

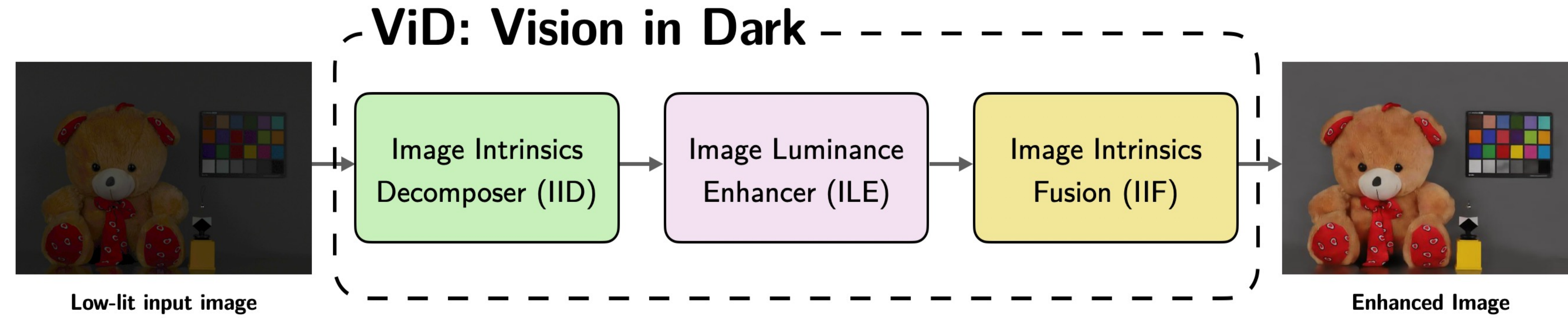
ABSTRACT

We propose a framework for enhancing images captured in extreme low-light conditions, termed Vision in Dark (ViD). Low-Light Image Enhancement (LLIE) techniques improve degraded low-lit images, addressing noise, color distortions, and insufficient brightness. Recent LLIE methods incorporate Retinex theory with deep learning, but they struggle with decomposing images into reflectance and illumination under extreme low-light conditions. ViD framework decomposes images into intrinsic components regardless of lighting conditions. ViD demonstrates a 13.9% performance increase over state-of-the-art methods on benchmark and custom datasets.

CONTRIBUTIONS

- A Retinex Theory-based deep learning framework for extreme low-light image enhancement and is named as Vision in Dark (ViD).
 - **Image Intrinsic Decomposer (IID)** to decompose given image into its intrinsic (reflectance and illumination components) in spite of extremely poor lighting conditions.
 - **Image Luminance Enhancer (ILE)** to adjust the input illumination in correspondence to groundtruth illumination.
 - **Image Intrinsic fusion (IIF)** for fusing preserved reflectance and adjusted illumination components to obtain enhanced images.
- We prepare custom extreme low-light dataset with high-resolution images, along with corresponding groundtruth information to train the proposed ViD.
- We demonstrate the results of proposed ViD pipeline on benchmark datasets in comparison with state-of-the-art enhancement methods using appropriate quantitative metrics.

ViD FRAMEWORK



METHODOLOGY

The proposed ViD pipeline includes Image Intrinsic Decomposer (IID) decomposes the image into reflectance and illumination. Reflectance describes light reflected by a surface, which remains constant post-capture, while illumination varies, Image Luminance Enhancer (ILE) enhances the illumination to meet ground-truth requirements. The illumination map provides ambient light levels and distribution, and Image Intrinsic Fusion (IIF) fuses the enhanced illumination with the retained reflectance to produce enhanced images. The proposed method is guided by following loss functions:

$$L_{IID} = L_{recon} + L_{IC} + L_{RC}$$

$$L_{ILE} = \alpha * L_{vgg} + \beta * L_1$$

$$L_{IIF} = \alpha * L_{vgg} + \beta * L_1 + \gamma * L_{MSSSIM}$$

REFERENCES

- Embedding fourier for ultra-high-definition low-light image enhancement. In ICLR, 2023.
- Deep retinex decomposition for low-light enhancement. arXiv preprint arXiv:1808.04560, 2018

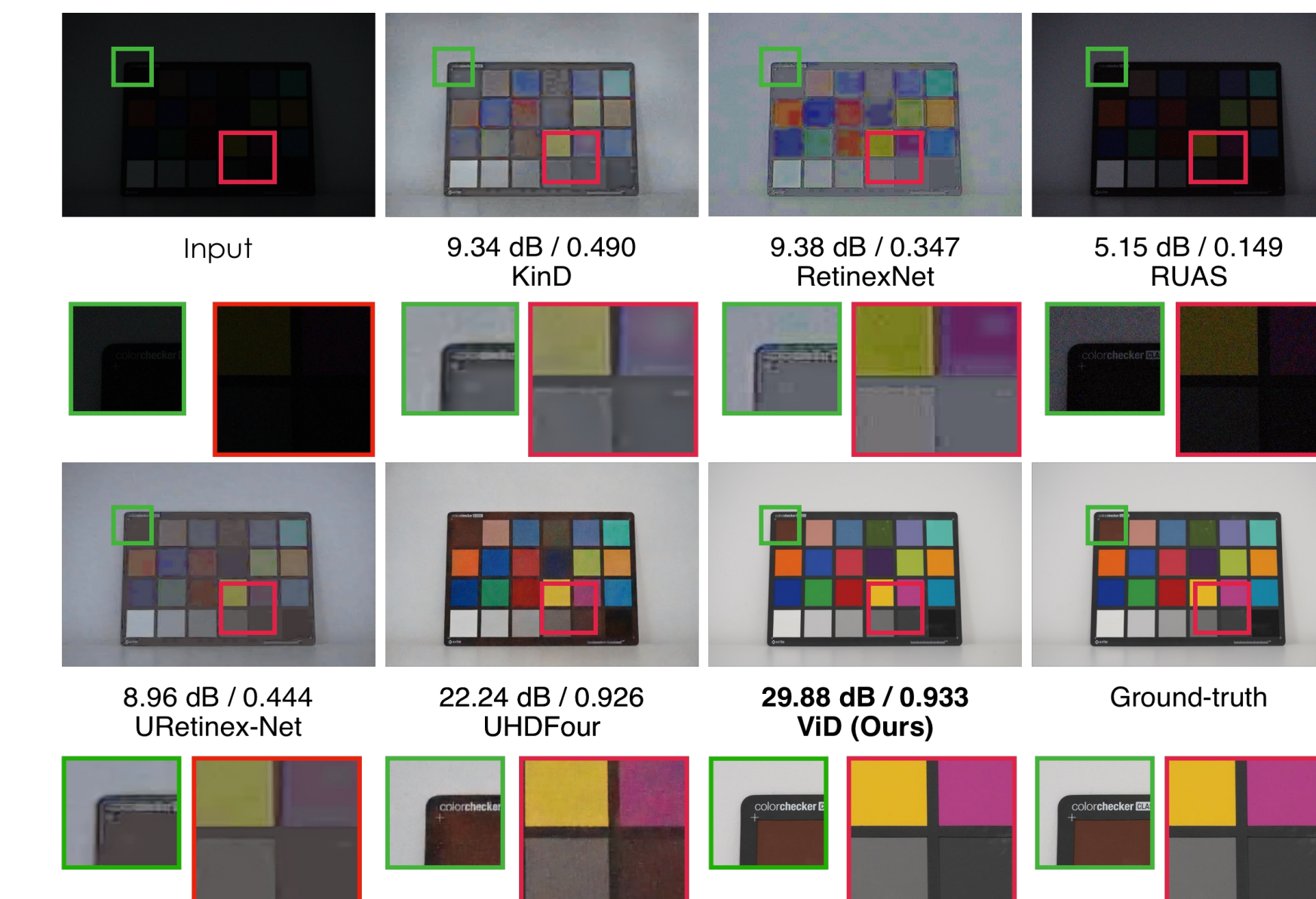
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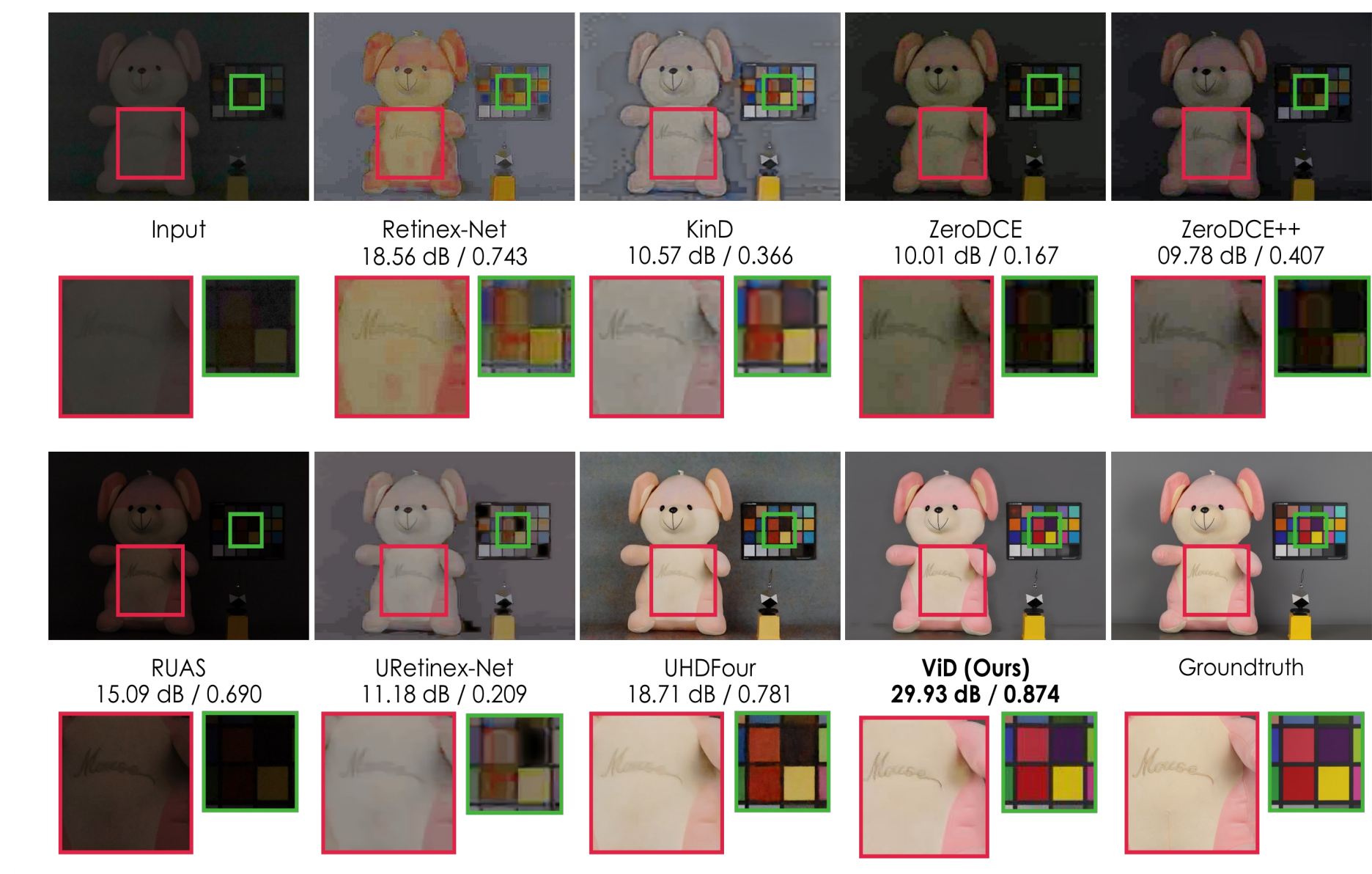
QUANTITATIVE RESULTS

Datasets	LoL		Cube++		UHD-LL		Custom Dataset	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
NPE [29]	16.96	0.481	13.28	0.378	18.29	0.587	15.29	0.341
LIME [7]	18.35	0.771	16.03	0.639	14.97	0.648	13.10	0.480
SRIE [4]	11.85	0.493	07.09	0.320	16.31	0.652	12.90	0.472
Retinex-Net [32]	15.90	0.372	09.41	0.358	16.95	0.734	18.56	0.743
KinD [38]	16.47	0.492	13.58	0.454	21.00	0.827	10.57	0.366
DRBN [34]	16.14	0.542	13.04	0.413	15.45	0.689	14.84	0.563
Zero-DCE [6]	16.79	0.557	14.30	0.465	17.08	0.664	10.01	0.167
RUAS [17]	18.22	0.717	18.60	0.538	11.76	0.701	15.09	0.690
EnlightenGAN [9]	16.34	0.796	08.71	0.203	17.63	0.767	08.91	0.016
URetinex-Net [33]	21.57	0.833	13.80	0.434	20.68	0.706	11.18	0.209
UHDFour [14]	23.09	0.870	15.99	0.538	26.22	0.900	18.71	0.781
ViD (Ours)	30.15	0.962	31.96	0.950	29.88	0.933	28.93	0.874

SOTA COMPARISON ON UHDFOUR DATA



SOTA COMPARISON ON CUSTOM DATA



ViD RESULTS

