Segmenting Retinal Vascular Net from Retinopathy of Prematurity Images using Convolutional Neural Network

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ABSTRACT

In this paper, we describe the experimentation with a convolutional neural network for segmenting retinal net from pathological fundus images of preterm born children. Segmenting retinal net from pathological fundus images is a fundamental task to aid computer diagnosis. We used U-net architecture for training and testing. Testing with ROPFI dataset, we obtained an area under the receiver operating curve equal to 0.9180; when average sensitivity is equal to 0.700, the average specificity is equal to 0.9710. This performance is higher than prior works using a similar dataset.

Keywords

Retinopathy of Prematurity; convolutional neural network; medical image processing.

1. INTRODUCTION

Artificial vision and computational learning applied to the study of the retina and support for the diagnosis of retinal pathologies is an area of constant contributions in the computer science and medical community. Retinal pathologies can occur in adults and children. Among the most common in adults are glaucoma, diabetic retinopathy, and hypertension retinopathy. The retinal pathology that children born prematurely may present is called retinopathy of prematurity (ROP). In this research work, we will apply image processing and deep learning using a convolutional neuronal network (CNN), to segment the vascular network in ROP images. Table 1 summarizes the most recent works, where the retinal net is segmented. We wanted to highlight recent works and observe pathological datasets.

We focused on datasets with images of patients born preterm with the possible presence of ROP, though we only found two works [3, 7]. The rest of the works segment retinal vasculature in datasets with adults' pathologies. Some papers reported the performance of their proposal in the complete dataset and only pathological images [11, 14]. In [11], the area under the receiver operating characteristic (AUC) reported 0.986, 0.988, 0.985, and 0.978 using the datasets DRIVE, STARE, CHASE-DB1, HRF, respectively, when testing used full datasets (including pathological and non-pathological images). In [14], their proposal is tested in DRIVE and STARE datasets, reporting an average accuracy of 0.9446 and 0.9503, respectively, when it used full datasets. The values shown in Table 1 are those reported with pathological images. We could notice a lower performance in the pathological cases, even when dealing with images of adults. Observing the techniques of artificial vision of these works, we can group them in two classes: the works in [2, 7, 8, 14] use image processing techniques without machine learning, the works in [3, 11, 13, 16] employ supervised non-deep, unsupervised, and deep learning. The main weakness of current approaches is that they were designed for processing adult retina. These proposals do not conduct a study for pathological images of premature children, except for work [3, 7]. Which presents visual results of important contribution. However, segmentation is assessed visually, that dataset is not public, and from the sample of presented images, it can be deduced that they are images that do not have a demarcation line. In other words, they are quite complete retinas with a high degree of tortuosity. The related works that we could find do not allow us to make a quantitative comparison. We also want to mention that there is a relevant number of computer-aided diagnosis studies for ROP. We have not included them in this work because they do not specifically deal with automatic segmentation.

In this article, we present a method based on CNN applied to the case of ROP. Fundus images of ROP present conditions specific to the child patient. The retina may be incomplete (due to possible detachment), the vessels are immature (thinner than in adults), have low contrast and brightness. The contributions of our work are a ROP dataset that will soon be public, a pre-processing method suitable for ROP images, and a retinal segmentation procedure using CNN. Regarding the ROP dataset, under the supervision of pediatric ophthalmologists, we have created a ROP dataset that

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contains original images, masks (to delimit retina area), and its corresponding manual segmentation.

The paper is organized as follows: Section 2 indicates the dataset and the methods used, Section 3 presents and discusses the results, and some conclusions and possible future works are commented in Section 4.

Table 1. Recent works for segmenting retinal net. Ref: reference. AUC: area under de ROC curve. Se: Sensitivity. Sp: Specificity. Acc: Accuracy.

Year	Ref.	Dataset	AUC	Se	Sp	Acc
2019	[7]	ROP NNEH	Visual Validation			
2019	[11]	DRIVE	0.976	0.822	0.979	0.951
		STARE	0.972	0.809	0.974	0.953
		CHASE-DB1	0.965	0.786	0.964	0.948
		HRF	0.974	0.819	0.968	0.951
2019	[2]	DRIVE	--	0.7260	0.9802	0.9563
2019	[3]	DRIVE	0.9752	0.783	0.8594	0.9531
		STARE	0.9853	0.8087	0.9012	0.9691
		CHASE-DB1	0.9789	0.7737	0.984	0.9623
		HRF	0.974	0.819	0.968	0.951
2019	[13]	DRIVE	--	0.8499	0.9693	--
		STARE	--	0.8316	0.9821	--
2019	[14]	DRIVE	--	0.7121	0.9784	0.9435
		STARE	--	0.7265	0.9687	0.9439
2018	[6]	DRIVE	0.9810	0.7540	0.9825	0.9624
		STARE	0.9900	0.8352	0.9846	0.9734
		CHASE-DB1	0.9810	0.8640	0.9745	0.9668
		HRF	0.9770	0.8010	0.8010	0.9650
2017	[5]	DRIVE	--	0.7367	0.9681	--
		FUNDUSROP D	--	0.6949	0.9518	--

2. MATERIAL AND METHODS

2.1 Dataset

This proposal is for segmenting ROP fundus images. Since we could not get public ROP fundus images, and because we want to test using real cases, we created a new ROP fundus images dataset (ROPFI). This set is formed by sixty-four images, whose dimensions are 480 x 640 pixels, in high and width, respectively, and their size is between 0.9MB and 6 MB. This data set is subdivided into three subsets: images, vascular net labeled manually, and masks. Regarding the generation of the image mask, two types are identified. When the image does not have a demarcation line, the mask has a circular shape to limit the entire retina. In contrast, when the image has a demarcation line, the mask takes an oval shape to limit only the area of the retina that contains vessels (See Figure 1. (e), (f)). The images of ROPFI dataset were acquired with a RetCam Shuttle camera (Clarity Medical Systems,

Inc.). The images of ROPFI dataset were acquired with a RetCam Shuttle camera (Clarity Medical Systems, Inc.), and correspond to patients of the Foundation Metrofraternidad of the Metropolitan Hospital (Quito, Ecuador). The images were provided for research goals, and they do not store any patient information.

2.2 Method

Our proposal is based on U-net CNN [9, 10]. We made some adjustments to get a good performance in the ROPFI dataset. We defined more convenient preprocessing tasks for ROPFI dataset, the size of patches in 56 x 56, and we experimented until 200 epochs.

The method follows these stages: preprocessing, preparing data format, training CNN, and testing with a pre-trained model.

2.2.1 Preprocessing

Fundus images acquired in children patients present greater difficulty to recognize the vessels. The patient is examined several times to acquire the images that capture the entire retina. They present low contrast and brightness, and small curve lines that could be confused with vessels (See Figure 1. (a) and (b)). Because of these characteristics, they require a pre-processing of greater effort than the images of adult patients. First, contrast and brightness enhancement are realized like a point operation [12]. Then, a gamma correction [12], which is a non-linear transformation, is applied. After that, contrast limited adaptive histogram equalization (CLAHE) over the luminance channel is performed [15]. The last preprocessing task is to convert the image to grayscale. The neural network will be trained and tested with images in a single channel. In Figure 1, two samples of preprocessed color images ((c) and (d)) are shown.

2.2.2 Architecture of the CNN

This work uses U-net [10] convolutional neural network. It is a fully convolutional network (FCN). It has twenty-three convolutional layers that are performed along three blocks (downsampling, bottleneck, and upsampling). Downsampling block presents four repetitions of: two convolutions – one max pooling. The number of feature maps starts in 64 and ends in 1024. Bottleneck block presents two convolutional layers. Upsampling block is composed for four repetitions of: a deconvolution, a concatenation with the corresponding downsampling step, a convolution, and an activation.

2.2.3 Images preparation

Before the training or testing, some scripts prepare data, including the conversion of images to grayscale, and their representation in format hierarchical data format version five (HDF5).

2.2.4 Training

The CNN was trained with twenty ROPFI images. The rest of the dataset was used for testing. The patch size set to 56 x 56 pixels, the number of patches for each image was 11,400, and the total of patches used in training was 228,000. The patches were taken randomly from the input image. A sample of patches used in training is in Figure 2. The best model is saved like pretrained model (the model with the lowest loss value in the validation stage). This method was trained in TensorFlow plus Keras, using a GeForce GTX 1070 Ti 8GB graphics card. The time of each training varied between 8 and 14 hours, depending on the parameters.

2.2.5 Testing

Testing used forty-four ROPFI images. The pretrained model is used. The test images are preprocessed, converted to grayscale, and represented into HDF5 format, and then passed to the prediction stage of their vascular network. In the process of prediction, the division into patches, the one-to-one prediction, and the reconstruction of the image will be performed. The first threshold whose true-positive-rate (TPR) is equal to or greater than 0.7 is selected. With this threshold, the predicted vascular network is composed and visualized.

Figure 1. Sample of images from ROPFI dataset. (a) and (b): input images. (c) and (d): preprocessed images. (e) and (f): masks.

Figure 2. Sample of patches for training CNN.

3. RESULTS AND DISCUSSION

The performance of the segmentation is measured as a binary classifier. Each pixel is classified as a vessel or non-vessel. For that, we can define a confusion matrix (See Table 2). The confusion matrix allows computing sensitivity (true positive rate, see expression (1)), specificity (false positive rate, see expression (2)). After that, a Receiver Operating Characteristic (ROC) curve can be created and its Area Under the Curve (AUC) is computed [1]. The neural network delivers a probability matrix. All possible classifiers (or probability thresholds) are represented in a ROC curve. The curve area provides a global idea of the capacity of the classifiers. A random testing image is shown in Figure 4. The segmented image by CNN (Figure 4(b)) is binarized with the first probabilistic threshold that set TPR equal to or higher than 0.7.

Table 3. includes the results of our proposal and two other works. The first work was reported in [7, 8]; in both articles, the segmentation results are validated visually. The second work [5] tested fifty ROP images and reported the true-positive rate (sensitivity) and the false-positive rate ($1 - \text{specificity}$). We obtained a higher performance.

Figure 3. Area under ROC curve of ROPFI testing.

Table 2. Confusion matrix to assess the segmentation. TP: true positive. FP: false positive. FN: false negative. TN: true negative. P: total of vessel pixels. N: total of non-vessel pixels.

	Manual label

		Vessel	Non-vessel
CNN prediction	Vessel	TP	FP
	Non-Vessel	FN	TN
Total		P	N

$$Se = \frac{TP}{P} \quad (1)$$

$$Sp = \frac{TN}{N} \quad (2)$$

Table 3. Comparison of testing ROPFI dataset with other similar ROP dataset. AUC: area under ROC curve. Se: Sensitivity. Sp: Specificity.

Dataset	Ref.	Number of images	AUC	Se	Sp
ROP NNEH	[7]		Visual validation		
FUNDUSROPD	[5]	50/50	--	0.6949	0.9518
ROPFI	--	44/64	0.9180	0.7000	0.9710

Figure 4. Sample of tested image: (a) input image, (b) its corresponding preprocessed image, (c) manual segmentation, (d) CNN segmentation.

4. CONCLUSIONS

This research addressed the segmentation of retinal vascular presence of ROP. The process of searching for related works showed that there are few articles in which the segmentation of the vascular network of images of premature births is quantified. Also, we could not find public datasets of this pathology. Several efforts were necessary: to generate a new clinical dataset, a specific pre-processing work, and several tests with the convolutional network until achieving superior results to previous ones. The new dataset, denominated ROPFI, includes three sub-datasets the original images, manual segmentation, and masks. The last one is delimiting the study to the retinal region. It was necessary to design a suitable

pre-processing and different from that used to process images acquired in healthy patients.

In future works, we want to deal with the ways to diagnose ROP, that are presented by an International Committee [4]. There are many possibilities of computational development to support physicians in the diagnosis of ROP, for example, identifying the demarcation line automatically, detecting optic nerve, macula and the zones of affection. We also noted, in a more comprehensive decision-making system textual patient data, and image data images could be combined. A complete pathological state could be specified.

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