Design and Implementation of Fuzzy Logic Classifier for Non-Proliferative Diabetic Retinopathy.

Mr. Bino. N[1*], Dr. Haris P. A.[2], Dr. Sheeba O.[3]

Abstract

Diabetic retinopathy is the one of the leading causes of vision loss across the globe, within increase in large number of diabetes mellitus patients. Early diagnosis and treatment are very essential for fast recovery. Non-proliferative diabetic retinopathy is the early stage of disease, identified by leaky and irregular shaped blood vessels. Colour fundus imaging technology is widely used by ophthalmologists to determine the nature of disease. The presence of noise and non-linear illumination are the major challenges. Image processing techniques could enhance the image and extract the various features of disease like the presence of microaneurysms, hemorrhages, hard exudates and soft exudates, followed by quantification of these features. In this paper, a fuzzy logic-based classifier is designed for the classification of non-proliferative diabetic retinopathy as normal, mild, moderate, severe and advanced from colour fundus images. The input to fuzzy inference system (mamdani type) are the extracted features from fundus image. Fuzzy rules judge the severity of disease by considering the true pixels from the input feature maps. This design is implemented using MATLAB code and results shows a high degree of accuracy in classification.

Keywords: Diabetic retinopathy, colour fundus imaging, Classification, Fuzzy Logic.

Introduction

Diabetes is a life style disease which leads to many health issues and malfunctioning of organs. Diabetic retinopathy (DR) is a very common disease among patients suffering from diabetes mellitus. The major risk factors include uncontrolled diabetes over a long period, high blood pressure, cholesterol, tobacco use, etc. The patient may suffer from blurred vision [1], spotted vision, fluctuating vision, dark areas in vision and loss of vision.

Diabetic retinopathy can be of two types [7]- non- proliferative diabetic retinopathy and proliferative diabetic retinopathy.

Non-proliferative diabetic retinopathy [10] is characterized by leaky and irregular shaped blood vessels with microaneurysms and the presence of hard [6] [15] and soft exudates. The blood vessels may rupture and leak (hemorrhages) into the retina. It also leads to accumulation of fluid near macula (macular edema), which decreases the vision. The more severe case of disease is the proliferative diabetic retinopathy [9] in which the damaged blood vessels[3] will be blocked and cause abnormal generation of new [21] and leaky blood vessels (neovascularization) [8] [20], which

Corresponding author: Bino. N

Address: [1*]*Asst. Professor, Dept. of ECE, Bishop Jerome Institute & Research Scholar, Kerala University;* [2*]*Professor, Dept. of ECE, College of Engineering,* Thiruvananthapuram; [3*] *Rtd. Professor, Dept. of ECE, TKM College of Engineering,* Kollam, Kerala, India.
E-mail: [1]binonelson@gmail.com; [2]haris786pa@gmail.com; [3]shb.odattil@gmail.com
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discolours the vitreous humor. It also develops scar tissue from the abnormal blood vessels leading to retinal detachment and excess pressure to develop within eye ball, leading to damage of optic nerve. The diagnosis and treatment of disease at an early stage is very crucial. Colour fundus images could provide large information about the stage of disease and helps in detection [12] and diagnosis.

The original image may be affected with noise [2] like gaussian noise and non-linear illumination due to curvature of eye or improper imaging operations. Image processing methods helps in restoring image features, extracting [25] the regions of interest and give more accurate predictions on the severity of disease.

Normal fundus image of retina appears to be having uniform and consistent hue and saturation of colour over the retinal area. Optic disc is brighter than other regions in retina and blood vessels appears to be narrow fibre like structure originating from optic disc and red in colour. The macular area appears as dark. But a diseased retina will show some other features, that could be identified as the disease symptoms. The preliminary symptom includes the presence of cotton-wool [4] spot or soft exudates representing accumulations of neuronal debris within the layer of nerve fibre. Deposition of lipid and proteinaceous material [14] such as fibrinogen and albumin by leaky blood vessels in the outer layer of retina is called hard exudates [5]. The presence of abnormal evagination of blood vessels called microaneurysms [17] [22] is a typical feature of diabetic retinopathy and its measure represents severity of the disease. In advanced stage of disease, tiny blood vessels get damaged and bleeds over the retinal area called hemorrhages [19], appears as red spots/ regions in image. Each of these features can be identified by the variations in hue and saturation levels in the fundus images. The presence of such features near to the macula leads to maculopathy [18]. Image processing techniques could segment these features and quantify it. Based on the measure of these features, the images can be classified into various classes representing severity of disease. Artificial neural networks [13] and fuzzy logic could effectively classify [23] [24] the images to various grades [16] of disease [11].

Input Image

The colour fundus retinal images were obtained from the standard dataset available from Kaggle called Indian Diabetic Retinopathy Image Dataset, the first database representative of an Indian population. The dataset consists of 80 colour fundus images along with its ground truth images corresponding to microaneurysms, hemorrhages, hard exudates and soft exudates. Also, a separate dataset of classified image set is provided based on the severity of disease labelled as normal, mild, moderate, advanced and severe. All images were JPEG format of 4288 X 2848 pixels size with a resolution of 300dpi. These images are resized to 600 X 400 pixels for the ease of computation.

In fundus image of normal retina, the optic disc, blood vessels, macular region and rest of the retinal layer are clearly visible. While in fundus image of DR affected retina, in addition to these, we can see the presence of microaneurysms, blood, soft and hard exudates, with variation in size, hue and saturation. These features of DR disease are used to classify images into various grades of the disease.

(a) Normal Retina (b) Diabetic Retinopathy affected Retina

Figure 1. Fundus retinal image of a normal and DR affected retina

Figure 1 shows the retinal fundus images of a normal and diabetic retinopathy affected eye. The captured image is a colour image of 24bit depth. The features in image depend upon the severity of disease.

Methodology

The methodology for classification of fundus images into various grades of diabetic retinopathy is discussed in this session. A block diagram representation is shown in figure 2.

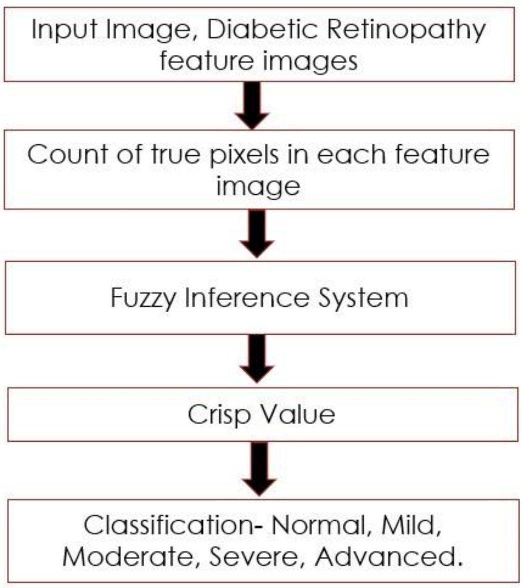

Figure 2. Shows the methodology of classification

The total image dataset is divided into two- truth set and test set. Truth set consists of 50 fundus images along with the ground truth images of its features and test set consists of 30 images along with ground truth images. The ground truth images in truth set are analysed, the number of true pixels in each is calculated. Each extracted feature is taken as the fuzzy inputs to the fuzzy inference system. The fuzzy output variable represents the grade of disease. The crisp value obtained by defuzzification is used to classify the images as normal, mild, moderate, severe and advanced according to the grade of the disease.

Fuzzy Inference System

The Fuzzy Inference system is capable of taking multiple inputs and make decisions based on the rule base. Proper selection of fuzzy variables, membership functions and their ranges are very essential for the accurate prediction of grade of disease. Fuzzy inference system for classification of diabetic retinopathy is shown in figure 3.

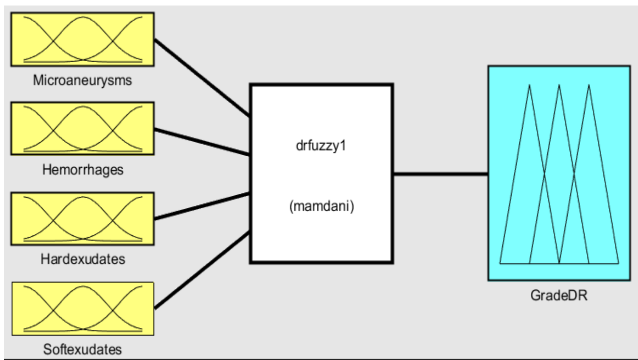

Figure 3. Fuzzy Inference System

Fuzzy Inputs:

The fuzzy inputs are the features representing extent of diabetic retinopathy, which includes microaneurysms, hemorrhages, hard exudates and soft exudates. Each ground truth image in truth set is rescaled to 600 X 400 pixels and count of true pixels is evaluated. After analysing the minimum, maximum and average values of true pixels, the fuzzy variable ranges are selected. The fuzzy variables defined for each input are normal, low, medium, high and very high, representing the severity disease feature. The following table represents the range of values chosen.

Table1. Fuzzy input variables and its range

Fuzzy input sets	Normal	Low	Medium	High	Very High
Microaneurysms	<10	5-300	250-600	500- 700	>600
Hemorrhage	<5	1- 1000	700-3000	2500- 7000	>6000
Hard Exudates	<75	50- 4000	3000- 7000	6000-11000	>10000
Soft Exudates	<100	75- 1500	1000- 2500	2000- 3500	>3000

The table 1 shows the range of true pixels in each fuzzy variables assigned for the inputs. The membership functions define the degree of membership of input to fuzzy variables, represented with a value between 0 and 1. The membership functions selected are sigmoid, triangular and z-shaped, depending upon the range of values for each input fuzzy variables. The fuzzy variables along with membership functions of inputs are shown below.

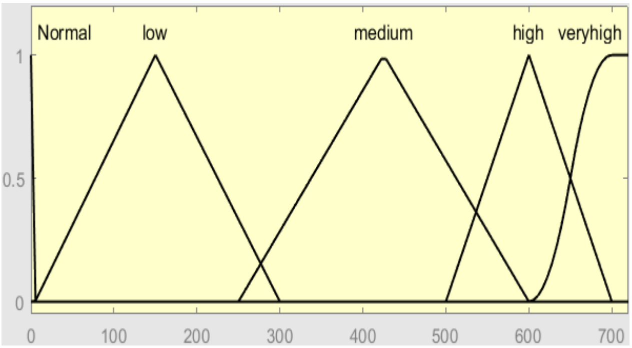

Figure 4. Membership functions of input variable microaneurysms

Figure 4 shows the fuzzy variables of the input ‘microaneurysms’ along with its membership functions. The fuzzy variable ‘normal’ is assigned with z-shaped membership function while ‘low’, ‘medium’, ‘high’ are assigned with triangular membership function. ‘very high’ variable is assigned with sigmoid membership function.

The z-shaped membership function is mathematically represented as

$$f(x;a,b) = \begin{cases} 1, & x \le a \\ 1-2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 0 & x \ge b \end{cases}$$

where ‘x’ is the input value, ‘a’ and ‘b’ represents the parameters of the function defining its shape. Here, ‘a’ and ‘b’ are assigned with values ‘0’ and ‘1’ respectively.

The triangular shaped membership function is mathematically represented as

$$f(x;a,b,c) = \begin{Bmatrix} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{Bmatrix}$$

where ‘x’ is the input value, ‘a’, ’b’ and ’c’ represents the parameters of function defining its shape. For the ‘low’ fuzzy variable, ‘a’, ‘b’ and ‘c’ are assigned with values 5, 150, 300 respectively.

The sigmoid membership function is mathematically represented as

$$f(x;a,b) = \begin{Bmatrix} 0, & x \le a \\ 2\left(\frac{x-a}{b-a}\right)^2, & a \le x \le \frac{a+b}{2} \\ 1-2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} \le x \le b \\ 1, & x \ge b \end{Bmatrix}$$

where ‘x’ is the input value, ‘a’ and ‘b’ represents the parameters of function defining its shape. For ‘very high’ fuzzy variable. ‘a’ and ‘b’ are assigned with values 600 and 700 respectively.

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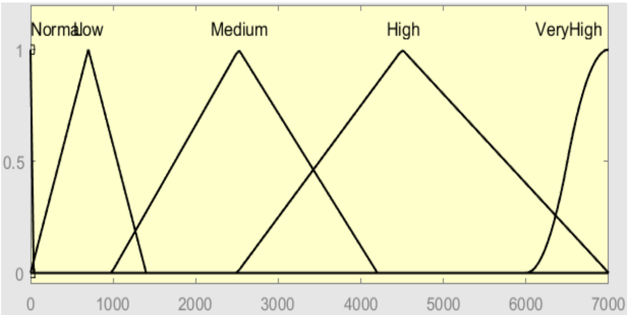


Figure 5. Membership functions of input variable hemorrhages

Figure 5 shows the fuzzy variables of the input 'hemorrhages' along with its membership functions.

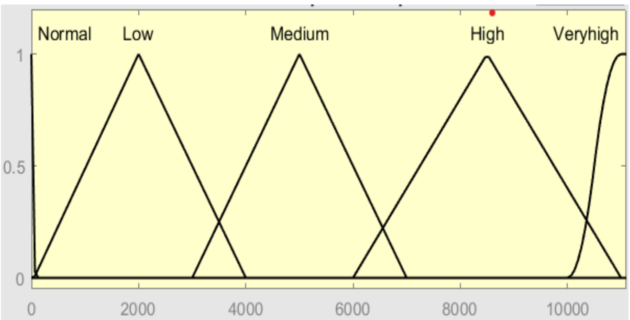


Figure 6. Membership functions of input variable hard exudates

Figure 6 shows the fuzzy variables of the input 'hard exudates' along with its membership functions.

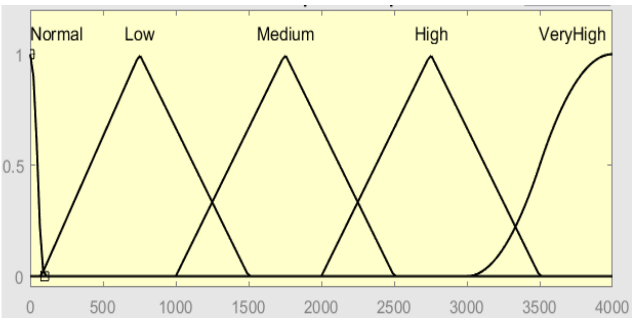


Figure 7. Membership functions of input variable soft exudates

Figure 7 shows the fuzzy variables of the input 'soft exudates' along with its membership functions.

Fuzzy output:

The fuzzy output represents the grade of disease. Based on the fuzzy inputs and rule base, output is predicted. Fuzzy output is assigned with five fuzzy variables namely normal, mild, moderate, severe and advanced. The range of these variables are represented in a scale from 0 to 100. The following table shows the range of fuzzy output variables.

Table 2. Fuzzy output variable

Fuzzy output	Normal	Mild	Moderate	Severe	Advanced
Grade of DR	<5	0-30	20-50	40-70	>60

Fuzzy Rule Base:

Fuzzy rule base is the heart of fuzzy inference system. It consists of a set of rules defined for all possible combinations of inputs using if – then statements. Multiple input conditions are connected by 'and' and 'or' connections. The accuracy of prediction depends upon the accuracy of rules defined. The following figure shows the rule editor in fuzzy inference system.

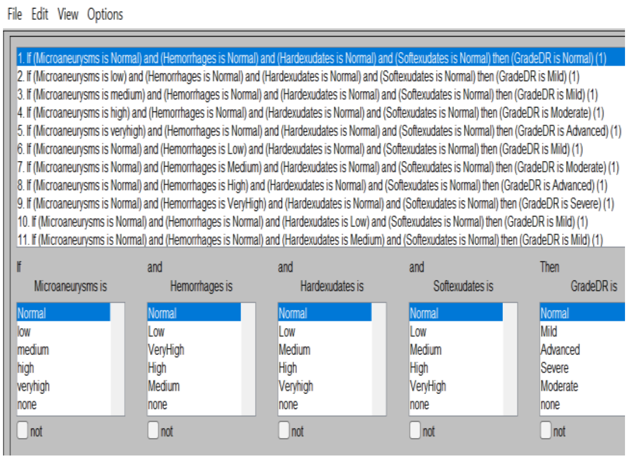


Figure 8. The rule editor in fuzzy inference system

Some of the rules defined in rule base are as follows:

- If (Microaneurysms is Normal) and (Hemorrhages is Normal) and (Hardexudates is Normal) and (Softexudates is Normal) then (GradeDR is Normal) (1).
- If (Microaneurysms is veryhigh) and (Hemorrhages is Normal) and (Hardexudates is

Normal) and (Softexudates is Normal) then (GradeDR is Advanced) (1)

- If (Microaneurysms is Normal) and (Hemorrhages is VeryHigh) and (Hardexudates is Normal) and (Softexudates is Normal) then (GradeDR is Severe) (1)

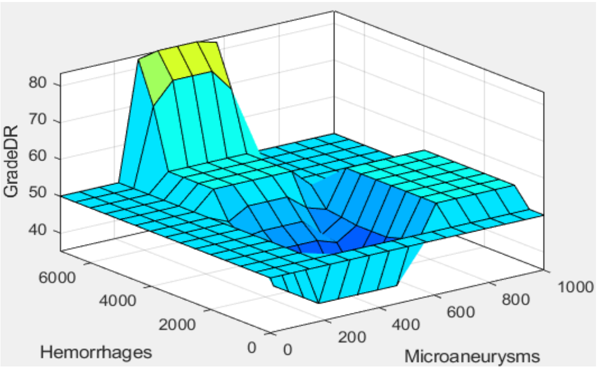


Figure 9. The surface rule view for hemorrhages and microaneurysms

The Figure 9 shows the surface view for rule base corresponding to hemorrhages and microaneurysms that defines the grade of diabetic retinopathy in the output fuzzy variable.

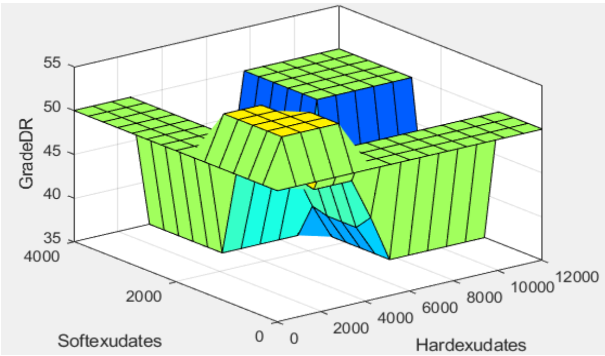


Figure 10. The surface rule view for soft and hard exudates

Figure 10 shows the surface view for rule base corresponding to soft and hard exudates that defines the grade of diabetic retinopathy in the output fuzzy variable.

FIS output:

Each input to fuzzy inference system may have different grades of membership with more than one fuzzy input variable. The fuzzy inference output is generated based on the fuzzy inputs and rule base and maps to fuzzy variables in the output. The output generated may also have association with different output variables with different grade of membership. A crisp value is generated by the defuzzification method centroid, mathematically represented as

$$\text{xCentroid} = \frac{\sum_i \mu(x_i) x_i}{\sum_i \mu(x_i)}$$

where μ(xi) is the membership value corresponding to the input xi.

Classification:

From the crisp value obtained, the grade of disease needs to be classified. This is done by assigning a range of values to each class. The assigned class and its range are as given in the table below.

Table 3. Classification of diabetic retinopathy with defuzzied value

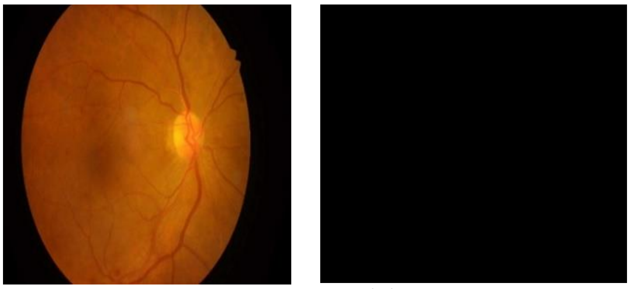
Class	Normal	Mild	Moderate	Severe	Advanced
Range	0-5	6-25	26-40	41-65	66-100

These range of values are selected as per the data obtained from test set.

Results and Discussion

The ground truth images in test set consists of 30 images, six from each grade of disease. The true pixels in the ground truth images were calculated and applied to the fuzzy inference system.

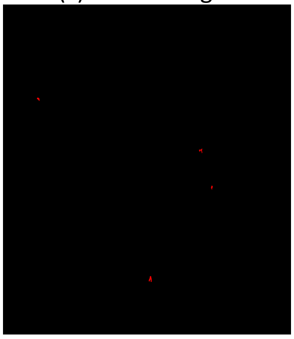
Some of the sample results are discussed in this session. The figure below shows fundus image correctly classified as normal.



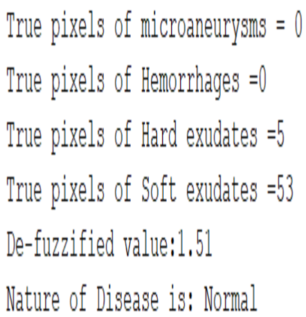
(a) Input image (b) Microaneurysms

(c) Hemorrhages

(d) Hard exudates



(e) Soft exudates



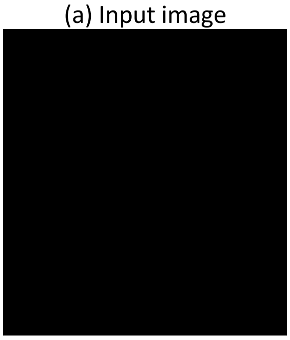
(f) Classified output

Figure 11. Normal image classified as normal

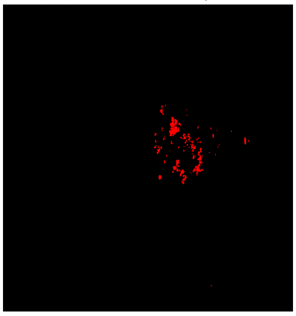
Fig.11 represents the output of an image classified as normal. Presence of hard and soft exudates are very low and no traces of hemorrhages or microaneurysms are found. Hence the classification is right.

(a) Input image

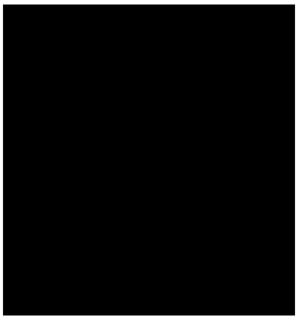
(b) Microaneurysms



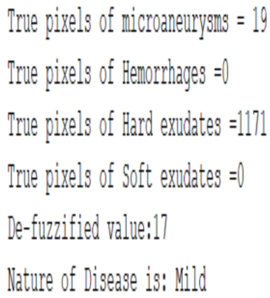
(c) Hemorrhages



(d) Hard exudates



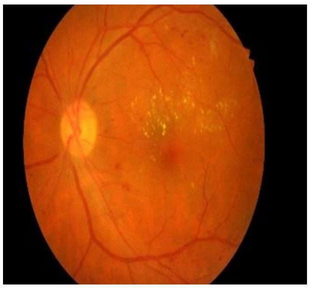
(e) Soft exudates



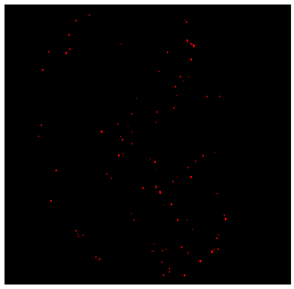
(f) Classified output

Figure 12. Image classified as mild diabetic retinopathy

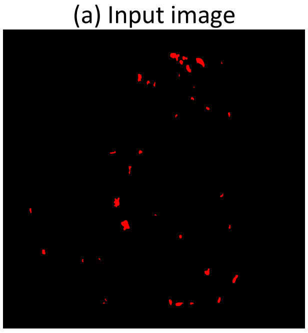
Figure 12 represents the command prompt output of an image classified as mild diabetic retinopathy. Presence of hard exudates are evident, soft exudates are at average level and no traces of hemorrhages or microaneurysms are found. Hence the classification is right.



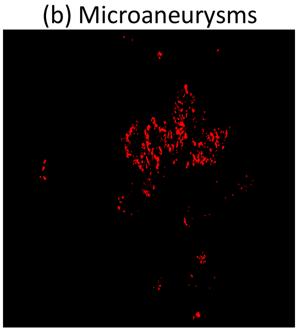
(a) Input image



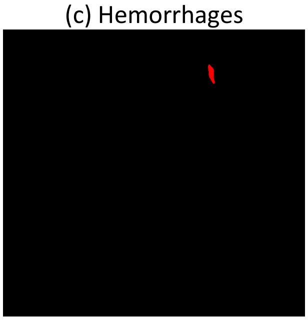
(b) Microaneurysms



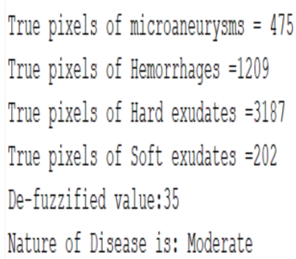
(c) Hemorrhages



(d) Hard exudates



(e) Soft exudates



(f) Classified output

Figure13. image classified as moderate diabetic retinopathy

Figure 13 represents the output of an image classified as moderate diabetic retinopathy. Presence of hemorrhages, microaneurysms along

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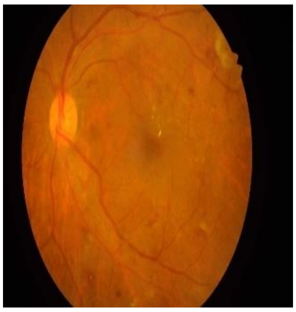
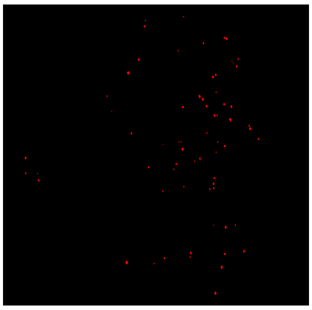
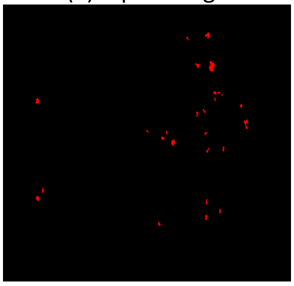
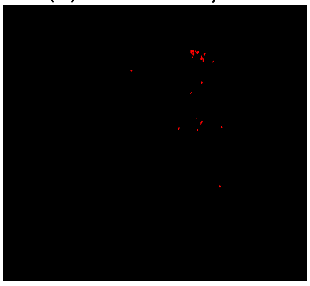
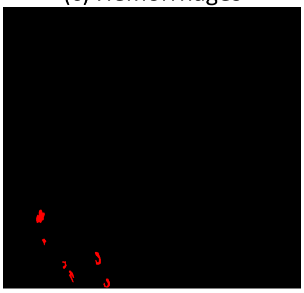
with hard and soft exudates is evident and hence the classification is right.


(a) Input image


(b) Microaneurysms


(c) Hemorrhages


(d) Hard exudates

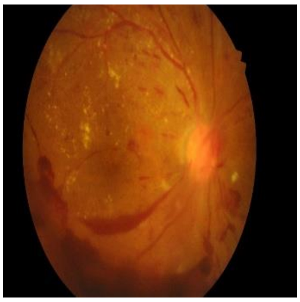

(e) Soft exudates

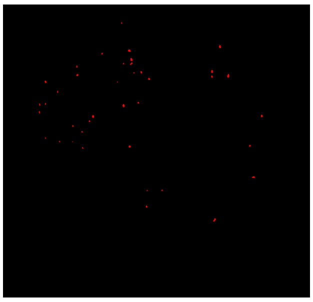
True pixels of microaneurysms = 194
True pixels of Hemorrhages =3996
True pixels of Hard exudates =252
True pixels of Soft exudates =1144
De-fuzzified value:45
Nature of Disease is: Severe
>>

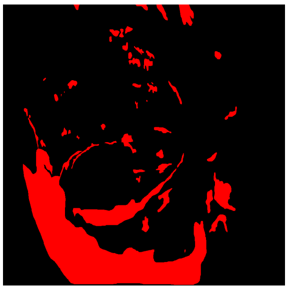
(f) Classified output

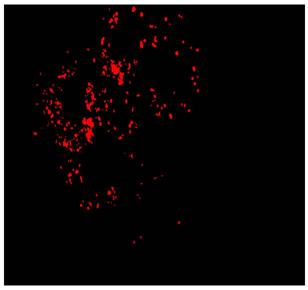
Figure 14. image classified as severe diabetic retinopathy

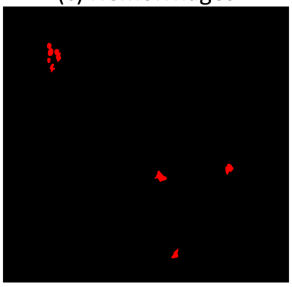
Figure 14 represents the output of an image classified as severe diabetic retinopathy. Presence of hemorrhages is high along with microaneurysms, hard and soft exudates and hence the classification is right.


(a) Input image


(b) Microaneurysms


(c) Hemorrhages


(d) Hard exudates


(e) Soft exudates

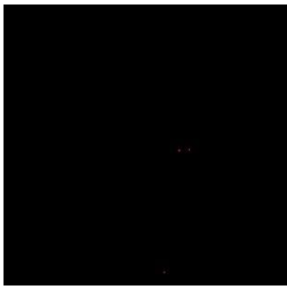
True pixels of microaneurysms = 275
True pixels of Hemorrhages =35685
True pixels of Hard exudates =3885
True pixels of Soft exudates =937
De-fuzzified value:81.3811
Nature of Disease is: Advanced
>>

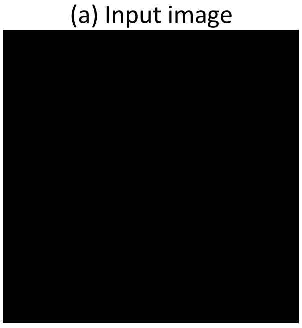
(f) Classified output

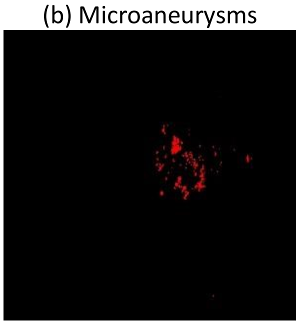
Figure 15. Image classified as advanced diabetic retinopathy.

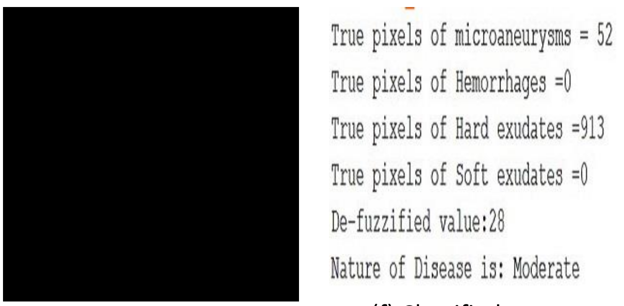
Figure 15 represents the output of an image classified as advanced diabetic retinopathy. Presence of hemorrhages is very high along with a high level of microaneurysms, hard and soft exudates and hence the classification is right.


(a) Input image


(b) Microaneurysms


(c) Hemorrhages


(d) Hard exudates



(e) Soft exudates (f) Classified output

Figure 16. image misclassified as moderate, but belongs to mild.

Figure 16 represents the output of an image classified as moderate, but originally belongs to mild diabetic retinopathy. Since there is presence of microaneurysms and hard exudates at low level & absence of hemorrhages and soft exudates, it can't be considered as moderate. Hence the classification is wrong.

Out of the 30 images, 28 images were classified correctly, showing an accuracy of 93.3%. Accuracy can be further increased by analysing a greater number of ground truth images.

Conclusion

Diabetic retinopathy is a serious disease affecting the eye which needs an early diagnosis and treatment. In this paper, we designed a fuzzy logic classifier for identifying fundus images as normal or different stages of non-proliferative diabetic retinopathy as mild, moderate, severe and advanced. This methodology has obtained an accuracy of 93.3% over this dataset. Accuracy can be further increased by analysing large number of truth image set and slightly modifying the design accordingly.

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