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Artificial Neural Network based Classification of Healthy Retina and Retina of Stroke Patients

*Jeena R S, **Sukesh Kumar A

*Department of ECE, College of Engineering, Trivandrum
Kerala, India.
** Associate Professor, Rajiv Gandhi Institute of development Studies
Trivandrum, Kerala, India.

(*jeena_rs@yahoo.com, ** drsukeshkumar@yahoo.in)

Abstract

The innovations in the field of retinal imaging have paved way to the development of tools for assisting physicians in stroke prediction. Diagnosis of stroke during initial stages is crucial for timely prevention and cure. This research work focuses on the prediction of stroke from retinal fundus images. Preprocessing of retinal fundus images is implemented by a combined approach of adaptive histogram equalization and median filtering. After detecting the optic disc by circular hough transform, image is binarised and then skeletonized. Various features like branching points, end points, mean diameter of the blood vessels, fractal dimension and temporal arcade angle are computed for the fundus images of healthy and stroke affected patients. Computed features were successfully trained and tested using feed forward Artificial Neural Network (ANN), which gave an accuracy of 98 %.

Key words

Stroke, Retinal fundus images, ANN

1. Introduction

Stroke is the fourth major cause of death in developing countries like India. In India, almost 2,000,000 strokes are reported a year. Nearly 20 percent of the victims are under 55 years of age. In Trivandrum, the capital of the Indian state of Kerala, the incidence rate of stroke per year is 135.0 and 138.0 (per 1, 00,000 inhabitants) in urban and rural community respectively [1].Stroke is a form of cardiovascular disease affecting the blood supply to the brain. Stroke [2] is a physical condition that occurs due to inadequate supply of blood to the brain cells. This damages the brain cells finally leading to their death. Stroke can be subdivided into two types: ischemic and hemorrhagic. Ischemic stroke accounts for almost 80% of the cases. It occurs as a result of an obstruction within a blood vessel supplying blood to the brain. Hemorrhagic stroke occurs when a weakened blood vessel ruptures. When an obstruction occurs within a blood vessel supplying blood to brain, the vessels carrying blood to eye will also be affected during the initial stages.

Retinal imaging allows diagnosis of various eye diseases as well as the prognosis of other complications of diabetes, hypertension and cardiovascular diseases like stroke. Cardiovascular disease manifests itself in the retina in a number of ways. Retinal arterioles share similar anatomical, physiological and embryological characteristics with cerebral arterioles. Researchers have suggested that changes such as microaneurysms or arteriolar narrowing seen in the retinal circulation may present risk factors for cerebrovascular disease such as stroke.[2] Morphological changes in blood vessel shape, branching pattern, width, tortuosity , retinal lesions, branching angle, branching coefficient and fractal dimension are some of the abnormalities in retinal vasculature associated with cardiovascular diseases like stroke.

The ability to image the retina and develop techniques for analyzing the images is of great interest. Research works show that microvasculature of retina and brain is closely linked in terms of anatomy and physiology [3]. Changes in the retinal blood vessels likely reflect similar changes in the cerebral vessels. This work is an extension of author's earlier works in stroke prediction. [4, 13]

2. Literature Survey

Contrast limited adaptive histogram equalization (CLAHE) was performed on retinal images to enhance local contrast. [5, 6] Additive model of non uniform illumination is used by Abdel Razik [7], together with adaptive histogram equalization. Philips et al. [8] proposed a large mean filter and large median filter are used for estimating the fundus background. The method proposed by Neha Gupta,et al.[11] is used for noisy images because noise degrades the quality of the image while transmission from one device to another on network [14]. A hybrid combination of Gabor filter and median filter is used.

OakarPhyo and AungSoeKhaing [10] proposed a method to convert the original RGB image into HSI image which was median filtered to remove the noise without blurring the edges.

This filtered image is enhanced to overcome the uneven illumination in the image. This enhancement was followed by morphological operations and otsu thresholding to detect the optic disc.

3. Methodology

A combined approach of retinal preprocessing using adaptive histogram equalization and median filtering has been implemented in this work. Laplacian of Gaussian (LoG) edge detection followed by circular hough transform is used for the detection of optic disc. Detection of optic disc is done primarily for the computation of temporal arcade angle. Image is binarized by thresholding and required morphological operations to remove the background. To reduce all objects in the vascular map to lines, skeletonization is done. Branching points and end points are detected and parameters like mean diameter, fractal dimension and temporal arcade angle for the preprocessed image are computed. This has been implemented for both healthy retinas and retinas of stroke patients .The extracted features are given to a Artificial Neural Network classifier and the performance metrics are evaluated.

3.1 Pre processing

Retinal fundus image preprocessing for feature detection mainly aims at the correction of non-uniform luminosity. The proposed method was tested with fundus images of the retina collected from a private hospital in Trivandrum. Database contains retinal fundus images of 30 normal and 20 stroke affected patients. Each image is of size 584 × 565 pixels, with a field of view of 35° and a spatial resolution of 20μm per pixel. The input image is initially subjected to adaptive histogram equalization.

Adaptive histogram equalization (AHE) transforms each pixel in a gray-scale image using a transformation function derived from a neighborhood region. Adaptive histogram equalization (AHE) [14]is suitable for improving the local contrast of an image and bringing out more detail. But, it has a tendency to amplify noise in relatively homogeneous regions of an image. The histogram equalized image is subjected to median filtering for removing the noise. The median filter is a non-linear filter which reduces the outcome of noise without blurring sharp edges. Median filtering operation replaces a pixel by the median of all pixels in the neighborhood of small sliding window. It gives better results than the neighborhood averaging. Median filter is robust and has the capability to remove outliers in the image.

3.2 Binarization and Skeletonization

The image is converted to binary form by applying thresholding. The structural shape of a plane region can be reduced to a line graph called skeleton. The skeleton of the region can be obtained by a thinning algorithm. After obtaining skeletonized output, the branching points and end points of the fundus skeleton are detected. The morphological opening function with disc shaped structuring element is applied on this skeletonized binary image to remove the background. [6]MATLAB Toolbox function still constructs structuring elements with a variety of shapes and sizes.

3.3 Detection of Optic Disc

The location of the optic disk is an important issue in retinal image analysis as it is a significant landmark feature. To compute the temporal arcade angle, the optic disc of the retinal fundus image needs to be located. Binary edge map is generated by laplacian of Gaussian and the Circle detection is done by hough transform. LoG and Hough transform are explained in 3.3.1 and 3.3.2 respectively.

3.3.1 Laplacian of Gaussian (LoG) for Edge detection

Laplacian of Gaussian (LoG) combines Gaussian filtering with the Laplacian for edge detection. In this approach, an image should first be convolved with a Gaussian.filter. This step smooths an image and reduces noise. Since the smoothing will result in spreading of edges, the edge detector considers as edges only those pixels that have locally maximum gradient. This is achieved by using zero crossings of the second derivative. To avoid detection of insignificant edges, only the zero crossings whose corresponding first derivative is above some threshold are selected as edge points.

3.3.2 Circular Hough Transform

The center and boundary of the optic disc are found by applying the Hough transform to the gradient image. The basic idea behind the Hough transform is to transform the image into a parameter space that is constructed specifically to describe the desired shape analytically. Maxima in this parameter space then correspond to the presence of the desired shape in image space. The circular Hough transform is almost identical to the Hough transform for lines, but uses the parametric form for a circle as denoted in equation (1),

$$(x-a)^2 + (y-b)^2 = r^2 \qquad (1)$$

where (a,b) is the coordinate of center of the circle that passes through (x,y) and r is its radius. The edge image is scanned and all the points in this space are mapped to Hough space. A value in particular point in Hough space is accumulated if there is a corresponding point in the retinal image space. The process is repeated until all the points in the retinal image space are processed. The resulting image is scaled between 0 and 1. After thresholding, the different regions were matched by different circles and the output image is computed by drawing circle with these points and adding this to the input image. The best circle shows the location of the detected optic disc.

3.4 Estimation of parameters

The various parameters computed from the skeleton of the fundus image include mean diameter, fractal dimension and temporal arcade angle.

i) Mean Diameter

An estimate of vessel diameters is calculated using the distance transform of the inverted binary preprocessed image. This gives the Euclidean distance of every 'vessel' pixel from the closest nonvessel pixel, and therefore doubling the maximum value of the distance transform along the thinned centrelines provides an estimate of the diameter of every vessel segment at its widest point [15]. Then, the mean diameter is computed.

ii) Fractal Dimension

Fractal dimension [17] is a complexity indicator determined by reactive vessels obtained from vascular tracking through the box counting dimension method. After vessel tracing was ascertained, D*f* is computed from the refined skeletonized vessel tracing using the Box-Counting method. The box counting equation briefly is:

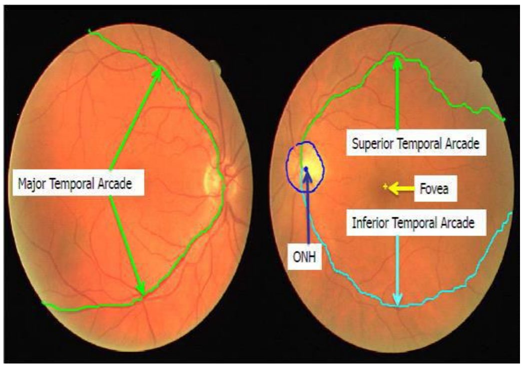
$$D_f = \lim_{r \to 0} \log(N[r]) / \log(1/r) \qquad (2)$$

where N(r) is the number of boxes overlying a fractal structure and *r* is the side length of each box.

iii) Temporal Arcade angle

The MTA angle has been defined as the angle between the superior and inferior temporal arcades (STA and ITA) as they diverge from the optic nerve head (ONH) towards the periphery of the retina.

Fig 1 . Major Temporal Arcade



After marking the center of the Optic disc, a circle of desired radius (r=200 pixels) is drawn depending upon the resolution of the image. The user is then prompted to mark the point of intersection of the circle with the superior vessel and inferior vessel [12]. The arcade angle is measured as the angle between the three marked points with the center of the Optic disc being the vertex using arctan $[(m1 - m2)/(1 + m1m2)]$, where $m1$ and $m2$ are the slopes of the two lines and $m2 > m1$.

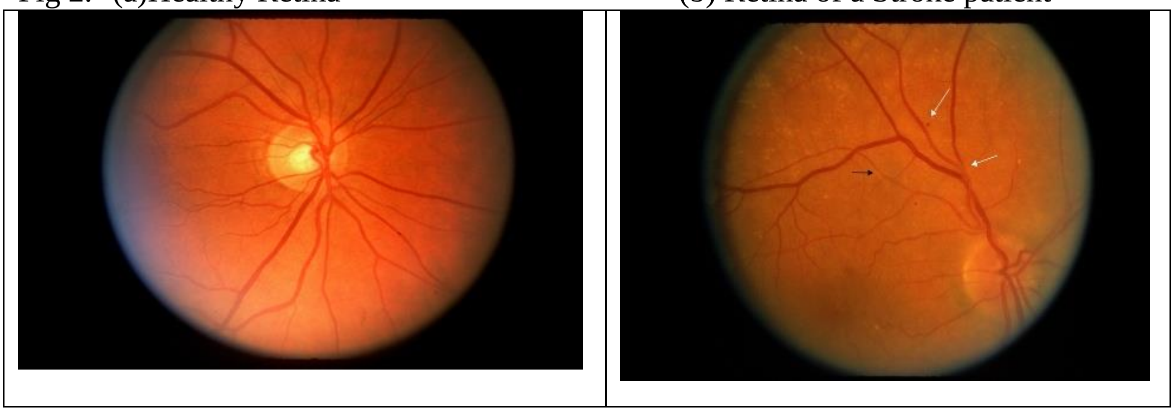
3.5 Artificial Neural Network (ANN) Classifier

This work focuses on the development of an artificial neural network model with 5 input parameters for the prediction of stroke .A multilayered feed forward neural network has been designed with 5 input nodes, a hidden layer with 5 hidden nodes and 2 output nodes. Backpropogation algorithm [16] with sigmoid activation function is used to train the feed forward neural network architecture.

4. Result

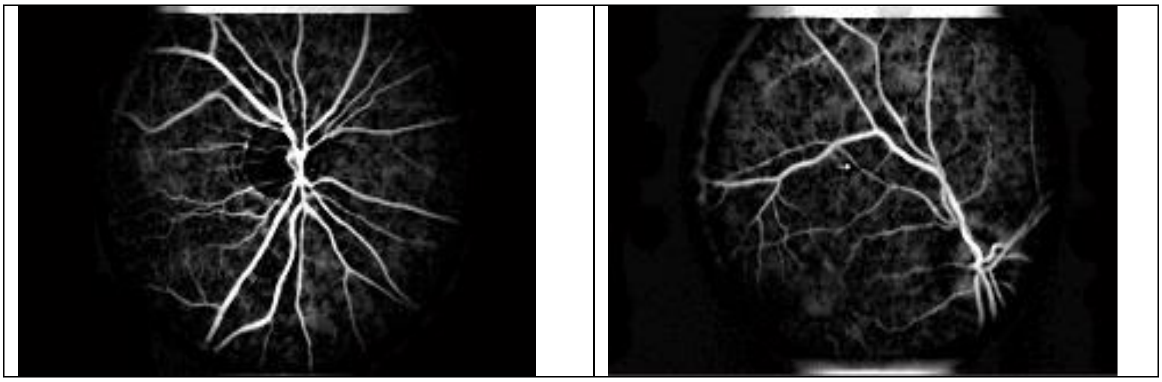
Fig. 2 shows the input images of a healthy retinal fundus and retina of a stroke patient.

Fig 2. (a)Healthy Retina (b) Retina of a Stroke patient



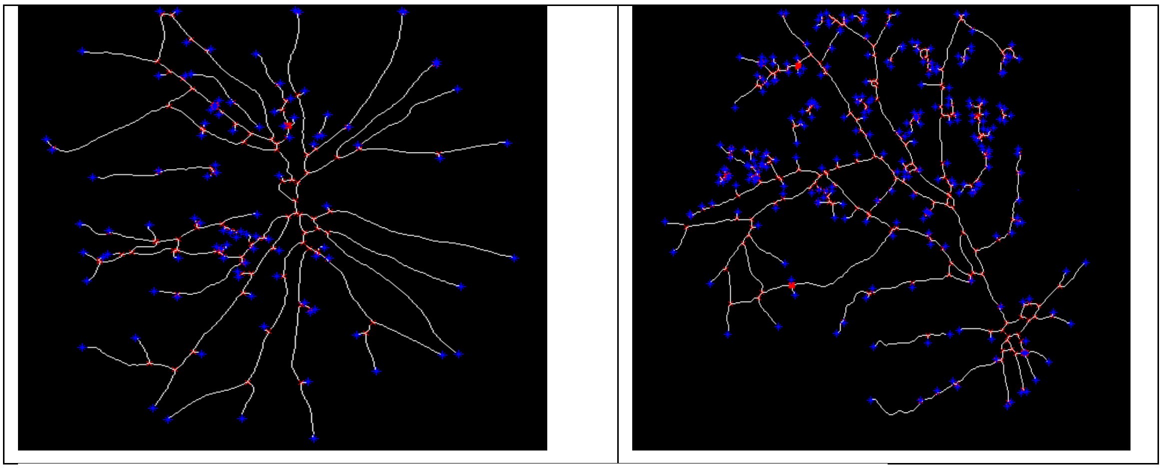
The preprocessed output is shown in figure 3.

Fig. 3 (a) Preprocessed Healthy Retina (b) Preprocessed retina of a Stroke patient



Preprocessed output is the converted to binary form by thresholding. Fig.4 shows the skeletonized output with branching points and end points .

Fig 4. (a) Detection of branching points and endpoints in Healthy Retina (b) Detection of branching points and endpoints in Retina of Stroke patient



Endpoints are shown in blue and branching points are shown in red.

Table 1 shows the values computed for both the images.

Table 1. Evaluation of parameters

Retinal Fundus Image	Mean diameter	Fractal dimension	Temporal Arcade angle(deg)	Number of End points	Number of branch points
Healthy Person	4.8	1.4	160.9	102	115
Stroke	2.7	1.77	129	283	303

patient					

Results show that number of branching points is much higher in the case of stroke patients and branching vessels seems to be more tortuous, which can be observed visually from the processed images. Healthy retinal fundus images seems to give a mean diameter in the range [4.5-7.8] and fundus images of stroke patient gives a mean diameter in the range [2.4-3.9]. Temporal arcade angle shows a wide variation in both healthy and stroke affected images. In the presence of stroke, the angle between superior and inferior temporal arcades seems to reduce considerably.

5. Performance Evaluation

Validation requires the calculation of statistical parameters like sensitivity, specificity, accuracy, precision and F1 score. Mathematically, it is defined as;

Sensitivity = TP / (TP + FN)

Specificity = TN / (FP + TN)

Accuracy = (TP+TN)/(TP + TN + FN + FP)

Precision = TP/(TP+ FP)

F1 Score = 2.TP/(2.TP+FP+FN)

The ability of the method to identify correct cases is given by Sensitivity. The fraction of correct classifications to the total number of classifications is given by accuracy. Precision is the likelihood that a retrieved case is relevant. F1 Score gives the harmonic mean of precision and recall (sensitivity).Number of samples in the training set was taken as 30 and number of samples in the testing set was chosen to be 20. This work has been implemented in MATLAB. Table 2 gives the statistical parameters computed for a multilayer feed forward ANN.

Table 2: Evaluation of Statistical Parameters

Statistical Parameters	**Values**
Sensitivity	100 %
Specificity	96 %
Accuracy	98 %
Precision	97 %
F1 Score	98 %

6. Conclusion

A machine learning based approach based on ANN is proposed in this work to predict the possibility of stroke by analyzing retinal parameters. Early detection of cardiovascular diseases like stroke through biomarkers derived from retinal imaging would allow patients to be treated more effectively. Retinal imaging aids in predicting the probability of stroke based on parameters evaluated from the vascular map. Performance of the system can be improved by incorporating more features and requires training from a much larger database.

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