

Enhancement of Videos Captured in Low-Light Conditions

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Introduction: Enhancement of Videos Captured in Low-light Conditions

- Videos captured under poor illumination conditions often exhibit poor characteristics which limits the performance of various machine vision.
- To counter this problem and enhance the videos which are captured in low-light conditions, we work on this problem statement.

Motivation for Enhancement of Videos Captured in Low-light Conditions



Figure: Autonomous vehicle's night driving scenario



Figure: face detection in low light

- The above figure illustrates how difficult it is for autonomous vehicles to recognize lanes on the road, also how difficult it can be to detect objects and faces in low-light conditions.
- The low dynamic range and high noise levels of videos will impact how well computer vision algorithms work.
- To make computer vision algorithms reliable in low-light situations, Enhancing low-light footage is essential for making videos more visible.

Literature Survey on Low-light Image Enhancement

LLCNN: A CNN for Lowlight Image Enhancement (Li Tao et al., CVPR 2017) [5]

They have used simple convolution network with residual network.

Inferences :

- Using multiple kernels
- Adaptively increases brightness and contrast

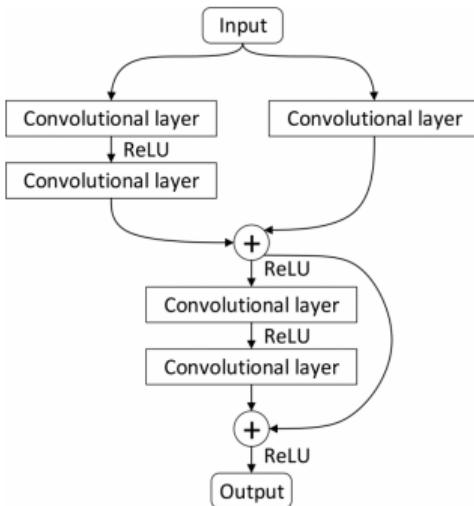


Figure: CNN architecture

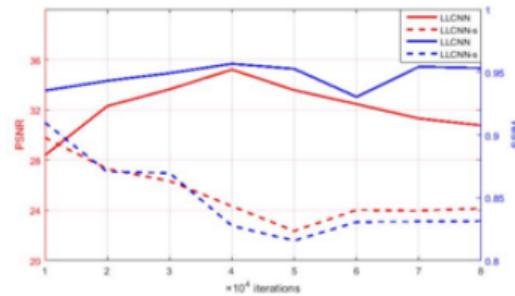


Figure: LLCNN and LLCNN-s
PSNR and SSIM

Literature Survey on Low-light Image Enhancement

Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement (Chunle Guo et al., CVPR 2020) [2]

Unsupervised learning technique using unpaired data.

Inferences :

- Network decreases the danger of overfitting
- Creates an image-specific curve

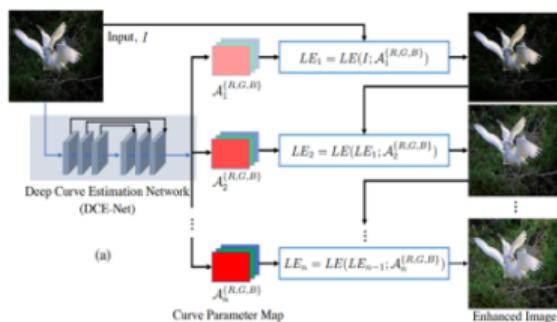


Figure: Framework of Zero-DCE

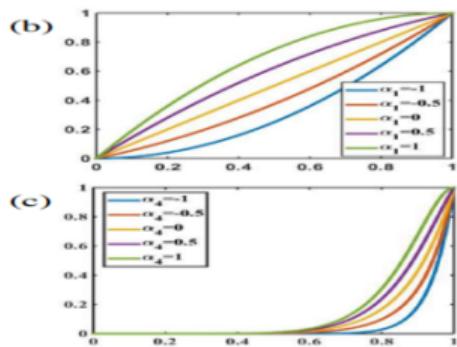


Figure: LE-curves with different adjustment parameters

Literature Survey on Low-light Image Enhancement

From Fidelity to Perceptual Quality: A Semi-Supervised Approach for Low-Light Image Enhancement (Wenhan Yang et al., CVPR 2020) [7]

A semi-supervised learning approach using DRBN.

Interference :

- Deep recursive band representation
- Connect fully-supervised and unsupervised frameworks

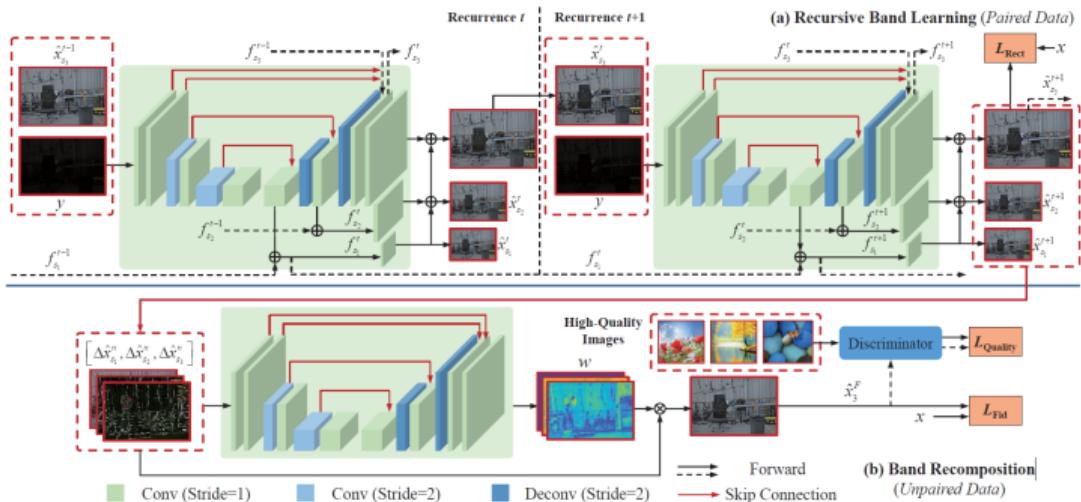


Figure: Framework of Fidelity to Perceptual Quality

Literature Survey on Low-light Image Enhancement

Extremely Low-light Image Enhancement with Scene Text Restoration (Po-Hao Hsu et al., CVPR 2022)[3]

Simple U-NET architecture used to restore the text to complete the pipeline

Inference :

- Improving both the low-light image quality
- Annotate the texts in the real low-light dataset .

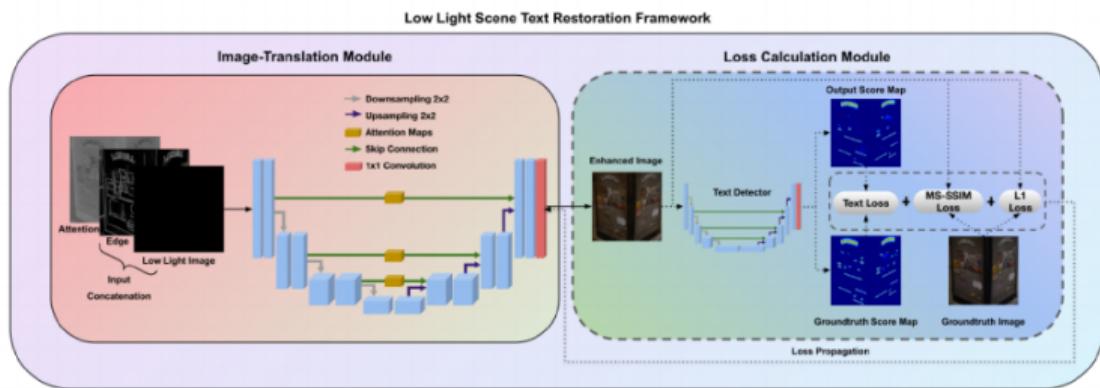


Figure: Framework of Low-light Image Enhancement with Scene Text Restoration

Problem Statement and Objectives

Problem Statement

To propose a learning-based technique for Enhancement of videos captured in Low-light conditions.

Objectives

- To Perform Extensive Literature Survey on Available SOTA Methods for Low-light Video Enhancement.
- To develop a learning-based algorithm for enhancement of video captured in low light conditions.
- To demonstrate the results of the proposed architecture using benchmark dataset in comparison with SOTA methods.

Dataset Analysis: SICE [4]

- Training Images : 2000
- Testing Images : 64
- The dataset is captured with multiple exposure levels

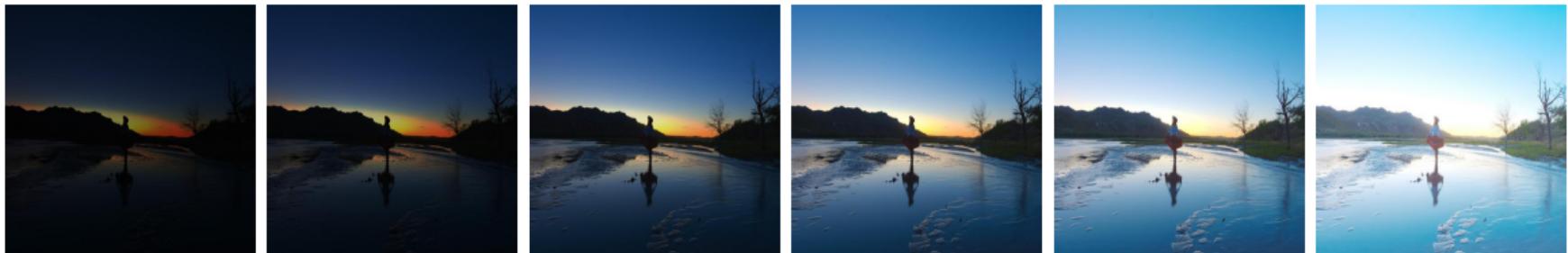


Figure: The above images depict low-contrast images with different exposure levels

Dataset Analysis: LOL [6]

- Training Images : 485
- Testing Images : 15

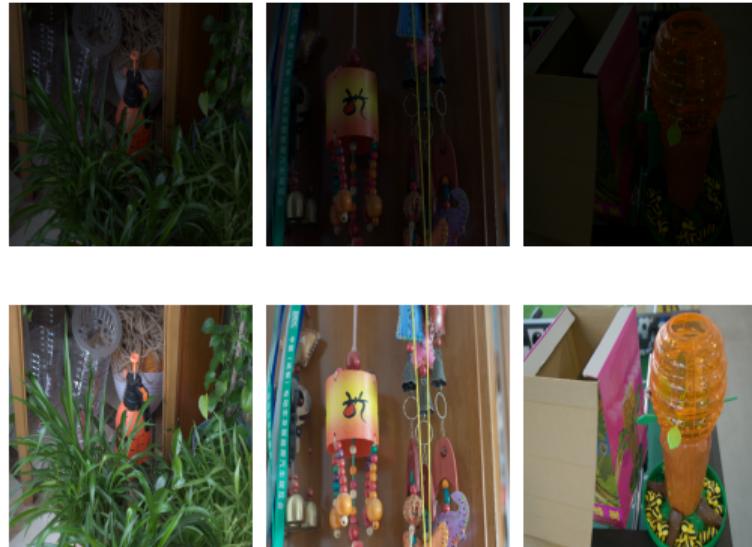


Figure: First row depicts low lit images, second row depicts ground truth images

Dataset Analysis: NTIRE [1]

- Training Images : 1220
- Testing Images : 50

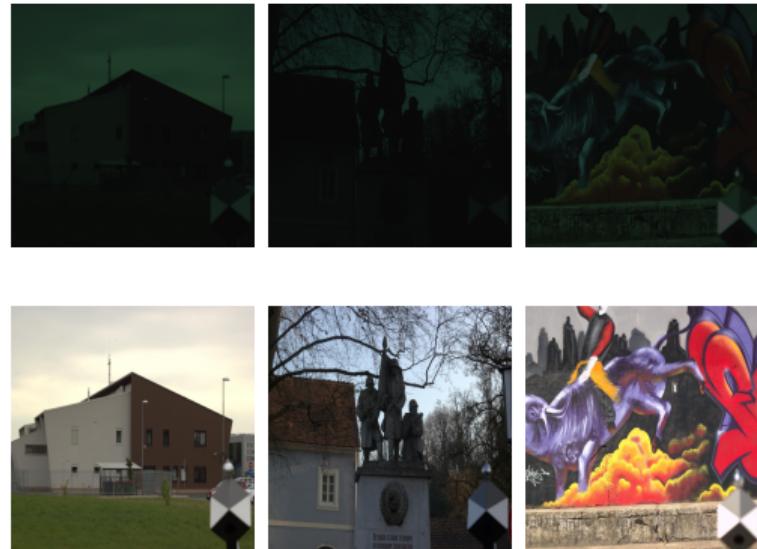


Figure: First row depicts NTIRE input images, second row depicts NTIRE ground truth images

Existing Architecture of Zero-DCE

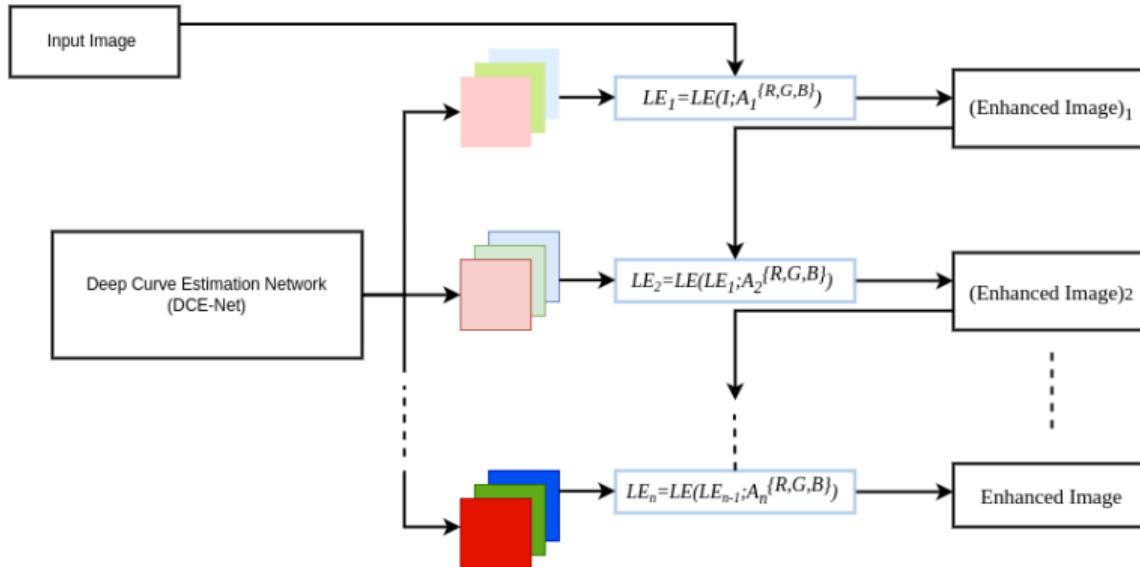


Figure: Framework of Zero-DCE

Proposed Block diagram: LLVE-Net

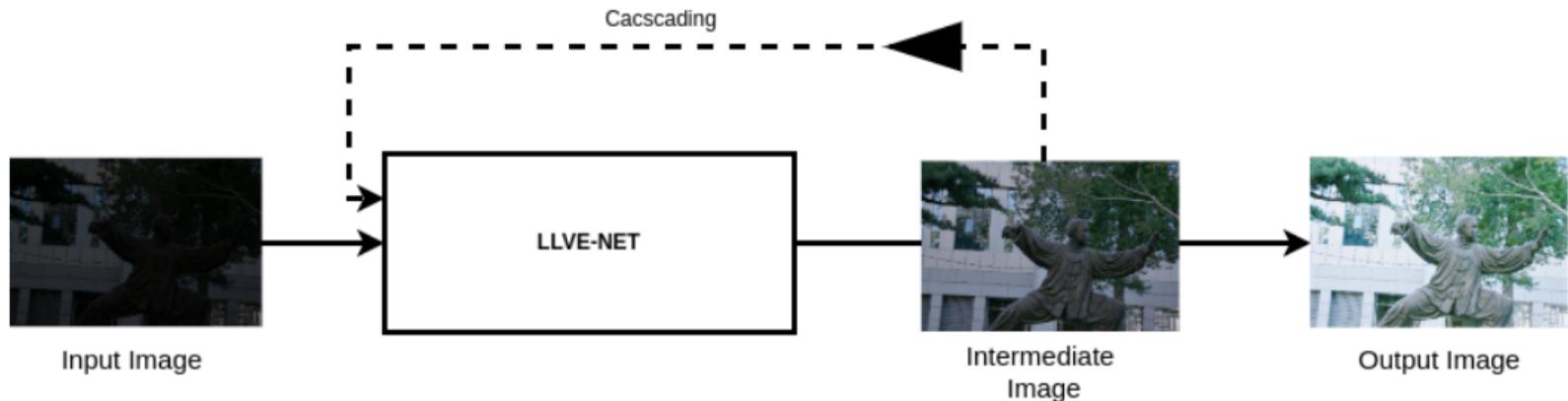


Figure: Block diagram of LLVE-Net

Proposed Architecture: LLVE-Net

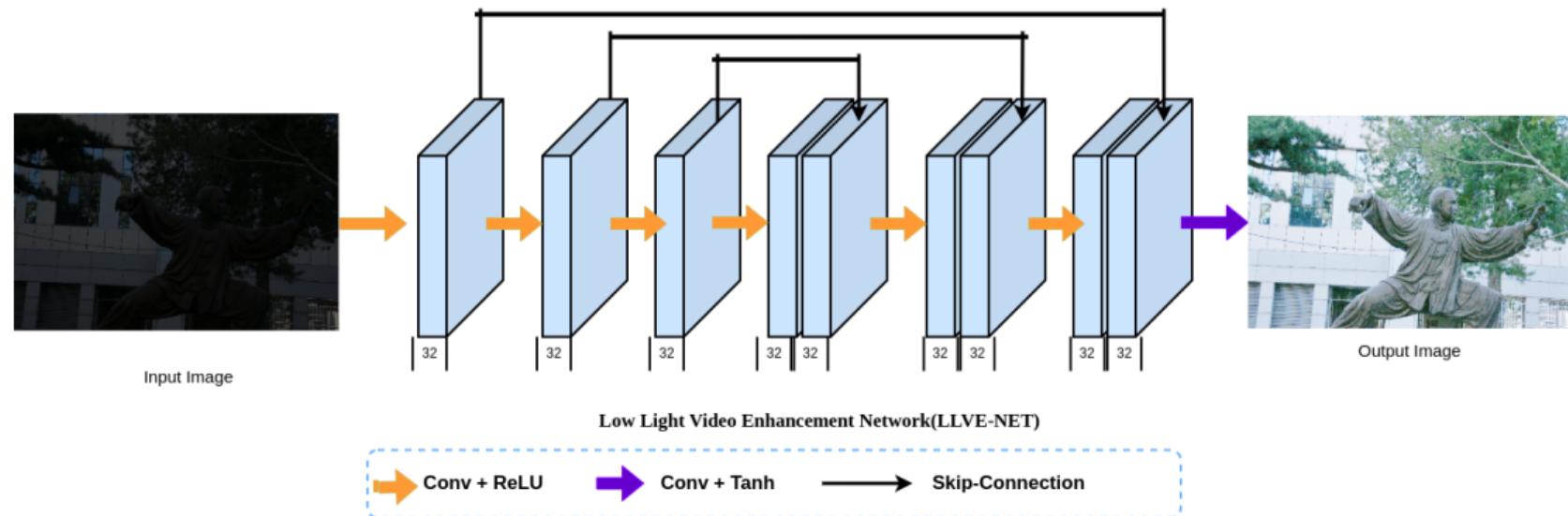


Figure: Architecture of LLVE-Net

Results of Zero-DCE

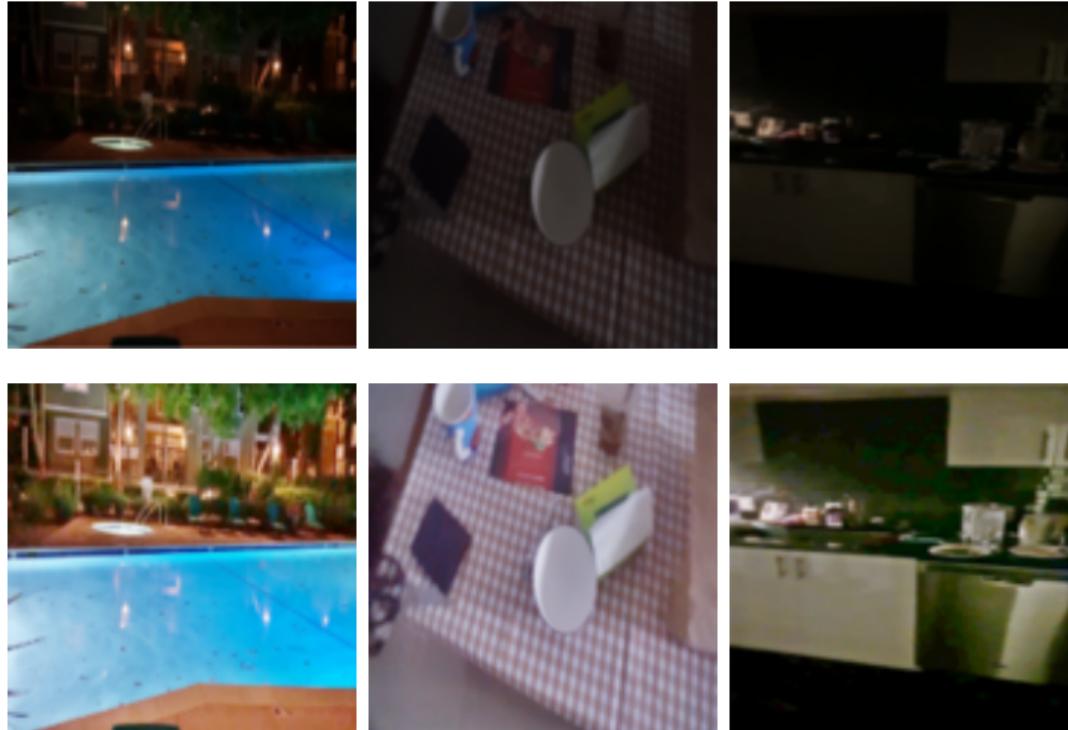


Figure: First row depicts input images of SICE dataset [4], second row depicts enhanced output images

Results of LLVE-Net

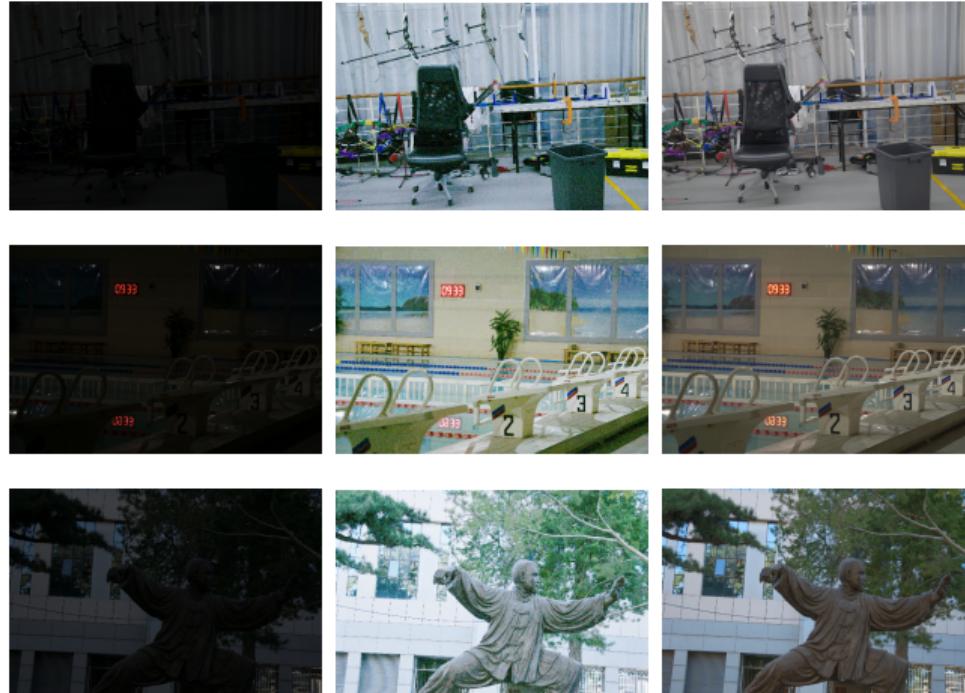


Figure: First column depicts low lit input images, the second column depicts output enhanced images, the third column depicts ground truth images

Results of Zero-DCE using NTIRE dataset

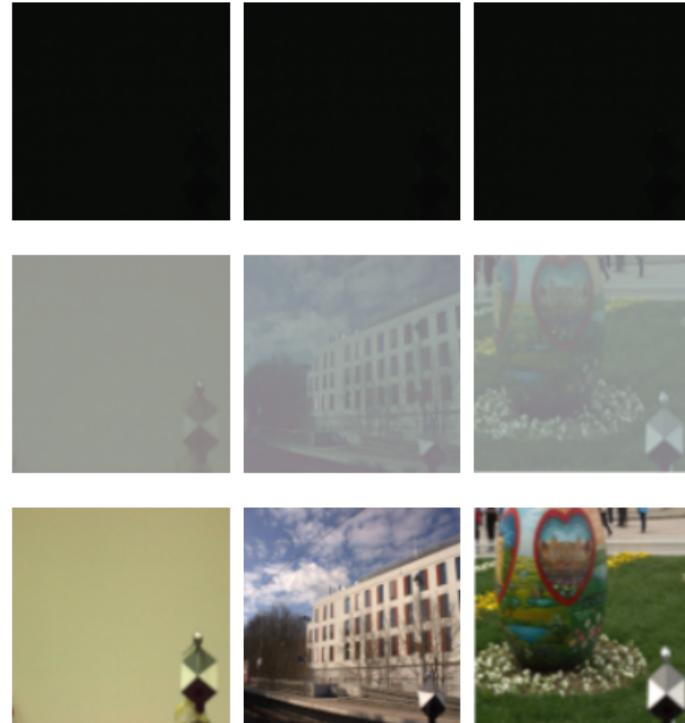


Figure: First row depicts NTIRE input images, the second row depicts output enhanced images, the third row depicts NTIRE ground truth images

Comparison of Evaluation Metrics

PSNR and SSIM Comparison		
MODEL	PSNR	SSIM
Zero-DCE	16.57	0.59
Zero-DCE(FEATURE LOSS)	19.64	0.59
LLVE-NET	27.4	0.7
Zero-DCE(NTIRE)	10.22	0.37

Figure: PSNR and SSIM Comparison

*Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB and maximum value of SSIM is 1.

Observations

- The output images of LLVE-Net consists of noise.
- The enhanced video generated from LLVE-Net consists of jitter.



Figure: Output image consisting noise

Future Work

- To develop a denoising algorithm as a plugin to our proposed architecture(LLVE-Net).
- To introduce a stopping criteria for the cascaded network.
- To introduce a method to reduce video jitter from the generated video.

Thank You

References : |

- [1] Egor Ershov et al. “The Cube++ Illumination Estimation Dataset”. In: *IEEE Access* 8 (2020), pp. 227511–227527.
- [2] Chunle Guo et al. “Zero-reference deep curve estimation for low-light image enhancement”. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020, pp. 1780–1789.
- [3] Po-Hao Hsu et al. “Extremely low-light image enhancement with scene text restoration”. In: *2022 26th International Conference on Pattern Recognition (ICPR)*. IEEE. 2022, pp. 317–323.
- [4] Shahidul Islam Khan and Abu Sayed Md Latiful Hoque. “SICE: an improved missing data imputation technique”. English. In: *Journal of Big Data* 7 (June 2020). Article. ISSN: 21961115. URL: <https://link.gale.com/apps/doc/A626539838/AONE?u=anon~94a45a71&sid=googleScholar&xid=eebe0390>.

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- [5] Li Tao et al. "LLCNN: A convolutional neural network for low-light image enhancement". In: Dec. 2017, pp. 1–4. DOI: [10.1109/VCIP.2017.8305143](https://doi.org/10.1109/VCIP.2017.8305143).
- [6] Chen Wei et al. "Deep retinex decomposition for low-light enhancement". In: *arXiv preprint arXiv:1808.04560* (2018).
- [7] Wenhan Yang et al. "From fidelity to perceptual quality: A semi-supervised approach for low-light image enhancement". In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020, pp. 3063–3072.