Disease Prediction Based On Retinal Images Using Deep Neural Networks

[1]T. Johnlayoni , [2]R. Praseela ,[3]P. Ragavi , [4]B. Dhivya

[1,2,4]Student, Department of computer Science and Engineering,
[4]Assistant Professor, Department of Computer Science and Engineering,
Arasu Engineering College, Kumbakonam, TamilNadu, India.

ABSTRACT--- *Retina is responsible for capturing the visual and it triggers the nerve impulses in the brain. The eye is sometimes said to provide a window into the health of a person. There are a number of diseases, particularly vascular disease that leave telltale markers in the retina. It enable optometrist curve to capture retinal blood supply. Retinal images for identifying and quantifying the effects of diseases such as cardio vascular diseases. A retinal image provides a information about 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. So in this project, we can implement based on neural network method to provide regional information about arteries and veins. And finally predict cardio vascular diseases and other diseases using CRAE and CRVE measurements.*

Keywords- *Vessel segment , CRAE, CRVE, Deep Neural networks, segmentation, SVM*

I. INTRODUCTION:

Eye is an important of human body. Retina of eye can provide variable information about human health. Retinal image processing is greatly required in diagnosing and treatment of many diseases affecting the retina. Retinal imaging is a recent technological advancement in eye care. It enables optometrist to capture a digital image of the retina, blood vessels and optic nerve located at the back of eyes.

II. DESCRIPTION:

Retinal images obtained using Adaptive Optics have the potential to facilitate early detection of retinal pathologies. Many researchers were working on retinal images to perform various image processing tasks for the beneficial of health sector. The result of image analysis relies on a preliminary phase of identifying good quality images, which have high contrast have proved the automatic assessment of quality of retinal images taken by

fundal camera with a reference image. Recently, AO has been combined with scanning laser ophthalmoscope and optical coherence tomography (OCT) to obtain images of retinal microvasculature and blood flow and three dimensional images of living cone photoreceptors respectively. opening which consisted of erode followed by dilate is applied first. Erode function protects the small blood vessels by reducing their sizes while dilate function blows up the larger remaining. The automatic analysis of retinal fundus, a number of algorithms have been proposed for extracting the vascular structure and for identifying non-vascular lesion (exudates, haemorrhages, ischemic regions). The first changes in the retina that point out the onset of a retinopathy, e.g. from a systemic disease, appear in the vessels. Changes in vessel structure can affected.

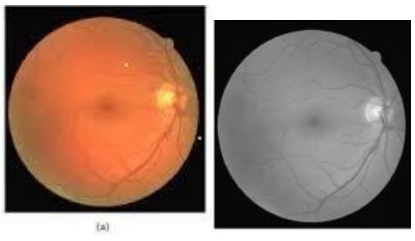
III. METHODOLOGIES:

Examination of blood vessels in the eye allows detection of eye diseases such as glaucoma and diabetic retinopathy. Traditionally, the vascular network is mapped by hand in a time-consuming process that requires both training and skill. Automating the process allows consistency, and most importantly, frees up the time that a skilled technician or doctor would normally use for manual screening. So we can implement automatic process to examine the blood vessels to identify the cardio vascular diseases and other diseases in retinal images. The proposed method utilizes the concept of active contours to remove noise, enhance the image, track the edges of the vessels, calculate the width of vessels and identify diseases. Implement deep neural network algorithm to segment blood vessels and calculate width of the blood vessels. Finally proposed approach provides vessel segmentation with good performance. This will be a powerful tool for analyzing vasculature for better management of a wide spectrum of vascular-related diseases. And then implement support vector machine algorithm to classify the retinal diseases using width values of retinal images. Finally categorize the vessels as artery and vein vessels. Retinal vascular caliber

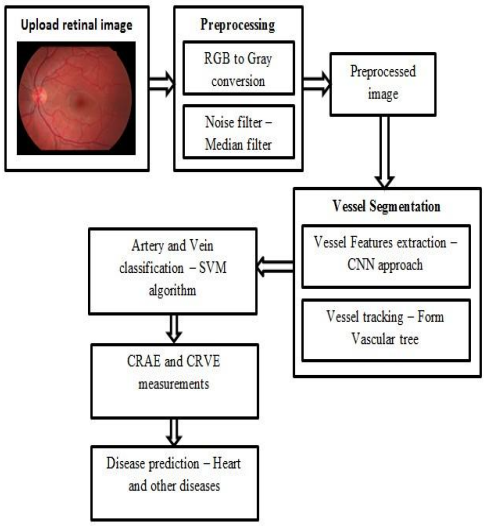
(CRAE and CRVE) was analyzed as continuous variables. We used analysis of covariance to estimate mean retinal vascular caliber associated with the presence versus absence of categorical variables or increasing quartiles of continuous variables to predict the cardio vascular and other diseases.

IV. TECHNIQUES AND ALGORITHMS:

The segmented vessels are classified into arteries and veins. Correct classification of vessels is vital, because heart diseases affect arteries and veins differently. The alterations in veins and arteries cannot be analyzed without distinguishing them. Segmented vessels are classified by the supervised method Support Vector Machine. After extraction of blood vessels, feature vector is formed based on properties of artery and veins. 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 labeling 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)= naCi j /(naCi j + nvCi) Where naCi j is the number of centerline pixels of a label classified as an artery and nvCi 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 will be assigned as an artery class, and the 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.



V. ARCHITECTURE DIAGRAM:



CONCLUSION:

We conclude that, our proposed system implemented successfully with accurate identification of true vessels to obtain correct retinal ophthalmology measurements. And we implement the post processing step to vessel segmentation. This step is used to track all true vessels and find the optimal forest. We can overcome wrong diagnosis of crossovers by using simultaneous identification of the significance of using structural information for A/V classification. Later vessel segmentation, it is possible to achieve more progressive analysis, such as measurements of diameters and lengths of the vessels, classification of veins and arteries, calculation of arteries venous ratio, and more prominently study the analytical and predictive values of these features on eye disease and a number of systematic diseases. Furthermore, we compared the preface of our approach with other recently proposed methods, and we conclude that we are achieving better results.

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