A Project Report on

# Automated Detection of Diabetic Retinopathy

Submitted in partial fulfilment of award of

BACHELOR OF TECHNOLOGY

Degree

in

COMPUTER SCIENCE ENGINEERING


By

MANSI BHATNAGAR (1508210070)

MOHD. ABAAN KHAN (1508210079)

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(2015-2019)


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Moradabad Institute of Technology

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# CERTIFICATE

Certified that the Project Report entitled **"Automated Detection of Diabetic Retinopathy"** submitted by Shanvi Sharma (1508210126), Muskan Johri (1508210086), Mansi Bhatnagar (1508210070), Mohd. Abaan Khan (1508210079) is their own work and has been carried out under my supervision. It is recommended that the candidates may now be evaluated for their project work by the University.

15/05/19

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# ABSTRACT

Diabetic Retinopathy is one of the leading causes of blindness and eye disease in working age population of developed world. This project is a attempt towards finding a automated way to detect this disease in its early phase. In this project I am using supervised learning methods to classify a given set of images into 5 classes. For this task I am employing various image processing techniques and filters to enhance many important features and then using neural for classification.

Retina is the outer lining of human eye where the image formation takes place. Any threat to retina causes severe eye defects and may lead to complete blindness. Strict control of blood glucose and blood pressure is critical for reduction of the incidence and progression of diabetic retinopathy (DR). Follow-up of patients with diabetes mellitus is protocol based and not based solely on the presence of symptoms. Staging of the level of DR (mild, moderate, or severe non proliferative DR vs. proliferative DR, PDR) drives the follow-up interval. The most common cause of visual loss in diabetic patients is diabetic macular

edema (DME). The results of multicenter, randomized studies suggest that the best visual results for DME currently are achieved with intra vitreal ranibizumab injections ± focal laser photocoagulation. Results using bevacizumab seem quite comparable to those with ranibizumab. In addition to treating DME, this approach also seems to reduce the likelihood of progression of DR. Selected patients also may benefit from intravitreal steroid treatment + focal laser therapy, but there is a relatively higher rate of glaucoma and cataract formation. Panretinal photocoagulation is currently the most effective treatment for high-risk PDR. Panretinal photocoagulation also should be considered for patients with severe non proliferative DR and early PDR, particularly if follow-up cannot be assured and/or if the patient has type 2 diabetes mellitus. Pars plana vitrectomy is used to manage severe complications of DR such as non clearing vitreous haemorrhage, severe fibro vascular proliferation, and retinal detachment. Adjunctive anti-vascular endothelial growth factor agents might enhance those results in selected subsets of patients. To measure the severity of a disease we need to determine different retinal tissue damages. These damages must be quantified to make useful predictions. Diabetic retinopathy is one of the common complications of diabetes. Unfortunately, in many cases the patient is not aware of any symptoms until it is too late for effective treatment. Through analysis of evoked potential response of the retina, the optical nerve, and the

optical brain centre, a way will be paved for early diagnosis of diabetic retinopathy and prognosis during the treatment process. In this paper, we present an artificial-neural-network-based method to classify diabetic retinopathy subjects according to changes in visual evoked potential spectral components and an anatomically realistic computer model of the human eye under normal and retinopathy conditions in a virtual environment using 3D Max Studio and Windows Movie Maker. Here we attempt to quantify retinal tissue damage through various image processing techniques. To verify our estimate we applied machine learning algorithms to create a classifier for detection of diabetic retinopathy and macular edema disease. Diabetic retinopathy & Macular Edema are diseases prone to diabetic people.

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Finally, we would also like to thank **Our Institute** for providing us with the facilities and the necessary resources to complete our work

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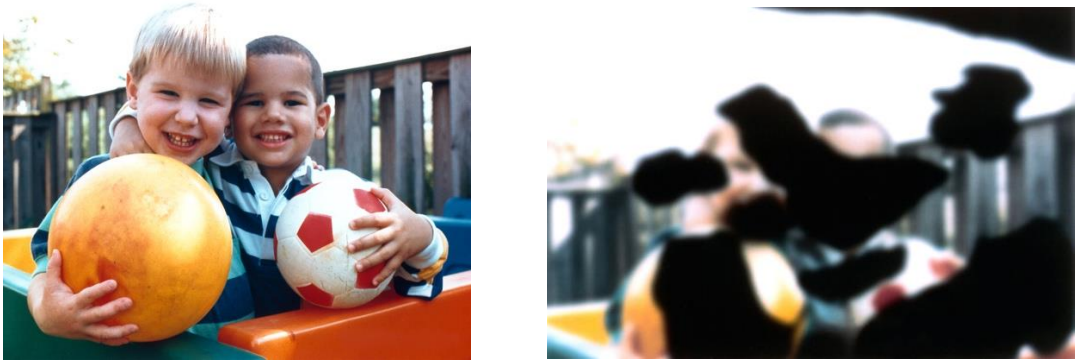
# CHAPTER 1

# INTRODUCTION

Diabetic retinopathy is a diabetes complication that affects eyes. It's caused by damage to the blood vessels of the light-sensitive tissue at the back of the eye (retina).Diabetic Retinopathy is a disease which is caused due to long term diabetes. It is a ocular manifestation of diabetes and around 80 percent of population having diabetes for more than 10 or more years has some stage of the disease. Also the longer a person is in this disease there higher are the chances of of having DR in his visual system. Researches shows that it contributes around 5% of total cases of blindness. By seeing below image one can see difference between image produced by normal eye and DR eye.



(a) Normal Eye (b) DR affected eye

**Figure 1.1: Comparison of vision**

At first, diabetic retinopathy may cause no symptoms or only mild vision problems. Eventually, it can cause blindness.

The condition can develop in anyone who has type 1 or type 2 diabetes. The longer you have diabetes and the less controlled your blood sugar is, the more likely you are to develop this eye complication.

There are various factors affecting the disease like age of diabetes, poor control, pregnancy but Researches shows that progression to vision impairment can be slowed or averted if DR is detected in early stage of the disease. One can see large no. of population suffering from the disease but still testing is done manually by trained professionals in real life which is quite time taking and lengthy process and usually due to miscommunication and delayed results eventually leads to delayed treatment and ignorance[1].

So aim of the project is to provide a a automated, suitable and sophisticated approach using image processing and pattern recognition so that DR can be detected at early levels easily and damage to retina can be minimized.

To study retina a retinal examination is done. The images of retina are taken through either fundus photography or Optical Coherence Tomography (OCT). OCT is a recent advancement in medical imaging. OCT data is 3-D profile consisting of different layers of retina. There are works on OCT data which focuses on determining the change in thickness of different retinal layers. Fundus photography involves capturing a photograph of the back of the eye. Specialized fundus cameras that consist of a microscope attached to a flash enabled camera are used in fundus photography. Fundus images are then analysed by ophthalmologists who look for certain patterns and defects in the image to predict diseases.

There are many problems in this system. World is short of highly qualified ophthalmologists. Due to this people have to wait for long before starting medications. This sometimes worsens the condition. Another crucial disadvantage is lack of agreement between different doctors on a single profile of fundus. We have started with fundus images to analyze retina.

Our project aims to analyze these defects through sophisticated image processing techniques. Based on known patterns and defects we extract features from fundus image. These features are taken and put into a classifier. The classifier comes out with a decision based on its learning. Diabetic Retinopathy is an active research area.

A lot of research has been done in last few years. Computer scientists and medical researchers have developed many algorithms for automatic detection of eye diseases, though accuracy has never been very great. Researchers have been trying new features and new algorithms to improve further. Joshi, Karule have used morphological operations for image segmentation. Hussain et al. have local variation operators and split and merge algorithm to detect fine exudates. Shraddha et al[3] detected exudates by calculating differential morphological profile (DMP).

Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.

This approach has very good specificity and PPV values as 99.99% and 98.23% respectively. In this report we have put our work in three different sections. In next section we have described the feature extraction procedures for blood vessels, micro aneurysms, exudates and haemorrhages. In the last section the data generated from these features has been visualised. Finally we have put the results and concluded our work[5].

## 1.1 CLASSIFICATION AND STAGES OF DIABETIC RETINOPATHY

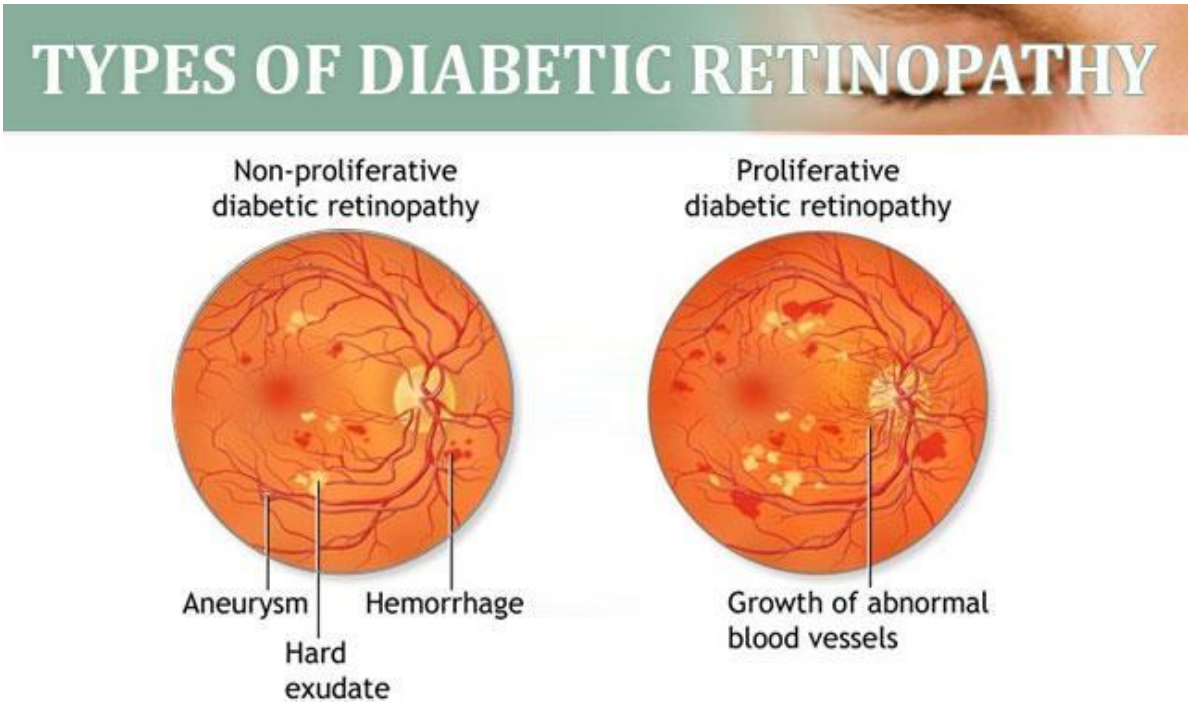



**Figure 1.2: Types of Retinopathy**

1. With NPDR, tiny blood vessels leak, making the retina swell.

2. In NPDR, your vision will be blurry,

3. PDR is the more advanced stage of diabetic eye disease.

4. PDR happens when the retina starts growing new blood vessels.

5. It might block all vision.

### 1.1.1 STAGES OF DIABETIC RETINOPATHY

**STAGE 1: NPDR (non-proliferative diabetic retinopathy)**

This is the early stage of diabetic eye disease. Many people with diabetes have it.
With NPDR, tiny blood vessels leak, making the retina swell. When the macula swells, it is called MACULAR EDEMA. This is the most common reason why people with diabetes lose their vision.

Also with NPDR, blood vessels in the retina can close off. This is called macular ischemia. When that happens, blood cannot reach the macula. Sometimes tiny particles called exudates can form in the retina. These can affect your vision too.If you have NPDR, your vision will be blurry.

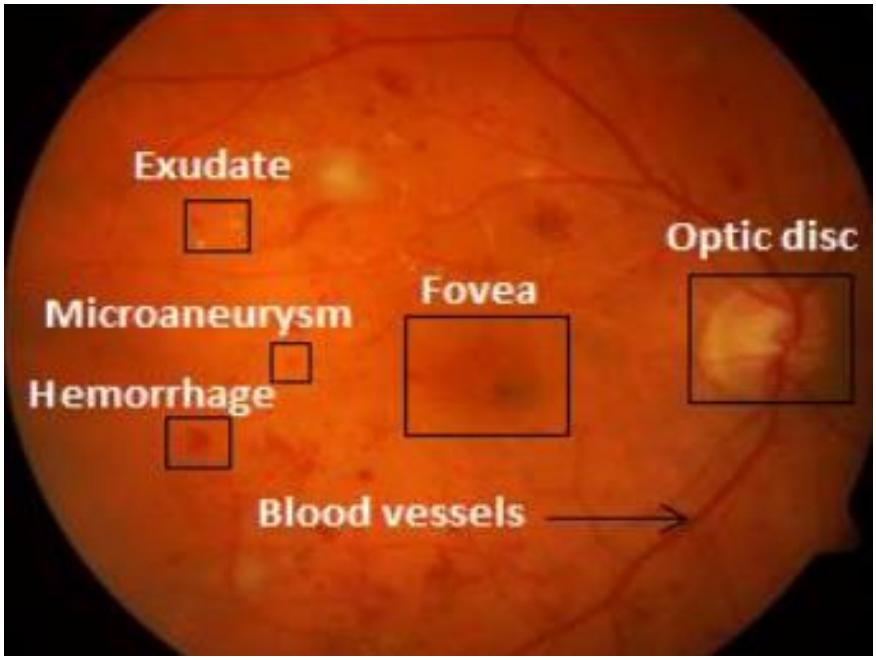



**Figure 1.3: NPDR Signs**

**STAGE 2: PDR (Proliferative diabetic retinopathy)**

Proliferative diabetic retinopathy is an eye disease that affects diabetics. It occasionally also affects individuals with pre-diabetic metabolic abnormalities (e.g. metabolic syndrome). The condition is characterised by the growth of tiny abnormal blood vessels (a process called neovascularisation) in the eye, and fibrous growth in the retina (the light-sensing area of the eye) and surrounding vitreous fluid (a layer of jelly-like substance that protects the retina and separates it from the lens).Neovascularisation (abnormal blood vessel growth) in diabetic retinopathy occurs in response to retinal ischaemia (lack of blood flow to the retina). New vessels may grow on the optic disc (where the optic nerves enter the eye) or elsewhere in the eye. Because the blood vessels are abnormal, they may bleed into the retina or vitreous fluid, causing spots of blood in the eye that block vision. Proliferative retinopathy is a sight-threatening condition. The abnormal blood vessel growth that characterises the disease also creates a risk of macular oedema. Macular oedema occurs if fluid from the vessels leaks and disturbs vision in the macula (the section of the eye that regulates clear, sharp vision). It is the leading cause of blindness in working-age people.

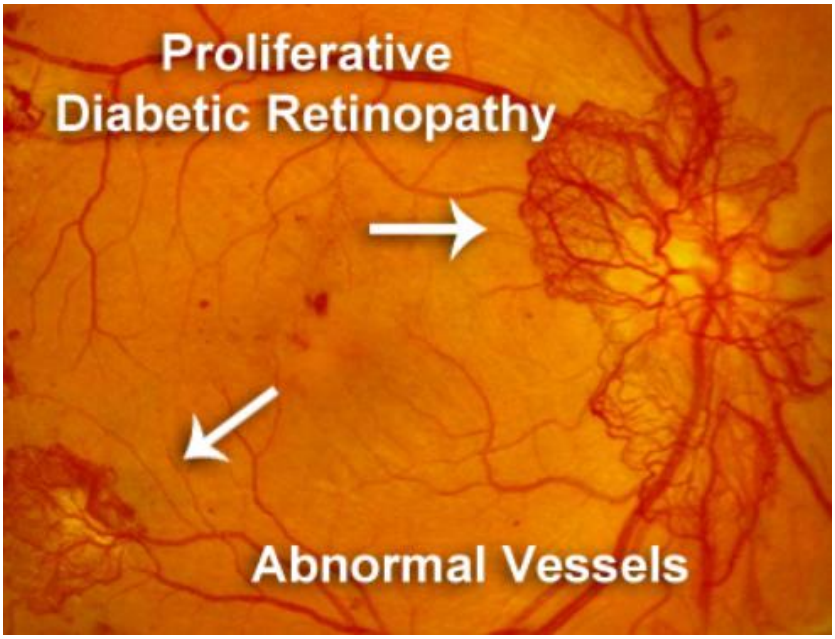



**Figure 1.4: PDR Signs**

## 1.2 RADON TRANSFORMATION

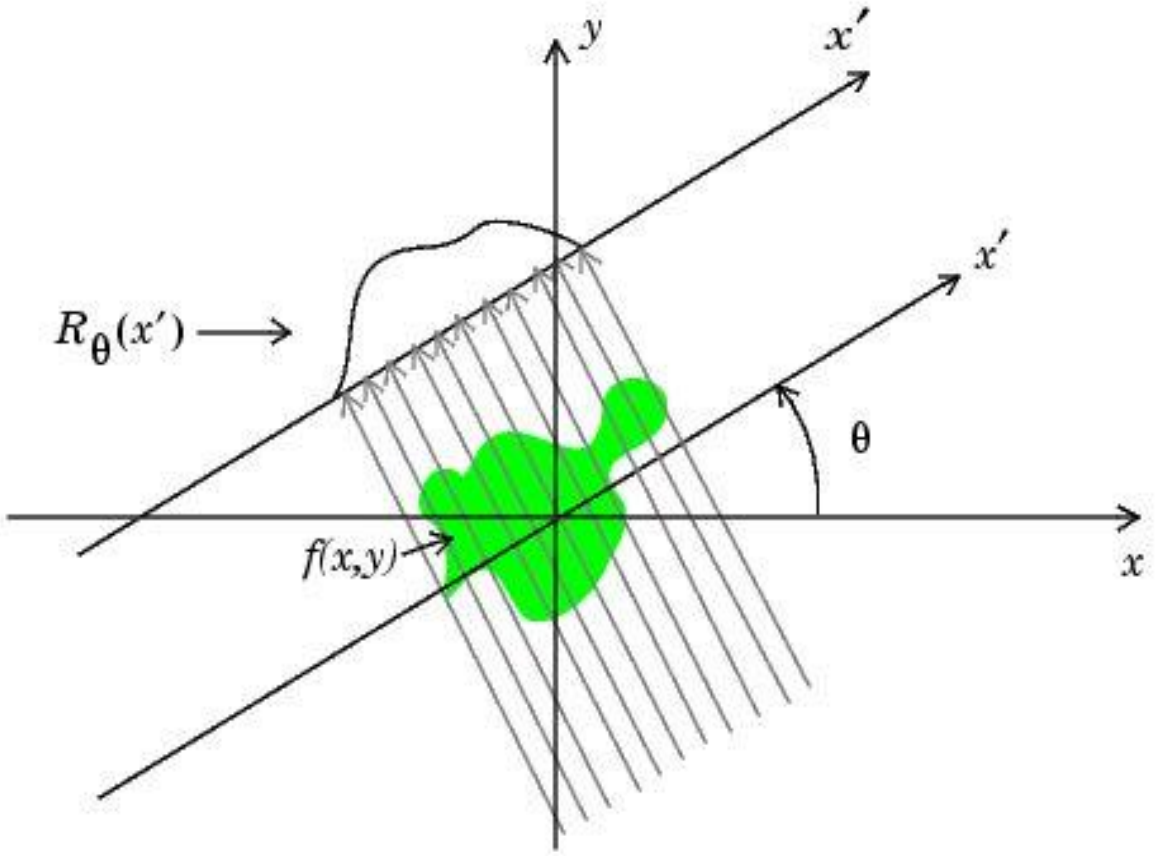



**Figure 1.5: Radon transform for a point R-theta(x')**

The Radon transform is an integral transform whose inverse is used to reconstruct images from medical CT scans. As given in the figure, we measure the projections as an integral of f along the z axis for every r . The orientation of the ( r , z ) coordinate axes relative to the x , y axes. The z axis is parallel to the direction of X-rays. For this analysis, we assume that the source and detectors employ parallel beam geometry. For a given $\theta \in [0, 180°)$, the X-rays are θ degrees counter clockwise from the y axis. The line integral along z is measured for every r at the given θ .

Since the image is only available to us as a function of x and y, we rotate the ( x , y ) coordinates to express them in terms of r and z. Also note that theoretically, projections are only required for $\theta \in [0, 180°)$. It does not matter which direction we integrate from along the z -axis.

## 1.3 OCT IMAGE ANALYSIS

OCT uses low-coherence interferometry to produce a two-dimensional image of optical scattering from internal tissue microstructures. OCT has longitudinal and lateral spatial resolutions of a few micrometres and can detect reflected signals as small as ~10 of the incident optical power.

Over the 15 years since the original description, optical coherence tomography (OCT) has become one of the key diagnostic technologies in the ophthalmic subspecialty areas of retinal diseases and glaucoma. The reason for the widespread adoption of this technology originates from at least two properties of the OCT results: on one hand, the results are accessible to the non-specialist where microscopic retinal abnormalities are grossly and easily noticeable; on the other hand, results are reproducible and exceedingly quantitative in the hands of the specialist.

OCT is based on imaging of reflected light. But unlike a simple camera image that only has transverse dimensions (left/right, up/down) it revolves depth. The depth resolution us of the order 0.01 mm or 0.4 thousandth of an inch. This provides cross-sectional views (tomography) of internal tissue structures similar to tissue sections under a microscope. Thus, OCT has been described as a method for non-invasive tissue ‘biopsy’. With this technique it is possible to perform non-invasive cross-sectional imaging of internal structures in biological tissues by measuring their optical reflections. OCT has been used to measure volume and total thickness of the retina along with structural changes of the

various cellular layers of the retina with the aid of segmentation algorithms. The role of OCT in the assessment and management of retinal diseases has become significant in understanding the vitreoretinal relationships and the internal architecture of the retina. OCT has also improved diagnosis and management of retinal diseases by reducing reliance on insensitive tests such as perimetry and subjective disc grading. Thickness differences characterizes regions with early pathological signs from normal regions and differences in optical properties and texture descriptors of normal and abnormal retinal tissue may also provide additional information of disease development in pathological eyes.

A potential improvement in the clinical application of OCT to eye diseases is the quantification of the anatomic changes along with the dysfunction of the cellular layers of the neurosensory retina.

Our preliminary results suggest that the fractal dimension of the intraretinal layers might provide useful information to differentiate MDR eyes, which are characterized by neurodegeneration at the early stages, from healthy eyes in addition to the structural information

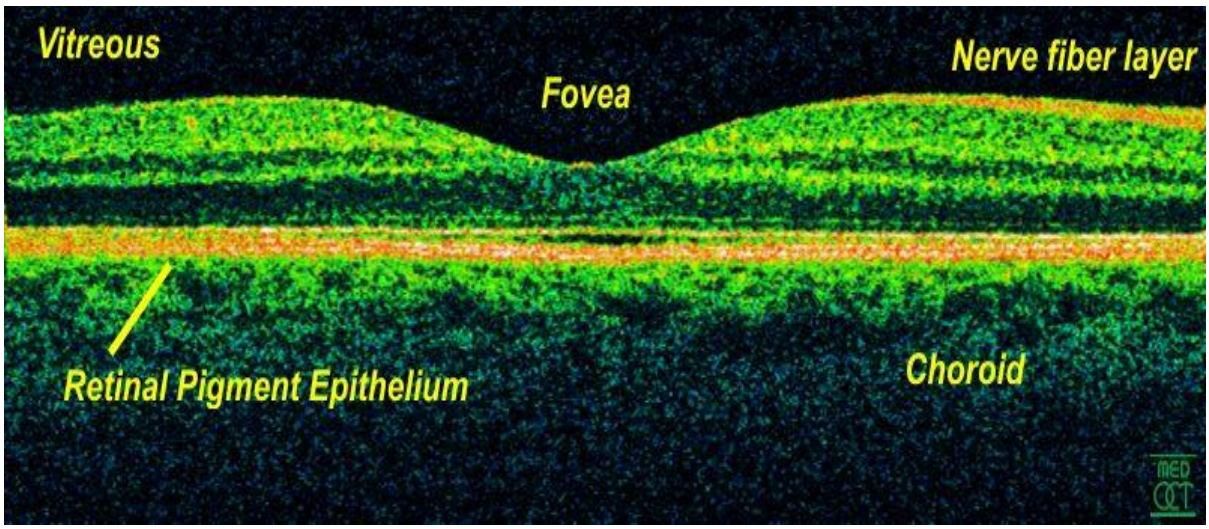



**Figure 1.6: An OCT cross-sectional image**

A potential improvement in the clinical application of OCT to eye diseases is the quantification of the anatomic changes along with the dysfunction of the cellular layers of the neurosensory retina. Our preliminary results suggest that the fractal dimension of the intraretinal layers might provide useful information to differentiate MDR eyes, which are characterized by neurodegeneration at the early stages, from healthy eyes. Fractal analysis provided a better sensitivity, offering a potential diagnostic predictor for detecting early neurodegeneration in the retina.

In this study, we evaluated the diagnostic power of a novel method based on the fractal analysis of OCT derived retinal tissue layer properties in discriminating normal healthy eyes from diabetic eyes with early neural loss.

Although texture measures of the retinal tissue are not standardized measures for detecting significant intraretinal changes, texture-based measures were obtained from OCT intensity images and used in the fractal dimension analysis. In addition, the fractal analysis' diagnostic outcome was compared with the standard approach that uses structural information extracted from OCT images. Specifically, we calculated fractal dimension and thickness using features measured locally for each intraretinal layer and evaluated their suitability to quantify retinal tissue damage.

A method based on the power spectrum was used to calculate the fractal dimension in OCT images . Since the average power spectrum of an image obeys a power law scaling, the fractal dimension was calculated from the power law detected in the graph of the power spectrum as a function of the frequency in the Fourier transform of the OCT image (gray scale). In this particular case, when the graph is plotted in a log-log scale the curve is approximately similar to a straight line and the dimension is provided by the slope of the line. The fast Fourier transform (FFT) was applied to the OCT reflectivity profiles to obtain the power spectrum.

$$FD = (5-B)/2 \qquad (1.1)$$

The mean value of the fractal dimension was calculated by averaging the fractal dimension measurements across all A-scans in each macular region of each intraretinal layer.

A potential improvement in the clinical application of OCT to eye diseases is the quantification of the anatomic changes along with the dysfunction of the cellular layers of the neurosensory retina. Our preliminary results suggest that the fractal dimension of the intraretinal layers might provide useful information to differentiate MDR eyes, which are characterized by neurodegeneration at the early stages, from healthy eyes in addition to the structural information.

## 1.4 FUNDUS PHOTOGRAPHY

Fundus photography involves capturing a photograph of the back of the eye i.e. fundus. Specialized fundus cameras that consist of an intricate microscope attached to a flash enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic discand macula. Fundus photography can be performed with colored filters, or with specialized dyes including fluoresceinand indocyanine green.

The models and technology of fundus photography has advanced and evolved rapidly over the last century.[2] Since the equipments are sophisticated and challenging to manufacture to clinical standards, only a few manufacturers/brands are available in the market: Welch Allyn, Digisight, Volk, Topcon, Zeiss, Canon, Nidek, Kowa, CSO, CenterVue, and Ezer are some example of fundus camera manufacturers.

The concept of fundus photography was first introduced in the mid 19th century, after the introduction of photography in 1839. The goal of photographing the human ocular fundus

was slowly but surely becoming more achievable. In 1851, Hermann von Helmholtz, introduced the Ophthalmoscope and James Clerk Maxwell presented a colour photography method in 1861.

In the early 1860s, Henry Noyes and Abner Mulholland Rosebrugh both assembled fundus cameras and tried fundus photography on animals. Although the news was encouraging and showed promise, the vision of capturing a satisfactory photo of a human ocular fundus was still far from reach. Early fundus photos were limited by insufficient light, long exposures, eye movement, and prominent corneal reflexes that reduced the clarity detail. It would be several decades before these problems could be rectified.

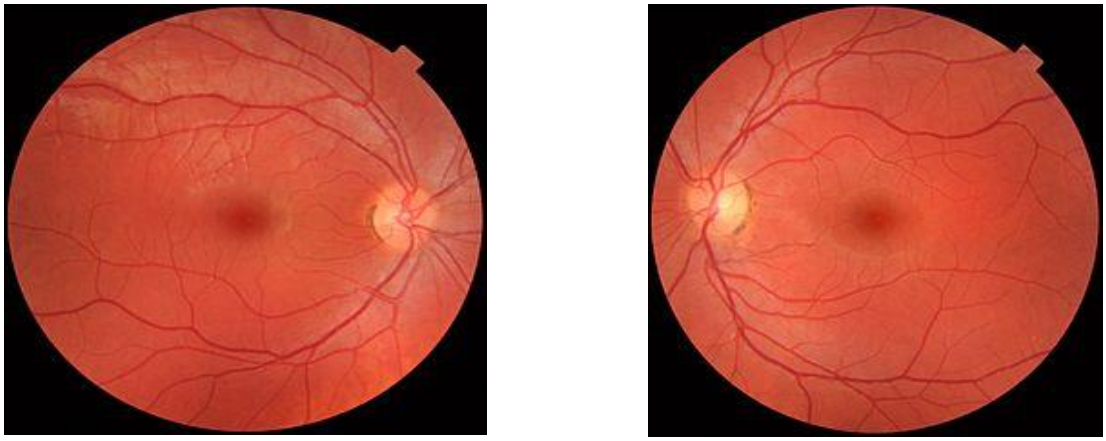
There has been some controversy regarding the first ever successful human fundus photo. Most accounts state William Thomas Jackman and J.D. Webster since they published their technique along with a reproduction of a fundus image in two photography periodicals in 1886.

Three other names played a prominent role in early fundus photography. According to some historical accounts, Elmer Starr and Lucien Howe may have been first to photograph the human retina. Lucien Howe is a well-known name in Ophthalmology, and together with his assistant Elmer Starr, they collaborated on the fundus photography project in 1886-88. Howe described their results as the first "recognizable" fundus photograph, apparently a nod to Jackman & Webster being the first to "publish" a fundus photograph. Based on the written accounts, Howe and Starr's image was more "recognizable" as a fundus.

For about 75 years a concerted effort was made to clearly photograph the fundus. Hundreds of specialists worked to overcome the problem, which was finally achieved in the early 20th century by Friedrich Dimmer, who published his photographs in 1921. Dimmer's fundus camera, developed about 1904, was a complicated and sophisticated

research tool and it was not until 1926 that Stockholm's Johan Nordenson and the Zeiss Camera Company were able to market a commercial device for use by practitioners, which was the first modern Fundus camera. Since then, the features of fundus cameras have improved drastically to include non-mydriatic, imaging, electronic illumination control, automated eye alignment, and high-resolution digital image capture. These improvements have helped make modern fundus photography a standard ophthalmic practice for documenting retinal disease.

Following the development of fundus photography, David Alvis, and Harold Novotny, performed the first fluorescein angiography (FFA) in 1959, using the Zeiss fundus camera with electronic flash. This development was huge feat in the world of Ophthalmology. Several countries began large-scale teleophthalmology programs using digital fundus photography around 2008.



(a) Right eye (b) Left eye

**Figure 1.7: Fundus images of right & left eye**

Normal fundus photographs of the right eye (left image) and left eye (right image), seen from front so that left in each image is to the person's right. Each fundus has no sign of disease or pathology. The gaze is into the camera, so in each picture the macula is in the

center of the image, and the optic disk is located towards the nose. Both optic disks have some pigmentation at the perimeter of the lateral side, which is considered normal (non-pathological). The orange appearance of the normal fundus is due to complexes of vitamin A as 11-cis-retinaldehyde with opsin proteins in the retina (i.e. rhodopsin). The left image (right eye) shows lighter areas close to larger vessels, which is regarded as a normal finding in younger people.

## 1.5 FRACTAL DIMENSIONS

Fractals are self-similar structures at every scale. As mathematical equations, fractals are usually nowhere differentiable. The mathematical roots of the idea of fractals have been traced throughout the years as a formal path of published works, starting in the 17th century with notions of recursion, then moving through increasingly rigorous mathematical treatment of the concept to the study of continuous but not differentiable functions in the 19th century by the seminal work of Bernard Bolzano, Bernhard Riemann, and Karl Weierstrass, and on to the coining of the word fractal in the 20th century with a subsequent burgeoning of interest in fractals and computer-based modelling in the 20th century. The term "fractal" was first used by mathematician Benoît Mandelbrot in 1975. Mandelbrot based it on the Latin frāctus meaning "broken" or "fractured", and used it to extend the concept of theoretical fractional dimensions to geometric patterns in nature.

We consider N=r^D, take the log of both sides, and get log(N) = D log(r). If we solve for D. D = log(N)/log(r). This generalized treatment of dimension is named after the German mathematician, Felix Hausdorff. It has proved useful for describing natural objects and for evaluating trajectories of dynamic systems.

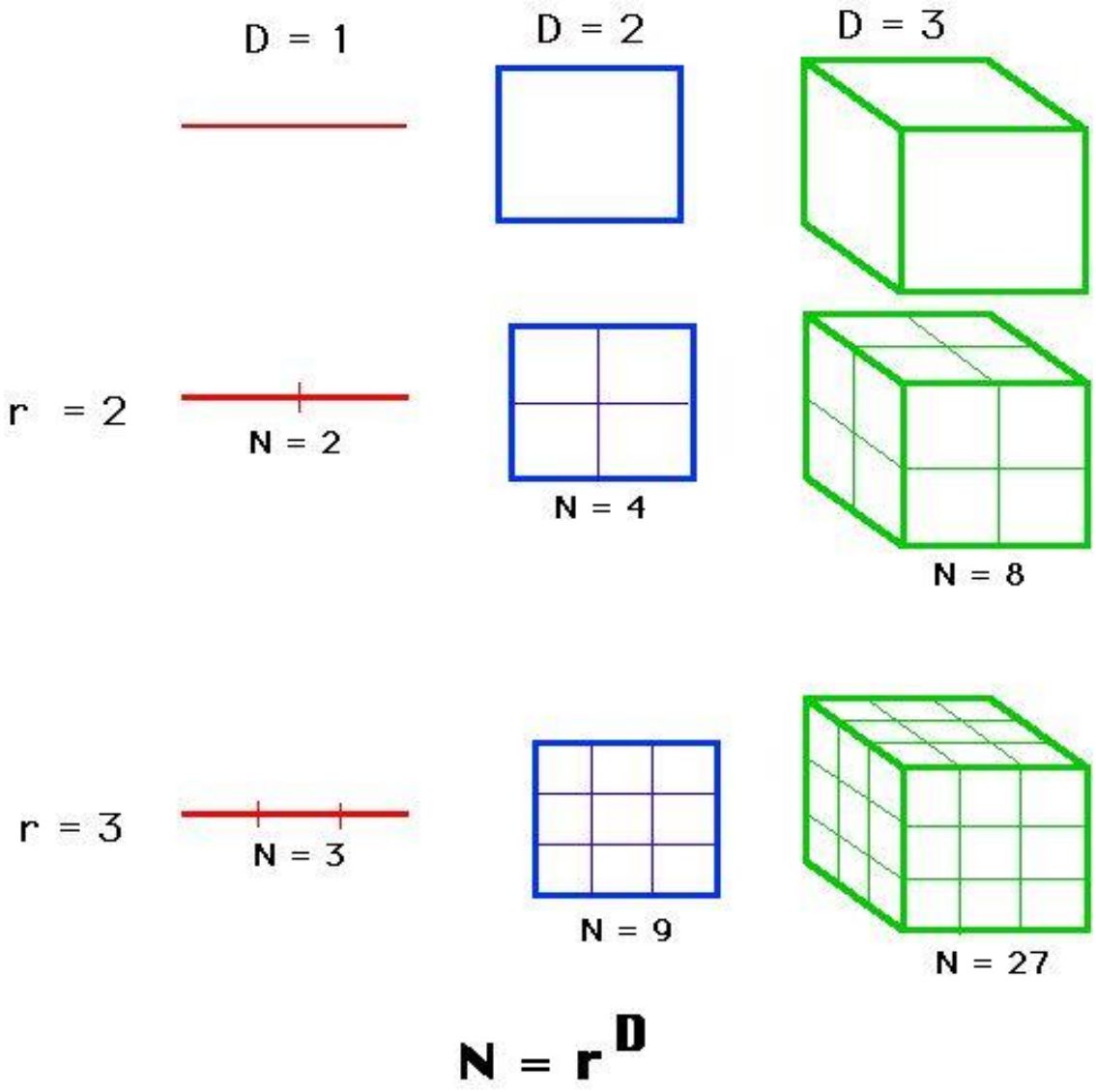



**Figure 1.8: Fractal Dimension for n=1,2 and 3**

Consider a square, if we subdivide it into smaller squares each with 1/2 the side length then it takes 4 of these smaller pieces to form the original square. If we subdivide the square into smaller squares each with 1/4 of the side length then it takes 16 of them to form the original square. As above we can write an expression for the number of pieces we need of size "s" to cover the original square, it is $N(s) = (1/s)^2$ . Repeat for a cube....$N(s) = (1/s)^3$. The exponents 1, 2, and 3 in the above examples are fundamental to our concept of the

dimension involved. This can be generalised to $N(s) = (1/s)^D$ where D is the dimension, an integer as above but it need not be. If we take logarithms of both sides we have $\log(N(s)) = D \log(1/s)$, in order words we can estimate the dimension by plotting $\log(N(s))$ against $\log(1/s)$ the slope of which is the dimension, if it isn't an integer then it's a fractional (fractal) dimension.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1. INTRODUCTION

Diabetic retinopathy is damage to the retina caused by complications of diabetes mellitus, which can eventually lead to blindness. It is an ocular manifestation of systemic disease which affects up to 80% of all patients who have had diabetes for 10 years or more. The detection of haemorrhages is one of the important factors in the early diagnosis of diabetic retinopathy (DR). The existence of haemorrhages is generally used to diagnose DR or hypertensive retinopathy by using the classification scheme. Diabetic retinopathy (DR) remains the commonest cause of blindness in the working age population of the developed world. Effective treatment is available if the condition is detected early, before visual symptoms occur. The need for a comprehensive DR screening programme has long been recognized and it is now feasible. It is a silent disease and may only be recognized by the patient when the changes in the retina have progressed to a level, that treatment is complicated and nearly impossible.

This disease can be prevented from developing into blindness if it is treated at an early stage. However, it has been recorded that approximately 3,000 people have lost their vision following the onset of DR. Fundus photographs obtained by the fundus camera are used to

diagnose DR. Digital imaging is widely used for diabetic retinopathy screening. The storage and transmission of digital images can be facilitated by image compression.

The ease and flexibility of digital photography has led to the widespread use of this technology for ophthalmic imaging, particularly for retinal screening. The retina is a forward extension of the brain and its blood vessels. Images of the retina tell us about retinal, ophthalmic, and even systemic diseases. The ophthalmologist uses images to aid in diagnoses, to make measurements, to look for change in lesions or severity of disease, and as a medical record.

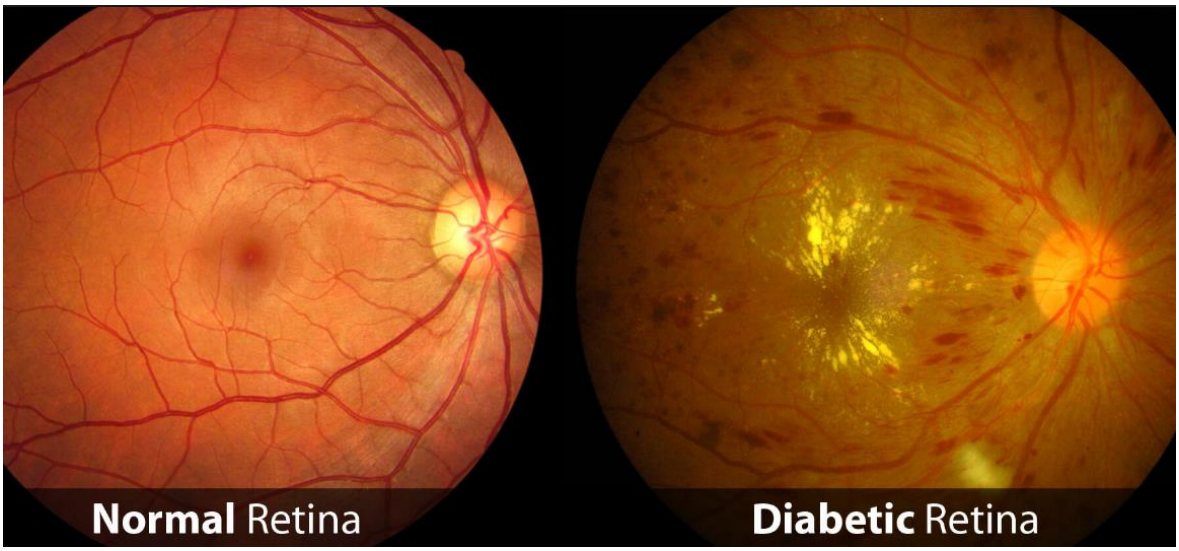



**Figure2.1: Comparison between normal eye and defective eye**

Although the accessibility of retinal fundus photographs suitable for screening these diseases, a large number of examinations will result in an increased burden for ophthalmologists. Computerized analysis of retinal fundus images can potentially reduce ophthalmologists' workload and improve diagnostic efficiency. The structure of retinal vessels is a prominent feature that reveals further information on the state of diseases that are reflected in the form of measurable abnormalities in diameter, colour, and tortuosity.

Thus, reliable methods of vessel detection that preserve various vessel measurements are needed. Pathologies in the ocular fundus are a major cause of blindness. These pathologies include diabetic retinopathy and age-related macular degeneration (ARMD). In both of these conditions, the distribution of blood and/or macular pigments is altered from the normal. Ocular fundus image can provide information on pathological changes caused by some eye diseases and early signs of certain systemic diseases, such as diabetes and hypertension. Pathological changes of the retinal vasculature are a feature of many diseases. For example, diabetic retinopathy is often characterized by the presence of new blood vessels, venous beading, micro aneurysms, and intra- retinal macular abnormalities. Several vascular diseases, such as diabetic retinopathy, have manifestations that require analysis of the vessels network. In other cases, e.g. pathologies like Retinal micro aneurysms and haemorrhages, the performance of automatic detection methods may be improved if regions containing vessels can be excluded from the analysis . A possibility of providing some automated assistance in this screening process lies in accurate computer measurement of vessel width and tortuosity near the posterior pole (back) of the retina.

Optic Disc is considered one of the main features of a retinal fundus image where methods are described for its automatic detection. OD Detection is a key preprocessing component in many algorithms designed for the automatic extraction of retinal anatomical structures and lesions. The relatively constant distance between the OD and the fovea can be used to help estimate the location of the latter. The OD is considered the exit region of the blood vessels and the optic nerves from the retina, also characterized by a relatively pale view owing to the nerve tissue underlying it.

The main features of a fundus retinal image are defined as the optic disc, fovea and blood vessels. The optic disc is the entrance and exit region of blood vessels to the retina and its localization and segmentation is an important task in an automated retinal image analysis system. Indeed, the fovea corresponds to the region of retina with highest sensitivity.
OD segmentation is also relevant for automated diagnosis of other ophthalmic pathologies. One of them and may be the most relevant is Glaucoma. It is the second most common

cause of blindness worldwide. This disease is identified by means of recognition of the changes in shape, color or depth that it produces in the OD

.

The economic and social consequences of vision loss in people with the eye disease diabetic retinopathy (DR ) could be reduced considerably if an inexpensive broad-based screening program existed for this disease. We have different types of diabetic retinopathy. It can be classified in different ways, but there are three main types:

- Non-proliferative retinopathy (NPDR)
- Proliferative retinopathy (PDR).

It is primarily a disease of retinal blood vessels. It is the result of two major processes affecting the retinal blood vessels: vessel closure and abnormal vessel permeability.

The earliestvessel closures in diabetic retinopathy are usually the capillaries. These small vessels are critical to the health of the retina, since they are needed to deliver oxygen and nutrients to the area and to carry away carbon dioxide and other waste products. The source of this capillary closure is not completely understood. Theories as to why these vessels close off include: Clumping of blood cells or other blood elements.

- Abnormality or damage to the endothelium (the cells lining the inner wall of the capillary). Swelling of an abnormally permeable vessel wall.
- Compression of the capillary by surrounding retinal.
- Swelling.

Retinal blood vessels are different from vessels elsewhere in the body. Most blood vessels are fenestrated, meaning that they have tiny openings that allow fluid to pass through the vessel wall. The openings are small enough to prevent the egress of larger blood elements such as blood cells and large proteins), but large enough to allow water and small molecules such as ions to pass. Retinal blood vessels, on the other hand, have tight junctions between the cells of the blood vessel wall, so all fluid and molecules exiting the

vessel have to pass through the cells.. It is visible on examination as a thickening and slight graying of the retina, and is often associated with exudates (yellow clumps or spots within the retina). Exudates are the result of fats and proteins leaking out of the permeable vessels along with water. The water can be quickly reabsorbed into the vessels or into the tissue under the retina, but the fatty material is absorbed only very slowly. These fatty exudates are left behind like a "bathtub ring", often in a ring-like shape surrounding the leakage site.

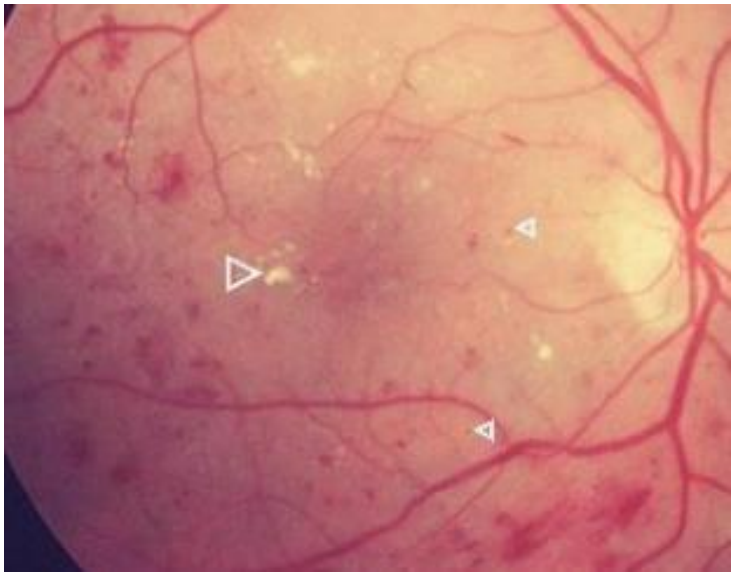


**Figure 2.2: Multiple micro aneurysms (small arrowheads) and haemorrhages.**

This photograph of a retina shows multiple micro aneurysms (small arrowheads) and haemorrhages scattered through the macular region. There is an area of diabetic maculopathy to the left of centre, with some associated yellow exudates (large arrowhead). Swelling in the retina is fairly common in background diabetic retinopathy, but it is not always significant swelling. In other words, retinal edema does not always affect vision and does not always need to be treated.

Edema in the retina is considered "clinically significant" if it is close enough to the centre of the retina to pose a risk to vision. This was defined more precisely in the Early Treatment Diabetic Retinopathy Study (ETDRS), a large multi-centre study designed to evaluate the usefulness of laser treatment for diabetic maculopathy. Contextual segmentation refers to the process of partitioning a data into multiple regions. The goal of segmentation is to simplify and / or change the representation of data into something that is more meaningful and easier to analyze.

Data segmentation is typically used to locate data in a vector. Segmentation is done using contextual clustering and classification of the exudates is done using radial basis function (RBF) network. The performance classification of exudates by using RBF and CC is better than that of using only CC.

## 2.2 TARGETED DEFECTS

- **Blood Vessels**: Diabetic retinopathy can cause blood vessels in the retina to leak fluid or haemorrhage (bleed), distorting vision. In its most advanced stage, new abnormal blood vessels proliferate (increase in number) on the surface of the retina, which can lead to scarring and cell loss in the retina.

- **Exudates:** Hard exudates are largely made up of extracellular lipid which has leaked from abnormal retinal capillaries, hence there is often associated retinal oedema (which is not visible using direct ophthalmoscopy). The underlying problem is often apparent as the exudates will form a ring or ‘criminate’ pattern around the leaking vessels (which may be seen as a cluster of microaneurysms).Hard exudates are found principally in the macular region and as the lipids coalesce and extend into the central macula (fovea), vision can be severely compromised.

- **Microaneurysms:** Microaneurysms are, as the name suggests, small sacular outpouchings that involve capillaries of many vascular districts such as the heart, kidney and eye. Ophthalmologists know that although they occur in several pathologic conditions such as hypertension, venous occlusion and hemorheologic diseases, including methemoglobinemia and sickle-cell disease, they are the hallmark of diabetic retinopathy.

- **Haemorrhages**: Haemorrhages may be ‘dot’ or’ blot’ shaped (termed ‘dot/blot haemorrhages’) or flame shaped depending upon their depth within the retina. The capillary network in the posterior retina is found in two layers; a superficial one in the nerve fibre layer and a deeper on within the inner nuclear layer. Haemorrhage within the nerve fibre layer tends to be flame shaped, following the divergence of axons. In the inner layer, haemorrhage is aligned at right angles to the retinal surface and is consequently viewed end-on when using an ophthalmoscope; these haemorrhages appear dot or blot shaped.

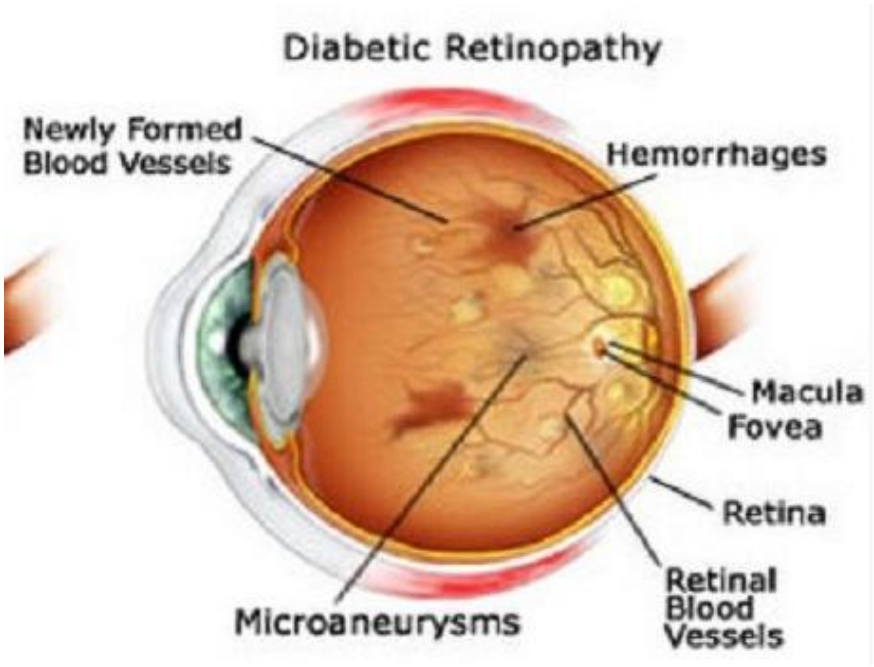



**Figure 2.3: Defects in Diabetic Retinopathy eye**

## 2.3 Machine Learning

Machine learning, a branch of artificial intelligence, concerns the construction and study of systems that can learn from data. Machine learning algorithms use computational methods to “learn” information directly from data without relying on a predetermined equation as a model. The algorithms adaptively improve their performance as the number of samples available for learning increases. Tom M. Mitchell provided a widely quoted and more formal definition: A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E. The core of machine learning deals with representation and generalization. Representing the data instances and functions evaluated on these instances are part of all machine learning systems. Generalization is the ability of a machine learning system to perform accurately on new, unseen data instances after having experienced a learning data instance. The training examples come from some generally unknown probability distribution and the learner has to build a general model about this space that enables it to produce sufficiently accurate predictions in new cases.

### 2.3.1 Algorithms

Since there are so many algorithms for machine learning, it is not possible to use all of them for analysis. For this research paper, we will be using five of them neural networks (NNET), random forest (RF), K-Nearest Neighbour (KNN) and support vector machine (SVM).

- **Neural Networks** : Within the field of machine learning n neural networks are a subset of algorithms built around a model of artificial neurons spread across three or more layers. There are plenty of other machine learning model which is notable for being adaptive in nature. Every node of neural network has their own sphere of knowledge about rules and functionalities to develop it-self through experiences learned from previous techniques that don’t rely on neural networks. Neural

networks are well-suited to identifying non-linear patterns, as in patterns where there isn't a direct, one-to-one relationship between the input and output. This is a learning training. Neural networks are characterize by containing adaptive weights along paths between neurons that can be tuned by a learning algorithm that learns from observed data in order to improve model. One must choose an appropriate cost function. The cost function is what is used to learn the optimal solution to the problem being solved. In a nutshell, it can adjust itself to the changing environment as it learns from initial training and subsequent runs provide more information about the world.

- **Random Forest**: Random forest algorithm can use both for classification and the regression kind of problems. It is supervised classification algorithm which creates the forest with a number of tress. In general, the more trees in the forest the more robust the forest looks like. It could be also said that the higher the number of trees in the forest gives the high accuracy results. There are many advantages of random forest algorithms. The classifier can handle the missing values. It can also model the random forest classifier for categorical values. The over fitting problem will never come when we use the random forest algorithm in any classification problem. Most importantly it can be used for feature engineering which means identifying the most important feature out of the available feature from the training dataset.

- **Logistic Regression:** Logistic regression is named for the function used at the core of the method, the logistic function.The logistic function, also called the sigmoid function was developed by statisticians to describe properties of population growth in ecology, rising quickly and maxing out at the carrying capacity of the environment. It's an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits.

$$1 / (1 + e^{-value}) \qquad (2.1)$$

Where e is the base of the natural logarithms (Euler's number or the EXP() function in your spreadsheet) and value is the actual numerical value that you want to transform. Below is a plot of the numbers between -5 and 5 transformed into the range 0 and 1 using the logistic function.

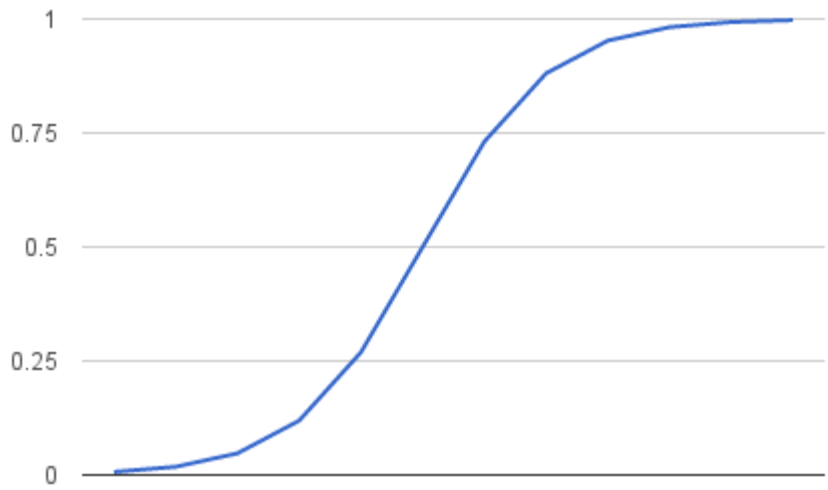



**Figure 2.4: Logistic Function**

Logistic regression uses an equation as the representation, very much like linear regression. Input values (x) are combined linearly using weights or coefficient values (referred to as the Greek capital letter Beta) to predict an output value (y). A key difference from linear regression is that the output value being modeled is a binary values (0 or 1) rather than a numeric value. Below is an example logistic regression equation:

$$y = e^{(b0 + b1*x)} / (1 + e^{(b0 + b1*x)}) \quad (2.2)$$

Where y is the predicted output, b0 is the bias or intercept term and b1 is the coefficient for the single input value (x). Each column in your input data has an associated b coefficient (a constant real value) that must be learned from your training data.The actual representation

of the model that you would store in memory or in a file are the coefficients in the equation (the beta value or b's).

- **Support Vector Machine**: The Support Vector Machine (SVM) is a state-of-the-art classification method introduced in 1992 by Boser, Guyon, and Vapnik. A more formal definition is that a support vector machine constructs a hyper plane or set of hyper planes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier . SVMs belong to the general category of kernel methods. A kernel method is an algorithm that depends on the data only through dot-products. When this is the case, the dot product can be replaced by a kernel function which computes a dot product in some possibly high dimensional feature space. This has two advantages: First, the ability to generate non-linear decision boundaries using methods designed for linear classifiers. Second, the use of kernel functions allows the user to apply a classier to data that have no obvious fixed-dimensional vector space representation.

- **K-Nearest Neighbours**: K-nearest Neighbours is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure. KNN has been used in statistical estimation and pattern recognition.

  KNN makes prediction for a new instance (x) by searching through the entire training set for the k most similar instances and summarizing the output variable for those k instances. For regression this might be the mean output variable, in classification this might be the mode class determine which of the k instances in the training dataset are most similar to new input many distance measure is used like Euclidean distance, Manhattan distance, Minkowski distance.

$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$ EUCLIDEANN

$$\sum_{i=1}^{k}|x_i - y_i|$$ MANHATTAN

$$\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q}$$ MINKOWSKI

## 2.4 IMAGE PROCESSING MECHANISM

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually ImageProcessing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too.

It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually ImageProcessing system includes treating images as two dimensional signals while applying already set signal processing methods to them.

Image processing basically includes the following three steps.

1. Importing the image with optical scanner or by digital photography.

2. Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.

3. Output is the last stage in which result can be altered image or report that is based on image analysis.

## 2.5 IMAGE PROCESSING TECHNIQUES

### 2.5.1 MORPHOLOGICAL IMAGE PROCESSING

It is a collection of non-linear operations related to the shape or morphology of features in an image. Morphological operations rely only on the relative ordering of pixel values, not on their numerical values, and therefore are especially suited to the processing of binary images. Morphological operations can also be applied to greyscale images such that their light transfer functions are unknown and therefore their absolute pixel values are of no or minor interest.

Morphological techniques probe an image with a small shape or template called a structuringelement. The structuring element is positioned at all possible locations in the image and it is compared with the corresponding neighbourhood of pixels. Some operations test whether the element "fits" within the neighbourhood, while others test whether it "hits" or intersects the neighbourhood:

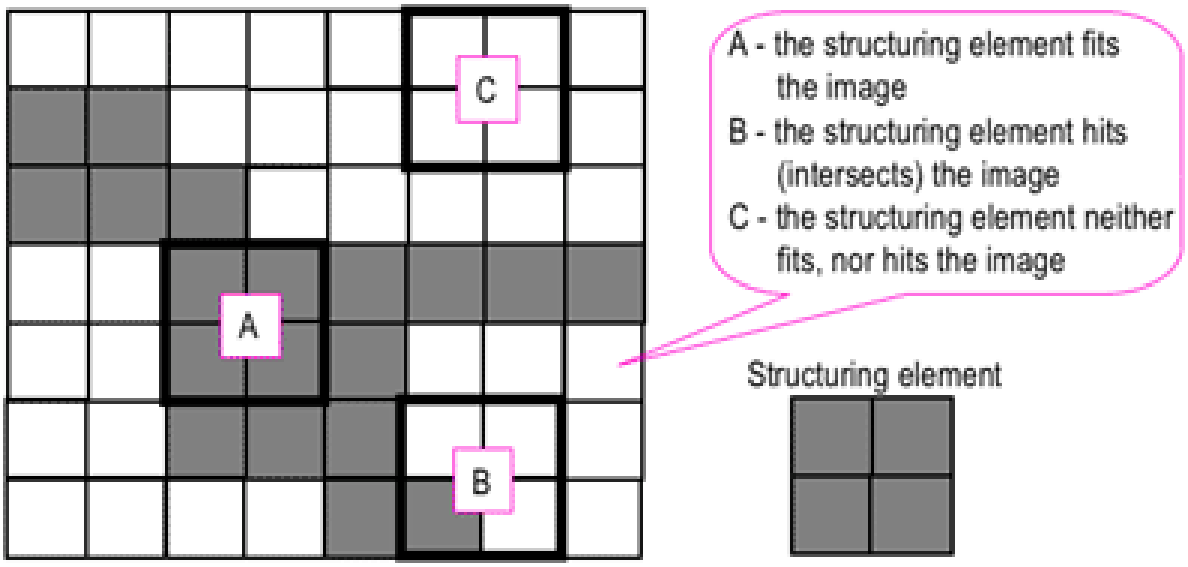



**Figure 2.5: Probing of an image with a structuring element**
(white and grey pixels have zero and non-zero values, respectively).

A morphological operation on a binary image creates a new binary image in which the pixel has a non-zero value only if the test is successful at that location in the input image.

### 2.5.2 CLAHE

Ordinary AHE tends to overamplify the contrast in near-constant regions of the image, since the histogram in such regions is highly concentrated. As a result, AHE may cause noise to be amplified in near-constant regions. Contrast Limited AHE (CLAHE) is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification.[3]

In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the

neighbourhood cumulative distribution function(CDF) and therefore to the value of the histogram at that pixel value.

CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4.

It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins. The redistribution will push some bins over the clip limit again (region shaded green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution procedure can be repeated recursively until the excess is negligible.

### 2.5.3 CANNY EDGE DETECTION

Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations. The general criteria for edge detection include:

1. Detection of edge with low error rate, which means that the detection should accurately catch as many edges shown in the image as possible

2. The edge point detected from the operator should accurately localize on the centre of the edge.

3. A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

Canny edge detection algorithm is one of the most strictly defined methods that provides good and reliable detection. Owing to its optimality to meet with the three criteria for edge detection and the simplicity of process for implementation, it became one of the most popular algorithms for edge detection.

### 2.5.4. THRESHOLDING

Thresholding is the simplest method of image segmentation. From agray scale image, thresholding can be used to create binary images .The simplest thresholding methods replace each pixel in an image with a black pixel if the image intensity is less than some fixed constant T , or a white pixel if the image intensity is greater than that constant. In the example image on the right, this results in the dark tree becoming completely black, and the white snow becoming completely white.


(a) (b)

**Figure 2.6: Thresholding image processing**

### 2.5.5 CONTOURS

A contour is a closed curve of points or line segments, representing the boundaries of an object in an image. In other words, contours represent the shapes of objects found in an image. If internal detail is visible in an image, the object may produce several associated contours, which are returned in a hierarchical data structure. Once we find the contours of the objects in an image, we can do things like determine the number of objects in an image, classify the shapes of the objects, or measure the size of the objects. The input to the contour-finding process is a binary image, which we will produce by first applying thresholding and / or edge detection. In the binary image, the objects we wish to detect should be white, while the background of the image should be black.

## 2.6 MODEL APPLIED

This chapter contains proposed model, dataset collection, description, data visualization and also classifying algorithms that are used for analysis performance

**Proposed Model:** Our First phase is data collection. We have collected our dataset from UCI Machine Learning repository website. The dataset contains features extracted from Messidor image set to predict whether an image have signs of diabetic retinopathy or not. Then features and labels of the dataset are identified. After that the dataset is divided into two sets, one for training where most of the data is used and the other one is testing. In training set four different classification algorithms has been fitted for the analysis performance of the model. The algorithms we used are k-Nearest Neighbour, random forest, support vector machine and neural networks. After the system has done learning from training datasets, newer data is provided without outputs.

The final model generates the output using the knowledge it gained from the data on which it was trained. In final phase we get the accuracy of each algorithm and get to know which particular algorithm will give us more accurate results for the prediction of diabetic retinopathy.

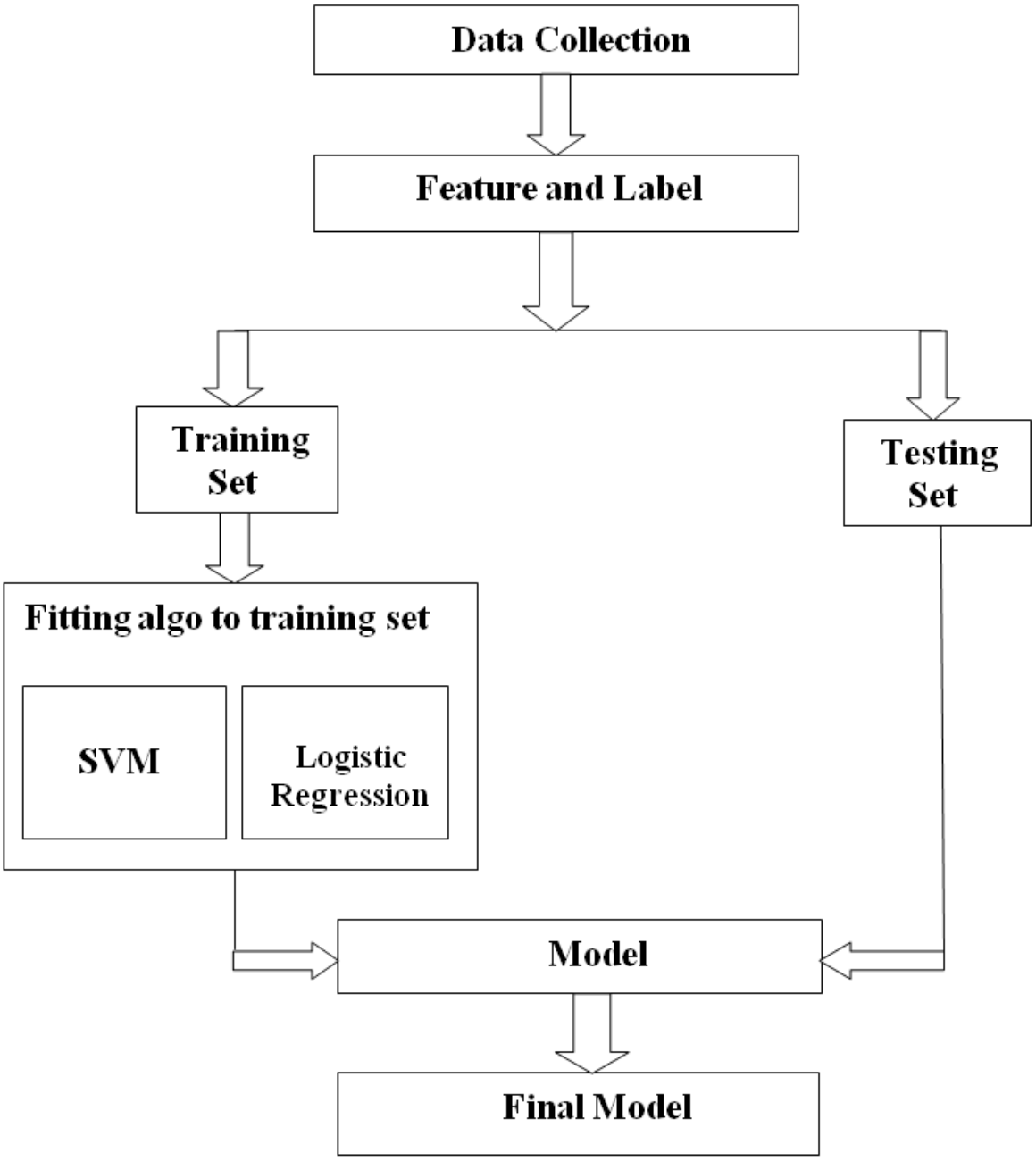



**Figure 2.7. Working Model**

## 2.7 IMPLEMENTATION

**STEP 1. DATA COLLECTION:-** In our project we have used a dataset that is obtained from the UCI Machine Learning Repository. This dataset contains features extracted from Messidor image set to predict whether an image contains signs of diabetic retinopathy or not. All features represent either a detected lesion, a descriptive feature of an anatomical part or an image-level descriptor. The Messidor database has been established to facilitate studies on computer-assisted diagnoses of diabetic retinopathy. We have seen different kind of datasets in kaggle, github and other websites which was used for different kind of projects based on diabetic retinopathy. As we wanted to work with 12 detection of diabetic retinopathy, this dataset will be appropriate for our work as it has different types of features.

**STEP 2. DATA DESCRIPTION:-** Our dataset contains different types of features that is extracted from the Messidor image set. This dataset is used to predict whether an image contains signs of diabetic retinopathy or not. The value here represents different point of retina of diabetic patients. First 19 columns in the dataset are independent variables or input column and last column is dependent variables or output column. Outputs are represented by binary numbers. “1” means the patient has diabetic retinopathy and “0” means absence of the disease.

**STEP 3. DATA VISUALISATION:-** Another important feature in the data distribution is the skewness of each class. Data visualization helps to see how the data looks like and also what kind of data correlation we have... A histogram is an accurate graphical representation of the distribution of numerical data. It is an estimate of the probability distribution of a continuous variable. Histograms are a great way to get to know your data. They allow you to easily see where a large and a little amount of the data can be found. In short, the histogram consists of an x-axis and a y-axis, where the y-axis shows how frequently the values on the x-axis occur in the data.

**STEP 4. SPLIT DATASET:-** Separating data into training and testing sets is an important part of evaluating data mining models. Typically, when separating a data set into two parts, most of the data is used for training, and a smaller portion of the data is used for testing. We have also split our dataset into two sets. One is for training and another for testing. The training set contains a known output and the model learns on this data in order to be generalized to other data later on. After the model has been processed by using the training set, we have tested the model by making predictions against the test set. Because the data in the testing set already contains known values for the attribute that we want to predict, it is easy to determine whether the model's guesses are correct or not. In addition, we have used 80% of our data for training and 20% for testing.

**STEP 5. APPLIYING ALGORITHM:-** We went through a process of trial and error to settle on a short list of algorithms that provides better result as we are working on classification of diabetic retinopathy, we used some machine learning classification algorithms. We get an idea from the data visualizations plots which algorithms will be suitable for the classification problem. The Machine Learning system uses the training data to train models to see patterns, and uses the test data to evaluate the predictive quality of the trained model. Machine learning system evaluates predictive performance by comparing predictions on the evaluation data set with true values (known as ground truth) using a variety of metrics. So, for our thesis we will evaluate four different machine learning algorithms –

- Neural Networks (NNET)
- Random Forest
- K-Nearest Neighbour (KNN)
- Support Vector Machine (SVM)

## 2.8 CONCLUSION

The effects of the eye abnormalities are mostly gradual in nature which shows the necessity for an accurate abnormality identification system. Abnormality in retina is one among them. Most of the ophthalmologists depend on the visual interpretation for the identification of the types of diseases. But, inaccurate diagnosis will change the course of treatment planning which leads to fatal results. Hence, there is a requirement for a bias free automated system which yields highly accurate results. In this paper, we are classifying normal and abnormal retina. We first present an summary of diabetic retinopathy and its causes. Then, a literature review of the maximum current automatic detection of diabetic retinopathy techniques is offered. Explanation and restrictions of retina databases which are used to test the performance of these detection algorithms are given. Here we project a vital assessment of the current researches associated with the retinopathy detection process. In this paper, we present a wide review of major researches on disease detection process based on various features.

# CHAPTER 3

# METHODOLOGY

Methodology of the project can be overseen as follows:

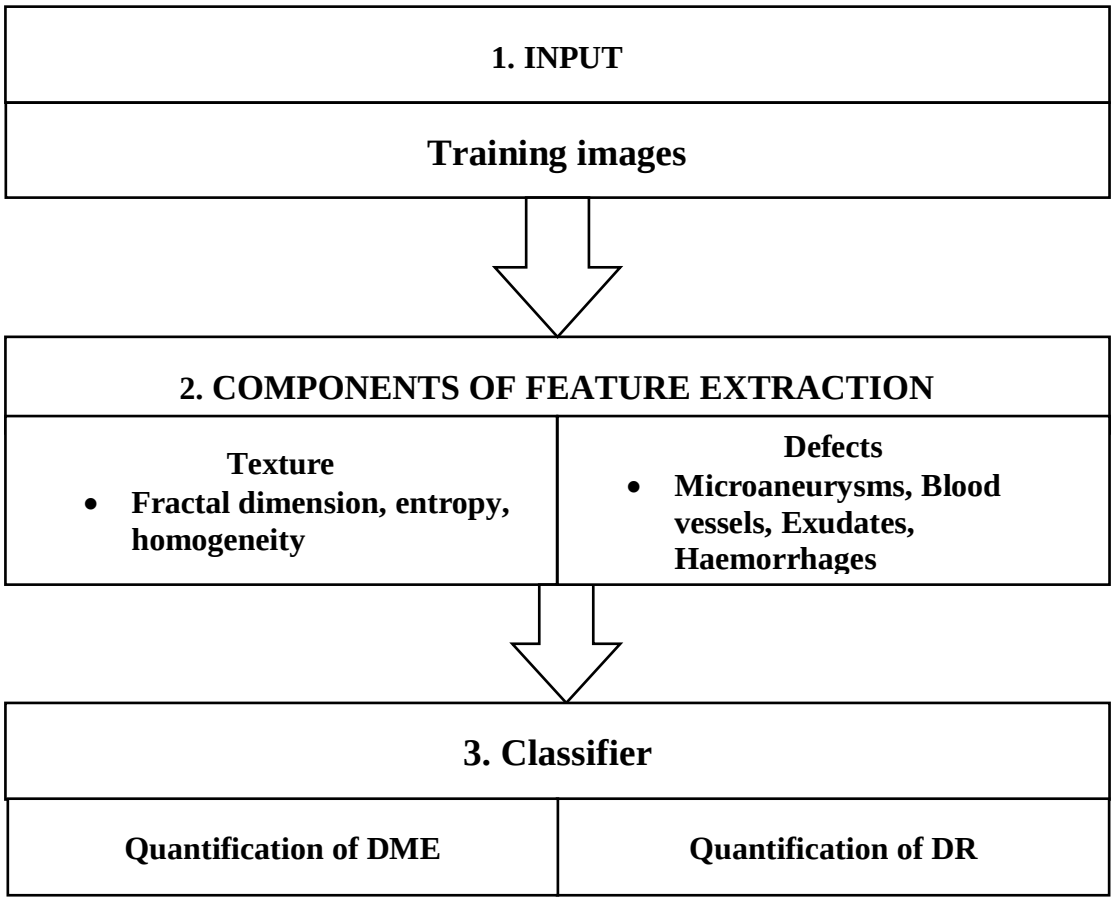



**Figure 3.1: Methodology Followed**

Method used in this project can be classified in two steps

- Image Processing and Feature Extraction
- Supervised learning

## 3.1 IMAGE PROCESSING AND FEATURE EXTRACTION

This is the most important step of the project as textures obtained will be taken as input material for neural nets which will classify the images in their respective classes.

### STEP 1. IMAGE COMPRESSION

As one can see there are different types of images in dataset with different resolution, different camera quality and different sizes My work is to classify them in different classes. So first problem I faced was related to heterogeneity of the dataset. For this compressed all my training and test images in 256*256 format.

### STEP 2. LAYER SEPARATION

In later parts we are going to use 6 features as input to classifier namely Red layer of parameter, Blue layer of parameter, Green layer of parameter, Red layer of area, Green layer of area, Blue layer of area so in this step all 3 layers of namely Red, Green and Blue are separated from the images.

### STEP 3. EQUALIZATION

After last step there are large intensity variations in the image and one can see that veins

and other eye features are not clearly seen there. For making intensity variations uniform I applied histogram equalization to the image. Histogram equalization is technique which identifies various intensity variations in the given image and increases its global contrast.For equalization I tried both Histogram Equalization and Contrast Limited Adaptive Histogram Equalization but Contrast Limited Adaptive Histogram Equalization giving a little better features than simple one. So in this step I have used CLAHE object for equalization purpose.[4]

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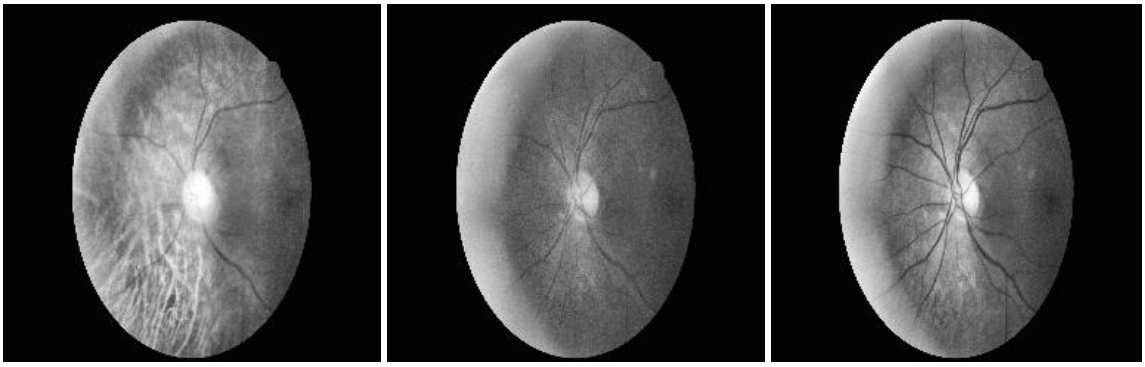

(a) Red Layer (b) Blue Layer (c) Green Layer

**Figure 3.2: Comparison in layers in CLAHE**

**STEP 4. MORPHOLOGICAL OPERATIONS**

In this part various morphological operations are employed to enhance blood vessels and to remove noise in the background. I used method proposed in (use cite here) to enhance to required features. Blood vessel rupture are main element of the disease DR. So it is important to extract and distinguish them from the background and remove background noise as much as possible. Two types of structuring elements are used in this step.

- Diamond like structure(for clearer veins)
- Disk like structure (to remove noise)

For this part I have used morphological openings. In this part I first used disc SE with R=5 then I used diamond of R=3.

**STEP 5. FEATURE EXTRACTION**

This is final image processing step for the project. In this step I will first extract perimeter from all three layers and then extract area of three layers.
In this step we proceed towards finding perimeters of all 3 layers. This is done by canny edge detection. In canny edge detection Gaussian filters are applied then using double threshold edge of intensity variation part is detected[21].

## 3.2 RETINAL IMAGE EXAMINATION TECHNIQUES

To study retina a retinal examination is done. The images of retina are taken through either fundus photography or Optical coherence Tomography (OCT). OCT is a recent advancement in medical imaging. OCT data is 3-D profile consisting of different layers of retina. There are works on OCT data which focuses on determining the change in thickness of different retinal layers.

Fundus photography involves capturing a photograph of the back of the eye. Specialized fundus cameras that consist of a microscope attached to a flash enabled camera are used in fundus photography. Fundus images are then analyzed by ophthalmologists who look for certain patterns and defects in the image to predict diseases. There are many problems in this system. World is short of highly qualified ophthalmologists. Due to this people have to wait for long before starting medications. This sometimes worsens the condition. Another crucial disadvantage is lack of agreement between different doctors on a single profile of fundus. We have started with fundus images to analyze retina.

This paper aims to analyze these defects through sophisticated image processing techniques. Based on known patterns and defects, features are extracted from fundus image. These features are taken and put into a classifier..

The abnormalities depicting the damage in the fundus images are:

- **Microaneurysm**- Microscopic blood-filled bulges in the artery walls. Microaneurysm occur as small dark round dots (~15 to 60mm) on fundus images.They are small buldges developed on weak blood vessels and a earliest sign of DR.
- **Exudates-**Exudates are another important feature s of retinal analysis. Exudates are Bright, small spots, consisting of lipids, which can have irregular shape.
- **Haemorrhages-** Haemorrhage are chunks of blood vessels on the retina because of leakage, appearing as red blobs, lying on the retina because of blood vessel rupture.
- **Blood vessels**- Formation of new blood vessels which are weak and disoriented which sometimes causes them to leak inside vitreous.

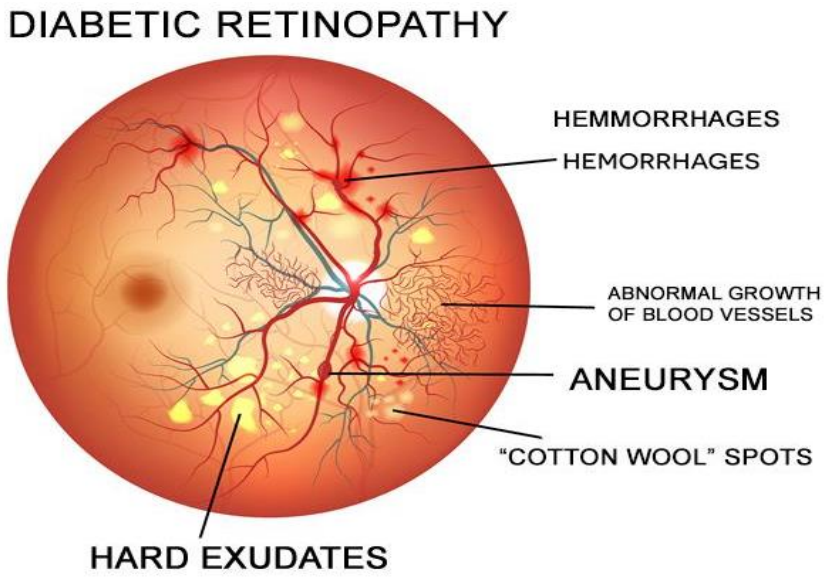


**Figure 3.3: Targeted defects in Diabetic Retinopathy detection**

## 3.3 STUDY OF FUNDUS IMAGES

The Ministry of Health estimates that 69 crore people in India have diabetes and the World Health Organization estimates that 34.7 crore people have this disease in India. DiabeticRetinopathy (DR) is an eye diseaseassociated with long-standing diabetes. Around 40% to 45% Indians with diabetes have some stage of the disease. Diabetic Retinopathy is the leading cause of blindness in the working-age population of the developed world. It is estimated to affect over 93 million people. Progression to vision impairment can be slowed or averted if DR is detected in time, however this can be difficult as the disease often shows few symptoms until it is too late to provide effective treatment.

Currently, detecting DR is a time-consuming and manual process that requires a trained clinician to examine and evaluate digital color fundus photographs of the retina. By the time human readers submit their reviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment. Also, India has a shortage of close to 1,27,000 ophthalmologists and lacks crucial eye health infrastructure and facilities.

Clinicians can identify DR by the presence of lesions associated with the vascular abnormalities caused by the disease. While this approach is effective, its resource demands are high. The expertise and equipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection is most needed. As the number of individuals with diabetes continues to grow, the infrastructure needed to prevent blindness due to DR will become even more insufficient.

The need for a comprehensive and automated method of DR screening has long been recognized, and previous efforts have made good progress using image classification, pattern recognition, and machine learning. Routine retinal screening for DR even at the time of diagnosis of type 2 diabetes may help in optimized laser therapy.. Developing CAD

systems raised a progressive need of image processing tools that provide fast, reliable, and reproducible analysis of major anatomical structures in retinal Fundus images. Segmentation of these retinal anatomical structures is the first step in any automatic retina analysis system.

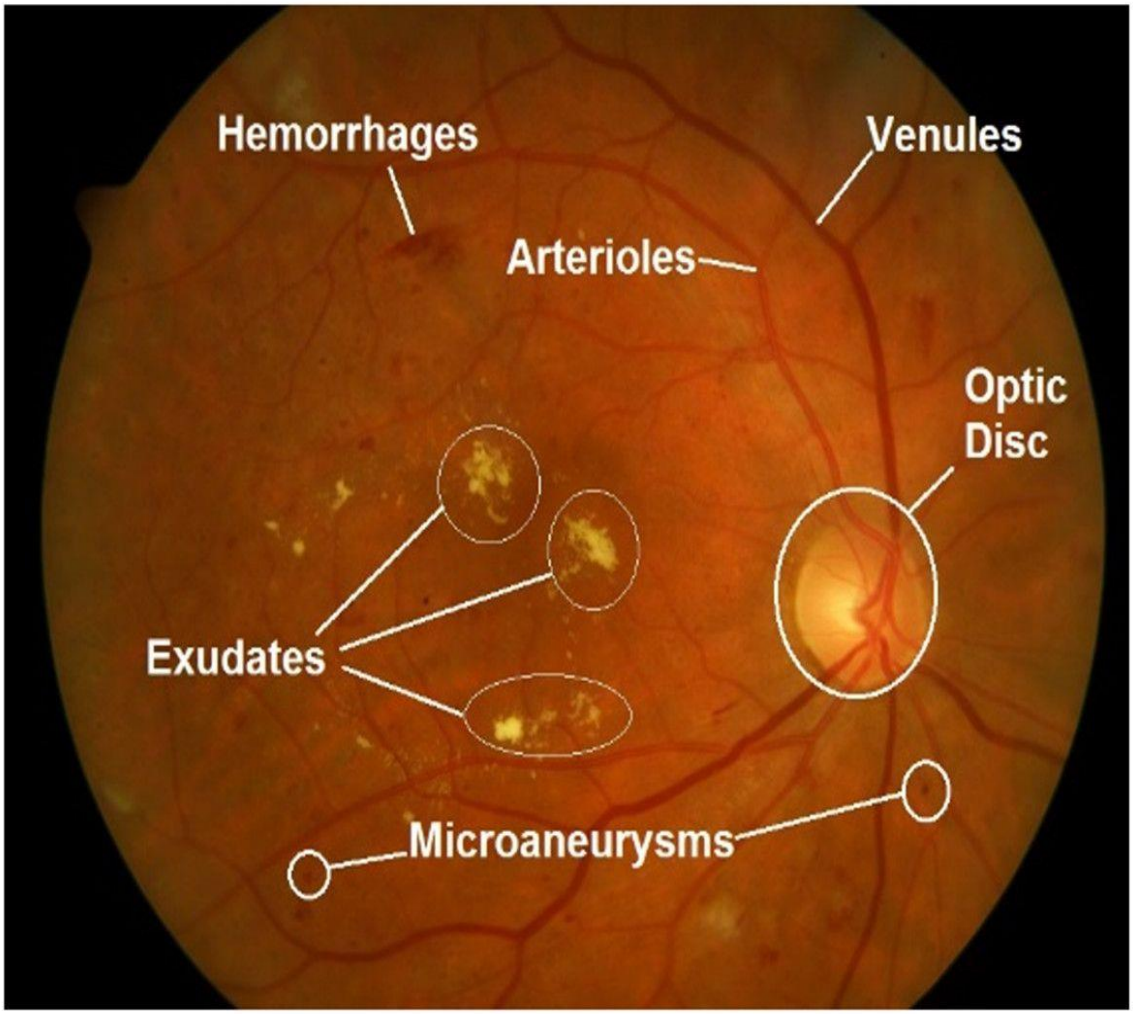


**Figure 3.4: Defects of DR in Fundus image**

## 3.4 STEPS OF FEATURE SEGMENTATION:

Retinal image segmentation includes several steps; morphological processing, thresholding, edge detection and adaptive histogram equalization. These steps will be explained in the following subsections.

### 3.4.1 MORPHOLOGICAL PROCESSING

Morphology is the study of shape. Mathematical morphology deals with the mathematical theory of describing shapes using sets. In image processing, Mathematical morphology is used to investigate the interaction between an image and a certain chosen structuring element using the basic operations of erosion and dilation. The main processes used here are dilation, erosion, opening, and closing. These processes involve a special mechanism of combining two sets of pixels. Usually, one set consists of the image being processed and the other constitutes the structuring element or kernel.

Two very important transformations are opening and closing. Intuitively, dilation expands an image object and erosion shrinks it. An essential part of the dilation and erosion operations is the structuring element (SE) used to probe the input image. A structuring element is a matrix consisting of only 0s and 1s that can have any arbitrary shape and size. Opening generally smoothes the contour in an image. Closing tends to narrow smooth sections of contours, eliminating small holes and filling gaps in contours. Algorithms combining the above processes are used to create mechanisms of edge detection, noise removal and background removal as well as for finding specific shapes in images. We will briefly review morphological operations used in this paper.

Let f(x, y) a finite-support grayscale image function defined on grid Z2 and B be a binary structuring element[16].

Opening: $f \circ B = (f \ominus B) \oplus (B)$. (3.1)

Closing: $f \bullet B = (f \oplus B) \ominus (B)$. (3.2)

Dilation: $(f \oplus B)(x, y) = \max\{f(x - s, y - t) | (s, t) \in B\}$ (3.3)

Erosion: $(f \ominus B)(x, y) = \min\{f(x + s, y + t) | (s, t \in B\}$. (3.4)

In practical image processing, it is sufficient to know that morphology can be applied to a finite set P if

1. We can partially order its elements.

2. Each non-empty subset of P has a maximum and minimum.

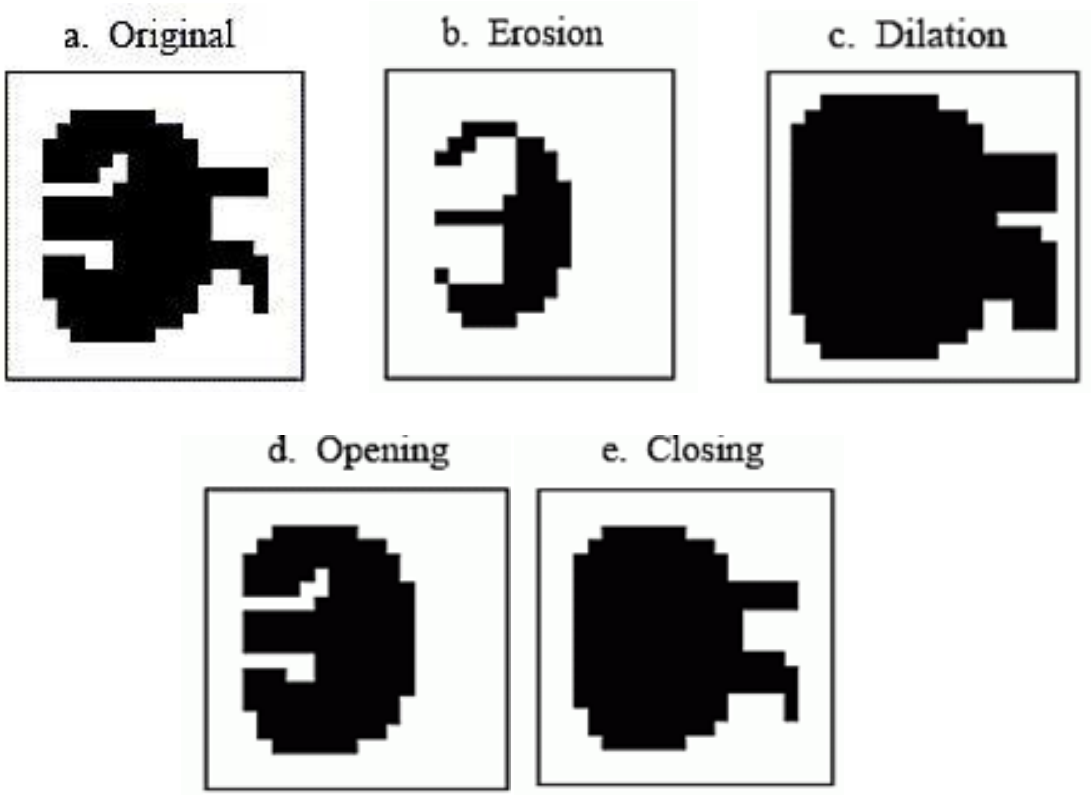


**Figure 3.5: Image showing morphological operations erosion, dilation, opening and closing on original image**

### 3.4.2. THRESHOLDING

Thresholding is useful to remove unnecessary details from an image to concentrate on essentials. In the case of Fundus images, by removing all gray level information, the blood vessels are reduced to binary pixels. It is necessary to distinguish blood vessels foreground from the background information. Thresholding can also be used to bring out hidden details. It is very useful in the imageregion, which is obscured by similar gray levels.

Therefore, choosing an appropriate threshold value is important, because a low value may decrease the size of some of the objects or reduce the number of these objects and a high value may include extra background information.

Thresholding helps us in converting image's features into numerical data which is then applied on various machine learning algorithms as finding binary values in images is easy. This provides as a channel to convert fundus images into numerical values. There are various thresholding algorithms such as OTSU, adaptive, etc.

This step is applied on morphed images which gives area of the 3 layers. This is done by adaptive thresholding. I have also tried using Otsu's thresholding and simple thresholding but later is giving better areas then other two. Thresholding can also be used to bring out hidden details. It is very useful in the imageregion, which is obscured by similar gray levels.

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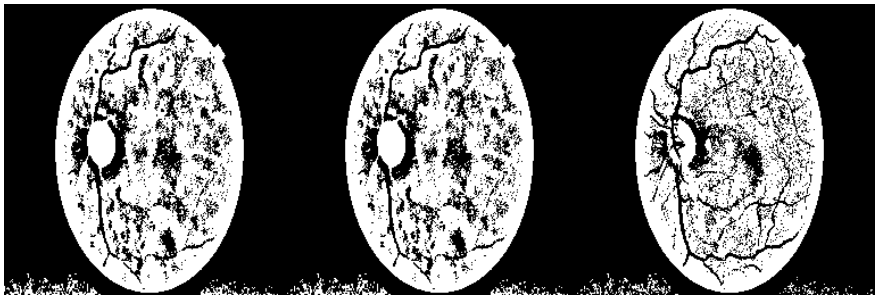
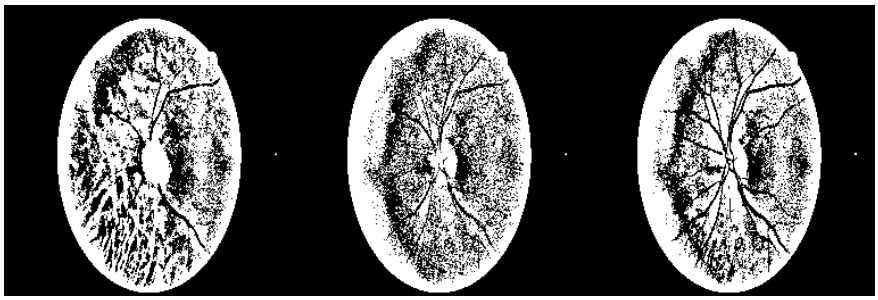


(a) Red Layer (b) Blue Layer (c) Green Layer



(d) Red Layer (e) Blue Layer (f) Green Layer

(g) Red Layer (h) Blue Layer (i) Green Layer

**Figure 3.6: Image layer comparison in thresholding.**

### 3.4.3. EDGE DETECTION

Canny method is used for edge detection. The Canny method performs better than the other edge detection methods, because it uses two thresholds to detect strong and weak edges, and for this reason, Canny algorithm is chosen for edge detection in the proposed technique. Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations.

The general criteria for edge detection includes:
1. Detection of edge with low error rate, which means that the detection should accurately catch as many edges shown in the image as possible.
2. The edge point detected from the operator should accurately localize on the center of the edge
3. A given edge in the image should only be marked once, and where possible, image noise should not create false edges.

The Process of Canny edge detection algorithm can be broken down to 5 different steps:

1. Apply Gaussian filter to smooth the image in order to remove the noise.

2. Find the intensity gradients of the image.

3. Apply non-maximum suppression to get rid of spurious response to edge detection.

4. Apply double threshold to determine potential edges.

5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

### 3.4.4. ADAPTIVE HISTOGRAM EQUALIZATION

Histogram equalization usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. A disadvantage of the method is that it isindiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images locally. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image.

While performing AHE if the region being processed has are relatively small intensity range then the noise in that region gets more enhanced. It can also cause some kind of artifacts to appear on those regions. To limit the appearance of such artifacts and noise, a modification of AHE called CLAHE can be used. The amount of contrast enhancement for some intensity is directly proportional to the slope of the CDF function at that intensity level. Hence contrast enhancement can be limited by limiting the slope of the CDF. The slope of CDF at a bin location is determined by the height of the histogram for that bin. Therefore, if we limit the height of the histogram to a certain level we can limit the slope of the CDF and hence the amount of contrast enhancement.

The only difference between regular AHE and CLAHE is that there is one extra step to clip the histogram before the computation of its CDF as the mapping function is performed.

Following is the overview of the algorithm for this function:

1. Calculate a grid size based on the maximum dimension of the image. The minimum grid size is 32 pixels square.

2. If a window size is not specified chose the grid size as the default window size.

3. Identify grid points on the image, starting from top-left corner. Each grid point is separated by grid size pixels.

4. For each grid point calculate the histogram of the region around it, having area equal towindow size and centred at the grid point**.**

5. If a clipping level is specified clip the histogram computed above to that level and thenuse the new histogram to calculate the CDF.

6. After calculating the mappings for each grid point, repeat steps 6 to 8 for each pixel in the input image.

7. For each pixel find the four closest neighbouring grid points that surround that pixel.

8. Using the intensity value of the pixel as an index, find its mapping at the four grid points based on their cdfs.

9. Interpolate among these values to get the mapping at the current pixel location. Map this intensity to the range [min:max) and put it in the output image.

Clipping the histogram itself is not quite straight forward because the excess after clipping has to be redistributed among the other bins, which might increase the level of the clipped histogram. Hence the clipping should be performed at a level lower than the specified clip level so that after redistribution the maximum histogram level is equal to the clip level. The CLAHE algorithm partitions the images into contextual regions and applies the histogram equalization to each one. This evens out the distribution of used grey values and thus makes hidden features of the image more visible.

## 3.5 TARGETED DEFECTS

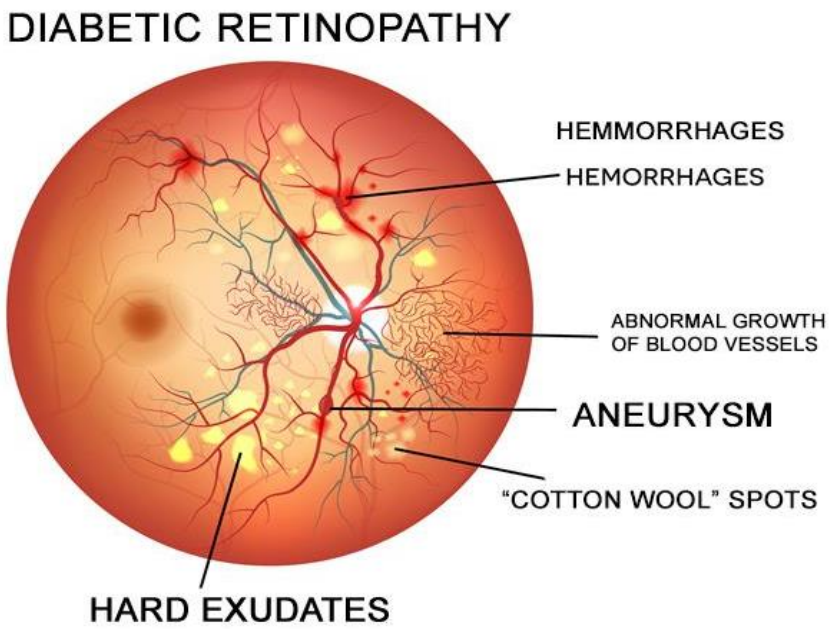



**Figure3.7: Defects in a DR eye**

### 3.5.1 DETECTION OF BLOOD VESSELS

Blood vessels are very important features which help in examination of retina. Blood vessels show different symptoms when an eye suffers from certain disease. There are swellings in the blood vessel when an eye has diabetic retinopathy. In non proliferative diabetic retinopathy the narrow blood vessels do not get enough blood supply because of blockage near optic nerve. It causes them to get broken down and release fluid in the retina. In the proliferative retinopathy this gets worse. To counteract it, retina tries to develop new blood vessels.

So detection of blood vessels becomes very important. We have used Alternate sequential Filtering (ASF) along with other image processing techniques to extract blood vessels. We also tried to work on red channel of image and get it segmented. But the presence of haemorrhages and clots made it difficult. In our procedure we have extracted green channel of image because it has greater contrast. We also tried to work on red channel of image and get it segmented. But the presence of haemorrhages and clots made it difficult. In our procedure we have extracted green channel of image because it has greater contrast. To further increase contrast we apply Contrast Limited Adaptive Histogram Equalization.

Applying ASF on this image gives us another image with average intensity of each region applied over it. Later we subtract this image from output of CLAHE. This gives us an image which contains faint traces of blood vessels with optic disk and other things removed. We binarize this image with a threshold T and get blood vessels segmented. The final image also contains noise and some undesirable elements.

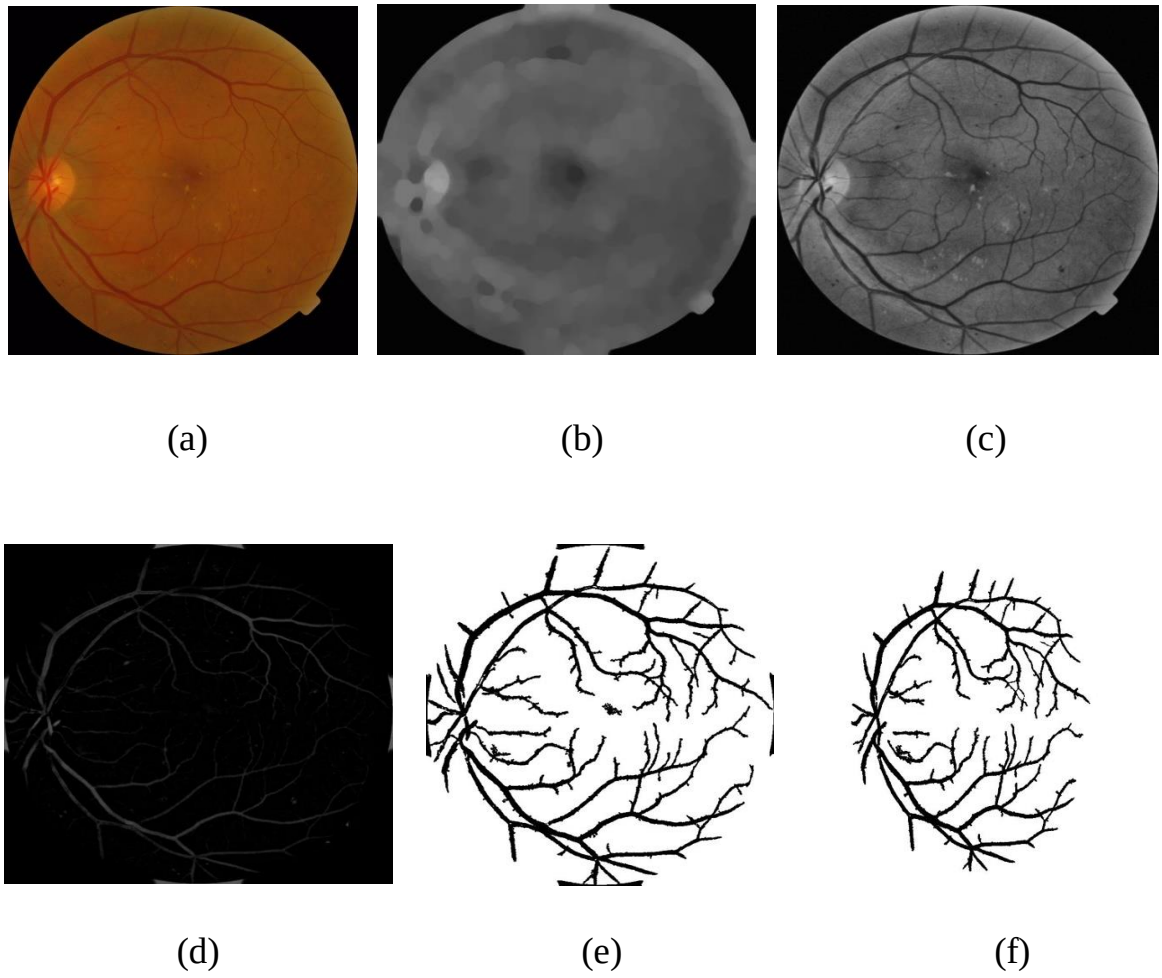



**Figure 3.8: Various steps in blood vessel segmentation**

(a) : Input image of fundus

(b) : Output of CLAHE on green channel

(c) : Alternate Sequential Filtering of (b)

(d) : Subtraction result of (b) and (c)

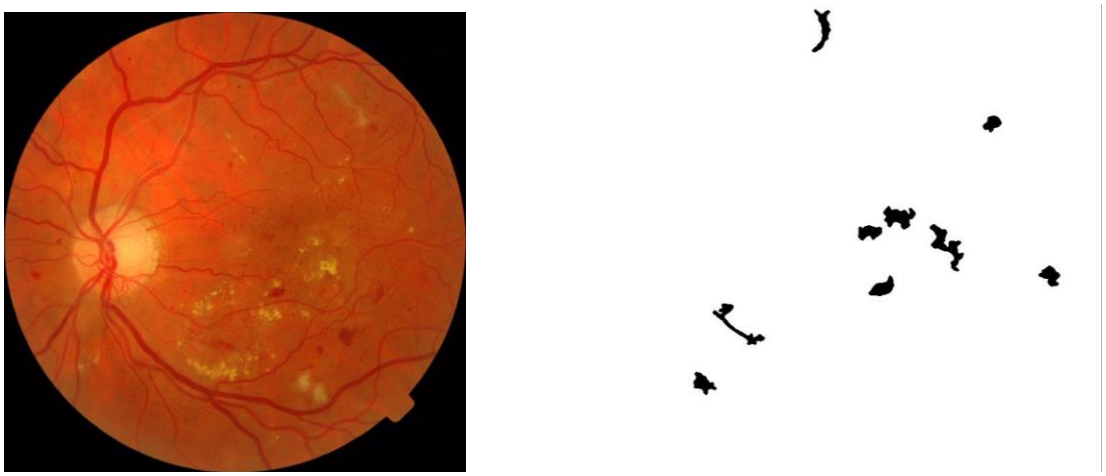
(e) : Thresholded image with noise and extra elements

(f) : Segmented blood vessels

### 3.5.2. DETECTION OF HAEMORRHAGES

Haemorrhages are chunks of blood vessels lying on the retina because of leakage. Presence of Haemorrhages are a good indicator of retinal damage. In a fundus image haemorrhages appear as red blobs. In proliferative diabetic retinopathy we see small as well as some very large traces of haemorrhages.

To detect haemorrhages we followed the same procedure as we did in blood vessel detection upto some steps.. This gives us an image which contains haemorrhages and small noise elements. To remove noise we apply a median filter on image. The new image has haemorrhages but also some small and broken blood vessels. To remove them we take all the contours and check if it can be approximated as a polygon of side greater than 5. Those which pass certainly have a non linear shape (i.e. complex circular) and are counted as haemorrhages.



(a) Original (b) Extracted Image

**Figure 3.9: Fundus image and its haemorrhages**

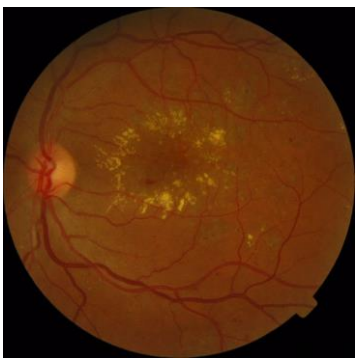
### 3.5.3. DETECTION OF EXUDATES

Exudates are another important feature of retinal analysis. Exudates are bulges of yellow and white colors appearing in the fundus. There are two types of exudates:

- Hard exudates
- Soft exudates.

Hard exudates consist of extracellular lipid which has leaked from abnormal retinal capillaries. Hard exudates are found principally in the macular region and as the lipids coalesce and extend into the central macula (fovea), vision can be severely compromised. Soft exudates looking like cotton wool, are nerve fibre layer infarcts. Exudates have been detected using red and blue channel. We know that yellow colour consists majorly of red and green color. We thresholded the red channel and green channel individually taking threshold T as (max(channel)+mean(channel))/2. These two binary channels were passed through AND gate which gives us all the yellow coloured pixels. Now in the image we have exudates along with optic disk. To remove optic disk we have devices an algorithm.

We make a window of suitable size which scans the image with a stride s. For every scan we calculate the mean intensity of every window. Since optic disk is bigger in size and has very high intensity, we get the maximum at optic disk. To remove it we mask it with a window of black color. Thus we get only exudates in our image.



(a) Original image

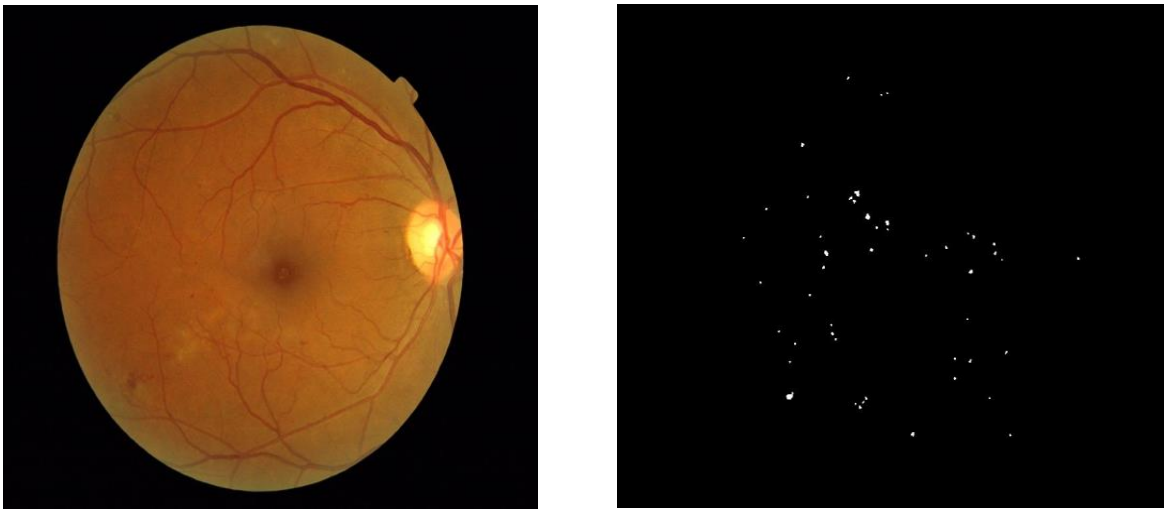
(b) Extracted Image

**Figure 3.10: Fundus and its segmented exudates**

## 4. DETECTION OF MICROANEURYSM

Microaneurysm occur as small dark round dots (~ 15 - 60 mm) on fundus images. They are small bulges developed on weak blood vessels and are earliest sign of DR. The images are pre processed to a standard size of 1488 x 2240 and are of *.tif format. The green channel of the image is extracted as it gives the best contrast between the microaneurysms and other bright parts such as optic disk, exudates, etc. Now, image contrast is further stretched by applying adaptive histogram equalization (CLAHE). The image contrast is stretched by applying adaptive histogram equalization before using edge detection (Canny method) to detect the outlines of the image. The boundary is detected by filling up the holes and a disc-shaped structuring element (SE) of radius 6 is created with morphological opening operation (erosion and dilation). The edge detection image is then subtracted from the image with boundaries to obtain an image without boundaries.

After that, the holes or gaps are filled, resulting in microaneurysms and other unwanted artifacts. The blood vessels which are detected using the above mentioned method are subtracted from the image of microaneurysms and artifacts.



(a) Original (b) Extracted Image

**Figure 3.11: Fundus images and its segmented microaneurysm**

## 3.6 TARGETED FEATURES

### 1. Calculation of Fractal Dimensions

Fractal dimension is measured as a feature to quantify for texture of retina. Consider a line, if we subdivide the line in half then it takes two bits to recreate the original line. If we subdivide the line into 4 pieces it takes 4 of them to cover the line. We can write this generally, if we have a line segment of length "s' then the number of segments that will cover the original line is given by

$$N(s) = (1/s)^1 \quad (3.5)$$

We have extracted Hausdorff fractal dimension using this algorithm:

- Pad the image with background pixels so that its dimensions are power of 2.

- Set the box size 'e' to the size of the image.

- Compute N(e), which corresponds to the number of boxes of size 'e' which contains at least one object pixel.

- If e > 1 then e = e / 2 and repeat previous step.

- Compute the points log(N(e)) x log(1/e) and use the least square method to fit a line to the points.

- The returned Hausdorff fractal dimension D is the slope of the line. This gives us fractal dimension for fundus images which quantifies texture of retina.

**2.Calculation of homogenity**

Hmogeneity is another feature that is used to examine the texture of the retinal image which is calculated using the Gray-Level Co-Occurrence Matrix (GLCM). GLCM is a statistical method of examining texture that considers the spatial relationship of pixels. It is created by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image. Several statistics can be derived from this matrix which provide information about the texture of an image. Homogeneity is one such statistic that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity weights values by the inverse of the contrast weight, with weights decreasing exponentially away from the diagonal as shown in the following equation. The addition of value ‘1’ in the denominator is to prevent the value ‘0’ during division. As homogeneity increases, the contrast typically decreases.

$$H=\sum\sum {}^{1}{}_{2}p_{d}(i,j)_{ij}\,1+(i-j) \qquad (3.6)$$

Where $p_d$ is the probability of having a pair of pixel values (i,j) occurring in each image and (i,j) denotes a possible pair of the horizontally adjacent pixels i and j.

**3. Calculation of Entropy**

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. If image has more than two dimensions, the entropy function treats it as a multidimensional grayscale image and not as an RGB image. Entropy is defined as:

$$E=-\sum\sum_{j}(p*log_{2}p)\,i \qquad (3.7)$$

where p is histogram values of gray scale image at different (i, j).

Entropy is a concept which originally arose from the study of the physics of heat engines. It can be described as a measure of the amount of disorder in a system. An organized structure, such as a crystal or a living organism, is very highly ordered and consequently has low entropy. When the crystal is heated sufficiently, it melts and becomes liquid, a much less ordered state. When the organism dies, it decays and becomes completely disrupted. In either system, its entropy increases. Another way of expressing entropy is to consider the spreadof states which a system can adopt. A low entropy system occupies a small number of such states, while a high entropy system occupies a large number of states.

In the case of an image, these states correspond to the gray levels which the individual pixels can adopt. For example, in an 8-bit pixel there are 256 such states. If all such states are equally occupied, as they are in the case of an image which has been perfectly histogram equalized, the spread of states is a maximum, as is the entropy of the image. On the other hand, if the image has been thresholded, so that only two states are occupied, the

entropy is low. If all of the pixels have the same value, the entropy of the image is zero. In this progression, as the entropy of the image is decreased, so is its information content. We moved from a full gray scale image, with high entropy, to a thresholded binary image, with low entropy, to a single-valued image, with zero entropy.

# CHAPTER 4

# FLOW CHART

## 1. APPLIED WORKING MODEL

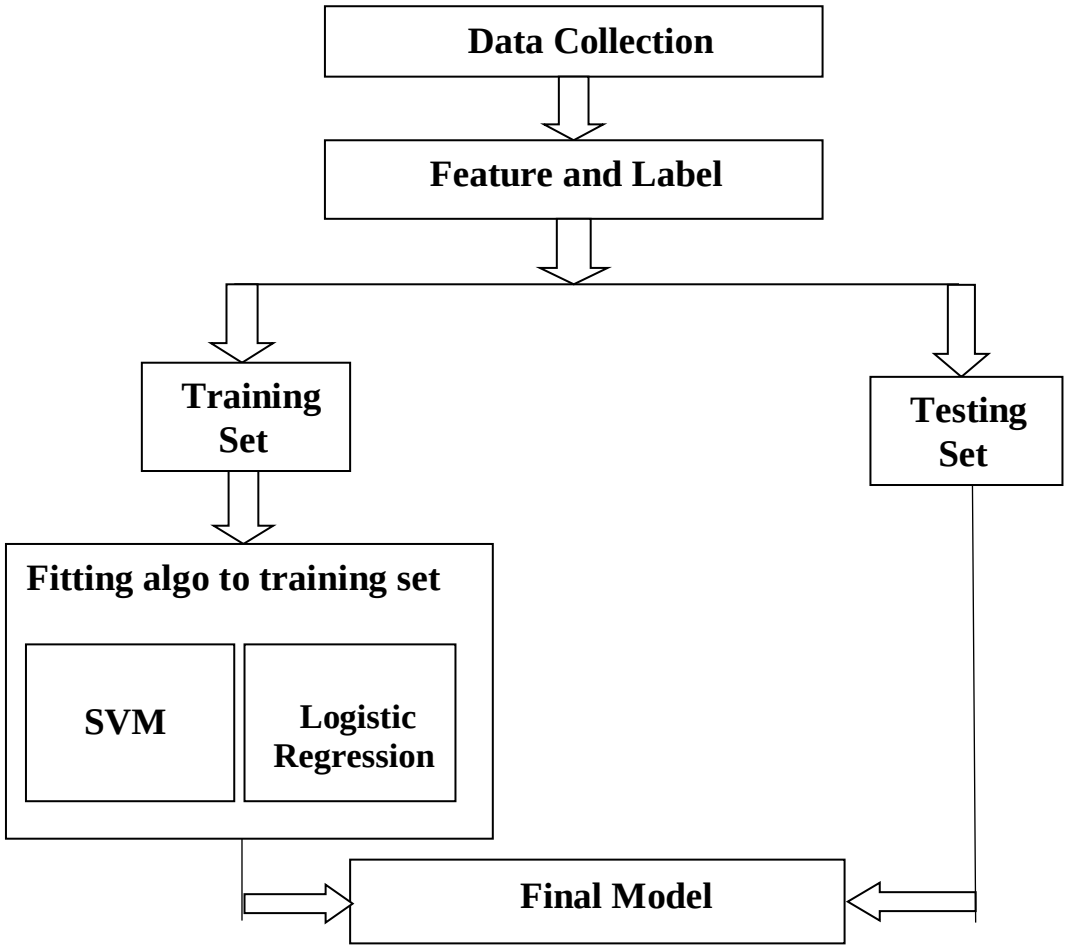



Figure 4.1 Working Model

## 2. BLOCK DIAGRAM FOR DR DETECTION THROUGH DIFFERENT TECHNIQUES:

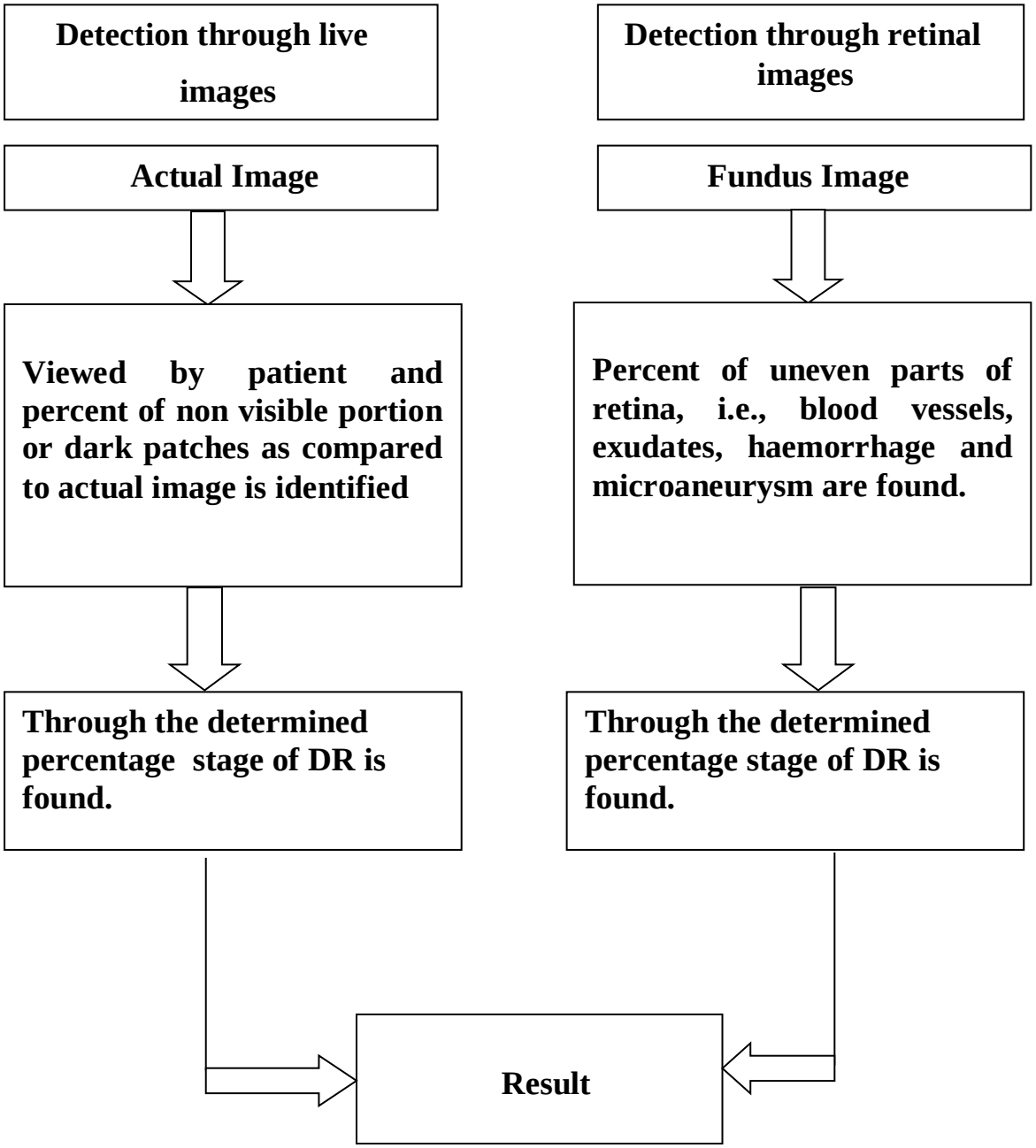



**Figure 4.2: Complete Block Diagram of DR Detection**

## 3. BLOOD VESSELS

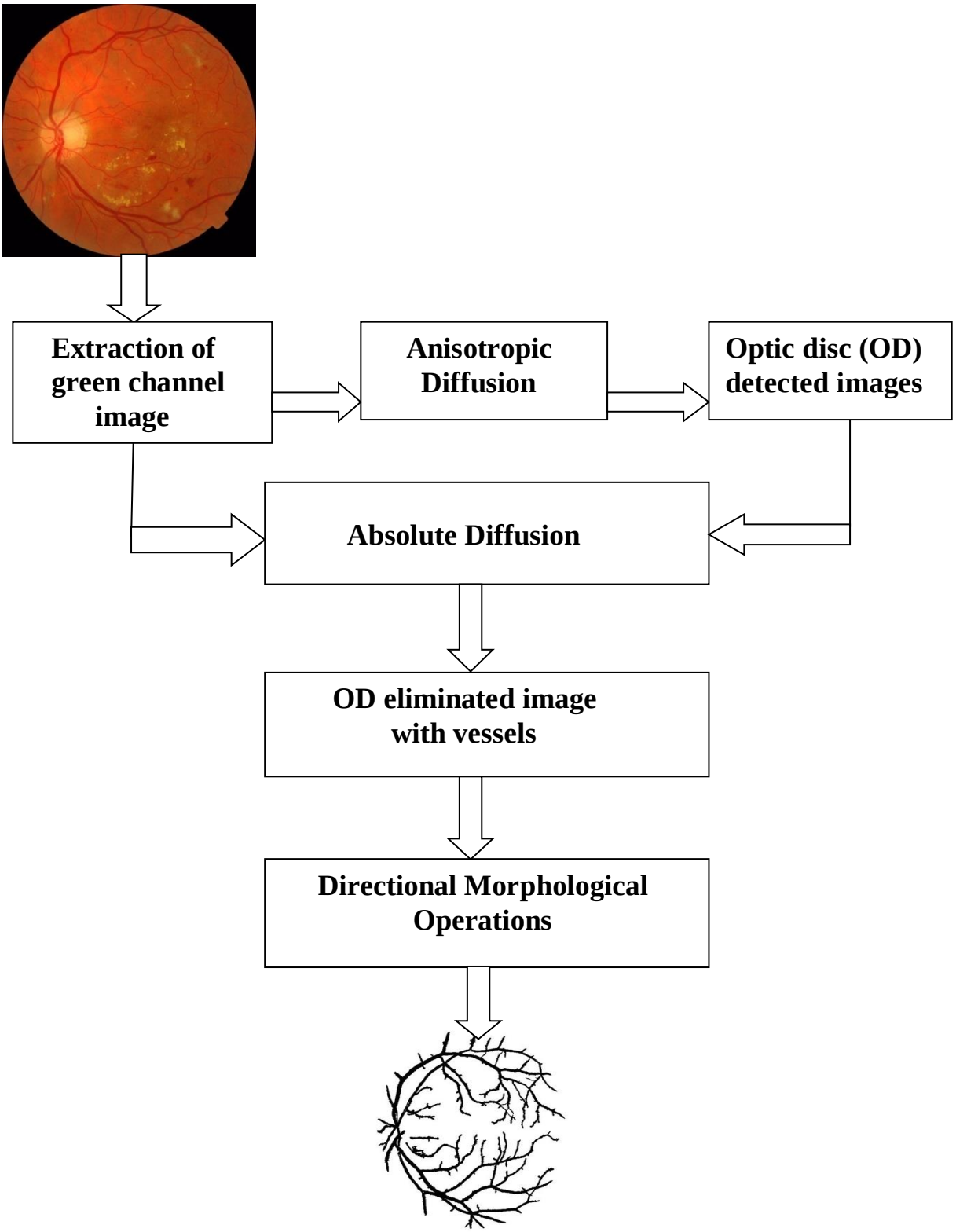



**Figure 4.3: Complete Flow Diagram of Blood Vessel Extraction System**

## 4. EXUDATES

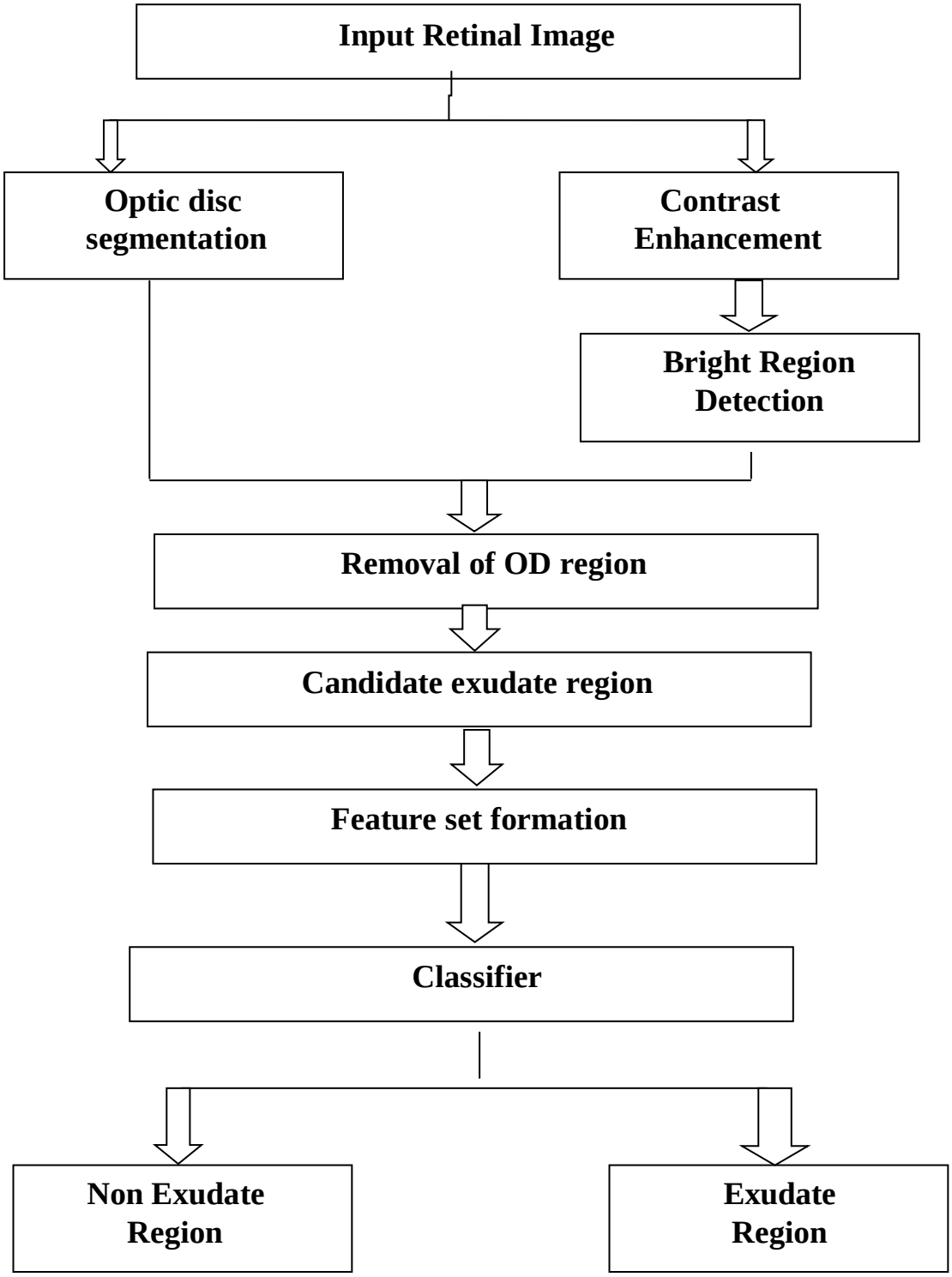



**Figure 4.4: Complete Flow Diagram of Exudates Extraction System**

## 5. HAEMORRHAGE

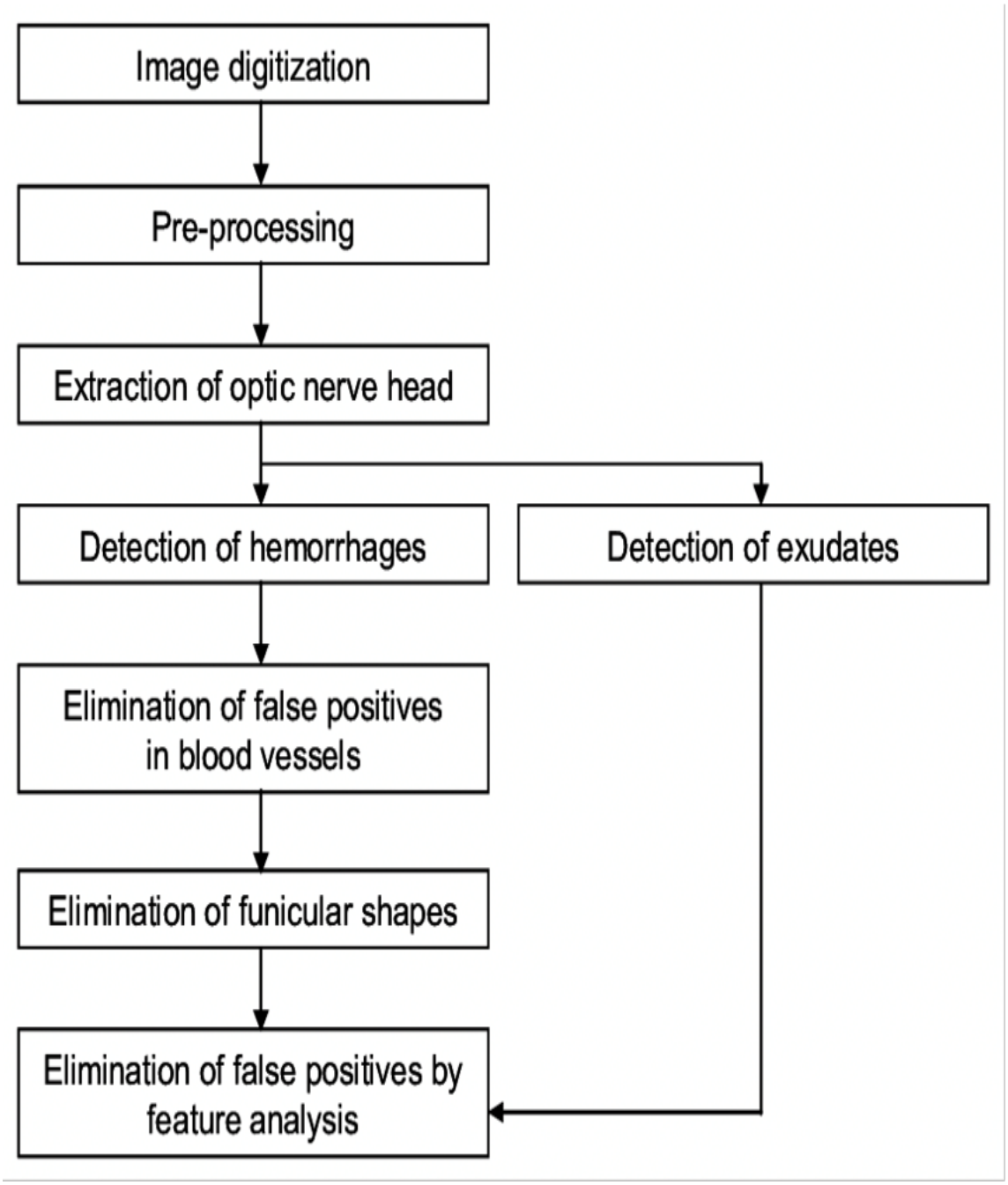



**Figure 4.5: Complete Flow Diagram of Haemorrhage Extraction System**

## 6.MICROANEURYSM

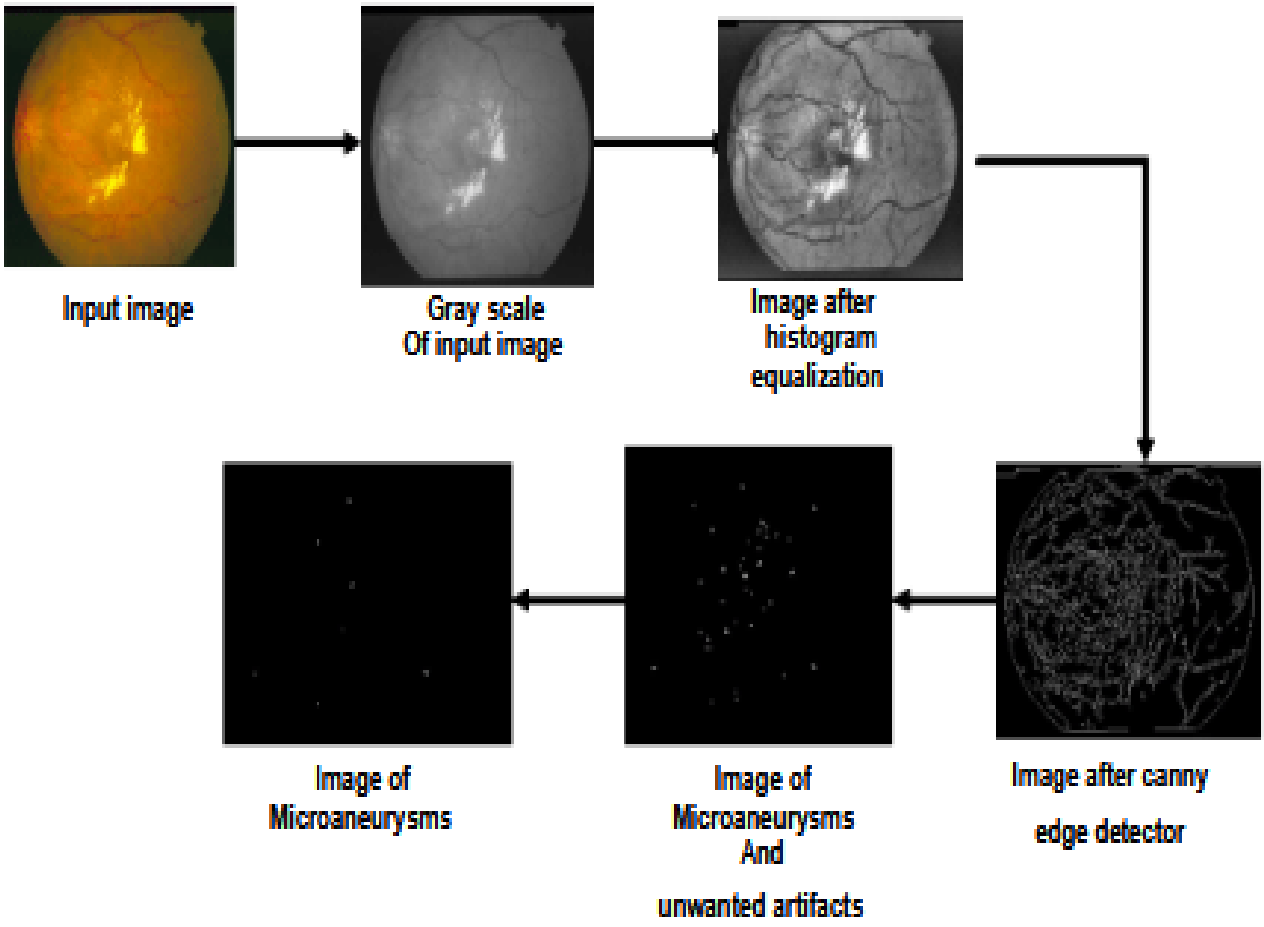



**Figure 4.6: Complete Flow Diagram of Microaneurysm Extraction System**

# CHAPTER 5

# STAGE PREDICTION, DATA ANALYSIS, RESULTS

## 5.1. STAGE PREDICTION OF DIABETIC RETINOPATHY

Diabetic retinopathy is the leading cause of new cases of legal blindness in the world, affecting 4.2 million People, 655,000 of whom have sight-threatening retinopathy. Identifying patients who are at increased risk of progression from non proliferative (NPDR) to proliferative diabetic retinopathy (PDR) is important for many reasons. From the patient's perspective, individuals who progress from NPDR to PDR frequently experience a decline in best-corrected visual acuity, which can have a profound impact on health-related quality of life . In addition, those who develop PDR are at substantially increased risk of serious complications that can result in permanent vision loss such as tractional retinal detachment, vitreous haemorrhage, and neo vascular glaucoma. From a societal perspective, the costs of caring for patients with PDR are four times greater than the costs of managing patients with NPDR. One study found the average cost of caring for patients with NPDR to be 292 USD, while it cost 1,207 USD to manage patients who develop PDR. Another study conducted by the National Health Services in Taiwan found that individuals who progressed from NPDR to PDR were noted to have an increase in expenditures of 3,482 USD.

We used Kaggle DR dataset to analyze and generate a training set. As per our analysis we wrote a conditional program to generate the training sets for every possible input and got their outputs. We generated around 15000 training sets out of our analysis, then we trained our ML algorithms with those training sets and after we preprocessed our fundus image data we provided it to ML algos to predict the output for those which it did gave us. We used two different ML algos for comparing outputs and change in both the algos if any. The used algos are “Logistic Regression” and “Support Vector Machine” because as we studied about these algos the suited our conditions best.

### 5.1.1 SUPPORT VECTOR MACHINE

In machine learning, support-vector machines (SVMs, also support-vector networks[1]) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).

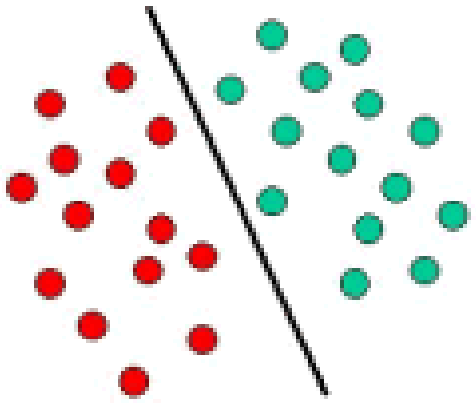


**Figure 5.1: Classifying**

The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks.

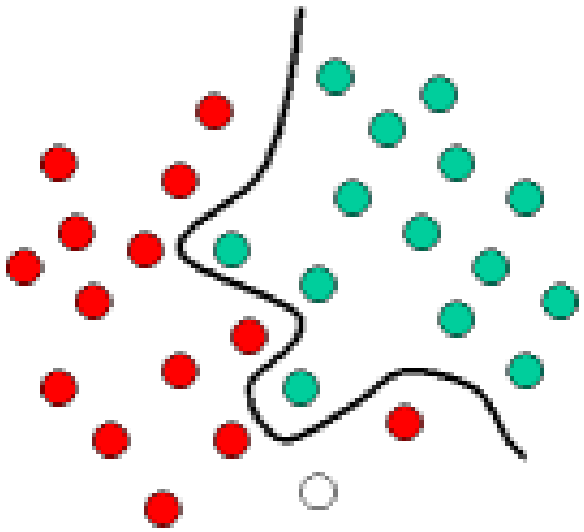


**Figure 5.2: Classification based on separate lines**

The illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation).

Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal line that can separate the GREEN and the RED objects.

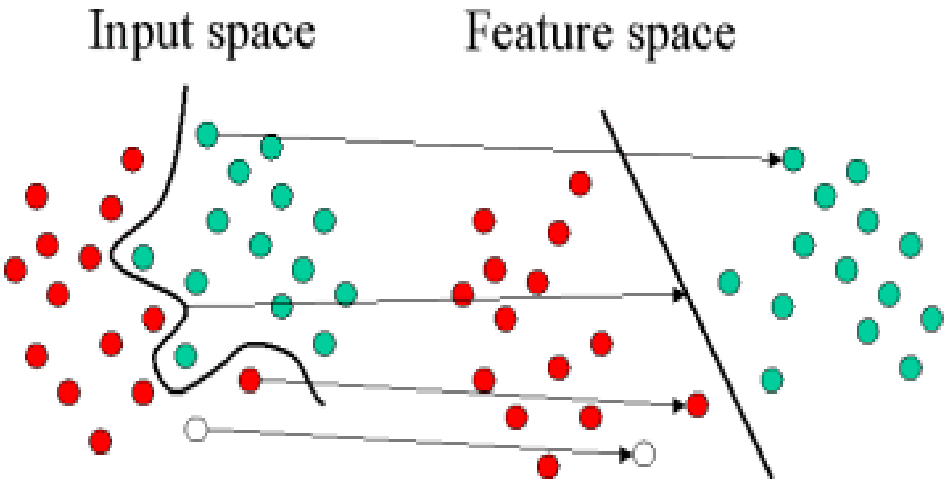



**Figure 5.3: Linear Separation**

### 5.1.2. LOGISTIC REGRESSION

Logistic Regression was used in the biological sciences in early twentieth century. It was then used in many social science applications. Logistic Regression is used when the dependent variable(target) is categorical.

For example,

- To predict whether an email is spam (1) or (0)
- Whether the tumor is malignant (1) or not (0)

Consider a scenario where we need to classify whether an email is spam or not. If we use linear regression for this problem, there is a need for setting up a threshold based on which classification can be done. Say if the actual class is malignant, predicted continuous value 0.4 and the threshold value is 0.5, the data point will be classified as not malignant which can lead to serious consequence in real time.

From this example, it can be inferred that linear regression is not suitable for classification problem. Linear regression is unbounded, and this brings logistic regression into picture. Their value strictly ranges from 0 to 1.

*Model*

Output = 0 or 1

Hypothesis => Z = WX + B

hΘ(x) = sigmoid (Z)

**Sigmoid Function**

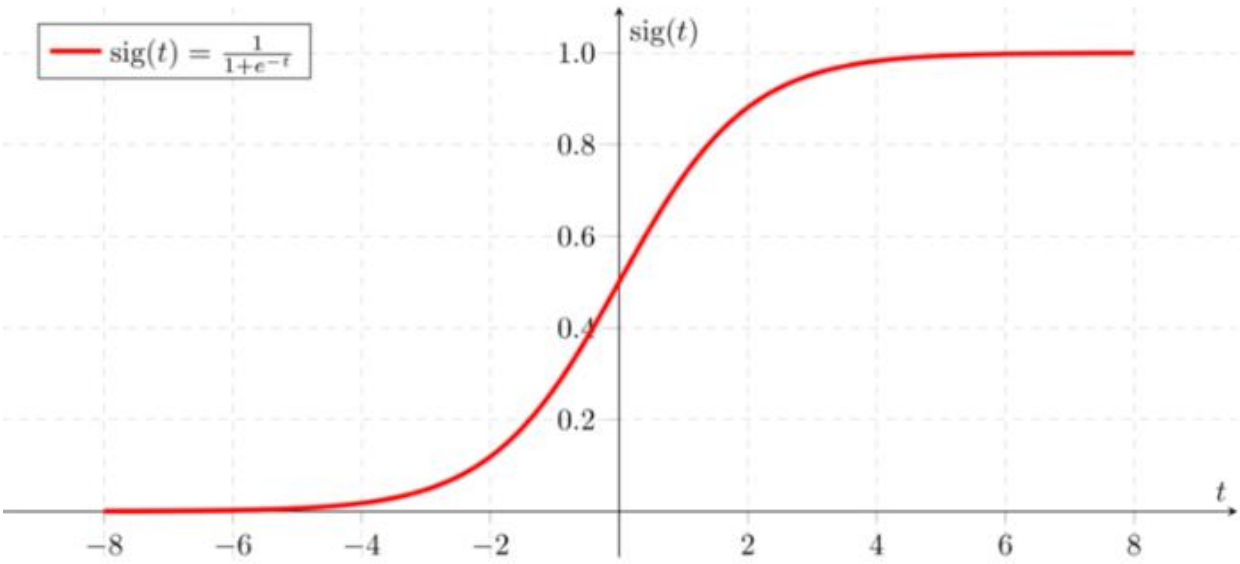



**Figure 5.4: Sigmoid Activation Function**

If ‘Z’ goes to infinity, Y(predicted) will become 1 and if ‘Z’ goes to negative infinity, Y(predicted) will become 0.

ANALYSIS OF THE HYPOTHESIS

The output from the hypothesis is the estimated probability. This is used to infer how confident can predicted value be actual value when given an input X.

Consider the below example,

X = [x0 x1] = [1 IP-Address]

Based on the x1 value, let’s say we obtained the estimated probability to be 0.8. This tells that there is 80% chance that an email will be spam.

Mathematically this can be written as,

$h_\Theta(x) = P(Y=1 | X; theta)$

Probability that Y=1 given X which is parameterized by ‘theta’.

$P(Y=1 | X; theta) + P(Y=0 | X; theta) = 1$

$P(Y=0 | X; theta) = 1 - P(Y=1 | X; theta)$

This justifies the name ‘logistic regression’. Data is fit into linear regression model, which then be acted upon by a logistic function predictingthe target categorical dependent variable.

## 5.2. STAGE PREDICTION WITH USER INTEFACE

There are two techniques included in this project for detection of percentage and stage of Diabetic Retinopathy.

1. Detection using Fundus Images of the defective eye.
2. Detection through live images by examining the dark sport percentage visible to defective eye person.

### 5.2.1 DETECTION USING FUNDUS IMAGES:

Step 1: Select the method want to be opted

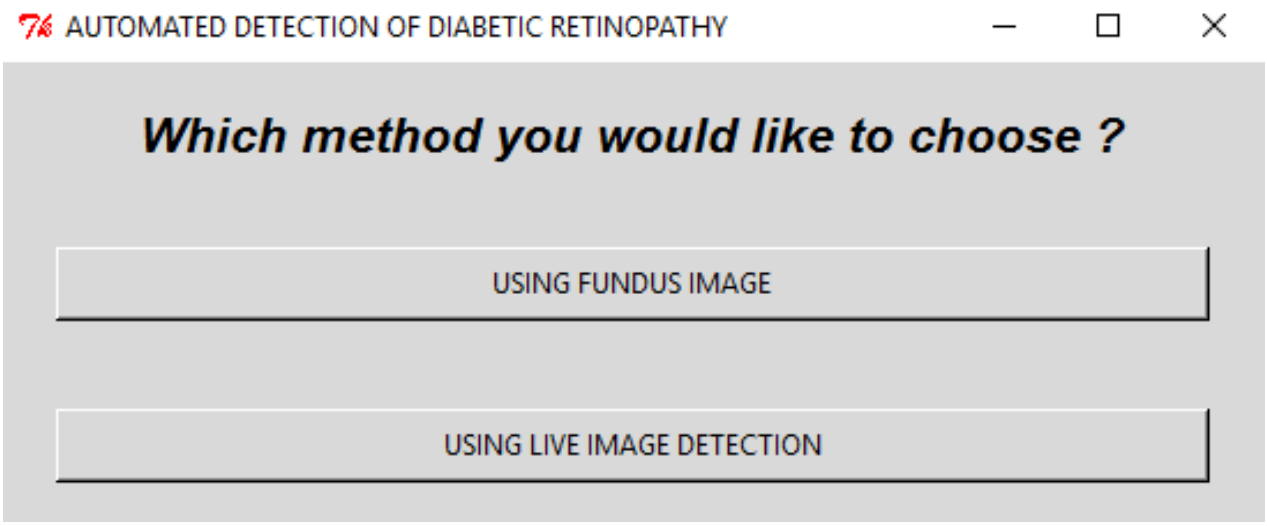



**Figure 5.5: Method choosing in Stage Prediction**

Step 2: Select the image to be processed and it will give you the result.

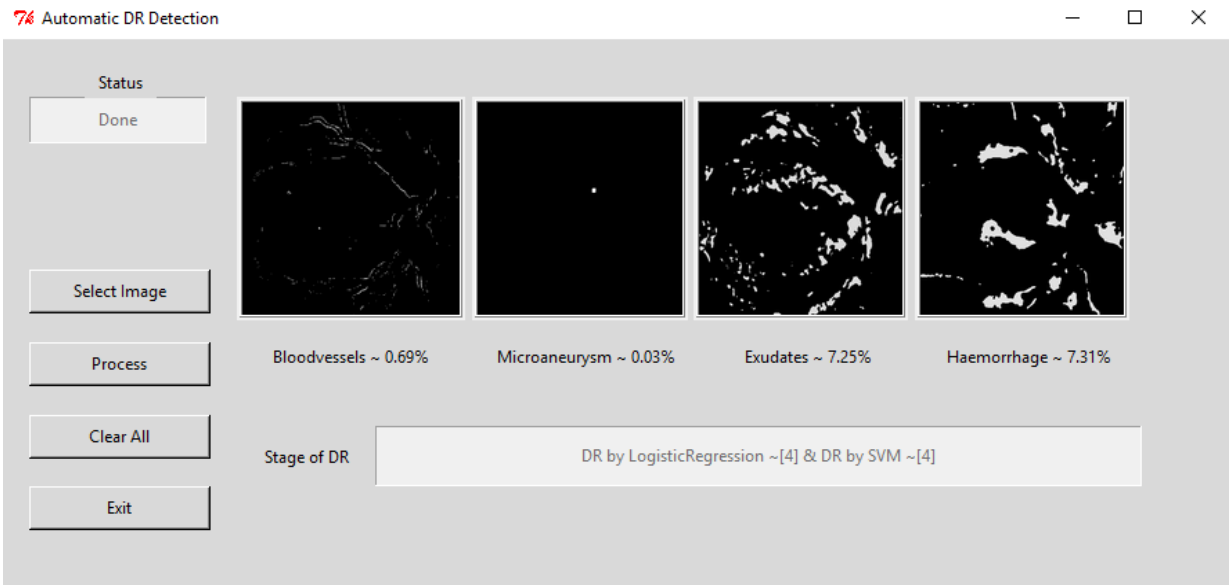



**Figure 5.6: Result of the image**

## 5.2.2. DETECTION USING LIVE IMAGES

As per our earlier findings with retinal images and stages of DR we came out with a set of conditions for partially blindness of an eye in this case when patient draws the area which is less visible they mark that much territory with mouse a which is totally free hand so they can draw purely that part which is not visible. After that we process that image and get the parts of image this happen twice for a single user. After that we take an average of both the image and pass it through our generated conditions to find out what is the approximate level of DR patient have. Following steps are followed for DR detection through live images:

Step 1: Select the method want to be opted.

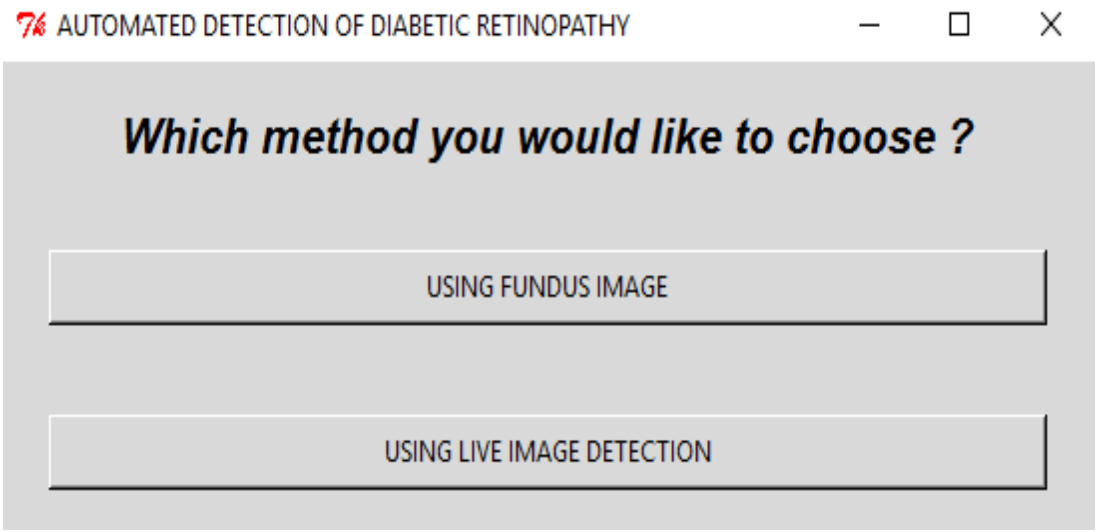



**Figure 5.7: Method choosing in Stage Prediction**

Step 2: Mark the dark patches visible to DR patient.

(May use more than one image for accurate results.)

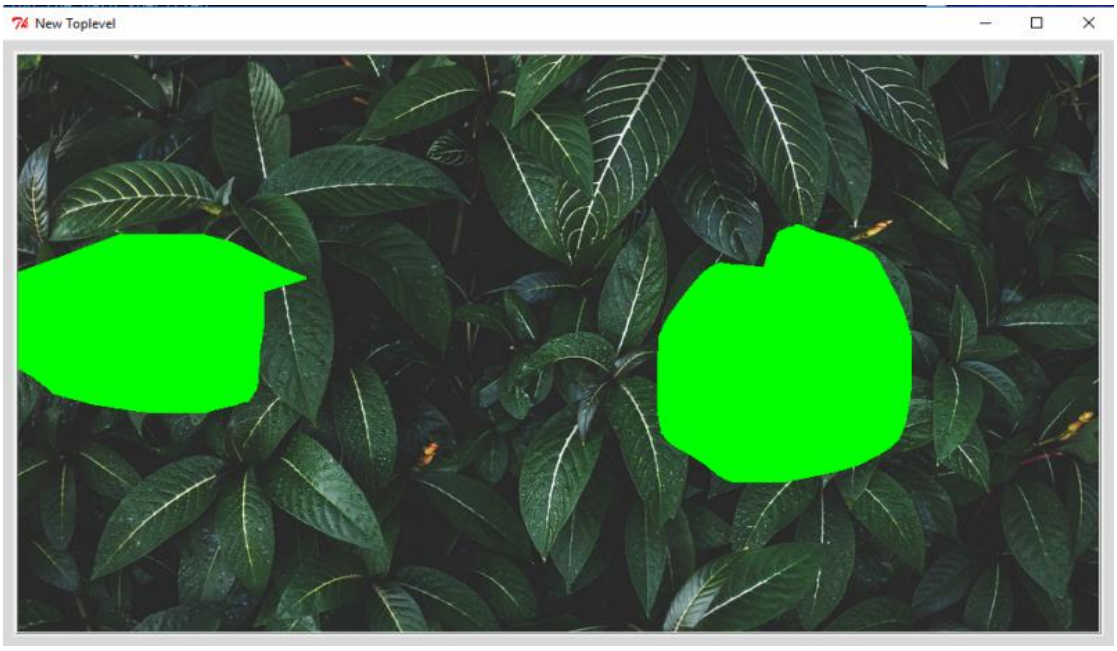



**Figure 5.8: Marking of dark patches visible to DR patient**

Step 3: Stage level is calculated and displayed.

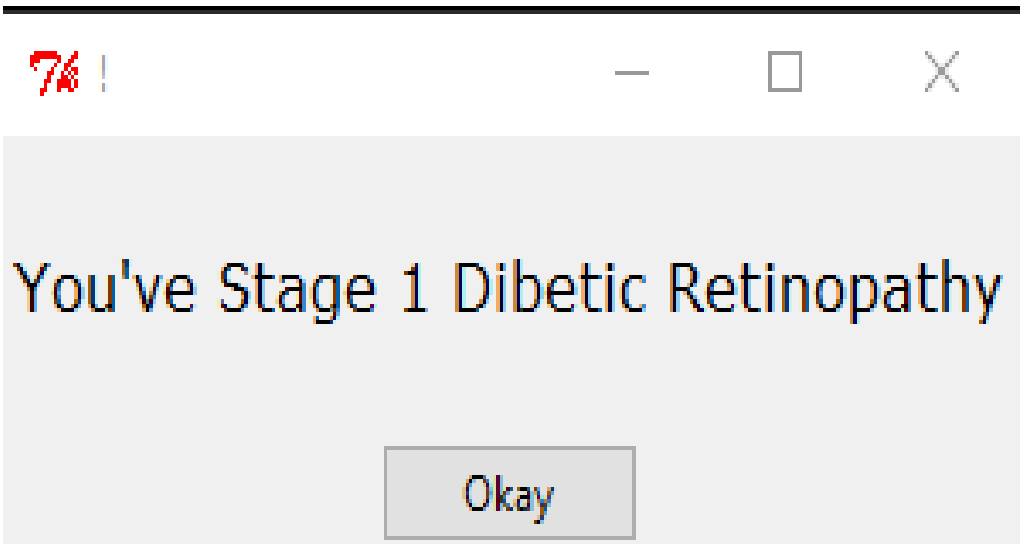



**Figure 5.9: Stage Prediction through live images**

Step 4: Stage Level and percentage is displayed on Command prompt.

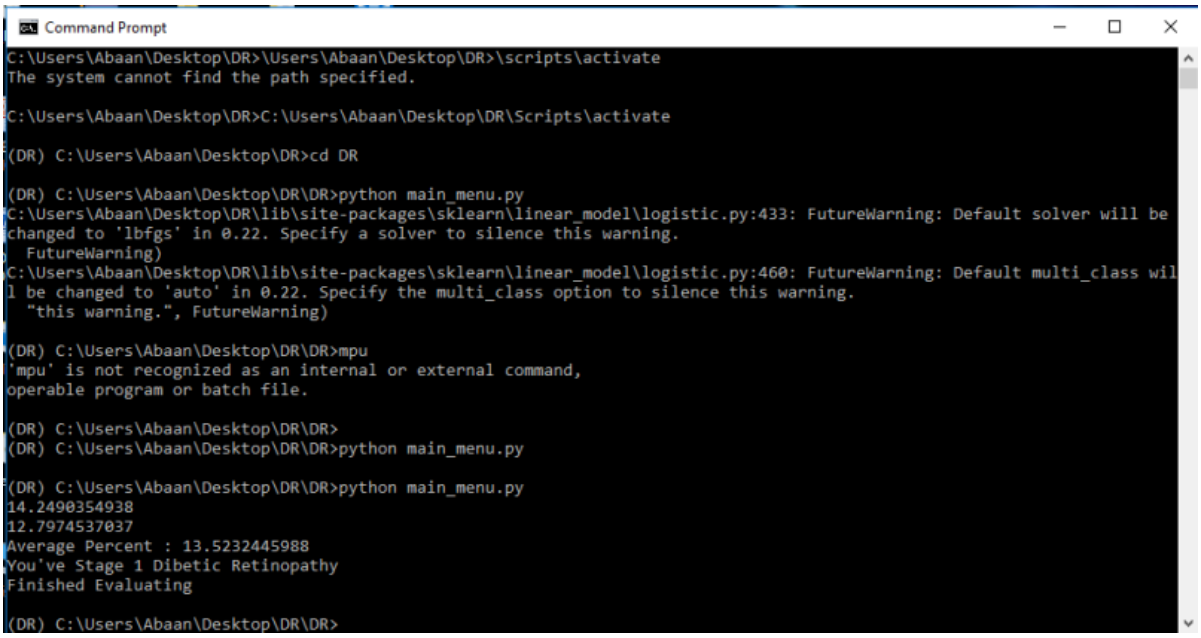



**Figure 5.10: Result in Command Prompt**

# CHAPTER 6

# CONCLUSION AND RESULTS

## 6.1. CONCLUSIONS

Our image processing techniques have been very consistent. We have been successful in detecting blood vessels, microaneurysms and exudates. Results of extraction of blood vessels are found to be better than most of other works. A binary classifier system has been designed for diabetic retinopathy retinal defect has been developed and tested. This system provides an early warning of diabetic retinopathy abnormalities for diabetic patients. Extraction of haemorrhages have a lower accuracy. Microaneurysms are most important factor With correlation matrix we have been able to find that fractal dimensions and entropy have a positive correlation.

This makes us free to drop one of these features without having much impact on accuracy. We have tried to construct an ensemble to predict if a patient has diabetic retinopathy using features from retinal photos. After training and testing the model the accuracy we get is quite similar. For both sets NNET is providing higher accuracy rate for predicting DR. Despite the shortcomings in reaching good performance results, this work provided a means to make use and test multiple machine learning algorithms and try to arrive to ensemble models that would outperform individual learners.

It also allowed exploring a little feature selection, feature generation, parameter selection and ensemble selection problems and experiences the constraints in computation time when looking for possible candidate models in high combinatorial spaces, even for a small dataset as the one used. The structure of our research has been built in such a way that with proper dataset and minor alternation it can work to classify the disease in any number of categories. We have tried our data on different models. The best accuracy achieved is for multiclass classification for macular edema with Random Forests Classifier using 1200 data points from MESSIDOR database.

## 6.2 RESULTS AND DISCUSSION

We fed our data into various Machine-Learning models and calculated various statistical measures.

| **Machine Learning Model** | **Accuracy** |
|---|---|
| Support Vector Machine | 0.6634867 |
| Logistic Regression | 0.6657898 |
| K-Nearest Neighbour | 0.5176392 |
| Random Forest | 0.6621927 |
| Artificial NN | 0.6500546 |
| Naïve-Bayes | 0.6482322 |
| Linear Discriminant Analysis | 0.6427890 |

**Table 1: Binary Classification of Diabetic Retinopathy with 1200 instances.**

From the above table it is clear that the accuracy of Support Vector Machine algorithm and Logistic Regression algorithm is the highest, thus, we used these two algorithm in stage prediction method for the high accuracy results.

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