# *A Report*

# *On*

# *Low-Light Image Enhancement using Zero Reference Deep Curve Estimation*


**By**

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# 1. Introduction

Images and visual data are very important to us. More than 80% of the data that human brain processes are visual. Images, if correctly taken convey a lot of information. Sometimes we get images which are hazy or maybe distorted. This is not very pleasing to our eyes and also, we do not get the correct information which the image wants to convey. Images captured in low light is one such type of image which is difficult to process. There may be various factors due to which certain images are taken under suboptimal conditions. Some of the factors include insufficient and unbalanced lighting conditions, under exposure during image capture, incorrect placing of objects against extreme back light etc.

## 1.1 Image enhancement and its techniques

Image enhancement techniques are there to overcome these difficulties. These techniques mainly perform certain operations like adjusting the brightness, contrast and sharpness, removing noise.

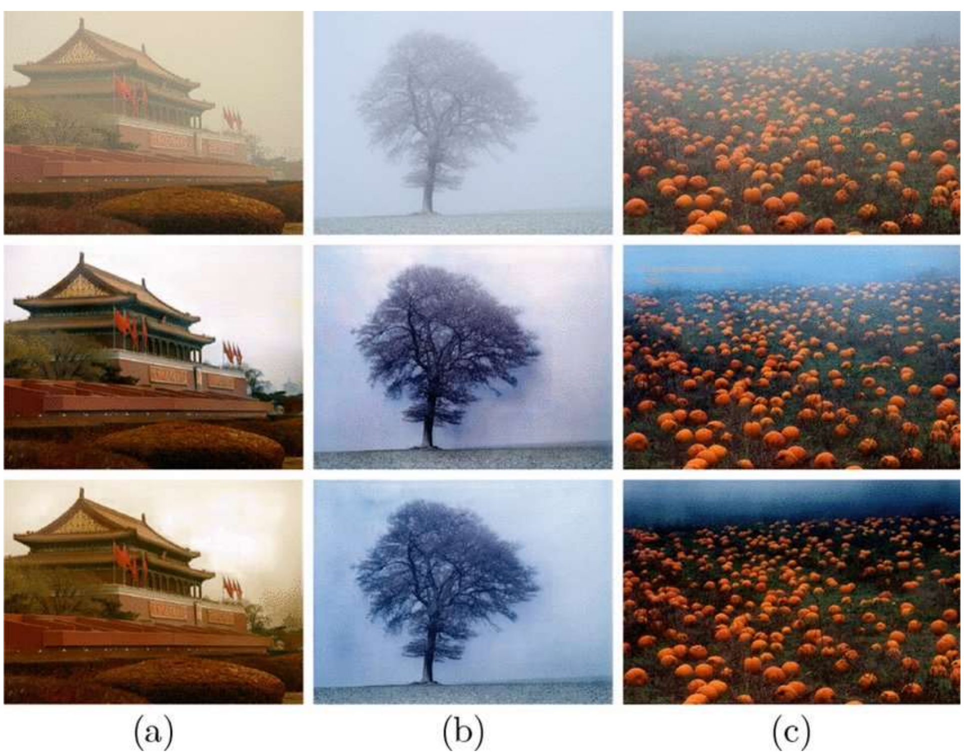



Figure 1: Images before and after enhancement

Some of the most commonly used image enhancement techniques are Filtering with morphological operators, Histogram equalization, noise removal using a Wiener filter, linear contrast adjustment, median filtering.

### 1.2 Deep curve estimation Technique

Lots of research is going on in this image processing field and new techniques for image enhancement is coming up. In this report we shall discuss a very novel method by which images can be enhanced. The technique used here is called Zero Reference Deep Curve Estimation. Most of the image enhancement techniques include image to image mapping and also paired data. This Deep Curve Estimation Network (DCE-Net) is devised to estimate a set of best-fitting Light-Enhancement curves (LE-curves) given an input image. The significant advantages of this method are as follows:

i) This method does not require any paired or unpaired data during training

ii) It may be applied quite accurately for diverse lighting conditions

iii) This method provides visually pleasing result in terms of image parameters such as brightness, colour, contrast

## 2. Objectives

- Taking low light image as input.
- Equalize the histogram of input images before training
- Enhancing the image using zero-reference DCE method
- Color balancing
- Noise removal from the input image

## 3. Methodology

A Deep Curve Estimation Network (DCE-Net) is devised to estimate a set of best-fitting Light-Enhancement curves (LE-curves) given an input image. The framework then maps all pixels of the input's RGB channels by applying the curves iteratively for obtaining the final enhanced image.

$$LE(I(x), \alpha) = I(x) + \alpha I(x)(1 - I(x))$$

{where x denotes pixel coordinates, LE(I(x); α) is the enhanced version of the given input I(x), $\alpha \in [-1, 1]$ is the trainable curve parameter, which adjusts the magnitude of LE-curve and controls the exposure level}. The LE-curve defined above can be applied iteratively to enable more versatile adjustment to cope with challenging low-light conditions.

$$LE_n(x) = LE_{n-1}(x) + \alpha_n LE_{n-1}(x)(1 - LE_{n-1}(x))$$

{α is formulated as a pixel-wise parameter, i.e., each pixel of the given input image has a corresponding curve with the best-fitting α to adjust its dynamic range.

$$LE_n(x) = LE_{n-1}(x) + A_n(x) LE_{n-1}(x)(1 - LE_{n-1}(x))$$

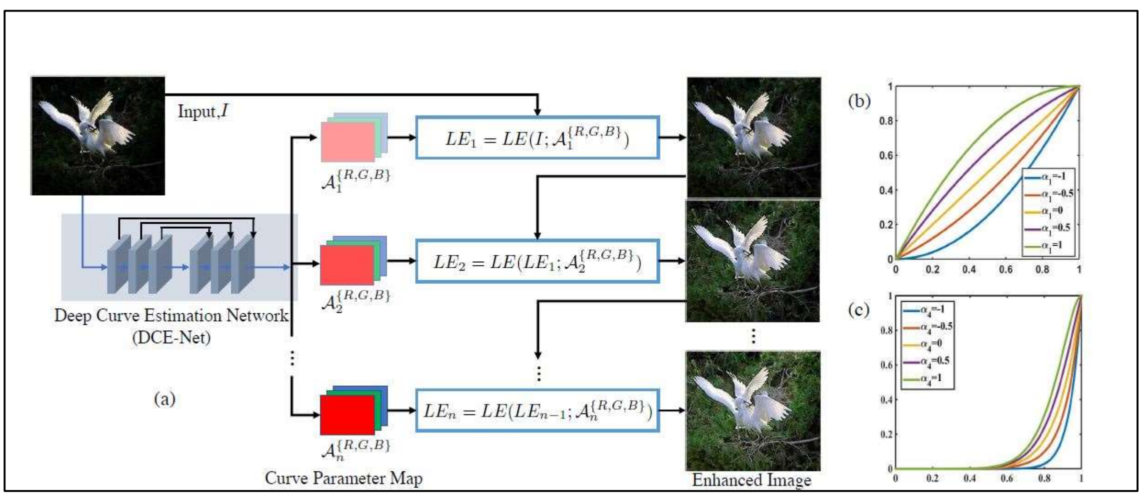



Figure 2 : The zero DCE algorithm

The input to the DCE-Net is a low-light image while the outputs are a set of pixel-wise curve parameter maps for corresponding higher order curves.

Just before the CNN we have proposed that the histogram of the input image can be equalized for better image enhancement using the CLAHE method. (Contrast Limiting Adaptive Histogram Equalization)

CNN of seven convolutional layers with symmetrical concatenation is used with each layer consisting of 32 convolution kernels of size 3x3 and stride 1 followed by ReLU activation function.

The last convolutional layer is followed by the Tanh activation function.

Neural networks have to implement complex mapping functions. Hence, they need activation functions that are non-linear so that they can approximate any function. This Tanh function introduces the needed non-linearity and thus it has been used.

For zero-reference learning in DCE-Net, a set of differentiable non-reference losses are formulated that allows us to evaluate the quality of enhanced images. The following four types of losses are adopted to train our DCE-Net.

i) Spatial Consistency Loss
ii) Exposure Control Loss
iii) Colour Constancy Loss
iv) Illumination Smoothness Loss.

Total Loss is calculated as sum off all the losses. So,

*Total Loss= Lspa + Lexp + WcolLcol + WtvA LtvA*

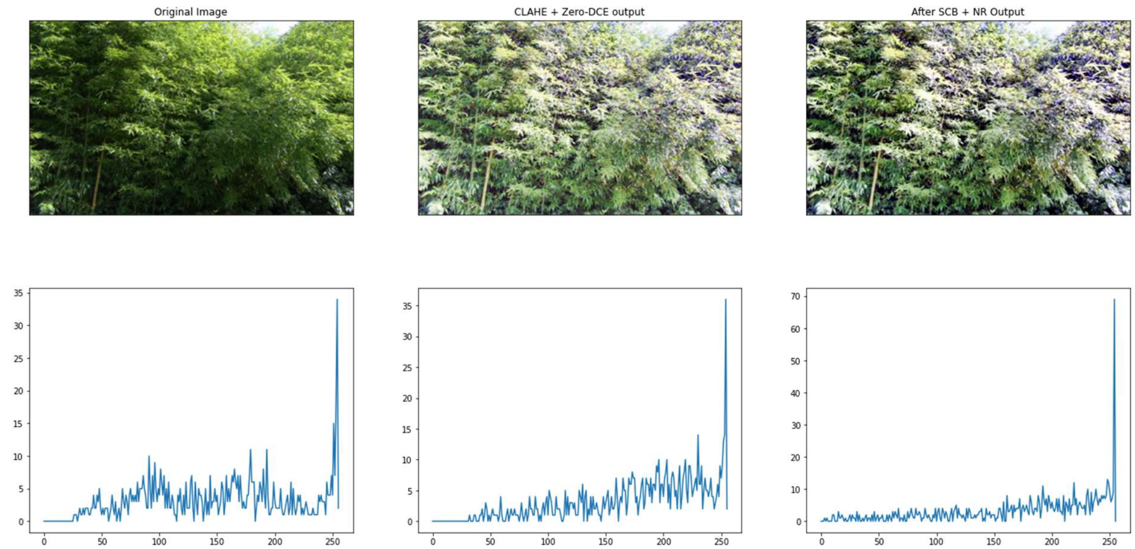
## 4. Implementation

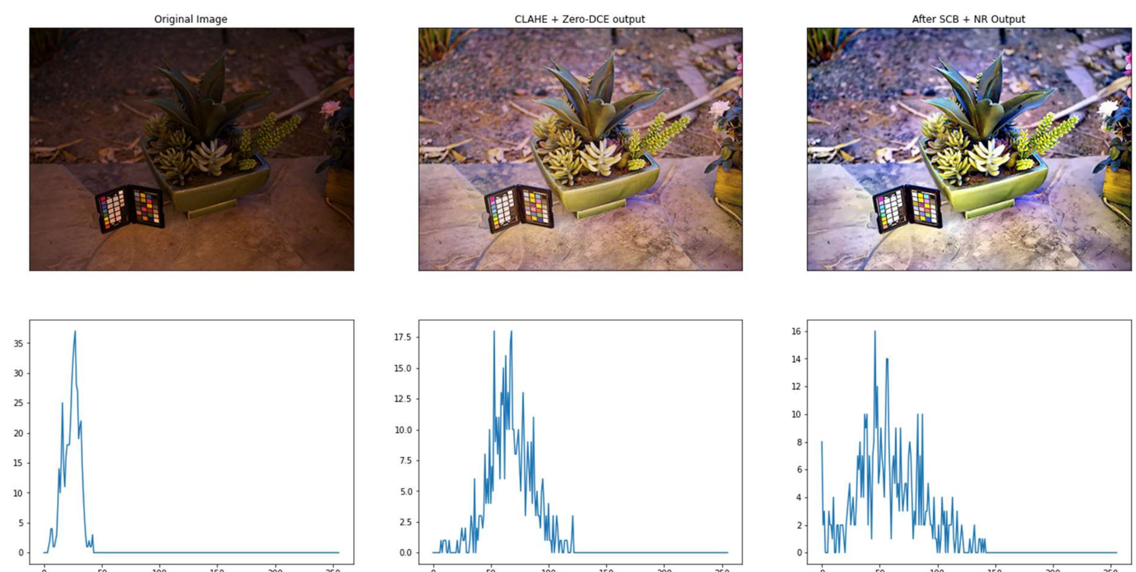
We Implement this framework on a Nvidia P100 GPU which is provided by Kaggle (Online Platform). A batch size of 8 is applied. In our proposed technique CLAHE algorithm is applied to each batch of images before going through the Zero-DCE net architecture. The filter weights of each layer are initialized with standard zero mean and 0.02 standard deviation Gaussian function. Bias is initialized as a constant.

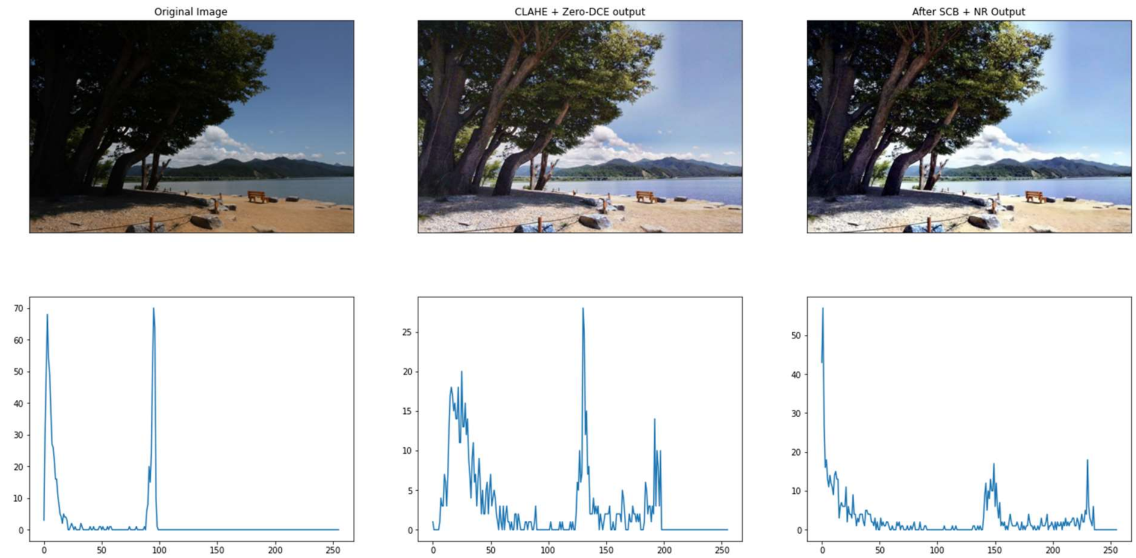
ADAM optimizer is used with default parameters and fixed learning rate 1e −4 for our network optimization. The weights Wcol and WtvA are set to 0.5, and 20, respectively, to balance the scale of losses. The Training ran for 200 epochs. We have proposed extra two steps that would enhance image.

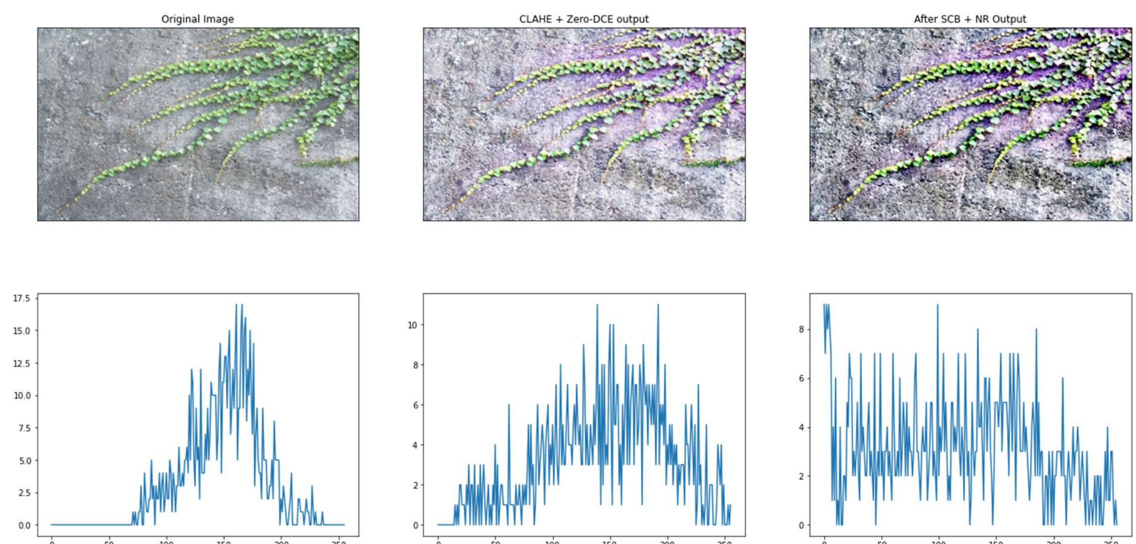
First Step is Simplest color balance followed by Noise Reduction which enhances the images further.

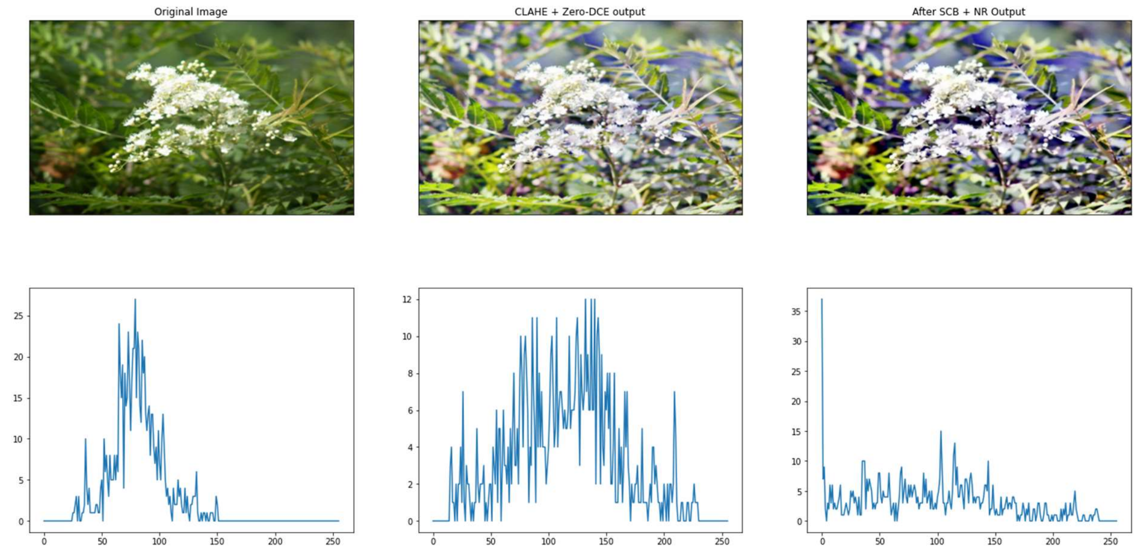
# 5. Results

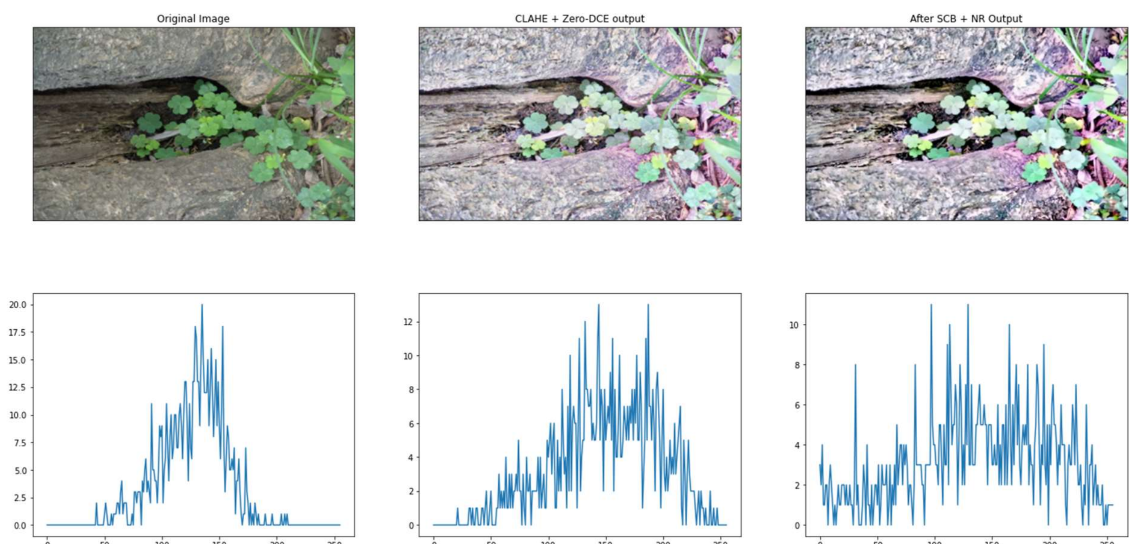

Original Image
CLAHE + Zero-DCE output
After SCB + NR Output

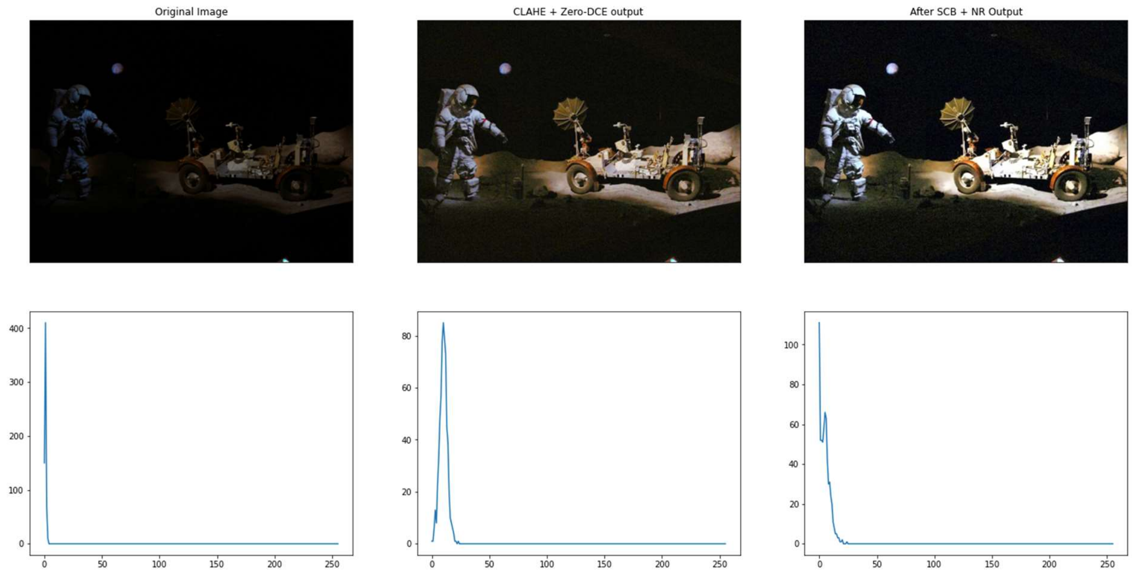

Original Image
CLAHE + Zero-DCE output
After SCB + NR Output


Original Image
CLAHE + Zero-DCE output
After SCB + NR Output


Original Image
CLAHE + Zero-DCE output
After SCB + NR Output


Original Image
CLAHE + Zero-DCE output
After SCB + NR Output


Original Image
CLAHE + Zero-DCE output
After SCB + NR Output


Original Image
CLAHE + Zero-DCE output
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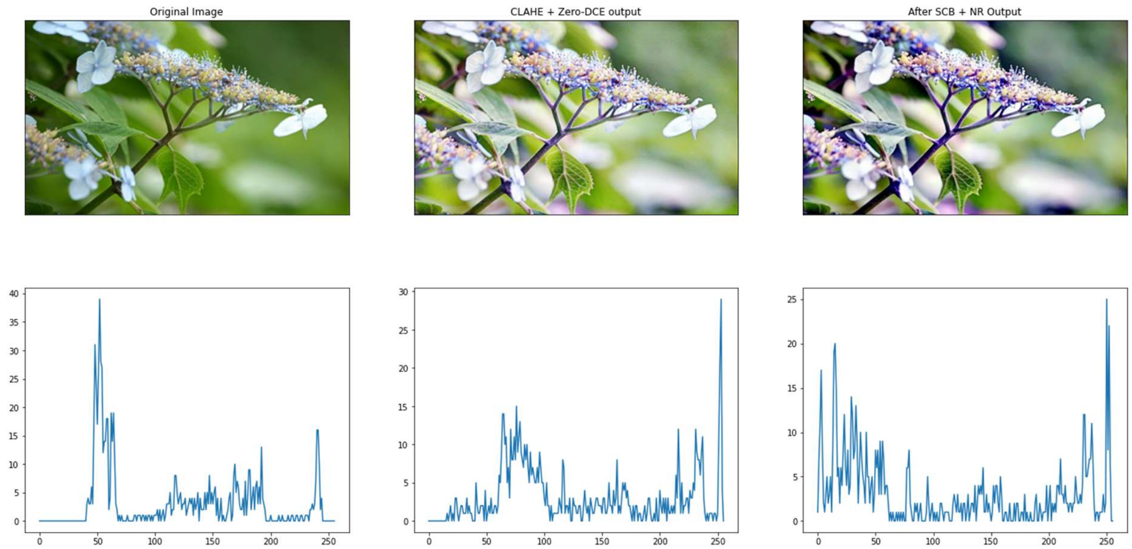
Original Image
CLAHE + Zero-DCE output
After SCB + NR Output



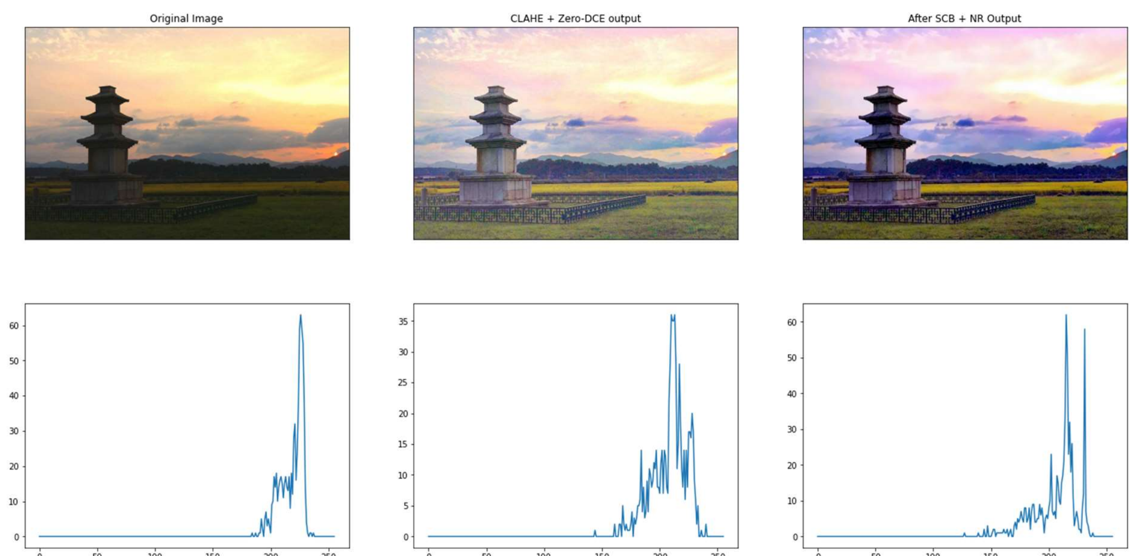




Figure3 : In Each Figure first is Original Image then Second is output after CLAHE and Zero-DCE and third is the output after SCB (Simple Colour Balance) and NR (Noise Reduction) with their respective histograms below. It is clearly visible that our proposed technique has better contrast and colour reproduction most of the time then the actual Zero-DCE implementation.

## 6. Conclusion

In this project we decided to address the problems faced while viewing images which are captured under suboptimal lighting conditions. Low light images were taken as input firstly. Histogram equalization was applied to the input image before training the model. After that, zero reference deep curve estimation technique was used for image enhancement. Simplest colour balance and noise removal were then performed on the zero DCE output. Finally, we calculated histogram of the images. Notable changes in the histogram indicated that successful enhancement of the images and also removal of unwanted noise. This is a quite efficient and novel technique which can be used in future for face detection also.

## 7. References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