Retinal Based Disease Prediction using Deep Neural Networks and SVM Classification Techniques

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Abstarct: *In medical field, diagnosis of diseases is competently carried out with the help of image processing. So that the retrieval of the relevant data from the amalgamation of resulting image is a hard process. Human eye is an important organ that reacts to light and has several purposes. The eye is composed of a number of components which include but are not limited to the cornea, iris, pupil, lens, retina, macula, optic nerve, choroid and vitreous. The significant health issues among the senior individuals are eye ailments. Retina is said to be one of the most important internal component of the eye. Retinal images could be used in several applications that help in diagnosing the disease and human recognition. They also play a major role in early detection of diseases related to cardio vascular diseases by comparing the states of the retinal blood vessels. Retinal Image Analysis (RIA) is a key element in detecting diseases in patients. Applications of retinal images are diagnosing the progress of some cardiovascular diseases, diagnosing the region with no blood vessels (Macula).Retinal image analysis is a complicated task particularly because of the variability of the images in terms of the color, the morphology of the retinal anatomical structure and the existence of particular features in different patients, which may lead to an erroneous interpretation In this work we detect the blood vessels effectively by using deep Neural Networks (NN) for segmentation and Support Vector Machine (SVM) for classification and the diagnosis of disease such as stroke, heart attack and cardio vascular diseases. The experimental result shows a better accuracy in predicting the disease.*

I. INTRODUCTION

Nowadays diseases related to eye are increasing and many people fell in to blindness. Image processing is the area which leads with image analysis and which involves the study of feature extraction, segmentation and classification. The process of recognizing the vessel patterns that are used to analyze the vessels in retinal image. Diabetic retinopathy one of the complicated disease which affects to the retina and outcome is the total blindness. Segmentation is the method of identifying regions of pixels in an image so as to find out the correlation with objects. The retina is internal part of the eye. In the center of retina there is the optic disk, a circular to oval shape. From the center of optical nerve radiates the major blood vessels of the retina. Detection of retinal blood vessels for disease diagnosis has provided more information about retinal blood vessels and disease. Compared with the other more traditional technology, detection of retinal blood vessels for disease diagnosis has the benefits of high anti-counterfeiting strength, small imaging devices, low cost, easy collection of images with contactless operation universality and liveness. Furthermore, since the blood vessels are located internally within the living body, the disease identification system is less affected by the outer skin surroundings (skin disease, humidity, dirtiness, etc.). Hence retinal blood vessels for disease identification are considered as one of the most promising solution for disease diagnosis in the future.

The blood vessels network is an important anatomical structure in human retina, which is use to recognize different types of disease. However, manual detection of blood vessels is not simple because the vessels in retina image are complex and have low contrast. For retinal anatomy ophthalmologist uses an ophthalmoscope. The programmed mining of blood vessels in retinal images is one of the important step in computer aided diagnosis and treatment of diabetic retinopathy, glaucoma, arteriosclerosis, obesity, retinal artery occlusion and hypertension. Retinal images are influenced by all the factors that affect the body vasculature in general. The human eye is a unique region of the human body where the vascular condition can be directly observed. In addition to fovea and optic disc, the blood vessels contribute one of the main features of an retinal fund us image and several of its properties are noticeably affected by worldwide major diseases such as diabetes, hypertension, and arteriosclerosis. Further, certain eye diseases such as choroidal neovascularization and retinal artery occlusion also make changes in the retinal vasculature. As per previous statements the segmentation of blood vessels in the retinal images can be a valuable aid for the detection of diabetic retinopathy and glaucoma diagnosis. Segmentation can be done by supervised, unsupervised or semi supervised. Here using semi supervised segmentation method because of easy to use labeled data and unlabeled data together. Semi supervised segmentation have much applications in medical image data sets.

An automated segmentation and inspection of retinal blood vessel features such as diameter, color and tortuosity as well as the optic disc morphology allows ophthalmologist and eye care specialists to perform mass vision screening exams for early detection of retinal diseases and treatment evaluation. This could prevent and reduce vision impairments; age related diseases and many cardiovascular diseases Also it reduces the cost of the screening. The basic retinal image processing is shown in figure 1.

Figure1:Retinal Image Processing

II. Related Work

Mariem_Ben_Abdallah,et.al,.. [1] proposed an algorithm for vessel extraction in retinal images. The first step consists of applying anisotropic diffusion filtering in the initial vessel network in order to restore disconnected vessel lines and eliminate noisy lines. In the second step, a multi-scale line-tracking procedure allows detecting all vessels having similar dimensions at a chosen scale. Computing the individual image maps requires different steps. First, a number of points are preselected using the Eigen values of the Hessian matrix. These points are expected to be near to a vessel axis. Then, for each preselected point, the response map is computed from gradient information of the image at the current scale. Also, not all the images show signs of diabetic retinopathy. Hence, a manual measurement of the information about blood vessels, such as length, width, tortuosity, and branching pattern, becomes tedious. As a result, it increases the time of diagnosis and decreases the efficiency of ophthalmologists. Therefore, automatic methods for extracting and measuring the vessels in retinal images are needed to save the workload of the ophthalmologists and to assist in characterizing the detected lesions and identifying the false positives Finally, the multi-scale image map is derived after combining the individual image maps at different scales (sizes). Two publicly available datasets have been used to test the performance of the suggested method.

Manvir Kaur,et.al,…[2] analyzed the process on images of retina with the help of Digital Image Processing (DIP) tool in which images are detected and then processed. At last we describe the problem of detecting edges in images as a diabetic retinopathy (DR), macular degeneration and glaucoma. The edge detection problem can be separated into three stages: filtering; detection; and tracing and images separated with the application of different algorithm based on local pixel characteristics which can control the degree of Gaussian smoothing. Filtered images are then applied to a simple edge detection algorithm which evaluates the edge fuzzy association value for each pixel; based on local image characteristics. Diabetic retinopathy is a complication of diabetes and is a major cause of blindness in developed countries. The patients might not notice a loss of vision until it became too severe, hence early diagnosis and timely treatment is vital to delay or prevent visual impair and even blindness. Retinal vessel segmentation can simplify screening for retinopathy by reducing the number of false positive results in micro aneurysm detection and may serve as a means of image registration from the same patient taken at different times by delineating the location of the optic disc and fovea. However, manual detection of blood vessels is not simple because the vessels in a retinal image are complex and have low contrast. Detecting abnormalities such as venous looping or beadings is critical for early treatment as they are in most cases indication of potentially sight-threatening retinopathy. In order to utilize these useful characteristics of retinal blood vessels this is very important to obtain their locations and shapes accurately. Blood vessels appeared as networks of either deep red or orange-red filaments that originated within the optic disc and were of progressively diminishing width.

Shuangling Wang,et.al,…[3] presented the hybrid method based upon convolutional neural network (CNN) and ensemble random forests (RFs) for automatic retinal blood vessel segmentation. We first employed a set of preprocessing steps to correct the non-uniform illumination of retinal images and to improve vessel contrast. We then used CNN to extract a set of hierarchical features which are not only invariant to image translation, scaling, skewing and other distortions, but also contain image based multi-scale information of the geometric structure of retina. We finally trained ensemble RFs to obtain a vessel classifier. The whole pipeline of the proposed method is trainable and automatic. Although these supervised methods have achieved satisfactory segmentation results in some scenarios, there are still some issues. In hand-designed feature extraction approaches, the features must be very carefully predefined before classification, making feature detection very time-consuming and tedious. Most importantly, hand-designed features have to be redesigned for datasets with different characteristics. In contrast, the approaches based upon feature learning can extract features automatically from the raw images. Moreover, CNN is supervised feature learner able to learn complex invariances such as scale and rotational invariance. However, the classification mechanism in ANN or its variants is fairly simple: usually nonlinear activation functions are employed in the last output layer to predict patterns, which results in the low performance of ANN.

Adam Hoover,et.al,…[4] used multiple vessel segmentations of the same image in order to reinforce the detection of convergent points. The idea is that the convergence should be detectable using vessel segmentations at different scales. To find the vessel network convergence, we describe a novel algorithm we call fuzzy convergence. The algorithm is a voting type method that works in the spatial domain of the image. The blood vessel segments may be modeled by line segments. The problem of finding the convergence of the vessel network may then be modeled as a line intersection problem. In order to automatically locating the optic nerve and blood vessel in retinal images using graph cut method. To segment and determine the blood vessels and optic disc from retinal images, the input retinal images are read which then under goes preprocessing, then to find the optical disc segmentation and blood vessel segmentation. The color based segmentation and gradient method used for blood vessel segmentation for achieving exceptional performance in segmenting the blood vessel and Hough circular transform is used for optical disc segmentation. For rule based validation is applied to validate proper optical disc segmented or not similarly validation of blood vessel segmentation.

Roberto Annunziata,et.al,…[5] proposed inpainting technique has a different focus. Indeed, neither texture synthesis nor a visually plausible image is needed. Our goal is to fill structures such as exudates in retinal images so that, when vessel enhancement is applied, the number of nearby false positives is greatly reduced. This goal is only achieved if exudates are filled in a smooth way that reduces or eliminates possible edges. A multiple-scale Hessian-based enhancement is applied to detect retinal vessels. This technique is fast and has proven to be effective when detecting vessels of normal eyes. The key idea of the proposed method is to apply Hessian-based enhancement after exudate inpainting. Moreover, it yields the best performance on pathological images, the target of most automated retinal image analysis tools. Indeed, a vessel segmentation algorithm is usually the first step for the automated detection of eye diseases. In order to be used in clinical practice, these methods should be robust enough to analyse pathological and non-pathological images without requiring user interaction. We propose a fully automated algorithm.

III. EXISTING METHODOLOGIES

Considering both data has been validated to boom the retinal imaging accuracy extensively. There are two essential classes such as vessel or non-vessel utilizing functions: to extract some sort of features (e.g., texture, color, and shape features), and to at once use pixels in a small neighborhood for joint type assuming that these pixels normally percentage the same magnificence membership. Existing algorithms are derived as follows:

A. MRF Model:

The MRF model, which combines retinal parts with vessles, is widely used in classification. It can provide an exact feature representation of pixels and their neighborhoods. The basic principle of MRF is to integrate spatial correlation information into the posterior probability of the spectral structures. Based on the maximum posterior probability principle, the classic MRF model can be expressed as follows:

$$\rho(x_i) = -\frac{1}{2}\ln|\Sigma k| - \frac{1}{2}(x_i - m_k)^T \Sigma_k^{-1}(x_i - m_k) - \beta \sum_{\partial i}[1 - \delta(\omega_{ki}, \omega_{\partial i})] \text{ ------ Eqn(1)}$$

where m_k and Σ_k are the mean vector and covariance matrix, respectively, of class k and the neighborhood and class of pixel i are represented by $\partial_i$and ω_k , respectively. The constant parameter β, called the weight coefficient, is used to control the influence of the spatial term. According to Equation (1), the MRF model can be separated into two components: the vessel term and non-vessel term. Thus, Equation (1) can be represented in the form

$$\rho(x_i) = a_i(k) + \beta b_i(k) \text{---------Eqn(2)}$$

where $a_i(k)$is the vessel term and $b_i(k)$ is the non-vessel term. Then

$$b_i(k) = \sum_{\partial i}[1 - \delta(\omega_{ki}, \omega_{\partial i})]$$

where $\delta(\omega_{ki}, \omega_{\partial i})$ is the kronecker delta function, defined as

$$\delta(\omega_{ki}, \omega_{\partial i}) = \begin{cases} 1 & \omega_{ki} = \omega_{\partial i} \\ 0 & \omega_{ki} \neq \omega_{\partial i} \end{cases}$$

When a center pixel has the similar elegance label as the rest of its community, this pixel has an excessive probability of being in a homogeneous area and has a strong consistency. Thus, those spatial framework relationships can be used to revise the magnificence labels. However, one-of-a-kind floor items showcase huge differences in distribution. For example, the overcorrection phenomenon can be recommended if pixels with complex boundary situations are given the equal weight coefficients as the ones in homogeneous areas. By assessment, full gain of the spatial context features of comparable regions cannot be taken if the spatial term is given a decrease weight. To address this trouble, within the area-constraint-based eMRF approach and the RHI-based totally aMRF technique, nearby spatial weights are described to be used in location of the global spatial weight to evaluation the variety of spatial continuity.

But above methodologies can handle difficult-to-separate classes with irregular class boundaries and these approach can't work on integration of sparse-MKL-based feature learning and sparse-representation-based classifier for vessel classification.

B. Deformable Models:

The recent one of the methods of contour detection is deformable models or snake. [12-16]. A snake is an active contour model that is manually initiated near to the contour of interest. This contour model deforms according to some criteria and image features to finally stay to the actual contour(s) in the image. An energy function is formulated to obtain an estimate of the quality of the mode in terms of its internal shape, and external forces e.g. underlying image forces and user-constraint forces. The energy function integrates a weighted-linear combination of the internal and external forces of the contour:

$$1 \le i \le L - N + 1, 1 \le j \le M - N + 1$$

The internal energy of the contour with respect to elastic deformations and the bending of the snake:

$$\epsilon_{internal}(v(s)) = \alpha_{elasticity}(s)\epsilon_{elasticity}(v(s)) + \alpha_{bending}(s)\epsilon_{bending}(v(s))$$

$$= \alpha_{elasticity}(s)\|v_s(s)\|^2 + \alpha_{bending}(s)\|v_{ss}(s)\|^2 \text{---Eqn(4)}$$

The first order derivative term $v_s(s)$ make the snake behave like a membrane and represent the elastic energy of the contour. The second order derivative term $v_{ss}(s)$ makes the snake act like a thin plate and represents the contour bending energy. Decreasing αelasticity allows the contour to develop gaps, while increasing $\alpha_{elasticity}$increases the tension of the model by reducing its length. Decreasing αbending allows the active contour model to develop corners, and increasing $\alpha_{bending}$ increases the bending rigidity, making the contour smoother and less flixible. Setting either of the weighting coefficients to zero permits first and second order discontinuities respectively. The external energy term ϵ_{image}represents the energy due to image forces like lines, edges and terminations of line segments and corners.

$$\epsilon^*_{image}(v(s)) = \alpha_{line}(s)\epsilon_{line}(v(s)) + \alpha_{edge}(s)\epsilon_{edge}(v(s)) + \alpha_{term}(s)\epsilon_{term}(v(s)) \text{-----Eqn(5)}$$

Existing approaches only consider vessel segmentation and can't analyze vessel classification.

IV. PROPOSED FRAMEWORK

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. Implement automatic process to examine the blood vessels to identify the cardio vascular diseases in retinal images. It utilizes the concept of active contours to remove noise, enhance the image, track the edges of the vessels, calculate the perimeter of vessels and identify the cardio diseases. Implement infinite perimeter active contour with hybrid region information IPACHI model to segment blood vessels and calculate perimeter of the blood vessels. An efficient and effective infinite perimeter active contour model with hybrid region terms for 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. Retinal vascular caliber CRAE and CRVE was analyzed as continuous variables. 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 diseases. The proposed framework contains following modules:

A. Image acquisition:

In this module is used to acquire a digital image. Retinal images of humans play an important role in the detection and diagnosis of cardiovascular diseases that including stroke, diabetes, arterio sclerosis, cardiovascular diseases and hypertension. Vascular diseases are often life critical for individuals, and present a challenging public health problem for society. The detection for retinal images is necessary and among them the detection of blood vessels is most important. The alterations about blood vessels such as length, width and branching pattern, can not only provide information on pathological changes but can also help to grade diseases severity or automatically diagnose the diseases. Upload the retinal images. The fundus of the eye is the interior surface of the eye, opposite the lens, and includes the retina, optic disc, macula and fovea, and posterior pole. The fundus can be examined by ophthalmoscope or fundus photography. The retina is a layered structure with several layers of neurons interconnected by synapses. In retina we can identify the vessels. Blood vessels show abnormalities at early stages also blood vessel alterations. Generalized arteriolar and venular narrowing which is related to the higher blood pressure levels, which is generally expressed by the Arteriolar to Venular diameter ratio. It constructed a dataset of images for the training and evaluation of our proposed method. This image dataset was acquired from publically available datasets such as DRIVE and STAR. Each image was captured using 24 bit per pixel (standard RGB) at 760 x 570 pixels. First, tested against normal images which are easier to distinguish. Second, some level of success with abnormal vessel appearances must be established to recommend clinical usage. As can be seen, a normal image consists of blood vessels, optic disc, fovea and the background, but the abnormal image also has multiple artifacts of distinct shapes and colors caused by different diseases.

B. Preprocessing:

It is the process opted to improve the image in ways that will increase the chances for success of the other processes. The gray scale conversion operation is to identify black and white illumination. Noise in colored retinal image is normally due to noise pixels and pixels whose color is distorted so implement median filter can be used to enhance and sharpen the vascular pattern for preprocessing and blood vessel segmentation of retinal images performing well in preprocessing, enhancing and segmenting the retinal image and vascular pattern. In the perspect of human it is highly sensitive to edges and fine details of an image, and since they are composed primarily by high frequency components, the visual quality of an image can be enormously degraded if the high frequencies are attenuated or completed removed. In contrast, enhancing the high frequency components of an image leads to an improvement in the visual quality. Image sharpening refers to any enhancement technique that highlights edges and fine details in an image. Printing and photographic industries widely use this image sharpening technique for increasing the local contrast and sharpening the images. Mainly, image sharpening consists of adding to the original image a signal that is proportional to a high-pass filtered version of the original image. In this filter, the original image is first filtered by a high-pass filter that extracts the high-frequency components, and then a scaled version of the high-pass filter output is added to the original image, thus producing a sharpened image of the original. Note that the homogeneous regions of the signal, i.e., where the signal is constant, remains unchanged.

C. Vessels segmentation:

In this module perform partitions an input retinal image in to its constituent parts or objects. Feature extraction and vessel segmentation steps using deep neural network model. It can create vascular network using active contour with vessel measure with neighborhood function. It can extract the map is a representation of the vascular network, where each node denotes an intersection point in the vascular tree, and each link corresponds to a vessel segment between two intersection points. For generating the graph, we have used active contour method. The nodes are extracted from the centerline image by finding the bifurcation points which are detected by considering pixels with more than two neighbors and the endpoints or terminal points by pixels having just one neighbor. In order to find the links between nodes vessel segments, all the bifurcation points and their neighbors are removed from the centerline image and as result we get an image with separate components which are the vessel segments. On the other hand, any given link can only connect two. Vessels segmentation binary mask is created by detecting vessels edges from sharpened image. The blood vessels are marked by the masking procedure which assigns one to all those pixels which belong to blood vessels and zero to non vessels. pixels. Final refined vessel segmentation mask is created by active contour model. An active contour model is also called snakes, is a framework in computer vision for delineating an object outline from the possibly noisy two dimensional image. In this approach, a snake is an energy minimizing, deformable spline influenced by constraint and image forces that pull it towards object contours and internal forces that resist deformation. Snakes may be understood as a special case of the general technique of matching a deformable model to an image by means of energy minimization. In two dimensions, the active shape model represents a discrete version of this approach, taking advantage of the point distribution model to restrict the shape range to an explicit domain learned from a training set. Finally provide the segmentation mask for preprocessed retinal images.

D. Vessel classification:

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

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

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 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.

E. Disease prediction:

Diagnosis the diseases using AVR ratio based on CRAE and CRVE measurements. The vessel measurements CRAE, CRVE have been found to be correlated with risks factors of cardiovascular diseases and are positive real numbers. The major systemic determinant for smaller CRAE is higher blood pressure whereas wider CRVE is mainly due to current cigarette smoking, higher blood pressure, systemic inflammation and obesity. A more recent study found a strong negative correlation between renal function and retinal parameters (CRAE and CRVE) in a cohort of eighty healthy individuals which suggests a common determinant in pre-clinical target organ damage. This is in support of earlier studies examining the association between retinal vascular signs and incident hypertension providing evidence that a decrease in CRAE is indeed an antecedent to clinical onset of hypertension and occurs prior to other signs of target organ damage. Besides the value of CRAE in predicting hypertension, it also shows great potential in other pathologies including stroke and diabetes. Generalized arteriolar narrowing as reflected by a decrease in CRAE is associated with an increased risk of stroke with measurements. The overall proposed framework is shown in fig 2.

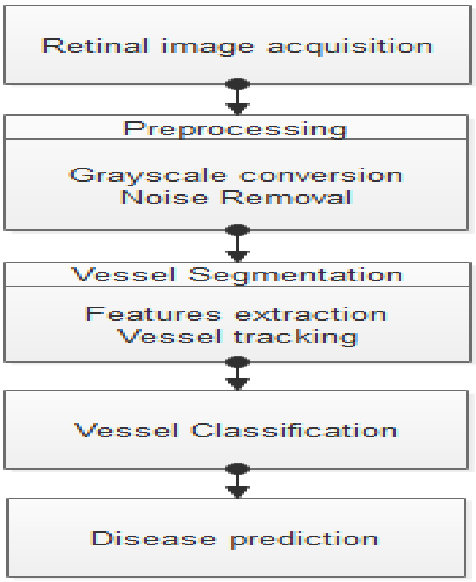
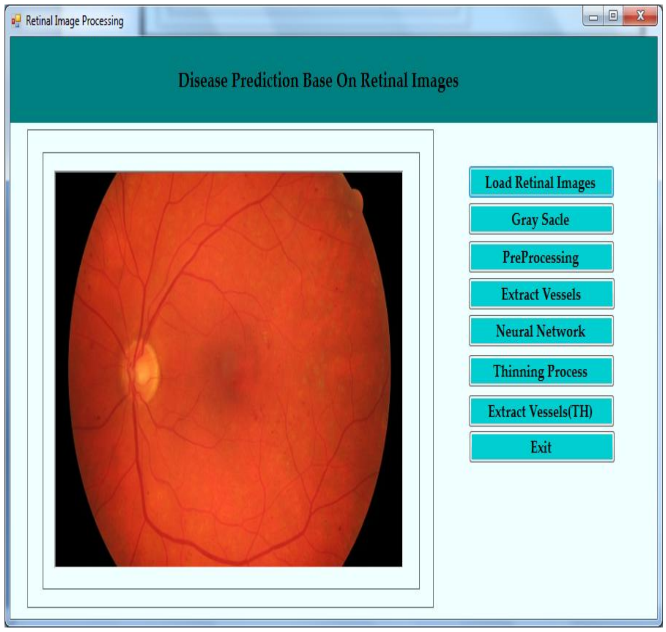


Fig 2 Proposed Framework

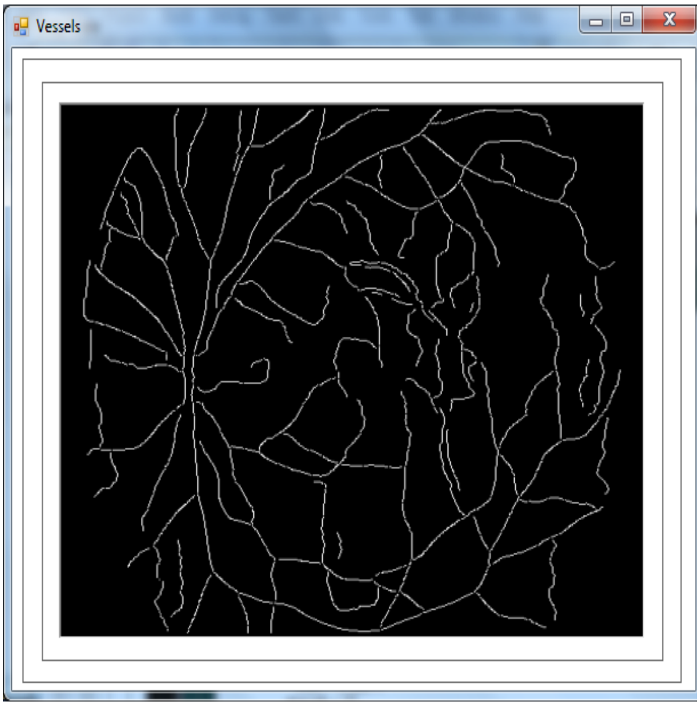
V. EXPERIMENTAL RESULTS

In experimental results we acquired retinal images from DRIVE datasets, are employed to evaluate the effectiveness of the proposed method. For all the statistics, we randomly pick out categorized pixels according to class for vessels or non-vessels from retinal images.The implementation results are shown in fig 3.

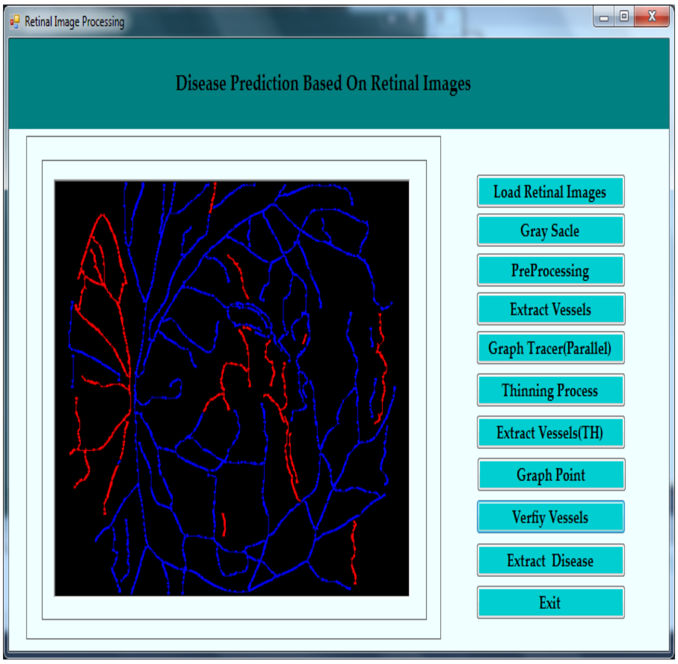


a) Input image

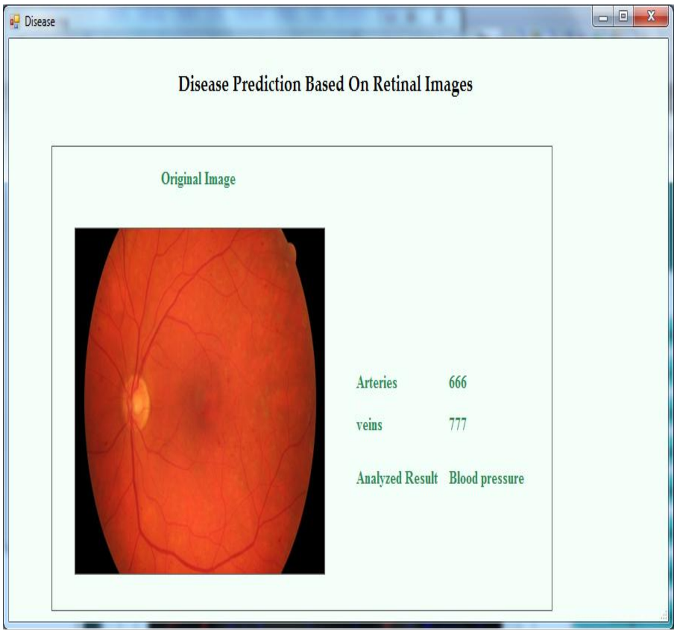
b) Preprocessing



c) Vessel Extraction



d) Vessel Classification



e) Disease Prediction

Figure 3: Implementation results

The following measures are used so that it will evaluate the overall performance of different type techniques. 1) Average Accuracy (AA): This metric suggests the common cost of the magnificence classification accuracy. 2) Overall Accuracy (OA): This metric refers back to the wide variety of samples which might be classified correctly divided by the range of take a look at samples. The performance of proposed work is illustrated in following graph as fig 4. From performance measures, our proposed system provides better accuracy results than state-art-algorithms.

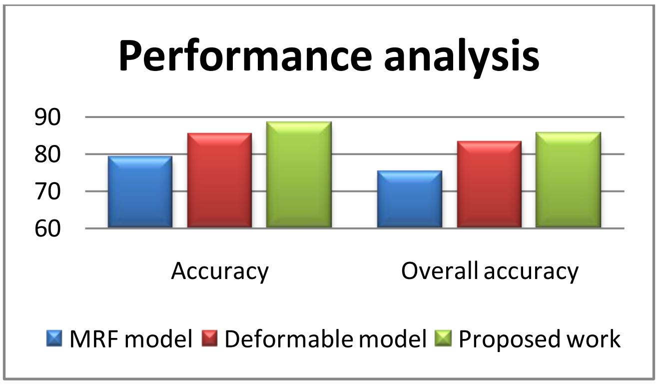


Figure 4. Performance graph

VI. Conclusion

We developed a new novel framework for disease classification to extract blood vessel information. Vessel Features are extracted as multi attributes profiles and we reduced the dimensionality by using supervised features extraction method such as median filter. And implementing CNN segmentation for improves the accuracy in results. The Proposed framework is considerably examined on extensively used blood vessel statistics to provide better accuracies. In addition, the new approach achieves better classification accuracies than other extensively used classification strategies, with acceptable CPU processing time. We emphasize that the proposed system is fully computerized, that's a exceedingly acceptable characteristic. In future, we can extend the framework to improve the accuracy in various kinds of datasets and try to analyze parallel processing approach and include other performance metrics.

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