

# NTIRE 2022 Efficient SR Challenge Factsheet

## Faster Residual Feature Distillation Network for Efficient Super Resolution

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### 1. Team details

- Team name: TOVBU
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- Rest of the team members: Yuanfan Zhang, Zuowei Cao, Lei Sun
- Affiliation: Platform Technologies, Tencent Online Video
- User names and entries on the NTIRE 2022 CodaLab competitions (development/validation and testing phases)

phase	User names	entries
development/validation	jklovezhang	3
testing	jklovezhang	3

- Best scoring entries of the team during development/validation phase

Model	PSNR	SSIM	runtime	Parameters	Extra Data
FasterRFDN	29.00	0.82	0.03(self-test)	376432	Flickr2K

- Link to the codes/executables of the solution(s)  
<https://github.com/enochgli/FasterRFDN>

### 2. Method details

- General method description

On the basis of Residual Feature Distillation Network, we proposed a novel efficient Faster Residual Feature Distillation Network (FasterRFDN) for single image super resolution with some further modification. The overall framework of the proposed method is shown in Fig. 1 and Fig. 2. The overall framework contains 4 faster residual feature distillation block (FRFDB)s. First, to further reduce the parameters and computational complexity of the FRFDB module, we effectively compress the number of channels of layered distillation. The number of channels in each layer from top to bottom is 64, 32, 16, 16, respectively. These distillation features are extracted by three  $1 \times 1$  and one  $3 \times 3$  convolutional filters. Then, these features fed to enhanced spatial attention (ESA) through concatenating each channel. Furthermore, in order to enhance the model's representational power, we increased the number of channels of the model to 64. Based on the aforementioned modifications, the proposed framework is more efficient than original version of the RFDN, and can speed up by about 15 percent.

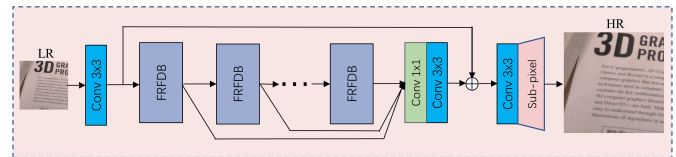


Figure 1. Overall framework of of faster feature distillation network(FasterRFDN).

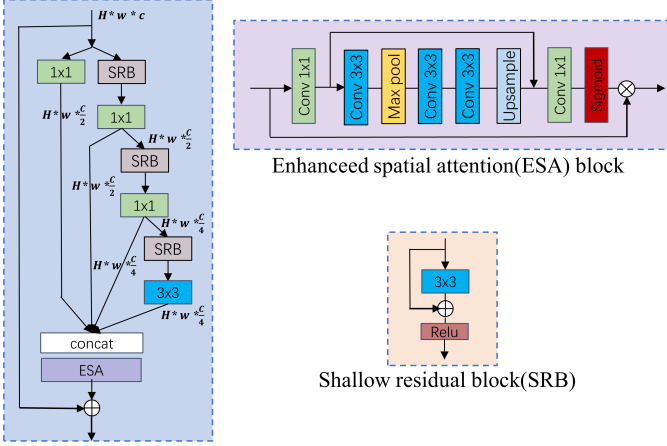


Figure 2. Faster feature distillation block(FRFDB).

### 2.1. Training strategy

Our training procedure can be divided into three stages.

1. Pretraining on DIV2K and Flickr2K (DF2K). HR patches of size  $256 \times 256$  are randomly cropped from HR images, and the mini-batch size is set to 64. The model is trained by minimizing L1 loss function with Adam optimizer. The initial learning rate is set to  $5e-4$  and halved at every 20w iters. The total number of epochs is 1600000.
2. Finetuning on DF2K. HR patch size is  $512 \times 512$ , and the mini-batch size are set to 64, respectively. The model is fine-tuned by minimizing psnr loss function. The initial learning rate is set to  $5e-5$  and halved at every 80000 iters. The total number of epochs is 480000.
3. Finetuning on DF2K again. HR patch size and the mini-batch size are set to  $640 \times 640$  and 16, respectively. The model is finetuned by minimizing L2 loss function. The initial learning rate is set to  $1e-5$  and Use a cosine learning rate.

### • Experimental results

Model	Method	PSNR
FasterRFDNv1	w l1loss	28.9701
FasterRFDNv2	w psnrloss	28.9912
FasterRFDNv3	w l2loss	29.0007

- Total method complexity (number of parameters, FLOPs, GPU memory consumption, number of activations, runtime)

Our method complexity :number of parameters is 376432, FLOPs is 22.379G, number of activations is 113.5526M, runtime is around 0.03 in titanxp GPU

- Which additional data has been used in addition to the provided NTIRE training and validation data (at any stage, if any)

We used the Flickr2k dataset as additional data for training

### 3. Other details

We planned submission of a solution(s) description paper at NTIRE 2022 workshop.

### References