COMPARATIVE ANALYSIS OF PERFORMANCE OF MULTI OBJECTIVE PSO AND NSGA II FOR THE CLASSIFICATION OF DIABETIC RETINOPATHY IN RETINAL IMAGES

A THESIS

Submitted by

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CERTIFICATE

This is to certify that all corrections and suggestions pointed out by the Indian /Foreign Examiner(s) are incorporated in the Thesis titled " COMPARATIVE ANALYSIS OF PERFORMANCE OF MULTI OBJECTIVE PSO AND NSGA II FOR THE CLASSIFICATION OF DIABETIC RETINOPATHY IN RETINAL IMAGES " submitted by Mr. Suresh Babu.V

21.3.18

Signature of the Supervisor

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Proceedings of the Ph.D. Viva-Voce Examination of Mr.Suresh Babu.V held at 09:30 AM on 21.03.2018 in Seminar Hall Surya Engineering College Erode

The Ph.D. Viva-Voce Examination of Mr.Suresh Babu.V (Reg. No. 100910521019) on his/her Ph.D. Thesis Entitled " COMPARATIVE ANALYSIS OF PERFORMANCE OF MULTI OBJECTIVE PSO AND NSGA II FOR THE CLASSIFICATION OF DIABETIC RETINOPATHY IN RETINAL IMAGES " was conducted on **21.03.2018** at 09:30 AM in the Seminar Hall Surya Engineering College Erode.

The following Members of the Oral Examination Board were present:

1.	Dr. Chandan Kumar Sarkar,Professor,Department of Electronics and Telecommunication Engineering,Jadavpur University,kolkata-700 032	Indian Examiner
2.	Dr. P Sukumar,Professor,Department of Electronics and Communication Engineering,Nandha Engineering College ,Perundurai Erode 638052	Subject Expert
3.	Dr. Vijayan.S,Professor, Department of Electrical and Electronics Engineering, Surya Engineering College,Erode	Supervisor & Convenor

The research scholar, Mr. Suresh Babu.V presented the salient features of his/her Ph.D. work. This was followed by questions from the board members. The questions raised by the Foreign and Indian Examiners were also put to the scholar. The scholar answered the questions to the full satisfaction of the board members.

The corrections suggested by the Indian/Foreign examiner have been carried out and incorporated in the Thesis before the Oral examination.

Based on the scholars research work, his/her presentation and also the clarifications and answers by the scholar to the questions, the board recommends that Mr.Suresh Babu.V be awarded Ph.D. degree in the **Faculty of Information and Communication Engineering**.

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CERTIFICATE

The research work embodied in the present Thesis entitled "**COMPARATIVE ANALYSIS OF PERFORMANCE OF MULTI OBJECTIVE PSO AND NSGA II FOR THE CLASSIFICATION OF DIABETIC RETINOPATHY IN RETINAL IMAGES"** has been carried out in the Department of Electrical and Electronics Engineering, Surya Engineering College, Erode. The work reported herein is original and does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion or to any other scholar.

I understand the University's policy on plagiarism and declare that the thesis and publications are my own work, except where specifically acknowledged and has not been copied from other sources or been previously submitted for award or assessment.

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ABSTRACT

Optometry is the healthcare profession that is concerned with eyes. It deals with vision, visual systems and vision information processing in humans. One who practices Optometry is called as Ophthalmologists, who are trained to improve vision, to identify and treat the diseases in eye. Detecting the disease in eye is crucial, which can be made easy through image processing techniques. The rapid growth in the field of Bio-Medical image processing, which is the method and art of creating visual representation of the body for clinical analysis and medical involvement, aids the physicians to easily identify the diseases that occurs in eye. The retinal images when diagnosed by Ophthalmologists reflect the presence of disease which includes Diabetic Retinopathy (DR), Retinopathy of Pre-Maturity (ROP) and Age related Macular Degeneration (AMD). To diagnose these diseases, color fundus images are being used. The Fundus Image Analysis (FIA) system proposed in this research work will serve as a second opinion for the ophthalmologist's diagnosis and also it serve as an automated tool for the detection of diabetic retinopathy while carrying mass screening.

Blood vessel and optic disc segmentation are very difficult processes. They are segmented basically based on three approaches: Thresholding process, tracking technique and machine trained classifier. The optic disc segmentation starts by defining the location of the optic disc. This procedure is used to converge the characteristic of vessels into the optic disc to calculate approximately its location. The disc area is then segmented using two different automated methods (MRF image reconstruction and compensation factor). Both methods use the convergence feature of the vessels to identify the position of the disc. This research proposes an effective algorithm for the efficient detection of diabetic retinopathy from optic images.

Images are denoised and the features like area of microaneurysm, area of vessels, homogeneity and entropy are extracted. For comparative analysis, the features extracted are selected and optimized through Multi-Objective Particle Swarm optimization (MPSO) technique and Non-dominated Sorting Genetic Algorithm – II (NSGA – II) technique. Then the selected features are treated with classifier algorithms like Back Propagation Neural Network (BPN), Support Vector Machine (SVM) and Fuzzy Classifier algorithms. The effectiveness of the algorithms is compared in terms of accuracy, sensitivity, specificity and precision.

An efficient algorithm for accurate classification of Diabetic Retinopathy has been attempted in this research work. Several classifier algorithms have been attempted for efficient classification and the performances have been compared. Out of the two optimization techniques, it is evident that NSGA – II provides superior performance, in terms of optimizing and selecting the features from the retinal fundus images. The analysis of the performances of various classifiers indicated that the fuzzy C means classifier provides superior results compared to its counterparts viz. BPNN, SVM, KNN and Fuzzy K means classifiers. Hence it is concluded that the proposed system when implemented can assist ophthalmologists for efficient classification of disease that occurs in human eyes.

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SURESH BABU V

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LIST OF ABBREVIATIONS

BPNN	-	Back Propagation Neural Network
IRMAs'	-	Intra-Retinal-Microvascular Abnormalities
K-NN	-	K Nearest Neighbour
NB	-	Naive Bayes
NPDR	-	Non proliferative Diabetic Retinopathy
NSGA	-	Non-Dominated Sorting Genetic Algorithm
PSO	-	Particle Swarm Optimization
PDR	-	Proliferative Diabetic Retinopathy
SVM	-	Support Vector Machine

CHAPTER 1

INTRODUCTION

Diabetic retinopathy is the major cause for the loss of vision also it affects the people of all ages from 20 to 60. It causes permanent loss of vision which cannot be retained. Diabetic retinopathy is the major reason for blindness and it remains as one of the most serious complications that result in too much sugar in blood or high blood glucose. The only way to treat this disease is to examine it in the early stage. If care has been taken in proper time vision loss can be prevented. The patient has to undergone annual eye examinations and fundus photography. Several programs have been designed throughout the world to overcome this problem also laser treatment has been introduced to reduce blindness in diabetic patient.

1.1 CAUSE OF THE DIABETIC RETINOPATHY

The change in the blood vessel at the backside of the eye, called retina causes the called disease called diabetic retinopathy. It occurs due to the swelling of blood vessel and blood leaking through the blood vessel also the abnormal new blood vessel growing on the surface of the retina. A thin layer of tissue which is sensitive to light is located at the back of the eye is known as retina. Retina acts like a projector, projecting the image when the light rays are focused onto the retina. Further they are transmitted to the brain and interpreted as the images. The center part which is of very small area of retina is called macula. The macula is responsible for sew or recognize a face and pinpoint vision which allows reading.

Macula is also responsible to see color but when it becomes swollen known as macular edema, it can cause blindness. When blood vessels become weak it can break and leak blood into the eye so the retina cannot project images to brain. This stage of diabetic is known as proliferative diabetic retinopathy which could result in blindness. The surrounding part of the retina which is responsible for your side or peripheral vision is called the peripheral retina. People usually do not notice the changes in their vision during the early stages of the disease. As the diseases progress it causes damage to both the eyes and causes the loss of sight which cannot be retained.

When the sugar levels in the blood are too high for a long period of time it causes damage to the tiny blood vessel which are called capillaries, which supply blood to the retina. These blood vessels begin to leak fluids and fats that lead to edema (swelling) which eventually causes these blood vessels to close off, called ischemia. The initial stage of the diabetic retinopathy is called background retinopathy which is also called as non-proliferative retinopathy. As diabetic eye problems are left untreated it could lead to Proliferative Diabetic Retinopathy (PDR).

Once the blood vessels are blocked due to ischemia it leads to the growth of new abnormal blood vessels in the retina which could lead to blurness is called Neovascularization. Neovascularization can cause damages to the retina through wrinkle or retinal detachment that may lead to glaucoma that causes damage to the optic nerve that carries images from eye to brain. To prevent diabetic retinopathy and vision loss blood sugar and blood pressure levels to be maintained strictly. As diabetic is a risk factor for cataracts, it can be prevented by controlling blood sugar and also regular screening of the eye.

1.2 TYPE OF DIABETIC RETINOPATHY

There are two types of diabetic retinopathy. They are background (nonproliferative) diabetic retinopathy and Proliferative diabetic retinopathy.

1.2.1 Background or Nonproliferative Diabetic Retinopathy (NPDR)

Early stage of diabetic retinopathy is known as Background or No Proliferative Diabetic Retinopathy (NPDR). At this stage blood vessels in the retina weaken begin to leak extra fluid and small amounts of blood into the eye also the other fats from the blood may leak into the retina. This leakage of blood vessels led to swelling (edema) in the retina and vision may be blurred or change. About one in five people with diabetics suffers from this problem. Mild NPDR does not affect the vision but once the diabetic gets severe it causes loss of vision.

NPDR can cause changes in the eye, including:

- Microaneurysms: small balloon like swelling in blood vessels of the retina that often leak fluid.
- Retinal hemorrhages: leakage of tiny spots of blood into the retina.
- Hard exudates: leakage of deposits of cholesterol or other fats from the blood into the retina.
- Macular edema: Due to the fluid leakage from the retina's blood vessels swelling or thickening of the macula occurs. When the macula gets swollen it doesn't function properly and cause vision loss.

- Macular ischemia: As small blood vessels blocks it leads to blurred vision and the macula no longer receives enough blood to work properly.

At this stage the damage is mild which can get severe as the disease progress. It occasionally progresses quickly, but usually changes slowly. The diabetes and blood pressure are to be well controlled, and as the diabetic last all the time the changes should be very slow and controlled. Unfortunately retinal damage increases, and maculopathy or proliferative retinopathy develop for many people with diabetes the over a few years. Retinopathy progresses in many different patterns. For example few patients develop leakage through blood vessel and others develop block of blood vessel which also causes blindness. The progression can be indicated through number of haemorrhages and microaneurysm. The retinopathy gets worse if the number of haemorrhages and microaneurysm. Progression gets slower when blood pressure drops below the targets.

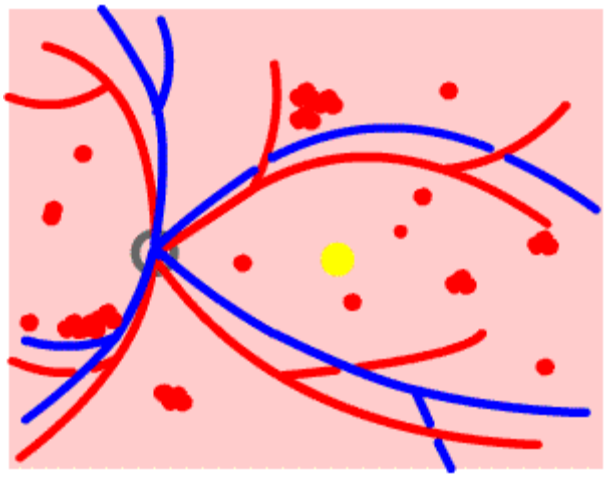


Figure 1.1 Microaneurysm Progressions

As the year passes retina has been damaged by the higher than normal sugar level, this condition is called pre-proliferative. In Figure 1.1, there are lot of haemorrhages which indicates severe forms of pre-

proliferative retinopathy as the retina is very ischaemic. To prevent the growth of new blood vessel laser treatment is needed. Proliferative retinopathy affects one eye if the other eye has already developed new vessels. In such case asymmetric is rarely possible where Anti-VEGF treatment may be helpful. Some clinics have replaced laser with Anti-VEGF injections. Initially small haemorrhages such as flecks of blood and tiny abnormal blood vessels occurs as the disease gets severe there are lots of haemorrhages and new vessels may grow. Hence there will be some damage to the tiny retinal vessels, such as intra-retinal-microvascular abnormalities (IRMAs') and there may be cotton wool spots which is indicated as areas of retinal damage.

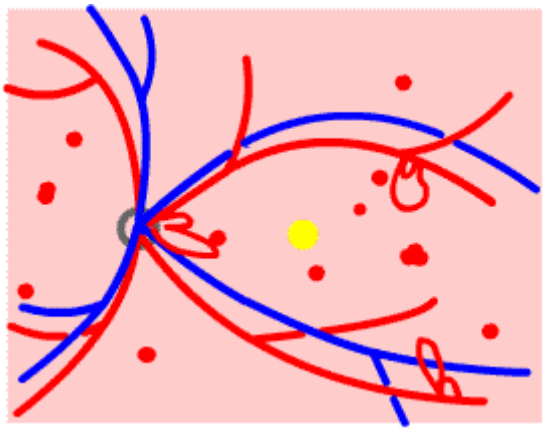


Figure 1.2 Intra-retinal-microvascular abnormalities

In Figure 1.2, a new blood vessel which is indicated in red grows in the front of the retinal surface. The new vessel growth in diabetes occurs in the retina and no other parts of the body. When a retina becomes damaged by a higher than normal sugar, over many years, it seems to release special growth hormones. Vascular Endothelial Cell Growth Factor is one of the main growth hormones. It seems to be manufactured and released by 'sick' retinal capillaries, and in turn makes other capillaries grow. This seems to be an exaggeration of one of the body's normal responses as the retina becomes

starved of nutrients, and then the retina makes chemicals that make new blood vessels grow to deliver more nutrients. The tiny laser burns allow more oxygen and nutrients to reach the retina, and this improves the retinal circulation. The retina then stops making the growth substances, and the 'new vessels' close up as a result. As prevention is better than cure, the blood glucose and pressure has to be controlled. In order to stop the growth of the new blood vessel laser treatment is very effective, it sometimes requires several laser session.

The new blood vessels may usually start to grow again in 4 to 8 months it requires more laser. 2 to 3000 or so light laser shots are applied to each eye at each session, but for an average insulin-dependent person about 5 sessions may be needed. After laser treatment regular examination of eye is needed. Angiogram shows there were no new vessels which can be seen through fundus photographs.

1.2.2 Proliferative Diabetic Retinopathy (PDR)

As the retinopathy advances blood vessels gets blocked or closed and it decreases the circulation of blood and oxygen which leads to the proliferative diabetic retinopathy. A new abnormal blood vessel grows to supply blood to the parts of retina where the original blood vessels closed and this is called neovascularization. These new blood vessels are also often accompanied by new tissue that may cause the damage to the retina. Proliferative retinopathy affects about one in 20 people with diabetes and can lead to severe loss of sight. As abnormal vessel growth continues it may cause glaucoma and other retinal damages. When compared with Proliferative Diabetic Retinopathy, Non Proliferative Diabetic Retinopathy is severe because it affects both central and peripheral vision.

PDR affects vision in number of ways such as:

- **Vitreous haemorrhage:** The gel in the centre part of the eye is called vitreous. As blood vessels bleeds into vitreous sit prevents light rays from reaching the retina and causes blindness. It does not create permanent vision loss as the blood is cleared vision may be retained, until the macula is not damaged.
- **Traction retinal detachment:** As the scar tissue from neovascularization shrinks it causes the retina to wrinkle. Vision can be severely affected and it may let to blindness if the macula and the large part of the retina are damaged.
- **Neovascular glaucoma:** Iris is responsible for colour pigment in eye. Neovascularization occurs as more number of retinal vessels is closed in the iris. As New abnormal blood vessels may block the normal flow of fluid in eye it builds up pressure in the eye and causes damage to the optic nerve.

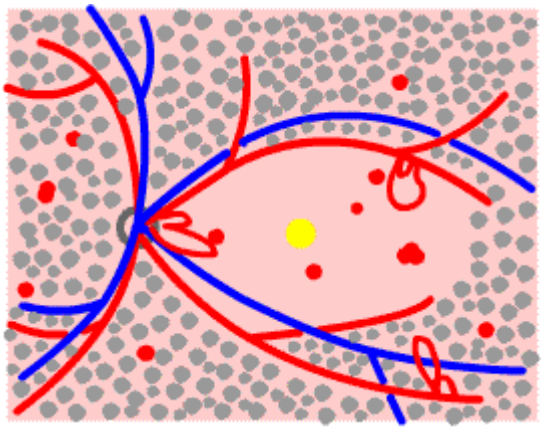


Figure 1.3 Severe proliferative retinopathy

In Figure 1.3, when the eye is affected by severest type of proliferative retinopathy, a lot of Anti-VEGF injections and laser will be needed over the years. The side vision and night vision may be badly affected. In 2016 Anti-VEGF injections got much better result than which has

been done previously, and expected to keep good vision. It has achieved best result for many patients with type 1 diabetes as they are benefited from an insulin pump,

Even though after the Anti-VEGF injections or laser treatment, the blood vessels still continues to grow despite they may bleed, causing haemorrhages such as this subhyaloid haemorrhage. More bleeding leads to vitreous haemorrhages. This makes it difficult to see like looking through cobwebs. A fluorescein angiogram is used to detect the areas of non-perfusion, but it can be estimated clinically. An angiogram is therefore seldom required prior to laser for proliferative retinopathy.

1.3 FUNDUS PHOTOGRAPHY

Fundus photography is used to documents the details of retina and the neurosensory tissue in the eyes which translates the optical images into the electrical impulses and sends to brain. The retina can be photographed directly as the pupil using light rays. The patient has to sit in front of fundus camera with their forehead against the bar to capture the retinal image. The light is focused into eye and aligns the fundus camera; a flash fire as the button is pressed and the shutter release to create a fundus photograph. These retinal photographs are used by Ophthalmologists to diagnose and treat eye diseases. Colour filters or dyes such as fluorescein and indocyanine green are used by fundus photography.

A fundus camera is nothing but a specialized low power microscope with an attached camera in it. Fundus cameras are described by the angle of view that is the optical angle of acceptance of the lens. The normal angle of view is of 30° and creates a film image 2.5 times larger than life. Fundus cameras can capture wide angle images between 45° and 140°

and provide proportionately less retinal magnification. A narrow angle fundus camera has an angle of view of 20° or less.

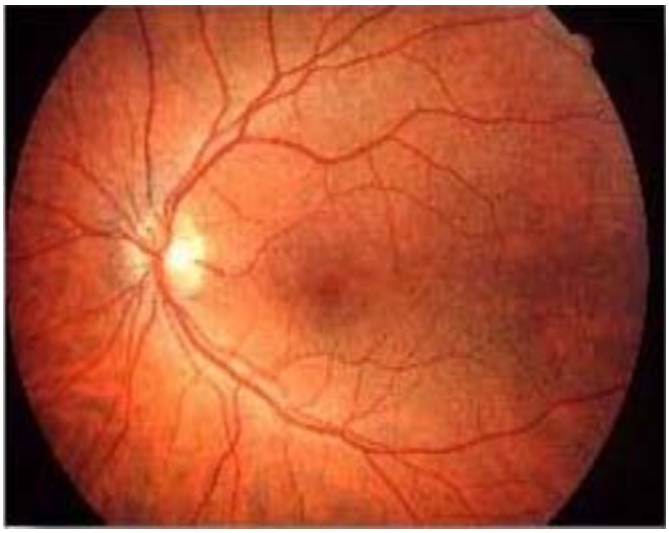


Figure 1.4 Normal Fundus Photograph

To place two images side by side as one exposure on a single 35mm frame Simultaneous stereo fundus cameras is used. In Figure 1.4, Electronic flash or viewing lamp is used as light source to generate light which is then projected into a round mirror through a set of filters. The round mirror reflects the light into a series of lenses which focus the light. To shape the light into a doughnut a mask is placed on the uppermost lens. The doughnut shaped light is reflected onto a round mirror with a central aperture which exits the camera through the objective lens and proceeds into the eye through the cornea.

The current ophthalmoscopic appearance of a patient's retina is visually documented as Fundus Photographs. To make a detail study of retina and to identify the changes in the retina these fundus photographs play a vital role. Here for example, the image of the retina affected by glaucoma it taken. In Figure 1.5 shows that the increased pressure in the eye which causes damage to the optic nerve is termed as Glaucoma. By using fundus

photographs changes in the optic nerve can be noted and proper diagnose can be done.

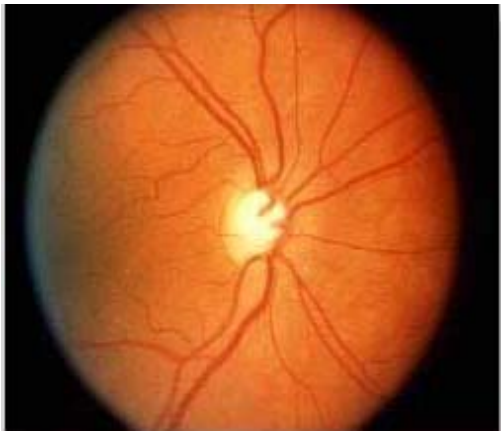


Figure 1.5 Glaucoma

Fundus photography is also used because it is easier to visualize the details the retina than direct examination also certain retinal landmarks that can be seen in fundus image are not clearly visible on fluorescein angiogram. In Figure 1.6 indicates that the diabetic retinopathy is nothing but the damage to the retina from diabetes such as blood vessel leakage, swelling and blocks can be seen clearly through fundus photographs and can be used for future diagnose purpose.

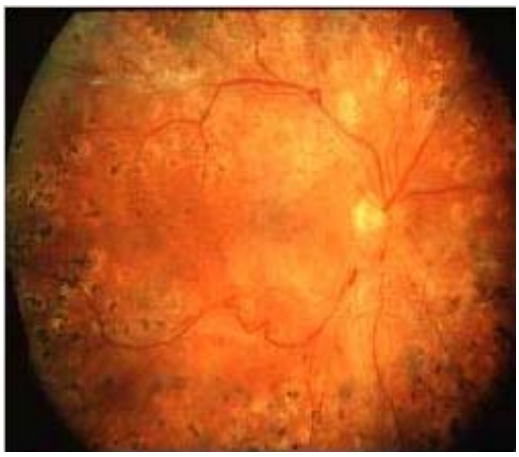


Figure 1.6 Diabetic Retinopathy

Optical coherence tomography is a camera that instantly captures cross-section view and sub-surface view of retina. Initially the light is focused through series of lens and then it is shaped as doughnut which is then passed through central aperture before passing through lens and retina. The light is then passed through un-illuminated hole formed by illumination system. Reflection of light is minimal because the light path of two systems is different and independent. As the image forming rays heads towards low powered telescopic eyepiece and when the button is pressed to capture picture, the mirror is interrupted in the path of illumination system which allows the light to pass from flash bulb to eye. As the mirror falls in front of observation telescope it redirects the light into capturing medium such as film or digital CCD, finally the focus image is formed on capturing medium.

Figure 1.7 Optical coherence tomography

In Figure 1.7 shows the Practical instruments for fundus photography perform the following modes of examination:

- Colour: To examine retina in full colour it is illuminated by white light.
- Red free fundus photography: Here filter is used in order to observe the lesions and other vascular abnormalities within the retina and the surrounding tissue. A green filter of about 540-

570 nm is used to block out the wavelength of red light. Hence a better contrast for viewing retinal blood vessels and associated hemorrhages and lesions such as drusen and exudates, and other nerve fibre layer defects and membranes is possible. This method is considered as superior method of observing colours in diabetic retinopathy progression assessment. Red free photography is a base line used regularly prior to Angiography.

- Angiography: It is a process in which fluorescent dye is injected into the blood stream for photographing or recording vascular flow within the retina and surrounding tissue. Light of specific wavelength when reaches the dye fluorescent it changes to a different colour. Barrier filters are employed to allow the auto fluorescent wavelengths of light to be photographed. As a result of this method number of photographs can be produced which show the movement and pooling of blood over a time as the dye passes though the retina and choroid. Angiography is further classified as two types as below:
- Sodium Fluorescein Angiography: This method utilizes blue excitation light of about 490 nm and yellow light of about 530 nm for imaging of retinal vascular disease. This method is routinely used to capture image of Macular defects and Diabetic Retinopathy among others.
- Indocyanine Green Angiography: This method utilizes near-infrared diode laser of about 805 nm and barrier filters that allow light of about 500 and 810 nm for imaging deeper choroidal diseases and to photograph it. ICG is useful for seeing choroidal vessel out pouching in choroidal vasculopathy, abnormal vessels supplying ocular tumors.

In fundus images artifact errors occurs while capturing the image. It depends on the factors such as captured image through the improper set up and alignment, patient, examiner and the fundus camera. Along with this patient cooperation and attitude are important to minimise the artifacts. One of the important tasks of the clinician is to ensure that the patient has understood the instruction clearly. Each of these factors must be taken into account when evaluating a fundus photograph. However some artifacts are not visible until the film is captured and normally this can be caused either from a mechanical problem in the camera or pupil size and blinking of the patient's eye.

The image captured when the patient blinks his eye leads to blurred and incomplete fundus image but it is not possible to instruct the patient not to blink when the fundus photo is taken. The patient may blink at any time to prevent the drying of the eye because a dry eye may also lead to a blurred fundus photo. So the patient is asked to blink several times to lubricate the eye before capturing image. While capturing the image correct alignment is more important and the picture is to be in clear focus. Joystick can be moved forward and backward if the fundus is not properly focused to capture the image appropriately. Once the image is in clear focus and proper alignment picture can be taken finally.

1.4 ANATOMY OF THE EYE

Our eyes are the most important sense organ. As the light enters the eye through the pupil vision is created. As lens in the camera play a vital role to send message to produce image on the film, the lens in the eye refracts the incoming light into the retina. The retina is made up by millions of specialised cells called rods and cones, that works together to transform the image into electrical energy, which is further sent to the optic disk on the retina.

Electrical impulse is transferred via optic nerve to be further processed by the brain. The Figure 1.8 shows the major parts of the eye.

1.4.1 Major Parts of the Eye

- **Iris:** As light enters the eye it gets regulated by iris. It is responsible for the colour and it is the visible part of your eye in front of the lens.
- **Pupil:** It is the centre part of the iris through which light enters the lens of the eye. The iris controls widening and narrowing (dilation and constriction) of the pupil.
- **Cornea:** the circular part of the front of the eyeball which is very transparent is called cornea. It refracts the light entering the eye onto the lens, which then focuses it onto the retina. The cornea is extremely sensitive to pain and contains no blood vessels.
- **Lens:** a transparent structure situated behind your pupil. It is enclosed in a thin transparent capsule and helps to refract incoming light and focus it onto the retina. A cataract is when the lens becomes cloudy, and a cataract operation involves the replacement of the cloudy lens with an artificial plastic lens.
- **Choroid:** the middle layer of the eye between the retina and the sclera. It also contains a pigment that absorbs excess light so preventing blurring of vision.
- **Ciliary body:** the part of the eye that connects the choroid to the iris.
- **Retina:** a light sensitive layer that lines the interior of the eye. It is composed of light sensitive cells known as rods and cones.

The human eye contains about 125 million rods, which are necessary for seeing in dim light. Cones, on the other hand, function best in bright light. There are between 6 and 7 million cones in the eye and they are essential for receiving a sharp accurate image and for distinguishing colours. The retina works much in the same way as film in a camera.

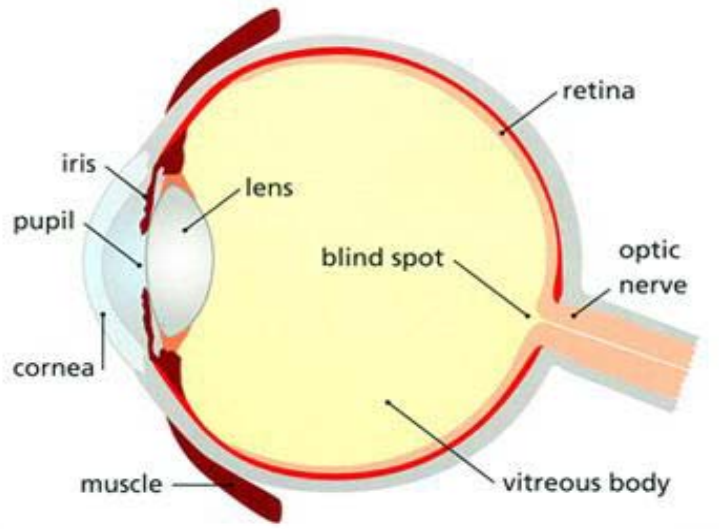


Figure 1.8 Anatomy of the eye

- **Macula:** a yellow spot on the retina at the back of the eye which surrounds the fovea.
- **Fovea:** forms a small indentation at the centre of the macula and is the area with the greatest concentration of cone cells. When the eye is directed at an object, the part of the image that is focused on the fovea is the image most accurately registered by the brain.
- **Optic disc:** the visible (when the eye is examined) portion of the optic nerve, also found on the retina. The optic disc identifies the start of the optic nerve where messages from cone and rod cells leave the eye via nerve fibres to the optic

centre of the brain. This area is also known as the 'blind spot'.

- **Optic nerve:** leaves the eye at the optic disc and transfers all the visual information to the brain.
- **Sclera:** the white part of the eye, a tough covering with which the cornea forms the external protective coat of the eye.
- **Rod cells** are one of the two types of light-sensitive cells in the retina of the eye. There are about 125 million rods, which are necessary for seeing in dim light.
- **Cone cells** are the second type of light sensitive cells in the retina of the eye. The human retina contains between six and seven million cones; they function best in bright light and are essential for acute vision (receiving a sharp accurate image). It is thought that there are three types of cones, each sensitive to the wavelength of a different primary colour – red, green or blue. Other colours are seen as combinations of these primary colours.

1.4.2 Effect and the Treatment of Retinopathy

Diabetic retinopathy has various stages depending on the how the disease has affected the vision of the patient. Early stage of the disease has no symptoms but as the disease gets severe there are few common symptoms such as blurred or unclear vision it is closely related with glucose levels of blood, flashes and sudden blindness. Diabetes may also cause other eye symptoms such as swelling and macular edema. As the fluid leaks from the blood vessel into the macula, which is the centre part of the eye where the pointed, clear and detailed vision occurs it gets swelled as a result it blurs the vision. People affected with proliferative retinopathy will soon have the

disease macular edema. Macular edema can occur at any stage of the disease as it gets progresses.

For nonproliferative retinopathy no treatment is needed until it has macular edema. As the disease gets progress to next stage such as proliferative or severe nonproliferative retinopathy recommended treatment is necessary. Using laser therapy vitreous hemorrhage or macular edema can be cured or progression can be slow down by shrinking the abnormal blood vessels. Treatment has best result before the new blood vessels start to bleed, but if it starts to bleed treatment can be done accordingly depending on the rate at which it bleeds. Vitrectomy is a kind of treatment done if the bleeding occurs at vitreous. Here the blood is removed from the centre of the eye and can be replaced with saline. The vitreous strands in the retina that causes tears in the eye and create traction which may even cause retinal detachment can be removed through surgery.

Symptoms of retinopathy can include:

- Vision gets blurred.
- At field of vision flashes of light may occur.
- Sudden blindness.
- At vision there may be spots.

1.5 THE RETINA

Light enters the eye from the left as shown in the Figure 1.9 by the yellow arrow. It passes through the clear jelly of the eye known as vitreous to reach the retina indicated in pink colour.

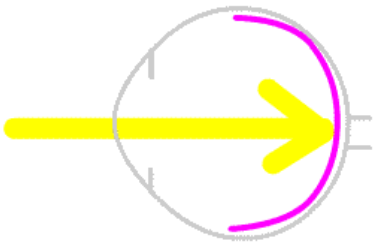


Figure 1.9 Light enters the eye from the left

Quarter of the people with the disease diabetic has been affected with retinopathy. The cells that convert the light into the electric signals are present at the retina which sends these signals to the brain through optical nerve.

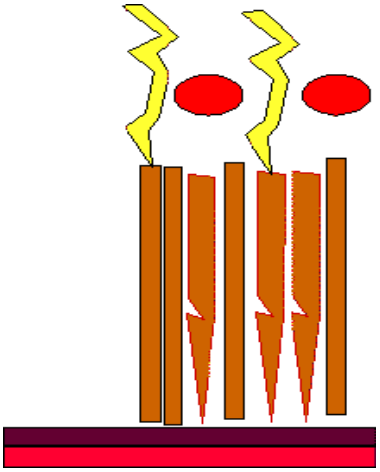


Figure 1.10 Light (yellow) falls onto the retina

In Figure 1.10, Light (yellow) falls onto the retina. The rods (the long straight cells) and cones (the cells with the pointed end) are the retina cells. The red ovals on the surface are tiny blood vessels (capillaries).

Retina in diabetes: When the sugar level in blood is high it leads to the diabetic. As the year passes the high sugar level can lead to the damage of the tiny blood vessels. If diabetic is for very long period that is of about 14 years or more likely this is to happen. The damaging process has three basic components. They are the leakage of blood vessels, special growth substance that makes other vessels grow, the vessels may gradually close and block.

The high glucose and blood pressure level at the blood causes damage to the tiny blood vessel in the retina and leads to diabetics.

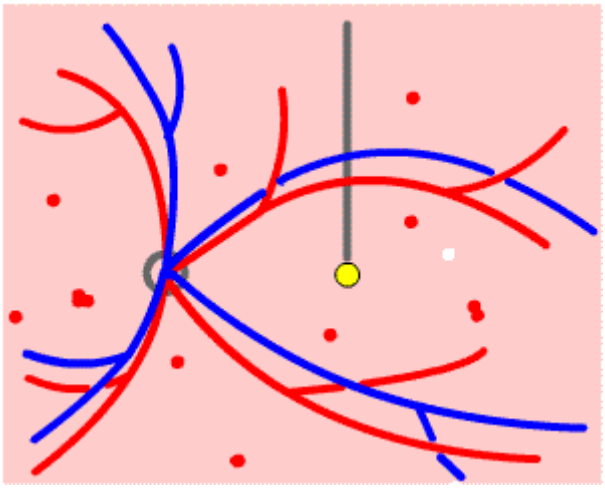


Figure 1.11 Small red dots damaged blood vessel

The small red dots are the damaged tiny blood vessel (Figure 1.11) commonly known as Microaneurysms. The large red blobs indicate small blood clot. The vision will not be affected at this stage. At the early stage damage to the retina is not that severe. Only few abnormalities are found in this stage which does not cause permanent loss of sight.

The four biochemical pathways lead to tissue damage. Cell tight junctions fail, permeability increases, cells swell, there is leukocyte infiltration, and then tissues may not get sufficient oxygen.

During the background or mild non-proliferative retinopathy the functions of retinal gradually starts to reduce. The capillary blood vessels blocks as the white blood cells stick to the capillary blood vessel walls. This further increases the shortage of oxygen in the tissues.

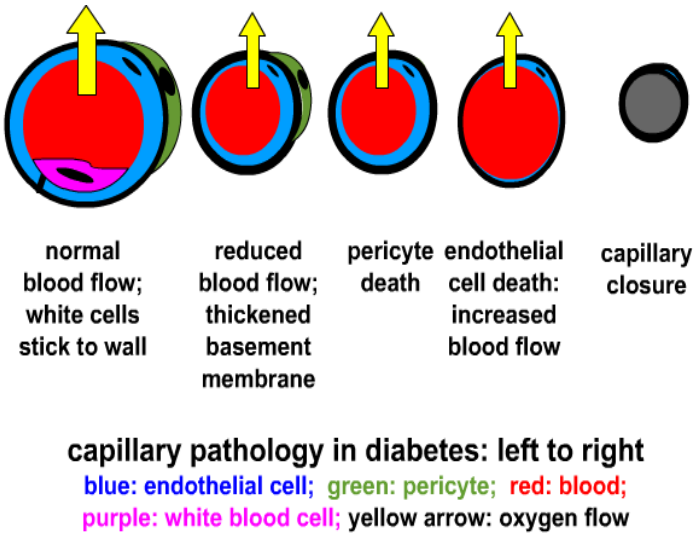


Figure 1.12 Pre-proliferative or moderate non-proliferative retinopathy

In Figure 1.12, pre-proliferative or moderate non-proliferative retinopathy the retina starts to increase blood flow through the larger blood vessels. As the white blood cells sticks to the walls of capillaries it develops thicker cell wall (membrane). The cells that support the blood vessel wall are

called Pericytes which will start to die during this stage. Due to the leakage of blood vessel which is called macula oedema and deposit on the wall will lead to the capillary block and only a very small amount of oxygen will reaches the retinal cells.

The new blood vessels grow as the result of more leakage of blood form the neighbour blood vessel. The sponge or swelling may arise due to the leakage of large quantity of fluids from blood vessels into eye. At the same time control of blood flow to the retina is faulty and blood flow to the retina increases. This naturally increases the retinal leakage further. As the blood vessel swells it become very weak and it either let fluid inside or outside the blood vessel which finally affects the vision loss.

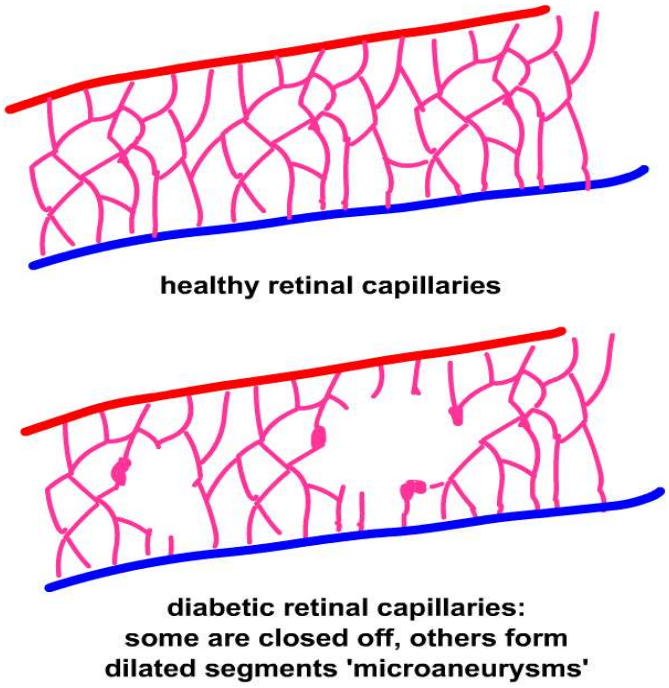


Figure 1.13 Retinal capillaries

In Figure 1.13, due to the endothelial cells produce VEGF and this stimulates other tiny blood vessels to grow. The new vessels are very delicate and can very easily bleed which can damage the eye very severely. After the

proliferation stage it is followed by scar formation. The centre part of the eye called the vitreous gel starts to shrink and which leads to the pull the retina off. The growth of new blood vessels and the leakage of the blood vessel can be prevented by using laser. An anti-VEGF drug is used to cure the diabetics by injecting it through injection. It is used to block the effect of VEGF and ceases the new vessels growing also it reduces retinal leakage for time being. When the tiny blood vessels are badly affected by diabetics it may gradually close and block the blood vessel. Hence the complete nutrients will not be able to reach the retinal which lead to the ischaemic macular disease.

1.6 OTHER FEW DISEASES AFFECTING THE EYES

1.6.1 Glaucoma

Glaucoma is a disease that damages the eye's optic nerve and can result in vision loss and blindness. With early detection and treatment the eyes can be protected against serious vision loss. It is shown in many large studies that eye pressure is a major risk factor for optic nerve damage. Anterior chamber is the space in the front of the eye. To nourishes nearby tissues a clear fluid flows continuously in and out of the chamber. At the open angle where the cornea and iris meet the fluid leaves the chamber. As the fluid reaches the angle, it flows through a spongy meshwork, like a drain, and leaves the eye.

In open-angle glaucoma, the fluid passes too slowly through the meshwork drain even though the drainage angle is open. The fluid builds up the pressure inside the eye which rises to a level that may damage the optic nerve. Controlling pressure inside the eye is important as it damages the optic nerve causes the vision loss. The pressure level at the blood is very important to be maintained properly or else it may lead to the series problem of retina and damage of the optic nerve.

In Figure 1.14, Glaucoma is detected through eye examination that includes the following:

Visual acuity test: The ability to see how well you see at various distances is measured through eye chart test.

Visual field test: It measures the ability of your peripheral that is the side vision. The loss of peripheral vision is a sign of glaucoma.

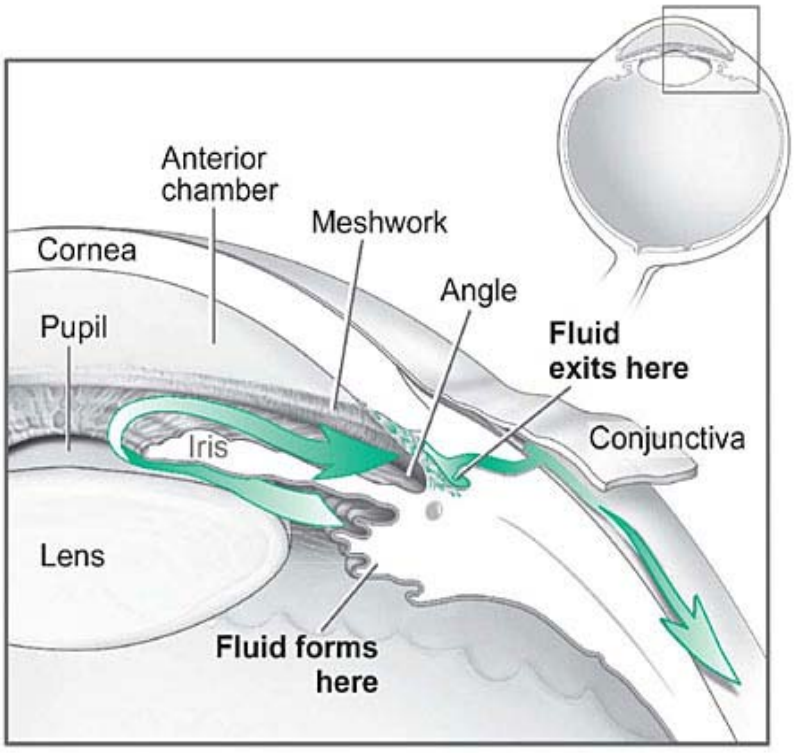


Figure 1.14 Glaucoma detected through eye examination

Dilated eye exam: During this test drops are placed in the eyes to broaden and dilate the pupils. Then a special magnifying lens is used to examine the retina and optic nerve to detect the signs of damage and other eye

problems. For several hours after the examination of eye close-up vision may remain blurred.

Tonometry is the method to measure the pressure inside the eye by using a device called a tonometer. The drops are applied to the eye to make it senseless and pressure inside the eye to detect glaucoma.

Pachymetry is the method to measure the thickness of the cornea. The eye care professional applies a numbing drop to the eye and uses an ultrasonic wave instrument to measure the thickness of your cornea.

Glaucoma can be cured through medicines such as drops, laser treatment and through surgery. Through these treatments only the remaining vision can be saved but they do not retain the vision which is already lost from glaucoma.

Medicines: Medicines such as eye drops or pills are most commonly used treatment for glaucoma during the early stage. These eye drops lowers the eye pressure when taken regularly. Few medicines can lower pressure inside the eye by helping fluid leakage out from the eye. Most people have no side effect problems. However, few medicines cause headache or other side effects such as causing stinging, burning, and redness in the eyes. There are many medicines available to treat glaucoma. If side effects result with one medicine, treatment with a different dose or a new medicine may be possible. Glaucoma often has no symptoms hence people may be tempted to stop taking or may forget to take the medicine. The drops or pills have to be taken as long as they help control the eye pressure. Make sure that the eye care professional instruct how to put the drops into the eye. For tips on To use glaucoma eye drops tips to be seen inside the back cover of the booklet.

Laser trabeculoplasty: Laser trabeculoplasty is a kind of treatment that helps the fluid to drain out of the eye. In many cases glaucoma medicines has to be taken after this procedure. Before starting the surgery, drops are applied to make the eye senseless. The patient sits facing the laser machine where the doctor holds a special lens to the eye. A beam of high intensity of light is aimed through the lens and reflected into the eye where flashes of bright green or red light are seen. The drainage holes in the meshwork are stretched through laser that makes several evenly spaced burns this allows the fluid to drain better. Laser surgery can cause side effect to the patient. Some drops are given to cure the side effects inside the eye also several visits to hospital have to be done to check eye pressure and eye monitored. If both the eyes are affected by glaucoma, both cannot be treated together. Laser treatment for each eye has to be scheduled several days or weeks apart. It is very good to reduce the pressure in the eye using laser surgery.

Conventional surgery: The new opening to leave the fluid out the eye can be done by conventional surgery. Only after the failure of medicines and laser surgery, the conventional surgery is often done to control pressure. Conventional surgery is also called trabeculectomy, which is performed in an operating room. Before the surgery small injections around the eye to numb it along with it medicine is given to help the patient to relax. To drain the fluid out of the eye a small piece of tissue is removed and new channel is created. After the surgery for several weeks eye drops must be used to prevent infection and inflammation. The drops used before and after the surgery is different from each other. Conventional surgery can be performed only on one eye where the other eye is treated only after few weeks of time apart. Conventional surgery is 60 to 80 percent effective for lowering the eye pressure. Suppose the new drainage opening becomes narrower a second operation is necessary. Conventional surgery works best if you have not

undergone any previous eye surgery like cataract operation. In few cases side effect of conventional surgery may reduce the vision power.

1.6.2 Other Forms of Glaucoma

Low-tension or **normal-tension glaucoma**: The optic nerve gets damage and the side vision becomes narrower for the people with normal eye pressure and causes low tension or normal tension glaucoma. For around 30 percent of the people the pressure in eye is reduced through medicines. Glaucoma may get worse other than that of low pressures. The treatment for low-tension glaucoma is as same as for open-angle glaucoma.

A**ngle-closure glaucoma**: Here the angle gets blocked by the parts of iris and so the fluid at the front of the eye cannot drain through that angle. People affected with this type of glaucoma may have a sudden increase in their eye pressure. Symptoms for this type of glaucoma include severe pain and nausea, redness of the eye and blurred vision. The eye can become blind without the treatment to restore the flow of fluid. Laser surgery and medicines can clear the blockage, lower eye pressure, and protect vision.

Congenital glaucoma: The children are born with a defect in the angle of eye that slows the normal drainage of fluid in it leads to the congenital glaucoma. The children affected with this disease usually have symptoms such as cloudy eyes, sensitivity to light, and excessive tearing. Medicines are not effective and can cause more serious side effects in infants and be difficult to administer hence conventional surgery is the effective method to treat this disease. As the surgery is done successfully, these children can have an excellent chance of retaining good vision.

Secondary glaucoma: This type of disease can develop as complications of other medical conditions. The advanced form of glaucoma is

called **neovascular glaucoma** and it is resulted from poorly controlled diabetes or high blood pressure. The other types of glaucoma sometimes occur with cataract, eye tumours and inflamed or irritated by a condition called uveitis. Glaucoma can also be develops after eye surgeries or serious eye injuries. Few drugs which are used to treat eye diseases can trigger glaucoma.

Secondary glaucoma caused by two eye conditions: **Pigmentary glaucoma** occurs when pigment from the iris blocks and slows the fluid drainage. **Pseudo exfoliation glaucoma** occurs when extra material is produced and shed off internal eye structures and blocks the meshwork which again slows fluid drainage. Depending on the cause for secondary glaucoma, treatments are included medicines, laser surgery, or conventional or other glaucoma surgery.

1.7 AGE RELATED MACULAR DEGENERATION

Age Related Macular Degeneration is a common eye disease and a leading cause for vision loss among people of age about 50 and older. It causes damage to the macula which is a small spot near the centre of the retina and the parts of the eye needed for sharp and central vision. This disease progress slowly so that vision loss does not occur for a long time in some cases. In other cases the disease progresses faster and may lead to a loss of sight in one or both eyes. A blurred vision which occurs due to damage of centre vision is a common symptom to indicate the progress of the disease. As the result blurred area may grow larger and larger which lead to the development of blank spots in your central vision. Also the vision may not appear to be as bright as they are used to be and leads to complete blindness, with no ability to see. The loss of central vision in AMD can interfere with day to day activities, such as the ability to see faces, drive, read, write, or do close work, such as cooking or fixing things around the house.

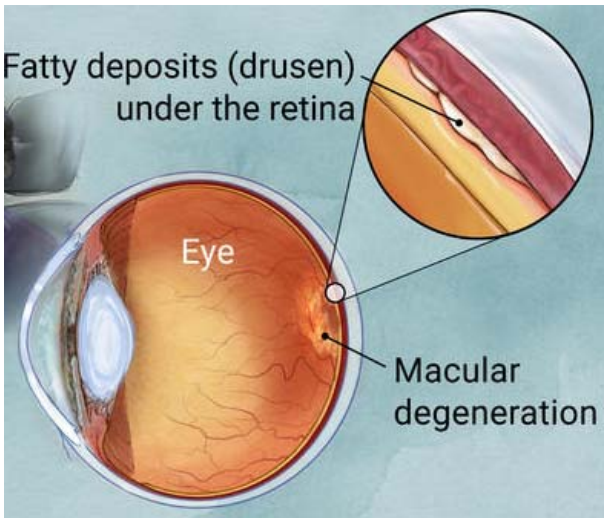


Figure 1.15 Macula

In Figure 1.15, the macula is made up of millions of light-sensing cells that provide sharp and central vision. Macula is the most sensitive part of the retina which is located at the back of the eye. The electrical signals are produced from the light in the retina and are sent to the brain through the optic nerve. In brain they are translated into the images which we are able to see. When macula gets damaged the centre of the field of view may appear blurry, distorted, or dark.

Age is a major risk factor for AMD. This disease most likely affects the people of age 60 it can also occur earlier. Other risk factors for AMD include:

Smoking: Research showed that smoke has double the risk of AMD.

Race: AMD is more common among Caucasians than among African-Americans or Hispanics/Latinos.

Genetics: People with a family history of AMD are at high risk. Researchers had identified nearly 20 genes that can affect the risk of developing AMD. Because AMD is influenced by so many genes plus environmental factors such as smoking and nutrition, there are currently no genetic tests that can diagnose AMD or predict who develop it.

Researchers have found links between AMD and some lifestyle choices like smoking. Hence it is able to reduce the risk of AMD or slow its progression by making healthy choices such as:

- By avoiding smoking
- To exercise regularly
- To maintain normal blood pressure and cholesterol levels
- To have healthy diet rich in green, leafy vegetables and fish.

The early stage and the intermediate stages of AMD usually start without any symptoms. The eye exam includes the following:

- **Visual acuity test:** This test measures how well the eyes can view at various distance using eye chart.
- **Dilated eye exam:** In this type of test eye care professional places drops in the eyes to widen or dilate the pupils. Through which it provides a better back view of the eye. A special magnifying lens is used to look at the retina and optic nerve to detect the signs of AMD and other eye problems.
- **Amsler grid:** In this method eye care professional instruct a patient to look into an Amsler grid. Any changes in central vision cause the lines in the grid to disappear or appear wavy which is indicated as a sign of AMD.

- **Fluorescein angiogram:** In this test a fluorescent dye is injected and as it flows through the blood vessels in the eye it capture image. Through this it is possible to detect leakage of blood vessel which occurs as AMD progresses. In rare cases side effect may occur due to the injection such as allergic reactions.
- **Optical coherence tomography:** Here ultrasound method is used, which uses sound to take picture of living tissues. OCT is similar except that it uses light instead of sound, to capture images of tissues. After the eyes are dilated the images are obtained through passing light and this type of light beam is painless.

During the examination of eye the professionals will look for yellow deposits beneath the retina. Many people develop this disease as a part of aging but the presence of large drusen may indicate AMD. There is also another sign of AMD which is change in the pigment appearance under the iris. In addition to the pigmented cells in the iris there are also pigmented cells beneath the retina. As these cells break down and release their pigment adark clumps is seen.

1.7.1 AMD Stages

There are of three stages in AMD, defined by the size and number of drusen under the retina.

- **Early AMD:** Early AMD will not cause vision loss. It is detected by the presence of drusen which are about the width of an average human hair.
- **Intermediate AMD: During this stage of Intermediate AMD most people do not have any symptoms**. People with intermediate

AMD typically have large drusen and pigment changes in the retina which can only be detected during an eye exam.

- **Late AMD: During this stage macula gets damaged due to larger sized drusen and which leads to the vision loss.** There are two types of late AMD:
    - Geographic atrophy: This type of AMD is also called dry AMD where there are light breakdown of the cells in the macula, and communicate to the visual information to the brain and supporting tissue below the macula. These changes lead to loss of sight.
    - Neovascular AMD: This type of AMD is also called as wet AMD where abnormal blood vessels grow underneath the retina. The new vessels can leak fluid and blood, which may lead to swelling and damage of the macula. The damage may be rapid and severe than the gradual course of geographic atrophy. There is large possible to have both geographic atrophy and neovascular AMD on the same eye.

Patient affected with early AMD will not probably be affected with late AMD. For example people who have early AMD in one eye and no signs of AMD in the other eye. But after 10 years about five percent will develop advanced AMD. For people who have early AMD in both eyes, about 14 percent will develop late AMD in at least one eye after 10 years. Once when AMD is detected further steps can be taken to reduce loss of sight from late AMD. People with late AMD in one eye will be able to do their day to day so they do not notice changes in the overall vision. As this continues it may soon lead to the late AMD in other eye.

CHAPTER 2

LITERATURE SURVEY

2.1 DIABETIC RETINOPATHY (DR) CAD METHODS

The algorithms that are utilized for the purpose of extracting features from images of digital fundus have been reviewed by Faust, Oliver, et al. (2010). Also the systems that make use of these features for the classification of images with individual fundus are discussed. The efficiency of classification of various DR systems is also discussed. Many of the systems that are reported are optimized to a great extent with regard to the images of analyzed fundus and so an individual result generalization is challenging. But this review proves that the results from these classifications have recently improved and is also getting further close to the capabilities of classification of ophthalmologists.

A demonstration was made by Rema & Pradeepa (2007) stating that 7 percent DR is present in subjects that are newly diagnosed and therefore a routine screening of retina for the DR even for cases of type 2 diabetes can be helpful in a laser therapy that is optimized. A retinal examination made annually through which an early detection is possible especially in cases of type 2 diabetes can bring down the risk of loss of eyesight. Additionally, the systematic considerations controlled systematically that can affect the onset as well as the progression of DR through a

multidisciplinary approach of health care that can remarkably bring down DR related visual impairment.

Mahar et al. (2010) identified a frequency for type-II Diabetes mellitus or DM in the population that is endogenous in the town of Gaddap and to further evaluate DR or Diabetic retinopathy for this group. This study was made based on community for both genders by establishing three centers for eye care with PHC facilities targeting the population of people above the age of 30. Those patients that needed intervention were accordingly managed. The data was first entered and later analyzed by using Microsoft Access and Microsoft Visual Basic 6. The results proved the importance of early screening of conditions of DR mainly for people that had DM for both its management and if possible prevention of complications that can be sight threatening preferably in the early stages of the disease and also reiterates the importance of primary care for the eye as a part of this system.

An automated technique for the identification of the stages of DR by using simple techniques of data mining and processing of image was proposed and presented by Acharya et al. (2009). Here the processing of images morphologically and techniques that used the SVM or the support vector machine was used for diagnosing health of the eyes automatically. This can identify various stages with an accuracy of above 85 percent, sensitivity of above 82 percent and a specificity of over 86 percent. The improvement in performance is increased further with the help of better features and diverse data.

Acharya Rajendra et al. (2008) made a proposal for automatic identification of DR whether normal, mild, moderate, severe or even prolific. HOS techniques were used to extract the parameters from raw images and also the SVM classifier. The paper presented a classification of five types of eye classes by means of SVM classifier. The protocol used a total of 300

subjects that had five types of conditions of the eye. A Sensitivity of 82% and a specificity of 88% was demonstrated.

Varun Saravanan & De Abhishek made a study for the implementation of a method of automated red lesion that was on the basis of the Niemeijer et al. (2004). This method extracted the objects of the candidate by means of morphological filtering of the image of the fundus which followed their classification on the basis of k Nearest Neighbour of feature vector clustering. These feature vectors are used as a subset of the ones used by Niemeijer. An evaluation was performed on the representative of the data set for a complete variety of the images that were found in the set of screening. This method is capable of detecting red lesions even though the specificity or accuracy was not so high.

Rema et al. (2006) made a study of the serum lipids and their association with DR or diabetic retinopathy in subjects with Type 2 diabetes. The strength of this study was that the population was based on a large population of South Indians living in urban areas owing to the fact that Chennai's demographics are similar to the population in the rest of Urban India and this can lead to a generalization to the whole of India and its urban population. But this study could not be generalized to the rural areas as well. The main drawback of this study is that is was cross-sectional and so speculations on the causality as well as the relationship that exist between the lipid and their sub-fractions as well as retinopathy needs a proper study of follow up. The association of DR with serum triglycerides and that of DME with LDL-cholesterol is quite significant.

Mutangana Francis (2008) further identified the chances of prevalence of DR, its pattern and also its association with the patients of diabetes by attending three clinics for diabetes in the town of Kigali, Rwanda. DR was identified and detected in 114 of a total of 391 patients that had

diabetes which was about 29.2 percent and out of this 237 patients had never gone through a fundus exam which was 60.6 percent. Further NPDR or non-proliferative diabetic retinopathy was detected in a total of 7 people which was 1.8 percent and CSME or clinically significant macula edema was detected in 15 which were 4.1 percent and finally PDR or proliferative diabetic retinopathy was detected in 18 patients which were about 4.6 percent of the total number. The DR is associative with high levels of blood pressure and chronic diabetes as well as high fasting blood sugar. There was however, no connection of DR with the patient's sex. The chances of DR in diabetic patients here is 29.2 percent and the number of those who had never had a fundus exam before was as noted earlier 60.6 percent. This is a high number and therefore requires a better system of referral for ensuring early detection and management of DR for this population.

A discussion about the people with diabetes of mellitus type 2 having a higher risk for morbidity and mortality owing to cardiovascular diseases was made by Ioannidis, George et al. (2004). More than 75 percent of the deaths are because of cardiovascular diseases. An examination was made to check on the connection of the RF or risk factors of clinical cardiovascular conditions with MA or microalbuminuria and also with DR was made and reliable evidence for CAD or asymptomatic coronary artery disease that was assessed by means of a SPECT method of RI scan with patients of DM2 was made. To conclude the findings suggested that the risk factors of MA, DR or CAD whether present or not constitute a portion of screening of DM2 outpatients and can also need a higher level of safety as trustworthy markers of diagnosis of asymptomatic CAD. Also, by means of such simple processes the clinician may be able to identify those patients who need further diagnosis and evaluation and also avoiding the economic burden. It is therefore evident that further studies has to be made to ensure that the

predictive values of all these factors is duly established to make sure the asymptomatic CAD is present or absent in outpatients of DM2.

The results of the international microaneurysm identification and detection competition that was organized by the ROC or the Retinopathy online challenge as a competition for the different aspects of detection of DR was presented by Niemeijer et al. (2010). Here the results of researchers using five methods by five teams for the same data set were compared. This was performed uniformly using a similar algorithm. The data set used here consisted of images of 50 different training that had a reference standard as well as 50 test images in which the organizers MN, BVG and MDA withheld the standards. The results that were obtained from the test data was duly submitted by means of a website after using standardized evaluation software to measure the performance. A detection of microaneurysms belonging to the test to ensure comparison with automatic methods was done by a human expert. The results proved that detection of microaneurysm was a very challenging task whether the method was automatic or human and that there is always a chance for improvement as even the method that performed best could not match up to that of the human expert. All data that was associated with Roc microaneurysm and its detection is available for public and submissions are continuously accepted by the website.

Kempen John et al. (2004) in order to develop a method which was computerized to test visual acuity for the purpose of clinical research to act as an alternative in ETDRS or Early Treatment for Diabetic Retinopathy Study and the protocol that can test it along with the evaluation of retesting its reliability in terms of the standard testing for ETDRS. To study a population of 265 patients by testing in multicenter setting in three clinical sites was organized. E-ETDRS or electronic visual acuity testing algorithm and S-ETDRS or standard ETDRS protocol was used two times on one of the eyes

of each patient to measure visual acuity. The E-ETDRS testing was duly conducted by means of EVA or electronic visual acuity tested that had a programmed Palm from the Palm, Inc., Santa Clara, from California in USA which was a hand-held device that can communicate with a personal computer that has a monitor of 17 inch and a 3 meter test distance. This protocol has a high reliability of test and retest and also has a good concordance with the testing of the S-ETDRS. However, computerized method was considered better in terms of capturing data electronically for all tested letters that need only a single distance testing that is done from 20/12 to 20/800, to potentially bring down the testing time and also the bias that is related to technicians..

2.2 SEGMENTATION METHODS IN RETINOPATHY

Soares João et al. (2006) made a presentation of a method for segmenting automatically the vasculature in the images of the retina. This method creates segmentations by classification of each image pixel as either a vessel or non-vessel on the basis of the feature vector of the pixel. These vectors consist of the intensity of the pixel and the responses of the Morlet wavelet transform that is two-dimensional taken from different frequencies of multiple scales which allows filtering of noise and the enhancement of the vessel in one step. A Bayesian classifier that has class conditional functions of probability density that is shown as Gaussian mixtures which can yield a quick classification and also model decision surfaces that are complex comparing them with classifiers known as linear minimum squared error type of classifier. The distributions of probability have been estimated on the basis of a set of training of pixels that are labeled and obtained from segmentations manually. The performance of these methods is evaluated in DRIVE and STARE databases that are labeled manually with images that are non-mydriatic. In case of the DRIVE database, an area in which the ROC or

receiver operating characteristic curve is achieved at 0.9598, which is slightly superior.

A procedure that has combined automated segmentation along with automated recognition of all the features that use proliferative retinopathy that is determined from the results that are wavelet-derived like median CD, wavelet moment etc., was combined by Jelinek Herbert et al. (2007). Additionally, a sample that is relevant clinically which is still included in images in which optimal quality is not present and the ones where the scars of pan retinal laser surgery and retinopathy's diverse progression and finally proliferation that show all areas of the ischemia or as blood vessels that are located near the optic disk or within the periphery. Those results that were obtained were through similar parameters of configuration for all the images. The removal of optic disc as well as preprocessing for improving the segmentation of the vessel is not needed as according to the wavelet transform's nature. Additionally, those classifiers barring naïve bayes or the LDA can also improve the results of the classifications. This is now being investigated for a larger image set.

Marín Diego et al. (2011) made a presentation of a new method that was supervised for detection of blood vessel in images of digital retina. This uses a NN scheme for the classification of pixels and also computes a vector of 7D that has a gray-level and features of moment invariants for the representation of pixels. This was also evaluated publicly on DRIVE as well as STARE database as they had retinal images marked precisely by experts. The performance of both sets was better than the current solutions. This process proves accurate mainly for STARE image vessel detection. This also outperforms many segmentation approaches including DRIVE and NN. The robustness and efficiency of this method along with its speed and simplicity

make it well suited for analysis of computer based retinal images like automated screening for early detection of DR.

Niemeijer Meindert et al. (2004) made a comparison of the performance of many algorithms of vessel segmentation on a database of retinal vessel images that are constructed newly. This segmentation is critical for detecting many diseases of the eye and has an important role to play in the screening system of automatic retinal diseases. Many of these methods have been published today but still an evaluation of all these methods in a database that is common for the screening of images is yet to be done. In order to make a comparison of the performance of these methods of segmentation a large data base of retinal images has been constructed. This contains a total of 40 images where trees have been segmented manually. Out of the forty, twenty have a second independent segmentation that is done manually. This ensures a comparison of performance between the automatic methods and also that of the human observer. This is a database easily available to the community doing research and those interested can upload the results of their segmentation in the website (http://www. Isi.uu.nl/Research/Databases). A comparison of the performance of five algorithms has been made. Four among these implemented as well. The fifth classification of the pixel is specifically developed in a supervised method. The accuracy of segmentation is made based on the gold standard as a measure of performance. The results have proved that the pixel method of classification is the best performer but the second observer continues to perform better.

Cornforth et al. (2005) made a description of a development of a methodology of segmentation for processing the images of retinal blood vessels using color photography that was non-mydriatic. This used analysis of wavelet and probabilities of supervised classifiers as well as procedures of adaptive threshold. Accurate identification of the blood vessels was shown to

study the changes in the network of vessels that can be used for detection of diameter changes in the blood vessels that are associated diabetes related pathophysiology. Connecting with suitable methods of extraction of features and methods of automated classification this method can perform an accurate test for DR that will give huge benefits to patients in screening them in early stages.

Sopharak et al. (2007) made a proposal after investigation on the automatic methods that helps in detection of images of low contrast that are taken from pupils that are not dilated. This has two steps of segmentation that are Fuzzy C-Means clustering based coarse segmentation and fine segmentation that uses morphological reconstruction. There are four features which are the intensity, the standard deviation based on intensity, the hue and the adapted edge that were chosen for the coarse segmentation. The results of the detection were validated on the basis of comparison with hand drawn ground truth of expert ophthalmologists. The specificity and the sensitivity for the detection of exudates is 86% and 99% respectively.

Salem Nancy et al. (2006) made a proposal of a new vector for every pixel in association with the K nearest neighbor classifier for segmentation of retinal blood vessels in images of digital colour fundus. This vector that is proposed has two features that are scale space which is the largest eigenvalue as well as the gradient magnitude which belongs to the image intensity that represents both attributes of every vessel which are parallel edges and piecewise linearity and an intensity of green channel image. For specificity and sensitivity the results can be compared with other method that are supervised and uses 31 set features but considering processing time this uses a smaller feature number leading to a reasonable decrease in processing time.

Staal Joes et al. (2004) made a presentation of a method for vessel segmentation in an automated manner with images of the retina that are of two-dimensional color. This can be used in the computer based analyses of images of the retina like automated screening in case of diabetic retinopathy. This was based on extracting ridges of images that approximately coincide with the centerlines of vessels. They are used for composing primitives as line elements. With this an image may be divided into patches and each image pixel that is closest to the element of line is composed. Each of these elements consists of a frame for local coordinate for the patch that corresponds to it. For each of these pixels a computation of feature vectors is made taking the properties belonging to the patches as well as its line elements. They are classified on the basis of the NN-classifier and feature selection using sequential forwards. This algorithm was duly tested in a database containing images that were manually labeled 40 in number. This method managed to achieve an area which is under the receiver that operates in a characteristic curve which is of 0.952. This method has been compared with two other rule based methods that were published recently which are those belonging to Hoover et al. and Jiang et al. This method's results prove that it is a significantly better one than that of the other two rule based methods with an accuracy 0.944 against 0.947 in case of a second observer.

Mendonca et al. (2006) made a presentation of a method that is automated for vascular network segmentation in images of the retina. This algorithm begins with vessel centerline extraction that is used as a guideline for vessel filling phases in subsequent cases. Presented an automated method for the segmentation of the vascular network in retinal images. To ensure that the differential operators of the outputs of the four directional operators have to be processed to choose the sets that are connected to the points of the candidate to be classified further as the pixels of the centerline that is used for deriving of features. The last of the segmentation is derived by using a region

growing method that is iterative and that integrates the contents of images that result from the width of the vessel on the basis of morphological filters. This approach was further tested on publicly available databases and results of it were duly compared with methods that were recently published. These results demonstrated that his algorithm outperformed all other solutions and also approximated the accuracy of an observer that was human which does not have a remarkable degradation in terms of specificity and sensitivity.

Lam et al. (2010) made a proposal of a multiconcavity approach of modeling to handle the healthy as well as the unhealthy retinas at the same time. The measure of differentiable concavity has been proposed to take care of bright lesions in a space that is perceptive. The measure of concavity that is line-shaped has been proposed for the removal of dark lesions that have a structure with intensity and is also different from the vessels that are line shaped in a retina. The measure of concavity that is normalized locally has been designed for handle noise that is distributed unevenly owing to the intensity of spherical variation in a retinal image. These measures of concavity have been combined in accordance to their statistical distributions for the detection of vessels in images of the retina. The results of the experiment are very encouraging as it consistently has yielded the best in comparison to the other methods termed as state-of-the-art of the retinas that are abnormal and the accuracy has outperformed the human observer that has not been achieved by the other benchmark methods. Another important aspect is that unlike the other methods that exist this method shows a very impressive performance on healthy retinas as well as an apt mixture of retinas that are pathologically healthy.

Martinez-Perez et al. (2007) made a presentation of a method that automatically segments blood vessels on the basis of multiscale extraction of feature. This method is capable of overcoming the problem of the different

variations that are in contrast and are inherent in the images by means of using both the first and the second spatial derivatives of the intensity image that procures and delivers vessel topology information. The approach further enables blood vessel detection of various lengths, widths and orientations. The local minima that are available over the scales of the gradient's magnitude and the maximum level of principal curvature belonging to the Hessian tensor have been used here for the growing procedure of the multiple pass regions. This is the growth that segments the blood vessels in a progressive manner by means of using information of feature along with spatial information. This algorithm is also tested on retinal images that are red-free as well as fluorescein and are taken from two public and two local databases. The comparison that is made with the first public database gives a value of 75.05% of TPR or true positive rate and 4.38% FPR or false positive rate. The values of the second database are 72.46% TPR and 3.45% FPR. The results on the public databases could be compared in terms of performance with that of the other authors. So our conclusion is that these are not sensitive values for the evaluation of the detection of vessel geometry and its performance. So a new approach that makes use of the measurements of the diameters of the vessels and the branching angles as a criterion of validation for comparison of images that are segmented and those that are segmented by hand from databases that are public have been proposed. There have been comparisons that are made between both the images that are hand segmented belonging to public databases and that proved a huge inter-subject variability in terms of geometric values. A final evaluation has been made by comparing the geometric values of the vessel that has been obtained from the images that are segmented between the fluorescein paired images and the red-free images the former as the ground truth. The results proved that the borders that were identified were less biased and also followed the vessel border more consistently and so were able to give geometric values that were more confident.

2.3 FEATURE EXTRACTION AND SELECTION METHODS USED IN DR

Priya & Aruna (2013) further made a diagnosis of DR in which there were three models which were PNN or Probabilistic Neural network, BS or Bayesian Classification and SVM or Support Vector machine and their performances were duly compared. The disease that spread in retinas were identified by the extraction of the retinal features like haemmorages of the NPDR images, the blood vessels etc., have been extracted from raw images by making use of techniques of image processing and later fed into the classifier for the purpose of classification. About 350 fundus images have been used for this among which 100 for the purpose of training and 250 for testing. The results of the experiments show that the PNN has a better accuracy percentage of 89.6, the Bayes Classifier an accuracy percentage of 94.4 and the SVM a percentage of 97.6. the inference that can be made here is that the SVM model is the one that has outperformed all the other models. Furthermore, this system is also run with a mere 130 images that are easily available from "DIARETDB0: The database for Evaluation and Methodology for DR and its results have proved that the PNN has a percentage of accuracy of 87.69, Bayes Classifier with 90.76 and SVM an accuracy percentage of 95.38 respectively.

Wisaeng et al. (2013) made a series of experiments for understanding the selection of features and the classification using classifiers of support vector machines. The images of the retina have been segmented on the basis of the following steps in preprocessing. They are color space selection, removal of noise, contrast enhancement and color normalization. For those sets of data with poor quality of images, the sensitivity is 94.46%, specificity is 89.52% and accuracy is 92.14%.

Sopharak Akara et al. (2008) made an investigation and proposed a set of operators that are optimally and morphologically adjusted for them to be used to exudate the detection on the patients of diabetic retinopathy and their low contrast images of their non-dilated pupils. They are detected automatically and are validated duly by means of comparing them with the ground truths that are hand-drawn by expert ophthalmologists. This was successful and the sensitivity as well as the specificity for detection was 80% and 99.5% for both respectively.

Niemeijer Meindert et al. (2005) made a proposal for a red lesion detection method on the basis of a hybrid approach that combines the works by Spencer et al. (1996) and Frame et al. (1998) along with two more important contributions. The first being a new red lesion detection system on the basis of pixel classification. By means of this technique both vasculature and red lesions have been separated from the image's background. Once this is removed all objects that remain are taken to be red lesions. Secondly, a huge number of new features have been added to the proposed one by Spencer and Frame. These objects have been classified by using all the features and the classifier known as k-nearest neighbor. An evaluation of all of this was performed on a set that had images that represented of all those that normally exist in a screening set. While the determination of whether this image has red lesions this system further achieves a 100% sensitivity and an 87% specificity. This method has been compared with many automatic systems and has proved to be better than all of them. Its performance is almost similar to that of a human expert who examines the images of red lesions present

Priya & Aruna (2012) made a diagnosis of DR with two models like PNN and SVM and have had their performances duly compared. The results of the experiments proved that PNN's accuracy was 89.6% and SVM's

97.608%. The inference here is that the SVM model can outperform the PNN. The DR here has been classified into two categories which are NPDR and PDR based on PNN and SVM. Both techniques that have been used for classifying this have been good in their performance though SVM has attained better results. So this work has ensured success in the method of diagnosing Diabetic Retinopathy and also helps in early detected which mutually brings down any need for manual work.

A presentation for a new system that is automated for detecting circinate that exudates in the images that are of retina was made by Lahmiri Salim & Mounir Boukadoum (2014). This operates as below: the color image is turned to gray levels and the CLAHE or contrast-limited adaptive histogram equalization has been applied onto it before it undergoes EMD or empirical mode decomposition as an IMF or the intrinsic mode functions. The uniformities as the entropies of the initial two IMFs are computed for forming a vector that is fed into an SVM for the purpose of classification. The results of the experiment by using a group of 23 normal and 22 with circinate exudates that are procured from STARE database a total of 45 images are used. The tenfold cross validation shows that this approach outperformed all of the previous works with its perfect classification. Additionally, the time taken for processing of image was only 4 minutes thus making this detection system that is circinate exudate a fit one for usage in any clinical environment.

Aquino et al. (2010) further presented a template based method for segmentation of the OD from all digital images of the retina. This method used techniques that are morphological and of edge detection and then followed it through Circular Hough Transform for obtaining an OD boundary and its approximation. This needs pixels that are located inside the OD as its initial information. To enable this methodology for location on the basis of an

algorithm that is voting type was further proposed. These were duly evaluated on all of the 1200 images from the MESSIDOR database that is publicly available. The procedure of location was successful in almost 99% cases taking up a computational time of 1.67 s. along with a standard deviation of 0.14 s. But this algorithm had an overlapping common area between the segmentations that were automated and also the OD regions that were true of about 86%. The computation time was 5.69 s this with a standard deviation of about 0.54 s. Further, the advantages as well as the disadvantages of these models that are used for the segmentation of OD was discussed and presented.

2.4 OPTIMIZATION FOR CLASSIFYING DR

Goldbaum (1996) duly concentrated on diagnosis that was automated. The images here were annotated by segmenting them based on their object of interest and the classification of the objects that were extracted was done along with the reasoning of the contents. Here the inferencing was got through Bayesian network that took examples from each disease. This is an effort at understanding the image in various fundus and also anticipates the medical imaging and its future. Once these capacities mature we can expect the ophthalmologists as well as the physicians to rely in these images and further use systems like STARE for reduction of repetitive work and also provide due help to the physicians when the diagnosis is challenging or in case of diseases that are unfamiliar and thereby manage a large database of images.

A new method that is therapeutic for SBP or Scotoma-based photocoagulation was developed by Pinz Axel et al. (1998) in the Vienna Eye Clinic for the purpose of diagnosis and treatment of muscular degeneration that is age-related and also needs retinal maps from images that are used for scanning ophthalmoscope. Here in this paper all details that are needed for analysis of images for the generation of maps are made. Software that is a

prototype that is fully automatic is also implemented as well as tested on a dataset that represents a clinical study of 50 patients. This map is needed for the treatment of SBP and can be extracted safely for all of the cases. So the algorithms that are presented here in this paper can be made applicable in every type of clinical routine with no need for any major modification.

Another proposal for an automated system for AMD detection that uses DWT or Discrete Wavelet Transform as well as strategies for feature ranking was made by Mookiah Muthu Rama Krishnan et al. (2014). The four order moments in statistics which are the mean, the variance, the skewness and the kurtosis taken as moments of energy, entropy as well as the Gini index based features that have been extracted from the coefficients of DWT. There are five tests that have been used. They are Wilcoxon, ROC or Receiver Operating Characteristics Curve, CBBD or Chernoff Bound and Bhattacharyya Distance, KLD or Kullback-Lieber Divergence and the t test. Another set of classifiers that are supervised like the SVM or the Support Vector System, DT or Decision Tree, NB or the Naïve Bayes, k-NN or the k-Nearest Neighbour and finally the PNN or the Probabilistic Neural Network were made use of for the evaluation of the measure of highest performance by making use of minimum features to classify normal as well as dry classes of AMD. This framework that has been proposed has got an average accuracy of a sensitivity of 93.70% and a sensitivity of 91.11% and finally a sensitivity of 96.30% that uses KLD ranking as well as SVM classifiers. Another AMDRI or AMD Risk Index that uses selected features for the classification of normal as well as dry class of AMD by using just one number was formulated. This system may be used for assisting clinicians as well as for AMD screening programs at a mass level.

A system that may be used for mass screenings that are automatic for DR was documented by Acharyau Rajendra et al. (2012). Four different

classes have been identified for this which are normal retina, NPDR or non-proliferative diabetic retinopathy, PDR or proliferative diabetic retinopathy and ME or Macular edema. A total of 238 retinal fundus images have been used in this analysis. There are five features like run percentage, long run emphasis, short run emphasis, correlation and homogeneity that were extracted from the images of digital fundus. All these have been fed into an SVM or a support vector machine classifier for classification to be done automatically. This classifier has various kernel functions like polynomial of 1, 2 or 3 order, radial basis function and linear those were studied. ROC or receiver operation characteristics curves had been plotted for the selection of the best classifier. This system was able to identify unknown classes with a high level of accuracy percentage of 85.2 and a sensitivity, specificity and AUC or area under curve of 98.9%, 89.5%, and 0.972 respectively by means of using a SVM classifier that has a polynomial kernel of an order 3. Another new integrated DR index or IDRI that uses various features that are able to conduct an identification of different classes with an accuracy of 100 percent.

Usher Dumskyj et al. (2004) further developed a system that automatically detects DR features in digital retinal images in color for the evaluation of its potential in the screening of Diabetic Retinopathy. Another system was employed which involved pre-processing for the purpose of standardizing color, enhancing contrast and also segmentation for revealing any possible lesions and classifying the lesions by using a neural network. This was a system that can be used when DR screening takes place. This had a sensitivity setting of 94.8% and the need for human grader examination can be brought down to half of the original requirement.

One of the abnormal signs was given focus by Wang Huan et al. (2000). This was the presence of lesions or exudates in the images of the retina. A novel approach that was a combination of a procedure of adjustment

of brightness along with a method of statistical classification and a verification strategy that was window based was proposed. The results of this experiment indicated that 100% accuracy was possible in the identification of retinal images along with exudates and at the same time maintaining an accuracy rate of 70% in the correct classification of normal retinal images as normal ones. This results in huge savings on the basis of the number of images of the retina and can be reviewed manually by professionals once a year.

Giancardo Luca et al. (2012) made a presentation of an automatic system that was new and based on exudate for detecting DME by means of non-stereo fundus images. This was based on the algorithm that was able to detect the exudates and also attached some level of confidence without using methods of machine learning for the purpose of separation of false positives from the true positives in a space of color analysis with new methods that characterize lesions with wavelet analysis. As according to our knowledge this approach for creating feature vector with both inner as well as outer lesion maps have not been tried before and now they proved to be a successful one. It can be confidently assumed that this approach can be applied to problems of all domains in which diagnosis or sometimes other classifications can be performed based on lesions that are uncertain and their segmentation. This method is proved effective when in conjunction with different aspects of detection of lesion and processing of retina can be pursued in the work of the future to try creating a diabetic retinopathy screening that is competitive and can diagnose the state of the disease transparently.

Forrester John (1997) brought about an automated system of digital image processing that gave an objective to quantify micro aneurysms in fluorescein angiograms. The automated processed included the registration of retinal images of the same eye for serial studies. The detector of micro

aneurysm has been trained in a database containing about 68 images of patients of diabetes and 394 true microaneurysms that have been identified by ophthalmologists. This microaneurysm detector has achieved a sensitivity of 82% with a 2.0 false positive per image. A test set that was independent and had 20 images that had 297 true micro aneurysms, has been used as a detector by clinicians was used to compare the micro aneurysm detector with clinicians. This further achieved 82% sensitivity with 5.7 false positives for every image and the ROC of the clinician receiver-operator-characteristic curve gave a 3.2 false positive for every image with a sensitivity of 82%. This could be trusted in detecting micro aneurysms as it had reliability, objectivity, full automation and speed.

Hijazi et al. (2012) made a proposal for comparing to techniques of data mining for supporting AMD's automated screening. The first one made use of spatial histograms for the maintenance of image color as well as spatial information for the representation of image on which a CBR or a Case based reasoning classification technique is duly applied. The second one is based on a decomposition based on hierarchy of that particular image which is set for generating a tree representation. A sub-graph mining technique which is weighted was applied to this in order to identify the sub trees that are across the data set. Those sub trees that are identified are later encoded as vectors on which techniques of standard classification may be applied.

Gagnon Langis et al. (2001) gave an overview of a procedure that was generic for detecting all anatomical structures that are important in images of color retina, the retinal network, the macula and the optic disk. This procedure has been duly tested on a 40 color fundus image database that has been got from a camera that is of low resolution and non mydriatic fundus. The results of the test show that this one was robust in terms of visual quality and were also independent as the acquisition is disk centered and macular

optic. The rate of success is 100% for the detection of optic disk and 95% for macula detection. Now the work is on the design of a protocol of quantitative measure to establish the performance of the extractor of vascular networks. The future work has extensive tests on various images that are procured from various digital cameras. These algorithms definitely have the need for modification to maintain the performance of detection at the present level. Lastly this procedure is used as a step of preprocessing for the lesion development of algorithms of detection that is connected with DR and other diseases of the retina.

Walter Thomas et al. (2002) made another proposal of an algorithm that detects the exudates which are present inside the macular region which is a main hallmark of macular edema and permits in detection with a high level of sensitivity. So, the detection of these exudates being an important task of diagnosis where computer assistance may be required. They are found in variations of high grey levels and the determinations of their contours are by means of techniques of morphological reconstruction. The optic disc has to be detected for this approach. This is done by techniques of morphological filtering and the transformation of watershed. This algorithm has been tested with a small database and its performance has been compared with that of a human grader. A mean sensitivity of 92.8% and a mean predictive value of 92.4% have been obtained here. The robustness based on the changes in parameter has also been evaluated.

CHAPTER 3

RETINAL MICRONEURYSM DETECTION AND POST ROCESSING FOR TRUE VESSEL EXTRACTION

Diabetic Retinopathy can be diagnosed at the early stage through the detection of microaneurysm and the blood vessels. Receiver operating characteristic is used to extract the features of blood vessels and the microaneurysm. The extracted features are then given to the neural network classifiers such as Back Projection Neural Network Classifiers, Naive Bayes classifiers and *k-Nearest Neighbor Classifier.* This chapter deals with comparative study of performance of these three classifiers.

3.1 DIABETIC RETINOPATHY DATABASE

The fundus images required for the detecting diabetic retinopathy can be obtained from diaretdb0 and diaretdb1 database. The samples from this type of database are used as benchmark for detecting diabetic retinopathy in digital images. The main task is to define a testing method and database which are used as benchmark for diabetic retinopathy detection. The fundus image from the database is used to compare the result obtained by applying various testing method.

There are of 89 colour fundus images in diaretdb1 database. Among them around 84 fundus images has the sign of diabetic retinopathy, remaining

5 images are normal image without any sign of diabetic retinopathy. Digital fundus camera is used to capture the images at various angles. The images in this database can also be used to compare with the image used for diagnostic purpose to evaluate whether it is suitable of diagnostic. The diaretdb1 database is also called as calibration level 1 fundus images.

There are of 130 colour fundus images in diaretdb0 database. Among them around 110 fundus images has the sign of diabetic retinopathy, remaining 20 images are normal images without any sign of diabetic retinopathy. Similar to diaretdb1 database diaretdb0 database also contain images captured by digital fundus camera. The diaretdb0 database is also called as calibration level 0 fundus images.

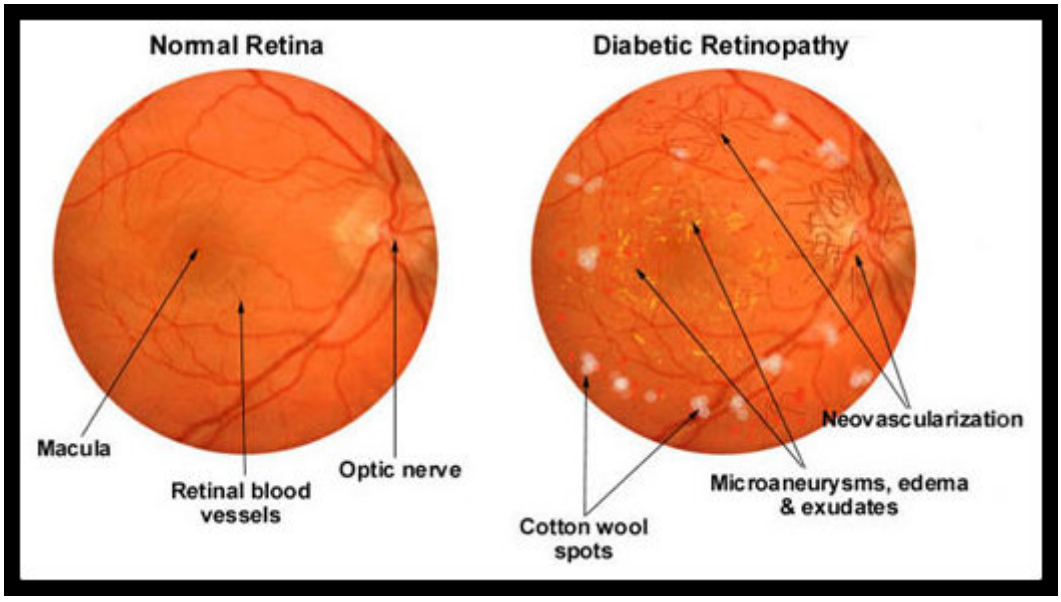


Figure 3.1 Normal Retina Vs Diabetic Retinopathy

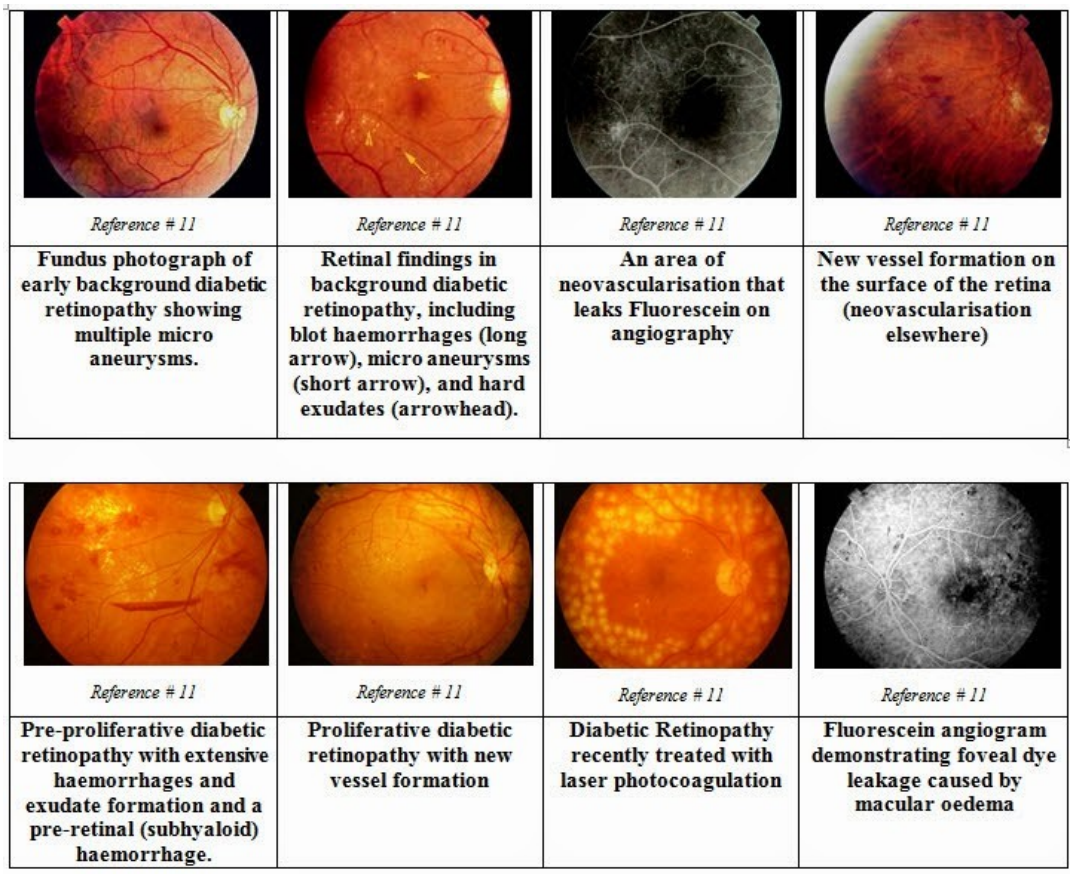


Figure 3.2 Feature Extraction

3.2 FEATURE EXTRACTION

Feature extraction method is used to extract the blood vessel in order to detect the diabetic retinopathy by using colour fundus images. This fundus image is nothing but an RGB image which consists of all three colours such as red, blue and green. Features can be extracted from image by separating each colour to a different channel and using only one channel. The information content in the blue channel is not much as it has only low contrast. Initially the retinal image which is used as input is pre-processed. Pre-processing is the first step at which the image get resized also the red and blue channels get separated. After which morphological operation such as dilation and erosion are performed on the image. Dilation is the process in which the object becomes thicker in the image. The structuring element is

used to shape and control the thickening. Erosion is the operation opposite to that of dilation. Erosion is the process in which object gets shrinks or thins image.

In order to improve the contrast in the image a technique called Adaptive histogram equalization is used which is different from ordinary histogram technique and are digital image processing technique. In this technique image is segmented into numerous part and local contrast is calculated which enhances the edges or boundaries in each segment of the image. Adaptive histogram equalization has the ability to amplify the noise present in the each segment of the image. To overcome this drawback an advanced technique called contrast limited adaptive histogram equalization is used.

In conventional histogram equalization technique same transformation obtained from image histogram is used to transform all pixels. But it can only work well in the image where the pixel is evenly distributed throughout the entire image. So in the image where the pixels are not evenly distributed some regions remain dark and some remains lighter hence this image cannot be enhanced.

Adaptive histogram equalization does not use the same transformation for the entire image instead it uses the transformation function derived from its neighbouring region. It is initially used for displays in aircraft cockpit. In general form, each pixel is transformed based on the histogram of its neighbouring pixels which is in square shape. The transformation function is proportional to the neighbouring pixels cumulative distribution function. The pixels at the boundary of the image should be concentrated more because it is used to differentiate the image from other image.

3.3 CANNY EDGE DETECTION

Canny edge detection is a technique used to extract the structural information from different vision to highlight the contrast of objects at the edges it also reduces the amount of data to process. Canny found that to detect the edge of the image at diverse vision is approximately same.

Criteria for edge detection include:

1. Edge to be detected with minimum possible error which means the accuracy should be high.
2. The centre of the edge is the point detected by the edge detector operator.
3. Edge to be marked correctly and false edge should not be created due to noise.

In order to meet the requirements canny found an optimum technique. Canny edge detection method is most effective when compared with other edge detecting techniques. This technique provides reliable and accurate edge detection. It can even detect boundary of the images which contains noises.

Algorithm for Canny edge detection:

1. In order to remove the noise and smoothen the image Gaussian filter is applied.
2. Intensity gradients of the image to be found.
3. Non-maximum suppression is applied in order to avoid spurious response.
4. The potential edge is detected by applying threshold twice.

5. Hysteresis is used to track the edge, the week and discontinuous edges are avoided and strong edge is detected.

False edge detection can be avoided by removing the noise hence necessary filter is used to filter the noise from the image. Usually Gaussian filter is used to remove the noise. Gaussian filter removes the noise affecting the edge detection and smooth the image. The kernel size of the Gaussian filter is to be chosen correctly because the performance of the filter depends on the kernel size. The sensitivity of the detector will reduce as the size of the kernel increases. Also by increasing the size of the kernel error occur at detecting the edge of the image. Most commonly used size of the kernel is 5×5, which can also vary according to the need.

In Canny algorithm the image can be pointed in variety of directions which can be detected using horizontal, vertical and diagonal filters. The edge detectors such as Roberts, Prewitt and Sobel use first derivatives in horizontal and vertical direction to determine the gradients and the direction of the gradient. The angle direction of the edge is approximated to one of the four angles such as 0°, 45°, 90° and 135°. For example if the angle lies between 0° to 22.5° and 157.5° to 180° it will be set to 0°. This method is efficient method as it is very accurate and robust method to detect the edge.

The traditional algorithm has defects such as:

1. Gaussian filter is used to smoothen the noise which will also smoothen the edge and the weak edges get missed.
2. The conventional canny edge detection algorithm uses the window of 2×2 size to calculate the gradient. But this method is prone to noise and there occur the chance to detect fake edge or to lose real edge.

3. The old canny edge detection algorithm requires two fixed global threshold values to avoid the chance of detecting false edges. When the image gets complex there is a need to determine new local as well as different global threshold value to detect the real edge. Those values are manually determined through number of experiments which leads to the computational complexity. Hence there occurs a huge difficulty to calculate those values when dealt with large number of images.

4. The convolutional detection method is not up to the satisfactory level of accuracy.

3.3.1 Receiver Operating Characteristics

A receiver operating characteristics is a graph used to depict the performance of different classifier. Receiver operating characteristics is a graph plotted between the hit rates and false rates of classifiers. It is used to analyses the behavior and the characteristics of different types of classifier. In medical field receiver operating characteristics plays a vital role to diagnose the image for testing purpose. Initially receiver operating characteristics graph is used in machine learning to evaluate and compare various algorithms. This type of characteristic curve has become significant one in the field of research and other developing sectors. Receiver operating characteristics graphs are basically very simple but when they are used in the field of research they create complexity. Also when they are practically implemented it leads to many drawbacks.

Initially classification begins with the one two classes. That is the element is classified into one of the two classes such as set of positive and negative labels. A classifier is used to map the elements in the labels in order

to predicted classes. Few classifiers produce continuous output to which different thresholds must be applied whereas other models produce a discrete output to predict class of that instance. The actual class and the predicted class can be differentiated by using the labels produced by the classifier. For a given classifier there are four possible outputs. They are true positive, true negative, false positive, false negative. When the actual output is positive and if it is classified by the classifier as positive it is called true positive. When the actual output is positive and if it is classified by the classifier as negative it is called as false negative. When the actual output is negative and if it is classified by the classifier as positive it is called false positive. When the actual output is negative and if it is classified by the classifier as negative it is called true negative.

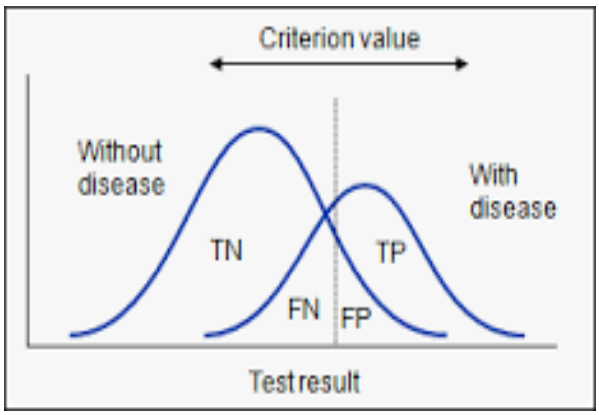


Figure 3.3 classifier

The classifier is already assigned with a set of training sequence and when the input is applied as a test set the classifier compares the test and the training sequence and produce the output. There is also a matrix form in which the numbers at the main diagonal represent the correct decisions and the numbers other than this main diagonal represent the errors. The true positive rate is also called as hit rate or recall of a classifier. The false positive

rate is called as false alarm rate of a classifier. The two important measures of performance of a classifier are sensitivity and specificity.

3.3.2 Sensitivity

When the actual output is positive and if it is classified by the classifier as positive it is called true positive. The true positive rate or recall is the measure of positives that are correctly identified as positives. For example the normal eye is correctly identified as there are no defects in it. False negative is avoided through sensitivity. In other words sensitivity can also be defined as the ability to correctly detect patients who have the sign of disease. In identifying disease the sensitivity is the ratio of people who is predicted as positive of disease to the people who have the disease.

Negative test result with high sensitivity helps to confirm the disease. When the test result has 100 percent of sensitivity it means all the patients with disease are correctly identified with the sign of disease. Hence the outcome of the test is useful to predict the presence of disease. Similarly the positive test outcome is not that much useful to confirm the disease. In sensitivity false positive is not taken into account. False positive result detects the presence of disease in the healthy people which is not true. So the positivity result with 100 percent of sensitivity is not useful for detecting the disease.

Precision and sensitivity are not similar. Precision is defined as the ratio between true positive to the true positive and false positive which is similar to the actual positive. While calculating sensitivity indeterminate samples are not taken into the account. Those samples are either omitted from the analysis or it is considered as false negative.

3.3.3 Specificity

When the actual output is negative and if it is classified by the classifier as negative it is called true negative. When the negatives are correctly identified as negative it is called true negative rate. For example the no defective eye is incorrectly identified as normal. False positive is avoided through specificity. In other words specificity can be defined as the ability to detect the normal patient as there is no sign of disease. It is ratio between the healthy people without disease to the test result negative of it.

The positive result with high sensitivity helps to confirm the presence of disease. When the test result has 100 percent specificity it means that the healthy people are detected with no sign of disease and the diseased people are correctly identified with the presence of disease. The negative test outcome is not useful for detecting the disease as it only produces negative outputs. Hence there is a chance to detect disease in the healthy people faultily. So the specificity with 100 percent do not include false negative. Therefore the by including negative result specificity of 100 percent is not possible and it cannot be used to correctly identify the presence of disease.

Let us consider an example in which people undergo examination to identify the disease. After taking the test the result can be positive or negative. Here positive means person identified with disease and negative where person is classified as not having the disease.

The test outcomes of each person may or may not match with the actual result.

- True positive: Diseased person correctly identified as having disease.

- False positive: Normal person without any disease incorrectly identified as having disease.
- True negative: Normal person correctly identified as not having disease.
- False negative: Diseased person incorrectly identified as normal person without any disease.

Let positive be identified and negative be rejected. Then

- True positive means correctly identified
- False positive means incorrectly identified
- True negative means correctly rejected
- False negative means incorrectly rejected

Predicted Value (predicted by the test)		Actual Value (as confirmed by experiment)	
		positives	negatives
	positives	**TP** True Positive	**FP** False Positive
	negatives	**FN** False Negative	**TN** True Negative

Figure 3.4 Actual Value Vs Predicted Value

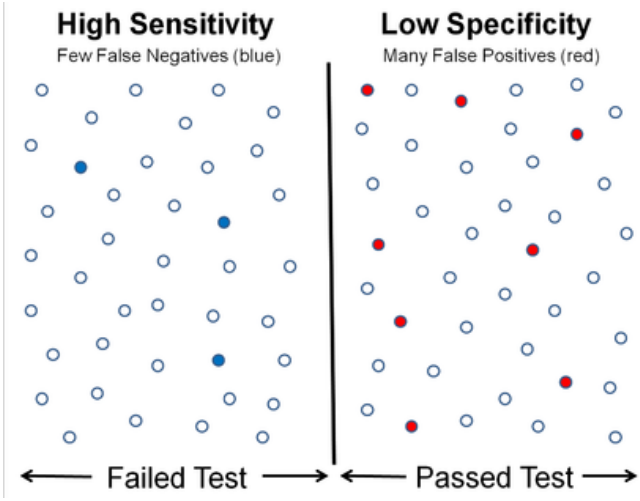


Figure 3.5(a) High sensitivity and low specificity

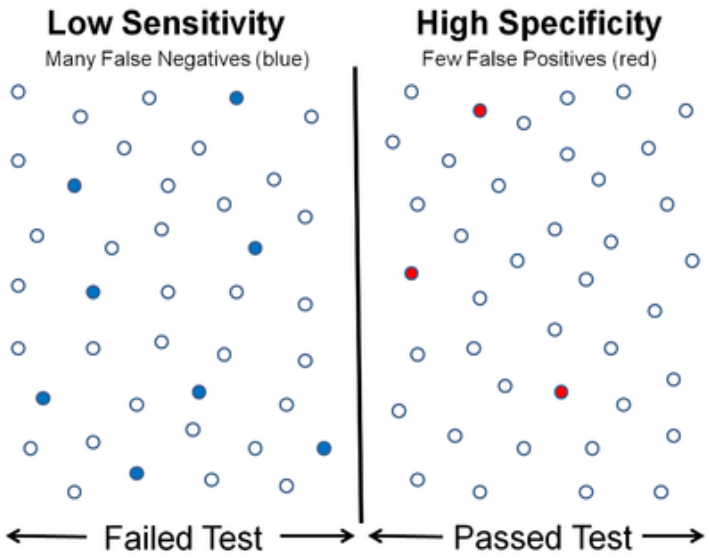


Figure 3.5(b) Low sensitivity and high specificity

For example let us consider the case of medical diagnosis where the sensitivity is defined as the ability to correctly predict the people with the sign of disease, whereas the specificity is defined as the ability to correctly detect the people without any disease. Specificity is also known as true positive rate and specificity is also known as true negative rate. Suppose 100 people undergo the test and around 48 of them are found positive then the sensitivity

is 48 percentages. Similarly if 100 people with no sign of disease undergo the test and if it is found that around 94 people is found negative then the specificity is of 94 percentages.

It is found that high specificity test result leads to confirm the disease and high sensitivity test result leads to confirm the absence of the disease. Receiver characteristic curve has the trade-off between specificity and sensitivity. It can also be said as trade-off between true positive rate and false positive rate. True positive rate is also called as recall and false positive rate is called as fallout.

3.3.4 Neural Network

Neural network which is generally known as Artificial Neural Network is defined as the system that consists of number of processing elements which are used to process the information when the input is applied externally.

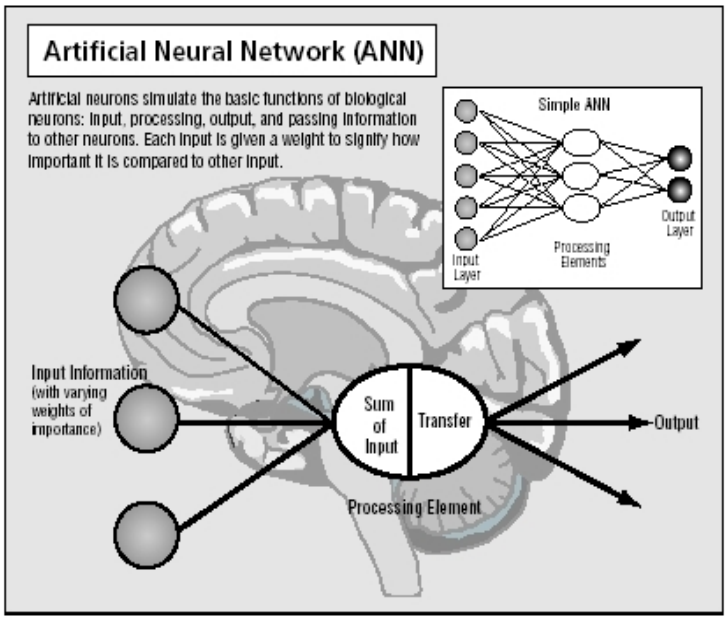


Figure 3.6 Artificial Neural Network

Neural network is similar to that of the human brain which consists of large number of neurons to process the information. Artificial Neural Network has loosely coupled neural structure of brain. Artificial Neural Network has hundreds or thousands of processing unit where the human brain has billions of neurons to process the information.

3.3.5 The Basics of Neural Networks

Basically the Neural networks are typically composed of layers. The layers are made up of a large number of interconnected nodes which contain an activation function. The neural network consists of input layer, output layer and few hidden layers. The inputs such as patterns are applied to the network through input layer which further communicates to the one or more hidden layers. The hidden layers the place where the actual processing of information takes place and it is done in the system of weighted connections. The hidden layers then communicate with the output layer.

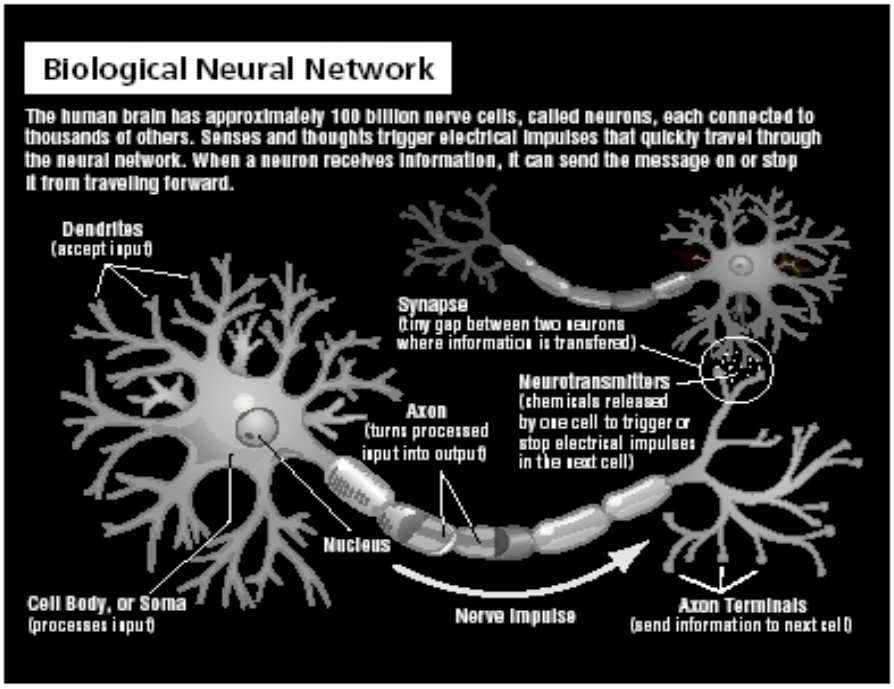


Figure 3.7 Biological Neural Network

3.3.6 Neural Network has Three Types of Learning Process

They are supervised learning, unsupervised learning and reinforcement learning.

3.3.6.1 Supervised learning

Here a set of example pairs are given and the objective is to find the function that matches the function in the examples. In other words it can be said that prior knowledge about the function is known hence matching can be done accurately. The mean squared error is commonly used method which tries to minimize the average squared error between the outputs of the network and the target value. One of the algorithm which tries to minimize the error probability in multilayer perceptrons is back propagation algorithm. The tasks which fall under the supervised learning are pattern recognition such as classification and function approximation. This supervised learning can be considered as learning in the presence of teacher which provides continuous feedback.

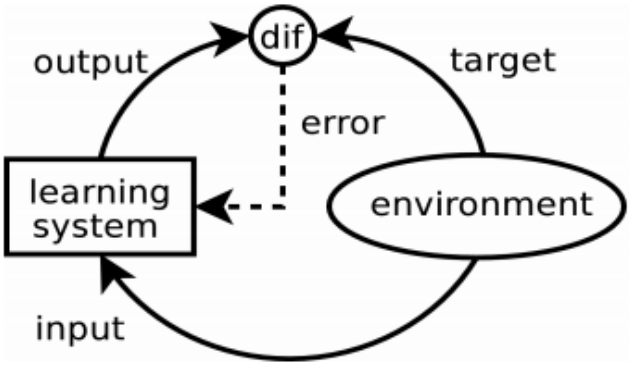


Figure 3.8 Supervised (with teacher)

3.3.6.2 Unsupervised learning

This process is similar to that of supervised learning but there is no instant feedback given. It is considered as learning without the teacher. The tasks that are included under the unsupervised learning are general estimation problems the applications include clustering, the estimation of statistical distributions, compression and filtering.

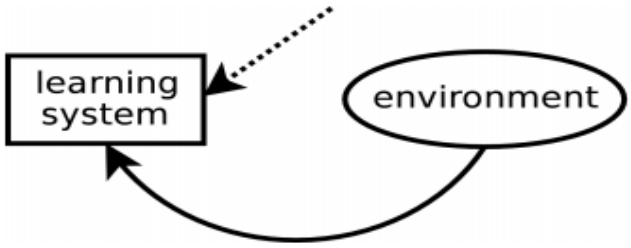


Figure 3.9 Unsupervised (self-organized)

3.3.6.3 Reinforcement learning

In this type data are usually not given but are generated by an agent's interacting with the environment. At each point in time the agent performs an action and the environment generates the data which are unknown. The main goal is to minimize the error which are not known in prior but can be estimated. Here the Marcov chain process is involved by which the environment agent generates the data. The tasks that falls under reinforcement learning are to control the problems, games and other sequential decision making tasks.

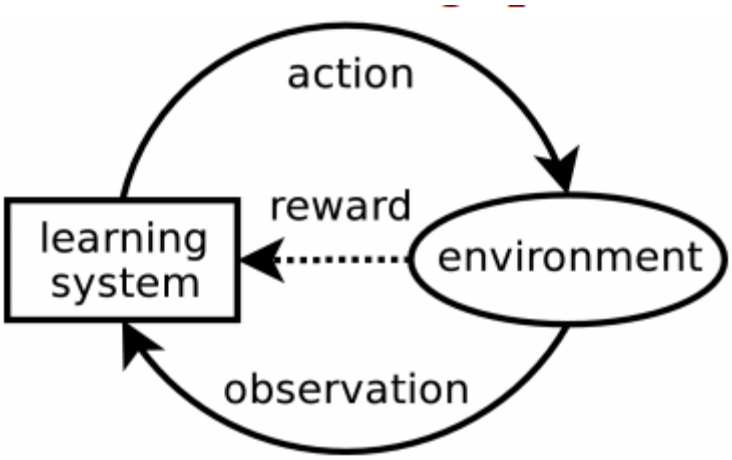


Figure 3.10 Reinforcement learning (partial feedback)

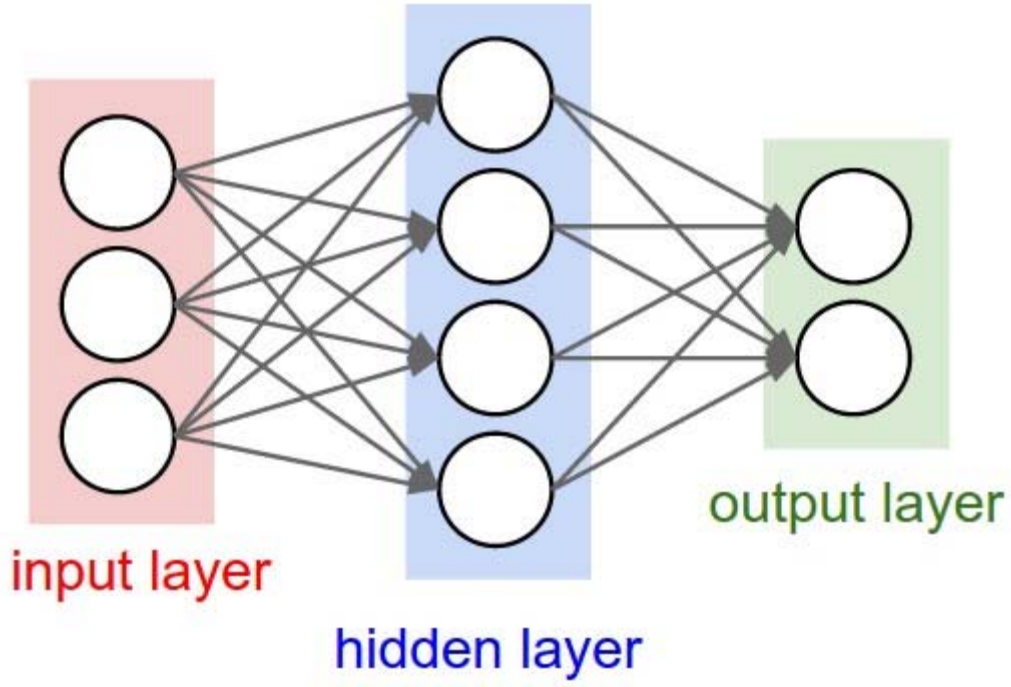


Figure 3.11 ANN Layers

3.3.7 Back Propagation Neural Network

The artificial neural network consists of some learning rule through which it can recognize the objects and other livelihoods. According to the input pattern applied at the input layer the weights get modified using learning rule. Although there are several learning rules the most commonly used one is delta rule. Delta rule is mostly used by the back propagation neural network which is one type of artificial neural network. Backward projection of error in neural network is shortly called as Back propagation neural network.

Learning process used in the Back propagation neural network is a supervised process in which for each time the input called new pattern is applied to the network in forward flow there occurs the backward flow of error in the weights. This backward flow of error adjusts the weight and result in error free propagation hence it is called as Back propagation neural network.

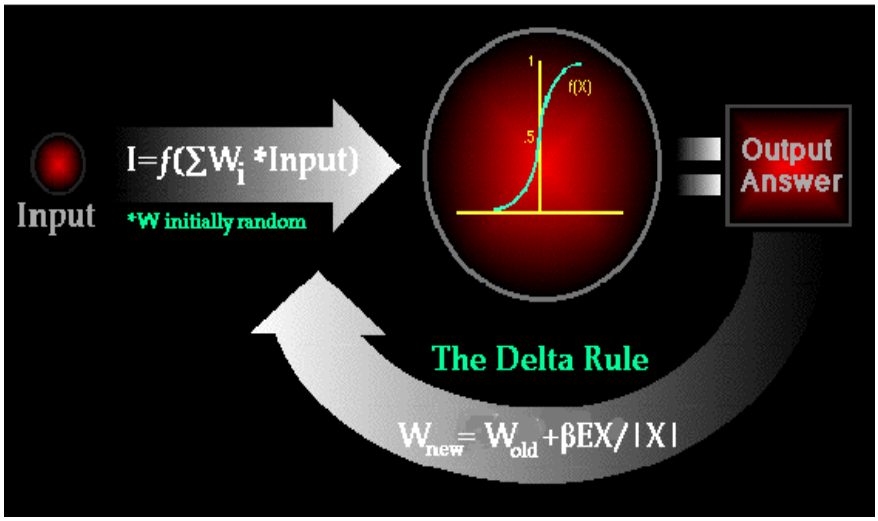


Figure 3.12 A single node example

To polarize the activity at the hidden layer and also to make it stable there are sigmoid activation function present at the hidden layer. Back

propagation neural network performs backward projection of error in order to adjust the weight and to minimize the error. In order to obtain the lowest possible error the best solution is global minimum. The surface of the error is hyper paraboloid in shape and assumed to be smooth but in most of the cases the surface is irregular with pits and hills. This irregular surface with pits and falls will lead to the local minimum which is not the best solution.

As the error nature of the space is not known in advance the neural network repeats the analysis large number of times in order to determine the best solution. The rate of convergence between the current solution and the global minimum is known as the speed of learning. Learning rule assists to control the speed and the momentum of the learning. At the error surface this momentum helps the network to overcome obstacles such as local minimum and settles at the global minimum.

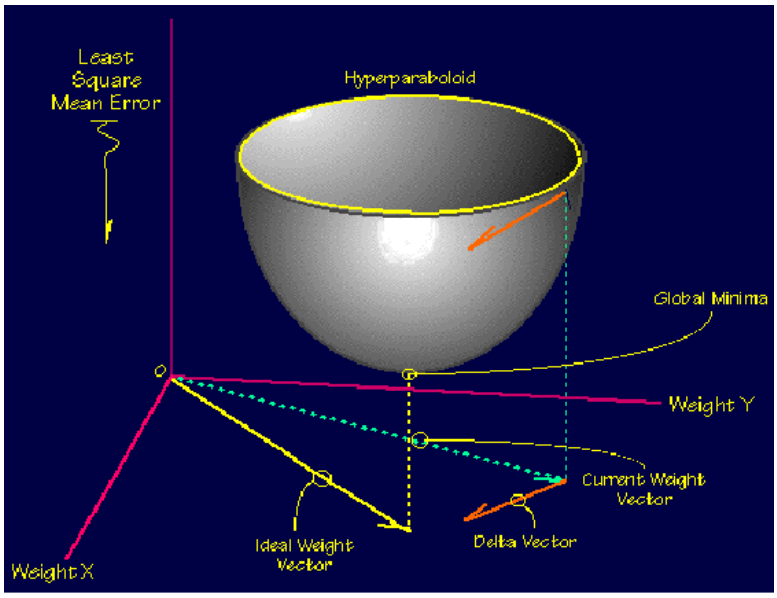


Figure 3.13 Least Square Mean Error

When the neural network is trained with specified set of training sequence it does not require back projection. The training sequence runs only in the forward direction. In this process the neural network already consist of

trained sequence and when the testing input is applied at the input layer of the network it is passed to the hidden layer. The hidden layer is the stage where the actual processing of the signal takes place and finally it is fed to the output layer. In few cases neural network is over trained and it responds to only one kind of input. So when other type of input is applied it cannot be processed.

3.3.8 K-Nearest Neighbors Classifier

K-Nearest Neighbors classifier in short called as k-NN classifier which is not a parametric method. The main application where it can be used is in pattern recognition.

This type of classifier can be used for:

Classification: When k-NN classifier is used for classification purpose it uses the value of its neighbors to assign to which class it belongs.

Regression: When k-NN classifier is used for regression purpose the output value is calculated as the average values of its k nearest neighbors.

In k-Nearest Neighbors classifier the activity function is only approximated locally and the computation are performed until the classification. This method is also called as lazy learning or instant based learning and it is very simple algorithm of machine learning. When this classifier is used for both classification and regression purpose it uses the weight calculated from the neighbors. In this type the contribution of the nearest neighbors is more than that of the contribution of distant one. For example when each neighbor consists of weight function to be contributes is equal to 1/d, where d is the distance from the neighbor. When the neighbors are taken from the set of object of which it belongs is called k-NN classification and when it is taken from the object property value it is called k-

NN regression. This is considered as training set for this algorithm and there is no need for additional training set. One of the main drawbacks of this algorithm is its sensitivity to local structures.

Example of k-NN classification

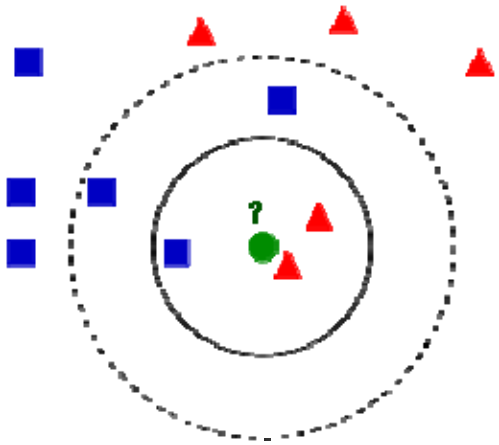


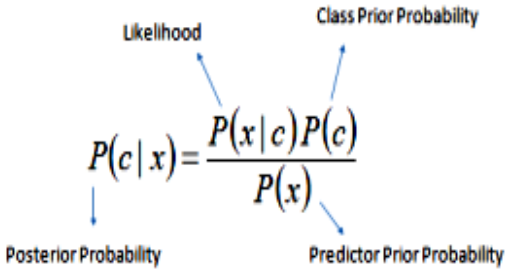
Figure 3.14 k-NN classification

The test sample (green circle) should be classified either to the first class of blue squares or to the second class of red triangles. If k = 3 (solid line circle) it is assigned to the second class because there are 2 triangles and only 1 square inside the inner circle. If k = 5 (dashed line circle) it is assigned to the first class because there are 3 squares 2 triangles inside the outer circle.

3.4 NB CLASSIFIER

Naive Bayes classifier is extremely fast when compared with other classifier algorithms. To predict the class of unknown data set it uses Bayes theorem of probability where there are thousands of data points and few variables in the training data set. When there is a classification problem in large data set this algorithm provides faster solution than others. Bayes' Theorem is used in this type of classification based on the assumption that the predictors are independent to each other.

In other words the Naive Bayes classifier assumes that some features in the class are unrelated to the other features in the class. Let us take an example, where a fruit let it be apple is red in colour and round in shape and about 2.5 inches in diameter. Here each features are independent to each other but all those together indicate apple fruit therefore it is called Naive. Naive Bayes model is very easy and simple also it performs well when compared with other classifier for large set of data. Posterior probability P(c|x) can be calculated from Bayes theorem from P(c), P(x) and P(x|c).



$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

where

- P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes).
- P(c) is the prior probability of class.
- P(x|c) is the likelihood which is the probability of predictor given class.
- P(x) is the prior probability of predictor.

Pros:

- It is simple and very fast to predict the class in large set of data.
- Multi class prediction can also be performed.

- Naive Bayes classifier requires only less number of training data.

Cons:

- When the test data set does not match with any of the training data set in categorical form then it will assign zero frequency. Hence to solve this problem we need simple smoothing technique which is called Laplace estimation.
- Naive Bayes is also known as a bad estimator so the probability outputs are not to be taken too seriously.
- Another limitation of Naive Bayes is the assumption of independent predictors. In real life it is almost impossible that we get a set of predictors which are completely independent.

3.5 PERFORMANCE EVALUATION

The fundamental advance of Back propagation Neural Network is that the transfer function at each node of the network and the error is projected backward to modify the internal network weights after each training samples. Back propagation Neural Network has the ability to generate complex decision boundaries as it approximate Bayesian posterior probabilities. Here various parameters such as number of samples, number of hidden nodes and learning rate must be considered. The performance of this classifier cannot be predicted in prior as other classifiers which are used for pattern classification. The training time is very large and the time required for recognizing the pattern is less also it require a large set of training sequences.

K-Nearest neighbor classifier is non-parametric method which has no assumption about the data set. But in the case of Naive Bayes it has assumption about the data set which is independent to each other. The Naive

Bayes is not flexible and has only elliptical, linear and parabolic boundaries which add advantage to the k-Nearest neighbor classifier since it is flexible. Naive Bayes cannot classify data point that relies on the marginal distribution which can be classified by the k-Nearest neighbor.

Naive Bayes is said to have predictors which are independent to each other. In real life it is almost impossible that we get a set of predictors which are completely independent. When the test data set does not match with any of the training data set in categorical form then it will assign zero frequency. Hence to solve this problem we need simple smoothing technique which is called Laplace estimation. But it is not required in the k-Nearest neighbor.

K-Nearest neighbor does not know which attributes to be given enough importance. Here the Euclidean distance between the data points to be calculated and all the attributes are given same importance than the important attributes. Naive Bayes is one of the classifiers that can handle missing data very well whereas in the k-Nearest neighbor classification cannot be done if the data is missing. KNN have one parameter more than NB which is the number of neighbours. This means you need to do model selection for KNN in order to determine the best neighbor which is not required in the Naive Bayes.

Hence when all the three classifiers are compared each has its own advantage and disadvantage. But when evaluated in performance wise it is seen that the k-Nearest Neighbour is best when compared with other two classifiers.

CHAPTER 4

AUTOMATIC SEGMENTATION OF FOVEA AND CLASSIFICATION OFDIFFERENT STAGES OF DIABETIC RETINOPATHY

This chapter explains the detection of fovea through which the diabetic retinopathy can be identified. Through the localization of fovea and blood vessels various stages of the diabetic retinopathy can be detected and necessary treatment can be taken. Initially the retinal image is subjected to pre-processing and then the features such as blood vessels and fovea are extracted by means of Fussy c-mean clustering. Finally the Fussy c-mean clustering is compared with the k-mean clustering.

4.1 FOVEA

The fovea literally means pits or pitfalls in Latin. Fovea is composed of large pack of cones and is in the form of pit located at the centre of the macula of eye.

The main reason for the sharp vision is eye is fovea. The sharp vision is very important for day to day human activities such as driving and reading. The parafovea belt is surrounded around the fovea which is surrounded by an outer layer called perifovea. The parafovea belt has high

density of cones made up of more than five rows of cells. The outer layer which is called perifovea is made up of more than four row of cell.

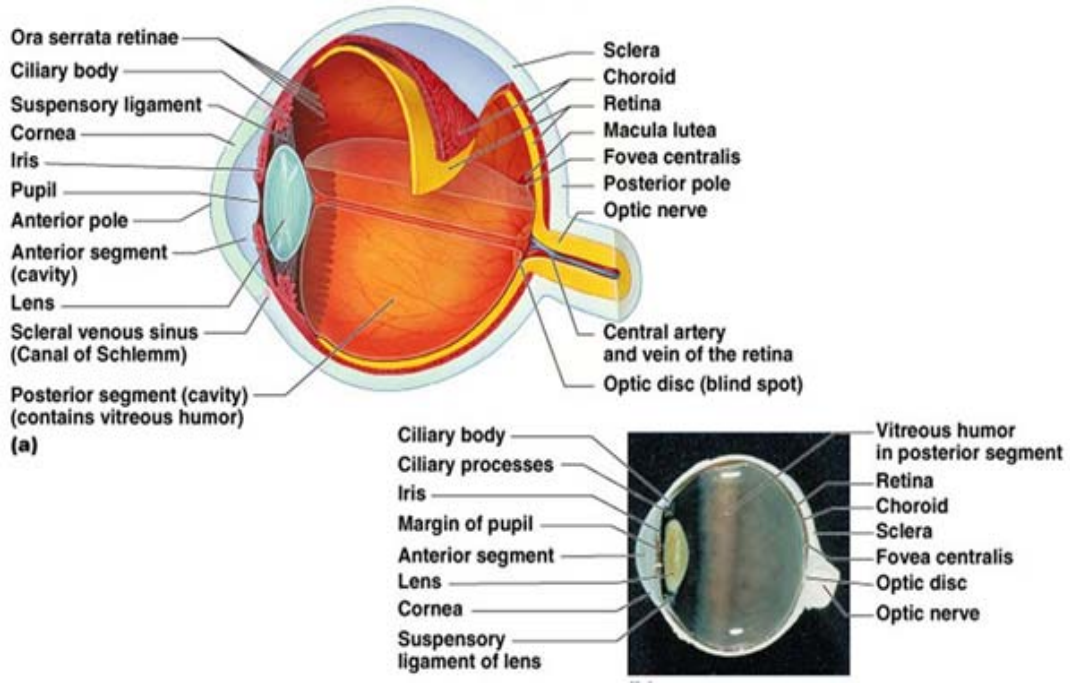


Figure 4.1 Fovea

The central fovea of about 100 micrometers has 50 percent of perifovea layer which consists of high density of cones. This layer is surrounded by an external peripheral region that has high information and low resolution of image. The nerve system plays an important role in carrying information from eye to brain. In which half of the nerve system carries information from fovea to brain while remaining half of the nerve system carry information from remaining part of the retina. The radius of the parafovea from the centre of fovea is about 1.25mm similarly the radius of the perifovea from the centre of fovea is about 2.75mm.

4.1.1 Anatomy of Macula

- The diameter of macula is about 5.5mm.
- Differentiated by the superior and interior arterial arcades.
- When seen horizontally it has elliptical shape.
- In retina it the region where the ganglion cells layer is greater than one layer of cell.
- It has yellow pigment at the outer layer.

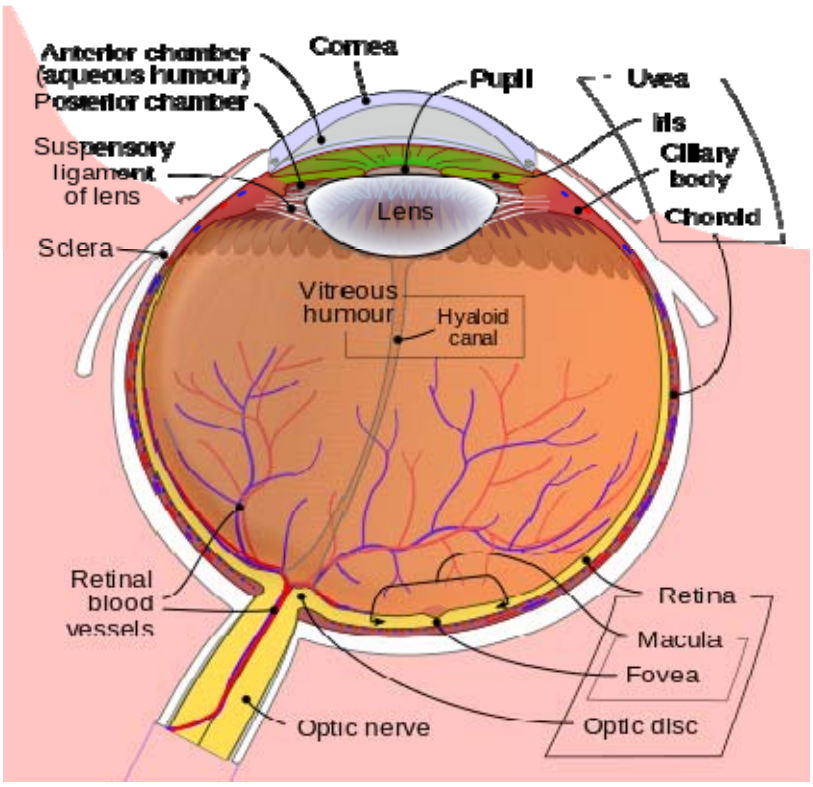


Figure 4.2 Retinal image

The retinal image captured by the OCT scan has the resolution of 3µm.

4.1.2 Anatomy of Parafovea

- Parafovea has the diameter of about 2.5mm.
- It is the region at which high density of cones are found.
- In retina it has the ganglion cells layer greater than 5 layer of cell.

4.1.3 Anatomy of Perifovea

- Perifovea has the diameter of about 2.5mm.
- This is a region which is sandwiched in the middle of the parafovea and macula.
- GCL has 2-4 layers of cells.

4.1.4 Anatomy of Fovea

- Fovea is the centre of macula in retina which is in the form of pits.
- It has the diameter of about 1.5mm.

4.1.5 Anatomy of Foveal Avascular Zone

- It has the diameter of about 0.5mm.
- The diameter of foveal avascular is approximately equal to the diameter of fovea.

4.1.6 Anatomy of Fovea Centralis

- The diameter of fovea is about 0.35mm.

- As the name suggest it is the centre part of the fovea which is in the form of pit.
- It has the group of cone of about 50 cones in the area of 100µm.
- It is the reason for sharp vision of the eye.

The centre and the interior part of the retina is known as fovea which is about 1.5mm in diameter. The photoreceptor layer which consists of large number of cones is the main reason for the pointed vision of the eye. Inside the region of fovea there is a layer which has no blood vessel is called foveal avascular zone which is of about 0.5mm in diameter. The structure of this region is in the form of depression at the centre of the fovea which allows the light to be sensed without any depression or any loss.

The centre part is surrounded by a layer called foveal rim which holds the neurons which comes out of the pit. The region inside the fovea which has no blood vessel is called foveal avascular zone it has large number of cones in it. This region receives large volume of the oxygen from the blood vessel. This region consists of only cone and there is no rod in it also the diameter is about 0.2mm. The cones present in this region in very compact and it looks like rods than that of the cones. The cones in this region are very closely packed in the form of hexagonal. As the number of rods in this region gradually increases the number of cones starts to decrease progressively.

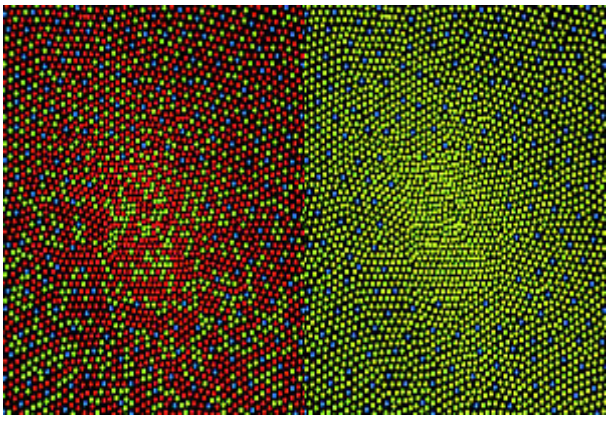


Figure 4.3 Structure of the cone distribution

Above Figure 4.3 shows the structure of the cone distribution in normal retina and a color blind retina (right).

The fovea occupies only the small region in the retina but it is the major reason to see the fine details of the image also the colours. The ratio of ganglion cell to photoreceptors in fovea is about 2:5. A single cone sends data to every ganglion cells of about 3 ganglion cells. As we know already the fovea is the region which has high density of cones in it. The vision of the eyes is limited by the density of cones in it. The green and red light are sensitive to the pigment to the cones in the centre part of the fovea. The fovea occupies only very small area of about 1% of the retinal size but it is the very important part of the eyes to produce very accurate and pointed vision.

In visual field the fovea can only see the centre part that is approximately double the width of the thumbnail. When the object to be viewed is larger, the angle is large. To view the large object the eye should constantly view the object at different portions to bring the complete image into the fovea. The dim lights are not sensitive to the fovea as it does not contain any rods in it. The sides of the eyes have rods in large density hence it can easily view the dim objects. Hence the astronomers observe the dim stars using the above mentioned method.

The high intensities of blue light can cause damage to the sensitive cones so the fovea can act as the protective coat against this effect. The fovea consist of a yellowish pigments that enhance the sharp vision and also reduces the effect of short wavelength (blue light) to fovea. The density of the blue cones is minimum at the centre of the fovea and maximum at the edges of the fovea. When the density of the blue cone is compared it is found that only one percent of its density is present at the centre of fovea.

The fovea has around 150000 cones at each square mm or about 380 cones per square mm. The distance between lens and fovea is called focal length of the eye is around 17mm. Each cone has the angular size of about 31 arc seconds. Peak density of the cone commonly ranges approximately below 100000 or above 325000. The pigment present at the fovea avoids the effect of blue light and when the fovea points to the light source which is polarized this effect is possible by the presence of Haidinger's brush. As the fovea has yellow pigment which resist the wavelength of the blue light, the distribution of blue light is minimum in the fovea. Hence the fovea region has very low sensitivity to the blue wavelength.

At normal conditions the dark spots are not visible as the information to the brain is stored in the blue light. Only when they are focused the dark spots are visible through the illumination of blue light. When the red and blue lights are mixed together we can view the dark red spot at the centre of the region which is surrounded by the fringes of red light. In order to obtain high stereo acuity in binocular two eyes converge at a point to fix bifoveal. Similarly in the case of vision brain associates with one eye through fovea of the other eye which is considered as extra area.

4.1.7 Diabetic Retinopathy Stages

Diabetes is most dangerous and highly threatening disease which affects various parts of the body. As of every parts of the body it also affects the vision and such disease is called diabetic retinopathy. When the disease is detected in early stage it can be cured and the vision can be retained. But as the disease gets worse it cannot be retained and the loss of vision is permanent.

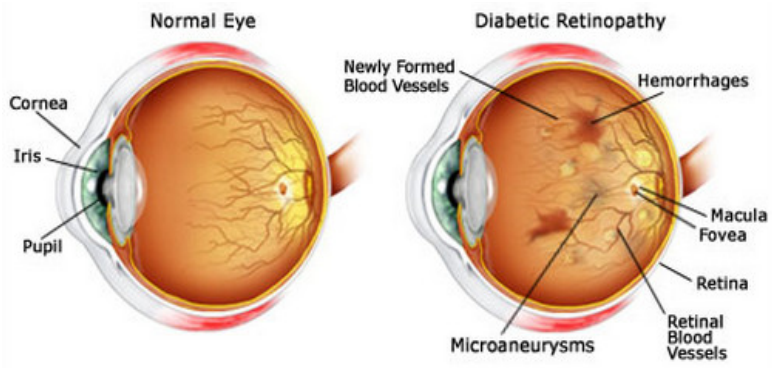


Figure 4.4 Diabetic Retinopathy

Diabetic retinopathy is directly related with the blood pressure and the sugar level present in the blood. Any change in the blood vessel such as blood pressure or sugar level it can directly affect the blood vessel and cause the diabetic retinopathy. When the disease is not detected in early stage it results in the leakage of the blood vessel and causes the blood vessel to bulge that leads to diabetic retinopathy.

Diabetic retinopathy is a disease which has various stages as the disease gets severe. The stages can be classified as mild nonproliferative retinopathy, moderate nonproliferative retinopathy, severe nonproliferative retinopathy and proliferative retinopathy. During the first stage of the disease that is mild nonproliferative retinopathy the blood vessel starts to leak blood and it bulges around small region of the blood vessel at retina of eye.

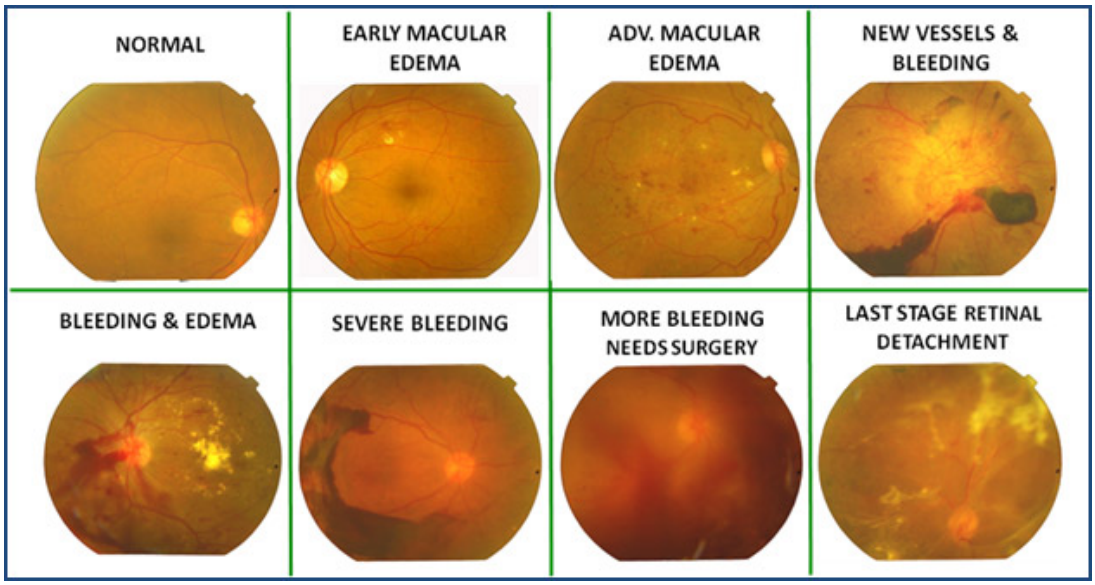


Figure 4.5 Advanced diabetic retinopathy

As the disease proceeds to next stage that is moderate nonproliferative retinopathy it causes clot in the blood vessels of the retina so that the blood flow is not adequate. In the stage three that is severe nonproliferative retinopathy the clot in the blood vessel gets severe and the blood flow gets blocked. If the blood flow is abnormal then new blood vessel cannot grow in the region where the old blood vessel gets damaged. In the final stage that is proliferative retinopathy abnormal new blood vessel start to grow in the region of retina. This advanced diabetic retinopathy stage will lead to permanent loss of vision loss.

4.1.8 Image Pre-processing

Initially after the acquisition of the image it is pre-processed in order to remove the noise and to resize the image. Pre-processing of the image does not degrade the image also it does not affect the information content of the image. In this process the unwanted information in the image is suppressed and the features of the image are enhanced so that it can be used for further process. Image pre-processing uses the concept of redundancy in

which the information contained in the neighbour pixels is nearly similar or equal. So when one pixel is removed from the image it can be replaced by the average value of the neighbour pixels. When a pixel in the image is distorted it can be removed and replaced by the average value of the neighbour pixels.

To suppress the unwanted information (noise) from the image, the image is first filtered. Then the image is subjected to the process of masking and cropping in order to focus the area of interest. MatLab tool provides facility for cropping the image to required size by choosing the appropriate dimensions to be cropped. The image can be cropped in rectangular size by using the mouse that is by simply clicking and dragging. The output obtained after the cropping is similar to that of the input, the only difference is that the image gets enlarged. The fundamental method to analyse the image is by taking the convolution of two dimensions. When a pixel is removed it can be replaced by the average value calculated from the average value of the k*k neighbour.

To remove the noise in the image a filter mask in the form of square matrix is applied to each pixels of the image. The two dimensional convolutional operator is represented as follows. Let the input image be f(x). The convolutional kernel h (a, b) is applied to the input image and g (x, y) is obtained as the output image. The kernel which is in square form is very small in dimension when compared with the image dimension.

Cropping involves following steps:

- Each pixel of the image is represented by the coordinates (x, y)
- Multiplication of each pixel in the image by the appropriate filter mask

- Summing all product together
- Finally the output image is normalized.

The filter used here is two dimensional Finite Impulse Response filter. The filter coefficient and the response of the filter are seen by changing the filter order and the filter coefficient. In order to minimize the blurring of the edges and make the edges sharp along with reducing the noise median filter is used. As this method only replaces the pixel value with its neighbour pixel it does not cause the loss of information in the image.

4.1.9 Intensity Adjustment and Histogram Equalization

Let the input image be represented as (p1, pn). After applying gray-scale transformation which is represented as T the output obtained is given as (q0, qn). Generally it is denoted as q=T (p) which is independent of the position of the pixel in the image. The gray- scale transformation is used to clip the image below p0 and above pn. The values p0 and pn are mapped to the q0 and qn. A constant usually alpha is used to explain the relationship between input and the output image is given by the curve. The image is distinguished between two end points that is bright end and the dark end.

When mapping the values if the alpha is less than 1 then it is marked towards the brighter end. Thus by correcting the alpha value the image can be modified between bright and dark image. The image should not be much brighter as well as more dark it should be in the proper contrast to identify the edges accurately. The histogram equalization technique is used in order to enhance the contrast of the image. Histogram is nothing but the intensity of the pixel, by equalizing the intensity of the pixel to the required level the image can be enhance.

Histogram equalization is performed on the gray image. The gray image consists of only black and white colour and is represented in one-dimensional array of elements. The value 0 represent black colour and the value 1 represent the white colour. An n array of element consists of number of pixels of gray value n. The pixel values are normalized and lie in the range of [0, 1].

Transfer function is given by $s = T(r)$, for any $r \in [0, 1]$

Transformation function satisfies the following conditions:

- T(r) is single valued and monotonically increasing in the interval [0, 1];
- $0 \leq T(r) \leq 1$ for all $r \in [0, 1]$.

The probability density function is used to characterize the original gray level and the transformed grey levels. Contrast is the feature which is used to separate the main object from its background. The transformation function is applied to control the probability density function of gray levels so that the appearance of the image can be modified. This principle is used in the histogram equalization technique which enhances the contrast in the image.

4.1.10 Brightness Thresholding

In this technique the fine details in the image are extracted. An image contains only two type of information such background level information and foreground level information. The image may contain many gray values among them two peak intensity value for foreground and background level is chosen. A common intensity value among those two peak intensity value is chosen this process is called binarization.

A common value acts as a threshold, the all intensity values below the threshold is considered as background level and the all intensity values above the intensity is considered as foreground level. Depending on the type of the image there are different types of binarization process. When the image contrast is poor or when the background intensity in not uniform, it is difficult to differentiate foreground and background levels of the image.

4.1.11 Clearing the Areas of a Binary Image

When the intensities of the image is not uniform or if the image is of very poor contrast it is difficult to separate the foreground image from the background region. To overcome this problem a small mask in the form of hexagon which is present near the region is added to the image in order to reduce the difficulty. This mask when added to the image it reshapes the image and also improves the brightness of the image. So that it is easier to separate the object from its background image.

Let us consider the white colour indicates the foreground and the black colour indicates background region of the image. The input and the output images are in the form of matrix. By using the logical AND operation on the input and the mask which is in the form of hexagon the output is obtained. By adding it the black regions are converted to the white colour representing the foreground image.

4.1.12 Edge Detection

The intensities of the pixels which are near to each others are almost same and they do not vary much but in the edges of the image intensities vary abruptly. During pre-processing the image the variation of the brightness of the image can be detected through the edge detectors. The edge detected by the edge operator is represented in the form of partial derivatives.

The change in the direction of the intensity is given by the gradients. So it can also be said that gradient describes the change in the intensity function that pointing to the direction which has maximum intensity.

Edge has both magnitude and direction so it is considered as vector quantity. The magnitude of the gradient is considered as the magnitude of the edge. The direction of the edge is the direction of the gradient shifted by -90 degree. The maximum intensity is shown by the direction of the gradient. The gradient operator uses more than one mask and by taking the difference between each mask it calculates the derivatives of the image.

The edge detectors also use the zero-crossing principle to detect the edge. Edge detectors such as Prewitt, Sobel, Robert and Canny methods can also be used to detect the edges of the image both horizontally and vertically. These operators are based on the principle of detecting the threshold values. Laplacian of Gaussian method is used to detect the threshold after the image is filtered through Gaussian filter. The derivatives of the Gaussian filter are used to find the threshold of the gradient in canny operator.

The image can be processed partially or as a whole. When the cursor is moved on the image the pointer changes to the cross mark so that the desired location of the image can be selected. After the desired portion of the image is selected, it can be subjected to filtering such as median filtering or low pass filter, it can also be sharpened or blurred, can increase or decrease the contrast.

Image pre-processing is the tool which is used to discard the unwanted information which is considered as noise from the image and to highlight the features of the image which is required for further processing. In MatLab there are many transformation and pre-processing tools. Filtering is performed by replacing the pixels with the average value of the neighbour

pixels. To remove the noise and to reduce the irregularities present in the image smoothing is performed which is similar to the suppressing of high intensity values in the image.

The region of the image which undergoes abrupt change is indicated by the derivatives that are based on the gradient operators. The Fourier transform suppress the low frequency component in the image. The both gradient operator and the Fourier transform methods are used in the software. Basically the edge detectors use the convolutional method to detect the edge. The edges which are detected are represented in partial derivatives form. To increase the brightness of the image gray-scale transformation is applied without affecting the image.

To improve the contrast of the image, the Intensity is adjusted also the histogram equalization is used. The output of the gray-scale transformation is the binary image. This method is used to separate the object from its background. To perform operation only on certain selected portion of the image masks are used which is polygon in shape. If it is difficult to separate the object from it background due to the poor image quality or irregular intensities it can be overcome by using the thresholding or masking method. If there are any corrections in the previous step it can be changed by returning to that stage. The image pre-processing is the technique used to improve and highlight the image using effective techniques.

Edge Detection method includes following three steps:

- Filtering:

  The quality of the image is influenced by the amount of noise present in it. When the image quality is poor the edge detector cannot detect the edges correctly. In order to improve the performance of the edge operators the noise

present in the image should be removed in the pre-processing stage using filter. The filters are used to remove the noise and to improve the strength of the image edges.

- Enhancement:

  Enhancement is the process to highlight the fine details of the image. In order to improve the performance of the edge operators along with filtering the fine details in the image should be highlighted. Enhancement is performed by calculating the magnitude of the gradient so that any change in the local intensity value can be determined.

- Detection:

  The edge points that are calculated through the gradient values are not considered as the edge points. Many other techniques are used to detect the correct edge points. Thresholding method is one among those techniques. In thresholding technique a intensity value is fixed, only the points whose intensity values are high is considered as strong edge points the remaining points with the intensity value less than threshold value is discarded (not considered as edge points).

The edge detection algorithms can also include the fourth step:

- Localization:

  The edge detection process in few cases includes the fourth step called localization. This process is used to detect the edge present near the pixel also the orientation of the edge but it is not accurate.

Generally misclassification leads to the error in edge detection:

- Edges that are falsely detected.
- Edges that are missed.

4.1.13 Fuzzy C-Means Clustering

To separate the data into various groups depending upon their similarities among those individual groups is called clustering. Clustering is a kind of unsupervised technique which has no feedback. The clustering method is not blindly a assumption method instead it has some common knowledge about it. In image processing this clustering algorithm is used for classification, identification and reorganization. In this chapter let us see about the overview of fuzzy clustering algorithms based on the c-means function. For the data that are quantitative which means numerical and qualitative which means categorical or a mixture of both the clustering techniques can be implemented.

In the pattern-recognition, the columns of this matrix are called patterns or objects, the rows are called the features or attributes, and Z is called the pattern or data matrix. The meaning of the columns and rows of Z depends on the context. In medical diagnosis, for instance, the columns of Z may represent patients, and the rows are then symptoms, or laboratory measurements for these patients. When clustering is applied to the model and identification of dynamic systems, the columns of Z may contain samples of time signals, and the rows are, for instance, physical variables observed in the system (position, pressure, temperature, etc.). In order to represent the system's dynamics, past values of these variables are typically included in Z.

Generally, one may accept the view that objects which are similar to each other can forms the group called cluster. The term "similarity" should

be understood as mathematical similarity, measured in some well-defined sense. In metric spaces, similarity is often defined by means of a distance norm. Distance can be measured among the data vectors themselves, or as a distance from a data vector to some prototypical object of the cluster. The prototypes (objects) are usually not known beforehand, and are sought by the clustering algorithms simultaneously with the partitioning of the data.

The prototypes may be vectors of the same dimension as the data objects, but they can also be defined as "higher-level" geometrical objects, such as linear or nonlinear subspaces or functions. Data can reveal clusters of different geometrical shapes, sizes and densities. The performance of most clustering algorithms is influenced not only by the geometrical shapes and densities of the individual clusters, but also by the spatial relations and distances among the clusters. Clusters can be well-separated, continuously connected to each other, or overlapping each other.

Many clustering algorithms have been introduced in the literature. Since clusters can formally be seen as subsets of the data. Clustering method can be classified based on the subsets (objects). The subsets can be either fussy or crisp. Hard clustering method helps to separate the data into different groups which are similar to each other. It classifies whether the object belong to a cluster or not. It is found that fuzzy clustering method gives better result when compared to hard clustering method. For example when an object belongs to a group it is indicated as 1 if it does not belong to that group it is indicated by 0.

The discrete nature of the hard partitioning also causes difficulties with algorithms based on analytic functions, since these functions are not differentiable. Another classification can be related to the algorithmic approach of the different techniques.

Agglomerative hierarchical methods and splitting hierarchical methods form new clusters by reallocating memberships of one point at a time, based on some suitable measure of similarity. With graph-theoretic methods, Z is regarded as a set of nodes. Edge weights between pairs of nodes are based on a measure of similarity between these nodes. Clustering algorithms may use an objective function to measure the desirability of partitions. Nonlinear optimization algorithms are used to search for local optima of the objective function. The remainder of this chapter focuses on fuzzy clustering with objective function. These methods are relatively well understood, and mathematical results are available concerning the convergence properties and cluster validity assessment.

Most analytical fuzzy clustering algorithms (and also all the algorithms presented in this chapter) are based on optimization of the basic c-means objective function, or some modification of it. Hence, we start our discussion with presenting the fuzzy c-means functional. A large family of fuzzy clustering algorithms is based on minimization of the fuzzy c-means functional formulated as the function J given by

$$J(Z,U,V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (\mu_{ik})^m \left\| z_k - v_i \right\|_A^2$$

where $U = [\mu_{ik}] \in M_{fc}$

is a fuzzy partition matrix of Z,

$V = [v_1, v_2, \ldots, v_c]$, $v_i \in V^n$

is a vector of cluster prototypes (centers), which have to be determined,

$$D_{ikA}^2 = \left\| z_k - v_i \right\|_A^2 = (z_k - v_i)^T A (z_k - v_i)$$

is a squared inner-product distance norm, and

$$m \in [1, \infty)$$

is a parameter which determines the fuzziness of the resulting clusters. The value of the cost function can be seen as a measure of the total variance of z k from vi.

4.2 PARAMETERS OF THE FCM ALGORITHM

FCM algorithm has the following parameters such as tolerance, fuzziness exponent, the number of clusters and the norm inducing matrix with partition matrix. Among those above mentioned parameters the factor that affects most is the number of clusters and the remaining parameter does not play a vital role as much as number of cluster. The number of cluster plays a major part in the case where the knowledge of the cluster structure is not known in prior. The structure of the cluster is not known in prior so the total number of cluster is computed then the decision is taken whether the real data belongs to the corresponding cluster group or not.

4.2.1 K-Means Clustering

K-Means clustering technique split the n data into various k number of group where each data belongs to the group having the nearest mean value. Here the vector quantization method is employed. The data mining is one of the major areas where the k-mean clustering is used. The grouping of data into various cluster group leads to Voronoi cells. The clustering also plays important role in other applications such as signal processing.

In this technique the mean value is calculated for each pixel so that the pixel having nearly equal means are grouped together. This technique is similar to that of the k-nearest neighbour classifier. It can be widely used in

the classification and recognition purpose. Initially the cluster centre is obtained by computed by the k-mean algorithm then the nearest neighbour classifier is applied to separate the data into existing groups. This algorithm is also known as nearest centroid classifier or Rocchio technique.

The drawbacks of the k-mean are:

- Initially the Euclidean distance is computed and then the variance is calculated which scatters.
- The appropriately chosen number of cluster leads to the poor result. Hence the algorithm is repeated number of times to check to determine the number of cluster.
- The wrong result may occur when it converge at local minimum.

The cluster model is the major limitation of k-mean cluster algorithm. When the cluster structure is spherical the mean value converge through the centre of the sphere. All the cluster structure is expected to be same. So the cluster centre computed for one cluster can be suitable for the nearest neighbor cluster. The output of the k-mean cluster depends upon the type of data set used. This algorithm produce correct result for few data set but fails in many other data sets. For example when k-mean algorithm is applied to a set of rose flower data set it fails to separate the different colour of flowers.

The Voronoi cell is the output obtained by the result of k-mean clustering. In this process the data is divided into the clusters by the computing mean. The Expectation maximization technique uses Gaussian model and are much better than k-mean clustering since it uses both the variance and the covariance. The Expectation maximization technique is

superior to k-mean clustering also the correlated clustering because it can work well on all type of clusters and also on various sizes of cluster.

K-means clustering is a kind of unsupervised learning which has no feedback and correction process. This process is very simple and easy way to categories each data into its cluster type. Here the centroid must be determined for each cluster. This centroid must be placed carefully in each cluster as it produces various results of different places. When the centroid is placed far away from each other it produces better result. Once the centroid is placed then the next step is to place the points which are near to the centroid point. The process is repeated for all points until no more point is left out.

The new centroid point is calculated then the process is repeated for newly calculated centroid. The newly calculated centroid value is performed on the same data points. The location of the centroid is varied and the steps are repeated for the same set of data points. There forms a loop as the result it until no more changes can be done. The main motive of this process is to minimize the error. The error, e is given as,

$$e = \sum_{j=1}^{k} \sum_{i=1}^{N} \left\| x_i^{(j)} - c_j \right\|^2$$

where $\left\| x_i^{(j)} - c_j \right\|^2$ is the distance between the centroid and the n data points.

The steps followed in the algorithm:

1. Initially the k points are placed into the space to be clustered. In this step the cluster groups are initially formed.
2. Then each point is assigned to the groups which are having the values close to the centroid.

3. Once the process is completed for all point then the new centroid value is calculated by changing its position.
4. The above two steps are repeated until no more place is left for the new centroid value. Through this process it aims to minimize the error.

Example:

Let us consider the n number of samples (x_1, x_2, …,x_n) which are similar to each other but falls on the different groups say k. The mean is calculated for each cluster group. Let the mean of each cluster be m_i. When the clusters are separated from each other perfectly then minimum-distance classifier can be used.|| $\mathbf{x} - \mathbf{m}_i$ || is the small distance when compared to all other distance.

To find the k means following procedure are involved:

- Initially means values are computed as $\mathbf{m}_1$, $\mathbf{m}_2$, ..., $\mathbf{m}_n$.
- The process is repeated until no more modification is made in the mean value
    - The mean value is used to classify the data into corresponding groups.
    - The mean values from $\mathbf{m}_1$, $\mathbf{m}_2$, ..., $\mathbf{m}_n$is repeated for all the data in the group.

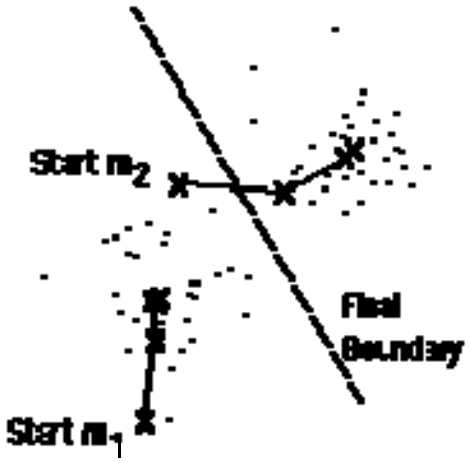


Figure 4.6 Mean value of the groups

The above Figure 4.6 shows how the mean value is placed in the different groups based on the centre values (centroid). This algorithm is known as greedy algorithm as the n data are grouped into k different cluster also by reducing the errors (distance from the data point and to the centre).

4.2.2 Disadvantages of the Algorithm

- The mean value is calculated by randomly choosing the data point k. There is no specific method defined.
- The output produced is mainly influenced by the starting value of the data. So the process is repeated for different starting data.
- The samples that are closest to the mean value are zero. So it can be omitted and cannot be upgraded.
- The distance between the centroid and the data set influence the result of the process.
- Also the total value k influences the results.

Among the above mentioned disadvantages the last one is very problematic because the number of cluster value is not known in prior. In

above mentioned example we have seen the 2 mean clustering. Now the performance of the 2-mean cluster is compared with the 3-mean cluster and the best among them is determined.

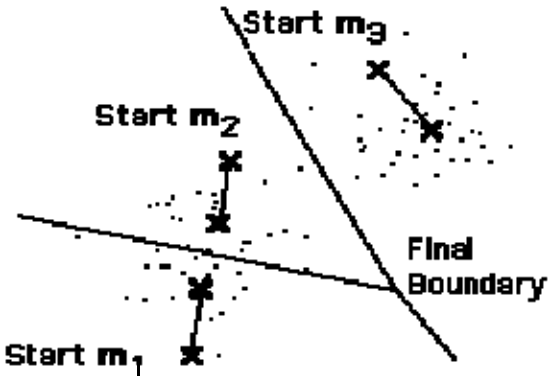


Figure 4.7 Mean cluster

For a given data point there is no specific method to determine the number of cluster. The process is repeated number of times to compare the result of each process with various k values. As the number of k value increases there is a chance of error also there is a risk of over fitting.

4.2.3 Comparison of k-mean Clustering and Fuzzy-c Mean Clustering

The k-mean clustering and fuzzy-c mean clustering are moreover similar to each other but the only difference is choosing the vector which decide how much of the data points are belonging to various clusters. The performance of the k-mean algorithm is inefficient when compared to the fuzzy c-mean algorithm as it performs many operations than it.

The k-mean clustering is called the hard mean clustering and the fussy c-mean clustering is called soft mean clustering. As the k-mean clustering has to repeat the process for k times or multiply the each data point

with number of cluster. The k-mean clustering is lengthy process when compared to the fussy c-mean clustering.

The clustering algorithm is chosen depending upon the size and shape of the cluster data. The size and the shape of the cluster data play an important role in deciding the cluster algorithm. The k-mean clustering and fussy-c mean clustering performance differs for various shapes of the cluster data. Their performances were better for circular and rectangular clusters but not for the ellipsoidal clusters. The k-mean clustering is best suited for elliptical clusters whereas the fussy-c mean clustering is well suited for circular and rectangular clusters.

When k-mean clustering method is applied on the real data which is in elliptical form then it gives better result when compared with the fussy-c mean clustering method. When k-mean clustering method is applied on the real data which is in form circular or elliptical then it gives poor result when compared with the fussy-c mean clustering method. It is revealed that FCM is better than KM in term of accuracy of clusters on the diabetes dataset.

However, in our study, neither KM nor FCM were successful to find the concave and other kind of arbitrary shaped clusters when they are not well separated. In the analysis of this kind of data structures we recommend that shape sensitive clustering algorithms should be used. For instance, the spectral clustering and hierarchical agglomerative methods for nested circular cluster structures.

On the basis of experimental results it is shown that Fussy c-mean clustering method gives better results for noisy clustered datasets. When large set of database is considered then the Fussy c-mean method is best suited because of its fast execution time.

CHAPTER 5

COMPARATIVE ANALYSIS OF CLASSIFICATION OF DIABETIC RETINOPATHY IN RETINAL IMAGES USING MULTI OBJECTIVE PSO AND NSGA II

5.1 INTRODUCTION

To recognize a number of diseases occurring in the human eye, managing retinal image is required. The categorizations of these ailments are carried out post reducing the images' noise. From the reduced imageries, its topographies are mined and centred on it with the imageries categorized into a number of sessions of ailments. Blood vessel and dissection of optic disc constitute a very tough method (Sopharak et al. 2009). They are mostly dissected on three approaches: Process inception, pursuing procedure besides skilled-based mechanism to classify. The optic disc dissection commences with describing its site. This technique is applied to unite the vessels' characteristic into the optic disc to just about compute its location. The disc area is later dissected with the help of two dissimilar mechanised procedures under image rebuilding besides reparation aspect Haddouche et al. 2010). Both the procedures apply the vessels' merging topography to recognise the discs' position.

Including dissecting blood vessel segmentation, managing retinal imagery comprises (Fraz et al. 2012), four basic procedures – segmenting optic disc, (Aquino et al. 2012) detecting ailment, (Goatman et al. 2011)

uncovering besides grouping (Wu et al. 2013). Blood vessels are viewed as thin stretched assemblies on the retina, with varied width and length. For fragmenting the blood vessel off the hollowed retinal imagery, a pre-processing course comprising an operative-adaptable equalising histogram besides transforming with strong expanse were employed.

As discussed previously, segmenting the optic disc occurs over MRF imagery rebuilding or recompenses aspect procedures. Information on mined blood vessels besides the optic disc is passed over to any of the classifying procedures for which Reproduction Connectionist Systems is used. Centred on the nerve cell, these are assigned to input and output layers (Jayanthi et al. 2010). The discrepancies are then transmitted rearwards. The system takes inputs through nerve cells in the input layer and the nerve cells in the output layer gives to the output layer. Network learning is the most vital job in Reproduction Connectionist Systems. For learning course, the modified topographies are mined block by block in one imagery. When a new imagery is applied, only the particular topographies are mined and the learned classifying mechanism is applied to organize the deviation in the retinal imageries.

The topographies mined are inaccurate besides being identical for ailments such as diabetic retinal disease glaucoma, high blood pressure, tiny aneurism, vein obstruction etc. (Taylor & Keeffe 2001). The chief phases of diabetic retinal disease are Non Multiplying Diabetic Retinal disease and Multiplying Retinal disease. The former is the primitive phase of diabetic retinal disease while the latter is a tiny blood vessel impediment of diabetes mellitus that can tip to irreparable optical loss. Their dimensions range from 10-100 microns, that is, lower than 1/12th of an average optics disc's diameter and are round-shaped. At this stage, the disease is not threatening to the eyes. The Non Multiplying Diabetic Retinal disease, an ailment being the primitive

phase, cannot be forecasted effortlessly. It requires analysis of bottom-most imagery wherein micro-aneurisms will be visible. Micro-aneurisms are minuscule blood-filled swellings in the vein walls. Several techniques are applied to detect diabetic retinal disease, the most famous technique being fundoscopy or funduscope. It is an analysis of the retina wherein the ophthalmologist gazes through a cut spotlight bio optical microscope having an exclusive enlarging lens, providing retina's narrow view thus enabling analysing leak in blood vessels, retinal bulge, pale, blubbery coatings on the retina called exudates, impaired fiber matter besides any change in the blood vessels (Babu et al. 2015).

5.2 OPTIMIZATION IS NP-HARD

Practical augmentation issues are invariably very perplexing to decipher, and many applications are required to deal with NP-hard problems and to solve the same, augmentation implements are to be applied, while there is no surety of obtaining optimal solution. In fact, there are no competent procedures for NP problems. Consequently, many problems require solution by trial and errors applying several augmentation techniques (Fister Jr et al. 2013). Besides, new procedures have been conceived to visualise if they are capable to cope with such perplexing augmenting constraints. Among such new procedures, Element Cloud Augmentation, Inherited procedure, strange exploration besides firefly procedure, have earned fame in view of their superior competence.

Inherited procedure is based on Darwin‘s Growth Concept. Commencing with a set of probable answers and changing the same while on various reiterations, the inherited procedure anticipates congregating on the most suitable answer. The operation commences with a set of probable answers or genes (normally in the system of minute cords) that are arbitrarily created or chosen. The complete set of such genes consists of a populace. The

genes progress while on various reiterations or creations. New creations (progeny) are created applying the defection and alteration techniques. Defection comprises dividing two genes and then merging one half of each gene with the other pair. Alteration comprises tossing a single bit of gene. The genes are then assessed applying some suitability norms with the best ones retained while the others discarded. This process recurs till one gene has the superior suitability and is thus considered as the best solution to the problem. These strictures are carried out using various methods (Jestin et al. 2011).

A populace-centred stochastic exploration procedure - PSO - applies cloud cleverness. It was first conceived during 1995 with a fundamental logic enthused by simulating social behaviour of birds flocking and fish schooling, etc. Originally, no one exactly knew of whereabouts of the food, however, with each reiteration, they became aware the distance at which the food was visible. The best approach will be to pursue a bird nearer to food besides from its own finest location. Every member of the populace is called an element and the entire populace is called a group. Every element has its own speed and a position in exploration space. Each element reminisces its own best location called the individual best, denoted by *pbest*, besides the whole group finding its best position, referred to as global best, denoted by *gbest*. The entire elements have suitability worth firmly decided by the process of augmentation. First, locations and speeds of every element are prepared arbitrarily. They were later permitted to hover over the exploration space and update their locations besides speeds finding an optimum answer (Sreejini & Govindan 2013).

Hence, a competent procedure that uses the augmented topography of the imageries besides classifying the imagery through suitable ailment is required. It will be praise worthy if the procedure could routinely detect the topographies more precisely and arrange them for accurate judgement. In the

forthcoming study, the imageries are noise-retardant and the topographies viz. area of micro-aneurism, location of vessels, and homogeneousness besides degeneration are extracted. The topographies are chosen and augmented using two dissimilar augmenting procedures, namely, Multiple Independent Element Group Augmentation besides Non-conquered Arranging Hereditary Procedure. The chosen topographies are later cured with dissimilar classifier procedures viz., Reverse Transmission Nervous System, Backing Trajectory Apparatus and incoherent classifier such as Incoherent C Resources grouping procedures which are discussed in previous chapters. In this work, Backing Trajectory Apparatus classifier is discussed.

5.3 METHODOLOGY

The Figure 5.1 portrays the slant flow operation of the forthcoming study task. From the bottom most retinal imageries, a record have been formed which would be considerably beneficial for educating the classifier procedures. On receiving a retinal imagery, it is pre-treated, where the imagery becomes noise-retardant. From the extracted topographies, proper topography is chosen over augmentation procedures. The augmented topographies are later carried over to classifying procedures for identifying besides classifying the disease. As shown in Figure 5.1, two classifying procedures were used.

5.3.1 Feature Optimization and Selection

Once, the topographies are mined from the noise-retardant imagery, the suitable topography is augmented and chosen to recognise the ailment. In this study, certain techniques were used for imagery topography augmentation and assortment. In both the procedures, suitability process and estimation of suitability forms the vital process.

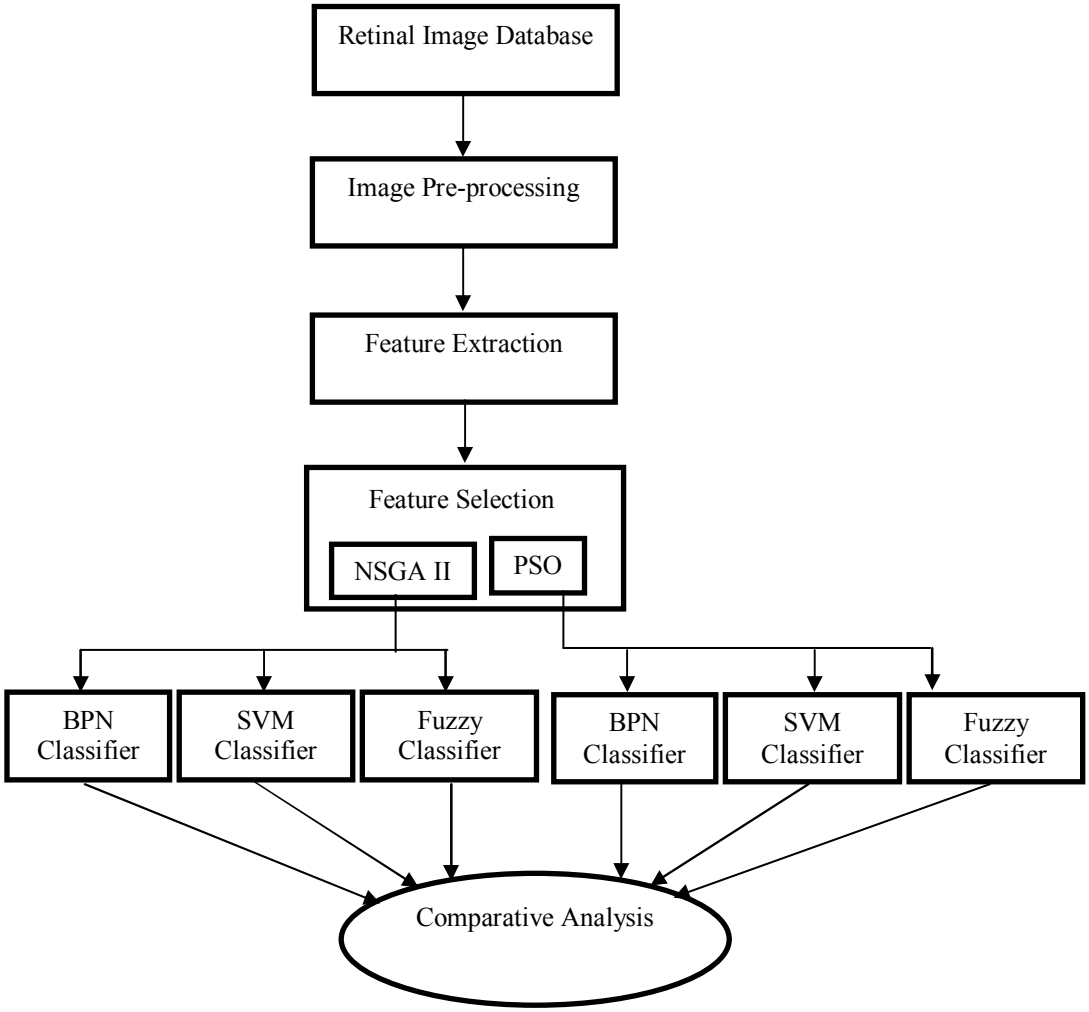


Figure 5.1 Flowchart of Proposed Methodology

Fitness Function: In this study, the suitability process is the expanse among two imageries. For two imageries I1 and I2, the expanse (dq) is the quadratic equation mistake of the minute area of illumination of the imageries as depicted in equation (5.1):

$$d_q(I_1, I_2) = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I_1(x,y) - I_2(x,y))^2 \qquad (5.1)$$

Estimating the Suitability: Matching two imageries pixel by pixel is very relaxed, even with the most efficient computers used currently. However, during the growth process, suitability requires repeated

calculations. Hence, it is vital to have a superior estimating technique. It is noticed that black minute areas of illuminations (0 values) do not tally in the suitability assessment. Hence, discarding the minute areas of illumination can enhance estimation speed. The finest way is to combine the turtleneck with the suitability estimation, with an outcome object called Aptness Estimating Turtleneck. When the Aptness Estimating Turtleneck draws an article, it analyses the corresponding minute area of illumination of the purpose imagery too. As per the outcome, if the minute areas of illumination are present in the end imagery, the minute area of illumination is arranged as fpixel and upixel if otherwise. The number of these minute areas of illumination is denoted by N_f and N_u. Before the evolution process, the number of black minute areas of illumination (N_0) and the number of white minute areas of illumination (N_1) can be calculated. Using such values, the number of minute areas of illumination which appear in the end imagery (not in the generated image) is determined. This kind of minute areas of illumination is called as mpixels. The number of these minute areas of illumination is signified by N_m and can be calculated in the (5.2):

$$N_m = N_1 - N_f \tag{5.2}$$

The unexamined minute areas of illumination are called npixels. The number of these minute areas of illumination is (5.3):

$$N_n = N_0 - N_u \tag{5.3}$$

From these reckonings, the suitability process can be altered and formed as in equation (5.4), with W as augmented weight functions.

$$\varphi = W_0 N_n + W_1 N_f - W_2 N_u - W_3 N_m \tag{5.4}$$

5.3.2 Non-Dominated Sorting Genetic Algorithm–II (NSGA–II)

The presence of multiple goals in an issue, in principle, paves way to a set of optimum resolutions (mainly identified as Pareto-optimum resolutions), instead of a sole optimum resolution. In the non-existence of any additional data, one of such Pareto-optimum resolutions is superior to the other. This warrants the user to find maximum possible Pareto-optimum resolutions. Standard augmentation procedures (including the multiple norm conclusion-making procedures) propose changing the multiple goal augmentation issue to a single goal augmentation one through underlining particular Pareto-optimum resolution at a time. When such a technique is to be applied for discovering manifold resolutions, it requires repeated applications in anticipation to find a different resolution at every reproduction run.

Over the past decade, a number of Multiple Goal Evolutionary Procedures were suggested. The principle reason for the same being their aptitude to find manifold Pareto-optimum resolutions in one solo replication run. Since evolutionary procedures function with a populace of resolutions, a simple evolutionary procedure can be stretched to preserve a various set of resolutions. Emphasising to move toward the true Pareto-optimum region, an evolutionary procedure can be used to locate manifold Pareto-optimum resolutions in one solo replication run.

The Non-Conquered Arranging Hereditary Procedure was one among the first such evolutionary procedures. Over the years, the main disapprovals of such approach are as follows (Deb et al. 2000).

High Calculating complication of non-conquered organising: The presently-used non-conquered organising procedure has a computing complication of O (MN^3) (where M is the number of objectives and N is the

population size). This makes computing costly for large sized populace. This huge complication rises due to that the convoluted in the non-conquered organising procedure in every generation.

Lacking superiority: Fresh results showed that superiority can significantly hurry up the conduct of the competent procedure, which can also help prevent the loss of good resolutions upon being found.

Requirement of stipulating the partaking stricture: Conventional techniques of certifying assortment in a populace in order to obtain a wide range of similar resolutions have trusted chiefly on the sharing concept. The main constraint faced in sharing is that it needs the description of a partaking stricture (σ_{share}). Though there were certain works on lively sizing of the partaking stricture, a stricture-less variety-protection technique is desired.

In this task, it addresses every one of such issues and suggest an enhanced variety, an extension of inherited procedure for multiple unbiased job augmentation. Its main goal is to enhance the suitability process to be more appropriate to a Pareto front controlled though a set of unbiased purposes. Alike the traditional inherited procedure; it includes machinists viz. choosing, hereditary defection and hereditary alteration too. In this proposed algorithm, the suitability process gained from equation (4.4) is applied to allocate a suitability worth for every gene (Deb et al. 2002). The suitability worth finds the quantum of a gene closer to the resolution of the issue. An individual (gene) with a greater suitability signifies an improved resolution.

The augmentation of suitability process is centred on the dimensions of Arena under Recipient Functioning Curvature besides maximum precision. To estimate an area under this, the imagery is initially sifted to obtain a gloomy level imagery with 0 and 1 intensities. A descending

inception among the values 0 and 1 is used on the filtered imagery to get 1000 binary imageries. For every binary imagery, the Real Optimistic Portion besides the Wrong Optimistic Portion is estimated. Recipient Functioning Curvature is a graphical patch of former Vs. latter, with larger the area under the curve, the better the performance of the filter. Centred on these former and latter, the minute areas of illumination are classified as true vessel minute areas of illumination besides false minute areas of illumination.

The true and false vessels minute areas of illumination are those that are detected as such in the resultant imagery and they are actually the respective vessel minute areas of illumination in the hand-tagged imagery. Hand-tagged imageries are gained from the retinal imagery by a human expertise applied for comparison purposes with automatically sensed vessels. After inception of the sifted imagery, the precision is estimated by computing the sum of true vessel minute areas of illumination and true non-vessel minute areas of illumination and dividing the sum by the number of Arena of Vision minute areas of illumination. Arena of Vision is the round area in the retinal imagery. Then mass for the 1000 thresholds are computed and their average yields the all-out precision for the overall imageries of the database.

5.3.3 Multi-Objective Particle Swarm Optimization (MOPSO)

A general Multiple Independent Augmentation Issues is defined as: diminish a process f (x), subject to p disparity and q parity issues in (5.5) and (5.6) (Reddy & Nagesh Kumar 2007).

$$\min . f(x) = \{ \underset{x \in D}{f_1(x)}\ f_2(x) \ldots f_m(x) \}^T \tag{5.5}$$

Where $x \in R^n$, f_i : $R^n \rightarrow R$ and

$$D = \begin{cases} x \in R^n : & l_i \le x \le u_i \quad \forall i = 1,...,n \\ & g_j(x) \ge 0, \quad \forall j = 1,...,p \\ & h_k(x) = 0, \quad \forall k = 1,...,q \end{cases} \tag{5.6}$$

where m is number of goals; D is possible exploration area; $x = \{x_1 x_2,\ldots, x_n\}^T$ is the set of n-measurable conclusion changeable (uninterrupted, distinct or number); R is the set of actual figures; R^n is n-measurable hyper-plane or area; and l_i and u_i are lesser and higher limits of i-th conclusion adjustable.

The aforesaid Multiple Independent Augmentation Issues must concurrently augment the trajectory process and yield Pareto optimum resolutions. Pareto front is a set of Pareto optimum (non-conquered) resolutions, being contemplated to be optimum, if no goal can be enhanced devoid of foregoing at least one other goal. Instead, a resolution x^* is discussed as conquered by another resolution x, if and only if, x is correspondingly good or improved than x^* in respect of entire goals.

For applying the element group augmentation strategy for solving multiple goal augmentation procedure, it is obvious that the original scheme has to be modified. In general, when solving a multi-objective problem, three main goals to achieve are: (Reyes-Sierra & Coello 2006):

- Make the most of the number of elements detected in the Pareto optimum set.
- Diminish the expanse of the Pareto front developed by the procedure with respect to the real (global) Pareto front (supposing it knows its location).
- Make the most of the detected spread of solutions; to enable it can have a dispersal of trajectories smoothly and uniformly to the extent possible.

In multiple goal issues, it can differentiate two essential attitudes for planning element group augmentation procedures. The first approach comprises procedures which contemplate every goal function individually. In such attitudes, every element gets assessed for only one unbiased process at a time, and the determining the finest locations is carried out in the same way as the single unbiased augmentation case. The chief test in such cases is the correct operation of the data being received from every unbiased operation for guiding the elements headed for Pareto optimum resolutions.

The next tactic comprises procedures that assess the entire unbiased processes for every element and centred on the theory of Pareto optimum, they deliver finest non-conquered positions (often referred to as front-runners) that are applied to assist the elements. In such strategies, determining front-runners is uncomplicated, since there can be numerous non-conquered resolutions in the vicinity of the element, but only one is normally chosen to take part in the speed update (Parsopoulos & Vrahatis 2008).

Pseudo-code of a general MOPSO algorithm (Durillo et al. 2009):

```
1: initializeSwarm()
2: initializeLeadersArchive()
3: determine minLeadersQuality()
4: generation = 0
5: while generation < max Generations do
6: for each particle do
7: selectLeader()
8: updatePosition()
9: mutation()
10: evaluation()
11: updatePbest()
12: end for
13: updateLeadersArchive()
14: determine minLeadersQuality()
15: generation ++
16: end while
17: returnArchive()
```

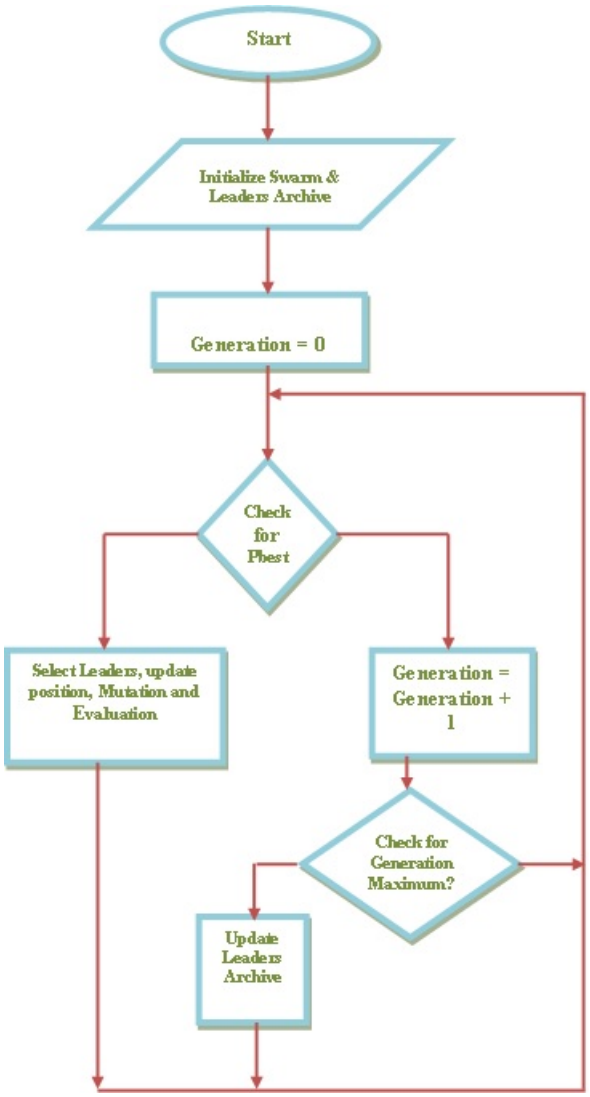


Figure 5.2 Flowchart of MOPSO

Pseudocode of a general MOPSO procedure: Post preparing the group (Line 1) in the notation resembling a simplified programming language of a general multiple unbiased element group augmentation procedure, the classic tactic is to apply an exterior document to preserve the front-runners obtained from the non-conquered elements in the group. Similarly, post preparing the front-runners' archive (Line 2), certain degree of feature has to be computed (Line 3) for all the front-runners to choose normally one front-runner for every element of the group. In the chief circlet of the procedure, the voyage of every element is carried out post choosing a front-runner (Lines 7-

8) and an optional alteration or instability machinist can be used (Line 9). The element is then assessed and its conforming *pbest* is restructured (Lines 10-11). Post every reiteration, the set of front-runners are restructured and the feature measure is computed again (Lines 13-14). Post the cessation status, the collection is given back as the outcome of the exploration

Augmentation issues are resolved applying element grouping augmentation with two steps. First is representing the resolution and the suitability process. The chief benefit of element group augmentation is its ability to take true numerals as elements. For the suitability process obtained at equation 4.4, the resolution is achieved. Through reiterations, an optimum solution is then arrived. The reiteration is motionless when the extreme reiteration numeral is attained or the least mistake status is fulfilled. In element group augmentation, the strictures to be regulated are quantity of elements, their dimension, extreme alteration (V_{max}), erudition features besides discontinuing situation (Blondin 2009). In element group augmentation, the best worth is attained on testing with the universal and native types of the resolutions. In this study, the multiple unbiased process includes making the most of the intra-expanse between minute area of illumination and their constellations, as quantified by $d_{max}(Z_i, x_i)$ and diminishing the inter-expanse among any pair of constellations as quantified byd_{min} (x_i). The features of minute area of illumination are computed as process off (x_i,Z_i) as shown in equation (5.7).

$$f(x_i Z_i) = w_1 \overline{d}_{\max}(Z_i, x_i) + w_2(z_{\max} - d_{\min}(x_i)) \qquad (5.7)$$

where, z_{max} is the extreme worth of minute area of illumination in the imagery set and Z_i is the medium signifying the allocation of minute area of illumination to the constellations of particle *i*.

Sustenance trajectory mechanism learning function is applied to analyse learning information to locate an optimum way to organize imageries hooked on their corresponding classes. Sustenance trajectory mechanism is a strong method for classifying information besides reversion. Sustenance trajectory mechanism replicas look for a subspace of a vector space that has dimension one less than the dimension of the vector space that can sequentially detach object classes. Assist trajectory mechanism is applied to differentiate several classifications (Priya & Aruna 2012).

Categorisation strictures are computed applying sustenance trajectory mechanism learning. The learning function examines learning information to locate an optimum way to organise imageries into their corresponding sessions. The learning information should be enough to be statistically noteworthy. The sustenance trajectory mechanism learning procedure is used to derive the categorisation strictures in accordance with computed attributes. The derived categorisation strictures are applied to organise the imageries. The imagery information can be differentiated into several groupings in terms of the planned sustenance trajectory classifying device. To fit non-sequential curves to the information, sustenance trajectory mechanism makes use of a seed process to plot the data towards a dissimilar space where a device to separate the space into two half spaces can be applied to do the parting.

Sustenance trajectory mechanism is used to non-sequential categorisation applying non-sequential seed process to plot the contributing information on a greater measuring attribute space wherein the contributing information can be detached with a sequential classifying agent.

For instance, tag pair (x_i, y_i) with $x_i \in \Re^n$, $y \in [1, -1]$ for $1 \leq i \leq n$ where n is the count of occurrences, the under mentioned (Mansour et al.

2013) augmentation issues require resolution for assist trajectory machining in (5.8):

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \tag{5.8}$$

Subject to (5.9):

$$y_i (w^T \phi(x_i)) + b_0 \geq 1 - \xi_i, \xi_i \geq 0 \tag{5.9}$$

In the foregoing equation, …is decision hyperplane standard trajectory, C is the fine stricture for mistake term and ϕ plots a learning occurrence x_i to greater measurable space with b_0 as arbitrary constant. The seed K is described as (5.10):

$$K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{5.10}$$

The Circular Origin Process' seed is described as (5.11):

$$K(x_i, x_j) = \exp(-\gamma \left\| x_i - x_j \right\|^2), \gamma \geq 0 \tag{5.11}$$

Where γ is seed stricture spread; hence in the above equation, there are two strictures, C and γto regulate the functioning of the classifying agent.

5.4 RESULTS AND DISCUSSION

Retinal images were collected from M/s. Vasan Eye Care Hospital, Coimbatore. This work was carried out with the patients at the hospital on DR. Then the databases of the images are created as normal and abnormal images. In this work, the BPNN, SVM, FCM and KNN methods are evaluated. The proposed methods such as MOPSO and NSGA II are also

evaluated. The sensitivity, accuracy, precision, specificity and execution time as shown in Tables 5.1 to 5.5 and Figures 5.2 to 5.6.

Table 5.1 Sensitivity (%)

Techniques	MOPSO	NSGA II
BPNN	98.1	98.4
SVM	98.9	99.4
FCM	99.2	99.6
KNN	98.2	98.5

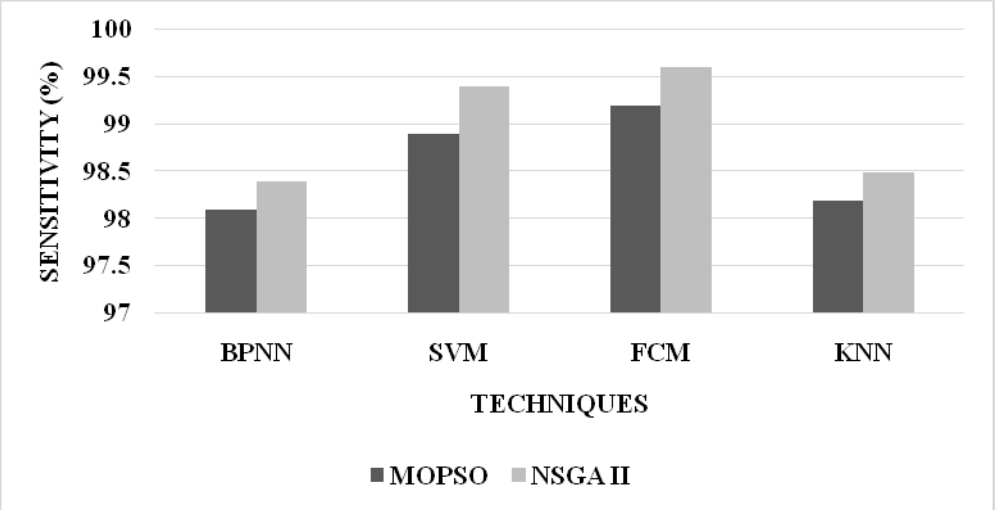


Figure 5.3 Sensitivity (%)

From the Figure 5.3, it can be observed that the FCM has higher sensitivity by 1.11% & 1.21% for BPNN, by 0.3% & 0.2% for SVM and by 1.01% & 1.11% for KNN when compared with MOPSO and NSGA II.

Table 5.2 Accuracy (%)

Techniques	MOPSO	NSGA II
BPNN	96.5	96.8
SVM	98.4	99.2
FCM	99.1	99.4
KNN	96.5	96.7

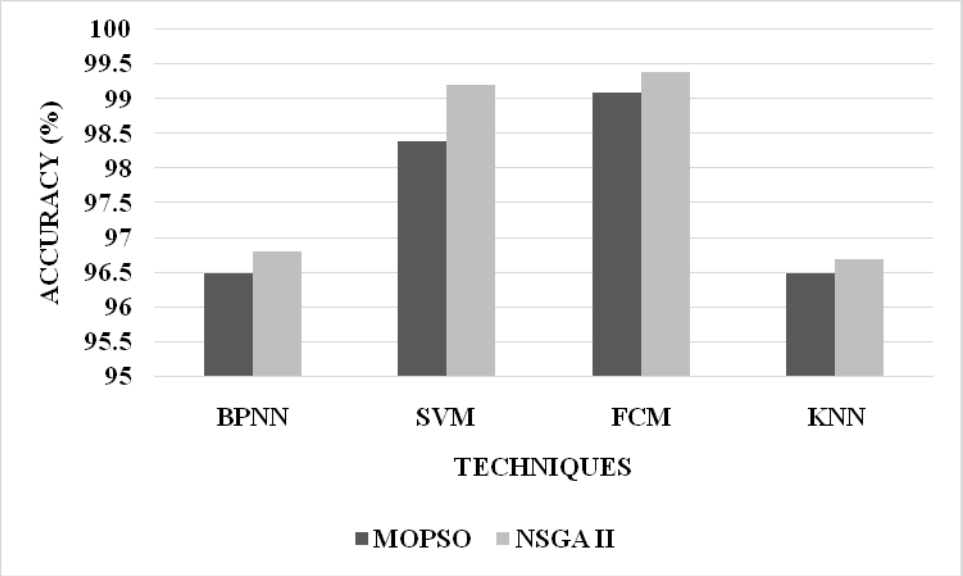


Figure 5.4 Accuracy (%)

From the Figure 5.4, it can be observed that the FCM has higher accuracy by 2.65% & 2.65% for BPNN, by 0.7% & 0.2% for SVM and by 2.65% & 2.75% for KNN when compared with MOPSO and NSGA II.

Table 5.3 Precision (%)

Techniques	MOPSO	NSGA II
BPNN	93.3	93.6
SVM	99.1	99.6
FCM	99.5	99.7
KNN	96.4	96.5

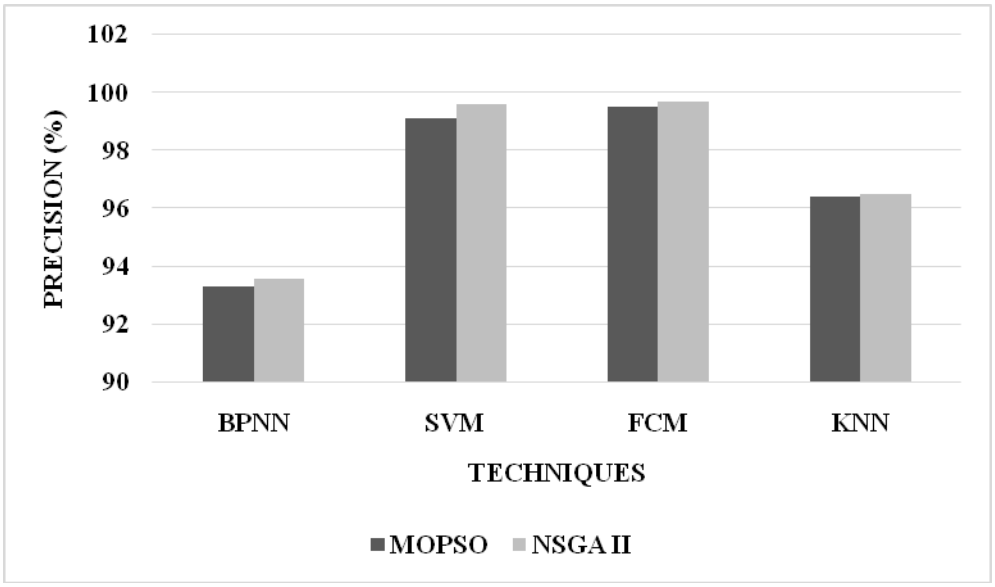


Figure 5.5 Precision (%)

From the Figure 5.5, it can be observed that the FCM has higher precision by 6.43% & 6.31% for BPNN, by 0.4% & 0.1% for SVM and by 3.16% & 3.26% for KNN when compared with MOPSO and NSGA II.

Table 5.4 Specificity (%)

Techniques	MOPSO	NSGA II
BPNN	91.2	91.8
SVM	93.7	95.1
FCM	95.2	95.8
KNN	92.4	92.7

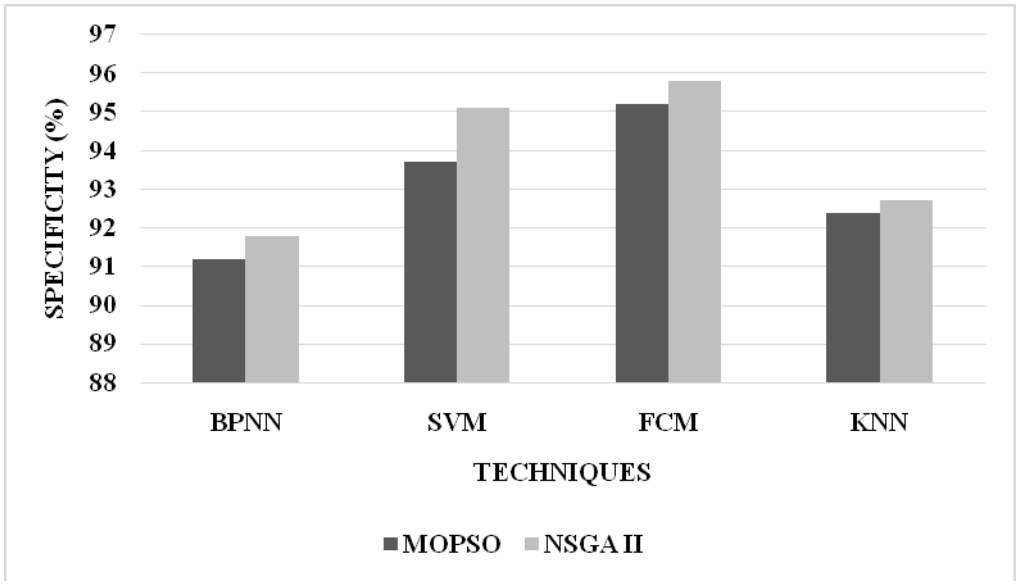


Figure 5.6 Specificity (%)

From the Figure 5.6, it can be observed that the FCM has higher specificity by 4.29% & 4.26% for BPNN, by 1.58% & 0.73% for SVM and by 2.98% & 3.28% for KNN when compared with MOPSO and NSGA II.

Table 5.5 Execution Time (ms)

Techniques	MOPSO	NSGA II
BPNN	320	310
SVM	285	278
FCM	265	260
KNN	274	269

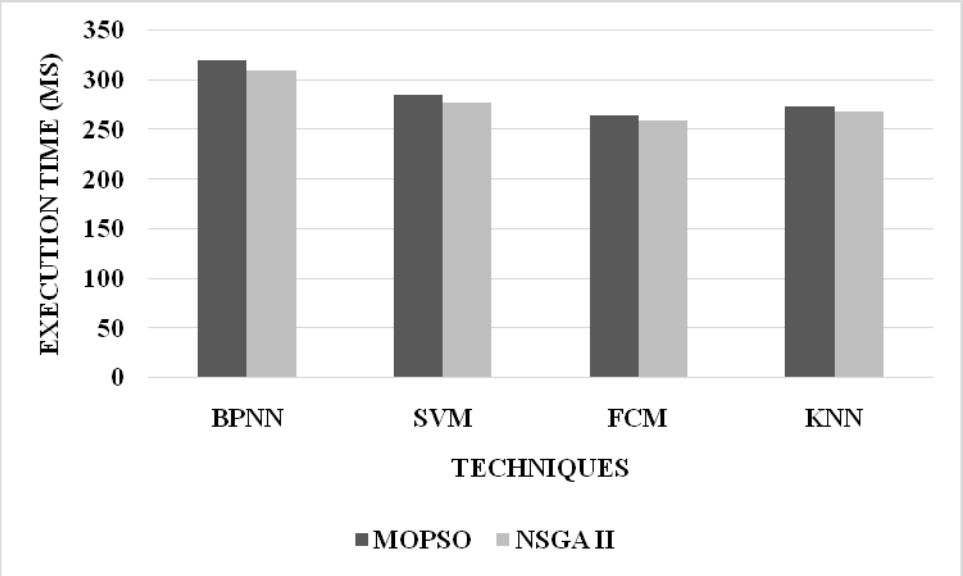


Figure 5.7 Execution Time (ms)

From the Figure 5.7, it can be observed that the FCM has lower execution time by 18.8% & 17.54% for BPNN, by 7.27% & 6.69% for SVM and by 3.33% & 3.4% for KNN when compared with MOPSO and NSGA II.

5.5 CONCLUSION

A competent procedure for precision categorisation of diabetic eye disease has been tried in this study. The topographies of the noise-retardant imagery have been augmented and chosen over multiple unbiased element

group augmentation techniques. Then from these selected topographies, the ailments are categorised over classifying mechanism. Several classifying procedures have been tried for competent categorisation and their contributions have been evaluated. Out of the two augmentation mechanisms, it is obvious that non-conquered arranging genetic procedure affords greater presentation, in terms of augmenting and choosing the topographies from the retinal bottom-most imageries. The scrutiny of the presentations of different classifying mechanism specified that the incoherent grouping classifying mechanism affords greater outcomes in comparison to its equivalents. Hence, it is settled that the forthcoming system, when put to use, can help ophthalmologists for competent categorisation of the ailment occurring in human eyes.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

Diabetic eye disease is the noteworthy ophthalmic investigative reason of loss of sight among working class people in developed besides developing nations. The chief root of diabetic eye disease is non-standard rise in blood glucose level, which harms vessel endothelium, resulting an enhance in the vessel porousness. Retinal imagery examination is one among the critical subjects in medicinal imagery dispensation. Over the last three decades, people were attempting to mine the dissimilar topographies (like blood vessels, optic disk, macula, fovea etc.) mechanically from retinal imagery. The preliminary indicators of diabetic eye disease are small vessel enlargements known as micro-aneurisms.

Thus a joint strategy for detecting micro-aneurism besides post dispensation for true vessel mining has been put to use with obtaining the precise outcomes. The forthcoming system is an innovative methodology overcoming the entire demerits of the prevailing system. Analysing the conduct of three dissimilar classifying mechanisms was carried out and their proportional results established that K Nearest Neighbour ordering mechanism outpaced the other two. This type of universal functions may be a new standpoint in detecting, classifying besides identifying retinal blood

vessels to detect micro-aneurism. The technique to perceive the fovea area of the eye and diabetic eye disease identification.

Two significant procedures are contemplated in analysing it involving the isolation of blood vessels with the next procedure dealing with the automated location of the optic disc, fovea. In the planned attitude of detecting blood vessel, structural operations besides geometric characteristic processes are applied to derive the output. Fovea procedure can be used in hospitals for doctors to easily perceive ailments happening on the eyes. A hospital study was performed to assess the prevalence of diabetic eye disease and allied risk issues among diabetic eye disease. The fundus images were collected from the hospital and were retained as the data base. While the program was running successfully, it displayed the yield of fovea region. The steady transmission of the diabetic eye disease is highly endorsed in as much as with the initial perception of procreating eye disease and timely laser photocoagulation surgery, which are recognized to thwart most of the diabetes- connected blindness. An automatic mechanism to perceive diabetic eye disease applying an incoherent grouping classifying mechanism clustering is planned and comparing the result with K Nearest Neighbour.

A competent procedure for precision categorisation of diabetic dye disease was tried in this study. The topographies of the noise-retardant imagery were augmented and chosen through non-conquered organizing hereditary procedures and multiple non-biased element group augmenting techniques from which, the diseases are categorised over classifying mechanism. Several classifying procedures were tried for competent categorisation and the contributions were compared. Out of the two augmenting techniques, it is evident that non-conquered organizing hereditary procedures provided greater outputs, in terms of augmenting and choosing the topographies from the retinal bottom-most imageries. Analysing the conduct

of various classifying mechanisms showed that the incoherent clustering classifying mechanism provided superior results compared to its equivalents classifying mechanism.

6.2 FUTURE WORK

The future work proposes to enhance the computing intricacy and implement several meta-partial search procedures besides various classifying mechanism.

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LIST OF PUBLICATIONS

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2. **Suresh Babu**, **V &** Vijayan, S 2016, 'Comparative Analysis of classification of Diabetic Retinopathy in Retinal Images Using Multi Objective PSO and NSGA II', International Journal of Printing, Packaging & Allied Sciences, December 2016, ISSN 2320-4387, vol. 4, no. 5, pp. 3552-3557. **(Annexure I). IF : -**