NTIRE 2025 Image Denoising ($\sigma = 50$) Challenge Factsheet -Image Denoising using NAFNet and RCAN-

Weijun Yuan
Jinan University
Guangzhou, China
yweijun@stu2022.jnu.edu.cn

Zhan Li
Jinan University
Guangzhou, China
lizhan@jnu.edu.cn

Ruting Deng
Jinan University
Guangzhou, China
routine@stu2022.jnu.edu.cn

Yihang Chen
Jinan University
Guangzhou, China
ehang@stu.jnu.edu.cn

Yifan Deng
Jinan University
Guangzhou, China
dyf010408@stu.jnu.edu.cn

Zhanglu Chen
Jinan University
Guangzhou, China
czhanglu@stu2024.jnu.edu.cn

Boyang Yao
Jinan University
Guangzhou, China
yaoboy@stu.jnu.edu.cn

Shuling Zheng
Guangdong University Of Foreign Studies
Guangzhou, China
3440989938@qq.com

Feng Zhang
Jinan University
Guangzhou, China
1569259893@qq.com

Zhiheng Fu
Jinan University
Guangzhou, China
2557502986@qq.com

1. Description

Recently, some research in low-level vision has shown that ensemble learning can significantly improve model performance. Thus, instead of designing a new architecture, we leverage existing NAFNet [1] and RCAN [3] as our basic network to design our pipeline for image denosing (NR-Denosing) based on the idea of ensemble learning, as shown in Fig 1. We find the results are better improved by employing both self-ensemble and model ensemble strategies.

2. Implementation Details

For the training of NAFNet, we utilize the provided DIV2K dataset. The model is trained with MSE loss. We utilize the AdamW optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.9$) for 400K iterations on an NVIDIA Tesla V100 GPU. The initial learning rate is set to 1×10^{-3} and gradually reduces to 1×10^{-7} with the cosine annealing. The training batch is set to 4 and the patch size is 384×384. Random horizontal flipping and rotation were adopted for data augmentation.

For the training of RCAN, the provided DIV2K dataset is also employed. The MSE loss is utilized with an initial learning rate of 1×10^{-4}. The Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.99$) is used for 100K iterations. The batch size is 3, and the patch size is 200. Data augmentation includes the horizontal flip and the 90-degree rotation.

During the inference phase, we apply a self-ensemble strategy for NAFNet and selectively adopt the TLC [2] method based on the size of input images; For RCAN, we utilize a self-ensemble strategy. Finally, the model-ensemble strategy is employed to combine the outputs of NAFNet and RCAN.

3. Team details

- Team name: JNU_620
- Team leader name: Weijun Yuan
- Team leader address, phone number, and email: Jinan University, Guangzhou, 17817975121, yweijun@stu2022.jnu.edu.cn
- Rest of the team members: Zhan Li, Ruting Deng, Yihang Chen, Yifan Deng, Zhanglu Chen, Boyang Yao, Shuling Zheng, Feng Zhang, Zhiheng Fu
- Team website URL (if any): None
- Affiliation: Jinan University, Guangdong University Of Foreign Studies
- Affiliation of the team and/or team members with NTIRE

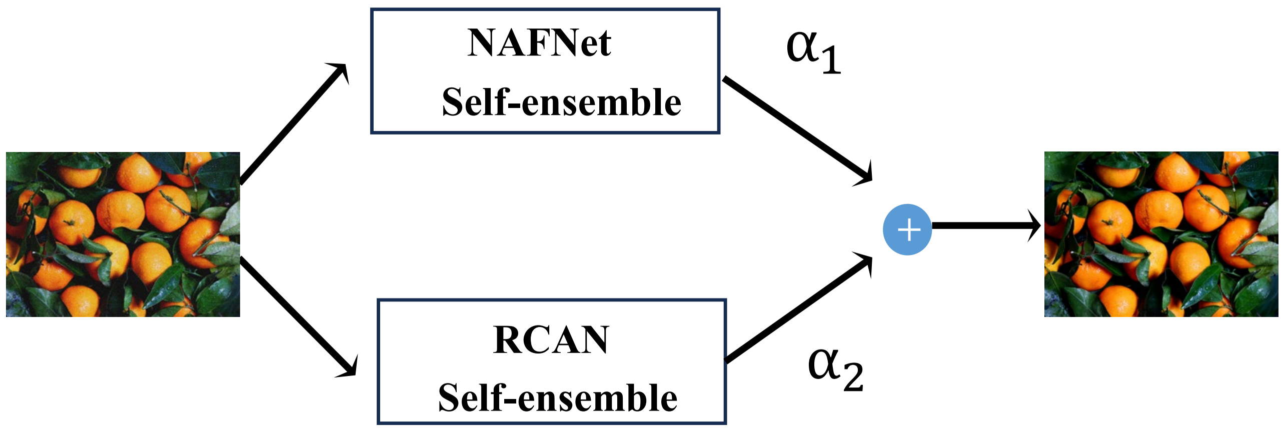

Figure 1. The pipeline of the proposed NRDenoising

2025 sponsors (check the workshop website): None

- User names and entries on the NTIRE 2025 Codalab competitions: Wedream
- Best scoring entries of the team during the development/validation phase: Validation phase: PSNR: **30.500558**; Test phase: PSNR: **29.553782**;
- Link to the codes/executables of the solution(s): https://github.com/Wedream-wj/NTIRE2025_Dn50_challenge

References

[1] Liangyu Chen, Xiaojie Chu, Xiangyu Zhang, and Jian Sun. Simple baselines for image restoration. In *European conference on computer vision*, pages 17–33. Springer, 2022. 1

[2] Xiaojie Chu, Liangyu Chen, Chengpeng Chen, and Xin Lu. Improving image restoration by revisiting global information aggregation. In *European Conference on Computer Vision*, pages 53–71. Springer, 2022. 1

[3] Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu. Image super-resolution using very deep residual channel attention networks. In *Proceedings of the European conference on computer vision (ECCV)*, pages 286–301, 2018. 1