International Journal of Engineering Research & Management Technology ISSN: 2348-4039

May-2016 Volume 3, Issue-3

Email: editor@ijermt.org www.ijermt.org

AUTOMATED AREADETECTION AND CLASSIFICATION TYPESINDIABETIC RETINOPATHY IN RETINAL FUNDUS IMAGES USING NEURAL INTELLIGENCE TECHNIQUES WITH MATHEMATICAL MORPHOLOGICAL OPERATIONS

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ABSTRACT: This paper focuses on Artificial Neural Network (ANN) to detect diabetic retinopathy in retinal fundus images. To develop this proposed system, a detection of micro-aneurysms, exudates and blood vessels is done from retinal fundus images. GLCM is formed using MATLAB function and several features like entropy, homogeneity, area of micro-aneurysms, exudates and blood vessels act as input to ANN. ANN is used to classify retinal images as mild, moderate and higher cases of diabetic retinopathy. In order to classify the DR images, different classes are represented using relevant and significant features.

KEYWORD: Diabetic Retinopathy (DR), fundus image, Area of Micro aneurysms, Area of exudates, Image processing, Morphological Operations, Optic Disc, Neural Intelligence techniques, Matlab.

I.INTRODUCTION

Diabetic retinopathy is the deterioration of retinal blood vessel which is caused by the complication of diabetes and it can eventually lead to blindness. The longer the patient has diabetes the higher are the chances of developing diabetic retinopathy. Diabetic retinopathy is characterized by the development of retinal Micro aneurysms, Hemorrhages and Exudates.

One of the stages in diabetic retinopathy is Non- Proliferative Diabetic Retinopathy (NPDR), which in this stage, the proliferative of blood vessels does not occur. Lesions of diabetic retinopathy consist of dark and bright lesions. The dark lesions comprise of micro aneurysms and hemorrhages, and the bright lesions include exudates which are yellow deposits of lipid and protein that leak from the capillaries.

There are two levels of diabetic retinopathy namely NPDR and PDR. No proliferative diabetic retinopathy is the early stage of diabetic retinopathy, and if the patient's blood sugar is uncontrolled it will be rise to proliferative diabetic retinopathy. No proliferative diabetic retinopathy (NPDR) consists of three levels which are mild, moderate, and severe NPDR. Digital retinal images which are used for automated detection of DR contain blood vessels, optic disc, macula and fovea as main components. Any changes in structure of retina or blood vessel is a sign of abnormality so these main components can be used to highlight the

II. DESCRIPTION OF WORK

The Area of hemorrhages, exudates and micro aneurysms increase as the degree of disease. Pigmentations of the retina also have striking resemblance to true MAs. As a current trend,Automatic computer based methods are proposed to assist eye specialists .An automated Micro aneurysm detector can prove to be an effective tool for automated identification of Diabetic retinopathy in clinical practice.

Automated assessment can save time of the human graders and also provide a history of changes in the fundus using the digital images.

III. METHODOLOGY

In this paper, we present an approach to improve disease stage detection in fundus retinal Images. Disease detection is based on the analysis of digital fundus images. The detection process starts with pre-processing of the images, which is followed by a data extraction phase. Then the extracted data are classified (see Fig.1).

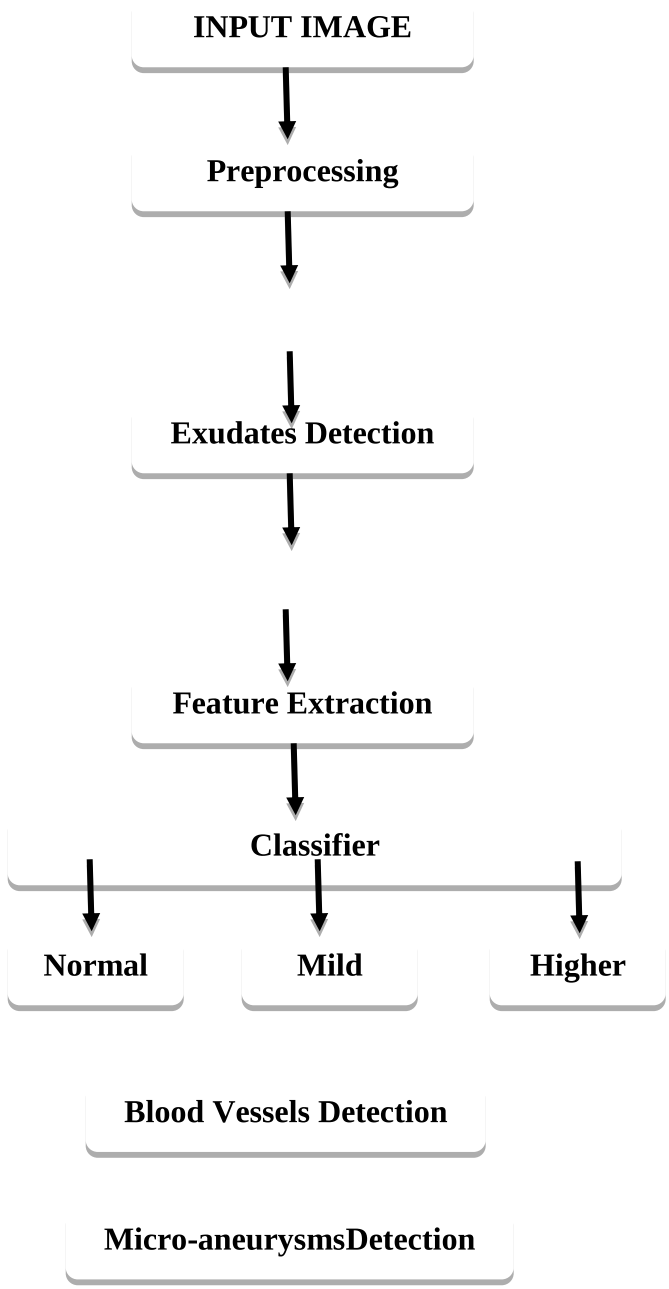


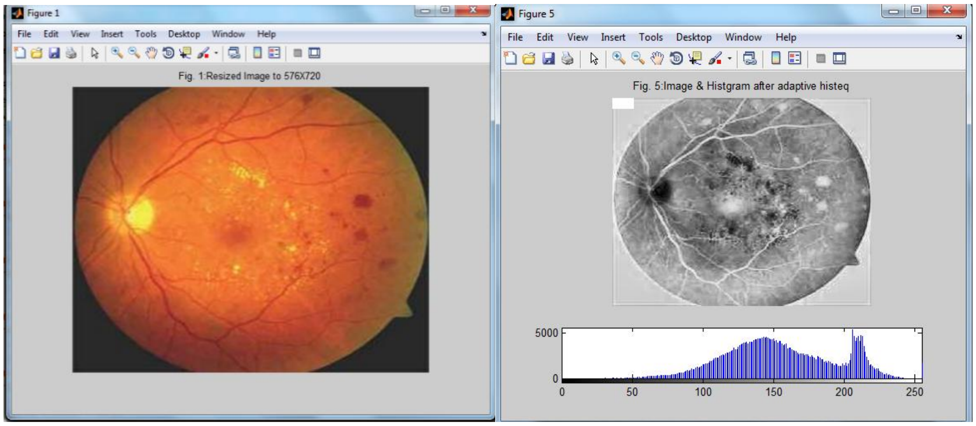
Fig 1.Block Diagram of Proposed System

A. PRE-PROCESSING

Step1: Image enhancement

We initially work on the RGB image; contrast of original RGB color image is increased so that Disease are highlighted. Then extract the green pixel matrix from original image and apply imcomplement function on green pixel image .imcomplement function are reversedblack and white pixels.

Fig.2 (a) and (b) shows original image and enhanced image.



(a) (b)

Fig.2 (a) and (b) shows original image and enhanced image.

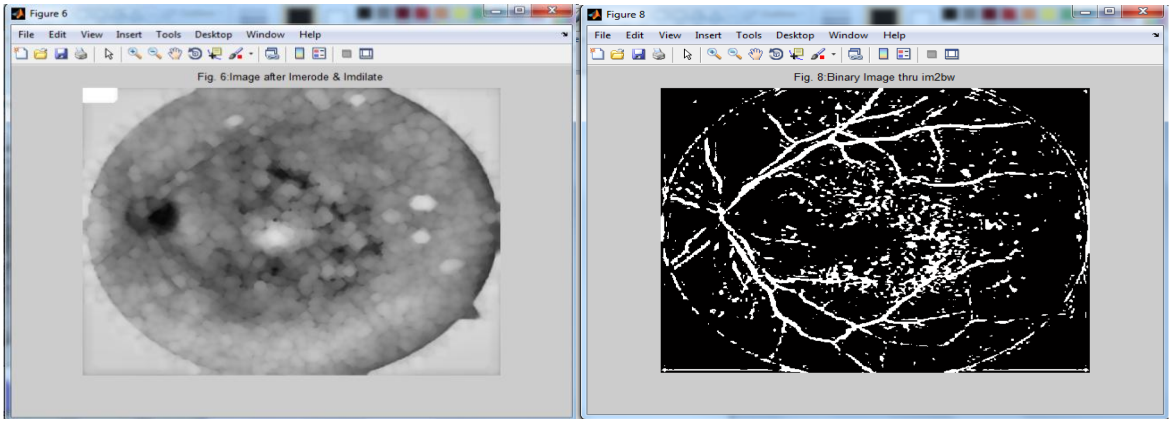
Step 2: Contrast Limited Adaptive Histogram Equalization:

CLAHE operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the 'Distribution' parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image.this is very effective in making more visible interesting prominent parts.

Step3: Image thinning, Erosion and skeletonization, Image Subtraction

Selecting a suitable threshold value for image is converted to binary form which shows only blood vessels and Disease. Image strengthening is done by setting pixel to 1 if five or more pixels in its 3-by-3 Neighborhood are 1's; otherwise, set the pixel to 0.

Image thinning removes pixels so that an object without holes shrinks to a minimally connected stroke, and an object with holes shrinks to a connected ring halfway between each hole and the outer boundary. Further erosion is performed with ball structuring element of {8,8}.With this operations blood vessels are thinned. To further suppress blood vessels we use skeletonization.



3(a) 3(b)

Fig.3 (a) and (b) shows image after imerod and dilation and im2bw black and white image.

B.BLOOD VESSELS DETECTION

Blood vessels are extracted in this project for the identification of diabetic retinopathy.the green channel of the image is applied with morphological image processing to remove the optical disk. Image segmentation is then performed to adjust the contrast intensity and small pixels considered to be noise are removed. Another green channel image is processed with image segmentation and combined with the mask layer. These two images are compared and the differences are removed. The obtained image would represent the blood vessels of the original image.

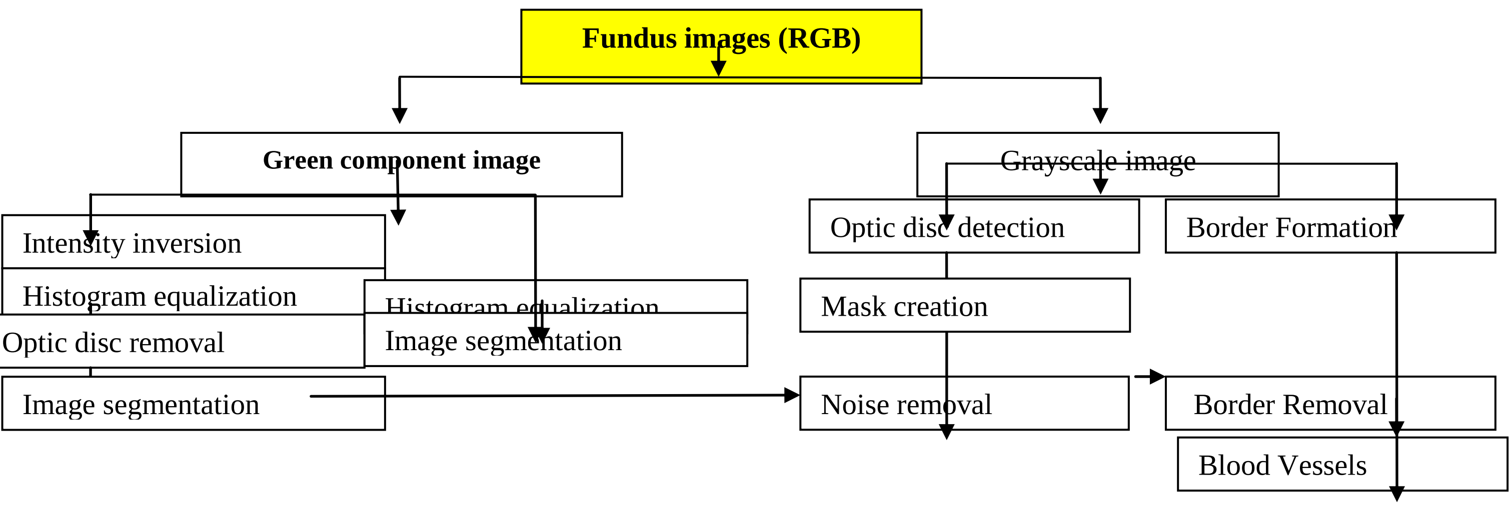


Figure 4 Flow Chart for blood vessels Detection

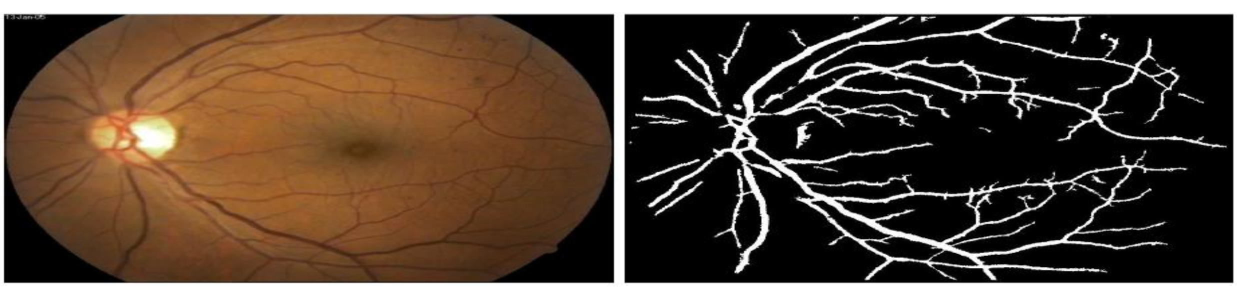


Figure 4.1 Fundus image (Left) with its blood vessels image (Right)

RESULTS

The area of the blood vessels is obtained by using two loops to count the number of pixels with binary 1 (white) in the final blood vessel image.

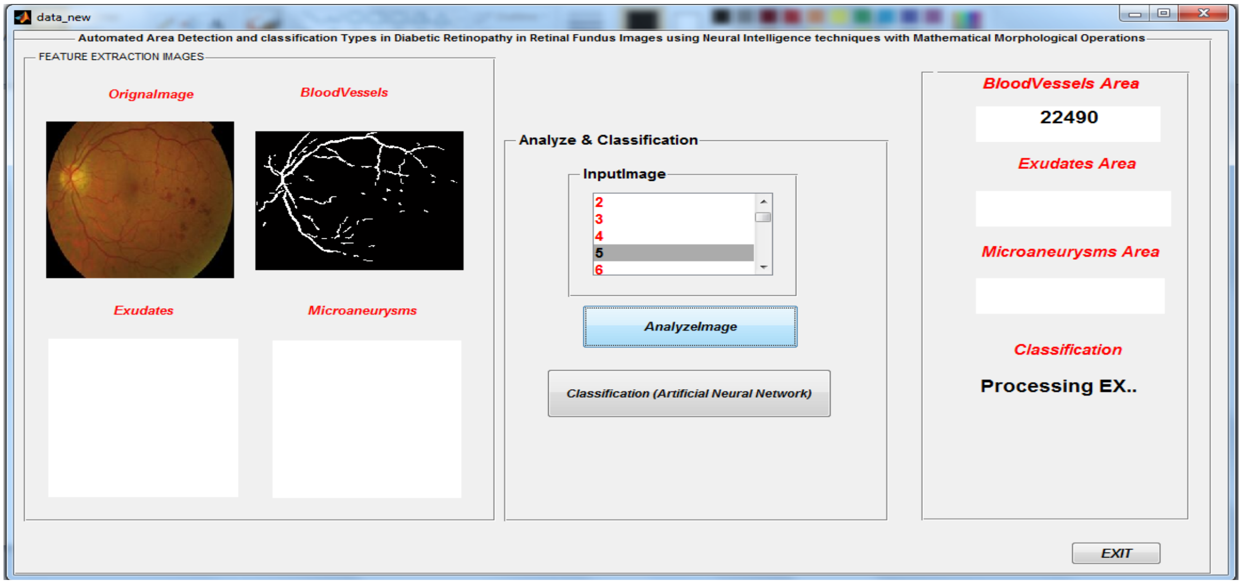


Figure 4.2 GUI For Fundus image (Left) with its blood vessels image (Right) and Area .

C.EXUDATES DETECTION

Exudates appeared as bright yellow-white deposits on the retina due to the leakage of blood from abnormal vessels. Their shape and size will vary with the different retinopathy stages. The grayscale image is first preprocessed for uniformity before the morphological image processing is applied to remove the blood vessels and identify the exudates region. The exudates are detected after removing the border, optical disk and non-exudates area.

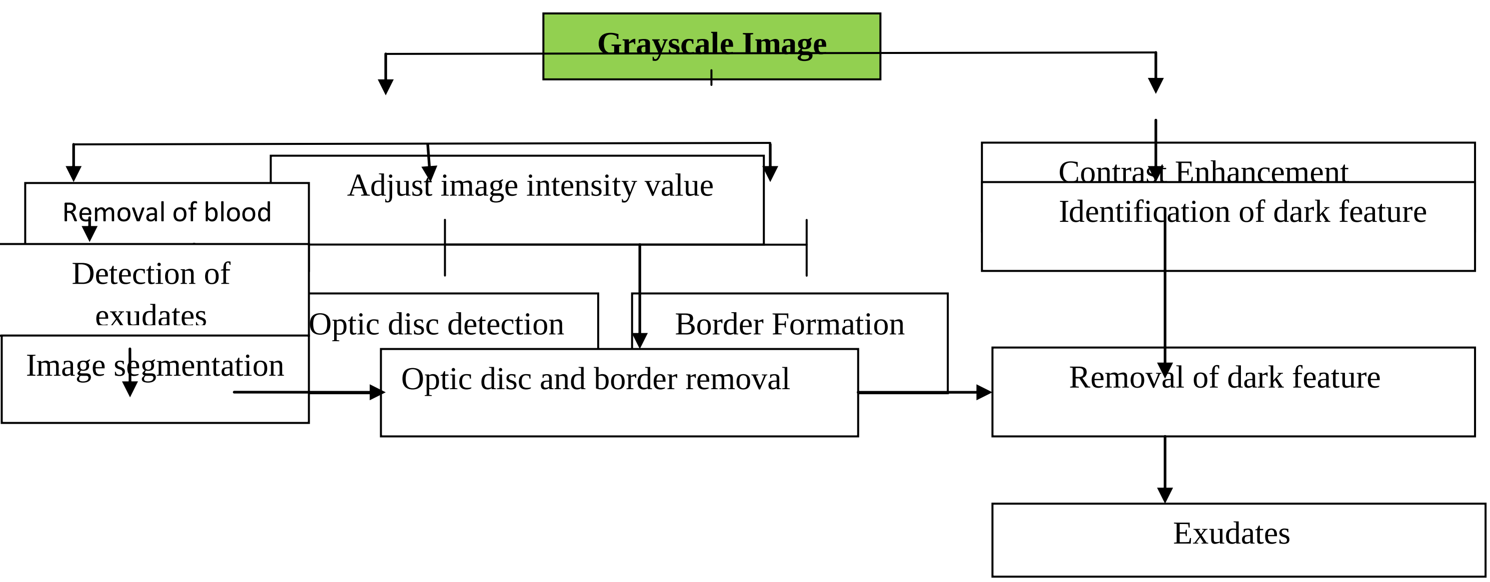


Figure 5 Flow Chart for Exudates Detection

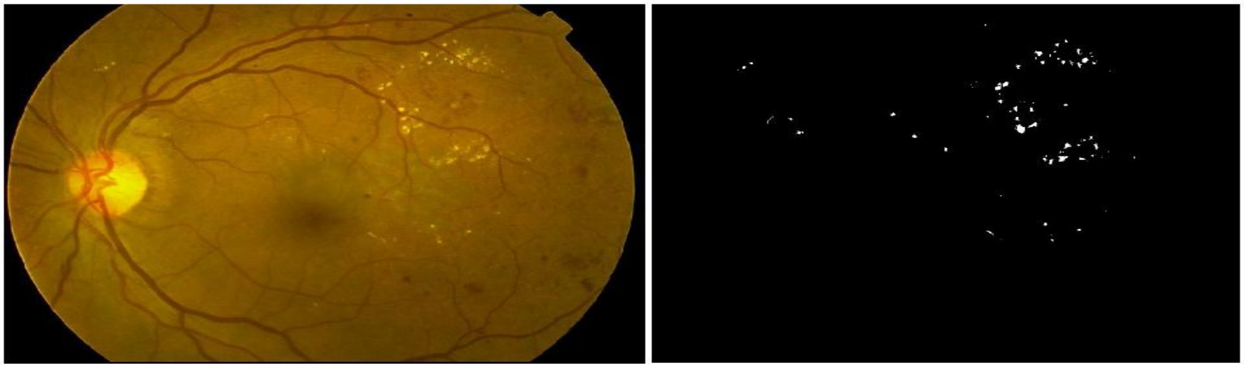


Figure 5.1 Fundus image (Left) with its Exudates image (Right)

RESULTS

The area of the exudates is obtained by using two loops to count the number of pixels with binary 1 (white) in the final exudates image.

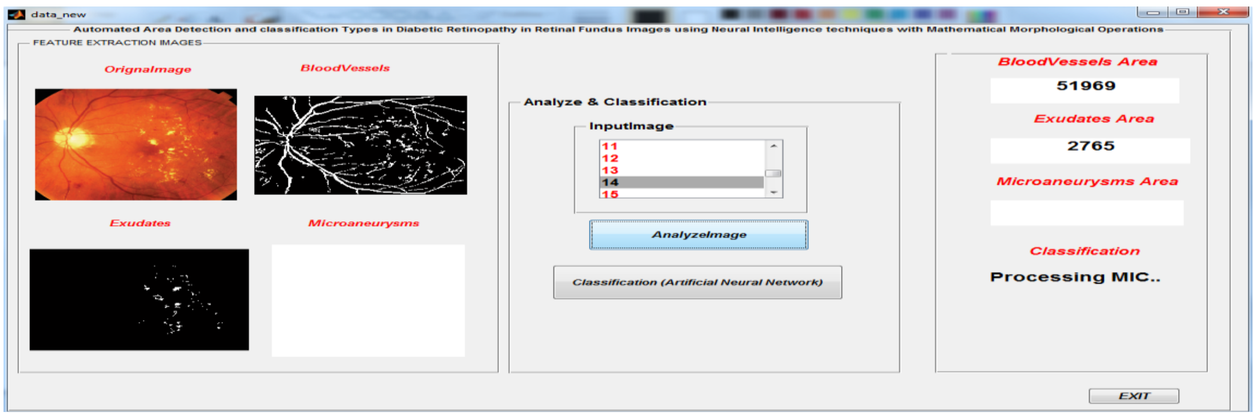


Figure 5.2 GUI For Fundus image (Left) with its Exudates image (Right) and Area .

D. MICRO-ANEURYSMS DETECTION

Micro aneurysms appeared as dark round dots (~15 to 60microns in diameter) on the fundus images. They are small bulges developed from the weak blood vessels and are the earliest clinical sign of diabetic retinopathy. Hence, it is essential to detect them during the mild stage. The number of micro aneurysms would increase with the stage of the retinopathy. The grayscale image is used to detect the circular border and optical disk mask. The green channel of the image first finds the edges using canny method before removing the circular border to fill the enclosed small area. The larger areas are then removed and applied with AND logic to remove the exudates. The blood vessels and optical disks are then removed to obtain the micro aneurysms.

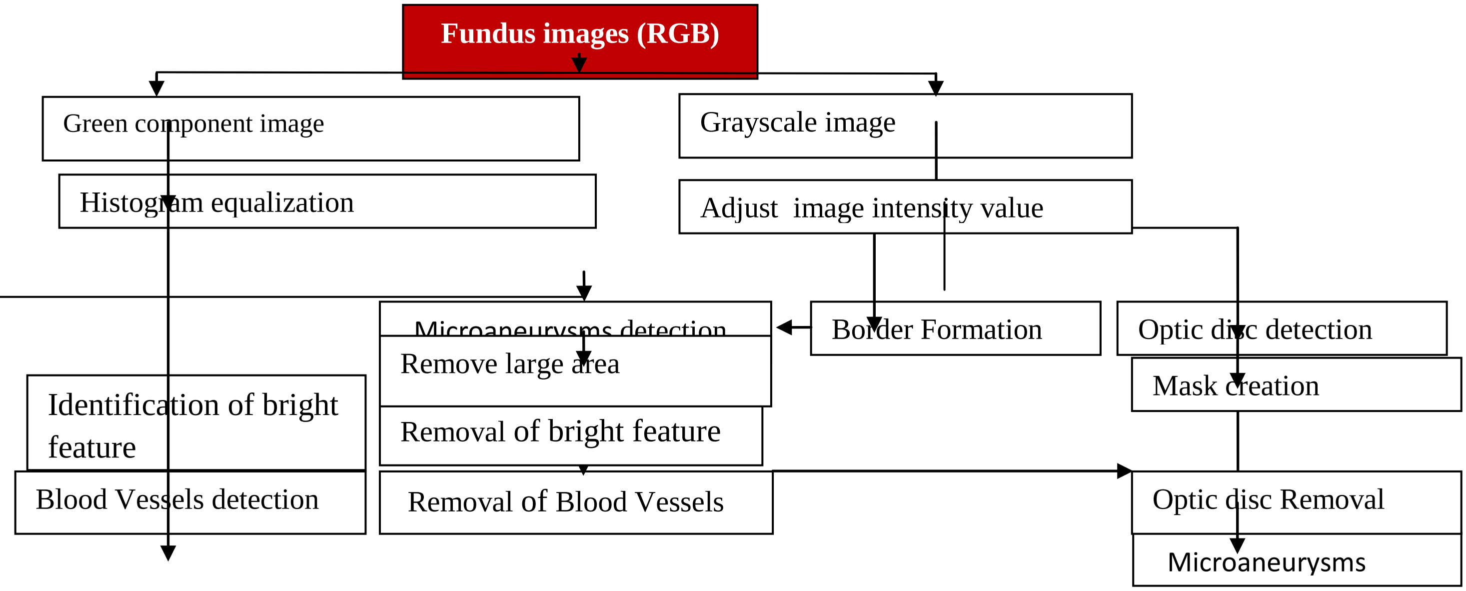


Figure 6 Flow Chart for Microaneurysms Detection

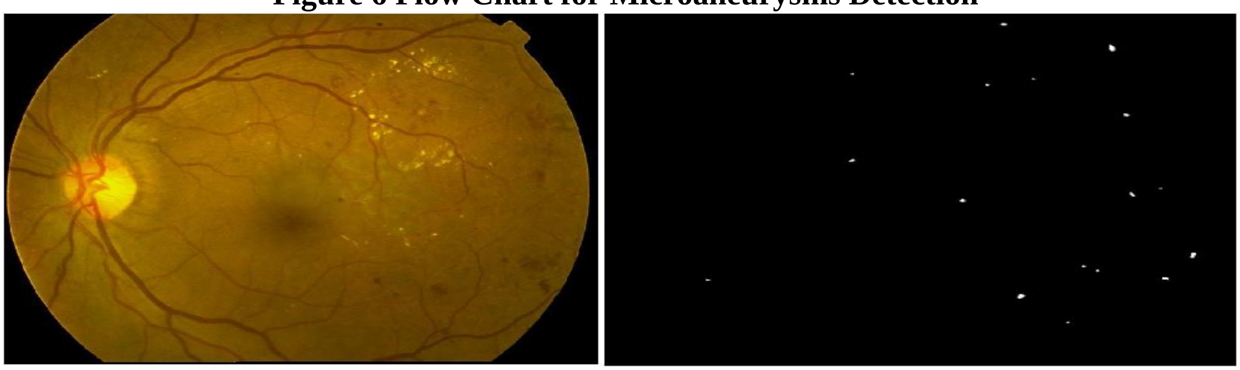


Figure 6.1 Fundus image (Left) with its microaneurysms image (Right)

RESULTS

The area of the micro aneurysms is obtained by using two loops to count the number of pixels with binary 1 (white) in the final micro aneurysms image.

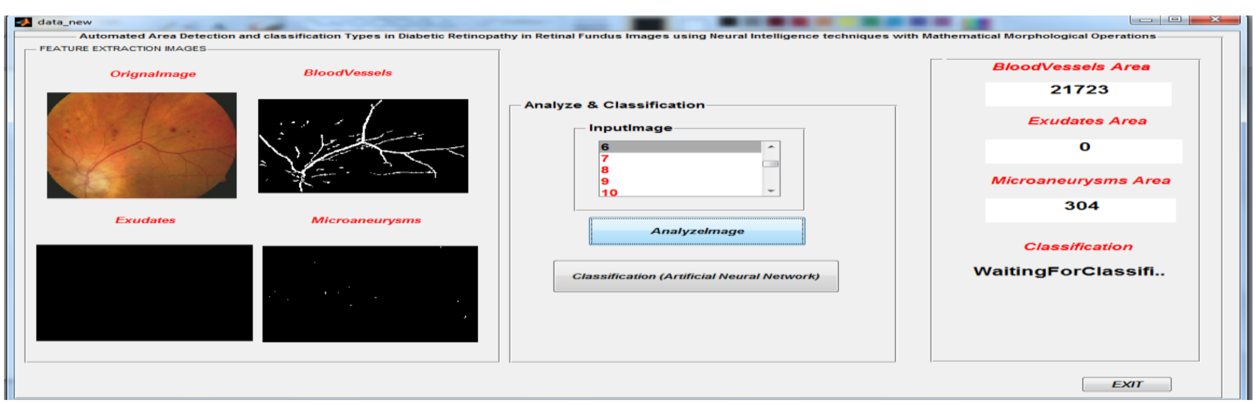


Figure 6.2 GUI For Fundus image (Left) with its microaneurysms image (Right) and Area .

E.FEATURE EXTRACTION

Feature analysis is the description of regions of an image by their variations in the pixel intensities or gray level such as its context of coarseness, smoothness or regularity. The basic types of computation are structural, statistical and spectral. Structural is the arrangement of texture elements while spectral is the analysis based in spatial frequency domain. Statistical is based on the intensity relationship of the pixels in statistical features like co-occurrence matrix. Co-occurrence matrix captures the spatial distribution of gray level and obtains features such energy, contrast, homogeneity and correlation.

Two texture properties of the image are being measured. Entropy is measured after applying histogram equalization to the green component of the image while homogeneity is by using Gray-Level Co-occurrence Matrix on the grayscale image.

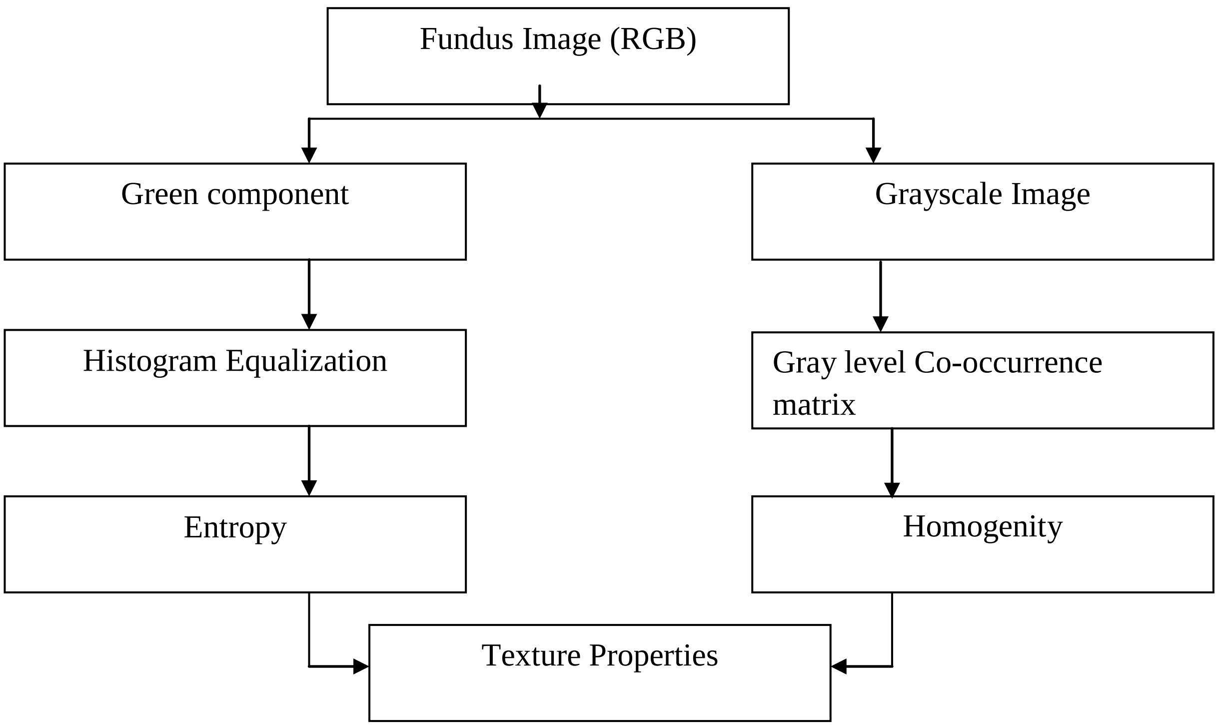


Figure 7.1 Block Diagram for Texture Identification

F.CLASSIFIER

For classification an appropriate number of training images are trained to detect the required For training and testing the fundus images, Artificial neural network models are specified by network topology and learning algorithms. We are designed three classes Normal, Mild, Higher. The respectively binaries are 00,01,10.

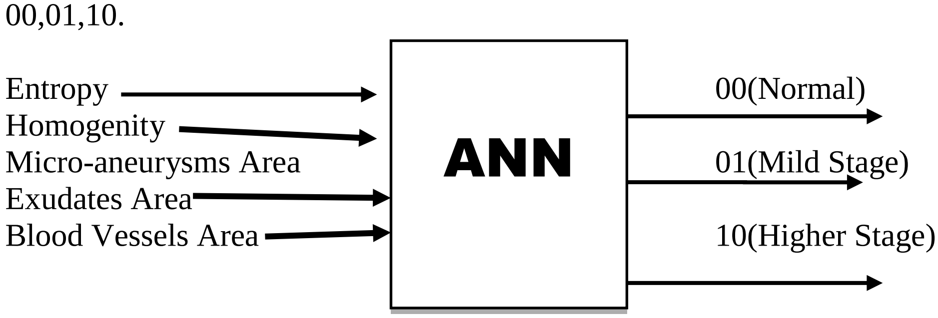
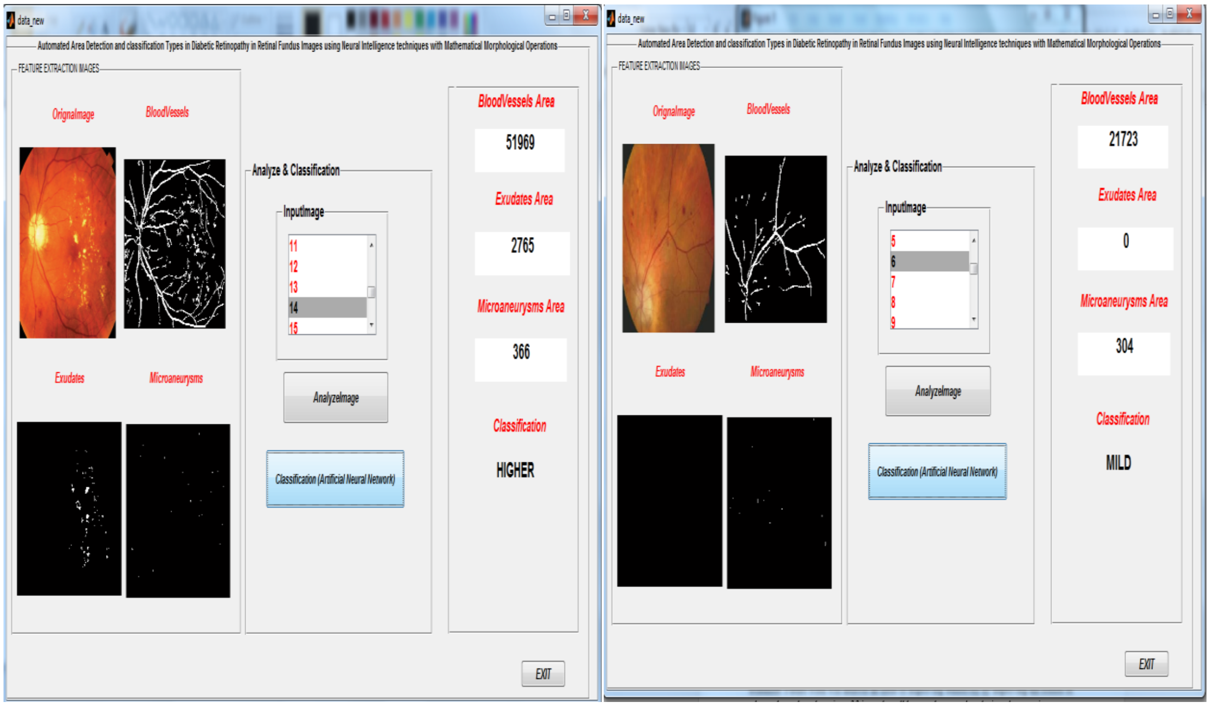


Figure 8 Block Diagram for ANN Inputs and classes

IV. RESULTS

The proposed framework increases accuracy of classification using Circular Hough transformation method. After performing the testing task, we have obtained the grading of Diabetic Retinopathy .For testing, input images were taken from the database, and the first stage is mild of Diabetic Retinopathy which is shown in fig. 9 (a) shows the binary status of 10. The second stage is Higher that consider Exudates, Micro-aneurysms and hemorrhages detection shows in fig.9 (b) through ANN classifier. With GUI representation on Matlab 2015a.



(a) (b)

Figure 9 GUI shows (a) class HIGHER (Left) (b) CLASS MILD(Right)

V.CONCLUSIVE DISCUSSION

A fast and reliable detection method for detecting Stages of disease has been presented in this work. This method is developed to detect Micro-aneurysms, Exudates and Blood Vessels Detection from DR fundus images. The micro aneurysm and blood vessel detection could also be added in order to facilitate ophthalmologists' decision on severity of the disease and to give laser treatment. Future work will address an issue of improving sensitivity by improving the results of other tasks such as detection of faint and small hemorrhages and analysis and comparisons on other classifiers like SVM…etc.

TABLE I.

Dataset for Fundus Image Classification

Category	No. of training Images	No. of testing Images	No. of Images/Class
Normal	20	100	120
Abnormal	65	100	165
Total	85	200	285

TABLE II

Category	No. o f Test Images	Neural network		
		CCI	MI	CA
Normal	70	68	2	97
Abnormal	70	69	1	98

Classification Accuracy of Classifiers

CCI = Correctly Classified Images, MI = Misclassified Images, CA = Classification Accuracy (in %)

VI .ACKNOWLEDGEMENT

My sincere thanks to my Mother Sunita Sharma for support and caring and also thanks to my friends and colleagues to my friend, Mr. Ashish Sairawat, I owe my debts that I can barely articulate, let alone repay. 'Finally, I wish to express my deepest gratitude to my mother, father, brother and sister who gave me the best in life and in their different ways, nourishing my faith in the holiness of the hearts affections, and in the truth of imagination

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