Identification of different stages of Diabetic Retinopathy using artificial neural network

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Identification of different stages of Diabetic Retinopathy using Artificial Neural Network

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***Abstract*— In this study, we recognize different stages of Diabetic Retinopathy (NPDR – Non Proliferative Diabetic Retinopathy and PDR – Proliferative Diabetic Retinopathy) and differentiate it from a normal eye with the study of fundus images. Features are extracted from these images and fed into the MLP (Multilayer Perceptron) for classification and the results have shown an accuracy of 94.11%.**

Keywords*— *Diabetic Retinopathy, Fundus Images, Exudates, Multilayer Perceptron (MLP)

I. INTRODUCTION

World Health Organization estimates that around 300 million will suffer from diabetes by the year 2025. One of the major effects of this disease is on human eye terming it as Diabetic Retinopathy. It can be classified as nonproliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). The disease causes an irreversible damage to the eye so early detection and diagnosis will help in reduction of damage to eye. Thus, doctors emphasize on routine medical check which the use of special facilities for detection and monitoring of the said disease. Researchers have recommended various techniques for helping the doctors using medical image processing. Our aim in this paper is to present an automated aid for doctors which combine medical image processing techniques with artificial neural network. This section of the paper describes eye anatomy along with a brief description of NPDR and PDR effects on the eye. In section 2, we describe the flow of our proposed work. Section 3 explains our image pre processing steps with extracted feature description. After that in section 4 multilayer perceptron, which is used for classification, is explained. Section 5 discusses results which were achieved from our study.

Our human eye, analogous to a camera, is an immensely complex and fragile organ which sends a huge amount of information to the brain. It is susceptible to many diseases and over the period of time it has increased many folds. In fact, "Prevent Blindness" estimates that the number of people with age-related eye diseases and the resulting vision impairment are expected to double within the next three decades [1]. One of the most prominent and critical eye diseases, which we shall cover in this study, is Diabetic Retinopathy.

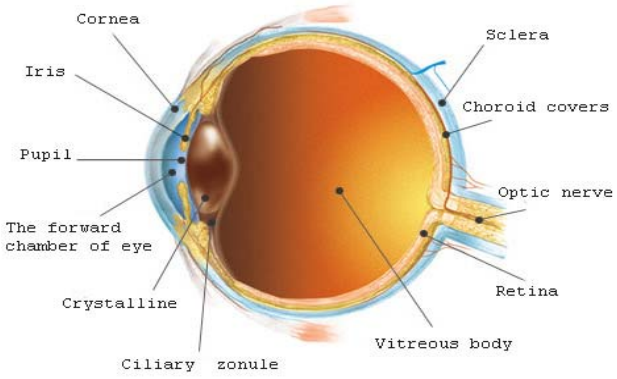

Fig 1. Structure of Human Eye

When the small blood vessels in the retina are damaged, it leads to Diabetic Retinopathy caused by complications of diabetes mellitus which can eventually lead to blindness if left untreated. Approximately 80% of all patients who have had diabetes for at least ten years suffer from some degree of diabetic retinopathy and consequently for people aged 25 to 74; it has become the most significant reason for new blindness.

Primarily, there are two types of diabetic retinopathy: Non proliferative diabetic retinopathy (NPDR) and Proliferative diabetic retinopathy (PDR). NPDR is the most primitive stage of Diabetic Retinopathy. During this condition, small amount of blood and other extra fluid leak into the eye due to damaged blood vessels in the retina. Due to closing of the blood vessels in the retina, PDR occurs inhibiting enough blood flow. In an attempt to supply blood to the area where the original vessels closed, the retina responds by growing new blood vessels, called neovascularisation. [2]

For diagnosis and monitoring of various eye diseases, ophthalmologists use fundus images which will be taken as input to our system as well. Fundus photography takes into account the retina, fovea, macula and optic disc and creates an image for it. Fundus images are digitized data given by fundus camera that can be used for detection of diabetic retinopathy.

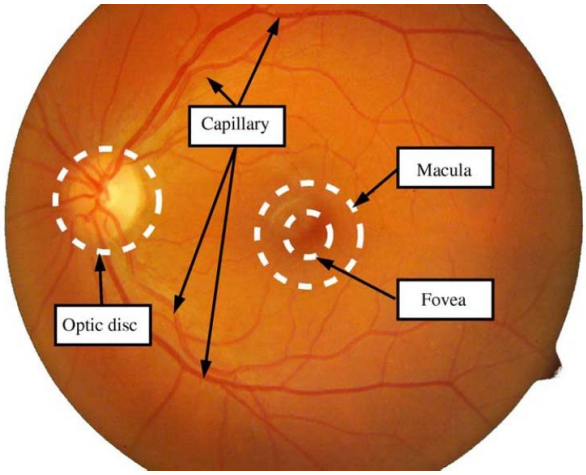

Fig 2. Fundus Image of Normal Eye [3]

Various regions of fundus images are -
Optic Disc: Circular portion at the back where nerve fibers join together to form optic nerve.
Macula: Part of retina which is the main cause for detailed vision.
Fovea: Located at the center of macula, it is the main reason for sharpest vision.

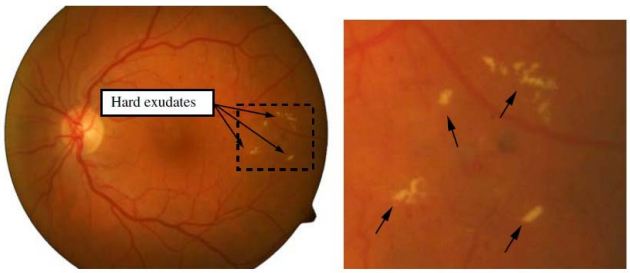

Fig 3. (a) NPDR showing hard exudates and (b) close up of hard exudates

Hard Exudates: Leakage in retina due to cholesterol and fat accumulation.

Microaneurysms: Small protrudes in blood vessels that leak fluid in retina.

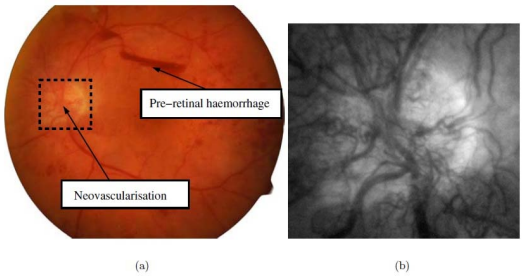

Fig 4. (a) PDR showing neovascularisation and Pre-retinal haemorrhage and (b) close up of neovascularisation

Pre-retinal haemorrhage: Delicate new blood vessels that bleed into the vitreous preventing light rays from reaching the retina.
Neovascularisation: New blood vessels that blocks the normal flow of fluid out of the eye.

The analysis of these fundus images through digital image processing forms the basis of our study. There has been an exponential and plethoric rise in cases of diabetic retinopathy and so, it becomes very essential for us to work on application of technology and tapping into huge potential of computer software towards enriching and advancing medical knowledge. Moreover, simplified approach of detection of various stages of diabetic retinopathy will ease the process of diagnosis and provide an efficient method to differentiate it from a normal eye.

II. PROPOSED WORK

In this paper, we present an approach for classification of diabetic retinopathy with the help of fundus images using Multilayer Perceptron (MLP) with back propagation. For identification of diabetic retinopathy, collected fundus images from hospitals undergo several image pre-processing techniques in order to extract desired features. Area of on pixels, mean and area of exudates are the three features extracted and fed into the neural network. MLP based training is applied to analyze the data and find an optimal way to classify images into Normal, NPDR or PDR categories.

A. Collection of Fundus Images

An elaborate search for professional fundus images yielded in collection of almost 150 images. The images were taken from two different hospitals in Noida and Delhi for the input data-set. Distinctly demarcated images of each category namely PDR, NPRD and normal eye were provided for efficient classification and improved training.

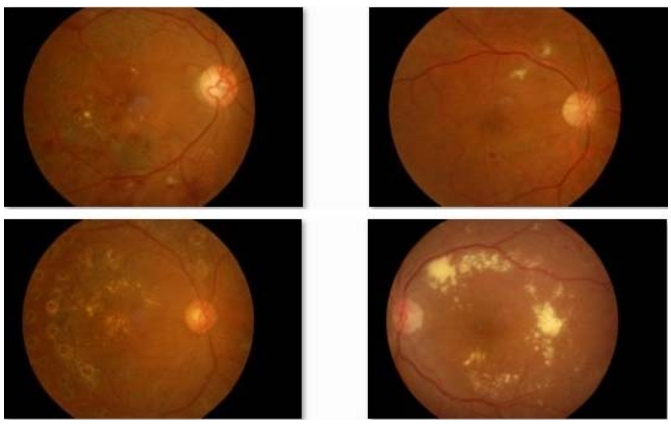

Fig 5. Sample of Fundus Image collected

III. IMAGE PRE-PROCESSING

Image pre-processing deals with enhancing data images prior to computational processing. It can significantly increase the reliability and efficiency of proposed system.

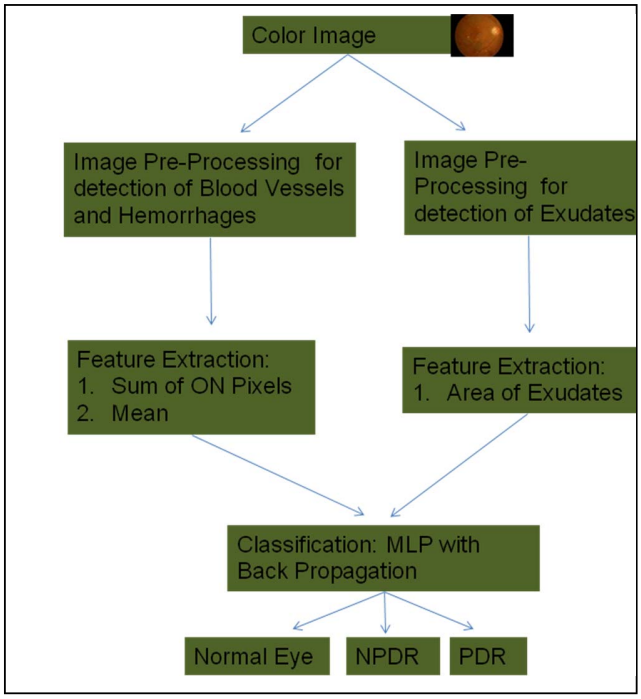

Fig 6. Flow Chart of Proposed System

A. Detection of Blood Vessels and Haemorrhages

For detection of blood vessels and hemorrhages, collected fundus images are processed by gray scale conversion, histogram equalisation, application of digital filters, gradient magnitude segmentation and finally fuzzy c clustering.

Gray Scale Conversion: Most of image pre-processing technique requires conversion of colour images into gray scale since it carries only intensity information and value of each pixel is a single sample. For its implementation, we first fetch the values of Red, Green and Blue (RGB) components and then combine 30% of red, 59% of green and 11% of blue. [4]

Fig 7. Gray Scale Image

Histogram Equalisation: After conversion into gray scale, contrast adjustment is brought about by histogram equalisation. Through this, intensities are better distributed on the histogram which is accomplished by effective spreading out of most frequent intensity values.

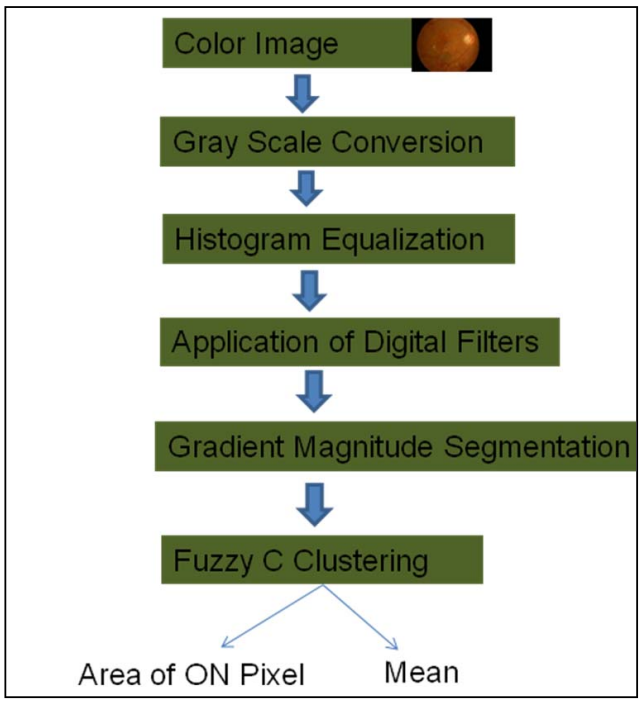

Fig 8. Flow Chart for detection of Blood Vessels and Hemorrhages

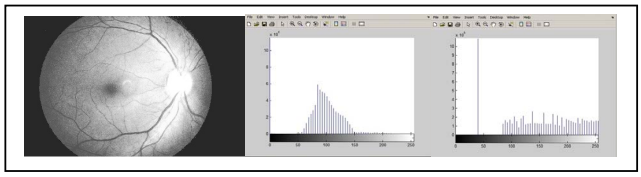

Fig 9. (a) Histogram Equalized Image (b) Before Application (c) After application

Applying Filter and Gradient Magnitude Segmentation: Digital 2-D filters are applied on contrast enhanced image for edge detection and typically, Sobel operator is used to find the approximate absolute gradient magnitude at each point so it is preferred over other operators. Moreover, detection of edges of blood vessels and haemorrhages requires emphasize on region of high spatial frequencies which is the basic principle of sobel operator.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

When the kernels are implemented on the input image, it results in different values of the gradient component in each layout (assume it to be Gx and Gy). These are joined together to give us the absolute magnitude of the gradient at all points and the layout of that gradient. [5] The gradient magnitude is given by:

$$|G| = \sqrt{Gx^2 + Gy^2}$$

The gradient is high at the borders and low inside the fundus images thus providing a somewhat distinction between blood vessels, haemorrhages and the other components of the image.

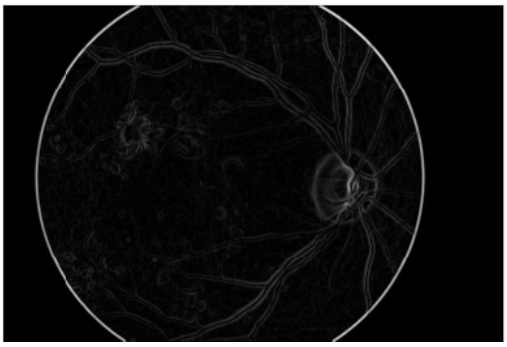

Fig 10. Gradient Magnitude Segmented Image

Fuzzy C Clustering: FCM (Fuzzy C Means) is a way to cluster or group together a single instance of data to belong to two or more other groups (clusters). The main aim is to recognize natural clusters of data from a huge data set to represent a better picture of system's behavior.

Here, it is used to detect blood vessels and haemorrhages in eye images by grouping them into one category as on pixels and the remaining part of the eye as another category as off pixels [6]. Threshold is calculated by 3-class fuzzy c-means clustering which outputs the binary image and threshold level of image. It often works better than Otsu's method since the latter gives larger or smaller threshold on fluorescence photos. A switch of cut-off position is taken as 1 for clear detection of components in binary form.

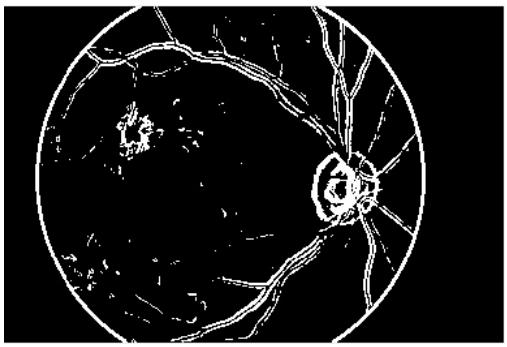

Fig 11. Detected Blood Vessels and Haemorrhages

B. Detection of Exudates

For detection of exudates, image processing is carried out by first selecting the green channel, gray scale conversion, conversion into binary through decided threshold, morphological closing and finally eliminating largest area (optic nerve) to get exudates.

Green Channel Selection and Gray Scale Conversion: As stated by Walter et al. [7], the exudates appear more contrasted in the green channel component than the other channels of the colour image. Hence, the green channel component images are used, in our method, to detect exudates. Consequently, the image is then converted to gray scale to further carry on processing.

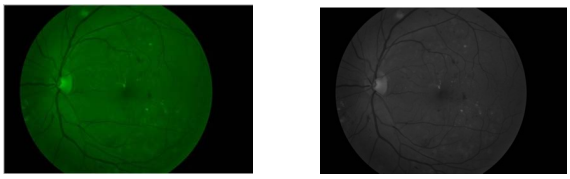

Fig 12. (a) Green Channel Selection (b) Gray Scale Conversion

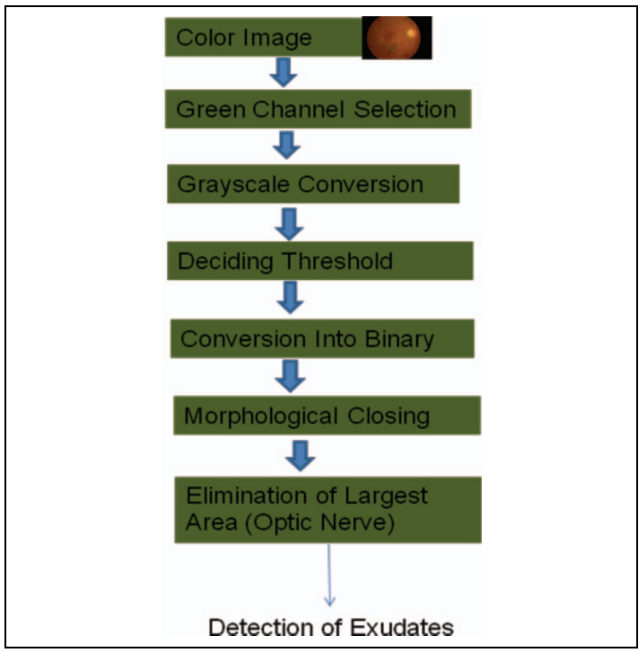

Fig 13. Flow Chart for detection of Exudates

Deciding Threshold and Binary Conversion: Using graythresh function on the gray scaled image, one level of threshold value is evaluated. But it was found that these values did not produce desired results for detection of optic disc and exudates. So, a factor of 0.15 was added to the previously calculated result and verified consistent with all the testing fundus images for detection of exudates and optic disc. Finally, with this new threshold level our image was converted into binary that consist of pixel values 1 and 0.

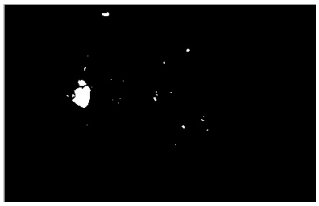

Fig 14. Detected Exudates and Optic Disc

Morphological Closing: The optic disc which is bright has similar features when compared to exudates, and thus can give false recognition; so it becomes necessary to remove it [8]. In fundus images, the optic disc is marginally separated with the presence of blood vessels at the extreme corner of the disc resulting in extremely close fragmented portions as seen in figure 11. In order to group them together dilation is performed, and then it is followed by erosion to separate the optic disc from the exudates (close operator). The structuring element used is 'disc' since it results in proper dilation of disjointed components of optic disc in a circular fashion [9].

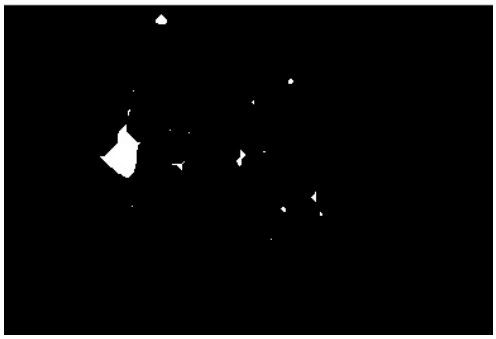

Fig 15.Morphologically Closed Image

Elimination of Largest Area and Detection of Exudates: Finally, using the regionprops each connected component in the image is formulated with respect to their areas. The region with the maximum area (optic disc) is found and then eliminated in order to get the rest of the binary images just containing the exudates.

Fig 16. Detected Exudates

C. *Feature Extraction*

We calculate three different parameters of feature extraction after all the above steps are followed:

1. Area of ON pixels: With reference to blood vessels and hemorrhages detection, the total sum of white pixels with value as '1' on the binary image helps us to differentiate between different stages of diabetic retinopathy.

2. Mean: It is a highly possible that the images are of uneven resolutions or sizes. Area of on pixels becomes unreliable as it could give less sum values of small fundus images with many hemorrhages as compared to bigger fundus images with no hemorrhages. Thus, there is a need to find out the arithmetic average which would then bring both the images at par during comparison.

$$\text{Mean} = \frac{\text{(Sum of ON pixels)}}{\text{(Total no. of ON + Black pixels)}}$$

3. Sum of exudates: The total area of exudates present in the image will also help us during classification of the disease. With exudates prominently present in NPDR, it becomes an important feature for efficient demarcation.

IV. MLP (MULTILAYER PERCEPTRON) BACK PROPAGATION FOR CLASSIFICATION

After the features are extracted, our neural network was trained using them as input data set. The artificial neural network (ann) type used in this study is MLP (Multilayer Perceptron) with back propagation. It is a feedforward ann that maps input data set to appropriate outputs and uses a supervised learning method, called back propagation, for network training. The connection weights are changed after every data process and on the basis of error in the output as compared to our expected results [10].

Training set are shown repeatedly until stopping criteria are met and each full presentation of all patterns is called an 'epoch' [11].

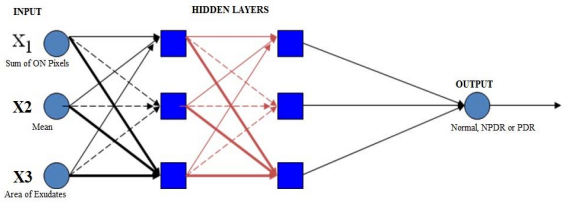

Fig 17. MLP Architecture of our system

The training, validation and testing was carried out with following details:
No. of hidden layers- 2
Total no. of samples-100
No. of images for testing- 34
Iteration count-56

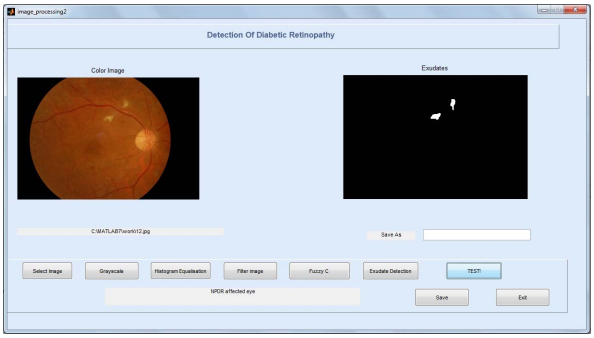

Fig 18. GUI of proposed system

V. RESULTS AND DISCUSSION

The features were extracted and served as input to the classifier with following results. The results of MLP classification are shown in Table 1 and thus, we can show that our classifier identifies all the normal and PDR tested images whereas in the case of NPDR it was unable to identify 2 images correctly.

TABLE I. RESULT OF MLP CLASSIFICATION

No. of Trained Images	No. of Tested Images	No. of correctly classified images	Accuracy (%)
100	34	32	94.11%

VI. CONCLUSION AND FUTURE WORK

This paper provides a basis of classification of Normal, NPDR or PDR affected eye with high accuracy percentage of 94.11%. These results strengthen the idea that MLP can be used efficiently as a classifier for detecting eye related diseases in fundus images. Even with such results and progress, our network won't give desired results in case the exudates areas at a particular section in fundus exceed that of optical disc. With these limitations and results, work should be carried on to derive several more features and develop more efficient systems.

ACKNOWLEDGMENT

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