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Early Detection of The Glaucoma and Other Intra-Ocular Pressure Elevation Diseases Using Hardware Efficient Machine Learning Approach

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Abstract
Nowadays, Glaucoma is one of the chronical diseases that entirely make the human eyes into the blindness. This disease is a consequence of an accumulation of aqueous humor in the eye due to a defect of its drainage system. This condition progressively elevates the intra-ocular pressure (IOP), affecting the optic nerve and resulting in permanent blindness if left untreated. In early stages, the glaucoma may be an asymptomatic. Hence, the proposed method is designed to detect the early stage of the glaucoma. This can be done by measuring the cup to disk ratio. For that, the proposed image processing algorithm is constrained with the three basic steps such as preprocessing, feature extraction and classification. In classification stage, we employ the SVM classifier to classify the normal and glaucoma images. The method is found to be efficient in hardware implementation when compared to other methods. The overall implementation will be held in the Matlab supporting environment.

Keywords: Glaucoma, SVM, Intraocular pressure, machine learning,

1.Introduction

Glaucoma is a chronic and irreversible neuro-degenerative condition that is one of the leading causes of preventable blindness in the world. In European countries glaucoma is the second main cause of blindness. The prevalence of blindness due to glaucoma continued to increase in Latin America over the last decade. This disease is a consequence of an accumulation of aqueous humor in the eye due to a defect of its drainage system. This condition progressively elevates the intra-ocular pressure (IOP), affecting the optic nerve and resulting in permanent blindness if left untreated.4 As glaucoma may be asymptomatic in its early stages, at least half of patients with this eye pathology remain undiagnosed, while more than half of those who are undergoing treatment do not have the disease. As glaucoma is a chronic life long disease, which if not timely diagnosed and treated can lead to blindness, the major challenge is to be able to screen for glaucoma to detect the large number of undiagnosed people. Current screening practice includes the examination of optic nerve head (ONH) through fundus imaging and measurement of the cup to disc ratio (CDR). The CDR is one of the most commonly used diagnostic criteria, even though it can be influenced by factors such as sex, age or race, etc.6 Inspection of other

retinal structures including nerve fiber defects or vessels, using such imaging modalities as optical coherence or Heidelberg Retinal tomographies is usually required to confirm the diagnosis.

Automated screening systems for glaucoma detection from fundus photographs are extremely valuable as they facilitate the early diagnosis of the disease, which is critical to prevent its progression. However, most recent strategies are based on analyzing properties of the ONH blood vessels1 or the nerve fiber layer for which it is essential to previously detect and segment these regions. As segmentation-based features are known to be significantly influenced by the precision of the underlying segmentation methods, an increasing scientific effort in the field of glaucoma detection is devoted to the development of new strategies based on overall image properties. Such approaches are based on transformations of the image intensities, texture analysis or combinations of image derived features with clinical and genetic information. An important limitation of these strategies, however, is that they rely on hand-crafted features, which require a significant engineering effort to develop, or in data that is too complex to obtain under certain clinical settings.

1.1. Importance of Image processing in Eye disease detection

Image processing plays a vital role in automatic screening of eye diseases. The recent development of computer software and image analysis techniques paved a path for the development of screening systems that predict and diagnose the defects in human eye. There are many types of imaging modalities used for medical diagnosis of various eye diseases.

Fundus imaging is highly preferred for diagnosing retinal diseases due to its low cost, portability and less risk to the patients. The eye disorders such as glaucoma, diabetic retinopathy (DR) and age-related macular degeneration (ARMD), can be diagnosed for follow-up management of patients from the digital fundus images. A direct diagnostic value of such a method relies upon a skilled and objective interpreter of the acquired images. However, such expertise is available only in multi-speciality hospitals.

In country like India, people in rural areas need to travel to urban areas to avail expert opinion. Therefore, assistance of a computer-based image processing algorithm may play an important role on the way to a successful recognition of crucial information contained in the fundus images. The detection of abnormalities such as drusen can be predicted using effective image processing algorithms, to detect the severity of the disease. Appropriate algorithms are needed to make an effective screening process.

1.2. Human Vision

The human eye can be compared with a camera which accumulates, focuses and transmits light through a lens, to make a picture of the environment. In a camera, the picture is captured on film, whereas in an eye, a thin layer at the back of the eye termed retina captures the picture. The white and opaque part of the eyeball is sclera, located as the outermost layer of the retina. The lens catches the external light rays from the cornea which is the transparent dome-shaped part of the retina. The external light rays first passes through the dome-shaped cornea, the part of retina that deflects the light towards the lens. The small region that lies between the cornea and the lens is known as anterior chamber.

The posterior chamber is located at the back of the lens and opposite to that of the anterior chamber. Posterior chamber measures more region than the anterior chamber and is packed with a transparent jelly-like fluid termed vitreous humour. The retinal layers will have a sharp focus of images because of the fluid pressure generated by this vitreous humour. The anterior chamber is covered by

thin, ring- shaped structure called iris. The ciliary body is formed by choroid which extends to the front of the eyeball which produces aqueous humour. The shape of the lens can be changed by contracting or relaxing the ciliary muscles located in the ciliary body. The ciliary body is connected with the lens by zonules that permit the lens to alter its form. The hole located in the front of the lens is called pupil.

The size of the pupil is adjusted by the muscles contained in the iris depending upon the amount of light that passes through the eyeball. Behind the eyeball there lies a light sensitive part called retina which contains photo receptors that senses the light. These light sensitive parts are further classified into rods and cones. Rods support the viewer to see in the dark while the cones permit to distinguish the color. The signals are transferred from retina to the brain through the nerve cells that are contained in the retina. The fovea contains increased number of cones located near the OD. The impulses are transmitted from the retina to the brain by the ganglion cells which is located in the optic nerve. Besides the OD there arises a small region called blind spot which contains no photoreceptors, subsequently it will not recognize the light that falls on it. The optic nerve at the center is contained with central artery and veins which supplies and drains the retina.

1.3. Vision Based Disorders

As a person ages, there arises several eye related problems that are more common. This eye related pathologies are listed below.

1.3.1. Hypertensive Retinopathy

Hypertensive retinopathy is retinal vascular damage caused by hypertension. Signs usually develop late in the disease. Funduscopic examination shows arteriolar constriction, arteriovenous nicking, vascular wall changes, flame-shaped hemorrhages, cotton-wool spots, yellow hard exudates, and optic disk edema. Treatment is directed at controlling blood pressure and, when vision loss occurs, treating the retina.

Symptoms and Signs

Figure 1.2 Hypertensive retinopathy

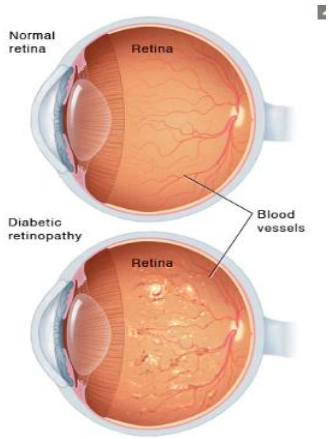


Figure 1.3 Diabetic retinopathy

Hypertensive retinopathy is managed primarily by controlling hypertension. Other vision-threatening conditions should also be aggressively controlled. If vision loss occurs, treatment of the retinal edema with laser or with intravitreal injection of corticosteroids or antivascular endothelial growth factor drugs (eg, ranibizumab, pegaptanib, bevacizumab) may be useful.

1.3.2. Diabetic Retinopathy

Diabetic retinopathy (die-uh-BET-ik ret-ih-NOP-uh-thee) is a diabetes complication that affects eyes. It's caused by damage to the blood vessels of the light-sensitive tissue at the back of the eye (retina). At first, diabetic retinopathy may cause no symptoms or only mild vision problems. Eventually, it can cause blindness. The condition can develop in anyone who has type 1 or type 2 diabetes. The longer you have diabetes and the less controlled your blood sugar is, the more likely you are to develop this eye complication.

Types

There are two types of diabetic retinopathy:

Early diabetic retinopathy: In this more common form — called non-proliferative diabetic retinopathy (NPDR) — new blood vessels aren't growing (proliferating). When you have NPDR, the walls of the blood vessels in your retina weaken. Tiny bulges (microaneurysms) protrude from the vessel walls of the smaller vessels, sometimes leaking fluid and blood into the retina. Larger retinal vessels can begin to dilate and become irregular in diameter, as well. NPDR can progress from mild to severe, as more blood vessels become blocked. Nerve fibers in the retina may begin to swell. Sometimes the central part of the retina (macula) begins to swell (macular edema), a condition that requires treatment.

Advanced diabetic retinopathy: Diabetic retinopathy can progress to this more severe type, known as proliferative diabetic retinopathy. In this type, damaged blood vessels close off, causing the growth of new, abnormal blood vessels in the retina, and can leak into the clear, jelly-like substance that fills the center of your eye (vitreous). Eventually, scar tissue stimulated by the growth of new blood vessels may cause the retina to detach from the back of your eye. If the new blood vessels interfere with the normal flow of fluid out of the eye, pressure may build up in the eyeball. This can damage the nerve that carries images from your eye to your brain (optic nerve), resulting in glaucoma.

1.4. 3. Glaucoma

Glaucoma is a group of eye conditions that damage the optic nerve, the health of which is vital for good vision. This damage is often caused by an abnormally high pressure in your eye. Glaucoma is one of the leading causes of blindness for people over the age of 60. It can occur at any age but is more common in older adults. Many forms of glaucoma have no warning signs. The effect is so gradual that you may not notice a change in vision until the condition is at an advanced stage. Because vision loss due to glaucoma can't be recovered, it's important to have regular eye exams that include measurements of your eye pressure so a diagnosis can be made in its early stages and treated appropriately. If glaucoma is recognized early, vision loss can be slowed or prevented. If you have the condition, you'll generally need treatment for the rest of your life.

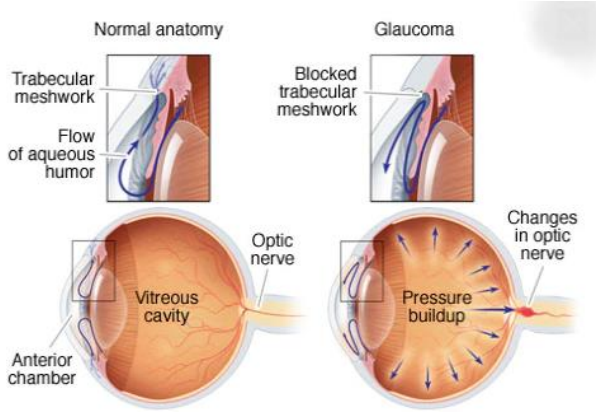


Figure 1.4 Glaucoma

1.4.4. Retinal Vascular Occlusion

Retinal vein occlusion is a blockage of the small veins that carry blood away from the retina. The retina is the layer of tissue at the back of the inner eye that converts light images to nerve signals and sends them to the brain.

Retinal vein occlusion is most often caused by hardening of the arteries (atherosclerosis) and the formation of a blood clot. Blockage of smaller veins (branch veins or BRVO) in the retina often occurs in places where retinal arteries that have been thickened or hardened by atherosclerosis cross over and place pressure on a retinal vein.

Risk factors for retinal vein occlusion include:

The risk of these disorders increases with age, therefore retinal vein occlusion most often affects older people.

1.4.5. Presbyopia

Presbyopia is the normal loss of near focusing ability that occurs with age. Most people begin to notice the effects of presbyopia sometime after age 40, when they start having trouble seeing small print clearly — including text messages on their phone. Worldwide, an estimated 1.3 billion people had presbyopia in 2011. This number is expected to increase to 2.11 billion by 2020, according to Market Scope. Though presbyopia is a normal change in our eyes as we age, it often is a significant and emotional event because it's a sign of aging that's impossible to ignore and difficult to hide.

Symptoms

1.4.6. Cataract

A cataract is a clouding of the normally clear lens of your eye. For people who have cataracts, seeing through cloudy lenses is a bit like looking through a frosty or fogged-up window. Clouded vision caused by cataracts can make it more difficult to read, drive a car (especially at night) or see the expression on a friend's face.

Most cataracts develop slowly and don't disturb your eyesight early on. But with time, cataracts will eventually interfere with your vision. At first, stronger lighting and eyeglasses can help you deal with cataracts. But if impaired vision interferes with your usual activities, you might need cataract surgery. Fortunately, cataract surgery is generally a safe, effective procedure.

1.4.7. Age-related macular degeneration (ARMD)

ARMD is an eye condition which causes irreversible vision loss. ARMD is a perpetual condition that causes dynamic harm to the macula, a little concentrated part of the eye that permits us to see fine purposes of interest clearly. The macula encounters ruinous and irreversible changes over the span of the ailment that endangers visual insight. The macula influenced by ARMD may experience smearing or dimness in the focal point of their vision and assignments, for instance, perusing and driving is influenced. The initial stage of ARMD is drusen. Drusens are stores of cell waste that work underneath the retina, is an imperative reason behind visual debilitation and sightlessness around the world. Drusen in ARMD can be classified into two forms: Hard drusen and Soft drusen. Hard drusens are less harmful and smaller in size when compared to soft drusen. Hard drusens have defined edges that can be easily recognised, whereas the edges of soft drusen and will vary in shape. It is accompanied by formation of new blood vessel and fluid build-up under these blood vessels in the retina. Due to bleeding in the retina, it causes intense loss of vision and it appears to be darker region in the fundus image. When it develops there is no visual limit in the affected locale because of perpetual loss of photoreceptors and retinal color epithelium. By 2020 due to the increase in population the disease is expected to increase by twofold. The amount of people affected by the ailment is depended on to rise because of expanding life span. It is the most typical occasion of irreversible visual impairment in the elderly populace in the developed countries. ARMD is the fundamental reason of visual impairment in people over years 50 and it is second just to diabetes as the contributing reason behind sightlessness in the 45 to 64 year age group. ARMD is not repairable, sometimes extreme vision damage can be avoided of the fact that certain strains of the infection react positively to laser treatment, particularly with right on time determination and brief intercession. It is essential to recognize and treat ARMD at the earliest stage to avoid preventable vision incident.

LITERATURE SURVEY

H. Zhang et al (2012) presented a novel color feature for iris classification, named as iris color Texton using RGB, HSI and lαβ color spaces. Extensive experiments are performed on three databases. The proposed iris color Texton shows advantages in iris image classification based on color information. Ahmad Nazri Ali (2013) suggested an approach to enhance the image histogram equalization method is applied to produce equalized contrast and more embellish iris pattern. A. A. Bhadra et al (2016) stated that bacterial and viral conjunctivitis may be very contagious. The algorithm detect whether an eye has cataract or has conjunctivitis or is a normal eye. M. D. Manchalwar and K. K. Warhade (2017)

considered three eye diseases such as cataract, conjunctivitis, and stye. Here HOG used for detection of the feature vector. Minimum distance classifier is used. A. Arslan et al (2016) described that vessel structure as viewed on the sclera, the white and opaque outer protective covering of the eye, is stable over time and unique to each person. The pattern of the sclera based blood vessels is a good database for the identification of several diseases and the thickness of the vessels give an indication of the mental state of the person. This makes the scanning and storing of the sclera vein pattern and the colour of the sclera a very good database for monitoring the physical and mental state of a person. Today, dry eye disease is a widely seen health problem. Accurate determination of region of interest has high priority for the algorithm to be applied in the diagnosis of dry eye disease. In this study, automatic detection and extraction of region of interest is studied on real dry eye patient data received after applying clinical fluorescein staining test (A. Arslan et al 2016).

T. Y. Mahesh and K. L. Shunmuganathan (2014) described that vessel structure as viewed on the sclera, the white and opaque outer protective covering of the eye, is stable over time and unique to each person. D. Selvathi and K. Suganya (2019) explored the machine learning technique to detect diabetic diseased using thermography images of an eye

Ashame et al (2018) integrated adaptive Otsu's Threshold, Hough transform and kirsch's template filtering for automated detection of candidate optic nerves. A proposed segmentation model is introduced, which integrates vessels detection mechanism to achieve better sensitivity rates and high performance. J. Wang et al (2020) developed a computer-aided retinal image screening system that can perform automated diabetic retinopathy (DR) grading and DR lesion detection in retinal fundus images. A modified object-detection method for this task via a region-based fully convolutional network (R-FCN) was done. S. Alver et al (2015) presented a novel approach using Discrete Wavelet Transform for the detection of diabetic retinopathy diseases from the retina images. A. Poshtyar et al (2016) developed an automatic method for the detection, extraction and quantitative analysis of atrophic regions that occurred on retinal surface in retinal diseases. The work presented by A. B. Jagadale et al (2019) uses slit lamp images from ophthalmologist at eye hospital with computer aided image processing to detect cataract at earlier stage. Hough circle detection transform for lens detection and support vector machine for categorization was used. R. Sigit et al (2019) stated that cataracts are the lens of the eye that becomes cloudy so that light cannot penetrate, varying according to its level from a little to total opacity. A single layer perceptron method was used. D. Patil et al (2016) studied and analyzed different cataract detection methods and techniques. This paper classifies various techniques stated and implemented until now based on three basic steps: 1)Pre-processing, 2)Feature extraction, 3)Classifier construction. H. I. Morales Lopez et al (2016) discussed the early cataract detection in a non common topic for ongoing research, considering that is one of the most common eye diseases, and is the leading cause of blindness globally. S. Roychowdhury et al (2016) presented a novel method that classifies neovascularizations in the 1-optic disc (OD) diameter region (NVD) and elsewhere (NVE) separately to achieve low false positive rates of neovascularization classification. S. Kumar and B. Kumar (2018) presented an improved diabetic retinopathy detection scheme by extracting accurate area and ate number of microaneurysm from color fundus images. For detection of microaneurysms, principal component analysis (PCA), contrast limited adaptive histogram equalization (CLAHE), morphological process was used. K. K. Palavalasa and B. Sambaturu (2018) presented a novel method false exudate lesion detections using the de-correlation stretch based method. Kirsch method, edge detection, thresholding, filters, noise removal, histogram equalization, optic disk removing and morphological classification

processes was done. This method is applied on the different images for accuracy. As a result early detection of diabetic retinopathy is aimed by the way focused on hard exudates and hard exudates are marked on different image (B. Yaşar et al (2018)). Z. A. Omar et al (2017) trained and tested using 49 and 89 fundus images, respectively. The images used in training were obtained from Hospital Serdang, Malaysia while images used in the testing were obtained from DIARETDB1 database. All of the images were categorized into four DR stages, namely mild Non-Proliferative Diabetic Retinopathy (NPDR), moderate NPDR, severe NPDR and Proliferative Diabetic Retinopathy (PDR).

3.1. Existing Method

Iris recognition is the globally accepted biometric technique used for automated person identification. This biometric method is globally preferred due to the following features: (a) Iris pattern is constant throughout a subject's lifetime, (b) Uniqueness (even identical twins also do not have a same iris pattern), (c) Reliability (Every person must have iris pattern), (d) Non-invasive. Specular reflection is the brightest pixel in the NIR/VW iris images. The light source used for eye image acquisition and reflective layers of the cornea region are the major causes of specular reflection. Specular reflection affects the iris segmentation module of iris recognition systems and increases the non-match rate. Hence, there is a need for specular reflection removal in iris images. The existing morphological dilation and region filling based specular reflection removal method for VW iris images is shown in Fig.3. The sequential steps of the proposed approach are detailed as follows.

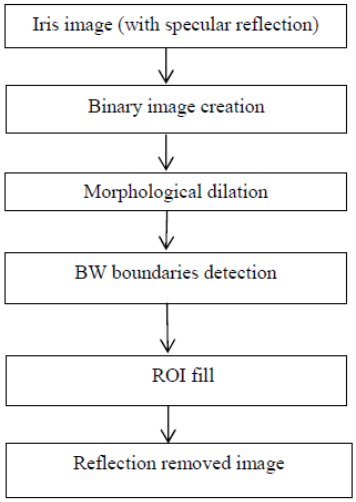


Figure 3.1 Existing method for specular

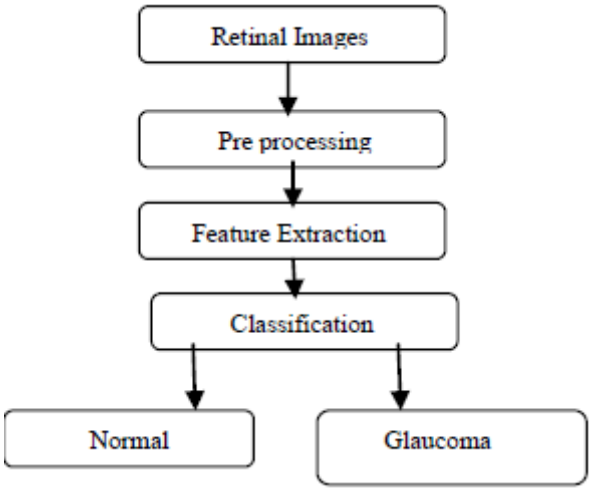


Figure 3.2. Proposed method for detecting the glaucoma reflection removal

In the initial step , the Red (R), Green (G), and Blue (B) colour bands of input iris image are separated. After colour band separation, maximum intensity pixels in R, G, and B colour bands are detected based on the intensity threshold value computed from the histogram analysis. After this, a binary image X is created from the threshold values of R, G, and B colour bands. In the binary image X, the specular reflection is shown as white pixels. The morphological dilation operation is performed using this binary image X and the structuring element S. The morphological dilation process is mathematically explained as

$dil(X,S) = X \oplus S$

$X \oplus S$ is denoted as $X \oplus S = \{x : Sx \cap X \neq « \}$

Also, X and S are the sets in two–dimensional Euclidean space. Sx is the translation of S and the intersection is nonempty. After morphological dilation operation, the outer boundaries of reflection regions are detected in the dilated image. After boundary detection, these boundaries are plotted in R, G, and B colour bands of the input RGB image. The regions inside the plotted boundaries are filled in all three colour bands by interpolates inward from the pixel values on the detected boundary using Laplace's equation. The detected boundaries in all three colour bands are filled with intensity levels closer to the neighbouring pixel's intensity and a reflection removed iris image is formed by adding these colour bands.

3.3. Proposed Method

To detect the glaucoma, initially, retinal images are capture using digital devices for image content. Then pre-processing is performed for equalizing and reshapes the irregularities on the images. In pre-processing, blood vessels are segmented and in painted to gain a vessel-free image. Then, Feature extraction is performed to reduce the dimensions effectively to represent the interested parts of an image as a concise feature vector for describing the large data set precisely. Pixel intensity values, textures, FFT coefficients and Histogram model are the methods used in feature extraction. Image Classification is performed which analysis the numerical properties of an image and organizes the data. Depending on the results obtained, the set of data is divided into discrete classes' i.e. normal eye or glaucomatous eye. The general glaucoma detection process is illustrated in Figure 3.2.

3.3.1. Enhancement of Optic Cup to Disc Ratio

The optic cup to disc ratio is one of the principle physiological characteristics which is employed for detection of glaucoma. The C/D ratio represents the depression in the optic disc in which neural tissue is absent and compared with overall optic disc size. A larger C/D ratio has greater risk of glaucoma. Below are the various steps mentioned to determine the CDR as illustrated in Figure 3.3.

a) ROI Determination: Region of Interest (ROI) is the small portion of an image which has been extracted and necessary operations has been performed on it. By creating a binary mask, one defines an ROI as a binary image that has the same size as of the image we want to process. In the mask image, pixels which lie in ROI has been set to 1 and all other pixels has been set to 0. By this process, in order to extract the optic disc has been traced out as optic disc occupies less than 5% of pixels in retinal fundus image. By localizing the ROI, it reduces the computational cost and also improves accuracy of segmentation .it is defined as a rectangle around the ROI centre with dimensions of twice the typical optic disc diameter, and has been used as the initial boundary for the optic disc segmentation.

b) Optic Disc Segmentation: Segmentation of optic disc and optic cup eliminates the disadvantages of conventional Optic Nerve Head (ONH) evaluation methods. There are various techniques for segmentation based on template matching, machine learning, active contour model, level sets and Hough transform. For calculating the vertical cup to disc ratio firstly the optic cup and disc segmented from the retinal images.

c) Optic Disc Smoothening: The detection of disc boundary from the previous step might not have actual shape, since the boundary can have effect on blood vessels which are entering into the disc. Therefore, ellipse fitting has been applied in order to reshape the disc boundary.

d) Optic Cup Segmentation: Optic cup segmentation is bit harder than optic disc extraction since the cup-disc boundary is less measurable than that of disc region and besides combines with increased visibility of blood vessels across the cup-disc boundary.

e) Optic Disc Smoothing: After detecting the cup boundary, ellipse fitting is used furthermore to remove few boundaries of optic cup occurred due to sudden changes in the curvature. Ellipse fitting is an important tool especially when portions of the blood vessels in the neuro-retinal rim which is outside the cup are included within the detected boundary. Based on the height of detected optic disc and cup, the cup to disc ratio (CDR) has been obtained.

f) Ellipse Optimization for optic disc and cup: Ellipse fitting algorithm is used for smoothening the optic disc and cup boundary. Usually, Ellipse fitting is based on least square fitting algorithm which assumes that the best-fit curve has minimal sum of deviations squared from given set of data points (least square error). It allows fitting the ellipse on a certain data points in a particular region of interest.
The risk of glaucoma has been predicted by CDR value; if CDR exceeds 0.65 indicates high glaucoma. Thus by enhancing the CDR ratio might be used for diagnosis of glaucoma.

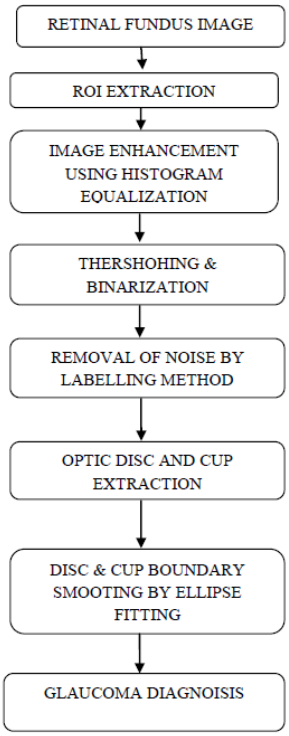


Figure 3.3. Glaucoma diagnosis using CDR Measurement

3.3.2. Glaucoma detection using SVM Classifier

A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one target value (i.e. the class labels) and several attributes (i.e. the features or observed variables). We have used support vector machine (SVM) classifier, a supervised learning model, for classifying normal eye fundus from glaucoma affected eye fundus. The goal of SVM is to produce a model (based on the training data) which predicts the target values of the test data given only the test data attributes.

SVM is designed to separate of a set of training images into two different classes, (x_1, y_1), (x_2, y_2),…(x_n, y_n) where xi in R^d, d-dimensional feature space, and y_i in {-1,+1}, the class label, with i=1..n. SVM builds the optimal separating hyper planes based on a kernel function (K). All images, of which feature vector lies on one side of the hyper plane, belong to class -1 and the others are belong to class +1. As we can see from Figure 3.4, H3 does not separate the two classes while H1 separate the two class with a small margin, only H2 gives a maximum margin between two classes, therefor it's the right hyper plane used by support vector machine. If the data of various classes can be separated as in Figure 3.4, then the linear SVM is used. Otherwise if the data of the classes cannot be separated, then the non-linear SVM classifier is used. However, instead of defining a function for the hyper plane itself; we define the margin in between the two classes. From Figure 3.5, we can see that the position of our hyper plane depends on the value of w where w is the (not necessarily normalized) normal vector to the hyper plane

4.IMPLEMENTATION RESULTS

MATLAB is used which is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, we can analyze data, develop algorithms, and create models and applications.

Module 1 Implementation - Preprocessing of Input Iris Images

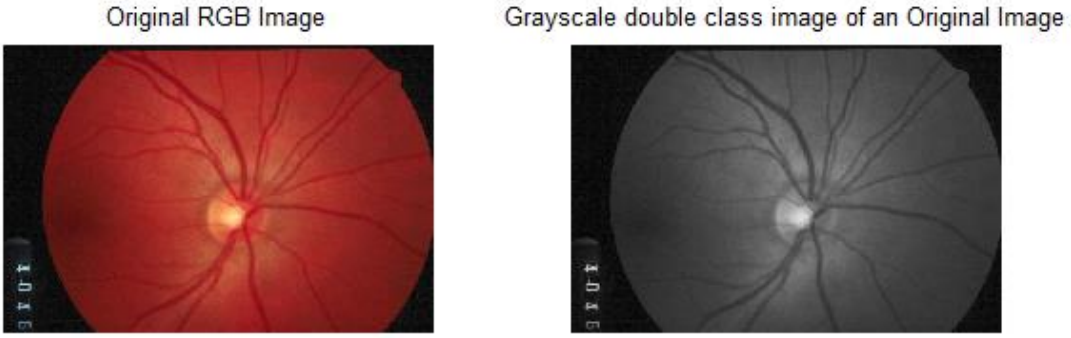


Figure 4.1 Input Iris Image and its Grayscale image

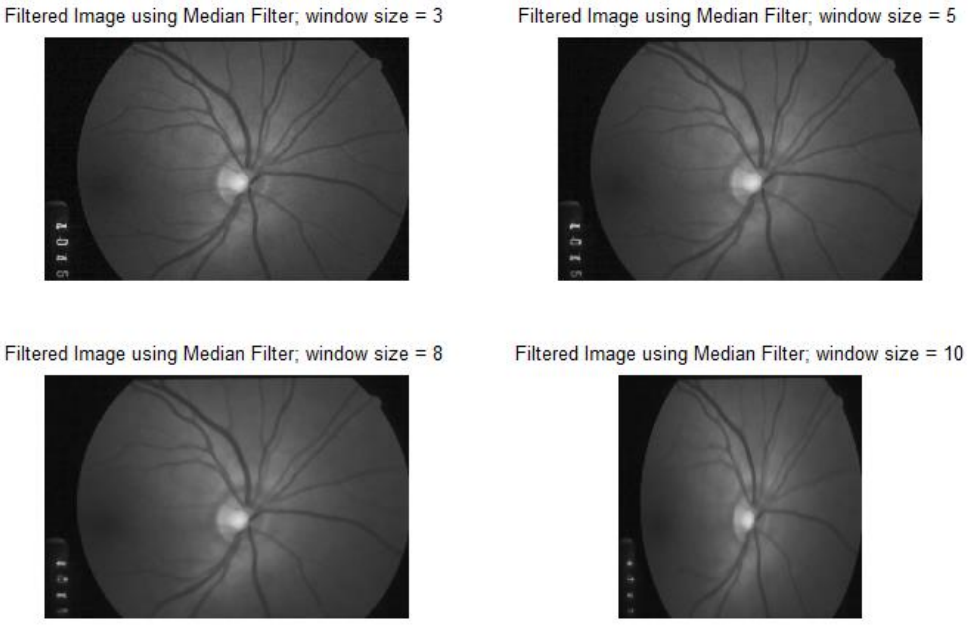


Figure 4.2 Denoised Iris Image by using Median filter with different window size

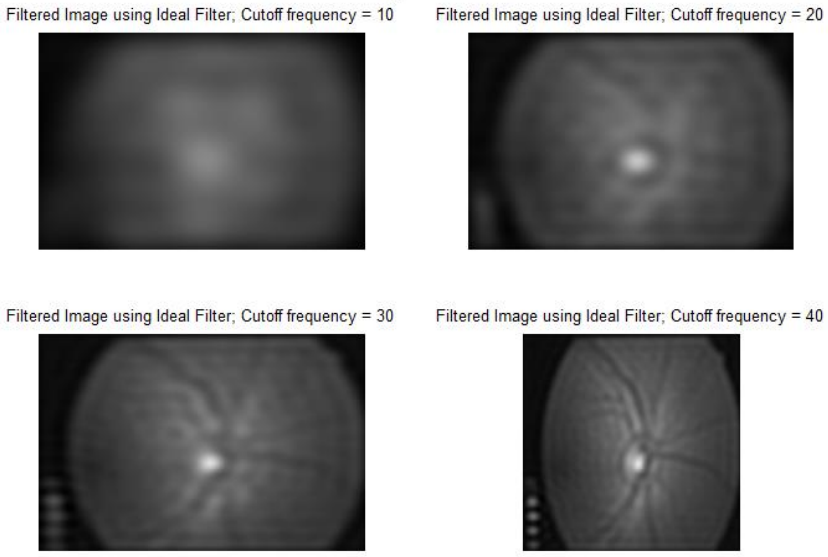


Figure 4.3 Denoised Iris Image by using Ideal filter with different Cutoff Frequencies

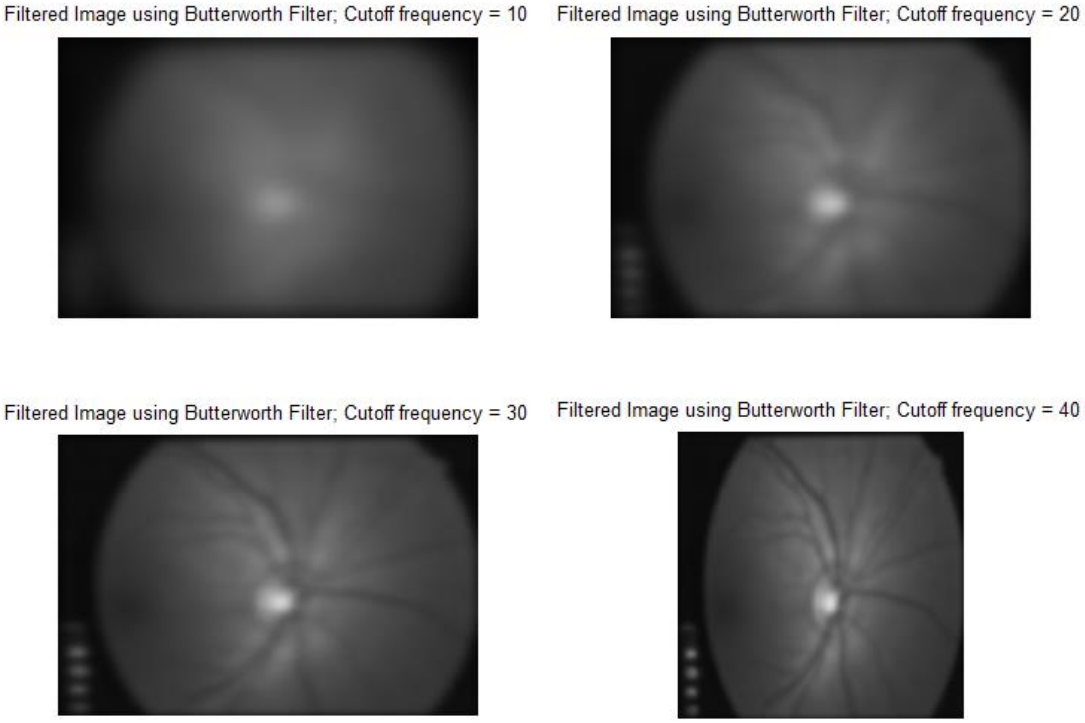


Figure 4.4 Denoised Iris Image by using Butterworth filter with different Cutoff Frequencies

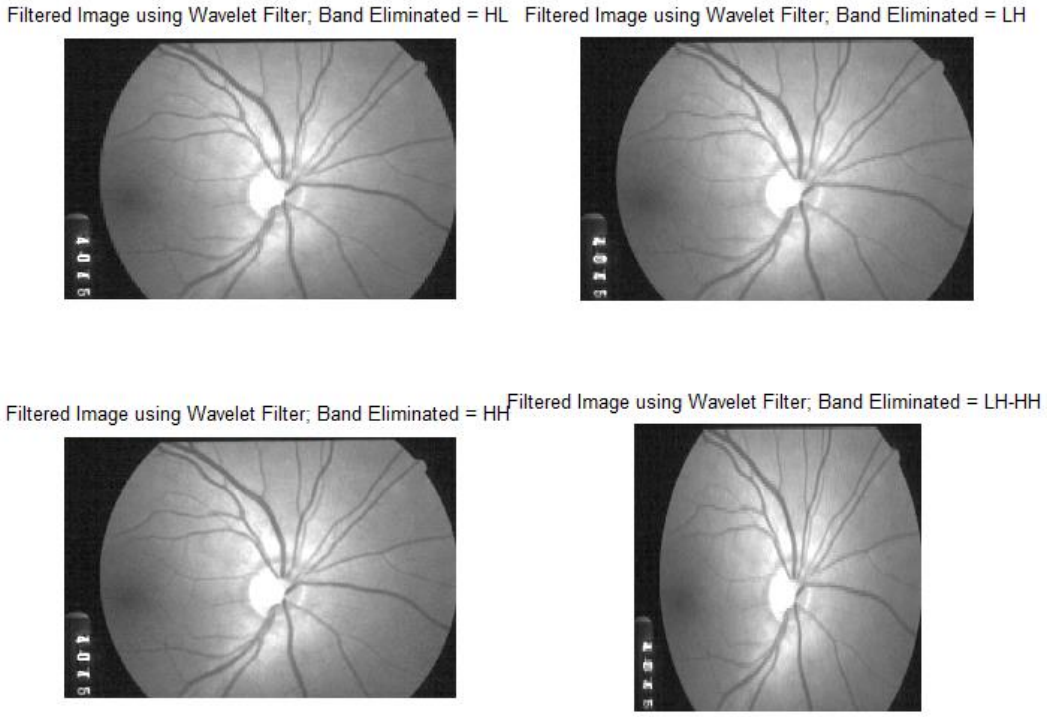


Figure 4.5 Denoised Iris Image by using Wavelet filter

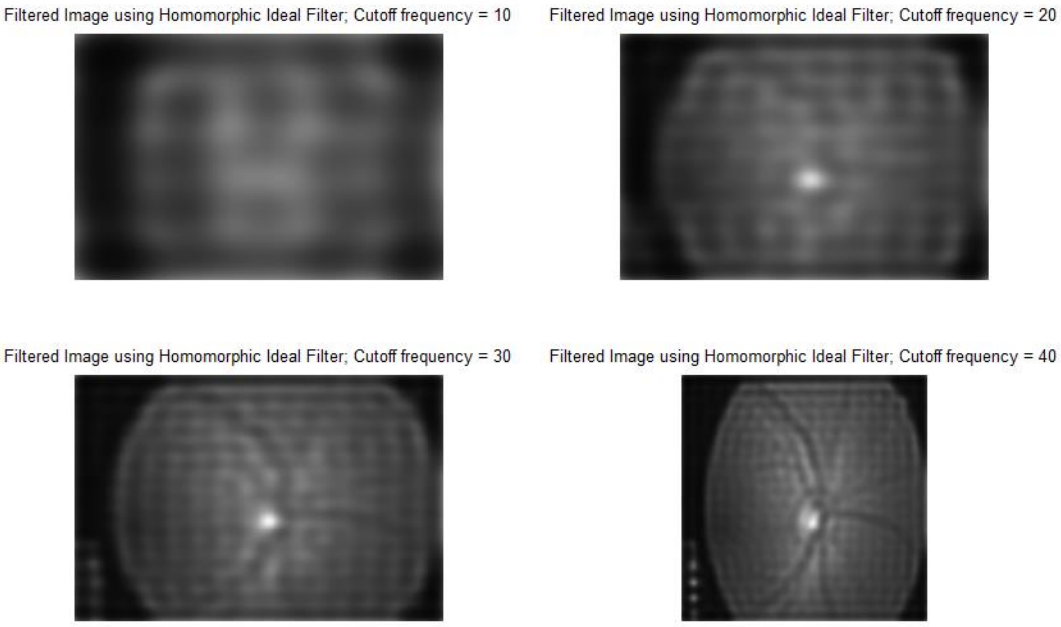


Figure 4.6 Denoised Iris Image by using Homomorphic Ideal filter with different Cutoff Frequencies

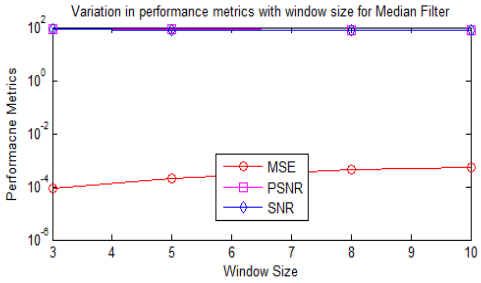


Figure 4.7 Performance metrics in Median filter

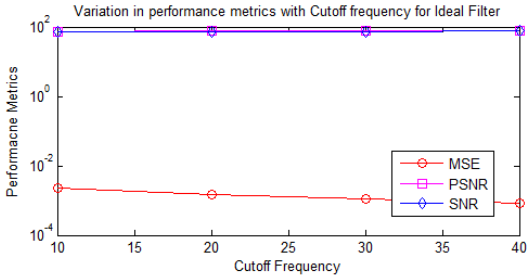
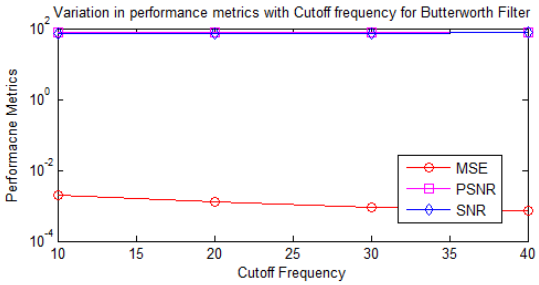


Figure 4.8 Performance metrics in Ideal filter with different with different window size cutoff frequencies



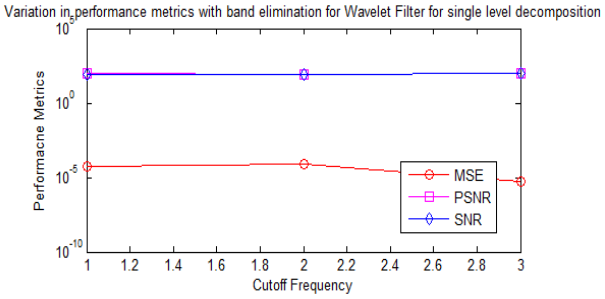


Figure 4.9 Performance metrics in Butterworth filter with different cutoff frequencies

Figure 4.10 Performance metrics in wavelet filter in single level decomposition

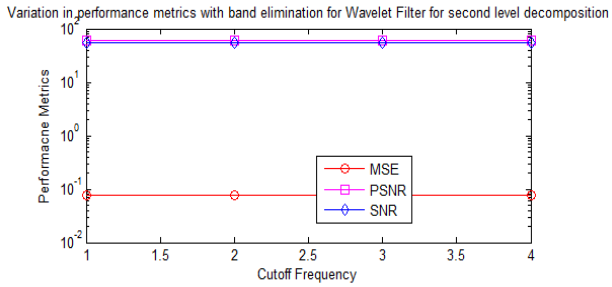


Figure 4.11 Performance metrics in wavelet filter in Homomorphic Ideal Second level decomposition

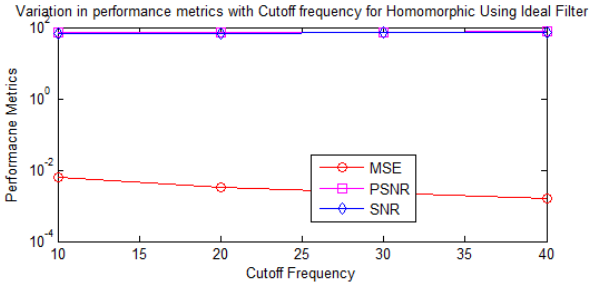
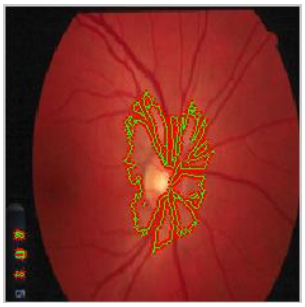
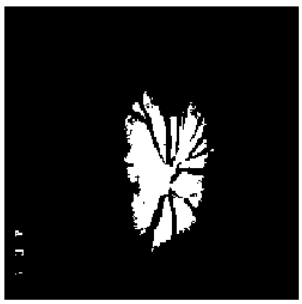


Figure 4.12 Performance metrics in filter with different cutoff frequencies

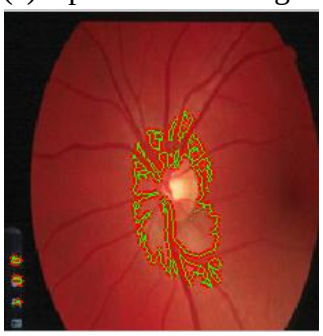
Module 2 Implementation - Iris Image segmentation to extract the Disc Ratio



(a) Optic Disc of image 1

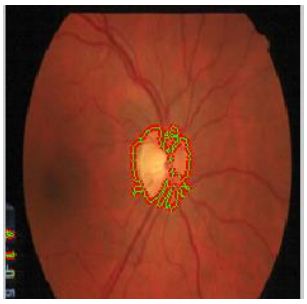


(b) Final OD Segmentation of image 1



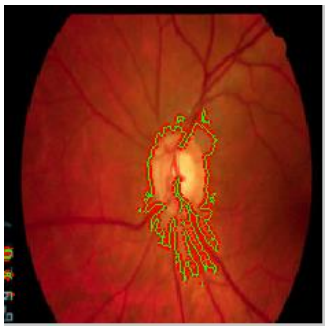
(c) Optic Disc of image 2

(d) Final OD Segmentation of image 2



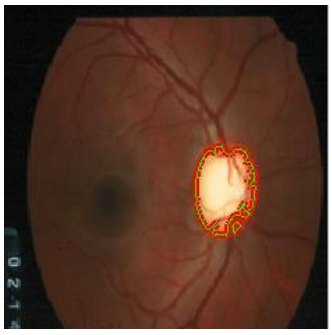
(e) Optic Disc of image 3

(f) Final OD Segmentation of image 3

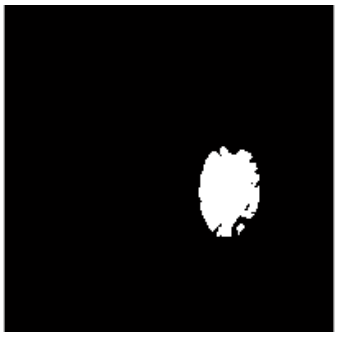


(g) Optic Disc of image 4

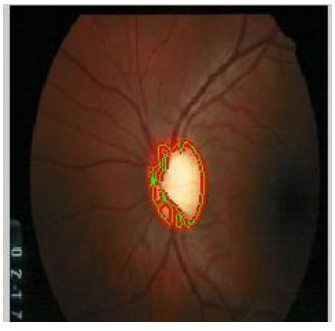
(h) Final OD Segmentation of image 4



(i) Optic Disc of image 5

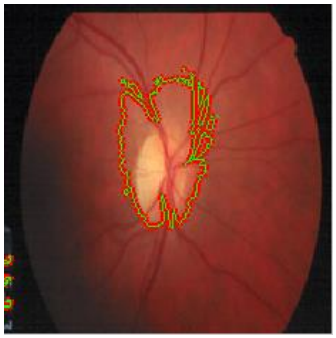


(j) Final OD Segmentation of image 5



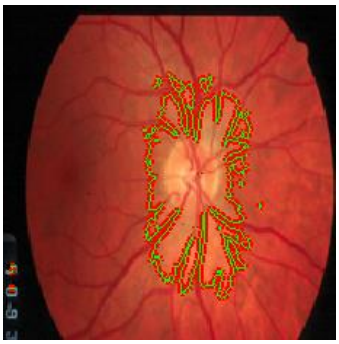
(k) Optic Disc of image 6

(l) Final OD Segmentation of image 6

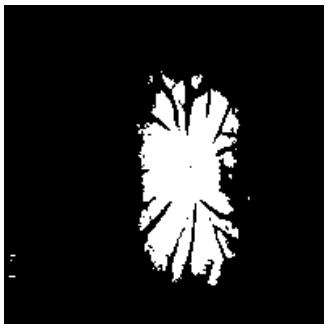


(m) Optic Disc of image 7

(n) Final OD Segmentation of image 7



(o) Optic Disc of image 8



(p) Final OD Segmentation of image 8

Figure 4.13 (a)–(p) Segmentation of the Iris Image to find the cup to disk ratio

Module 3 Implementation - Iris Image Classification to detect Glaucoma

Table 4.1 Classification of the Iris images

Image Set	Cup to Disc Ratio (CDR)	Normal/ Glaucoma Images
Image1	0.2097	Normal Image
Image2	0.1166	Normal Image
Image3	0.1906	Normal Image
Image4	0.1164	Normal Image
Image5	0.3055	Glaucoma Image
Image6	0.2506	Normal Image
Image7	0.1183	Normal Image
Image8	0.3403	Glaucoma Image

CONCLUSION

In this project, the existing approach iris image processing is extended to classify the glaucoma disease. The proposed method involves the different filtering approach in the preprocessing stage such as median, ideal, Butterworth and wavelet filters. The parameter comparisons of such algorithms are also done. In the second stage of processing involves the segmentation process. The disc ratio is measured in this stage. The third stage involves the classification of the glaucoma images from the image database. The proposed system involves the SVM classifier to perform the classification task. The proposed is very helpful for early detection of the glaucoma disease.

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