Effect of Image Enhancement as Pre-Processing Step on Blood Vessel Segmentation using Deep Neural Network

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Absract—**In this paper, we investigate the influence of image enhancement techniques as pre-processing steps in segmentation of retinal blood vessels using deep convolutional networks. For the implementation of our algorithm, we used publicly available DRIVE database. As deep neural networks requires extensive computational resources, an insight was taken first using simple neural networks which revealed a better performance in using sharpening techniques as pre-processing step. Our study shows that using sharpening filter can provide above 90% accuracy in segmenting blood vessel with 10 times less data than normal.**

Keywords—Hypertensive Retinopathy,, Fundus Image, Deep neural networks, Sharpening filter

I. INTRODUCTION

Symptoms of various diseases like diabetes and hypertension can manifest in the retina for example microaneurysm, hemorrhage or change in the vessel thickness. These abnormalities are generally diagnosed from the retinal fundus image. Diagnosis by naked eye can sometimes be impossible, hence automatic methods are required. The first step of automatic diagnosis of these abnormalities from the fundus image involves segmenting the vessel from its background.

The segmentation of blood vessels is a rather saturated area of research and many different approaches have been explored. These includes edge/boundary detection based approaches, region growth based approaches, feature extraction based approaches, and lastly convolutional neural network. In [1] Paweł Liskowski and Krzysztof Krawiec implemented a robust CNN architecture that do well both in DRIVE and STARE database. It also gives a spectacular accuracy of 95% in knowledge transfer mode. Zero-phase Component Analysis (ZCA whitening) was also explored as pre-processing step but found to be ineffective.

In this paper we explore six different image enhancement technique as pre-processing step for segmentation of retinal blood vessel using deep convolutional networks. A simple neural networks and small dataset is used to visualize the effect of the different image enhancement technique and the result was then verified using deep neural nets.

II. DATA PREPARATION

We used publicly available The DRIVE database which contains a sample of 40 subjects, 7of which show mild signs of early diabetic retinopathy, and the remaining ones represent the clinical norm. The database is divided into the training set and the test set, both composed of 20 images taken from different patients. For every image, manual segmentation of retinal vessels is provided. As in many other studies, in our approach the decision on the class of a particular pixel is based on an m * m patch centered at that pixel (see Figure 1). A triple of such patches, each reflecting image content at the same location for the RGB channels, forms the input fed into a neural network.

Figure 1. Example of patches taken from DRIVE database image

For simple neural net a small dataset is formed from the extracted patches where m = 27. From each image 1000 random patch was generated. The dataset was balanced that is the ratio of positive and negative patch from each image was 1:1 (500 positive and 500 negative patches). So the training set contained 20000 patches and test set contained 20000 patches. For deep neural net 3 different dataset was formed based on size. The patch per image extracted for these dataset were 1000, 4000, and 10000. Two different patch size used where m = 13 and m = 27. Details are shown in Table I.

TABLE I: Dataset used for deep neural net training

Dataset	Patch size (m)	Patch per Image	Positive	Negative
I	27	1000	20000	20000
II	27	4000	80000	80000
III	27	10000	200000	200000
IV	13	1000	20000	20000
V	13	4000	80000	80000
VI	13	10000	200000	200000

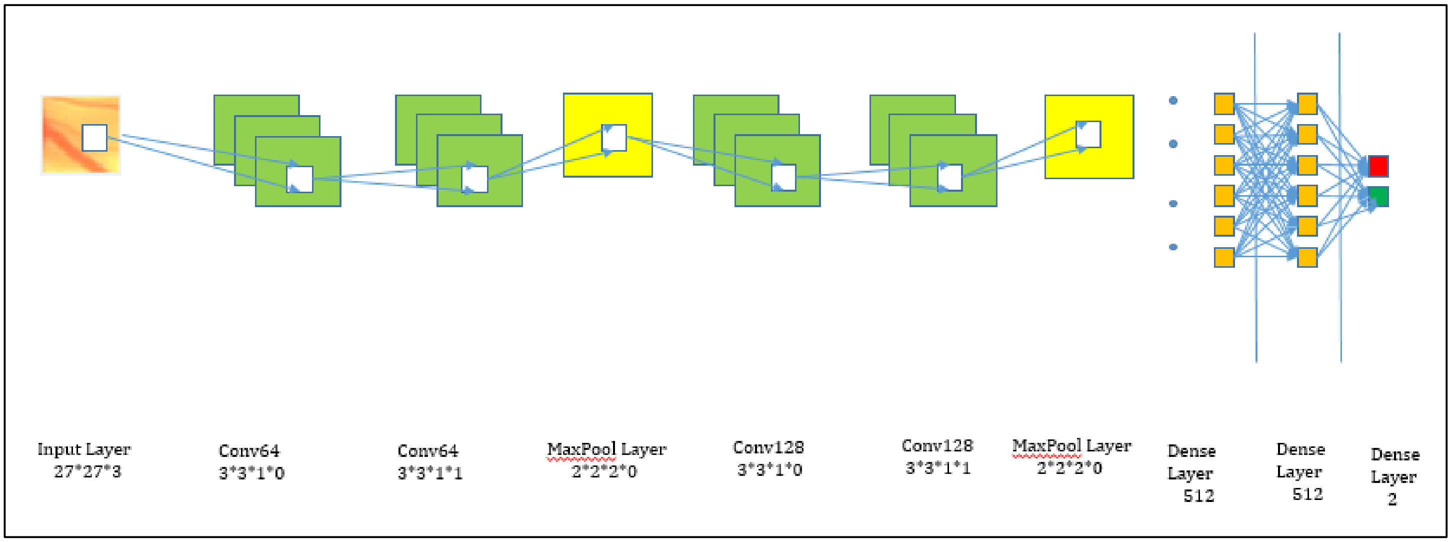


Figure 2. Architecture of deep neural network that has been used. It has four convolutional layer in two stack and a maxpool layer after each convolutional stack. Last maxpool layer is connected to a fully connected layer followed by another FC layer and a two neuron output layer.

III. Network Architecture and Experiment

A. Simple classifier architecture

The simple classifier we used is a simple one-hidden layer (see Figure 3) neural network. The input layer contains 2187 (27 * 27 * 3) neurons. The hidden layer was the same size as input layer and fully connected to it. The output layer contains two neurons that classifies a patch as vessel or non-vessel.

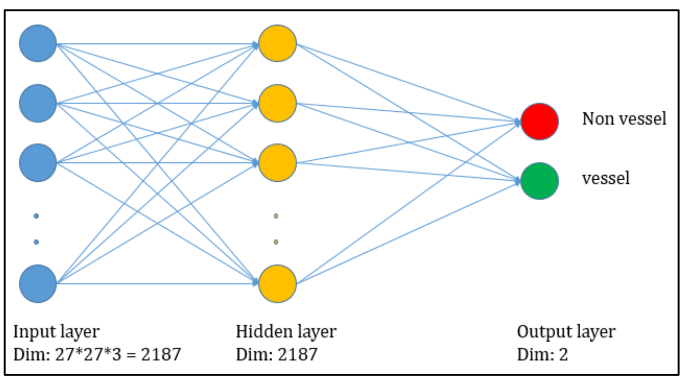


Figure 3. Simple classifier architecture. Input layer and hidden layer size 2187 and the output layer size 2.

B. Deep neural network architecture

The Deep neural network has four convolutional layer in two stacks (see Figure 2). The layers in first stack uses 64 filters and the layers in second stack used 128 filters. A maxpool layer after each convolutional stack is introduced to compensate for translational invariance. The convolutional layer uses standard 3 * 3 filters and the maxpool layer uses standard 2* 2 filters. Last maxpool layer is followed by two fully connected layer. We used a dropout layer with a 0.5 dropout rate between the two FC layers. The last FC layer is connected to a two neuron output layer.

We used ReLu activation as it render sufficient non-linearity consuming less computing resources. The output layer activation is softmax which scores the probability of a patch being vessel and non-vessel within the range of 0 and 1.

IV. Experiment

A. Pre-processing

The data were pre-processed before fed into the simple classifier. We used six image enhancement techniques based on contrast enhancement, smoothing, and sharpening –

a. Green Channel Image
b. Histogram Equalization
c. Gaussian Filtering
d. Median Filtering
e. Laplace Filtering
f. Sobel Filtering

As only sharpening filter showed improved result in simple classifier experiment we used only Sobel filtering in deep neural net training.

B. Training

For simple classifier we used back-propagation with adam optimization technique to train network parameter. We used FloydHud cloud service to run our model. For simple classifier training, we used Intel Xeon® 2 Cores CPU with 8 GB RAM 100 GB SSD.

We used Stochastic Gradient Descent (SGD) optimizer for deep neural nets training. A momentum of 0.9 and learning rate of 10^{-4} provided the best result. L2 regularization with a value of $l2 = 0.5 * 10^{-4}$ is used to avoid over-fitting. The training is done on Tesla K80 GPU with 12 GB Memory, 61 GB RAM and 100 GB SSD in FloydHub platform.

V. RESULT

Figure 4. shows the accuracy simple classifier model in segmenting blood vessel using different pre-processing techniques. We see enhanced image patches does not produce better result than the original data but, sharpening filter yielded almost same accuracy. We can conclude that sharpening filter can produce better result than the other techniques.

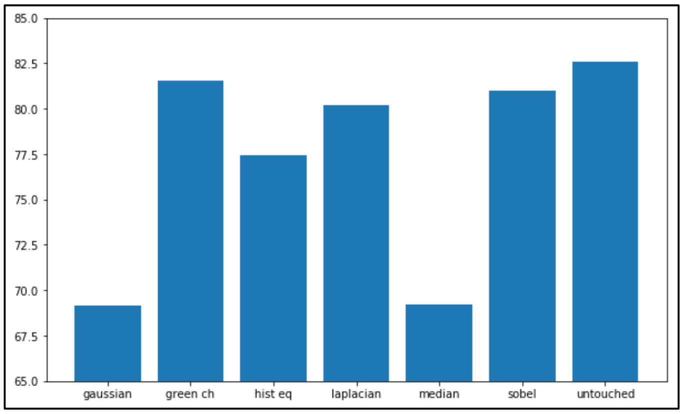


Figure 4. Accuracy of simple classifier on segmentation of blood vessel using different image enhancement technique as pre-processing step

The reason behind better performance of sharpening filtered data might be the high gradient between the vessel border and its neighboring background. As there is a high gradient between the vessel border and background (see Figure 5) gradient based techniques such as laplacian and sobel provided better result. Although green channel image provided better result than sharpening filter, due to its less information content, it does not produce better result in deep neural nets where information content is more important.

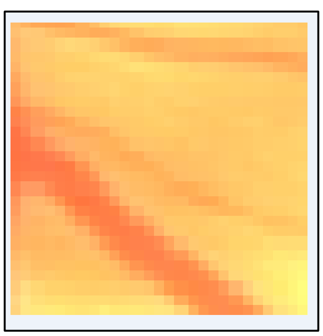
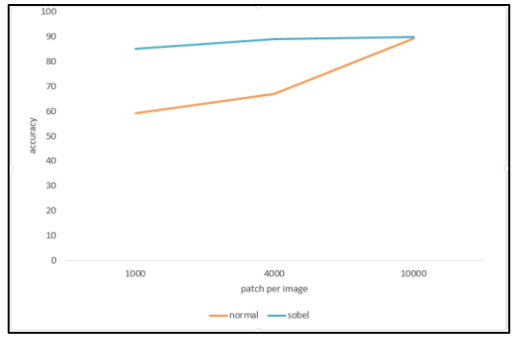


Figure 5. High gradient between a vessel border and background

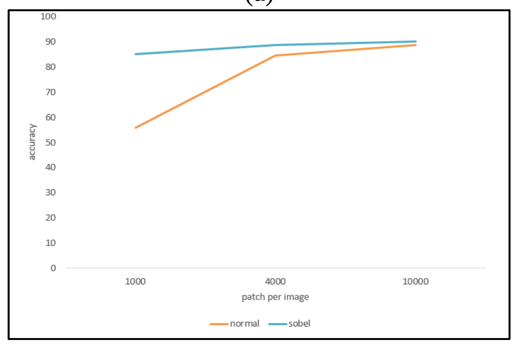
So from the simple classifier experiment we derived the following hypothesis –

Due to high gradient between the vessel border and its neighboring background pre-processing step involving image sharpening will produce better result in segmentation of retinal blood vessel.

Figure 6. shows the result of segmentation of blood vessels using deep neural networks using sobel filtered and normal data (data without any preprocessing). As can be seen from the figure the sobel filtered data produces improved accuracy when the dataset is small. But the accuracy does not improve significantly for larger size of data.



(a)



(b)

Figure 6. Accuracy of segmentation of blood vessel on sobel filtered data (blue) and normal data (orange) in dataset with patch size 13 *13 (a) and 27 * 27 (b). In both cases sobel filtered data gives better accuracy for small dataset but in large dataset the difference is minimal.

VI. CONCLUSION

This study brings evidence that image enhancement techniques such that sharpening filters can improve accuracy of deep neural networks significantly for segmentation of retinal blood vessels. It is of great importance because there are not always a pool of large data to train deep neural nets. As our study shows sharpening filter can reach above 90% accuracy in using 10 times less data.

VII. REFERENCES

[1] P. Liskowski, K. Krawiec, “Segmenting Retinal Blood Vessels with Deep Neural Networks,” IEEE Transactions on Medical Imaging, vol. 35, no 11, pp 2369 – 2380, 2016.