NTIRE 2023 Image Denoising ($\sigma = 50$) Challenge Factsheet
Scaling Up NAFNet for Denoising

1. Introduction

This factsheet template is meant to structure the description of the contributions made by each participating team in the NTIRE 2023 challenge on image denoising with noise level $\sigma = 50$.

Ideally, all the aspects enumerated below should be addressed. The provided information, the codes/executables and the achieved performance on the testing data are used to decide the awardees of the NTIRE 2023 challenge.

Reproducibility is a must and needs to be checked for the final test results in order to qualify for the NTIRE awards.

The main winners will be decided based on overall performance and a number of awards will go to novel, interesting solutions and to solutions that stand up as the best in a particular subcategory the judging committee will decided. Please check the competition webpage and forums for more details.

The winners, the awardees and the top ranking teams will be invited to co-author the NTIRE 2023 challenge report and to submit papers with their solutions to the NTIRE 2023 workshop. Detailed descriptions are much appreciated.

The factsheet, source codes/executables, trained models should be sent to **all of the NTIRE 2023 challenge organizers (Yawei Li, Yulun Zhang, and Radu Timofte)** by email.

2. Email final submission guide

To: yawei.li@vision.ee.ethz.ch
yulun100@gmail.com
timofte.radu@gmail.com
cc: your_team_members
Title: NTIRE 2023 Image Denoising Challenge - TEAM_NAME - TEAM_ID

To get your TEAM_ID, please register at Google Sheet. Please fill in your Team Name, Contact Person, and Contact Email in the first empty row from the top of sheet. Body contents should include:

a) team name

   HIT-IIL

b) team leader's name and email address

   Rongjian Xu, ronjon.xu@gmail.com

c) rest of the team members

   Zhilu Zhang, Yunjin Chen, Dongwei Ren, Wangmeng Zuo

d) user names on NTIRE 2023 CodaLab competitions

   Xman, Spider-Man

e) Code, pretrained model, and factsheet download command, e.g. `git clone ...`, `wget ...`

   git@github.com:ronjonxu/Ntire2023-GaussDenoise.git

f) Result download command, e.g. `wget ...`

   wget https://drive.google.com/file/d/1hL44SFtAkNwPW-U9e9FluGqdonS$_Oq1N/view?usp=sharing$

   - Please provide different urls in e) and f)

Factsheet must be a compiled pdf file together with a zip with .tex factsheet source files. Please provide a detailed explanation.

3. Code Submission

The code and trained models should be organized according to the GitHub repository. This code repository provides the basis to compare the various methods in the challenge. **Code scripts based on other repositories will not be accepted.** Specifically, you should follow the steps below.

1. Git clone the repository.
2. Put your model script under the `models` folder. Name your model script as `[Your_Team_ID]_[Your_Model_Name].py`.
3. Put your pretrained model under the `model_zoo` folder. Name your model checkpoint as `[Your_Team_ID]_[Your_Model_Name].[pth or pt or ckpt]`

4. Modify `model_path` in `test_demo.py`. Modify the imported models.

5. `python test_demo.py`

Please send us the command to download your code, e.g. `git clone [Your repository link]` When submitting the code, please remove the noisy and denoise images in `data` folder to save the bandwidth.

4. Factsheet Information

The factsheet should contain the following information. Most importantly, you should describe your method in detail. The training strategy (optimization method, learning rate schedule, and other parameters such as batch size, and patch size) and training data (information about the additional trainning data) should also be explained in detail.

4.1. Team details

- Team name

  HIT-IIL

- Team leader name

  Rongjian Xu

- Team leader address, phone number, and email

  92 Xidazhi Street, Nangang District, Harbin City, Heilongjiang Province, Harbin Institute of Technology

  (+86)-18845158423

  ronjon.xu@gmail.com

- Rest of the team members

  Zhilu Zhang, Yunjin Chen, Dongwei Ren, Wangmeng Zuo

- Team website URL (if any)

  No

- Affiliation

  Harbin Institute of Technology

- Affiliation of the team and/or team members with NTIRE 2023 sponsors (check the workshop website)

  No

- User names and entries on the NTIRE 2023 Codalab competitions (development/validation and testing phases)

  Xman, Spider-Man

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

  PSNR:30.74 dB SSIM: 0.86

- Link to the codes/executables of the solution(s)

4.2. Method details

You should describe your proposed solution in detail. This part is equivalent to the methodology part of a conference paper submission. The description should cover the following details.

- General method description (How is the network designed.)

  Recently, some research in image generation has shown that the number of model parameters plays a critical role in model performance. Thus, instead of designing a new architecture, we directly scale up the existing network as our denoising model. We adopt NAFNet [1] as our basic network. And we find the results are better improved by increasing the number of channels than depth. Finally, limited by GPU resources, we only double the channel number of NAFNet. In the inference phase, we use a self-ensemble strategy and selectively adopt the TLC method [2] based on the size of input images.

- Representative image / diagram / pipeline of the method(s)

  Our network architecture is the same as NAFNet [1] and only doubles the channel number. Please see NAFNet [1] for the method pipeline.

- Training strategy

  We use the provided DIV2K and LSDIR datasets as training images. The model is trained with PSNR loss. We utilize AdamW optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.9$) for total 125K iterations on 8 NVIDIA A100 GPUs. The learning rate is initially 3e-4, and gradually reduces to 1e-7 with the cosine annealing. The training batch size is set to 64 and the patch size is 256×256.

- Experimental results

- References

  1. Simple Baselines for Image Restoration [1]

  2. Revisiting global statistics aggregation for improving image restoration [2]

Additionally, you can refer to the following items to detail your description.

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

  The number of parameters: 459.1M.

  The number of FLOPs: 581.44G.

- Which pre-trained or external methods / models have been used (for any stage, if any)

  No.

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

  No.

- Training description

  Please see 'Training strategy'.

- Testing description

  In the inference phase, we use a self-ensemble strategy and selectively adopt the TLC method [2] based on the size of input images.

- Quantitative and qualitative advantages of the proposed solution

  We show that scaling up the model is very helpful for denoising performance.

- Results of the comparison to other approaches (if any)

  No.

- Results on other benchmarks (if any)

  No.

- Novelty degree of the solution and if it has been previously published

  Little.

- It is OK if the proposed solution is based on other works (papers, reports, Internet sources (links), etc). It is ethically wrong and a misconduct if you are not properly giving credits and hide this information.

  Our solution is based on NAFNet [1] and TLC [2].

5. Other details

- Planned submission of a solution(s) description paper at NTIRE 2023 workshop.

  No.

- General comments and impressions of the NTIRE 2023 challenge.

  It's a good opportunity for CVers.

- What do you expect from a new challenge in image restoration, enhancement and manipulation?

  Nothing more, it is good enough now.

- Other comments: encountered difficulties, fairness of the challenge, proposed subcategories, proposed evaluation method(s), etc.

  No.

References

[1] Liangyu Chen, Xiaojie Chu, Xiangyu Zhang, and Jian Sun. Simple baselines for image restoration. In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part VII*, pages 17–33. Springer, 2022. 2, 3

[2] Xiaojie Chu, Liangyu Chen, Chengpeng Chen, and Xin Lu. Revisiting global statistics aggregation for improving image restoration. *arXiv preprint arXiv:2112.04491*, 2021. 2, 3