IMAGE ANALYSIS TECHNIQUE FOR DETECTING ARMD IN THE RETINA

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Abstract: Age-related macular degeneration is an eye disease, that gradually degrades the macula, a part of the retina, which is responsible for central vision. ARMD occurs in one of the two types, 1. Dry ARMD and 2. Wet ARMD. The purpose of this paper is to diagnose the retinal disease ARMD. The extent of the disease spread in the retina can be identified by extracting the features of the retina. Detection of ARMD disease is done using Radial Basis Function Neural Network (RBFNN) method and the two types are classified and diagnosed successfully. The accuracy of the proposed system is 80%.

Keywords: Macula, Retina, Radial Basis Function Neural Network, Accuracy.

I. INTRODUCTION

Age-related macular degeneration (ARMD) is a disease that causes progressive damage to the macula. Macula is the central part of the retina that allows us to see fine details. When the macula degenerates, blurring or darkness occurs in the center of the vision and tasks such as reading and driving are affected. The words on a page may look blurred, a dark or empty area may appear in the center of the vision, or straight line may look distorted. ARMD can be classified into two types as dry and wet ARMD. Fig. 1 shows the dry and wet ARMD images.

A. Dry ARMD: The health of the retina deteriorates with age in some people due to the appearance of drusens. Drusens are accumulation of lipid and other waste material from different layers of the retina. These are markers of age-related macular degeneration. The dry form of ARMD is more common, more than 85% of cases are categorized as dry macular degeneration.

B. Wet ARMD: Wet ARMD occurs when abnormal blood vessels behind the retina start to grow under the macula. These new blood vessels tend to be very fragile and often leak blood and fluid. The blood and fluid raise the macula from its normal place at the back of the eye. Damage to the macula occurs rapidly. 10%-15% of cases are categorized as wet macular degeneration.

Wet ARMD usually begins as the dry form. Wet ARMD is more severe than dry form, if allowed to continue without treatment it will completely destroy the macula.

The proposed system of [1], automatically detect and segment retinal diseases with the help of a neural network based classifier. The proposed system of [2] relied on the accurate segmentation of the vasculature of retina by determination of spatial features. In [3], they aimed at histogram approach for screening in age-related macular degeneration. In [4], they aimed at locating optic nerve using fuzzy convergence of blood vessels. In [5], the principle of mathematical morphology is used to segment drusen areas in order to
diagnose ARMD. In [6], small and vague drusen which is very hard-to-diagnose was detected through unsupervised learning. In [7], histogram based adaptive thresholding is used for the automatic detection and mapping of drusen in the retinal images. In [8], radial basis function is employed for functional approximation in time-series modeling and pattern classification. In [9], fisher’s linear discriminant and radial basis function are combined for identifying the presence of covert information in a carrier image. In [10], radial basis function network was first adapted for classification problems and then used customized evolutionary algorithms to evolve RBFN.

II. PROPOSED WORK

In this paper, an automated approach for classification of the disease ARMD using fundus images is presented. In order to diagnose the disease ARMD, features are extracted from the enhanced images. After the features are extracted, a radial basis function neural network classifier is used to classify the type of disease and diagnose the disease. RBFNN is applied to analyze training data to find an optimal way to classify images into their respective classes namely Dry ARMD, Wet ARMD or Normal. The main goal is to detect automatically and segment the disease age-related macular degeneration in retina without any human supervision and interaction. The proposed work of this paper consists of four modules, A. Image Enhancement, B. Anatomic Structure Detection, C. Feature Extraction, D. Classification of the disease using RBFNN. Fig. 2 illustrates the block diagram of the proposed system for diagnosis of ARMD.

(A) Image Enhancement

Image enhancement is the first step in the automatic diagnosis of retinal images. Image Enhancement improves the quality of the images for human viewing. The purpose of image enhancement is to remove blurring and noise, increasing contrast for the reliable extraction of features since the abnormalities in feature extraction will produce poor results in the noisy background. Fig. 3 illustrates the block diagram of the image enhancement.

Steps for image enhancement:

(a) The color retinal image is taken as an input image.
(b) The green component is extracted from the input image.
(c) After green component conversion, adaptive histogram equalization is used to enhance the contrast and to improve the quality of the retinal image.
(d) Finally an-isotropic diffusion is applied to remove the noise from the ARMD images.

(a) Input Retinal Image: A combination of normal and ARMD affected images are taken for enhancement. The size of the input retinal images are 1500×1000 pixels. It can be enhanced with the help of the following steps. Fig. 4 shows the input retinal image of normal and affected ARMD images.

(b) Green Channel Extraction: The retinal image is taken in the RGB form by the fundus camera. A fundus camera or retinal camera is a specialized low power microscope with an attached camera designed to photograph the
(c) Adaptive Histogram Equalization:
Adaptive histogram equalization is an image processing technique used to improve contrast in images. It is considered an image enhancement technique capable of improving an image’s local contrast, bringing out more detail in the image. So it is applied to the gray scale converted eye image. The main objective of this method is to define a point transformation within a local fairly large window with the assumption that the intensity value within it is a stoical representation of local distribution of intensity value of the whole eye image. The local window is assumed to be unaffected by the gradual variation of intensity between the eye image centers and edges. The point transformation distribution is localized around the mean intensity of the window and it covers the entire intensity range of the image. Consider a running sub image \( W \) of \( N \times N \) pixels centered on a pixel \( P(i,j) \), the image is filtered to produce another sub image \( P \) of \( (N \times N) \) pixels according to the equation below:

\[
P_n = 255 \left( \frac{\phi_w(p) - \phi_w(Min)}{\phi_w(Max) - \phi_w(Min)} \right)
\]

\[
\phi_w(P) = \left[ 1 + \exp \left( \frac{\mu_w - P}{\sigma_w} \right) \right]^{-1}
\]

and \( Max \) and \( Min \) are the maximum and minimum intensity values in the whole eye image, while \( \mu_w \) and \( \sigma_w \) indicate the local window mean and standard deviation which are defined as:

\[
\mu_w = \frac{1}{N^2} \sum_{i,j} \varepsilon(k,l)P(i,j)
\]

\[
\sigma_w = \sqrt{\frac{1}{N^2} \sum_{i,j} \varepsilon(k,l)(P(i,j) - \mu_w)^2}
\]

As a result of this adaptive histogram equalization, the dark area in the input eye image that was badly illuminated has become brighter in the output eye image while the side that was highly illuminated remains or reduces so that the whole illumination of the eye image is same. The results of eye images after applying Adaptive Histogram Equalization are shown in Fig. 6.
(d) Anisotropic Diffusion: Anisotropic diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image. Anisotropic diffusion resembles the process that creates a scale-space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family are given as a convolution between the image and a 2D isotropic Gaussian filter, where the width of the filter increases with the parameter. This diffusion process is a linear and space-invariant transformation of the original image. Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. As a consequence, anisotropic diffusion is a non-linear and space-variant transformation of the original image. The filter iteratively uses diffusion equation in combination with information about the edges. As a consequence, the homogenic (but noisy) areas are blurred and the edges are preserved. The anisotropic diffusion equation is defined as,

\[ I \text{ div}(c(x, y, t) \nabla I) = c(x, y, t) \Delta I + \nabla c^T I \]

where div is the divergence operator, \(\nabla\) is a gradient and \(\Delta\) is a Laplacian operator, \(c\) represented the conduction coefficient function. Index’t’ denotes the time (iterations). The filtering or non-linear smoothing approach using anisotropic diffusion is applied on green band of fundus image after histogram equalization to smooth unwanted data, such as small and tiny capillaries. The results of eye images after applying anisotropic diffusion are shown in Fig. 7.

(B) Anatomic Structure Detection

The purpose of locating anatomic structure is to detect the blood vessel based on segmentation of vascular arcades. Detection of the anatomic structure is the characterization of the normal or disease state that exists in the retina.

(a) Discrete Wavelet Transform: The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are obtained from a single prototype wavelet \(\psi(t)\) called mother wavelet by dilations and shifting:

\[ \psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \]

where \(a\) is the scaling parameter and \(b\) is the shifting parameter. The mother wavelet used to generate all the basis functions is designed based on some desired characteristics associated with that function.

\[ [cA, cH, cV, cD] = \text{dwt2}(X, 'wname') \]

computes the approximation coefficients matrix \(cA\) and details coefficients matrices \(cH, cV, cD\) (horizontal, vertical, and diagonal, respectively), obtained by wavelet decomposition of the input matrix \(X\) where \(X\) is the given input eye image after applying adaptive histogram equalization. The ‘wname’ string contains the wavelet name. In this paper, Reversed Biorthogonal wavelet is used. The results of eye images after applying Discrete Wavelet Transform are shown in Fig. 8.
The Kirsch edge detection algorithm uses a 3×3 table of pixels to store a pixel and its neighbors while calculating the derivatives. The 3×3 table of pixels is called a convolution table, because it moves across the image in a convolution-style algorithm. The Kirsch edge detection algorithm identifies both the presence of an edge and the direction of the edge. Fig. 9 shows the results of eye images after applying Kirsch template.

There are eight possible directions in the Kirsch Operator: North, South, East, West, North East, North West, SouthEast and South West as shown in Fig. 10. The direction is perpendicular to the edge. For a convolution table, calculating the presence and direction of an edge is done in three major steps.

1. Calculate the derivative for each of the eight directions.
2. Find the value and direction of the maximum derivative.

\[
\text{EdgeMax} = \text{Maximum of eight derivatives} \\
\text{DirMax} = \text{Direction of EdgeMax}
\]
3. Check if the maximum derivative is above the threshold.
Medical diagnosis is the field that deals with the automatic detection of disease based on input. Automatic diagnosis systems have enabled early detection of diseases and hence contribute towards timely preventive measures. Hence these classification techniques assist the doctors as an expert system for decision making.

III. EXPERIMENTAL RESULTS

The performance measure of RBFNN classification are shown in Table 1. The sensitivity and specificity of the proposed system are 81.81% and 76.47% respectively. The accuracy of the proposed system is 80%. Table 2 shows the percentage of accuracy of the test data. Fig. 12 shows the ROC curve for the system.

<table>
<thead>
<tr>
<th>True Positive</th>
<th>False Positive</th>
<th>True Negative</th>
<th>False Negative</th>
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<tbody>
<tr>
<td>54</td>
<td>8</td>
<td>26</td>
<td>12</td>
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Table 2

<table>
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<tr>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
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<tbody>
<tr>
<td>81.81%</td>
<td>76.47%</td>
<td>80%</td>
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IV. CONCLUSION

ARMD is the most common cause of irreversible vision loss over the age of 50. As a result of Macular degeneration the central vision deteriorates, resulting in dark spots and cloudiness. The two different kinds of ARMD are identified as Dry ARMD and Wet ARMD. The input color retinal image is converted into green component and then adaptive histogram equalization is used, then an-isotropic diffusion is applied. After that, anatomic structure detection was done using DWT and kirsch template. Next the features are extracted from the Blood vessel detected images. Finally, the normal, dry and wet types of Macular degeneration are classified with the help of radial basis function neural network. This method may be enhanced by taking some more features and by combining with other pattern classification models.

References


