NEURAL NETWORK BASED EFFICIENT GLAUCOMA DETECTION USING DENET

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ABSTRACT: Glaucoma is a chronic eye disease that leads to irreversible vision loss. The cup to disc ratio (CDR) plays an important role in the screening and diagnosis of glaucoma. Thus, the accurate and automatic segmentation of optic disc (OD) and optic cup (OC) from fundus images is a fundamental task in now a days biomedical applications. Biomedical application with image processing technology plays an important role in now a days. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth.

KEYWORDS: Glaucoma, cup to disc ratio, optic disc, Optical Nerve, Deep learning,

INTRODUCTION:

Automated Image analysis and processing is of great significance in early detection, screening and treatment planning of various retinal, ophthalmic and systemic disease especially because if its non-invasiveness [5] . Precise detection and accurate analysis of ophthalmic pathologies for timely treatment is essential in preventing vision loss. The development of Computer Assisted Diagnostic (CAD) systems for assisting the clinicians in diagnosis and prognosis of retinal diseases has a vital role in improving the healthcare, particularly in the developing countries with shortage of professional ophthalmologists [6]. Accurate localization and precise segmentation of Optic Disc (OD) is the first step in developing CAD systems for early detection of ophthalmic diseases like Glaucoma and diabetic retinopathy. Glaucoma is causing visual loss and blindness around the globe at second highest rate. The Glaucoma patients are mostly ignorant at early stages about the affects until visual loss progress and over the 5-year period, damage to optic nerve fiber increases to 63% [10]. Glaucoma is characterized by the change in color, shape and depth of OD. The presence of parapapillary atrophy produces bright regions around the OD rim distorting the elliptical shape [6]. Moreover, the progression in optic nerve fiber damage causes the structural changes in OD, optic nerve head and nerve fiber layer which results in an increase in Optic Cup to Disc ratio (CDR). The CDR can be accessed by estimating the diameter and the area of OD, the area of rim and Optic Cup diameter. The accurate and fast OD segmentation and analysis is the first step towards the development of computer assisted diagnostic system for Glaucoma screening in large population based studies. DR is an eye disease which causes complications due to enormous level of glucose in blood of diabetic patients. Diabetic Macular Edema (DME) is commonly associated with DR which causes the swollen retina by fluid leaking in macular blood vessels. The number and position of exudates relative to fovea in retina can be assessed to find the risk of future disease development. This step needs the accurate identification of landmark features in fundus images such as the Optic Disc.

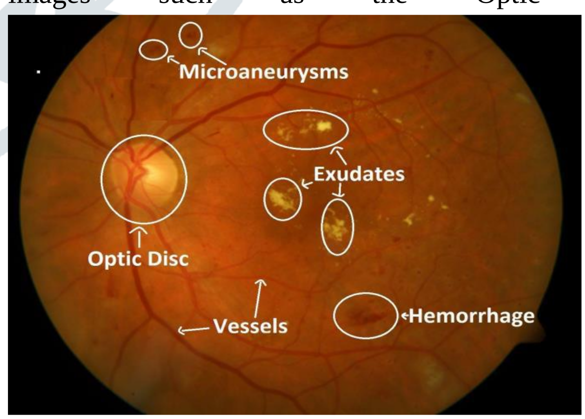

Figure-1: Retinal image features

Deep convolutional neural networks [2, 1] have led to a series of breakthroughs for image classification [2, 5, 4]. Deep networks naturally integrate low/mid/highlevel features [50] and classifiers in an end-to-end multilayer fashion, and the "levels" of features can be enriched by the number of stacked layers (depth). Recent evidence[1, 4] reveals that network depth is of crucial importance, and the leading results [4]on the challenging ImageNet dataset [36] all exploit "very deep" [41] models, with a depth of sixteen [4] to thirty [1].

LITERATURE SURVEY:

The problem of optic nerve detection has rarely received unique attention. It has been investigated as a precursor for other issues, for example as identifying a starting point for blood vessel segmentation [1,2]. It has also been investigated as a byproduct of general retinal image segmentation, for instance into separate identifications of arteries, veins, the nerve, the fovea, and lesions [1,6,12]. Here we review these related works.

In [12] a method is presented to segment a retinal image into arteries, veins, the optic disk, the macula, and background. The method is based upon split-and-merge segmentation, followed by feature based classification. The features used for classification include region intensity and shape. The primary goal of the paper was vessel measurement; the nerve was identified only to prevent its inclusion in the measurement of vessels. Ten healthy retinas and ten retinas with arterial hypertension were used for experiments. Quantitative results for nerve detection were not provided. A similar approach was taken in [6], in which the segmentation was accomplished using matched spatial filters of bright and dark blobs. Quantitative results for nerve detection were not provided.

In [7] a method is presented to segment a retinal image into vessels, the nerve, the fovea, scotomas, and subretinal leakages. Nerve detection is based upon the transform of gradient edges into a Hough space describing circles. The search is restricted to one-third of the image based upon apriori knowledge of the expected general location of the nerve. Eleven retinas with age-related macular degeneration (ARMD) were used for experiments. In 10 out of 11 cases, the nerve was successfully detected.

In [1] a method is presented to segment a retinal image into arteries, veins, the optic disk, and lesions. Nerve detection is based upon tracking the vessel network to a common starting point. The tracking process uses the angles between vessels at branch points to identify the trunk. A result is shown for two images; quantitative results were not provided.

DISC-AWARE ENSEMBLE NETWORK (DENET)

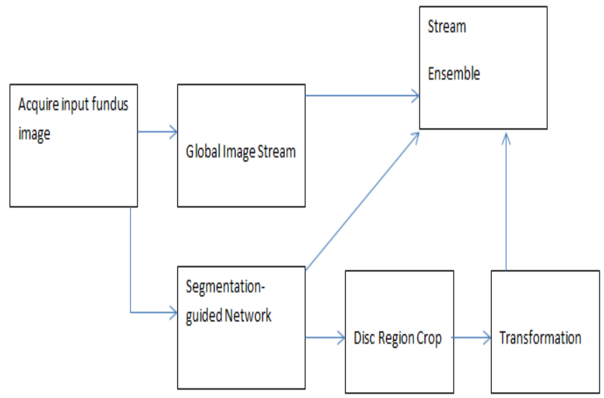

Figure-2: Proposed block

Our Disc-aware Ensemble Network (DENet) takes into account two levels of fundus image information, that is the global image and the local disc region, as shown in below Fig.. The global image level provides the coarse structure representation on the whole fundus image, while the local disc region is utilized to learn a fine representation around the optic disc.

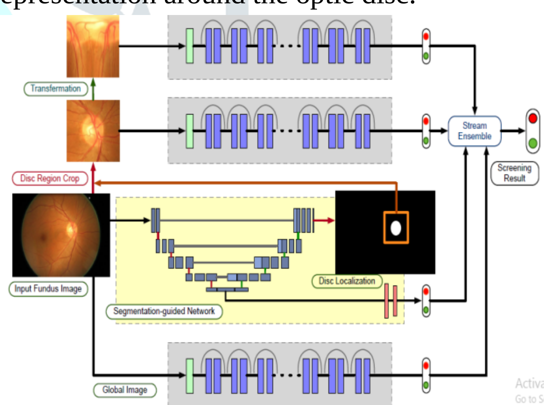

Fig-3: Architecture of our DENet

FUNDUS IMAGE LEVEL:

In our DENet, two streams are employed to learn representations on the global fundus image level. The first stream is a standard classification network by using Residual Network (ResNet) [3]. The ResNet is based on a Convolutional Neural Network and introduces the shortcut connection to handle the vanishing gradient problem in very deep networks, as shown in Fig-3 We utilize a ResNet-50 as the backbone modelto learn the global representation on the whole fundus image directly, which consists of 5 down-sampling blocks, followedby a global max pooling layer and a fully connected (FC) layer for glaucoma screening The input image of this stream is resized to 224_224 to enable use of pre-trained model in [4] as initialization for our network.The second global level stream is the segmentation-guided network, which localizes the optic disc region and produces a detection result based on the disc-segmentation representation. As shown in Fig. 3 the main architecture of the segmentation-guided network isadapted by the U-shape convolutional network (U-Net) in [3], which is an efficient fully convolutional neural network for biomedical image segmentation. Similar to the original U-Net architecture, our method consists of the encoder path (left side) and decoder path (right side). Each encoder path performs convolutional layer with a filter bank to produce a set of encoder feature maps, and the element-wise rectified-linear non-linearity (ReLU) activation function is utilized. The decoder path also utilizes the convolutional layer to output the decoder feature map. The skip connections transfer the corresponding feature map from encoder path and concatenate them to up-sampled decoder feature maps. Finally, a classifier utilizes 1 _ 1 convolutional layer with Sigmoid activation as the pixel-wise classification to produce the disc probability map. Moreover, we extend a new branch from the saddle layer of the U-shape network, where the size scale is the smallest (i.e., 40_40) and the number of channel is the highest (i.e., 512-D). The extended branch acts as an implicit vector with average pooling and flatten layers. Next it connects two fully connected layers to produce a glaucoma classification probability. This pipeline embeds the segmentation-guided representation through the convolutional filters on decoder path of the U-shape network.

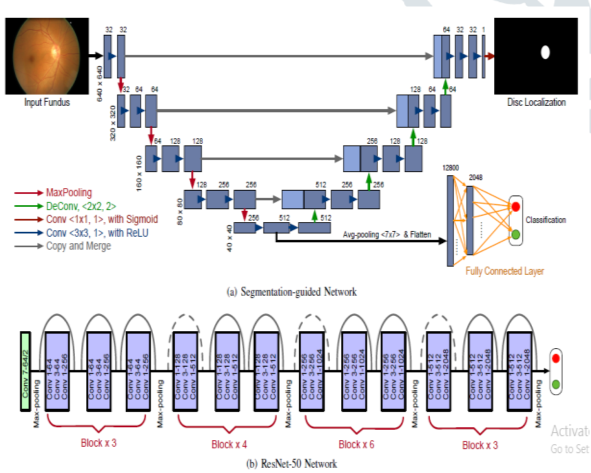

Fig-4: (A) The detailed architecture of our segmentation-guided network

In our global fundus image level networks, two loss functions are employed. The first one is the binary cross entropy loss function for glaucoma detection layer. The other is the Dice coefficient for assessing disc segmentation [12], which is defined as:

$$L_{Dice} = 1 - \frac{2\sum_i^N p_i g_i}{\sum_i^N p_i^2 + \sum_i^N g_i^2},$$

where N is the pixel number, pi 2 [0; 1] and gi 2 f0; 1g denote predicted probability and binary ground truth label for disc region, respectively. The Dice coefficient loss function can be differentiated yielding the gradient as:

$$\frac{\partial L_{Dice}}{\partial p_i} = \frac{4p_i \sum_i^N p_i g_i - 2g_i(\sum_i^N p_i^2 + \sum_i^N g_i^2)}{(\sum_i^N p_i^2 + \sum_i^N g_i^2)^2}.$$

These two losses are efficiently integrated into backpropagation

via standard stochastic gradient descent (SGD). Note that we use two phases for training the segmentationguided model. Firstly, the U-shape segmentation network for disc detection is trained by pixel-level disc training data with Dice coefficient loss. Then the parameters of CNN layers are frozen and the fully connected layers for the classification task are trained by using glaucoma detection training data. We use the separate phases to train our segmentation-guided model instead of the multi-task based single stage training, with the following reasons: 1) Using the disc-segmentation representation on screening could add diversity of the proposed network. 2) The pixel-level label data for disc segmentation is more expensive than image-level label data for glaucoma detection. The separate stage could employ different training datasets and configuration (e.g, different batch sizes and image numbers). 3)

OPTIC DISC REGION LEVEL:

The second level in our network is based on the local optic disc region, which is cropped based on the previous segmentation-guided network. The local disc region preserves more detailed information with higher resolution and it is benefited to learn a fine representation. Two local streams are used in our network to learn representations on the local disc region. In our method, we apply the pixel-wise polar transformation to transfer the original image to the polar coordinate system. Let p(u; v) denote the point on the original Cartesian plane, and its corresponding point on polar coordinate system is denoted p0(_; r), as shown in Fig. 4, where r and _ are the radius and directional angle of the original point p, respectively.

Three parameters are utilized to control the polar transformation: the disc center O(uo; vo), the polar radius R, and the polar angle _. The polar transform mapping is

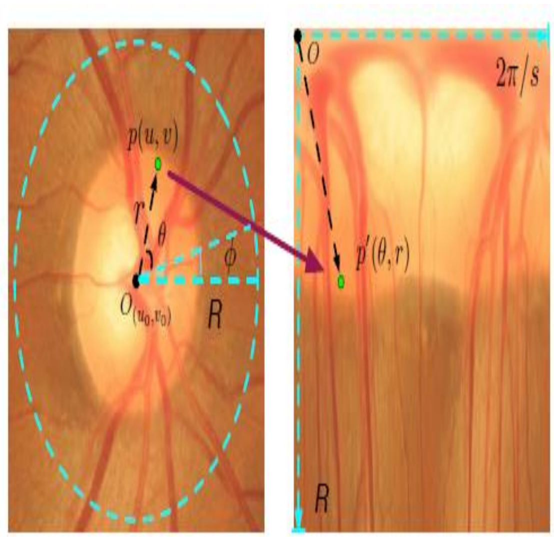

Fig-5:. Illustration of the mapping from Cartesian coordinate system

$$\begin{cases} u = u_o + r\cos(\theta + \phi), \\ v = v_o + r\sin(\theta + \phi), \end{cases}$$

$$\begin{cases} r = \sqrt{(u - u_o)^2 + (v - v_o)^2}, \\ \theta = \tan^{-1}(\dfrac{v - v_o}{u - u_o}) - \phi. \end{cases}$$

The height and width of polar image are set as the polar radius R and discretization 2_=s, where s is the stride. The disc polar transformation has the following advantages:

1) Since the disc and cup are structured as near concentric circles shape. The polar transformation could enlarge the cup region by interpolation. The increased cup region displays more details. As shown in Fig. 4, the proportion of cup region is increased and more balanced than that in original fundus image.

2) Due to the pixel-wise mapping, the polar transformation is equivariant to the data augmentation on the originalfundus image [33]. For example, moving the transformation center O(uo; vo) corresponds to the drift translation in polar coordinates. Using different polar radius R is the same as augmenting with various scaling factor. And changing the polar angle _ will shift in horizontal coordinate in the image. Thus the data augmentation of deep learning can be done by using the polar transformation with various parameters.

MORPHOLOGICAL IMAGE PROCESSING:

Binary images may contain numerous imperfections. In particular, the binary regions produced by simple thresholding are distorted by noise and texture. Morphological image processing pursues the goals of removing these imperfections by accounting for the form and structure of the image. These techniques can be extended to greyscale images.

BASIC CONCEPTS

Morphological image processing is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

CONVOLUTIONAL NEURAL NETWORKS :

Convolutional neural networks. Sounds like a weird combination of biology and math with a little CS sprinkled in, but these networks have been some of the most influential innovations in the field of computer vision. 2012 was the first year that neural nets grew to prominence as Alex Krizhevsky used them to win that year's ImageNet competition (basically, the annual Olympics of computer vision), dropping the classification error record from 26% to 15%, an astounding improvement at the time. Ever since then, a host of companies have been using deep learning at the core of their services. Facebook uses neural nets for their automatic tagging algorithms, Google for their photo search, Amazon for their product recommendations, Pinterest for their home feed personalization, and Instagram for their search infrastructure.

RESULT:

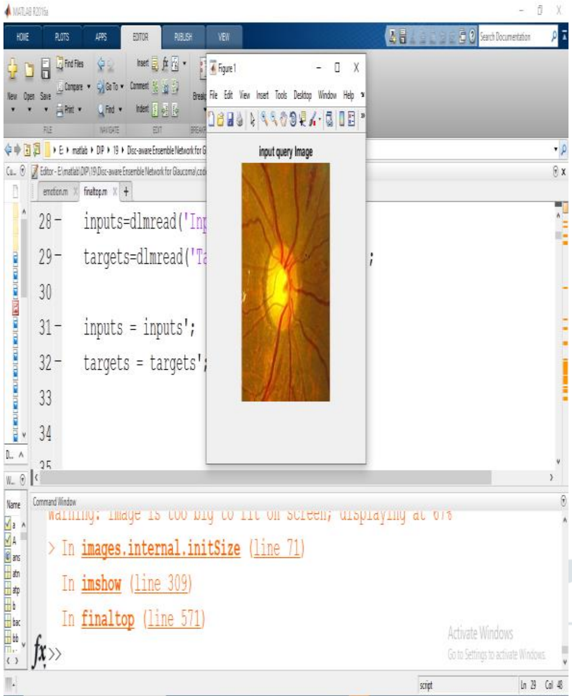

Fig-6: Input image

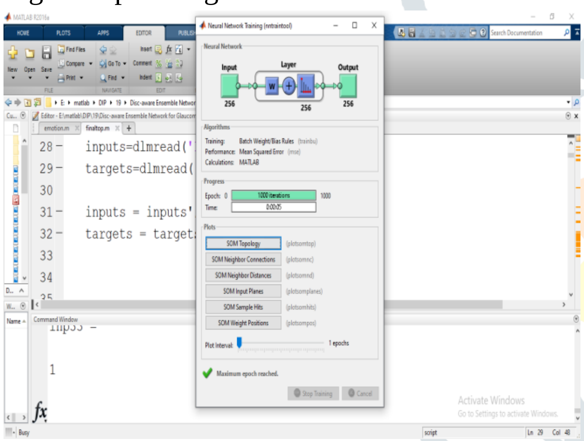

Fig-7: Neural Network architecture plot

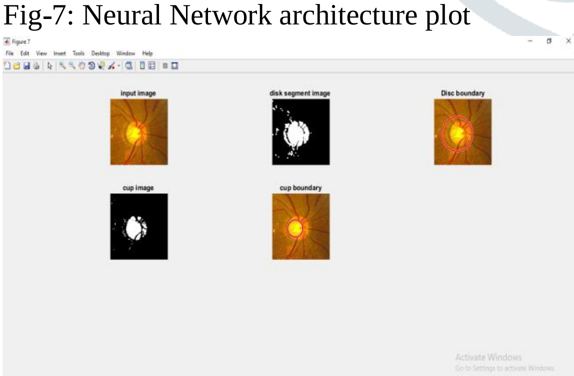

Fig-8: Classification Results

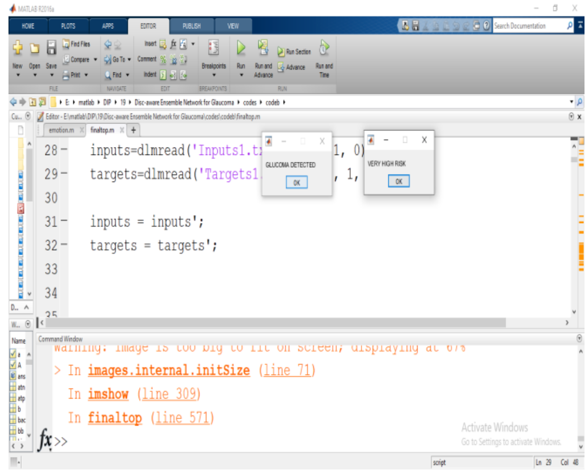

Fig-9: Final results

CONCLUSION:

Glaucoma is kind of eye disease which leads to damage of optic nerve and vision loss. It is asymptotic in the beginning but eventually leads to loss of vision, if untreated. Finally, this project proposed a novel Disc-aware Ensemble Network (DENet) for automatic glaucoma screening, which integrates four deep streams on different levels and modules. The multiple levels and modules are beneficial to incorporate the hierarchical representations, while the disc-aware constraint guarantees contextual information from the optic disc region for glaucoma screening.

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