LEVERAGING SEGMENTATION POWER OF UNETS TO LOCALISE 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. The fovea on other hand is located at the center of a darker region responsible for sharp central vision. 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 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 localisation, fovea localisation, convolutional neural network, diabetic macular

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 an fast, robust automated method to detect the location of the optic disc and fovea.

Our approach uses a deep learning model with loss function as Euclidean Distance to optimize the model on fundus images. After detection of optic disc we extracted a patch for segmentation of optic disc to separate the contrasting part so that automated disease detection algorithms dont confuse the patch with an anomaly. Our method was also able to find the location of fovea. Detection of fovea due to its less contrasting features is hard and hence not much work has been done towards it in the past. Our approach along with optical disc detection is performing on fovea detection too with good precision. 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.

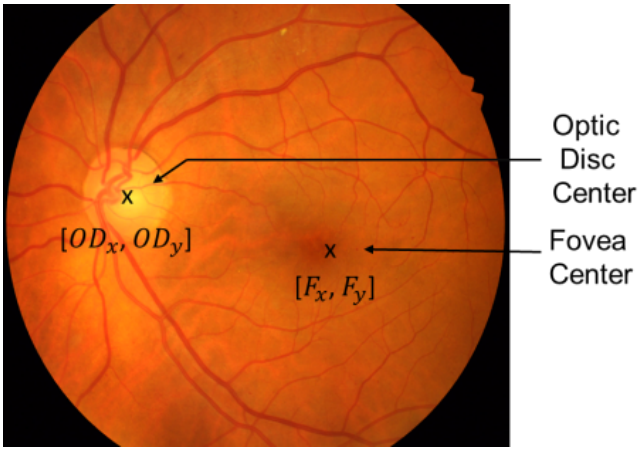

Fig. 1: Fundus image showing coordinate of optic disc and fovea centre.

2. METHODS AND TECHNIQUES

The Model consisted of two subsequent approaches to do localisation. The initial model was a Convolution based model to get a tentative position of the Fovea and the Optical Center. The Next Model worked on a patch around the predicted value of the previous model to improve the accuracy. The motivation for such a step was to first get a global view of the image and then focus on a local area for predicting the coordinates.

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, 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 which are 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 also 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.

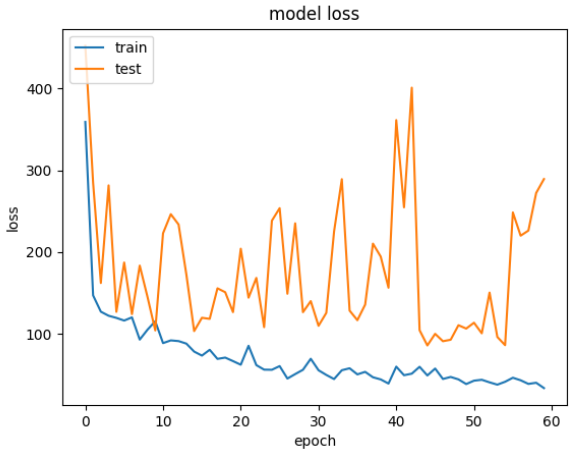

Fig. 2: Loss Curve for the first 60 epochs of Model 1

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 made a mask of the same dimension with the original coordinate being represented by circular area of radius 10.

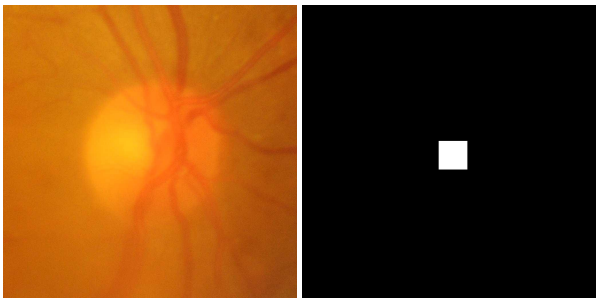

Fig. 3: Patch Of Image and Mask

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 which will segment the square blob out. 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 this the coordinates are found from the resulting blob by taking an average of the x and y values of the blob area.

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. CONCLUSION

This paper proposed a novel method for automated optic disc localisation in fundus images. To develop this robust localisation model, we have done data augmentation and provided the small patches of image instead of single large image. Hence, the proposed lesion segmentation technique will significantly help ophthalmologists for initial Diabetic Macular Edema diagnosis.

7. REFERENCES

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