Methodology Comparison of Low-Light Image Enhancement

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Abstract

The discipline of computer vision faces a significant challenge with low-light picture augmentation, and numerous methods have been developed to solve this problem. In this paper, we analyze four commonly used techniques for improving low-light images: histogram equalization, brightness-preserving dynamic histogram equalization (BPDHE), retinex and learning-based DCE-Net. We put these strategies into practice and assessed them using measures: Average Absolute Mean Brightness Error (AAMBE), Lightness Order Error (LOE), Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Our review gave us the chance to evaluate the advantages and disadvantages of each technique and pinpoint ways to enhance the learning-based strategy. Although histogram equalization is known to improve contrast, it might unintentionally magnify noise in photographs taken in low light. While maintaining the original brightness levels, brightness-preserving dynamic histogram equalization tries to improve both brightness and contrast. Additionally, we looked into the retinex-based approach, which places an emphasis on improving structural details and overall image quality. The learning-based method DCE-Net, trained on the ExDark dataset using loss functions such as Color Constancy Loss, Exposure Loss etc. showed us that choosing an appropriate dataset with fitting loss functions can work but it can still be outperformed by simpler traditional algorithm such as BPDHE. Through our study, we gained valuable insights into the performance of these methods and their suitability for low-light image enhancement tasks.

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1. Introduction

Images sometimes are captured under poor lighting conditions (effect of dim, uneven light or back-lit), which can be stem from environmental or technical problems like insufficient illumination or limited exposure time. In general, these images have problematic aesthetic quality and poor visibility which may cause failures in high-level computer vision tasks such as object tracking, recognition and tracking. Figure 1 demonstrates some examples of the images captured under such poor lighting conditions in our data-set. Low-light image enhancement is a computer vision task that involves improving the perception or aesthetic quality of an image captured under these low-light conditions.This enhancement process makes images brighter, cleaner, more visually appealing while keeping noise and distortion as small as possible. Therefore, nowadays, low-light image enhancement techniques are used in many areas ranging from computational photography, autonomous driving to visual surveillance.

Figure 1. Examples of images captured under poor lighting conditions in our test data-set. The problems of these images are, respectively, back lit, dim light and uneven light.

The conventional techniques used in low-light image enhancement are based on Histogram equalization (HE) methods and Retinex model methods. The histogram-equalization based methods distributes the intensities on a histogram when the intensity values of an image lie within a small range. However, the histogram equalization based methods tends to generate unrealistic results by neglecting noise existing in low-light images. The Retinex-based methods decompose an image into a reflectance (enhanced image) and illumination components. Even though Retinex-based methods receive relatively more attention, these methods have some limitations too. **1)** Ideally, in Retinex-based models, the reflection component is considered as enhanced image but under various illumination conditions this may lead to unrealistic enhancement results (loss of details and distorted colors). **2)** The classical form of Retinex-based decomposition does not includes a noise component so noise might be amplified during enhancement process. **3)** Also, complicated optimization process of Retinex-based methods causes relatively longer run time.

Due to these limitations of conventional methods and improvements in the field of deep learning, deep learning based low-light image enhancement methods are started to use in recent years. Generally, deep learning based methods achieves better quality, robustness and computational time over conventional methods. However, deep learning based methods have limited generalization capability (dataset dependent issue) and they still struggles from noise existed in the images.

In this project, we focus on comparison of conventional methods and deep learning based enhancement techniques on various metrics. While doing this comparison, we use implementations of some of the baseline conventional methods in the literature. Based on the papers we found, we try to implement a deep learning based method from scratch or improve some existing method. Also, we implement some metrics that we found in literature and allow us to compare results of techniques quantitatively. Furthermore, we are planning to conduct a user survey to evaluate our results subjectively if we have a remaining time.

2. Related Work

As stated in the introduction section, one of the conventional techniques used for low-light image enhancement is Retinex model. The techniques based on Retinex model decompose image into reflectance and illumination components. However, the classical approach of these Retinex model based techniques ignores the noise component in the images, which is amplified in the enhancement process. Li et al. (2018) propose a structure revealing robust Retinex model, which applies an additional noise map with conventional Retinex model, to decrease this amplification of noise in the enhanced image. In addition, they propose a new optimization function that uses novel regularization terms for reflectance and illumination. Also, they use an augmented Lagrange multiplier based alternating direction minimization algorithm without logarithmic transformation to robust the optimization process (1). Another problem of the Retinex model based approaches is that they work well on limited type of images such as only overexposed ones or only underexposed ones. However, the algorithm should be able to work on both type of images ideally. Also, some images contains both very underexposed and overexposed regions (partially underexposed and overexposed). For this reason, Zhang et al. (2019) propose a dual illumination estimation algorithm where images are separately cast the under-exposure and over-exposure correction. By using this technique, they get two intermediate correction results, which are the one restores overexposed regions and the one restores the underexposed regions. Then, they utilize from multi-exposure image fusion to blend the visually best parts of the two corrected images and the first image into a final enhanced image (2).

In comparison to traditional methods, the article also reviews deep learning-based methods. As a detailed survey, articles (3; 4), on ”Low-Light Image and Video Enhancement: A Comprehensive Survey and Beyond”, investigate deep learning-based approaches and found that they produce better results than traditional approaches. However, they also note that there are still challenges to be addressed, such as preserving image details, avoiding artifacts, and handling complex scenes. The articles investigate various deep learning methods, including Supervised Learning (SL), Reinforcement Learning (RL), Unsupervised Learning (UL), Zero-Shot Learning (ZSL), and Semi-Supervised Learning (SSL). Some commonly used methods include convolutional neural networks (CNNs), generative adversarial networks (GANs), and recurrent neural networks (RNNs), which were used for various tasks, such as image denoising, color correction, and image/video restoration. The articles indicate that different methods show varying results on different datasets, suggesting that the method should be chosen based on the dataset. The articles also indicate that CNNs and GANs show promising results in low-light image and video enhancement especially CNNs.

The article (3) shows that the image quality can be improved by including different CNN architectures, loss functions, and training strategies. The article notes that one of the most important factors in CNN networks is the loss function. Many loss functions have been proposed for deep learning-based low-light image enhancement, including L1, L2, perceptual loss, adversarial loss, and their combinations. The authors note that adversarial loss is widely used for its ability to generate visually realistic results, while perceptual loss is favored for its ability to maintain image content and structure. They also mention that the choice of loss function depends on the specific task and dataset, and there is no universal loss function that works well for all scenarios. The articles also discuss several metrics to evaluate images, such as peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and perceptual quality assessment. These metrics are analyzed in more detail in the experimental results section.

3. The Approach

Our approach in this project can be divided into three main sections. Our first goal is to study and understand the low light image enhancement literature. After learning about the existing methods we will try to recreate these methods. The existing methods are divided into three: histogram equalization, retinex and learning based methods. We will try to recreate the most popular and promising methods amongst these approaches.

After recreating these methods and getting results from these methods we will evaluate them based on some metrics. Some of the metrics are brightness error (AAMBE), lightness order error (LOE), entropy, mean squared error (MSE) etc. Then after evaluating these methods on these metrics we will identify which methods excel at some attributes and under perform at some.

Below is a diagram summarizing our approach:

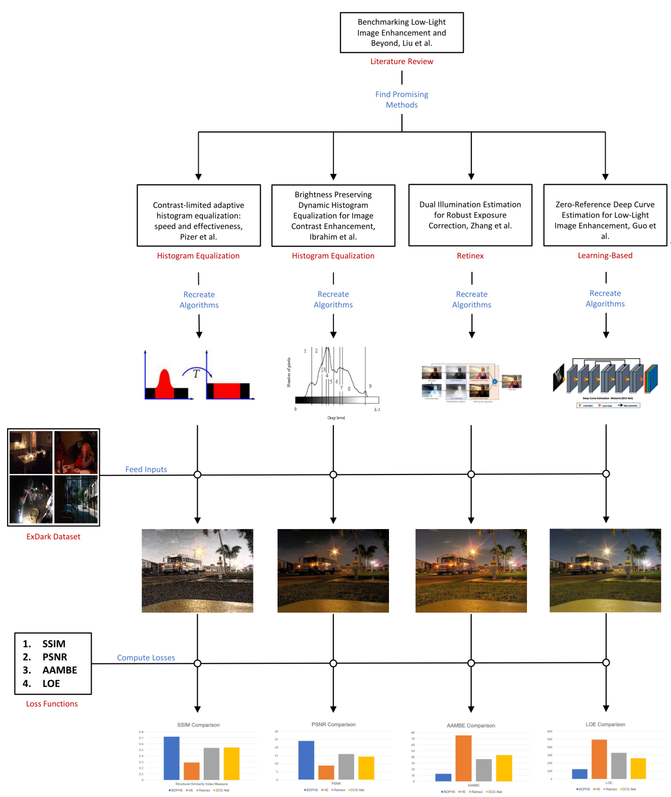

Figure 2. Summary of approach

In this part we will explain the low light image enhancement methods we have implemented:

3.1. Histogram Equalization

The aim of histogram equalization is to distribute the intensities in an image evenly. This method is especially useful for images in which the main portion of the intensity values lie within a small range. Histogram equalization spreads that small range into a wider range. However the main problem with histogram equalization is that it is indiscriminate. In some images it can highlight the noise while diminishing the usable signals thus decreasing the signal to noise ratio (5).

To perform histogram equalization first the image needs to be decreased down to one channel. The operation can not be done on more than one channel separately and then concatenated. Therefore, if the image is an rgb image, it needs to be turned into an hsv image and all the operations needs to be done on the value channel while hue and saturation channels are untouched. Then, on that one channel an intensity histogram needs to be created and using that histogram a cumulative distribution function needs to be created and calculated for every pixel intensity in the image. Then using the equation below the new equalized intensity value needs to be calculated for every pixel intensity in the image (5).

$$h(v) = round(\frac{cdf(v) - cdf_{min}}{(M * N) - cdf_{min}} * (L-1))$$

Where M is the width and N is the height of the image. L is the every possible integer the intensity values can get, it is 256 in most cases. After applying the above equation to one of the test data obtained from the ExDark dataset, the result is shown in the experimental results part. Note that the contrast in the image is increased however the noise in the background and foreground is amplified. The reason for this is histogram equalization is indiscriminate of the noise and usable signal (5; 6)

3.2. Brightness Preserving Dynamic Histogram Equalization (BPDHE)

The problem with histogram equalization is that it changes the mean brightness of the image. This deteriorates the image. BPDHE offers a solution to this problem. The dynamic in the title means that the histogram equalization is done on different sections of the image and brightness preserving means that the final image's brightness will be close to the initial image. The process is consists of 5 parts (7):

1. Get the intensity histogram of the image and smooth the histogram using Gaussian filter. This is important because it will help identify the local maximums.

2. After smoothing the histogram find the local maximums.

3. Create dynamic ranges around the local maximums.

4. Do histogram equalization separately in the dynamic ranges.

5. Finally to preserve the mean brightness, normalize the image to match the initial brightness.

After applying these steps we got the image shown in the Experimental Results part. Compared to the image obtained after regular histogram equalization, the mean brightness of the image matches the initial image much better and the noise amplification is reduced, resulting in a lower noise to signal ratio (7).

3.3. Retinex

In classical single-channel Retinex based approaches, image can be decomposed to pixel-wise product of the enhanced image and single channel illumination map. By making this assignment, image enhancement process can be considered as illumination estimation problem. The equation below demonstrates the decomposition equation used in classical Retinex models.

$$I = I' \times L$$

This classical version of Retinex based models, do not work on well on overexposed or partially overexposed images since it requires $L > 1$ to get I". Therefore, in this project we preffer to use dual illumination approach of Zhang et al. (2019). According to this approach, we first inverted image and calculated illumination map for both original and inverted images. Since the overexposed regions in the original image becomes underexposed regions in the inverted image, the problem is eliminated with this approach. The equation below demonstrates the calculation of inverted image (2).

$$Iinv = 1 - I$$

Afterwards, there is need to estimate illumination map for both original and inverted images. The first illumination map is constructed by taking the maximum RGB color channels as the illumination value at each pixel. Then, Zhang et al. (2019) calculates the desired illumination map as follows. The calculation of w terms (spatially varying smoothness weights) are demonstrated in detail by the Zhang et al. (2019). After calculating illumination maps for both inverted and original images, they calculated enhanced versions for both. For the fusion of these images, they have used multi-resolution image fusion technique origanted by Burt and Adelson. In the project, we have used their techniques on our dataset and produced our results with this approach. However, this methods has a limiation as well. Similar to most of the Retinex based implementations, this implementation of the Zhang et al. (2019) does not consider the noise component existed in low-light images. Therefore, the noise component is somehow amplified after the fusion of images (2).

$$\arg\min_{L} \sum_{p} \left(\left(L_p - L'_p\right)^2 + \lambda \left(w_{x,p} \left(\partial_x L\right)_p^2 + w_{y,p} \left(\partial_y L\right)_p^2 \right) \right)$$

3.4. Learning-based Method (DCE-Net)

Learning based methods are generally categorized into two groups, which are CNN-based and GAN-based methods. Most of the CNN-based methods require paired data (low-light image as input and enhanced version of it as output) for training. However, the collection of paired data for such a training process is time-consuming and resource-intensive. Unlike CNN-based methods, GAN-based methods do not require paired data for training. Most of the GAN-based methods can learn enhancing low-light images from normal/low light unpaired image data. However, the GAN-based methods requires careful selection of unpaired data for training. Again, it's time-consuming and exhaustive process. In order to eliminate these problems, we preferred to use Zero-DCE technique proposed by Guo et al. (2020). Zero-DCE uses zero reference learning strategy thus it eliminates the need of paired and unpaired data. Also, Zero-DCE uses zero-reference loss functions, which allows implicit evaluation of the output image quality. These strategies lying behind Zero-DCE makes it superior to data-driven learning based techniques.

The logic behind Zero-DCE is estimation of a set of best fitting Light-enhancement (LE) curves given an input low-light image. Afterwards, it maps all pixels of the image's RGB channels separately by applying curves iteratively. The below equation demonstrates the quadratic curve formulation used in the Zero-DCE framework. Here, x denotes pixel coordinates while LE represents iterative nature of the light enhancement curves. A is parameter map with the same size of given image (it holds best fitting constants for each image pixel).

$$LE_n(\mathbf{x}) = LE_{n-1}(\mathbf{x}) + \mathcal{A}_n(\mathbf{x}) LE_{n-1}(\mathbf{x})(1 - LE_{n-1}(\mathbf{x}))$$

The input of the DCE-Net is low light image while the outputs are a set of higher order curve parameters given in the curve formulation. The architecture of the neural network contains 7 convolutional layers with symmetrical concatenation. Each convolutional layer has 32 convolutional kernels of size 3 by 3 (with a stride 1). In the original paper of the DCE-Net, each layer is followed by a RELU activation function but we replaced it with Leaky RELU activation function (to achive better performance). The last convolutional layer is followed by a tanh activation function. It produces 24 parameter maps for 8 iterations (3 set of parameter map for each RGB channel). In total, the neural network architecture of the DCE-Net contains 79,416 trainable parameters, which makes it very light-weight and efficient with respect to other learning-based methods. The following figure demonstrates the architecture of DCE-Net used in this paper. The only difference of the our architecture is replacement of RELU activation by Leaky RELU activation function.

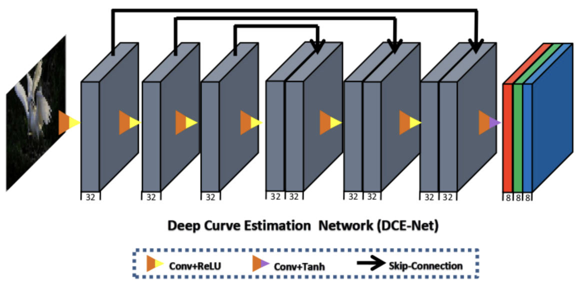

Figure 3. The neural network architecture of DCE-Net proposed in the paper.

In the paper, four different loss functions are used to enable zero-reference learning and evaluate quality of enhanced images. These are spatial consistency loss, exposure control loss, color constancy loss and illumination smoothness loss. According to Guo et al. (2020), The spatial consistency loss encourages spatial coherence of the enhanced image through preserving the difference of neighboring regions between the input image and its enhanced version. The exposure control loss measures the distance between the average intensity value of a local region to the well-exposedness level. The color constancy loss corrects the potential color deviations in the enhanced image and builds the relations among the three channels of the image. Lastly, the illumination smoothness loss preserves the monotonicity relations between neighboring pixels. The formulation of these loss functions are given in the paper. Apart from these loss functions, we used texture preservation loss. It refers to a loss function or metric that quantifies the perceptual similarity between two images based on their texture features (8).

4. Dataset

In this project, we have used Exclusively Dark Image Dataset (ExDark). This dataset is a collection of 7,363 low-light images from very low-light environments to twilight (10 different low-lighting conditions) with 12 object classes. The below figures demonstrates the image distributions for different conditions and classes of the dataset.

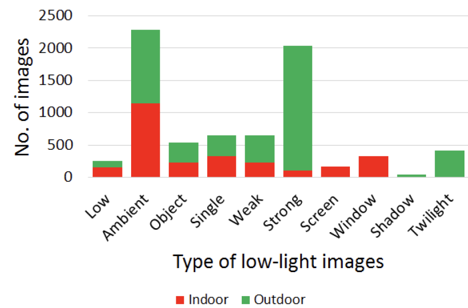

Figure 4. The distribution of the images of dataset under 10 different lighting conditions.

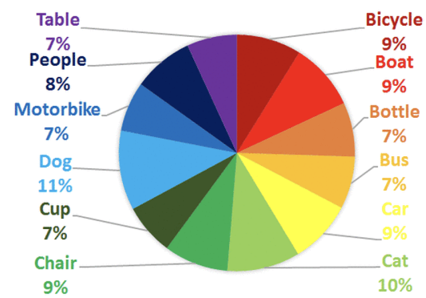

Figure 5. The distribution of the images of dataset for 12 different classes.

In the training process of DCE-Net, we have used 400 images for each class. For testing, we have used 3 images for each class. The rest of the images in each class are used for validation process. We have used the same test dataset not for only DCE-Net but for the conventional methods during metric calculations.

5. Experimental Results

For the analyzing the experimental results for low-light image enhancement methods we used the article [3]. In the article the authors discuss various performance metrics that are commonly used to evaluate the effectiveness of low-light image and video enhancement methods. These metrics include peak signal-to-noise ratio (PSNR), mean squared error (MSE), structural similarity index measure (SSIM), perceptual quality assessment (PQA), and visual information fidelity (VIF).

The article notes that while PSNR and MSE are widely used metrics, they may not always correlate well with human perception of image quality. In contrast, SSIM, PQA, and VIF are designed to better align with human visual perception and have been shown to provide more accurate assessments of image quality.

The authors also discuss the importance of using a diverse set of evaluation metrics to ensure a comprehensive evaluation of the performance of an enhancement method. Additionally, they note that the choice of metrics may depend on the specific task and application, and it is important to carefully select the appropriate metrics to evaluate a given method.

Additionally, there are also metrics to evaluate the brightness and lightness of images. As suggested in article (3), the Lightness Order Error (LOE) is used to evaluate traditional method results. LOE reflects the naturalness of an enhanced image, and a smaller LOE value indicates better preservation of the lightness order. the formula for LOE metric is given below:

$$LOE = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=i+1}^{N} sign(l_i - l_j) \cdot sign(\hat{l}_i - \hat{l}_j)$$

where N is the number of pixels, l_i and l_j are the lightness values of pixels i and j in the original image, and $\hat{l}_i$ and $\hat{l}_j$ are the lightness values of pixels i and j in the enhanced image. $sign(\cdot)$ is the sign function, which returns -1 for negative numbers, 0 for 0, and 1 for positive numbers. We applied all four algorithms to 30 images taken from ExDark dataset and calculated the LOE score for all 30 images and got their averages. Below are the results:

	HE	BPDHE	Retinex	DCE-Net
LOE	494	123	329	261

Up until now, in project 3, we have applied three traditional methods: BDPHE, HE, and Retinex. The approaches for these methods are described in part 3. These results show that BDPHE gives the best result for our dataset on average. However, it should be noted that these values are the average values for all datasets. Each image and different dataset can give different results.

Another method commonly used to evaluate the performance of low-light image enhancement methods is the Average Absolute Mean Brightness Error (AAMBE). As described in (7), the AAMBE formula is used and defined as follows:

$$AAMBE = \frac{1}{N} \sum_{i=1}^{n} |E_n(X) - E_n(Y)|$$

where N is the total number of test images, $E_n(X)$ is the average intensity of test image n, while $E_n(Y)$ is the average intensity of the corresponding output image. Smaller value of AAMBE shows that the average intensity of the input and the average intensity of the output are almost equal. So, the method that can preserve the mean brightness of the image is the method with small value of AAMBE. We applied all four algorithms to 30 images taken from ExDark dataset and calculated the AAMBE score for all 30 images and got their averages. Below are the results:

	HE	BPDHE	Retinex	DCE-Net
AAMBE	75.4	12.4	36.5	43.1

Once again, BDPHE, HE, Retinex method evulated according to AAMBE metric. While Retinex was found to be very close to Histogram Equalization in terms of AAMBE, BDPHE still gave the best result for our dataset. Keeping the mean brightness is important feature for enhancement algorithm since we want the contrast to increase while staying true to the original image and simply upping the brightness can drift away from the original and give undesired colors such as human skin turning white. It's important to note that these values are the average values across all datasets, and different images and datasets can produce different results.

SSIM which stands for Structural Similarity Index Measure is a widely used image quality metric. It quantifies the similarity between two images. It evaluates based on structural and quality differences. It requires two images, a reference image and a distorted image which in our project is the output of our algorithms. The metric checks how well the luminance, contrast and the structure of the image is kept or how much they are degraded. Its value range from 1 to -1, where 1 indicates perfect similarity, 0 indicates no similarity and -1 indicates perfect anti-correlation. SSIM is calculated using the formula below:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where x is the reference image, y is the output image from the algorithms, μ is mean and σ is the variance. We applied all four algorithms to 30 images taken from ExDark dataset and calculated the SSIM score for all 30 images and got their averages. Below are the results:

	HE	BPDHE	Retinex	DCE-Net
SSIM	0.292	0.729	0.533	0.537

The highest value obtained is from BPDHE, this means that it was able to keep the luminance, contrast and the structure of the initial image the best. This by itself does not mean it is the best algorithm, however if two algorithms are being compared and the rest of the metrics give similar values and we are comparing them only based on SSIM, it means that the one with the highest SSIM value was able to keep up with the other algorithm on the other metrics while being faithful to the original image. Retinex and DCE-Net scored very similar, but when the amount of time and computation required to train the DCE-Net is considered, Retinex has better efficiency. Histogram equalization performed the worst but it is expected since it a very old method and methods such as BPDHE took HE as a base and improved the method.

PSNR which stands for Peak Signal-to-Noise Ratio, measures the amount of noise present in an image compared to the original, reference image. The PSNR score is especially an important metric in low light imag enhancement because the dark images contain a lot of noise because of the lack of lights captured by the sensors and when enhanced instead of enhancing the noise, the useful signals need to be enhanced, thus this metric can evaluate whether that is being done or not. It evaluates the fidelity and quality of the image. It measures the ratio of the peak signal power to the mean squared error between two images. The higher the PSNR value, the lower the perceived noise in the image. However, PSNR calculations are done on pixel-wise differences so sometimes the score might not match with human perception and although it evaluates the image quality it can not be used only by itself to assess the image. The formula for PSNR is below:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2.$$

The PSNR (in dB) is defined as:

$$\begin{aligned} PSNR &= 10.log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20.log_{10}\left(\frac{MAX_I}{MSE}\right) \\ &= 20.log_{10}(MAX_I) - 10.log_{10}(MSE) \end{aligned}$$

where m is the width and n is the height of the image, I is the reference image and K is the output image and MAX_I is the maximum pixel value of the image. We applied all four algorithms to 30 images taken from ExDark dataset and calculated the PSNR score for all 30 images and got their averages. Below are the results:

	HE	BPDHE	Retinex	DCE-Net
PSNR	8.792	24.065	15.909	14.342

Just like the rest of the metrics BPDHE scored the best by getting the highest score, while Retinex and DCE-Net have very close scores and in the second place and finally histogram equalization is in the last place. BPDHE applies Gaussian filter before equalizing the histogram and this is a big factor in reducing the noise.

Overall when evaluating all the metrics as a whole BPDHE performs the best and in second place Retinex and DCE-Net however, since DCE-Net is a learning-based method that needs to be trained it requires much more time and computation compared to the simplicity of Retinex. Finally histogram equalization came last ine very metric as expected since it is an outdated method. However, this shows how much advancement has been completed in the low-light image enhancement field. Histogram equalization is the founding method and most of the other methods took it as a base and improved it.

5.1. Qualitative Results

In quantitative analysis, the best result was achieved with the BPDHE method. However, the qualitative results do not support this finding. According to the qualitative analysis, the image with the best illumination and detail was obtained using the DCE-Net algorithm. Although BPDHE produces a good result, it is not as bright as Retinex and DCE-Net. The Retinex algorithm also produces very good results and aims to maintain color consistency, but it is not as effective as DCE-Net in terms of detail and illumination. The Histogram Equalizer method yielded the worst output compared to the other methods. Here are the reults:

Figure 6. Left to right row order, Input image, HE, BPDHE, Retinex, and DCE-Net results of the input image

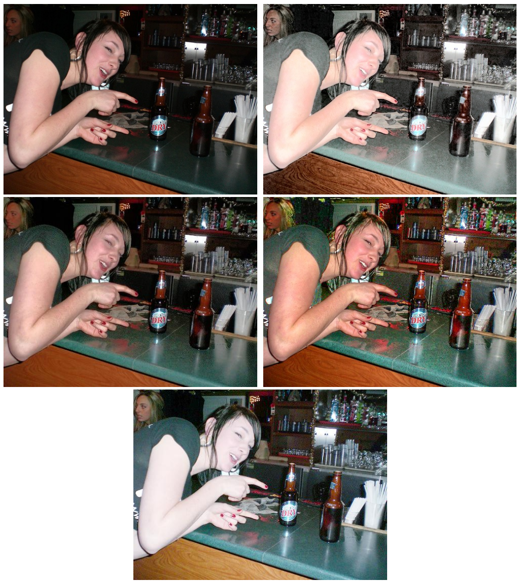

Figure 7. Left to right row order, Input image, HE, BPDHE, Retinex, and DCE-Net results of the input image

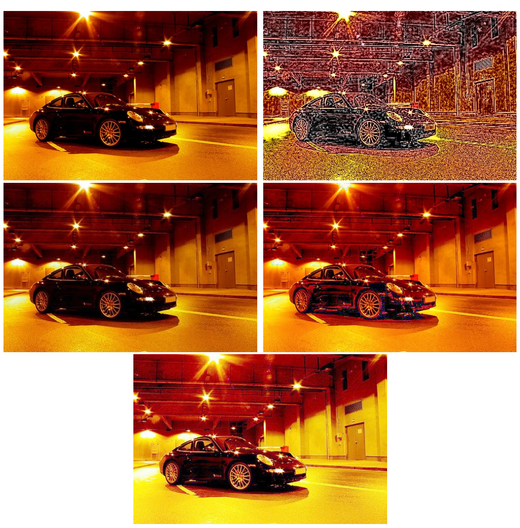

Figure 8. Left to right row order, Input image, HE, BPDHE, Retinex, and DCE-Net results of the input image

Figure 9. Left to right row order, Input image, HE, BPDHE, Retinex, and DCE-Net results of the input image

Figure 10. Left to right row order, Input image, HE, BPDHE, Retinex, and DCE-Net results of the input image

6. Conclusions

In conclusion, this progress report discussed the implementation and evaluation of various low light image enhancement methods, namely histogram equalization (HE), brightness preserving dynamic histogram equalization (BPDHE), Retinex, and DCE-Net. AAMBE (Average Absolute Mean Brightness Error) and LOE (Lightness Order Error) metrics were used to evaluate the techniques. Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) were added as new measures to further enhance the evaluation. The addition of these measures and techniques made it possible for a more thorough study.
The BPDHE approach produced the best results, according to the quantitative analysis, since it had the lowest AAMBE and LOE scores and the highest PSNR and SSIM ratings. The qualitative analysis, however, produced different results. The DCE-Net algorithm outperformed both BPDHE and Retinex to produce the image with the best illumination and detail. Although BPDHE produced a respectable result, it lagged behind Retinex and DCE-Net in terms of brightness. Retinex likewise generated acceptable results, emphasizing color consistency, although it performed less well in terms of detail and lighting than DCE-Net. Out of all the methods tested, the Histogram Equalizer method performed the worst.
Moving forward, future studies should investigate additional low light picture improvement methods by doing a more thorough literature review. Multiple metrics can be used to compare these new methods to existing ones and provide a more thorough review. A fresh low light picture enhancing technique should also be developed so that it can be compared to the strategies outlined in the literature. These enhancements can help us comprehend low light picture enhancement techniques more thoroughly.

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