RETINAL BLOOD VESSEL SEGMENTATION CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

Separation of the Retinal Artery in Fundus images is a field of study that relies on computer models to separate the blood vessels in the Retina Image. The main difficulty mentioned in previous publications is the development of a single solution that can differentiate between different types of blood vessels and has a different set of comparisons. Our proposed approach to this paper is based on the use of multi-segmentation size using the Neural Network. This approach assumes the inclusion of three different pixel sizes in each pixel area transmitted to each Convolutional Neural Network. The detected algorithm is tested with publicly available DRIVE, CHASE and STARE data sets, containing retina images commonly used in this policy. The performance of the proposed system is calculated according to the accuracy of detection, sensitivity, specificity, and the area under the ROC curve. Our model is compared with other segmentation models with encouraging results obtained. The proposed algorithm is a useful tool for automatically retinal image analysis. The separation of each pixel in the image is finally combined to reach the final image with the blood vessels in the Fundus image is normal or abnormal. The proven accuracy of the proposed algorithm is better for our work.

I. INTRODUCTION

Images of retinal fundus have been widely used in the diagnosis, diagnosis, and treatment of cardiovascular diseases [1], including age-related macular degeneration (AMD), diabetes (DR), glaucoma, high blood pressure, arteriosclerosis, and choroidal neovascularization, among which is AMD. and DR are considered to be the two leading causes of blindness [2]. Vessel segregation is a fundamental step in analyzing the density of images of the retinal fundus [3]. A fragmented vascular tree can be used to extract morphological features of blood vessels, such as length, width, branching and angles. In addition, the vascular tree has been adopted in the image registry of various retina [4] and retinal mosaic [5] as a stabilizing element in photography. In [6], the vascular tree is used for biometric identification due to its variability. Manual dissection of the artery tree in the retina images is a tedious task that requires knowledge and skill. In the development of a computer-assisted eye diagnostic program, the automatic detection of retinal vessels has been adopted as an important and challenging step. The size, shape and degree of stiffness of the retina vessels can vary greatly in different localities. The diameter of the vessel usually ranges from 1 to 20 pixels, depending on both the anatomical diameter of the vessel and the image resolution. The presence of shipwreck, branching and centerline retinex makes it difficult to classify vessels accurately using artificially designed features.

Retinal imaging is used by physicians to diagnose, diagnose, treat, and diagnose various eye and cardiovascular diseases [1,2]. In particular, analysis of retinal blood vessels is used in the diagnosis of diabetic retinopathy [3]. Analysis of the retinal blood vessels is time-consuming, stressful and often prone to errors. To resolve these problems, the analysis of blood vessels in the retina images needs to be done automatically. The first step in the automation system is classification.

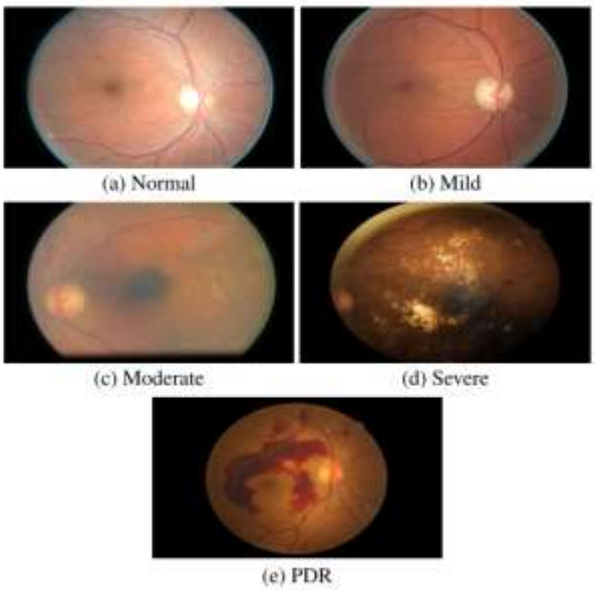


Fig.1. Retinal images

Some of the published methods are a combination of other simple models known as hybrid models. Suggested successful shipping. The idea of these methods is to use each detector. Significantly, these methods are very complex and time consuming. In this paper, we propose a simple method of classifying retina vessels based on classical edge features and neural network. We think each classical edge models have their own advantages yet to be used.

In the next section, we introduce the building materials and methodology used in this project.

II. RELATED WORK

M. Ikram, Y. Ong, C. Cheung, T. Wong [1] introduced "Measurements of retinal vascular caliber: clinical significance, current knowledge and future perspectives" The retinal vasculature provides a unique window to examine the health of blood vessels. casually and directly in vivo. . Advances in fundus imaging and retina imaging techniques have led to more accurate and precise test of retinal vascular caliber volume measurement.

L. Klein, B.E.K. Klein, S.E. Moss, T.Y. Wong [2], proposed to evaluate the association of retinopathy in non-diabetic individuals over 15 years of accumulated diabetes and high blood pressure.

S. Guigui, T. Lifshitz, J. Levy, [3] reviewed current diagnostic methods for diabetic retinopathy, with a focus on nonmydriatic digital fundus imaging. Methods: Documents from Medline were reviewed from 1976 to November 2011 to determine the different combinations of terms "diabetes retinopathy," "testing," "fundus photography," and "nonmydriasis."

F. Zana, J.C. Klein [4] introduced an algorithm based on mathematical morphology and curve assessment to detect vessel-like patterns in a noisy environment. Such patterns are very common in medical imaging. The vessel detection is interesting in the calculation of blood-related parameters. X. Jiang, D. Mojon [5] proposed a standard dynamic local boundary framework based on a multithreshold validation test. Hypotheses of objects are produced to combine both using hypothetic thresholds and accepted / rejected by the verification process.

A.M. Mendonca, A. Campilho [6] introduced the automated method of differentiating vascular network into retinal images. The algorithm begins with the extraction of the ship lines, which are used as guidelines for the next ship filling phase. For this purpose, the results of the four-direction operators are considered to select the connected sets of candidate points that will be further subdivided into intermediate pixels using vessel-based features.

M.S. Miri, A. Mahloojifar [7] introduced "Retinal image analysis using curvelet transform and multistructure elements morphology by reconstruction" Retina images can be used in a number of applications, such as ocular fundus function and human visualization. M.M. Fraz, S.A. Barman, P. Remagnino [8] Changes in morphology, width, branch pattern or retinal vascular malformations are an important indicator of various clinical and physical problems.

X. You, Q. Peng, Y. Yuan, Y.-M. Cheung, J. Lei [9] Analysis of retinal blood vessels is of interest in clinical trials, especially in the diagnosis of diabetic retinopathy. In this paper we introduce a new method of differentiating blood vessels in retinal images.

A. Hoover, V. Kouznetsova, M. Goldbaum [11] Describes the automatic method of detecting and placing blood vessels in images of ocular fundus. Such a tool should be considered useful by eye care professionals for the purposes of patient examination, medical examination, and clinical research. B.S. Lam, Y. Gao, A.W.-C. Liew [12] The formation and appearance of a blood vessel network in the retinal fundus is an important part of diagnosing various eye-related problems, such as diabetes and high blood pressure. In this paper, a method of automatic retinal detachment is proposed using the same filtering techniques integrated with the AdaBoost separator. L.C. Rodrigues, M. Marengoni M [14] Vascular separation of retinal fundus cells is a key step in the clinical identification of certain eye diseases. Successful diagnosis of vascular pathologies in angiographic images is an important factor and usually depends on the differentiation of vascular structure.

S. Chaudhuri, S. Chatterjee, N. Katz, M. Nelson, M. Goldbaum [15] "Detection of blood vessels in retinal images using the same two-dimensional filters" Blood vessels often have different localization, as well as the use of existing filters. Edge detection algorithms produce unsatisfactory results. T.B. Saha, D. Tchiotsop, R. Tchinda, G. Kenné [17] Parasites live in a host and receive their own food or at an expensive cost of that host. Cysts represent a type of resistance to the spread of parasites. Self-examination of images of small seats is time consuming and dependent on a human expert. In this paper, we propose an automatic detection system that can be used to identify various intestinal parasite cysts in their small digital images. P. Liskowski, K. Krawiec [22] "Separating retinal blood vessels by deep neural networks" The vascular network of the human eye is an important diagnostic feature in ophthalmology. Its segregation in fundus thinking is an insignificant task due to the variable size of the vessels, the relatively low differences, and the possible presence of pathologies such as microaneurysms and bleeding.

H. Fu, Y. Xu, D.W.K. Wong, J. Liu, [23] retinal detachment technology has become an important part of diagnostic and diagnostic medicine. However, separation of the retina vessels is a challenging task due to the complex distribution of blood vessels, the low difference between the target and the background, and the presence of light and potential pathologies.

Here each classical edge models have their own advantages yet to be used.

In the next section, we introduce the building materials and methodology used in this project. Database of retina images and related activity are presented in Chapter II. Chapter III describes the proposed approach. In Section VII, test and interview results are presented. Finally, this paper concludes with paragraph VIII.

III.PROPOSED METHOD

To overcome the problems with the existing system, the proposed method uses an in-depth learning method known as the Convolutional Neural Network (CNN) to handle a large number of unconventional and non-labeled fundus images. Meanwhile, in-depth learning strategies and algorithms are based on cost-effective and cost-effective human-like methods, and time-saving strategies. CNN methods are best known for their accuracy when working with non-labeled image data [8]. Sensitivity while processing accuracy is also very high compared to other models when you train the composition with fundus images (and non-label data).

Segmentation of Blood Vessel Techniques

The generalized algorithm for edge-based segmentation has the following steps.

1. Apply the derivative operator to detect edges of the image
2. Measure the strength of edges by measuring amplitude of the gradient
3. Retain all edge having magnitude greater than threshold T (removal of weak edge)
4. Find the position of crack edges; the crack edge is either retained or rejected based on the confidence it receives from it predecessor and successor edges
5. Step 3 and 4 are repeated with different values of threshold so as to find out the closed boundaries; segmentation of an image is achieved

Materials and methods

In order to test and evaluate the proposed system, we used retinal images and corresponding manual segmentations obtained from the public databases available online (CHASE_DB1, DRIVE and STARE). All algorithms have been developed in the MATLAB environment. The architecture of our system is shown in Fig. 2. As presented in this figure, a feature vector is extracted from the digital image. The resulting feature vector is used as the input of the neural network. The neural network is then trained to provide the image contours corresponding to the blood vessels present in the retinal image.

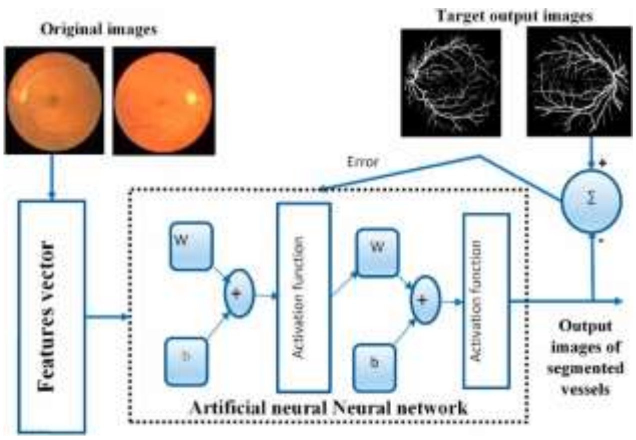


Fig. 2. Block diagram of the proposed system.

Features vector

We used a feature vector with eight measures characterizing each pixel. These measurements include the image gradient obtained with conventional edge detection filters (four characteristics), the Laplacian image obtained from the Laplacian of gaussian filter (one characteristic) and the morphological transformation (three characteristics).

Pre-processing

Amongst the three RGB (Red Green Blue) components of color images, the green channel presents the best contrast to distinguish vessels from the background, while the red and blue channels are very noisy [4]. Therefore, the green channel was selected for use in the feature vector extraction process. Before applying each edge detection filter, the following technique was applied to the green channel of fundus images to improve the image quality.

The Roberts filter

The Roberts filter is a discrete approach to the derivative of step 1 of a function. This is the gradient of the function. If I(x, y) represents a gray level of a pixel (x, y) in an image, then the amplitudes of the gradients in x and in y can be written respectively as follows:

$$G_x = I(x+1, y) - I(x, y)$$

$$G_y = I(x, y+1) - I(x, y)$$

This amounts to convolving the image with the following two filters.

$$R_x = \begin{bmatrix} 1, & 0 \\ 0, & -1 \end{bmatrix} \text{ and } R_y = \begin{bmatrix} 0, & 1 \\ -1, & 0 \end{bmatrix}$$

The amplitude of the gradient is defined by: G(x,y)=Gx2+Gy2

$$G(x, y) = \sqrt{G_x^2 + G_y^2}$$

If the outline is straight (step), the Roberts' filters places the one pixel outline to the left or above but its thickness will be respected. However, noise can also be a sudden local variation in gray levels (Speckle noise for example): these filters are therefore very sensitive to noise because they accentuate, by derivation, the noise present in the image. In addition, these filters gives a thick outline if it is a ramp type contour.

Operators of Prewitt and Sobel

The principle of the methods proposed by Prewitt in 1970 and by Sobel in 1978 is identical [44]. The calculation of the gradient is carried out using two masks, the first making a horizontal derivative and the second a vertical derivative. The masks are given as follows for the horizontal and vertical contours respectively:

$$M_h = \begin{bmatrix} -1, & 0, & 1 \\ -C, & 0, & C \\ -1, & 0, & 1 \end{bmatrix}$$

$$M_v = \begin{bmatrix} -1, & -C, & -1 \\ 0, & 0, & 0 \\ 1, & C, & 1 \end{bmatrix}$$

When C = 1, they are the operators of Prewitt, when C = 2, they are those of Sobel. Compared to the previous ones, these masks have the advantage of producing two effects. In addition to calculating the gradient in one direction, these masks perform the smoothing. This smoothing makes these masks a little less sensitive to noise than the previous ones.

The canny operator

The first step is to reduce the noise of the original image before detecting its edges. This makes it possible to eliminate the isolated pixels which could induce strong responses during the calculation of the gradient, thus leading to false positives. The Optimal detector used by canny filter is the first derivative of the Gaussian [45]. The gradient of a 2D Gaussian is given as follows:(8)

gx(x,y)=−xσ2e−x2+y22σ2

$$g_x\,(x,y) = -\frac{x}{\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$g_y\,(x,y) = -\frac{y}{\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where σ determines the degree of smoothing. Mask size increases with the value of σ.

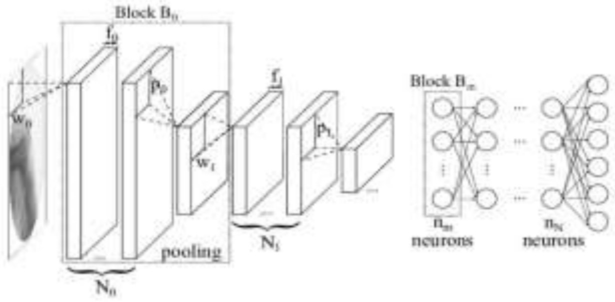


Fig. 3. Pictorial representation of convolutional network

Add Input Layer

The input shape, a function, which is the defined size of the input image, has been declared. This is the input of the CNN model. It is a convolution layer with 32 filters and a kernel of size 3x3 and the activation argument takes the value “ReLU” and the padding argument takes the value “same”.

Add Hidden Layers

Our model has 3 hidden layers. The first hidden layer is a “Convolutional Layer” with 32 filters and a kernel of size 3x3 which is succeeded by a “Max Pooling layer” and, one dropout layer. The second hidden layer is a convolutional layer with 64 filters and a kernel of size 3x3 and the activation argument takes the value “ReLU” and the padding argument takes the value “same”. The third hidden layer is a convolutional layer consisting of 64 filters and a kernel of size 3x3, then a max-pooling and a dropout layer. Then add the model called “Flatten” to the data into a 1-dimensional array for inputting it to the next layer.

Neural network

Feed networks also called MLP (Multi-Layer Perceptron) contain a series of sensory layers. The first layer has a connection from the network input while the next layer has a connection from the previous layer. The final layer produces network output. The cascade feed-forward neural network (CFNN) is a type of feed network with additional connections from input to each layer, and from each layer to all subsequent layers [17].

Our artificial neural network structure is shown in Fig. 4. It is a cascade feed-forward neural network composed of input layer, output layer and four hidden layers. The first hidden layer contains eight neurons with a hyperbolic tangent sigmoid as a transfer function. Some hidden layers have ten sensors each. Hidden Layer 2 and Hidden Layer 4 use hyperbolic tangent sigmoid as a transfer function. Log-sigmoid transmission function is used for hidden layer 3.

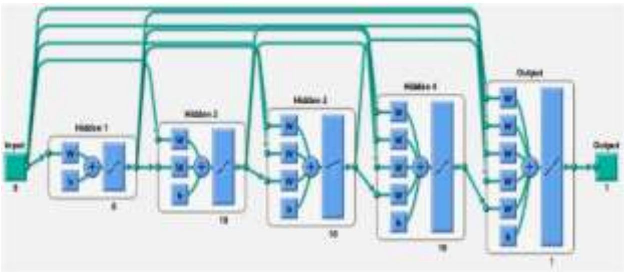


Fig. 4. Selected Neural network topology.

For a MLP with n neurons in the input layer, k neuron in a hidden layer and one in the output layer, its mathematical equation can be written as follows:

$$y = f^0 \left(b_0 + \sum_{j=1}^{k} w_j^0 f_j^h \left(b_j + \sum_{i=1}^{n} w_{ij}^h x_i\right)\right)$$

When f0 is a function of activating the output layer, fjh activates the hidden layer j, xi represents the input, y output. b0 is bias of the output and bj is bias in the hidden layer j. From the MLP equation, the number generated from the CFNN model can be estimated.

Input is a set of factors that can allow CFNN to differentiate and identify the type of retinal blood vessels as a concert and so on as the absence of a concert. The set of features used are those presented in the previous section. The output y gives a value of about 1 in a ship's pixel obtained and 0 undetected.

To perform any task related to image processing, it is mandatory to perform the processing in advance to make the images fit the input data. For example, converting images into appropriate form, that is, from PNG or JPEG files to data for neural models or networks. The database contains eye retina images taken using fundus images. Images contain artifacts and some of them are less focused, less descriptive, or overly explicit, etc. Also, some of the images have low light or low lightning conditions and make it difficult to detect differences between images and magnification. in danger of judgment.

EXPERIMENTAL RESULTS AND DISCUSSION

Our method has been tested on three publicly available repositories (DRIVE, STARE and CHASE_DB1). These information sites provide two classification results made by two different experts in each image. We select the result of the separation of the person who precedes it as the basic truth.

We explored our approach to the publicly available DRIVE database, which contains 40 images separated by a test and training set, both of which contain 20 images. An example of the original image and hand-to-hand separation of the same image is shown in the illustration. In the retinal detachment process, the effect is the result of separation based on pixels. Note that we do not rely on any vertical and horizontal divisions, as we take semantic partitions as pixel layouts, in which each pixel is defined locally. Therefore, the method is not affected by bottom-up separation errors.

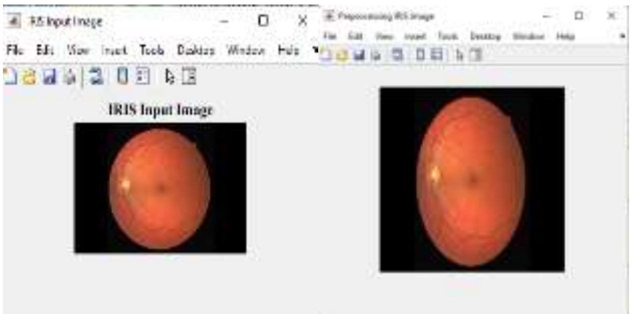
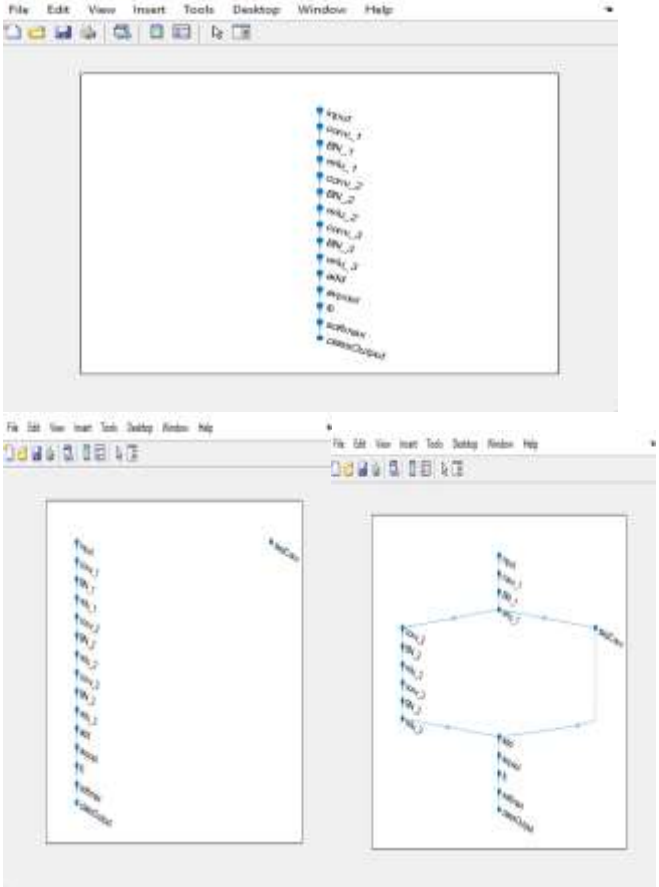


Fig 5 Original Image preprocessing Image



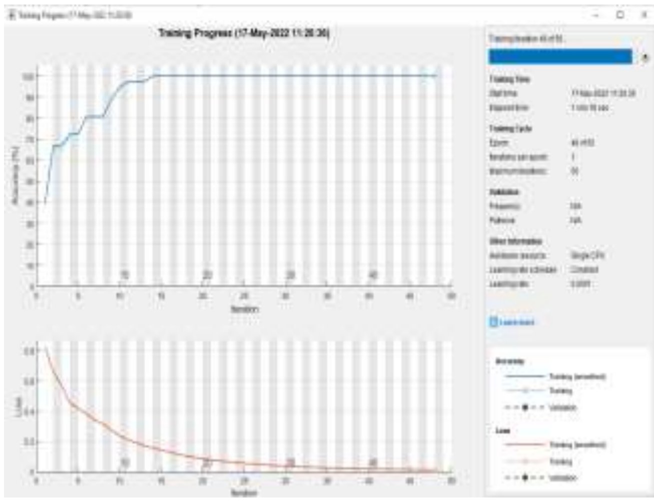


Fig. 6 Training Progress of Iris image dataset

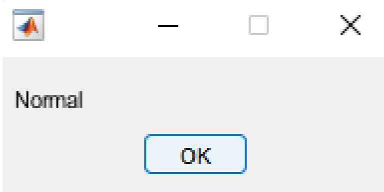


Fig. 7. Training progress and identification

CONCLUSION

In this paper, we have proposed a novel method of differentiating the retina vessel based on classical edge finders and neural network. Automated diagnostic systems or vision systems are used to significantly reduce the amount of time spent diagnosing a disease while saving the effort and expense of medical professionals or "opticians" and results in better patient care. This supervised method is trained and tested in the DRIVE, STARE and CHASE databases. The test results showed a map of the high quality shipping opportunities. Our approach is solid with a variety of ship angles and different light conditions. Compared to the standard methods, the proposed method provides better performance in terms of specificity, accuracy and location under the ROC curve. As with most alternatives, the sensitivity gained is still to be improved. We have therefore shown that a combination of classical contour detectors provides much better results when compared to the latest and more complex methods of retinal blood vessel separation. The "high diversity and bias" of these structures allows CNN to see a wide range of non-diabetic diseases and such innovative approaches are used to transform the medical industry and benefit physicians and patients.

For future work, we believe that variation in neural network architectures could be developed to further improve the results obtained by reducing spurious detections in vessel segmentation.

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