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Performance Analysis of Wavelets and Neural Network Retina Fundus Image for Efficient Image Segmentation

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Abstract:
Retinopathy has become a commonly spread disease in the world and it causes many complications. The purpose of this paper is to extract features from retina digital images based on a further analysis of high frequency components (HH) obtained with the Discrete Wavelet Transform (DWT). One of the common vision threatening complications of Diabetic Retinopathy. It occurs when blood vessels in the patient's retina begin to leak into the macula region of eye. In particular, the DWT is applied to the retina photograph to obtain its high-high (HH) image sub band using db1, symlet, biorthogonal wavelet transform. Then, a further decomposition by DWT is applied to the HH image subband of the previous step to obtain HH*. Finally, statistical features are computed from HH* Discrete Wavelet Transform (DWT) based features and Adaptive Neural Inference System is reported. The computational results show that present stage(i.e., normal or abnormal) and gives overall accuracy and sensitivity, specificity.

Keywords: Discrete wavelet transform, Neural network, Diabetic retina, Hard exudates, fundus.

I. INTRODUCTION

Computer-aided diagnosis (CAD) has been the subject of a lot of research as a tool to help health professionals in medical decision making. As a result, many CAD systems integrate image processing, computer vision, and intelligent and statistical machine learning methods to aid radiologists in the interpretation of medical images and ultimately help improve diagnostic accuracy. The typical process starts with a segmentation stage to identify one or more regions of interest (ROI) in the image of interest. Then, the ROI(s) is processed for image enhancement and/or feature extraction before classification. Because the segmentation step requires prior knowledge of discriminate image features and its implementation typically calls for numerous parameter settings, recent works have attempted to eliminate it. These approaches realize feature space reduction by applying one or more transforms to the whole image and extracting the feature vector to classify from one or more of the obtained components. Diabetic Retinopathy is caused due to the increase in intraocular pressure of the eye. The intraocular pressure increases due to malfunction or malformation of the drainage system of the eye. The anterior chamber of the eye is the small space in the front portion of the eye. A clear liquid flow in and out of the chamber and this fluid is called aqueous humor. The increased intraocular pressure within the eye damages the optic nerve through which retina sends light to the brain where they are recognized as images and makes vision possible[1]. The goal of this paper is to develop an algorithm which automatically analyze eye ultrasound images and classify normal eye images and diseased Diabetic Retinopathy eye images. The two central issues to automatic recognition feature extraction from the retinal images and classification based on the chosen feature extracted. Several pathologies affecting the retinal vascular structures due to diabetic retinopathy can be found in retinal images.

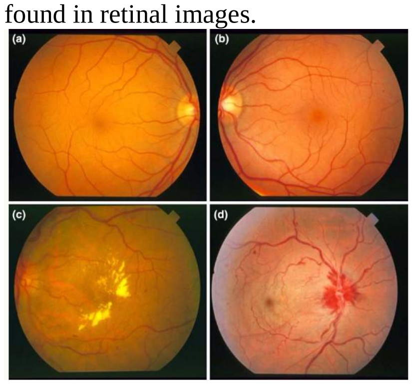


Figure .1. a. Normal retinal image,
b. Normal retinal image,
c. Retinal image with background diabetic retinopathy,
d. Retinal image with central retinal vein occlusion

Ophthalmologists use digital fundus cameras to non-invasively view the optic nerve, fovea, surrounding vessels and the retinal layer .Since retinal imaging is non-invasive, there is a rapid increase in the number of images which are being collected. Diagnosing these large volumes of images is expensive, time consuming and may be prone to human error. To aid the doctors with this diagnostic task, a computer-aided diagnosis scheme could offer an objective, secondary opinion of the images.

II. RELATED PROBLEMS

Dynamic Thresholding

In this method we have applied median filtering onto the input image directly if it is in grayscale, otherwise we have to convert the input image into grayscale before applying median filtering.

It corresponds to the boundary between two regions or a set of points in the image where luminous intensity changes very sharply. The presence of an edge within a grayscale image indicates that there is a change in the grayscale from one region to another. This approach is subtraction of median filtered image from input image (in case of the input image is in grayscale form) or subtraction of median filtered image from grayscale form on input image (in case of the input image is in RGB form). Image subtraction is used to find changes between two images of same scene. Thresholding is one of the most useful and easy to implement technique for image segmentation. If in an image consists of light objects on a dark background, in such a way that object and background pixels have intensity values grouped into dominant modes, then we can extract light objects from background using thresholding operation. Depends on the value of thresholding parameter (T). The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. For the proposed method we have used dynamic thresholding technique. The value of thresholding parameter is calculated for each pixel and it's neighbourhood pixel. The thresholding values we are getting are low specification value.

III.PROPOSED METHOD

Multi-Level Discrete Wavelet Transform

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. The DWT decomposes an input image into four components labeled as LL, HL, LH and HH [9]. The first letter corresponds to applying either a low pass frequency operation or high pass frequency operation to the rows, and the second letter refers to the filter applied to the columns. The lowest resolution level LL consists of the approximation part of the original image. For multimedia processing, Discrete Wavelet Transform (DWT) based image coding has better performance than traditional DCT based image coding, especially for low bit-rate applications. Therefore many famous coders have been proposed to effectively compress images or frames processed via DWT. The remaining three resolution levels consist of the detail parts and give the vertical high (LH), horizontal high (HL) and high (HH) frequencies. Figure 3 shows three-level wavelet decomposition of an image.

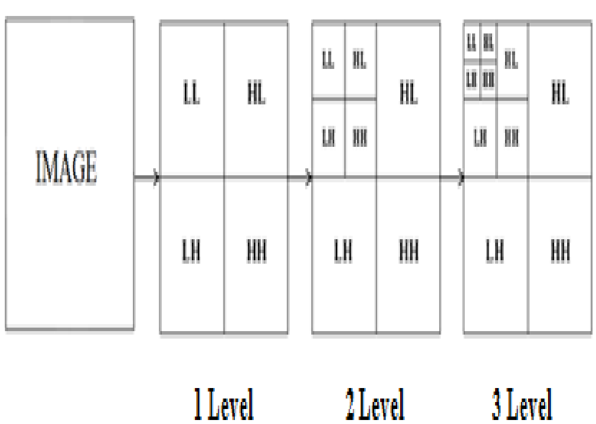


Figure .2. Wavelet-based texture analysis in retina

In clinical diagnostic approaches (e.g. ABCD rule of ceroscopy and pattern analysis) dermatologists look into the visual differences within the retina and also changes in the appearance of the retina over the time.

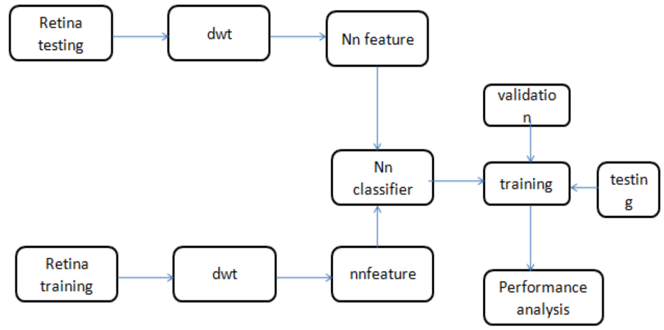


Figure. 3. Wavelet-based texture analysis on retina Images

These visual characteristics can be captured through texture analysis. Wavelet-based texture analysis provides a multi resolution analytical platform which enable us to characterize a signal (an image) in multiple spatial/frequency spaces. The multi-scale characteristics of wavelet can be very useful since dermoscopy images are taken under different circumstances such as various image acquisition set up (lighting, optical zooming, etc) and versatile skin colors on disease affected analysis. The 2D wavelet transform has been widely applied in image processing applications. There exists two wavelet structure; (1) Pyramid-structured wavelet transform which decomposes a signal into a set of frequency channels with narrower bandwidths in lower frequency channels, useful for signals which their important information lies in low frequency components [8], (2) Tree-structured wavelet analysis which provides low, middle and high frequency decomposition which is done by decomposing both approximate and detail coefficients as shown in Figure. In dermoscopy image analysis, the lower frequency components reveal information about the general properties (shape) of the lesion, which is clinically important, and the higher frequency decomposition provides information about the textural detail and internal patterns of the retina which is also significant in the diagnosis. Thus the decomposition of all frequency channels are useful in this application. Therefore, the tree-structured wavelet analysis can be more informative for classification of retina funds.

Neural Networks

Neural networks have been used to solve the image segmentation problem. Generally, the method involves mapping the problem into a neural network by means of an energy function, and allowing the network to converge so as to minimize the engery function. The network classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input Layer, Radial Basis Layer and the Competitive layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.

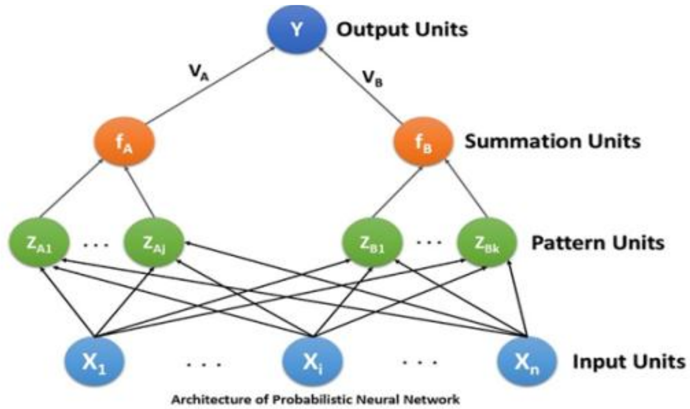


Figure. 4. Neural network analysis on retina

IV. RESULT ANALYSIS:

Accuracy:- Accuracy is also used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition. among the total number of cases examined. To make the context clear by the semantics, it is often referred to as the "rand accuracy. It is a parameter of the test.it shows in the command window..

Acc=(Tp+Tn)/(Tp+Tn+Fp+Fn)

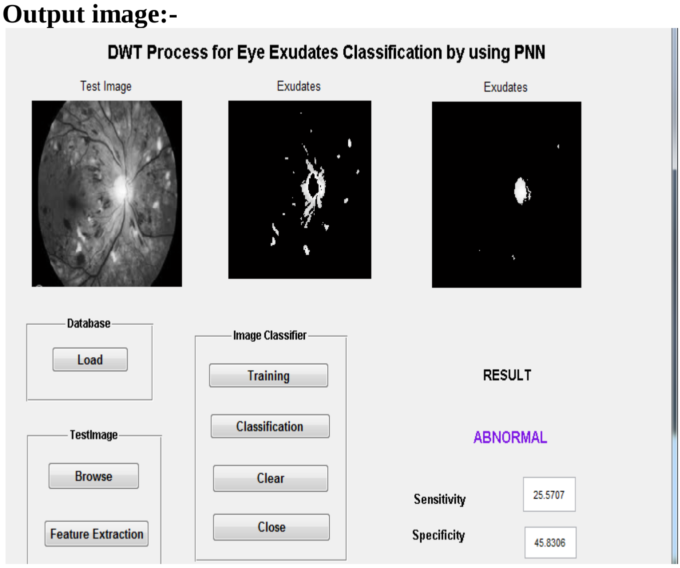
Sensitivity:-In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease (true positive rate).

Sensitivity =Tp/(Tp+Fn).

Specificity:-Whereas testspecificity is the ability of the test to correctly identify those without the disease (true negative rate).

Specificity =Tn/(Tn+Fp).

Output image:-



V. CONCLUSION:

This project implemented a retina fund affected on image classification using texture features and it will be classified effectively based on neural network. Here, probabilistic neural network was used for classification based on unsupervised leaning using wavelet and curve let statistical features and target vectors. The clustering was estimated from smoothing details of images accurately for effective retina disease affected part on segmentation.

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