Exploring Low Light Image Enhancement Techniques that Work Best for my Smartphone

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***Abstract*—There has been a significant advance in deep learning techniques and parallelly, in image enhancement. Problems like deblurring, super-resolution, denoising, and low-light image enhancement are among the common problems in this domain. This paper explores the modern as well as traditional image enhancement techniques, in particular, low-light image enhancement techniques and their performance on images taken from a smartphone camera. It looks at the best performing models in the LOL and other low-light image enhancement benchmarks to find the state-of-the-art techniques in image enhancement. Historically used techniques like the Histogram Equalization, and Gamma Correction are also tested. Results indicate that even these ancient techniques can still produce decent results in certain situations, whereas, visually, the deep learning models appear brighter and sharper in most situations, and themselves vary from each other.**

Keywords—Low-light Image Enhancement, Smartphone Night Photography, Image Processing

I. Introduction

It is a common knowledge that photography during the night suffers from the problem of low visibility of information and degradation of image quality. This occurs mainly due to insufficient lighting conditions. Enhancing such images can have a huge impact on tasks such as surveillance, autonomous driving, robot navigation, photography, biometrics, and problems in deep learning such as classification and detection. Papers have also highlighted how robust facial recognition systems can be created by utilizing low-light image enhancement techniques [7]. Hence, it is one of the important problems to tackle in image processing and deep learning.

As seen from [1], the traditional image processing techniques mostly derive from the concept of Histogram Equalization and Retinex theory. Histogram Equalization-based methods deal with improving contrast or the dynamic range of the image by manipulating the pixel frequency histogram. The Retinex theory-based methods have found more attention and mostly rely on decomposition of a low-light image to two components: reflection, and illumination. Gamma Correction is also one of the commonly used low light enhancing techniques. [6] is an extensive survey of such traditional techniques in low-light image enhancement.

The traditional methods usually suffer from amplification of noise and degraded images. As deep learning techniques have evolved, image enhancement using these techniques has also been a significant boost in this domain. Their good performance in other domain translates well in low-light image enhancement. Since the first low-light enhancement deep learning technique was presented [2], a lot of work has followed.

As smartphone cameras are getting better, it might be interesting to enhance the low-light images directly from a smartphone camera as these devices are usually more portable than a high-end camera, and more affordable for everyone. Smartphone camera quality is one of the highly sought out features by smartphone buyers [15]. An efficient image-enhancement technique has the potential to be one of the key factors in improving the smartphone camera quality.

In this paper, we look at some of the commonly known traditional low-light image enhancement techniques: Histogram Equalization (HE) and its variant: Contrast Limited Adaptive HE; Gamma Correction; Multi-Scale Retinex; and the state-of-the-art deep learning techniques namely EnlightenGAN [3], LLFlow [5], and ZeroDCE [4]. We collect a dataset of 44 image pairs of low and high exposure images of the same scene. We then perform qualitative and quantitative evaluation of these image enhancement techniques on these images.

II. Related Work

Conventionally, Histogram Equalization based methods were used to improve the dynamic range of the image. Variations of HE was used to enhance the image globally or at local regions [19], [26]. [6] provides an extensive survey of the traditional techniques used for low-light image enhancement. Methods that work on the frequency domain like homomorphic filtering, and simple non-linear transformation methods such as gamma correction, and Retinex-theory based methods are notable. We can also find modern deep learning techniques that are also based on the Retinex-theory [21], [22], [11].

Traditional image processing algorithms simply take an input image and tune the features within to produce an enhanced image. Deep learning models on the other hand are data driven and make use of large-scale image datasets to learn how to enhance images. [2] was said to be the first deep learning-based approach to tackle the problem of image enhancement. Other deep learning techniques have followed this work and vastly improved on the task of image enhancement.

Among them, CNN-based techniques are typically trained under a supervised setting on low and high light image pairs [23], [11], [5]. However, this is mentioned as a problem in several papers including [3], [4]. The problem is in simultaneously capturing a pair of low-light and a normal exposure ground-truth image. Typically, this is done by changing the exposure and ISO settings of the camera. However, this requires a lot of time and careful observation to filter out images corrupted by shakiness, incorrect focus, and object movement. An example is [24], where they have collected RAW image pairs from high-end cameras. The LLFlow paper [5] also highlights the importance of formulating a proper loss function while performing this kind of mapping from a low-light image to a well-lit counterpart.

They formulate the problem of finding a well-lit image from a low-lit image to be a one-to-many relationship and use a Normalizing Flow model to learn this distribution. This is also the current best-performing model on the LOL dataset for this task of supervised low-light image enhancement.

On the other hand, adversarial networks might also rely on paired training data [25], [26] for image enhancement problems. But we highlight that they have also been used under unsupervised setup. EnlightenGAN [3] is one of such methods that is trained under an unsupervised setting of low-lit and well-lit images. This method does not rely on a pair of images and is expected to generalize better on new sensors and images.

Yet another approach is to completely disregard being data-driven and not requiring any kind of paired or unpaired data. ZeroDCE [4] is one such work that relies on careful design of the loss functions such that no external images are required for the model to learn. This is also a low-cost model and can be easily implemented on a mobile device.

III. Datasets

A. Smartphone Dataset

A low-light image enhancement dataset was collected using a Redmi Note 7 Pro smartphone camera with parameters: 48 MP, f/1.8, (wide), 1/2.0", 0.8µm, PDAF. The default camera application was used to tune the ISO and the exposure. Low-light images had an exposure of 1/30th of a second and an ISO of 3200 whereas the well-lit images had an exposure of 32 seconds and an ISO of 100. Most low-light image enhancement datasets use a similar approach to collect the noisy and ground-truth image pairs. [11]. This dataset is experimentally used once to train the LLFlow model and otherwise as a benchmark to compare the image enhancement techniques in terms of qualitative results and image quality evaluation metrics.

Fig. 1. Sample Smartphone Dataset Image Pairs

B. Other Datasets

The common benchmark in low-light image enhancement is the LOw-Light (LOL) dataset [11]. The dataset comprises 500 image pairs of low and well-lit images taken by changing the ISO and exposure settings of the camera. They also eliminate any misaligned images potentially caused due to shaking or object movement. This is used specifically to train the LLFlow model from scratch.

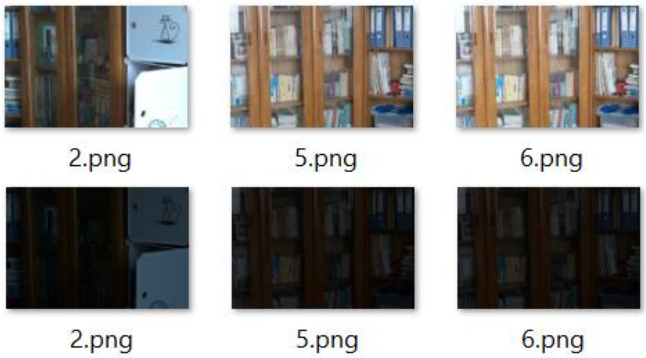

Fig. 2. Sample LOL Dataset Image Pairs

Similarly, EnlightenGAN is trained on their own tailored dataset with around 1000 unpaired low-lit and well-lit images they took from several sources [3]. For the ZeroDCE model, they train it on a subset of the SICE dataset [8].

IV. Methodologies

A. Image Enhancement Metrics

1) Peak Signal-to-Noise Ratio (PSNR)

PSNR is a common metric used to measure the performance in image enhancement or compression problems. In cases where there is no distortion, or other kind of shift such as rotation and translation between two images, this could be a reliable metric for comparing the visual quality between two images [13].

Here, the idea is to simply calculate the mean squared error between the individual pixels of a reference image and the possibly noisy image. Let us define MAX_I as the maximum possible pixel value of the image (for an 8-bit representation of a channel, this would be 255). Then, the PSNR between the two images is given by

$$PSNR = 10\ \log_{10}\left(\frac{MAX_I^2}{\mathrm{MSE}}\right)$$

Where MSE is the mean squared error between the individual pixels of two given images.

2) Structural Similarity Index Measure (SSIM)

SSIM [12] was introduced as a quality assessment based on the degradation of structural information which is commonly used in current image enhancement benchmarks. Different from PSNR, SSIM looks at the visible structures in the image. The simplified equation for SSIM looks like:

$$SSIM(x,y) = l(x,y)^{\alpha} \cdot c(x,y)^{\beta} \cdot s(x,y)^{\gamma}$$

Where l, c, and s give the comparison of lightness, contrast, and structure respectively, between two image windows x and y of same dimensions.

B. Image Processing Algorithms

For these simple image processing algorithms, we just process each low-light image from the smartphone dataset using these techniques and compare the PSNR and SSIM values with the ground truth values.

1) Histogram Equalization

Histogram Equalization is one of the common image processing techniques used for image enhancement. It improves the contrast of the image and improves the dynamic range. The idea is to calculate the Probability Mass Function for the frequency of each pixel value. Then use this PMF to calculate the Cumulative Distributive Function, from which we multiply the max possible pixel value (for 8-bit channel, this would be 255), and round the resulting values. The table we get as a result tells us which values the old pixel values should be mapped to and in doing so, we get the enhanced image.

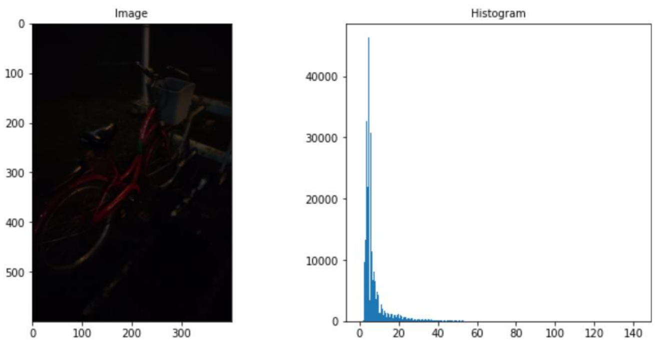

Fig. 3. Before Histogram Equalization

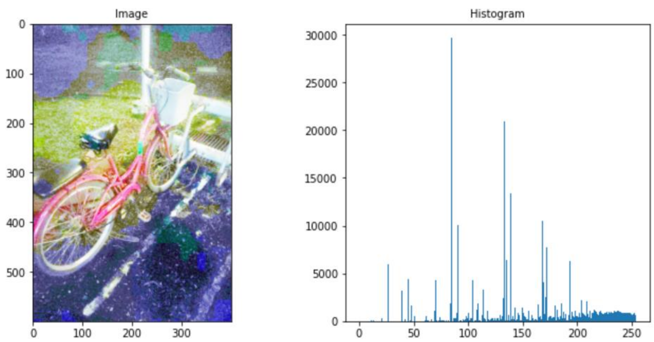

Fig. 4. After Histogram Equalization

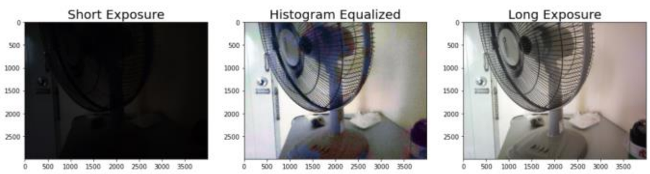

Fig. 5. Result of applying Histogram Equalization

2) Contrast Limited Adaptive Histogram Equalization

Adaptive Histogram Equalization just extends on the normal HE. We instead divide the image into a grid and apply HE individually on these grid cells. This is with an aim to enhance the image considering the local features. While this simple approach could work, there is a bigger chance of amplification of noise signals. To prevent noise, a clip limit is applied to form this as Contrast Limited Adaptive Histogram Equalization. This might result in a somewhat dimmer image than the regular AHE or HE, but with significantly less noise.

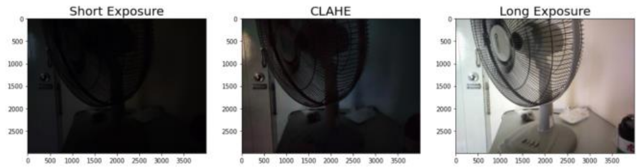

Fig. 6. Result of applying Contrast Limited Adaptive Histogram Equalization

3) Multi-Scale Retinex

Retinex theory [16] was initially developed to model the human eye perception of light intensities. The core idea behind the Retinex theory is that we believe the human eyes to have different perceptions of lightness, relative to the surrounding area in a scene. Another property is that humans exhibit a logarithmic response to lightness [17]. Using this, we derive a Single-Scale Retinex equation:

$$R(x,y) = \frac{\log I(x,y)}{\log[F(x,y) * I\,(x,y)]}$$

Where R(x,y) is the resulting enhanced image; I(x,y) is the input image; * is the convolution operation; and F(x,y) is a surround function. This surround function gives a center-surround average of a pixel. Typically, a Gaussian function with a variance (σ^2) is used for this purpose. For the case of Multi-Scale Retinex, we provide multiple sigma values in this Gaussian function and take the weighted average.

Fig. 7. Input Low-light image (left), Result of applying Multi-Scale Retinex (center), ground-truth image (right)

4) Gamma Correction

Gamma correction is one of the more commonly used image processing techniques. It can be written as the equation:

$$V_{out} = AV_{in}{}^{\gamma}$$

Where A is a constant (usually 1), V_{out} is the resulting output after applying gamma correction by raising the V_{in} to the power γ.

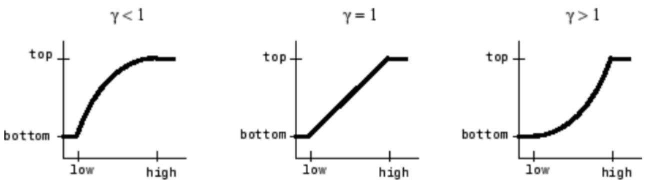

Fig. 8. Change on the image intensity curve after applying different values of gamma (Image Source: [18])

We can see from the curves what supplying different values of gamma does to the curve. Basically, using a lower value of gamma shifts the intensities towards brighter regions, and thus results in a brighter image. However, using a much lower value would also introduce noise.

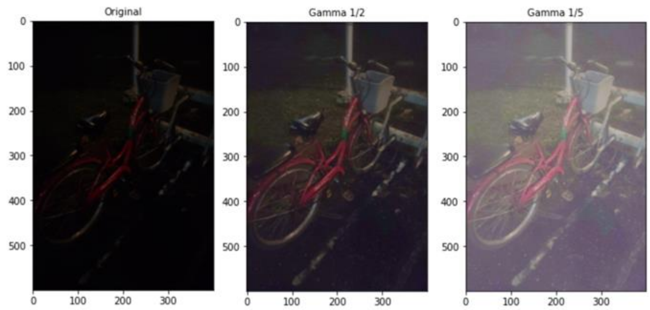

Fig. 9. Results of applying different gamma values for gamma correcting a dark image

Fig. 10. Input Low-light image (left), Result of applying Gamma Correction (center), ground-truth image (right)

C. Deep learning Techniques

For these deep learning algorithms, we either pretrain the model with a different dataset, and then pass the low-light images from the smartphone dataset to get enhanced images or attempt to train the model using the smartphone dataset itself. Finally, we compare the PSNR and SSIM values between these enhanced images and the ground truth images.

1) EnlightenGAN

The EnlightenGAN [3] paper proposes to solve the low-light image enhancement problem using unpaired images for training a deep generative model. The main idea behind taking this approach is that it is quite difficult to obtain paired image samples for low-light enhancement tasks. Whereas getting unpaired samples for low-light and well-lit images is relatively simple. They take a similar approach to CycleGANs [9] except they have a one-way generative model and no cycle-consistency. They use a special loss function to preserve the image content after enhancement which allows this kind of unidirectional approach. In addition, they use a dual-discriminator structure to capture both local and global image features. The structure of the EnlightenGAN can be seen in Figures Fig. 11 and Fig. 12.

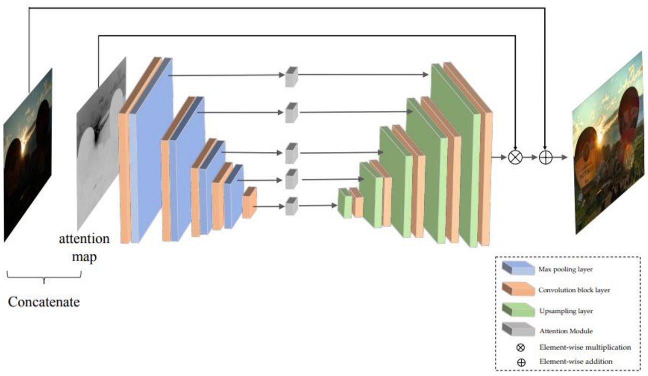

Fig. 11. The Generator Network of the EnlightenGAN.

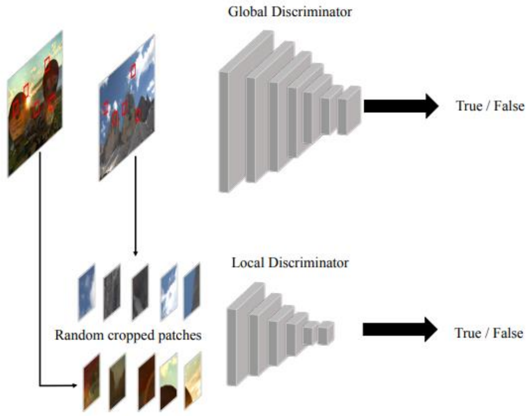

Fig. 12. The dual-discriminator Structure of the EnlightenGAN.

For inference, we take a model pretrained on the same unpaired dataset as mentioned in their paper and pass our low-light images through it to get enhanced images.

Fig. 13. Input Low-light image (left), Result of enhancing the image using EnligthenGAN (middle), ground-truth image (right)

2) LLFlow

LLFlow [5] has a different approach in that it uses a paired dataset of low and well-lit images. Unlike previous papers, which have simply attempted to enhance the images by minimizing a simple loss function between the well and low-lit images like the L_1 loss, they attempt to use a Normalizing Flow [14] where we go from a simple initial probability distribution to another through a series of invertible mappings. Normalizing Flow is well-suited to move from one distribution to the other and suited for the task at hand. Additionally, to obtain a good prior distribution to feed to the Normalizing Flow network, they train an encoder to learn to produce an "illumination-invariant color map" from the input image. These color maps should be the same for static scenes despite the change in the amount of illumination. The invertible network then takes this color map as a prior distribution and attempts to move towards the enhanced distribution.

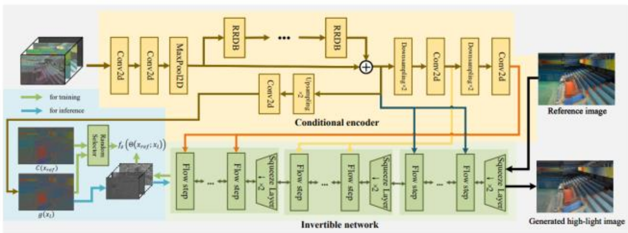

Fig. 14. The Full Network Structure of the LLFlow Model

The small version of the LLFlow model was initially trained on the smartphone dataset with 39 out of the 44 image pairs split into the training set and the remaining into the evaluation set. However, the resulting images after passing new low-light images through this model were contaminated with significant blur and noise. Later, the LLFlow was trained on the LOL dataset as in the original paper, which gave significantly better results.

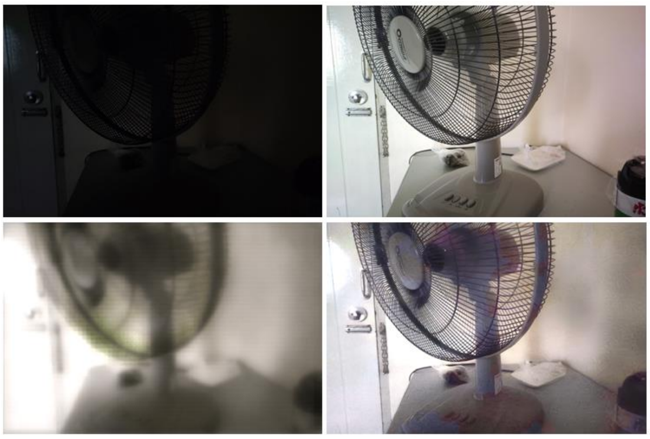

Fig. 15. Input Low-light image (top left), Result of enhancing the image using LLFlow trained on the smartphone dataset (bottom left), Result of enhancing the image using LLFlow trained on the LOL dataset (bottom right), ground-truth image (top right)

3) ZeroDCE

Lastly, ZeroDCE [4] uses yet another approach for solving the low-light image enhancement problem. Instead of trying to learn a mapping between paired or unpaired data, they try to estimate a pixel-wise curve that can be applied iteratively to the image pixels to enhance the image. Their approach does not require a paired or an unpaired set of images, and instead, the learning of the model comes from carefully tuned loss functions. The loss functions they use jointly preserve the neighboring regions between the input and modified images, maintain the exposure, correct color deviations, and preserve the local monotonic relationship around the neighboring pixels. Their Deep Curve Estimation Network attempts to estimate a set of light enhancement curves per pixel for an input image, which is then mapped onto all the three RGB channels. A simple equation shows how the learning works:

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

Where, x is the pixel coordinate, the left-hand side is the enhanced version of the input image I(x), and α is the trainable curve parameter. This parameter is learned individually for each pixel, and this curve is applied iteratively to get higher order curves. The model is pretrained on a subset of the SICE dataset [8].

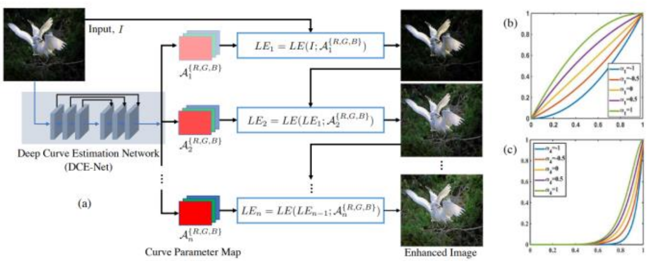

Fig. 16. Structure of the ZeroDCE model. The DCE-Net estimates the pixel-wise curves, which is then applied iteratively to enhance the image

Fig. 17. Input Low-light image (left), Result of enhancing the image using ZeroDCE (middle), ground-truth image (right)

V. Results and Discussion

Here, we look at the quantitative and qualitative results after passing the low-light images from the smartphone dataset through these algorithms and deep learning models. The resulting images from each technique will be handed out along with this paper.

A. *Simple Image Processing Techniques*

TABLE I. Comparison of Results

	PSNR		SSIM	
	Train	***Eval***	***Train***	***Eval***
HE	10.06897	9.325281	0.228195	0.198176
CLAHE	12.3710	11.88387	0.272981	0.229236
MSR	10.2786	9.456501	0.146031	0.121461
GC	14.83047	15.34708	0.503369	0.483064

Gamma Correction gives us the best PSNR and SSIM results. We would expect this method to introduce the least amount of distortion and as maintaining the best structural similarity between the enhanced and high-exposure images among the non-deep learning techniques.

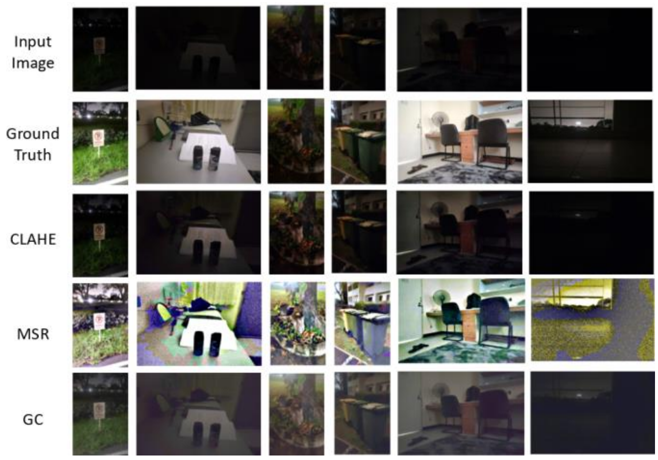

Fig. 18. Comparison of enhancement results produced by the image processing techniques on a sample of the smartphone dataset

We can notice from these images that while the MSR technique increases the image brightness, it also amplifies the noise significantly, resulting in the lowest MSNR and SSIM values. The visibility is still not very good in the case of CLAHE. Gamma Correction seems to work best among these techniques both qualitatively, as well as quantitatively.

B. *Deep Learning Techniques*

TABLE II. COMPARISON OF RESULTS

	PSNR		SSIM	
	Train	***Eval***	***Train***	***Eval***
EnlightenGAN	14.895612	14.942990	0.5010898	0.5234190
LLFlow	19.608817	19.157604	0.6273875	0.6076063
ZeroDCE	15.196760	14.989276	0.474415	0.4128483

The LLFlow model produces the highest PSNR and SSIM scores among the three deep learning models. This is consistent with their claim of having the best scores on the LOL dataset. However, the other models, although they were expected to generalize better to the real world, were not as good (at least quantitatively).

Also, simply looking at these scores, Gamma Correction can be seen outperforming the EnlightenGAN and ZeroDCE in most cases or coming very close otherwise. However, when we qualitatively compare the enhanced images side-by-side, the deep learning models more often produce better-looking images (subjective).

Fig. 19. Image enhanced using EnlightenGAN (left), Gamma Correction (middle), and (ZeroDCE)

Although the images enhanced by the deep learning models in the above image look brighter, they tend to have altered color information or some level of noise. However, the quality of the images could be an entirely subjective matter.

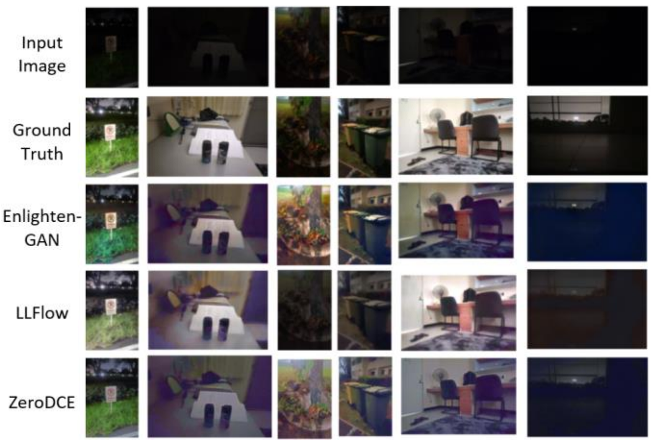

Fig. 20. Comparison of enhancement results produced by the deep learning techniques on a sample of the smartphone dataset

We can notice that the images enhanced by these algorithms can vary a lot. The third and fourth images from the left are significantly dimmer from the LLFlow output compared to the other models. However, one could perhaps argue that these images look closer to the ground truth image that would have come from a higher exposure. We can also notice the similarities between the ground truth and the enhanced images for LLFlow in other images. We could thus argue, LLFlow produces more realistic results that are closer to the ground truth and is likely more reliable if we simply want to get a more natural-looking image. However, one might also make a case that the ZeroDCE and EnlightenGAN models are producing results brighter than the ground truth, and more visually pleasing on many occasions. Perhaps, this explains the lower quantitative scores compared to LLFlow.

VI. CONCLUSION

In this paper, we looked at several traditional and deep learning techniques for low-light image enhancement. We tried to collect our own dataset of low-lit and well-lit images to compare the results from these enhancement techniques. Visually, we observed that even the simple traditional techniques can make objects invisible to the human-eyes appear visible by enhancing the image. If the goal would be only to recover the object information (from a human perspective), these techniques might work fine, however, if the requirement is to obtain a high-quality image, then we must rely on the state-of-the-art deep learning techniques. We noticed the challenging aspects of this problem, particularly in data collection for paired samples (although we found the model trained on this paired dataset performing the best). As a future direction, perhaps a careful combination of these traditional techniques and deep learning techniques would yield better results? Additionally, we might want to explore the use of small models like ZeroDCE [4], which has a low number of parameters directly on mobile devices like smartphones or JetBots; or real-time video processing.

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