional vector this carried out by convolution layer with filter kernel size of [3x3], filters number are 32 filters. After that, convolutional layer followed by Relu. This can be express by next equation:

$$F_3(\mathrm{I}) = \mathrm{Max}\ (0, W_3 * F_2(\mathrm{I}) + b_3) \qquad (5)$$

Where $W_3$ a weight of third convolution layer is, $b_3$ is a bias of third convolution layer.

Then to increase PSNR value, batch normalization layer used.

### D. Reconstruction

High dimensional vector from the previous layer reconstructed into three dimensional vectors (channels), this carried out by convolution layer kernel size of [3x3], and filters number are 3 filters. After that, convolutional layer is followed by Relu. This can be express as following equation:

$$F_4(\mathrm{I}) = \mathrm{Max}\ (0, W_4 * F_3(\mathrm{I}) + b_4) \qquad (6)$$

Where:

$W_4$: is a weight of fourth convolution layer, and

$b_4$: is a bias of fourth convolution layer.

Fig.2 illustrates the network architecture and Table1 is show briefly parameters of the network.

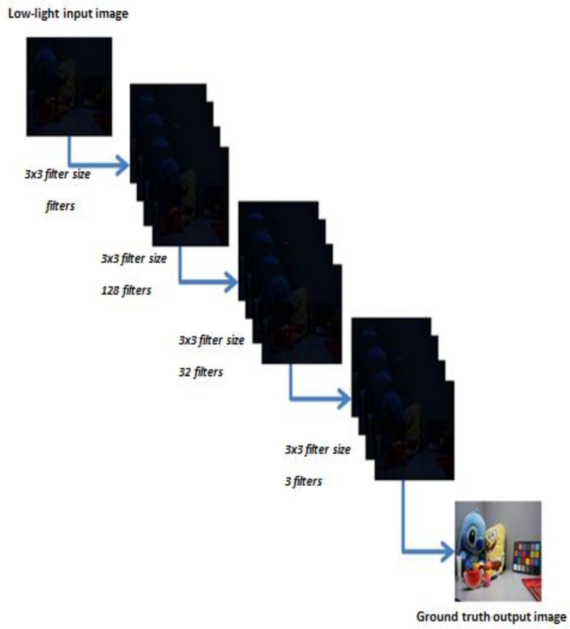


**Fig. 2: The network architecture.**

**Table1: Parameters of the network.**

| 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 |

## V. TRAINING

CNN network has been trained using the defined architecture, and the training dataset. And by using Adam optimizer as one of the optimization algorithm which is widely used in such image issues.

The epoch number of training set to 400. Larger number of epochs, which means longer time for training .This training, took approximately two day and half to be train.

The learning rate is set to 0.01 dropped by 0.1rate for each 60 epochs. The mini Batch Size is 128 and it is trained by using CPU with Intel® core_i5 and RAM 6 GB, and by using Windows 10 operating system with Matlab version 2018. Table2 is showing some values of training root mean square results.

**Table 2: Some values of training root mean square results.**

| Epoch No. | Iteration No. | Time elapsed hh:mm:ss | Mini-Batch RMSE | Base Learning |
|---|---|---|---|---|
| 1 | 1 | 00:00:01 | 2295.21 | 0.01 |
| 70 | 32600 | 09:09:26 | 321.38 | 0.001 |
| 120 | 56200 | 16:19:48 | 256.31 | 1.0000e-04 |
| 180 | 84500 | 25:26:18 | 327.16 | 1.0000e-05 |
| 250 | 117600 | 35:38:32 | 203.72 | 1.0000e-06 |
| 310 | 146000 | 45:05:29 | 216.96 | 1.0000e-07 |
| 400 | 20000 | 59:09:45 | 150.69 | 1.0000e-08 |

## VI. DATASET

This proposed model used public (LOL) dataset [6] for trained and tested. It is consisted of 500 low/normal pair's images. Fig.3 show samples of public (LOL) dataset and Fig.4 shows how this dataset is divided.


**Fig. 3. Samples of public (LOL) dataset.**

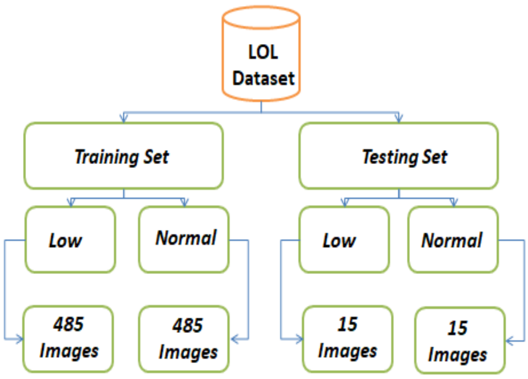


**Fig.4: Dataset dividing**

## VII. TESTING

The proposed model has been tested by using testing data set of the (LOL) has which consisted of 15 low/normal light pairs images to evaluate and the trained network by determining PSNR and SSIM values. Fig.5 illustrates testing results, and Table3 shows SSIM/PSNR values for the images shown in the Fig.5.

**Table 3: SSIM/PSNR values**

| | SSIM | PSNR(dB) |
|---|---|---|
| Figure 4 (a) | 0.81 | 27.29 |
| Figure 4 (b) | 0.84 | 24.7 |
| Figure 4 (c) | 0.85 | 21.8 |

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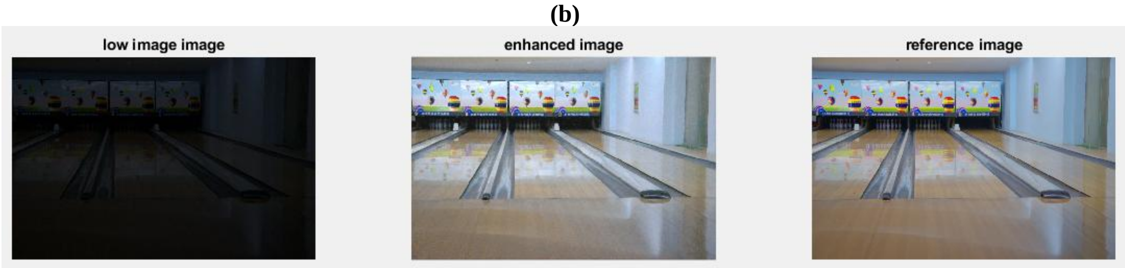
| | | |
|---|---|---|
| Figure 4 (d) | 0.81 | 28.75 |
| Figure 4 (e) | 0.76 | 23.8 |
| Figure 4 (f) | 0.83 | 18.4 |

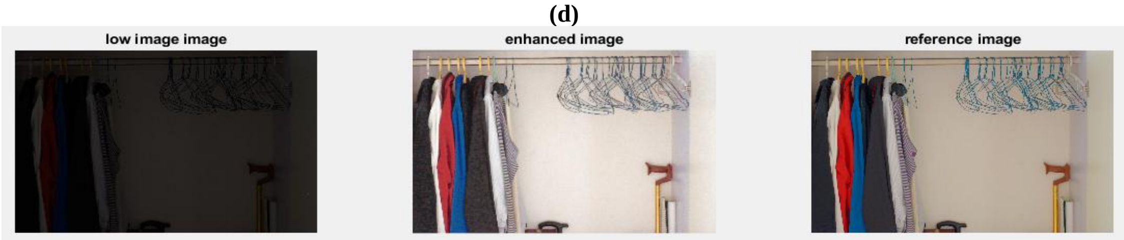

(a)


(b)




(c)


(d)




(e)

**Fig.5: Testing results**

Fig.6 shows Histograms plot of the low light enhanced, and reference images.

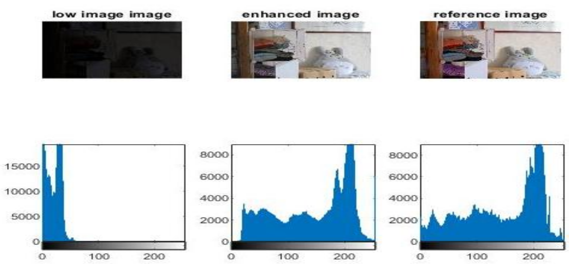



**Fig.6 Histogram plot**

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## VIII. EFFICIENCY TESTING

To make sure that the proposed model is work efficiently, it has been tested by using images from ExDark dataset [10], Google search and images that taken from reality life. The results of this test showed in Fig.7.

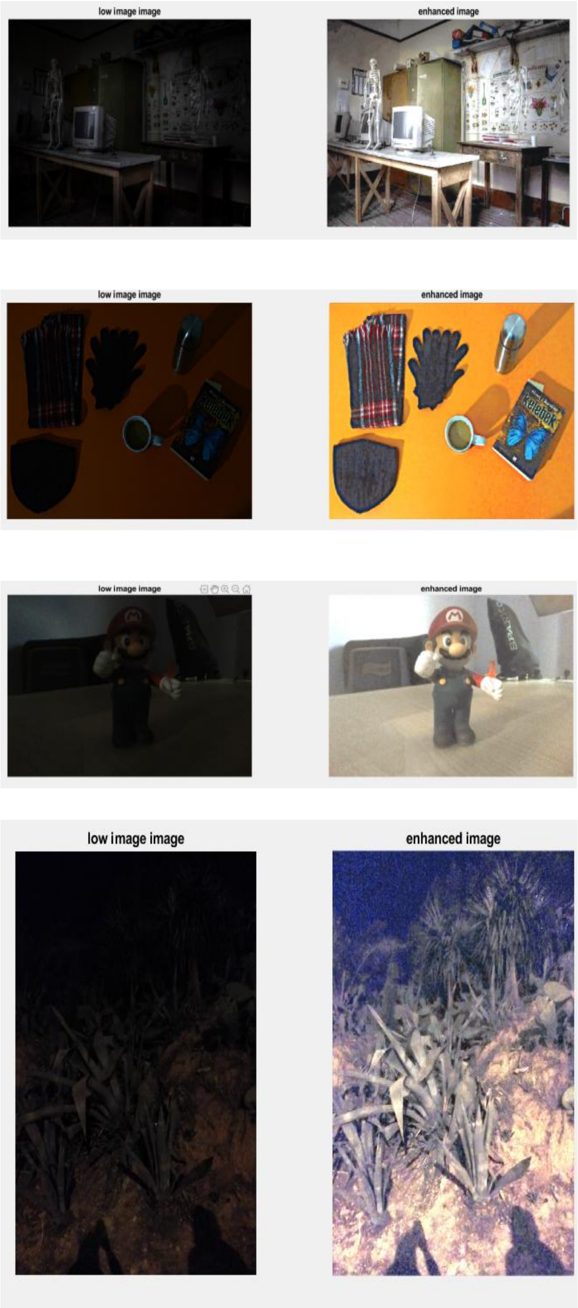


**Fig.7 Efficiency Testing**

## IX. RESULTS DISCUSSION

The overall process of the model included training data testing phases showed in Fig.8.

According to the testing results of the proposed model, the average value of SSIM estimated as 0.8 and the average value for PSNR estimated as 21(dB). It is worth mentioning that this model worked without any pre/post processing, this means the proposed model well working.

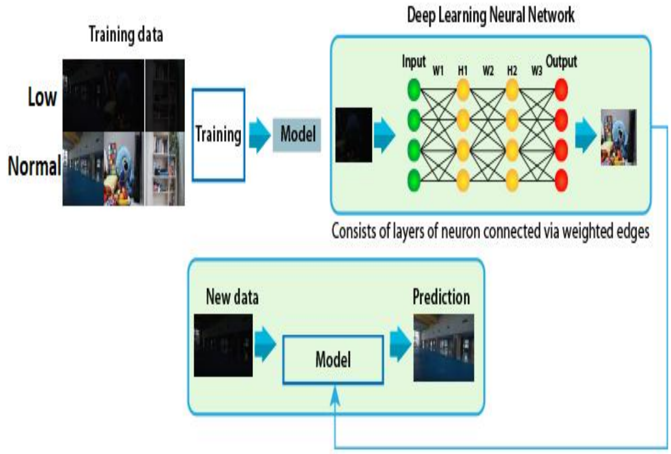


**Fig.8 The overall process**

## X. CONCLUSION

CNN depend on the size and the quality of the dataset and the performance of it depend on the depth of CNN structure.

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