

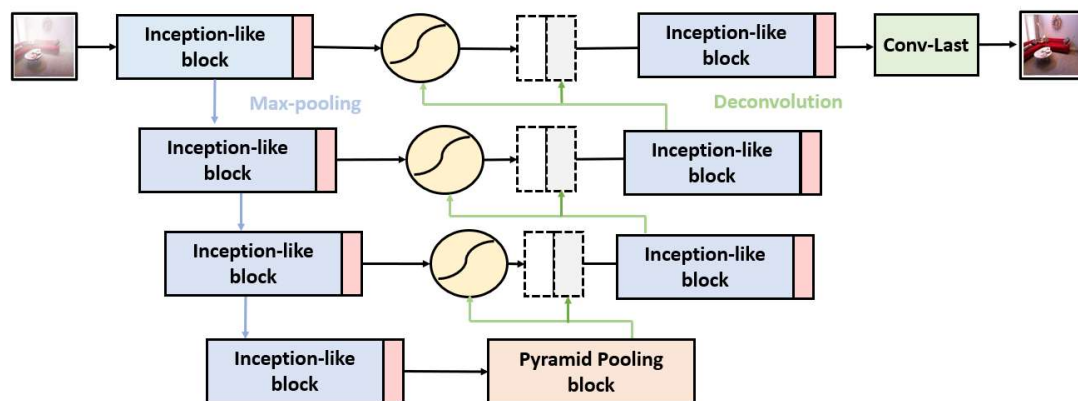
API : Attention Gate based Model with Pyramid Pooling and Inception-like block for Image Dehazing

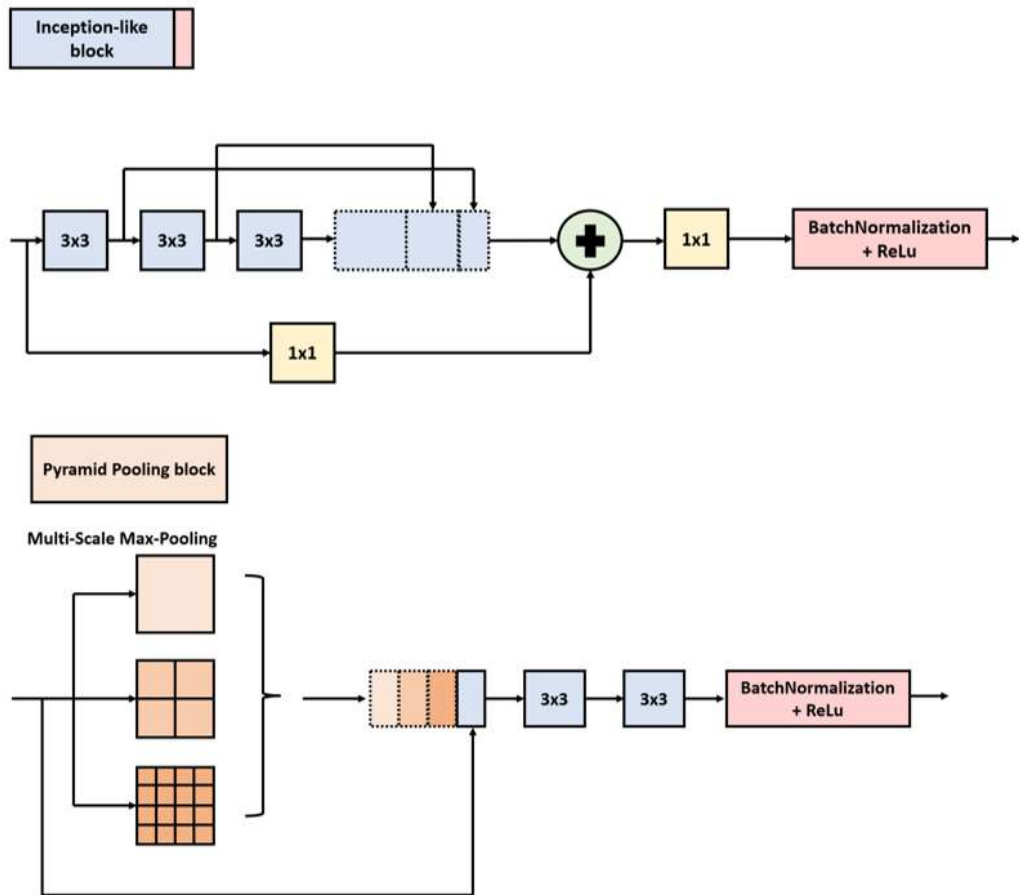
I. Abstract

It's hazardous that bad weather condition makes things less clear e.g., haze, fog, heavy rain and snow; to ensure safety in haze, the proposed model, a Deep Learning based method for image dehazing, contains the Inception-like block, Pyramid Pooling block, and Attention Gate mechanism to enlarge SSIM (Structural similarity) and PSNR (Peak signal-to-noise ratio) to get clear image.

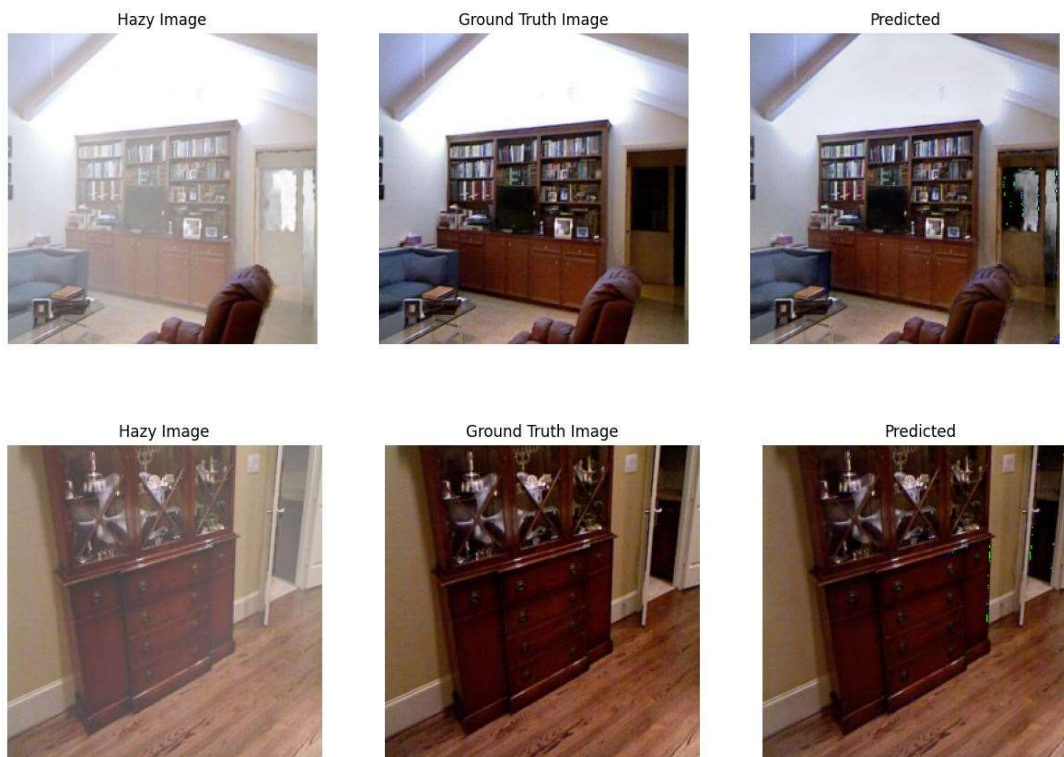
II. Methodology

The Inception-like block and Pyramid Pooling block use varying kernel size in parallel to extract different scale features of images in order to enlarge receptive field. Attention Gate is a successful method of image segmentation in medical field. Therefore, I noticed that the haze image losing target structures needs to highlight salient features. Finally, I show the experimental result of image dehazing and compare other state-of-the-art method.





III. Experimental Result



IV. Quantitative Analysis

TABLE I
COMPARATIVE RESULTS OVER D-HAZY DATASET

| Method | SSIM | PSNR |
|-------------|---------------|--------------|
| CycleGAN | 0.6490 | 13.69 |
| CycleDehaze | 0.6746 | 12.54 |
| DCP | 0.7060 | 11.59 |
| C^2MSNet | 0.7201 | 12.71 |
| DehazeNet | 0.7270 | 13.40 |
| CAP | 0.723 | 13.19 |
| MSCNN | 0.7231 | 12.82 |
| DDN | 0.7383 | 10.96 |
| CDNet | 0.7411 | 13.84 |
| RI-GAN | 0.8179 | 18.82 |
| RYF-Net | 0.8230 | 17.56 |
| ReViewNet | 0.8239 | 20.64 |
| API | 0.8607 | 19.32 |

TABLE II
COMPARATIVE RESULTS OVER RESIDE-STANDARD
SOTS INDOOR DATASET

| Method | SSIM | PSNR |
|-------------|---------------|--------------|
| CycleGAN | 0.5738 | 14.16 |
| CycleDehaze | 0.6923 | 15.86 |
| FVR | 0.7483 | 15.72 |
| C^2MSNet | 0.8152 | 20.12 |
| DCP | 0.8179 | 16.62 |
| CAP | 0.8364 | 19.05 |
| DehazeNet | 0.8472 | 21.14 |
| RI-GAN | 0.8500 | 19.83 |
| AOD-Net | 0.8504 | 19.06 |
| RYF-Net | 0.8230 | 17.56 |
| CDNet | 0.8852 | 21.30 |
| ReViewNet | 0.8716 | 21.44 |
| API | 0.9337 | 22.73 |

V. Reference

- [1] Gui, J., et al. A Comprehensive Survey on Image Dehazing Based on Deep Learning. 2021. arXiv:2106.03323.
- [2] K. He, J. Sun and X. Tang, "Single Image Haze Removal Using Dark Channel Prior," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 12, pp. 2341-2353, Dec. 2011, doi: 10.1109/TPAMI.2010.168.
- [3] M. Ju, C. Ding, W. Ren, Y. Yang, D. Zhang and Y. J. Guo, "IDE: Image Dehazing and Exposure Using an Enhanced Atmospheric Scattering Model," in IEEE Transactions on Image Processing, vol. 30, pp. 2180-2192, 2021, doi: 10.1109/TIP.2021.3050643.
- [4] B. Li, X. Peng and Z. Wang, and J. Xu and D. Feng. " Aod-net: All-in-one dehazing network ," In IEEE International Conference on Computer Vision, pages 4780–4788, Los Alamitos, CA, USA, oct 2017. IEEE Computer Society
- [5] Liu, Z., et al. Generic Model-Agnostic Convolutional Neural Network for Single Image Dehazing. 2018. arXiv:1810.02862.
- [6] A. Mehra, M. Mandal, P. Narang and V. Chamola, "ReViewNet: A Fast and Resource Optimized Network for Enabling Safe Autonomous Driving in Hazy Weather Conditions," in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 7, pp. 4256-4266, July 2021, doi: 10.1109/TITS.2020.3013099.
- [7] Oktay, O., et al. Attention U-Net: Learning Where to Look for the Pancreas. 2018. arXiv:1804.03999.
- [8] Lou, A., S. Guan, and M. Loew. DC-UNet: rethinking the U-Net architecture with dual channel efficient CNN for medical image segmentation. 2021.