LEVERAGING SEGMENTATION POWER OF UNETS TO SEGMENT THE OPTICAL DISC CENTER

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ABSTRACT

An important process of automated detection of retinal diseases in fundus images is detection of the optic disc and fovea. The optic disc have texture that is different from the neighboring part of the retinal image, which might trick the automatic disease detection algorithm to think of it as an anomaly. Location of optic disc is also useful in automated tracking of glaucoma. Proximity of lesions around the fovea has clinical relevance. Instead of more classical approaches we used a simple Convolutional Neural Network to get a soft model localising the optical point and then harness the strong segmentation power of UNet algorithm. This gives better results in terms of accuracy and number of computations required, with an end to end solution.

Index Terms— optic disc segmentation, convolutional neural network, diabetic retinopathy, UNet, segmentation.

1. INTRODUCTION

Recent advances in the field of deep learning has led to a deluge of research in the field of medical imaging. This work is focussed on a problem in the field of medical imaging that involves localisation. Advances in object localisation are driven by success of region proposal methods and region based convolutional neural networks. This work is part of a larger project to develop an automated screening system for diabetic retinopathy. In this paper we present a fast, robust automated method to segment the Optical Center.

Our approach uses a deep learning model with loss function as Euclidean Distance to optimize the model for segmentation. Due to the less data points the task of segmentation is done after a tentative location of the optical Center is found.

The main problem with the traditional methods which are developed for fovea centered images is that they require vascular arch. Whereas in the real world the screening data in a typical screening environment is acquired at different sites, using different cameras and operators. This leads to a substantial variability in the image quality as well as imperfect adherence to the standard protocols for images. These methods that require the visibility of the complete vascular arch generally assumes that these images are standard images with prefect conditions and are not suited for application in the real world. This is where deep learning help in generalization on the data.

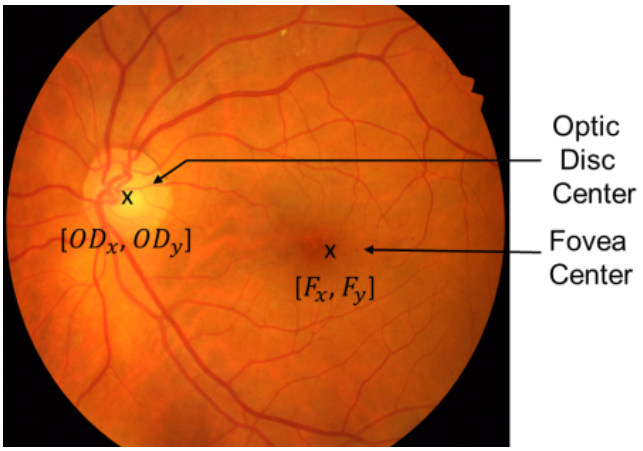

Fig. 1: Fundus image showing coordinate of optic disc and fovea centre.

2. METHOD AND TECHNIQUES

The Model consisted of two subsequent approaches. The initial model was a Convolution based model to get a tentative position of the Optical Center.

The Next Model worked on a patch around the predicted value of the previous model to predict the mask. The motivation for such a step was to first get a global view of the image and then focus on a local area for getting the mask. It also helped with the less number of data points while training the UNet for segmentation.

3. MODEL 1

3.1. Data Preprocessing

The dataset consist of 413 RGB retinal images for both optic disc and fovea detection. We converted each image to grayscale images and resize it to 200 x 200 x 1. For data augmentation techniques we used horizontal flipping.

3.2. Network Architecture

After data preprocessing, the input consists of grayscale images, each of size 200 x 200. 200 x 200 matrix is convolved with 3 x 3 x 12 filters to produce 12 feature maps. Each feature map is then passed through a Batch-Normalisation layer followed by rectified linear unit (ReLU) activation function. After that, the 12 feature maps are convolved with a 3 x 3 x 24 filters which are followed by Batch-Normalisation layer and ReLU activation layer to produce 24 feature map. On each feature map a max-pooling sizing 2 x 2 is applied. Again, these 24 feature maps are convolved with a 3 x 3 x 24 filters, again followed by Batch-Normalisation layer and ReLU activation layer. Lastly, the neurons of every feature maps are flattened and connected fully to a 256 neurons, which are further fully connected in sequence to neurons of size 128, 32, 8 and 2.

We trained our model on Keras framework with Tensorflow backend on NVIDIA GTX 1080 GPU. The data set was split in the ratio of 80:20 for training and testing purpose. The initialisation of network weight is done using the Xavier Uniform initializer. The model was trained for 150 epochs with batch size of 8. We used Adam optimiser with learning rate 1e-3 for first 60 epochs, 1e-4 for next 60 epochs and 1e-5 for last 30 epochs. We used Root Mean Squared Error (RMSE) as our loss function.

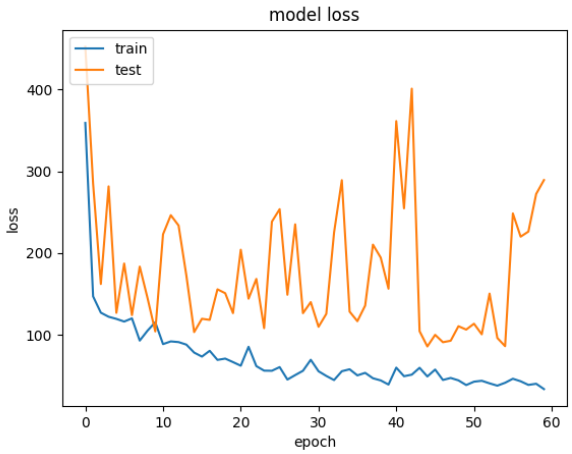

Fig. 2: Loss Curve for the first 60 epochs of Model 1

4. MODEL 2

4.1. Data Preprocessing

This time we worked with the coordinates predicted from the previous model. We used them to get a local view around the point by making a patch of 512x512. Corresponding to this patch we also cropped the mask. With this patch of the image and the corresponding patch of the mask we set forward to use UNet to segment the Optical Center.

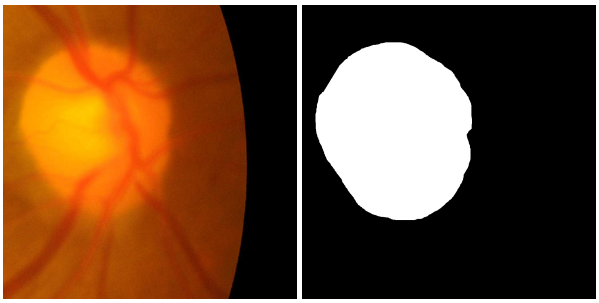

Fig. 3: Patch Of Image and Mask

4.2. Network Architecture

After this step we have patches and corresponding masks of size 512x512. Now we try to learn this mask from the patches with the help of UNet to segment the Optical Center. The UNet architecture used is described below.

The network architecture consists of a contracting path (left side) and an expansive path (right side). The contracting path includes the standard structure of a convolutional network & the iterated application of two 3x3 convolutions. Each contracting layer is followed by batch normalization and then activation function as rectified linear unit (ReLU). It also consists of a 2x2 max pooling operation with stride 2 for down-sampling. We started with 16 feature channels of 512*512 patch image and at each down-sampling step we double the number of feature channels till 1024 feature channels. Every step in the expansive path consists of an up-sampling of the feature map followed by a 2x2 up-convolution that halves the number of feature channels. In expansive path the up-sampling output is concatenated with the corresponding feature map from the contracting path, and two 3x3 convolutions, each followed by a batch normalization layer & ReLU. At the final layer a 1x1 convolution is used to map each 16-component feature vector to the desired number of classes.

In the model, we have used pixel-wise weighted binary cross entropy as loss function. In this, weightage given to losses of white square blob and rest of the area is in the ratio 6:1. We have given more weightage to blob as they are very less in area. We dont want to miss any blob area in the image so more weightage is given to them. The optimum weightage was chosen after iterating over several other weights. We train by Adam Optimizer with an initial learning rate of 1e-4, and exponential decay rates for 1st and 2nd moment estimates as 0.9 and 0.999 respectively. We used a batch size of 4 for 50 epochs.

After generating the mask of the area the mask of the whole image was generated centering the prediction on the predicted coordinate of model 1.

5. PERFORMANCE EVALUATION

We used Euclidean distance as evaluation metric for both localization of Optic Disc and Fovea. Euclidean distance is calculated as the square root of the sum of the squared differences (in pixels) between ground truth and algorithmic located optic disc and fovea coordinates.

6. RESULTS

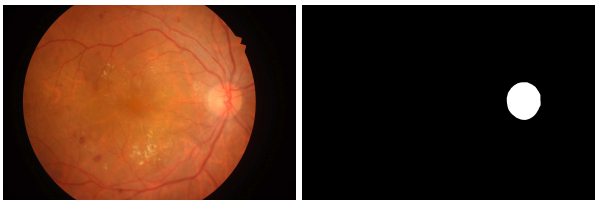

Fig. 4: Result of the model on retinal fundus image

Table 1: Evaluation Metrics

Sensitivity	0.996
Specificity	0.565
Positive Predictive Value	0.718

7. CONCLUSION

This paper proposed a novel method for automated optical disc segmentation in fundus images. To develop this robust model, we have done data augmentation in both model 1 and model 2. After training the model and hyperparameter tuning, we have detected almost all the optical center with correct shape and size at precise locations. Hence, the proposed optical Center segmentation technique will significantly help ophthalmologists for initial Diabetic Macular Edema diagnosis.

8. REFERENCES

[1] M. D. Abramoff, M. Niemeijer, and S. R. Russell, Automated detection of diabetic retinopathy: barriers to translation into clinical practice, in Expert Review of Medical Devices , vol. 7, no. 2, 2010, pp. 287296.

[2] T. Kauppi, V. Kalesnykiene, J.-K. Kmrinen, L. Lensu, I. Sorr, A. Rani- nen, R. Voutilainen, H. Uusitalo, H. Klviinen, and J. Pietil, Diaretdb1 diabetic retinopathy database and evaluation protocol, Proc. of the 11th Conf. on Medical Image Understanding and Analysis (MIUA2007) , pp. 6165, 2007.

[3] C. Sinthanayothin, J. F. Boyce, H. L. Cook, and T. H.Williamson, Automated localisation of the optic disk, fovea, and retinal blood vessels from digital colour fundus images, Br. J. Ophthalmol, , vol. 83, no. 8, pp. 902910, 1999

[4] M. Niemeijer, B. van Ginneken, M. Cree, A. Mizutani, G. Quellec, C. Sanchez, B. Zhang, R. Hornero, M. Lamard, C. Muramatsu, X. Wu, G. Cazuguel, J. You, A. Mayo, Q. Li, Y. Hatanaka, B. Cochener, C. Roux, F. Karray, M. Garcia, H. Fujita, and M. Abramoff, Automatic detection of red lesions in digital color fundus photographs, IEEE Transactions on Medical Imaging , vol. 29, no. 1, pp. 185195, January 2010.

[5] M. Fraz et al., Blood vessel segmentation methodologies in retinal imagesA survey, Comput. Methods Prog. Biomed. , vol. 108, no. 1, pp. 407433, Oct. 2012.

[6] Roychowdhury, Sohini, Dara D. Koozekanani,and Keshab K. Parhi. "Screening fundus images for diabetic retinopathy", 2012 ConferenceRecord of the Forty Sixth Asilomar Conferenceon Signals Systems and Computers(ASILOMAR), 2012.

[7] C. Sinthanayothin. "Automated detection of diabetic retinopathy on digital fundus images",Diabetic Medicine, 2/2002

[8] Yutong Xie, Jianpeng Zhang, Yong Xia,Michael Fulham, Yanning Zhang. "Fusing texture, shape and deep model-learned information at decision level for automated classification of lung nodules on chest CT",Information Fusion, 2018

[9] "Medical Image Computing and Computer-Assisted Intervention MICCAI 2017", SpringerNature, 2017

[10] U-Net: Convolutional Networks for Biomedical Image Segmentation Olaf Ronneberger, Philipp Fischer, Thomas Brox Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234–241, 2015, available at arXiv:1505.04597 [cs.CV]

[11] Fast Detection of the Optic Disc and Fovea in Color Fundus Photographs. Meindert Niemeijer, Michael D. Abrmoff and Bram van Ginnekenaa