香港中文大學（深圳）
The Chinese University of Hong Kong, Shenzhen

ICCV 2019
Seoul, Korea

# Lightweight and Accurate Recursive Fractal Network for Image Super-Resolution

Juncheng Li, Yiting Yuan, Kangfu Mei, and Faming Fang*

*International Conference on Computer Vision, 2019*

*Learning for Computational Imaging (LCI) Workshop*

MIVRC: https://github.com/MIVRC SRRFN: https://github.com/MIVRC/SRRFN-PyTorch Homepage: https://junchenglee.com

# CONTENTS

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# 01 Introduction & Motivation

# Introduction & Motivation

## What is SISR ?

Single Image Super-Resolution (SISR) aims to reconstruct a super-resolution (SR) image from its degraded low-resolution (LR) one, which is receiving increasing attention in academia and industry.

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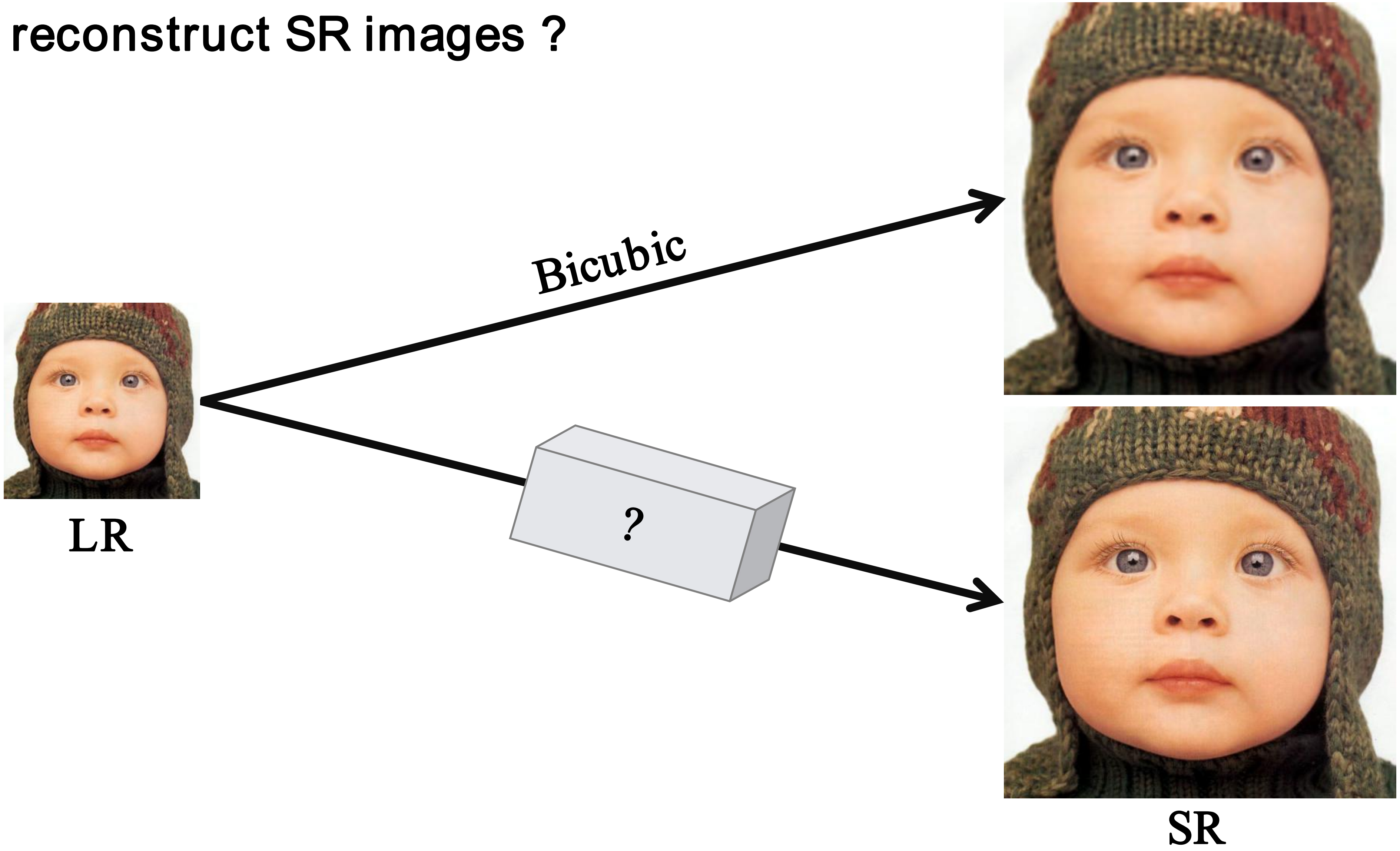
## What is the role of SISR ?

SISR has been widely used for computer vision tasks such as medical image enhancement, video superresolution, and facial illusion. The quality of SR images largely affects the accuracy of image recognition and segmentation tasks.

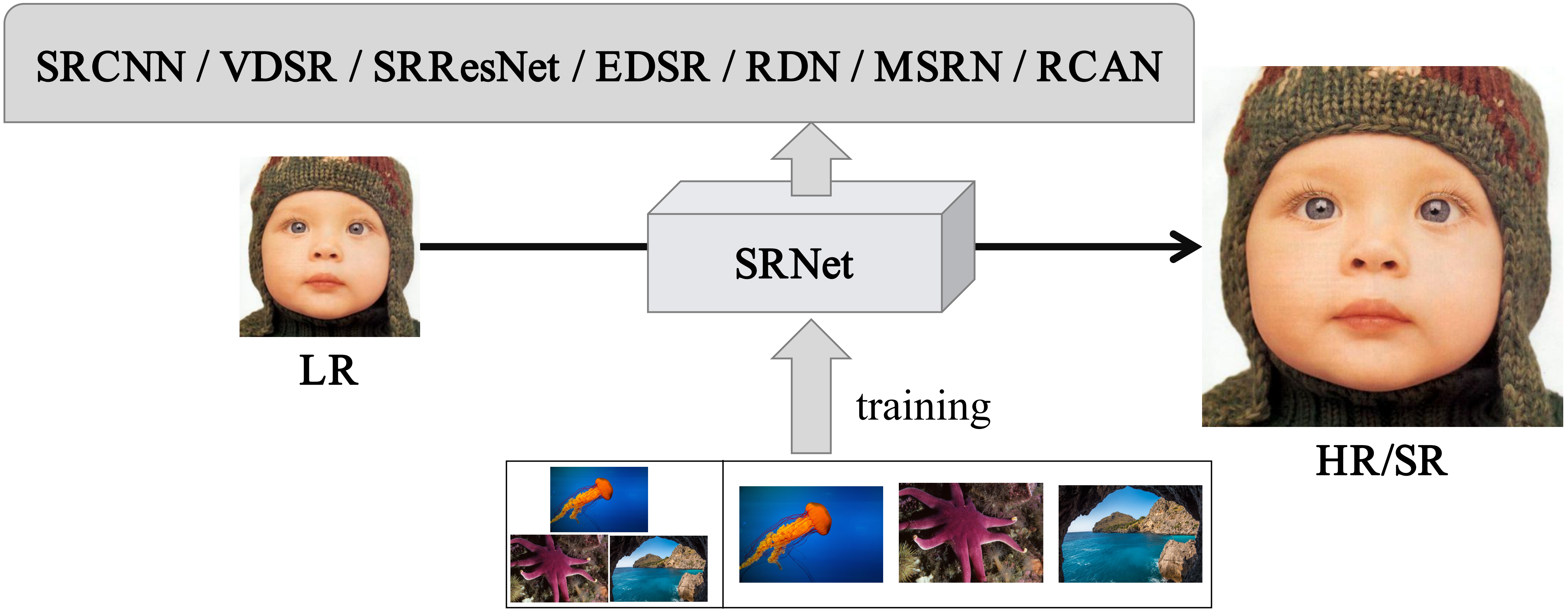
# Introduction & Motivation

How to reconstruct SR images ?

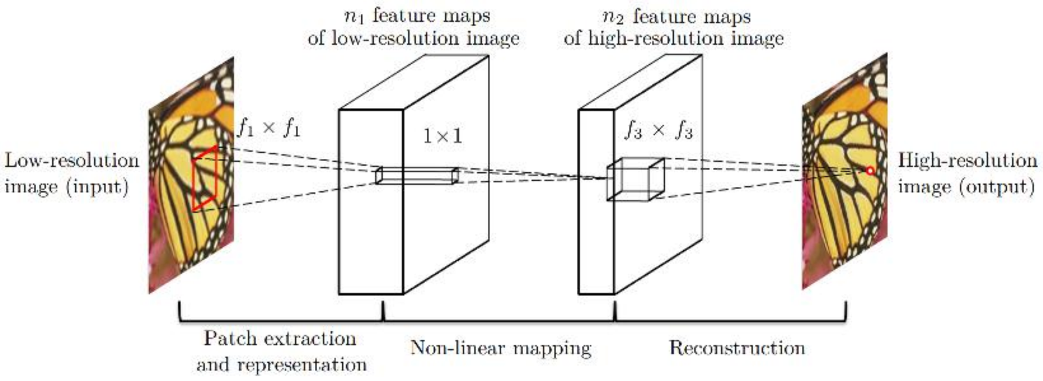


# Introduction & Motivation

How to reconstruct SR image ?

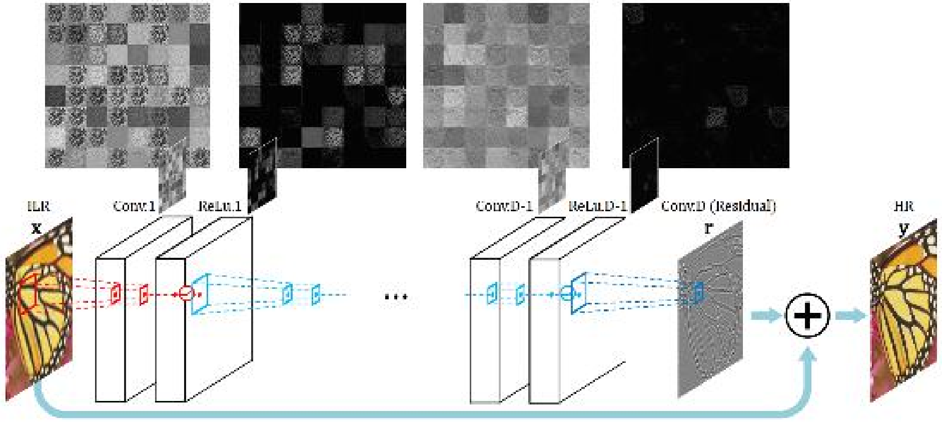


# Introduction & Motivation



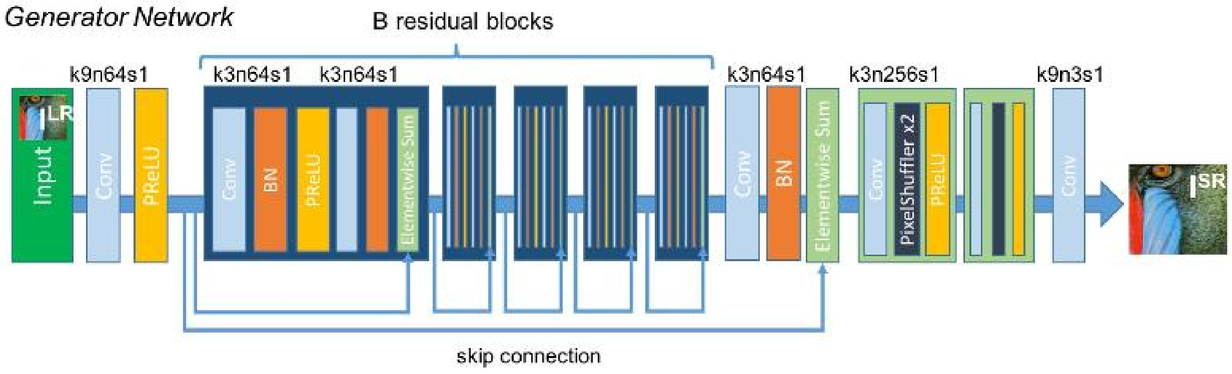

SRCNN

*Chao Dong, Chen Change Loy, Kaiming He, and Xiaoou Tang. Learning a deep convolutional network for image super resolution.*




VDSR

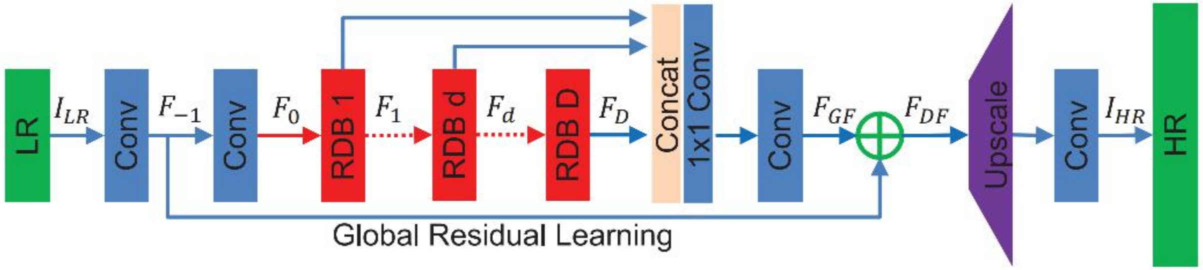
*Jiwon Kim, Jung Kwon Lee, and Kyoung Mu Lee. Accurate image super-resolution using very deep convolutional networks.*




SRResNet

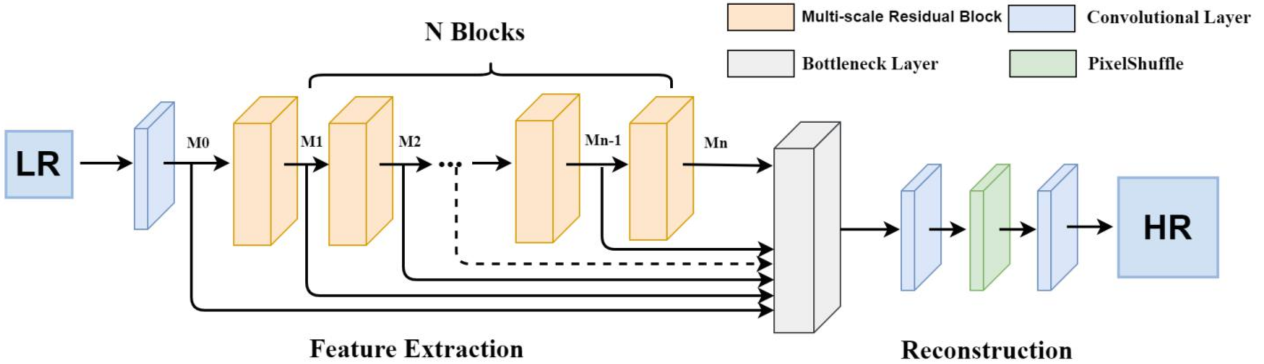
*Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham.Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network*

# Introduction & Motivation



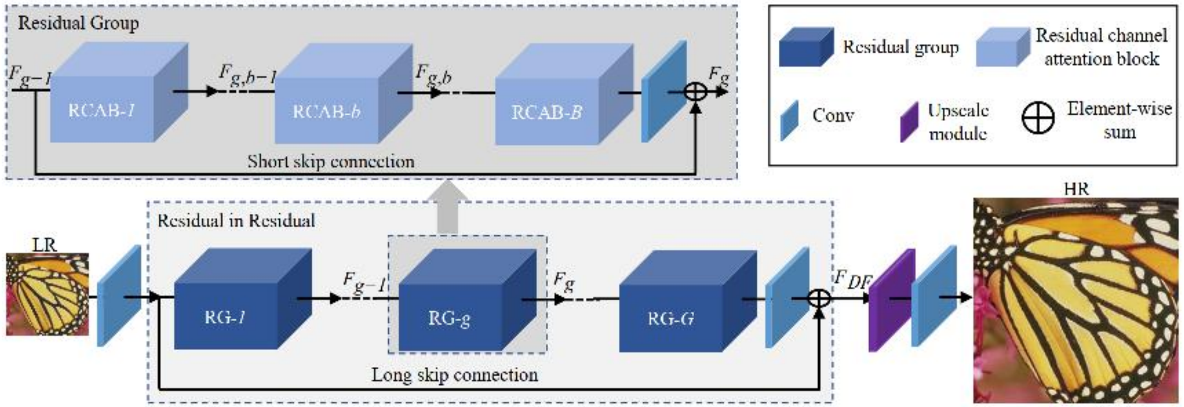

RDN

*Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, Yun Fu.*
*Residual Dense Network for Image Super-Resolution*




MSRN

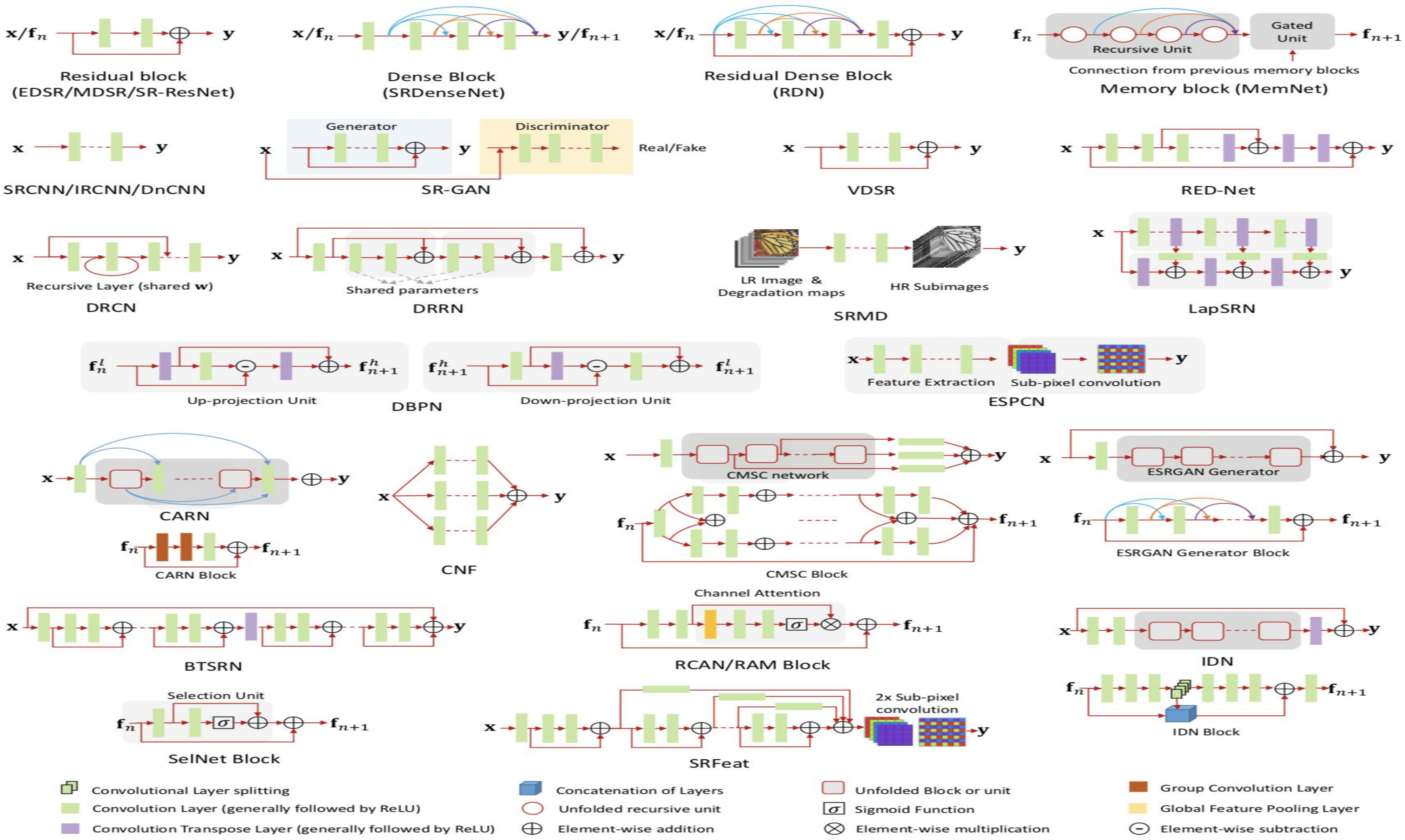
*Juncheng Li, Faming Fang, Kangfu Mei, Guixu Zhang.*
*Multi-scale Residual Network for Image Super-Resolution*




RCAN

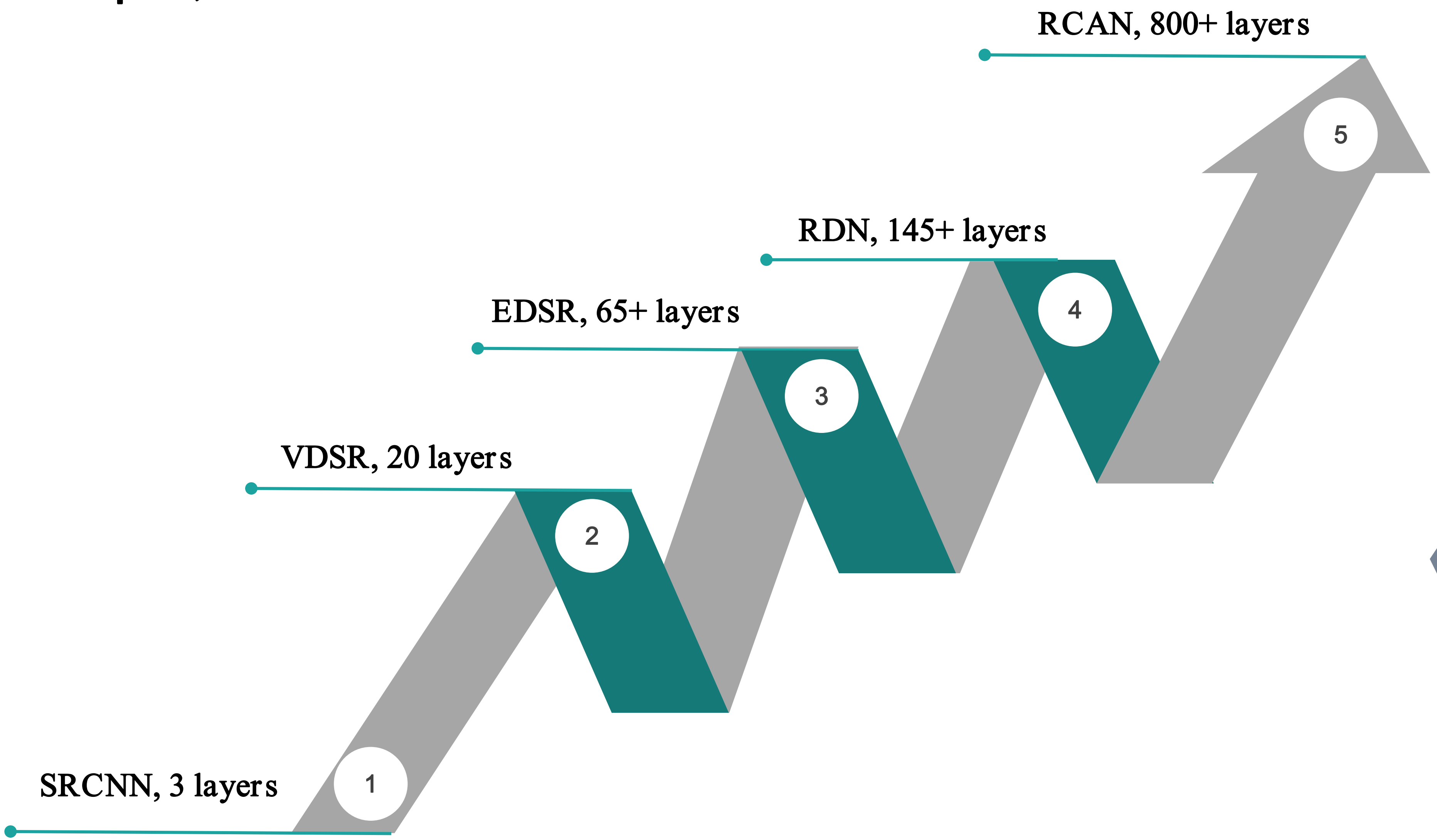
*Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu.*
*Image Super-Resolution Using Very Deep Residual Channel Attention Networks.*

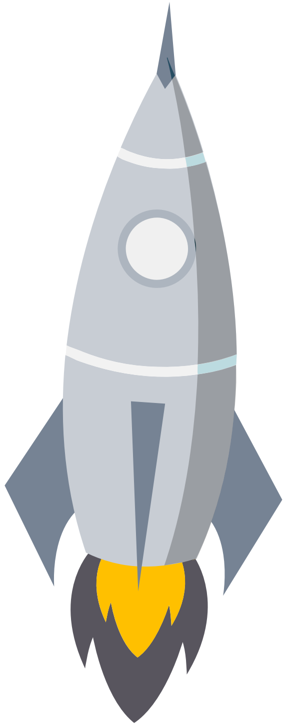
# Introduction & Motivation



# Introduction & Motivation

## The deeper, the better ?

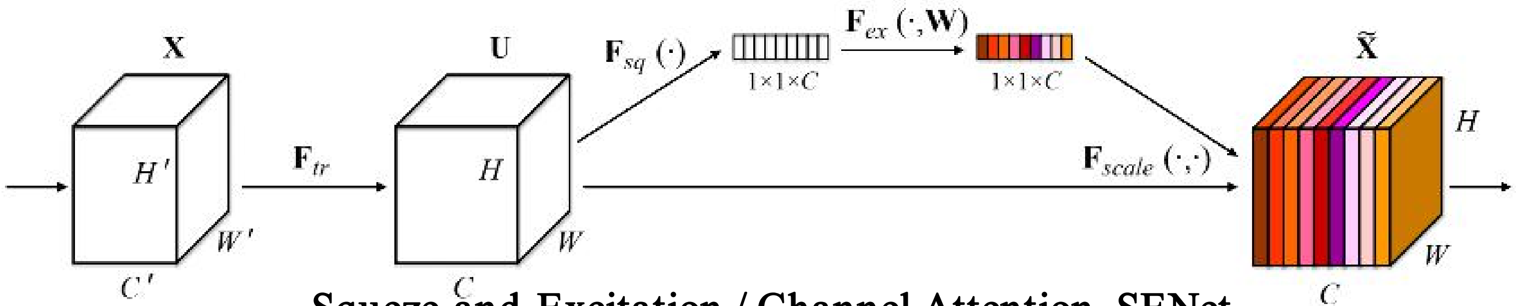


# Introduction & Motivation



## Channel attention mechanism necessary for SISR ?




Squeze-and-Excitation / Channel Attention, SENet

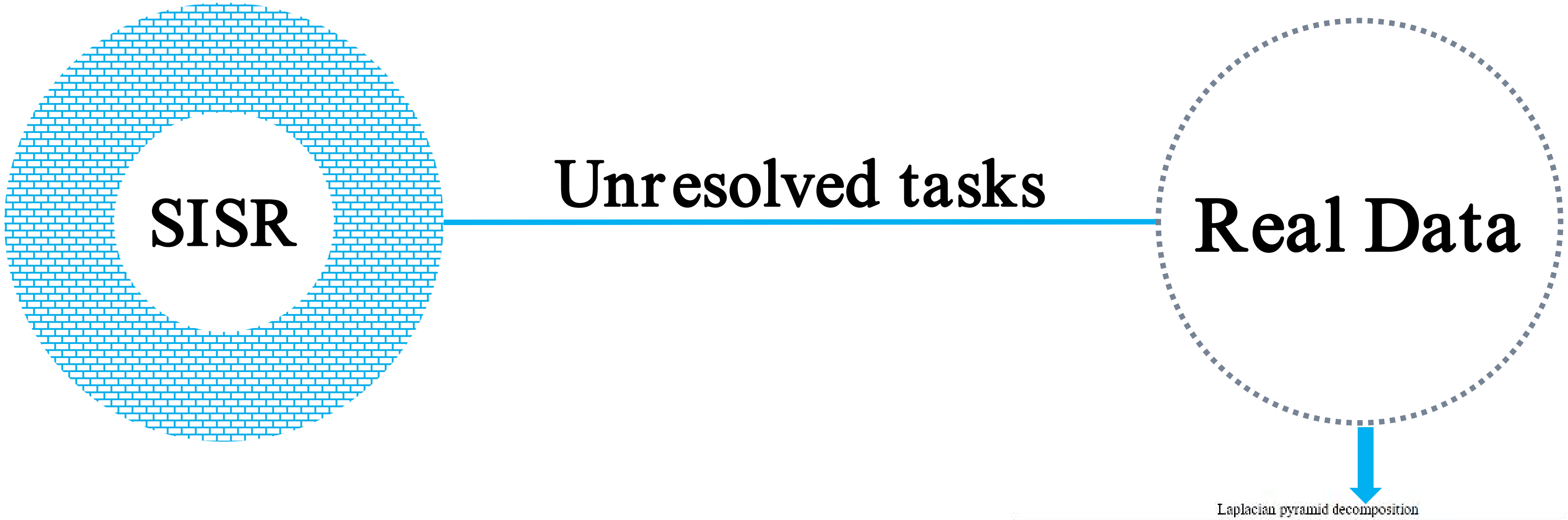
*Jie Hu, Li Shen, Gang Sun.Squeeze-and-Excitation Networks.*

| Method | RIRN(×2) | | RCAN(×2) [50] | |
|---|---|---|---|---|
| Scale | PSNR/SSIM | Time (s) | PSNR/SSIM | Time (s) |
| Set5 | 38.24/0.9613 | 0.21s | **38.26/0.9615** | 0.60s |
| Set14 | 33.91/0.9206 | 0.33s | **33.98/0.9210** | 1.11s |
| BSD100 | 32.37/0.9021 | 0.24s | **32.39/0.9024** | 0.75s |
| Urban100 | 33.10/0.9370 | 1.04s | **33.24/0.9377** | 3.78s |
| Manga109 | 39.31/0.9784 | 1.22s | **39.37/0.9785** | 4.55s |
| Average | 35.39/0.9399 | 0.61s | **35.45/0.9402** | 2.16s |

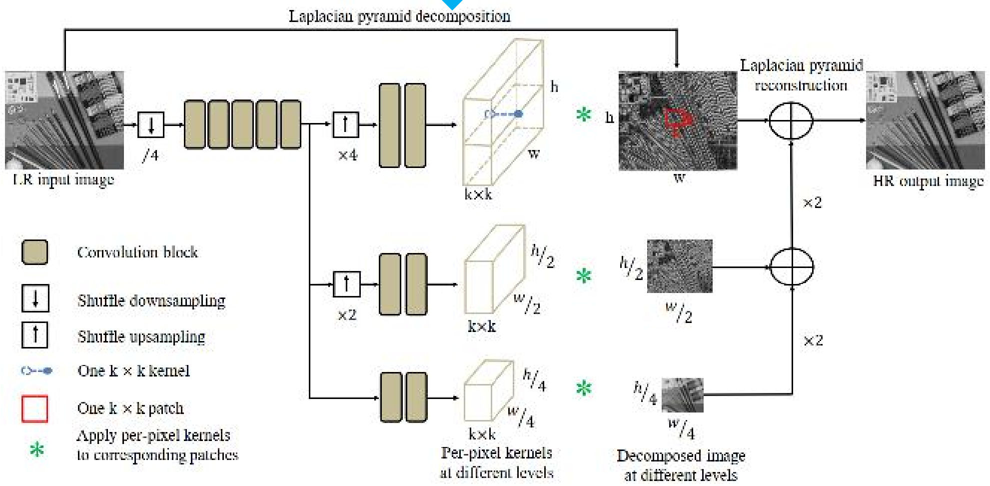
Table 1. The performance comparison with and without the CAM.

# Introduction & Motivation

Previous works on simulating degradation models still meaningful ?




RealSR:



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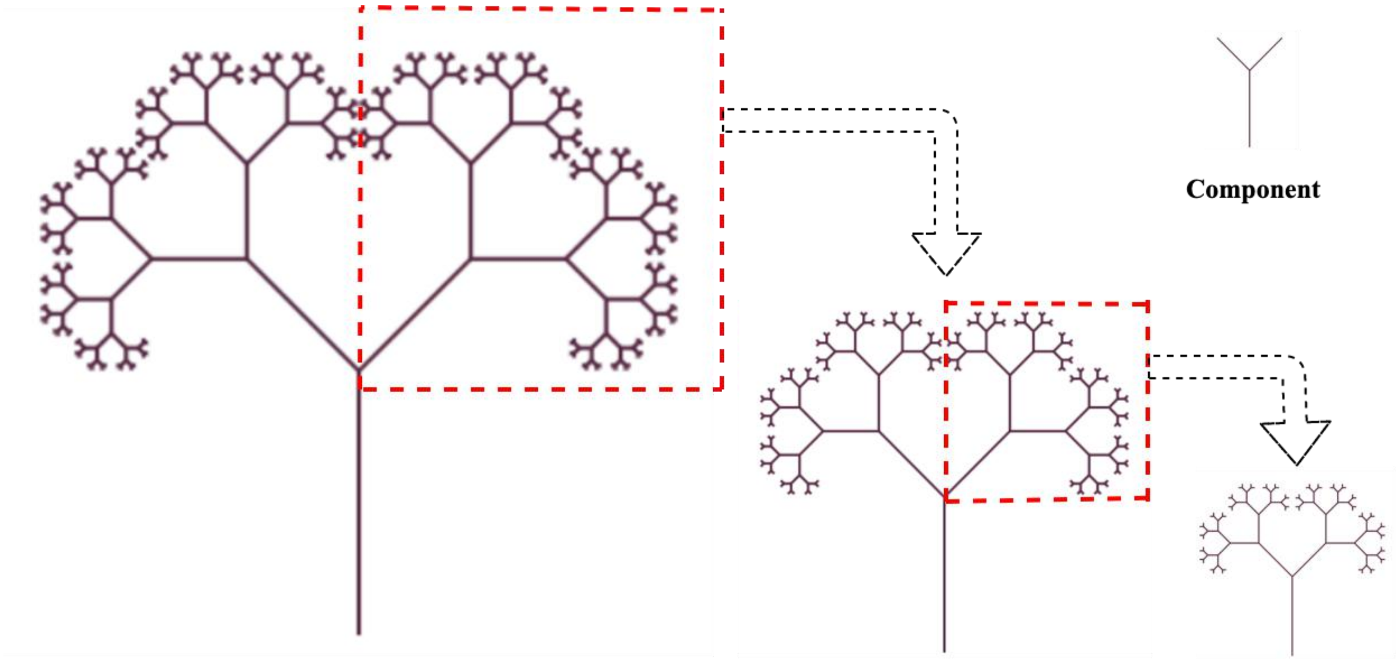
## How to design a network with infinite possibilities ?




Fractal Tree

The fractal structure was proposed by B.B.Mandelbrot in 1973, which is usually defined as "a rough or fragmentary geometry, it can be divided into several parts, and each part is (at least approximately) an overall reduced shape". It has the following characteristics:

(a). self similarity
(b). infinitely fine structure
(c). can be defined by a simple method and generated by recursion and iteration.

# Introduction & Motivation

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## Motivation:

1、We aim to explore a lightweight and accurate SISR framework.

2、We aim to simplify the design of network structure by introducing the fractal structure.

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## Contribution:

A. We propose a fractal module (FM) to simplify the model design, which can generate an infinite number of new structures via a simple component. Meanwhile, the fractal structure can be easily integrated with modern modules to create unlimited possibilities.

B. We develop a Super Resolution Recursive Fractal Network, which introduces the fractal module and recursive learning mechanism to maximize the model performance.

C. SRRFN achieves superior results with fewer parameters and faster execution time. Especially, it achieves state-of-the-art results in BD and DN degrade models.

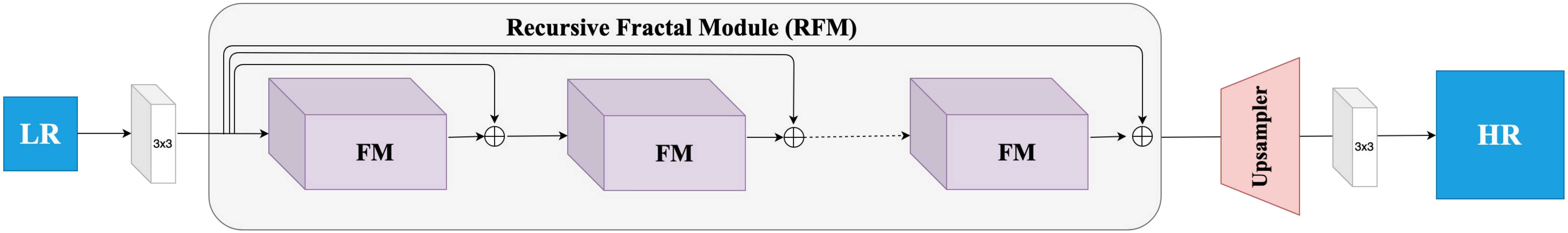
# 02

# Method : SRRFN

## Lightweight and Accurate Recursive Fractal Network for Image Super-Resolution

# Method： SRRFN






$$L'_{in} = F_{in}(I_{LR}),$$

$$L'_{out} = F_{RFM}(L'_{in}),$$

$$L_{sr} = F_{UP}(L'_{out}),$$

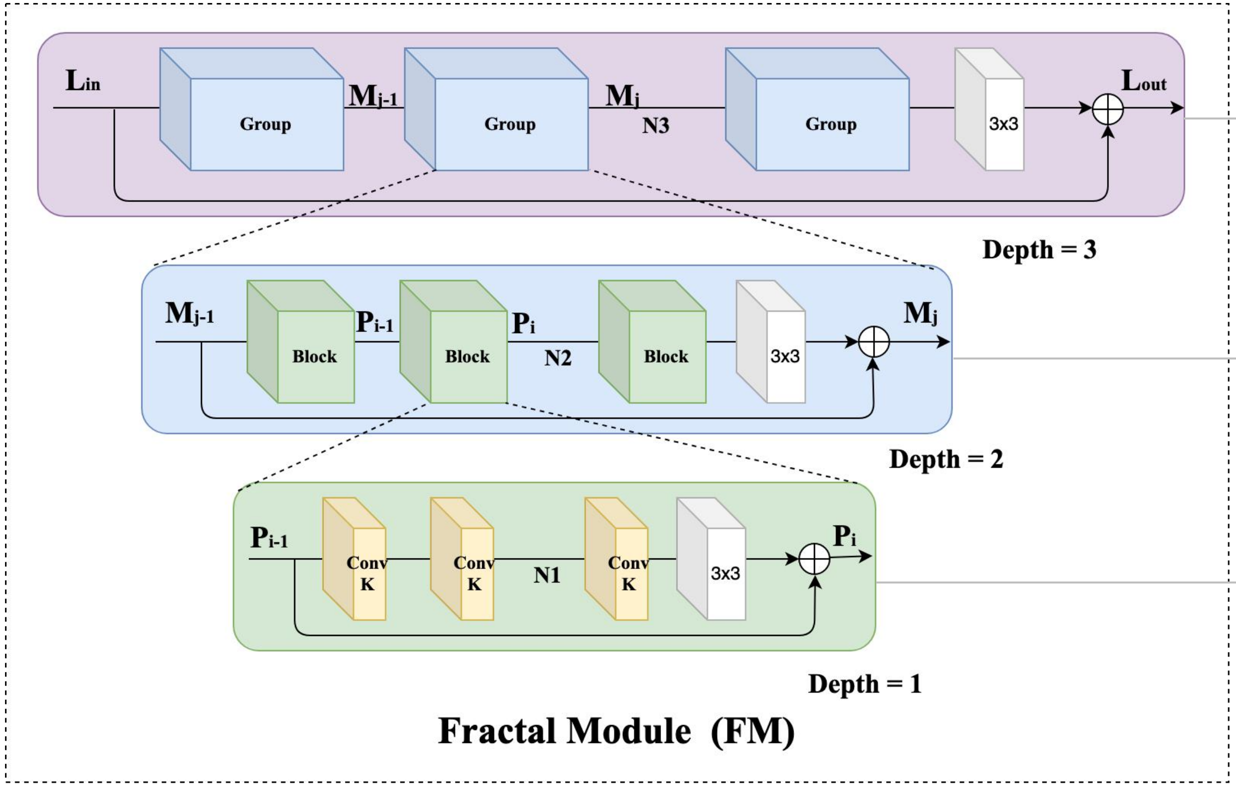
$$I_{SR} = F_{out}(L_{sr}).$$

**Loss function：**

$$\hat{\theta} = arg\ \min_{\theta} \frac{1}{N} \sum_{i=1}^{N} \left\| F_{\theta}(I_{LR}^{i}) - I_{HR}^{i} \right\|_1$$

# Method： SRRFN

## Fractal Module (FM):



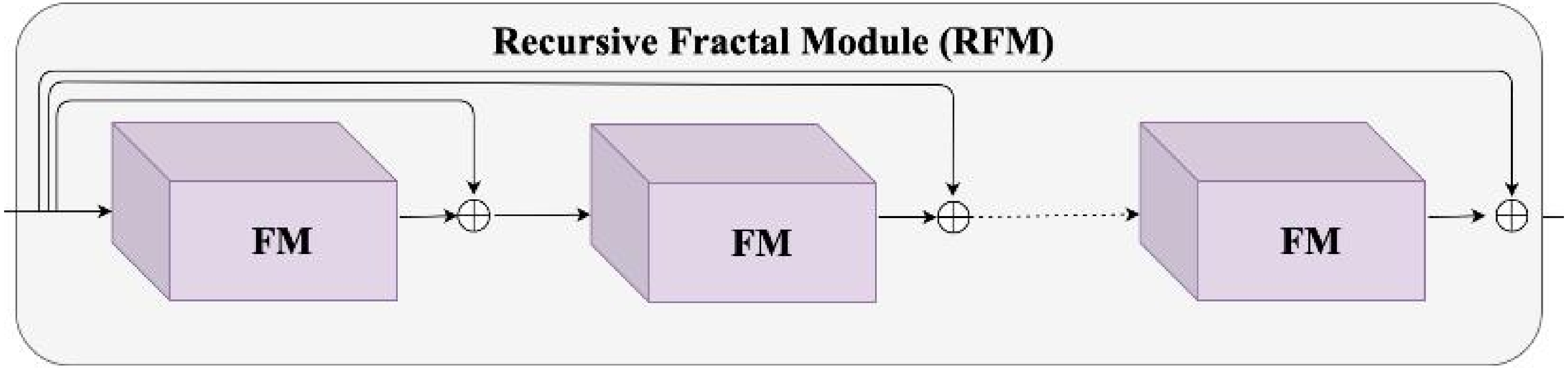

$$L_{out} = C^{d3}_{3\times3}(G_{N_3}(\ldots(G_1(L_{in}))\ldots)) + L_{in}$$

$$M_j = C^{d2}_{3\times3}(B_{N_2}(\ldots(B_1(M_{j-1}))\ldots)) + M_{j-1}$$

$$P_i = C^{d1}_{3\times3}(C_{N_1}(\ldots(C_1(P_{i-1}))\ldots)) + P_{i-1}$$

# Method： SRRFN

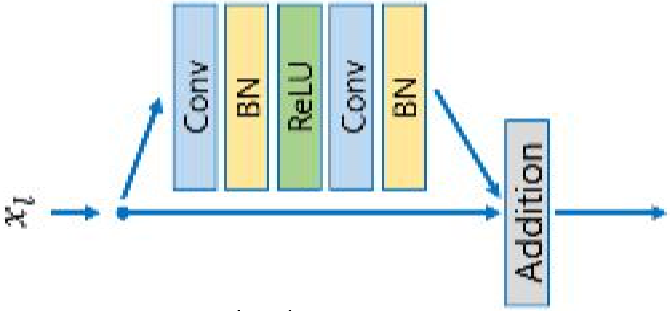
## Recursive Mechanism (RM):



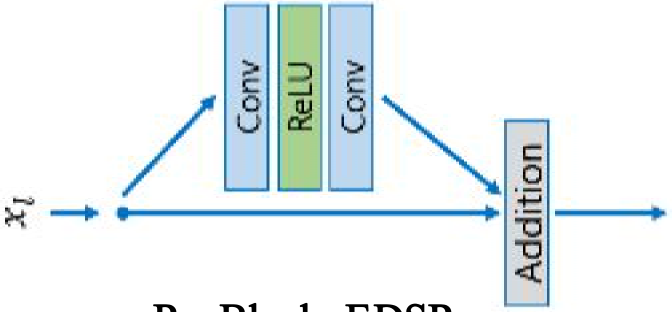

$$L^s = F_{FM}(L^{s-1}) + L^0$$

# Method：SRRFN

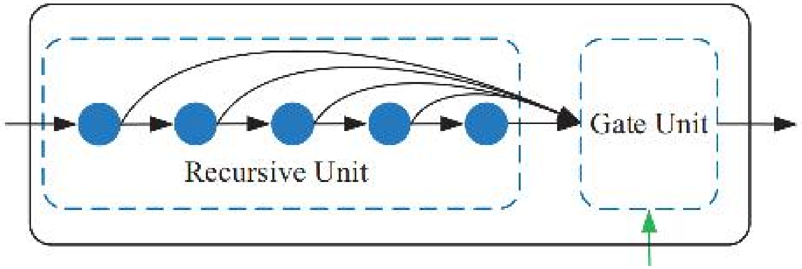
## Integration with Modern Modules：



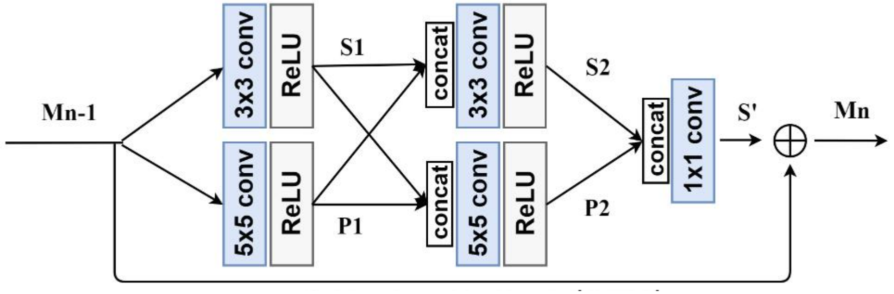

ResBlock, SRResNet



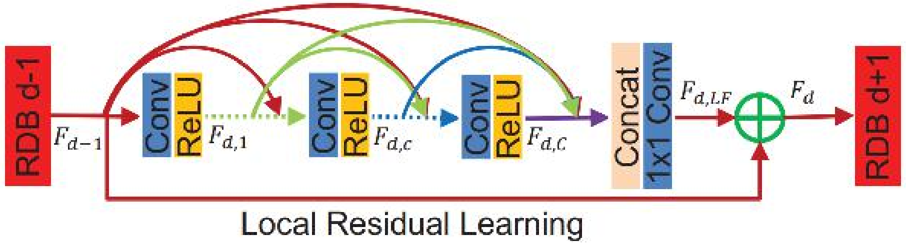

ResBlock, EDSR




MemoryBlock, MemoryNet




Multi-scale Block, MSRN




ResdualDenseBlock, RDN

# 03 Experiments

# Experiments

BI:

| Algorithm | Scale | Set5 [3] PSNR / SSIM | Set14 [45] PSNR / SSIM | BSDS100 [2] PSNR / SSIM | Urban100 [15] PSNR / SSIM | Manga109 [31] PSNR / SSIM | Average PSNR / SSIM |
|---|---|---|---|---|---|---|---|
| Bicubic | ×2 | 33.66 / 0.9299 | 30.24 / 0.8688 | 29.56 / 0.8431 | 26.88 / 0.8403 | 30.80 / 0.9339 | 30.23 / 0.8832 |
| SRCNN [6] | ×2 | 36.66 / 0.9542 | 32.45 / 0.9067 | 31.36 / 0.8879 | 29.50 / 0.8946 | 35.60 / 0.9663 | 33.11 / 0.9219 |
| LapSRN [21] | ×2 | 37.52 / 0.9591 | 33.08 / 0.9130 | 31.80 / 0.8950 | 30.41 / 0.9101 | 37.27 / 0.9740 | 34.02 / 0.9302 |
| VDSR [18] | ×2 | 37.53 / 0.9590 | 33.05 / 0.9130 | 31.90 / 0.8960 | 30.77 / 0.9140 | 37.22 / 0.9750 | 34.09 / 0.9314 |
| MemNet [35] | ×2 | 37.78 / 0.9597 | 33.28 / 0.9142 | 32.08 / 0.8978 | 31.31 / 0.9195 | 37.72 / 0.9740 | 34.43 / 0.9330 |
| SRMDNF [47] | ×2 | 37.79 / 0.9601 | 33.32 / 0.9159 | 32.05 / 0.8985 | 31.33 / 0.9204 | 38.07 / 0.9761 | 34.51 / 0.9342 |
| MSRN [24] | ×2 | 38.07 / 0.9608 | 33.68 / 0.9184 | 32.22 / 0.9002 | 32.32 / 0.9304 | 38.64 / 0.9771 | 34.99 / 0.9374 |
| D_DBPN [] | ×2 | 38.09 / 0.9600 | 33.85 / 0.9190 | 32.27 / 0.9000 | 32.55 / 0.9324 | 38.89 / 0.9775 | 35.13 / 0.9378 |
| MDSR [26] | ×2 | 38.11 / 0.9602 | 33.85 / 0.9198 | 32.29 / 0.9007 | 32.84 / 0.9347 | 38.96 / 0.9776 | 35.21 / 0.9386 |
| EDSR [26] | ×2 | 38.11 / 0.9602 | 33.92 / 0.9195 | 32.32 / 0.9013 | 32.93 / 0.9351 | 39.10 / 0.9773 | 35.27 / 0.9387 |
| RDN [51] | ×2 | **38.24 / 0.9614** | 34.01 / 0.9212 | 32.34 / 0.9017 | 32.89 / 0.9353 | 39.18 / 0.9780 | 35.33 / 0.9395 |
| SRRFN (Ours) | ×2 | 38.18 / 0.9612 | 33.97 / 0.9210 | 32.35 / 0.9018 | 33.04 / 0.9361 | 39.23 / 0.9781 | 35.35 / 0.9396 |
| SRRFN+ (Ours) | ×2 | **38.24 / 0.9614** | **34.13 / 0.9224** | **32.39 / 0.9023** | **33.24 / 0.9378** | **39.43 / 0.9786** | **33.49 / 0.9405** |
| Bicubic | ×3 | 30.39 / 0.8682 | 27.55 / 0.7742 | 27.21 / 0.7385 | 24.46 / 0.7349 | 26.95 / 0.8556 | 27.31 / 0.7943 |
| SRCNN [6] | ×3 | 32.75 / 0.9090 | 29.30 / 0.8215 | 28.41 / 0.7863 | 26.24 / 0.7989 | 30.48 / 0.9117 | 29.44 / 0.8455 |
| VDSR [18] | ×3 | 33.67 / 0.9210 | 29.78 / 0.8320 | 28.83 / 0.7990 | 27.14 / 0.8290 | 32.01 / 0.9340 | 30.29 / 0.8630 |
| LapSRN [21] | ×3 | 33.82 / 0.9227 | 29.87 / 0.8320 | 28.82 / 0.7980 | 27.07 / 0.8280 | 32.21 / 0.9350 | 30.36 / 0.8631 |
| MemNet [37] | ×3 | 34.09 / 0.9248 | 30.00 / 0.8350 | 28.96 / 0.8001 | 27.56 / 0.8376 | 32.51 / 0.9369 | 30.62 / 0.8669 |
| SRMDNF [47] | ×3 | 34.12 / 0.9254 | 30.04 / 0.8382 | 28.97 / 0.8025 | 27.57 / 0.8398 | 33.00 / 0.9403 | 30.74 / 0.8692 |
| MSRN [24] | ×3 | 34.48 / 0.9276 | 30.40 / 0.8436 | 29.13 / 0.8061 | 28.31 / 0.8560 | 33.56 / 0.9451 | 31.18 / 0.8757 |
| MDSR [26] | ×3 | 34.66 / 0.9280 | 30.44 / 0.8452 | 29.25 / 0.8091 | 28.79 / 0.8655 | 34.17 / 0.9472 | 31.46 / 0.8790 |
| EDSR [26] | ×3 | 34.65 / 0.9280 | 30.52 / 0.8462 | 29.25 / 0.8093 | 28.80 / 0.8653 | 34.17 / 0.9476 | 31.48 / 0.8793 |
| RDN [51] | ×3 | 34.71 / 0.9296 | 30.57 / 0.8468 | 29.26 / 0.8093 | 28.80 / 0.8653 | 34.13 / 0.9484 | 31.49 / 0.8799 |
| SRRFN (Ours) | ×3 | 34.74 / 0.9296 | 30.62 / 0.8478 | 29.29 / 0.8100 | 28.98 / 0.8689 | 34.36 / 0.9491 | 31.60 / 0.8811 |
| SRRFN+ (Ours) | ×3 | **34.84 / 0.9303** | **30.70 / 0.8490** | **29.35 / 0.8110** | **29.21 / 0.8721** | **34.66 / 0.9505** | **31.75 / 0.8826** |
| Bicubic | ×4 | 28.42 / 0.8104 | 26.00 / 0.7027 | 25.96 / 0.6675 | 23.14 / 0.6577 | 24.89 / 0.7866 | 25.62 / 0.7250 |
| SRCNN [6] | ×4 | 30.48 / 0.8628 | 27.50 / 0.7513 | 26.90 / 0.7101 | 24.52 / 0.7221 | 27.58 / 0.8555 | 27.40 / 0.7804 |
| VDSR [18] | ×4 | 31.35 / 0.8830 | 28.02 / 0.7680 | 27.29 / 0.7267 | 25.18 / 0.7540 | 28.83 / 0.8870 | 28.13 / 0.8037 |
| LapSRN [21] | ×4 | 31.54 / 0.8850 | 28.19 / 0.7720 | 27.32 / 0.7270 | 25.21 / 0.7560 | 29.09 / 0.8900 | 28.27 / 0.8060 |
| MemNet [37] | ×4 | 31.74 / 0.8893 | 28.26 / 0.7723 | 27.40 / 0.7281 | 25.50 / 0.7630 | 29.42 / 0.8942 | 28.46 / 0.8094 |
| SRMDNF [47] | ×4 | 31.96 / 0.8925 | 28.35 / 0.7787 | 27.49 / 0.7337 | 25.68 / 0.7731 | 30.09 / 0.9024 | 28.71 / 0.8161 |
| MSRN [24] | ×4 | 32.25 / 0.8958 | 28.63 / 0.7833 | 27.61 / 0.7377 | 26.20 / 0.7905 | 30.57 / 0.9103 | 29.05 / 0.8235 |
| D_DBPN [10] | ×4 | 32.47 / 0.8980 | 28.82 / 0.7860 | 27.72 / 0.7400 | 26.38 / 0.7946 | 30.91 / 0.9137 | 29.26 / 0.8265 |
| RDN [51] | ×4 | 32.47 / 0.8990 | 28.81 / 0.7871 | 27.72 / 0.7419 | 26.61 / 0.8028 | 31.00 / 0.9151 | 29.32 / 0.8292 |
| EDSR [26] | ×4 | 32.46 / 0.8968 | 28.80 / 0.7876 | 27.71 / 0.7420 | 26.64 / 0.8033 | 31.02 / 0.9148 | 29.33 / 0.8289 |
| MDSR [26] | ×4 | 32.50 / 0.8973 | 28.72 / 0.7857 | 27.72 / 0.7418 | 26.67 / 0.8041 | 31.11 / 0.9146 | 29.34 / 0.8287 |
| SRRFN (Ours) | ×4 | 32.56 / 0.8993 | 28.86 / 0.7882 | 27.75 / 0.7424 | 26.78 / 0.8071 | 31.22 / 0.9159 | 29.43 / 0.8306 |
| SRRFN+ (Ours) | ×4 | **32.66 / 0.9006** | **28.95 / 0.7900** | **27.81 / 0.7437** | **26.98 / 0.8113** | **31.56 / 0.9190** | **29.59 / 0.8329** |

# Experiments

**BI:**

| Algorithm | Scale | Set5 [3] PSNR / SSIM | Set14 [45] PSNR / SSIM | BSDS100 [2] PSNR / SSIM | Urban100 [15] PSNR / SSIM | Manga109 [31] PSNR / SSIM | Average PSNR / SSIM |
|---|---|---|---|---|---|---|---|
| DRCN [19] | ×2 | 37.63 / 0.9584 | 33.06 / 0.9108 | 31.85 / 0.8947 | 30.76 / 0.9147 | 37.63 / 0.9723 | 34.19 / 0.9302 |
| MS-LapSRN [22] | ×2 | 37.78 / 0.9600 | 33.28 / 0.9150 | 32.05 / 0.8980 | 31.15 / 0.9190 | 37.78 / 0.9760 | 34.41 / 0.9336 |
| DRRN [35] | ×2 | 37.74 / 0.9590 | 33.23 / 0.9140 | 32.05 / 0.8970 | 31.23 / 0.9190 | 37.92 / 0.9760 | 34.43 / 0.9330 |
| SRFBN [25] | ×2 | 38.11 / 0.9609 | 33.82 / 0.9196 | 32.29 / 0.9010 | 32.62 / 0.9328 | 39.08 / 0.9779 | 35.18 / 0.9384 |
| SRRFN (Ours) | ×2 | **38.18 / 0.9612** | **33.97 / 0.9210** | **32.35 / 0.9018** | **33.04 / 0.9361** | **39.23 / 0.9781** | **35.35 / 0.9396** |
| DRCN [19] | ×3 | 33.85 / 0.9215 | 29.89 / 0.8317 | 28.81 / 0.7954 | 27.16 / 0.8311 | 32.31 / 0.9328 | 30.40 / 0.8625 |
| MS-LapSRN [22] | ×3 | 34.06 / 0.9240 | 29.97 / 0.8360 | 28.93 / 0.8020 | 27.47 / 0.8370 | 32.68 / 0.9390 | 30.62 / 0.8676 |
| DRRN [35] | ×3 | 34.03 / 0.9240 | 29.96 / 0.8350 | 28.95 / 0.8000 | 27.53 / 0.7640 | 32.74 / 0.9390 | 30.64 / 0.8524 |
| SRFBN [25] | ×3 | 34.70 / 0.9292 | 30.51 / 0.8461 | 29.24 / 0.8084 | 28.73 / 0.8641 | 34.18 / 0.9481 | 31.47 / 0.8792 |
| SRRFN (Ours) | ×3 | **34.74 / 0.9296** | **30.62 / 0.8478** | **29.29 / 0.8100** | **28.98 / 0.8689** | **34.36 / 0.9491** | **31.60 / 0.8811** |
| DRCN [19] | ×4 | 31.56 / 0.8810 | 28.15 / 0.7627 | 27.24 / 0.7150 | 25.15 / 0.7530 | 28.98 / 0.8816 | 28.22 / 0.7987 |
| DRRN [35] | ×4 | 31.68 / 0.8888 | 28.21 / 0.7722 | 27.38 / 0.7240 | 25.44 / 0.7640 | 29.46 / 0.8960 | 28.43 / 0.8090 |
| MS-LapSRN [22] | ×4 | 31.74 / 0.8890 | 28.26 / 0.7740 | 27.43 / 0.7310 | 25.51 / 0.7680 | 29.54 / 0.8970 | 28.50 / 0.8118 |
| SRFBN [25] | ×4 | 32.47 / 0.8983 | 28.81 / 0.7868 | 27.72 / 0.7409 | 26.60 / 0.8015 | 31.15 / 0.9160 | 29.35 / 0.8287 |
| SRRFN (Ours) | ×4 | **32.56 / 0.8993** | **28.86 / 0.7882** | **27.75 / 0.7424** | **26.78 / 0.8071** | **31.22 / 0.9159** | **29.43 / 0.8318** |

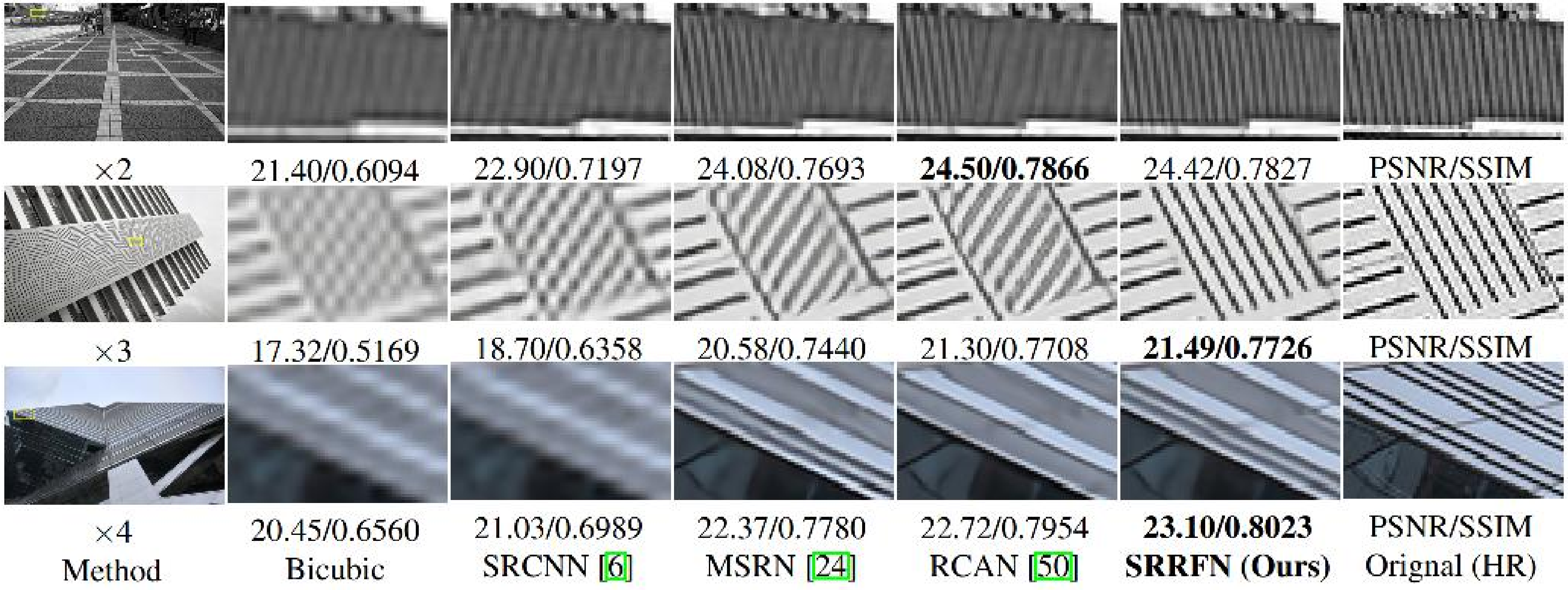
**BD:**

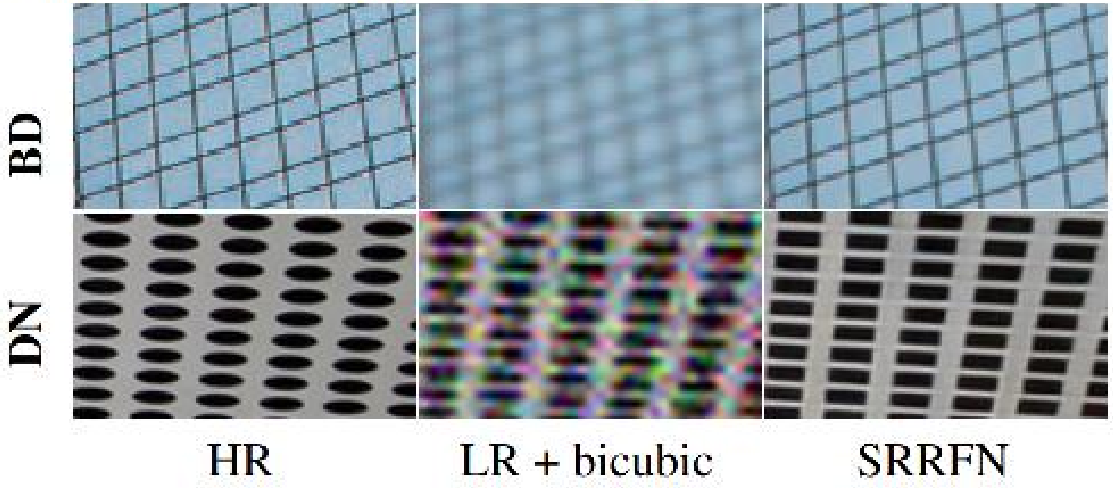
**DN:**

| Model | Methods | Set5 PSNR / SSIM | Set14 PSNR / SSIM | BSDS100 PSNR / SSIM | Urban100 PSNR / SSIM | Manga109 PSNR / SSIM | Average PSNR / SSIM |
|---|---|---|---|---|---|---|---|
| **BD** | Bicubic | 28.34 / 0.8161 | 26.12 / 0.7106 | 26.02 / 0.6733 | 23.20 / 0.6601 | 25.03 / 0.7987 | 25.74 / 0.7318 |
| | SRCNN [6] | 31.63 / 0.8888 | 28.52 / 0.7924 | 27.76 / 0.7526 | 25.31 / 0.7612 | 28.79 / 0.8851 | 28.40 / 0.8159 |
| | VDSR [18] | 33.30 / 0.9159 | 29.67 / 0.8269 | 28.63 / 0.7903 | 26.75 / 0.8145 | 31.66 / 0.9260 | 30.00 / 0.8547 |
| | SRMD(NF) [47] | 34.09 / 0.9242 | 30.11 / 0.8364 | 28.98 / 0.8009 | 27.50 / 0.8370 | 32.97 / 0.9391 | 30.73 / 0.8675 |
| | RDN [51] | 34.57 / 0.9280 | 30.53 / 0.8447 | 29.23 / 0.8079 | 28.46 / 0.8581 | 33.97 / 0.9465 | 31.35 / 0.8770 |
| | SRFBN [25] | 34.66 / 0.9283 | 30.48 / 0.8439 | 29.21 / 0.8069 | 28.48 / 0.8581 | 34.07 / 0.9466 | 31.38 / 0.8768 |
| | RCAN [50] | 34.70 / 0.9288 | 30.63 / 0.8462 | 29.32 / 0.8093 | 28.81 / 0.8647 | 34.38 / 0.9483 | 31.57 / 0.8795 |
| | SRRFN (Ours) | 34.77 / 0.9293 | 30.67 / 0.8469 | 29.31 / 0.8096 | 28.85 / 0.8653 | 34.51 / 0.9489 | 31.62 / 0.8800 |
| | SRRFN+ (Ours) | **34.86 / 0.9299** | **30.76 / 0.8479** | **29.36 / 0.8105** | **29.06 / 0.8682** | **34.80 / 0.9502** | **31.77 / 0.8813** |
| **DN** | Bicubic | 24.14 / 0.5445 | 23.14 / 0.4828 | 22.94 / 0.4461 | 21.63 / 0.4701 | 23.08 / 0.5448 | 22.99 / 0.4977 |
| | SRCNN [6] | 27.16 / 0.7672 | 25.49 / 0.6580 | 25.11 / 0.6151 | 23.32 / 0.6500 | 25.78 / 0.7889 | 25.37 / 0.6958 |
| | VDSR [18] | 27.72 / 0.7872 | 25.92 / 0.6786 | 25.52 / 0.6345 | 23.83 / 0.6797 | 26.41 / 0.8130 | 25.88 / 0.7186 |
| | SRMD(NF) [47] | 27.74 / 0.8026 | 26.13 / 0.6974 | 25.64 / 0.6495 | 24.28 / 0.7092 | 26.72 / 0.8424 | 26.10 / 0.7402 |
| | RDN [51] | 28.46 / 0.8151 | 26.60 / 0.7101 | 25.93 / 0.6573 | 24.92 / 0.7362 | 28.00 / 0.8590 | 26.78 / 0.7555 |
| | SRFBN [25] | 28.53 / 0.8182 | 26.60 / 0.7144 | 25.95 / 0.6625 | 24.99 / 0.7424 | 28.02 / 0.8618 | 26.82 / 0.7599 |
| | SRRFN (Ours) | 28.57 / 0.8194 | 26.69 / 0.7155 | 25.98 / 0.6630 | 25.21 / 0.7506 | 28.21 / 0.8646 | 26.93 / 0.7626 |
| | SRRFN+ (Ours) | **28.66 / 0.8211** | **26.75 / 0.7169** | **26.02 / 0.6639** | **25.34 / 0.7538** | **28.37 / 0.8672** | **27.03 / 0.7646** |

# Experiments

BI:



# 04 | Investigation & Discussion

# Investigation & Discussion

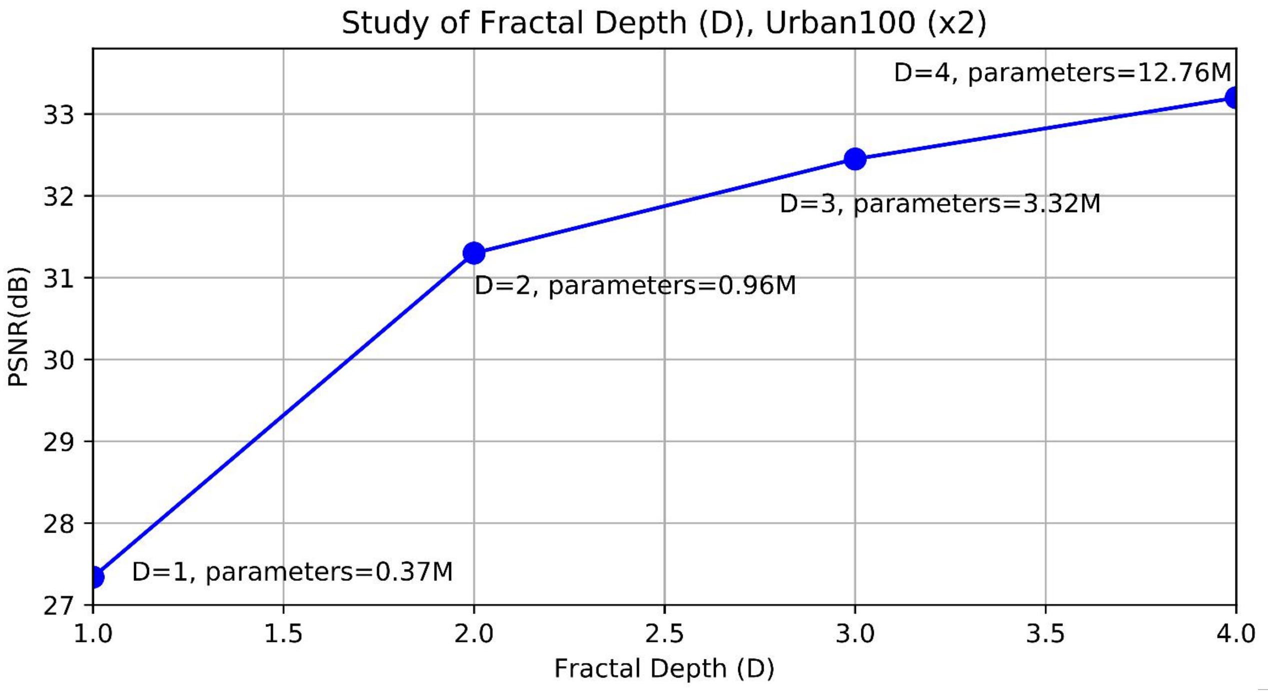
## RCAN & SRRFN:

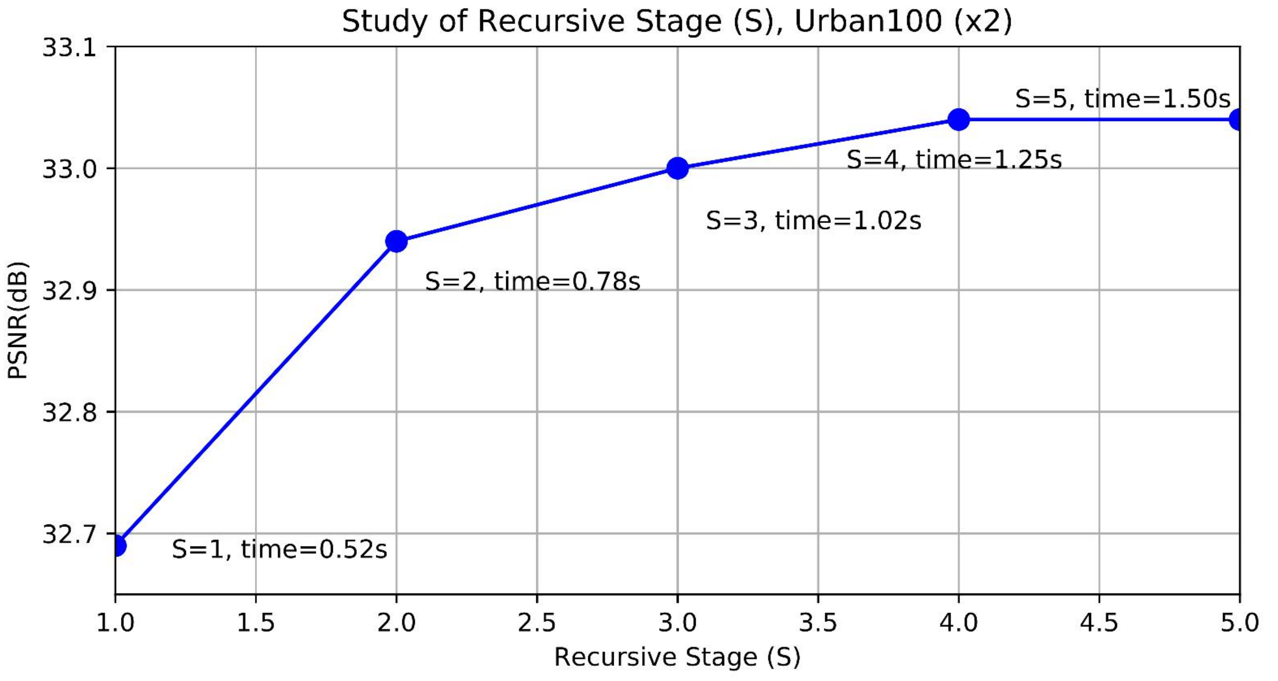
| Algorithm | Scale | Parameters | Set5 [3] PSNR / SSIM / Time | Set14 [45] PSNR / SSIM / Time | BSDS100 [2] PSNR / SSIM / Time | Urban100 [15] PSNR / SSIM / Time | Manga109 [31] PSNR / SSIM / Time | Average PSNR / SSIM / Time |
|---|---|---|---|---|---|---|---|---|
| RCAN [50] | ×2 | 15.44M | **38.27 / 0.9614** / 0.60s | **34.12 / 0.9216** / 1.11s | **32.41 / 0.9027** / 0.75s | **33.34 / 0.9384** / 3.78s | **39.44 / 0.9786** / 4.55s | **35.52 / 0.9405** / 2.16s |
| SRRFN (Ours) | ×2 | 4.06M | 38.18 / 0.9612 / 0.21s | 33.97 / 0.9210 / 0.35s | 32.35 / 0.9018 / 0.24s | 33.04 / 0.9361 / 1.07s | 39.23 / 0.9781 / 1.25s | 35.35 / 0.9396 / 0.61s |
| RCAN [50] | ×3 | 15.63M | **34.74 / 0.9299** / 0.34s | **30.65 / 0.8482** / 0.55s | **29.32 / 0.8111** / 0.41s | **29.09 / 0.8702** / 1.89s | **34.44 / 0.9499** / 2.33s | **31.65 / 0.8818** / 1.10s |
| SRRFN (Ours) | ×3 | 4.24M | **34.74** / 0.9296 / 0.17s | 30.62 / 0.8478 / 0.23s | 29.29 / 0.8100 / 0.16s | 28.98 / 0.8689 / 0.62s | 34.36 / 0.9491 / 0.79s | 31.60 / 0.8811 / 0.39s |
| RCAN [50] | ×4 | 15.59M | **32.63 / 0.9002** / 0.30s | **28.87 / 0.7889** / 0.40s | **27.77 / 0.7436** / 0.30s | **26.82 / 0.8087** / 1.21s | **31.22 / 0.9173** / 1.50s | **29.46** / **0.8317** / 0.74s |
| SRRFN (Ours) | ×4 | 4.21M | 32.56 / 0.8993 / 0.16s | 28.86 / 0.7882 / 0.19s | 27.75 / 0.7424 / 0.16s | 26.78 / 0.8071 / 0.47s | **31.22** / 0.9159 / 0.58s | 29.43 / 0.8318 / 0.31s |

Quantitative comparisons (PSNR/SSIM, Parameters, and Execution time) with RCAN

# Investigation & Discussion

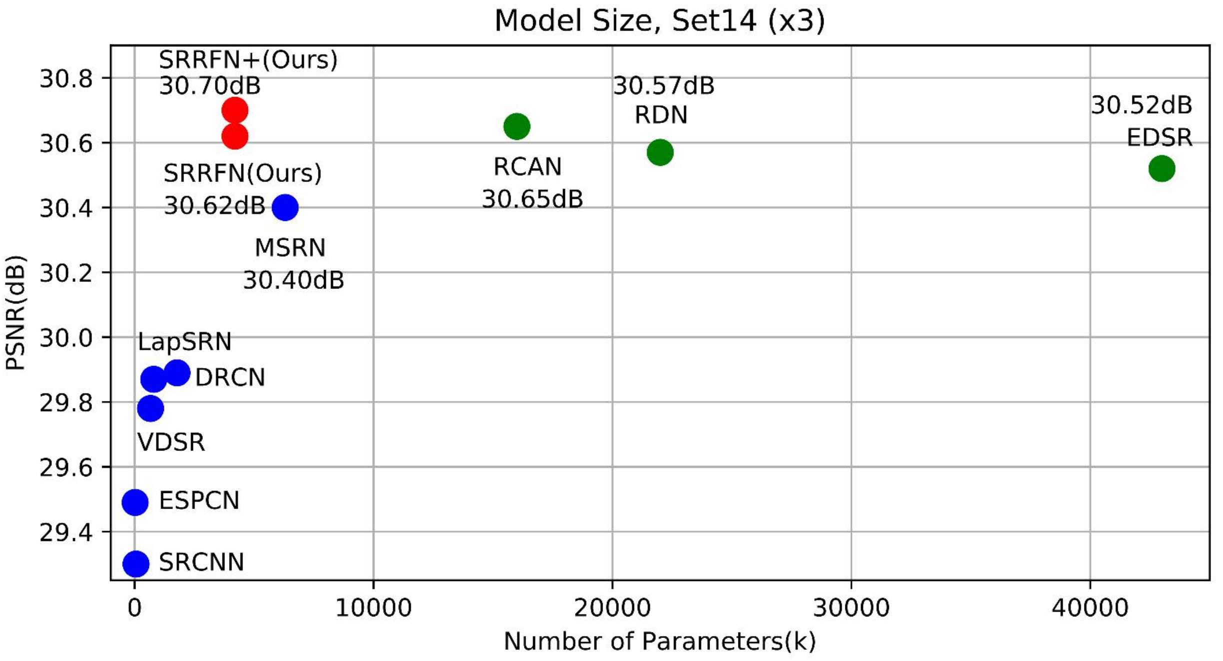
## Study of Fractal Depth (*D*) & Recursive Stage (*S*):

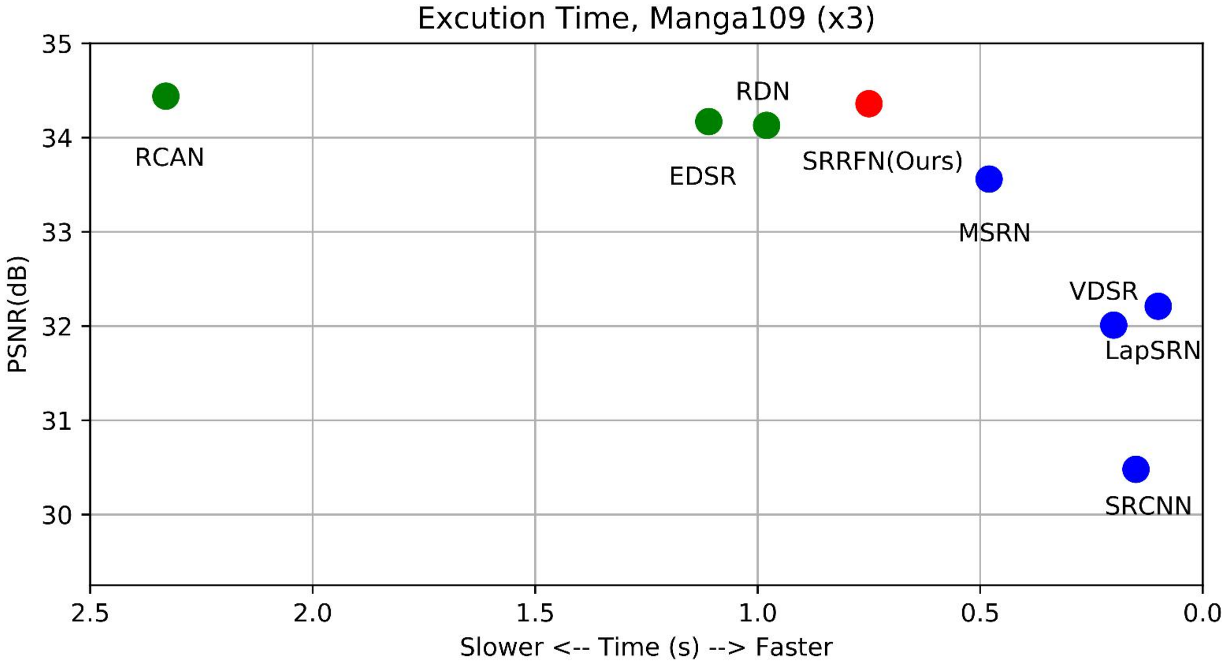


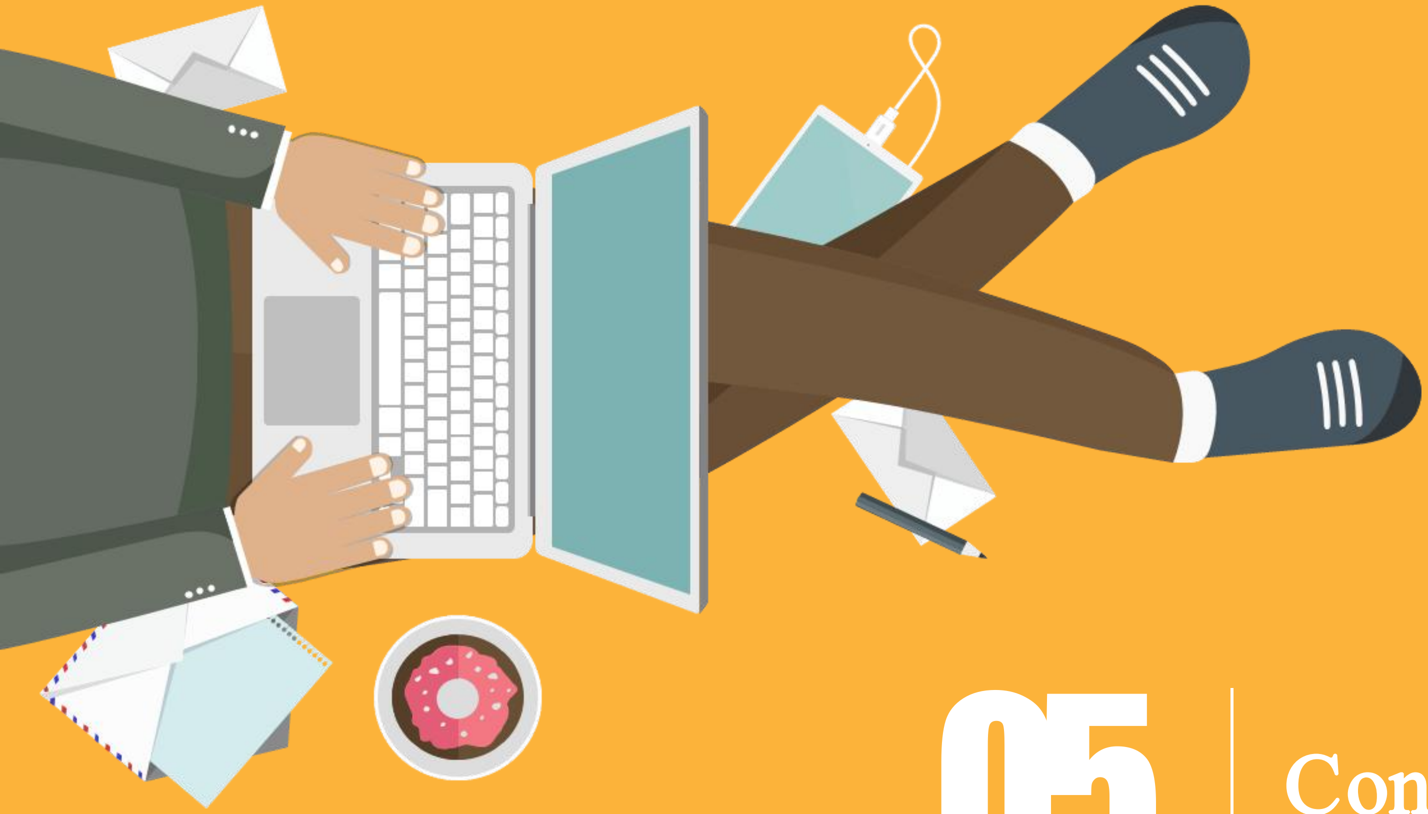



# Investigation & Discussion

## Model Size and Execution Time:





# 05 | Conclusion

## Conclusion

ICCV 2019 Seoul, Korea

We proposed a Super-Resolution Recursive Fractal Network (SRRFN). This is a lightweight and accurate SR framework.

SRRFN introduces the fractal module (FM) for feature extraction and uses recursive mechanism for recursive residual learning, which achieves competitive results with fewer parameters and faster execution time.

# Investigation & Discussion

ICCV 2019 Seoul, Korea

## Benefits of SRRFN:

1、The fractal module can greatly simplifies the model design and can construct an infinite variety of topological structures through a simple basic component.

2、These topologies structure provide a large number of search paths that enable the network to extract abundant image features to reconstruct high-quality SR images.

## Limitations of SRRFN:

1、Which module to choose as the basic component ?

2、How to set the fractal depth (*D*) as the final model depth?

AutoML + Fractal Module


# THANKS

Q & A

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