Analysis of Retinal Images for Accurate Drusen Extraction

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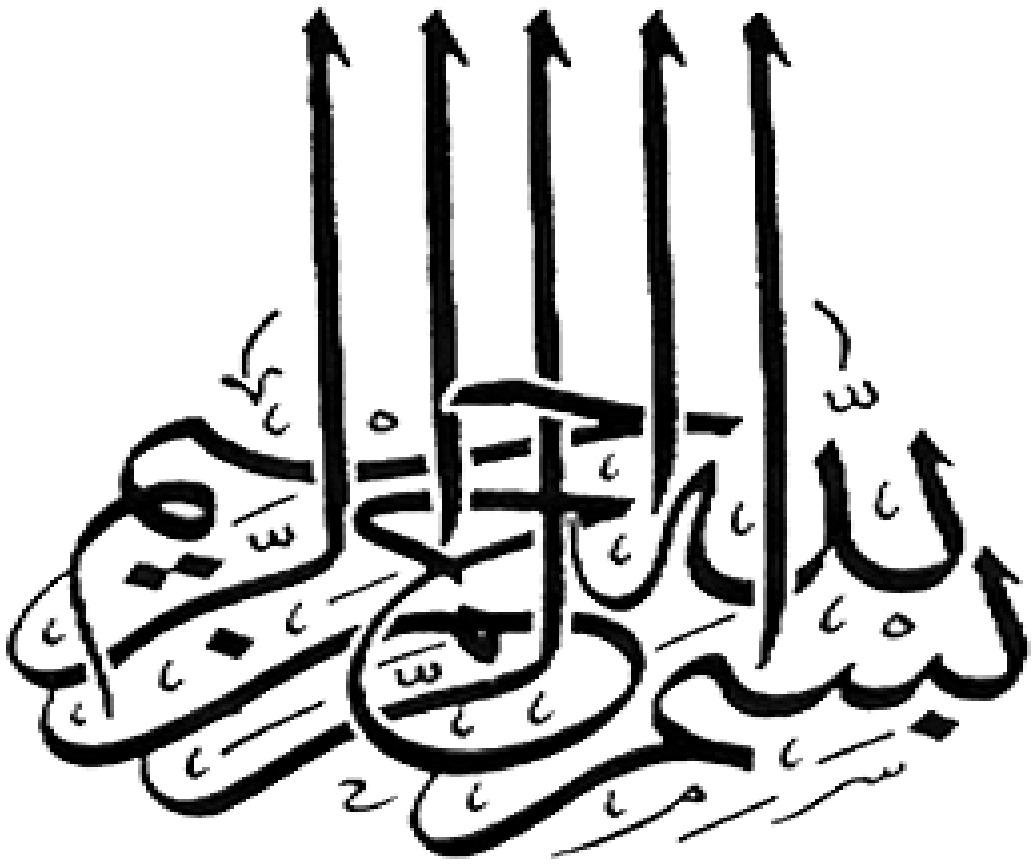

In the Name of Allah, the Most Gracious. The most Merciful.

ٱقۡرَأۡ بِٱسۡمِ رَبِّكَ ٱلَّذِي خَلَقَ ﴿١﴾ خَلَقَ ٱلۡإِنسَٰنَ مِنۡ عَلَقٍ ﴿٢﴾ ٱقۡرَأۡ وَرَبُّكَ

ٱلۡأَكۡرَمُ ﴿٣﴾ ٱلَّذِي عَلَّمَ بِٱلۡقَلَمِ ﴿٤﴾ عَلَّمَ ٱلۡإِنسَٰنَ مَا لَمۡ يَعۡلَمۡ ﴿٥﴾

1. Read! In the Name of your Lord Who has created (all that exits).2. He has created man from a clot (a piece of thick coagulated blood).3. Read! And your Lord is the Most Generous.4. Who has thought (the writing) by the pen.5. He has thought man that which he knew not.

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A thesis submitted in partial fulfillment of the requirements for the degree of

MS Computer Engineering

Thesis Supervisor:

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Thesis Supervisor's Signature:

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OCTOBER, 2014

Declaration

I certify that this research work titled "*Analysis of Retinal Images for Accurate Drusen Extraction"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

Signature of Student

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

Signature of Student

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Signature of Supervisor

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Copyright Statement

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First of all, I would like to thank Allah Almighty who gave me the ability to complete this thesis. He is the ONE I always looked to in the event of trouble and He always created a way for me out of the trouble. I would not be what I am today if He did not want me to be.

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Abstract

Medical systems based on state of the art image processing and pattern recognition techniques are very common now days. These systems are of prime interest to provide basic health care facilities to patients and support to doctors. Age related Macular degeneration is the leading cause of severe vision loss in people over age 60. It occurs when the small central portion of the retina, known as the macula, deteriorates and can be a source of significant visual disability. Drusen represents the only visible sign of Macular degeneration in patients.

However, to diagnose the "bright lesions "associated with age-related macular degeneration (AMD), namely drusens, lesions must be differentiated from exudates, the "bright lesions" associated especially with diabetic retinopathy, which can have similar appearance. In this thesis, we propose image processing and pattern recognition based system to automate the detection of drusens and the system is capable of differentiating among these different lesion types, it assists the ophthalmologists in early detection of the disease. The proposed system applies basic image pre-processing steps to enhance the lesions present in the given images. On the basis of these enhanced images, the system creates the features vector for bright lesion type. Bright lesions and background pixels are classified through KNN classifier. Feature vector for the bright regions are than computed for exudate and drusen discrimination. At the end SVM Classifier detects and differentiates among different lesion types by using given feature set. The statistical analysis is performed on publicly available standard retinal image databases.

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Chapter 1

1 Introduction

Medical imaging is the development of techniques that are used to visualize the physical property and appearance of the living subject. The automatic system for processing medical images can act as an agent for medical diagnosis. These medical images not only provide information about disease but also serve to provide treatment about the disease. Different imaging modalities such as mammography, molecular imaging, X-ray, Computed Tomography (CT) scan, Magnetic Resonance Imaging (MRI), diagnostic ultrasound, Optical Coherence Tomography(OCT) and Fundus Fluorescein Angiography (FFA) provides information about different organs of body for the diagnostics and treatment of particular disease.

Age related macular degeneration (AMD) is one of the growing cause of vision loss among the people at age 50 or above. AMD adversely affects the central part of retina known as macula. Macula is responsible for the central sharp vision. Macula is made up of millions of light sensing cells, with natural aging process the cells present in macula slowly break down. The early signs of AMD are drusens which are actually extracellular material of macula. They are yellow deposit under retina. The symptoms of AMD and the symptoms of diabetic retinopathy known has exudates can have similar appearance. This can affect the diagnosis of right kind of disease. Figure 1.1 shows the normal image and vision with age related macular degeneration.

a) b)

Figure 1.1 a) Vision with normal eye, b) Vision with age related macular degeneration.

There are some systems for automatically detecting drusens and grading macular degeneration but very few researchers focuses on the differentiating symptoms of AMD and retinopathy. In this thesis, analysis of retinal images is being proposed with image processing and pattern recognition techniques to differentiate drusens and exudates.

1.1 Motivation

In developed countries like in Pakistan AMD is one of the leading causes of blindness. For the majority patients of AMD, there is no cure due to late diagnosis of disease. In Pakistan, number of patients lost their vision due to lack of information or unavailability of treatment.

Due to the lack of trained people any research for automatic medical system will be quite useful at national level. Limited number of medical resources, patients to doctor low ratio and the need of proper diagnostic at the right time are the issues which make this area of research more attractive and beneficial. Self-diagnostic software for retinal diseases can help in development of a tele screening system to provide easy to access and cost effective solution.

The main advantage of such an automated medical diagnostic system is to assist ophthalmologists and to save their time. It would be a cost effective solution for the people of rural areas. They can get screening at remote station without wasting their time and money through computer aided diagnostic system. This system will also set new trends of telemedicine system in Pakistan.

The purpose of the thesis is to provide self-diagnostic software for retinal abnormalities in remote areas and to assist ophthalmologist for early diagnostic of disease.

1.2 Scope and Objectives

The research in medical image processing is interesting because it provide a way of collaboration among engineering work and medical problems. The research in retinal image processing will assist ophthalmologist by providing them an automatic system for the detection of disease. Some of the research objectives are as follow:

1) To provide an automatic system to detect age related macular by using image processing and pattern recognition algorithms.
2) To automatically discriminate drusen from exudates. They can have similar appearance.

3) The objective of the proposed system is not to bypass physician's role in clinical practice but to aid physicians in time consuming screening of retinal images.
4) To provide easy access to common man for telescreening the disease
5) To improve and to provide knowledge of medical field to engineering researchers

1.3 Challenges

Pattern recognition, digital image processing and computer vision opens new doors for research and development in medical imaging. The key challenges related to age related macular degeneration research in the above areas are as follow.

1.3.1 Region of interest Detection

The main symptoms of AMD are drusens which are located near macula which is responsible for sharp vision. So it is very important to locate the area of interest where exudates and drusens exist. Due to random presence of these bright lesions around macula makes it difficult to localize the macula.

1.3.2 Reliable differentiation of drusens from exudates

As the bright lesions exudates and drusens associated with AMD and diabetic retinopathy has similar appearance on the surface of retina. So it is crucial to extract such feature set which can make the classifier able to discriminate these bright lesions.

1.3.3 Design of accurate and efficient classifier

It is very important to choose right kind of classifier for your system which can classify the given patterns efficiently and accurately by using the given feature set. We have to design such a classifier which can differentiate among exudates and drusens.

1.4 Structure of Thesis

The thesis is structured as follows:

Chapter 2 of my thesis contains medical perspective of age related macular degeneration. Chapter 3 contains literature review having state of the art techniques for developing automated system for AMD. Chapter 4 contains proposed methodology explained in detail followed by experimental results in chapter 5. Chapter 6 contains conclusion and future work.

Chapter 2

2 Age Related Macular Degeneration

This chapter provides details about age related macular degeneration in medical perspective, it will explain causes and signs related to the disease.

2.1 The Human Eye Anatomy

The structure of human eye is shown in figure 2.0. Light passes into human eye through cornea and focuses on retina with the help of lens. The retina than converts the focused light into signals and transmits those signals to brain through optic nerve. With respect to this thesis we are interested into few small anatomical pats of eye that are highlighted in figure 2.1.

Retina is the thin layer composed of photoreceptor cells and neural tissues that convert received light into signal. Macula is the central part of retina which is responsible for the central sharp vision. The centre of macula is known as fovea. The macula appears darker circular region on the surface of retina. It contains high concentration of photoreceptor cells. There are two types of photoreceptor cells i.e. rods and cones. The cone cells are wider than rods. There are three types of cones each responsible for perceiving different wave length of light i.e. short medium and long. Rods show sensitivity to low level of light. Therefore rods are responsible of night vision.

Retinal pigment epithelium (RPE) is the thin layer of retina beneath photoreceptor cells and neural tissues. This layer provides nourishment to the retinal cells and takes off the waste material of those cells. This layer provides protection to retina by providing it filtered blood. It maintains blood retinal barrier and provide active transportation to and from the photoreceptor cells (rods and cones) of retina.

Posterior to RPE Bruch membrane exists that is the barrier to separate RPE from Choroid and supplies blood to outer layer of retina.

Optic disc is the bright yellow circle where all the retinal blood vessels converge. Optic disc contains no photoreceptor cell that is why is also known as blind spot it can only send signals to brain.

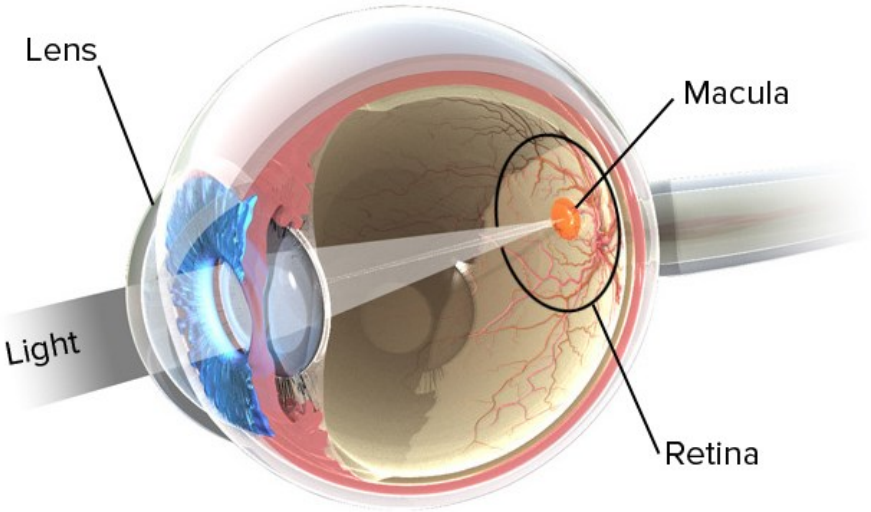


Figure 2.1 Eye Anatomy [1]

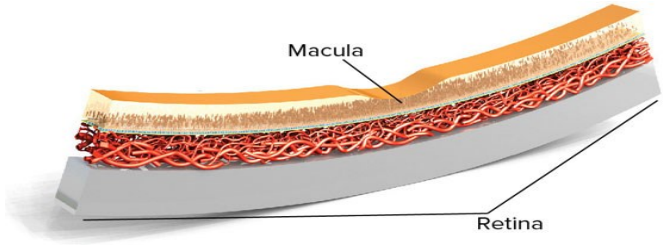


Figure 2.2 Position of macula [1]

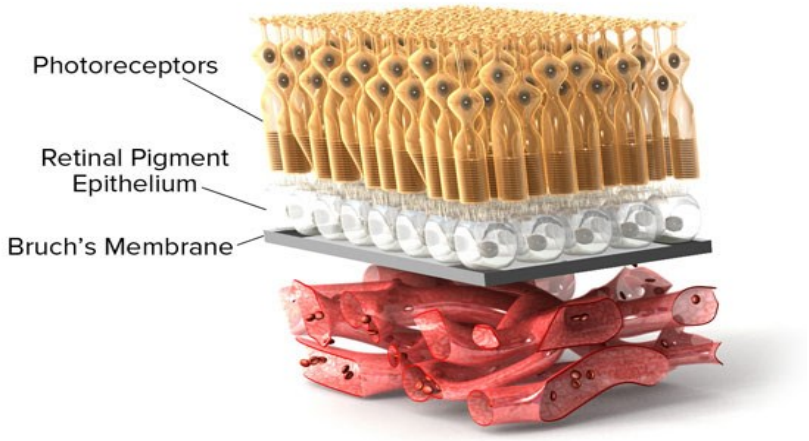


Figure 2.3 Highlighted layers of retina [1]

2.2 Age related macular degeneration

Medical Age related macular degeneration is an ocular disease and leading cause of vision loss at age 50 and above. As the name implies, the disease affects elderly. It is responsible for destroying central and sharp vision. Currently it is estimated that about 2 million

Americans are affected by AMD and by the year 2020 it is projected to be closer to 3 million as life expectancy increases and the aging population expands

Many changing due to aging have been identified on the surface of retina like degeneration of Retinal pigment epithelium which is responsible for the removal of metabolic waste product of rods and cones. RPE provides nutrition to these photoreceptor cells. Many blood components are harmful for retina and RPE keep them away from retina by providing it filtered blood.

Retina is the most affected part of eye due to the failure of RPE. On the first stage this failure affects the macula that provides central sharp vision. Severe vision loss may occur if the disorder continues to develop on retina there are two types of AMD Wet AMD and dry AMD. Earlier macular degeneration can progress into either of these forms. Most cases of AMD are "dry" (80%) while the remaining 20% of cases are considered "wet." Early AMD consist of retinal or sub retinal drusen (yellow-white spots) and/or retinal pigment abnormalities.

2.2.1 Epidemiology of AMD

AMD has been identified as the leading cause of blindness in the developed part of the world and ranks as the third leading cause globally [2].

Previous population-based surveys on AMD which have used standardized classification protocols based on fundus photography have reported varying prevalence. The Beaver Dam Eye Study [3-5] from USA found late AMD in 7.7 % in their cohort aged 75-86 years old. The Blue Mountains Eye Study [6-8] found a lower prevalence of 5.7 %. In Europe results from two larger surveys have been published.

The Rotterdam Study [9-11] reported a prevalence of 3.7 % in people aged 75-84 years old. The European Eye Study [12] is a multi-centre survey including participants 65 years and older from 7 European countries. High prevalence of late AMD was reported among Inuit on Greenland aged _60 years of 9.5 % [18].

2.2.2 Dry AMD:

When RPE degenerates or get thin with the age factor this may lead to the failure of eye to dispose waste product of metabolic process of photoreceptor cells. The waste product accumulates between Bruch membranes (BrM) and RPE. This deposit is called drusens as shown in figure 2.3. Drusens are tiny yellow and white deposit made up of lipid and fatty protein. They are the early signs of age related macular degeneration.

Drusens can have many shapes and size scattered apart from each other. There are two types of drusens, soft drusens and hard drusens.

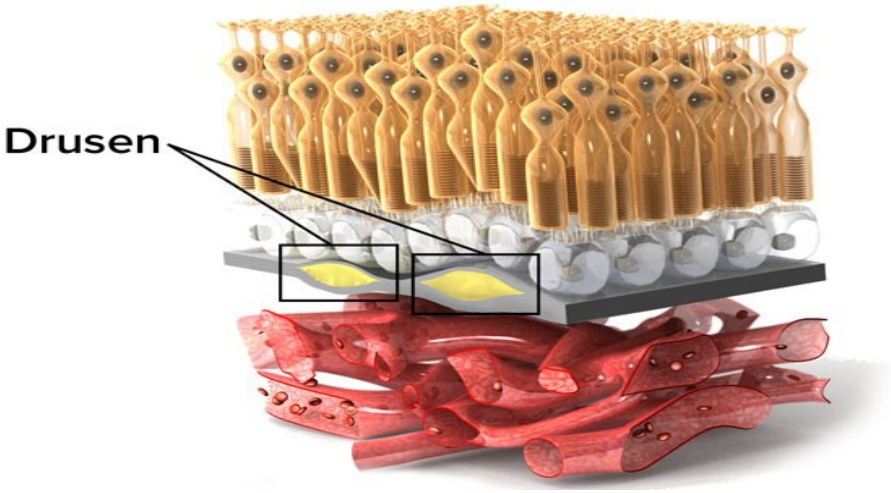


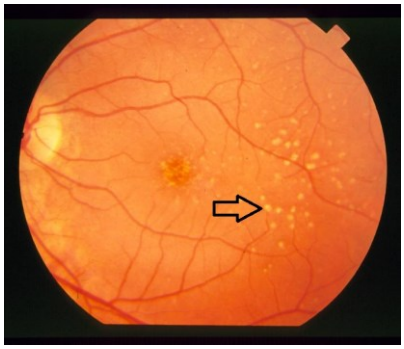
Figure 2.4 Drusen [1]

2.2.3 Hard Drusen

Hard Drusens are tiny, small and round shape lesion. They have sharp and distinct border as shown with black arrow in figure 2.5(a). Hard drusens are thought to be less harmful and they appear as yellow deposit. These types of drusens are common among people of age 50 or above and they are the early indication of AMD.

2.2.4 Soft Drusen

Some drusens become large and get closer to other drusens this may lead to cluster of drusens with less distinct border as pointed with black arrow in figure 2.5(b). The development of this type of drusens leads to the risk for wet AMD. It can also be the cause of RPE detachment.



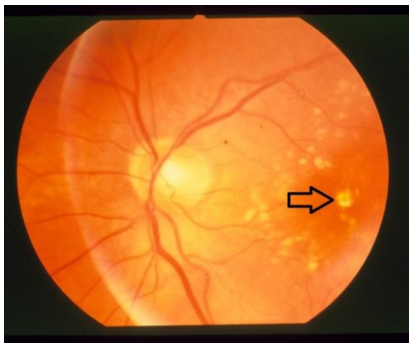


Figure 2.5 (a) Hard Drusen **(b) Soft Drusen**

2.2.5 Wet AMD

Wet AMD accounts for only 10 % of patients with AMD whereas 90 % of the AMD patients with significant vision loss have this form of the disease [14, 15, 16].As the RPE is also responsible for providing filtered blood from choroid vessels, oxygen and nutrients to photoreceptor cell.

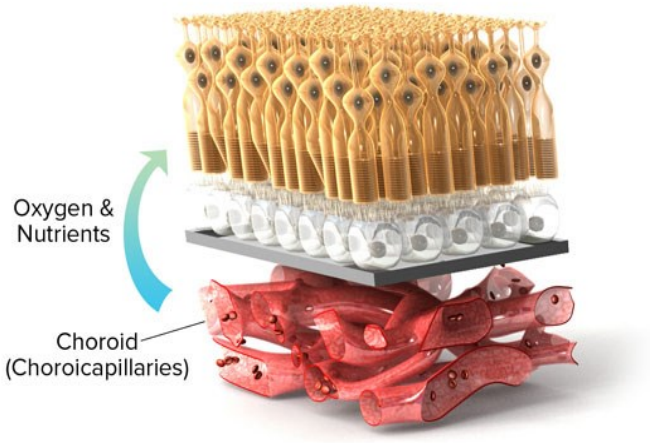


Figure 2.6 Normal Retina

The presence of drusens between RPE and Bruch's membrane blocks many blood vessels into retina beneath macula. These newly developed vessels as shown in figure 2.7 frequently bleed causing macula to swell.

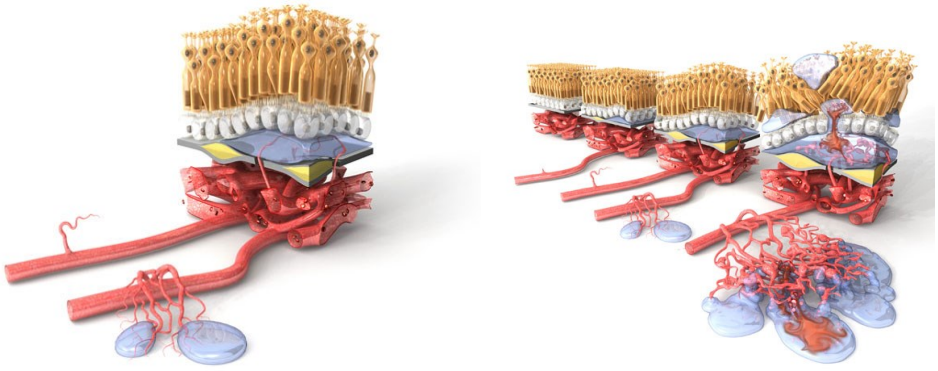


Figure 2.7 Vessel Leakages [1]

The accumulation of this interregional fluid leads to the detachment of RPE and Bruch's membrane from retina and thus results a complete vision loss as shown in figure 2.8. This process can present the appearance of dark spot.

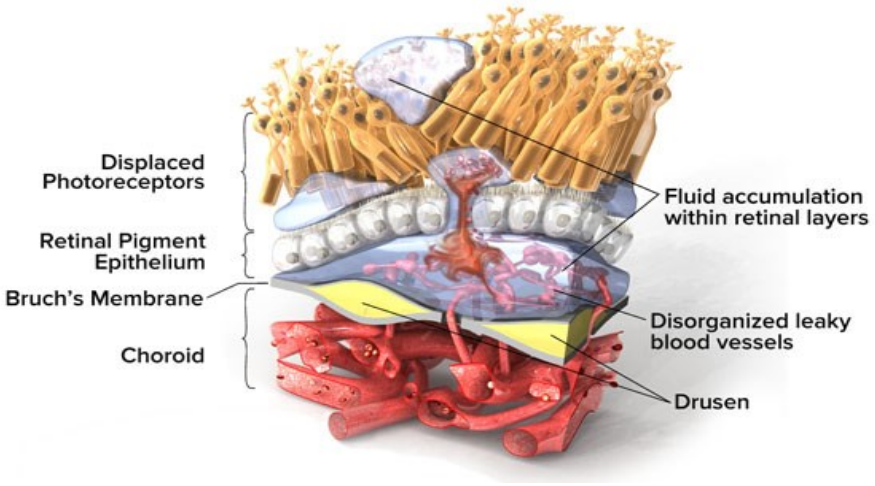


Figure 2.8 Detachment of RPE and Bruch's membrane

2.3 Diabetic Retinopathy

Diabetic retinopathy (DR) is the progressive sight threatening disease for the patients of diabetes. High level of sugar due to the presence of little insulin is the cause of diabetes. High level of sugar can affect the eye function in number of ways. This high level sugar can affect the small blood vessels inside retina and causing them to leak. This leak causes fluid to seep into retina. The central part of retina which is also known as macula become swollen and stop functioning properly.

There are following two stages of diabetic retinopathy.

2.3.1 Non-proliferative Diabetic Retinopathy

The retinal blood vessels can have small leaks in diabetic retinopathy. This leak can cause the fluid to move into the central part of retina that is macula. The fluid can be blood or fatty material they can appear as a lesion on the surface of retina such as exudates and haemorrhages. Exudates are yellow pale deposit while haemorrhages are dot-and-blot as shown in figure 2.9.The patients with wet macula or exudates on macula can lost their central vision. If one eye is affected other eye can also frequently affected

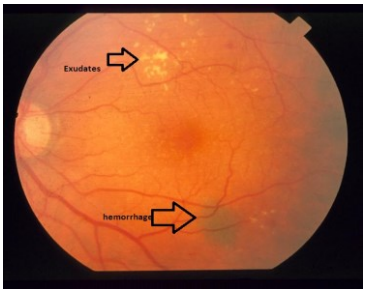


Figure 2.9 Exudates & Haemorrhage [1]

2.3.2 Proliferative Diabetic Retinopathy (PDR):

As the retina has high metabolic requirement. In PDR the blood vessels close off and thus block a way to provide nutrient to large area of retina. The blockage of retinal blood vessel can lead to the development of abnormal vessels known as neovascularization. These abnormal blood vessels does not provide nutrient to retina but they are dangerous for retina functioning. Neovascularization can cause different problem one problem is the leakage of blood from these abnormal blood vessels into vitreous cavity.

The other problem is the development of scar tissues in retina which can detach the retina from other layers of eye which can lead to severe vision loss.

2.4 Exudates and Drusens:

Drusen and exudates have a similarity i.e. they both come in the category of bright lesions. But there are many other features on the basis of which drusen and exudates can be differentiated. These differences are listed below:

Table 2.1 Difference between Drusen and Exudates

Drusen	Exudates
Dull Yellow	Bright Yellow
Fuzzy boundaries	Sharp Boundaries
Small Size	Small to Large
Greater in Frequency	Random
Almost Roundish	Round / irregular
Drusen usually are in symmetrical positions at the posterior pole of each eye	Exudates may be asymmetrical.
Drusens have no signs of thickening	Exudates are associated with retinal thickening

Chapter 3

3 Literature Review

Diagnoses of age related macular degeneration and diabetic retinopathy required the detection of Drusen and exudates. In pattern recognition an image processing there are four different methods are used to detect Drusen and exudates. This includes segmentation, morphological operation, thresholding, feature extraction and classification. This chapter contains the literature review of most recent methodologies used to detect Drusen.

3.1 Retinal component analysis

Before analysing the lesion of retinal surface some of the retinal components are to be analysed for better results. Some of the retinal components are removed in pre-processing steps and some are enhanced for the lesion detection.

3.1.1 Blood vessel segmentation

Marin et al. [17] proposed a supervised method for blood vessel segmentation. Based on gray level and invariant features a 7-D feature vector is computed and neural network is used for classification. Results are shown on two publicly available databases DRIVE and STARE with accuracy of 0.9595 and 0.9646 respectively and area under curve (AUC) of 0.9598 and 0.9769 respectively.

Method based on supervised classification of blood vessels as well as new vessels was proposed by [18] the classification was performed by using SVM classifier. A Gabor wavelet based segmentation of blood vessel was proposed in [19].which classify each pixel as vessel or non-vessel by using kernel based classifier.

Yavuz, Z et al. proposed an automatic system in [20] for segmenting blood vessels based on Gabor filter and top-hat transform. A p-tile thresholding method was performed to obtain binary vessel image. The system obtained 94.02% accuracy for STARE database and 94.59% accuracy for DRIVE. Matched filter based approach was used in [21] to enhance blood vessels on the background. Paper [22] used a 2D wavelet based method for enhancement and segmentation of blood vessels. The algorithm was evaluated on DRIVE and STARE database. The method achieves 94.85% accuracy and receiver

under accuracy of 0.9669. [23] Proposed colour let transform method for the segmentation of retinal blood vessels.

3.1.2 Optic disk segmentation

Kumara et al. [24] proposed an automatic system to detect optic disk boundary by using active contour model. The result shows 90% accuracy for detecting optic disk in retinal images. Paper [25] presented a method to localize optic disk in retinal images through cumulative histogram. Further the removal of blood vessel is done using a method say anisotropic diffusion.

Optic disk detection method was proposed in [26] along with other retinal component detection like fovea and blood vessel. An improved conture model segmentation based on Lab color space was proposed in [27]. In [35] author localize the optic disk boundary through average filter and thresholding. Optic disk is localized by using Hough transform.

3.1.3 Vascular pattern detection

Paper [28] presented ridge based vessels segmentation method. The proposed algorithm divides the image into patches and assign each pixel of an image to its nearest ridges which coincides to the centreline of vessels. Feature vectors are computed for each pixel and classified through KNN and sequential forward feature selection. The method achieves an area under the receiver operating characteristic curve of 0.952.
[29] [30] and [31] proposed matched filter based vascular pattern detection in retinal images.in [32] author used multiscale matched filter to enhance vessels and then compute six dimensional measurement vector for each pixel.

Soares et al. compute feature vector for each pixel based on pixel intensity and Gabor wavelet transform at multiple scales in[33].Bayesian classifier with class-conditional probability density functions (likelihoods) described as Gaussian mixtures classifies each pixel as vessel or non-vessel. DRIVE and STARE databases are used for evaluation process, the algorithm achieves 0.9614 accuracy over DRIVE database. [34] Presented and an amplitude-modified second-order Gaussian filter to detect vessels

3.2 Image Enhancement

Image enhancement techniques are utilized for getting better image quality. So that in the post processing steps components can easily be detected.

3.2.1 Illumination Correction

Grisan et al. proposed illumination correction method based on hue, saturation and value color spaces [36]. The proposed system fits an illumination model in saturation and value channel. [37] Correct the uneven illumination through global-local histogram equalization using partially overlapped window.

Paper [38] correct non-homogenous illumination by utilizing intensity information from green and red channel. The green channel histogram is modified through histogram matching by using the information of red channel histogram.[39] compensate the illumination by estimating background illumination variation and then compensate this variation in whole image. In [40] Shannon entropy based method was utilized for the correction of illumination in retinal images. Shannon's entropy is based on Parzen windowing method with the spline-based shading model.

3.2.2 Contrast enhancement

[41] Enhance the contrast of the retinal image through colourlet transform based on multiscale method. The algorithm application on DRIVE database shows enhancement on low contrast and dynamic range images.

To estimate degradation of retinal image [42] used non uniform sampling from single plane. The correction factor is utilized to enhance each color plane. [43] Improve the contrast through contrast limiting adaptive histogram equalization applied on green channel.

3.3 Lesion detection on retinal surface

In this section some of the previously proposed methods for the detection of lesion types drusens and exudates are discussed.

3.3.1 Drusen detection

ThaYbaoui proposed a method to divide an image into three parts [44]. The background ambiguous pixels called fuzzy pixels and third part as drusen pixels. Fuzzy logic was applied to ambiguous pixels to classify them as drusen or background. [45] Applies Mexican red hat wavelet approach to compute feature vector composed of horizontal, vertical, diagonal and backward convolution results of wavelet for each pixel. Each pixel

has 10D feature vector. Support vector data description method classifies each pixel as drusen or non-drusen.

A learning based detection scheme was presented [46].The method differentiate drusen from background through geometrical structure at different scales and decomposing hessian matrix into Eigen values and employing two Eigen values, while SVM is being used as classifier. The SVM classifier trained achieved accuracy, sensitivity, specificity and area under curve of 0.82, 0.84, 0.76 and 0.80 respectively.

Paper [47] proposed fountain algorithm based segmentation method for drusen detection. The initialized pixel called fountain is been compared with its 8-neighbours to find the minimal intensity value pixel. After finding the minimal value a new fountain is initialized.at the end the algorithm returns number of regions. Watershed transform is used to identify the drusen regions.

Damon et al. presented a method based on dense sampling to generate structured pixels in [48]. These structured pixels are clustered through hierarchical kmeans. This hierarchical word transform was classified through svm. The process achieves 95.46% accuracy on 350 images.

Ziyang et al. presented a method for detecting drusens and grading age related macular degeneration (AMD) [49] by first localizing macula using minimum gray scale intensity value. Macular region is overlaid with mask to grade AMD. Drusens are detected through coarse search of maximum region intensity.

Gabor filter response is been used in [50] the dark regions were suppressed through morphological operation and then for bright regions feature set was computed to classify each bright pixel as drusen or non drusen through SVM classifier.3D profile and texture of drusens are used in [51] to detect and count drusens. [52] Employ cellular Neural Network (CNN) templates approach to classify AMD as wet or dry.
Histogram-teased adaptive local thresholding (HALT) based technique to detect drusens on the surface of retina was proposed in [52].

Yuanjie Zheng et al. proposed an optimal color descriptors and robust multiscale local image descriptors based method for drusen detection in [53].

3.3.2 Exudate Detection

Amit Kumar Mishra et al. [54] proposed geometry based scheme for detecting hard exudates. The scheme utilizes non-linear kernel function optimized by using information geometry. The database was obtained from Instituto de Oftalmobiolog a Aplicada at the

University of Valladolid, Spain. The system provides accuracy 96.67% with 3 features of non-linear distance metric learning. Paper [55] presented an algorithm for exudate detection based on multi-channel histogram analysis. The algorithm achieves specificity and sensitivity for the detection of exudates and normal cases were 95.5% and 88.45% respectively.

Maximum entropy thresholding applied on region of interest based segmented region of retinal image to detect exudates was proposed in [56].Xiang Chen et al. [57] proposed a method for extracting hard exudates by combining morphological reconstruction and histogram segmentation based methods. SVM classified these regions as exudates or normal regions through 44 features such as region area, compactness, circularity, mean standard deviation etc. The algorithm was evaluated on DIARETDBI database and it achieve sensitivity of 90.0%

Exudate detection based on non-uniform illumination background subtraction method was proposed in [58].background is estimated through weighted surface fitting. The background is subtracted from the image (other retinal components like vessels optic disk are segmented and removed already).the foreground pixels contains only exudates.in [59] pixels having contrast to back ground are segmented. Optic disk is identified in these regions through hough transform. Vessels are removed by using morphological operation. Final estimation of drusen is carried out through morphological reconstruction.

3.3.3 Drusen Exudates Differentiation

Niemeijer et al. [60] proposed a method for automatically detecting exudates, cotton wool in fundus images and differentiate them from drusens. The machine learning based automatic system grouped bright pixels and normal pixels separately based on probability binary map. knn classifier is used for this purpose. Suspicious pixels are suppressed through another trained KNN. At the end exudates, drusens and cotton wool identified among bright lesion through linear discriminant analysis. The area under the curve for this approach is 0.95.

Paper [61] presented a method based on bag of word approach to differentiate exudates from drusen in fundus images. The input image is divided into same size of patches by keeping the optic disk at the left side of all images. Color, texture, edge, size and patch orientation based features were extracted from each patch than code book was created. All the patches in databases are categorized in k clusters. Centroid of each k clusters is treated as visual words. Bag of word is used for supervised classification. A

weighted nearest neighbour approach is used for classification using the similarity metric as distance. The algorithm was evaluated on publically available EUGENDA, STARE and MESSIDOR data set. The approach achieves 0.90 Area under the ROC.

The next chapter elaborates the complete proposed system including proposed system, segmenting candidate bright lesion and then region classification for drusens or exudates

Chapter 4

4 Proposed System

This chapter presents complete methodology followed for the detection and differentiation of drusens and exudates.

4.1 System Overview

Age related macular degeneration is leading cause of irreversible vision loss among older individuals. Drusens are the early sign for the disease. Automatically screening individuals may allow the detection of intermediate AMD which is curable. This chapter presents complete description about the detection of drusens on the surface of retina and its differentiation from exudates. On the pre-processing step the system localize and extract optical disk, detect the vascular pattern and its extraction, correct the illumination and enhance the contrast of the fundus images. The system extract vessels and optic disk to improve the quality of the algorithm and to reduce false positive results for the accurate detection of drusens.

The pre-processing step improves the quality of the image and eliminate the unwanted retinal components for further processing. Feature set was computes on the second step to classify each pixel as normal or bright lesion. Connected component analysis classify set of pixels as a part of some region or having area less than a specified threshold. On the next step detailed feature set is computed for each region specified in the previous step. A hybrid classifier differentiate drusens and exudates from these regions. Figure 4.1 shows the detailed flow diagram of the proposed system. It shows the output of main steps and starting from input and final results.

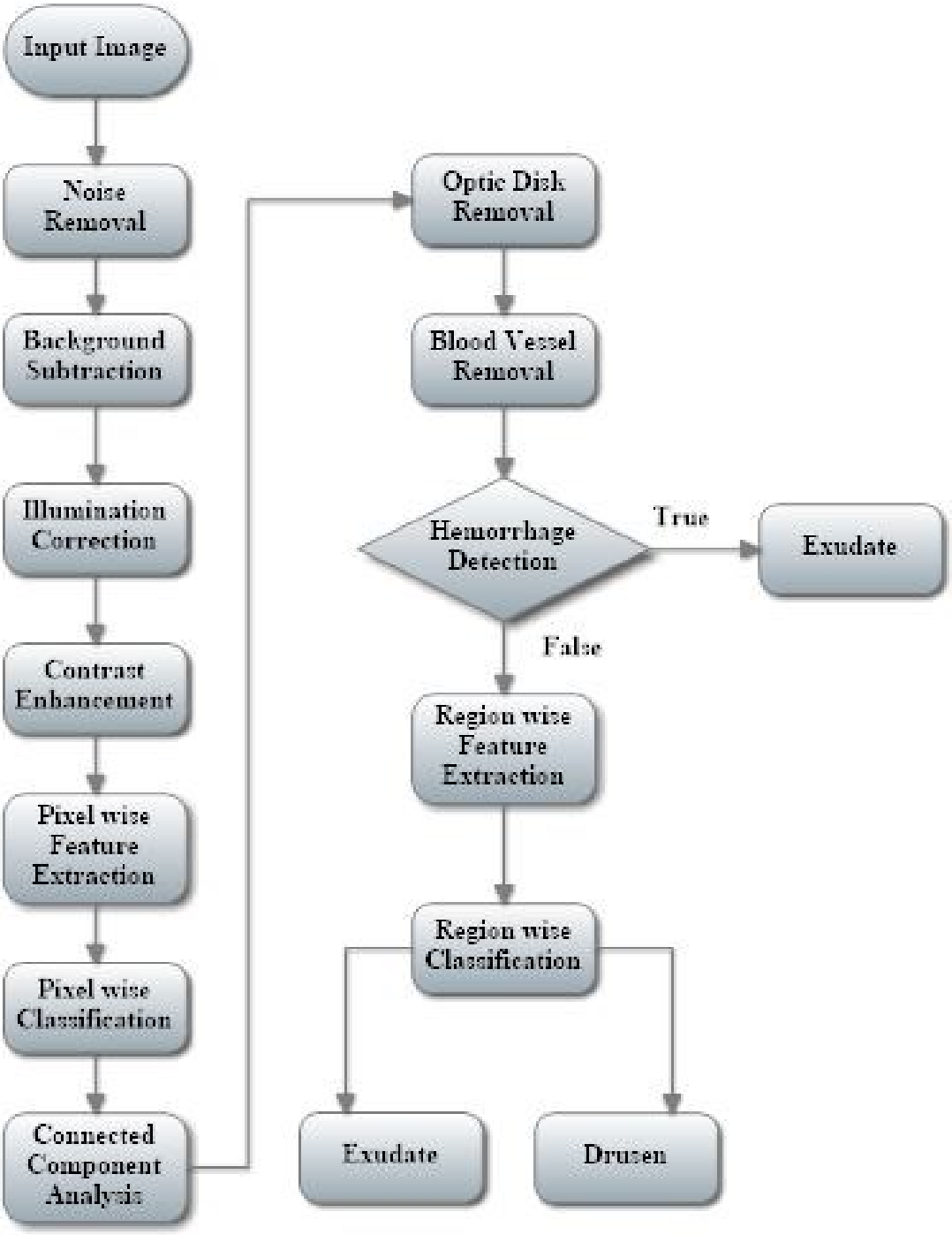


Figure 4.1 Proposed System Overview Flow Diagram

4.2 Retinal Component Extraction

Retinal components extraction like blood vessels and optic disk is required for accurate detection of bright lesion and to avoid false positive results. Method described in [22] and [35] are used for blood vessel segmentation and optic disk localization and extraction.

4.2.1 Blood Vessels Segmentation and Removal

Automatic system presented in [22] adopted for the enhancement and segmentation of blood vessels. Figure 4.2 shows systematic overview of multilayered thresholding technique and segmentation.

Figure 4.2 Blood Vessel Segmentation

4.2.2 Optic Disk Localization and Detection

The details of three step procedure optic disk localization, region of interest extraction and optic disk detection is given in [35]. Figure 4.3shows block diagram of optic disk localization to detection steps.

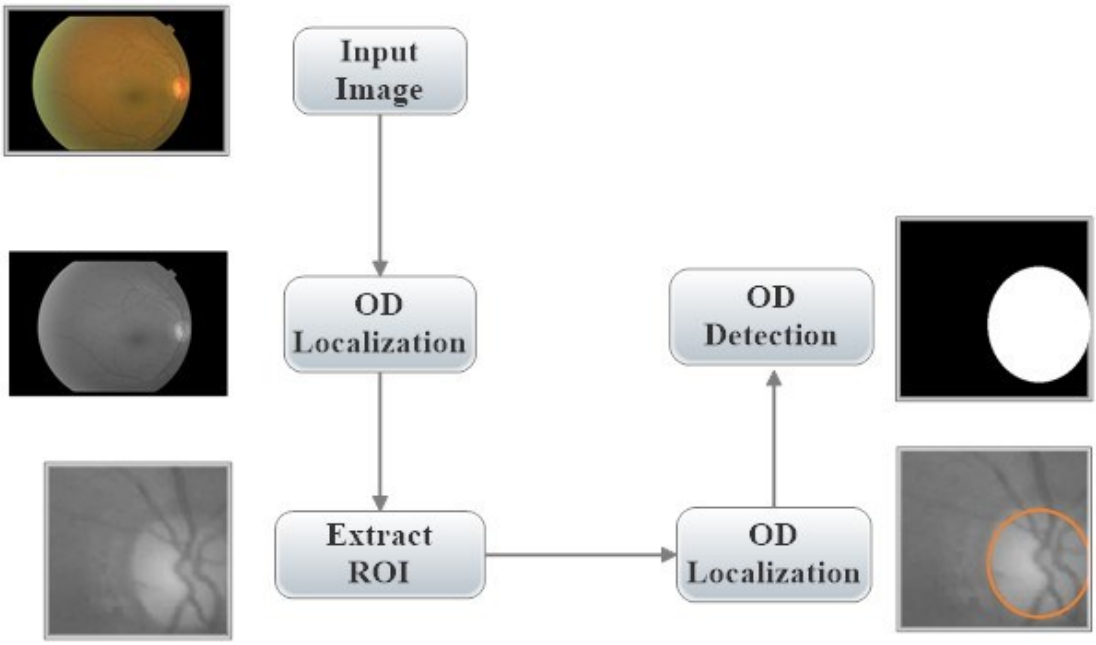


Figure 4.3 Flow Diagram of OD Localization and Detection

4.3 Image Processing

Due to image acquisition process fundus images may have different qualities with respect to color, brightness, noise level and illumination. So it is essential for any automatic system to balance such things in the images to get better results.

4.3.1 Noise Removal

To make the system more efficient it is necessary not to process noisy image for feature extraction and abnormality detection. For this purpose HSI color space is utilized because this color space is closer to human color perception and noise can easily be removed from this color space. Algorithm described in [62] is used for noise removal in fundus images. Figure 4.4 depicts the algorithm steps

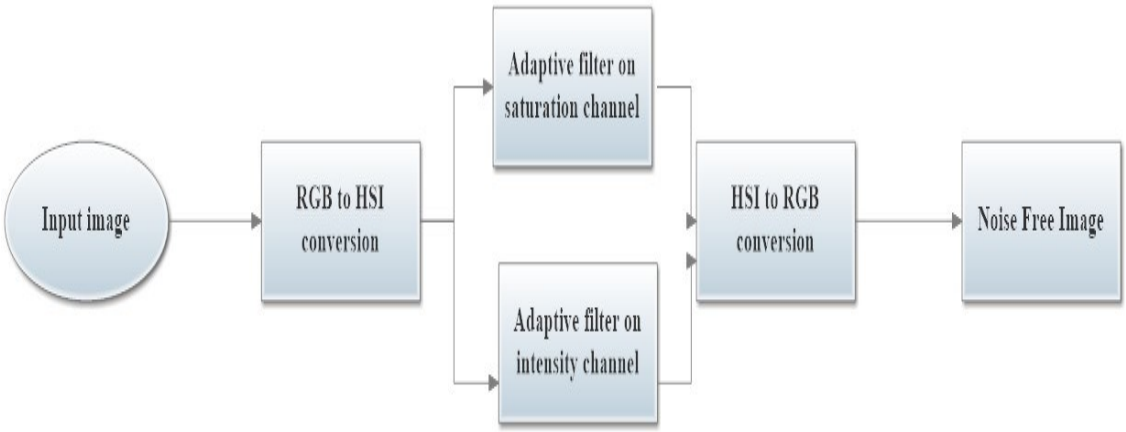


Figure 4.4 Block Diagram for Noise Removal

4.3.2 Illumination Correction

Variation of illumination in the fundus images require illumination correction for better results in further processing. Figure 4.5 illustrates the overview of illumination correction step.

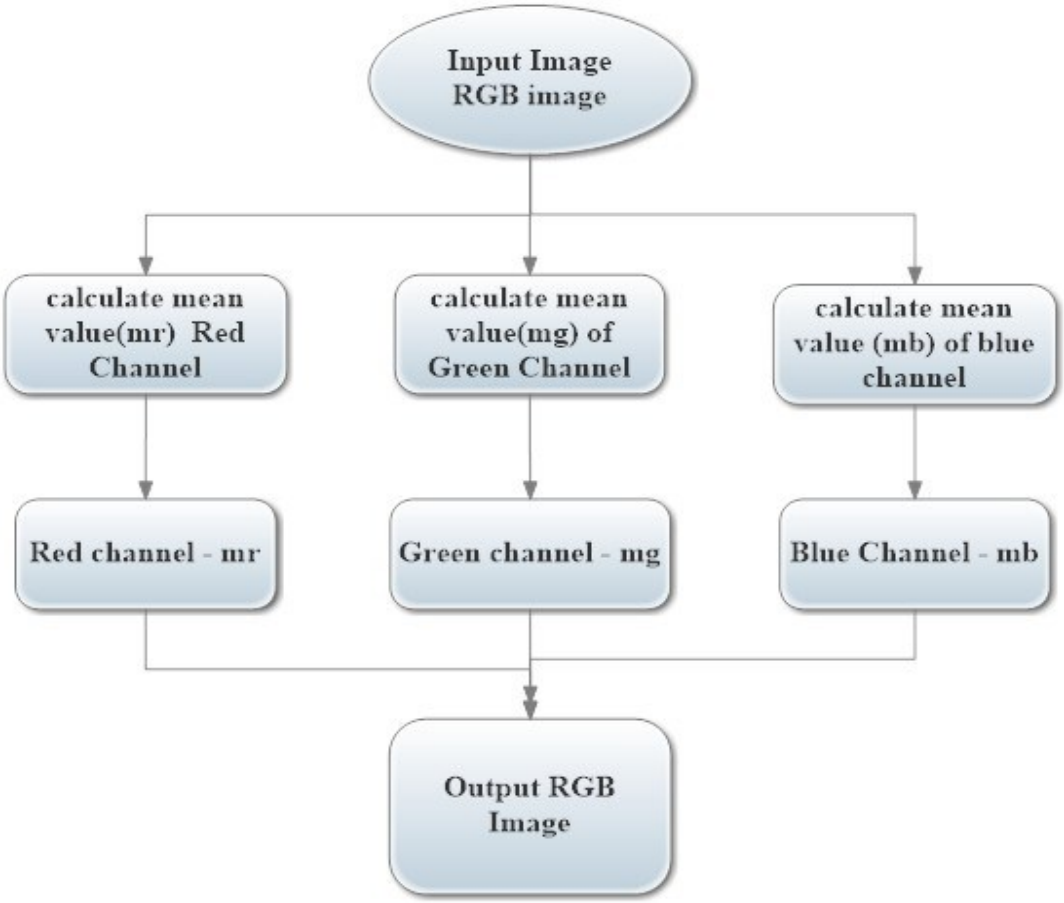


Figure 4.5 Illumination Correction

4.3.3 Contrast Enhancement

Fundus images can be of high or low contrast due to image acquisition process. It becomes essential to normalize the contrast of input image to improve the process of bright lesion detection afterwards. Following steps are followed

1. Extract green channel from color image
2. Apply contrast limiting adaptive threshold [63] on green channel using JXJ sliding window and given as

$$g = 255\frac{[\varphi_j(\varphi_f)-\varphi_j(\varphi_{fmin})]}{[\varphi_j(\varphi_{fmax})-\varphi_j(\varphi_{fmin})]} \quad 4.1$$

Where φ_j is the sigmoid function for a window defined as

$$\varphi_j(\varphi_f) = [1 + e^{\frac{m_j-\varphi_f}{\sigma_f}}]^{-1} \quad 4.2$$

$\varphi_{fmax}, \varphi_{fmin}$ are maximum and minimum intensity value of smooth green channel image respectively. m_j and σ_f are the mean and variance of intensity values within the window.

3. Combine the resulting channel into color image again

Figure 4.6 shows some results of contrast enhancement technique.

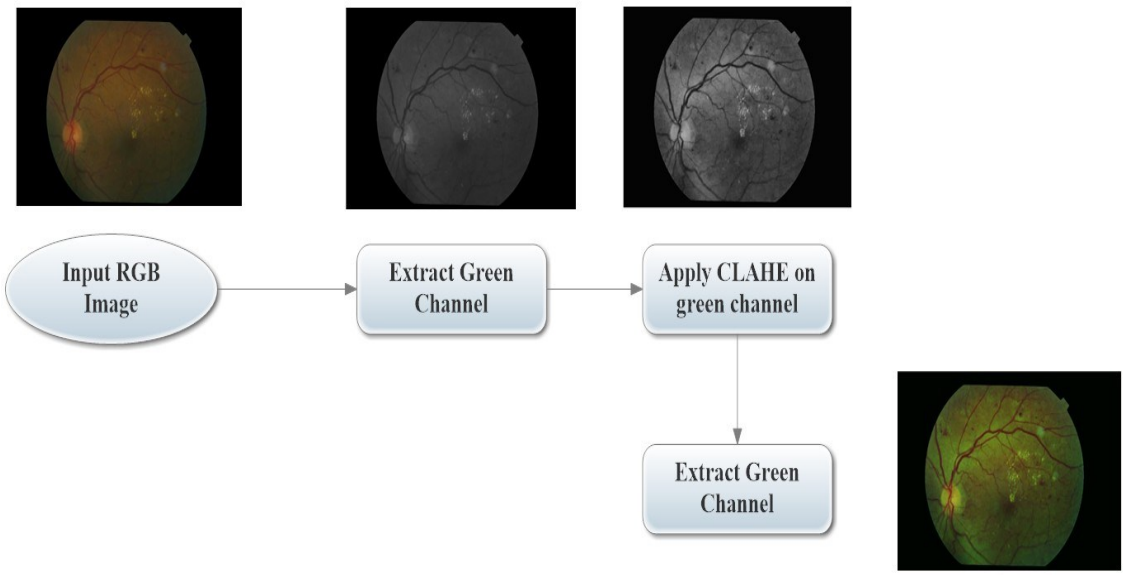


Figure 4.6 Contrast Enhancement using CLAHE

4.3.4 Bright Lesion Detection

After extracting optic disk and blood vessels the fundus image only contains lesion on its surface. Which are enhanced during the process of illumination correction and contrast enhancement.

4.4 Pixel wise Analysis

In fundus images bright lesions are usually Drusen and exudates representing two different diseases. Drusen lesion is of pale yellow color while exudates appear as bright yellow lesion. The strategy for pixel wise analysis is to detecting bright lesion pixels and to classify each pixel as bright lesion or non-bright lesion.

As bright lesion has brighter contrast as compared to background. A symmetric Gaussian filter is used to create unsharp mask in order to enhance the edges of input image. Gaussian filter for two dimension is given by

$$\mathbf{G(x)} = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-x^2}{2\sigma^2}} \quad \textbf{4.3}$$

In our case standard deviation $\sigma = 2$ and size of filter $= [5\ 5]$.pixel wise analysis of fundus image classify the pixels into two classes i.e. background and bright lesion based on color features and Gabor filter features.

4.5 Feature Set for Bright Lesion Detection

A number of features for each pixel are computed to classify them in two classes. The feature which are used for bright lesion detection are as follow

1. ***f1-f3****:* Red, green and blue channel of RGB color space
2. ***f4-f6***: Hue, saturation and intensity channel of HSI space
3. ***f7-f9***: Cyan, magenta and yellow color feature from CMYK space
4. ***f10-f12***: In-phase and quadrature information from YIQ color space
5. ***f13-f15***: Luma, blue difference and red difference information of YCBCR color space
6. ***f16-f18:*** Lightness and color opponent dimension from LAB color space
7. ***f19-f20:*** Inverted red and green image
8. ***f21-f29*** : Maximum, additive and average responses of Gabor filter at frequency 0.25, 0.50 and 0.75

Gabor filter can be represented by Gaussian kernel function. Gabor filter equation for two Dimension is given as follow.

$$\mathbf{Z(x, y, \sigma, \Omega, \theta, r)} = \frac{1}{\sqrt{\pi r\sigma}} e^{\frac{-1}{2}\left(\frac{d1^2}{\sigma^2}+\frac{d2^2}{\sigma^2}\right)} (d1(\cos\Omega + i\sin\Omega)) \quad \textbf{4.4}$$

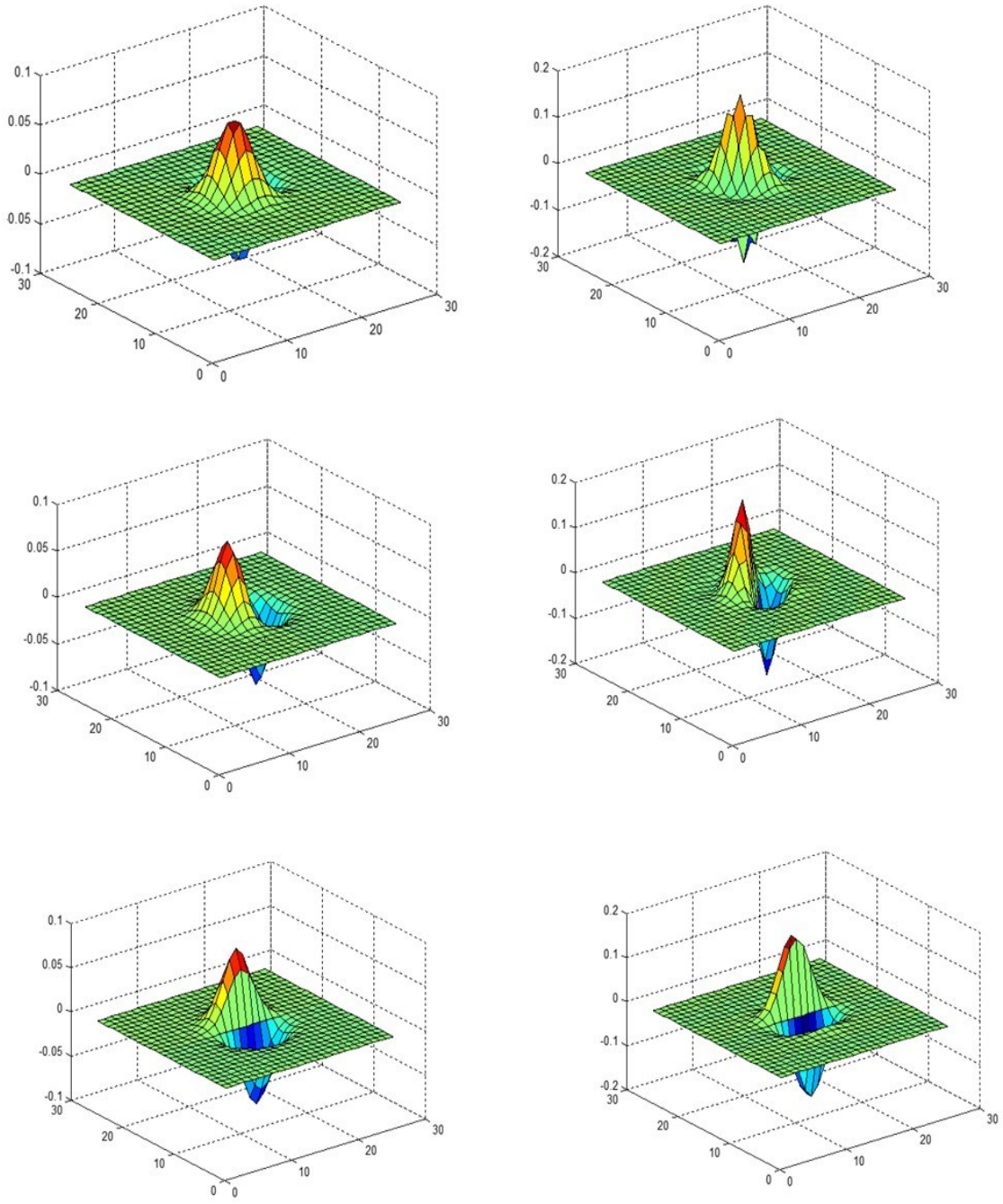


Figure 4.7 Gabor Filter Bank 3-D kernel with scale=2 and orientation = $\{\frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi\}$

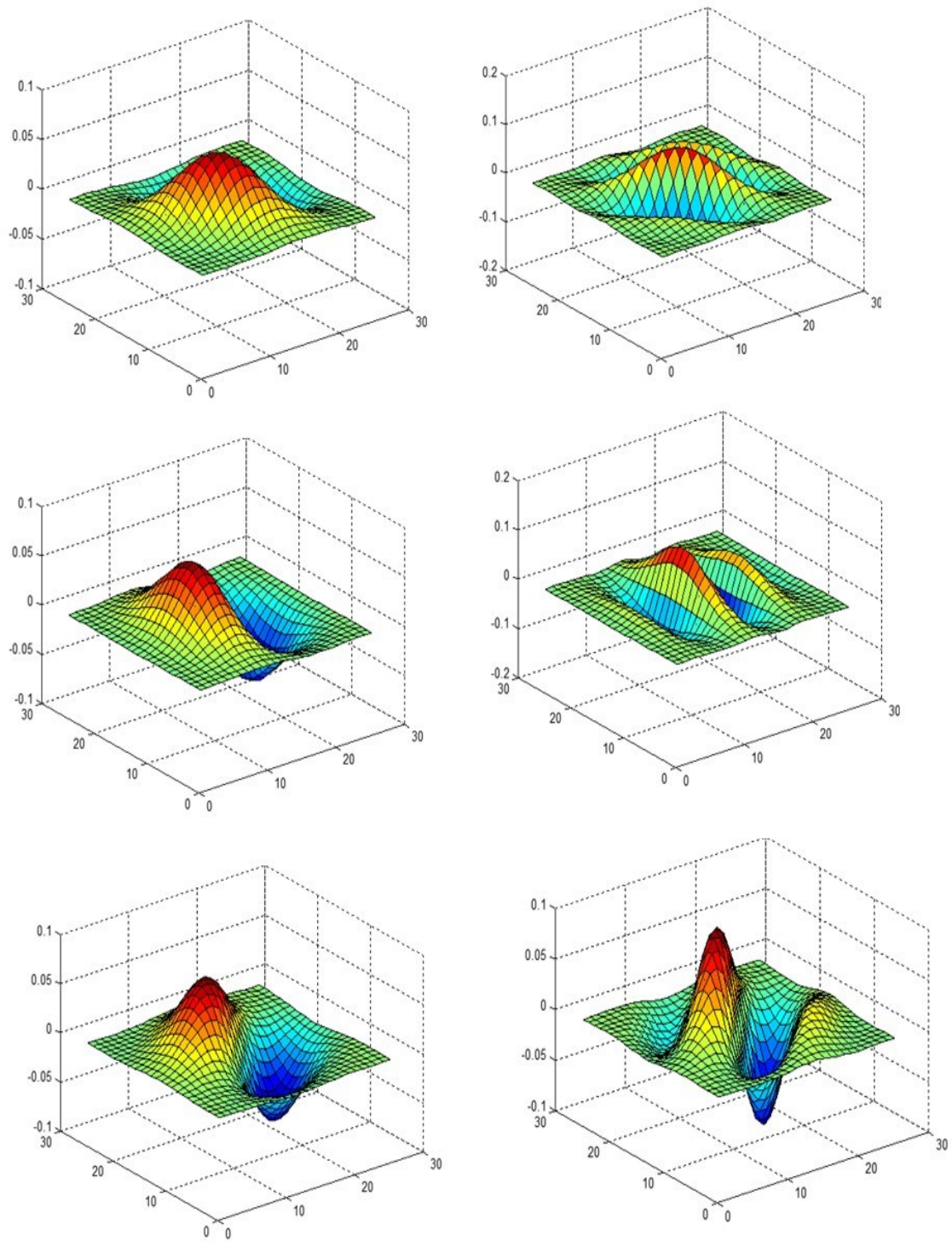


Figure 4.8 Gabor Filter Bank 3-D kernel with scale=5 and orientation = $\{\frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi\}$

Here $\sigma, \Omega, \theta \; and \; r$ are standard deviation of Gaussian, Spatial Frequency, orientation of filter and aspect ratio respectively.

Where$d1 = x\cos\theta + y\sin\theta$ and $d2 = -x\sin\theta + y\cos\theta$. To get Gabor filter response for feature vector. Green channel of input image I is convolved with Gabor filter G centred

at location (s, t) to get Gabor filter responses $\gamma$for selected values of θ, σ and Ω is given in equation 4.5

$$\boldsymbol{\gamma(s,t,\theta,\sigma,\Omega) = \sum_x \sum_y I(x,y).G(s-x,t-y,\theta,\sigma,\Omega,r)} \quad \textbf{4.5}$$

For the maximum Gabor filter Responses $M_\gamma(\sigma,\Omega)$ is computed using Equation 4.5 for θ spanning from 45 upto 180 with the step of 45

$$M_\gamma(\sigma,\Omega) = \max[\,\gamma(\sigma,\theta,\Omega)] \quad \textbf{4.6}$$

For average Gabor filter Response Avg(σ,Ω) Is computed using equation 4.5 for each frequency value Ω spanning from 45 angle to 180.

$$\boldsymbol{Avg(\sigma,\Omega) = \frac{\sum_x \sum_y I(x,y).G(s-x,t-y,\theta,\sigma,\Omega,r)}{N}} \quad \textbf{4.7}$$

Where N is the number of responses at each frequency over different values of θ

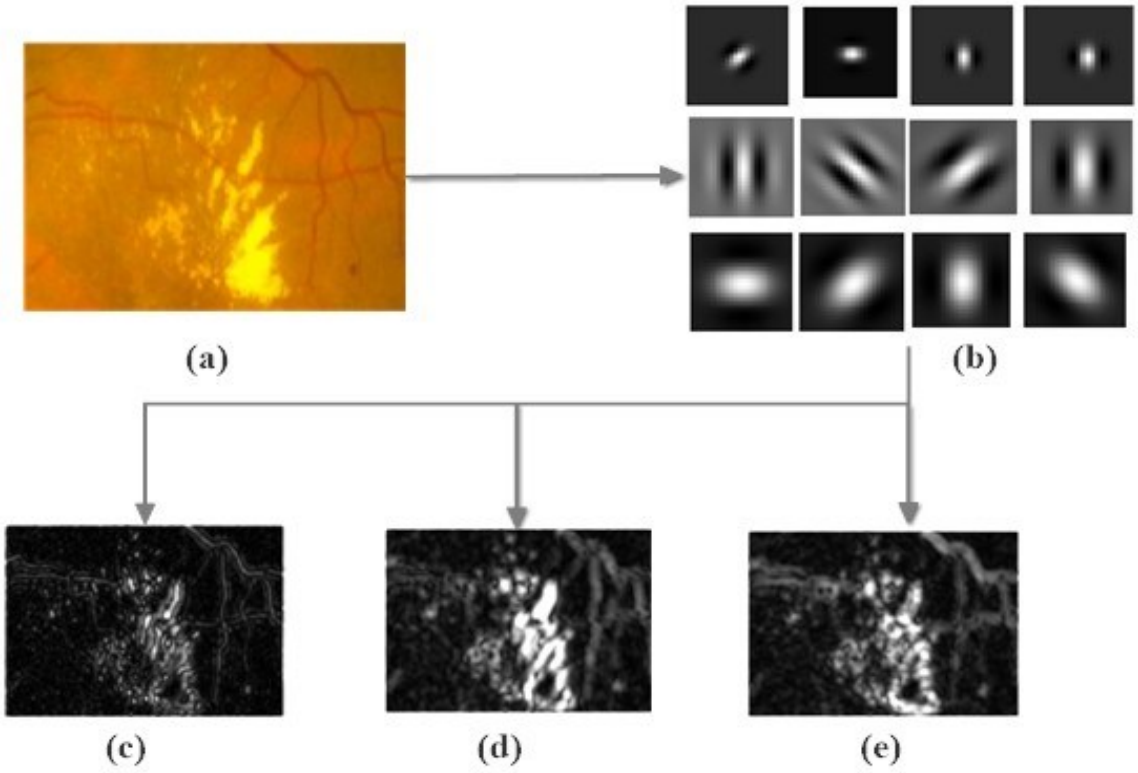


Figure 4.9 Bright Region Enhancement using Filter Bank (a) Segmented Retinal Image Containing Different Bright Regions (b) Filter Kernels with Different Scales and Orientation (c) Average Filter Response (d) Maximum Filter Response (e) Sum of filter responses

List of features mentioned above are extracted for all training samples but not all of them are useful in improving the accuracy. It is necessary to select features which can improve the classification accuracy, sensitivity and specificity. Statistical test are used to select quality features. One type of test is Wilcoxon rank sum test, which tests whether

the normal or abnormal class median values differ significantly. A feature can also be useful if class distributions differ in shape instead of median values. This is accessed using Ansari-Bradley test which determines the dispersions of the normal or abnormal class feature values which differ significantly following subtraction of the median values. If neither the median nor the dispersion differ between normal and abnormal classes then the feature is unlikely to be useful for classification.

Table 4.1 shows performance table for above mentioned features using these two tests. According to the scores of the features they are sorted in descending order for each test. Table 4.1 shows the features for bright lesion and background classes and their scores in respective test, according to the Wilcoxon rank test f28,f26, f25, f29 and f23 are the top five features giving best scores. All these five features are Gabor filter responses. The poorest five features are f20, f14, f17, f15 and f8, which are invert of green channel, blue difference value of YCBCR color space, color opponent dimension from LAB color space, red difference from YCBCR and Magenta color information from CMYK respectively. In Ansari test, f18, f3, f19, f1, f11 are the features which shows no difference in the dispersion between the background and bright lesions. So, these kind of features are meaningless for the classification process.

Table 4.1 Performance of All Features Calculated Using Wilcoxon and Ansari-Bradley Tests for Background and Bright lesion.

Rank sum test		**Ansari Bradley test**	
Features	**Scores**	**Features**	**Scores**
f28	26.2708387	**f8**	13.2003361
f26	26.2684673	**f26**	13.1972635
f25	26.2579371	**f25**	13.1577969
f29	26.1579994	**f22**	13.0543055
f23	26.1396996	**f23**	13.0466417
f22	26.1315693	**f29**	12.3332457
f21	24.4038234	**f28**	12.0038321
f24	24.0280795	**f4**	8.75033536
f27	23.9837094	**f21**	6.80356422
f16	20.8112732	**f24**	6.51638167
f13	20.6636805	**f27**	6.26809593
f10	20.6557626	**f12**	2.87426169
f9	20.6023377	**f17**	2.28399547
f2	20.4560342	**f15**	1.92433435
f6	19.8330158	**f7**	1.79983014
f7	18.8972527	**f6**	1.64495421
f18	15.5137583	**f16**	1.56875222

f11	14.038495	**f10**	1.34363806
f1	13.3824192	**f13**	1.33453094
f12	12.9704957	**f2**	1.32559674
f4	12.9551667	**f20**	1.32559674
f5	3.42908741	**f5**	1.10170112
f3	-2.7498323	**f9**	0.9980883
f19	-13.382419	**f14**	0.38857061
f8	-14.258202	**f11**	-0.0919735
f15	-16.687167	**f1**	-0.2577634
f17	-18.677644	**f19**	-0.2577634
f14	-20.113966	**f3**	-1.7155983
f20	-20.456034	**f18**	-4.6875647

Another type of feature selection is through Gaussian Mixture Model (GMM) and Support Vector Machine (SVM) which provide accuracies for different combination of feature set. Mixture Model is the type of density model with different function in our case the function is based on Gaussian. Once model is generated Conditional probability can be computed. The model extract useful information from the dissimilarities between the data objects. On the basis of dissimilarities placement of data objects in same cluster or different cluster is been decided. The probability distribution of dissimilarity variable is considered s mixture model consisting of interclass and intraclass dissimilarity Gaussian distribution. Figure 4.11 shows some testing results of input image shown in figure 4.10 for different combination of features with certain accuracies provided by GMM. Which provide high accuracies

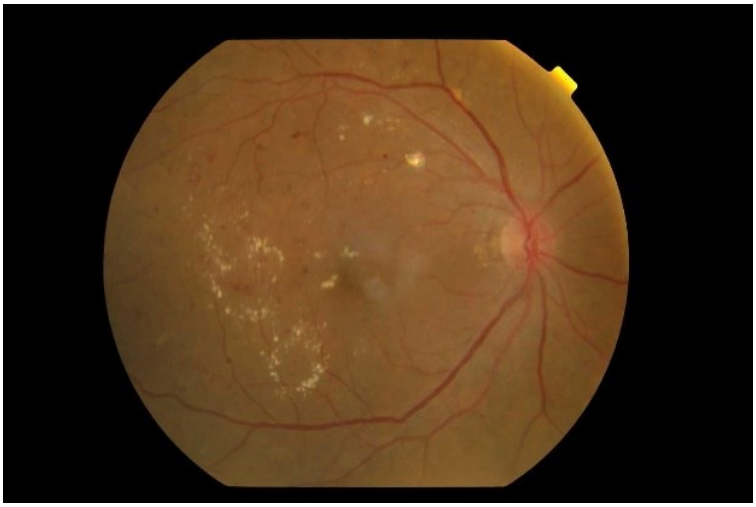


Figure 4.10 Input image for testing different combination of features

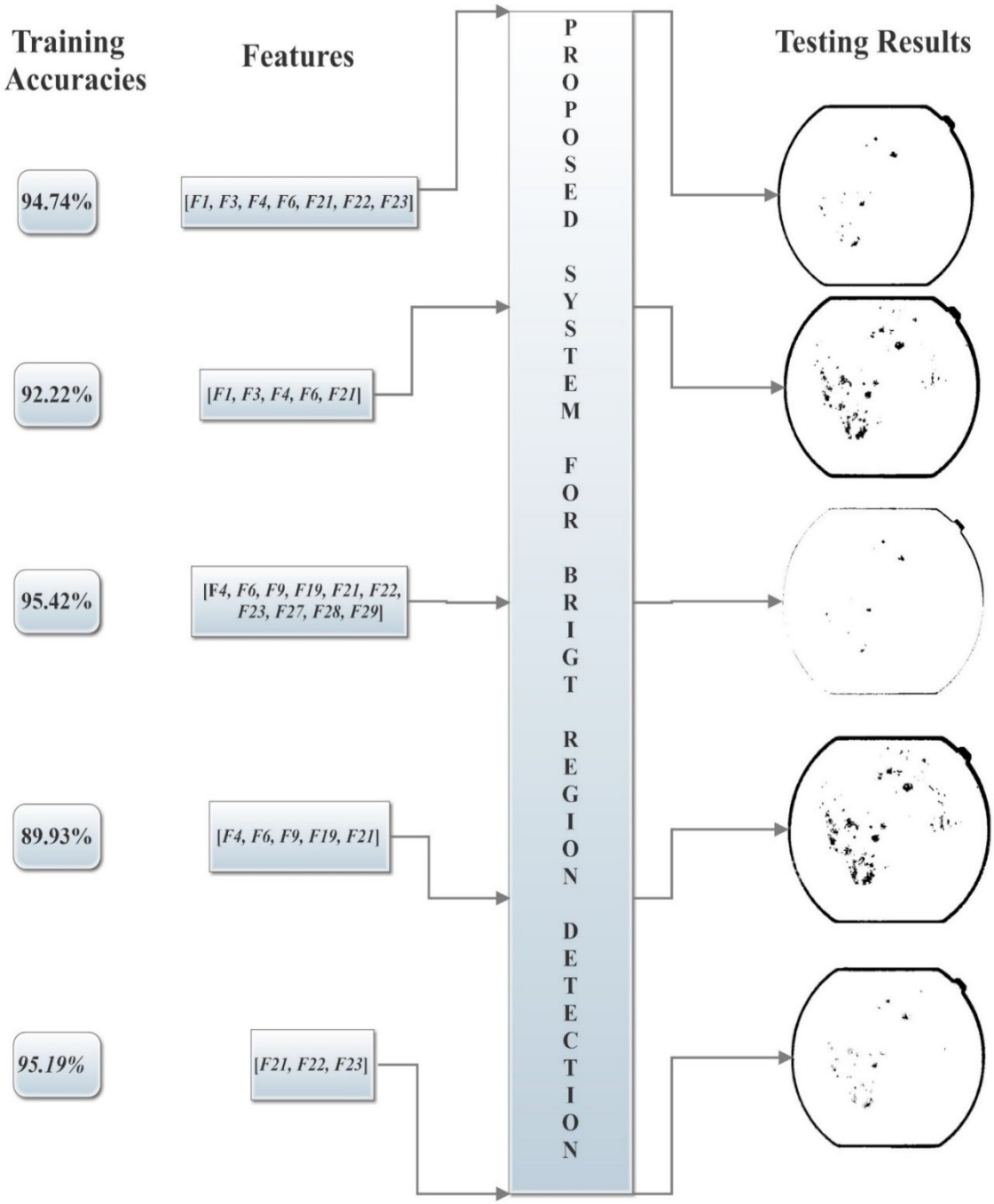


Figure 4.11 Training Accuracies for the given features and their test results on proposed system

From the above figure it can be observed that feature set [*f1, f3, f4, f6, f21*] and [*f4, f6, f9, f19, f21*] having 92.22% and 89.93% accuracies with GMM test are showing good results on a test image. Because they are highlighting approximately all the bright lesion on retinal surface.in figure 4.11 rest of the feature set having high accuracies with GMM did not perform well on the test image. Support vector machine with linear kernel implements feature selection on the basis of greedy algorithm. SVM provides maximum

margin by using a separating hyper plane with robustness with input dimensionality and data distribution.

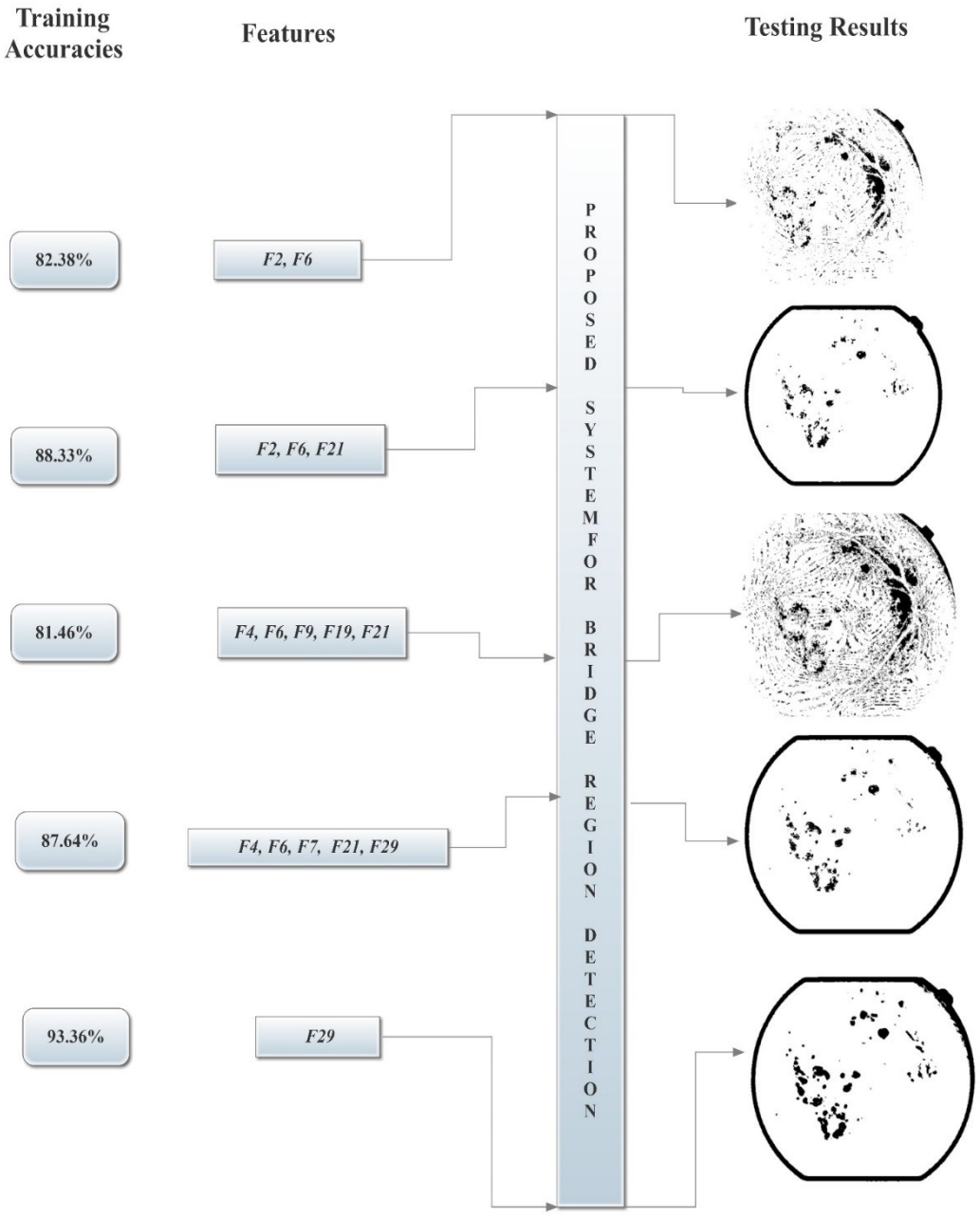


Figure 4.12 Training Accuracies with GMM for different combination of features and their test results on proposed system

Figure 4.12 shows that feature set [*f2, f6, f21*], [*f4, f6, f7, f21, f29*] and [*f29*] having training accuracies for SVM 88.33%, 87.64% and 93.36% respectively performs well on testing. While feature set [*f2, f6*] and [*f4, f6, f9, f19, f21*] having accuracies 82.38 and 81.46 respectively for SVM does not performs well on training.

4.6 Classification

The classification stage takes the input image with features mention above and classify each feature as bright lesion or non-bright lesion. Use K nearest neighbour classifier which classify the patterns on distance measures. The feature vector is passed to Knn with two classes defined as C1={Background} and C2={Bright Lesion}.KNN computes distance vector of features from training feature vector as given in equation 4.3 and classify the pattern to the class which have less distance to that pattern's feature vector. The training dataset for this purpose is computed using fundus images containing drusen and exudates. We took k=9 for classification through KNN. Figure 4.6 shows the result of the Bright lesion detection step.

$$\mathbf{D(x, y)} = \sqrt{\sum_{n=1}^{j} (x_n - y_n)^2} \qquad \mathbf{4.8}$$

Where x_n represents feature vector of training dataset while y_n represents feature vector of input image. J is the number of features.

4.7. Connected component Analysis

Previous step specify some regions on the input image which can have bright lesion. But these regions may include some suspicious pixels which are not the part of bright lesion and they occupy very small region as compared to bright lesion size. So it is essential to remove these suspicious pixels from the image to avoid false positive results from further processing.

Connected component algorithm finds the set of pixels have same value. These region may also contains optical disk which are false lesion regions and need to be removed before further processing. Figure shows the segmented bright candidate lesions before and after removal of OD region.

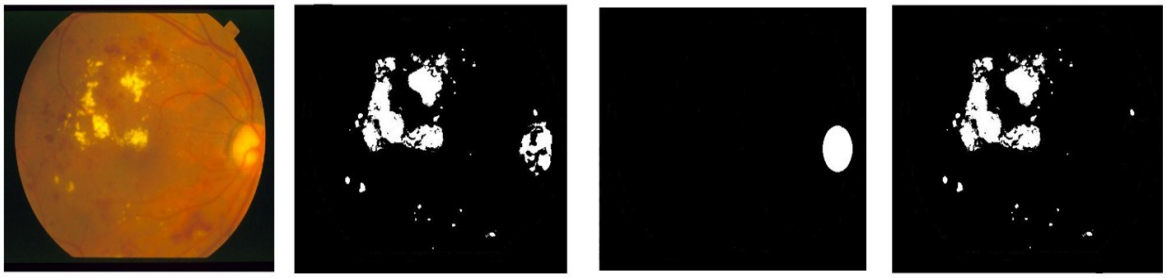


Figure 4.13 Bright Region Enhancement and Extraction (a) Original Image (b) Bright Region Classification Result (c) Segmented OD region (d) Candidate Bright Lesion after removing OD

The next stage in proposed system extracts different features for all candidate regions and finally classifies it using Support Vector Machine (SVM).

4.8 Hemorrhage detection

Hemorrhages are the red lesion appear due to the sensitive blood vessel leakage and usually present with exudates. As exudates are the symptoms of diabetic retinopathy so when level of sugar in the blood increases the sensitive blood vessels in retina can burst and this causes Hemorrhage and exudates marks to appear on the surface of retina. Hemorrhage does not appear with drusens. But it does not mean that image having exudates must have hemorrhages. There are some fundus images having exudates without hemorrhages.

Bright lesions are once detected than hemorrhage detection is being performed to identify blood lesion. This detection will specify whether the bright lesion is drusen or exudates. For this detection blood vessels can be a counter mark for red lesion detection. So these vessels are removed from the input image through the method described in [63].

4.9 Drusen and Exudates Differentiation

Once the candidate region has been specified. The most important step in this automatic system is to correctly differentiate drusens from exudates. Drusen appear are pale yellow lesion while Exudates has bright yellow color. It becomes difficult for naked eye to differentiate them.

For differentiating drusens from exudates set of feature is computed for accurate classification. The description of features which are used in proposed system is as following:

1. ***f1*:** Area. Which is the total number of pixels in candidate region.

2. ***f2*:** Eccentricity. Which is the ratio of the distance between foci of ellipse and its major axis length and it is equal to 0 for a circular region.
3. ***f3:*** Perimeter. Which is the boundary that surrounds the area of candidate region.
4. ***f4:*** Mean intensity. Which is value of all green channel pixels within candidate region.
5. ***f5:*** Aspect ratio. Which is the ratio of major axis length to minor axis length of candidate region.
6. ***f6:*** Compactness. $\boldsymbol{C = \frac{P^2}{4\Pi A}}$ is another measure of circularity where A and P are the area and perimeter of candidate region.
7. ***f7, f8, &f9:*** Mean HSV (hue, saturation and value) values of all pixels inside candidate region.
8. ***f10:*** Mean Intensity value of contrast enhanced green channel pixels within candidate region. The adaptive histogram equalization given in equation 4.1 is used for contrast enhancement.
9. ***f11:*** Mean gradient magnitude value for boundary pixels of candidate lesion.
10. ***f12:*** Mean gradient value of neighborhood pixels in a square region outside the candidate lesion.
11. ***f13.*** Third moment value of all pixels in square region including candidate region pixels and its neighboring pixels. It is the measure of skewness.
12. ***f14.*** Entropy value of all pixels in square region including candidate region pixels and its neighboring pixels.
13. ***f15.*** Mean range filter value of a local range of fundus image using a 5 X 5 neighborhood where range is the difference between maximum and minimum values in the specified neighborhood.
14. ***f16:*** Mean entropy filter (*f16*) value of local entropy image calculated using a 7 X 7 neighborhood.
15. ***f17:*** Mean top and bottom hat filters. These are the mean values of morphological top and bottom filters respectively applied to green channel of fundus image. A circular structuring element of radius 5 is used for these filters.
16. ***f18, f19 & f20:*** Mean inverse top and bottom hat filters. These are the mean values of green channel intensity after subtraction of morphological top and bottom filter outputs.
17. ***f21:*** Energy (*f21*) is the sum of square of all pixels intensities within candidate region.

4.9.1 Classification

Candidate region represented with feature set are classified through SVM. The proposed classification for drusen exudates detection is described here. Previous steps provide candidate regions of bright lesions if an image represented by I and having N candidate bright region lesion such that I = $\{v_1, v_{2,} v_3 \ldots\ldots\ldots v_n)$. Each region is a sample and represented by k number of features for classification. If f represent feature than

i^{th}candidate region or sample can be represented as $v_i = \{f_1, f_2, f_3, \ldots \ldots \ldots . f_k\}$. where i=1, 2, 3…….. N

For candidate lesion classification SVM is utilized.

4.9.2 Support Vector Machine

The original algorithm of SVM separates different regions from each other with maximum margin by using a separating hyperplane. Letv_i, $x_i, v_i \in K_d^N$ $x_i = \{-1,1\}, i =$ 1 ... .N for linearly separable data. Hyperplane can be represented by s and r such that

$$\boldsymbol{x_i(s.v_i + r) > 0} \quad \textbf{4.9}$$

Where x_ii is the class of i^{th} feature vector of v_i Two hyperplanes are generated using *s* and r such that no sample lies between these planes and all samples with x = 1 should be on one side of planes and samples with x=-1 should be on other side. The distance between these two planes is defined as

$$\boldsymbol{Margin = \frac{2}{|s|}} \quad \textbf{4.10}$$

It is desirable to maximize the distance or margin between planes by minimizing w. or there should be no sample between these planes. So rewriting this equation

$$\boldsymbol{x_i(s.v_i + r) \geq 1} \quad \textbf{4.11}$$

In above equation one thing that makes optimization of *s* difficult is the dimension$v$. But Langrange Multiplier β_i can be used for solving the problem. Such that $s = \sum_{i=1}^{N} \beta_i x_i v_i$ and $s = \sum_{i=1}^{N} \beta_i x_i = 0$ shows that β_i is the only value on which optimization of *s* depends. Samples which corresponds to non-zero β_i can only contribute in determining hyperplane. The decision rule for hyperplane for the samples (also known as support vectors) is defines as

$$\boldsymbol{x(v) = sign[\sum_{i=1}^{N}(\beta_i x_i K(v, v_i) + r)]} \quad \textbf{4.12}$$

To make non-linear feature map kernel i.e.$K(v, v_i)$ is used through mapping input feature space to higher dimension space. Based on Radial basis function (RBF) SVM with nonlinear function is defined as used.

$$\boldsymbol{K(v, v_i) = e^{(-\gamma||v - v_i||^2}} \quad \textbf{4.13}$$

Least squares SVM is applied using LS-SVM toolbox [64] to implement SVM with RBF kernel.

This chapter include complete proposed system containing step by step procedures. From input images to detection of bright lesion and then differentiation among lesion is also described in this chapter. Next Chapter described the evaluation of proposed system to validate its performance. A number of retinal image databases are available for proper testing of AMD related algorithm. The details regarding datasets and complete evaluation of proposed system is given in next chapter.

Chapter 5

5 Experimental Results

For diagnosing right kind of disease it is critical to get accuracies in medical image analysis. This is the reason the proposed system was evaluated thoroughly. This chapter includes the information about the dataset used, results of the proposed system and material used for evaluation.

5.1 Dataset

Dataset are essential for the evaluation of the proposed methodology and results of different algorithm on the same dataset can facilitate the comparison process. The dataset should contain the abnormalities with high qualities of image required by the proposed system. In addition to abnormalities there should be normal images in the dataset to better test the algorithm. The information about normal and abnormal images in the dataset is called ground truth. Ground truth is important to get accuracy of the system. For higher accuracies the results of the proposed system will be consistent ant with the ground truth. For drusens and exudates detection and differentiation system some of the bench mark dataset are publically available. These dataset are used for evaluating different system for detecting drusens and exudates and comparing their results with the ground truth. Databases used for most of th times to detect retinal abnormalities are as follow.

DIARETDB (Standard Diabetic Retinopathy Database) this is publically available database contain images for Diabetic retinopathy lesion. The dataset consist of 89 images 5 images are normal while 84 images shows different abnormalities of diabetic retinopathy disease. The images are of size 1500X1152

MESSIDOR database is established to facilitate the diagnosis of diabetic retinopathy. It contains 1200 images with different resolution as 1440 X960, 2240 X1488 and 2304X1536. 1200 images set is divided into 3 sets annotated by 3 ophthalmologic departments. Each set consist of 400 images.

HEI-MED (Hamilton Eye Institute Macular Edema Dataset) is another dataset for detecting exudates of diabetic macular edema. The dataset contains 169 images in which 54 images having exudates while rest of the images are normal.

STARE (Structured Analysis of Retina) dataset contains 400 images of size 700X605 of jpeg format. 60 images contains drusen lesion 51 images are from diabetic

retinopathy disease and 30 images are normal. Rest of the images contains symptoms of different other retinal disorders. The images were acquired using Topcon TRV-50 retinal camera.

DRIVE (Digital Retinal Images for Vessel Extraction) is the database designed to compare different results of vessels segmentation of fundus images. Its image resolution is 768 X 584.

Figure 5.1 and 5.2 shows randomly selected images from STARE database and AFIO (Armed Forces Institute of Pathology) annotated images respectively, these databases which have been used to report the validity of proposed system. Total 297 images are used. The detailed description about all databases is given in Table 5.1.

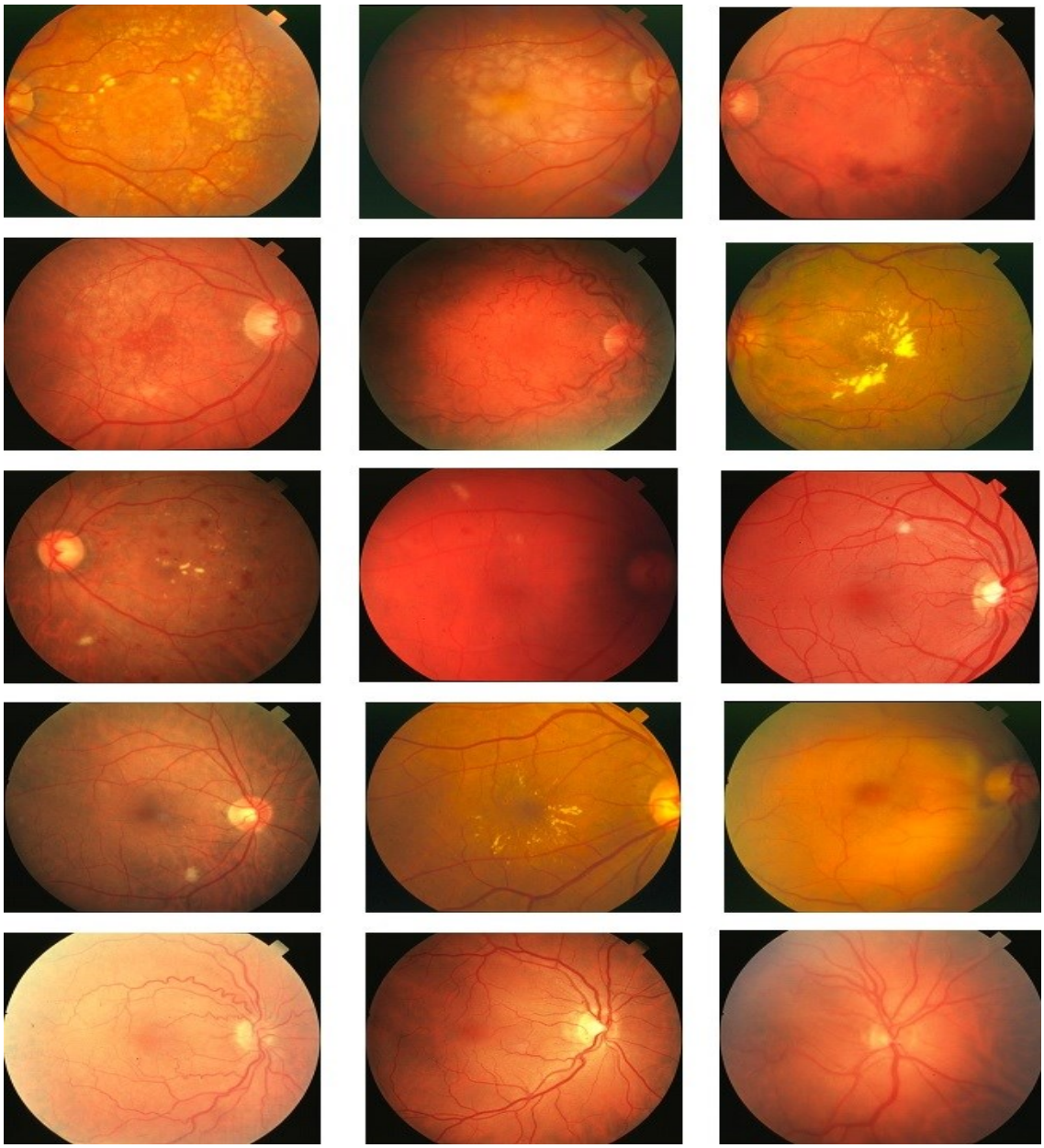


Figure 5.1 Retinal Image from STARE Database

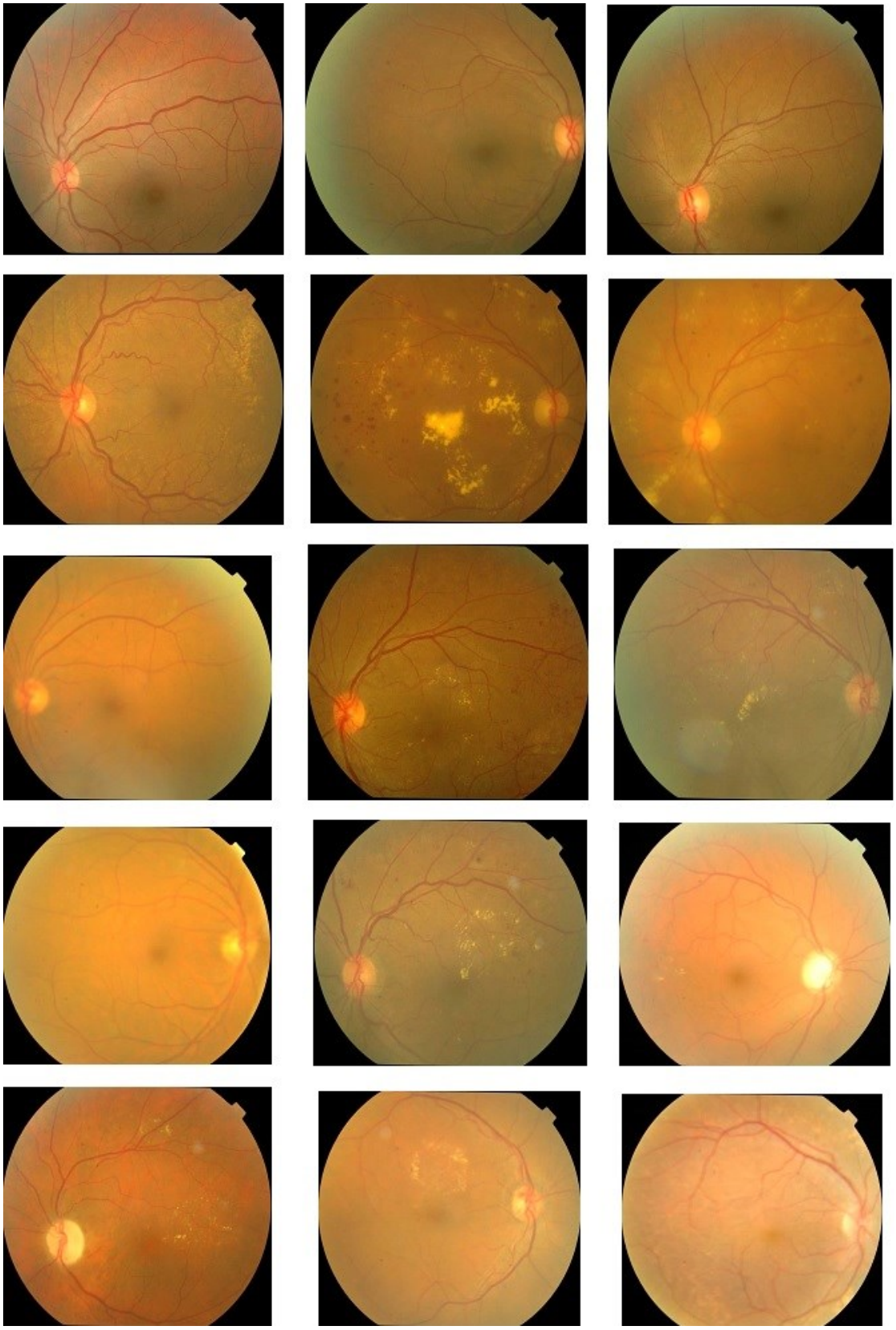


Figure 5.2 Retinal Image from AFIO

Table 5.1 Database Description

DATABASES	IMAGES	NORMAL	AMD	DIABETIC RETINOPATHY
STARE	122	35	24	63
AFIO	165	50	15	100
Total Images	297	85	39	163

5.2 Results

For training and testing evaluation dataset for the proposed system is divided. 40% dataset is utilized for testing and 60% dataset is reserved for training. Testing for different stages of proposed system is performed several time and average results are shown in this chapter. Different evaluation parameter are kept into the process of evaluation like accuracy, sensitivity, specificity, area under receiver operating characteristics (ROC) curves (AUC) and positive predictive value (PPV). Sensitivity, specificity and PPV are the rate of true positive, true negative and precision respectively while accuracy is the rate of correctly classified images and total number of images in testing process. Accuracy, sensitivity, specificity, and PPV are specified below.

$$\mathbf{Accuracy} = \frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \quad \mathbf{5.1}$$

$$\mathbf{Sensitivity} = \frac{\mathbf{TP}}{\mathbf{TP+FN}} \quad \mathbf{5.2}$$

$$\mathbf{Specificity} = \frac{\mathbf{TN}}{\mathbf{TN+FP}} \quad \mathbf{5.3}$$

$$\mathbf{PPV} = \frac{\mathbf{TP}}{\mathbf{TP+FP}} \quad \mathbf{5.4}$$

Where

- TP: true positive means bright lesions are correctly classified
- TN: True negative means background is correctly classified
- FP: False positive means background is wrongly classified as bight lesion
- FN: False negative means bright lesion is wrongly classified as background

A total of 297 retinal images from STARE and AFIO databases with different resolution, lesions and with a lot of variations are used. The tests are performed on two levels, i.e. bright lesion detection and drusen exudates differentiation. Results are shown with different parameters as mentioned above.

5.2.1 Bright Lesion Detection Results

Bright lesion detection is important for further processing of the proposed system. STARE and AFIO database is used for bright lesion detection as these two databases contain exudates and Drusen lesion. Figure 5.3 and 5.4 illustrate the bright lesion detection results for proposed feature based system.

Optic disk removal from the bight lesion region is essential to remove false positive pixels. Figure 5.3 and 5.4 shows the optic disk removal from the bight regions. The failure cases are the ones in which OD is hardly visible in addition to presence of exudates and drusens. Table 5.2 summarizes the results of bight lesion detection for all databases.

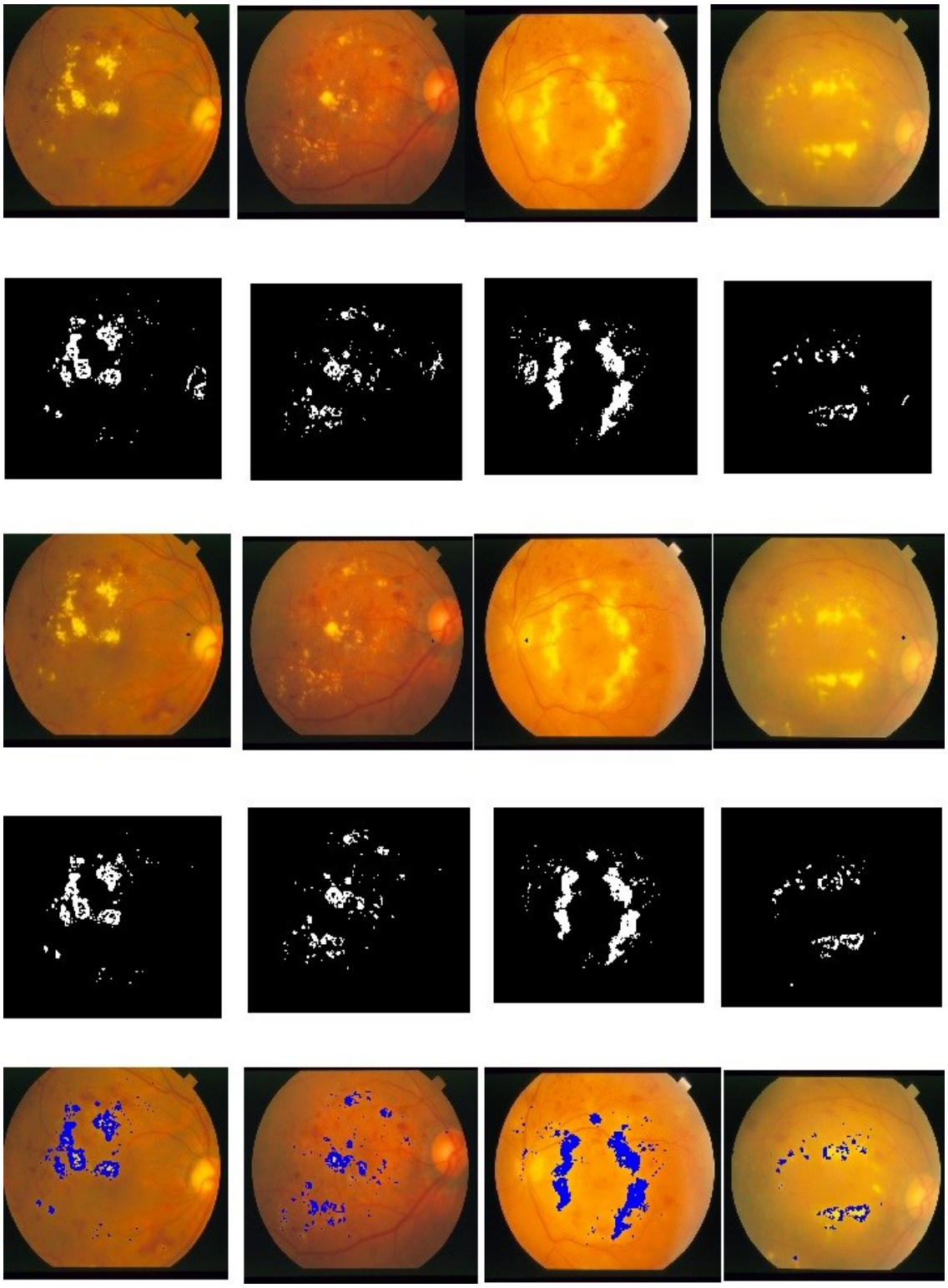


Figure 5.3 Bright lesion detection over STARE images: Row1) Original Images Row2) Bright Lesion Detected Binary Image Row3) Optic Disk Region detection Row4) optic disk removed binary Row5) Images Bright Lesion Highlighted with Blue color

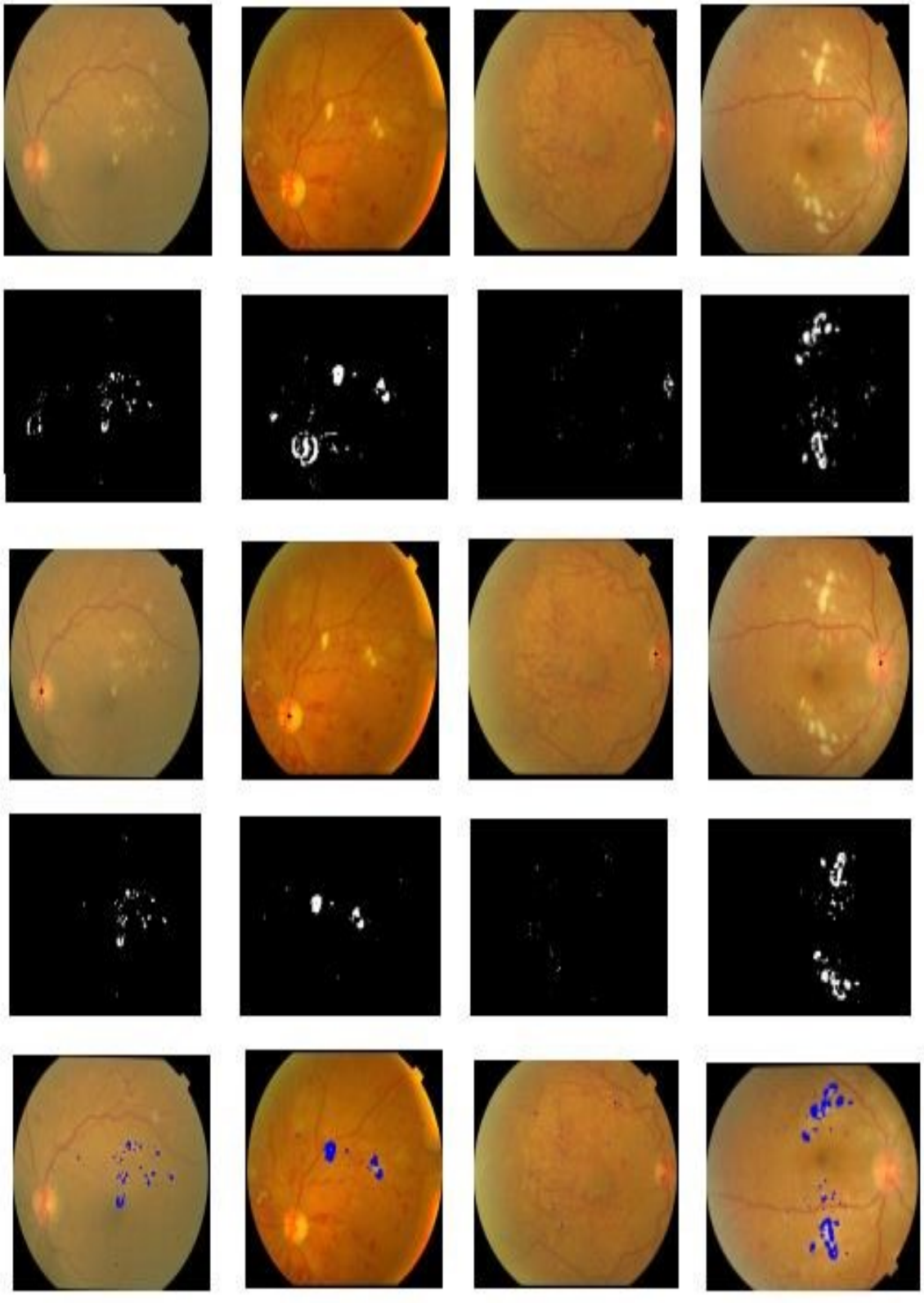


Figure 5.4 Bright lesion detection over AFIO images: Row1) Original Images Row2) Bright Lesion Detected Binary Image Row3) Optic Disk Region detection Row4) optic disk removed binary Row5) Images Bright Lesion Highlighted with Blue color

Table 5.2 Performance Evaluation of Proposed System as Compared to Other Methods for Bright Lesion Detection

Method	Database	Accuracy	Sensitivity/Specificity
Zheng, et al. [46]	AREDS, Local	82%	0.84 / 0.76
Yuanjie Zheng [53]	STARE	74%	0.75/0.63
Ziyang [49]	Singapore Eye Research Institute	75%	0.75/0.75
Niemeijer et al. [60]	Local	90%	0.77/0.88
Proposed Method	STARE	93.42%	0.96/0.80
Proposed Method	AFIO	93 %	0.98/0.90

5.2.2 Hemorrhage Detection Results

Hemorrhage detection is another test for exudates verification in the fundus images, because hemorrhages usually exist with the exudates lesion. So it is important to detect that if any red lesion is present in the fundus image along with bright lesion. STARE and AFIO database are again tested for hemorrhage detection. But before this detection blood vessels are removed from the image to avoid false positive pixels and area. Figure 5.5 and 5.6 illustrate the blood vessels detection results

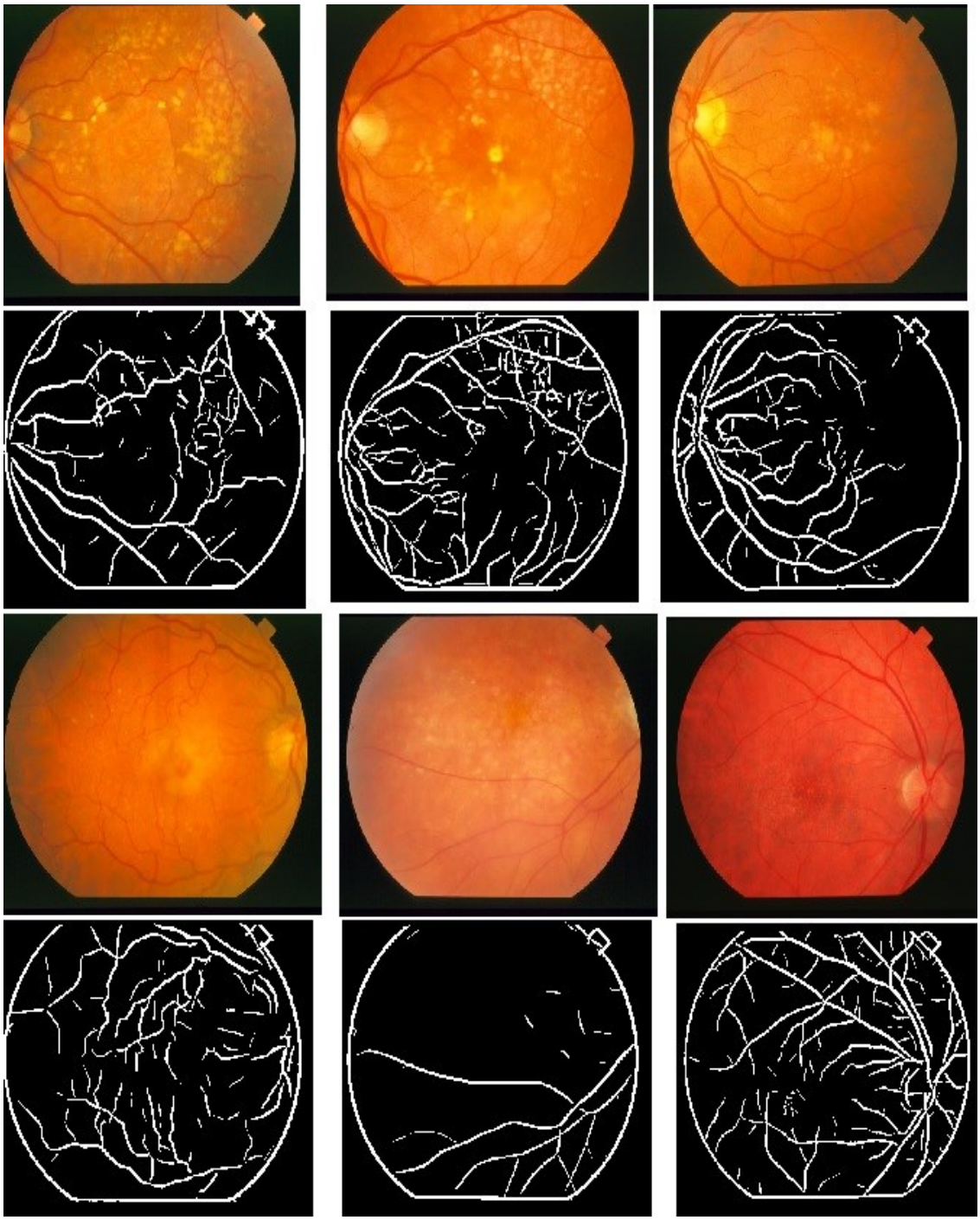


Figure 5.5 Blood vessels detection over STARE images: Row1 & Rw3) Original Images Row2& Row4) Blood vessels Detected Binary Image

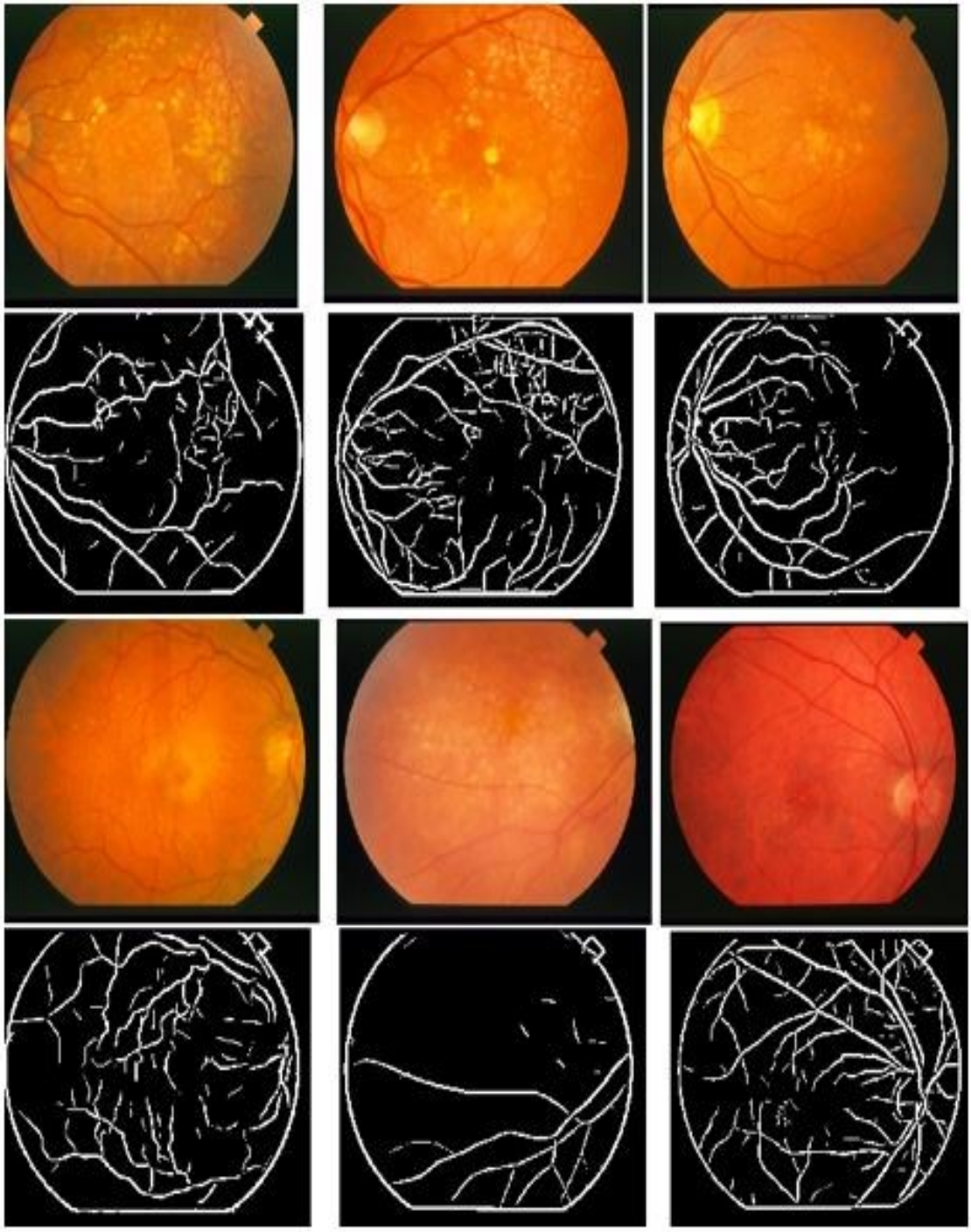


Figure 5.6 Blood vessels detection over AFIO images: Row1 & Rw3) Original Images Row2& Row4) Blood vessels Detected Binary Image

Figure 5.7 shows some Hemorrhage detection results on fundus images

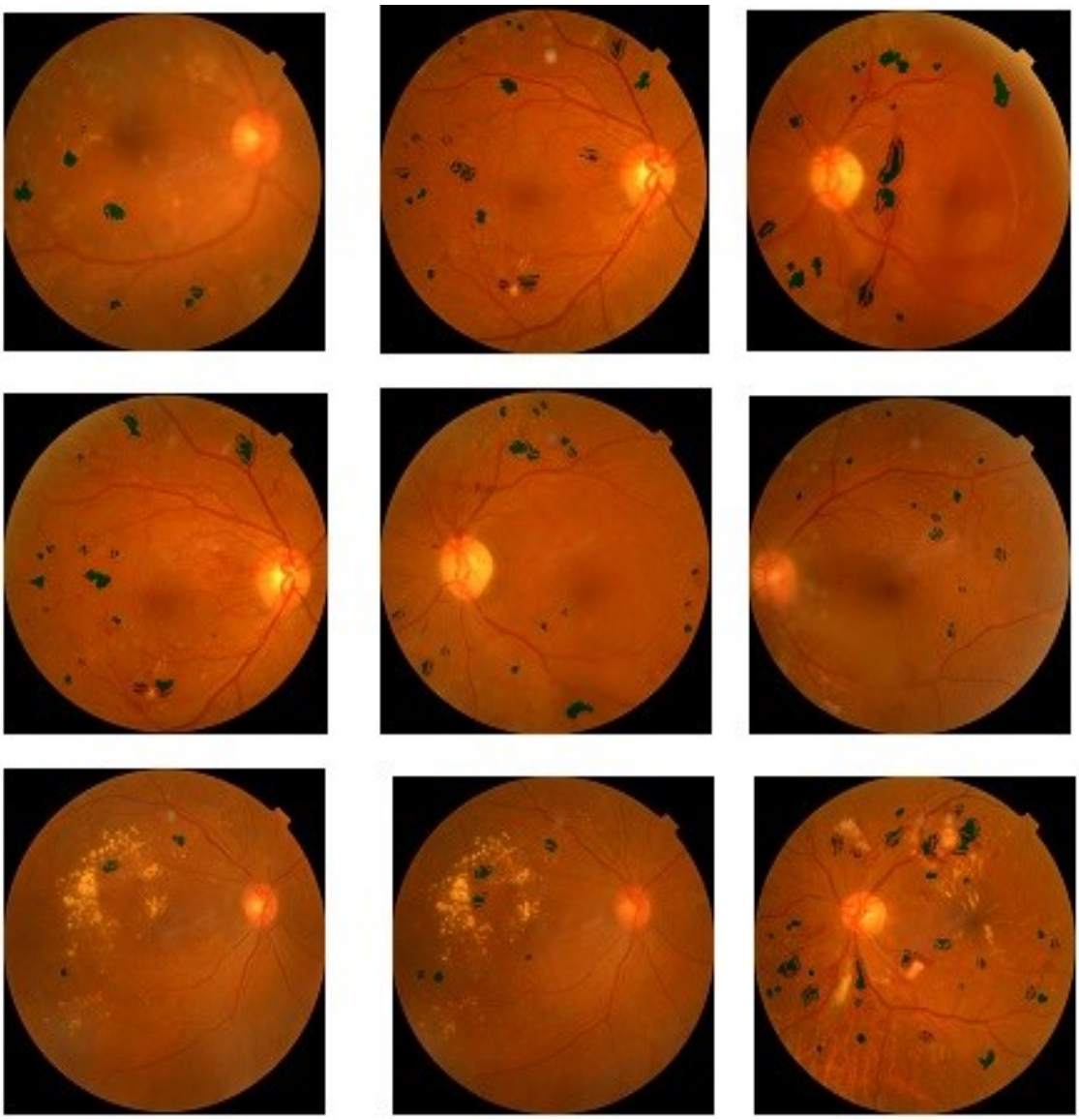


Figure 5.7 Hemorrhage Blood vessels detection over AFIO images highlighted with green color

5.2.3 Exudates and Drusens Discrimination Results

Exudates and drusens lesion's discrimination is one of the major step for this thesis. As these two lesion have similar appearance on the retinal surface.so it become difficult for the Ophthalmologist to differentiate these lesion and their respective disease. There is some research work related to the discrimination of these two lesions i.e. drusen and exudate. The proposed method was evaluated on STARE and AFIO databases and it shows significant results and good performance. Table 5,3 shows the result of proposed methodology and previous research.

Table 5.3 Performance Evaluation of Proposed System as Compared to Other Methods for Lesion Discrimination

Method	Databases	Accuracy	Sensitivity/Specificity
Niemeijer et al. [60]	Local	0.90	0.98/0.87
Van Grinsven [61]	MESSIDOR,STARE and EUGENDA	0.90	-
Proposed Method	STARE	90%	0.91/0.88
Proposed Method	AFIO	94%	0.93/0.96

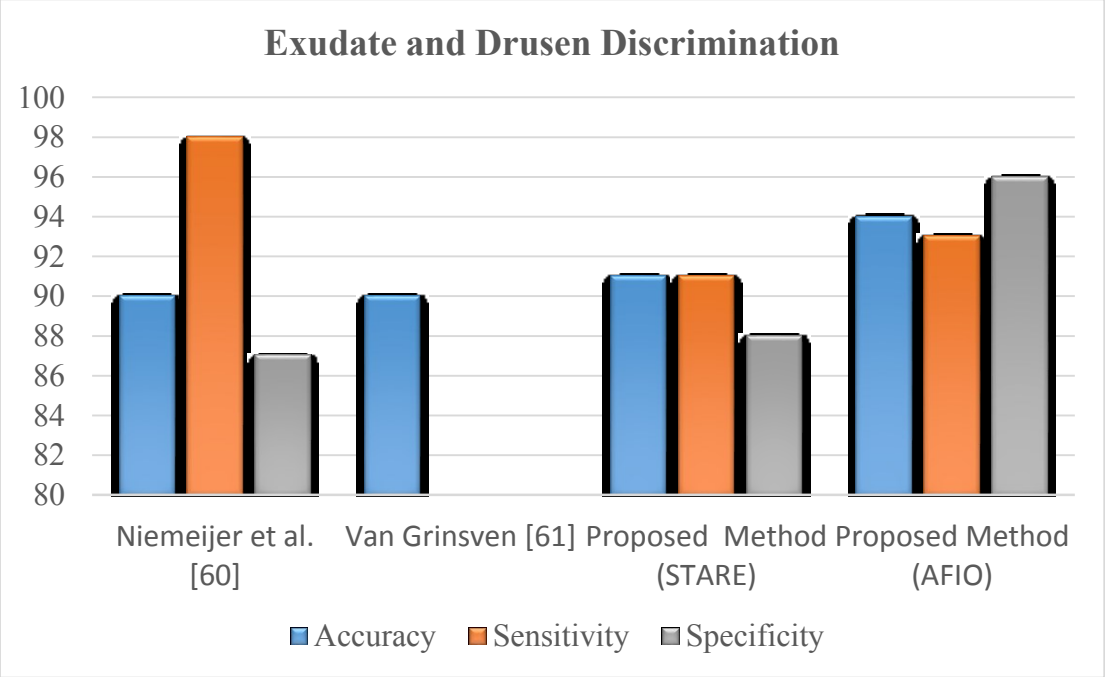


Figure 5.8 Graphical Representation of Exudate and Drusen Discrimination Results

Chapter 6

6 Conclusions and Future Work

6.1 Conclusions

Medical image analysis provides a new research area for diagnosing and grading the disease. Different automatic systems were developed in this research area for characterization and detection of different lesion in different types of medical images. Effective image analysis is essential to achieve high performance.

Age related macular degeneration is the ocular disease that can cause total vision loss at advance stage. Early diagnosis and treatment of the disease is important to avoid blindness. In this research an automatic system fo screening AMD though differentiating its lesion from exudates a symptom of Diabetic retinopathy. The proposed methodology detects Drusen and exudates on retinal surface fist removes false positive pixels from these deselected lesions and then differentiate among these lessons types. A novel method for lesion detection using feature set is proposed here. Feature set for the first step is composed of color and filter based features while for the second stage it consists of statistical based features. Bight lesions were detected through KNN classifier and they are differentiated among drusens and exudates by using SVM classifier.

The proposed system is evaluated on publically available dataset STARE, Locaaly collected database of AFIO images. Statistical measures like accuracy, sensitivity and specificity for the performance are also calculated for the proposed methodology.

The system achieved average accuracies of 93% and 92% for bright lesion detection and drusens and exudates differentiation respectively. The performance of the system is improved as compared to previously published methods due to the emphasis on every stage of system for example the removal of OD pixels to reduce the number of false regions, accurate blood vessel extraction prior to Hemorrhage detection, use of sound feature sets with the help of good descriptors and finally two classifiers at different stages of proposed system. The results demonstrated that the proposed system can be used in automated medical system for diagnosing age related macular degeneration.

6.1.1 Contribution

The main contributions of the research are

1. It proposed a complete system for diagnosing Age Related Macular degeneration
2. The proposed system detect all bright region in Fundus image
3. The proposed system differentiates drusens and exudates from the bright lesion
4. The system shows promising results in detecting and differentiating lesion.
5. Different classifier for different stages of the proposed system.

6.2 Future Work

This research can be extended by using images of optical coherence tomography (OCT) for diagnosing and differentiating lesion of AMD from other disease. The lesion can be detected by measuring thickness of retina.

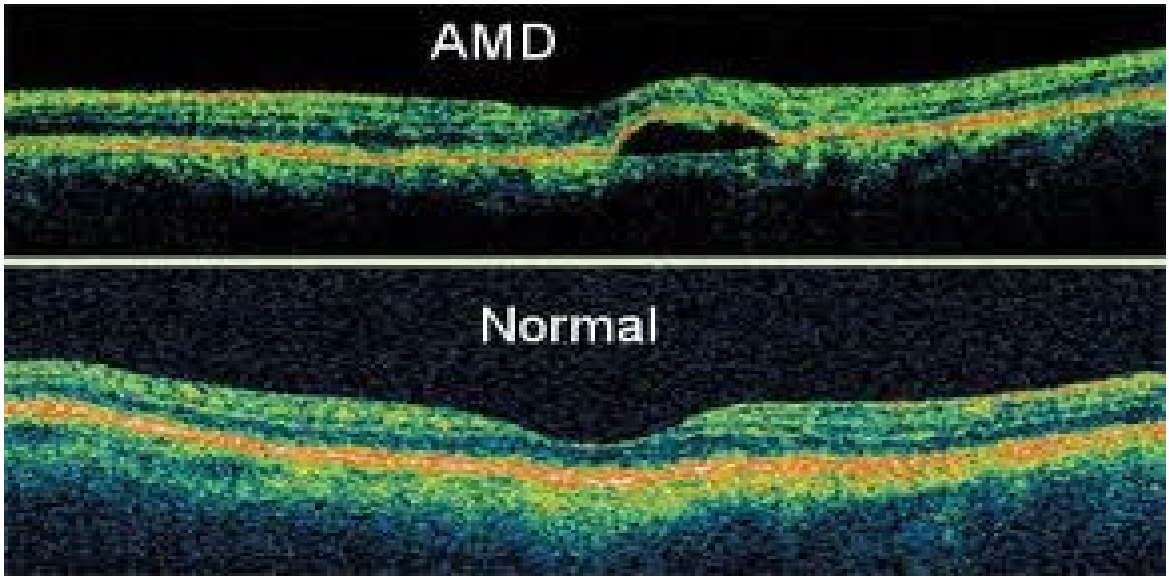


Figure 6.1 OCT images of AMD and Normal Retina [65]

The proposed method can be further proposed for the OCT images to differentiate drusens and exudates and for the detection of bright lesion. Quality assessment of retinal image can also be done for the purpose of preprocessing which is yet another research area

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