LightNet: Generative Model for Enhancement of Low-Light Images

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ABSTRACT

In this work, we propose a generative model for enhancement of images captured in low-light conditions. Sensor constraints and inappropriate lighting conditions are accountable for degradations introduced in the image. The degradations limit the visibility of the scene and impedes vision in applications like detection, tracking and surveillance. Recently, deep learning algorithms have taken a leap for enhancement of images captured in low-light conditions. However, these algorithms fail to capture information on fine grained local structures and limit the performance. Towards this, we propose a generative model for enhancement of low-lit images to exploit both local and global information, and term it as LightNet. In proposed architecture LightNet, we include a hierarchical generator encompassing encoder-decoder module to capture global information and a patch discriminator to capture fine grained local information. Typically, the encoder-decoder module downsamples the low-lit image into distinct scales. Learning at distinct scales helps to capture both local and global features thereby suppressing the unwanted features (noise, blur). With this motivation, we downsample the captured low-lit image into 3 distinct scales. The decoder upsamples the encoded features at respective scales to generate an enhanced image. We demonstrate the results of proposed methodology on custom and benchmark datasets in comparison with SOTA methods using appropriate quantitative metrics.

CONTRIBUTIONS

- We prepare customised low-light dataset, captured with varying ISOs and Exposures along with corresponding ground-truth information to train deep learning algorithms.
- We propose a hierarchical generative model with patch GAN to capture local information explicitly for low-light conditions.
- We propose a combinational loss function to exploit local illuminance keeping global features intact.
- We demonstrate the results of proposed LightNet on NTIRE 2022 [1] challenge dataset and our custom low- light dataset using appropriate quality metrics.

METHODOLOGY

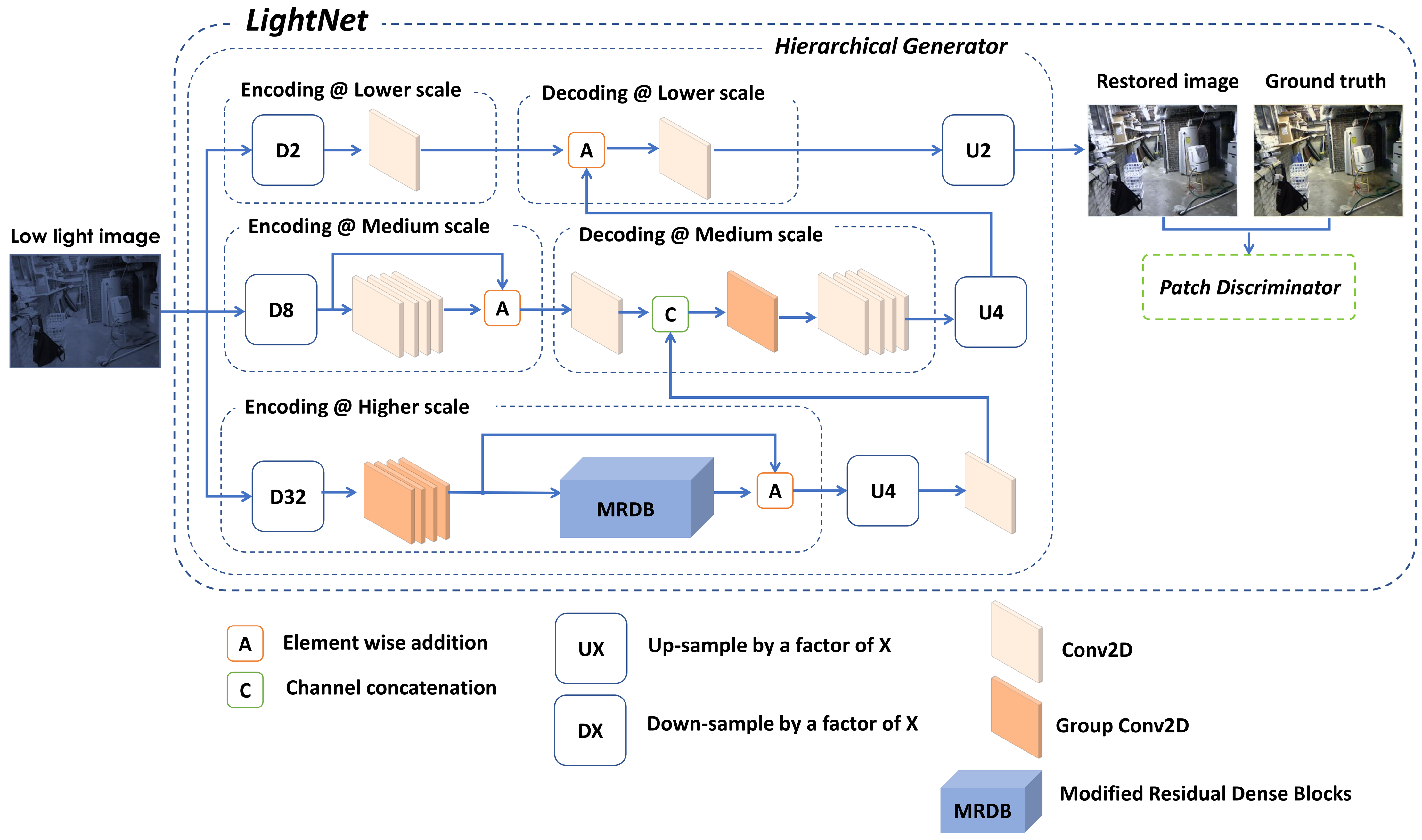
The methodology employs a hierarchical generator with encoder and decoder blocks, encompassing Encoding at Lower-Scale, Medium-Scale, and Higher-Scale. A novel component, the Modified Residual Dense Block (MRDB), focuses on learning local features and fine-grained structural details in Higher-Scale Encoding phase. In the decoding stage, MRDB outputs are merged at two levels, Decoding at Medium-Scale and Decoding at Lower-Scale, to produce the enhanced low-light image. Additionally, a patch-based discriminator is included to capture local color information and contrast information, aiding in both local and global color and contrast reconstruction. To optimise the approach, a combinational loss function is proposed, enabling the capture of local color, contrast, and content features, thus enhancing the overall image quality. The total loss is shown below;

$$\text{Total loss} = \alpha * A + \beta * B + \gamma * C$$

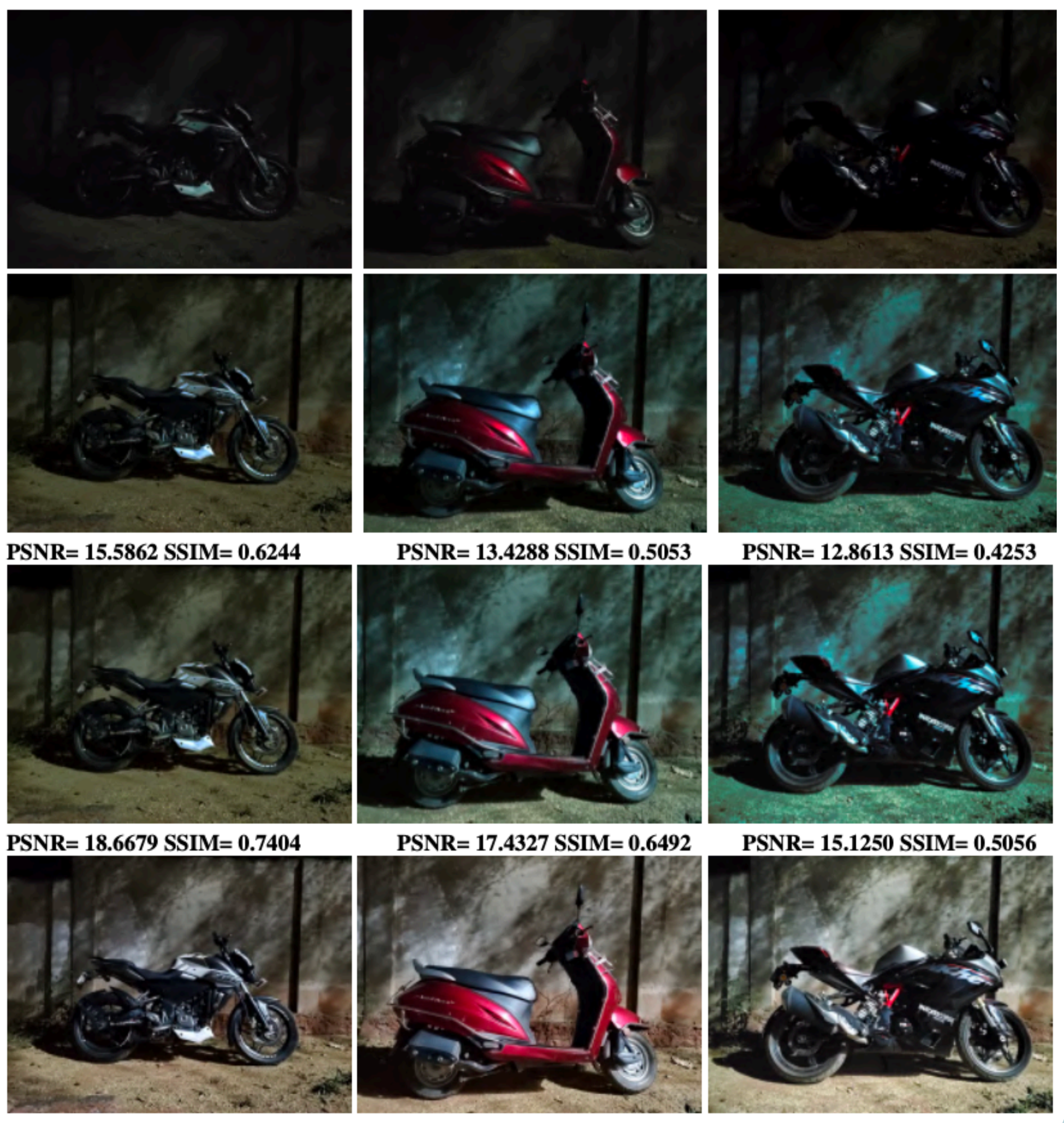
where,

$A = L_{VGG/i,\,j}$, $B = L_{color}$, $C = \text{MS–SSIM}$. We set the values of $\alpha = 0.3$, $\beta = 0.4$, $\gamma = 0.3$ heuristically.

OVERVIEW OF THE FRAMEWORK



ENHANCEMENT ON CUSTOM DATASET



CUSTOM DATASET SAMPLES

ENHANCEMENT ON SID

QUANTITATIVE METRICS LightNet

Exposure (in seconds)	1/2s		1/180		1/24000	
Quantitave Metrics	PSNR↑		PSNR↑		PSNR↑	
Methods	ISO 50	ISO 100	ISO 50	ISO 100	ISO 50	ISO 100
LIME [13](2016)	17.63	17.33	18.20	19.83	6.51	7.52
RetinexNet [23](2018)	12.71	10.89	16.24	14.13	11.09	12.22
Zero DCE[12](2020)	14.12	10.95	19.35	17.55	5.96	7.01
Zero DCE++ [21](2021)	13.10	10.49	20.86	17.14	5.99	7.14
Enlighten Anything[33](2023)	20.61	21.35	18.08	19.51	-	11.24
UHDFour [22](2023)	25.59	26.23	22.10	24.35	16.09	16.78
LightNet(Ours)	**31.17**	**31.98**	**30.03**	**30.34**	**25.61**	**26.11**

REFERENCES

1. Egor Ershov et.al In *Proceedings of the IEEE/CVF Conference on Computer Vi- sion and Pattern Recognition (CVPR) Workshops*, pages 1287–1300, June 2022.
2. Chen Chen, Qifeng Chen, Jia Xu, and Vladlen Koltun. Learning to see in the dark. In *Proceedings of the IEEE con- ference on computer vision and pattern recognition*, pages 3291–3300, 2018.