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Low Light Image Enhancement using Convolutional Neural Network

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Abstract: Great quality images and pictures are remarkable for some perceptions. Nonetheless, not each and every images are in acceptable features and quality as they are capture in non-identical light atmosphere. At the point when an image is capture in a low light state the pixel esteems are in a low-esteem range, which will cause image quality to decrease evidently. Since the entire image shows up dull, it's difficult to recognize items or surfaces clearly. Thus, it is vital to improve the nature of low-light images. Low light image enhancement is required in numerous PC vision undertakings for object location and scene understanding. In some cases there is a condition when image caught in low light consistently experience the ill effects of low difference and splendor which builds the trouble of resulting undeniable level undertaking in incredible degree. Low light image improvement utilizing convolutional neural network framework accepts dull or dark images as information and creates brilliant images as a yield without upsetting the substance of the image. So understanding the scene caught through image becomes simpler task.
Keywords: Image Enhancement, Low light Images, CNN.

I. INTRODUCTION

Low light environment is dependable to lose the definite realities or data of any surface. The low light image upgrade now and then causes to improve the clamor in a dim area. Accordingly, just low light image upgrade can't defend the great difference. To control this issue, we need to support the differentiation of various low light images to separate the detail of the info image. Low light is brought about by various reasons. It can happen from a lacking wellspring of light, the shadow of an article, under a low illumination or brilliance solid light debilitating, and so forth

Late to the helpless episode brilliance or coating acquired by the items, images or photographs caught under the low light climate are slanted to help from low clearness, specifically, decline contrast, blur tone, and murky scene subtleties. This downside is a great trouble for most of the applications in particular PC or cell phone visual and computational photography which are in a general sense intended for top notch inputs, including object acknowledgment, satellite imaging, keen vehicles, and so forth Consequently, to see the scene subtleties covered up inside the dull districts to overhaul the in general noticeable quality moreover, which is habitually alluded to as "low light image enhancement". Intuitively, the worldwide pixel power intensification is the simple method to lift or upgrade the clearness of a low-light image. In any case, many low light images are not debased consistently, that implies the brilliant districts and dull locales may endure simultaneously inside a similar image, and the most splendid areas might be over-improved unavoidably when the unlighted locale gets noticeable.

PC vision is a hypothetical field that is worried about separating undeniable level data from advanced images. Advanced image handling is an extra field that manages preparing, for example, image upgrade, image pressure, and so on Both these fields have been dynamic for quite a long time and there has been a huge improvement in every one of them. Cells and computerized cameras use image handling plans to create great images. Numerous PC vision based identification calculations, for example, face discovery have been proposed, and their precision is close or stunningly better than the human's presentation. We believe that there is still space for improvement. Numerous image handling and PC vision undertakings can profit by a profound learning approach.

The main objectives of this image enhancement are shown below:

- Object recognition in image will become simple.
- Make location understanding will simplify through satellite images.
- Image perception information can improved for viewers.
- To improve universal and confined contrast of the weekly illuminated images.
- Image transformation is suitable for computer processing and human.
- To avoid noise amplification and to desire a good real time image.
- The motivation of the Low light image enhancement technique is that will provide solutions for weekly illuminated.
- In spite of having numerous image enhancement techniques, we are obtaining deep learning techniques.
- One can implement the deep learning techniques in real time applications.

- Histogram and RGB Histogram will the enhancement result and how it is changed with respect to input image.
- We also specify that how number of iterations will enhance the images.
- We also specify the over enhancement and under enhancement of the image with respect to number of iterations.

II. LITERATURE SURVEY

Panetta et al (2010)[38] developed a parameterized logarithmic framework for image enhancement. It is a non-linear transformation technique. This technique is used for both color and gray scale images. This method is more effective for gray scale images. It use a non-linear function i.e., Logarithmic function is to convert the gray values of an image. This function suggested that there is a logarithmic relation between the every pixel value in the resultant and the relative pixel value in the actual image. This technique is more acceptable for dark images because it can stretch the lower gray values of the image and compress the higher values which are out of dynamic range [0, 255].

S. Lee et al (2015)[28] proposed an adaptively partitioned block based contrast enhancement and its application to low light level video surveillance. Li et al (2014)[29] proposed an over view survey of HE technology. The main purpose of this Histogram Equalization, it will distribute all pixel values of an image uniformly in all feasible ways. Thus resultant image have high contrast and large dynamic range. On the basis of HE characteristics, the HE method uses the CDF to adjust the output image. It will have PDF (Probability Density Function) that leads to a uniform distribution of histogram.

Kim et al (1998)[67] proposed an enhancement technique is brightness-preserving bi-histogram equalization (BBHE) to sustain the contrast of the image. Here, the actual image is split into sub-images I_L and I_U using the mean contrast of the low light image. Then it has to satisfy the conditions that is $I = I_L \cup I_U$ and $I_L \cap I_U = \phi$. Histogram Equalization of each sub-image is then applied to the uneven contrast in the local areas of the enhanced images.

Jobson et al (1996)[17] and (2002)[16] proposed a multi-scale retinex for color image enhancement and multi-scale retinex for bridging the gap between color images and the human observation of scenes. It simple known as Multiscale Retinex. It will maintain a balance between color constancy and compression dynamic range. It is an extension of single scale algorithm.

Jobson et al (2004)[15] proposed a Retinex processing for automatic image enhancement. It is also called as Multiscale Retinex with color restoration method (MSRCR). The SSR and MSR techniques will apply on R, G, and B channel separately. When we compare with input image the proportions of R, G and B channel will change after enhancement. Thus resultant image get distorted. To overcome this situation MSRCR has been proposed by Jobson et al. This algorithm contains a color recovery factor [C] for each channel.

$$C_i(x,y) = f\left(\frac{I_i(x,y)}{\sum_{i=1}^{3} I_i(x,y)}\right) = \beta \times log\left(\alpha \times \frac{I_i(x,y)}{\sum_{i=1}^{3} I_i(x,y)}\right)$$

Toet et al (2011)[55] proposed an augmenting full color fused multi band night vision imagery with synthetic imagery in real time. This method will retain the distinctive facts caught by abundant sensors and also enhance the image with clarity. This algorithm will perform arthematic operations such as addition and subtraction. This method can be carry out in hardware as a real time application.

Yan et al (2016)[69] proposed an automatic photo adjustment using deep neural networks. It is the first deep learning method for image enhancement. Lore et al (2017)[9] proposed an LLNet: A deep auto encoder approach to natural low light image enhancement. They adopted a framework of stacked sparse de-noise for training an LLNet. This will produce a low light image enhancement. Park et al (2018)[44] proposed a dual auto-encoder network for retinex based low light image enhancement. In this method the structure reconstruction loss was taken as loss function and self-encoder is used to learn the features using deep learning network.

Tao et al (2017)[25] proposed Low light image enhancement using CNN and bright channel prior. They merged a bright channel prior with a CNN (Convolutional Neural Network). Park et al (2017)[39] proposed a low light image restoration using bright channel prior based variational retinex model. This method will combine interframe compensation, scene detection and edge compensation techniques. Yu et al (2017)[68] proposed a low illumination image enhancement method based on a fog degraded model. This technique will solve the transmittance problem based on a CNN and a foggy degradation model. In this atmospheric light map and transmission map are combined with guided filtering to get a enhance image.

Z. Xiao et al (2017)[62] and S.C. Huang et al (2013)[46][47] developed a diabetic retinopathy retinal image enhancement and efficient contrast enhancement with weight distribution separately. Both used the same non-linear function i.e., gamma correction or gamma function. γ is a parameter and one can obtain numerous different curves and enhancement. $\gamma > 1$, it will encode with a compressive power law and it is called as encoding gamma. In this transformation gray value with low area are stretched dynamically in a range and gray values with high area are compresses. $\gamma<1$, it will decode with an expansive power

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law and it is called as decoding gamma. In this decoding gamma gray values with low area are compress and gray values with high area are stretched in a dynamic range. $\gamma = 1$, it is neither decoding gamma nor encoding gamma. The output of this $\gamma=1$ is same as input. Where γ denotes the parameter of gamma correction. The transformation will depend on gamma value.

III. METHODOLOGY

The suggested Zero-DCE is better than present driven techniques in three ways. To start with, it investigates another learning system, i.e., one that requires no reference image, henceforth disposing of the requirement for combined and unpaired information. Second, the network is prepared by considering into account characterized non-reference loss functions. This technique permits resultant image quality to be certainly assessed, the after effects of which would be repeated for network learning. Third, our strategy is profoundly proficient and practical. These benefits profit by our no reference learning system, lightweight network structure, and successful non-reference loss functions.

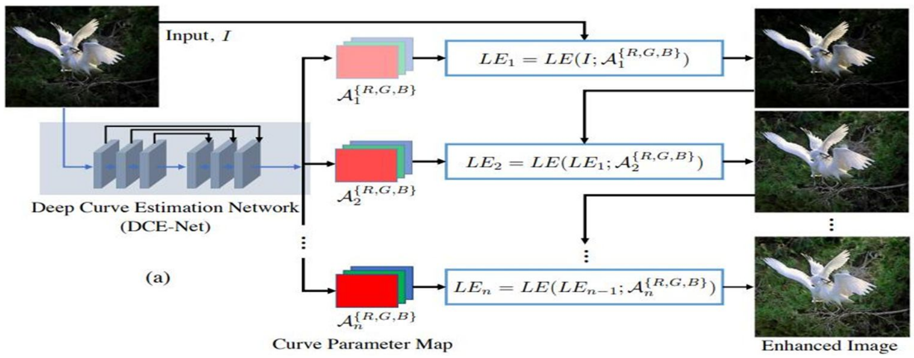

Figure 1 Structure of Network

The structure of strategy in figure in shown above Figure 1. A Deep Curve Estimation Network (DCE-Net) is formulated to appraise a bunch of best fitting Light Enhancement curves (LE curves) given an actual image. The system at that point maps all pixels of the information RGB channels by applying the curves iteratively for acquiring the last improved image. We next detail the vital parts in No DCE, in particular LE-curve, DCE-Net, and non-reference loss functions in the following sub chapters.

A. Deep Curve Estimation Network (DCE Net)

Deep Curve Estimation Network is familiar with the mapping between an actual image and its best fitting curve parameter maps. The contribution to this network is low light image and the output is a bunch of pixel wise bend boundary maps for comprising higher order curves. We utilize a CNN of seven convolutional layers with balanced correction. Every layer comprises of thirty two convolutional kernels of size 3x3, stride 1 and ReLU function. In that first six layers are activated by ReLU activation function. The last convolutional layer is activated by Tanh activation function. It produces 21 parameter maps for 7 iterations. For every iteration it requires three parameter curve maps for Red, Green and Blue channel. DCE Net will play a vital role in this project. It can trainable on various parameter and 5 GB of the actual image of various size. The training is done on various types of images and taken all images that are from low light to over enhanced images.

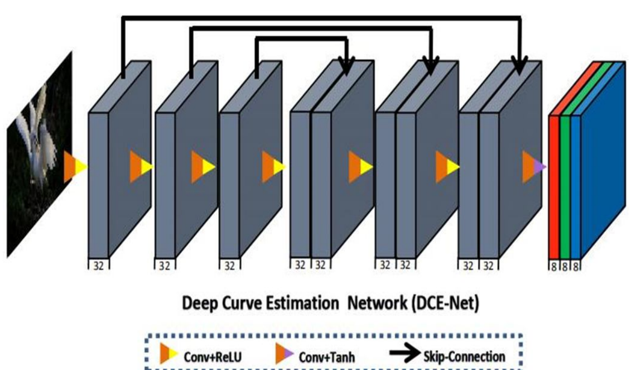

Figure 2 Deep Curve Estimation Network

The above Figure 2 shows the DCE (Deep Curve Estimation) network of the methodology. It consist of convolutional layers with activation function ReLU and Tanh.

B. Light Enhancement Curves (LE-Curves)

Enlivened by the curves change utilized in photograph altering programming, we endeavor to plan a sort of curve that can plan a low-light image to its upgraded form consequently, where the self-versatile bend boundaries are exclusively subject to the actual image. There are three targets in the plan of such a bend:

- Every pixel worth of the improved image ought to be in the standardized scope of [0,1] to keep away from data misfortune prompted by flood truncation.
- This curve must be tedious to protect the distinctions of adjoining pixels
- The type of LE curve need to be pretty much as basic as could be expected and differentiable during the time spent slope back-spread.

To accomplish these three goals, we plan a quadratic equation or curve, which can be communicated as:

$$LE(I(x);\alpha) = I(x)\left[1 + \alpha\left(1 - I(x)\right)\right] \qquad \text{-(1)}$$

Where x signifies pixel's position, LE(I(x); α) is the improved form of the actual input I(x), $\alpha \in [-1, 1]$ is the trainable curve parameter, which changes the greatness of LE-curve and furthermore manages the openness level. Every pixel is standardized to [0, 1] and all activities are pixel-wise. We independently apply the LE-curve to three channels i.e., RGB rather than exclusively on the light channel. The three channel change can all the more likely save the characteristic tone and decrease the threat of over saturation. We describe more subtleties in the valuable facts.

A representation of LE-curves with various changes in parameter α is shown in Fig. 4.1.1(b). Plainly the LE-curve agrees with the three previously mentioned targets. Likewise, the LE-curve empowers us to increment or abatement the unique scope of an information images. This ability is helpful for upgrading low-light districts as well as eliminating over-openness relics.

1) *Higher-Order Curve:* The LE curve characterized in Eq. (1) can be appealed iteratively to empower additional adaptable acclimation to adapt to testing low-light conditions. In particular,

$$LE_n(x) = LE_{n-1}(x) + \alpha_n LE_{n-1}(x)\left(1 - LE_{n-1}(x)\right) \text{-(2)}$$

Where n is the number of iterations, which controls the architecture. We put the worth of n=7, which can manage most cases palatable. Eq. (2) can be debased to Eq. (1) when n is equivalent to 1. Figure 4.1.1(c) gives a model appearance high-order curves with various α and n, which have all the more impressive change ability (i.e., more prominent arch) than the curves in Figure 4.1.1(b).

2) *Pixel-Wise Curve:* A higher order curve can change an image inside a more extensive powerful reach. Regardless, it is as yet a universal change because α is utilized in entire pixels. A worldwide planning leads to over saturated or under saturated nearby native region. To resolve this issue, we figure α as a pixel-wise parameter, i.e., every pixel of the provided information image has a relating curve with the best-fitting α to change its dynamic reach. Consequently, Eq. (2) can be rewritten as:

$$LE_n(x) = LE_{n-1}(x) + A_n LE_{n-1}(x)[1 - LE_{n-1}(x)] \text{ -(3)}$$

Where A will be a parameter map of a similar size in the provided image. Here, we expect that local region pixels will have a similar intensity (additionally a similar change curves), and subsequently the adjoining pixels in the yield result actually protect the dreary relations. Along these lines, the pixel-wise higher-order curves additionally consent to three targets.

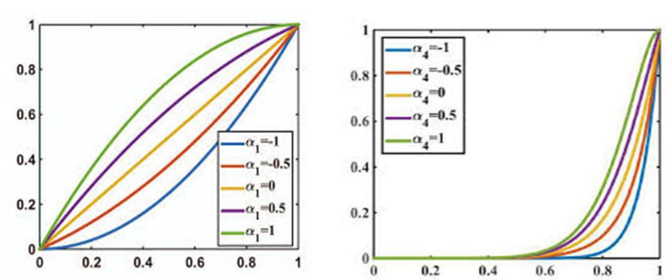

Figure 3 LE-curves with various changes in parameter α and number of iteration n

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The above figure 3 tells about the number of iterations with respect to alpha parameter.

An illustration of the assessed curve parameter maps of RGB channels in Figure above. As appeared, the best-fitting parameter maps of various channels have comparative change propensity yet various qualities, showing the significance and contrast among the RGB channels of a weekly illuminated image. The curve boundary map precisely shows the brilliance of various areas (e.g., the two sparkles on the divider). With the fitting maps, the improved adaptation image can be straightforwardly fetched by pixel-wise curve mapping. As demonstrated in Figure shown in starting of methodology, the improved rendition uncovers the substance in dim regions and jellies the splendid areas.

C. Non Reference Loss

To empower No reference learning in DCE-Net, we propose a bunch of miscellaneous non-reference losses that permit us to assess the nature of resultant images. The accompanying four kinds of losses are received to train DCE-Net.

1) *Spatial Consistency Loss:* The spatial consistency loss L_{spa} supports spatial coherence of the improved image through protecting the distinction of adjoining locales between the actual image and its improved rendition:

$$L_{spa} = \frac{1}{K}\sum_{i=1}^{K}\sum_{j\in\Omega(i)}(|Y_i - Y_j| - |(I_i - I_j)|)^2$$

Where K is the quantity of neighborhood area, and Ω(i) is the four close areas (top, down, left, right) focused at the area i. It indicates Y and I as the average intensity value of the neighborhood area in the improved version and actual image, separately. We observationally set the size of the close by area to 4×4. This loss is consistent given other local region sizes.

2) *Exposure Control Loss:* To restrict under or over saturated regions, we plan a design an exposure control loss L_{exp} to control the saturation level. The exposure control loss evaluated the distance between the mean intensity values of a neighborhood area to the well-exposedness level E. We follow existing practices to set E as the gray level in the RGB color model. We set E to 0.6 in our preliminaries notwithstanding the way that we don't find a great deal of execution differentiation by setting E inside [0.4, 0.7]. The loss L_{exp} can be formulated as:

$$L_{exp} = \frac{1}{M}\sum_{k=1}^{M}|Y_k - E|$$

Where M represents the number of non-overlapping neighborhood regions of size 16×16, Y is the mean intensity value of a neighborhood area in the improved image.

3) *Color Constancy Loss:* From Gray World color constancy theory that color in every sensor channel averages to gray over the whole image, planning a color constancy loss to rectify the possible color deflections in the improved image and also build the connection among the three nearby channels. The color constancy loss L_{col} can be formulated as:

$$L_{col} = \sum_{\forall(p,q)\in\varepsilon}(J^p - J^q)^2 \quad \varepsilon = \{(R,G),(G,B),(B,R)\}$$

Where J^p represents the mean intensity value of p channel in the improved image, (p, q) represents a pair of channels.

4) *Illumination Smoothness Loss:* To save the monotonicity connections between adjacent pixels, we add an illumination smoothness loss to every curve parameter map A. The illumination smoothness loss L_{tvA} is defined as:

$$L_{tvA} = \frac{1}{N}\sum_{n=1}^{N}\sum_{c\in\xi}(|\nabla_x A_n^c| + |\nabla_y A_n^c|)^2, \xi = \{R,G,B\},$$

Where N is the number of iteration, the horizontal and vertical gradient operations are represent as ∇_x and ∇_y, separately. Total Loss. The total loss can be formulated as:

$$L_{total} = L_{spa} + L_{exp} + W_{col}L_{col} + W_{tvA}L_{tvA}$$

Where W_{col} and W_{tvA} are the weights of the losses.

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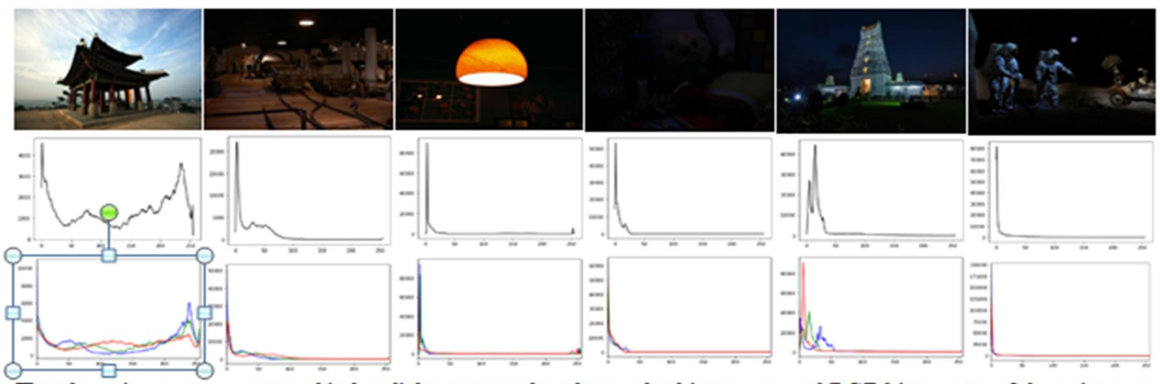
The results of methodology with histogram and RGB histogram and comparison of various image processing techniques with methodology are shown in next section. We have taken some real time low light images forsake of enhancement. The results, comparison and image captured from phone all are shown in next section.

IV. RESULTS

Low Light Image   Very Low Light   Extreme Low Light   Dark Images   Night Time Images   Space Images



The above images are captured in low light state and we have plot histogram and RGB histogram of those images.

The below images are enhanced images and we have plot histogram and RGB histogram of those images.

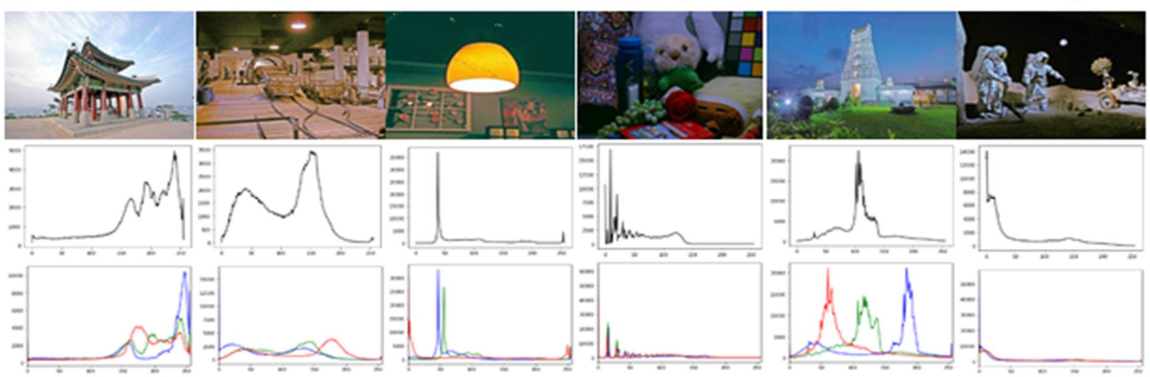


Figure 4: The above images are captured in low light state and enhanced images with histogram and RGB histogram

These images come under low light images. Here, we observe histogram that the lower pixel values have more frequency when compare to low light images category. So, images are more dark when compare to low light image. Here, detecting object is somewhat difficult. After enhancement, we observe that low pixel frequency is decreased. Medium and high pixel frequency is increased. This indicates that color and contrast correction is improved. We can detect object very easily. The histogram of both input and enhanced will tell you how RGB colors are improved in the images. This type of condition we observe in dim light and in sunset.

Low light image   Enhanced image   Low light image   Enhanced image   Low light image   Enhanced image

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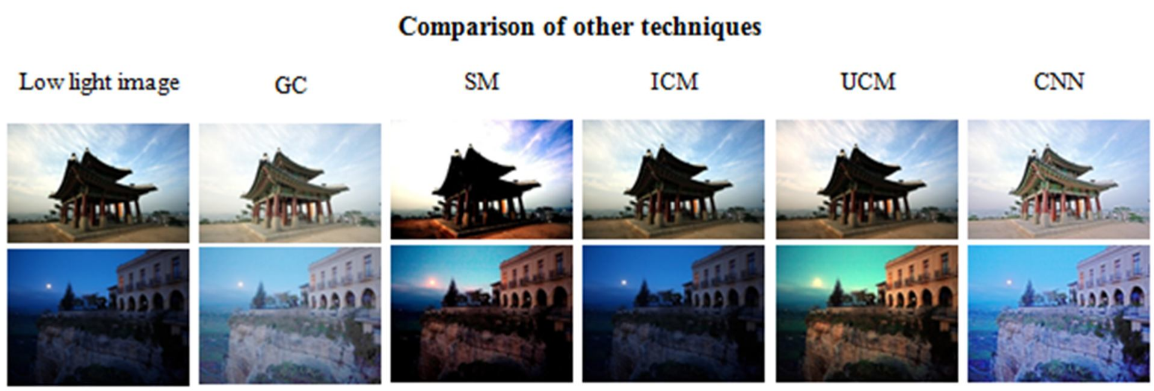
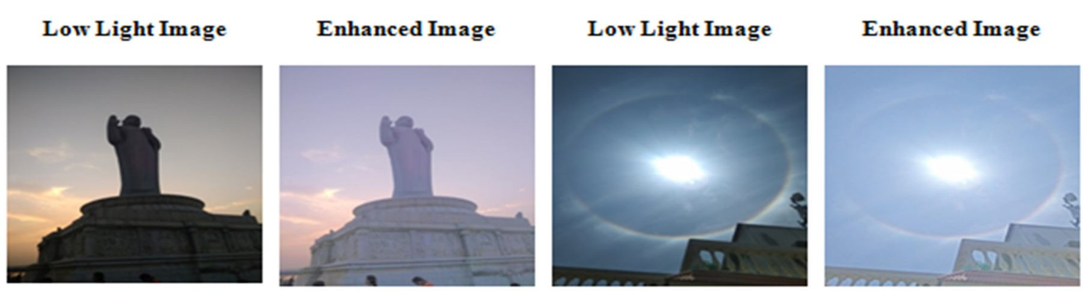
Comparison of all categories images with their enhancement outputs. We have kept images of low light, very low light, extreme low light, dark light and cloudy images and their enhancement images using convolutional neural network. First, third and fifth column represent low light images and second, fourth and sixth column represent enhanced images.

The above images are comparison of low light images and Histogram Equalization (HE) and its modified techniques such as BHE (Bi-Histogram Equalization), CLAHE (Contrast Limited Adaptive Histogram Equalization), RS (Rayleigh Stretching) and RGHS (Relative Global Histogram Stretching). These techniques are image enhancement techniques which are widely used in image processing domain.



The above images show the comparison of other techniques such as GC (Gamma Correction), SM (Statistical Model), ICM (Integrated Color Correction Method), UCM (Unsupervised Color Correction Method), CNN (Convolutional Neural Network). Out of them, CNN, GC, BHE and HE are producing more enhanced images. But we know the drawbacks of GC, BHE and HE. So, I will say that CNN produce better results among all other image enhancement techniques. Because in some techniques some kind images will does not produce better results.

Analysis Of Images Captured From Phone (Real Time Images Analysis)



The above images are captured from Tank Bund, Hyderabad respectively.

We have taken input image or low light image and their histogram, RGB histogram is taken on left side. Enhanced images and their histogram and RGB histogram are taken on right side. To compare low light image with enhanced image, we are taking histogram and RGB histogram for analysis.

Observations: If we observe that, all low light images having high frequency of pixels on left side of the histogram and RGB histogram. This indicates that images are in low light state. We know that pixel values zero (0) will take black color and pixel value 255 will take white color. All other color will lie between the values zero to 255. We have 256 pixels. The range of pixels is [0, 255].

After enhancement, we observe that the high frequency of pixels is distributed on histogram and RGB histogram. This indicates that contrast correction and color correction will take place. So, we are able to identify object in an image.

V. CONCLUSION

We implemented a Convolutional Neural Network for low light image enhancement. In this method, it can be trained without reference images. This can attain by working out the low light image enhancement problems. Sometimes, traditional image enhancement techniques do not provide sufficient or acceptable results. In this situation, one needs to obtain machine learning and deep learning techniques. Because, these techniques are more efficient than traditional techniques.

When compared with other literature survey methods, this method will provide efficient and accurate outputs. The time taken for training is more. But, time taken for testing is less. Thus it has more time efficient. It can test images within less time. As we are using online software tool, that will train the images with less time when compared with Jupyter notebook. As we are taking around 5GB data for training. If we want to train with large size of data set, then we require more storage in Google drive. As our drive has capacity of 15GB, we don't require any upgrades.

VI. FUTURESCOPE

Low light image enhancement can apply for space images and satellite images. The space or universe consists of many stars. Along with stars, universe consists of empty with low light state. This low light state occurs due to stars. Sometimes, the images captured in space using satellites are in low light state due to rotation and revolution of earth and sun. The light may scatter sometimes. In these situations we can work on space images and satellite image. This technique can introduce in satellites, so that we can get enhanced images.

Exploration robots such as underwater or Marine exploration are also one of the domains for low light image enhancement. Using this technology one minimize risk. The cost and time efficiency can be improved. Manual cost can be minimized. We can get full enhanced images with more accuracy. These images can be useful for research and observation purpose also.

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