

# LensNet: An End-to-End Learning Framework for Empirical Point Spread Function Modeling and Lensless Imaging Reconstruction

Jiesong Bai<sup>1,2</sup>, Yuhao Yin<sup>2</sup>, Yihang Dong<sup>1</sup>, Xiaofeng Zhang<sup>3</sup>,  
Chi-Man Pun<sup>2</sup>, Xuhang Chen<sup>1,4</sup>



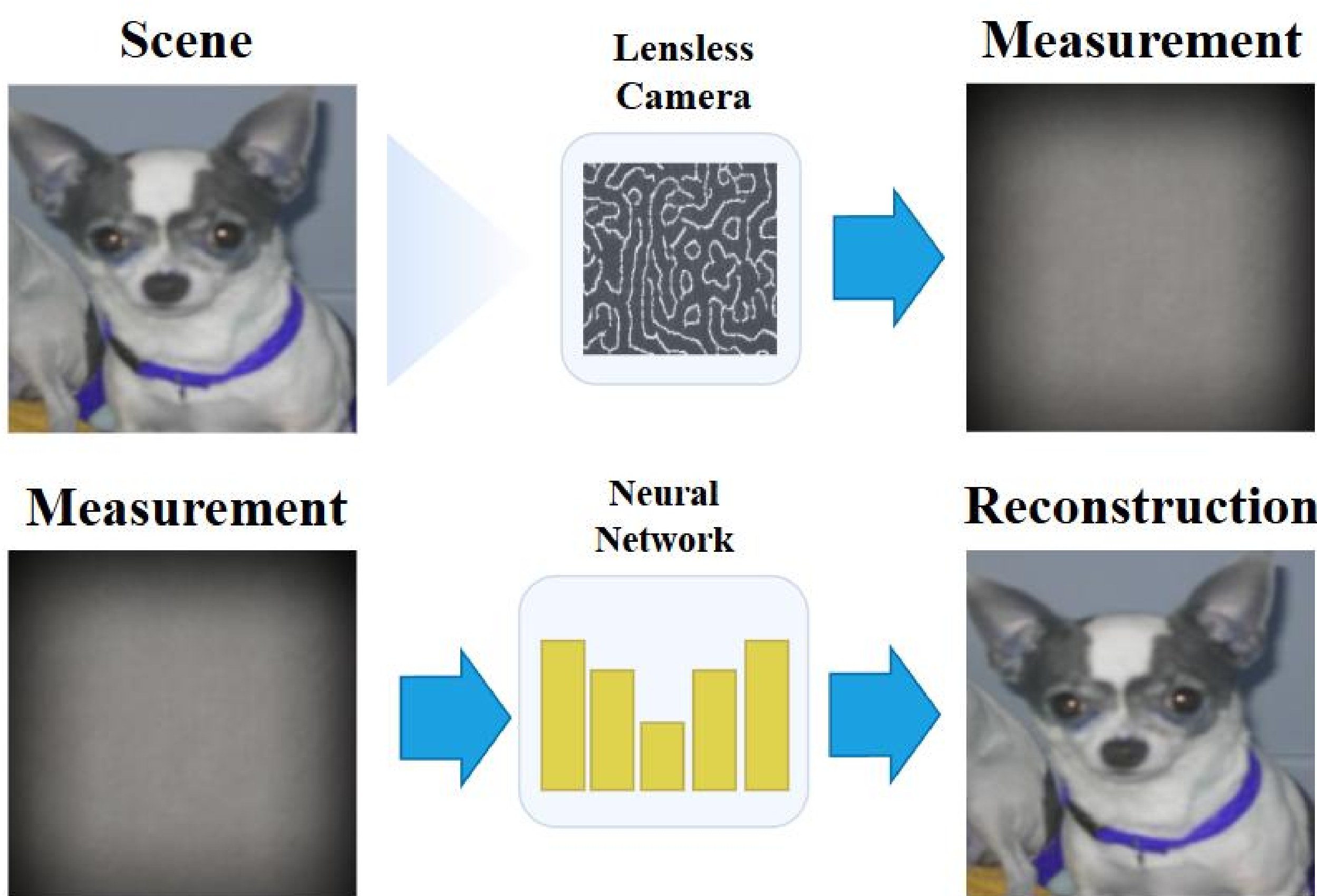
<sup>1</sup>UM <sup>2</sup>SHU <sup>3</sup>SJTU <sup>4</sup>HZU

## Introduction

❖ **Lensless imaging** avoids the use of lenses altogether and instead uses computational algorithms to reconstruct scenes. **However**,

➢ **Adaptability of the PSF** (Point Spread Function): Traditional methods rely on static or pre-calibrated PSF models, making them difficult to adapt to real-world imaging conditions such as illumination variations, sensor noise, resulting in degraded reconstruction quality.

➢ **High-frequency recovery bottlenecks**: While existing deep learning-based reconstruction methods have made progress, they still suffer from blurring or loss of high-frequency information.



❖ **Our method**: We propose a novel end-to-end deep learning framework (**LensNet**) for lensless imaging that dynamically captures multi-scale features in both spatial and frequency domains, substantially improving the fidelity and accuracy of image reconstructions over conventional methods.

## Results

### Dataset

➢ **DiffuserCam, MWDNs**. Both datasets undergo a standard preprocessing pipeline to ensure consistent input dimensionality, facilitating a robust and fair comparison of lensless imaging strategies.

### Comparison with Other Methods

Table 1: Performance comparison on two datasets: DiffuserCam and MWDNs. Metrics include PSNR (dB), SSIM, and LPIPS. Best results are highlighted in red and bold.

Method	DiffuserCam			MWDNs		
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓
Wiener [1949]	7.33	0.083	0.770	9.44	0.045	0.731
Vanilla GD	13.27	0.432	0.585	16.70	0.503	0.429
Nesterov GD [1998]	12.16	0.394	0.518	17.06	0.671	0.362
FISTA [2009b]	11.09	0.341	0.554	16.25	0.697	0.368
ADMM [2011]	12.76	0.442	0.541	17.76	0.638	0.343
APGD [2015]	12.13	0.385	0.518	17.34	0.448	0.439
TikNet [2020]	19.75	0.720	0.221	26.57	0.913	0.075
FlatNet [2020]	21.16	0.720	0.231	19.08	0.841	0.178
LenslessGAN [2021]	22.51	0.737	0.193	27.49	0.913	0.077
UDN [2022]	20.00	0.688	0.250	26.98	0.908	0.081
MWDN [2023]	25.74	0.816	0.132	31.74	0.957	0.030
<b>LensNet</b>	<b>27.46</b>	<b>0.863</b>	<b>0.099</b>	<b>33.22</b>	<b>0.960</b>	<b>0.024</b>

### Implementation Study

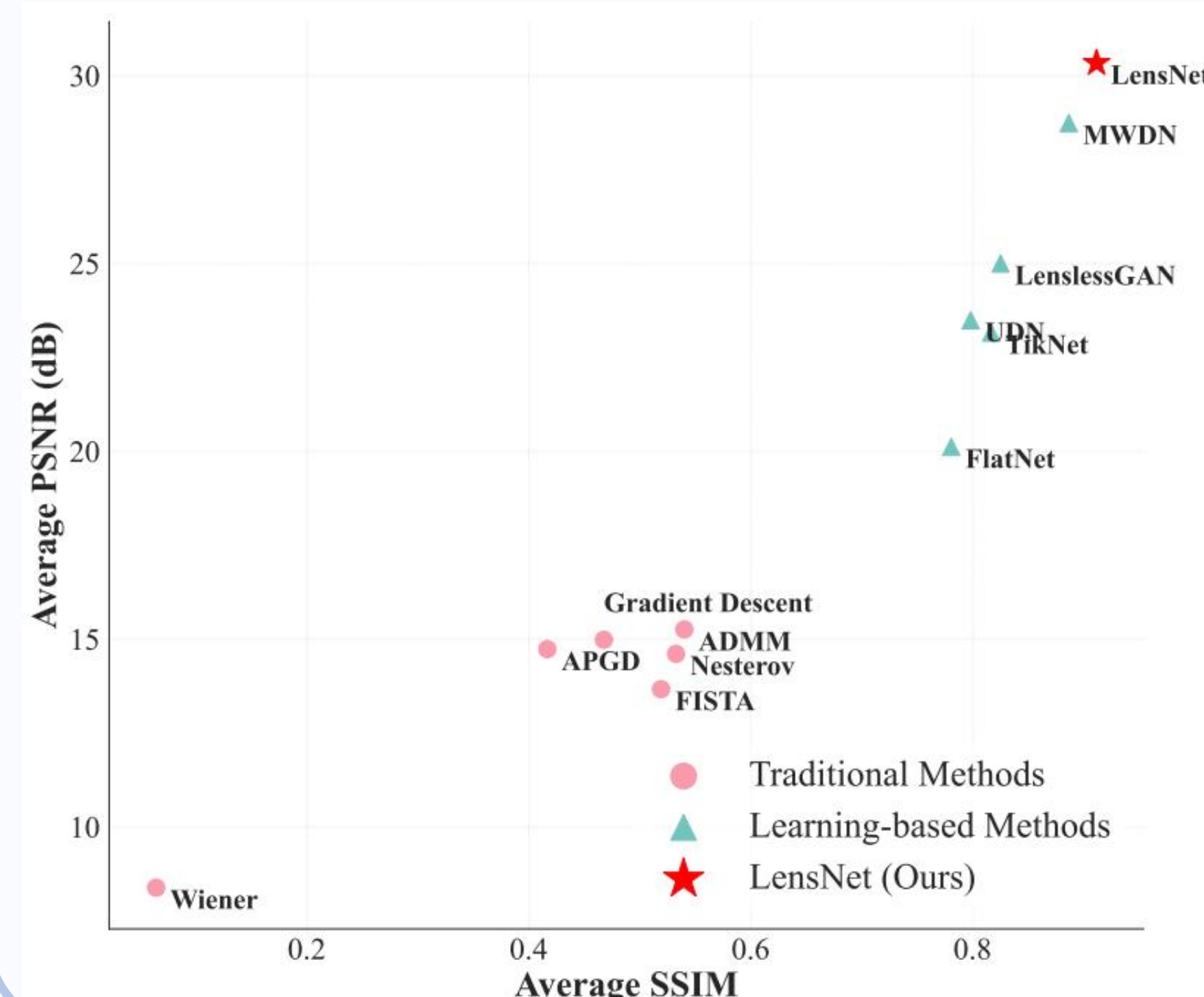


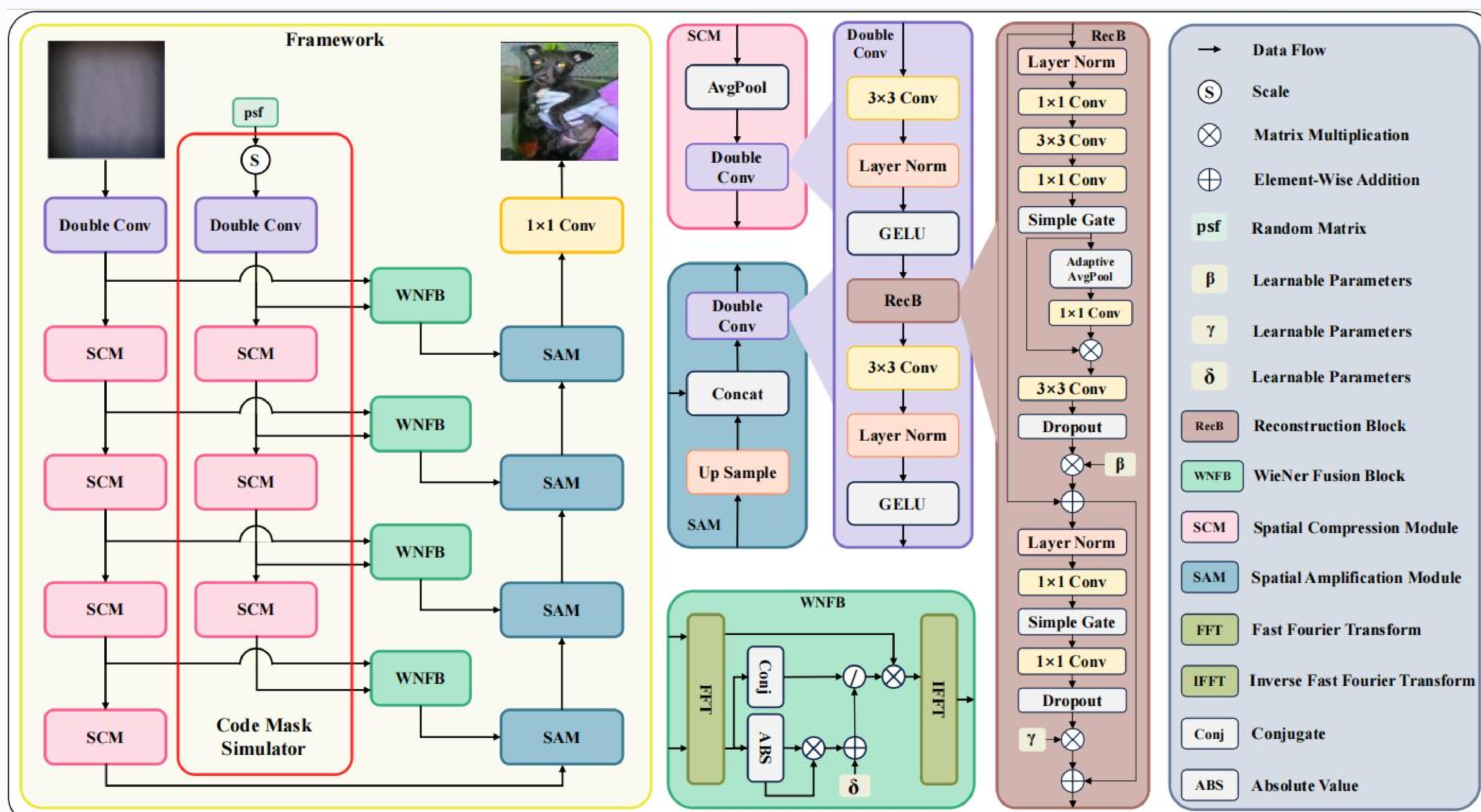
Table 2: Ablation Study on LensNet

Methods	PSNR↑	LensNet SSIM↑	LPIPS↓
ThreeDown	25.68	0.910	0.084
w/o RecB	30.36	0.945	0.044
w original PSF	31.92	0.954	0.031
Ours	<b>33.22</b>	<b>0.960</b>	<b>0.024</b>

Table 4: Comparison of Parameter Count and FLOPs

Method	Params (M)	FLOPs (G)
Ours	31.18	115.10
FlatNet	59.13	220.42
LenslessGAN	11.77	13.82
MWDN	21.96	83.85
TikNet	59.13	220.42
UDN	1.04	2.37

## LensNet Framework



### Code Mask Simulator

The **CMS** captures the intensity distribution features in measurement, which encode the coded mask pattern. Consequently, the system's PSF can be inferred from **these learned mask distributions**.

### Spatial Amplification Module

The **SAM** could integrate spatial and frequency domain information more comprehensively. Serving as a multi-scale fusion mechanism, the SAM leverages information from both domains to produce high-quality reconstructions, ensuring that critical **spatial details and global consistency** are well-preserved.

## Resources

**Paper:**  
<https://arxiv.org/pdf/2505.01755>  
**Code:**  
<https://github.com/baijiesong/Lensnet>

## Acknowledgments

This work was supported by the Science and Technology Development Fund, Macau SAR, under Grant 0141/2023/RIA2 and 0193/2023/RIA3.

## Contact

For more information, please contact: [jiesongbai.7@gmail.com](mailto:jiesongbai.7@gmail.com) or friend me via WeChat.  
<https://baijiesong.github.io/>

