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Automatic Detection and Classification of Diabetic Lesions for Grading Diabetic Retinopathy Using Fuzzy Rule-Based Classification System

By

Rubya Afrin

Roll No: 1707501

A thesis submitted to Khulna University of Engineering & Technology
for the partial fulfillment of the degree of
Master of Science in Computer Science and Engineering

Department of Computer Science and Engineering
Khulna University of Engineering & Technology
Khulna 9203, Bangladesh
October, 2020

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Declaration

This is to certify that the thesis work entitled "Automatic Detection and Classification of Diabetic Lesions for Grading Diabetic Retinopathy Using Fuzzy Rule-Based Classification System" has been carried out by Rubya Afrin in the Department of Computer Science and Engineering (CSE), Khulna University of Engineering & Technology (KUET), Khulna, Bangladesh. The above thesis work or any part of this work has not been submitted any university or elsewhere for the award of any degree or diploma.

10.2020

Signature of Supervisor
(Dr. Pintu Chandra Shill)

Signature of Candidate
(Rubya Afrin)

Approval

This is to certify that the thesis work submitted by **Rubya Afrin** entitled "Automatic Detection and Classification of Diabetic Lesions for Grading Diabetic Retinopathy Using Fuzzy Rule-Base System" has been approved by the board of examiners for the partial fulfillment of the requirements for the degree of Master of Science in Computer Science and Engineering in the Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh in October, 2020.

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Author

Abstract

Diabetic Retinopathy (DR) is a chronic, progressive retinal disease which is the most common cause of legal blindness. The disease is threatening to eyes as it shows no signs of visual abnormality at the initial stage. It gradually decreases patient's eye-sight and drives into blindness in future. Hence, the early detection of DR is vital to prevent the complete vision loss of diabetes patients. Traditional diagnosing system of DR requires quite trained ophthalmologists for monitoring the retina periodically. Moreover, several physical tests like fluorescein angiography, visual acuity test, and ocular coherence tomography are involved to detect DR which also require a lot of time to process. In this paper, a fuzzy rule-based classification technique is proposed for automatic detection and classification of retinal lesions for grading DR. The proposed technique consists of preprocessing of fundus images, extraction of candidate retinal lesions, formulation of feature set, and classification of DR. In the preprocessing phase, the technique eliminates background noises and extracts optic disc from the retinal fundus image. Four leading lesions; blood vessels, microaneurysms, haemorrhages, and exudates are extracted using different image processing techniques and two textural features; contrast and homogeneity are calculated in the detection phase. Then, these six input features; blood vessels area, microaneurysms count, haemorrhages area, exudates area, contrast and homogeneity are fed to fuzzy if-then rule-based classifier for predicting normal, mild NPDR, moderate NPDR, severe NPDR and PDR stages of DR.. A total of 520 retinal fundus images are collected from four public database; STARE, DIARETDB0, DIARETDB1 and MESSIDOR and the images are successfully classified by the fuzzy rule-based classifier with accuracy up to 92.42%. The sensitivity and specificity of the classifier are 92.44% and 94.29% respectively. The simulation result on publicly standard image datasets exhibits that the intended technique gives promising results in identifying retinal lesions and it has better capability of classifying several stages of DR compared with other existing automatic diagnosing system.

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CHAPTER ONE

Introduction

1.1 Background

Diabetic Retinopathy (DR) is one of the diabetes complications and is an significant cause of visual disability and blindness. The disease is threatening to the eye as it attacks the retina and slowly takes away the vision from the patients. Hence, it is vital to have a regular eye examination for initial detection and early treatment. This thesis is about the development of a medical decision support system for automatic DR screening and classification in eye fundus images.

Diabetes Mellitus (DM) is a complex disease resulting in severe complications in various parts of the body. Nevertheless, good control of DM will avoid or delay various complications, including DR. Thus, screening and early treatment can avoid significant loss of vision. Such efforts to control this enduring disease as well as the early complications detection such as DR should be strengthened, because DR is an asymptomatic condition in its initial stage. But, slowly it becomes threatening to the vision of the patients. Considering these complications and the rising numbers of diabetic patients, the screening of DR is vital to prevent the complications. To achieve this, significant resources will be required for the management of the condition including human resources, to increase the current workload within the field of disease diagnostics.

1.2 Motivation

Now a day, a lot of people are affected by DR the rate is growing day by day. The disease could severely damage the retina and make the patients blind. But, the severity rate could be minimized if diagnosis of DR is taken on time. Traditional diagnosing process of identifying the severity of DR requires quite trained ophthalmologist who has to diagnose a lot of retinal fundus images of retina for

detecting the malformations. The process is quite expensive and involves much time to execute manually. This makes the rise of, over last few decades, automatic Computer-Assisted Diagnostic (CAD) tool, intended to assist the medical experts for minimizing this expenses and manual effort by providing fast, accurate and reliable tool. Image based computerized diagnosis system is such a tool which can ascertain whether the patient under examination is in the preliminary stage or advanced stage of DR. Therefore, the proposed diagnostic tool can greatly assist the DR patients in getting proper treatment and protecting their eyes from becoming blind.

1.3 Objectives

The aim of this research is to investigate automatic methods for detection of lesions and classification of DR stages which can contribute towards improving DR management and, subsequently, to develop an efficient system for DR screening. With this developed approach, a diabetic patient could have an assistance of periodic eye-screening and protect themselves from become blind. The main objectives of our thesis are-

- To detect the candidate retinal lesions (blood vessels, microaneurysms, haemorrhages and exudates) from retinal fundus images using image processing techniques.
- To extract textural features of fundus images (contrast, homogeneity) along with retinal lesions.
- To design fuzzy database and fuzzy if-then rules based on medical expert's and prior knowledge.
- To classify the fundus image according to its severity using fuzzy rule-based classification system.
- To predict the unknown stages of diabetic retinopathy.

1.4 Methodology

A classification technique named fuzzy rule-based classification system (FRBCS) is proposed for automatic detection of retinal lesions and classification of DR. The proposed system utilizes different image processing methods to detect abnormal retinal lesions automatically, and then predict the severity of DR disease to get early treatment and prevent complete blindness.

The proposed technique consists of preprocessing of fundus images, detection of candidate retinal lesions, formulation of feature set, and classification of DR stages. In the preprocessing phase, the technique eliminates background noises and detects optic disc from the retinal fundus image. Four leading lesions; blood vessels, microaneurysms, haemorrhages, and exudates are extracted using different image processing approaches in lesion extraction phase. A feature set is formulated based on the pixel area of each candidate lesion which is further used in classifying that region.

The classification of DR stages is performed using FRBCS. This FRBCS operates on fuzzy if-then rules which are induced from membership functions for each fuzzy set. In fuzzy classification system, each attribute of the detected lesion is expressed by linguistic value and represented as fuzzy values with trapezoidal membership function. A number of pre-specified fuzzy sets and fuzzy rules, collected from ophthalmologist's knowledge, are considered for each input feature of FRBCS. Moreover, fuzzy rules which are described as linguistic values are easy to understand and need not to re-train the system if new rules are added to it. Therefore, fuzzy classification system has been developed to predict the DR for cost-effective screening process.

The simulation result on publicly standard fundus image datasets exhibits that the intended technique gives promising results in identifying retinal lesions and it has better capability of classifying several stages of DR compared with other existing automatic diagnosing system.

1.5 Organization of the thesis

Chapter 2 represents the relevant background materials. This also comprises elaborated concept of diabetic retinopathy, retinal lesions and their several stages; Non- Proliferative DR and Proliferative DR. This chapter also encloses several definition of fuzzy rule-based classification system; like fuzzy sets, membership function and fuzzy rules. It also briefly describes some of the existing prominent detection and classification techniques while aiming at their shortcomings. It also contains supreme benefits of grading DR by the proposed technique.

Chapter 3 describes the proposed detection and classification technique using FRBCS and explains its working process in detail. The chapter also illustrates the overall block diagram of our proposed technique. The chapter includes the detail processes of detection and extraction of candidate lesion such as blood vessels, microaneurysms, haemorrhages, and exudates using several image processing methods. It then describes the fuzzy rule-based classification technique for categorizing the images into different levels of severity of DR. It also describes the feature set formulation process and if-then rules used for predicting DR.

Chapter 4 demonstrates the simulation results of our proposed technique on publicly standard retinal fundus image datasets. Here, the chapter validates the improved performance of FRBCS while comparing with other classification algorithms.

Chapter 5 lists the concluding observations collected from experiments. The chapter also explains what up-coming researches are required to explore in future for more desirable diagnosing approaches.

CHAPTER TWO

Literature Review

2.1 Introduction

In this chapter, the background of diabetic retinopathy and its several stages are introduced. Then the basic concept of fuzzy rule-based classification system (FRBCS) is also discussed. Some related works for automatic screening process of diabetic retinopathy with several algorithms are stated along with their shortcomings. The chapter also represents how the shortcomings of the existing classification systems are overcome by the proposed technique.

2.2 Diabetic Retinopathy

Diabetes is one of the common disease around the world and the leading cause of ocular complications, amputations, and end-stage retinal disease. The disease occurs due to inadequate secretion of insulin from the pancreas or improper usage of produced insulin through the body [1]. Long-term diabetes causes an eye threatening disease and specific microvascular complication known as Diabetic Retinopathy (DR). DR is a vision abnormality which is occurred due to severe damage of the blood vessels and frequent leakage of fluid onto the retina [1][2]. Approximately, 126.6 million people are suffering from DR around the world and it is projected that the number will raise to 191.0 million by 2030 [3].

Usually, a patient has no symptom or abnormality at the initial stage of the disease. Moreover, most of the symptoms are not visible to bare eye. But, gradually it becomes threatening to the retina and drives into total vision loss to the patients [1][4]. About 40% of diabetes patients are suffered from DR; among which 5% face vision-threatening effect of the disease [5].

When an ophthalmologist looks into an eye using an ophthalmoscope, the retina of the eye is viewed as figure 2.1.

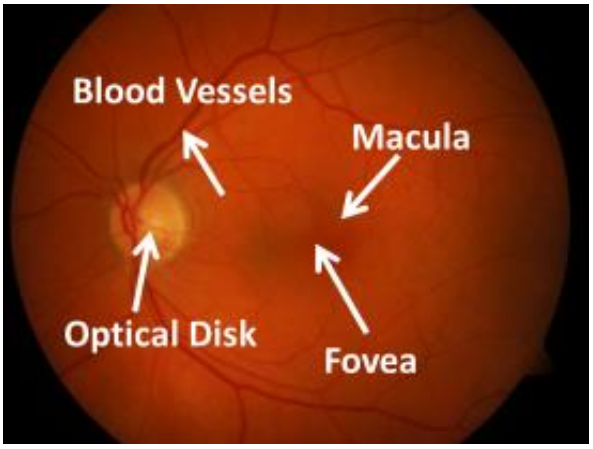


Figure 2.1 Human Retinal Fundus Image with Basic Structure

At the middle of the retina, an oval-shaped to circular whitish region measuring around 2 × 1.5 mm is the optic disk. From the middle of the optic disk, the blood vessels are radiated and spread over the surface of the retina. The macula is also an oval-shaped spot area found in middle of the retinal surface. At the center of the macula, slightly oval, blood vessel-free and reddish spot is known as fovea. The development of DR gradually damages the tiny blood vessels; as a result, several abnormal components like Microaneurysms (MAs), Haemorrhages (HMs), Cotton Wool Spots (CWS), Exudates (EXs), and irregularly growth of blood vessels are found onto retinal surface.

Depending on the above components, DR is generally categorized as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [1]. They have been discussed in the next subsections.

2.2.1 Non-Proliferative Diabetic Retinopathy (NPDR)

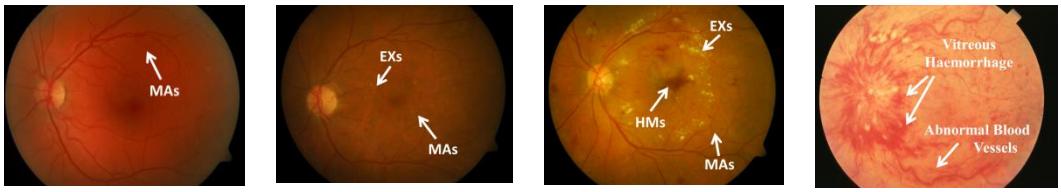
Non-Proliferative Diabetic Retinopathy (NPDR) is the primary stage of DR which is occurred due to impaired blood vessels resulting leakage of fluid onto the retina [2]. The presence of MAs, HMs, and EXs (hard and soft) depicts the occurrence of NPDR and it could progress from mild, moderate to severe along with several intensities of the lesions [2][4]. The details are described below:

- **Mild Non-Proliferative Diabetic Retinopathy (Mild NPDR)**

Mild NPDR is the earliest phase of NPDR that is occurred due to one or more microaneurysm with or without haemorrhages or exudates (Figure 2.2 (a)).

- **Moderate Non-Proliferative Diabetic Retinopathy (Moderate NPDR)**

Moderate NPDR is the progressive phase of NPDR that is specified by numerous microaneurysms, blot-and-dot haemorrhages, venous beading, or/and soft exudates (Figure 2.2 (b)).



(a) (b) (c) (d)

Figure 2.2 Human fundus retinal images with (a) mild NPDR (b) moderate NPDR (c) severe NPDR (d) PDR.

- **Severe Non-Proliferative Diabetic Retinopathy (Severe NPDR)**

Severe NPDR is the most severe phase of NPDR. It is caused due to more microaneurysms, venous beading, hard exudates and severe intra-retinal microvascular abnormalities (IRMA) (Figure 2.2 (c)).

2.2.2 Proliferative Diabetic Retinopathy (PDR)

The advanced stage of DR is known as Proliferative Diabetic Retinopathy (PDR). PDR is specified by abnormal growth of fragile blood vessels (neovascularization) that causes vitreous haemorrhages onto the retinal surface (Figure 2.2 (d)).

2.3 Fuzzy System

Fuzzy system is a system which works using fuzzy logic [6]. The system has been using successfully in a rising number of medical areas for the use of linguistic rules to define systems [7][8]. Two most vital considerations for designing any fuzzy

system are - generating the fuzzy rules and defining the membership functions for each fuzzy set [6][9]. The detail descriptions of fuzzy system are described below:

2.3.1 Fuzzy Logic

Fuzzy system operates the data using fuzzy logic. In 1965, fuzzy logic theory was first introduced by Zadeh [10]. Fuzzy logic (FL) is a computational model which involves defining and manipulating vague information is such a way which resembles both human-like communication and reasoning procedures [11][12]. FL is the extension of classical logic which works on a set defining with a crisp boundary. On the other hand, a *fuzzy set* is a set which works on without a crisp boundary [9][10]. Classically, two-valued logic often regards 0 to be false and 1 to be true. However, FL works with truth values between 0 and 1, and these values are considered as degree of truth. This degree of truth is defined by *membership function*s which provide flexibility for modeling the fuzzy sets into linguistic expressions [13].

Let us assume that X is a number of objects represented by x, then a *fuzzy set A* (a set of ordered pairs) in X is defined as [13]:

$$A = \{(x, \mu_A(x)) \mid x \in X\} \tag{2.1}$$

Here, μ_A is known as *membership function* (MF) of the *fuzzy set A*. Each element of X is assigned to its membership value in the range from 0 to 1, i.e., $\mu_A(x) \in [0,1]$ by the MF. This membership value measures the degree of membership of each element in X to the *fuzzy set A*.

The process of designing a fuzzy system involves modeling the imprecise behavior of system based-on fuzzy sets. Each fuzzy system consists of system variables known as *linguistic variables (or fuzzy variables)* and each linguistic variable consists of its possible values known as *linguistic values (or fuzzy values)* [7][8]. Each fuzzy variable is represented by fuzzy set in each fuzzy system. As an example, if we consider temperature is a fuzzy variable of a fuzzy system, its possible values in terms of subjective descriptions probably be “very cold”, “cold”,

"normal", "hot", and "very hot". Here, each fuzzy value is defined by a fuzzy set and each fuzzy set is uniquely specified by its MF. A probable interpretation of fuzzy variable "temperature" with its fuzzy values is displayed in the following figure 2.3. In the example, temperature has fuzzy values labeled by *very cold, cold, normal, hot, very hot* which are represented by five different fuzzy sets. Here, each fuzzy set is expressed by a unique MF and plotted as degree of membership μ_A versus fuzzy input variable "temperature''.

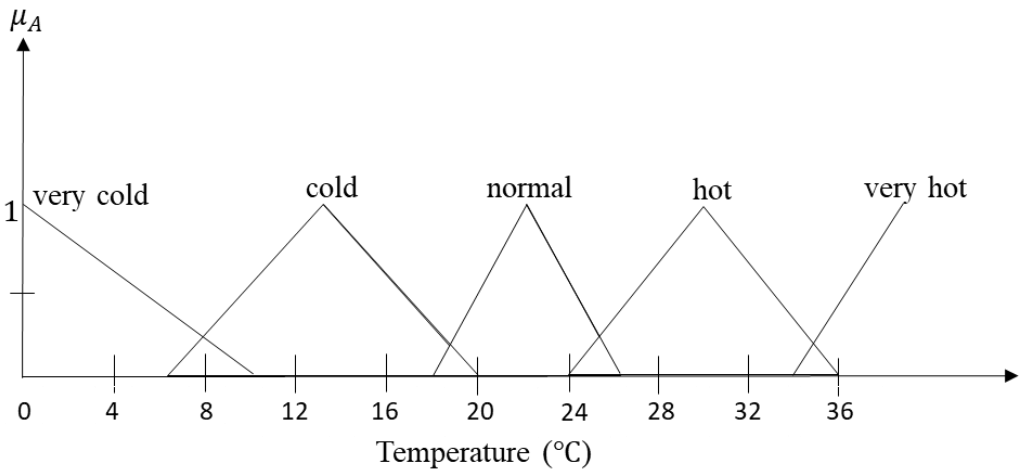
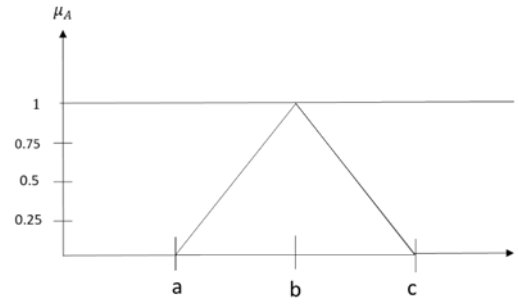


Figure 2.3 An example of *fuzzy* variable "temperature" and its *fuzzy* values (*very cold, cold, normal, hot, very hot*) expressed in triangular *fuzzy sets*

In the figure, triangular membership function is utilized for representing each *fuzzy set*. Triangular membership function is the most simple membership function, which specified by three points {a, b, c} where a is the lower limit, c is the upper limit and a < b < c. Triangle membership function is defined as follows:

Table 2.1 Triangular Membership Function

$\mu_{triangle}(x; a, b, c)$ $= \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a < x \le b \\ \frac{c-x}{c-b}, & b < x < c \\ 0, & x \ge c \end{cases}$	

2.3.2 Fuzzy Rule Based System

Fuzzy rule-based system (FRBS) is a technique which works based on fuzzy rules. The rules are defined by fuzzy logic (FL). FL is a tool which represent several forms of knowledge of the problem domain being solved, also for modeling the relationships and interactions that exist among its different variables [14][15].

A single *fuzzy if-then rule* has the following form:

$$\text{if } x \text{ is } A \text{ then } y \text{ is } B \tag{2.2}$$

here, A and B represent linguistic values characterized by fuzzy sets on universe of discourses X and Y respectively. The first part (if-part) of the above if-then rule "x is A" is termed as antecedent/ premise, while the second part (then-part) "y is B" is termed as consequent/ conclusion of the rule. For example, a fuzzy rule could be

If food is excellent then tip is high

Here, the antecedent, "excellent" is a definition which returns a discrete value between 0 and 1. In contrast, the consequent, "high", characterized by a fuzzy set which assigns to calculate the output variable "tip".

The antecedent part of a fuzzy rule could have several parts like

If it is raining and road is slippery then driving speed is slow

where each part of the antecedent are measured at the same time and concluded to a discrete value by different fuzzy logical operators. Moreover, the consequent part of a fuzzy rule could also have several parts like

If weather is hot then ac temp is low and fan speed is high

in which all parts of the consequents are calculated equally for obtaining consequence of the antecedent.

The common form of a fuzzy rule defined as

$$\text{if } x_1 \text{ is } A_1, x_2 \text{ is } A_2, \ldots \ldots, x_i \text{ is } A_i$$
$$\text{then } y_1 \text{ is } B_1, y_2 \text{ is } B_2, \ \ldots \ldots, y_k \text{ is } B_k$$

where, each x_i represents the input variable (antecedent), each y_k represents the output variable (consequent) whose value will be concluded, and each fuzzy variable A_i and B_k is a fuzzy set specified by a membership function. These *if-then* rules defined with different fuzzy sets are combined using three basic fuzzy logic operations, "F-AND" (Fuzzy Intersection of two fuzzy sets, "F-OR (Fuzzy Union of two fuzzy sets", and "F-NOT" **(**Fuzzy Complement of one fuzzy set) [16]. The fuzzy logic operations are defined as follows:

$$\mu_{A \text{ and } B}(x) = \mu_A(x) \wedge \mu_B(x) = \min\{\mu_A(x), \mu_B(x)\}$$

$$\mu_{A \text{ or } B}(x) = \mu_A(x) \vee \mu_B(x) = \max\{\mu_A(x), \mu_B(x)\}$$

$$\mu_{not\ A}(x) = \neg\, \mu_A(x) = 1 - \mu_A(x)$$

where A and B are fuzzy variables which are combined to form fuzzy-logic expressions by using these fuzzy logical operators.

2.3.3 Fuzzy Inference System

A fuzzy inference system is characterized by a fuzzy rule-based system which utilizes fuzzy logic instead of boolean logic for representing and manipulating about the data [17]. The system involves mapping a input variable to an output variable based on fuzzy logic. The procedure of the system includes different phases that we have discussed previously i.e., fuzzy sets, fuzzy logic, fuzzy logic operators, membership functions and fuzzy if-then rules and. The basic construction of a fuzzy inference system includes four main modules, as illustrated in figure 2.4.

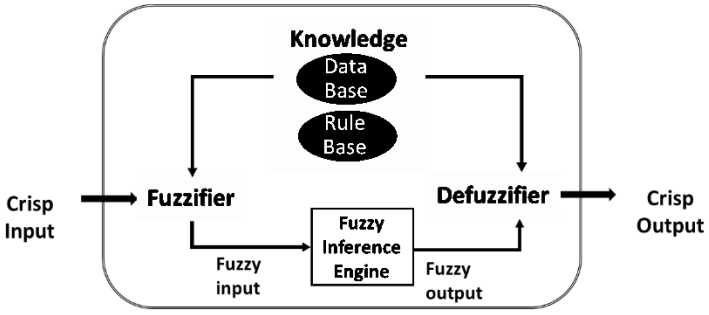


Figure 2.4 A Fuzzy Inference System

1) Fuzzifier: The main task of fuzzifier is to convert the crisp (original-valued) input values into fuzzy values using input membership function.
2) Knowledge Base: The knowledge base includes a *rule base*, that includes number of fuzzy if-then rules and a *database* that characterizes the membership functions employed in fuzzy if-then rules. The inference system looks for data specified in the *if* parts of fuzzy rules. These data will be discoverd either in *then* parts of other fuzzy rules, in the knowledge base, or by querying of the user.
3) Inference Engine: The inference engine of a fuzzy inference system operates on a number of fuzzy rules and makes fuzzy inference to obtain fuzzy output.
4) Defuzzifier: The task of defuzzifier is to transform the fuzzy output value into a crisp value obtained as a result of inference engine.

2.4 Fuzzy Rule Based Classification System

The natural growth of numerous diseases and vague behavior of medical records need a reliable framework which can handle uncertainty of ambiguous medical problems efficiently [14][15][18][19][20]. This inevitably makes the fuzzy rule-based classification system (FRBCS) a powerful tool for classifying the severity of DR using comprehensible linguistic representation of medical records [14][15][18]. FRBCS is one of the most powerful tools for solving multi-classification problem domain [21][22]. The system operates based on human-understandable rules which are defined by linguistic labels [18]. The two basic elements of FRBCS are *Knowledge base* and *Fuzzy Reasoning Method*. Knowledge base (KB) is consists of rule base (RB) and database (membership functions), in which the linguistic labels are characterized by rules and the membership functions [23]. Fuzzy Reasoning Method (FRM) is the technique for identifying a new pattern based on the information contained in the knowledge base [23][24].

2.4.1. Fuzzy If-Then Rule

Let us consider, a classification problem domain has *C* class problems with n-dimensional pattern space and *m* given training patterns $x_p = (x_{p1}, x_{p2}, \ldots\ldots, x_{pn})$, $p = 1,2, \ldots\ldots, m$. First, the attribute values of the given training pattern are normalized into the unit interval [0,1] by which the pattern space is transformed into the n-dimensional unit hypercube $[0,1]^n$; thus attribute values of each pattern are $x_{pi} \in [0,1]$ for $p = 1,2, \ldots\ldots, m$ and $i = 1,2, \ldots., n$.

For a n-dimensional and *c*-class problem, the fuzzy *if-then* rule could be defined in the form as follows:

$$\text{Rule } R_i\text{: if } x_1 \text{ is } A_{i1} \text{ and if } x_2 \text{ is } A_{i2} \text{ and } \ldots\ldots \text{ and if } x_n \text{ is } A_{in} \quad \text{then class } C_i \text{ with } C_{Fi}\,, \quad i = 1,2, \ldots\ldots N \tag{2.3}$$

here, R_i presents the label of i^{th} fuzzy if-then rule, X = $\{x_1, x_2, \ldots\ldots x_n\}$ is the pattern vector on n-dimension, $A_{i1}\ldots\ldots A_{in}$ are the antecedent of fuzzy sets for the ith attribute on the unit interval [0,1], C_i represent one of the c classes (i.e.,

consequent class), C_{Fi} is a certainty grade of fuzzy if-then rule R_i and N presents the total number of fuzzy rules.

2.4.2. Fuzzy Rule Generation

Let us consider that for a *C* class pattern classification problem, *m* training patterns $x_p = (x_{p1}, x_{p2}, \ldots\ldots, x_{pn})$, $p = 1,2, \ldots\ldots, m$, are given for a n- dimensional space. The consequent class C_i and the certainty grade C_{Fi} of each fuzzy if-then rule are calculated using the following steps [25]:

Step I: The compatibility grade of each training pattern $x_p = (x_{p1}, x_{p2}, \ldots\ldots, x_{pn})$ with fuzzy if–then rule R_i is calculated using the product operation as follows:

$$\mu_i(x_p) = \mu_{i1}(x_{p1}) \times \ldots\ldots\ldots \times \mu_{in}(x_{pn}) \tag{2.4}$$

where $\mu_{ij}(x_{pj})$ represent the membership function of A_{ij}

Step II: For each class *h*, the sum of the compatibility grades $\beta_{class\ h}(R_i)$ of *m* training patterns with the fuzzy if–then rule R_i is calculated by:

$$\beta_{class\ h}(R_i) = \sum_{x_p \in class\ h} \mu_i(x_p), h = 1,2, \ldots\ldots c \tag{2.5}$$

Step III: Class $\hat{h}$ which has the maximum sum of $\beta_{class\ h}(R_i)$ is found by:

$$\beta_{class\ \hat{h}}(R_i) = \max_{1 \le k \le c} \{\beta_{class\ k}\ (R_i)\} \tag{2.6}$$

Here, if two or more than classes obtained the maximum value, then the consequent class C_i of the fuzzy rule R_i could not be measured separately. In that case, C_i is termed as $C_i = \phi$, then the grade of certainty CF_i of R_i is $CF_i = 0$. On the other hand, if a single class $\hat{h}_i$ have the maximum value, the certainty grade CF_i with $C_i = \hat{h}_i$ is determined as follows [15]:

$$CF_i = \frac{\beta_{class\ \hat{h}}(R_i) - \bar{\beta}}{\sum_{h=1}^{c} \beta_{class\ h}(R_i)} \tag{2.7}$$

with

$$\bar{\beta} = \frac{\sum_{\substack{h=1 \\ h \neq \hat{h}}}^{c} \beta_{class\ h}(R_i)}{c-1} \tag{2.8}$$

2.4.3 Fuzzy Reasoning Method

After developing *N* fuzzy if-then rules using eq. (2.3), both the consequent class C_i and the certainty grade CF_i are calculated for each of the *N* rules. Then, a new pattern $X = \{x_1, x_2, \ldots\ldots x_n\}$ could be classified using the following steps [15]:

Step I: The maximum valued class, $\alpha_{class\ h}(X)$ is calculated for class h, $i = 1,2, \ldots\ldots, C$, as follows:

$$\alpha_{class\ h}(X) = max\ \{\mu_i(X).\ CF_i \mid C_i = h\ \} \tag{2.9}$$

Step II: Class h^*, that take the maximum value of $\alpha_{class\ h}(X)$ is determined by:

$$\alpha_{class\ h^*}(X) = \max_{1 \leq l \leq c} \{\alpha_{class\ l}(X)\} \tag{2.10}$$

Here, if two or more classes obtained the equal (maximum) value using in eq. (2.9), then the new pattern *X* could not be classified (i.e. *X* is remained as an unclassified pattern), otherwise *X* is assigned to class h^*.

2.5 Related work

Several researchers have proposed a number of techniques for developing an automatic screening system to detect and classify the DR at early stage. In [26] the authors presented an effective method for segmenting blood vessels based on changing the basic line detector length. The method detected the line responses at changing scales and combined them for producing the final segmentation of vessels for each fundus image. They evaluated the outcome of their proposed method by both quantitatively and qualitatively using three public datasets and achieved over

90% accuracy for detecting abnormal blood vessels. However, they did not demonstrate the achieved sensitivity or specificity.

Welfer *et al.* [27] proposed a method for detecting both microaneurysms and haemorrhages in retinal images. The proposed system applied mathematical morphology operations and removing the retinal anatomy for extracting red lesions. The mean sensitivity and specificity of the paper was found 87.69% and 92.44% respectively. Niemeijer *et al.* [28] represented a robust system for detecting red lesions in color fundus images by classifying the features using K-nearest neighbor. The paper described the process of detecting and quantifying Microaneurysms, presented in digitized fluorescein angiograms. The sensitivity and the specificity were found 100% and 87% respectively. An improved method for detecting the red lesions of DR in fundus images using pixel classification method and mathematical morphology is described in [29]. They have obtained sensitivity of 100% and specificity of 91%.

A hybrid technique for detecting hard exudates was described in [30]. The method combined both morphological image processing techniques and fuzzy classifier to correctly identify hard exudates from soft exudates in retinal fundus images. In the initial phase, optic disk is eliminated and the exudates are found by mathematical morphology; then the hard exudates are separated by adaptive fuzzy logical algorithm which utilizes RGB color space values of each retinal image. But, the authors used only 40 images for evaluating the method and obtained sensitivity of only 75.43%. A similar work with 688 images was performed in [31] using a filter bank Bayesian classifier to segment the candidate exudates. They have removed both the spurious exudates and optic disc region to extract exudates correctly. The reported accuracy of the work was 97.59%.

Sinthanayothin *et al.* [32] has established a screening system for detecting the notable features of NPDR analyzing digital color retinal images. They have used a new method named Moat Operator merged with the recursive region growing segmentation algorithms for automated detection of NPDR features. This paper

detected exudates and haemorrhages for classifying NPDR stages. They have estimated their segmentations based on segment instead of pixel and. demonstrated the result of only 30 images.

Nayak *et al.* [33] carried out an automatic identification technique for the main stages of DR i.e., normal, NPDR and PDR using Artificial Neural Network (ANN). They have preprocessed the image, applied morphological image processing methods and used texture analysis method to identify the features like; hard exudates area, blood vessels area and the contrast. However, they considered only blood vessels and hard exudates for classifying DR and used a private dataset of 140 retinal images. A hybrid technique based on higher-order spectra with support vector machine (SVM) was proposed in [34]. But they did not detect any lesion for classifying DR stages. They had also utilized a private dataset of 300 retinal fundus images and demonstrated sensitivity of 82% and specificity of 88%. A similar concept is considered in [35] for DR screening system where an integrated DR index and SVM were used for DR classification. The authors detected five texture features, i.e.; homogeneity, correlation, short run emphasis, long run emphasis, and run percentage. The extracted features were classified using SVM of several kernel function (linear, radial basis function, polynomial order 1, 2, and 3) and determined 85.2% accuracy, 98.9% sensitivity, 89.5% specificity and 0.972 area under curve (AUC) by SVM technique with polynomial kernel of order 3.

Yun *et al.* [36] proposed a feed forward neural network classifier with three-layer for identifying normal, moderate DR, severe DR and PDR stages. They have used histogram equalization, morphological operations and binarization to identify six features namely, red layer of perimeter (RLP), green layer of perimeter (GLP), blue layer of perimeter (BLP), red layer of area (RLA), green layer of area (GLA) and blue layer of area (BLA) of veins, haemmorrhages and microaneurysms. The method analyzed 124 private retinal photographs and demonstrated sensitivity more than 90% with specificity of 100%. Acharya *et al.* [37] developed a computer-based detection technique using morphological image processing and SVM methods for automatic screening of DR. In this paper, 331 private retinal images

were analyzed and obtained an accuracy of 85.94% for classifying all stages of NPDR and PDR.

The stages of only NPDR is considered in [38]. They have proposed a new decision support framework using rule-based classifier for detecting the boundaries of the bright object. They did not consider dark regions for NPDR classification and used only one publicly available dataset. They have shown an average accuracy of 97% for classifying NPDR. An identical observation is found in [39] where early lesions with basic fundus structures are detected and severity is demonstrated by international criteria of DR.

For detecting microaneurysm and haemorrhage, two features; thresholding and shape were utilized in [40] to identify normal and abnormal retinal fundus images. This paper illustrated that classifying DR lesions of fundus images is possible using simple methods without considering the presence of noise and blurring of images. But, it could be crucial in times of variation in illumination and other properties of image. So, advanced techniques are needed to apply for efficient detection of lesions. To improve the diagnosing technique of DR, trace transform techniques are being developed in [41]. They classified the features using SVM with quadratic, polynomial, radial basis function kernels and probabilistic neural network (PNN) along with genetic algorithm (GA) and achieved 99.41% and 99.12% accuracy applying PNN–GA and SVM quadratic kernels, respectively.

In [42] the authors have segmented and separated exudates, haemorrhages and microaneurysms using a 10-layer convolutional neural network (CNN). Instead of lesion or image, they estimated their segmentations based on per pixel basis not just automatically, but also simultaneously. The 10-layer network was trained in two stages and each input fundus image was stabilized before feeding into the network to improve the classifier performance.

A similar assessment of CNN classifier was done by [43] to study the efficacy of CNN technique for the diagnosis of DR using fundus images and identifying its severity accurately. In this study, CNN architecture and data augmentation

techniques are combined to achieve accuracy of only 75% using 5,000 validation fundus images.

Kele Xu *et. al.* [44] proposed deep CNN methodology for classifying DR automatically. To enhance the effectiveness of the algorithm, they have applied data augmentation techniques to extend the datasets artificially by label-preserving transformation and to minimize overfitting label on the image datasets. They have applied translation, stretching, rotation and flipping techniques onto the labeled image dataset and conducted the classification task using Gradient boosting machines and CNN techniques.

Choosing the best classifier performance for detecting DR is proposed in [45]. The paper involves extracting abnormal signs, like hard exudates area, blood vessels area, bifurcation points, texture and entropies of fundus images. They have used 13 features which are statistically significant $(p < 0.0001)$ for PNN, Decision Tree (DT) C4.5, and SVM and identified the top performance with PNN classifier which was optimized using GA and Particle Swarm Optimization (PSO) techniques. They have also validated 96.27% average sensitivity, 96.08% specificity and 96.15% classification accuracy by threefold cross validation with PNN classifier.

Most of the researchers mentioned above have used images from private databases for the detection and classification of DR. Therefore, it becomes difficult to compare the result and improve the performance of existing screening system. Moreover, many of them did take into account of identifying all possible candidate lesions (blood vessels, MAs, HMs, and EXs); so that the stages of DR could be wrongly classified. Most of the researches have given emphasis on either a high level of sensitivity or specificity and do not consider the accuracy and computation time.

The proposed technique in this thesis is effective enough to identify the limitations of most of the above-mentioned researches. This technique is able to detect all possible candidate lesions of DR, i.e., blood vessels, MAs, HMs, and EXs and also able to classify five stages of DR; normal, mild NPDR, moderate NPDR, severe

NPDR and PDR automatically. The use of FRBCS makes this technique more reliable to handle the uncertainty and continuity of DR diagnosing. Moreover, different image processing techniques are optimized for lesion detection and vital features utilized for classification concurrently. Computation time along with accuracy are considered for classifying DR and results of simulation validate its supreme effectiveness to obtain significantly better classification result compared to other classification techniques.

2.6 Conclusions

This chapter represents the concept of diabetic retinopathy and the basic model of fuzzy rule-based classification system. It also describes numerous existing detection and classification methods of diabetic retinopathy using different machine learning algorithm. The shortcomings of those techniques were identified and to overcome those limitations, various aspects of the proposed technique were stated.

CHAPTER THREE

Proposed Methodology

3.1 Introduction

This chapter describes the concept, working procedure of the proposed detection and classification algorithm of diabetic retinopathy using fuzzy rule-based classification system in detail.

3.2 Proposed Methodology

In this study, we propose an automated diagnosis technique of diabetic retinopathy (DR) using fuzzy rule-based classification system (FRBCS) that is capable of identifying different retinal lesions; blood vessels, microaneurysms (MAs), haemorrhages (HMs), exudates (EXs) and also predicting the severity of DR based on detected lesions features. The overall block diagram of the proposed technique is illustrated in the figure 3.1.

The proposed technique is partitioned into two phases: detection phase and classification phase. In the detection phase, the retinal fundus images are passing through different image processing techniques and morphological operations as adaptive histogram equalization, opening, closing, erosion, top-hat transformation, dilation etc. [46][47]. The fundus images were preprocessed with the above techniques to remove the background noise and generate a high-intensity image. Then, the optic disk and normal blood vessels were detected and eliminated from the image to extract only abnormal components (fragile blood vessels, MAs, HMs, and EXs). Next, a feature set is formulated from each of the candidate lesions to feed to the Fuzzy classifier. At last, in the classification phase the image is classified into five stages i.e. normal, mild NPDR, moderate NPDR, severe NPDR, and PDR using fuzzy classification system.

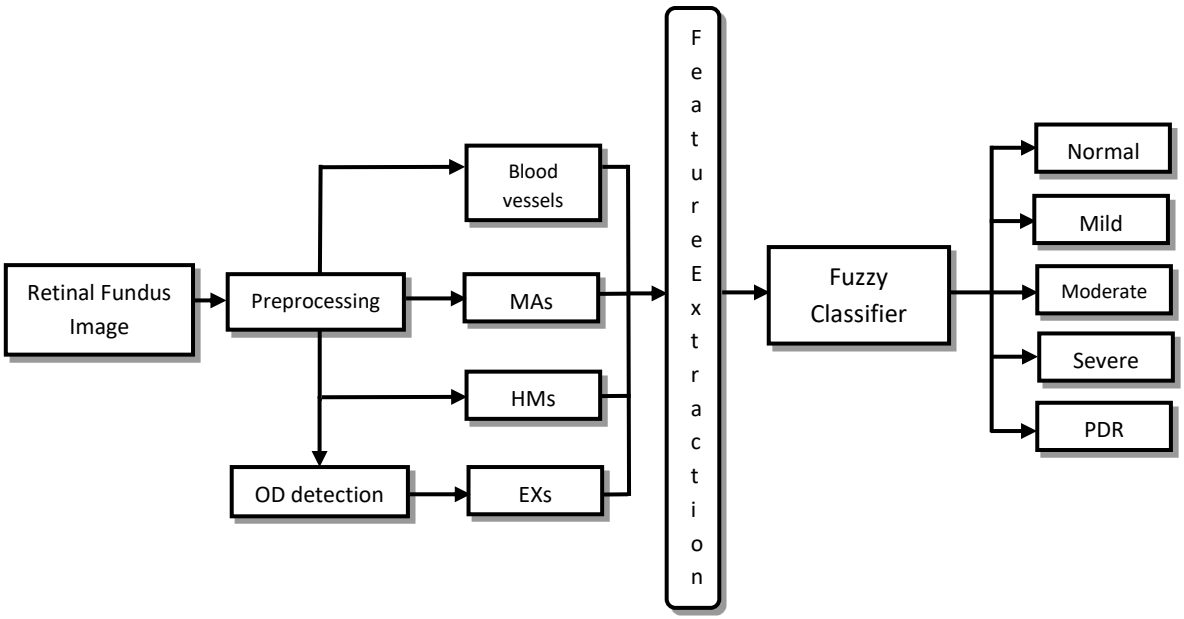


Figure 3.1 Overall block diagram of the proposed DR classification system

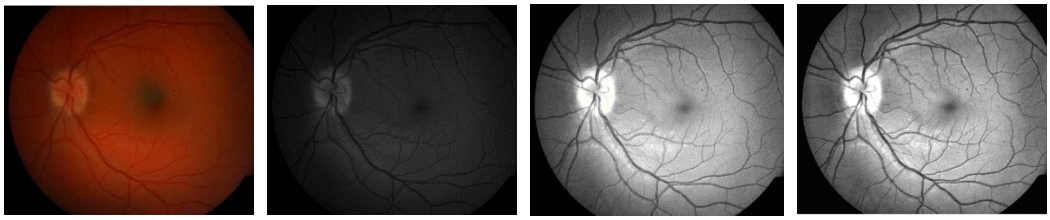
The detail description of our proposed technique is as follows:

3.2.1 Detection of Lesions

3.2.1.1 Preprocessing

Preprocessing is the primary step of candidate lesions detection. The RGB fundus images often suffer from low contrast, noises, and undesirable artifacts. Hence, the retinal images were preprocessed before applying any other segmentation processes. The preprocess steps involved the color channel extraction, contrast enhancement and filtering to remove the non-uniform background and to minimize the unwanted noises from the image. At first, the retinal fundus image I_{RGB} was resized to 520×480 pixels to get a uniform image. Next, the green channel of the fundus image I_{green} was extracted because green channel displays the highest contrast between the retinal lesions and the background compared to red or blue channel [32]. Image adjustment techniques have been used to increase the intensity of the I_{green} image and to make the lesions more visible. Then, a median filter has been applied to I_{green} image of size 3*3 pixels to get filtered image I_{MF}. The

processes smooth the image reducing the distortions appeared in different image boundaries. Finally, the contrast of the image was enhanced by the contrast limited adaptive histogram equalization (CLAHE) and produced the preprocessed image I_{PR}. The outputs of preprocessing step are shown in figure 3.2.



(a) (b) (c) (d)

Figure 3. 2 The results obtained from preprocessing steps (a) Original retinal image I_{RGB} (b) Green channel image I_{green} (c) Adjusted filtered image I_{MF} (d) Contrast enhanced image I_{PR} using CLAHE.

3.2.1.2 Blood Vessels Detection

Blood vessels are one of the normal components of human retina, but the abnormal growth of vessels depicts the signs of PDR. So, blood vessels detection is important to classify the stages of DR correctly. Vessels appear darker than the retinal background and they are connected as a tree structure [48]. We have worked on the preprocessed image I_{PR} and applied morphological operations for detecting the blood vessels.

Morphological operations are one of the image processing techniques that process an image by applying a structuring element (SE) i.e., disk, ball, octagon etc. [46] [47]. The operations were performed to remove the noisy background and smooth over the intensity range of the image. Opening and Closing are the two operations of morphological operations which are duel to each other. Opening operation contains erosion followed by dilation, while closing operation involves dilation followed by erosion. Opening and closing operations of a grey-scale image $I\ (x, y)$ with structuring element *SE (s, t)* are indicated by eq. (3.1) and (3.2) respectively [46].

$$I \circ SE = (I \ominus SE) \oplus SE \quad (3.1)$$

$$I \bullet SE = (I \oplus SE) \ominus SE \quad (3.2)$$

where, $\ominus$ and $\oplus$ represent the erosion and the dilation operation respectively.

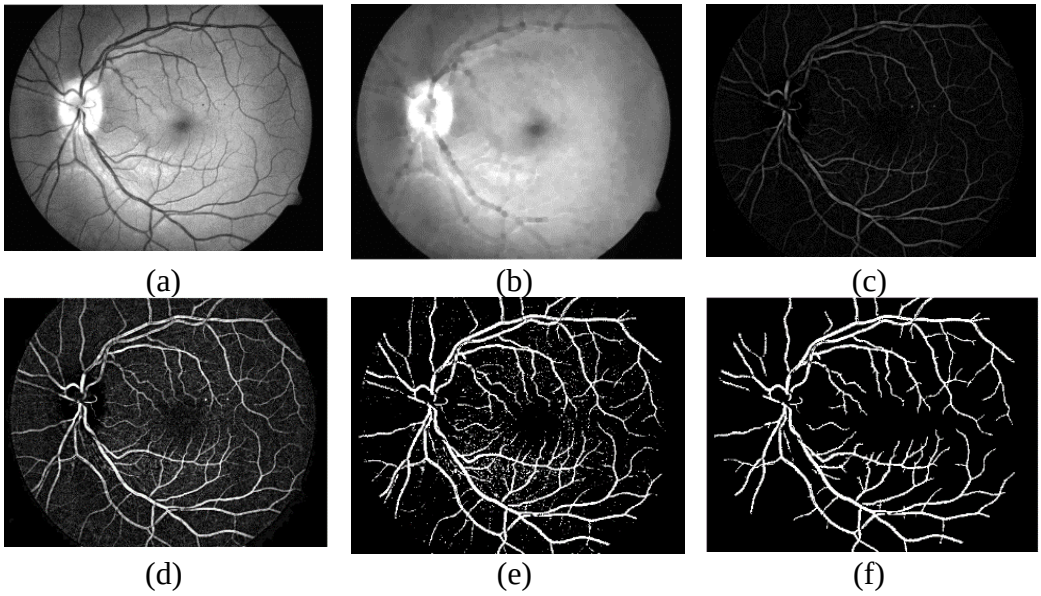


Figure 3. 3 The detection steps of blood vessels (a) Preprocessed image I_{PR} (b) Closing image I_{close} (c) Subtracted image (d) Contrast enhanced image (e) Detected vessels with unwanted noises (f) Extracted blood vessels (binary image).

We have applied the closing operation on the image I_{PR} using a disk shaped SE of radius R=10 and obtained the closing image I_{close} by using eq. (3.2). Closing operation eliminates small holes in the contours of fundus image which assists in extracting the vessels. The closing image I_{close} was subtracted from the preprocessed image I_{PR} to separate the blood vessels from the background. After a series of operations, the background of the fundus image was not as noisy compared to original image and the contrast enhancement was allowing the vessels to be seen more clearly than before. Finally, an optimized threshold value T was applied for segmenting the image into two classes (black and white) based on their intensity and obtained a binary image removing unwanted noises. Different stages of blood vessels detection are illustrated in figure 3.3.

3.2.1.3 Microaneurysms Detection

Microaneurysms are the initial recognizable sign of DR. They appear as tiny red dots (approximately 10 to 100 μm in diameter) dispersed on the blood vessels wall [13][29]. As blood vessels and MAs have almost identical color and MAs do not appear on the blood vessels, blood vessels are eliminated from the image to identify MAs correctly.

We have utilized the green channel of RGB image I_{green} for detecting MAs. Before enhancing the intensity of the image, the complement of $I_{green}$was performed to sharpen the edge of blood vessels area using the following equation:

$$I^c = \{z | \, z \notin \, I \,\} \tag{3.3}$$

Here, the complement of I, I^c is the set of all points z, such that z is not an element of I.

Then, the CLAHE operation was applied to the complemented image I^c similar to preprocessing steps. To detect the edges of blood vessels, canny edge detection technique was used. The Canny edge detection technique detects the connected edges using derivative of Gaussian filter and removes spurious noise simultaneously. The edge detection by the canny technique was obtained using eq. (3.4).

$$I_{Canny} = edge\ (I^c,\ 'Canny') \tag{3.4}$$

After detecting the edges of the vessels, the holes or gapes were filled with disk shape SE of radius 6. Subsequently, the image with edge detected was subtracted from the holes filled image to obtain an image having no boundaries. Next, the segmented vessels obtained from blood vessels detection section were subtracted from the image without boundaries to achieve the candidate MAs [49]. After that, the unwanted pixels (greater than MAs) were removed from the image to detect MAs. The processes of MAs detection are demonstrated in figure 3.4.

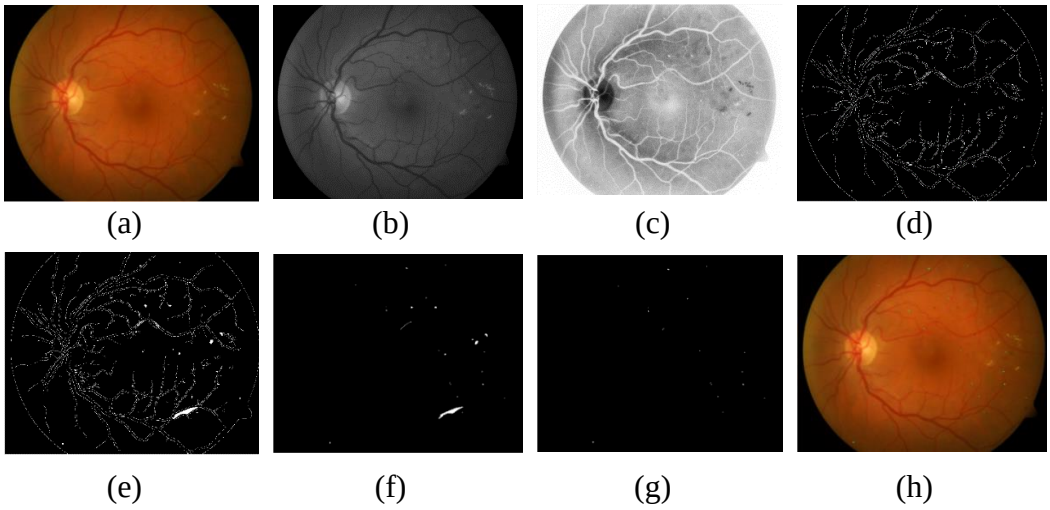


Figure 3. 4 The detection processes of Microaneurysms (a) Original retinal image I_{RGB} (b) Green channel image I_{green} (c) Adjusted complemented image (d) Edge detected image using Canny I_{Canny} (e) Holes Filled image (f) Image without boundaries (g) Detected MAs removing unwanted pixels (h) MAs detected on the original image I_{RGB} with green color.

3.2.1.4 Haemorrhages Detection

Haemorrhages are the dark lesions of DR like MAs. HMs are 'dot', 'blot' or 'flame' shaped and often larger than MAs in size [32]. Both MAs and HMs are red in color similar to a normal component, blood vessels. Therefore, blood vessels and MAs are removed from the image prior to HMs detection.

Histogram matched image I_{RG}, obtained from both red channel I_R and green channel I_G was utilized for detecting HMs. The intensity information of I_{RG} image helped to eliminate the harsh edges of brighter lesions (EXs) effectively [29]. The image was enhanced and filtered by contrast adjustment and median filter to eliminate the variation intensity from the background within the image. Then, the enhanced image was complemented to sharpen the boundaries of the red lesions (MAs and HMs) using eq. (3.3).

A morphological opening operation (details in section 3.2.1.2) was performed using eq. (3.1) to separate the largest circle (optic disk) from the complemented image. A

ball-shaped SE with radius 15 was used to identify the circle and was eliminated by subtracting the opening image from the complemented image. During this process, the contrast of both the blood vessels and the dark lesions were enhanced equally. An effective relative entropy-based thresholding technique [50] was applied to obtain the optimal threshold value for retaining the candidate HMs along with blood vessels and MAs.

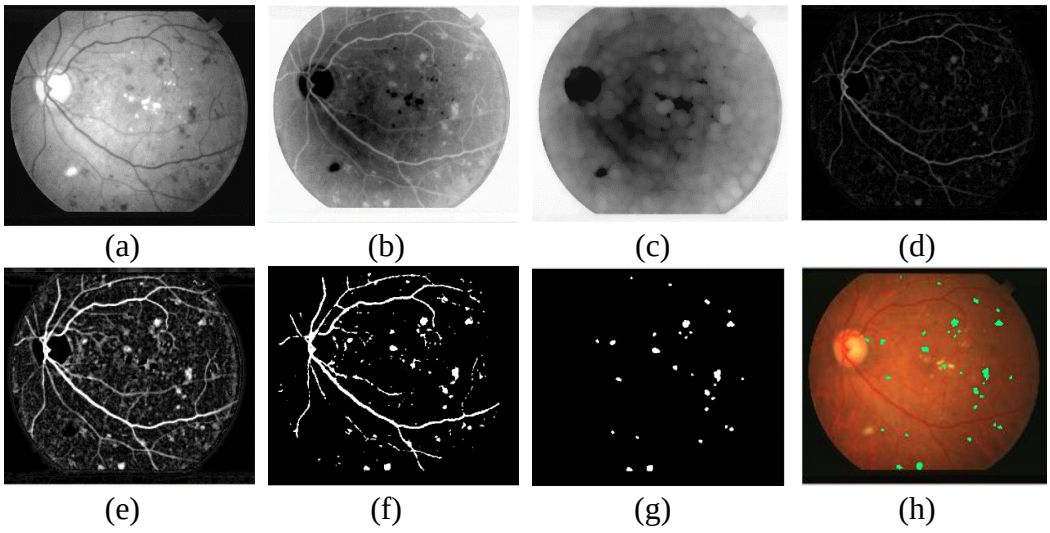


Figure 3. 5 The results of Haemorrhages detection steps (a) Histogram-matched image I_{RG} (b) Complemented image I^c (c) Opening image I_{open} (d) Subtracted image (e) Enhanced dark components (f) Candidate HMs along with blood vessels and MAs (g) Binary image containing HMs (h) HMs detected on the original image I_{RGB} with green color.

At last, the segmented blood vessels and MAs (described in the previous two sections) were subtracted from the binary image (containing blood vessels, MAs and HMs) and detected the HMs. The results of HMs detection steps are displayed in figure 3.5.

3.2.1.5 Exudates Detection

Exudates detection is the most crucial stage of lesions detection for DR. EXs are one of the abnormal components of human retina which are white-yellowish in color and often are irregular in shape [51]. They are the bright lesions of DR having

the highest intensity, but the color and the intensity of EXs are similar to a normal component, optic disk (OD). EXs can be wrongly diagnosed as OD which results in erroneous classification. For this reason, OD was detected and removed from the image before detecting EXs.

3.2.1.5.1 Optic Disk Removal

Optic disk (OD) is more or less circular or slightly elliptical in shape with a size of approximately 80 ×80 pixels in retinal images. Usually OD is the brightest region of retinal fundus image. Red channel has the benefits of making the bright areas (OD, EXs) more sharp and clear against the retinal background [51]. Hence, red channel of retinal images I_R is utilized for detecting OD. Next, the intensity of the red channel image I_R was enhanced by contrast stretching method to remove the intensity variation from the background and separate only the highest intensity structures remain on the image.

From the previous research works, it is known that the area of OD is usually larger than EXs in most of the retinal fundus images. Therefore, both closing and opening techniques were applied sequentially on the contrast stretched image for extracting the largest bright region of the image using eq. (3.2) and (3.1) respectively. We have used a flat disk shaped of SE=20 to perform both closing and opening operations. Finally, the binary image is obtained by applying the required threshold value. The OD detection and removal process is presented in figure 3.6.

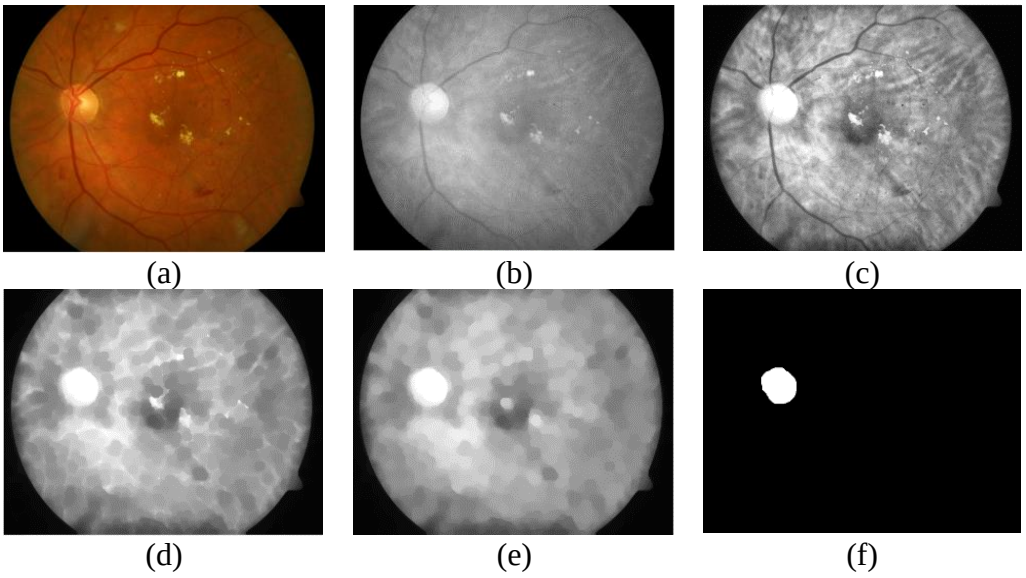


Figure 3. 6 The segmentation of optical disk (a) Original retinal image I_{RGB} (b) Red channel image I_R (c) Contrast enhanced image (d) Closing image I_{close} (e) Opening image I_{open} (f) Segmented OD

3.2.1.5.2 Exudates segmentation

The OD removal image was used for EXs segmentation. First, the green channel of the original image $I_{green}$was extracted and applied the CLAHE method to enhance the intensity as previously described. Then, the image was complemented to highlight the bright EXs. The complement of an image was found by eq. (3.3). The complemented image was adjusted and again complemented to spread the bright pixel intensity more consistently over the intensity range [36]. After that, the binary regions of EXs were extracted from the complemented image by applying an optimized threshold value T. Figure 3.7 exhibits different steps of EXs segmentation.

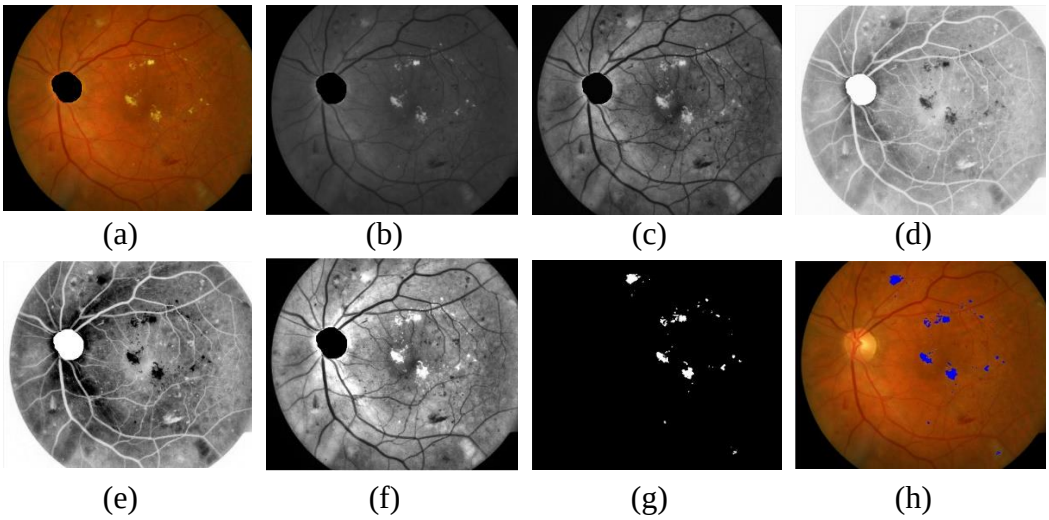


Figure 3. 7 Exudates segmentation steps (a) OD removal image (b) Green channel image I_{green} (c) Contrast enhanced image using CLAHE (d) Complemented image (e) Adjusted image (f) Complemented image (g) Binary image using threshold (h) EXs detected on the original image I_{RGB} with blue color.

3.2.1.6 Textural Features Analysis

Along with diabetic lesion detection, it is important to analyze textural features for increasing the performance of the classification system. Texture analysis is associated with characterization of regions of an image by its spatial variations in pixel intensities. There are different types of computation methods, among which two texture properties were extracted; contrast and homogeneity from retinal images that are derived from Gray-Level Co-occurrence Matrix (GLCM). The GLCM functions represent the texture features of an image by determining the consistency in pixel brightness values (gray levels) and a particular spatial relationship occurring in a pixel pair of that image.

1) Contrast:

Contrast estimates the quantity of local intensity variations of GLCM in an image. It returns the estimation of intensity contrast between a pixel and its neighboring pixel of an image which is described as follows:

$$\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(i-j)^2\, p_d(i,j) \tag{3.5}$$

where $p_d(i,j)$ is the probability of obtaining a pair of pixels (i,j) occurring in adjacent to each other into $M \times N$ GLCM.

2) Homogeneity:

Homogeneity calculates the values of closeness distribution in the GLCM values to the diagonal of GLCM values. It estimates the values by inversing the contrast weight which are declining exponentially from the diagonal as given in (3.6). It becomes large if local textures have minimum changes.

$$\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\frac{1}{1+(i-j)^2}p_d(i,j) \tag{3.6}$$

3.2.2 Classification of DR Stages

In this section, we have employed the classification of DR stages using fuzzy rule-based classifier according to detected lesions described in the previous section.

3.2.2.1 Design of Proposed FRBCS

In this work, FRBCS technique is proposed for assisting both the patients and the medical experts for diagnosing DR. The designing procedure of the proposed system are: first, to assemble all the necessary information which is frequently evaluated by the medical experts for DR screening, second, to analyze the

relationship of several considered features with possible stages of DR, and finally, to provide an automatic diagnostic aide.

The development of FRBCS for analyzing DR has been increased immensely in recent years for its adaptive behavior and human problem-solving capacity [52] [53][54]. FRBCS used fuzzy logic which gives more promising results compared to traditional mathematical models for uncertain, vague and complex problems [52][55]. Moreover, fuzzy classification system is particularly good at handling uncertainty and vagueness by expressing the knowledge in a simple linguistic way along with modeling the relationship and interactions among its variables [56]. Hence, we have carried out the diagnosis of DR using FRBCS.

The designing procedure of the proposed FRBCS is:

I) *Construction of database:* The database which consists of the linguistic sets for defining linguistic rules and the membership functions for defining the linguistic labels is defined by prior expert knowledge. Each linguistic label associated to each linguistic variable is also considered. Linguistic variables characterize the different features that are responsible for DR screening (antecedents of the rules) and the potential stages of DR related to the appearance of those features (consequents of the rules). In our work, six input features have been considered for constructing the linguistic variables of rule antecedents:

- Blood vessels area
- MAs counts
- HMs area
- EXs area
- Contrast
- Homogeneity

Each linguistic variable is divided into three linguistic labels; low, medium and high as presented in Table 3.1. Antecedents of the rules are formed by above 6

linguistic variables which are responsible features for DR and their associate linguistic labels (low, medium and high). Thus, 6 linguistic variables and 18 linguistic labels associated with the rule antecedents are stored in the database. The consequents of the rules are the outputs of the system. Consequents of the rules are formed by the probability of suffering DR associated with responsible features. In this work, we have considered five stages of DR; normal, mild NPDR, moderate NPDR, severe NPDR and PDR for rule consequents in the data base.

Table 3.1 Fuzzy sets for input features of DR

Input features	**Low**	**Medium**	**High**
Blood Vessels Area	40,000-100,000	80,000- 150,000	130,000-200,000
MAs counts	0- 5	3-10	8-30
HMs Area	0- 200	100- 800	600- 8000
EXs Area	0 -450	350-2200	1650-9000
Contrast	0.0206 - 0.0283	0.0241-0.0352	0.0271-0.045
Homogeneity	0 -0.978	0.974-0.985	0.981-0.99

II) *Construction of Fuzzy rule base:* To model the problem domain, the linguistic "if-then" rules are constructed based on rule antecedents and rule consequents in the above data base. We have considered 6 features and each feature is divided into 3 levels, so the number of rules will be $3^6 = 729$ which is undoubtedly expensive for both computational complexity and storage

requirements. Thus, the rule base designing (construction and modification) was established under the supervision of an expert ophthalmologist. Among 729 rules, the expert has selected 87 rules without sacrificing the classification performance [57] which is shown in Table 3.2.

Table 3. 2 Fuzzy rules for DR classification system

Rule	Blood Vessels	MAs	HMs	EXs	Contrast	Homogeneity	Stage
1.	Low	Low	Low	Low	Low	Low	Mild
2.	Low	Low	Low	Medium	Low	Medium	Moderate
3.	Low	Low	Low	High	Medium	High	Severe
4.	Low	Low	Medium	Low	Low	High	Moderate
5.	Low	Low	Medium	Medium	Medium	High	Moderate
6.	Low	Low	Medium	High	Medium	Medium	Severe
7.	Low	Low	High	Low	High	High	Severe
-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-
45.	Low	Low	High	High	Low	High	Severe
46.	Low	Medium	Low	Low	Medium	Medium	Mild
47.	Low	Medium	Low	Medium	High	Medium	Moderate
48.	Medium	Medium	Low	High	Medium	High	Severe
49.	Medium	Medium	Medium	Low	High	Low	Moderate
50.	Medium	Medium	Medium	Medium	Medium	High	Moderate
51.	Medium	Medium	Medium	High	Low	High	Severe
-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-
81.	Medium	High	Low	Medium	High	Low	Severe
82.	High	High	Low	High	High	High	PDR
83.	High	High	Medium	Low	Low	High	PDR
84.	High	High	Medium	Medium	Medium	High	PDR
85.	High	High	Medium	High	High	Medium	PDR
86.	High	High	High	Low	High	Low	PDR
87.	High	High	High	High	High	High	PDR

III) Designing of the fuzzy inference systems:

In this research work, Mamdani fuzzy system [58] is selected for developing the proposed FRBCS. For defining the membership functions (MFs) of each fuzzy set, triangular membership function is applied for both the rule consequents and rule antecedents. The above 6 features (blood vessels area, MAs counts, HMs area, EXs area, contrast and homogeneity) are considered as input to form the fuzzy sets and MFs, 87 rules are used for processing the rule antecedents and 5 DR stages (normal, mild NPDR, moderate NPDR, severe NPDR and PDR) are considered as outputs of the fuzzy inference systems.

3.2.2.2 Classification by Proposed FRBCS

The final stage of our proposed system is to classify the DR stages using FRBCS. The detected blood vessels, MAs, HMs and EXs are evaluated in pixels (non-zero) along with the textural features of each retinal image for classifying DR stages. If no abnormal component is detected, the image is classified as normal. When any lesion is found in the image, it is considered as an affected image suffering from DR. Besides, the FRBCS classifies the DR stages according to the rules of fuzzy inference system and gives the output classified according to fuzzy rules of FRBCS defined above. A region was considered to be in the abnormal stage whether the average fuzzy value was greater than 0.25. The other abnormal stages, i.e., mild, moderate, severe, and PDR were computed accordingly ranges between 0.25 and 1.

3.3 Summary

This chapter first depicts the working procedure of the proposed method through a well-organized flowchart followed by detail representation of the lesion detection and fuzzy classification algorithm for automated diagnosing of diabetic retinopathy.

CHAPTER FOUR

Simulation Results

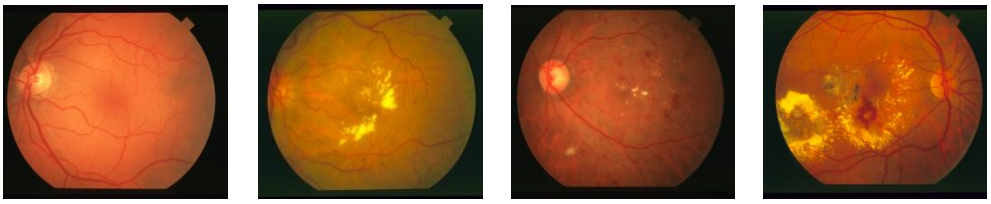
This chapter represents the experimental retinal data sets and simulation results of the proposed fuzzy rule-based classification system (FRBCS) for grading the severity of diabetic retinopathy (DR). The proposed system has been implemented in MATLAB (R2014b) and executed in an Intel Core i5 computer with 1.80 GHz CPU and 8 GB RAM under windows 10 operating system (64 bit). The chapter also covers the evaluation and comparison of the proposed technique with other classification methods in order to interpret the effectiveness of FRBCS in classifying DR.

4.1 Data Sets

We have used four standard public datasets; STARE, DIARETDB0, DIARETDB1 and MESSIDOR for training and testing of our proposed DR diagnosis system. The datasets were used to estimate the validity of our proposed technique and compare the result with existing techniques for DR classification problem.

4.1.1 STARE

The first dataset STARE (STructured Analysis of the REtina) was developed for analyzing the structural pattern of retinal images [59]. STARE was a project which was conceived and initiated at the University of California, San Diego, USA. The dataset has 400 retinal fundus images which were captured by Top Con TRV-50 fundus camera. The images have a resolution of 700× 605 pixels with 24 bits per pixel. There are two sets of ground-truth vessel annotations are available in online which are used to check the accuracy of segmented blood vessels in retinal fundus images. The retinal images with different DR classes of STARE dataset is displayed in the figure 4.1.

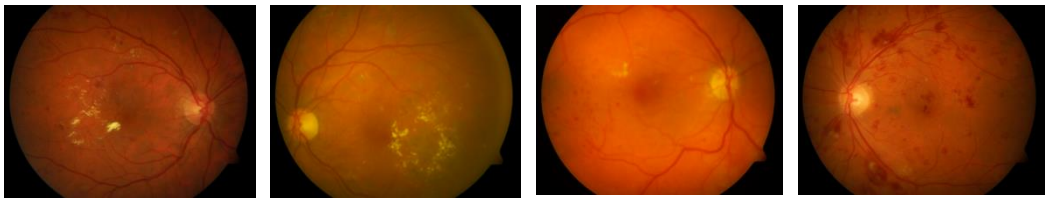


(a) (b) (c) (d)

Figure 4. 1 Retinal fundus images of STARE data set with different DR stages.

4.1.2 DIARETDB0 and DIARETDB1

DIARETDB0 [60] and DIARETDB1 [61] are the most popular datasets used for DR screening. These two datasets are widely used in research publication for their great variety of DR lesions and available ground truth of detected lesions for evaluation. The DIARETDB0 dataset contain 130 color retinal fundus images. Of them 20 images are normal and 110 have diabetic retinopathy signs. On the other hand, DIARETDB1 has 89 images of which 84 have at least one/ more mild signs of DR and 5 are considered as normal as per the evaluation of all participated experts. Both the datasets contain RGB images with a resolution of 1500 ×1152 pixels which were acquired by 50^0 field-of-view (FOV) digital fundus camera with varying imaging settings controlled by the approach. The retinal fundus images DIARETDB0 and DIARETDB1 with different DR classes are presented in figure 4.2.

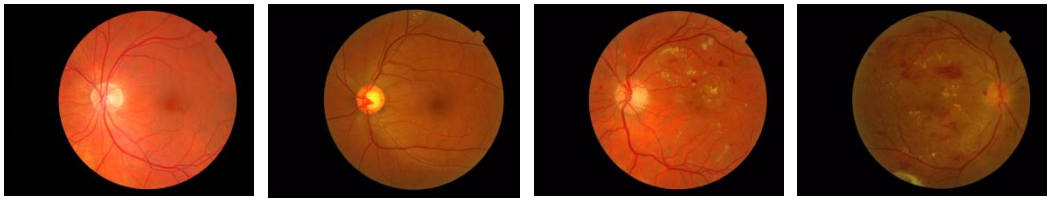


(a) (b) (c) (d)

Figure 4. 2 Retinal fundus images of DIARETDB0 and DIARETDB1data set with different DR stages.

4.1.3 MESSIDOR

The last dataset MESSIDOR was established for facilitating the lessons on computer-aided diagnosing of DR [62]. The dataset contains 1200 retinal color images and captured by Topcon TRC NW6 non-mydriatic camera of a 45^0 FOV. The images were taken by having 8 bits per color plane with resolution of 1440×960 pixels, 2240×1488 pixels and 2304×1536 pixels. Few retinal images of MESSIDOR with different DR classes are shown figure 4.3.



(a) (b) (c) (d)

Figure 4.3 Retinal fundus images of MESSIDOR dataset with different DR stages.

Using the four datasets mentioned above, we have constructed the training and testing datasets for detection and classification of DR: The detailed descriptions of the constructed datasets with different DR stages are shown in Table 4.1.

Table 4.1 Descriptions of datasets with manual classifications of DR stages.

Dataset	No. of images	Normal	Abnormal	Mild	Moderate	Severe	PDR
STARE	120	15	105	21	35	38	11
DIARETDB0	180	20	160	55	38	59	8
DIARETDB1	80	31	49	24	17	5	3
MESSIDOR	140	23	117	38	42	30	4
Total	520	89	431	138	132	135	26

4.2 Simulation Results of Data Sets

The simulation results of both lesion detection and DR classification are carried out on four data sets. Figure 4.4 shows the graphical user interface (GUI) of the proposed technique implemented in MATLAB.

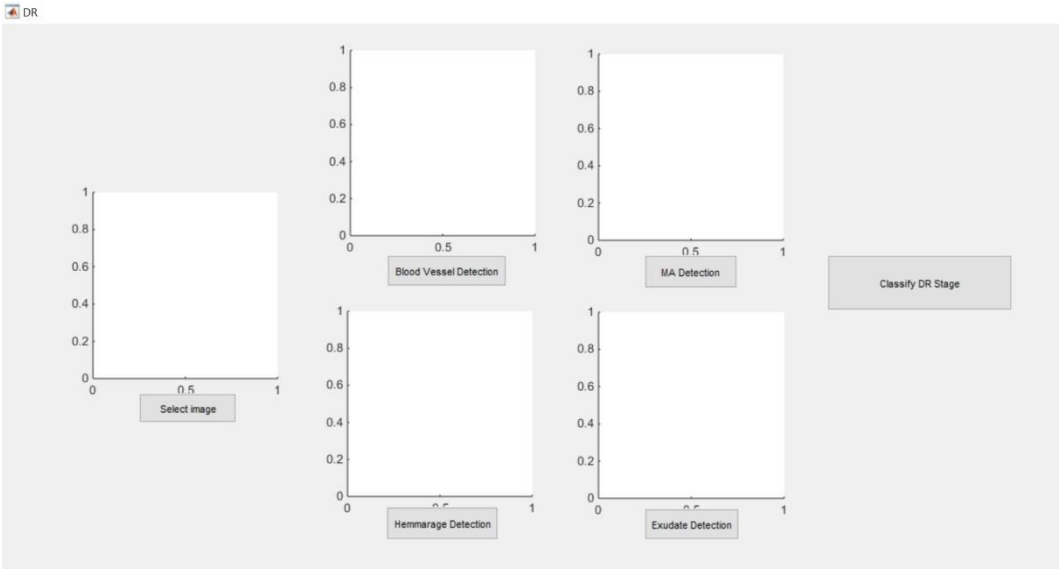


Figure 4.4 Graphical User Interface of the Proposed DR Classification System

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4.2.1 Lesion Detection

4.2.1.1 Lesion Detection on STARE Data Set

Figure 4.5 shows the detection of blood vessels, microaneurysms, haemorrhages and exudates of STARE data set by the proposed image processing techniques.

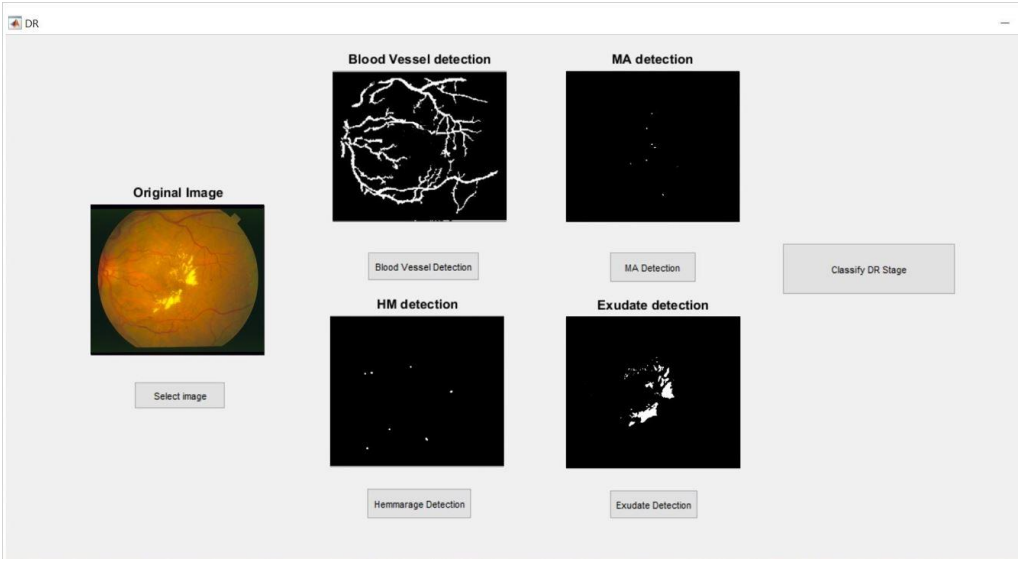

Figure 4.5 The lesion detection of STARE data set (a) original retinal image (b) blood vessels (c) microaneurysms (d) haemorrhages (e) exudates

4.2.1.2 Lesion Detection on DIARETDB0 and DIARETDB1 Data Set

Figure 4.6 and 4.7 display the detection of blood vessels, microaneurysms, haemorrhages and exudates of DIARETDB0 and DIARETDB1 data sets respectively by the proposed image processing techniques.

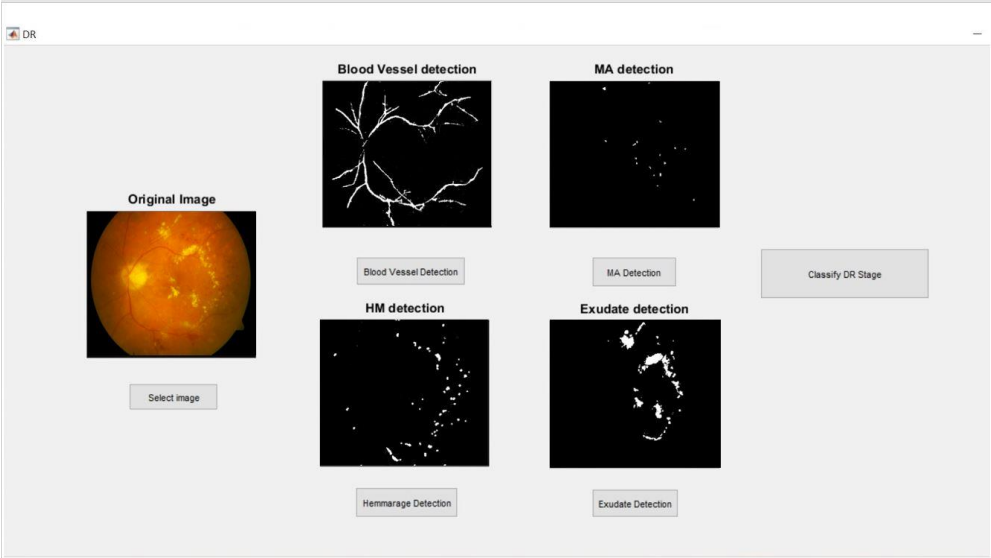

Figure 4.6 The lesion detection of DIARETDB0 data set (a) original retinal image (b) blood vessels (c) microaneurysms (d) haemorrhages (e) exudates

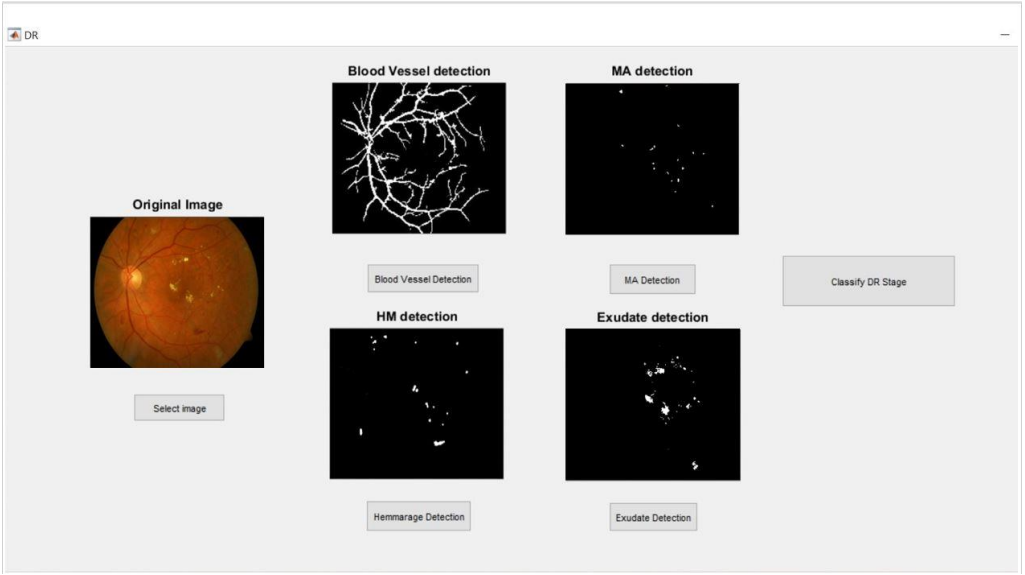

Figure 4.7 The lesion detection of DIARETDB1 data set (a) original retinal image (b) blood vessels (c) microaneurysms (d) haemorrhages (e) exudates

4.2.1.3 Lesion Detection on MESSIDOR Data Set

Figure 4.8 displays the detection of blood vessels, microaneurysms, haemorrhages and exudates of MESSIDOR data set by the proposed image processing techniques.

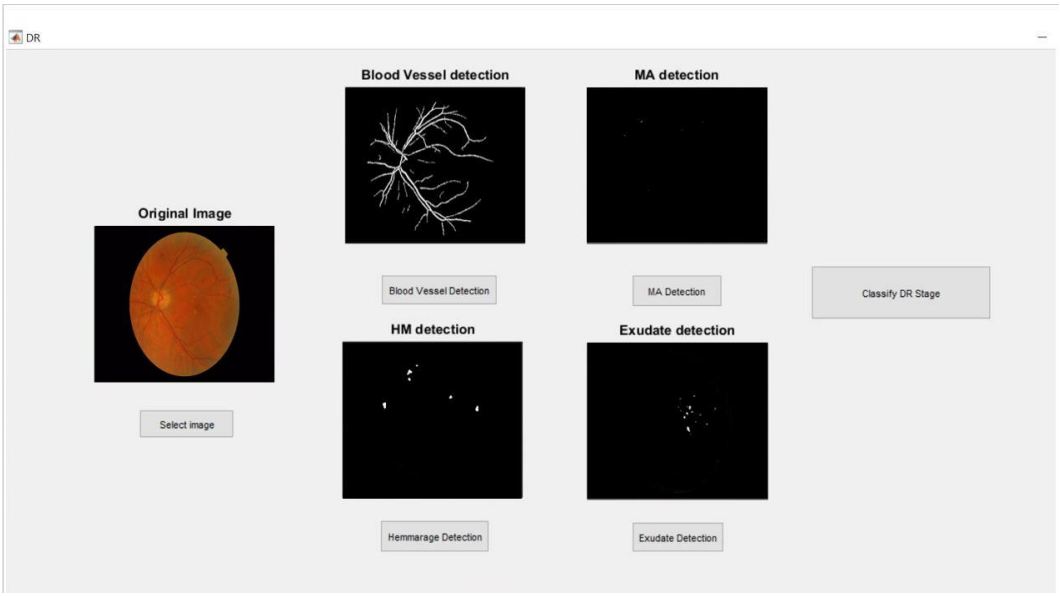

Figure 4.8 The lesion detection of MESSIDOR data set (a) original retinal image (b) blood vessels (c) microaneurysms (d) haemorrhages (e) exudates

4.2.2 Classification of DR Stages

We have used a fuzzy inference system (FIS) toolbox in MATLAB for implementing the proposed FRBCS. Figure 4.9 shows the FIS editor where each input feature (blood vessels, MAs, EXs, contrast, homogeneity, HMs) is on the left side and output of DR stage is on the right side. The editor also shows the number of inputs (6), output (1) and fuzzy rules (87) at the bottom.

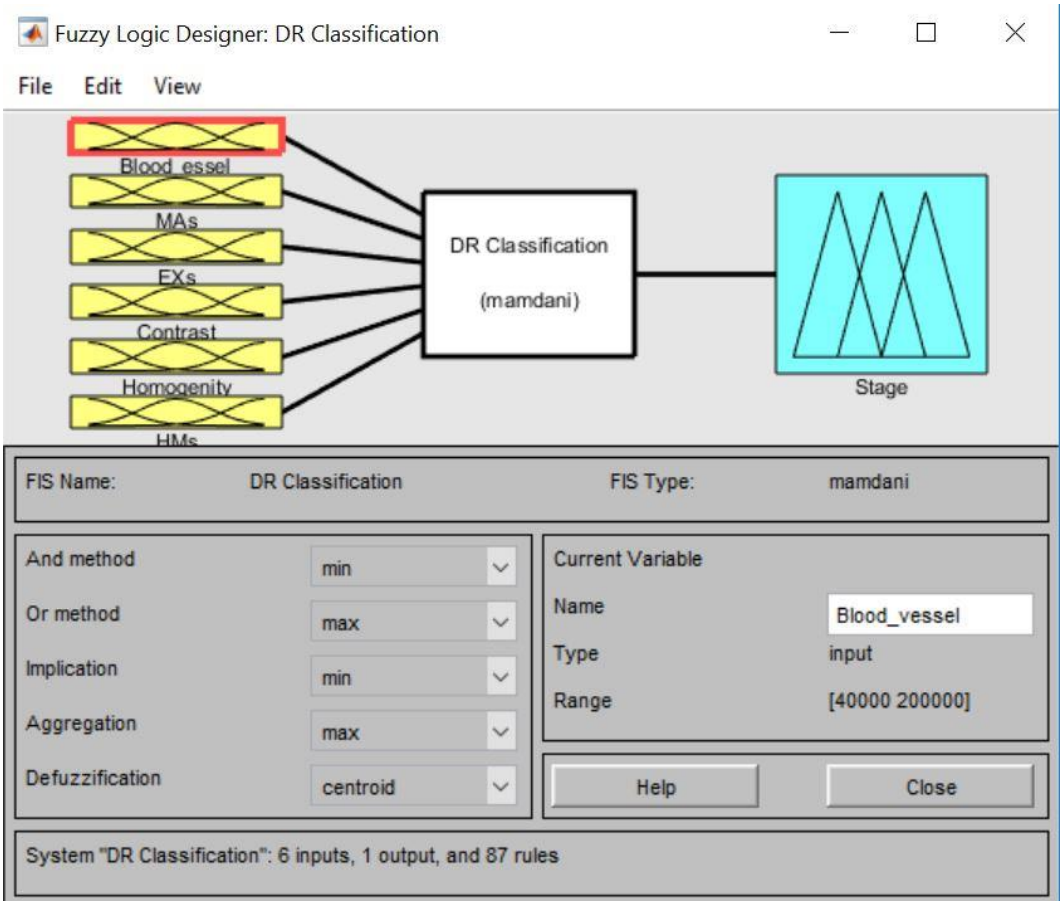

Figure 4.9 Fuzzy Inference System Editor of the Proposed FRBCS

The MFs of each input feature are shown in figure 4.10. where the range of each feature is set according to the Table 3.1 in chapter 3. Each MF is triangular and divided into 3 levels; low (L), medium (M) and high (H).

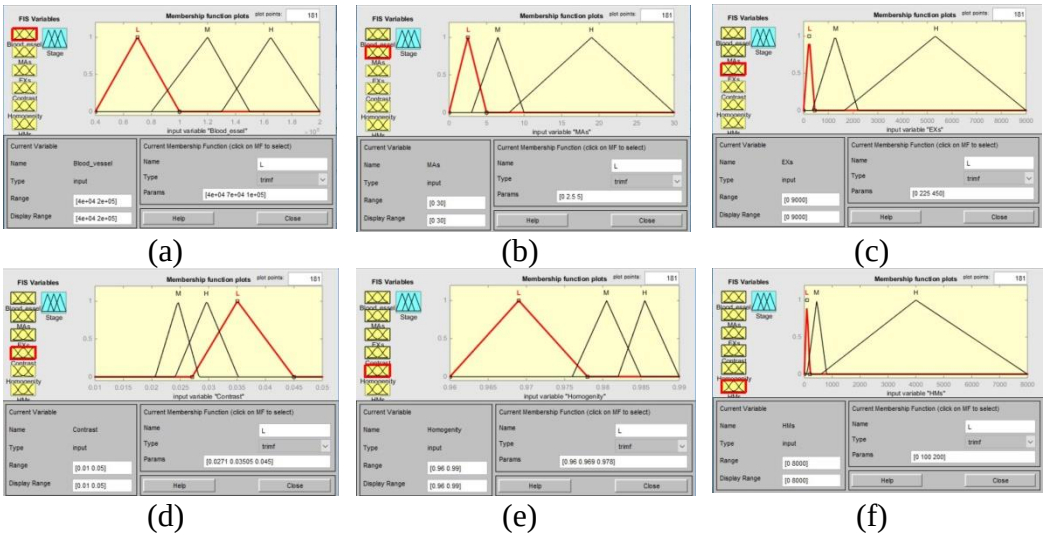

Figure 4.10 The FIS membership functions (MFs) of input features (a) blood vessels (b) MAs (c) EXs (d) contrast (e) homogeneity (f) HMs

The fuzzy if-then rules constructed in section 3.2.2.1 are set using rule editor of FIS shown in figure 4.11 and according to the fuzzy rules the stages of DR is evaluated shown in figure 4.12.

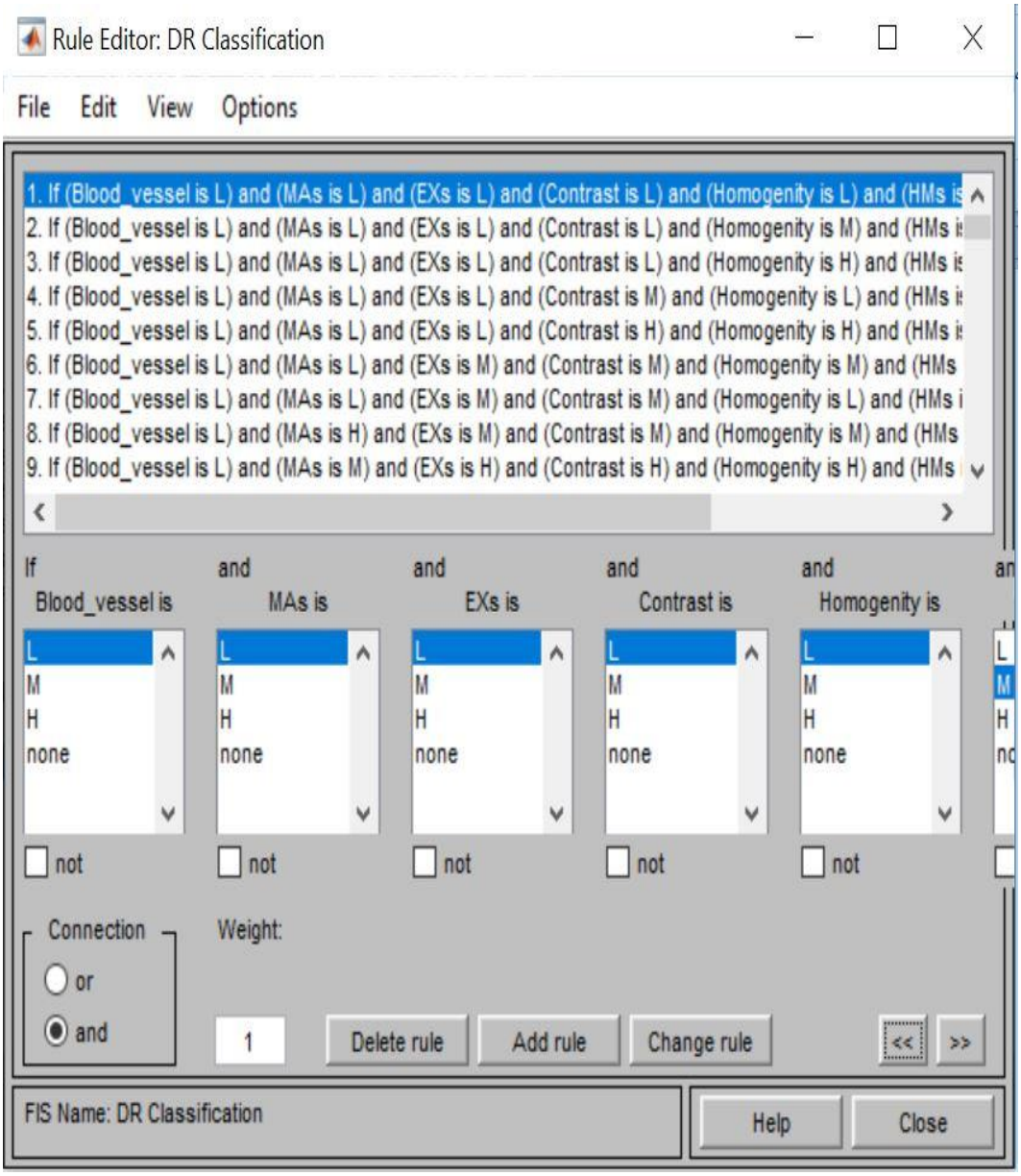

Figure 4.11 FIS Rule Editor of the Proposed FRBCS

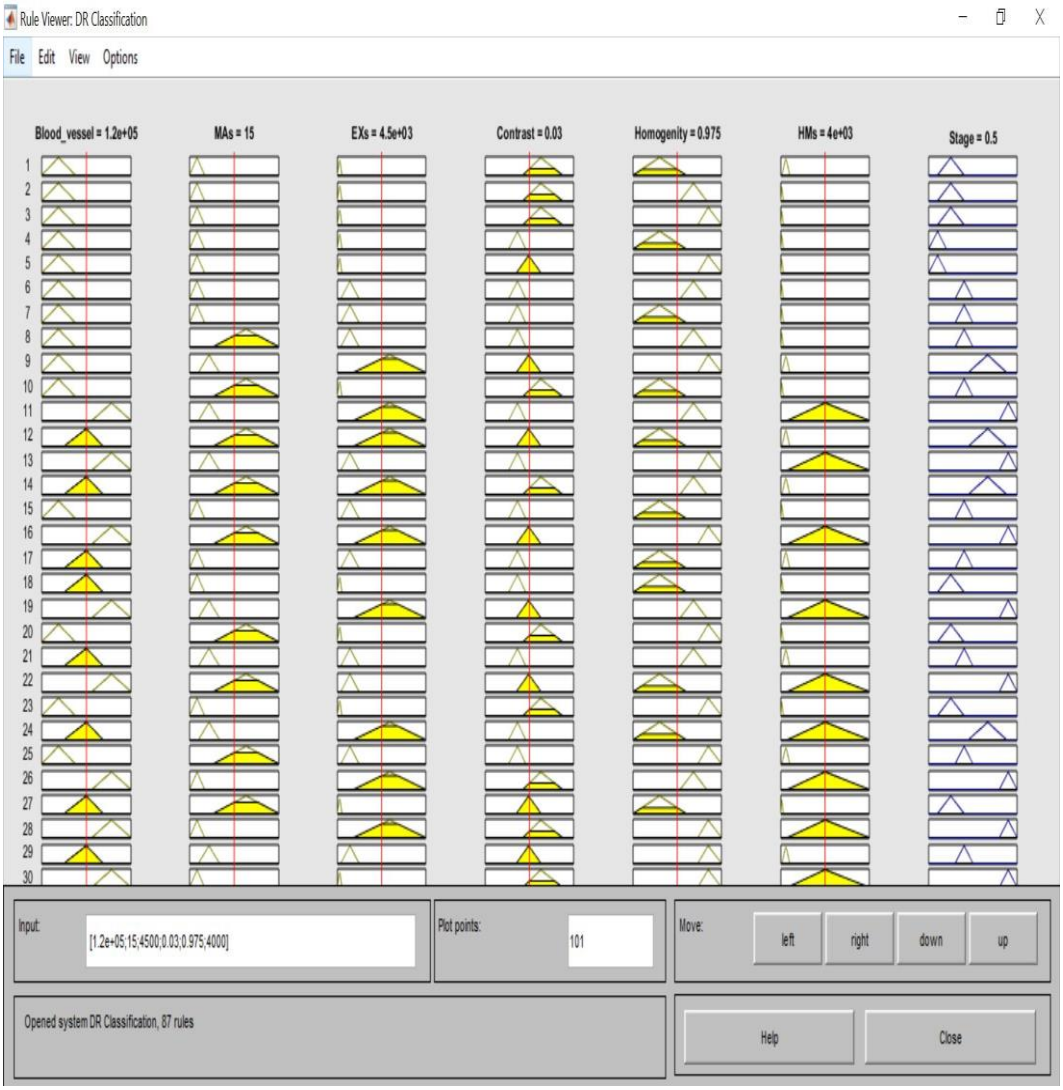

Figure 4.12 FIS Rule Viewer of the Proposed FRBCS

4.3 Performance Analysis of Proposed FRBCS

The simulation results performed on different datasets are evaluated by certain measurements to illustrate the effectiveness of the proposed FRBCS. We have divided the four datasets into two parts: One part (60% of total retinal images) was used for developing the classifier (training images) and the remaining part (40% of total retinal images) was used for validating the developed classifier (testing images). The experiment was repeated several times and obtained the averaged

accuracy to avoid any biased outcome resulted from the specific choice of training and testing images.

Table 4.2 represents the results of our proposed DR classification technique using fuzzy rule-based classifier. The results demonstrate that the fuzzy classifier is effective in giving overall 92.42% correct prediction of the unknown DR stages. Table 4.2 also illustrates that our proposed FRBCS is able to predict correctly normal, mild NPDR, moderate NPDR, severe NPDR and PDR up to 94.29%, 89.09%, 90.57%, 98.15% and 90% respectively.

Table 4.2 Results of Fuzzy rule-based classification system

Stages	**No. of retinal images**	**No. of training images**	**No. of testing images**	**No of correctly classified images**	**Percentage (%) of correct classification**
Normal	89	54	35	33	94.29
Mild	138	83	55	49	89.09
Moderate	132	79	53	48	90.57
Severe	135	81	54	53	98.15
PDR	26	16	10	9	90.0
Average					92.42

The performance of the proposed classification technique was also estimated by measuring sensitivity, specificity and positive predictive value (PPV) which were determined using eq. (4.1), (4.2) and (4.3) respectively. These parameters can be analyzed by using the confusion matrix as described in Table 4.3 and the calculated results are presented in Table 4.4.

Table 4.3 Confusion Matrix

		Disease Status	
		Positive	***Negative***
Classifier Result	***Positive***	TP	FN
	Negative	FP	TN

where,

- *TP (True Positive):* An abnormal image which is correctly classified as abnormal by the classifier.
- *TN (True Negative):* A normal image which is correctly classified as normal by the classifier.
- *FP (False Positive):* A normal image which is erroneously classified as an abnormal image by the classifier.
- *FN (False Negative):* An abnormal image which is erroneously classified as a normal image by the classifier.

$$Sensitivity = \frac{TP}{TP+FN} \tag{4.1}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4.2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.3}$$

Overall, the classifier has shown a sensitivity of 92.44%, a specificity of 94.29%, and a positive predictive value of 98.76%.

Table 4.4 Sensitivity, Specificity and Positive Predictive Accuracy of the Proposed FRBCS

Classifier	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	PPA (%)
Fuzzy	159	33	2	13	92.44	94.29	98.76

4.4 Comparative Analysis with Existing Techniques

To validate our proposed FRBCS, the simulation results described in section 4.3 are compared with other existing classification technique such as Sinthanayothin *et al.* [32], Nayak *et al.* [33], Acharya *et al.* [34], Yun *et al.* [36], Acharya *et al.* [37]. The comparison is determined by sensitivity, specificity and accuracy for classifying the

stages of DR as illustrated in Table 4.5. From the table, it is showed that the proposed technique detected maximum number of features for grading DR. The sensitivity of our technique is 92.44% which is higher than the other existing methods. The specificity and accuracy of the proposed classifier are 94.29% and 92.42% respectively which are also high for the considered retinal fundus images.

Table 4.5 Comparative analysis of FRBCS with other existing techniques

Author	**Detected Features**	**Method**	**Sensitivity (%)**	**Specificity (%)**	**Accuracy of classification (%)**
Sinthanayothin *et al.*[32]	Haemorrhages, Exudates	Moat operator	80.21	70.66	Not reported
Nayak *et al.* [33]	Blood vessels, Exudates	Artificial Neural Network	90.32	100	93.64
Acharya *et al.* [34]	-	Support vector machine	82.5	88.9	82
Yun *et al.* [36]	Blood vessel	Artificial Neural Network	91.7	100	84
Acharya *et al.* [37]	Blood vessels, Microaneurysms, Haemorrhages Exudates	Support vector machine	82.35	86.49	85.94
Proposed Method	Blood vessels, Microaneurysms, Haemorrhages, Exudates, Contrast, Homogeneity	Fuzzy rule-based classification system	92.44	94.29	92.42

4.5 Discussion

Segmentation of microaneurysms, haemorrhages and exudates in each retinal image is challenging as evidenced by the huge variation in retinal image quality in our study. Moreover, classification result is significantly influenced by the correct detection of retinal lesions. Therefore, the detection of each lesion, as an input, is vital to ensure the efficient prediction of DR. The exudate detection is more accurate than the other lesions detection; that is why the severe stage of DR is classified with highest accuracy (98%). This thesis is mainly focused on the accuracy and the efficiency of fuzzy rule-based classifier which is comparatively higher than the other existing classification methods. The output result generated from our proposed system will not ensure the accurate screening process, but the result definitely be effective in detecting important diagnostic features and classifying individuals into .the correct retinopathy stage.

4.6 Conclusion

This chapter illustrates the simulation results and performance comparison of the proposed technique. The simulation results demonstrate that the proposed technique performs superior in detecting most retinal lesions compared to other existing systems for classifying DR stages. The method shows its promising performance in detecting maximum features which makes it an effective diagnostic tool to be used for early diagnosis of DR.

CHAPTER FIVE

Conclusions and Discussions

5.1 Conclusions

The automatic classification of diabetic retinopathy (DR) is a growing research area intended to minimize the workload of traditional diagnosing process. In this work, we propose an automatic technique for detection and classification of DR using fuzzy rule-based classification system (FRBCS) and it was successfully accomplished. This technique is capable of both detecting DR lesions and classifying DR stages based on its severity. Detecting textural features along with several DR lesions increases the efficacy of the proposed technique. Moreover, fuzzy logic of FRBCS makes the classification system more comprehensive and reliable representing the diagnostic knowledge in a simple and clearer linguistic manner. The proposed detection and classification technique has been statistically evaluated on four public retinal image data sets. The simulation results demonstrate the supreme capability of the proposed technique in both detecting DR lesions and classifying DR stages with average accuracy of 92.42%, sensitivity of 92.44% and specificity of 94.29%. Moreover, compared with other existing detection and classification approaches, the proposed technique is able to detect maximum DR lesions and classify the unknown stages of DR more accurately. The experimental results validate that the overall performance of the proposed technique is effective in grading DR stages and the system can provide assistance to an ophthalmologist for detecting DR (and its severity level) in a more efficient, reliable and faster way.

5.2 Future Works

A few follow-up researches that could be done after this research work are:

- The lesions detection method can be improved by identifying each lesion more accurately. This research work however, focused on the performance of fuzzy rule-based classifier rather than feature detection accuracy.

Moreover, other important DR features, like neovascularisation and cotton wool spots also required to be detected, as per the standard medical severity labels for DR. The accuracy of DR classification is largely depends on the correct detection of lesions. Thus, the DR screening process could be more efficient if more features are taken into account with higher detection accuracy.

- This work also to be extended by the analysis of computational time and storage requirement for both the detection and classification processes. Moreover, fuzzy rules could be minimized according to medical experts in order to develop more consistent screening tool.

- Furthermore, the research work could be improved by implementing other hybrid image processing methods based on fuzzy approaches. Fuzzy image processing which includes fuzzy histogram equalization, fuzzy filtering, fuzzy edge detection etc. could be a powerful technique in handling complex and vague data sets of retinal images for lesion detection.

- The research work can be extended by detecting Maculopathy along with DR. For detecting Maculopathy, the localization and the extraction of both macula and fovea are important, because maculopathy is characterized by lesions found in macula and the fovea (found at the center of the macula). Thus, extraction of these retinal structures and detection of Maculopathy could be included with DR classification system.

- The work can be extended by improving the classification sensitivity, specificity and accuracy on wide range of retinal images to provide more consistent tool which could be a diagnostic aid for DR screening.

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