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A Brief Review on Retinal Image Analysis for Accurate Diagnosis of Diabetic Retinopathy

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Abstract

In recent years, Diabetic Retinopathy (DR) is observed as one of the leading causes of visual impairment in most of the over the world. Moreover, the rise of DR put the health experts into a typical condition. To lessen this problem, an automated DR diagnosis through retinal image analysis has come into picture in which the retinal image is subjected to different mathematical algorithms for the identification of DR related anomalies. In retinal image analysis, retinal vasculature segmentation followed by classification occupied a major part of work. From the past few years, different researchers suggested different method for retinal image segmentation. This paper outlines a full-pledged survey on the earlier suggested methods which are broadly classified as mathematical morphology methods, deformable methods, vessel tracking method and machine learning methods. Along with these methods, we also surveyed some method those concentrated on the quality enhancement of retinal images. We also outlined the details of different standard retinal images datasets those were employed for experimental validation.

Keywords: Diabetic Retinopathy, Retinal vessels, contrast enhancement, contours, morphology, tracking, machine learning, datasets.

[1.] INTRODUCTION

Since last ten years, a rapid growth in the technology has been observed towards collection of medical information about various parts of the body to analyze them automatically. The parts of the human body may be obtained more effectively by using this new advanced equipment and can be portrayed in a cardinal format. This results a better quality and long lost record. Furthermore, the main benefit is quick access, accessing without loss in the data quality and electronic storage, ultimately in the automatic medical data analysis gives accurate results. Many medical signal/image models such as x-ray imaging, mammogram, “Magnetic Resonance Imaging (MRI)” Retinal Fundus images, “Electroencephalogram (EEG)”, Electrocardiography (ECG)” etc., may be acquired in order to achieve automization in the medical field.

1.1 Retinal Fundus Imaging

Retinal fundus images are one of the medical image samples that are acquired using a special camera called fundus camera [1]. To capture the detailed structure of retinal image,Fundus camera can be considered as a low power microscope. After illuminating the retina, the retinal

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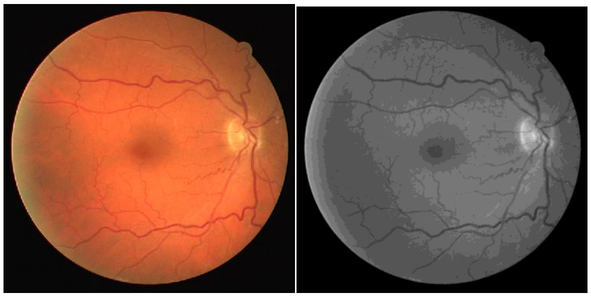
structure is imaged through a camera that is coupled to fundus camera.In general, the human eye's interior surface can be captured using a fundus camera. Mainly it is comprised of Retinal Vasculature (RV), Macula,Posterior Pole [2] and Optic Disc (OD). The fundus images are also called as fundus angiography, it is an invasive imaging, and the structure of the retina is photographed by injecting a small amount of fluorescent dye into the vein of the patient's arm. After the dye is implanted, it will move towards the major blood flow that leads to the retinal vessels. The term "angiography" formerly derived from Greek Language using two words namely "Angeion" and"Graphein" which means "vessels" and "record or to write" respectively. They are illuminated with blue color after reaching the fluorescence into retinal vessels, and appeared as a bright region flashing with a combination of green and yellow color. Additionally fundus camera is fitted with specific fitters to allowthe light to be imaged or photographed, which results a high contrast retinal image. Figure.1 shows the sample retinal fundus image in both gray and color. The ability of ophthalmologist to study the physiology and pathology of retinal fundus images are highly revolutionized.Furthermore, this can be used in the treatment and diagnosis of eye related issues like Glaucoma, AMD and DR etc.



(a) **(b)**

Figure.1 (a) Color Retinal image and (b) Gray retinal image

1.2 Eye related diseases

In eye, brain or in cardiovascular system there are so many diseases are generated. Directly/Indirectly effected diseases by the eye can be diagnosed using retinal images. Here, an overview about diseases which are diagnosed through retinal images.

1.2.1 Diabetic Retinopathy

In Recent days, the Visual impairment has been occurred due to most common disease i.e., Diabetic Retinopathy (DR). It is a compilation of Diabetes Mellitus (DM) and can cause permanent blindness and Visionloss. In India, 21.70% Type-2DM patients reported retinopathy prevalence was of age greater than or equal 40 years [3]. One and only solution to minimize this value is that early screening and diagnosis and it also reduce the patients from (blindness) vision loss and blindness [4]. In the eye,the retinal vessels are damaged due to the issue of hyperglycemia which leads to mainly two problems such as Ischemia and breakdown. In Ischemia,new blood will grow, which may cause bleeding, called the advanced stage of DR, named as Proliferative Diabetic Retinopathy (PDR). The second means breakdown of the retinal barrier which may result is the fluid leakage, photoreceptors damage and Diabetic Macular Edema (DME).

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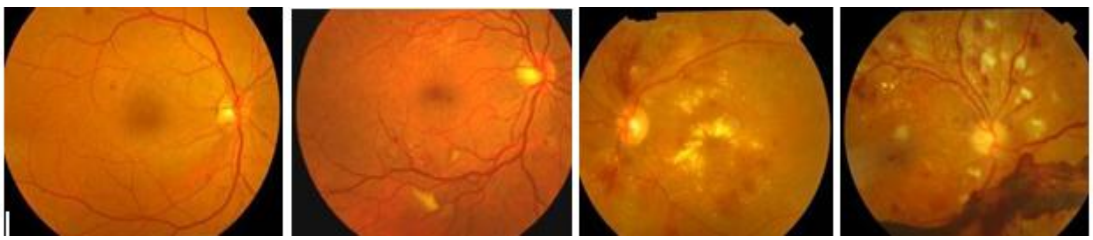
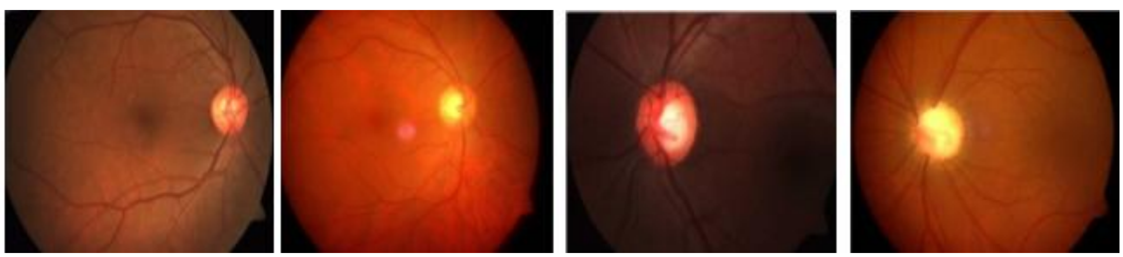
1.2.2 Glaucoma

After DR, Glaucoma is the second most common disease that leads to blindnessand it is distinguished by the Continuous damage to the optic nerve and further loss of visual field [5]. After Cataract, Glaucoma reported as 60 million cases in 2010 and 80 million cases in 2020 [6]. The only solution is to reduce this risk of vision loss due to glaucoma was early diagnosis and treatment. Glaucoma is not a retinopathy like the DR; it's called neuropathy and acts upon retina causes damage to the ganglion cells and their axons. By calculating the disc and cup areas as well as "Cup to Disc Ratio (CDR)" Progression was tracked and from the retinal image the glaucoma is diagnosed for assessing the presence and progression of glaucoma. The important structural measure is cup to disk ratio and it is calculated as the ratio of optic disc cup and the Neuro Retinal Rim (NRR) surface area. Predominantly in refractory cases the Glaucoma is treated with ocular pressure lowering drops through surgery.



(a) (b) (c) (d)

Figure.2 (a) Mild NPDR, (b) Moderate NPDR and (c) Severe NPDR, and (d) PDR



(a) (b) (c) (d)

Figure.3 (a) Normal Image, (b) Mild Glaucoma, (c) Moderate Glaucoma and (d) Severe Glaucoma

1.3 Retinal Image Processing

The Retinal images must be analyzed more carefully to get an efficient diagnosis for the above specified diseases. The main objects which were generally used for this analysis are Retinal Vascular Structure, Optical disk, cottonwool spots, Exudates, and Micro Aneurysms Hemorrhages (MAHM) are analyzed. For example,breadth of Retinal vessels those exist around OD is approximately150 µm. Next, the MAHMs appear like red and small spots, results in hemorrhages, whereas the hard exudates look like bright yellow colored dots. Based on the above mentioned spatial dispersal of retinal image attributes the rigorousness of Glaucoma or DR is calculated. These retinal image attributes are considered and need to be extracted and compared with normal healthy person's retinal image attributes to analyze the status of disease. For example,the retinal image having extra vessels in the PDR and those extra vessels are

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identified by the segmentation and comparison with the normal person's retinal image vessels. Next the Glaucoma status is diagnosed by the comparison and computation of CDR among healthy and unhealthy person's retinal images.Segmentation is required for all these purposes. Based on this analysis, the retinal image processing can be done in three phases (i) Preprocessing (ii) Attributes Segmentation and (iii) Classification.

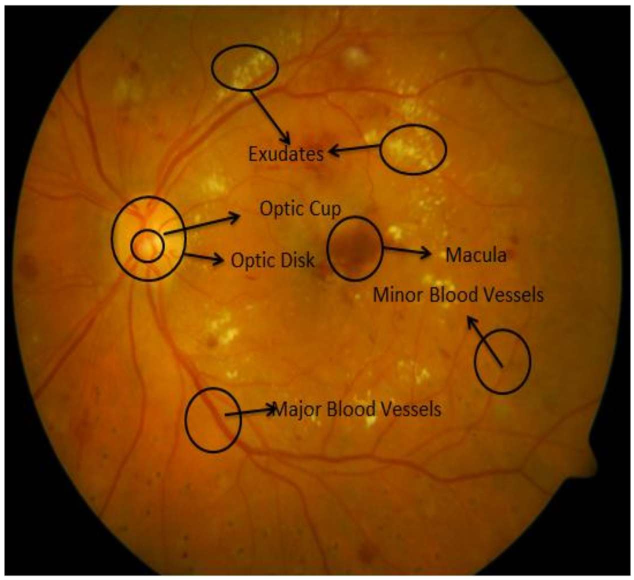


Figure.4 anatomy of retinal image

In the first phase i.e., in preprocessing phase, the image normalization is required for contrast enhancement, removal of noise and adjustment of color etc. for retinal images. Next in the 2nd phase i.e., segmentation phase, using many signal processing algorithms [7], [8] the preprocessed images are passed to segmentation stage, and finally in the last classification phase, the segmented attributes are compared with standard attributes and based on this classification is done.In the past years, several methods are employed towards retinal image segmentation. Based on the earlier developed methods the main the objective of this paper is to represent detailed survey in two phases namely (1) Preprocess, and(2) RV Segmentation.Firstly we explore about several performance metrics and databases. In the next section, we explain about the earlier proposed segmentation techniques deeply and also conduct a comparison between them.

The rest of the paper was structured into four sections. Section II explains different performance metrics and standard databases.Section III discussed about different segmentation algorithm finally Section IV concludesthe paper.

[2.] PRELIMINARIES

Several retinal image databases are explained here which are publicly available. For the diagnosis of retinal diseases, the retinal images are subjected to segmentation to extract the vessel structure. To validate the segmentation model, it was tested over standard datasets and which were captured under surveillance of medical experts. After testing the developed model, the performance is evaluated using different performance metrics. Overall description about the datasets and the performance metrics are explained clearly in this section.

2.1 Data bases

Two popular datasets majorly used by the authors working on retinal images. The datasets are(1)"Digital Retinal Image for Vessel Extraction (DRIVE)" and (2) "Structured Analysis of the Retina (STARE)" [10]. Moreover some other datasets also available and they are "Automated Retinal Image Analyzer (ARIA)" dataset [11] "Diabetes Retina Database(DIARETDB)" dataset [12], Methods for Evaluating Segmentation and Indexing techniques Dedicated to Retinal (MESSIDOR)" data set [13], "High resolution Fundus (HRF)" dataset [14], "Retinal Vessel Image set for Estimation of Widths (REVIEW)" dataset [15] and "Vessel Registration for a reliable Computation of ArteriovenousRatio (VICAVR)" dataset [16].

2.1.1 DRIVE

The DRIVE consists of 40 color fundus images and these are publicly available under a special screening program for DR in Netherlands. A camera called as "Canon CR5 non Mydriatic 3-CCD" is used to capture all the images of DRIVE under Field of View (FOV) of 45 degrees. The screening includes 453 total people of age between 31 and 86, and the photographs are captured in JPEG Format. Only 7 images among 40 images holds pathology, such as hemorrhages, changes in epithelium and exudates. 768x584 is the resolution of every image in this database and each color plane represented in 8 bit. The total set of 40 images is separated into two sets called training and testing and 20 images are present in each set. The every image FOV is round and 540 pixels is approximated breadth. For every image segmented retinal vascular structures in manual also available in this dataset. Three observes are involved in the manual segmentation. First two observers are main authors and 3rd is a student from the department of Computer Science experienced Ophthalmologist trained all these observers. With the help of first observer in the training set, first 14 images are segmented and the next 6 are done with the help of second observer. In the test set the images are segmented into twice and the segmented sets A and B. Complete segmented set A done by first two authors and the set B completely done by third author. The first 13 images in set A are get by first observer and the rest of 3 images are by second observer. Set A consists of 57764 Vessel Pixels (VP) and 39,60,494 Non Vessel Pixels are marked by observers. Moreover, in set B, total number of VPs and NVPs are 5,56,532 and 39,81,611 respectively marked by third observer.Some samples of this dataset are shown in figure.5.

2.1.2 STARE

Totally this database consists of approximately 400 raw fundus images those were captured using "Top con TRV-50 Fundus camera" at 35 degree FOV and these images are captured at California University, Sandiago. The resolution and color plane of every image of this data base are 605x700 & 8-bit representation respectively. The FOV of each image diameter is approximately 650x500 pixels. Here, in this dataset segmentation is done by 2 observers is manual. The percentage of pixels are totally marked as VPs by 10.4% by observer 1 and 14.9% by observer 2. At the second observation, highest percentages of segmented vessels are observed due to he takes many thinner vessel also as vessel pixels.Some samples of this dataset are shown in figure.6.

2.1.3 MESSIDOR

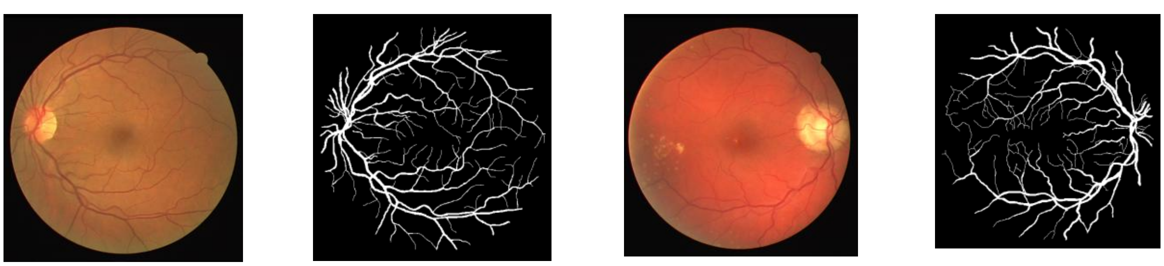
This consists of 1200 retinal fundus images which are a largest dataset. These images are captured by “non-mydriatic 3CCD camera (TOP Con TRCNW6)” at 45 degree FOV at three different ophthalmology departments. Multiple resolutions are observed as 1440x960, 2240x1488 and 2304x1536 by this dataset. All the images in this dataset are .TIFF format. Out of 1200 retinal images, 800 were taken with pupil dilation and remaining 400 were taken without dilation in pupil. Every image in the standard reference includes DR grading as well as risk of macular Edema.Some samples of this dataset are shown in figure.7.

2.1.4 IMAGERET

This the publicly available dataset developed in the year 2008. This dataset categorized into two subclasses called “DIARETDBO” and “DIARETDBI”. Totally “DIARETDBO” consists of 130 color retinal images, among 100 retinal images having abnormalities that indicate DR symptoms (Ex. MAHMs and Neovascularization, soft and hard exudates) and the remaining 20 are normal. In DIARETDBI consists totally 89 images among only 5 are healthy, the remaining 84 are having several abnormalities that indicate the DR symptoms of mild proliferative (ex:micro aneurysms). With unknown settings used by 50° FOV digital Fundus camera captures all the images in dataset. In this dataset all the images are in .png format.The other name for “DIARETDBO” is “calibration level 0” and “DIARETDBI” is “calibration level 1” images.Some samples of this dataset are shown in figure.8.

2.1.5 ARIA online

Under research, the “ophthalmology department, clinical sciences university of Liverpool, UK” developed this dataset in collaboration with “St.Pauls Eye unit, Royal Liverpool university Hospital Trust, Liverpool UK”. In 2006 this dataset is created which consists of 212 images and they are categorized into 3 datasets: one dataset consists of 92 images with AMD, the second set consists of 59 images with diabetes and third data set consists of 61 images. The Fovea location is traced using two experts, OD and RV as the standard reference. The resolution is 768x576 for each image and every color plane represented in 8-bit. Using “Zeiss FF450 plus Fundus Camera” at 50 degree FOV all the images are captured and stored in .TIFF format without any compression.



(a) (b) (c) (d)

Figure.5 DRIVE images, (a) Normal image (b) Segmented normal image (c) Pathological image and (d) Segmented pathological image

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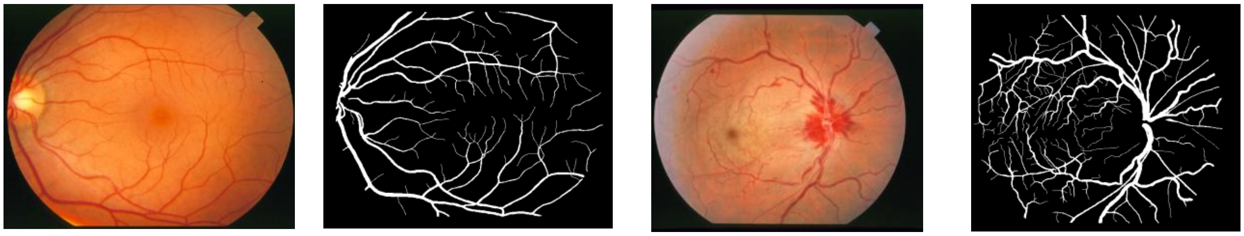
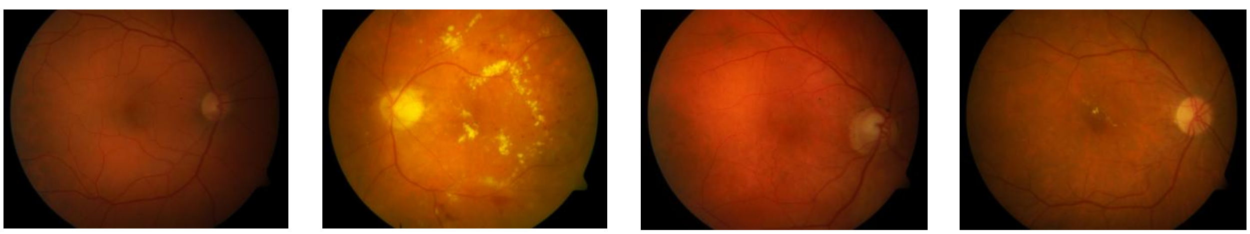


(a) (b) (c) (d)

Figure.6 STARE images, (a) Normal image (b) Segmented normal image (c) Pathological image and (d) Segmented pathological image

Figure.7 Samples of MESSIDOR dataset



(a) (b) (c) (d)

Figure.8 (a) Normal DIARETDB0 image (b) Pathological DIARETDB0 image (a) Normal DIARETDB1 image (b) Pathological DIARETDB1 image

Table.1 Databases Details

Database Name	**Images**	**Resolution**	**FOV**	**Year**	**Fundus Camera**
DRIVE	40 (20-training, 20 testing)	768×584	45^0	2004	Canon CR5 non-mydriatic 3-CCD camera
STARE	400	605×700	35^0	2000	TopCon TRV-50 fundus camera
MESSIDOR	1200	1440×960, 2240×1488 and 2304×1536	45^0	2004	non-mydriatic 3CCD camera (Topcon TRCNW6)
DIARETDB0	130	1500×1152	50^0	2008	Fundus Camera

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DIARTEBD1	89	1500×1152	50^0	2008	Fundus Camera
ARIA Online	212	768×576	50^0	2006	Zeiss FF450+ fundus camera

[3.] LITERATURE SURVEY

Over Retinal image segmentation algorithms aclear literature survey is carried out in this section. Since for the analysis of DR, the main components are RV, we focused on the methods those mainly aimed at the segmentation of RV. In this survey, the algorithms categorized into 2 types; they are (1) Preprocessing and (2) RV segmentation.

3.1 Preprocessing

The main goal of preprocessing techniques is to mitigate the image from different variation such as fundus thickness, light diffusion, fundus camera reflectivity existence of abnormalities. Due to some other reasons like owing to the pigmentation, illumination, acquisition angle, difference in the cameras variations occur in the images. Misclassification may occur due to this variation presence in the retinal images. To nullify these variations it needs to be preprocessed before segmentation.

In retinal images Contrast Enhancement (CE) is a widely used preprocessing technique. To increase the image quality CE is used by ensuring a perfect discrimination between vessels and background. In retinal images commonly used technique for CE is “Histogram Equalization (HE)” [17, 18]. Comparison between quality of enhanced image and standard reference image is done in HE and it is more qualitative. Meanwhile HE doesn’t preserve the mean brightness of Image (MBI). Moreover the HE techniques are classified in to two categories such as “Global Histogram Equalization (GHE)” and “Adaptive Histogram Equalization (AHE)”. In GHE [19], the equalization is done in a global fashion. However during equalization the complete range of Grey scale intensities was taken into account and hence the resultant images had shown a washed-out appearance. Hence in the retinal image enhancement, the global information can’t ensure a satisfactory result.

To tackle this problem, AHE takes each pixel’s local window into account and calculates a new intensity value depending on the pixel intensities within that window. However noise also gets enhanced if noise is present in AHE. To solve this issue, in many retinal image processing approaches, a pre-processing technique is employed as an adaptive CE referred as “Contrast Limited Adaptive Histogram Equalization (CLAHE)” [21-23, 25]. Though it is done locally, the MBI is not preserved in CLAHE also. For retinal images, MBI is an important.Furthermore, CLAHE has the disadvantage of introducing ringing artefacts at edges and amplifying noises in flat regions.

To simplify this problem a solution is defined through “Dynamic Histogram Equalization (DHE)” [20]. In this method, after the partition of histogram using local minima the MBI is preserved based on the histogram remapping. Due to histogram peakremapping effects on the MBI, this approach also not good. In response to this issue instead of peakremapping Crisp histogram is applied in extended DHE by Ibrahim and Kong [24] and it is called as “Brightness-Preserving DHE”. However the MBI of output image will vary due to the consideration of inexact grey pixel intensities of image.

Based on the CE in retinal images, some other approaches are also implemented. In [26] Multi-Dictionary coding and sparse coding are employed. ForCE in retinal images, they discoveredRepresentation Dictionary (RD) and Enhanced Dictionary(ED) as two different dictionaries. The information is multi-dictionary is optimized based on the patches extracted through RD and RD.Next, for CE and smoothening of retinal images Rampal et al.[27] employed a new filter named as “Complex Diffusion based Shock Filter(CDSF).By combing the MultiScale Top hat transform (MSTT) andHistogram Fitting Stretching(HFS) an integrated CE model developed by Liao et al. [28], an effective quality was attained using this hybrid model. Though this hybrid model attained an effective quality, it has introduced some external artifacts like spontaneous variations in the color levels, artificial boundaries, and loss information in retinal images. To solve these issues, [29] developed a new CE model based on normalized convolution with the help of “Partial Differentiation Equations (PDEs)”.This method extracts noise in the retinal image and CE is done using “Relaxed Median Filter(RMF).

Similarly to the methods used above, LiXionget al. [30] enhanced theRetinal image quality based on scattering model of image formation. Based on back ground and foreground, two parameters named back ground illumination and transmission map are calculated. This computation is done using a new integrated model with global spatial entropy and mahalanobis distance which is developed through which the foreground and background region in lowintensity and high intensity regions respectively. With blurred images also, this method gives good result.

Besides, all these methods didn’t perform the contrast enhancement based on the level of contrast available on an image. This may results in degraded contrast in the case of image with high level of contrast. In general CE used as a pre-processing step, then the algorithm provides good results with its default metrics. Combination of AHE and GHE is termed as hybrid CE [31]. Y.M.S Reddy etal. [32] and M.N.Naik etal. [33] adopted the contrast enhancement through Mutual Relation and Spatial Correlation between pixels of a local window after the transformation of the retinal image through Discrete Cosine Transform (DCT). These methods had shown an excellent performance in the provision of an improved quality of image with an additional computational complexity.

M. Zhou et al. [34] proposed a CE algorithm based on a luminance gain matrix that was obtained by gamma correction of the value channel in HSV (Hue-Saturation-Value) colour space. The luminance gain matrix is used to enhance R, G and B channels respectively. Contrast is then enhanced in the luminosity channel of L*a*b colour space by CLAHE. Similarly, SimaSahu et al. [35] employed the same CLAHE algorithm for CE and noise removal in retinal images. This method used several set of filters along with CLAHE for CE in retinal images. Different set of filters namely median filter, wiener filter, Gaussian filter, weighted median filter and Average filter are employed for denoising. Gupta, B. Tiwari, M. [36] proposed an overall CE method for retinal images. Initially, they calculated a gain matrix with the help of luminance values which were obtained by adaptive gamma correction method and it was used to enhance all the three colour channels of retinal images. Afterwards, Quintile based HE is employed to enhance the overall visibility of images. A. A. Bala et al. [37] proposed used Multi-resolution curvelet transform and adaptive sigmoid mapping of Histogram Equalization for CE in retinal images. Initially, they decomposed the retinal image into several sub bands through curvelet transform and then they applied hard thresholding over each coefficient to remove the noise.

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3.2 Retinal Vascular Segmentation

In the retinal image analysis,RV segmentation is the major concern for the diagnosis of several eye related issues. In the identification of anatomy and retinal pathologies, accurate segmentation of RV is a major requirement. Moreover, the RVs segmentation is also beneficial in the spatial alignment and registration of images. The RV structure designed with veins and arties, which is organised as a tree structure consists of main branches and sub branches. Here, thebranches mean major vessels and sub-branches mean minor vessels. The artery divided into multiple branches, retinal image supplied with four quadrants in the inner layers. In the same way, OD can join using retinal veins. RV's have low reflectance when compare to the other retinal surfaces thus they appear as dimmer than the back ground. Generally, the RVs, the chord and retinal capillaries absorb and reflect the light. The thickness of the vessels wall and refraction index has negligible effect on the width of blood column. However arteriosclerosis is associated with fibrosis and thickening of the vascular barrier, which affects the indices of refractions and increases the width of the light reflex.

3.2.1 MathematicalMorphology

In RV structure morphology, generally the linear segments are involved. Morphological handling for the identification of certain shapes is more resistive to noise variations in retinal image. In mathematical morphology, image frame consists of shape of objects instead of pixel intensities. In general mathematical morphology operators are first implemented on binary images and latterly they extended to grey and coloured images.Using a known structuring element the image undergoes the transformation in mathematical morphology. Morphological closing, dilation,opening and erosion are the general operations those werecarried out under mathematical morphology.

Kundu and Chatargee[38] introduced "Morphological Angular Scale Space (MASS)" with an aim of retinal vessel segmentation. The method involves variation length in linear structuring element with various angles. At every level, this method finds the components connected and also ensures RV's connectivity. Next, by considering length variation in structuring element scale space is evaluated. Further, at certain scale the final retinal vasculature is calculated by finding the vesselness.

For the segmentation of retinal vasculature,Prucci etal. [39] proposed a watershed algorithm. In this method, firstly the algorithm is tested over an input retinal image to segment into various blocks, with each block is assigned with unique grey-level. Further, for each block, the contrast is computed based on the difference between the center and its neighbor block through their intensities. The contrast and direction map of every block were calculated based on the amplitude and difference sign. At last, the retinal vasculature is segmented depends on the watershed block which has positive difference.

For the segmentation of RV in retinal images, Jiang et al. [40] developed to get more accuracy and speed retinal vascular center line detection method and morphology based global thresholding [42] method for capillaries. Through STARE and DRIVE dataset, this method is validated. In the same way for retinal vessel segmentation U.Ozkava et al. [41] developed a basic mathematical morphology and processed only green channel for segmentation. To get clear vessel geometry, an adaptive threshold with a Gaussian window of size 5x5 is used and for sharpening the image, a wiener filter of size 3x3 is used. Furthermore, Otsu thresholding is used to soften the image followed by morphological process to obtain retinal Vasculature.

3.2.2 Deformable models

Deformable models consider the surfaces or curves present in the self-image domain through which the shape of RVs can be determined under the both external and internal pressures. While deformation the first one concentrates on the smoothening and second one concentrates on vessel boundary. To find the matching class of specific objects, before the deformation the most basic version of these algorithms considered the shape variations forming the shape as a curve. In general, two theories termed as Curve Evaluation theory and Energy Minimization theories are considered for deformation. Both in pathology and non-pathology, these algorithms are most suitable for the vessel structure segmentation.

Based on Snake contours, Jin et al. [44] built a segmentation model under this category. This method involves three phases;(1) the retinal image first segmented into various blocks using hessian feature boundaries and linear structure seeds. (2) Next, every segment is represented with average pixel intensity within the region and then the snake energy function is computed to realize the location of snake with the help of neighbour ones. (3) Finally, a region growing method was employed to obtain the ultimate vessel area and finally post-processing is employed through a context feature.

For Retinal image segmentation, Zhao et al. [45] introduced an infinite perimeter Active Contour Model (ACM) having hybrid regions. Hybrid information used in this approach is by mixing pixel intensities with enhanced local map based on phase. Here the local phase information was utilized to preserve the vessel boundaries while the pixel intensities guarantee an accurate segmentation.

A geometric deformable model proposed by Gong et al [46] is based on "Level set LS" using local region area descriptor.Initially, in this approach, a contour is detected and it was used for retinal image segmentation into different regions. In this approach, initially a contour is detected and utilized to segment the retinal image into different regions considering the existence of pixel inside and outside of contour. To redefine the energy function, a clustering algorithm was employed that yield a cluster value in the region called as new area evidence. In retinal images, this approach terminates the effect of homogeneity at pixel intensities.

To detect edges,Dizdaro et al.[47] proposed a new method for retinal image segmentation by modifying the LS method. Herein the method, the Seed points are detected initially through the determination of centerline sampling depends on the identification of ridges. Then through this map, RV structure is detected. Further Z.Xiao et.al [48] proposed a Bayesian method with spatial constraints for retinal vasculature segmentation. This approach treats that there exist a mutual dependency between the posterior probabilities of adjacent pixels. Next by applying the modified LS function, blood vessels are detected based on the energy function minimization.

Further, Lei Wang et.al [49] proposed a new ACM based method by taking the vesselness values and pixel intensities of image to overcome the non-homogeneity problem of ACM. Based on the local phase vesselness of RVs, the vesselness is determined. This method also computed a new energy function based on the multi feature Gaussian distribution at regularization and it is integrated into LS approach. For the segmentation of RV retinal images, Y. Zhao et al. [50] proposed a new approach in three phases;. Non homogeneity correction in image through retina, enhancement of vessel based on local phase information and graph cut method assisted vessel structure segmentation through ACM.Moreover the problem commonly defined in this approach is automatic initialization for initial set of seed points.

3.2.3 Vessel Tracking

In general, to extract a vessel connected with two points, vessel tracking (VT) approaches are employed. These works were implemented over the entire vessel structure whereas morphological and deformable model works at single level only. To find the vessels longitudinal Cross sectional center, some vessel properties like vessel average width and vessel tortuosity are considered. For the calculation of accurate vessel width and individual vessel information VT algorithms are more suitable and this cannot be determined using other approaches. However, seed points are the initial requirement for vessel tracking algorithm.

Based on this motivation, in the past so many methods are introduced for retinal image segmentation using Vessel tracking [54, 56]. Chutatape et al. [51] used the "Extended Kalman Filter (EKF)" to trace the Centers of vessels after initializing the seed points from the circumferential OD. Further an area in the form of semi-ellipse is structured around the OD as a probing area for next vessel edge points; vessel tracking is done based on Bayesian theory. Further, De et al. [52] proposed a new approach for filamentary region extraction of retinal structure. This approach depends on the connecting tracing problem and the "Digraph matrix forest Theorem (DMFT)" in algebra.

Further, based on probabilistic theory, Yin et al. [53] developed a vessel tracking method for RV segmentation. Herein the method, for the detection of edge points, the grey level statistics and preceding information is required. Then by using 'Gaussian Curve and Bayesian" with maximum a posterior (MAR) confined vessels are computed. For the determination of vessel structure, Bhuyian et al. [55] developed an edge based vessel tracking method and these are verified through "Central Retinal Artery Equivalent (CRAE)" and "Central Retinal Vein Equivalent (CRVE)". Furthermore, to extract vessels from retinal images, Chen et al. [57] utilized anisotropic minimal paths and paths cores for the extraction of vessels from retinal images which were evaluated by optimally oriented flux centreline map (OOFCM).

3.2.4 Machine Learning

Machine learning has been emerged in engineering due to its strong roots in engineering filed especially in pattern recognition applications. Pattern recognition has undergone considerable developments for many years, which have applicability in various fields; retinal vasculature segmentation is one. Typically, the machine learning algorithms are categorized into 3 categories such as; unsupervised, supervised and reinforcement learning. In supervised learning, for every instance of input, there will be an output while in remaining two this flexibility can't be viewed because they have information lack. In this section, we have surveyed both supervised and unsupervised approaches those focused on the RV segmentation. Table.2 shows the comparison between different retinal vessel segmentation methods.

Based on this inspiration, recently, Ren et al., [58] proposed to categorize the pixels in the retinal images into two classes; non-drusen and drusen. Initially in this approach, initially, the some blocks are extracted from a grayscale retinal image and then a "Generalized Low-Rank Approximation of Matrices (GLRM)" and "Supervised Manifold Regularization (SMR)" are

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employed to extract the features. Then the features are vectored and fed to SVM for classification.

Maji et al., [59] employed "Deep Neural Network (DNN)" for the discovery of VPs and NVPs. This approach employed 12 "Convolutional Neural Network (CNN)" layers; every layer is trained individually with 60,000 randomly selected blocks of size $M \times N \times P$, where M = N = P = 31. These blocks are extracted from 20 retinal color and raw images from DRIVVE. At testing phase, the probabilities of vesselness are evaluated at every layer individually. Finally the responses are summed and divided by total number of blocks to find the pixel's vesselness value. Further, Avjit and Sonam [60] considered the RVs segmentation issue as a multi-label inference issue and suggested a fully connected CNN mode for retinal vessel structure prediction.

Next, Lahari et al., [61] employed an ensemble of two parallel levels of stacked denoised auto encoders. Every kernel is allocated to detect the orientation of vessel. The first level of ensemble consist of n-trained parallel stacked denoised auto-encoders those have similar architecture [63]. The second stage ensemble is designed based on the training of two stacked auto-encoders in a parallel manner. The final structure is designed din such a way that the output is much satisfactory. Then the decision of distinct responses of ensembles is fused at the simple soft-max decision classifier.

Li et al., [62] also employed DNN for cross model retinal vessel segmentation. This approach considers the relation between retinal image and vessel map. Maji et al., [64] also employed DNN for an extensive detection of RVs. This design is a hybrid design and designed based on the combination of DNN and ensemble learning. The DNN is employed for unsupervised vesselness of RVs through auto encoder with the help of RV structure blocks those are trained sparsely. Next, the learned patches are utilized as weights in DNN, and the response of DNN was used in random forest to identify the vascular issues.

Next, Vega et al., [65] a new model, called as "Lattice Neural Network with Dendritic Processing (LNNDP)" for RV segmentation. Unlike the tradition models like SVM, this approach didn't require any parameter; rather it builds the structure automatically and solves the problem. Further, in the approach developed by Wang et al., [66], the retinal vasculature segmentation is accomplished through feature learning and ensemble classifier. This approach combined the CNN with random forest algorithm in which the CNN is engaged for feature extraction and RF is employed for vessels classification.

Wilfred and Edward [67] proposed to extract the Gabor and Movement invariant features from retinal image and classified through "Artificial Neural Network (ANN)". In this, the "Multi-Layer Perceptron Neural Network (MLPNN)" is accomplished for the identification of vessels. Furthermore, the back propagation algorithm is also employed for the weights updating at feed-forward neural network.

Fraz et al., [68] employed a joint RVs segmentation framework with the help of bagged and boosted Decision Trees (DT). In this approach, the retinal image is represented with a set of features based on the gradient vector analysis with it's orientation, morphology, strength of line measures and responses of Gabor filter. This feature vector is more effective in the provision of discrimination between pathological and normal images. One more method is designed by Fraz et al., [69] in which the feature vector is composed of features obtained through Morphology, Gabor filter, multiscale decomposition, and line strength. A feature vector of size 7-D is constructed to encode the spatial intensity and fed to Bayesian classifier and "Gaussian Mixture Model (GMM)" for the classification.

Marin et al., [70] proposed to segment the retinal images through Neural Network model. This approach extracts the grey-level movement invariant features and constructs a 7-D vector for every retinal image and classified through NN algorithm. Next, in the RVs segmentation method proposed by Lupascu et al., [71], a 41-D feature vector is created for every pixel which encodes the multi-scale geometry, spatial properties and intensity structure. The training is testing is done through Adaboost classifier

Table.2 Comparison between different methods

Reference	Method	Classifiers	Databases used	Year
Ren et al., [58]	GLRM and supervised manifold regularization	SVM	DRIVE, STARE	2018
Maji et al., [59]	12 CNN layers	CNN	DRIVE	2016
Avjit and Sonam [60]	CNN	CNN	DRIVE	2017
Lahari et al., [61]	Parallel stack of auto encoders	CNN, soft-max	DRIVE,	2016
Li et al., [62]	Binary Vessel map	DNN	DRIVE, STARE	2016
Maji et al., [64]	DNN based vesselness	Ensemble learning and DNN	DRIVE	2015
Vega et al., [65]	LNNDP	NN	DRIVE, STARE	2015
Wilfred and Edward [67]	Gabor and Movement invariant features	ANN	DRIVE, STARE	2014
Fraz et al., [68]	Gradient vector analysis with its orientation, morphology, strength of line measures and responses of Gabor filter	bagged and boosted decision trees	DRIVE, STARE	2012
Fraz et al., [69]	Morphology, Gabor filter, multiscale decomposition, and line strength.	Bayesian classifier and GMM	DRIVE, STARE	2011
Marin et al., [70]	grey-level movement invariant features	NN	DRIVE, STARE	2011

[4.] DISCUSISON AND CONCLUSION

Retinal image segmentation has gained a significant importance from the past few years due to its widespread applicability in the diagnosis of several eye diseases like DR, Glaucoma, AMD etc. For such kind of diagnosis, the retinal image segmentation is required which extracts the major components such as retinal vessels, exudates, MAHMs etc. Particularly, the DR effects on the retinal vessels and hence the retinal vasculature segmentation is more important and has occupied a top position in eth research in retinal image analysis. Based on the features of retinal vasculature, several authors developed several methods and they are categorized into several categories based on the suggested methodology.

This paper aims the full-pledged survey over the retinal image analysis methods. Broadly, all those methods are divided into two categories such as pre-processing method and segmentation methods. The main aim of pre-processing methods is to make the retinal image more qualitative and free from external effects like non-uniform illumination, noises and artifacts etc. In pre-processing, the green layer is extracted from retinal colour image and it is subjected to colour normalization or contrast enhancement or noise removal etc. After this phase, the segmentation is employed over the enhanced image to obtain the required vessel structure. Towards such operation, different methods are suggested and they are broadly classified as mathematical morphological models, deformable models, vessel tracking models, and machine learning models. Finally a fair comparison is also stipulated and based on this analysis we have understood that there is neither technique to obtain higher segmentation performance in the view of all performance measures. From this survey, we postulate the following postulates;

1. The quality enhancement methods are not concentrated on the spatial relationship between neighbour pixels. Mostly, they concentrated on the CE and for this purpose, they applied a linear mapping between input and output grey levels of image. This kind of CE makes the retinal image either over enhance or introduced ringing artifacts.

2. Most of Vessel structure segmentation method employed complex methods like ACM, snake models etc. which involves a huge complexity. Moreover, they also not concentrated on the extraction of minor vessels which are more important in eth diagnosis of DR.

3. Most of the approaches are computationally expensive and require an additional hardware complexity. The presence of lesions and noise in some retinal images results in a significant degradation in the performance due to the wrong classification of noise and lesions as a vessel pixels. This would results in false vessel detection and tends to reduce the diagnosis accuracy. Furthermore, the performance is degraded in the case of discontinuities in the vessel branches. Next, the intrusions of the blood vessels in the optic disk make it computationally sensitive because they tend to break the continuity of the boundary of optic disk. Since the optic disk is a bright and elliptical spot of the retinal image, the contrast variations also effect the optic disk segmentation.

4. From the earlier studies it is already proved that the performance of an approach which extracts almost all the features in a combined fashion gives more efficient performance compared to individual feature extraction. However the main disadvantage with combined feature extraction is computational complexity. There is a requirement of too much mathematical morphological operation for the extraction of combined features. The increment in the computational complexity is directly proportional to the size of dataset as well as the size of retinal images.

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