NTIRE 2025 Image Denoising ($\sigma = 50$) Challenge Factsheet
Effective Denoising via Adaptive Kernel Dilation Transformer

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1. Team details

- Team name: AKDT
- Team leader name: Alexandru Brateanu
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- Rest of the team members: Raul Balmez, Ciprian Orhei, Cosmin Ancuti
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  Alexandru Brateanu (University of Manchester)
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- Affiliation of the team and/or team members with NTIRE 2025 sponsors (check the workshop website): N/A
- User names and entries on the NTIRE 2025 Codalab competitions (development/validation and testing phases): albrateanu
- Best scoring entries of the team during development/validation phase: Test result: 28.82 dB PSNR and 0.837 SSIM. We did not enter the competition during development phase, so we did not submit our results there.
- Link to the codes/executables of the solution(s): Code for inference is available here: https://github.com/albrateanu/AKDT_NTIRE and link to denoising results Google Drive. Additionally, we also provide the original codebase for the model implementation/training/testing: https://github.com/albrateanu/AKDT.

2. Method details

- General method description:
  In this work, we employ **AKDT**, a Transformer network based on the Restormer [4] framework, that proposes a novel convolutional structure with learnable dilation rates: the Learnable Dilation Rate **LDR** Block. We use **LDR** to then formulate the Noise Estimator (**NE**) module, which we then integrate within the attention and feed-forward mechanisms to obtain the Noise-Guided Multi-headed Self-Attention (**NG-MSA**) and the Noise-Guided Feed-forward Network (**NG-FFN**).
  AKDT was initially formulated as part of our paper published in February 2025 [2]. We improve the overall framework by optimizing the training process through new loss functions, as proposed in [1, 3]
- Representative image / diagram / pipeline of the method(s): Figure 1 shows the overall framework of our proposed **AKDT**.
- Training strategy: To train our network, all training image pairs of the DIV2K data, and empirically select the submission model weights. Input images undergo data augmentation techniques (random flipping, rotation) and are processed as 600×600 randomly-cropped patches, with a batch size of 4. **AKDT** is trained for 150k iterations with the ADAM optimizer, using a Cosine Annealing scheme for the learning rate, initialized as $2e-4$. To optimize our network, we utilize a hybrid loss capable of capturing pixel-level, multi-scale and perceptual cues, as proposed in [1, 3], leading to increased effectiveness in high-resolution, high-fidelity restoration.
- Experimental results: We only evaluate performance on the NTIRE testing server, obtaining 28.82 dB PSNR and 0.837 SSIM.

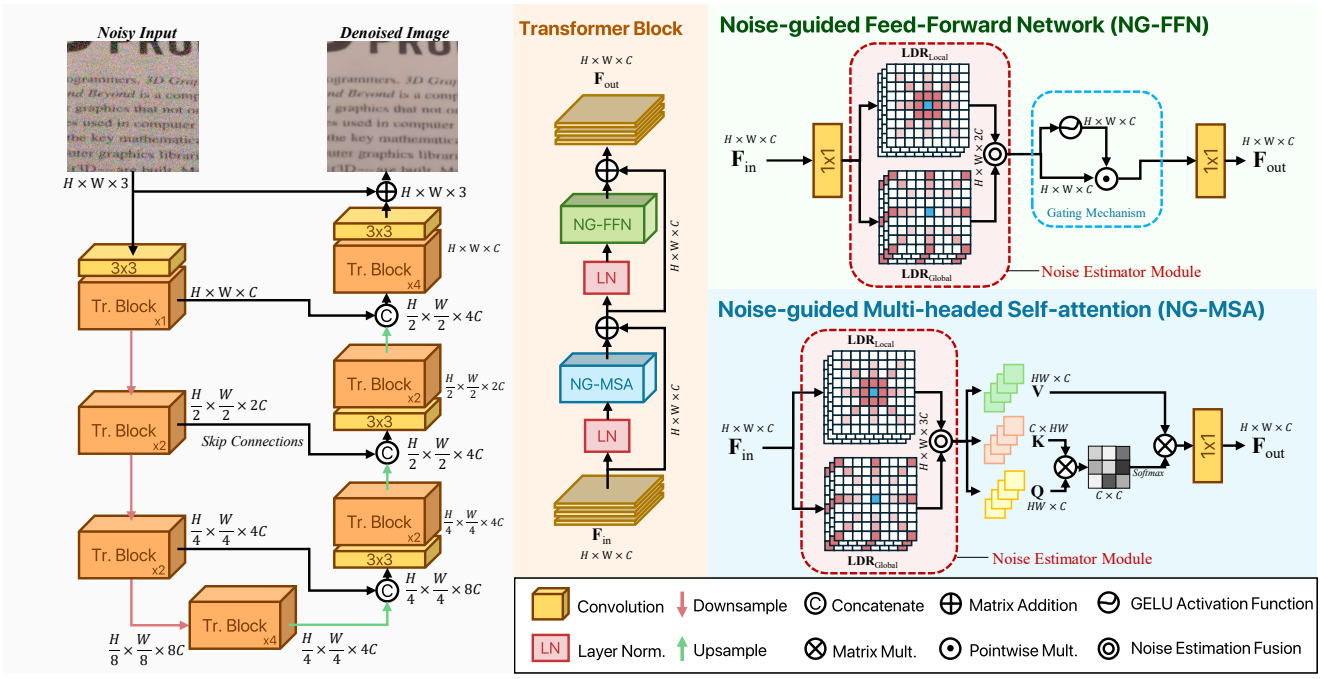

Figure 1. Overall Framework of our Adaptive Kernel Dilation Transformer (**AKDT**).

- Total method complexity (number of parameters, FLOPs, GPU memory consumption, number of activations, runtime): **AKDT** has: 7.07 Million Parameters, 93.32 GFLOPS (on $256 \times 256 \times 3$ tensors), and takes approx. 2000ms for $2000 \times 3000 \times 3$ input tensors on one RTX 3090 GPU.
- Which pre-trained or external methods / models have been used (for any stage, if any): The method is based on AKDT [2], with improvements on loss functions as in [1, 3].
- Which additional data has been used in addition to the provided NTIRE training and validation data (at any stage, if any) : N/A
- Results of the comparison to other approaches (if any): N/A
- Results on other benchmarks (if any): **AKDT** reaches state-of-the-art on standard denoising benchmarks (as per paperswithcode.com): AKDT @ paperswithcode.com
- Novelty degree of the solution and if it has been previously published: Solution has been published (**AKDT** [**?**], Hybrid Loss function [1, 3].
- 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: We have provided all required credits and references - to the best of our knowledge.

3. Other details

- Planned submission of a solution(s) description paper at NTIRE 2025 workshop: Yes.
- General comments and impressions of the NTIRE 2025 challenge: Good impressions. Testing servers worked ok and we appreciated the higher test submission cap.
- What do you expect from a new challenge in image restoration, enhancement and manipulation?: To tackle new challenges and participate further.
- Other comments: encountered difficulties, fairness of the challenge, proposed subcategories, proposed evaluation method(s), etc.: N/A

References

[1] Alexandru Brateanu and Raul Balmez. Kolmogorov-arnold networks in transformer attention for low-light image enhancement. In *2024 International Symposium on Electronics and Telecommunications (ISETC)*, pages 1–4, 2024.

[2] Alexandru Brateanu, Raul Balmez, Adrian Avram, and Ciprian Orhei. Akdt: Adaptive kernel dilation transformer for effective image denoising. In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications - Volume 3: VISAPP*, pages 418–425, 2025.

[3] Alexandru Brateanu, Raul Balmez, Ciprian Orhei, Cosmin Ancuti, and Codruta Ancuti. Enhancing low-light images with kolmogorov–arnold networks in transformer attention. *Sensors*, 25(2), 2025.

[4] Syed Waqas Zamir, Aditya Arora, Salman Khan, Munawar Hayat, Fahad Shahbaz Khan, and Ming-Hsuan Yang. Restormer: Efficient transformer for high-resolution image restoration. In *CVPR*, 2022.