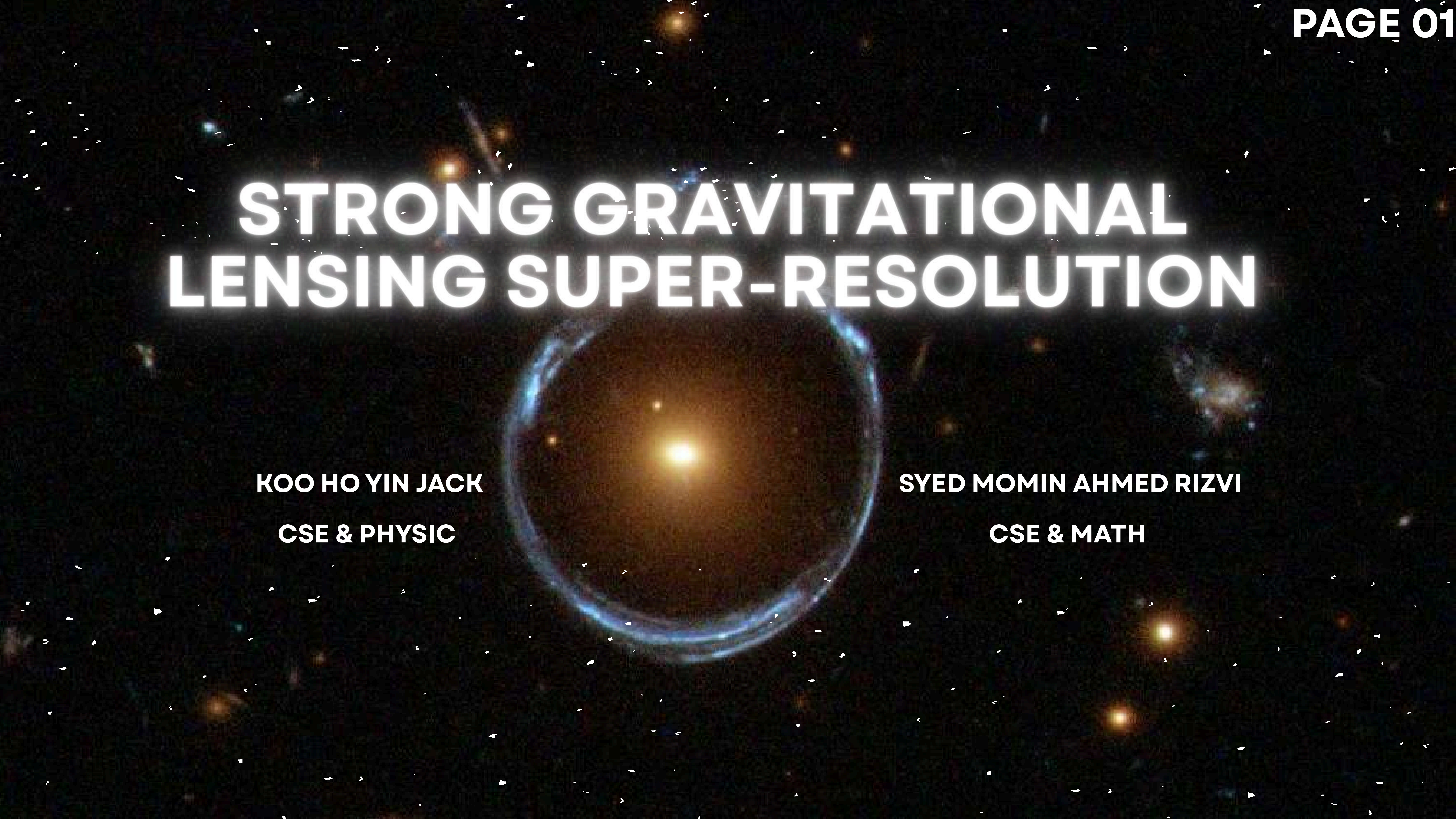


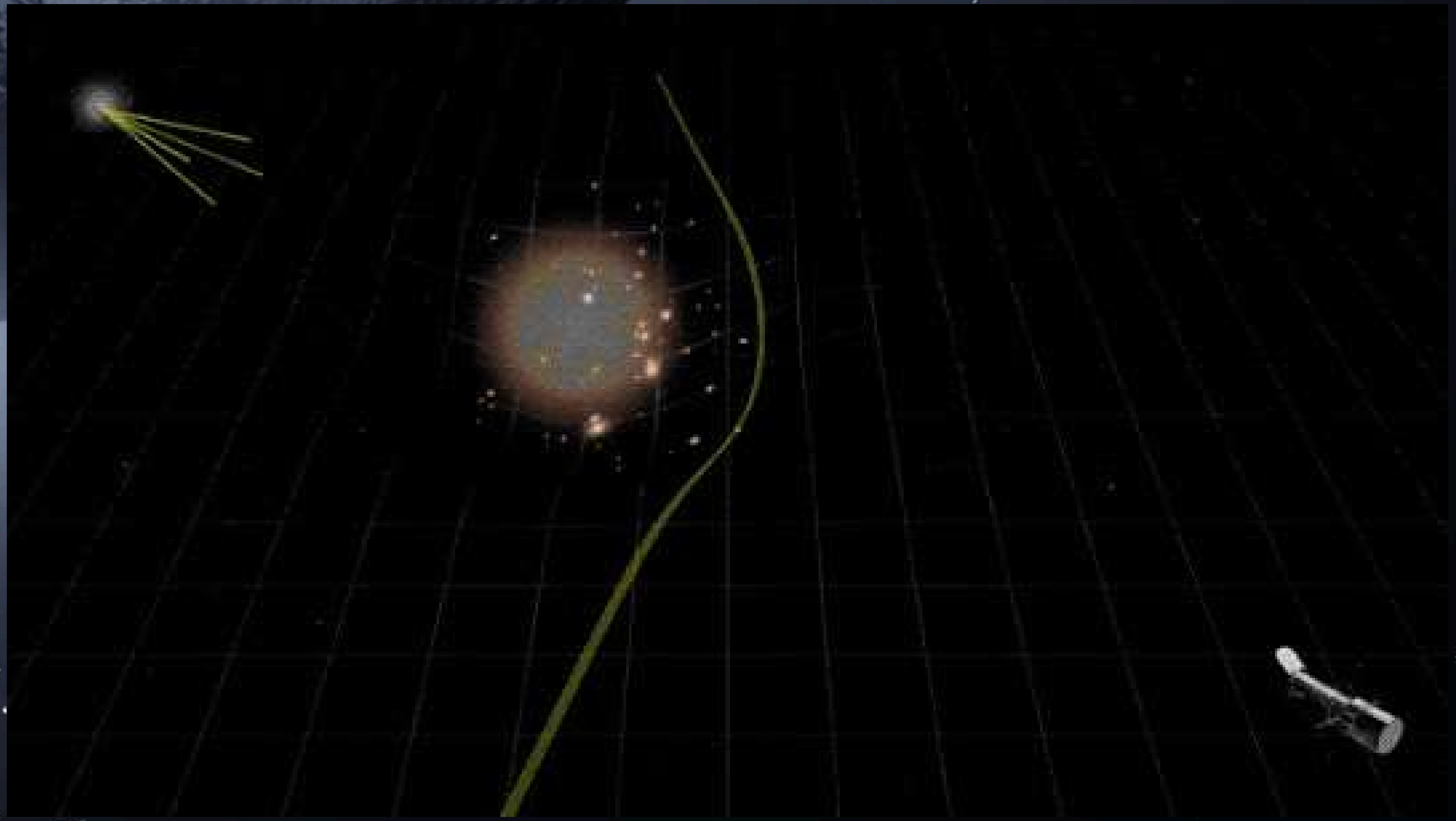
STRONG GRAVITATIONAL LENSING SUPER-RESOLUTION

KOO HO YIN JACK
CSE & PHYSIC

SYED MOMIN AHMED RIZVI
CSE & MATH

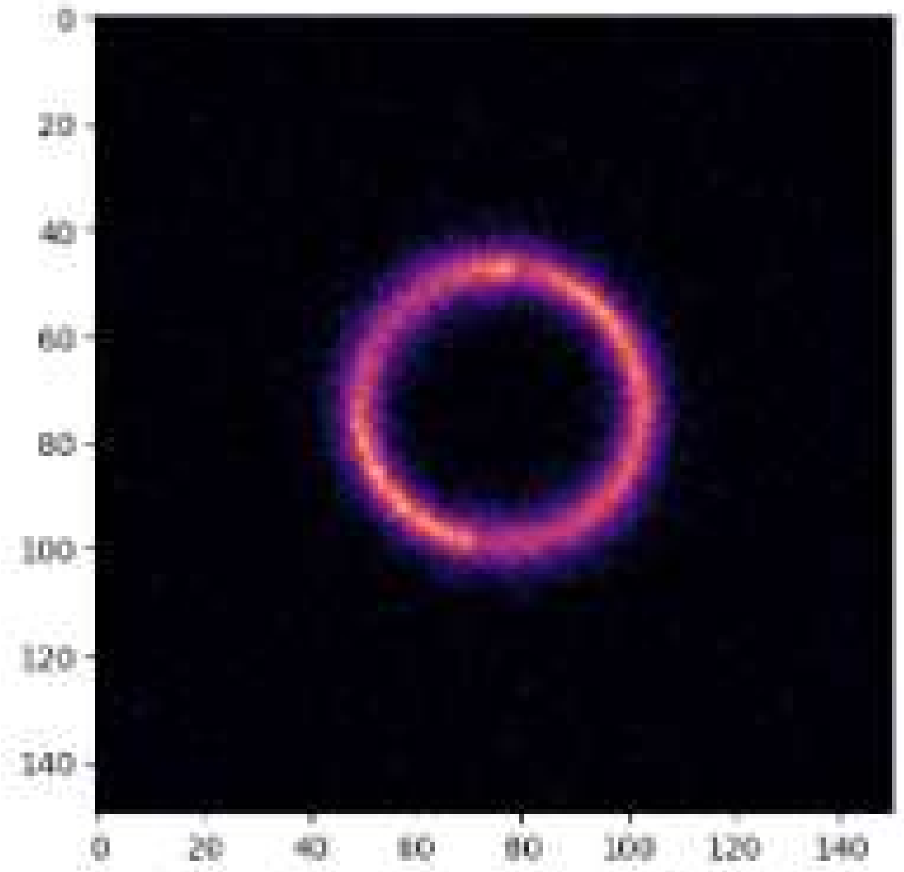
WHY IS GRAVITATIONAL LENSING INTERESTING?

- Gravitational lensing occurs when a massive celestial body is heavy enough to bend the path of light.
- However, for some observed lenses, the normal matter there does not have enough gravity to bend spacetime.
- This suggests the existence of a new matter, **dark matter**

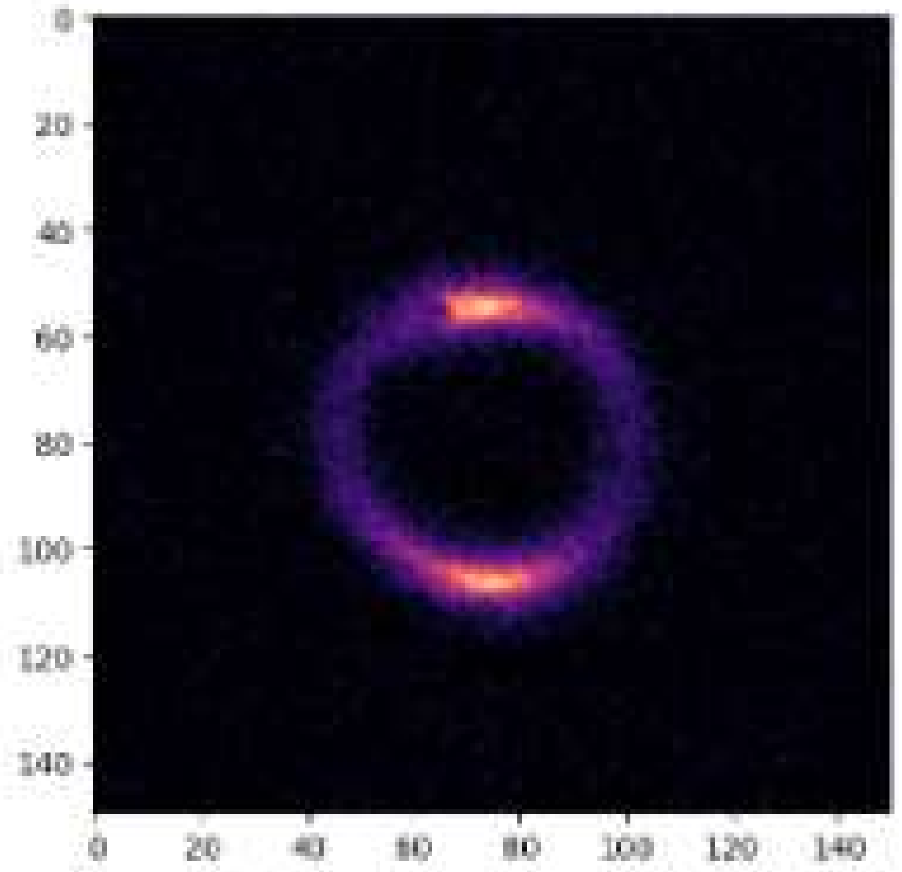


THE SHAPE OF GL DETERMINES THE TYPE OF DARK MATTER

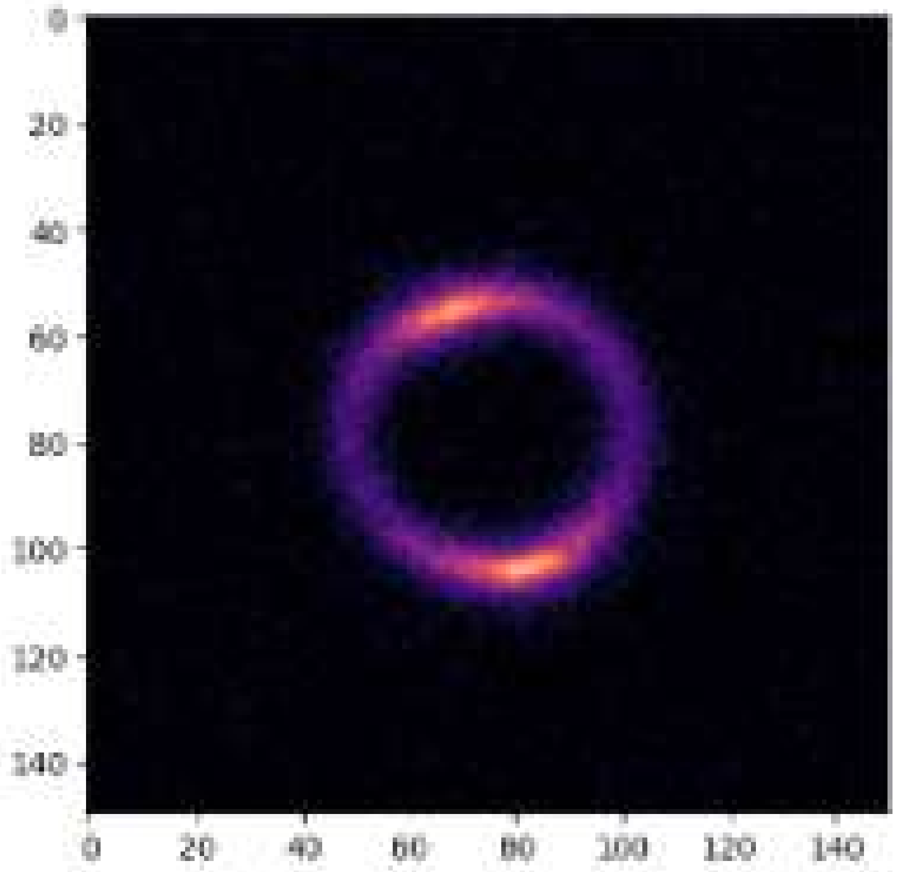
AXION DARK MATTER



COLD DARK MATTER



NO-SUBSTRUCTURE DARK MATTER

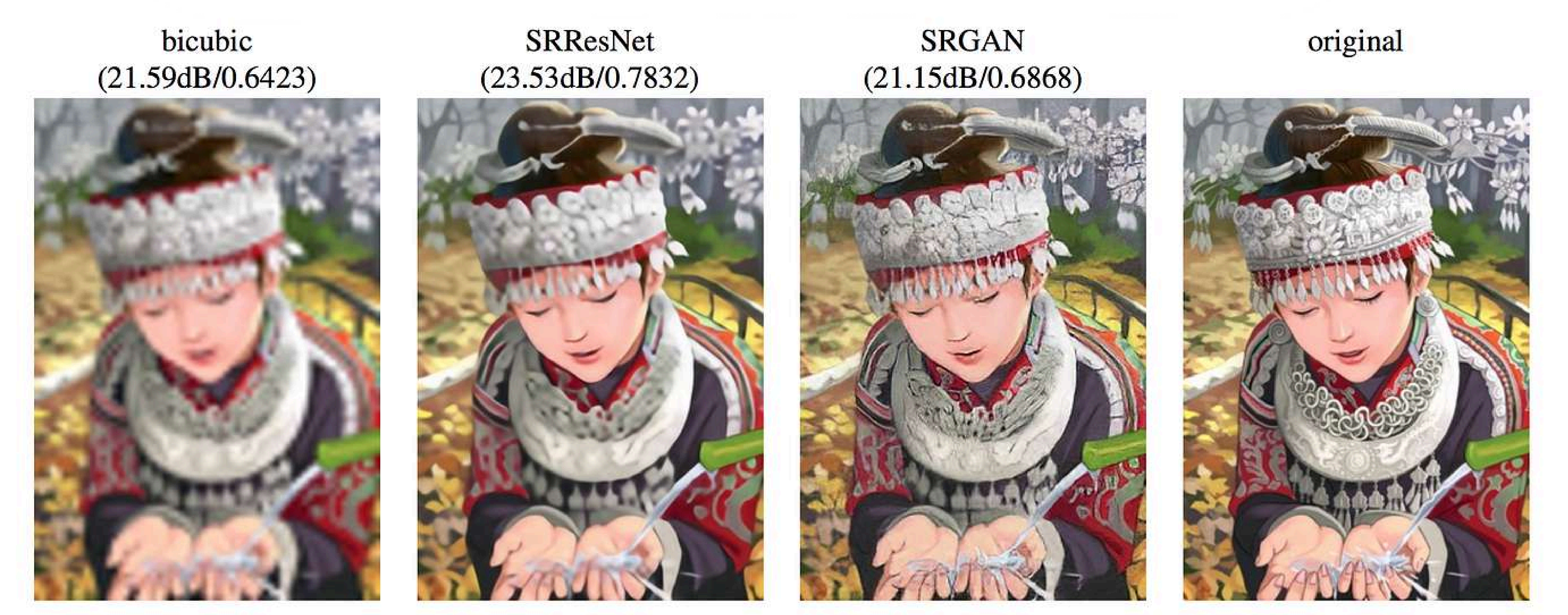


THERE IS JUST A SMALL PROBLEM, THE LENS IS TOO BLURRY TO SEE THE SHAPE

SIMULATED IMAGE

OBSERVED IMAGE

THIS IS WHERE DEEP LEARNING IS USEFUL



SUPER-RESOLUTION!!

RELATED WORK

1. CLASSIFICATION OF SIMULATED GLS WITH DIFFERENT TYPE OF DARK MATTER:

Deep Learning the Morphology of Dark Matter Substructure

Stephon Alexander,[1,2] Sergei Gleyzer,[3] Evan McDonough,[1,2] Michael W. Toomey,[2,*] and Emanuele Usai[2]

[1] *Brown Theoretical Physics Center, Brown University, Providence, RI, USA*
[2] *Department of Physics, Brown University, Providence, RI, USA*
[3] *Department of Physics and Astronomy, University of Alabama, Tuscaloosa, AL, USA*

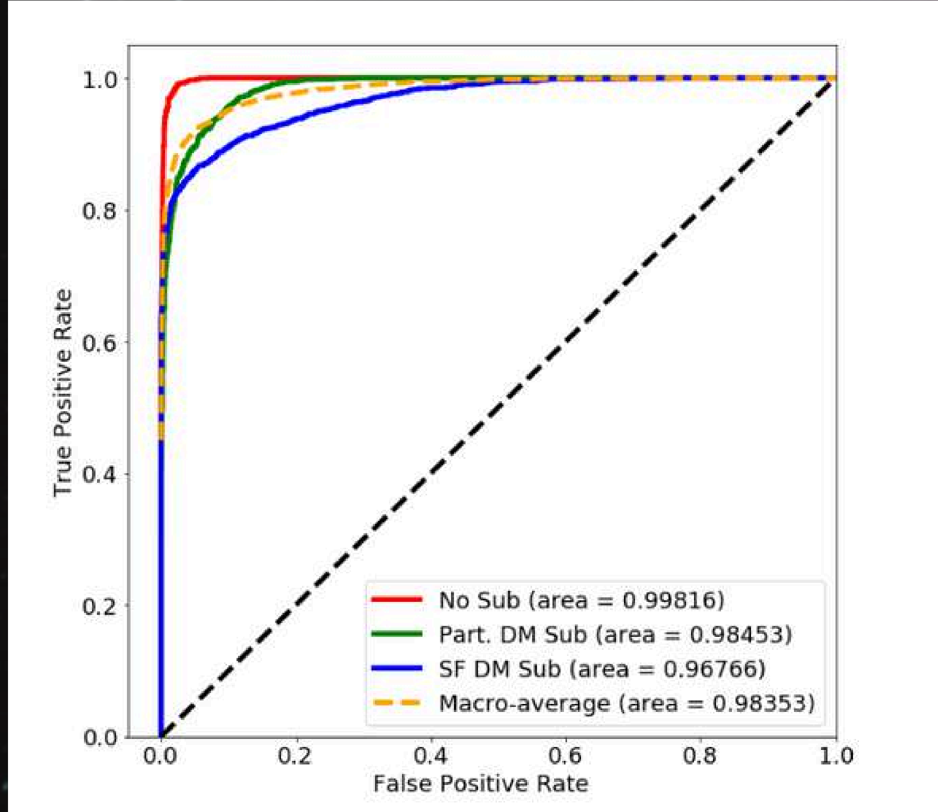
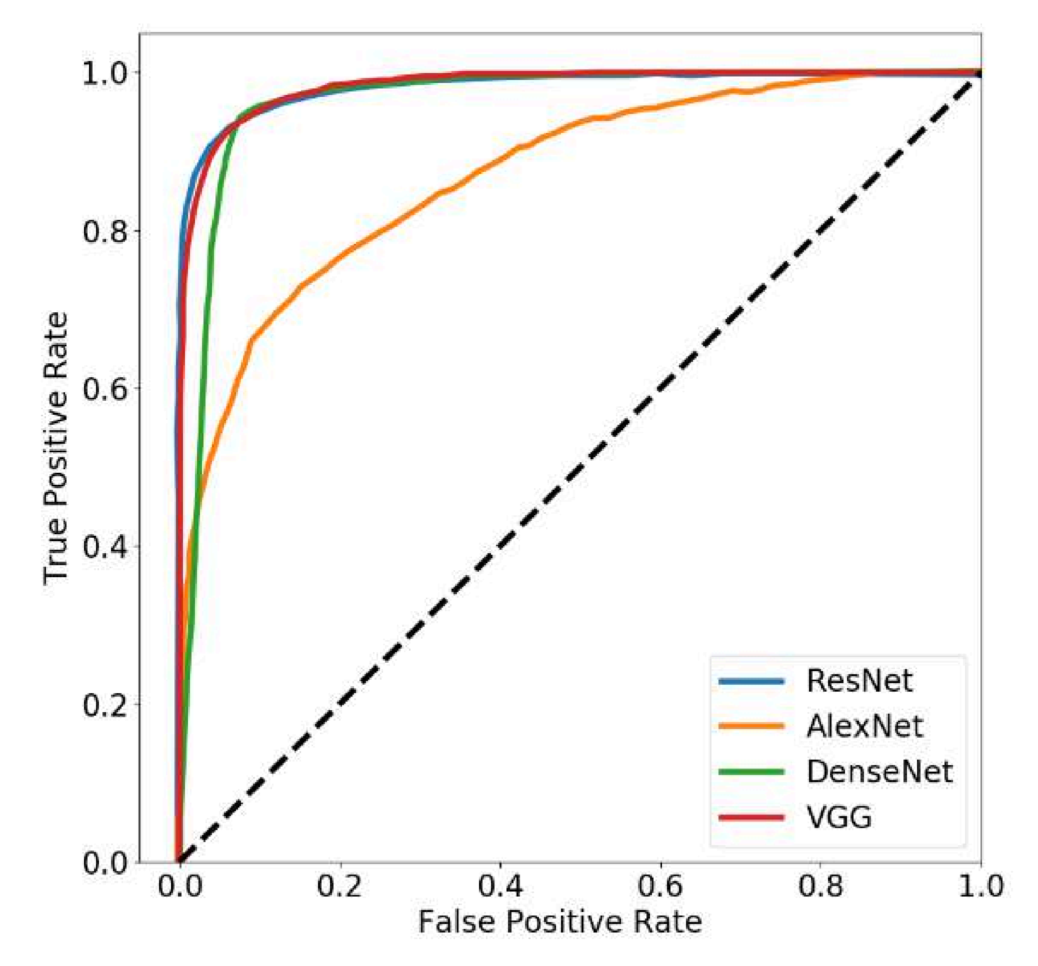


FIG. 6. ROC curve for multiclass substructure classification with *ResNet*, as discussed in Section VI A.



RELATED WORK

2. NEURAL NETWORK BASED SUPER-RESOLUTION

DeepLense / Super_Resolution_Pranath_Reddy /

Super-Resolution for Strong Gravitational Lensing

LICENSE MIT | PYTHON | PYTORCH

This work was done as part of Google Summer of Code (GSoC) 2023

Model	MSE	PSNR	SSIM
RCAN	0.00089	30.50028	0.56995
Residual Dense Network (RDN)	0.0009	30.49815	0.57196
SRResNet (18 Blocks)	0.0009	30.49482	0.57325
EDSR	0.0009	30.49347	0.57424
FSRCNN	0.0009	30.45184	0.56641
Hybrid FSRCNN (Feature Extraction Layers - Equivariant, Upscaling Layer - Convolutional)	0.00091	30.42472	0.57249
Bilinear Interpolation (Baseline)	0.00333	24.7818	0.30323
Equivariant FSRCNN	0.08281	19.35347	0.54386

RELATED WORK

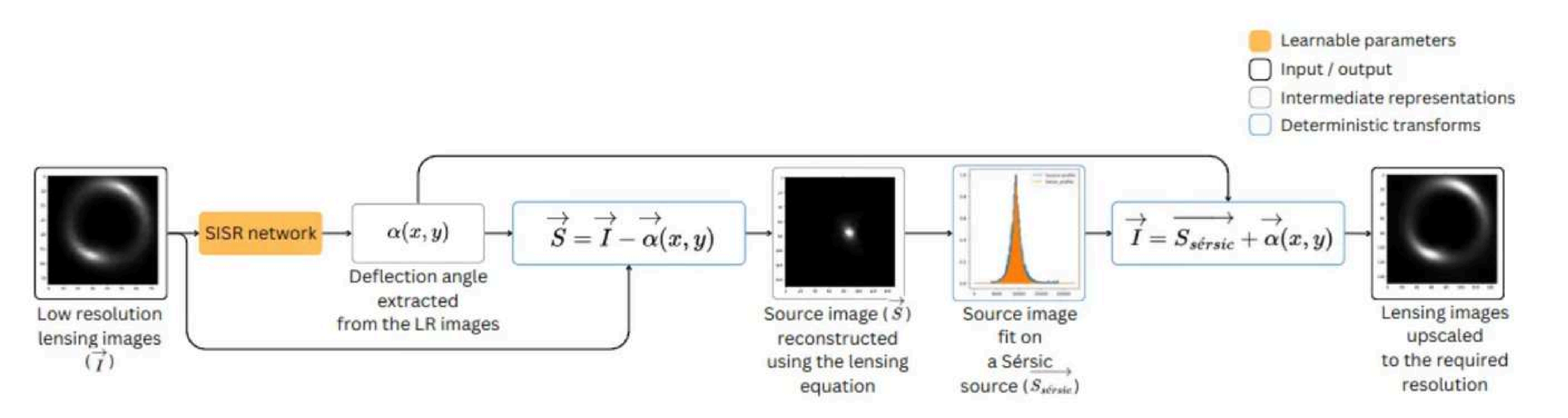
3. PHYSICS-INFORMED NEURAL NETWORK BASED SUPER-RESOLUTION

Physics-Informed Unsupervised Super-Resolution of Lensing Images: GSoC 2024 x ML4Sci

A Anirudh Shankar Follow 15 min read · Nov 3, 2024

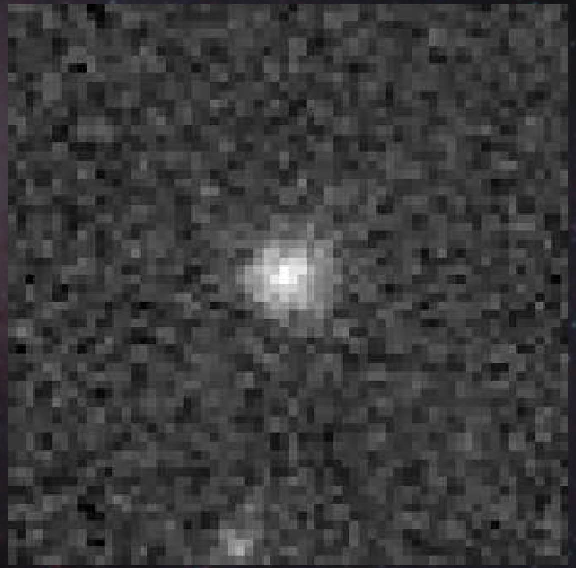
SERSIC PROFILE

$$I(R) = I_0 \exp\left(-kR^{1/n}\right)$$



LIMITATION OF EXISTING METHOD: THEY ONLY USE SIMULATION DATA

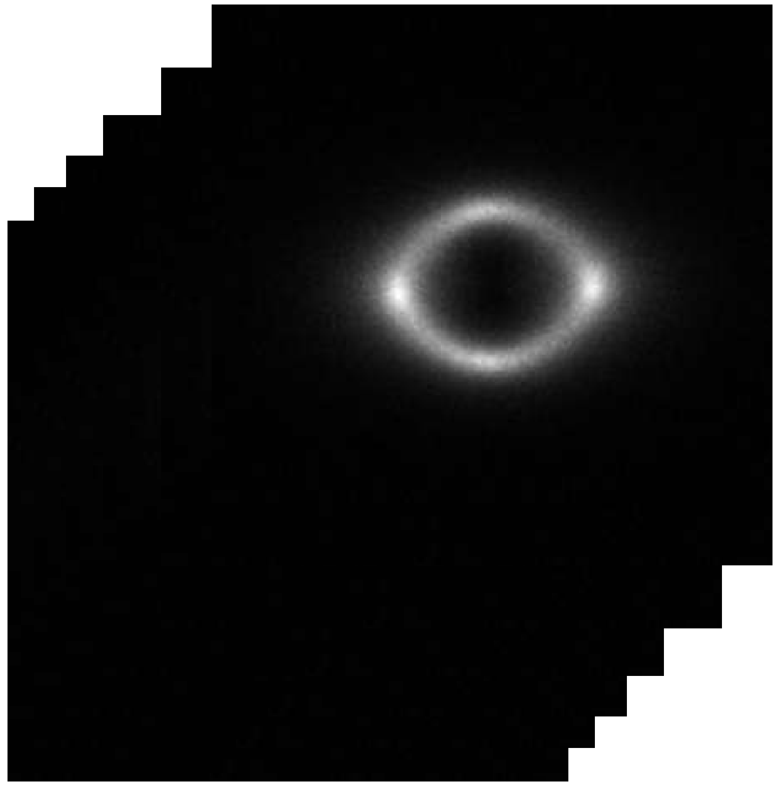
V.S.



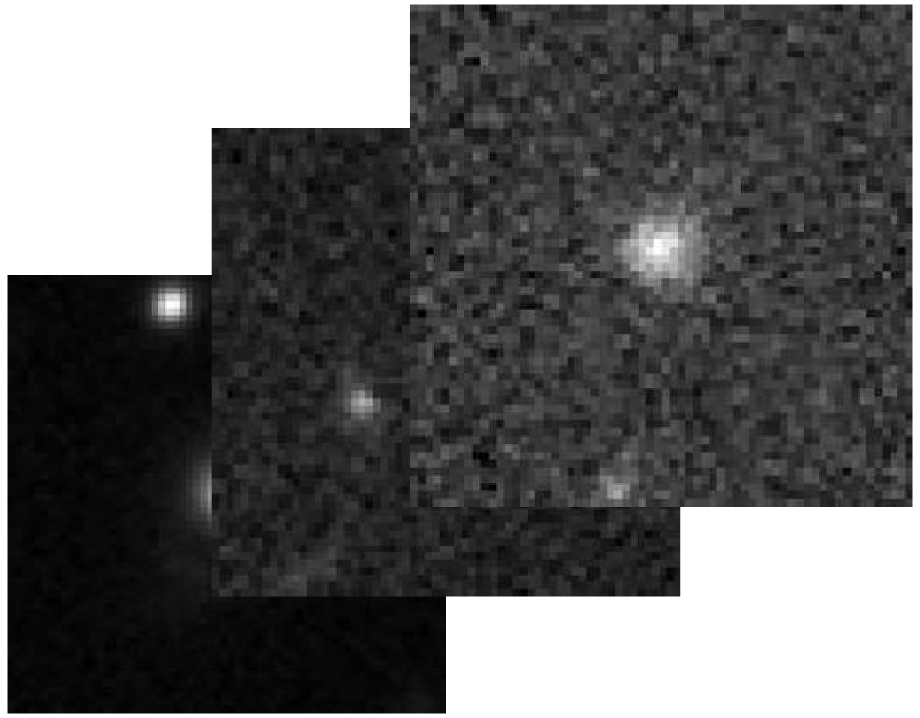
REALITY IS ALWAYS MORE DIFFICULT

QUESTION:
CAN WE USE OBSERVED DATA FOR TRAINING?

HERE COMES ANOTHER PROBLEM, OBSERVED DATA ARE TOO SMALL



10000 SIMULATED HR-LR PAIR



300 OBSERVED HR-LR PAIR

OUR SOLUTION: TRANSFER LEARNING

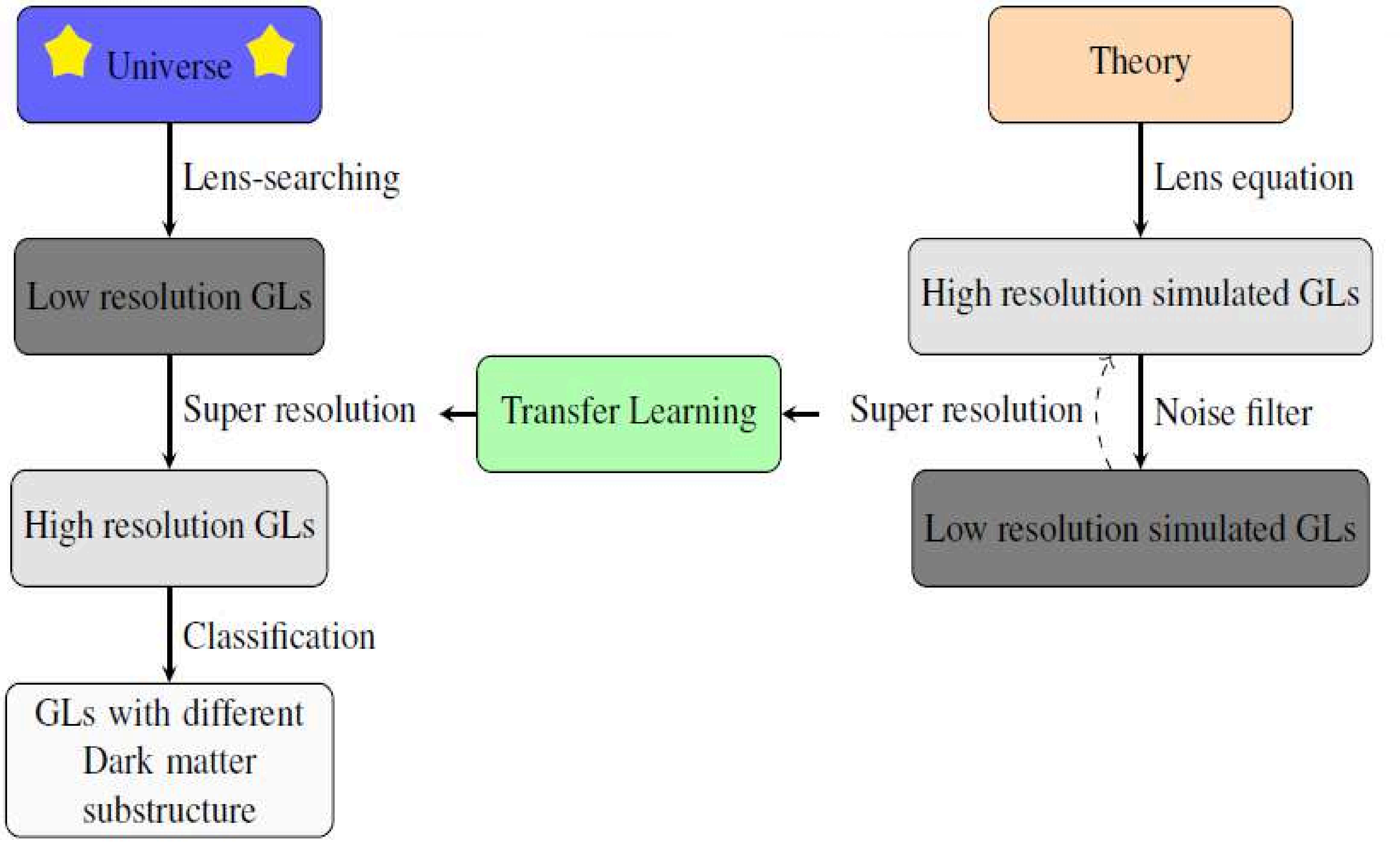


Figure 1. General Scheme in the search of Dark matter

DATA

Google
Summer of Code

@

ML
4
SCI

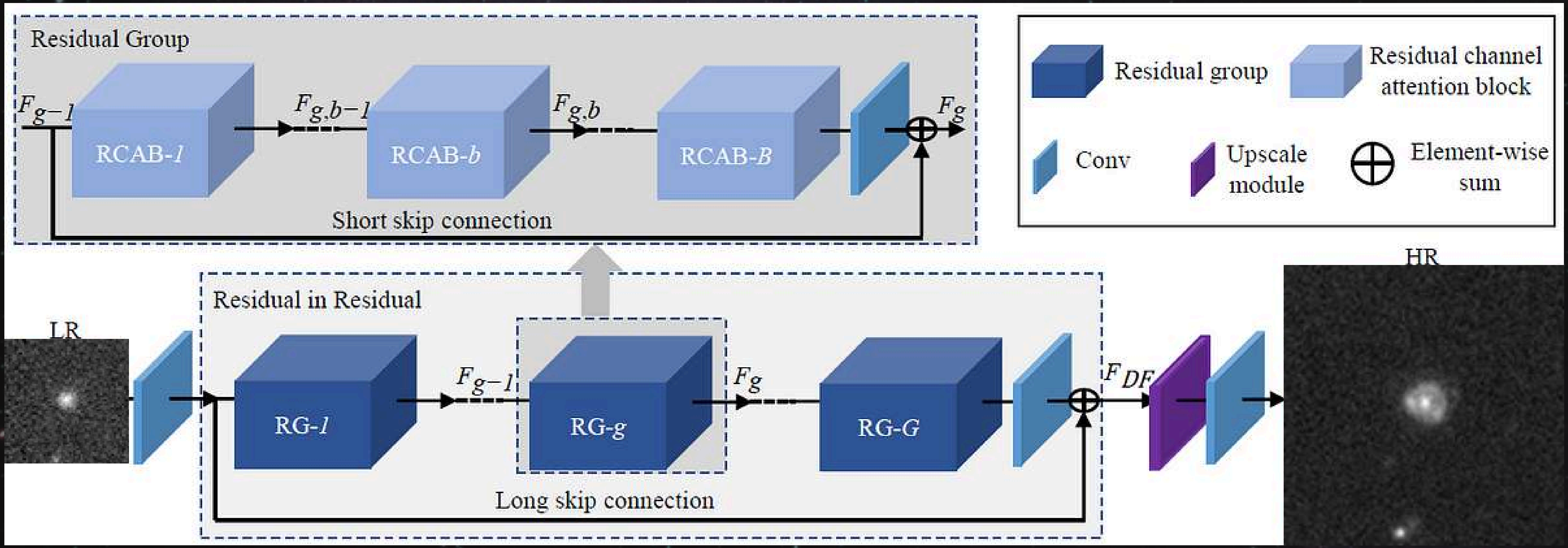
Machine Learning
for Science

EVALUATION METRIC

1. **MSE: measure average pixel-wise difference**
2. **SSIM: measure local variations and textures**
3. **PSNR: Peak Signal-to-Noise Ratio**

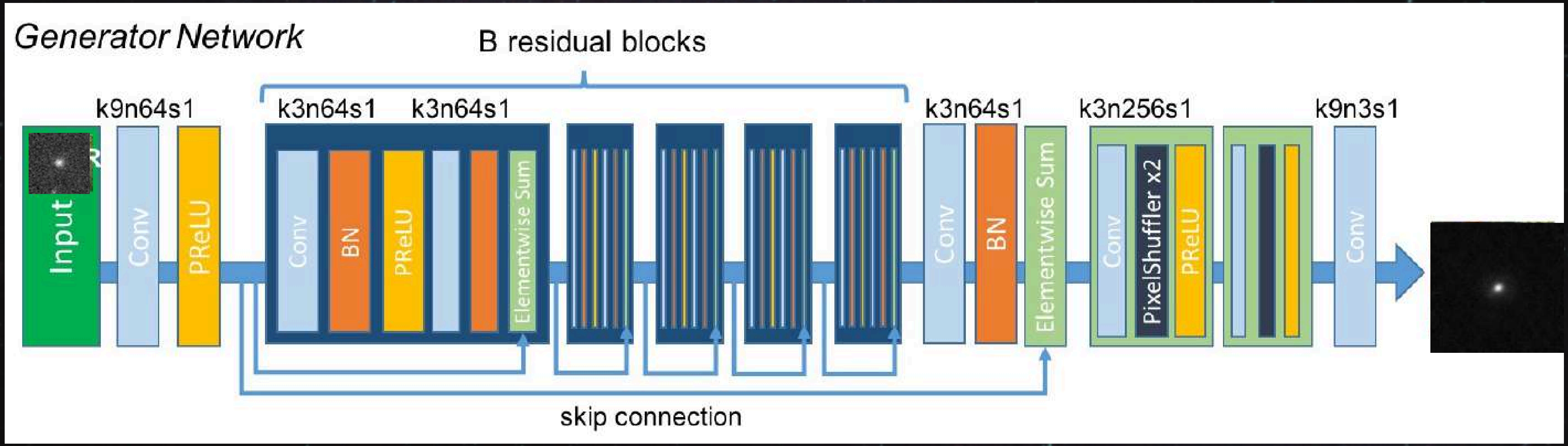
MODEL USED

1. RESIDUAL CHANNEL ATTENTION NETWORK(RCAN):



MODEL USED

2. SUPER-RESOLUTION RESIDUAL NETWORK(SRRESNET):



MODEL USED

2. SUPER-RESOLUTION RESIDUAL NETWORK(SRRESNET):

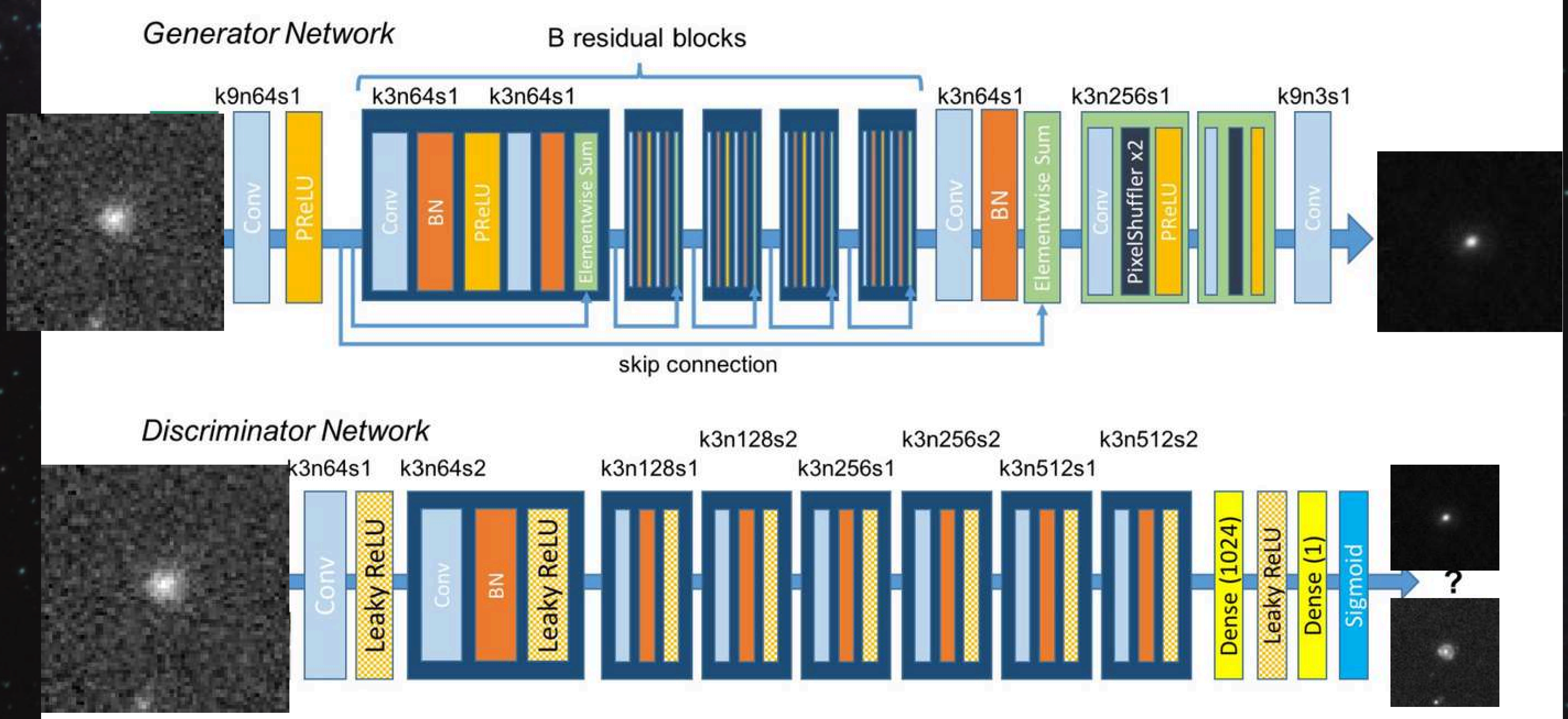
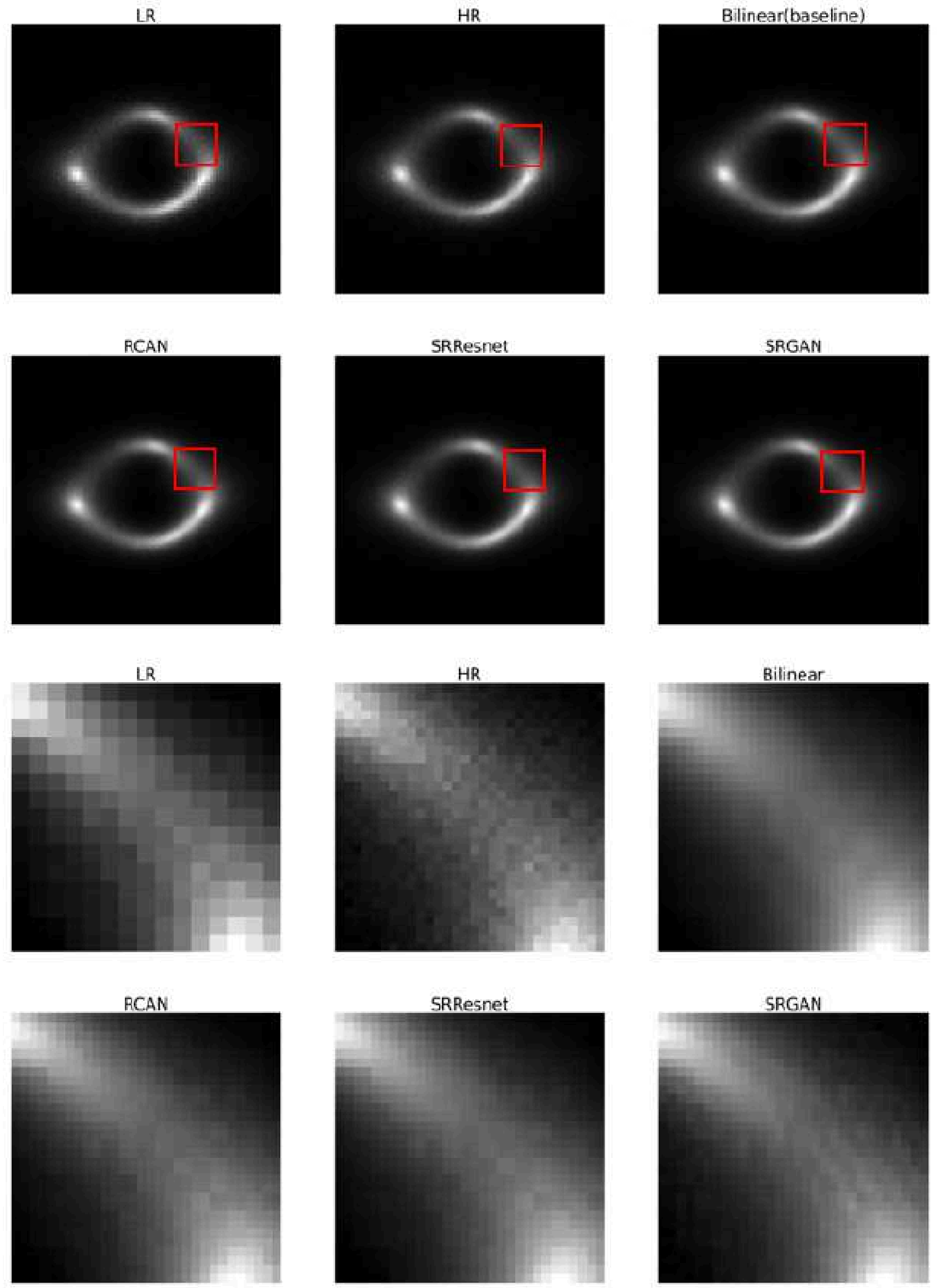


Figure 4: Architecture of Generator and Discriminator Network with corresponding kernel size (k), number of feature maps (n) and stride (s) indicated for each convolutional layer.

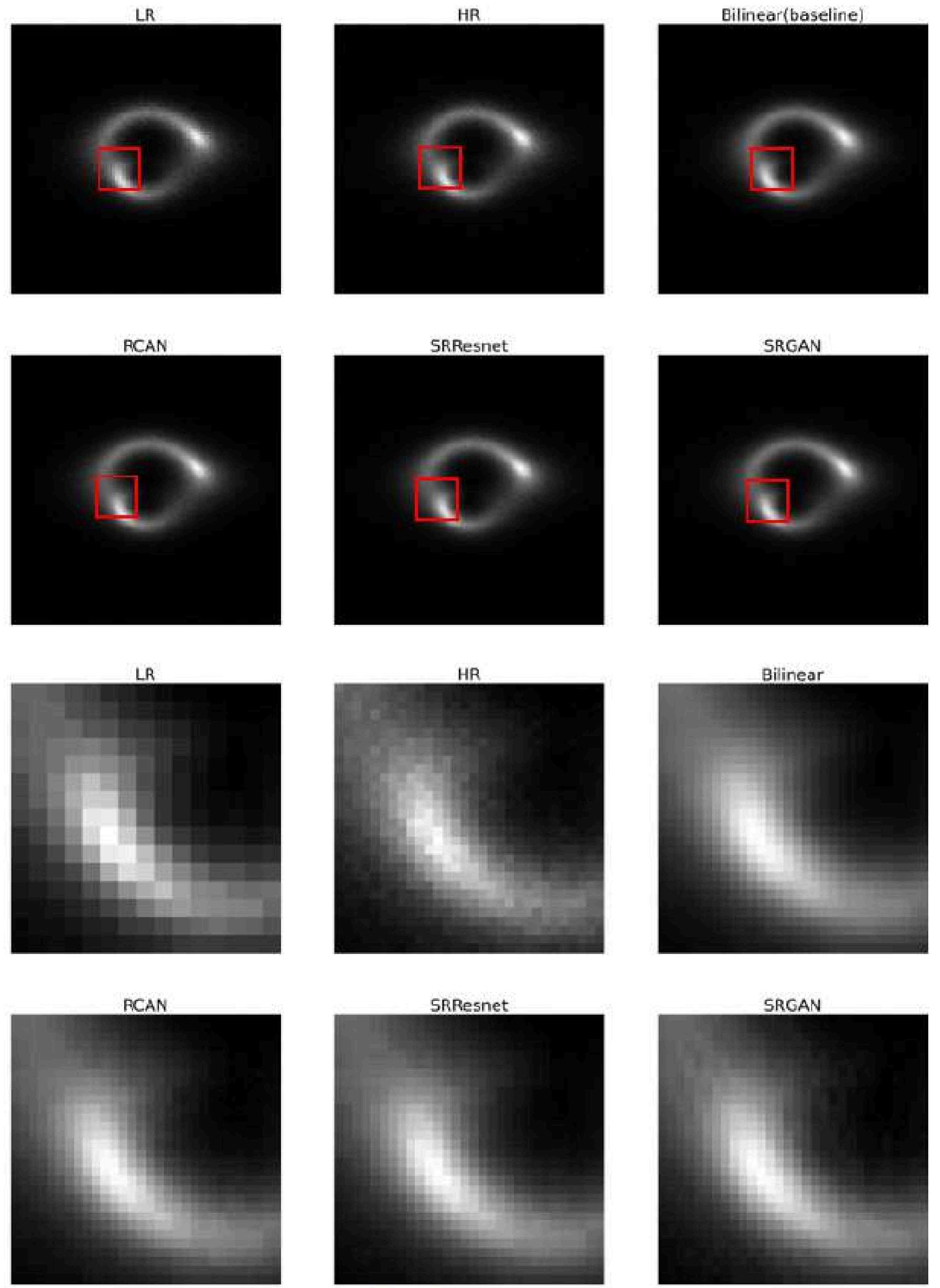
SIMULATED DATA RESULT

	Bilinear (baseline)	RCAN	SRResnet	SRGAN
MSE	0.00006921	0.00006035	0.00005981	0.002784
SSIM	0.9756	0.9772	0.9765	0.5664
PSNR	41.64	42.23	42.27	26.52

SIMULATED DATA RESULT



(a) Sample 1

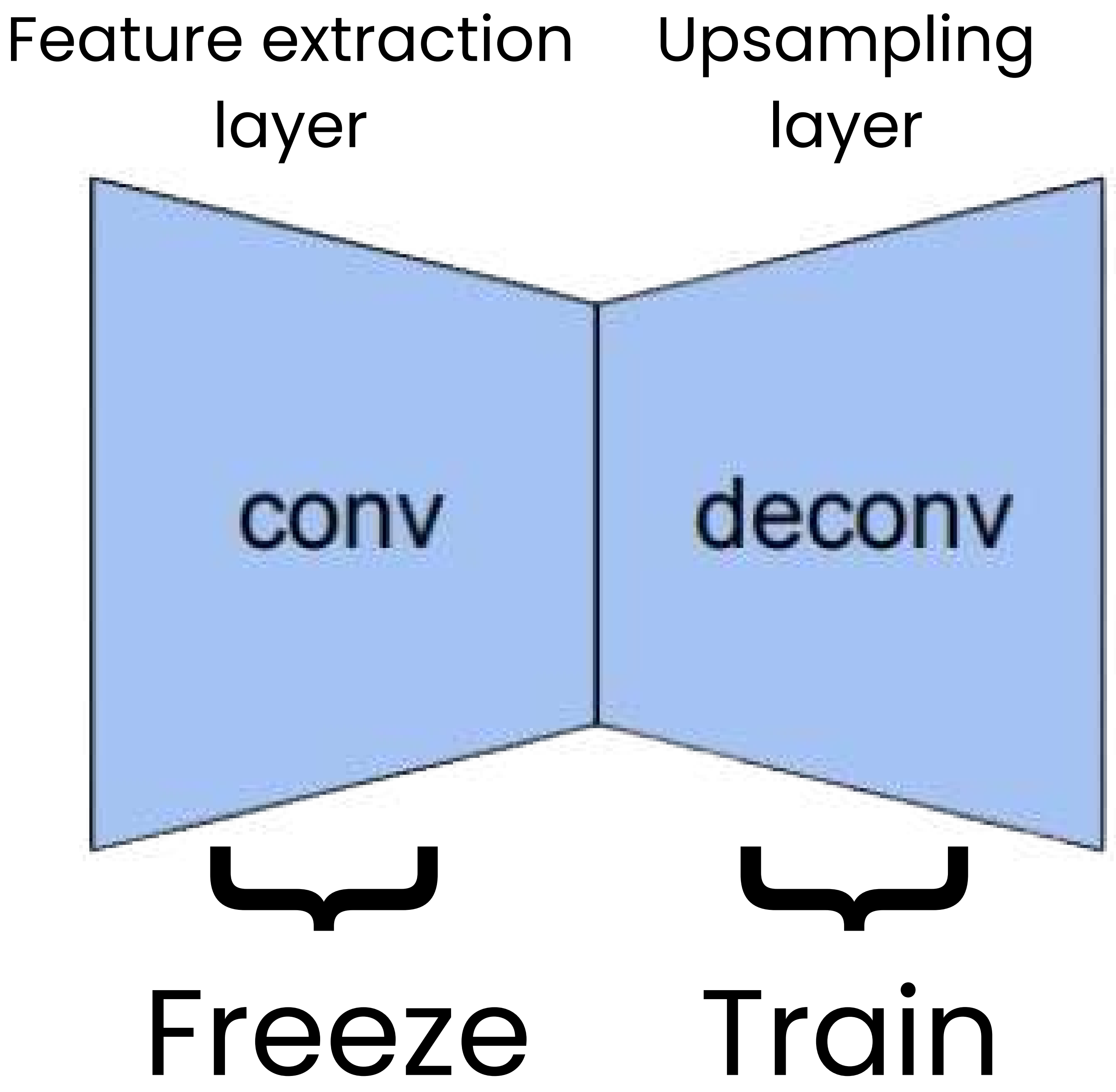


(b) Sample 2

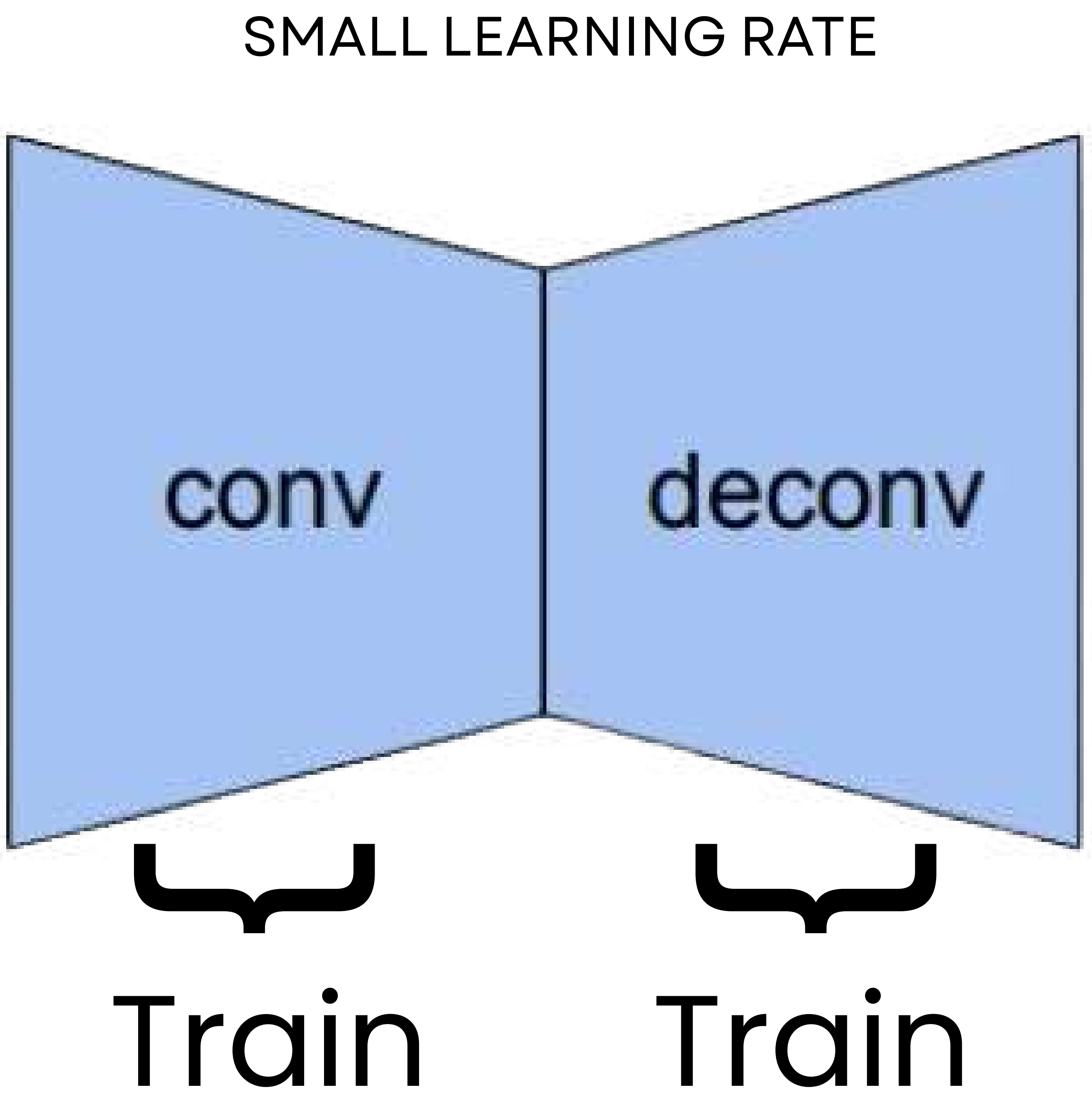
TRANSFER LEARNING

- After obtaing our base model, we can apply our model on real data

LAYER FREEZING

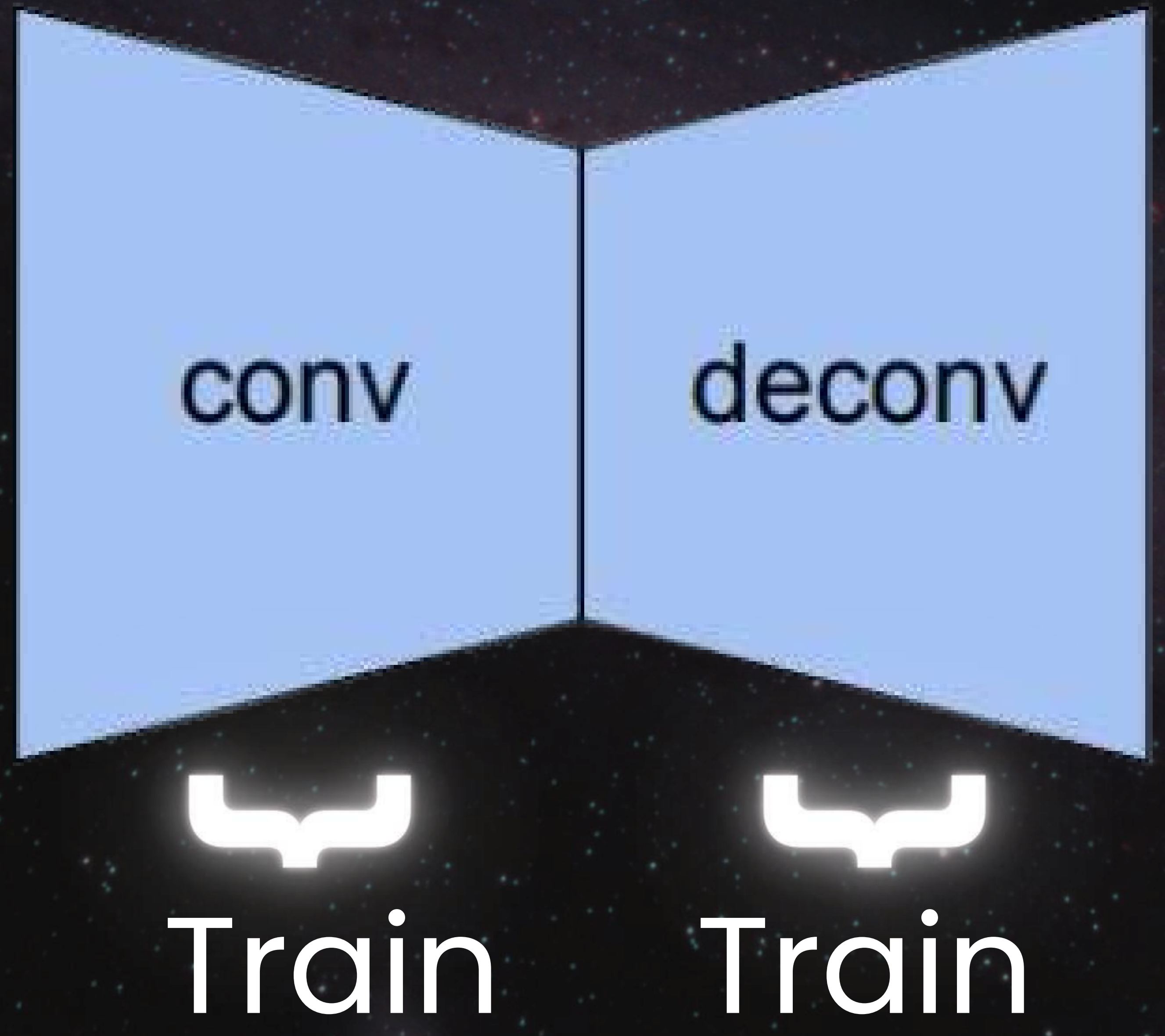


FINE-TUNING



FINE-TUNING

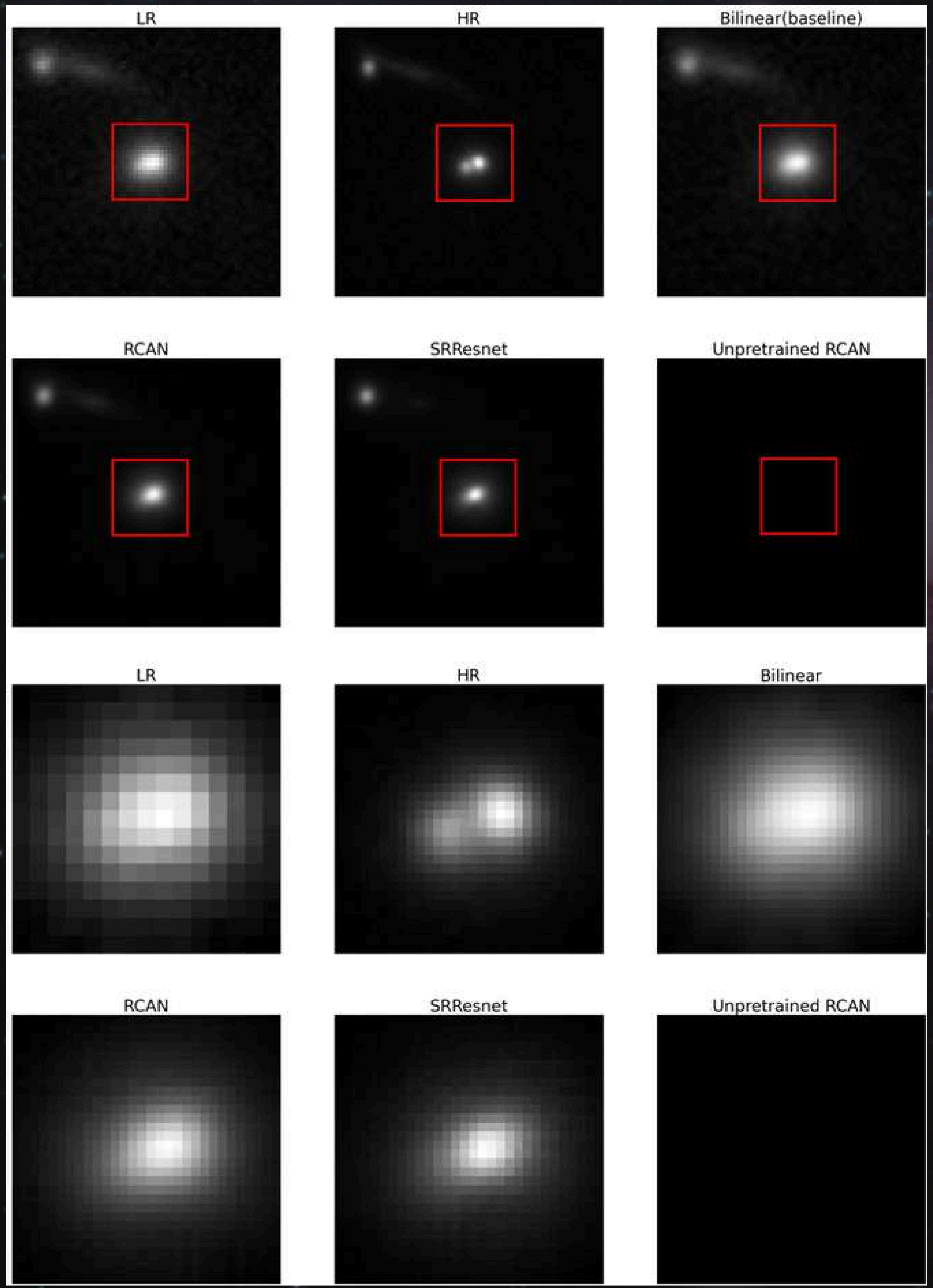
- Unfreeze all layers and use a smaller learning rate to train

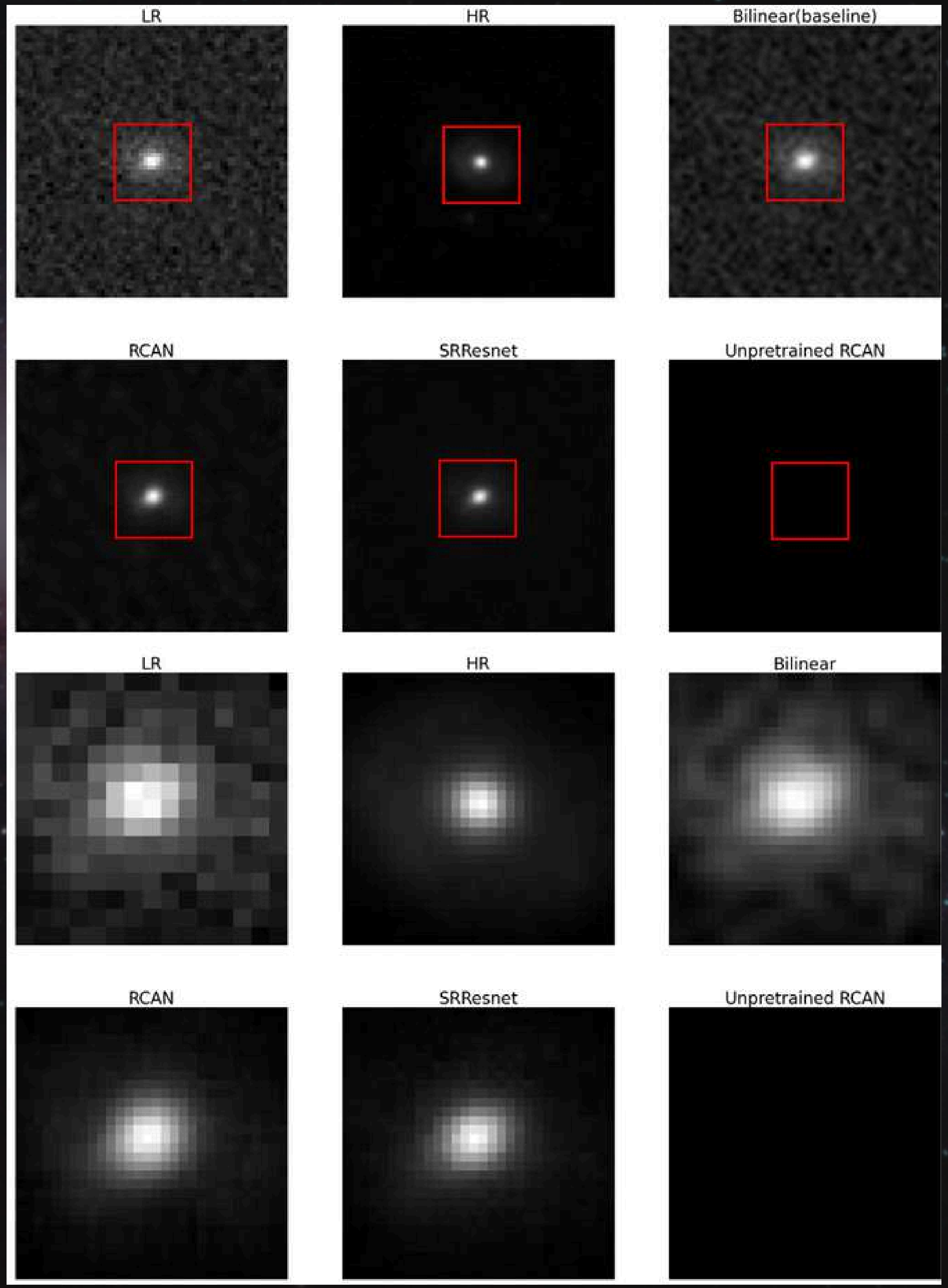


OBSERVED DATA RESULT

	Bilinear (baseline)	RCAN	SRResnet	Unpretrained RCAN
MSE	0.01010	0.004488	0.004609	0.008310
SSIM	0.4467	0.7756	0.7388	0.3280
PSNR	24.05	32.57	29.99	24.58

OBSERVED DATA RESULT





FUTURE WORK

- Simulate different types of gravitational lensing.
- Check if super-resolution images increase accuracy

REFERENCE

1. STEPHON ALEXANDER ET AL. DECODING DARK MATTER SUBSTRUCTURE WITHOUT SUPERVISION. ARXIV PREPRINT, ARXIV:2008.12731, 2020.
2. ATAL GUPTA. SINGLE IMAGE SUPER-RESOLUTION WITH DIFFUSION MODELS.
3. NASA. FOCUSING IN ON GRAVITATIONAL LENSES, 2023.
4. MICHELLE NTAMPAKA ET AL. DEEP LEARNING THE MORPHOLOGY OF DARK MATTER SUBSTRUCTURE. ARXIV PREPRINT, ARXIV:1909.07346, 2019.
5. J. PRESKILL, M. B. WISE, AND F. WILCZEK. COSMOLOGY OF THE INVISIBLE AXION. PHYSICS LETTERS B, 120(1-3):127–132, 1983.
6. PRANATH REDDY. SUPER-RESOLUTION FOR STRONG GRAVITATIONAL LENSNG.
7. ANIRUDH SHANKAR. PHYSICS-INFORMED UNSUPERVISED SUPER-RESOLUTION OF LENSING IMAGES: GSOC 2024 X ML4SCI. MEDIUM,2024.
8. G. STEIGMAN AND M. S. TURNER. COSMOLOGICAL CONSTRAINTS ON THE PROPERTIES OF WEAKLY INTERACTING MASSIVE PARTICLES. NUCLEAR PHYSICS B, 253:375–386, 1985.
9. YULUN ZHANG, KUNPENG LI, KAI LI, LICHEN WANG, BINENG ZHONG, AND YUN FU. IMAGE SUPER-RESOLUTION USING VERY DEEP RESIDUAL CHANNEL ATTENTION NETWORKS. ARXIV PREPRINT, ARXIV:1807.02758, 2018. PUBLISHED IN ECCV 2018.

THANK YOU