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CVPR
VANCOUVER, CANADA

DNF: Decouple and Feedback Network for Seeing in the Dark

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Poster: THU-AM-158

Project Page: https://github.com/Srameo/DNF

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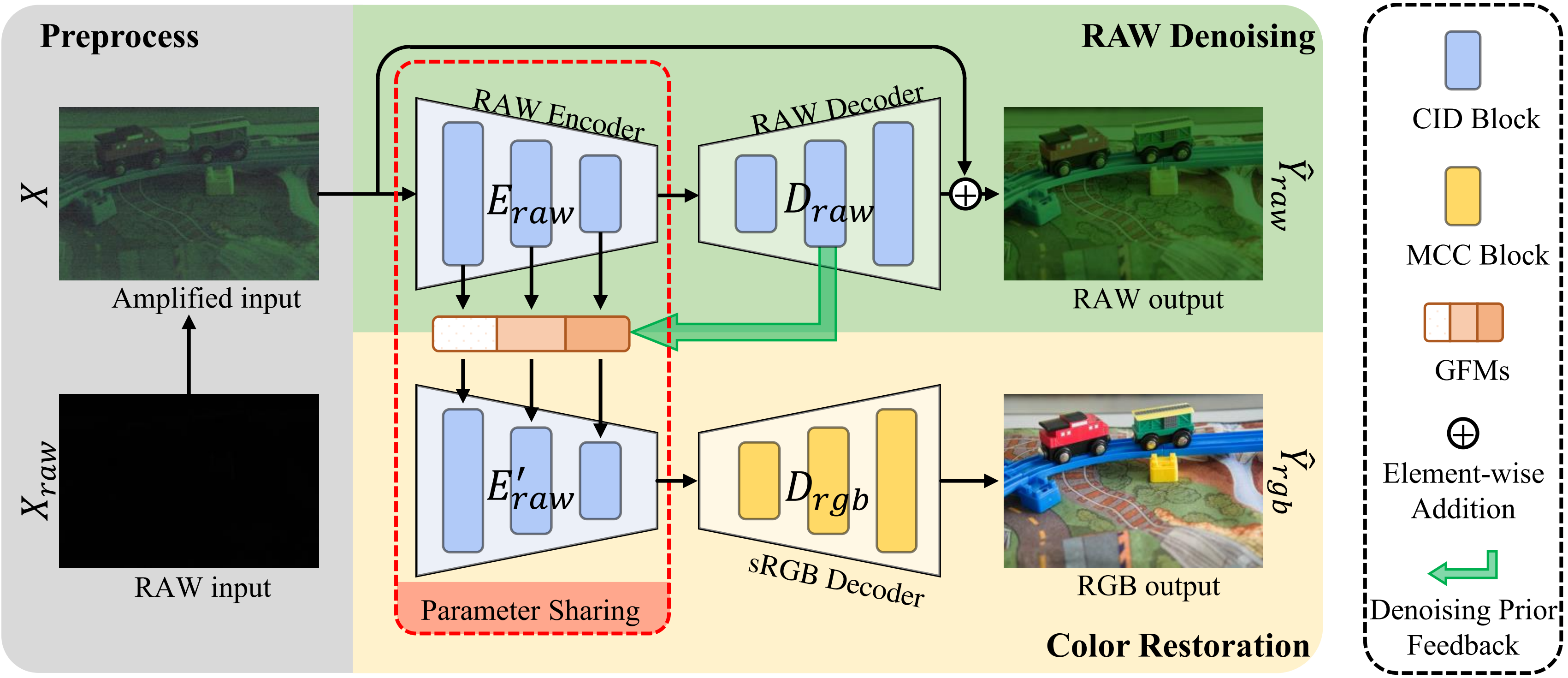
Quick Review

- Aiming at low-light image enhancement for RAW images.
- Domain-specific Task Decoupling
  - Decouple into domain-specific tasks: denoising in RAW and color restoration into sRGB, exploiting the domain-exclusive properties.
- Denoising Prior Feedback
  - The feature-level dataflow empowered by the Denoising Prior Feedback aggregates complementary features across stages and reduces the error accumulation.



Performance

- High Efficiency
  - Compared with the previous state-of-the-art method, DNF gains a significant margin improvement with only **19% parameters** and **63% FLOPs.**

- Significant Performance
  - **0.97dB** PSNR improvement on the Sony dataset of SID and **1.30dB** PSNR improvement on the Fuji dataset of SID.

Table 1. Quantitative results of RAW-based LLIE methods on the Sony and Fuji subsets of SID [2]. The best result is in **bold** whereas the second best one is in underlined. Metrics with ↑ and ↓ denote higher better and lower better, respectively. Methods with * indicate that the model is trained and inference with a downsampled resolution, and we manually upsample the results to the original resolution during testing. Methods with # indicate that the model is trained and inferenced with only the images of small digital gains (×100) on the SID datasets. "-" indicates the result is not available.

Category	Method	Params.	FLOPs	Sony			Fuji		
				PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓
Single-Stage	SID [2]	7.7 M	48.5 G	28.96	0.787	0.356	26.66	0.709	0.432
	DID [22]	2.5 M	669.2 G	29.16	0.785	0.368	-	-	-
	SGN [5]	19.2 M	75.5 G	29.28	0.790	0.370	27.41	0.720	0.430
	LLPackNet [12]	1.2 M	7.2 G	27.83	0.755	0.541	-	-	-
	RRT [13]	0.8 M	5.2 G	28.66	0.790	0.397	26.94	0.712	0.446
Multi-Stage	EEMEFN [47]	40.7 M	715.6 G	29.60	0.795	0.350	27.38	0.723	0.414
	LDC* [35]	8.6 M	124.1 G	29.56	**0.799**	0.359	27.18	0.703	0.446
	MCR# [4]	15.0 M	90.5G	29.65	0.797	0.348	-	-	-
	RRENet [7]	15.5 M	96.8 G	29.17	0.792	0.360	27.29	0.720	0.421
	Ours	2.8 M	57.0 G	**30.62**	0.797	**0.343**	**28.71**	**0.726**	**0.391**

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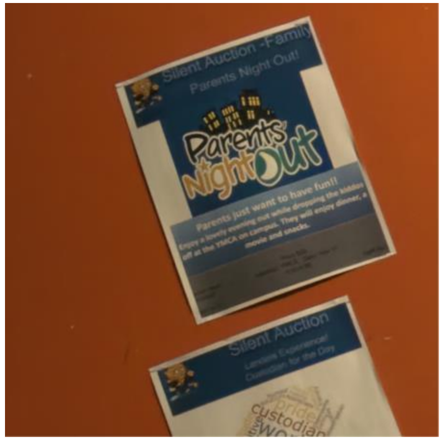
Background

What Makes RAW Better?

Low-light input

Enhanced in sRGB

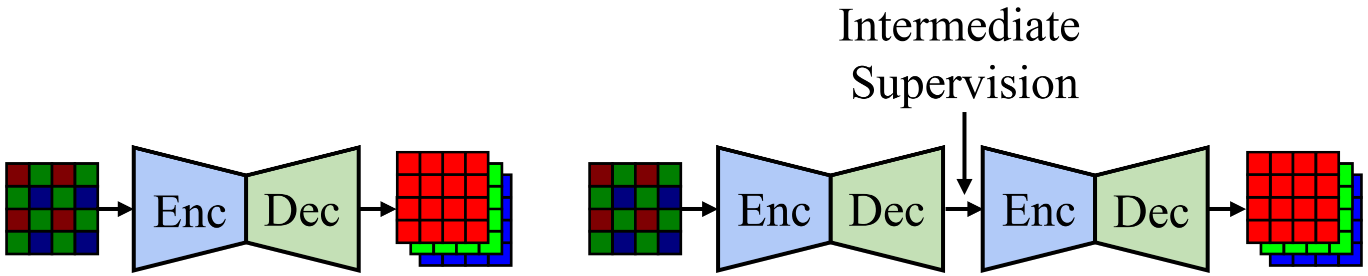


Enhanced in RAW

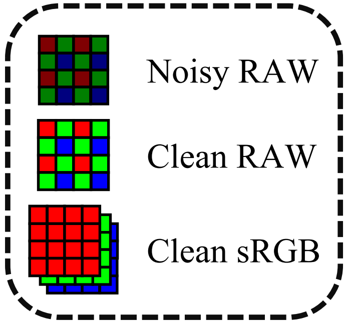
- Signal is linearly correlated with photon counts
- Noise distributions are tractable before ISP
- Higher bit depth distinguishes low-intensity signals

Background

Current Methods



(a) Single-stage (b) Multi-stage



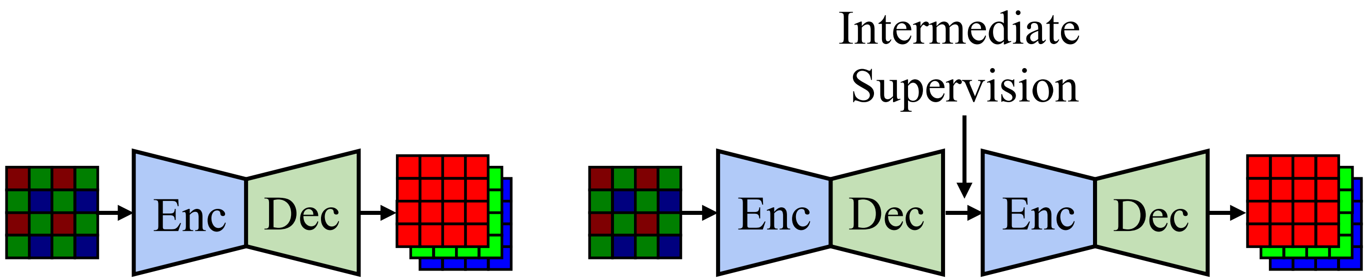
Direct Mapping
from noisy RAW domain
to clean sRGB domain

Errors & Information Loss
accumulated by only propagating
images across stages

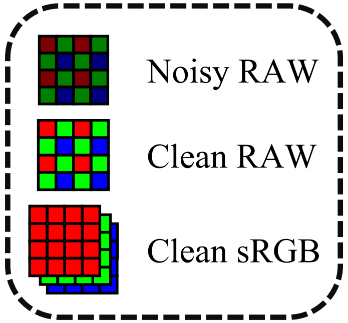
Domain Ambiguity

Lossy Image-level Dataflow

Motivation



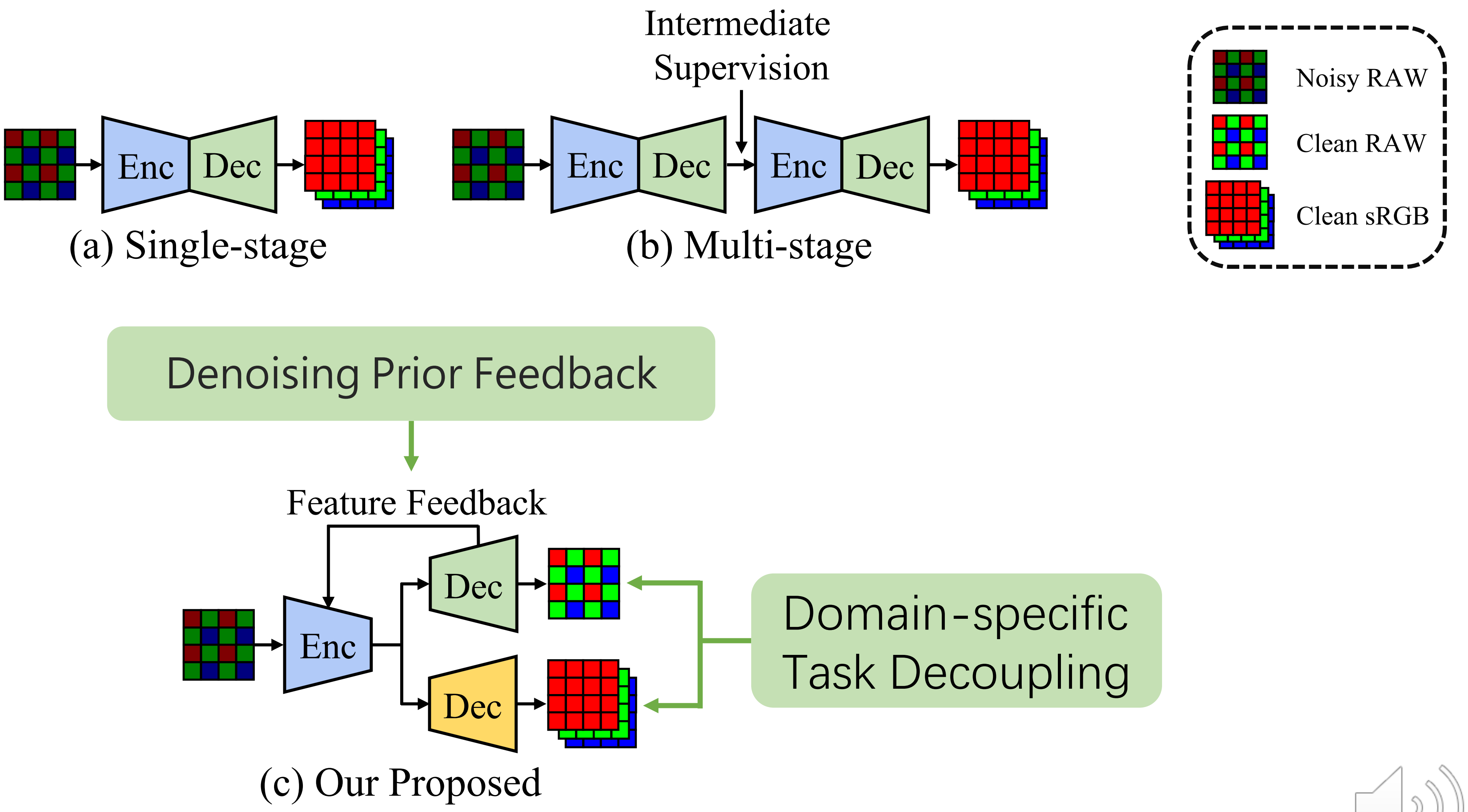
(a) Single-stage (b) Multi-stage



Domain Ambiguity → Domain-specific Task Decoupling

Lossy Image-level Dataflow → Denoising Prior Feedback

Motivation


Intermediate
Supervision
Enc
Dec
Enc
Dec
Enc
Dec
(a) Single-stage
(b) Multi-stage
Noisy RAW
Clean RAW
Clean sRGB
Denoising Prior Feedback
Feature Feedback
Enc
Dec
Dec
Domain-specific
Task Decoupling
(c) Our Proposed

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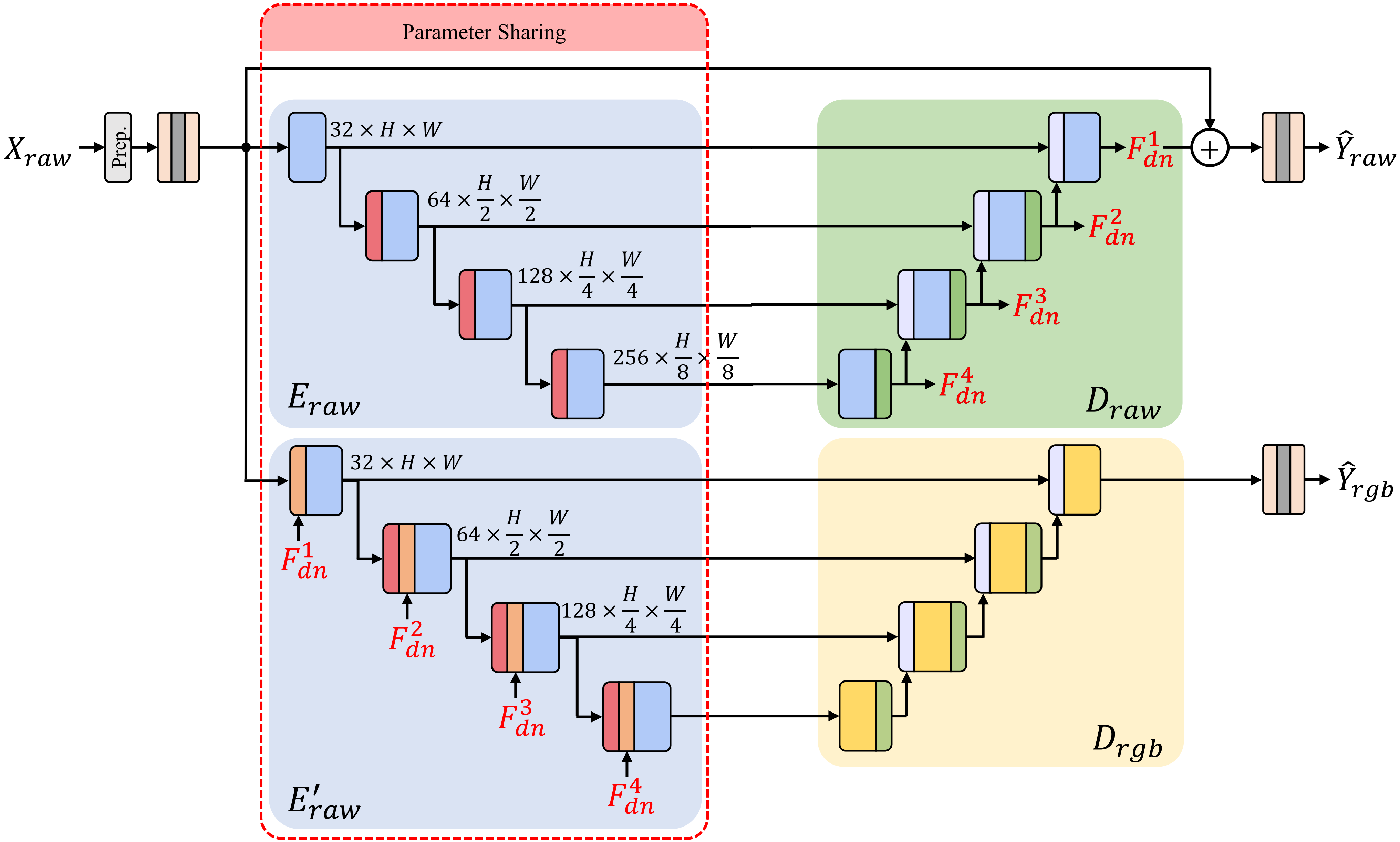
Pipeline



Ablation Studies

Table 3. Ablation study on the deouple and feedback framework. Sup. denotes the supervision of the denoising decoder.

Module	Replacement	PSNR	SSIM
RAW Sup.	w/o Sup.	30.48	0.795
	sRGB Sup.	30.20	0.796
Feedback	Single-Stage	30.16	0.792
	Mulit-Stage	30.32	0.795
GFM	Conv	30.40	0.795
	w/o Gate	30.35	0.794
	SKFF [40]	30.37	0.795
Original		**30.62**	**0.797**

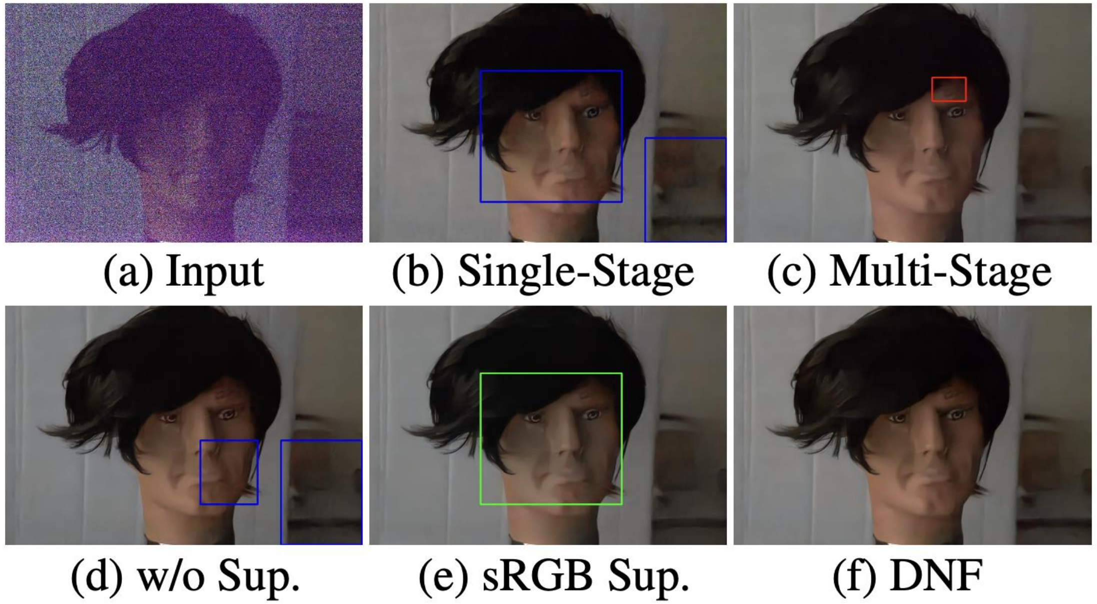


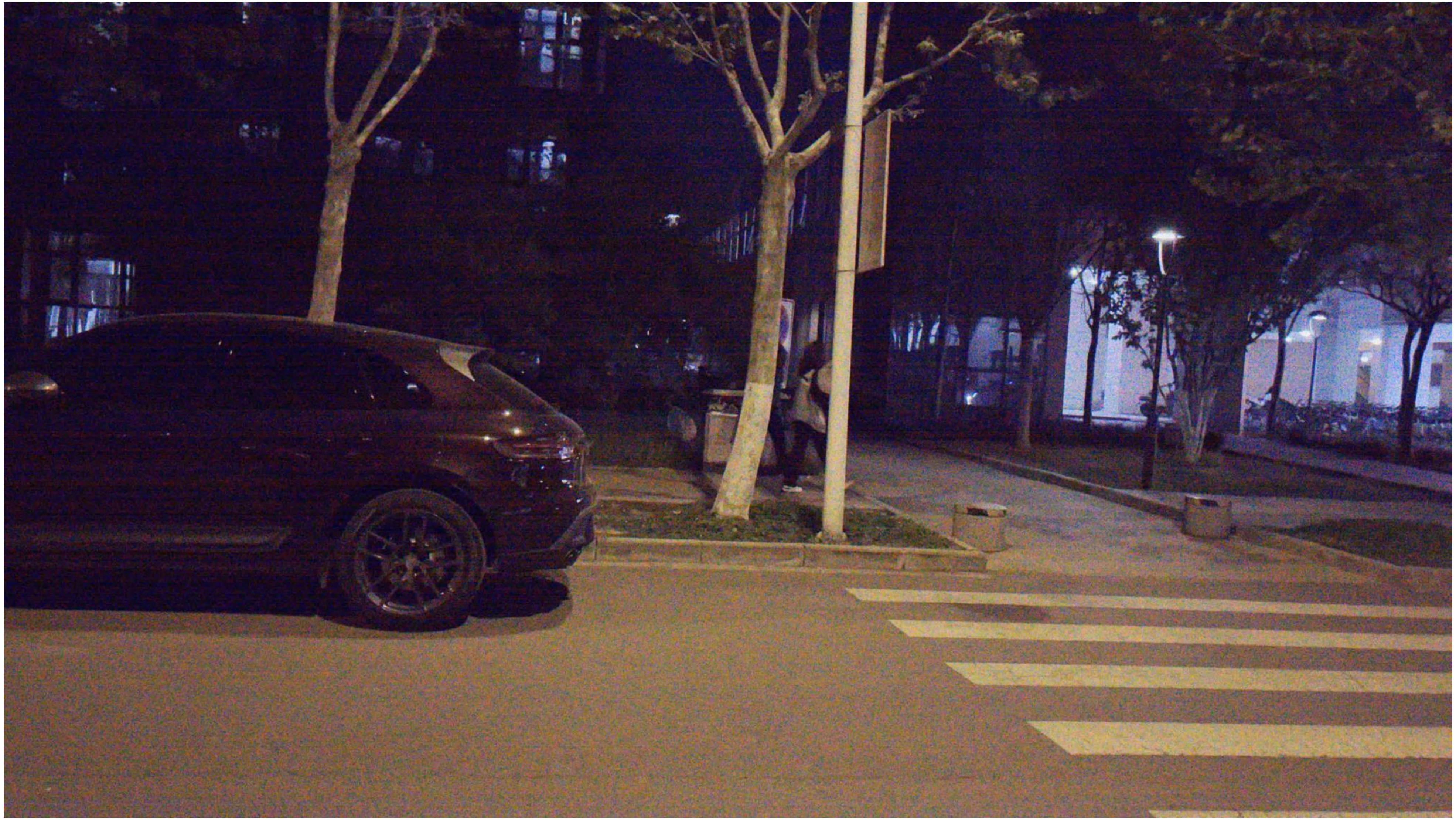
Figure 7. Visual comparisons between our DNF and ablated models (*Zoom-in for best view*). blue, red, green boxes represent remaining noise, detail loss, and color shifts, respectively.

Results

LDC[1] | EEMEFN[2] | **DNF (Ours)** | GT

[1] Xu, Ke, et al. "Learning to restore low-light images via decomposition-and-enhancement." *CVPR*. 2020.
[2] Zhu, Minfeng, et al. "Eemefn: Low-light image enhancement via edge-enhanced multi-exposure fusion network." *AAAI*. 2020.

Results



Thanks!

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Pi Lab Website: https://pi-lab.xyz
MCG-NKU Website: https://mmcheng.net