Denoising Diffusion Post-Processing for Low-Light Image Enhancement
Supplementary Material

Savvas Panagiotou*, Anna S. Bosman

These supplementary materials are structured as follows: the architecture of LPDM is presented in Fig. 1; additional LPDM examples on unpaired datasets are provided in Fig. 2; finally, LPDM examples on the LOL test set are shown in Figs. 3 and 4.

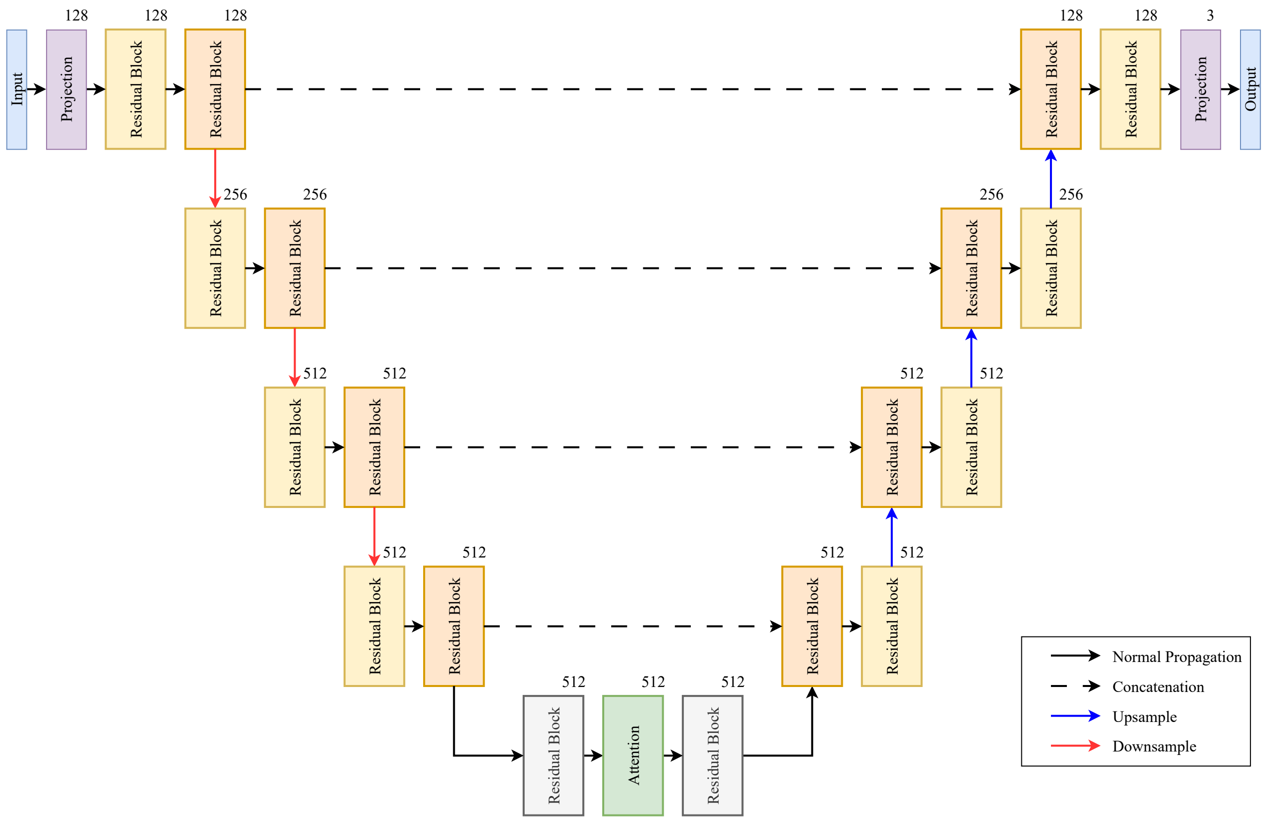

Figure 1: The U-Net architecture used to model LPDM. The residual blocks contain the layers depicted in the main paper. The number of output channels is displayed above each block. Although there are 4 concatenation stages, there are a total of 12 concatenations which occur. The output of each yellow block in the encoder is concatenated to the input of the corresponding mirrored yellow block in the decoder. Concatenation is applied similarly for the orange residual blocks and the purple convolutional projection blocks. The output of each downsampling layer is concatenated to the corresponding input of each upsampling layer.

*Corresponding author

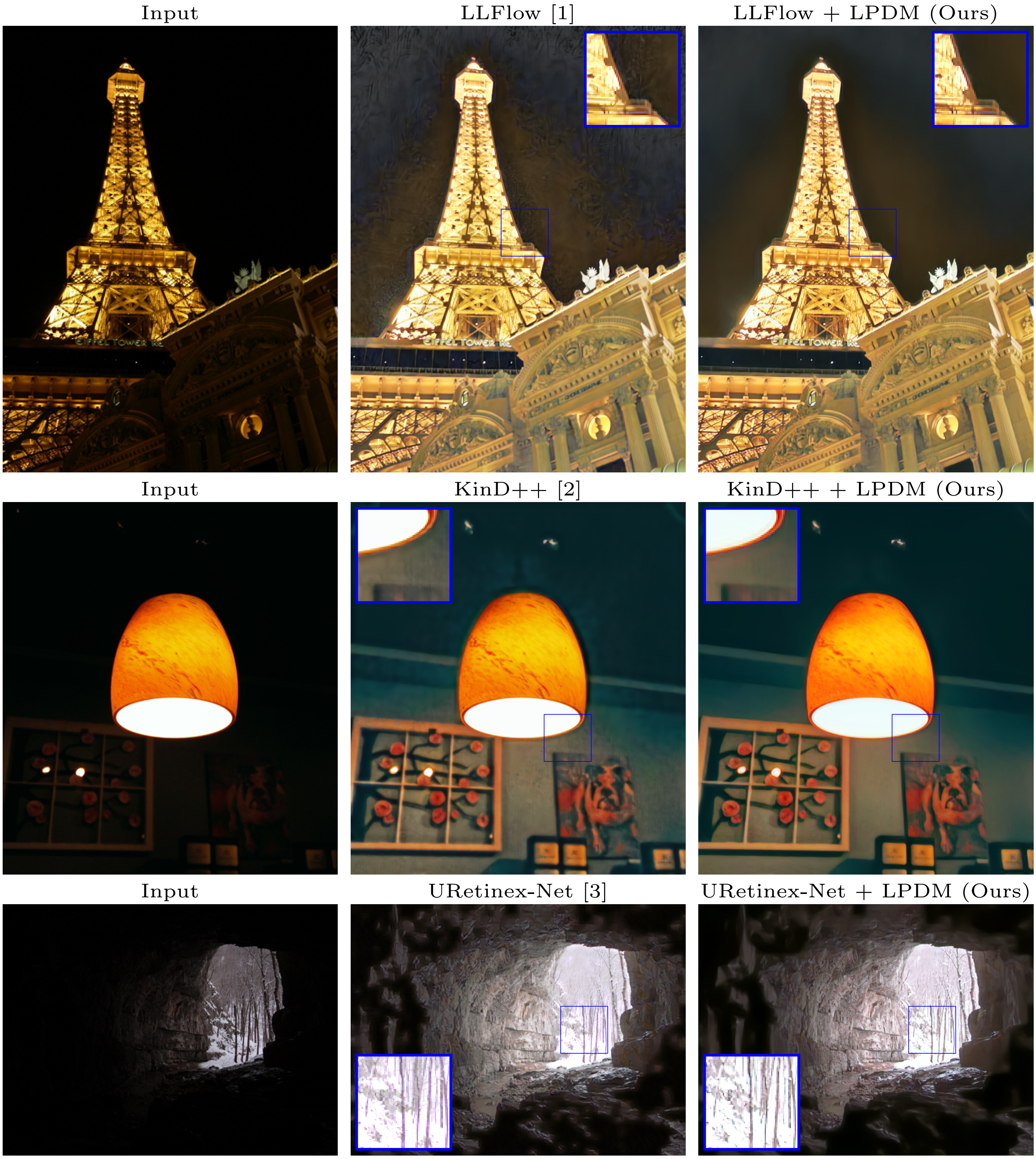

Figure 2: Qualitative results of the proposed approach on a variety of unpaired evaluation datasets for a variety of LLIE methods. There are no ground truth images for these datasets. Each respective column represents $\boldsymbol{c}$, $\boldsymbol{x}_0^{\eta}$ and $\boldsymbol{x}_0^{DM}$. The LPDM parameters used are $\phi = 300$ and $s = 30$.

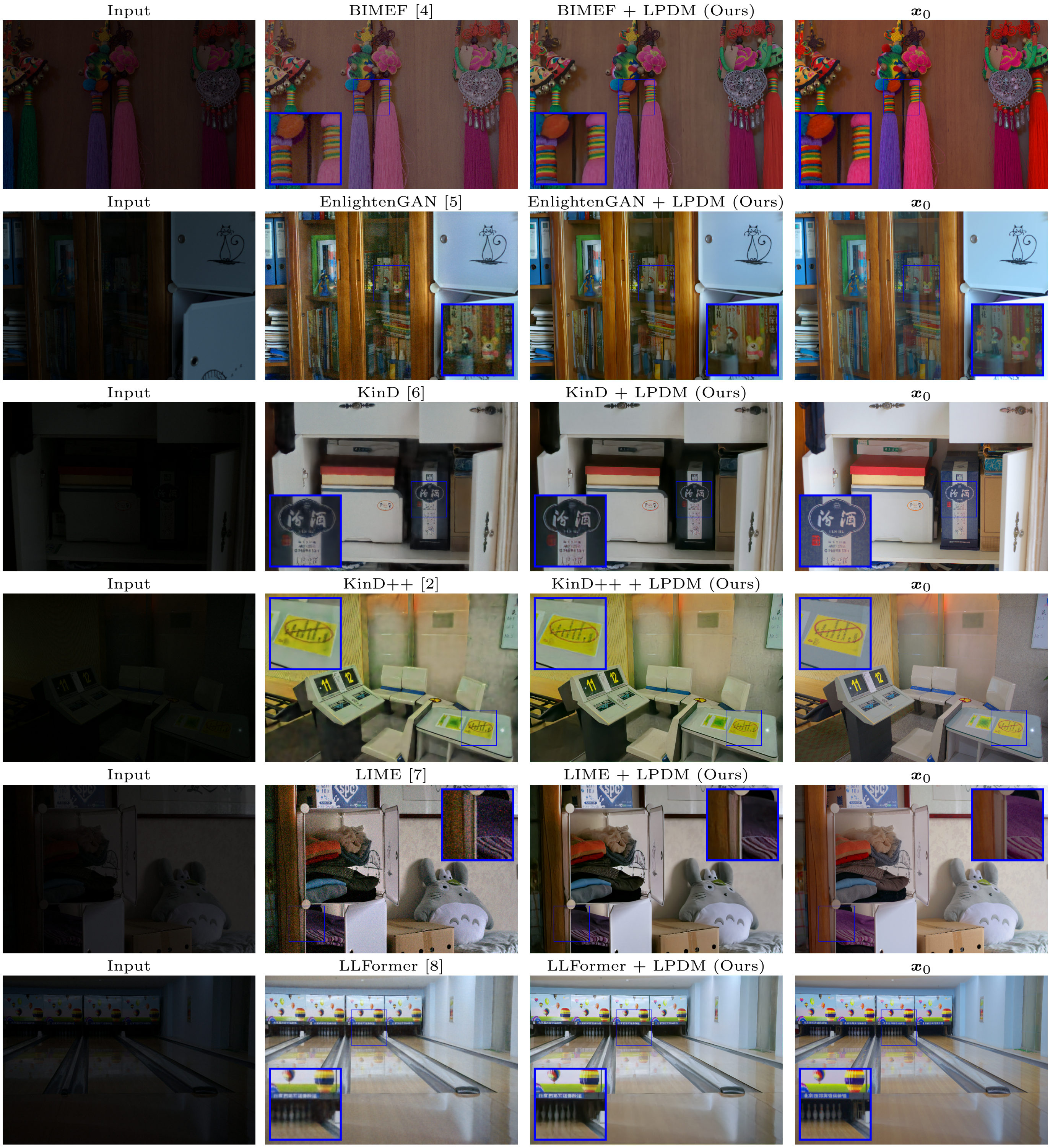

Figure 3: Qualitative results of the proposed approach on the paired LOL test set for a variety of LLIE methods. Each respective column represents $\boldsymbol{c}$, $\boldsymbol{x}_0^{\eta}$, $\boldsymbol{x}_0^{DM}$ and $\boldsymbol{x}_0$. The LPDM parameters used are $\phi = 300$ and $s = 30$.

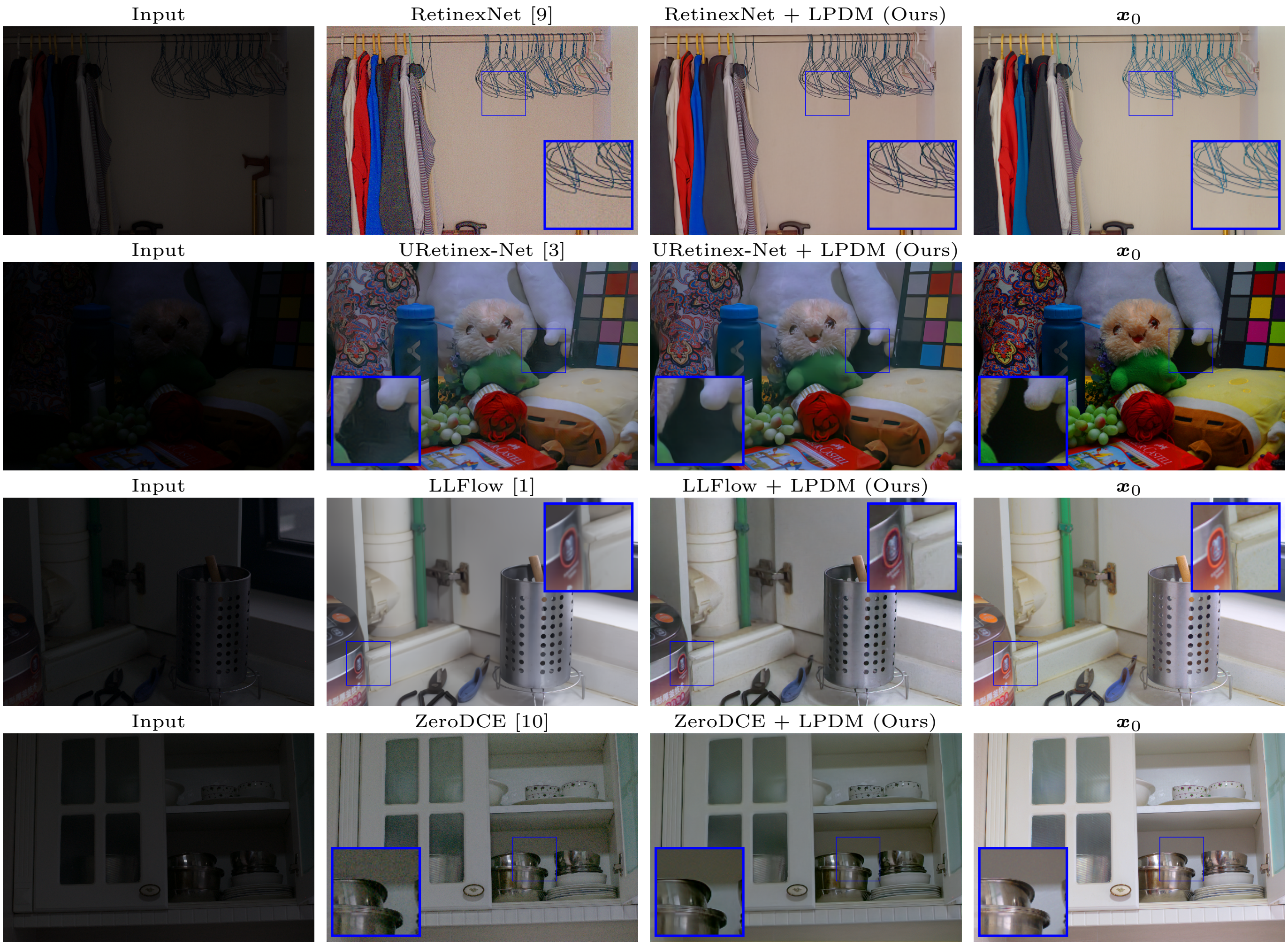

Figure 4: Continuation of Fig. 3

References

[1] Y. Wang, R. Wan, W. Yang, H. Li, L.-P. Chau, A. Kot, Low-light image enhancement with normalizing flow, in: Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 36, 2022, pp. 2604–2612.

[2] Y. Zhang, X. Guo, J. Ma, W. Liu, J. Zhang, Beyond brightening low-light images, International Journal of Computer Vision 129 (2021) 1013–1037.

[3] W. Wu, J. Weng, P. Zhang, X. Wang, W. Yang, J. Jiang, Uretinex-net: Retinex-based deep unfolding network for low-light image enhancement, in: 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 5891–5900. doi:10.1109/CVPR52688.2022.00581.

[4] Z. Ying, G. Li, W. Gao, A bio-inspired multi-exposure fusion framework for low-light image enhancement, arXiv preprint arXiv:1711.00591 (2017).

[5] Y. Jiang, X. Gong, D. Liu, Y. Cheng, C. Fang, X. Shen, J. Yang, P. Zhou, Z. Wang, Enlightengan: Deep light enhancement without paired supervision, IEEE Transactions on Image Processing 30 (2021) 2340–2349.

[6] Y. Zhang, J. Zhang, X. Guo, Kindling the darkness: A practical low-light image enhancer, in: Proceedings of the 27th ACM international conference on multimedia, 2019, pp. 1632–1640.

[7] X. Guo, Y. Li, H. Ling, Lime: Low-light image enhancement via illumination map estimation, IEEE Transactions on Image Processing 26 (2) (2017) 982–993. doi:10.1109/TIP.2016.2639450.

[8] T. Wang, K. Zhang, T. Shen, W. Luo, B. Stenger, T. Lu, Ultra-high-definition low-light image enhancement: A benchmark and transformer-based method, arXiv preprint arXiv:2212.11548 (2022).

[9] C. Wei, W. Wang, W. Yang, J. Liu, Deep retinex decomposition for low-light enhancement, in: British Machine Vision Conference, 2018.

[10] C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, S. Kwong, R. Cong, Zero-reference deep curve estimation for low-light image enhancement, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020.