Optic Disc and Cup Segmentation using Ensemble Deep Neural Networks

Pengshuai Yin[1], Guanghui Xu[1], Jingwen Wang[1], Yuguang Yan[1], Huaqing Min[1], Qingyao Wu[1], and Mingkui Tan[1]

South China University of Technology, Guangzhou, China

Abstract. We propose an ensemble network for optic disc and cup segmentation. The ensemble network consist of 8 different networks such as Mask-RCNN, M-Net etc. For each network, we use different data augmentation methods such as dehazing and multiscale detail manipulation. Each network learns different aspects of the data. Then we design a voting algorithm to combine the results of these models. Our final result achieves dice optic disk/cup:0.95/0.86. The MAE-CDR is 0.057. The result is without any postprocessing steps such as ellipse fitting or conditional random field.

1 Introduction

Retinal fundus photographs have been widely used by clinicians to diagnose glaucoma which is the second leading cause of irreversible blindness worldwide [23]. Early screening and classification of glaucoma is quite important for preserve vision. To diagnose glaucoma in retinal fundus images, some clinical measurements are proposed, such as the vertical cup to disc radio(CDR) [18], disc diameter [16] and rim to disc area ratio (RDAR). CDR is the common choice for clinicians. For normal eyes, CDR is 0.3 to 0.4. A larger CDR may indicate glaucoma. In order to calculate CDR automatically, we need to segment the optic disc(OD) and optic cup(OC) in fundus image.

A lot of research has been done for optic disc and cup segmentation. These research can be generally classified as template based methods [31, 3, 9], deformable based methods [19, 25, 20, 30, 29, 22], pixel classification based methods [2, 24, 28], label transfer based methods [26], superpixel based methods [11, 27, 10] and deep neural network based methods [6, 7, 15, 14, 32]. Among them, the state of the art method is M-Net [14]. M-Net use multi-scale information along with side-output.

Our method focus on the segmentation of OD and OC in fundus images. The motivation of our method is to use ensemble methods. Ensemble methods are learning algorithms that construct a set of classifies and classify new data points by by taking a weighted vote of their predictions. Ensembles can often perform better than any single classifier [12]. Many methods for constructing ensembles have been developed. Our basic idea for constructing ensembles is to manipulating the training set. The most straightforward way of manipulating the training set is called Bagging [5]. Bagging presents the learning algorithm with a training set that consists of a sample of m training examples drawn randomly with replacement from the original train set of m items. Such a training set is called a bootstrap replicate of the original training set, and the technique is called bootstrap aggregation. Motivated by the idea of Bagging. We divide the training dataset into several parts. We use different image preprocessing methods on each part and train a convolutional neural network for each part. The final segmentation is got by a weighted vote of each network.

The main contribution of our work is we proposed a ensemble deep neural network using Bagging. Our ensemble network is train on ORIGA and REFUGE dataset [1].

2 Proposed Method

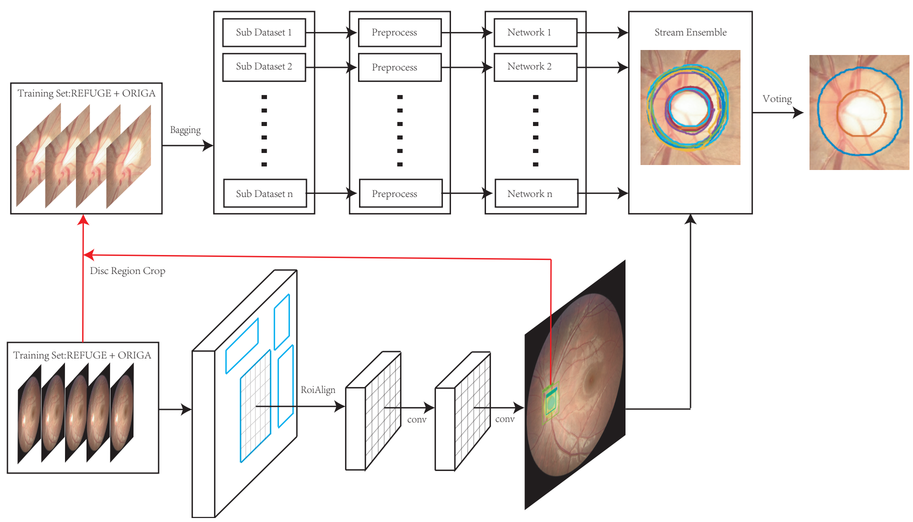

Fig. 1. Pipeline for segmentation. First, we train a MASK-RCNN to extract the region of interest. Then the dataset is divided into several parts. We use different image preprocessing technique for each part and we train a neural network for each part. The result for all the networks are ensembled and we vote the result to get the final prediction

Our pipeline is shown in Fig. 1. The design is based on the idea of ensemble learning and bagging. We ensemble different networks and voting for final result.

The first step is to localize the optic disc and cup. Mask-RCNN [17] is framework that can localize and segment simultaneously. We use Mask-RCNN to locate and segment OD and OC. After the localization, we crop the disc region to build a new training dataset. Then we divide the training set into n part. We use different image preprocessing method for each part and we train a network for each part. The final result is a voting of all the part.

2.1 Image Preprocessing

We use different image preprocessing techniques fo r different networks. The techniques we used are haze removing and multiscale detail manipulation.

Haze Removeing. The goal of image dehazing is to remove some of the effects of atmospheric absorption and scattering. For fundus image, haze could happen because a cataract in human lens will attenuate the retinal image. A cloudy camera lens also reduces the quality of image. Haze often obscures important details of optic disc and cup. Dehazing can achieve more accurate optic cup segmentation [8]. We use nonlocal dehazing [4] to preprocess the image. We use the official implementation of [4]. The implementation could be obtained from http://github.com/danaberman/non-local-dehazing.

Multiscale Detail Manipulation. Multiscale detail manipulation(MDM) [13] enhances an image by boosting features at multiple scales. [13] utilizes edge-preserving multiscale image decomposition based on the weighted least squares optimization. We decompose **CIELAB** lightness channel into three-levels:coarse-scale, medium-scale and fine-scale. We use the the average image to train the network.

2.2 Ensemble networks

Our ensemble network compose 8 different networks. Each with different image preprocessing step. The ensembles are shown in table.1.

Table 1. Our ensemble networks

Baseline Structure	Dataset	Image Preprocessing	Pretrained model
U-Net[21]	Origa	None	From scratch
U-Net[21]	Reguge	Dehazing	From scratch
U-Net[21]	Reguge	MDM	From scratch
M-Net[14]	Origa	None	From scratch
M-Net[14]	Reguge	Dehazing	From scratch
M-Net[14]	Reguge	MDM	From scratch
Mask-RCNN-ResNet101[17]	Origa+Refuge	Dehazing+MDM	Micosoft COCO
Mask-RCNN-ResNet101-inception[17]	Origa+Refuge	Dehazing+MDM	Micosoft COCO

2.3 Voting

We vote the final result for segmentation. The first step is to remove the noise point. Some models successfully segment the area in some images while others make wrong segmentation in some images. We calculate the mean and valiance of the boundary points to judge the wrong prediction. Then the final vote is done by calculate the 80 percent overlap area of all the model.

3 Experiments and Discussion

We test our pipeline on REFUGE competition. The training set of REFUGE contains 400 images. The training and validation dataset is acquired from two different machines. They have domain shift. Our ensemble method is a simple idea to deal with domain shift. This is because ensemble methods learn different parameterizations of the source domain. The combination is good compare to use one parameterization only.

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