Blood Vessel Segmentation in Retinal Images Using Convolutional Neural Networks

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ABSTRACT

Extracting the vasculature is a crucial process in the automated identification of retinal disorders. Despite numerous methods suggested for blood vessel segmentation, many of them struggle with accurately segmenting delicate blood vessels due to their reliance on low-level spatial information or their tendency to produce false positives at the extremities of vessel branches. Intermittent instances of excessive division and insufficient division are leading to inaccurate outcomes when measuring the breadth of blood veins in quantitative research. The suggested blood vascular segmentation approach demonstrates highly favorable outcomes, achieving a dice coefficient of 0.84 on the STARE database and 0.844 on the DRIVE database.

Index Terms – Image analysis, GANs, Blood Vessels, Neural Networks

1. INTRODUCTION

The study of blood vessel map of retinal images provide symptomatic and systematic information in Diabetic Retinopathy analysis and eye problems that arise due to hypertension. Apart from diabetic retinopathy many vision threatening vascular diseases such as Artery and Vein Occlusion can be early detected by analyzing vascular structure that are extracted from retinal images. The proposed method will assist automated retinal image analysis. Vast literature is available on retinal blood vessel extraction.

Across the strata over the years the problem of blood vessel extraction using many computer vision algorithms are assumed that the vessels possess particular shape and structure, accordingly many algorithms are developed. Line and edge detection using filters, 2-D filters, usage of manually segmented ground truth images along with some heuristic techniques [1-6] are underlying operations in most of these methods. With the advancement in Artificial Intelligence and many machine-learning based methods extracted vasculature in more efficient manner. A technique known as gradient boosting and Conditional Random Field (CRF) [7-8] with structured SVM are used to extract features automatically. In recent years, a usage of Convolutional Neural Networks (CNNs) in computer vision applications has gained acceleration and is producing remarkable results. Several studies have indicated that blood vessel extraction using CNNs shown improved performance even with respect to manual segmentation [9].The application of Generative Adversarial Network (GAN) will provide a cutting edge method to overcome the limitation in the extraction of blood vessels. The extraction of vasculature can be treated as image translation task [10]. Here an segmented vessel is obtained from input retinal images where extracted vessel maps are constrained to retain all the sharper and clearer features of vessel maps of human experts.

The proposed framework using GANs has two networks namely discriminator and generator. The basic functionality of generator is to generate out vessel maps for a given input retinal image whereas discriminator tries to discriminate output images of generator from manually segmented gold standard images. When the generator is constrained it produces almost identical images as gold standard the discriminator cannot differentiate output images from gold standard one. The proposed method uses GANs to segment blood vessels in retinal images. With the advent of GANs the proposed method can detect faint blood vessels with few false positives.

2. PROPOSED METHOD

This section includes all the structural details of the proposed method.

2.1 Architecture

The proposed blood vessel segmentation uses GAN's (see Fig.1) where the generator structure generates probability map(with probabilities between 0 to 1) of vessels for each given input image. The size of probability map is same as original image. Probabilities are indicators of each pixel corresponding to a blood vessel. This vessel map and input image are given to discriminator network. The discriminator has to identify whether this vessel map is exactly same as gold standard or not. In other words it tells whether image is generator output or gold standard image. The proposed model is depicted in Fig. 1.

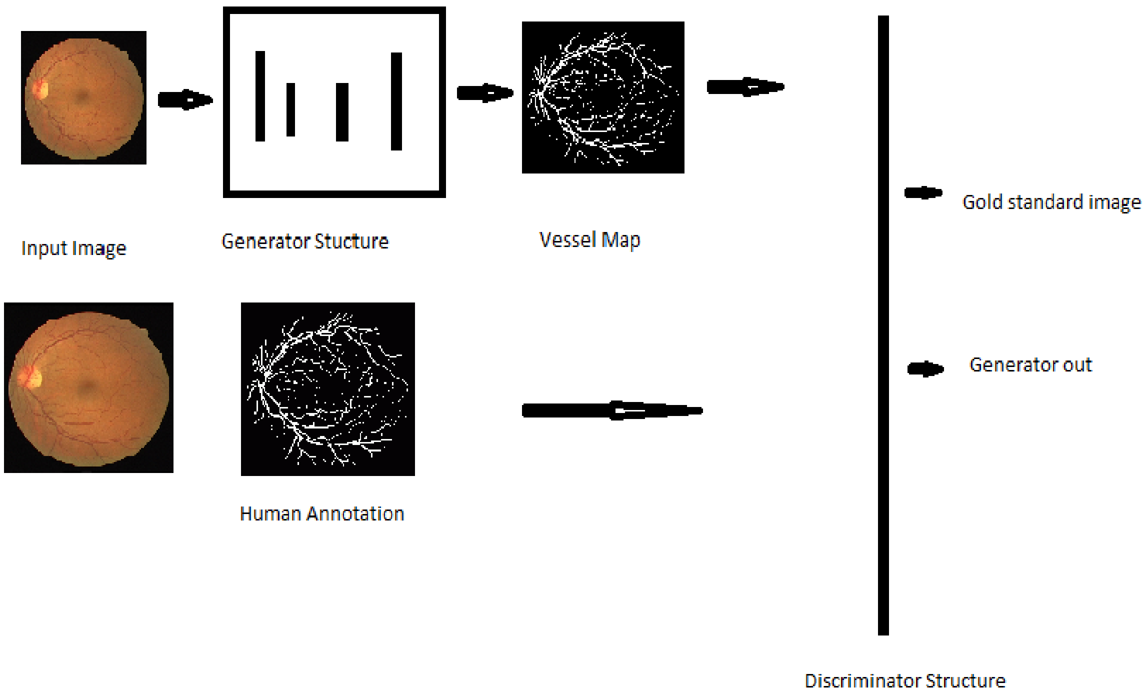


Fig 1: Illustration of Proposed Framework for Blood vessel segmentation

The generator is built on ideas of U-net [12]. In U-net the feature maps from initial convolution layers are connected to unsampled layers in skip-connected [9] fashion which maintains low-level features. The edges and blobs are usually belonging to low level features, which can be exploited in accurate segmentation. To roll out the discriminator in the proposed method several models have been tested and finally incorporated based on the outcomes in [11]. The generator and discriminator are supposed to fight with each other before discriminator identifying best vessel map. In the proposed GAN method, each pixel will be authenticated by the discriminator and image level judgment is performed by image GAN.

Description of Objective Function

The training process of both generator and discriminator network is performed in such a way that the discriminator has to produce best possible prediction. A proper error or cost function has to be selected in order to update the weights of the network to improve the performance. It is obvious that if the error is large then the network is not doing well, the prediction is bad hence error has to be reduced. The error function that is used to train the GANs is LOG loss function. To get better understanding assume z as input feature to network, G(z) generator output and D(G(z)) is final prediction. The label D(G(z)) must be '1' if generator output is exactly same as manually annotated gold standard image and it will be zero if both are opposite..A reliable generator network always produces a probability map that is close to that one of gold standard images. Therefore a generator network always want connections in such a way that the label produced by discriminator close to one, The error function at generator and discriminator are defined as

$$E_G = -\left(\ln(D(G(z)))\right) \qquad (1)$$

and

$$E_D = -\left(\ln(1 - D(G(z)))\right) \qquad (2)$$

The derivatives of these two functions with respect to weights will help to update weights in order to improve prediction. The GAN uses segmentation loss and an objective loss and a final objective function[11] is defined as

$$G^* = \arg\min_G \left[\max_D E(G,D)\right] + \lambda L_{SEG}(G) \qquad (3)$$

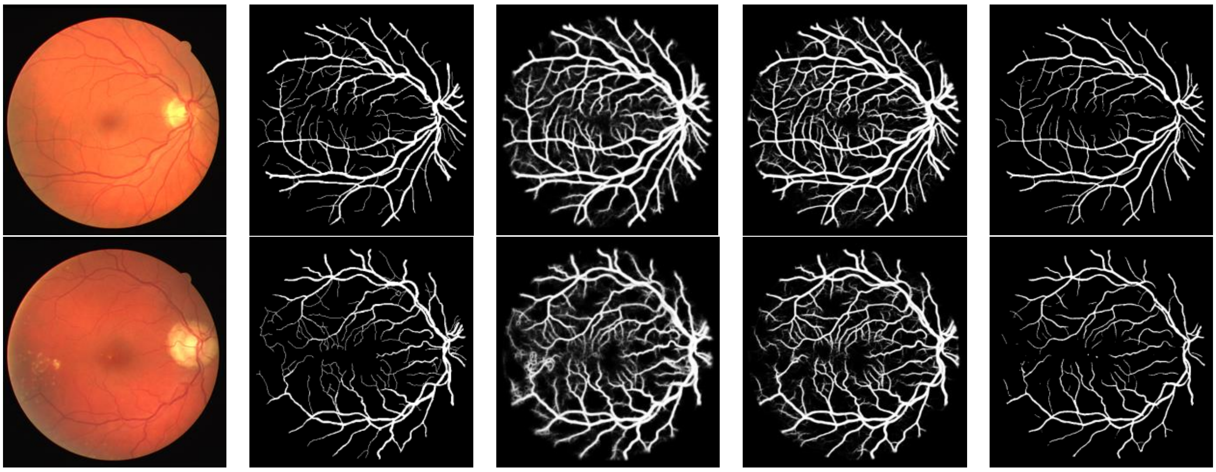
3. EXPERIMENTS

Experimental Setup

The present algorithm is tested on twenty images of two publicly available databases namely DRIVE and STARE. Keras library functions with tensorflow backend are used for implementation. From STARE database 13 images are used for training and 7 images are used for testing. The red, green and blue channels are of each image is first normalized to z-score. Then every image is augmented with rotation and right-left flips. Now these augmented images are divided into training and testing validation sets at a rate of 10:1. An ADAM optimizer with β= 0.4 is used. To implement objective function as given in equation 3 the parameter λ is fixed at 10 and finally the learning rate is selected as 2e-5. The proposed setup is evaluated using area under ROC, area under curve for precision and dice coefficient.

Results

The segmented blood vessels of the proposed method for an image from DRIVE database is presented in Fig.2. For the comparison purpose results for 4 other images from DRIVE dataset is incorporated in Fig 2.



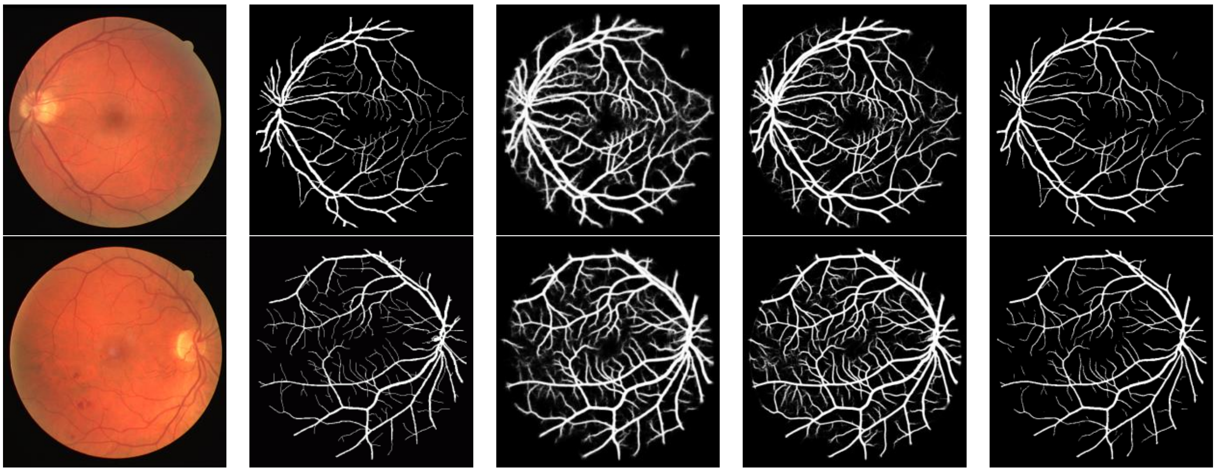


Fig. 2. Segmentation results. The first column has original color retinal images from DRIVE

To compare the performance of proposed method, the results from DRIU [8] and HED [13] are also presented in Fig 2. Further, the proposed method is evaluated using parameters like area under ROC (AUC), area under precision curve(APC) and dice coefficient. The evaluated parameters for various methods along with proposed method are tabulated in Table 1.These results confirm that our method out performs not only other methods but also ability of manual segmentation of DRIVE database.

The images in second column indicate gold standard images obtained from Ist manual segmentation. The 3rd and 4th column images represent the segmentation results from DRIU[8] and HED methods. The results of proposed method are incorporated in 5th column. The segmentation results clearly indicate that the proposed method fare better in reducing false positives while faint blood vessels are taken care of properly.

Table 1: Perfomnce Indicators on DRIVE dataset

Model	AUC	PUC	DICE
DRIU[8]	0.943	0.803	0.832
HED[13]	0.931	0.780	0.768
Human Segmentation	0.967	0.813	0.838
Proposed Method	0.971	0.625	0.844

4. CONCLUSIONS

This paper introduces an efficient method using neural networks to segment blood vessels in retinal images. Essentially this method uses a model known as Generative Adversarial Networks which encompasses a network known as discriminator. As indicated by results the discriminator accurately segment blood vessels and more clearly compared to other models. The method also results in very few false positives when compared to other state-of-art methods.

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