Optimization Techniques Are Best Choice to Segment Blood Vessels from Retinal Fundus Images

N.C.Santosh Kumar, Y.Radhika

Abstract: ***The mostly affected disease which has been a curse to human kind is diabetes. This disease, irrespective of the age, causes extreme impact upon the eyes of the patients indicating abnormalities which manifests in tree-like structured blood vessels of the retina. It is so important to diagnose such patients with diabetes at the initial stage so as to save them from reaching blindness. Blood vessel segmentation in retinal fundus images is an adequate way and takes a critical role in medication and diagnosis of distinct retinal-related diseases and disorders. In this paper, a comprehensive review of various categories of segmentation techniques is presented with main focus on proving the magnificence of optimization techniques as the right choice in the process segmentation. The effectiveness of this work is straightened in relative study of discrete methods.***

Keywords: ***Retinal fundus images, blood vessels segmentation, ant colony optimization, particle swarm optimization, bee colony optimization, genetic algorithm***,

I. INTRODUCTION

According to [1], the reason for vision loss and deaths in large count has been the result of reach of diabetes onto retina. The retinal blood vessel segmentation is a tool that helps ophthalmologists to perform perfect detection, proper diagnosis, ideal treatment, and faultless evaluation of retinal pathologies that include diabetic retinopathy, macular degeneration which is age-related, hypertension, glaucoma etc. The authors in [2] have mentioned that finding disorders in an automated diagnosis system by means of automated retinal blood vessels' segmentation is the primary step. The retinal tree-shaped structure of blood vessels has useful attributes that include width, tortuosity, length, branching pattern and angles which have high diagnostic significance that reveal the disorders in the retinal part of the eye so as to infer the condition of the patient. Also, this vascular blood vessel configuration which is unique for each individual [3] is critical in the process of biometric identification. An important aspect of automated vessel segmentation is retinal images registration related to a patient which is being taken at various points of time. The manual system of segmentation of blood vessels is a time taking tedious process and requires training. The automated segmentation process is not an easy task but is quite challenging since it deals with complex structures of blood vessels in retinal images that are impacted by various sources. Those different Impediments relating to the configurations of blood vessels, issues of contrast, presence of noise make the segmentation process complex. Moreover, the composites which are anomalous such as microaneurysms, diseased regions and lesions, soft and hard exudates make the segmentation task a difficult if the input image under consideration is diseased one. The figure 1 presents non-healthy and healthy retinal images.

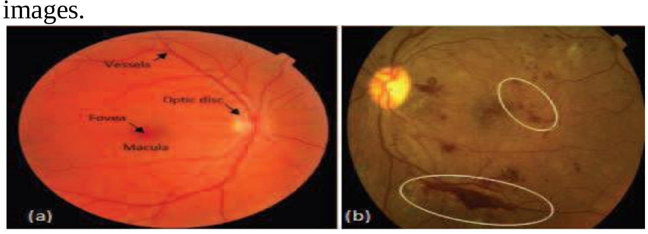

Figure-1 (a) Example of a healthy eye (b) Retinal image with leakage blood vessel of an unhealthy eye

The organization of the rest of the paper is as follows: Section 2 outlines various online databases which are in use so far. Section 3 deals with a detailed description of different approaches with their performance assessment which then proceeds with explanation of category-wise methods being proposed to segment blood vessels. Section 4 provides a meticulous experimental comparison of described category-wise methods of previous section. Section 5 proceeds with discussion of the distinct optimization techniques which have improved the effort of segmentation and proves them as the best choice. Section 6 gives the conclusion of this review.

II. MATERIALS

Generally, a database is a collection of objects. These objects may have similarity among them and sometimes are related to each other. It is to mention that the splendid work which has been done by researchers as part of the screening programs, research collaborations, individual interests etc, have given standard references for the quality research in this field of segmentation of retinal blood vessels. These standards are framed as benchmarks for performance comparison of algorithms that are proposed and also used as an assessment metric for various eye-related issues. A dataset is container of sets of retinal images that may be training or test set, reference standards, ground truth images etc. The discussion which is followed gives a briefing on few datasets that are mentioned in the Table 1 and have been in use by many researchers.

Drive

This database was introduced by author [4] in the year 2004 and this dataset photographs were founded from Netherland's screening

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program on diabetic retinopathy where the photographs were taken from 453 people of 31 to 86 age group. And it has 40 images being captured by Canon CR5. Each image was taken using 8 bits per color plane at 768x584 pixels and is stored using compressed JPEG format. Training dataset contains a single manually segmented vessel system for every image. Test images manually segmented are available as two sets of which one set is useful as ground truth and the other set is for comparison of human observer with the computer generated segmentation.

Stare

This database was introduced by author [5] and it is a dataset which contains annotations associated to 39 eye related disorders. It consists of 397 fundus images with an image pixel of size 700x605 which was captured by TRV-50 fundus camera. For this dataset, two experts have segmented manually with 10.4% and 14.9% of vessel pixels. The first expert's segmentation is taken as ground truth.

HRF

This dataset was first introduced by a collaborative research group [10] which supports the comparative study of segmentation algorithm of retinal fundus images. It contains 18 image pairs of same eye by using Canon CR-1 camera. And, using a different acquisition setting Canon CR-1 fundus camera, having a field of view of 45°, 18 image pairs of the same eye from 18 human subjects are captured.

Messidor: This is the largest database having 1200 images of retina and is available online being provided by the partners of Messidor program. Messidor database is the outcome of Messidor project [7] where images stored in TIFF format are obtained at three different ophthalmology departments who have used a non-mydriatic 3CCD camera with 1440 x 960, 2240 x 1488 or 2304 x 1536 pixel resolution. The important aspect of this database is that it contains a diabetic retinopathy's grading and the details of macular edema risk for each image.

Aria

The result of research collaboration between Royal Liverpool University Hospital Trust, Erpool, UK, the Department of Ophthalmology, Clinical Sciences, University of Liverpool, Liverpool, UK [8], and ST.Paul's Eye Unit is the ARIA online database which consists of three distinct sets where the first set possesses 92 images that are related to macular degeneration, the second set is with 59 images related to diabetes and the third set is a control cluster of 61 images. Two experts have marked the optic disc, blood vessels outline, and the location of fovea as a standard of reference. The images are stored in TIFF file format where each image being captured is a color image with a 768x576 pixel resolution

ImageRet

This database [9] which has two sub-categories namely DIARETDB-0 and DIARETDB-1 has 130 images of which images that are normal are 20 and the remaining 110 images are related to diabetic retinopathy. Four experts have marked the microaneurysms, hard and soft exudates, and hemorrhages as a standard of reference. Each image being captured with 50o FOV has a size of 1500x1152 and is stored in PNG image format.

Drions

This database was introduced by authors [6] and consists of 110 color retinal images and this image was digitalized by using high-resolution scanner HP-PhotoSmart-S20 with a resolution of 600x400 and 8bit /pixels.

Table 1: Gives a list of available databases for usage in research on segmentation of retinal blood vessels in retinal fundus images along with the details of the benefits

Sno	Database Name	Image Support Count	Benefits
1	DRIONS	112	Optic disc contour was annotated
2	DRIVE	60	Comparative studies on blood vessel segmentation
3	CHASE	28	Poor contrast of Blood vessel is compared
4	HRF	45	It Supports related work of automatic segmentation on ocular fundus images
5	STARE	400	Anatomical and pathological features of blood vessel segmentation is provided
6	BIOLM LAB	60	Retinal vessel tortuosity evaluation
7	DIARET DB 0, DIRARET DB 1	349	Developed image processing method for diagnosis of diabetic retinopathy
8	MESSIDOR	1200	Improves the development of automatic diagnosis
9	HEL-MED	169	Quality of images were graded
10	ARIA	450	The boundaries are delimited

III. METHODS

Segmentation is a process which sub-divides a single big object into number of constituent objects. In image segmentation, a particular image is partitioned into separate regions so that the output is the image formed with the collection of segments. To get a good quality of segmentation results, the input original image is processed to eliminate the consequences of illumination and noise and then the image is enhanced.

Then, the process of segmentation is done by using different segmentation techniques. In the following lines, a nutshell of the work being done by various researchers is presented with the explanation of the benefits of each algorithm to show the essence of few algorithms of the literature and the summary of these algorithms is disclosed in Table 2.

Zhu Chengzhang et al.[11] have done their work by using a supervised learning scheme for segmentation of retinal vasculature in color images by means of multi-scale and multi-orientation morphological transformation based upon divergence of vector field. Gehad Hassan et al [12] have done their work to extract retinal image vessels by means of mathematical morphology for suppressing the background and performing smoothing and to enhance the image. They then used K-means clustering to segment the image. D. Marin et al. [13] have done their work for classification of pixels by using neural networks and their representation is done by computing 7-D vector that encompass the features of gray-level and also moment invariants-based features. Soares et al. [14] have done their work by using Gabor filters for detection of retinal fundus image. For each featured pixel 2D complex Gabor filters were assigned and their remaining work is done by using Bayesian classifier for classification of their results into pixels. Martina Melinscak et al.[15] have used a GPU based implementation of convolutional neural networks concerning deep max-pooling for retinal blood vessel segmentation and they showed the effectiveness of deep learning approach. Petar Sekulić et al [16] used support vector machine for blood vessel detection and their proposed work is done for feature extraction from preprocessed retinal image which effort in defining the movement of ants in ACO (Ant Colony Optimization) algorithm. Rattathanapad et al [17] used multilevel line detection for the segmentation blood vessels at gaussian smoothing parameters and then line primitives are merged into single vessels. Foracchiam et al. [18] have done their work for identification and location of optic disk in retina by using Geometrical parametric model followed by parabolic structure. And this parametric model plays a key role in detecting the of vessel's center-line points. And the center-line direction is also detected and model parameters are identified by annealing optimization techniques. Chandani Nayak and Lakhwinder Kaur [19] have done their work to eradicate usual and unusual appearances in retinal images to develop an automatic system for authentic vessel segmentation. And they also used directional structures and thresholding techniques for vessel segmentation. Hoover et al [20] have done their work by using matched filtering technique to detect and outline the vascular tree like structure in retinal ocular fundus images, which utilizes the vessel features that are local as well as global to cooperatively segment the vessel network.

Shilpa Joshi et al.[21] worked to trace the tree like structures by using green channel of fundus RGB color images and disc structuring elements. And, they also used morphological operators for smoothening of the background. Yong Yang et al [22] have done their work for the extraction blood vessels by using a hybrid automatic approach that involves mathematical morphology for smoothening, strengthening, and enhancing the blood vessels and then applied fuzzy clustering models for segmenting the vascular structure, followed by a screening procedure in order to reduce the noise and also to remove weak edges. Sukhpreet Kaur et al [23] have done their work of segmentation by using artificial neural networks. And for the changes of blood vessel structure, training features such as Gabor filtering and the gray level feature vectors that are vital in segmentation, included.

Table 2: Comparative analysis of the above mentioned methods

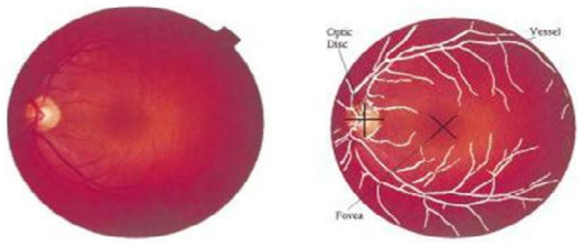
Sno	Ref Name	Algorithms/Methods Used	Benefits	Database Used
1	ZHU Chengzhang et al 2016	Multi-scale and multi-orientation based Morphological transformation	Segment vessel structure in color fundus images	DRIVE
2	Gehad Hassan et al, 2015	K-means and mathematical morphological model	Segmented retinal image is extracted and enhanced	DRIVE
3	Marin et al 2011	Neural networks	Detection of retinal vascular structure in retinal fundus images	DRIVE, STARE
4 5	Soares et al, 2006 Martin melinscak et al	Complex Gobor filter+ Bayesian classifer Deep max pooling neural network	Retinal fundus images are detected from blood vessels To identify the effectives of the learning approach of blood vessel segmentation	DRIVE DRIVE

6 7	Milija bajcet et al Rattathanapad et al, 2012	Support vector machine Multilevel line detection	For feature extraction of vessel detection Extraction and segmentation of retinal vessels	DRIVE DRIVE
8	Foracchia M et al, 2004	Geometrical parametric model and optimization techniques	Optic disk in retinal image is identified and located and model parameters are detected	STARE
9	Chandani nayak et al, 2014	Directional structures thresholding techniques	Vessel segmentation for the eradication of normal and abnormal appearances	DRIVE
10	Hoover A et al, 2000	Matched filtering	Locating and segmenting outline of vascular of blood vessels from ocular fundus images	DRIVE
11	Shilpa joshi et al 2012	Green channel fundus images +morphological operations	To trace and smoothens the background	DRIVE
12	Yong yang et al, 2008	Hybrid automatic approach+ mathematical morphological model and fuzzy c-means based clustering	Extraction of retinal vessels and smoothening and strengthening blood vessels are enhanced	DRIVE
13	Sukhpreet kaur et al, 2016	Gabor filtering, Intensity and Gray level feature	Enhancement of both series of normal and abnormal images with realizing good accuracy	DRIVE

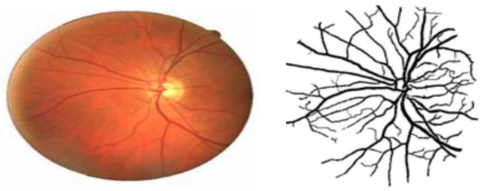
3.1 SUPERVISED CLASSIFICATION METHOD

The outcome is known, the parameters to simulate the algorithm is set before proceeding to the segmentation process are the key features of supervised- classification methods. Sinthanayothin et. al [24] worked for automation of anatomical structures' localization in retinal images from digital color fundus images. Their success rate is reported with an average sensitivity of 0.833 and specificity of 0.91% respectively. They used neural networks and principal component analysis to identify the key components of the retinal fundus color images inside retina. Abramoff et al [25] have done their relative work on segmentation of blood vessel methods on STARE and DRIVE database. Their success rate is reported based on accuracy, sensitivity, as 0.9416 and 0.7145 and R0C curve as 0.9294 respectively. They used Gaussian derivative model and k-NN classifier algorithm for the extraction of feature vector of each pixel. Staal et. al. [26] used ridge-based algorithm on color images of retina and achieved an accuracy of 0.9442 and 0.9516 on DRIVE and STARE datasets respectively. Automated segmentation on 2D retinal images is done by using image ridges and knn classifier. Soares et al. [27] worked with 2-D morlet wavelet along with supervised classification. Their success rate is reported with an accuracy of 0.9466 and ROC curve is reported as 0.9614. They used Gabor filter in combination with Gaussian mixture model for the representation of each feature vector. Ricci et al [28] worked with line operators in association with support vector machine classification for the segmentation to obtain unsupervised pixel classification with 0.9563 and 0.9584 accuracy on DRIVE and STARE datasets and their ROC curve is measured as 0.9558 and 0.9602 respectively. A. Osareh et al [29] have done their work for an automatic segmentation from color images of the retina and their experimental result demonstrates the value of 0.974 of ROC curve, 96.50% sensitivity and 97.10 specificity. They used Gabor filter method which is multi-scale along with GMM classifier algorithm for identification and segmentation. Lupascu et al [30] came with a classifier for the detection of blood vessels which is tested with an average sensitivity of 77% and with an average accuracy of 93.2% on DRIVE database. They reported that heavy computation and manual intervention in a particular image can be avoided by using AdaBoost classifier. Xu and Luo [31] used radial projection method and semi-supervised approach. The work results an accuracy of 0.9328 and sensitivity of 0.7760. They used Wavelets, Hessian matrix and SVM for the identification of tinny vessels inside the retina which also helped in decreasing the effort involved in false detection of pathological regions inside the retina. You et al. [32] method on DRIVE database reported the average accuracy, sensitivity and specificity is 0.9434, 0.7410, and 0.9751 respectively and for the STARE database, the measures takes values as 0.9497, 0.7260, and 0.9756, respectively. They used semi-supervised classification using SVM technique with radial projection. They endeavored to improve thin vessels detection by the proposed method where it also decreased the false detection of vessels in pathological regions. Marin et al. [33] used neural networks with a new-fangled supervised method. The method was evaluated on the publicly available DRIVE and STARE databases, with an accuracy of 0.9452 and 0.9526, sensitivity as 0.7067 and 0.6944 and specificity as 0.9801 and 0.9819 and ROC curve as 0.9588 and 0.9769.They mentioned that blood vessel detection can be done by using Gray level neural network method.

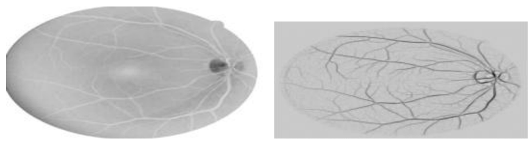
Here some example images are shown:



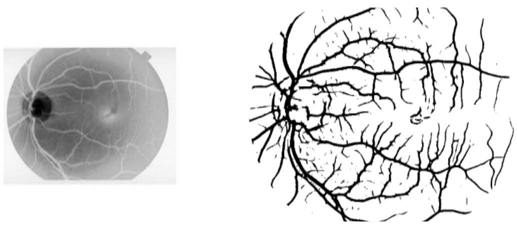
Sinthanayothin's input digital color retinal image and corresponding output image



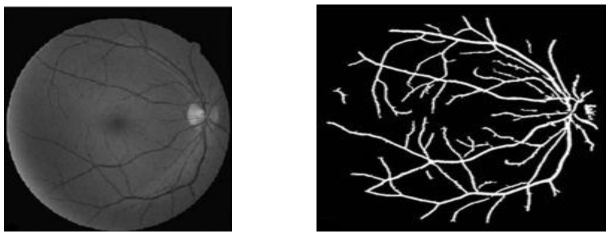
A. Osareh's input and corresponding output image



Elisa Ricci's green channel retinal input image and its output image on DRIVE database



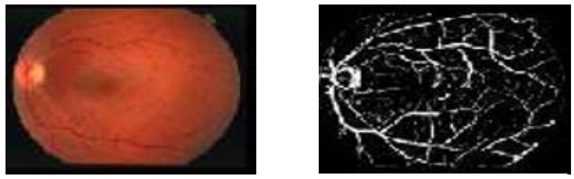
i)) Elisa Ricci green channel retinal input image on STARE database ii) Elisa Ricci green channel retinal output image on STARE database



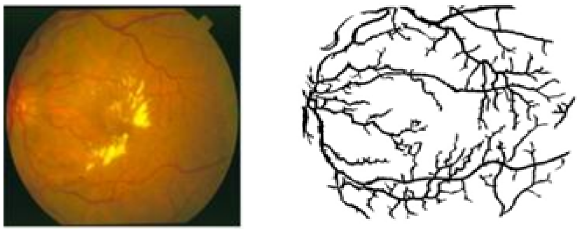
E) i) Lili Xu green channel retinal input image ii) Lili Xu green channel retinal output image

3.2 UNSUPERVISED CLASSIFICATION METHOD

Ng et al [34] worked for detection of vessels inside the retina with maximum likelihood approximation of parameters from scale space analysis for the image formation and computation. Their performance measures reported as specificity with 0.7000 and sensitivity of 0.9530. Kande et al. [35] used unsupervised method for the segmentation of pathological red and green channel retinal fundus images. And their success rate is evaluated with ROC curve of 0.9518 and 0.9602 on both DRIVE and STARE database respectively. They used clustering method called fuzzy c-means for the rectification of color fundus image illuminations. Salem et al [36] have done their work with partial supervision strategy. This methodology achieved 0.9750 specificity and 0.8215 sensitivity on the STARE database. They mentioned that the segmentation of small diameters and low contrasts in blood vessels could be identified using radius clustering algorithm. Villablobos-Castaldi et al. [37] got 0.9759 accuracy, 0.9648 sensitivity and 0.9480 specificity. They used local entropy and matrix co-occurrence algorithm to identify the flexibility in the process of segmentation.



J. Ng's input and its output image on STARE database

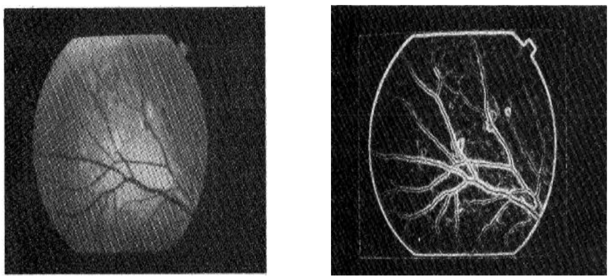


Giri Babu Kande's input and output image image

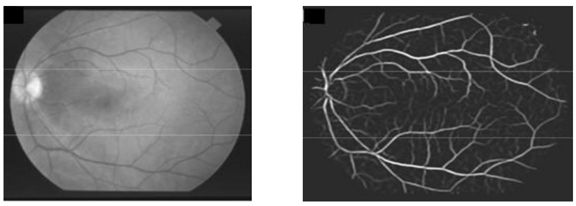
3.3 MATCHED FILTERING

Chaudhuri et al. [38] used Matched Filters of 2D for segmentation and detection of retinal vascular structure. And the results are compared on DRIVE dataset based on their accuracy and specificity as 0.8773 and 0.7878 respectively. Hoover et al [39] worked for locating retinal blood vessel in significant disagreement for the identification of vessel structure in ocular fundus images using matched filter that is threshold probing. And the methodology achieved 0.9267 accuracy, 0.6751 sensitivity, 0.9567 specificity on publicly available STARE datasets. Xiaoyi and Mojon[40] worked with adaptive local thresholding verification method and multi-scale threshold probing method for the detection of blood vessels inside the retina with 0.9212 accuracy and 0.9114 Area Under Curvature on DRIVE database. Yao and Chen[41] used simplified version of PCNN with fast 2D-Otsu method, and has achieved 0.8635 sensitivity and 0.972 specificity evaluations on the STARE database. And they also used 2-D Gaussian matched filter algorithm for the enhancement and later used neural networks to get a simplified segmentation result. Al-Rawi et al [42] achieved output segmented images that are identified by using improved Gaussian matched filter algorithm. And their methodology reported 0.9535 accuracy and 0.9435 ROC on DRIVE database. Zhang et al [43] worked on false detections of blood vessels that could be reduced by using Gaussian matched filter with first-order derivative method. The methodology achieved an accuracy of 09382, 0.7120 sensitivity, and 0.9724 specificity, on the database DRIVE. For STARE database, their respective measures are reported as 0.7120, 0.0276 and 0.9382. Cinsdikici and Aydin[44] have done their work for the identification of vasculature that passes ophthalmoscope image. It achieved 0.9293

accuracy and ROC area as 0.9407 on DRIVE database. They worked with matched filter along with an optimization technique called ant-colony optimization for the extraction of the complete vasculature structure and optimal parameters are deduced. Amin and Yan [45] worked for the detection of high speed blood vessels where image's phase congruency generation is change in the soft classification of image illuminations. The algorithm is applied on both DRIVE and STARE and attained an 0.92 accuracy and area under the ROC as 0.94. They used phase congruency and log-Gabor filters for soft classification of blood vessels for the complete extraction of binary vessel tree. And it can be found by thresholding.
Here are some of the examples of matched filter approach :



Chaudhuri's input image and output image



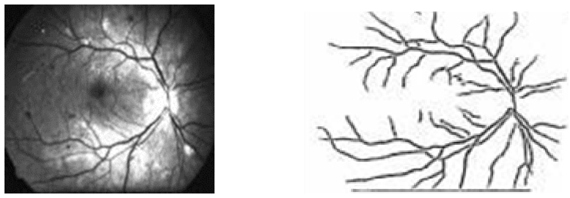
Yao and Chen's input image and output image

Zhang's input image and output image

3.4 MORPHOLOGICAL PROCESSING

Zana et al. [46] worked towards extraction vascular-pattern based segmentation in a noisy environment by using Mathematical Morphology method. The results are compared on DRIVE database with 0.9377 accuracy, 0.9377 sensitivity, and 0.6971 specificity along with ROC curve as 0.8984. Fraz et al. [47] have detected the vasculature with localizing centerlines of blood vessel. They used morphological bit plane model for the extraction of tree like structure inside the retina. Their technique is implemented on MESSIDOR STARE, DRIVE databases with 0.9430 accuracy, 0.1752 sensitivity, 0.9769 specificity on DRIVE database and 0.9447 accuracy, 0.7311 specificity, 0.9680 specificity on STARE database. Miri and Mahloojifar[48] worked by using curvelet transform method and multi scale model for the elimination of ridges by preserving the thin vessels unchanged and their performances are measured on DRIVE database 0.9458 accuracy, 0.7352 sensitivity and 0.9795 specificity.

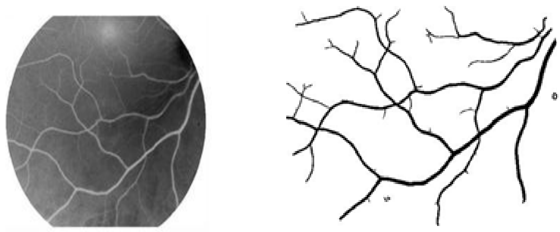
Here is one of the examples of input and output retinal images:



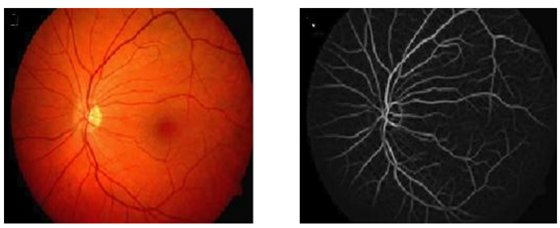
K) Zana and Klein's input and output image.

3.5 MULTISCALE APPROACH

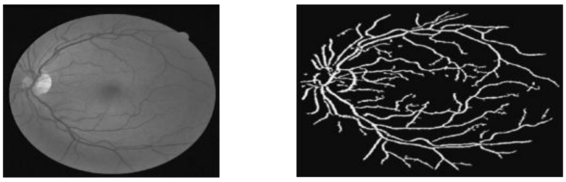
Martinez-Perez et al.[49] worked for the segmentation of vasculature vessel structure by using first and second order derivatives. Their results are measured as 0.9181 accuracy, sensitivity of 0.6389 on DRIVE. Martinez-Perez et al.[50] have worked with retinal images that are red-free and fluorescein, by using hessian tensor maximum principal curvature method. Their performance measures are noted for DRIVE as 0.9344, 0.7246, and 0.9655 for accuracy, sensitivity, specificity respective measures 0.9410, 0.7506, 0.9569 on STARE database. Martinez-Perez et al [51] have done their work for the insight segmentation and had improved implementation using region growing and multiscale approach model. Their performances are measured on DRIVE database with 0.9220 accuracy, 0.660 sensitivity and 0.9612 specificity and 0.9240, 0.779, 0.9409 on STARE database. Anzalone et al [52] used scale space modular supervised algorithm and their performances are measured with 0.9587 accuracy, 0.8069 sensitivity and 0.9477 specificity. Farnell et al [53] endeavored to enhance blood vessels in digital fundus photographs by means of multi-scale line operators. Their performances are measured with DRIVE, STARE databases with 0.940 Area under Curvature. Vlachos and Dermatas[54] have worked for the extraction and segmentation of multi-scale retinal blood vessel segmentation. Their results were evaluated on DRIVE database with 0.929 as accuracy, 0.747 as sensitivity and 0.955 as specificity. They utilized line tracking method that is multi-scale for segmentation. Here are some of the retinal input and output retinal images of multiscale approach:



L) i)Martinez-Perez input and output image



M) Farnel's input colour image and output colour image

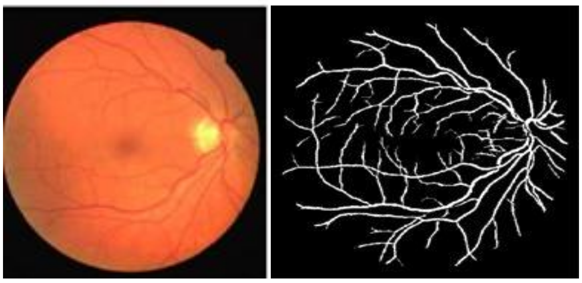


N) Marios Vlachos input and output image

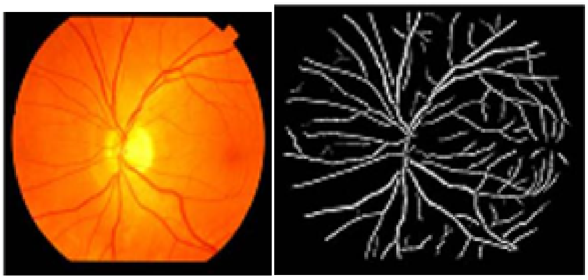
3.6 MODEL BASED APPROACH

Vermeer et al. [55] have worked with laplacian profile model and thresholding model. Their experimental results are evaluated on GDX and STARE databases with 0.924 sensitivity and 0.921 specificity on GDX database and have achieved 0.9287 accuracy and ROC of 0.9187 on STARE database respectively to optimize exact properties of the retinal blood vessels respectively. Li et al [56] used multi resolution hermite model and their experimental results are evaluated with 0.780 sensitivity and 0.978 specificity on DRIVE database and 0.752 and 0.980 on STARE. Lam and Hong [57] came with a novel vessel segmentation technique and extraction of pathological vasculature by using laplacian operators. Their experimental results are evaluated on STARE database with 0.9474 accuracy and ROC as 0.9392 respectively. Lam et al [58] worked with multi-scale concavity modeling method. And their experimental results on DRIVE and STARE databases are with 0.9479 accuracy and ROC as 0.9614 on DRIVE database and 0.9567 and 0.9739 on STARE. database respectively. Espona et al [59] worked with angiographies by using snake model and their experimental results are evaluated with 0.9316 accuracy and 0.6634 specificity and 0.9682 sensitivity. Espona et al [60] moved with a combination of morphological process in snake method for the segmentation and their results are evaluated on DRIVE database with 0.9352 accuracy, 0.7436 sensitivity and 0.9615 specificity. Al-Diri et al [61] involved ribbon twin active counter model in maintaining the width consistency to capture every edge vessel structure by using vessels measurement active contour models and their results are tested with 0.9610 accuracy, 0.7282 sensitivity and 0.955 specificity DRIVE and 0.9087, 0.7521, 0.9681 on STARE respectively. Zhang et al [62] work is based on nonlinear projection by using local adaptive thresholding method. And their performances are estimated with 96.1% accuracy and 0.9772 specificity is achieved on DRIVE database, and 0.9087 accuracy, 0.7373 sensitivity and 0.9736 specificity on STARE database.

Here, one of the examples of model based approach is disclosed:



Zang;s input image and output image on DRIVE database

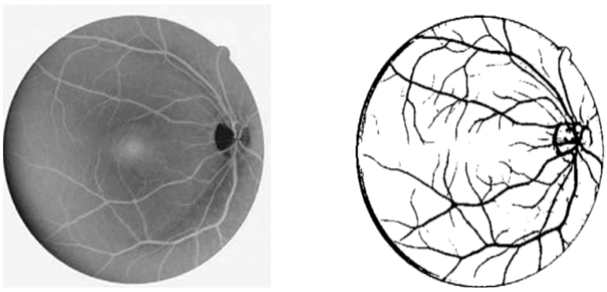


Zang's input image and output image on STARE database

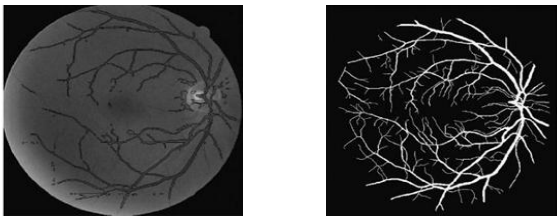
3.7 PARALLEL IMPLEMENTATION METHOD

Renzo et al [63] have used cellular neural networks for template expansion segmentation of retinal vessel color images have. Their experiment is evaluated on DRIVE database with 0.9348 accuracy and area under curvature ROC as 0.9261 respectively. Alonso-Montes et al [64] have done their work for the extraction of vascular tree shaped structure and their results were evaluated with an accuracy of 0.9185 and ROC curve as 0.9011 respectively in order to achieve real time requirement of improved computation. Palomera-Perez et al [65] have done their work for the detection of feature extraction and region growing using ITK implementation methods of ITK parallel implementation method and their experimental results are evaluated with an 0.9250 accuracy, 0.64 sensitivity, 0.967 specificity DRIVE and 0.926,0.769,0.9449 on STARE respectively.

Here are some of the examples of parallel implementations:



Renzo's input green channel retinal and output segmented image



Alonso-Montes's input retinal image and output retinal

From the discussions above, it is very clear that much of the research has been done and numerous algorithms have been proposed by various authors, which fall in different categories, proved that the impact of poisonous disease so named as 'diabetes' which is inferring various pathologies could be handled very effectively and blindness to the diabetic patients could be avoided.

This review brings out not only the essence of distinct and effective techniques that are proposed to segment blood vessels, but also the importance of optimization techniques that have been vital in segmentation process. The main focus of this review is to prove that optimization techniques could be a better choice in dealing the optimistic blood vessel pixels for more effective segmentation.

The next section gives a very elegant comparison of various categories of algorithms discussed in this section. In order to limit the paper, only few of the techniques related to each of the category is presented and their relative performance measures are projected to witness the segmentation accuracy of most of the algorithms to have a good comparison between proposed approaches that are without optimization techniques which is tabulated in Table 3 and with optimization techniques can be seen in Table 4.

When Table 3 and Table 4 are compared, a clear understanding of the majesty of optimization techniques could be witnessed.

3.8 PERFORMANCE COMPARISON

This section discloses effective comparisons of segmentation results of the techniques so far are discussed.

Table 3: Performance comparison of various categories of classification methods

SNO	Algorithm	Year	Image processing technique	Data base	Accuracy	Sensitivity	Specificity	Area under ROC curve
16	Sinthanayothin et al	1999	neural networks and principal component analysis	Local dataset	-	0.833	0.91	_
17	Abramoff et al	2004	Gaussian derivative and k-NN classifier	DRIVE	0.9416	0.7145	-	0.9294
18	Staal et al	2004	k-nearest neighbor classifier	DRIVE	0.9442	-	-	0.952
				STARE	0.9516	-	-	0.9614
19	Soares et al	2006	Gabor filter and Gaussian mixture model (GMM) classifier	DRIVE	0.9466	-	-	0.9614
				STARE	0.9480	-	-	0.9671
20	Ricci and Perfetti et al	2007	Line operator and Support Vector Machine (SVM)	DRIVE	0.9563	-	-	0.9558
				STARE	0.9584	-	-	0.9602
21	Osareh and Shadgar et al	2009	Multiscale Gabor filter and GMM classifier	DRIVE	-	-	-	0.9650
22	Lupascu et al	2010	Feature based AdaBoost classifier	DRIVE	0.9597	0.72	-	0.9561
23	Xu and Luo et al	2010	Wavelets, Hessian matrix and SVM	DRIVE	0.9328	0.7760	-	-
24	You et al	2011	Radial projection and semi-supervised classification using SVM	DRIVE	0.9434	0.7410	0.9751	-
				STARE	0.9497	0.7260	0.9756	-
25	Marin et al	2011	Gray level and moment invariant based features with neural network	DRIVE	0.9452	0.7067	0.9801	0.9588
				STARE	0.9526	0.6944	0.9819	0.9769
	UNSUPERVISED CLASSIFICATION METHODS							
26	Ng et al	2010	Maximum likelihood scale space analysis parameters	DRIVE	-	0.7000	0.9530	-
27	Kande et al.	2009	Spatially weighted fuzzy C-means clustering	DRIVE	0.8911	-	-	0.9518
				STARE	0.8976	-	-	0.9298

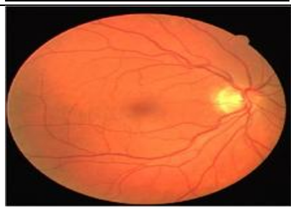
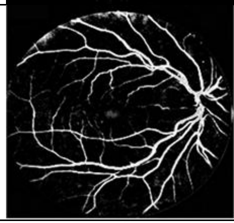
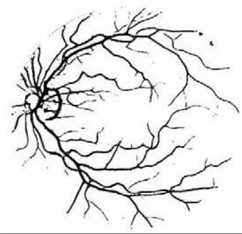
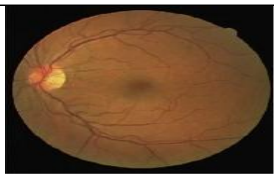
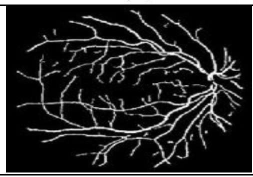
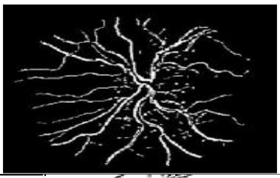
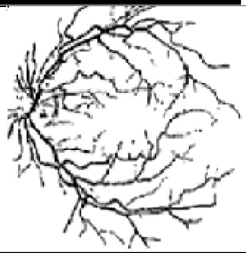
28	Salem et al	2007	Radius clustering Algorithm (RACAL)	STARE	-	0.8215	0.9750	-
29	Villalobos-Castaldi et al	2010	Local entropy and co-occurrence matrix (GLCM)	STARE	0.9759	0.9648	0.9480	-
	MATCHED FILTERING							
30	Chaudhuri et al	1989	Two dimensional matched filter	DRIVE	0.8773	-	-	0.7878
31	Hoover et al.	2000	Matched filtering and threshold based probing	STARE	0.9267	0.6751	0.9567	-
32	Xiaoyi and Mojon	2003	Multiscale threshold probing	DRIVE	0.9212	-	-	0.9114
				STARE	0.9337	-	-	0.8906
33	Yao and Chen	2009	Gaussian based Matched Filtering neural network	STARE	-	0.8035	0.972	-
34	Al-Rawi et al	2007	Improved Gaussian matched filter	DRIVE	0.9535	-	-	0.9435
35	Zhang et al	2010	Gaussian matched filter in combination with first order derivative.	DRIVE	0.9382	0.7120	0.9724	-
				STARE	0.9484	0.7177	0.9753	-
36	Cinsdikici and Aydin	2009	Matched filtering and ANT colony optimization	DRIVE	0.9293	-	-	0.9407
37	Amin and Yan	2010	Phase Concurrency and log-Gabor filter	DRIVE	0.92	-	-	0.94
	MORPHOLOGICAL PROCESSING							
38	Zana and Klein	2001	Morphological processing and cross curvature evaluation	DRIVE	0.9377	0.6971	-	0.8984
39	M.M. Fraz et al.	2011	Vessel centerline detection and morphological bit-plane slicing	DRIVE	0.9430	0.7152	0.9769	
				STARE	0.9442	0.7311	0.9680	
40	Miri and Mahloojifar	2011	Curvelet transformation and morphological model	DRIVE	0.9458	0.7352	0.9795	-
	MULTISCALE APPROACH							
41	Martinez-Perez et al	1999	maximum principal curvature	DRIVE	0.9181	0.6389	-	-
42	Martinez-Perez et al	2007	Maximum principal curvature and gradient descent magnitude region growing	DRIVE	0.9344	0.7246	0.9655	-
				STARE	0.9410	0.7506	0.9569	-
43	Perez et al	2007	ITK serial implementation	DRIVE	0.9220	0.660	0.9612	-
				STARE	0.9240	0.779	0.9409	-

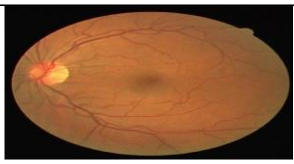
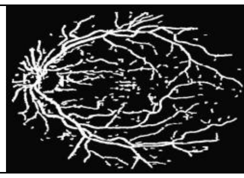
44	Anzalone et al	2008	Scale space analysis and parameter search	DRIVE	0.9587	0.8069	0.9477	-
45	Farnell et al	2008	Multiscale Line Operators	STARE	-	-	-	0.940
				Aria	-	-	-	0.895
46	Vlachos And Dermatas et al	2009	Multiscale line tracking	DRIVE	0.929	0.747	0.955	-
	MODEL BASED METHODOLOGIES							
47	Vermeer et al.	2004	Laplacian profile model	GDx	-	0.924	0.921	-
				STARE	0.9287	-	-	0.9187
48	Li et al.	2007	Multi resolution Hermite model	DRIVE	-	0.780	0.978	-
				STARE	-	0.752	0.980	-
49	Lam And Hong et al	2008	Divergence of vector fields	STARE	0.9474	-	-	0.9392
50	Lam et al	2010	Multi concavity modeling	DRIVE	0.9472	-	-	0.9614
				STARE	0.9567	-	-	0.9739
51	Espona et al	2007	Snakes in combination method	DRIVE	0.9316	0.6634	0.9682	-
52	Espona et al	2008	Snakes in combination method	DRIVE	0.9352	0.7436u	0.9615	-
53	Al-Diri et al	2009	Ribbon Twin active contour model	DRIVE	0.9610	0.7282	0.9551	-
				STARE	0.9087	0.7521	0.9681	-
54	Zhang et al	2009	Nonlinear projections, variational calculus	DRIVE	0.9610		0.9772	-
				STARE	0.9087	0.7373	0.9736	-
	PARALLEL HARDWARE IMPLIMENTATION BASED METHODS							
55	Renzo et al	2007	CNN classifier with virtual template expansion	DRIVE	0.9348	-	-	0.9261
56	Alonso-Montes et al	2010	CNN with virtual template expansion	DRIVE	0.9185	-	-	0.9011
57	Palomera-Perez et al	2010	ITK parallel implementation	DRIVE	0.9250	0.64	0.967	-
				STARE	0.926	0.769	0.9449	-

IV. OPTIMIZATION TECHNIQUES IN SEGMENTATION

To find an optimum or unconstrained solution of differentiable functions, optimization methods are used and the purpose of optimization is to achieve the efficient result. There are various types of optimization techniques in image processing. Ant colony optimization, Lion, Bee colony optimization, Particle swarm optimization, fire fly optimization these are some of the optimization techniques. When coming deep into it, PSO is used for the image segmentation, image enhancement and for pattern recognition. (ACO) is used for the image edge detection and optimization both are used to generate normal and abnormal images in that firefly will get attracted towards the brighter ones. Hassan et al. [66] used PSO based Novel segmentation approach for the extraction of retinal fundus vasculature of retinal images based on PSO, for the determination of n-1 optimal n-level thresholds on fundus images. The researchers applied preprocessing operators in order to suppress the background and perform smooth and contrast enhancement in the retinal images and then have used PSO based multilevel thresholding for the segmentation of retinal vasculature. The optimization technique named ‘Ant Colony System (ACS)’, is a meta-heuristic looking calculation which was first proposed by M. Dorigo and L.M. Gambardella [67] for tackling the voyaging sales rep issue (TSP). The ACS depends on reproducing the scavenging conduct of ants that are genuine. In nature, when ants start hunting down substances, various ants move out in arbitrary ways. When an ant moves, it stores a synthetic substance called ‘pheromone’ where other ants follow the trail of pheromone. Ants can figure out the shortest path by the use of pheromone. The shorter way is based on pheromone focus which stays for longer time that increasingly attract different ants which are then pulled into it. Along these lines the most limited way is the special case which draws in different ants [68]. Kavya et al. [69] did their work using bee colony optimization, where this optimization technique is used probe the cluster centers of objective function of fuzzy c-means and for the localization of small vessels fitness function of pattern search approach is hired. Al-Rawi et al.[70] used morphological clustering method by combining both genetic algorithm and FCM fuzzy clustering algorithm for the retinal vascular segmentation. To obtain global optimal solution genetic algorithm is used and then the outcome of genetic algorithm is utilized as the preliminary input to the FCM algorithm and then vice versa. N C Santosh Kumar and Radhika Y[71] have given an accuracy of 96% of segmentation, where they have used Particle Swarm Optimization (PSO) to bring out optimum pixels among all the intensity pixels of the input image. Later, they computed Maximum Principal Curvatures of the optimized pixels upon which they applied morphological operators to segment the blood vessels. The authors of [72] and [73] have used Particle Swarm and Ant Colony optimization techniques respectively, that gave good segmentation accuracy, listed in Table 4.

Table 4: Performance comparison of methods that used optimization techniques

S.NO	Author	Optimization technique used	Data set	Accuracy	Input Image	Output Image
1	Gehad Hassan et al (2015)	Particle Swarm Optimization (PSO)	DRIVE	97.75		
2	Kavya.k et al (2016)	Artificial Bee Colony (ABC)	DRIVE	96.35		
3	Al-Rawi, M., & Karajeh, H. (2007)	Genetic Algorithm	DRIVE	0.9582 (ROC)		
4	N.C.Santosh kumar et al (2019)	Particle Swarm Optimization	DRIVE	0.9618		
			STARE	0.9708		
5	Sreejini, K. S., & Govindan, V. K. (2014) [72]	Particle swarm optimization (PSO)	DRIVE	96.33		

6	Cinsdikici, M. G., & Aydın, D (2009) [73]	MF/Ant Colony Optimization	DRIVE	0.9407		

The accuracy rate in the above table proves that optimization is a better choice in carrying out the segmentation process. Various authors those who have proposed distinct techniques related to various categories of segmentation techniques have given an accuracy rate which approximated to 95% except a couple of authors including Castaldi et al. [37] , Zhang et al [62] , Al-Diri et al [61] who have been outstanding in their segmentation approach without any involvement of optimization technique.

V. CONCLUSION:

The essence of retinal image related diagnostic systems lies in segmentation algorithms. Despite of many outstanding techniques which have been proposed, the scope of research in this area is still open to carry out. In this review, various forms of segmentation schemes along with their performances are presented with primary focus on deriving the optimization techniques as a better choice in the segmentation procedure. With a detailed discussion of promising and prominent methods (without and with involvement of optimization techniques) that have been proposed in the literature for segmentation, it is evident that the optimization techniques are the difference makers. This review provides the practitioner a better framework to engage with the optimization to achieve best and accurate results.

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