# DETECTION OF CARDIOVASCULAR DISEASE BY RETINAL IMAGES

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*Abstract*: The eye is sometimes said to provide a window into the health of a person for it is only in the eye that one can actually see the exposed flesh of the subject without using invasive procedures. That 'exposed flesh' of course, the retina, and the light sensitive layer at the back of the eye. There are a number of diseases, particularly vascular disease that leave tell-tale markers in the retina. The retina can be photographed straightforwardly with a fundus camera and now with direct digital imaging there is much interest in computer analysis of retinal images for identifying and quantifying the effects of diseases such as diabetes. A retinal image provides a snapshot of what is happening inside the human body. In particular, the state of the retinal vessels has been shown to reflect the cardiovascular condition of the body. Retinal images provide considerable information on pathological changes caused by local ocular disease which reveals diabetes, cardiovascular disease and stroke. However, automatic retinal segmentation is complicated by the fact that retinal images are often noisy, poorly contrasted, and the vessel widths can vary from very large to very small. So in this , we can implement automate segmentation approach based on active contour method to provide regional information using Lebesgue measure.

## I. INTRODUCTON

Blood vessels can be conceptualized anatomically as an intricate network, or tree-like structure, of hollow tubes of different sizes and compositions including arteries, arterioles, capillaries, venules, veins. Their Continuing integrity is vital to nurture life and any damage to them could lead to profound complications, including stroke, diabetes, cardiac disease and hypertension, to name only the most obvious. Vascular diseases are often life-critical for individuals, and present a challenging public health problem for society. The detection and analysis of the vessels in medical images, is a fundamental task in many clinical applications to support the early detection, diagnosis and optimal treatment. In line proliferation of imaging modalities, there is an ever increasing demand for automated vessel analysis systems for which where blood vessel segmentation is the first and most important step. As blood vessels can be seen as linear structures distributed at different orientations and scales in an image, various kernels have been proposed to enhance them in order to ease the segmentation problem. In particular, a local phase based filter recently introduced by Lathen et al. Seems to be superior to intensity based filters as it is immune to intensity in homogeneity and is capable of faithfully enhancing vessels of different widths. It is worth nothing that a morphological filter such as path opening in combination with multiscale Gaussian filters has shown some interesting results. The main disadvantage of morphological method is that they do not consider the known vessel cross-sectional shape information, and use of an overly long structuring element may cause difficulty in detecting highly tortuous vessels.

Recent years have witnessed the rapid development of methods for vessel segmentation. Broadly speaking, all of the established segmentation techniques may be categorized as either supervised or unsupervised segmentation with respect to the overall system design and architecture. Supervised segmentation methods use the training data to train a classifier. The main reasons of using retinal images are twofold: first, there are well-established public datasets available for research and application purposes. These datasets are often used as benchmarks for developing new segmentation algorithms and for comparing them to state-of-the-art approaches. Secondly, retinal vessel analysis is important to the study of not only retinal diseases but also many systemic diseases (e.g. stroke and cardiovascular diseases).It also discuss and uses the active contour model.

## II. RELATED WORK

### *1. Extraction using matched filter:*

Accurate extraction of retinal blood vessels is an important task in computer aided diagnosis of retinopathy. The Matched Filter (MF) is a simple yet effective method for vessel extraction. However, a MF will respond not only to vessels but also to non-vessel edges. This will lead to frequent false vessel detection. Among the various retinal vessel extraction methods, the classical matched filter (MF) method is a representative one and it has advantages of simplicity and effectiveness. The MF detects vessels by simply filtering and thresholding the original image. Considering the fact that the cross-section of a vessel can be modelled as a Gaussian function, a series of Gaussian-shaped filters can be used to “match” the vessels for detection. However, the MF will have strong responses to not only vessels but also non-vessel edges, for example, the edges of bright blobs and red lesions in retinal images. Therefore, after thresholding the response image, much false detection can result. So proposed a novel retinal blood-vessel extraction method, namely the MF-FDOG, by using both the matched filter (MF) and the first-order-derivative of the Gaussian (FDOG). The retinal vessels were detected by simply thresholding the retinal image’s response to the MF but the threshold was adjusted by the image’s response to the FDOG. The proposed MF-FDOG method is very simple; however, it reduces significantly the false detections produced by the original MF and detects many fine vessels that are missed by the MF. Although the MF employs the prior knowledge that the cross-section of a vessel in a retinal image is Gaussian shaped, it does not fully exploit other information of the vessel profile; in particular that the Gaussian shaped cross section is symmetric with respect to its peak position. If this property can be properly used, it is possible to distinguish the symmetric vessel structures from those asymmetrical non-vessel edges (e.g. the step edge) in a simple but efficient way, and hence the vessel extraction accuracy can be improved.

### *2. Retinal blood vessel detection:*

Nowadays, computer-aided image analysis is turning into more and more necessary to with

efficiency and safely handles massive amounts of high-resolution retinal pictures. Developments in acquisition technology modify U.S. to capture increasing amounts of high-resolution retinal pictures, with new detail. for example, the utilization of digital cameras for retinal screening in polygenic disorder is generating AN ever increasing massive information for retinal analysis in high risk people. In clinical routine, such massive amounts of information raise challenges for retinal image analysis and process. Hence, it's necessary to develop laptop algorithms capable of process current massive databases of those retinal pictures. Currently, information science is undergoing fast advances driven by the utilization of superior computing, leading to the event of sensible medical applications. especially, a completely unique multi-scale feature extraction and region growing for segmentation of retinal blood vessels, developed in Matlab, has been planned achieving significantly correct segmentation results. withal, this effort is comparatively slow and unable to method high-resolution pictures attributable to memory limitations. an alternate computationally economical version has been enforced victimisation the Insight Segmentation and Registration Toolkit (ITK), reaching to solve speed and memory limitations. However, though this implementation permits to process higher-resolution retinal pictures, it needs a substantial time for process and proposes a parallel implementation for retinal vas segmentation, capable of achieving accuracy almost like the ITK serial version, whereas providing a quicker process of higher-resolution pictures and bigger knowledge sets. The challenge of deploying a parallel segmentation formula is to stay the quantity of communication low. during this work, a completely unique approach is conferred wherever the image is divided into sub-images. every sub-image to be processed ought to have overlapping regions so as to possess an occasional rate of communications. Moreover, it's shown that victimisation this new methodology improves the segmentation method time while not compromising the formula accuracy.

## III. PROPOSED WORK

In the proposed system, the retinal vessels are being segmented and the diseases in the human body are detected. Mostly the cardiovascular diseases are detected using the retinal image. The photo of the eye is taken and it is used to detect the diseases. The diameters of the vessels are calculated with high carefulness. Once the CRAE and CRVE ratios are the calculated it is compared with the datasets. It will clearly show what disease is being affected in our body.

The methods used in the system are:

1. Image acquisition
2. Grey scale conversion
3. Vessel extraction
4. Vessel classification
5. Disease diagonisis

*1. Retinal vessel segmentation:*

The cluster center is updated until the difference between adjacent objective function, as displayed in equation is close to zero or practically less than a predefined small constant.

$$J = \sum_{i=1}^{N}\sum_{j=1}^{C} U_{ij}^{2}\left\|X_i - C_j\right\|^2$$

$$U_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|X_i - C_j\right\|}{\left\|X_j - C_k\right\|}\right)^2}$$

$$C_j = \frac{\sum_{t=1}^{N} U_{ij}^{2} X_t}{\sum_{t=1}^{N} U_{ij}^{2}}$$

Where N is the number of features, C is the number of clusters which take as in search. $U_{ij}$ is the degree of the membership of $x_i$ in the cluster j, $x_i$ is the i[th] of the d-dimensional measured data.

*2. Vessel classification:*

The features get extracted on the basis of centerline extracted image and a label is assigned to each centerline, indicating the artery and vein pixel. Based on these labelling phase, the final goal is now to assign one of the labels with the artery class (A), and the other with vein class (V). In order to allow the final classification between A/V classes along with vessel intensity information the structural information and are also used. This can be done using SVM classification. The trained classifier is used for assigning the A/V classes to each one of the sub graph labels. First, each centerline pixel is classified into A or V classes, then for each label (Ci j , j = 1, 2) in sub graph i, he probability of its being an artery is calculated based on the number of associated centerline pixels classified by LDA to be an artery or a vein. The probability of label Ci j to be an artery is

$$Pa(Ci\,j\,) = na\,Ci\,j\,/(na\,Ci\,j\, + nvCi)$$

Where na Ci j is the number of centerline pixels of a label classified as an artery and nv Ci j is the number of centerline pixels classified as a vein. For each pair of labels in each sub graph, the label with higher artery probability w other as a vein class. Finally, to prevent a wrong classification as a result of a wrong graph analysis, we calculate the probability of being an artery or a vein for each link individually.

*3. Graph theoretical model*:

In this project, proposes a new method for segmenting piecewise constant images with irregular object boundaries: a variant of the region information where the length penalization of the limitations is replaced by the area of their neighbourhood of thickness . The aim is to keep well details and irregularities of the boundaries while denoising additive Gaussian noise. The energy of the model is:

$$F(\tau, r_n) = L^2(\gamma - \tau) + \sum_{n=1}^{N} \lambda_n R_n$$

Where $L^2$the 2D Lebesgue measure is $R_n$ is the nth region information and N is the total number of different region terms. The first term $L^2$ is the area of $\gamma$ neighborhood of the edge set$\tau$. Here we consider $L^2(\gamma - \tau) \approx \int_{\Omega}^{\alpha} e^{-\left(\frac{\phi(X)}{\gamma}\right)^{\alpha}}$ for a large and even number $\alpha$

which is an approximation of the $\gamma$ neighborhood area in a given image$U_0(X)$.

*4. Support Vector Machine:*

Classification is done with the help of SVM classifier. In the recent years, SVM classifiers have established excellent performance in a variety of pattern recognition troubles. The input space is planned into a high dimensional feature space. Then, the hyper plane that exploits the margin of separation between classes is constructed. The points that lie closest to the decision surface are called support vectors directly involves its location. When the classes are non-separable, the optimal hyper plane is the one that minimizes the probability of classification error. Initially input image is formulated in feature vectors. Then these feature vectors mapped with the help of kernel function in the feature space. And finally division is computed in the feature space to separate out the classes for training data. A global hyper plane is required by the SVM in order to divide both the program of examples in training set and avoid over fitting. This phenomenon of SVM is higher in comparison to other machine learning techniques which are based on artificial intelligence. Here the important feature for the classification is the width of the vessels. With the help of SVM classifier we can easily separate out the vessels into arteries and veins. The SVMs demonstrate various attractive features such as good generalization ability compared to other classifiers. Indeed, there are relatively few free parameters to adjust and it is not required to find the architecture experimentally. The SVMs algorithm separates the classes of input patterns with the maximal margin hyper plane. This hyper plane is constructed as:

$$f(x) = \langle w, x \rangle + b$$

Where x is the feature vector, w is the vector that is perpendicular to the hyper plane and $b\|w\|^{-1}$ specifies the offset from the beginning of the coordinate system. To benefit from non-linear decision boundaries the separation is performed in a feature space F, which is introduced by a nonlinear mapping $\varphi$ the input patterns. This mapping is defined as follows:

$$\langle \varphi\,(x_1), \varphi(x_2) \rangle = K(x_1, x_2)\ \forall (x_1, x_2) \in X$$

for some kernel function K (·, ·). The kernel function represents the non-linear transformation of the original feature space into the F. Then we calculate Artery vein ratio that is a high-quality parameter to examine retinal vascular geometry. It was developed as a common measure of the ratio between the normal diameters of the arterioles with respect to the venules. It is includes of two components, the central retinal artery equivalent (CRAE) and the central retinal vein equivalent (CRVE), expressed as a quotient. CRAE and CRVE are computed by iteratively combining the mean widths of consecutive pairs of vessels in the arteries and veins respectively, as follows:

$$CRAE = 0.88 * (w_1^2 + w_2^2)^{\frac{1}{2}}$$

$$CRVE = 0.95 * (w_1^2 + w_2^2)^{\frac{1}{2}}$$

where $w_1$, $w_2$, is a pair of width values. Then Artery vein ratio can be calculated as

$$AVR = \frac{CRAE}{CRVE}$$

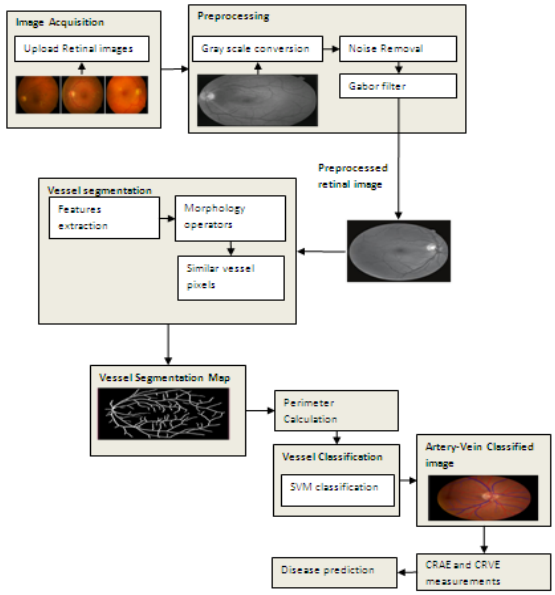


Fig 1

Architecture of retinal image processing

## IV. CONCLUSION

Thus in our proposed work by using the AVR ratio the disease in the retina can be detected. Vessel Extraction is done by using morphological operation .Greyscale conversion is used to choose an accurate threshold value and for detecting edges. Morphological operation is necessary for segmentation to extract exact body of the vascular network. After vessel detection by applying region properties different features are extracted. The features which are extracted are Intensity, Area, Centroid, Intensity, Perimeter and Diameter. A/V classification is done with the help of SVM classifier. SVM is trained to detect whether the retinal image is abnormal or normal.

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