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Diagnosis of Diabetic Retinopathy from Fundal Photography

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ABSTRACT

Diabetic Retinopathy is an eye disease caused by Diabetes Mellitus. It is a major disease that has affected millions of people, the rate of people getting affected will increase exponentially in the upcoming years. It is caused by high blood sugar due to diabetes. It can be treated early during the starting stages, the vision problem will reduce. This project aims to create a system that can integrate image processing techniques together to predict whether the retinal image received from the patient is affected by DR or not. Color retinal images are important tools for diagnosing diabetic retinopathy. Images are captured from a fundus camera, stored on a computer, analyzed using a feed propagation neural network. Diabetic Retinopathy can be deducted by using Hemorrhages and Exudates deduction. After the elimination of the optic nerve and nerve cup, hemorrhages and exudates are deducted. The network is trained to recognize features in the retinal image. The digital filtering techniques and different features of extraction by GLCM are evaluated. ANN classification identifies the type of the diabetic retinopathy disease. The images are used to evaluate the neural network training tools for training state, regression, performance. The confusion matrix is also identified in this project.

KEYWORDS

Image processing, Hemorrhage Deduction, Exudates Deduction, GLCM Features, Neural Network, ANN Classification.

Introduction

People with diabetes can have eye disease defined as Diabetic Retinopathy. It is a problem of diabetes and a leading cause of blindness. It damages the blood vessels in the retina and causing them to leak fluid and distort vision. DR may cause no symptoms of diabetes or only mild vision problems in the retina. Sometimes, it can cause blindness. The condition can promote in anyone who has type 1 or type 2 diabetes. Type 1 diabetes or diabetes mellitus is also called insulin-dependent diabetes. It is an autoimmune condition and it does not produce enough insulin in the pancreas. Type 2 diabetes used to be called non-insulin-dependent or adult-onset diabetes and the cells have stopped responding well to insulin. There are two main stages of diabetic eye disease are Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The early stage of DR is NPDR and it weakens the walls of the retinal blood vessels. The PDR stage is the post-stage, and an advanced stage of DR and it has abnormal blood vessels. Hemorrhage and Exudates detection are the types of NPDR stages. A hemorrhage occurs when blood outflows from the retinal vessels. Exudates can be prevented only in early methods of screening process. Normal retina and Diabetic Retinopathy is shown in Fig.1.

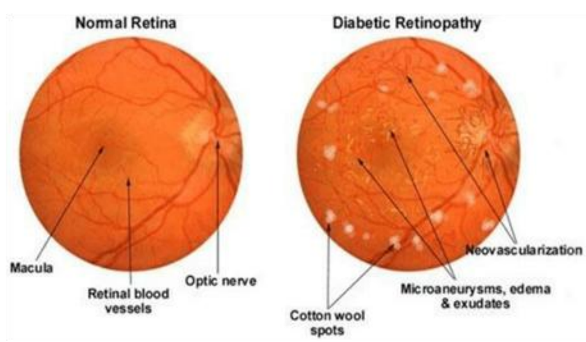

Fig. 1. Normal retina and Diabetic Retinopathy

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In the proposed system, first, eliminate the optic nerve by the segment and then apply the blurred mask to the original image so that the optic cup is detected and also the circular mask is applied to eliminate the optic cup. After the elimination of the optic nerve and optic cup, the hemorrhage and exudates pathology is identified. Hemorrhages are the dark area of the retina and exudates are the white area of the retina. To segment, the pixels based on the particular threshold value, post processing is done through erosion and dilation process. Then feature is calculated by GLCM and classify the disease by ANN.

Objective

The main objective of this project is aimed to develop the digital image processing algorithms for diagnosing DR from fundus photography to identify the components of the retinal image. Deduct the hemorrhage and exudates detection of the Diabetic retinopathy. The GLCM features consist of contrast, correlation, energy, homogeneity, entropy, standard deviation, area are calculated and also classify the ANN classification.

Methodology

The retinal images are used for different sources for detecting and training the DR and it consists of 12 retinal images from the dataset of DIARECTDB. The hemorrhage and exudates deduction of DR, neural network training, confusion matrix is performed using MATLAB R2018a with the MATLAB Image Processing Toolbox. Methods of Diabetic Retinopathy are based in the following steps as illustrates in Fig. 2.

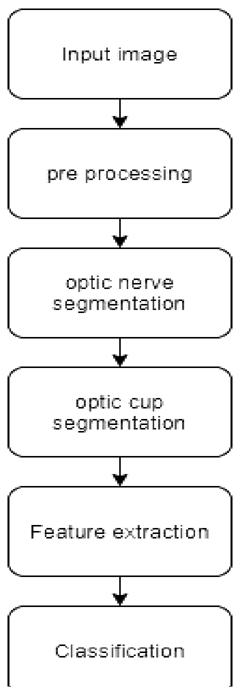

Fig. 2. Methods of Diabetic Retinopathy

A. Input Image

In the Diabetic Retinopathy method, to collect the input color fundus images from the standard Dataset of Diabetic Retinopathy is DIARECTDB.

B. Preprocessing Module

In this module, convert the RGB image capture by the camera into an HSV color model. After, conversion of the color model, to separate the color plane. The color plane involves color information in images. ‘Comparing’ sections

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in images is the concept used in image processing. Comparison of the Gray scale requires simple scalar algebraic operators. In color plane extraction, first, convert the HSV image in to a gray image and then filter, the obtained result using median filtering.

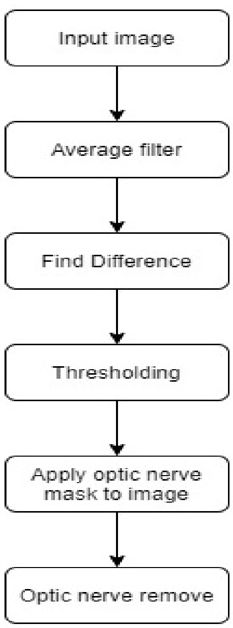
C. Segmentation Module

Threshold operation is used to create binary images in image processing. The grayscale samples are accumulated into two parts as background and object. In this case, a multilevel threshold is performed using Otsu's method. More than one threshold is determined for a given image and segmentation is done creating certain regions. One background with many objects is the result of this multilevel threshold. It is a clustering-based image threshold.

D. Hemorrhages Deduction

The presence of hemorrhages in the retina is the earliest symptom of diabetic retinopathy. Early automated hemorrhage deduction can help to reduce the incidence of blindness. Hemorrhages will occur when the microaneurysms burst.

Initially read the images of DR and to contrast enhancement of the gray image. To apply the average filter and take the difference between the gray image and then apply the applicable threshold. Hereafter, convert to binary and remove small pixels in that image. To apply overlay and masking and remove the optic nerve from the image. YUV color spaces are used for the decoupling of luminance and color information. Convert the YUV to a gray image. To find out the optic disk and remove the optic cup. Finally, detect the hemorrhage deduction. The optic nerve segmentation and optic cup segmentation are shown below in Fig.3 and Fig.4.



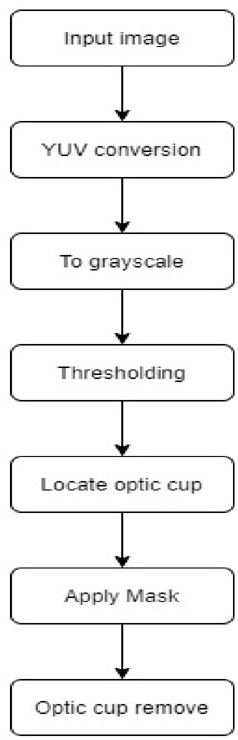


Fig. 3. Optic nerve Segmentation **Fig. 4.** Optic Cup Segmentation

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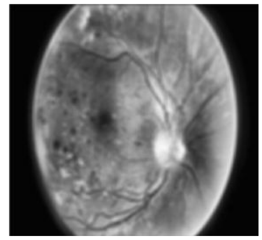
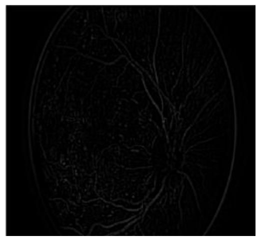
The step-by-step processes for the deduction of hemorrhages are shown below in Fig.5.

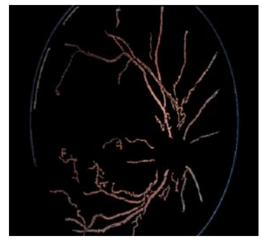
a) Input image



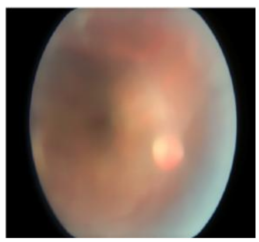
b)Filtered image



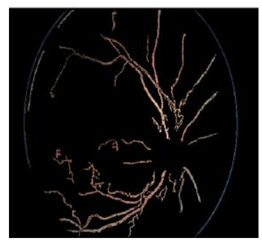
c) Subtracted image



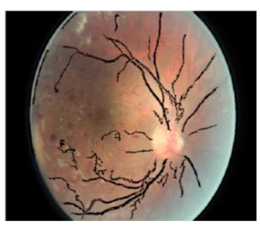
d) Overlay



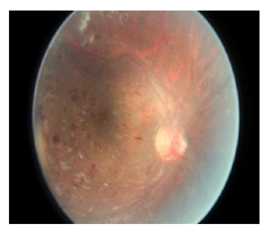
e) Blending image



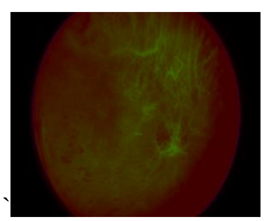
f) to apply mask



g) applying mask



h) remove nerve



i) YUV model

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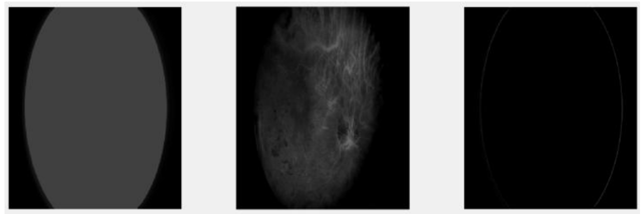
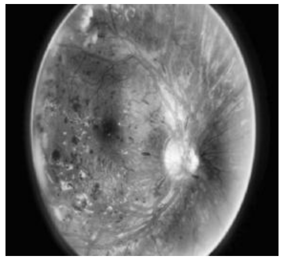
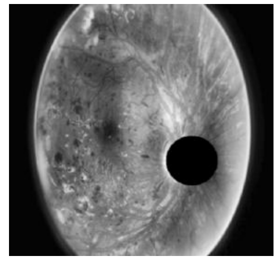


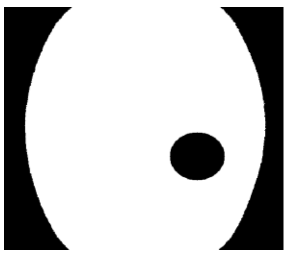
j) YUV model Conversion



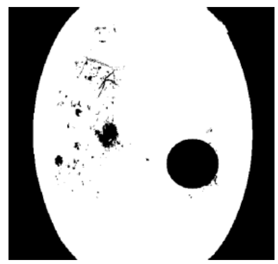
k) YUV to Gray



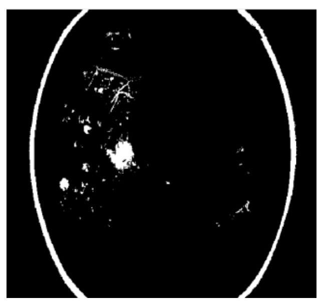
l) optic cup removal



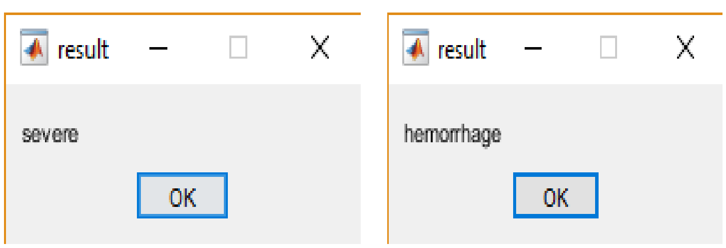
m) background



n) Hemorrhages deduction



o) removed hemorrhage



p) Results of Hemorrhage Deduction

Fig. 5. Processes in Hemorrhages deduction

E. Exudates Deduction

The leaked fluid produces sediments composed of lipid byproducts called exudates. Exudates are yellow and appear

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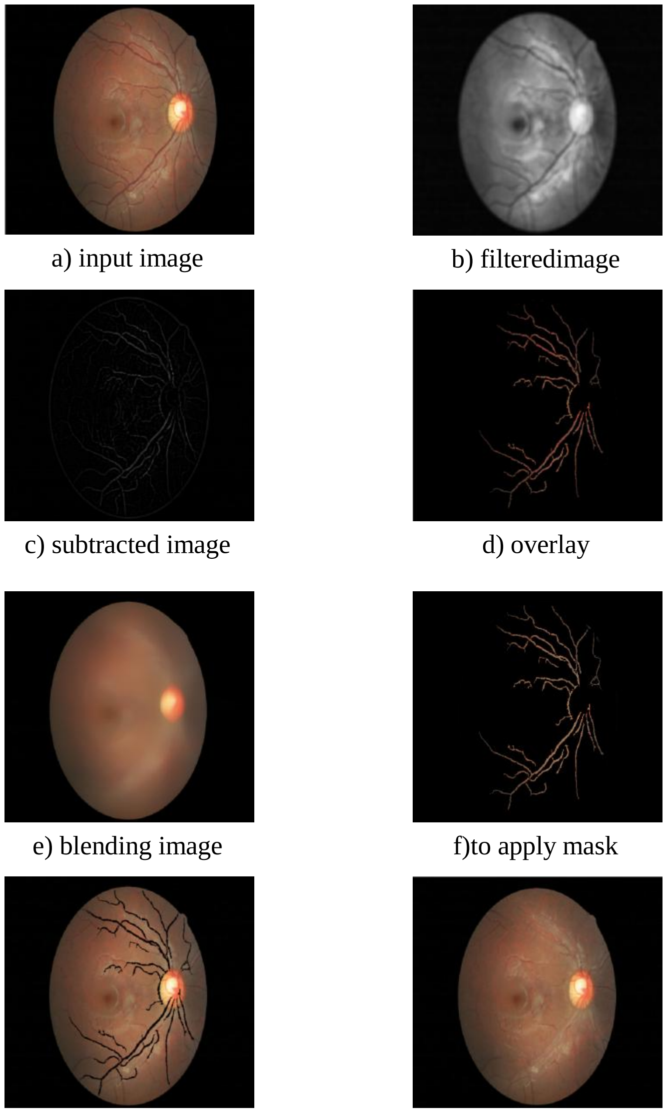
in different sizes and locations within the retina. Read the image of diabetic retinopathy and the contrast enhancement of the gray image. To apply the average filter and take the difference between the gray image and then apply the applicable threshold. After that convert to binary and remove small pixels in that image. To apply overlay and masking and remove the optic nerve from the image. YUV color spaces are used for thedecoupling of luminance and color information. Convert YUV to the gray image. To find out the optic disk and remove the optic cup. After applying the threshold and remove the optic disk. Subsequently, deduct the exudates deduction.

The step-by-step processes for the exudates deduction are shown below in Fig.6.



a) input image

b) filteredimage

c) subtracted image

d) overlay

e) blending image

f)to apply mask

g) applying mask

h) remove nerve

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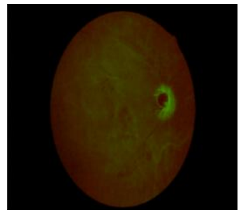
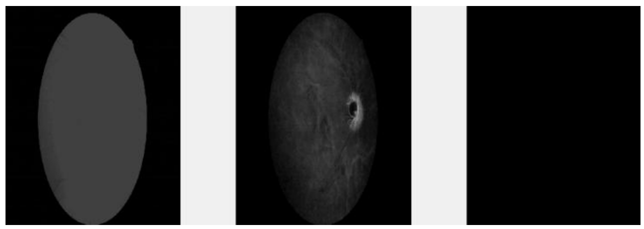
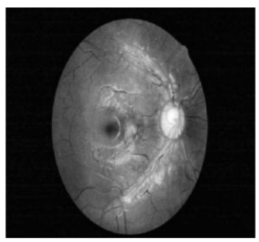


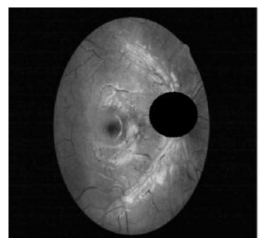
i) YUV Model



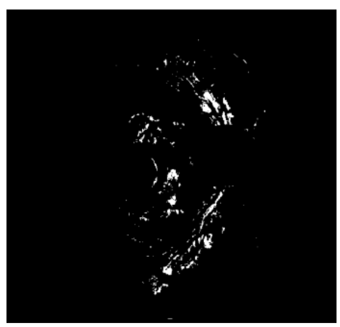
j) YUV model conversion



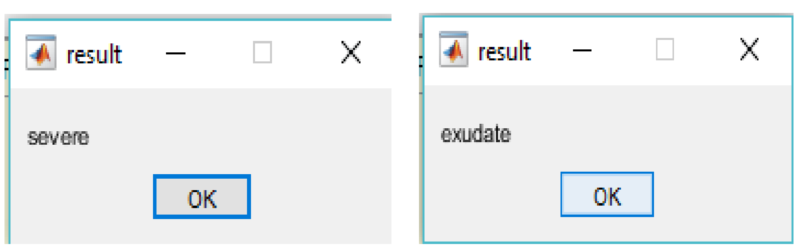
k) YUV to Gray



l) optic cup removal



m) exudates deduction



n) Results of Exudates deduction

Fig. 6. Processes in Exudates Deduction

F. Post Processing Module

Morphological operation in image processing provides a mathematical tool for shape analysis in both binary and

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grayscale images. It can be used in the representation and description of region shapes are boundaries, skeletons, and the convex hull and also used for filtering, thinning, pruning. In morphological operation, there are two fundamental operations consist of dilation and erosion, in terms of the union of an image with translated shape termed as structuring element. This is a fundamental step in extracting objects from an image for successive analysis. The fundamental operations in morphological can be indexed as

1) EROSION

It is one of the two basic operators in the area of mathematical morphology. It is mostly applied to binary images, but some versions work on grayscale images. The basic effect of the operator on a binary image is to erode the boundaries of regions of foreground pixels. Hence, areas of foreground pixels shrink in size, and holes within those areas become larger.

2) DILATION

It is the system that grows or thickens the objects in an image and is known as a structuring element. Graphically, structuring elements can be represented either by a matrix of 0s and 1s or as a set of foreground pixel.

G. *Feature Extraction*

1) Gray Levl Co-occurrence Matrix

The co-occurrence matrix is referred as Gray Level Co-occurrence Matrix (GLCM), Gray Level Co-occurrence Histograms (GLCH), spatial dependence matrix. The co-occurrence matrix or co-occurrence distribution is a matrix or a distribution used to define the distribution of co-occurring values at a given offset in an image. The co-occurrence matrix C is defined over an array of ‘n × m’ of an image I. It is parameterized by an offset (Δ x, Δ y) as follows:

$$C_{\Delta x,\Delta y}(i,j)=\sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases}1 & if\ I(p,q)=i\ and\ I(p+\Delta x,q+\Delta y)=j\\ 0 & otherwise\end{cases}$$

Where,

i and j -image intensity values of an image,
p and q -spatial positions in an image I
Δ x, Δ y-offsets, that depend on the direction (θ) and the distance (d) at which the matrix is computed.

The feature extraction consists of contrast, correlation, energy, homogeneity, entropy, standard deviation, mean, area. Features involve contrast, correlation, energy, homogeneity, entropy, standard deviation, mean, area are used to classify the types of disease by applying an artificial neural network.

a) Coding ofGLCM features

```
I=Iout;
offsets0 = [zeros(40,1) (1:40)'];
glcms = graycomatrix (I,'Offset',offsets0);
stats = graycoprops (glcms, 'Contrast Correlation EnergyHomogeneity')
%Contrast
c = stats. Contrast;
Contrast = c (1)
 %Correlation
C = stats. Correlation;
Correlation = C (1)
%Energy
E = stats. Energy;
```

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```
Energy = E (1)
% Homogeneity
H = stats. Homogeneity;
Homogeneity = H (1)
% Entropy
en = entropy(I)
% standard deviation
sd = std(std(double(I)))
% mean
mean = mean(double(I(:)))
% area
area = bwarea(double(I(:)))
data= [Contrast; Correlation; Energy ;Homogeneity ;en; sd; mean]/100;
```

b) Results of Features

The results of GLCM features are

```
Level=
        0.0314
Stats:
        Struct with fields :
                Contrast:[1x40 double]
        Correlation: [1x40 double]
                Energy: [1x40 double]
                Homogeneity: [1x40 double]
Contrast=
        0.0367
Correlation=
        0.7861
Energy=
        0.9697
Homogeneity=
        0.9942
En =
        0.1695
Sd =
        8.3783
Mean =
        1.1433
Area =
        3112
```

2) Artificial Neural Network (ANN) Classification

ANN is an important data mining tool used for classification and a parallel distributed processor. They can provide suitable solutions for problems, which are generally characterized by non-linear, complex and imperfect (or) error-prone sensor data, and lack of a clearly stated mathematical analysis. A benefit of neural networks is that a model of the system can be built from the available data. It can be done by texture feature extraction and then applying the back propagation algorithm.

After detecting the features, the extracted features are applied to the Artificial Neural Network for the classification of severity of the disease. It is a computer-based system for the simulation of the network based on the human nervous system.

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3) Artificial Neural Nets

The artificial neural net is organized into different structural arrangements or topologies. The artificial neural net is shown in Fig.7.

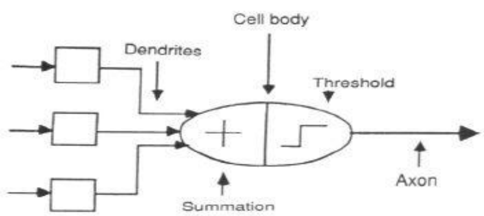

Fig.7. Artificial Neural Nets

a) ANN Classification

```
load net1
y = round(sim(net1,data));
if y == 1
        msgbox('type 1','Result');
elseif y == 2
        msgbox('type 2','Result');
elseif y == 3
        msgbox('type 3','Result');
end
```

The results of ANN classification as shown in Fig.8.

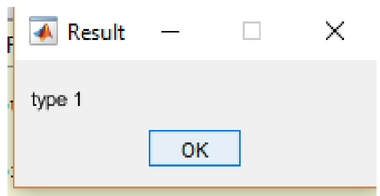

Fig. 8. Results of ANN Classification

H. Feed Forward Neural Network

In this network, the back propagation algorithm is computationally effective and supports optimization and adaptive techniques. It consists of three layers are input layer, hidden layer, output layer. This network is a general nonlinear modeling tool because it is very suitable for tuning by optimization and one-to-one mapping between input and output data.

I. Training of the Feed Forward Neural Network

Feed forward neural network has been trained by using a back propagation algorithm. It can be divided into two types of training or learning modes to back propagation algorithm namely sequential mode and batch mode respectively. In sequential mode learning, a given input pattern is propagated forward and error is determined and back propagated, and the weights are revised. Weights are updated only after the entire set of training networks has been presented to the network in batch mode learning. Hence, the weight update is only performed after every epoch. It is beneficial to accumulate the weight correction terms for several patterns. Hereabouts batch mode learning is used for training. The neural network training tools as shown in Fig.9.

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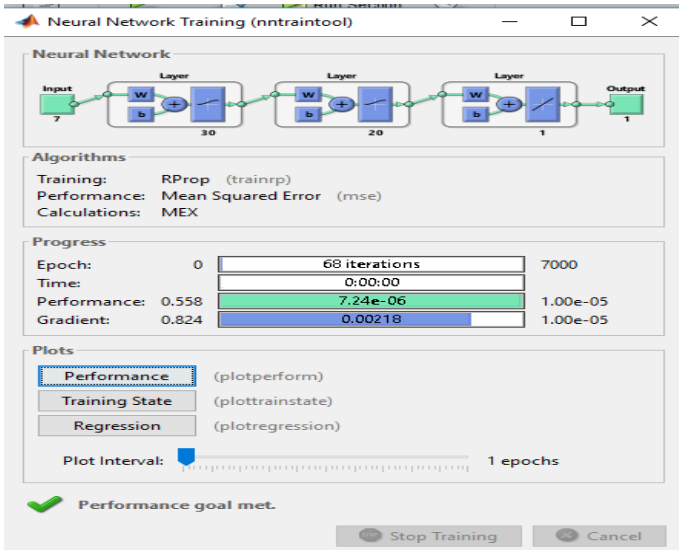

Fig. 9. Neural Network Training Tool

The Neural network training tools of training state, regression and performance are shown in the Fig.10 a), 10 b), 10 c).

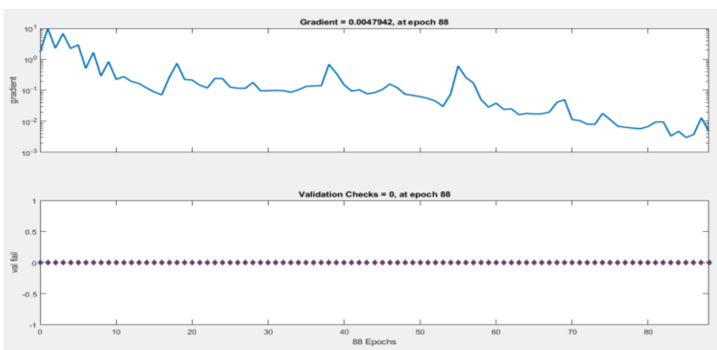

Fig. 10. a) Neural network training in Training State

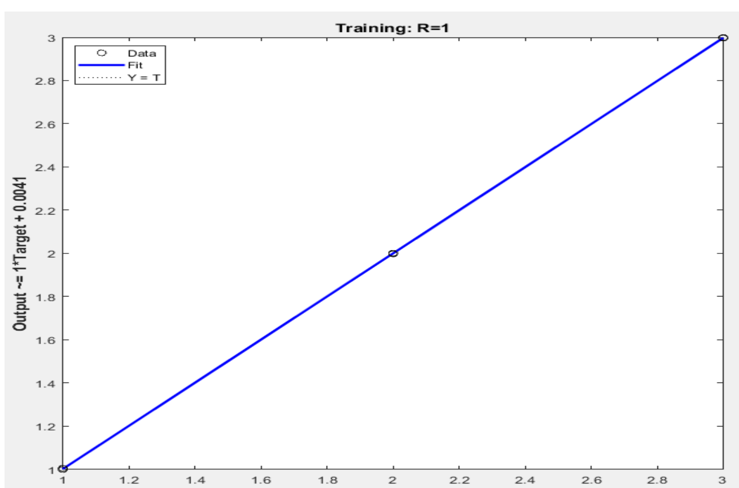

Fig. 10. b) Neural network training in Regression

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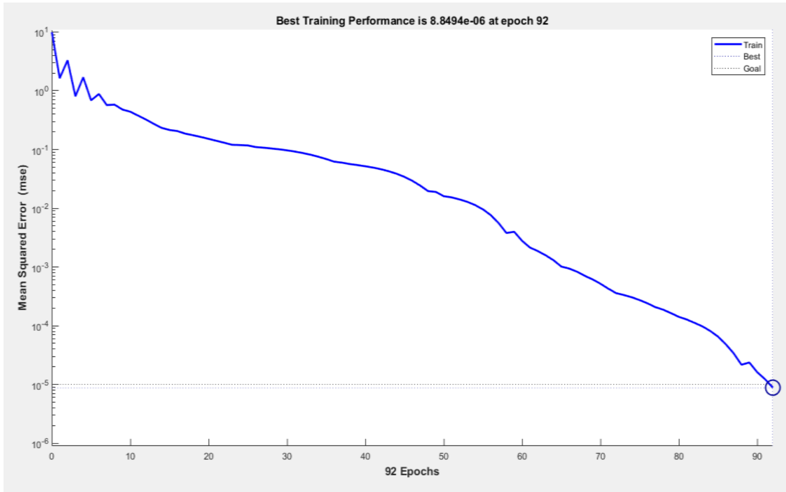

Fig. 10. c) Neural network training in Performance

Also, the neural network recognizes a certain pattern of data only and it entails difficulties to learn logically to identify the error data from that image. Noisy image data and filtered output image data are introduced for training for improving the learning and understanding properties of neural networks. Inputs for neural network training are Noisy image data and filtered output data and noise-free image is considered as a target image for the training of the neural network. Back propagation is related to the network training principle and the parameters of this network are then iteratively tuned and the training of the neural network is completed.

J. Confusion Matrix

This matrix explains the total number of observations in each cell. The rows belong to the target class and the column belongs to the output class. Diagonal cell belongs to correctly and off-diagonal cell belongs to incorrectly classified observations. Both the number of observations and the percentage of the total number of observations are shown in the cell. The confusion matrix is shown in the Fig.11.

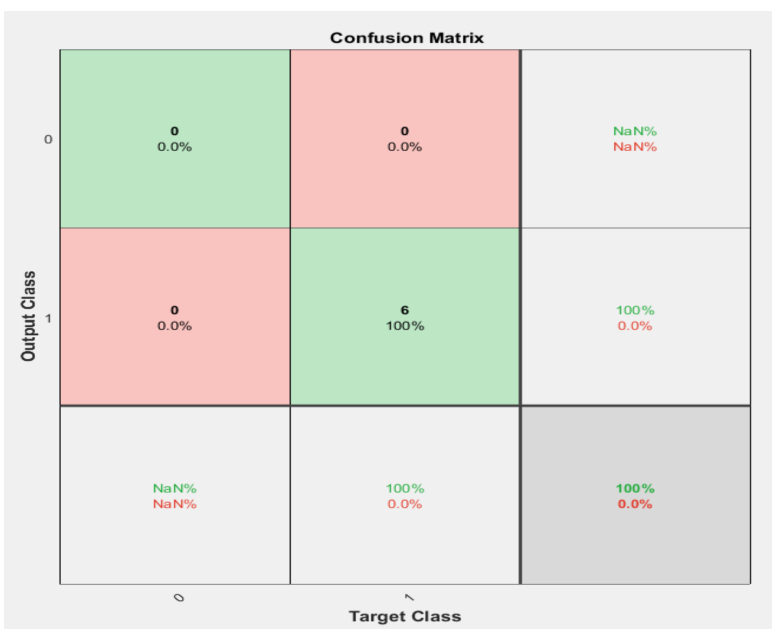

Fig. 11. Confusion Matrix

Conclusion

This paper has proposed diagnosing diabetic retinopathy from fundal photography using image processing. The symptoms of DR include blurred vision, difficulty seeing colors, eye floaters. Without medical treatment, it can cause blindness. Detection at an initial stage is vital for the patients. Hemorrhage and Exudates deduction are the types of NPDR stage. Hemorrhage and Exudates deduction is also deducted after the elimination of optic nerve and optic cup. GLCM features are extracted by ANN classification. Neural network training with training state, regression and performance are identified and also find the Confusion matrix. In future work, to optimize the classifier performance with more number of images, extracting details feature and using the different type of classifier.

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[2] Sight Savers: The structure of the human eye.

website: http://www.sightwavers.or.uk/html/eyeconditions/humaneye_detailed.html

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