Deep Learning Residual-like Convolutional Neural Networks for Optic Disc Segmentation in Medical Retinal Images

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Abstract: Eye diseases such as glaucoma, if undiagnosed in time, can have irreversible detrimental effects, which can lead to blindness. Early detection of this disease by screening programs and subsequent treatment can prevent blindness. Deep learning architectures have many applications in medicine, especially in medical image processing, that provides intelligent tools for the prevention and treatment of diseases. Optic disk segmentation is one of the ways to diagnose eye disease. This paper presents a new approach based on deep learning, which is accurate and fast in optic disc segmentation. By Comparison proposed method with the best-known methods on publicly available databases DRIONS-DB, RIM-ONE v.3, the proposed algorithm is much faster, which can segment the optic disc in 0.008 second with outstanding performance concerning IOU and DICE scores. Therefore, this method can be used in ophthalmology clinics to segment the optic disc in retina images and videos as online medical assistive tool.

1 INTRODUCTION

Digital retinal fundus images are used for the primary exploration of ophthalmic. Glaucoma is amongst the main retinal illness, which is the cause of vision loss and blindness in the world (Federation, 2013). Early detection of this disease by screening programs and subsequent treatment can prevent blindness. Computer systems are beneficial for diagnostic retinal image analysis and can be the first phase in automated screening (Fraz et al., 2015). Glaucoma is the second most important reason of blinding in recent years. Based on research about 80 million persons to be disturbed with glaucoma by the year 2020 (Gao et al., 2019; Quigley and Broman, 2006). The optic nerve fibers damaged by glaucoma cannot be recovered. So the most effective way is early detection to avoid injury of retina vessels and nerve fibers. The reason of glaucoma is commonly dependent on the increase of Intraocular Pressure (IOP) in the eye, which results from obstruction of intraocular fluid (Xu et al., 2012). The correct reason of this obstruction in most of the time is unknown, but the other factors like old age, steroid medication will affect the disease (Jackson and Radhakrishnan, 2014). The optic nerve carries the data from the eye to the brain. By increasing the IOP, the optic nerve damaged. Glaucoma does not represent any signs until it has developed to advanced steps (Bajwa et al., 2019). Nevertheless, if glaucoma is recognized early, it is possible to reduce the disorder. World Health Organization (WHO) announces glaucoma as the second biggest cause of blindness in the world whose effects lead to irreversible vision (Bourne et al., 2017). Glaucoma is usually determined by taking the medical history of a sick person and assessment manually of Optic Disc (OD) using ophthalmology to evaluate the configuration and coloration of the optic nerve (Chen et al., 2015). Optic Disc is the region of the optic nerve connecting to the retina of each eye. In the case of glaucoma, the intraocular pressure damages the nerve fibers, and the optic disc begins to deform, and color changes to pale (Xu et al., 2012). In Figure 1 a healthy optic disc with three various steps of glaucoma shown sequentially. Cup-to-Disc Ratio (CDR), Optic disc size, Ratio of Neuroretinal Rim, etc., are some of the significant architectonic signs of glaucoma in retinal fundus images (Abbas, 2017). These signs are usually around the optic disc, which is Region Of Interest (ROI). Thus, segmentation of this region, which is de-

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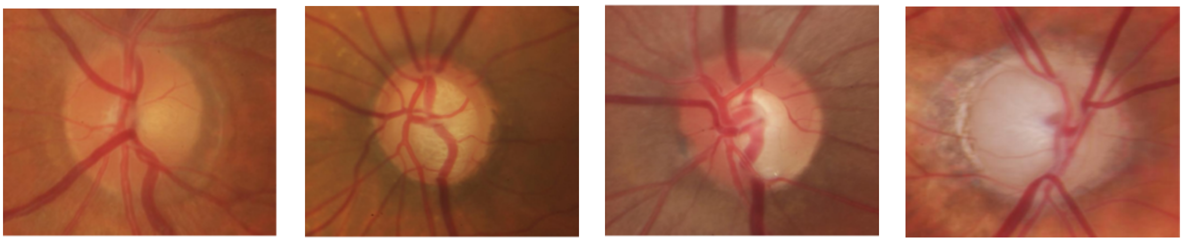


(a) (b) (c) (d)

Figure 1: Glaucoma in retinal fundus images. (a)normal disc, (b)glaucoma onset, (c)critical glaucoma, (d)advance glaucoma.

tecting the optic disc, is helpful for clinical evaluation by the ophthalmologists. Nevertheless, automated optic disc segmentation methods that used for glaucoma detection should be sensitive. Cause a small error in recognize Of optic disc may affect the diagnosis and treatment seriously (Mookiah et al., 2012). Image segmentation is a fundamental part of many optical understanding systems that includes division images into numerous segments or regions (Szeliski, 2010). Image segmentation has been used in many applications, especially in medical image analysis such as tumor boundary extraction and optic disc segmentation(Forsyth and Ponce, 2002). The other method for optic disc segmentation is utilizing a novel vibrational level set function on the red channel of the retinal fundus images (Wong et al., 2008). In another algorithm, localized the optic disc was applied by using template matching; after that, morphological filtering removed the blood vessels. At last, the boundary information combines with the local edge vector to operate the deformable contour was used to detect the optic disc regions (Yu et al., 2012; Zhang et al., 2008). For optic disc segmentation task, a method based on mathematical morphology is proposed to detect and segment the optic disc in images (Welfer et al., 2010). This method is expanded by combining a multiscale morphological approach (Welfer et al., 2013). A template-based approach for OD segmentation is utilized edge detection and morphological methods conformed by circular Hough transformation to estimated circular objects (Aquino et al., 2010). However, in the past few years, deep learning networks have used as a new efficiency method in image segmentation tasks with an extraordinary performance that attaining the highest accuracy and speed rates. The deep convolutional neural network can extract indicated features from the input images automatically. There are various models developed for medical image segmentation, which based on FCNs (Long et al., 2015) models. A U-shaped convolutional neural network was proposed to segment optic disc, and advancement was achieved by in comparison with the exert of old methods (Sevastopolsky, 2017). For optic disc segmentation task, the polar transformation and multi-label loss function method were applied in a U-shaped (Fu et al., 2018). The team extended this algorithm one year later and suggested a Stack-U-Net network architecture (Sevastopolsky et al., 2018), which is based on a U-Net (Ronneberger et al., 2015) network. The other optic disc segmentation method has a U-Shape with Densely connected convolutional blocks (Al-Bander et al., 2018), based on DenseNet (Huang et al., 2017). In optic disc segmentation tasks, low time and high accuracy are essential. In this paper, a network designed based on deep learning and segmented the optic disc with the low time, which can help the ophthalmology clinic to evaluate the retina disease like glaucoma.

2 THE PROPOSED METHOD

This paper develops a deep learning algorithm for optic disc segmentation and designs a new network architecture based on a residual model. In this paper, a new approach called residual-like convolutional neural network applied for optic disc segmentation in retinal color fundus images. In the structure of this network, there are some layers which based on residual layers in ResNet (He et al., 2016). For optic disc segmentation, in pixel-level where features can be take out from various sized windows, but at the identical time, passing some features from first layers to resultant layers, as residual layers do, should be useful. Residual block structure seems to be suitable for such roles when needed to construct data that be similar to the input image. Another benefit of using residual blocks is the amplify and improved gradient circulation, which has a positive effect on network convergence. Figure 2 is the residual layer that proposed in this paper. As shown in Figure 1 in this paper, in this convolutional network, the RELU activation function is used after the end of each convolution layer, and after that batch normalization is used. The Relu function gives an output x if x is positive and 0 otherwise. Also, the Sigmoid activation function is applied to the

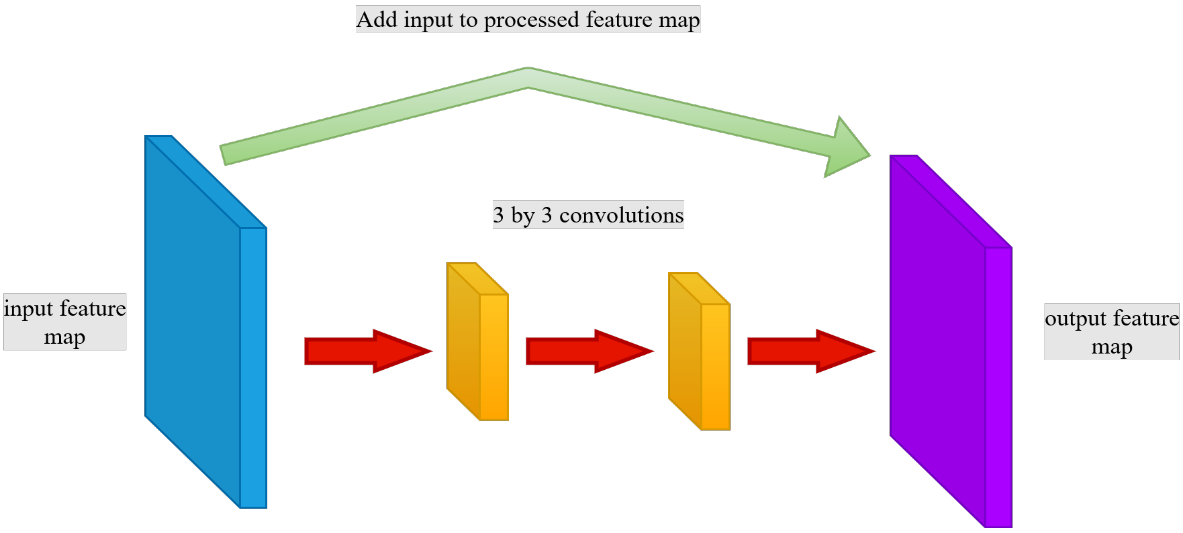


Figure 2: Residual layer used in proposed network.

last layer. As shown in Figure 2 the network at first, extracts the features from an input image and then upsamples the feature map. In this paper, the output of the proposed network is a binary image shown in Figure 5. For evaluating the results, loss function defined as:

$$l(A,B) = -\log d\ (A,B) \tag{1}$$

A is a predicted output, comprising probabilities that each predicted pixel appertains to the foreground, and also B is a correct binary output. For binary images d(A; B) is an expansion of Dice score. Dice score calculates the expanse of overlapping regions between any two images. Dice (Dice, 1945) to gauge the similarity of two samples, such as image and ground truth, is defined as:

$$Dice(A,B) = \frac{2|A \cap B|}{(|A| + |B|)} \tag{2}$$

The ranges value of the Dice coefficient is between 0 and 1. In this study RMSprop (Tieleman and Hinton, 2012) optimizer is used with a learning rate of 0.0002. There are different datasets

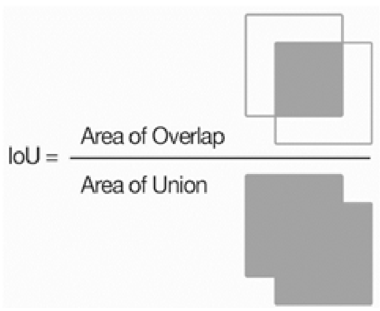
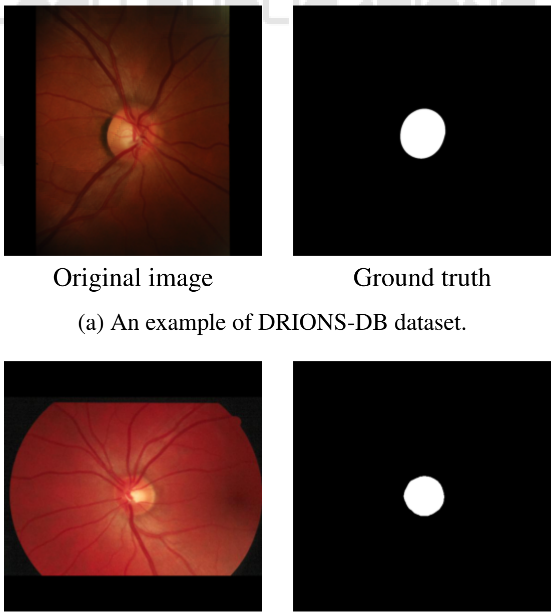


Figure 3: Intersection-over-Union (IOU).

for optic disc segmentation. In this paper, we have used two well-known datasets and then compare the results of the proposed method with the other methods that have used these datasets. As shown in Figure 4 DRIONS-DB (Carmona et al., 2008) and RIM-ONE v.3 (Fumero et al., 2011) (110 and 159 images,respectively) datasets used to evaluate the results, which comprise the manual segmentation of the optic disc. Another parameter for the quality of the trained algorithm evaluated by Intersection-over-



Original image | Ground truth

(a) An example of DRIONS-DB dataset.

Original image | Ground truth

(b) An example of RIM-ONE v.3 dataset

Figure 4: Some examples from RIM-ONE v.3 and DRIONS-DB datasets.

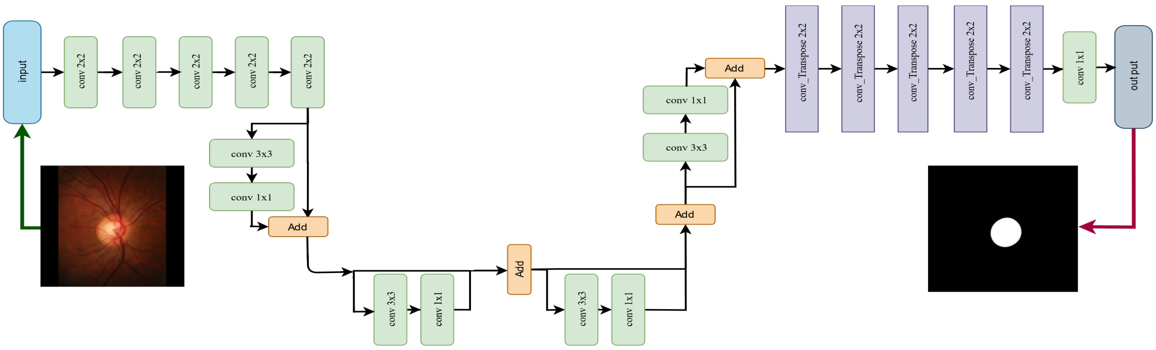
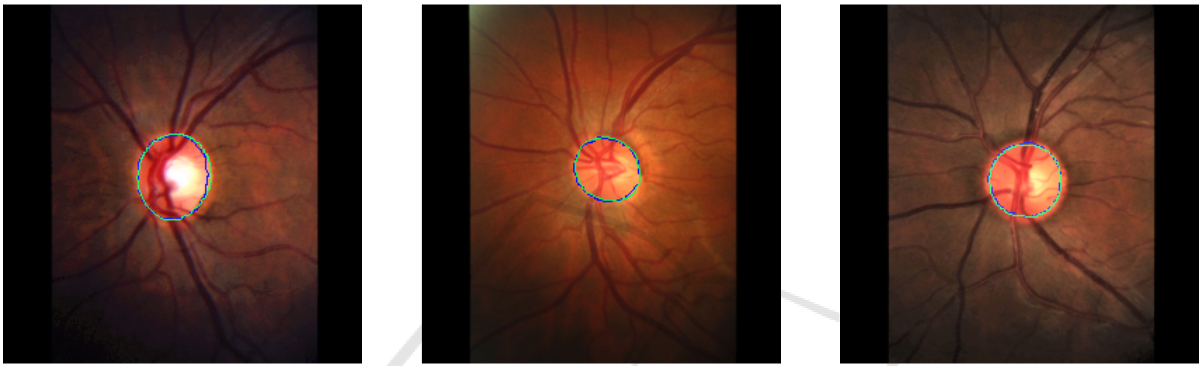
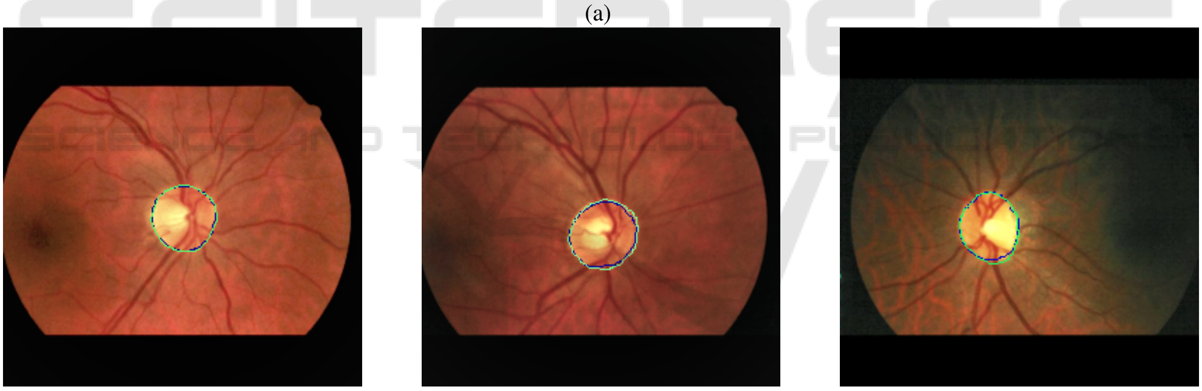


Figure 5: Proposed network structure.



(a)



(b)

Figure 6: (a) Examples from RIM-ONE v.3 for OD segmentation by the proposed method. The green contour refers to the ground truth, and blue is prediction, (b) Examples from RIM-ONE v.3 for OD segmentation by the proposed method. The green contour refers to the ground truth, and blue is prediction.

Union, as well as called the Jaccard Index, is one of the well-known metrics in image segmentation. Intersection-over-Union(IOU) is the region of overlap between the ground truth and predicted segmentation, and defined as:

$$IOU = \frac{|A \cap B|}{|A \cup B|} \tag{3}$$

3 EXPERIMENTS AND RESULTS

The Dice coefficient and IOU score do not depend on the object scale and image scale.

IOU is a score that used in image segmentation. As shown in Figure 3 IOU score is necessary to evaluate the percentage of overlap between ground-truth and predicted segmentation. IOU score is similar to the Dice coefficient that often used for loss function

Table 1: Comparison of the proposed method with existing methods(on DRIONS-DB).

	DRIONS-DB Dataset		
Methods	Dice	IOU	predict time (s)
Proposed method	0.9452	0.8853	0.008
(Walter et al., 2002)	0.6813	-	-
(Morales et al., 2013)	0.9084	-	-
(Abdullah et al., 2016)	0.9102	0.851	43.2
(Rehman et al., 2019)	0.8990	0.8210	31.10
(Zahoor and Fraz, 2017)	-	0.8862	1.60
(Fan et al., 2017)	0.9137	0.8473	-
(Ramani and Shanthamalar, 2020)	0.8962	0.8217	1.41
DRIU (Maninis et al., 2016)	0.94	0.89	0.1
(Sevastopolsky, 2017)	0.97	0.88	0.13

Table 2: Comparison of the proposed method with existing methods(on RIM-ONE v.3).

	RIM-ONE v.3 Dataset		
Methods	Dice	IOU	predict time (s)
Proposed method	0.9371	0.87	0.008
(Zilly et al., 2017)	0.94	0.98	5.3
(Maninis et al., 2016)	0.96	0.89	0.13
(Joshua et al., 2019)	0.96	0.88	0.03
(Sevastopolsky, 2017)	0.95	0.89	0.1
(Civit Masot et al., 2019)	0.97	-	-

in the training network. IOU ranges from 0-1, which 1 (100) indicate fully overlapping segmentation. For training this algorithm, we use free GPU service of the Google Colab framework.

4 CONCLUSIONS

In this paper, we prove that our algorithm based on Residual-like CNN can detect OD in shorter time, better than other reported methods on retinal fundus images. The best preponderance of the proposed method, simple programming, accurate, and the lowest prediction time, which is 0.008 per second. The results by IOU and DICE scores were evaluated and, great performances for optic disc segmentation were achieved. The lowest prediction time and experiment results express that optic disc segmentation can be done automatically in ophthalmology clinics as online predictions medical assistive tool.

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