POSTER: Image Resizing Level Impact on Eye Fundus Optic Disc and Optic Cup Segmentation

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ABSTRACT

Optic disc (OD) and Optic Cup (OC) segmentation play an important role in the automatic assessment of eye health where the Convolutional Neural Networks (CNNs) have been extensively employed. The application of CNNs requires identical image size to work properly but the eye fundus images vary due to different datasets. In this paper we evaluate eye fundus image resizing level impact on OD and OC segmentation. For this evaluation we apply the most popular medical images segmentation autoencoder named U-Net. The experiments demonstrate that OD and OC segmentation results are improved averagely by 5.5 percent resizing images to size of 512x512 than 128x128.

Keywords

OD and OC segmentation, Convolutional Neural Networks.

1. INTRODUCTION

Diseases such as glaucoma, diabetic retinopathy, hypertension can be diagnosed from biomedical images, more specifically from eye fundus images. Therefore, biomedical image analysis is required where an image segmentation is one of the initial steps. Manual image segmentation is a time-consuming task that is closely related to the expertise of the medical profession. This encourages researchers to develop fast and accurate solutions for automated image segmentation [Vir20]. Segmentation distinguishes and defines different objects in the image, thus classifying them into different object classes.

Solving image segmentation tasks by applying CNNs, the size of images plays an important role [Zhu21] as CNNs require identical image size but the size varies due to different datasets. Most of the lately proposed networks are working on the images of the same dataset but it has a poor segmentation accuracy for different fundus images datasets (Table 2. and Table 3.). To make the network to be working for different datasets, the mixed images strategy can be

applied but then the alignment of image size is needed. In this paper we focus on evaluation of image resizing level and its impact on OD and OC segmentation as these are one of the key parameters in glaucoma identification.

2. RELATED WORK

Lately many CNN based methods have been proposed for OD and OC segmentation in fundus images (some achieved results are shown in Table 4.). Liu W et. al. [Liu20] presented an autoencoder for OD segmentation called Multi-level Light U-Net and Atrous Spatial Pyramid Pooling that aimed to implicate the significant spatial information in high-level semantic feature maps. The proposed Light U-Net (LU-Net) incorporates the encoder module of two max-pooling operations for down-sampling and the decoder consisted of two up-sampling operations. The reduction of convolutional layers and pooling operations helped to avoid the loss of the spatial information. Liu B. et. al. [Liu21] proposed a U-Net based autoencoder named Densely Connected Depth-wise Separable Convolution Network (DDSC-Net) for OD and OC semantic segmentation. The usage of depth-wise separable convolution layers reduced the amount of computation that made the proposed network to differ from the original U-Net. Sevastopolsky A. [Sev17] presented a universal approach based on U-Net for automatic OD and OC segmentation. The modification presented in the paper contained less filters in all convolutional layers compared to the original U-Net and did not contain an increasing number of filters to reduce resolution. These changes made the architecture much lighter in terms of number of parameters and training time. Veena H.N. et. al. [Vee21] designed two separate CNN models composed of 39 layers for OD and OC segmentation to calculate the Cup-to-Disc-Ratio (CDR). The increased number of layers helped to extract more features and minimize the errors. According to the authors, one of the main problems of the existing CNN model is the change of image resolution during the model training process. That causes the loss of essential information. The authors proposed to solve this problem by adding an up-sampling layer for each down-sampling layer. By this approach the lost image resolution was recovered and the output image resolution was the same as the resolution of the input image. Gao J. et. al. [Gao20] proposed a Recurrent Fully Convolution Network (RFC-Net) for automatic joint segmentation of OD and OC. This network was able to capture high-level information, subtle edge information and minimize the loss of spatial information. The authors achieved an improvement of OD and OC segmentation performance by applying the polar transformation, multi-scale input and multiple output, four recurrent units and adding skip connections. Zhu Q., et. al., [Zhu21] proposed an encoder-decoder named GDCSeg-Net for OD and OC segmentation and applied mixed training strategy based on different datasets to solve image segmentation for different fundus image datasets problem that existing deep learning networks are facing. The network was conducted by a novel multi-scale weight-shared attention (MSA) module and densely connected depth-wise separable convolution (DSC) module. With these modules, OD and OC feature information was obtained more effectively and helped to improve the segmentation performance.

3. RESEARCH METHODOLOGY AND METHODS

To evaluate the impact of image resizing to the OD and OC segmentation results, we use the original U-Net network [Ron15] that is realized on several different scenarios:

1. The U-Net is trained on Drishti-GS (101 images of size 2047x1759) [Siv15] training dataset and tested on testing dataset of Drishti-GS, RIM-ONE v.3 (159 images of size 2144x1424) [Rim21] and Kaunas Clinics (39 images of size 1920x1440) [Kau21].

2. The U-Net is trained on the RIM-ONE v.3 training dataset and tested on testing dataset of RIM-ONE v.3, Drishti-GS and Kaunas Clinics.

3. The U-Net is trained on Kaunas Clinics training dataset and tested on testing dataset of Kaunas Clinics, RIM-ONE v.3 and Drishti-GS.

4. The U-Net is trained on dataset compiled from all these datasets and tested on testing datasets of RIM-ONE v.3, Drishti-GS and Kaunas Clinics separately.

The images are divided into training and test datasets. As the number of images in training datasets is too small, a data augmentation on each dataset is performed. By applying a random horizontal, vertical, and diagonal flip on each image by 20%, the number of images is increased to 3000 for each dataset that is used as training datasets. The test datasets consist of 39 original eye fundus images of each dataset. The images for training and test datasets are individually cropped by area of their OD (Fig 1.). The sizes of images vary from 340x340 to 1308x1308.

4. EXPERIMENT AND RESULTS

The experiments of OD and OC segmentation are performed on cropped images resized into pixel values of 512x512, 256x256 and 128x128 by bilinear interpolation. The learning rate of 0.1 and batch size of 3 are used. The training runs for 250 epochs. Table 4. shows the computation time on GPU 5 cores with 70 GB memory [ITR22] needed to train the network according to image size. The segmentation performance is evaluated by Dice score, which is defined as follow:

$$Dice = \frac{2TP}{2TP+FP+FN} \quad (1)$$

where *TP* denotes true positive, *FP* – false positive and *FN* – false negative.

The results of Dice are presented in Table 1. for OD segmentation and in Table 2. for OC segmentation. The results of Dice of other methods are presented in Table 3. The visual comparison of OD and OC segmentation results of one scenario is shown in Figure. 2.

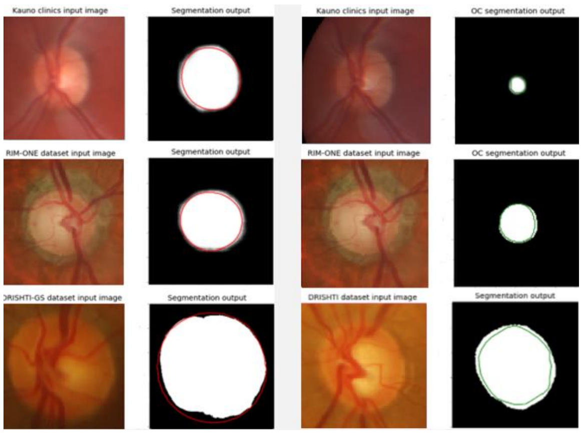

Figure 2. Visual comparison of OD and OC segmentation, where red circle indicates the ground truth of OD, green - the ground truth OC.

Train dataset	Test dataset								
	Kaunas Clinics			Drishti			RIM-ONE		
	128x128	**256x256**	**512x512**	**128x128**	**256x256**	**512x512**	**128x128**	**256x256**	**512x512**
Kaunas Clinics	0.9213	0.9441	0.9530	0.7914	0.8249	0.8516	0.7514	0.7989	0.8285
Drishti	0.7028	0.7346	0.8075	0.9348	0.9659	0.9760	0.7125	0.7737	0.8248
RIM-ONE	0.7495	0.7710	0.8118	0.7112	0.7721	0.8242	0.9210	0.9558	0.9657
Mixed	0.8702	0.8913	0.9161	0.9116	0.9386	0.9528	0.8875	0.9093	0.9341

Table 1. OD segmentation results of the experiment.

Train dataset	Test dataset								
	Kaunas Clinics			Drishti			RIM-ONE		
	128x128	**256x256**	**512x512**	**128x128**	**256x256**	**512x512**	**128x128**	**256x256**	**512x512**
Kaunas Clinics	0.8698	0.8770	0.8861	0.4008	0.4297	0.4990	0.3918	0.4037	0.4448
Drishti	0.4015	0.4220	0.4905	0.8593	0.8765	0.9053	0.5368	0.5706	0.6066
RIM-ONE	0.4007	0.4114	0.4514	0.5223	0.5657	0.5930	0.8261	0.8769	0.9068
Mixed	0.7873	0.8231	0.8699	0.8006	0.8449	0.8990	0.7938	0.8304	0.8767

Table 2. OC segmentation results of the experiment.

Other methods	Input Image Resolution	Image resolution after resizing	REFUGE		Drishti		RIM-ONE	
			OD	**OC**	**OD**	**OC**	**OD**	**OC**
Liu W et. al., LU-Net [Liu20]	448x448	-	0.982	-	0.997	-	-	-
Liu B. et. al., DDSC-Net [Liu21]	480x480	240×240	0.960	0.890	-	-	-	-
Liu B. et. al., DDSC-Net [Liu21]	560x560	240×240	-	-	0.978	0.912	-	-
Sevastopolsky A., U-Net [Sev17]	256x256	128x128	-	-	-		0.95	
Sevastopolsky A., U-Net [Sev17]	512x512	128x128	-	-	-	0.85	-	0.82
Zhu Q., et. al., GDCSeg-Net [Zhu21]	512x512	-	0.964	0.894	0.974	0.900	0.956	0.824
Veena H.N. et. al., CNN [Vee21]	512x512	-	-	-	-	0.971	-	-
Veena H.N. et. al., CNN [Vee21]	128x128	-	-	-	0.988	-	-	-
Gao J. et. al., RFC-Net [Gao20]	400x400 - 900x900	512x512	-	-	0.9788	0.906	-	-

Table 3. OD and OC segmentation of other methods

	Image size		
	512x512	256x256	128x128
Computational time of one epoch	176 ms/step	50 ms/step	20 ms/step

Table 4. Computation time to train the network.

CONCLUSION

The experiments indicate that the higher image resolution, the better OD and OC segmentation results are achieved but the cost of computation time to train the network on images of size 512x512 in comparison of images with size of 128x128 increased by 8 times. The highest Dice score is achieved by training the network on mixed images dataset with the images resized to 512x512. The Dice score of 0.9161 for OD and 0.8699 for OC is achieved on Kaunas clinics dataset, 0.9528 for OD and 0.8990 for OC on Drishti-GS, 0.9341 for OD and 0.8767 for OC on RIM-ONE. The bilinear interpolation is applied to resize the images but it causes the loss of OC boundaries. Due to this, the other interpolation methods such as nearest-neighbor or bi-cubic will be investigated in our future work to evaluate the impact of interpolation on emphasis of segment.

5. ACKNOWLEDGMENTS

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6. REFERENCES

[Ron15] Ronneberger, O., Fischer, P., Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation (2015).

[Liu20] Liu, W., Lei H., Xie, H., Zhao, B., Yue, G., Lei, B. Multi-level Light U-Net and Atrous Spatial Pyramid Pooling for Optic Disc Segmentation on Fundus Image, Springer, 2020.

[Liu21] Liu, B., Pan, D., Song, H. Joint optic disc and cup segmentation based on densely connected depthwise separable convolution deep network. BMC Med Imaging, 2021.

[Sev17] Sevastopolsky, A. Optic disc and cup segmentation methods for glaucoma detection with modification of U-Net convolutional neural network. Pattern Recognit. Image Anal. 27, 618-624, 2017.

[Zhu21] Zhu, Q., Xhen, X., Meng, Q., Song, J., Luo, G., Wang, M., Shi, F., Chen, Z., Xiang, D., Pan, L., Li, Z., Zhu, W. GDCSeg-Net: general optic disc and cup segmentation network for multi-device fundus images. Biomedical Optics Express, 2021.

[Vee21] Veena, H.N., Muruganandham, A., Senthil Kumaran, T. A novel optic disc and optic cup segmentation technique to diagnose glaucoma using deep learning convolutional neural network over retinal fundus images. Journal of King Saud University-Computer and Information Sciences, 2021.

[Gao20] Gao, J., Jiang, Y., Zhang, H., Wang, F. Joint disc and cup segmentation based on recurrent fully convolutional network. PLoS ONE 15(9): e0238983, 2020.

[Vir20] Virbukaite, S., Bernataviciene, J. Deep Learning Methods for Glaucoma Identification Using Digital Fundus Images. Baltic J. Modern Computing, Vol. 8, 2020.

[Siv15] Sivaswamy J, Krishnadas K. R, Joshi G. D, Jain Madhulika, Ujjwal and Syed Abbas T. Drishti-GS: Retinal Image Dataset for Optic Nerve Head (ONH) Segmentation. IEEE ISBI, Beijing, 2015.

[Rim21] RIME-ONE v.3 Dataset Homepage, http://medimrg.webs.ull.es/research/retinal-imaging/rim-one/, last accessed 2021.

[Kau21] Kaunas Clinics Dataset, a private dataset collected during the project "Development of a depersonalized eye fundus images database". Vilnius Regional Biomedical Research Ethics Committee permit No:158200-18/11-1057-572, last accessed 2021.

[ITR22] IT Research Center of Vilnius University, https://mif.vu.lt/lt3/en/about/structure/it-research-center#about-center, last accessed 2022.