Generative Modeling for Retinal Fundus Image Synthesis

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Abstract

Medical imaging datasets typically do not contain many training images, usually being deficient for training deep learning networks. We propose a deep residual variational auto-encoder and a generative adversarial network that can generate a synthetic retinal fundus image dataset with corresponding blood vessel annotation. Our initial experiments produce results with higher scores than the state of the art for verifying that the structural statistics of our generated images are compatible with real fundus images. The successful application of generative models to generate synthetic medical data will not only help to mitigate the small dataset problem but will also address the privacy concerns associated with medical datasets.

1 Introduction

Very recently, data driven generative modeling based medical image synthesis became popular. In the medical imaging domain, one of the first application of generative model was by Tulder et. al [1] in MRI image synthesis. In the context of retinal imaging synthesis for blood vessel segmentation Costa et. al [2] proposed a model to generate color fundus images from blood vessels but the method relied upon existing blood vessel structure as it did not generate simulated blood vessels. Similar kinds of work were done by Iqbal et. al [3] to generate color fundus images but this method also was dependent on existing blood vessel structure. In an another work Costa et. al [4] generated blood vessels along with corresponding fundus images but the generated blood vessels were of 256X256 resolution which in the context of retinal fundus images was of much lower resolution. Our proposed model has several important contributions over previously published works:

- This adversarial residual training framework and de-noising algorithm helped to generate less blurry output images.
- The model learnt inherent distribution of the image and generated plausible high resolution retinal fundus images of 512X512 (and 1024X1024 with the super resolution model) with their blood vessel annotations unlike previously existing methods.
- Number of training images used were as low as 20.
- The complete generated dataset will be made available online for public research use.

2 Methodology

In the first step of the proposed pipeline, a deep residual variational auto-encoder network was proposed. VAE assumes Gaussian prior while calculating L_2 loss function and hence the output tends to get blurry. To avoid the inherent blurriness problem residual layer is added [5]. Deconvolution based image denoising algorithm is used for finer output image generation. Image-to-image translation with the general adversarial network (pix2pix) is performed to map the blood vessel image to the corresponding color fundus image. Here the model is trained with blood vessels and corresponding fundus images to generate corresponding fundus images from blood vessels. The pipeline above can also produce images of both blood vessel annotations and color fundus images of 512X512 resolution. The next part implements an image super-resolution algorithm called enhanced deep super-resolution network [6] to increase the resolution of generated images. It is to be noted that PSNR ratio decreases with the increase of up-sampling factor hence the minimum up-sampling factor of 2 is used here to make the image size of 1024X1024.
For training, all the networks only 20 images and corresponding blood vessel annotations are used from DRIVE dataset[7]. Data augmentation strategies are performed to increase the size of training data. A 12 GB Titan V GPU is used to run the codes.

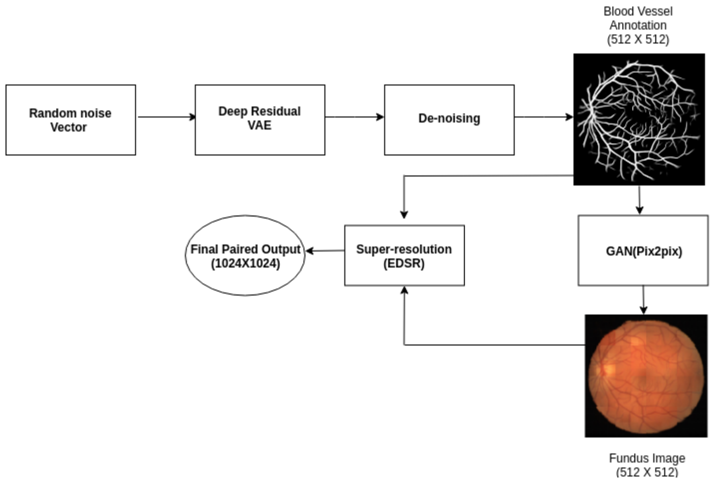

Fig. 1: Complete Schematic of Proposed Pipeline

3 Results

In table 1 comparative analysis of generated data with related works is given. It can be seen that our model performs better than existing models in the context of practicability and computational complexity. A Structural Similarity Index Measure (SSIM) [8] is a widely used index to measure image quality with a particular reference image and is considered as a better metric than mean square error calculation. Because the DRIVE dataset has been used for training the model, one blood vessel image and one fundus image from DRIVE dataset have been taken as reference to calculate the SSIM values. 20 artificially generated blood vessels and 20 corresponding fundus images have been generated for calculating SSIM values. Artificially generated fake blood vessel annotations achieved SSIM values 0.74 on average compared with this particular image from the original dataset whereas the images in the original dataset have 0.78 SSIM on average compared with the same image in the original dataset. To the best of our knowledge there is only one artificially created publicly available fundus image dataset [9] for research purposes. SSIM analysis has been done with this dataset and images of blood vessel annotations from this dataset achieved SSIM value of 0.64 which is lesser than the results with our method. More detailed results will be presented at SPIE Medical Imaging 2020, Houston.

Reference	SSIM Value
[9]	0.64
Ours	0.74

Table 1: SSIM Image Quality Analysis

Reference	Blood Vessel Annotation	Resolution	Online Availability	Training Image
[4]	No	512X512	No	614
[3]	No	512X512	No	10
[2]	Yes	256X256	No	634
Ours	Yes	**512X512, 1024X1024**	**Will be available**	**20**

Table 2: Comparative Analysis with Relevant Literature

4 Conclusion

In this work, a complete pipeline is presented for generating artificial realistic high-resolution retinal fundus images and corresponding blood vessel annotations. Only a few training examples (20 images) were shown to be need to assign parameters for the network that are able to produce the artificial images. The quality of the artificially produced images is better than the state of the art reported upon in the literature using the SSIM score. This model can possibly also be applied to various other tasks to generate realistic-looking images for different medical imaging tasks like image segmentation etc.

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