NTIRE 2025 Efficient SR Challenge Factsheet -Reparameterized Residual Local Feature Network for Efficient Image Super-Resolution-

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1. Method

We propose a reparameterized residual local feature network (RepRLFN) for efficient image super-resolution, which is influenced by existing studies such as RepRFN [1] and RLFN [3]. Fig 1 illustrates the overall architecture of RepRLFN, which has been extensively validated in previous studies.

We replace the RLFB in RLFN with our reparameterized residual local feature block (RepRLFB). RepBlock is the main component of RepRLFB, which employs multiple parallel branch structures to extract the features of different receptive fields and modes to improve performance. At the same time, the structural re-parameterization technology is leveraged to decouple the training and inference phases to avoid the problem that computational complexity increases caused by the introduction of multi-branch.

2. Training details

The proposed RepRLFN consists of 4 RepRLFBs, with the number of feature channels set to 48. The details of the training steps are as follows:

1. In the first stage, the model is pre-trained on DIV2K. HR patches of size 480×480 are randomly cropped from HR images, and the mini-batch size is set to 32. The model is trained by minimizing the L1 loss function using the Adam optimizer. The initial learning rate is set to 5e-4 and is halved every 200 epochs. The total number of epochs is 800.

2. In the second stage, the model is fine-tuned on 800 images from DIV2K and the first 10k images from LSDIR. HR patches of size 640×640 are randomly cropped from HR images, and the mini-batch size is set to 32. The model is fine-tuned by minimizing the L2 loss function. The initial learning rate is set to 2e-4 and is halved every 5 epochs. The total number of epochs is 25.

3. In the third stage, the model is fine-tuned again on 800 images from DIV2K and the first 10k images from LSDIR. The HR patch size and minibatch size are set to 640×640 and 32, respectively. The model is fine-tuned by minimizing the L2 loss function. The initial learning rate is set to 1e-4 and is halved every 5 epochs. The total number of epochs is 20.

4. In the fourth stage, the model is fine-tuned on 800 images from DIV2K and the first 10k images from LSDIR. The HR patch size and minibatch size are set to 640×640 and 32, respectively. The model is fine-tuned by minimizing the L2 loss function. The learning rate is set to 5e-5, and the total number of epochs is 10. To prevent over-fitting, the model ensemble via stochastic weight averaging [2] (SWA) is performed during the last 8 epochs to obtain the final model for testing.

3. Team details

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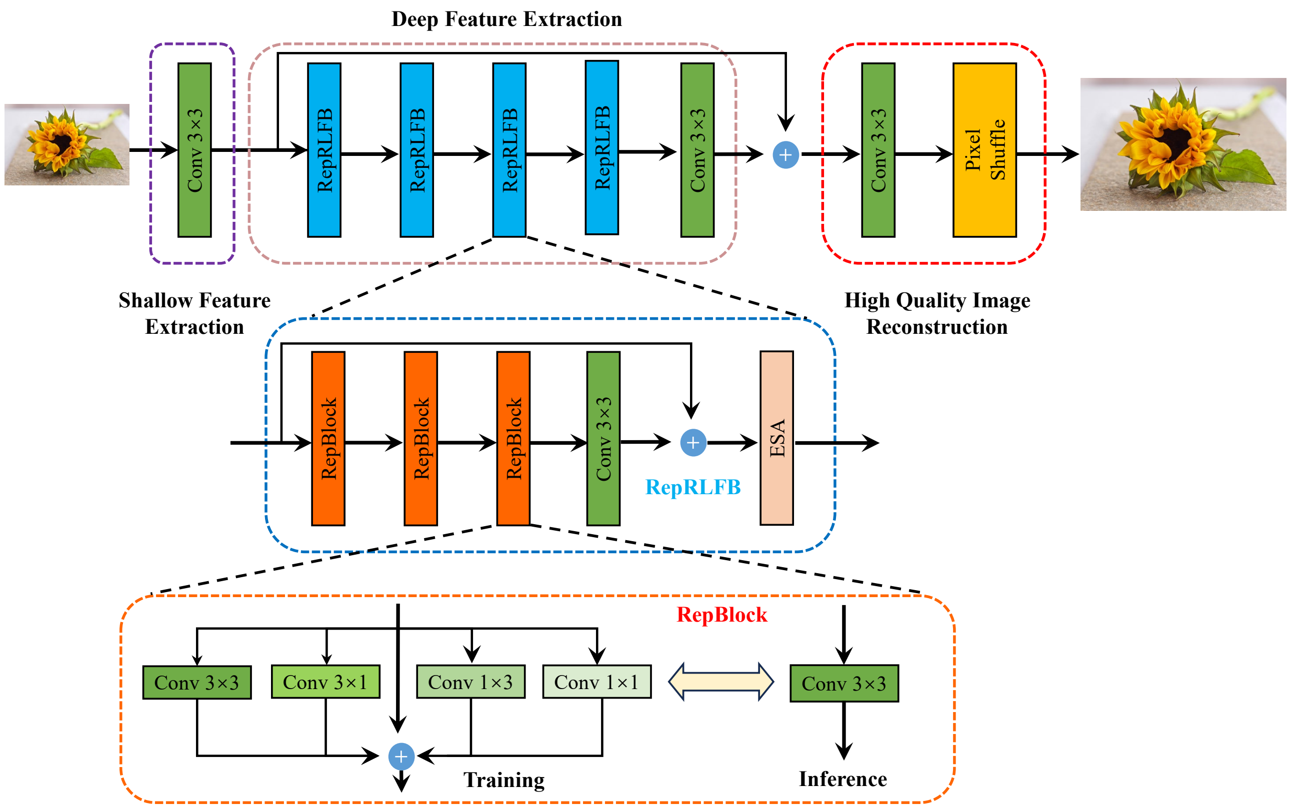

Figure 1. The network architecture of RepRLFN

- Team website URL (if any): None
- Affiliation: Jinan University
- Affiliation of the team and/or team members with NTIRE 2025 sponsors (check the workshop website): None
- User names and entries on the NTIRE 2025 Codalab competitions (development/validation and testing phases): Wedream
- Best scoring entries of the team during the development/validation phase: Validation phase: PSNR: **26.90**; Test phase: PSNR: **27.01**;
- Link to the codes/executables of the solution(s): https://github.com/Wedream-wj/NTIRE2025_ESR

References

[1] Weijian Deng, Hongjie Yuan, Lunhui Deng, and Zengtong Lu. Reparameterized residual feature network for lightweight image super-resolution. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 1712–1721, 2023. 1

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[3] Fangyuan Kong, Mingxi Li, Songwei Liu, Ding Liu, Jingwen He, Yang Bai, Fangmin Chen, and Lean Fu. Residual local feature network for efficient super-resolution. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 766–776, 2022. 1