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Research paper

Classification of Diabetic Maculopathy from Retinal Images

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Abstract

Diabetes mellitus is a significant cause for visible loss and vision deficit. All patients with type 1 diabetes and greater than 60% of type 2 diabetes suffer a few degrees of retinopathy, due to diabetes for a long time. The damage of the normal vision, contingent upon the significant of damage of the macula, is due to diabetes retinopathy, which extends to Maculopathy. The main objective of this work is to design a method and develop software to identify the seriousness of diabetic maculopathy, using image processing techniques on retinal images. The proposed framework classifies different types of maculopathy as Normal or clinically important and non-clinically significant maculopathy from fundus images. The features had been separated from the original fundus image with morphological operations and strengthened with two classifiers, the Artificial Neural method (ANN) and probabilistic neural methods (PNN). The proposed method established that ANN has the best characterization performance efficiency of 96.67% compared to PNN.

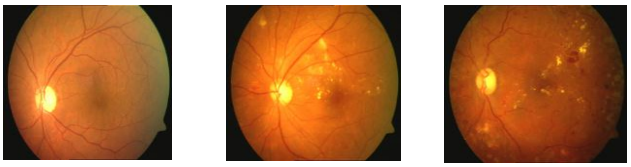
Keywords: *Image processing, classification, Diabetic maculopathy, Feature extraction, macular Segmentation.*

1. Introduction

One of the greatest concern and immediate challenges to the current health care is the severe progression of diabetes. Many of the complications of diabetes do not show until after many years of having the disease. They usually develop silently and gradually over time, although people with diabetes are not having any signs of complications, they may still eventually develop them. Retinopathy can occur with all types of diabetes and can lead to blindness if left untreated. If the condition is detected early enough for laser treatment, most of the blindness can be prevented but many patients remain undiagnosed even as their disease is causing severe retinal damage. Retinopathy is usually occurred due to damage to the tiny blood vessels next to the retina which has some tiny microaneurysms, and tiny leaks of fluid (exudates) or bleeds (haemorrhages). If these abnormalities cited above extend to the macula area the impact becomes more severe, the name of this condition is diabetic maculopathy. There are four different categories of maculopathy disorders, namely normal, mild maculopathy, moderate maculopathy and severe maculopathy of retina. Mild and moderate maculopathy are classified as Non-clinically significant maculopathy (Non-CSME) whereas severe maculopathy is classified as clinically significant maculopathy (CSME).

Both non-clinically significant maculopathy (Non-CSME) and clinically significant maculopathy (CSME) are two types of maculopathy lead to vision loss. In Non-CSME stage, exudates start to leaks out from the damaged vessels which results from diabetes. In this stage, the patient's vision is not seriously affected because the exudates locations are far away from the fovea. In CSME stage, most of the retinal blood vessels are damaged and the leakage area increases. This result exudates leak out and deposit very close to the fovea. Hence, this affects the very centre of the macula area and will affect the vision.

The fundus images of normal eye, Non-CSME fundus image and CSME fundus image is shown in Figure 1.



(a) (b) ©

Figure 1: Fundus images: (a) normal (b) non-clinically significant maculopathy (c) clinically significant maculopathy

The current methods to detect and assess diabetic maculopathy are manual, expensive, potentially inconsistent, and require highly skilled personnel to facilitate the process by obtaining a large amount of fundus images . Hence, there is a need to have a good, automatic method based on modern digital image processing techniques that can perform faster and yield consistent results in non-invasive way[1]. A worldwide clinical diabetic retinopathy and diabetic macula oedema ailment seriousness scale progress methods were proposed by Wilkinson and others [2] to aid the retinal screening. Maculopathy is characterized by yellow sores near the macula and is an infirmity in the macula area of the retina. The macula area is a totally unstable area wherein the focal point of the macula, called fovea, a minor locale that is responsible for sharp vision[3]. Maculopathy exists when there are any exudates, hemorrhages or micro aneurysms inside the macula region. Screening or identification of diabetic maculopathy tells whether the patient has to refer to an ophthalmologist or not. Consequently, the mixed identification of diabetic retinopathy and maculopathy is fundamental to successfully control the diabetic retinopathy. Prior research work on Diabetic Retinopathy proposed a preparatory

method for the diabetic retinopathy screening [4], which recognized the fundus images into two classes; normal(no evident retinopathy) or strange (retinopathy) by the utilization of non-fluffy systems. At that point, the researchers continued a screening framework to go over the side effects of retinopathy [5]. Fuzzy Histogram Equalization and Circular Hough Transform end up noticeably showed to create higher impacts when compared with the essential method which executed the grayscale transformation, histogram leveling and Circular Hough Change systems. The retinal fundus images are the sources in the diagnosis and treatment of various eye diseases in clinics. Recognition of ordinary and abnormal retina are two essential learnings of diabetic retinopathy, proposed by Mookiah et al. [6] and Priya et al. [7]. Vimala and Kajamo hideen et al.[8], expressed the Exudates present in the macula which is the center portion of the retina is called maculopathy or macular edema, and the retinal images were preprocessed via. Contrast Limited Adaptive Histogram Equalization (CLAHE) where Macula which is the darkest region was obtained. To classify the preprocessed image into Exudates and Non-Exudates, a set of features based on color and texture were extracted. Classification was done using support Vector Machine This method appears promising as it can detect the severity of the disease where some morphological tasks have been connected. Likewise, a programmed framework in which it creates a binary map for possible exudate regions using filter banks and formulates a detailed feature vector for all regions. The system uses a Gaussian Mixture Model-based classifier to the retinal image in different stages of maculopathy by using the macula coordinates and exudates feature set.As per Tariq et al. [9], Punnolil et al[11]. Siddalinga swamy and Prabhu [10] first the Optic Disc is to be detected and eliminated. Then the features are extracted from segmented image and the feature vectors are then classified into exudates and non-exudates using Support Vector Machine (SVM) Classifier. A robotized examination which featured the referable maculopathy in retinal image for diabetic retinopathy screening transformed into proposed through Hunter et al. [12], while Chowriappa et al.[13] proposed a decision system to classify DM fundus images into normal, clinically significant macular edema (CMSE). Dynamic Fuzzy Histogram Equalization (BPDFHE), uses fuzzy statistics of digital images for their representation and processing. Representation and processing of images in the fuzzy domain enables the technique to handle the inexactness of gray level values in a better way, resulting in improved performance known as the Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) progress toward becoming proposed by methods for Sheet et al. [14], and later changed into utilized as a part of virtual pathology photos by Garud et al. [15].

2. Methodology

In the proposed method retinal images from MESSIDOR data base are considered as the resources. They are first preprocessed, then the features are identified for the further analysis. For the feature extraction i.e, to detect the location of the optic disc, fovea and macular region Image processing techniques are used and these are discussed in the following section. Hard exudates on the macula are the major abnormalities in Maculopathy. The exudates in the macular regions are identified as the features to feed into the feed-forward neural network and probabilistic neural network classifiers for classification of normal, non-CSME and CSME maculopathy images. The performances of the two classifiers are compared. Figure 1 shows the fundus images of normal, non-clinically significant and clinically significant diabetic maculopathy. Figure 2 shows the block diagram of the proposed system for identification of the diabetic maculopathy stages.

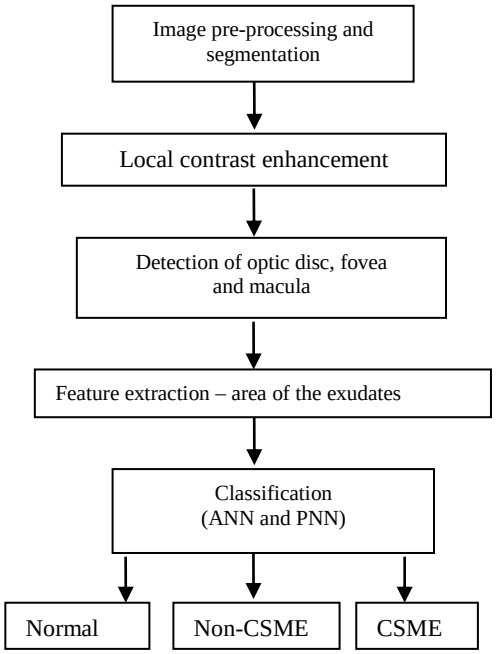


Figure 2: Proposed system for identification of the diabetic maculopathy stages

2.1. Image Preprocessing:

There is an extensive dissimilarity in the colour of the fundus taken from different patients. This dissimilarity is due to different acquision systems used, ambient brightness and also from region, race ,age etc. This causes difficulty in recognizing the foreground objects and back ground intensities from the color images. Under these conditions, there is every possibility that these lesions may erroneously be classified as background colour. Therefore, colour normalization is necessary to be performed. Pre-processing consists of RGB image is converting the RGB image into to a green channel or grayscale image. Then the intensity levels are adjusted through histogram equalization. Figure 3 below shows original image and pre-processed image.

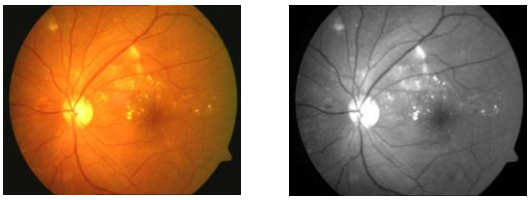


Figure 3: (a)Original Image(b)Pre-processed image

2.2 Image Segmentation

Image segmentation is a process of partitioning image pixels based on image features. This is to separate pixels that have different intensities into different regions, groups the pixels that are spatially connected and have similar intensity into different region. The process is based on a threshold intensity level. Figure 4 below shows segmented image from a gray scale image. Optic disc macula region and few exudates are visible from the image.

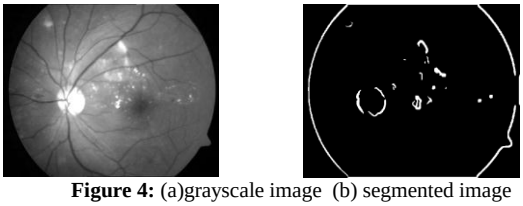


Figure 4: (a)grayscale image (b) segmented image

2.3 Detection of Optic Disc

The optic disc is the exist point of retinal nerve fibers from the eye and the entrance and exist point for the retinal blood vessels. It appears with similar intensity, colour and contrast to other features on the retinal image. While blood vessels also appear with high contrast as the optic disc, the green channel of the image with morphological closing operator on the intensity channel eliminate the vessels which may remain in the optic disc region. A flat, octagonal morphological structuring element with a fixed radius of fifteen was used. A column wise neighborhood operations was applied to set each output pixel of the image to the variance value of the input pixels of 8x8 sliding neighborhood. Figure5 shows the output images at consecutive operations from the gray scale image.

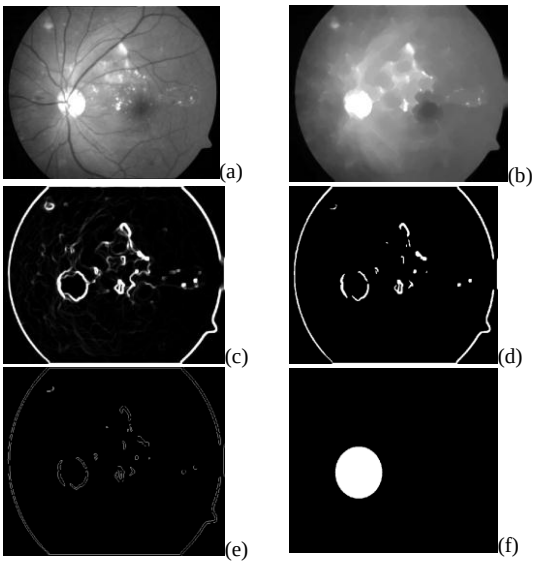


Figure 5: (a) Gray scale image (b) morphological closing (c) column wise neighborhood operations (d) segmentation, (e) Optic disc detection, (f)Circular mask on optic disc .

2.4.Detection of fovea

The centre of the fovea is usually located at a distance of approximately 2.5 times the diameter of the optic disc, from the centre of the optic disc. After locating the optic disc, the macula region can be determined by setting an area of restriction in the vicinity of the image centre, as determined by the optic disc centre. Two circle binary masks from the centre of the optic disc are drawn and the restriction area is set as 478x216 pixels and is identified as the macula region. Once the macula region is identified, the location of the minimum of this region was taken as the centre of the fovea.

2.5 Detection of Exudates

Exudates appear as bright patterns in colour fundus images and they are well contrasted with respect to the background that surrounds them. The shape and size of the exudates vary considerably

irregular during the progress of the disease. There are other features such as optic disc and blood vessels in the images that cause difficulty to detect exudates. They have high level variation and brightness patterns as compare to the exudates. The regions of the exudates are obtained after the removal of the optic disc, circular border and the four side of the image border.Morphological image processing techniques are used for detection of exudates. Dilation and erosion are the two fundamental morphological operations. Closing and opening are applied extensively for detecting the exudates. The algorithm developed uses a morphological operation to smooth the background, allowing exudates to be seen clearly. Two types of structuring elements are used. They are octagon elements to remove the vessels from the image and disk-shaped elements to identify the exudates. Morphological closing is then applied to the image. The dilation function is to fill the exudates while erosion function is to expand their sizes. Figure 6 shows the extraction of exudates and the exudates in the macula region.

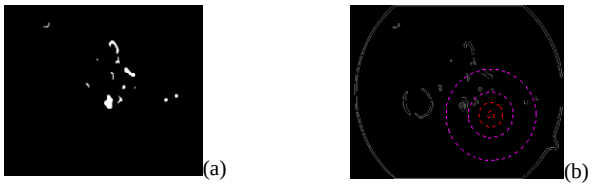


Figure 6: Exudates (a) Morphological closing operation, (b) Exudates in macular region

2.6. Features used for classification

The purpose of feature extraction is to reduce representation set of features, which distinguish input data. In this work, the exudates in the macular region are focused to identify the diabetic maculopathy stages. The below four main features are chosen for identifying the severity in the maculopathy images. These four regions in the macular area are stated.

R1 - the area of the exudates in the Foveola region;

R2 - the area of the exudates in the Fovea region;

R3 - the area of the exudates in the Parafovea region;

R4 - the area of the exudates in the Perifovea region.

Two classifiers are used in this work, the Artificial Neural Network (ANN) and the Probabilistic Neural Network (PNN), for classification. The performance of these two classifiers are compared. The ANN used for this project is the feed-forward network and uses supervised learning to train the neural network. Supervised learning is a technique in which the network is trained by providing it with input and matches it with a desired output. Feed-forward network often has one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. The network will only be tested for accuracy when it is undergoes training with the weights being adjusted according to its learning rules. A three layers network with sigmoid activation function is chosen as the classifier for this work. The input layer has four neurons corresponding to four features that were extracted from the data. The input neurons feeds the values to each of the neurons in the hidden layer which has a total of eleven neurons. Figure 7 shows the three layer feed-forward neural network used for classification. The three different classes for the output are represented as shown in Table 1.

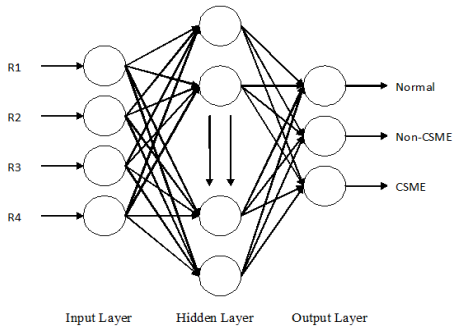


Figure7: Three layer feed-forward neural network classifier

Table1: Binary output for three classes

Classes	Binary Ouput
Normal	00
Non-CSME	01
CSME	10

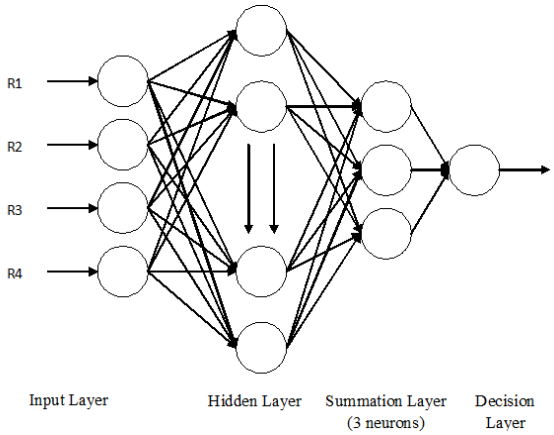


Fig8: PNN structure for classification

Table2: Integer output for three classes

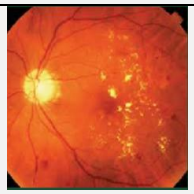
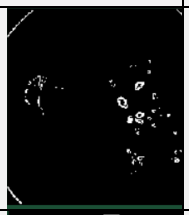
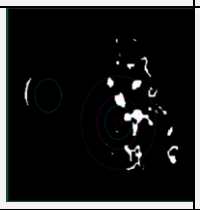
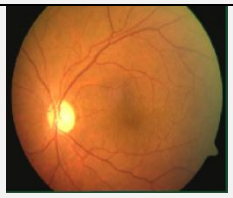
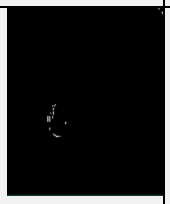
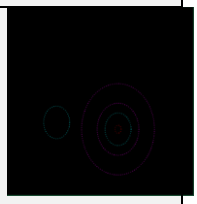
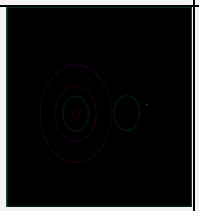
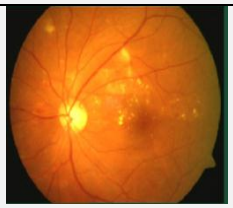
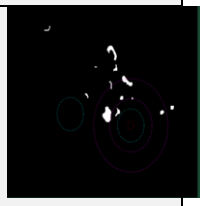
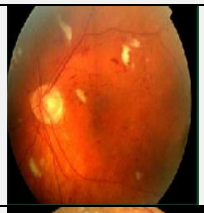
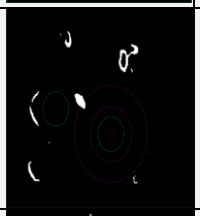
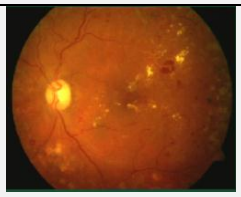
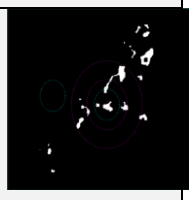
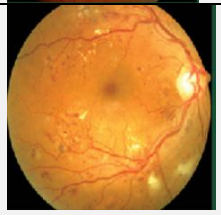
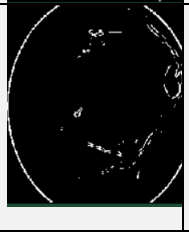
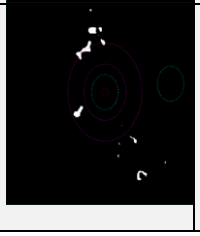
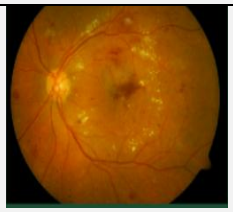
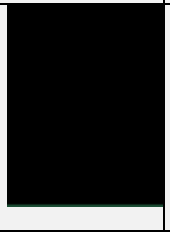
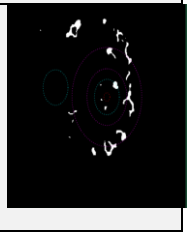
Classes	**Integers Ouput**
Normal	1
Non-CSME	2
CSME	3

The Probabilistic neural network (PNN) used in this work consists of four layers which are input layer, hidden layer, pattern layer or summation layer and decision layer. It has four neurons in the input layer corresponding to four features that were extracted from the input data. The input neurons feed the values to each of the neurons in the hidden layer. This layer has one neuron for each case in the training data set. The resulting values from the hidden layer are fed into the pattern layer / summation layer with three neurons since the classifier is trained with three different classes. The decision layer compares the weighted vector for each target class accumulated in the summation layer and uses the largest vector to predict the, target class of Normal or CSME or Non CSME. Figure 8 shows the four layers PNN used for classification. The three different classes for the output are represented as shown

3.Results

Table 3 shows the detection of exudates by the proposed method and Table 4 shows the statistical results of the same And the severity of diabetic maculopathy. The area covered by the exudates in the four regions (R1, R2, R3 and R4) are considered as parameters for identifying the severity in the maculopathy images . Data for the ANN and PNN classifiers is the total number of white pixel which indicates the exudates in each region. In normal and non-CSME images, the R1 and R2 values are zero due to the black area on the foveola and fovea regions. whereas there are R1 values in the minority of the CSME images and R2 values in all CSME images as compare to other images due to the number of white pixels exit in these regions. In majority of the CSME images, the R3 and R4 values are higher as compare to non- CSME images due to the area tends to be white.

Table 3 : Exudates Detection

S.No	Original Image	Segmented Image	Exudates Detection	S.No	Original Image	Segmented Image	Exudates Detection
1				6			
2				7			
3				8			
4				9			

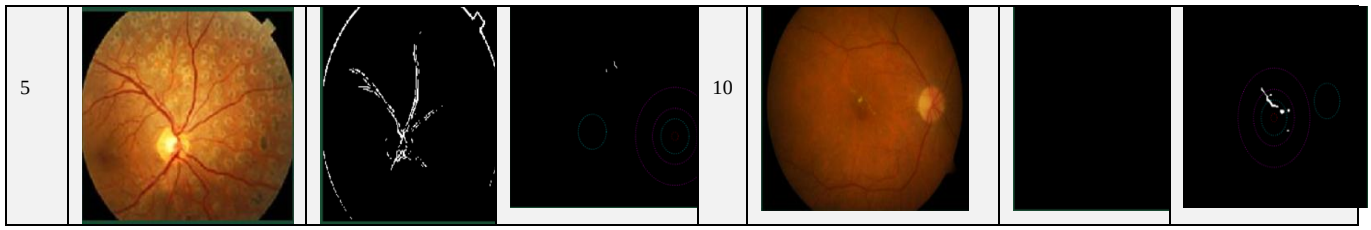


Table4: Classification of diabetic maculopathy

S.No	Image	Foveo-la(R1) In pixels	Fovea(R2) In pixels	Parafovea(R3) In pixels	Perifovea(R4) In pixels	Result
1	Image1	0	308	2225	4432	Clinically Significant
2	Image2	0	0	0	0	Normal Eye
3	Image3	0	0	0	470	Non-Clinically Significant
4	Image4	0	0	0	1492	Non-Clinically Significant
5	Image5	0	0	0	0	Normal Eye
6	Image6	0	0	0	0	Normal Eye
7	Image7	0	0	188	1919	Non-Clinically Significant
8	Image8	286	500	621	2320	Clinically Significant
9	Image9	0	120	429	2788	Clinically Significant
10	Image10	0	0	372	1970	Non-Clinically Significant

thus the number of white pixels is more in this class. In normal image, the values are zero due to black area on the parafovea and perifovea regions stages of Diabetic Maculopathy and have obtained accurate and precise results. In this work, a morphological step to automatically detect optic disc and exudates in the macular area from the images in attempting to detect the maculopathy at an early stage is detected. The optic disc was detected and eliminated prior to the exudates detection because both appear with similar intensity.

There are misclassified from the abnormal images and might need further diagnosis. This system intends to help ophthalmologists in detecting the diabetic maculopathy faster and more easily. The results show here indicated that the automatic diagnosis of diabetic maculopathy can be very successful. It is not a final result application but this system can give a preliminary diagnosis tool for ophthalmologists in evaluating the stages of maculopathy. This system is helpful in diagnosing the non-clinically significant maculopathy. So, the one can detect maculopathy at an early stage and hence the loss of vision can be prevented. The accuracy and performance of the classifiers can be further improved by increasing the size of the training data. By extracting the proper features from the optical images can enhance the classification results. The software for feature extraction and the program for classification of retina images are written in MATLAB 2015a which can be enhanced with future version.

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