**Retinal image synthesis from multiple landmark inputs using GAN**

ABSTRACT

Medical datasets, especially medical images, are often imbalanced due to the different incidences of various diseases. To address this problem, many methods have been proposed to synthesize medical images using generative adversarial networks (GANs) to enlarge training datasets for facilitating medical image analysis. For instance, conventional methods such as image-to-image translation techniques are used to synthesize fundus images with their respective vessel trees in the field of fundus image. We propose a new preprocessing pipeline named multiple-channels-multiple-landmarks (MCML), aiming to synthesize color fundus images from a combination of vessel tree, optic disc, and optic cup images. We compared both single vessel mask input and MCML mask input on two public fundus image datasets (DRIVE and DRISHTI-GS) with different kinds of Pix2pix and Cycle-GAN architectures.

Objective

To synthesis retinal image from landmarks of retinal image using Generative adversarial Network

Summary of discussion

We will be training the model in google colab. We are using pix2pix model in the project. Fused images will be used for prediction. Images will be fused using multi-channel fusion using opencv. SSIM and PSNR will be used as evaluation measure (These measures are used to compare Original image and generated image) .

Literature Survey

* Retinal image synthesis from multiple‑landmarks input with generative adversarial networks , Zekuan Yu1 , Qing Xiang2 , Jiahao Meng2 , Caixia Kou2 , Qiushi Ren1 and Yanye Lu3

In this paper, a multiple-channels-multiple-landmarks (MCML) GAN-based fundus image generation method was proposed. As discussed above, we can draw a conclusion that, the architecture of generator and the resolution of paired images, which are two essential properties of GANs, play key roles in generating high-quality image of synthetic fundus images

* End-to-End Adversarial Retinal Image Synthesis , Pedro costa, Adrian galdran

In this work, a generative model capable of synthesizing new vessel networks and corresponding eye fundus images was presented. This model learns the underlying structure of the manifold of plausible retinal images from examples of pairs of vessel networks and eye fundus images . Once trained, it can generate both synthesized vessel networks and retinal images, that are shown to contain rich visual information and to be different from the training examples. The method is capable of generating realistic vessel geometries and retinal image texture, while keeping the global structure consistent.

* Z. Shen, H. Fu, J. Shen and L. Shao, "Modeling and Enhancing Low-Quality Retinal Fundus Images," in IEEE Transactions on Medical Imaging, vol. 40, no. 3, pp. 996-1006, March 2021

In this article, we have proposed a clinically oriented fundus enhancement network, named cofe-Net, to correct low-quality fundus image while preserving accurate lesion areas and retinal structures. Furthermore, a complete degradation model has also been introduced to generate adequate training image pairs. Experiments support our insight into the problems of fundus image correction and degradation factor modeling. Our cofeNet can boost the performance for different clinical tasks, such as vessel segmentation and disc/cup detection. Our method can also assist ophthalmologists in ocular disease diagnosis through retinal fundus image observation and analysis, while also being beneficial to automated image analysis systems

GUI

* GUI will be created using tkinter
* GUI will contain a button to choose fused image
* The generated retinal image will be displayed on the same window

System Model

Stage1

* Data preparation

- Segmenting all images using pre-trained u-net model and retrieve vessel images

- Fusion of optic cup,optic disk and vessel images using image fusion technique

- Create array of retinal images and corresponding fused images

Stage2

* Create discriminator (PatchGAN)

- Convolutional layer

- Batch normalization layer

- LeakyRELU activation layer

- Sigmoid activation layer

* Create generator (U-net)

- Create encoder block

- Create decoder block

- Create U-net based generator using encoder and decoder blocks

* Create GAN model using discriminator and generator

Stage3

* Training GAN model in google colab

- Train GAN model using prepared data

- Save model to local device

* Image generation

- Choose fused image from dataset

- Generate retinal image using trained model

Testing

* Input : Fused image
* Output : Generated retinal image