Retinal Blood Vessel Segmentation Using Ensemble of Single Oriented Mask Filters

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ABSTRACT

This paper describes a method on segmentation of blood vessel in retinal images using supervised approach. Blood vessel segmentation in retinal images can be used for analyses in diabetic retinopathy automated screening. It is a very exhausting job and took a very long time to segment retinal blood vessels manually. Moreover these tasks also requires training and skills. The strategy involves the applications of Support Vector Machine to classify each pixel whether it belongs to a vessel or not. Single mask filters which consist of intensity values of normalized green channel have been generated according to the direction of angles. These single oriented mask filters contain the vectors of the neighbourhood of each pixel. Five images randomly selected from DRIVE database are used to train the classifier. Every single oriented mask filters are ranked according to the average accuracy of training images and their weights are assigned based on this rank. Ensemble approaches that are Addition With Weight and Product With Weight have been used to combine all these single mask filters. In order to test the proposed approach, two standard databases, DRIVE and STARE have been used. The results of the proposed method clearly show improvement compared to other single oriented mask filters.

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1. INTRODUCTION

One of public health major concern nowadays is diabetis mellitus (DM). In the year of 2030, World Health Organization (WHO) have predicted that about 2.48 million of Malaysians would have DM. DM is a complex disease that will result with organ complications. However, to prevent progression of the various organ complications, DM should be controlled. One complications that due to DM is diabetic retinopathy (DR). Diabetic eye disease usually will cause visual loss among adults of working age in Malaysia [1]. Patients with DM who have registered for the first time at ophthalmology clinics in Ministry of Health (MOH) hospitals revealed that 36.8% of patients had DR while percentage of having sight threatening DR is about 14.7%. This data was retrieved from diabetic eye registry of the Ministry of Health (MOH) of Malaysia [2]. 80% of all patients who have had DM for 10 years or more have been affected by DR. Out of 50 million blind people in the world, approximately 2.5 million people are blind due to DR [3]. In order to prevent visual impairment, eye screening for diabetic patients' is one of cost-effective scheme [2]. In many cases, screening and early treatment can avoid massive visual loss. However, to segment retinal blood vessels manually is very exhausting job and took a very long time. Moreover these tasks also requires training and skills [4]. Due to this scenario, it is very important to have an early detection and investigation of eye disease by segmenting retinal blood vessel images automatically.

Medical images are usually disturbed by signal dropout, noise, poor contrast along boundaries, confusing anatomical structures, motion, imbalanced intensities of the region and multi-modal distribution of the intensity. The medical image segmentation will be a highly challenge due to these problems that cause intensity heterogeneity and highly constructions of tissues and organs [5]. Significant improvement is still needed even though there are many methods have been proposed. This is due to the limitations of the methods which include poor segmentation when merging of close vessels, missing of small vessels, detection of false vessels at the optic disk and many more [6].

Automatic classification of retinal blood vessel features lie in pattern recognition techniques. Techniques in pattern recognition have been divided into two approaches that are supervised and unsupervised approaches. Supervised approaches need some information on training images that give label to a particular pixel whether belongs to a vessel or not, while unsupervised approaches do not need any previous information [4]. Supervised approaches usually are superior than unsupervised ones and can achieve excellent results for healthy retinal images [4],[7],[8]. Rules for vessel segmentation are learnt by a classifier based on training on manually segmented images in supervised approaches.

The primary objective of this work is to develop a method that can segment blood vessel in retinal images using supervised approaches. Support vector machine (SVM) [9] have been used as a learning algorithm. The work done by Sampe et al. [10] have been enhanced in this work. The description of a particular pixel have used grey level values of neighbourhood of this target pixel, ***P***. A target pixel is the pixel to be described. Instead of using neighbourhood of 4-direction of grey level values that include upper, bottom, left and right sides of a target pixel in Sampe et al [10], eight single oriented mask filters of 3 X 3 neighbourhood of grey level values have been generated and used in this work. The concept of orientation have been used in this work due to some low level features like lines, edges, corners and junctions appear in images in various orientations [11]. Ensemble approaches is one way to increase the performance of classifiers [12]. Hence, a new approach of segmenting retinal blood vessel using the ensemble of all single oriented mask filters is presented. Methods of ensemble of all single oriented mask filters have been compared with using only one single mask filter and Sampe et al. [10] method.

The rest of the paper is organized as follows: Section II reviews some related works and the proposed method is being discussed in Section III. Experimental results are shown in Section IV. Section V discusses and concludes this paper.

2. RELATED WORKS

There are many methods for retinal blood vessel segmentation have been proposed. Salem et al. [13] have employed nearest neighbor clustering algorithm and scale space features to segment blood vessels from retinal images. This was the modified version of K-nearest neighbor (KNN) classifier but do not require any training set. Features used for classification are the intensity of green channel, the local maxima of the gradient magnitude and the local maxima of the largest eigenvalue. In this work, they have combined concepts of supervised and unsupervised methods where image pixels are clustered depending on the feature vector without using a training set.

Another method for retinal blood vessel segmentation have been proposed by [14]. The area of the matched filter response image that have been hypothesized was thresholded using probing technique iteratively with decreasing threshold value. For every iteration, attributes that are based on region for a particular area are tested and finally, a decision has been made whether the area is vessel or not. Pixels under study that are not categorized as vessel are reprocess for further investigation. In a work done by [6], a multi-scale line detection is used to segment retinal blood vessel. The concept of changing the length of a basic line detector have been used in their work. Therefore, they have attained line detectors at varying scales. Then, line responses from various scales were combined linearly to produce the final segmentation. In [15], quadrature filters have been used to combine line filters and edge detection easily across various scales since a typical line filters were easily affected to variations of intensity. Edge detection was used to improve the segmentation of the vessel walls. However, they found that the segmented results were very susceptible to noise. Then, energy optimization techniques have been used to solve the problems and it has shown good results in 2D and 3D typical medical images.

A supervised approach was proposed by [16] in automating segmentation of retinal blood vessels. In their opinion, a pixel representation is not optimal for vessel structure. Hence, features used in this work are based on extraction of image ridges. The ridge pixels were grouped into sets that determine straight line elements and a KNN classifier was used for classification. Another supervised method was done by [17].

This method have used a neural network scheme for pixel classification with features comprised of 7-D vector of gray level and moment invariant-based features to represent a pixel.

Ricci and Perfetti [7] have proposed the usage of line operators as feature vectors and SVM was used for pixel classification. Average gray level have been evaluated at fixed length of lines at various orientations together with orthogonal lines that have passed through a target pixel. This was used as line operators. This line detector was invariant towards contrast and illumination due to the computation of local differential of the line strength. Sampe et al. [10], have used SVM [9] to segment mitochondria in fluorescence micrographs. In order to give a description of a pixel, they have used 4-neighbourhood grey level values that include the upper, bottom, left and right sides of a particular pixel. SVM have been used to classify this pixel whether foreground or background. However, small foreground objects like lines, edges, corners and junctions normally appear in various orientations [11]. Hence, this method unable to detect some small foreground objects.

3. PROPOSED METHOD

Basically, SVM is utilized to separate foreground and background by supervised learning of the ground truth images. In this work, class label of 0 and 1 will be used as 'non vessel' and 'vessel' respectively. The fundus retinal images are color images that consist 3 different channels that are blue, red and green. Green channel is found to contain a lot of useful information [18] and hence is used for further preprocessing. Preprocessing involve several steps which include smoothing, sharpening, contrast enhancement and Gaussian filter. Then the intensities from this image is used to develop filters for training data. In order to use SVM, the image need to be converted to the numerical format for SVM. In this work, SVM is implemented using LIBSVM that is a library support for Support Vector Machine [19]. Procedures of SVM classification using LIBSVM are:

Step 1: Transform data to the format of an SVM package

First, 8 single oriented mask filters have been developed according to the location of target pixel, ***Y***. Reference pixel, ***X***, is used to represent the location that are based on orientations 0, 45, 90, 135, 180, 225, 270 and 315 degrees. Intensity values of a neighborhood of 3x3 window are chosen as the features for each class label. Class label is the value of pixel in ground truth image that have the same location of target pixel, ***Y***. Hence, each mask filters contained intensity values of a 3x3 neighbourhood of each pixel. It is shown as in Figure 1. We have done experiments using 5x5 window and 7x7 window. However, the results are not good compared to 3x3 window. Furthermore, the small size of neighbourhood pixels is used in this work because to achieve high de noising with low complexity [20].

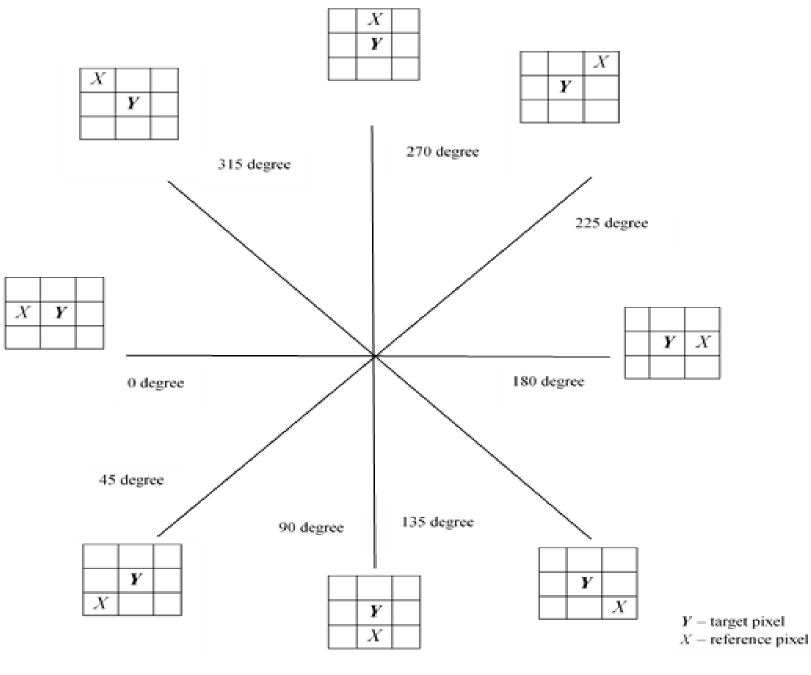


Figure 1. Oriented mask filters for 3x3 neighbourhood of target pixel, ***Y***

Step 2: Cross Validation and Training

We have selected randomly 5 training images from DRIVE [21] database, with every DRIVE image have the size of 584 x 565 pixels. The proposed method involved a lot of data and we are looking at representation of each pixel. In total, we have about 1.6 x 10^6 of pixels in training data for each angle. Most of the cases were found to be redundant cases as shown in Figure 2.

X – Reference pixel based on orientation

Class Label	(*i*-1,*j*)	(*i*-1,*j*+1)	(*i*-1, *j*+2)	*X*(*i*,*j*)	(*i*, *j*+1)	(*i*, *j*+2)	(*i*+1,*j*)	(*i*+1,*j*+1)	(*i*+1, *j*+2)
0	0.484	0.484	0.484	0.479	0.479	0.479	0.474	0.474	0.473
0	0.484	0.484	0.484	0.479	0.479	0.479	0.474	0.474	0.473

Figure 2. Example of redundant cases that happen in representing a particular pixel in 0 degree

They are omitted in order to minimize computation time and the removal have decreased the data to 9 x 10^5. From this, 8000 training data are chosen at random where it consist of 4000 data with label 0 and 4000 data with label 1 and these data is trained across the 5-folds cross validation.

Step 3: Test

To test the accuracy of the classifier, we have used 35 test images from DRIVE database [16] and 20 images from STARE database [14] for each angle. The same training images from DRIVE database have been used to evaluate STARE database. This is because the proposed method is based on pixel classification and both databases consist of retinal images. Hence, it can be used for evaluating STARE database. The results of the classifier were given in the form of probability where the probability of label 0 and label 1 have been given for each pixel.

Step 4: Ensemble Approach

Our objective is to compare whether combined mask filter is better than any single oriented mask filter. We have combined all eight single oriented mask filters by applying ensemble approaches idea namely Addition With Weight and Product With Weight [12].

We put weights for each orientation based on the results obtained from five training images. At first, we test the model obtained from SVM by using training images. After that, we calculate accuracy for every image obtained for each mask filter. Then, for each mask filter, average accuracy have been obtained and ranked into descending order. Based on this rank, weights for every mask filter have been assigned. Mask filters that have higher average accuracy have been given higher weight while mask filters that have lower average accuracy have been given lower weight. Ensemble approaches used in the experiment are as follows:

Addition With Weight - we get the total addition of probability of label 0 and label 1 for eight angles for a particular pixel in each location.

$$P(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) = \sum_{k=1}^{8} w_k P_k(x) \tag{1}$$

Product With Weight - we get the total product of probability of label 0 and label 1 for eight angles for a particular pixel in each location.

$$P(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8) = \prod_{k=1}^{8} w_k P_k(x) \tag{2}$$

For each ensemble approach used, the label that produced the largest probability have been taken as the final decision for each pixel whether ‘vessel’ or ‘non vessel’. By applying ensemble approaches to combine the probabilities of label 0 and label 1, a new image is constructed. The new image is then has been compared with the ground truth image available. Figure 3 shows the block diagram for the proposed method.

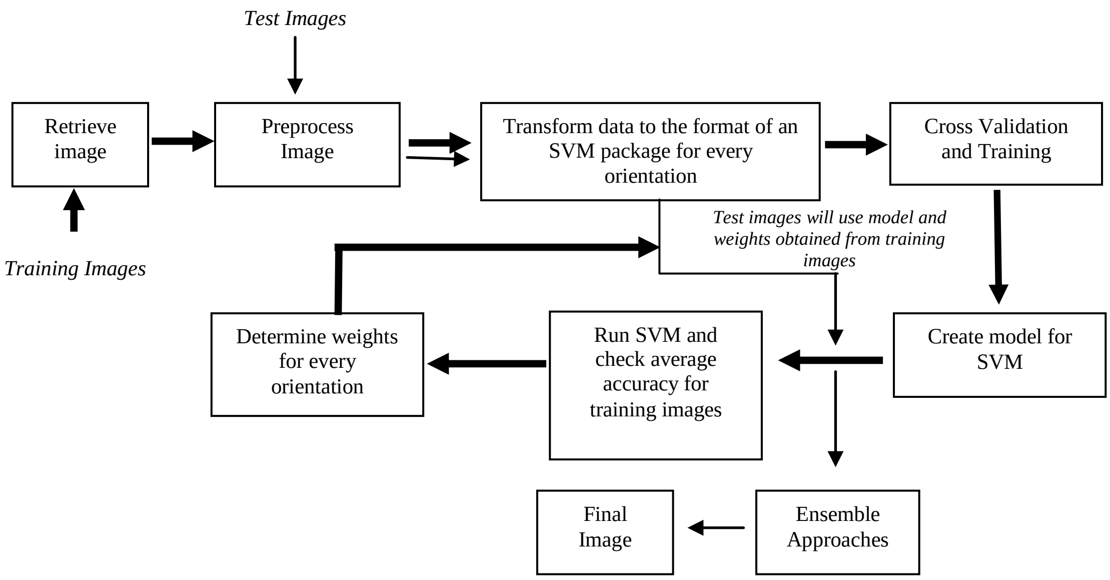


Figure 3. Block diagram of the proposed method

4. EXPERIMENT AND RESULTS

Two standard databases which comprise retinal images are used to train and test the blood vessel segmentation. They are namely as DRIVE [16] and STARE [14] databases. These databases are publicly available and are chosen to be used in this experiment since they provide manual segmentation for performance evaluation and have been widely used by other researchers.

The DRIVE database consists of 40 eye-fundus color images which is divided into two sets i.e. a test set and a training set. Each set contains 20 images with diameter 768 x 584 pixels. There are two sets of ground truth images that have been prepared by two different experts for each image. In this experiment, the first expert's work have been used for evaluating algorithm performance.

Another twenty eye-fundus color images with diameter 700 x 605 pixels come from STARE database. Same as DRIVE database, there are two sets of ground truth images prepared by two different experts. For evaluation of algorithm, the first expert's work have been used.

For the retinal images, 20 images are randomly selected from the combination of DRIVE and STARE databases. The five images used for training were excluded from the test for the accuracy of the classifier. The experiment consist of 50 runs and the resulting images are compared to their corresponding ground truth images.

The outcome of the supervised binarization process is a pixel-based classification. The pixels are classified as either 'vessel' (1) or 'non vessel' (0) pixels. Hence, there could have been four possible outcomes, i.e. a true positive (*TP*), a true negative (*TN*), a false negative (*FN*) and a false positive (*FP*). *TP* and *TN* occur when a pixel is correctly classified as a 'vessel' or 'non vessel', respectively, while *FN* and *FP* occur when a pixel is incorrectly classified. The performance measure used for the experiment is Accuracy. The metric is defined as in equation (3).

$$\text{Accuracy} = (TP+TN)/(TP+FN+TN+FP) \tag{3}$$

Another quality measurement of the segmentation result is the misclassification error (*ME*) [22], which is a measure that regards image segmentation as a pixel classification process. It reflects the ratio of 'non vessel' pixels that has been incorrectly classified as 'vessel', and conversely, the ratio of 'vessel' pixels that have been erroneously assigned to 'non vessel'. The *ME* is formulated as in equation (4).

$$ME = 1 - ((|B_O \cap B_T| + |F_O \cap F_T|)/(|B_O| + |F_O|)) \tag{4}$$

where B_o and F_o are the 'non vessel' and 'vessel' pixels of the ground truth image, respectively, B_T and F_T are the 'non vessel' and 'vessel' pixels in the segmented image, respectively, and | . | is the cardinality of the set where cardinality means a measure of the number of elements of a particular set. In this case, it is referring to number of pixels. The expression $(|B_O \cap B_T|)$ refers to number of pixels that have been correctly classified as non vessel while $(|F_O \cap F_T|)$ refers to number of pixels that have been correctly classified as vessel in segmented image. The expression $((|B_O \cap B_T| + |F_O \cap F_T|)/(|B_O| + |F_O|))$ values range from 0 to 1 since it gives the ratio of pixels that are correctly classified based on ground truth image. As a whole, the *ME* values range from 0 to 1, where a lower value of *ME* means a better quality of the segmented image. The root mean square error (*RMSE*) [23] is also used to measure the quality of the segmented image. The *RMSE* is formulated as in equation (5).

$$RMSE = \sqrt{(1/n)\sum_{i=1}^{n} e_i^2} \tag{5}$$

where *e* is the error between the ground truth image and the segmented image. A lower value of *RMSE* means a better quality of the segmented image. Training images have been used to test the model obtained from SVM for every orientation. Each final image obtained have been compared with ground truth images available and its accuracy was calculated using equation (3). Thus, from five training images, average accuracy for each mask filter have been calculated and based on these results, weights have been given to each filter. The average accuracies obtained have been ranked in descending order. Single mask filter that achieve higher average accuracy have been given higher weights, while single mask filter that achieve lower average accuracy have been given lower weights. In these retinal images, most parts are ‘non vessel’ (0) that is black, hence higher weight have been assigned to ‘non vessel’ (0). This is given as in equation (6) and (7).

$$\text{Non vessel (0): } w_{0k} = 2/m \tag{6}$$

$$\text{Vessel (1): } w_{1k} = 1/m \tag{7}$$

where *m* is the ranking for eight single mask filters that are based on average accuracy results in training images. Weights that have been used for each single mask filter are:

‘Non vessel’ (0):
0 degree - $w_{01} = 2/8$; 45 degrees - $w_{02} = 2/4$;
90 degrees - $w_{03} = 2/6$; 135 degrees - $w_{04} = 2/5$;
180 degrees - $w_{05} = 2$; 225 degrees - $w_{06} = 2/7$;
270 degrees - $w_{07} = 2/3$; 315 degrees - $w_{08} = 1$.

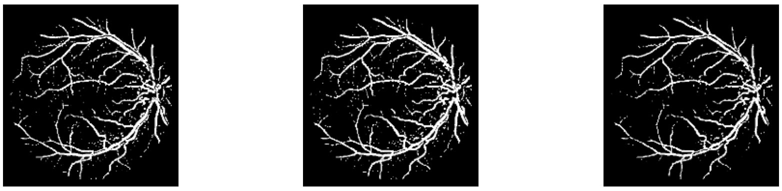
‘Vessel’ (1):
0 degree - $w_{11} = 1/8$; 45 degrees - $w_{12} = 1/4$;
90 degrees - $w_{13} = 1/6$; 135 degrees - $w_{14} = 1/5$;
180 degrees - $w_{15} = 1$; 225 degrees - $w_{16} = 1/7$;
270 degrees - $w_{17} = 1/3$; 315 degrees - $w_{18} = 1/2$.

Table 1. Average accuracy, average misclassification error and average root mean square error results and their respective standard deviations for single mask filter, Sampe et al. method [10], Addition With Weight (proposed) and Product With Weight (proposed) method

Method	Average Accuracy	Average ME	Average RMSE
Single Mask Filter	0.9228 ± 0.0190 (180 degree)	0.0772 ± 0.0190 (180 degree)	0.2758 ± 0.0335 (180 degree)
Sampe et al. [10]	0.9149 ± 0.0251	0.0851 ± 0.0251	0.2886 ± 0.0420
Addition With Weight (Proposed)	0.9311 ± 0.0127	0.0689 ± 0.0127	0.2613 ± 0.0242
Product With Weight (Proposed)	0.9328 ± 0.0121	0.0672 ± 0.0121	0.2582 ± 0.0233

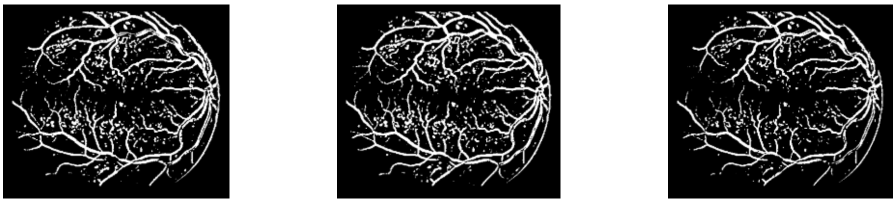
The results of the experiment for retinal blood vessel segmentation are shown in Table 1. The ensemble approaches have been compared with single mask filter (180 degree – which give the highest average accuracy result) and Sampe et al. method [10].

From Table 1, it can be seen that Product With Weight have achieved the highest average accuracy. It can also be noticed that average accuracy of Addition With Weight are higher than any single mask filter and Sampe et al. method [10]. We can conclude that the ensemble of single mask filters have increased the accuracy of retinal blood vessel segmentation.



Accuracy: 0.9391 (a) Accuracy: 0.9328 (b) Accuracy: 0.9449 (c)

Figure 4. Retinal blood vessel segmentation from DRIVE database (a) Single Mask Filter (b) Sampe et al. [10] method (c) Product With Weight (proposed)



Accuracy: 0.8999 (a) Accuracy: 0.8960 (b) Accuracy: 0.9168 (c)

Figure 5. Retinal blood vessel segmentation from STARE database (a) Single Mask Filter (b) Sampe et al. [10] method (c) Product With Weight (proposed)

The results of average ME and average RMSE also have showed that they have the lowest value for Product With Weight. From the standard deviations, it can be seen that the values are smallest for Product With Weight for all measures used in the experiment. It have demonstrated the robustness of the proposed method. In order to check whether the average accuracy for the proposed method is significantly higher than single oriented mask filter and Sampe et al. [10] method, significance tests are also have been performed. All the significance tests are carried out using paired *t*-tests at a significance level of 5%. The results have showed that the proposed method have improved the average accuracy significantly compared to the single oriented mask filter and Sampe et al. [10] method where, all the *p*-values obtained are less than 5%. Figure 4 and Figure 5 show the retinal blood vessel segmentation obtained by using proposed method compare to single oriented mask filter and Sampe et al. [10] method. From the images obtained, most of the noise have been eliminated in the proposed method and hence the accuracy have been increased. There are no post processing done to the images obtained in the experiment.

5. DISCUSSION AND CONCLUSION

The results of the experiment have shown that the proposed method outperform single oriented mask filter and Sampe et al. [10] method. The reason why oriented single mask filters have been used here is due to some low level features normally appear in arbitrary orientations. By introducing single mask filters that are based on angles, we can identify the best single oriented mask filter that characterizes a particular pixel and we can also examine the classifier response at various orientations. Weaknesses and strengths of a particular orientation can be reduced and retained, respectively when the single oriented mask filters are combined. As a conclusion, ensemble of single oriented mask filters is better than any single oriented mask filter and Sampe et al. [10] method. One of the advantage of the proposed method is that it is easy and capable of giving good results. However, this method consume a lot of time and the ground truth images will be highly used for training the models. We plan to optimize weights for each single oriented mask filters and will look into their effect on retinal blood vessel segmentation.

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