Automatic Segmentation of Microaneurysm in Retinal Fundus Images

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Abstract: Diabetes interferes with the body’s ability to use and store sugar (glucose), which it can cause damage throughout the body. Generally, Microaneurysm (MA) is the first clinically observable lesions in the Diabetic Retinopathy (DR). Since interference of biological objects in eye fundus images are similar to MA, locate Microaneurysm lesions precisely is a challenging task for researches. This research employs U-Net Convolutional Neural Network to model saliency of objects in images, global and local context are both taken into account to provide a better initialization for the process. Feature extraction techniques are applied first to assign a local saliency value to each pixel by considering its local context from fundus images such as ORB, SURF, and MSER. The extracted feature vectors are applied for training the network. The sum of the weighted salient object regions produce the final saliency map, then implements U-Net to segment MA lesions. Our experiment has carried out using the publicly available Indian Diabetic Retinopathy Image Dataset (IDRiD), which has used in "Diabetic Retinopathy: Segmentation and Grading Challenge" workshop and our proposed method has given an outstanding accuracy of 98.78 %.

1. Introduction

Diabetes grows rapidly in the world. When someone has diabetes, their body cannot maintain healthy levels of glucose in the blood [9]. Glucose is a fundamental source of energy for our bodies. Abnormal levels of glucose may produce health problems. It can affect the kidney (diabetic nephropathy), heart (diabetic cardiomyopathy), particularly plantar nerves (diabetic neuropathy), and also eyesight (diabetic retinopathy) [12]. Early detection and diagnosis play key role on reducing the percentage of visual impairment caused by diabetes. Therefore, detection of MAs is needed in a Computer-Aided Diagnosis (CAD)

In recent years, deep convolutional networks have many applications, e.g. image classification, segmentation, detection, tracking and captioning [14,17]. Since 2012, many Deep Convolutional Neural Network (DCNN) models have been designed, such as CapsuleNet, GoogleNet, AlexNet, VGG. A deep learning-based approach (CNN in particular) can obtain satisfactory results for segmentation classification tasks[3]. However, in some cases, models have used classification tasks on very large scale datasets like ImageNet, so that, small architecture models are used for semantic image segmentation as like as fully convolutional network (FCN). However, in some medical image processing domains, a class label is assigned to a pixel. [27].
In recent years, deep convolutional networks have received widely attention in segmentation. Though initially developed for image labeling, some methods are designed to a semantic segmentation, which is used for classification [18]. In 2015, U-shaped full convolutional network has been proposed for image segmentation. The U-Net adopts downsampling and upsampling steps to finally obtain a general information combining localization and context, which is a good way to form a segmentation map. This ensures that The advantage of U-Net is to preserve the full context of the input images [5].

The rest of the paper is organized as below: in Section II, we have described the related works of this research, In Section III we have described the preliminaries, namely preprocessing steps and materials of this research. Section IV and V are dedicated to our proposed method. Then, section VI is described by our experimental results and analysis. Finally, in section VII, we have concluded our work along with the future work.

2. Related Works

Automatic MAs segmentation is a challenging task because the MAs size is small, even only a few pixels. It is hard to differentiate MAs and other lesions with visually similar fundus structures such as hemorrhages, blood vessels and junctions in thin vessels etc [11]. Therefore, many algorithms have been developed for MAs segmentation. Mainly, segmentation algorithms of MAs are divided into unsupervised and supervised learning methods [6].

Unsupervised learning methods are used to extract the accused area of microaneurysms and classify it use the appropriate classifier. Mathematical morphology and rule-based classifier algorithms have been used to extract blood vessels from fundus images in Baudoin et al. [21], Kandeet et al. [22], Spencer et al. [23] and Fleming et al. [24]. Supervised learning-based methods are used to extract the type of features like color, texture, shape, intensity, and orientation. Jayanthi et al. [2] used the double-ring filter method for analyzing the detection of microaneurysms. The method has given a sensitivity of 68% at 15 false positives per image. A supervised learning algorithm is used to generate an inferred function, then the feature vectors are applied into some classifiers to train, which can recognize MA and non-MA regions at a pixel level.

Apart from the MA detection approaches that have mentioned above, deep learning methods have obtained a big move in many image domain such as classification, segmentation and object detection [17,26,27]. The method from the paper [18] applies the fully convolutional network (FCN) to segment true-color images and received satisfactory results.

Nevertheless, there are also some drawbacks of FCN. For example, FCN is time-consuming and acquire need magnanimous training data. It also does not consider the information among pixels. Ronneberger et al. [25] proposed a network called U-Net, which is outperformed FCN because it can obtain more accurately results and taking shorter time.

Based on the analysis above, we adapt and modify deep classification architectures, using the saliency map to makes the object more prominent and well-defined boundaries of the salient object, and implement U-Net for detecting the MAs.

3. Preliminaries

3.1 Materials

In this experiments, we have used the Retinal Lesions data that associated with Diabetic Retinopathy from Indian Diabetic Retinopathy Image Dataset (IDRiD), which has been utilized inIEEE International Symposium on Biomedical Imaging (ISBI-2018) for the "Diabetic Retinopathy: Segmentation and Grading Challenge" workshop. There are of 81 images in total that are divided to use in training and testing phases. Only the ground-truth locations of the MAs are indicated for training set images. The ground truths of the MAs for the training and the testing set were provided by the original dataset.

Images are labeled into two classes according to the ground truth. In the extracted image, the pixel is labeled as 1 if the interested area has microaneurysms otherwise as 0. The fundus image dataset has been divided into training set and testing set.
3.2 Preprocessing

A median filtering operation is used for image enhancement. The background region may dominate after image enhancement. A shade correction algorithm is used to reduce the slow background variation. The image with shade corrected is obtained by subtracting the image with a low pass filter, a median filter is used to obtain the result image to rectify for background changes \([7,11]\).

\[
f(x,y) = \text{median}\{g(s,t)\}
\]

\((s, t \in S_{xy})\)  

Original RGB image, red plane, green plane and blue plane of retinal fundus image are shown in Fig.1.

![Fig 1. Retinal images. (a) Original RGB plane (b) Red plane (c) Green plane (d) Blue plane](image)

Threshold is used for the image, which eliminates high contrast vessels. And Morphological reconstruction is designed for exudate detection. After detecting the exudate, then we remove it to detect MA easier. Vessel has a size smaller than 10 pixels or diameter smaller then \(\lambda < 125 \mu m\) (size of MA). The result of the retinal fundus image after preprocessing steps is shown in Fig.2. Close-ups MA are shown in Fig.3(a) through Fig.3(d).

![Fig 2. The result of preprocessing steps](image)

![Fig 3. Close-ups of MA (a) Original RGB image (b) Green plane (c) Green plane after contrast enhancement (d) Shade corrected image](image)

4. Methodology

4.1 Saliency Map

In computer vision, saliency is a kind of image segmentation, which is the process of partitioning a digital image into many parts \([13]\). The objective of a saliency map is to facilitate the image. The result of a saliency map is a set of contours extracted from the image. It has the same size as the input and output image of saliency maps. The filter size needs to change to obtain a different size with the original image \([1]\). Key points possess rich local features of an image. We used the oriented FAST (Features from Accelerated Segment Test) and rotated BRIEF (Binary Robust Independent
Elementary Features) (ORB) for key point detector, Speeded-Up Robust Features (SURF) for low-level image descriptors, and Maximally Stable Extremal Regions (MSER) for stable regions detector.

When there are lots of interference terms, the saliency map will mark the region of MA incorrectly [26]. In this model, the element-wise feature accumulation is performed outside of the U-Net architecture.

![Figure 4. Framework of the proposed system](image)

### 4.2 U-Net

U-Net model is used to segment the image, which each label is assigned to a pixel. U-net model applies convolutions and pooling operations to extract image features [4], and upsampled and downsampped operations are used to generate the final segmentation.

### 5. Experimental Result

The network is modified by an iterative propagation. The energy function is obtained by the cross-entropy loss function. The soft-max is as follows:

$$ p_c(i,j) = e^{O_c(i,j)}/\sum_{c'} e^{O_{c'}(i,j)} $$  \hspace{1cm} (2)

where $p_c(i,j)$ is the probability map that the pixel $i,j$ is assigned to class $c$, and $O_c(i)$ is the activation in feature channel $c$ at position $(i,j)$ in the last layer. Cross-entropy loss function is used in this network, defined as follows:

$$ E = \sum_{i,j} \sum_{c=1}^{C} [p'(c)(i,j)] \log(p_c(i,j))^{-1} $$  \hspace{1cm} (3)

where $p'(c)(i,j)$ is the true distribution.

To verify our proposed method, we used several criterions:

- Intersection-over-Union (IoU) score: $|A \cap B|/|A \cup B|

- Dice coefficient: $2|A \cap B|/(|A| + |B|)$

where $A = (a_{i,j})_{i=1}^{H}j=1$ is a predicted output map, and $B = (b_{i,j})_{i=1}^{H}j=1$ is a correct binary output map [4]. Our proposed method has showed 0.9019 of Jaccard Index (IoU). The proposed model has predicted with an accuracy of 98.78%.

![Figure 5. Generated accuracy for the proposed method](image)
6. Conclusion and Future Works

In this paper, we have proposed a method for Microaneurysms segmentation in the retinal fundus image based on pixel classification. The proposed method approach 0.9019 of Jaccard Index (IoU) using saliency map to give more information about the retinal fundus image dataset to provide a better initialization for the training process. In future we will expand our research area mainly to detect other lesions, such as hemorrhage, soft exudates, and also focus on optic disc to grade the severity of the presence of Diabetic Retinopathy.

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References

[1] Laurent Itti, Christof Koch, and Ernst Niebur. (2009) ‘A Model of Saliency–based Visual Attention for Rapid Scene Analysis’, IEEE Trans. Pattern Anal. Mach. Intell., 20, 1254-1259.

[2] R. Jayanthi, Kavitha. N, ManjuPaarkavi. R, and K. Bommanna Raja. (2016) ‘A Review of Various Retinal Microaneurysm Detection Method for Grading of Diabetic Retinopathy’, IRJET Vol.03 Issue.02.

[3] MdZahangir Alom, Mahmudul Hasan, Chris Yakopcic, Tarek M. Taha, and Vijayan K. Asari. (2018) ‘Recurrent Residual Convolutional Neural Network based on U-Net (R2U-Net) for Medical Image Segmentation’

[4] ArtemSevastopolsky. (2017) ‘Optic Disc and Cup Segmentation Methods for Glaucoma Detection with Modification of U-Net Convolutional Neural Network’, Pattern Recognition and Image Analysis.

[5] Wang Xiancheng, Li Wei, Miao Bingyi, Jing He, Zhangwei Jiang, Wen Xu, ZhenyanJi, Gu Hong, and Shen Zhaomeng. (2018) ‘Retina Blood Vessel Segmentation Using a U-Net Based Convolutional Neural Network’, ELSEVIER.

[6] B. Antal and A. Hajdu. (2012) ‘An ensemble-based system for microaneurysm detection and diabetic retinopathy grading’, IEEE transactions on biomedical engineering 59 (6) 1720–1726.

[7] Pooja G. Shetty, Shrinivas A. Patil, and Avadhoot R. Telepatil. (2014) ‘Detection of Microaneurysm and Diabetic Retinopathy Grading in Fundus Retinal Images’, IJETT Vol.13 No.7.

[8] V.A. Aswale and J.A. Shaikh. (2017) ‘Detection of Microaneurysm in Fundus Retinal Images using SVM Classifier’, IJEDR Vol.5 Issue.4.

[9] Bo Wu, Weifang Zhu, Fei Shi, Shuxia Zhu, and Xinjian Chen. (2017) ‘Automatic detection of microaneurysms in retinal fundus images’, Computer Medical Imaging and Graphics 55 pp. 106-112.

[10] Baidaa Al-Bander, Waheed Al-Nuaimy, Bryan M. Williams, and Yalin Zheng. (2018) ‘Multiscale sequential convolutional neural networks for simultaneous detection of fovea and optic disc’, Biomedical Signal Processing and Control 40 pp. 91-101.

[11] P. Chudzik, S. Majumdar, F. Caliva, B. Al-Diri, and A. Hunter. (2018) ‘Microaneurysm detection using deep learning and interleaved freezing’, Medical Imaging 2018: Image Processing, Vol. 10574, International Society for Optics and Photonics, p. 1057411.

[12] Jen Hong Tan, U. Rajendra Acharya, Sulatha V. Bhandary, Kuang Chua Chua, and Sobha Siva Prasad. (2017) ‘Segmentation of optic disc, fovea, and retinal vasculature using a single convolutional neural network’, Journal of Computational Science 20 pp. 70-79.

[13] R. Achant, S. Hemami, F. Estrada and S. Susstrunk, “Frequency-tuned salient region detection”, IEEE Conf. on Computer Vision & Pattern Recognition, 22(9-10): pp. 1597-1604, 2009.

[14] Di Niu, Peiyuan Xu, Cheng Wan, and Jun Cheng. (2017) ‘Automatic Localization of Optic Based on Deep Learning in Fundus Images’, IEEE 2nd International Conference on Signal and Image Processing.
[15] Wen Cao, Juan Shan, Nicholas Czarnek, and Lin Li, (2017) ‘Microaneurysm Detection in Fundus Images Using Small Image Patches and Machine Learning Methods’, Research Gate.

[16] NoushinEftekheri, HamidrezaPourreza, and EhsanSaeedi, (2017) ‘Microaneurysm Detection in Fundus Images Using a Two-step Convolutional Neural Networks’.

[17] KeleXu, DaweiFeng, and HaiboMi, (2017) ‘Deep Convolutional Neural Network-Based Early Automated Detection of Diabetic Retinopathy Using Fundus Image’, Molecules.

[18] XiayuXu, Rendong Wang, Tao Tan, and FengXu, (2018) ‘An improved U-Net architecture for simultaneous arteriole and venule segmentation in fundus image’, MIUA.

[19] KanchanNemade and Prof. K. S. Bhagat, (2015) ‘Microaneurysms Detection from Retinal Image and Diabetic Retinopathy Grading’, IJETTCS.

[20] SehirliEftal, Kamil, TuranMuhammed, and Dietzel Alexander, (2015) ‘Automatic Detection of Microaneurysms in RGB Retinal Fundus Images’, IISTE.

[21] Baudoin, C., Lay B., & Klein, J. (1984) ‘Automatic detection of microaneurysms in diabetic fluorescein angiography’, Revue depidemiologie et de santepublique, 32, 254-261.

[22] Kande, G.B., Savithri, T.S. &Subbaiah, P.V. (2010) ‘Automatic detection of microaneurysms and hemorrhages in digital fundus images’, Journal of Digital Imaging, 23, 430-437.

[23] Spencer, T., Olson, J., McHardy, K., Sharp P., & Forrester, J. (1996) ‘An image processing strategy for the segmentation and quantification in fluorescein angiograms of the ocular fundus’, Computer Biomed Res, 29, 284-302.

[24] Fleming, A.D., Philip, S., Goatman, K.A., Oslon, J.A. & Sharp P.F. (2006) ‘Automated microaneurysms detection using local contrast normalization and local vessel detection’, IEEE Trans Med Image, 25, 1223-1232.

[25] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, (2015) ‘U-Net: Convolutional Networks for Biomedical Image Segmentation’, MICCAI.

[26] Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, (2014) ‘Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps’.

[27] Long, J., Shelhamer, E., Darrell, T., (2015) ‘Fully Convolutional Networks for Semantic Segmentation’, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3431-3440.