Image Noise Reduction Using Deep Convolutional and Fully Connected Neural Networks[1]

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Target Audience: Researchers in Communications, Electronics, Artificial Intelligence, Computer and Data Science.

PURPOSE: The main purpose is to define and compare multiple models, which result in high enough PSNR of image after noise reduction while using a reasonable computational resource efficiently in 20 epochs.

METHODS: In this Project, we have compared two different architectures of deep neural network, fully connected and convolutional neural networks, and in our CNN, we have exploited the symmetric gated connections and non-symmetric connections architectures from Zhao[3]. These symmetric gated connections could help the model to learn the noise distribution more rapidly and the optimization problem could converge to the optimum point as well. In our CNN model, we used 4 layers of convolutions and deconvolutions to extract the features and rebuild the clean image. Both FC and CNN models use the autoencoder-based architectures. These models have been trained with 15k images (Grayscale, RGB) with two different optimizers, Adam and SGD. All the instances are standard 8-bit images with 64*64 dimensions.

RESULTS: The implementations result in clean images with satisfactory quality and Adam optimizer performs better rather than SGD. By the comparison between symmetric and non-symmetric architectures, it has been demonstrated that symmetric gated connections between layers could help the model perform more promising. Moreover, using 3in3 kernels in convolution layers also could help the network find details in the recovered images rather than 5in5 kernels.

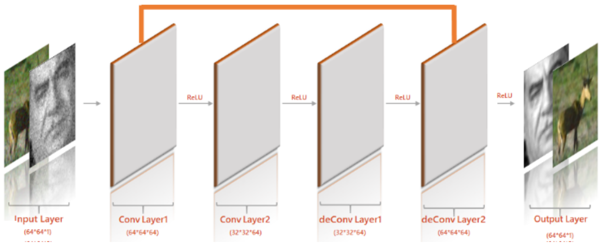

Fig.1. CNN network architecture with symmetric gated connections

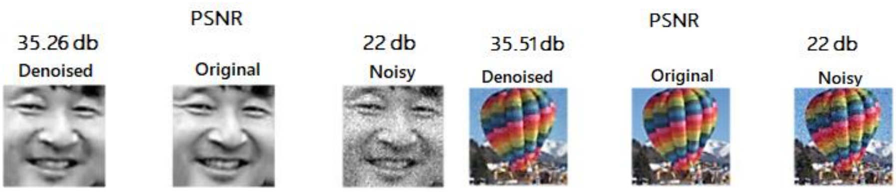

Fig.2. Visualizations of results with symmetric gated connections optimized by Adam optimizer – from left to right PSNR: 35.26 dB/ 35.51 dB (σ of AWGN noise = 12.75)

DISCUSSION: We can discuss the comparisons considering various factors such as the optimizer, the architecture, and the kernel size. We aim to present a comparison between an adaptive and non-adaptive optimizer, therefore and by being popular, we have used SGD and Adam. The models trained using the Adam optimizer have performed considerably better than the ones with SGD while the Adam optimizer uses momentum and exponentially weighted averages of gradients. The outputs of the models trained with Adam can be rated as follows: CNN with symmetric gates, CNN with non-symmetric gates. The reason is, using the symmetric connections gives the model the ability to use the features extracted in the former convolution layers in the deconvolution or upsampling layers. The fully connected model performed poorly and resulted in a low PSNR, since there will be much greater number of parameters to train using the FC layers let alone the effect of convolutional layers in enhancing the performance in vision applications. In CNN models, we can observe a decent better performance in using 3in3 kernels while training the model with both optimizers in 20 epochs. This is due to the more preserved details and features in the output of a convolution layer while using a 3in3 kernel compared with a 5in5 one.

CONCLUSION: In this project we have compared autoencoder-based models of CNN and FC and the results showed us that the convolution-deconvolution networks perform far better than a fully connected network. Besides, the Adam optimizer performs better noise cleaning on both the RGB and gray-scale images than the SGD. We have observed that a symmetric gated connection can not only speed up convergence of the gradients to the global minima, but also it performs more efficiently since it makes the upsampling layers use the extracted features directly to rebuild the image.

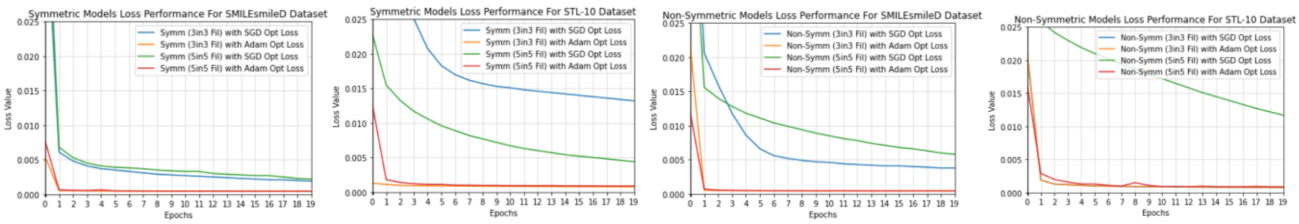

Fig.3. Decrement of loss from left to right: - Symmetric models with grayscale images – Symmetric models with RGB images – Non-symmetric models with grayscale images – Non-symmetric models with RGB images

1. https://github.com/Smmehdihosseini/Image-Denoising-with-Deep-Learning
2. Smmehdihosseini@gmail.com
3. https://web.stanford.edu/class/cs331b/2016/projects/zhao.pdf