Retinal Image Generation using GAN

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***Abstract*—The scarcity of fundus images in medical field is a worrying issue as it is important in analysing eye diseases.The existing dataset contains retinal images in which it's important landmark part optic disk and optic eye are unsmooth and blurry which will affect when diseases like galucoma and diabetic retinopathy are assessed.The existing methods only focus on generating retinal images using vessel segmanetation which will give the computer aided diagnosis only a little help in disease diagnosis. Here we are proposing a method to generate retinal images by fusing the three important landmarks of eye which will help us to create a better vessel and optic disc part and building a GAN Model to generate retinal images using this fused image.**

***Index Terms*—Retinal Image, GAN**

I. INTRODUCTION

The ability to generate meaningful synthetic information is highly desirable for many computer-aided medical applications, where annotated data is often scarce and costly to obtain. A wide availability of such data may allow researchers to develop and validate more sophisticated computational techniques. This pressing need for annotated data, particularly images, has largely increased with the advent of deep neural networks, which are progressively becoming the standard approach in most machine learning tasks. The retina is a layered tissue lining the interior of the eye that enables the conversion of incoming light into a neural signal that is suitable for further processing in the visual cortex of the brain.ocular diseases, such as macular degeneration and glaucoma, the first and third most important causes of blindness in the developed world. A number of systemic diseases also affect the retina. Complications of such systemic diseases include diabetic retinopathy from diabetes, the second most common cause of blindness in the developed world.

GANs introduce the concept of adversarial learning, as they lie in the rivalry between two neural networks.Generative adversarial networks (GANs) are a generative model with implicit density estimation, part of unsupervised learning and are using two neural networks. Thus, we understand the terms "generative" and "networks" in "generative adversarial networks".The principle is a two-player game: a neural network called the generator and a neural network called the discriminator. The generator tries to fool the discriminator by generating real-looking images while the discriminator tries to distinguish between real and fake images. During training, the generator progressively becomes better at creating images that look real, while the discriminator becomes better at telling them apart. The process reaches equilibrium when the discriminator can no longer distinguish real from fake images.Thus, if the discriminator is well trained and the generator manages to generate real-looking images that fool the discriminator, then we have a good generative model: we are generating images that look like the training set. After this training phase, we only need the generator to sample new (false) realistic data.

For the proposed solution we are using DRISHTI-GS is a comprehensive dataset of 101 retinal images that include 70 glaucomatous eyes and 31 normal eyes. All the images have the manual segmentations of optic disc and optic cup annotated by four experts. After acquiring the dataset we are using a pretrained U-net Model to segment the vessel images and optic cup and optic disc images.Optic Cup is the bright central part of the optic disc and which is an essential parameter for detecting glaucoma. Compared to the optic disc, the optic cup is smaller in size. For a healthy patient, the optic cup shape is one-third of the optic disc. If the size of the optic cup increases than the standard size, it leads to glaucoma.Vessel images , optic cup and optic disc images are then fused using multi channel fusion to create a numpy array of fused images.A pix2pix model is used in our method to build GAN architecture.Unet architecture with encoder and decoder block is used in it's generator block which will help in improving training speed and accuracy. A patchGAN is used in the discriminator block which is used to identify and classify the images as patches in images.Then GAN model images and fused images are combined to generate realistic fundus images.we will be training the model in google colab.SSIM and PSNR will be used as the evaluation metrics.

The output of our proposed method will be a GAN Model which will be able to generate clear quality fundus image from the given input fused image.The optic disc and cup part of the generated fundus image will be clear and sharp which will help to analyze the image for various diseases.

II. LITERATURE SURVEY

Previously, researches have been performed on Retinal Image synthesis and most of them use Generative adversarial networks. Papers that deal with high accuracy and reliable fundus synthesis systems have been chosen and their advantages and drawbacks have been analysed. In [1], a multiple-channels-multiple-landmarks (MCML) GAN-based fundus image generation method was proposed.Two types of GANs were implemented in this work for comparison studies. One is the Pix2pix model that learns a generator from an image A to an image B. The other model is Cycle-GAN, which is good at realizing image-to image translation tasks by unpaired datasets. The goal is to learn two generators G1 and G2 from image A to B and image B to A, respectively. The results demonstrate that pix2pix model MCML method has superior performance compared to the fundus image generated from only vessel tree input. The synthesized images using the proposed method are realistic in look and contain more details, demonstrating better image quality.

paper [2] proposes a method for generating fundus images based on "Combined GAN" (Com-GAN), which can generate both normal fundus images and fundus images with hard exudates, so that the sample distribution can be more even, while the fundus data are expanded.In the first stage, an image segmentation technique is used to segment a vascular tree from the existing fundus image set, and an im-WGAN is trained based on the segmented vascular tree. In the second stage, based on the vascular tree segmented from the real image and the corresponding complete fundus image, a vascular tree-complete fundus image pair is formed to train the im-CGAN proposed in this paper. Based on the expanded vascular tree image set, the trained im-CGAN generator is then used to generate a complete fundus image pair.The generated fundus images are added to the existing fundus image set to further expand the fundus datasets.

In [3], 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. In [4]], they propose a retinal image enhancement method, called CycleCBAM, based on CycleGAN to realize the migration from poor quality fundus images to good quality fundus images. It does not require paired training set any more, that is critical since it is quite difficult to obtain paired medical images. In order to solve the degeneration of texture and detail caused by training unpaired images, they enhance the CycleGAN by adopting the Convolutional Block Attention Module (CBAM). Cycle-CBAM method can not only restore the image with poor illuminance, but also restore the color of the blurry area for the blurry fundus image.

Retinal Image Analysis (RIA) aims help clinicians with the diagnosis of diseases such as diabetes, glaucoma and cardiovascular conditions. In [5] approach consists of a learning phase and a generation phase. In the Learning phase, data describing vascular morphology and texture are collected from annotations of real images. Models are specified and their parameters learned from the training data. In the generation phase, the models obtained are used to create synthetic vascular networks. The two vascular trees obtained, one for the arteries and one for the veins, are combined together and superimposed on synthetic backgrounds to create complete synthetic fundus camera images. High-Resolution Fundus (HRF) images database and retinal images of the GoDARTS bioresource are used.

III. System Architecture

The Architecture of this proposed system consists of mainly three parts. A) Retina Vessel Segmentation B) Fusion and Training of GAN

A. Retina Vessel Segmentation

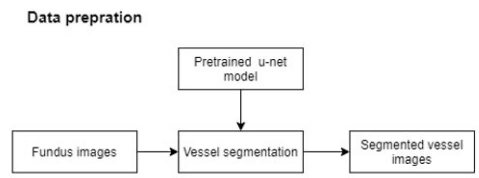

Fig. 1. Vessel Segmentation

Data Preparation includes collection of data and segmentation of vessel,cup and disc images from it for multi channel fusion purpose.The proportion of thin blood vessels in a retina image is small. So in the deep learning method, the misclassification or omission of some thin vessel pixels does not greatly affect the segmentation accuracy, but it leads to unsatisfactory segmentation maps, which causes the network to pay more attention to segment thick vessels than thin vessels. Here we use a pre-trained unet model to segment vessel images.

B. Fusion and Training of GAN

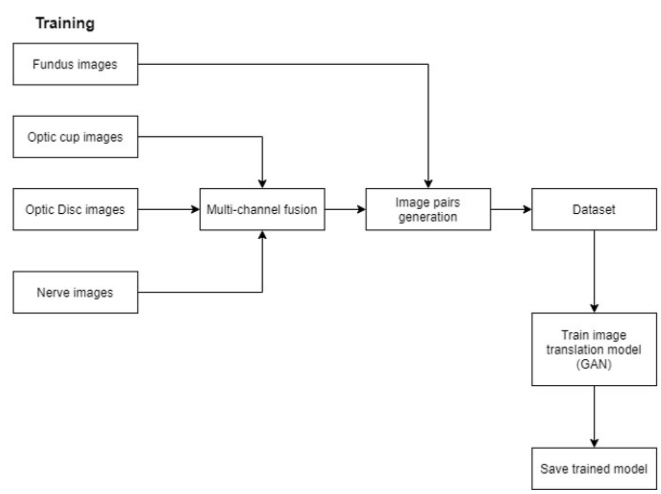

Fig. 2. Training

Three Landmarks of retinal image that is optic disk, optic cup and vessel images are then merged to create our fused image which is to be given as the input source image for gan training.In Gan training Generator and discriminator are created to train the GAN model. We keep the generator constant during the discriminator training phase. As discriminator training tries to figure out how to distinguish real data from fake, it has to learn how to recognize the generator's flaws. That's a different problem for a thoroughly trained generator than it is for an untrained generator that produces random output.Similarly, we keep the discriminator constant during the generator training phase. Otherwise the generator would be trying to hit a moving target and might never converge.It's this back and forth that allows GANs to tackle otherwise intractable generative problems.

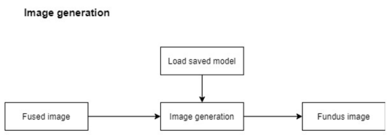

Fig. 3. Image generation

IV. Model Building

GANs are a clever way of training a generative model by framing the problem as a supervised learning problem with two sub-models: the generator model that we train to generate new examples, and the discriminator model that tries to classify examples as either real (from the domain) or fake (generated). The two models are trained together in a zero-sum game, adversarial, until the discriminator model is fooled about half the time, meaning the generator model is generating plausible examples.

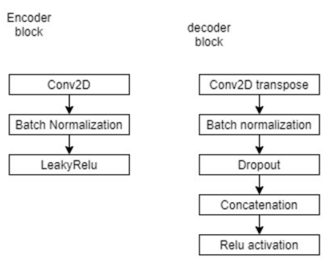

Fig. 4. Generator model

Generator model is created using U-net architecture which consist of encoder decoder block.U-Net is an architecture for semantic segmentation. It consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolutional network.Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU.

The PatchGAN discriminator used in pix2pix is another unique component to this design. The PatchGAN / Markovian discriminator works by classifying individual (N x N) patches in the image as "real vs. fake", opposed to classifying the entire image as "real vs. fake". discriminator works here as a binary classification CNN model.

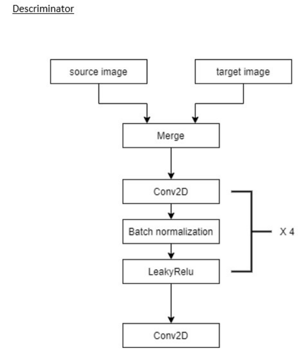

Fig. 5. Discriminator model

After defining generator and discriminator model, we load our dataset and unpack arrays. we generate real and fake samples to train the discriminator model.The number of iteration is determined by taking the product of batch size and the number of epochs.as the training progress we update the discriminator and generator model and save the GAN model.

V. Result

In Fig.6 we can see our input image that is the fused image and our generated and expected image.The generated image is almost as good as the expected image with our landmarks generating better colour and texture consistent result.The average PSNR and SSIM Values of our images are 0.872 and 24.155 respectively which is a decent quality measurement.

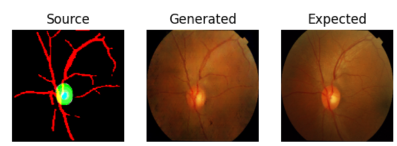

Fig. 6. Source, generated and expected Image

Conclusion and Future Scope

We were able to create a GAN Model that could generate synthetic retinal images demonstrating better image quality with the help of multi channel fusion method. The benefit we see in this system is that the optic cup and dick region of generated image is clear and smooth which helps in identification of different eye diseases.In future work, we can create abundant retinal images by only giving fused retinal images as input.

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