Image Enhancement Techniques for PSR regions of the Moon

Bharath Raam Radhakrishnan
University of California, San Diego
bradhakrishnan@ucsd.edu

Aneesh Ojha
University of California, San Diego
anojha@ucsd.edu

Abstract

Permanently Shadowed Regions (PSR) of the Moon are located in the poles of the Moon, which are the regions where sunlight does not illuminate the surface. The research aims to enhance the imagery in these regions of the moon to aid in mission planning. The research explores techniques which can perform low light image enhancement techniques, which can preserve the underlying texture of the image. The preservation of texture is a critical criterion in this regard, as they hold the information about the terrain in the PSR, which is crucial in mission planning. To address this issue, we proposed and experimented with a variety of enhancement algorithms ranging from Dual-Illumination estimation, Controlled Light Enhancement Diffusion (CLED) models, and CNN Based enhancement models(LoLi-IEA). We also introduced a novel approach utilizing pix-pix SAR colorization to help perform terrain classification. The qualitative and quantitative performance of low light enhancement techniques are measured using Lightness order error(LOE) and SPAQ (a perceptual image quality measure) respectively to help analyze the best performing technique.

1. Introduction

Permanently shadowed regions(PSR) are the regions in lunar surface, which are never illuminated by sunlight. These regions occur at the poles of the moon. This phenomenon is a direct effect of the Moon's rotational axis being tilted by only about 1.5° relative to the plane of its orbit around the Sun. This minimal axial tilt means that at the poles, some craters and depressions remain in constant shadow, as sunlight never reaches their floors. But, why are we eager to learn about these poorly illuminated dark abyss?

1.1. Why explore the PSRs?

Permanently shadowed regions are one of coldest region in the solar system, with temperatures reaching up to -200 degree Celsius (nearly close to absolute zero). The absence of direct sunlight and very low temperatures provide a very conducive environment to trap volatile substance such as carbon dioxide and sulfur dioxide alongside water trapped as ice. The potential discovery of water ice is the driving force for space explorations in the enigmatic permanently shadowed regions. In order to aid in mission planning in the permanently shadowed regions we need to have the knowledge about the terrain in those regions. This is usually achieved by sending out exploratory satellites, which will provide us the crucial information to understand the environmental and terrain conditions to perform mission planning for rovers accordingly.

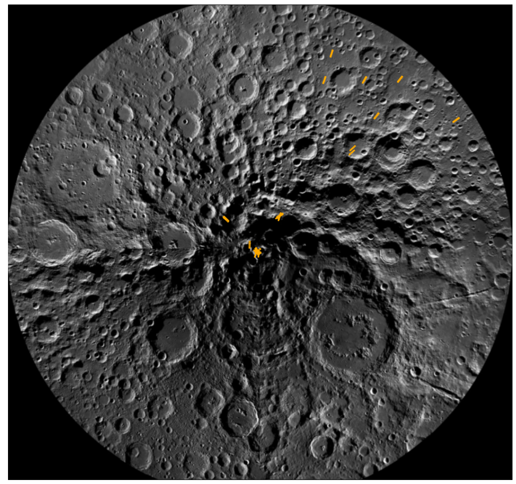
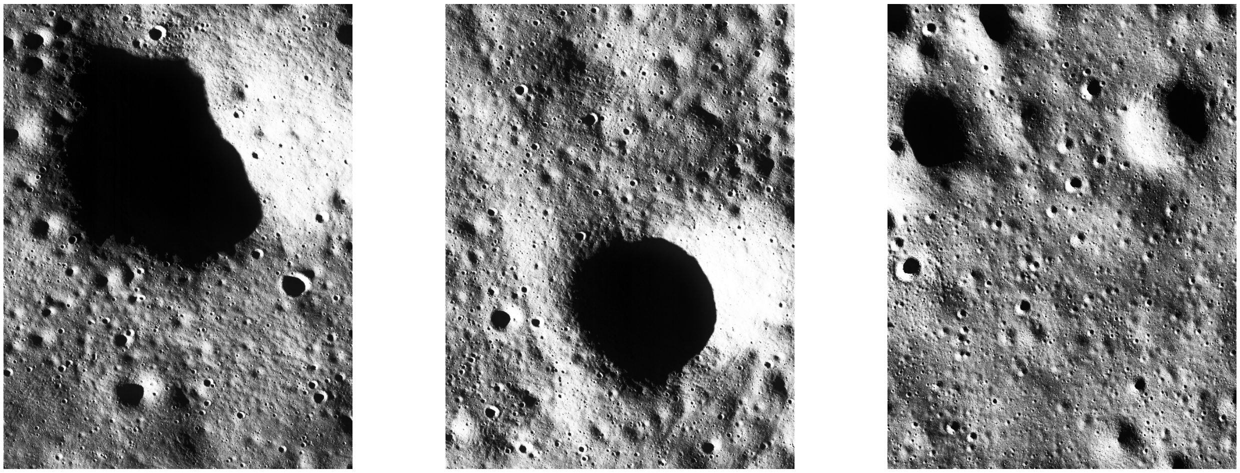


Figure 1. Polar Stereographic image of the South pole of the moon with PSR highlighted.

1.2. Problem Formulation

As it turns out the permanently shadowed regions are not completely dark, as shown in Figure 2, whilst they don't receive direct sunlight, they are poorly illuminated by the light scattered by the surrounding craters and mountains. This is the foundational principle to model the problem statement at hand as low light image enhancement problem. We aim to explore existing low-light enhancement methods, and experiment if they are suitable for enhancement of PSR region. The major performance criteria in choosing an algo-



(a) Sample 1. (b) Sample 2. (c) Sample 3.

Figure 2. Samples of Permanently Shadowed Region as observed by Chandrayan-2 Orbiter High Resolution Camera

rithm is that it should preserve the texture even when enhanced, as the texture in the image contains the information about the terrain. Another major criteria for the any learning based algorithm we develop should be capable of one-shot / few shot learning methodology, due to the lack of extensively labeled and annotated dataset for the permanently shadowed region. It is because of the above reason we are evaluating our methodologies utilizing no reference based image quality assurance metrics such as, Lightness Order Error and SPAQ[4].

2. Literature Review and Previous Methods

2.1. Traditional Methods

Low-light imaging has been a long standing problem and has to be handled on a case to case basis, due to the nature of the problem itself. Exposure correction is a traditional approach utilized in low light image enhancement. A rudimentary approach to exposure correction is performing local and/or global histogram equalization[1] on the input image provide an enhanced output. One of the popular approach is utilizing LIME[5], which optimizes the illumination map of an image to produce an enhanced image by enforcing structure priors. Retinex theory [8]is a widely pursued research direction that builds upon the foundational model of Dual Illumination Estimation[16], a methodology we have implemented for PSR enhancement . These techniques require compute extensive parameter tuning for the algorithm to produce the best possible enhancement, which is elucidated in the findings of this research

2.2. Learning Based Techniques

With the rapid development in Artificial Intelligence and Machine Learning, researchers have explored in its application in low-light imaging enhancement techniques. Kin Gwn Lore et al[9]. proposed a deep auto encoder based learning method for low light image enhancement, they intelligently brightened an image without over sampling lighter portion of the image with high dynamic range. Deep neural networks[2] are utilized to develop noise source agnostic de noising frameworks, which eliminates the need for knowing about the noise statistics and behavior before denoising the images. These techniques are employed to perform low light image enhancement alongside with noise reduction. Convolution neural networks and diffusion models are the forerunners in low light image enhancements. Controllable Light Enhancement Diffusion (CLED) [15]model is a state of the art model, upon which we built our methodology enhance PSRs. ReCoRo, a GAN based light enhancement model which allowed spatial/regional control over the measure of enhancement the model introduced. This is the baseline model which was used as the guideline to building our CLED based PSR enhancement model. LoLi-IEA[10] is CNN based model which adaptively performs both global and local enhancement.

2.3. Adaptive SAR Image Processing

Synthetic aperture radar (SAR) is an active imaging technology used by satellites, which transmit microwave pulses and analyze their reflections from Earth's surface, capturing data regardless of light conditions or weather. Unlike RGB images, which rely on sunlight and are hindered by clouds, SAR can penetrate cloud cover and operate at night, ensuring reliable data capture[13]. With multi-polarization techniques, SAR provides unique insights into terrain characteristics[7], enabling detailed surface analysis that optical imagery cannot achieve. Recent research in synthetic aperture radar (SAR) image process-

CVPR
#Team 27

ing has increasingly focused on addressing challenges related to image diversity, colorization, and generative techniques, which have improved noise handling, spatial detail preservation, and applicability to PolSAR techniques[3]. Zhang et al.[6] introduced terrain-specific colorization using Multidomain Cycle-Consistency GANs, excelling in simple landscapes like farmlands but struggling with complex textures. Other works using deep neural network-based methods[11] reconstruct fully polarimetric SAR images from single-polarization grayscale data but require extensive data. Similarly, pix2pix models and other cyclic adversarial networks face limitations in handling diverse datasets.

3. Datasets

3.1. Permanently shadowed region Dataset

The dataset of permanently shadowed regions are acquired from the Space Applications Centre (SAC) - ISRO[12]. These are collected utilizing the orbiter high resolution camera onboard the Chandrayan-2 satellite. These data points are packaged in a Planetary Data System Version 4 (PDS4) data format. Each data point contains a radiometrically corrected and calibrated high resolution image of the permanently shadowed region. Each high resolution image is a RGB image of resolution 93,653 x 12,000 pixels.

3.2. SAR Imagery Dataset

The study utilizes the SEN1-2 dataset, a comprehensive collection of 282,384 co-registered image patches from Sentinel-1 (SAR) and Sentinel-2 (optical) satellites, encompassing global land masses across all four meteorological seasons which are available under the open access license CC-BY and available for download provided by the library of the Technical University of Munich: https://mediatum.ub.tum.de/1436631. The dataset contains 8-bit single-channel SAR images representing 8-bit color optical images using bands 4, 3, and 2. All images are standardized to a 256 × 256 pixel resolution. Notably, the SAR images exclusively feature VV polarization data, constraining the analysis to the conversion of VV-polarized SAR images to RGB optical representations. To do the computational processing, the dataset was integrated into a ConcatDataset class, enabling simultaneous access to SAR and optical images. The model was trained using data from the spring season, while testing was conducted with data from the summer season.

4. Methodology

4.1. Dual Illumination estimation for PSR enhancement

The crux of Dual illumination estimation for low light image enhancement is that an image I can be characterized

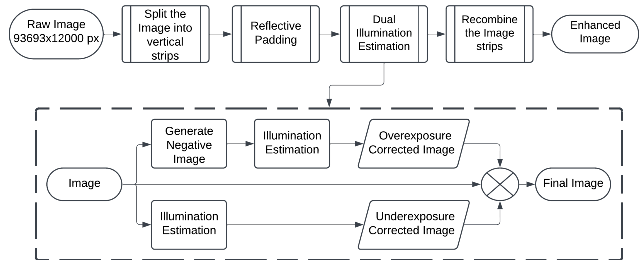


Figure 3. Dual Illumination Estimation Enhancement Framework

as a pixel-wise product of the desired enhanced image I' and a single-channel illumination map L. So, by optimizing the illumination map we can acquire a well enhanced image. The novelty of a Dual illumination estimation framework is that it a utilizes a single illumination estimation framework to correct both over and under enhancement in a given image. This is achievable because we process both original image and its negative, the illumination estimation corrects under exposure in original image and over exposure in negative images respectively. This is plausible because over exposure in image presents itself as an under exposed region in negative images. Upon using a vanilla method of dual illumination estimation streaking artifacts were observed, which we had resolved by pre-processing the image by applying reflective padding. The illumination estimation framework is linear estimation process, which has 2 major parameters, lambda (λ) and gamma(γ) . The parameterλ controls how similar the new estimate of the illumination(L') is close to original illumination map(L), which is generated by choosing the channel with the highest intensity, removal of optically redundant data. The parameter γ dictates the gamma correction applied to the enhanced image.

4.2. Mask Based Controllable Light Enhancement Diffusion(Mask-CLED)

Controllable Light Enhancement Diffusion framework employs a conditional diffusion model to enhance regions of images to a desired brightness level. Specifically for low-light enhancement, we are required to generate coherent normal-light images that share the content with the input low-light image . Instead of learning the one-to-one mapping between the two domains, we are interested in approximating the conditional distribution using the available paired image samples from the dataset. We employed a binary masking algorithm which generates a mask highlighting the regions of interest for brightness enhancement. This was just a vanilla binary threshold applied on the image, we thresholded at intensity level of 25. This led to a very crude and noisy mask for regions of interest. Dilation was applied on the image, which helped us expand and feather the edges of the mask. Post dilation, we employed blob de-

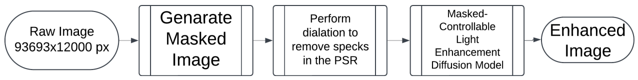


Figure 4. Mask-CLED Model

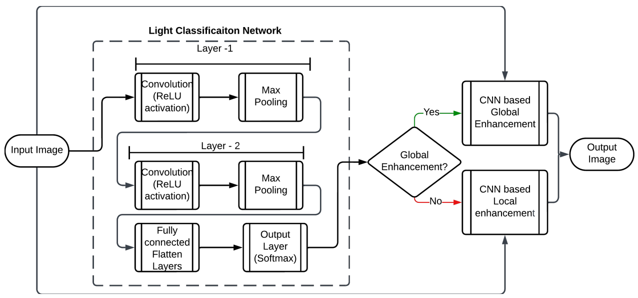


Figure 5. LoLi-IEA Enhancement Framework

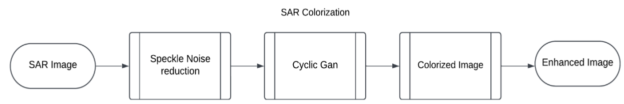


Figure 6. SAR Colorization Framework

Layer	Input	Output	Kernel Size	Stride
Conv 1	3	32	3x3	1
Pool 1	32	32	2x2	2
Conv 2	32	64	3x3	1
Pool 2	32	32	2x2	2
Flatten 1	64*56*56	128	-	-
Flatten 2	128	2	-	-

Table 1. Light Classification CNN Architecture

tection to check for overlapping regions of interest which were merged to produce a single enhancement region. We discarded any regions of interest which are smaller than a user specified pixel size. This is all done to reduce the computations required for enhancement, and also upon experimentation we observed bulky and dense masks for region of interest provided a better enhancement and preservation of texture in the process. The enhancement is controlled using a brightness level parameter(λ), this is an embedded parameter in that is embedded into the diffusion model. The baseline brightness level is extracted by averaging the pixel values, which is encoded as a discrete nxn embedding matrix[15] and any intermediate values is filled in using bilinear interpolation.

4.3. LoLi-IEA - CNN based PSR enhancement

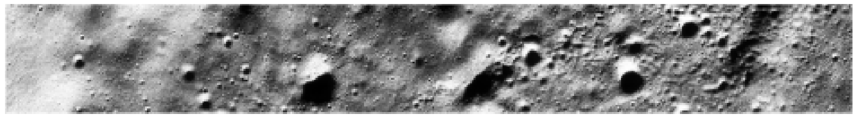
This is an extension of the work presented by Ezequiel Perez-Zaratea et al.[10], we tested the transferability of the model to permanently shadowed region enhancement. This is is a two stage staggered CNN enhancement methodology. The first stage CNN model performs light classification, this determines if local or global enhancement is needed, based on which it is passed on to a CNN based enhancement network. The second network performs the required light estimation for illumination enhancement. The light classification model is trained to detect regions of the images, which require local or global enhancement. It is a light weight model with 2 convolution blocks and 2 fully connected layers. We utilize max pooling in between convolution layers, alongside with a dropout of 0.5. ReLu is used as the activation function for the convolution layers and softmax activation in the last layer. The first stage model takes in a image and classifies if the image requires global or local enhancement.

The second stage CNN model, performs the illumination estimation required for enhancement. The network emphasizes the repeated application of convolutions and the integration of features learned at various levels through defined skip connections. This approach prevents the loss of information from earlier convolutional layers, making it particularly effective for image enhancement in low-light conditions by enabling training based on the image's classification.

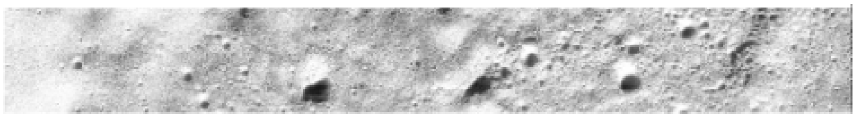
4.4. SAR Colorization

The research employed pix2pix, a Generative Adversarial Network (GAN) variant, for converting SAR images to optical images. This approach uses the unique architecture of GANs, where a generator network creates increasingly realistic images while a discriminator network attempts to distinguish between real and generated images, thereby identifying key regularities and features. Pix2pix distinguishes itself from traditional GANs by using original images as input instead of random noise, introducing dropouts for added variability, and combining U-Net's encoder-decoder structure with the generator. A critical part is the incorporation of L1 loss in the generator's loss function, which prevents image blurring and ensures a closer approximation to the original image. Unlike standard GANs that generate images from noise through dimension extension and reduction, pix2pix starts with the original image and uses dropouts as a noise mechanism. The method was particularly suited for SAR images, which are characterized by speckle-like noise and was trained using Sentinel-1 and Sentinel-2 image pairs that share identical topography—a dataset challenging to create manually. The training was conducted with 100 epochs and a mini-batch size of 128, focusing on transforming SAR and grayscale images into high-quality RGB optical representations.

CVPR #Team 27

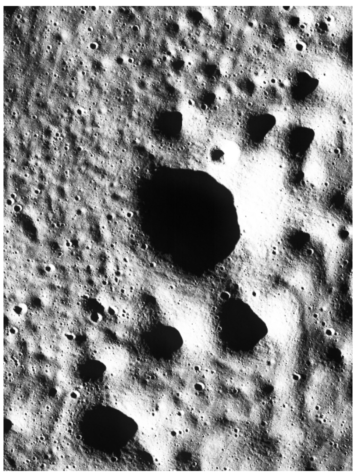


(a) Input Image

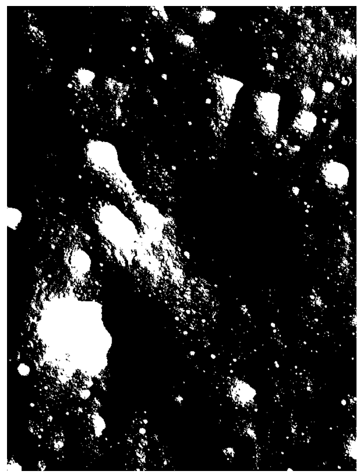


(b) Enhanced Image

Figure 7. Output from Dual Illumination estimation enhancement



(a) Input Image



(b) Binary-threshold mask post dilation

(c) Enhanced Image

Figure 8. Outputs of CLE Diffusion model enhancement

5. Simulations and Experiments

The samples of permanently shadowed regions of the moon were taken and processed through the proposed methodologies and their qualitative and quantitative performance is discussed in this section. We have used the metrics Lightness order Error(LOE)[14] and SPAQ[4]- a perceptual image quality assessment metric, to gauge the performance of our methodologies. The optimal scenario is to have high SPAQ and low LOE scores.

As discussed previously, we observed streaking artifacts in the enhanced images when we used Dual illumination estimation techniques which we had resolved using reflective padding. Furthermore, we ran experiments to understand the influence the parameter lambda and gamma had on the enhanced image. The experiment results are plotted in Figure 11 & 12, from which we can conclude that we need to choose the lowest viable γ value for any given λ to achieve the lowest possible lightness order error. Also, γ is independent of the parameter λ, which is apparent from the constant lightness order error we achieve when we vary λ for a given γ . So we can empirically choose γ value in accordance with our use case.

The Mask-Controllable light diffusion model gave qualitatively better result than dual diffusion illumination estimation model, as indicated by the Figure 14, which was the virtue of the regional enhancement control capabilities of the diffusion model. We ran experiments to understand how the brightness level parameter influences the quality of the enhanced image, this is plotted as a SPAQ score versus brightness level plot in Figure 13. It is quite evident that the score peaked at brightness level 6 from the plot.

We then shifted our focus to our Convolutional Neural Network-based enhancement technique for enhancement of permanently shadowed region of the moon. The reason of experimenting with LoLi-IEA was to alleviate the overhead of region of interest mask generation used in Mask-CLE diffusion model. Our hunch paid off, as we got a better SPAQ score in comparison to dual illumination estimation enhancement and Mask-CLED model as shown in Figure 14.

The SAR Colorization uses Cyclic Generative Adversarial Networks (GAN) to develop terrain mapping and colorization techniques. By analyzing SAR imagery across differ-

(a) Input Image (b) Enhanced Image

Figure 9. Output from LoLi-IEA model

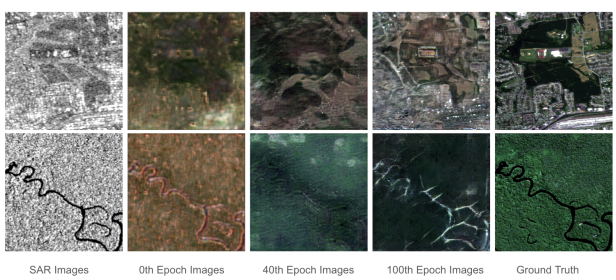


Figure 10. SAR colorization outputs at using model trained upto different epochs

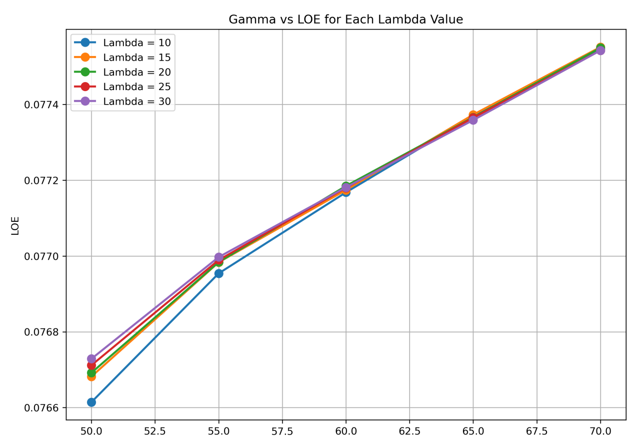


Figure 11. A plot showing Gamma Vs. LOE variation in Dual Illumination Estimation Enhancement

ent seasonal contexts, the research demonstrated a notable learning progression, with the most substantial improvements around the 40th training epoch. After this critical

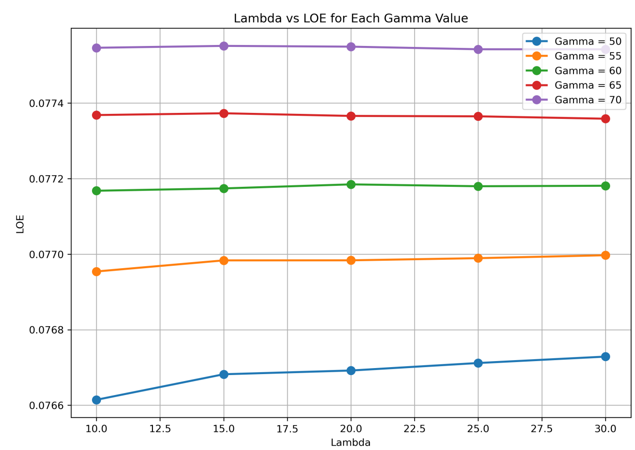


Figure 12. A plot showing Lambda Vs. LOE variation in Dual Illumination Estimation Enhancement

point, while the colorization enhancements became incrementally subtle, the results maintained consistent stability. The research methodology strategically employed a training approach that utilized spring season datasets for model development, with subsequent testing and analysis conducted using summer season data, thereby ensuring a comprehensive evaluation of the GAN model's performance across seasonal variations. The generated color images successfully captured broad landscape features like rivers but notably struggled to render precise building details, resulting in blurry architectural representations when converting SAR images to RGB optical-like imagery.

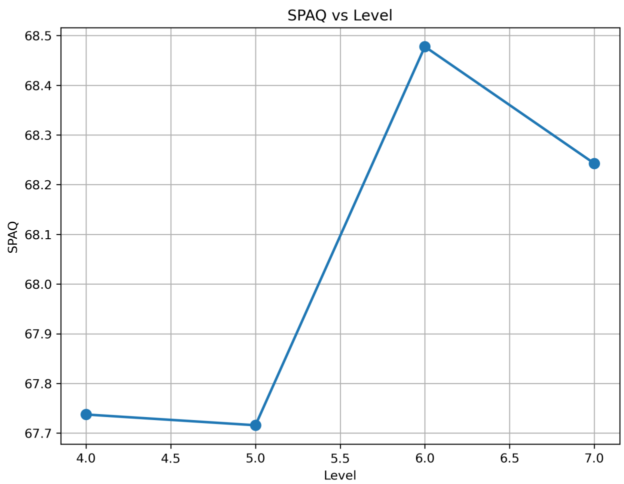


Figure 13. A plot showing variation of SPAQ over different brightness levels in Mask-CLE Diffusion model

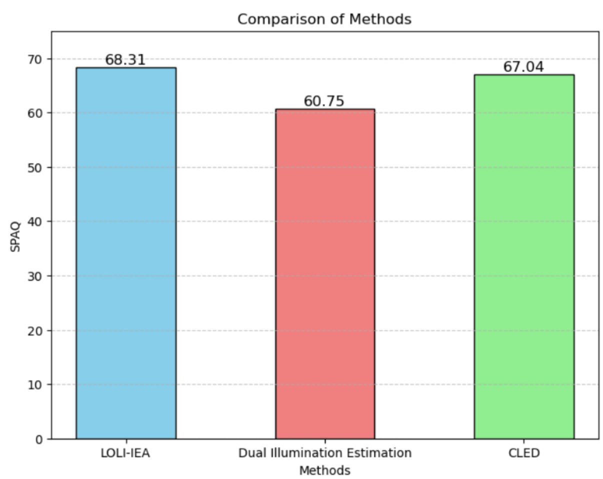


Figure 14. SPAQ Score comparison across different methodologies

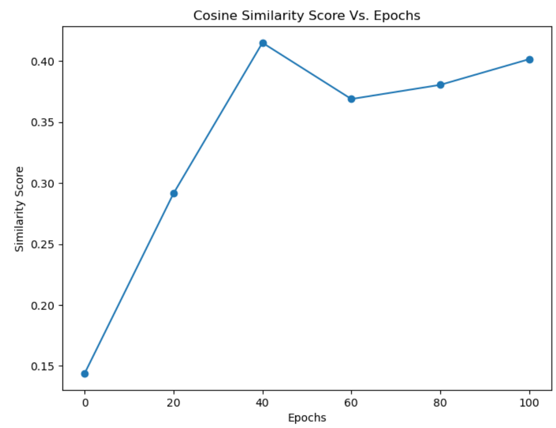


Figure 15. A plot of Cosine similarity score vs Epochs for the Pix-Pix SAR colorization model

6. Conclusion

In conclusion, the results of our enhancement strategies highlight the need for a context-aware and adaptable approach to reveal hidden details in Permanently Shadowed Regions. Among the low-light enhancement techniques, both CLED and LoLi-IEA performed similarly, with LoLi-IEA being preferred due to its reduced overhead from not requiring explicit ROI mask generation. However, these methods did not improve near-zero regions of the images. Our hypothesis of colorizing SAR images to better understand terrain texture was supported by the results, demonstrating the effectiveness of texture mapping in semantically similar regions. This approach holds promise not only for Earth's terrain but could also be applied to lunar surfaces once labeled data and SAR images of the moon are available, offering potential for future research.

7. Contribution

Bharath Raam Radhakrishnan, worked on setting up the experimental framework, including problem formulation and data collection for Dual Illumination estimation, CLE Diffusion models and LoLi-IEA models. Aneesh Ojha, worked on the development and fine tuning of SAR Colorization pix-pix cyclic gan model. The contribution percentage of the authors towards the research presented in the paper is as follows

- Bharath Raam Radhakrishnan - 50%
- Aneesh Ojha - 50%

References

[1] M. Abdullah-Al-Wadud, M. H. Kabir, M. A. Akber Dewan, and O. Chae. A dynamic histogram equalization for image contrast enhancement. *IEEE Transactions on Consumer Electronics*, 53(2):593–600, 2007. 2

[2] Fabio Agostinelli, Forest Anderson, Michael Rasmus, and Honglak Lee. Adaptive multi-column deep neural networks with application to robust image denoising. In *Advances in Neural Information Processing Systems*, pages 1493–1501, 2013. 2

[3] NASA Earth Observing System Data and Information System (EOSDIS). Synthetic aperture radar (sar). https://www.earthdata.nasa.gov/learn/earth-observation-data-basics/sar, 2024. Accessed: 2024-12-15. 3

[4] Yuming Fang et al. Perceptual quality assessment of smartphone photography. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3674–3683. IEEE, 2020. 2, 5

[5] X. Guo, Y. Li, and H. Ling. Lime: Low-light image enhancement via illumination map estimation. *IEEE Transactions on Image Processing*, 26(2):982–993, 2017. 2

[6] Yun Ji, Shuang Wang, Zhicheng Zhang, and Xiaoyong Wu. Sar-image colorization using multidomain generative adversarial networks. https://www.semanticscholar.org/paper/SAR-Image-Colorization-Using-Multidomain-Generative-Ji-Wang/03baf8ebeed934636a6fd5392a5f2498f7e7a49d, 2018. Accessed: 2024-12-15. 3

[7] Sandia National Laboratories. What is sar? https://www.sandia.gov/radar/pathfinder-radar-isr-and-synthetic-aperture-radar-sar-systems/what-is-sar/, 2024. Accessed: 2024-12-15. 2

[8] Edwin H. Land. The retinex theory of color vision. *Scientific American*, 237(6):108–128, 1977. Accessed: 2024-12-15. 2

[9] Kin Gwn Lore, Adedotun Akintayo, and Soumik Sarkar. Llnet: A deep autoencoder approach to natural low-light image enhancement. *Pattern Recognition*, 61:650–662, 2017. 2

[10] Ezequiel Perez-Zarate et al. Loli-iea: Low-light image enhancement algorithm. In *Applications of Machine Learning*, page 40. SPIE, 2023. 2, 4

[11] Qian Song, Wensheng Wang, Zhicheng Zhang, Hongwei Li, Xiaoyong Wu, and Shuang Liu. Sar image colorization using multidomain generative adversarial networks. *IEEE Transactions on Geoscience and Remote Sensing*, 57(9):7030–7043, 2019. 3

[12] Ahmedabad/ISRO Space Applications Centre (SAC). Permanently shadowed regions dataset - chandrayaan-2. https://vedas.sac.gov.in/static/pdf/SIH_2024/SIH1732_CH2_PS.pdf, https://chmapbrowse.issdc.gov.in, 2024. 3

[13] Author(s) Unknown. Synthetic aperture radar (sar) and its applications, 2005. Accessed: 2024-12-15. 2

[14] Shuhang Wang, Jin Zheng, Hai-Miao Hu, and Bo Li. Naturalness preserved enhancement algorithm for non-uniform illumination images. *IEEE Transactions on Image Processing*, 22(5):1830–1841, 2013. 5

[15] Yuyang Yin et al. Cle diffusion: Controllable light enhancement diffusion model. In *Proceedings of the 31st ACM International Conference on Multimedia*, pages 8145–8156. ACM, 2023. 2, 4

[16] Qing Zhang, Yongwei Nie, and Wei-Shi Zheng. Dual illumination estimation for robust exposure correction. *IEEE Transactions on Image Processing*, 28(4):2057–2069, 2019. 2