Earlier Stage Identification of Glaucoma Disease using Segmentation Algorithm in IRIS Image

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Abstract - **The eye is one of the most important sensory organs in the human body. Eye diseases are a common health issue around the world. Two such diseases are cataract and conjunctivitis. Cataract causes a sort of clouding on the lens leading to compact vision and if kept untreated for long leads to permanent blindness. Conjunctivitis or pink eye is a state where the conjunctiva of the eye is inflamed by an infection or by an allergic reaction. It can affect one or both eyes and it leads to redness or discharge. Bacterial and viral conjunctivitis may be very contagious. The proposed method to diagnose the eye diseases is based on the effective computation approach. Iris images were reserved before and after the treatment of eye disease and the output shows the mathematical difference obtained from treatment. This identification system was effectively withstood with most ophthalmic disease like corneal oedema, iridotomies and conjunctivitis. This proposed iris recognition may be used to solve the Iris related problems that could cause in key biometric technology and medical diagnosis. New glaucoma diagnostic technologies are penetrating clinical care and are altering quickly. Having a systematic review of these technologies will help clinicians and decision makers and help detect gaps that need to be addressed.**

Keywords: Glaucoma disease, Iris Images, Medical Image Processing, Medical Image Segmentation

1. INTRODUCTION

Biomedical image processing has intimate with dramatic enlargement, and has been a knowledge base analysis field attracting experience from math, computer sciences, engineering, statistics, physics, biology and drugs. Computer-aided diagnostic process has already become a very important a part of clinical routine. Among a charge of recent development of technology and use of varied imaging modalities, a lot of challenges arise; for instance, a way to method and analyze a big volume of images so top quality data is created for illness diagnoses and treatment. The human eye belongs to a general cluster of eyes found in nature referred to as "camera-type eyes." even as a camera lens focuses lightweight onto film, a structure within the eye known as the tissue layer focuses lightweight onto a photosensitive membrane known as the membrane.

The most common issues with vision are nearsightedness (myopia), long-sightedness, (hyperopia), a defect within the eye caused by non-spherical curvature (astigmatism) and age-related long-sightedness (presbyopia), consistent with the National Eye Institute. It is a scenario that is caused by the injury to the eye's nervus opticus that gets severer over time. It's usually related to a rise within the pressure within the eye. Eye disease tends to be genetic and turns up late in life. There are four differing types of eye disease that embody chronic glaucoma, acute closed-angle eye disease, Secondary eye disease, traditional tension eye disease. Early diagnosis of glaucoma is dangerous to thwart permanent structural damage and irreversible vision loss. Detection of glaucoma typically depends on examination of structural damage to the optic nerve combined with measurements of visual function. To benefit the clinician in evaluation of visual function and structure, computer-based devices such as confocal scanning laser ophthalmoscopy, scanning laser polarimetry, and optical coherence tomography offer quantitative assessments of structural damage, and visual function testing contains standard automated perimetry as well as selective techniques, including short-wavelength automated perimetry and frequency-doubling technology perimetry are available.

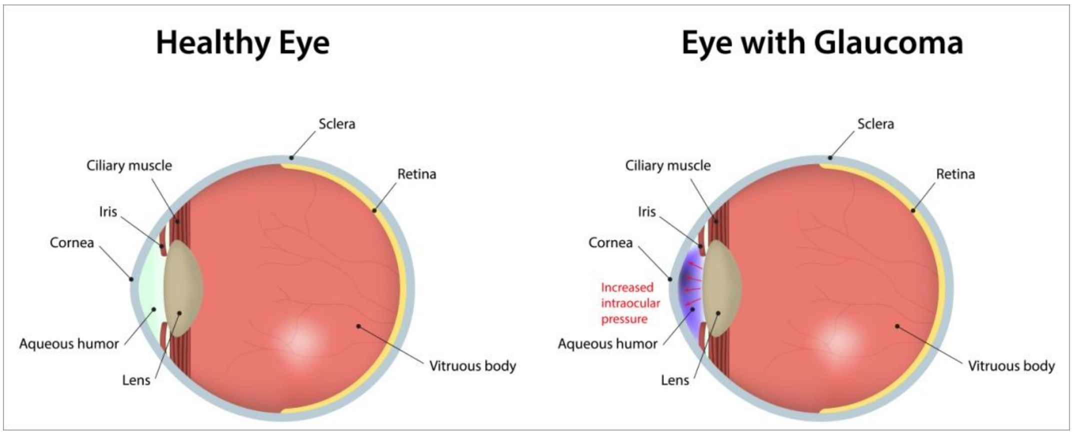


Figure 1. Image of Healthy and Glaucoma Affected Eye

2. REVIEW OF LITERATURE

Medical diagnosis is one of the most significant area in which image processing procedures are practically applied. Image processing is an significant phase in order to increase the accurateness both for diagnosis procedure and for surgical operation. Medical image processing needs continuous enhancements in terms of methods and applications to help increase quality of services in health care industry. The methods used for interpolation, image registration, compression, medical diagnosis are to be enhanced to be abreast with growing demands in the industry and emerging technologies pertaining to mobile computing and cloud computing. In this paper we present the present state-of-the-art of medical image processing and its capacities to harness the hardware resources including ever growing medical platforms for refining quality of clinical observes in terms of speed, accuracy, innovation, and globalization and so on.

Mohammad Karimi Moridani (2009) discussed the mechanisms of the techniques like electroencephalography (EEG), positron emission tomography (PET), single photon emission computed tomography (SPECT), functional magnetic resonance imaging (fMRI), and magneto encephalography (MEG) that led to a new era in the study of are outlined, together with an assessment of their strengths and weaknesses Rajeev Ratan, Sanjay Sharma, S. K. Sharma (2009) developed brain tumor segmentation method and validated segmentation on 2D and 3D MRI Data after a manual segmentation procedure of tumor identification, the investigations has been made for the possible use of MRI data for improving brain tumor shape approximation and 2D and 3D visualization for surgical planning and assessing tumor. Linda K. McEvoy et al (2009) did stepwise linear discriminant analysis to identify regions that can aid discrimination of HC subjects from subjects with AD.

Muhammed et al. (2014) combined the Ant Colony (ACO) approach with the matched filter for blood vessel detection. The parameters are enhanced using ACO and a comparative analysis is performed with the un-optimized network to display the superior nature of the proposed approach. Retinal vessel graph based vascular network detection is implemented by Bashir et al. (2014). The algorithm used in this work is a junction resolution algorithm which forms the complete graph of the blood vessels. But the little accuracy due to many training errors is the major problem of this work. Multi scale quadrature filtering based retinal blood vessel detection is proposed by Gunnar et al. (2009). This method combined the concept of both line and edge detection. The experimental results claim that the proposed approach is greatly robust in nature.

3. PROPOSED SCHEME

In this section the proposed scheme for the earlier detection of glaucoma identification is performed. The overall architectural design for the proposed method is shown in Figure 2.

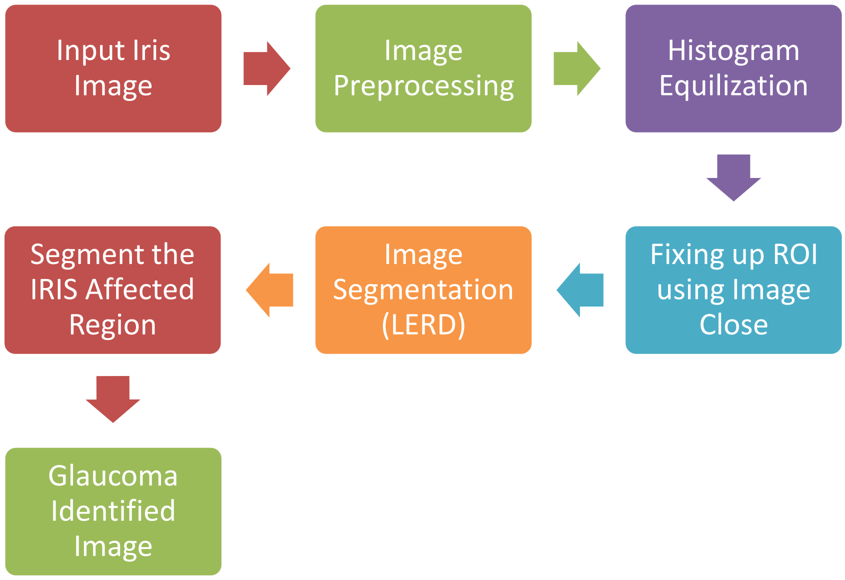


Figure 2. Overall Architectural Design for Glaucoma Identification

3.1. Objective of the work

Key release angle glaucoma is a progressive optic neuropathy and its improvement is related with the loss of tissue in the neuro-retinal rim of the optic disc with a consequential enhance in the size of the optic cup. To evaluate glaucoma in fundus images, optic cup to disc ratio, one of the significant physiological characteristics for the diagnosis of the eye disease, is usually taken into consideration during assessment. The main aims of this paper are

- To evident such physiological changes in the fundus images, features are necessary to quantitatively examine structural and functional abnormalities in the eye both to observe variability and to quantify the progression of glaucoma.
- The aim of this thesis is to automatically classify normal and glaucoma eye images based on the structural features and the distribution of texture features in the fundus images.
- Further prominent features are to be evaluated and selected for enhanced specificity and sensitivity for glaucomatous image classification

3.2. Image Acquisition

The retinal image will be acquired using a fundus camera placed in front and close to the patients face such that an clear fundus(retinal) image is obtained. This fundus image will be used for extracting the necessary features required by the employed terminologies with the help of Matlab Software. All images were taken with the dimension of 2896 x 1944 pixels and PNG uncompressed image format. Apart from these, no other imaging constraints were imposed on the acquisition process.

3.3. Pre-Processing

Noise not only lowers image quality but also can cause feature extraction algorithms to be unreliable. The de-noising and feature enhancement techniques presented in this thesis will improve the reliability of image processing. In image processing it is frequently necessary to perform high degree of noise reduction in an image before performing higher-level processing steps, such as edge detection. The median filter is a non-linear digital filtering method, is used to eliminate noise from images. The concept is to inspect an example of the input and choose if it is delegate of the signal. This is achieving using a window including of an odd number of samples. The values in the pane are sorted into arithmetical order; the median value, the sample in the inside of the window, is preferred as the output. The oldest sample is redundant, a new sample obtains, and the calculation repeats.

3.3.1. Mean Filter

Mean filtering is a simple, intuitive and easy to implement technique of smoothing images, i.e. decreasing the amount of intensity variation between one pixel and the next. It is frequently used to decrease noise in images. The idea of mean filtering is simply to substitute each pixel value in an image with the mean (`average') value of its neighbors, with itself. This has the effect of eliminating pixel values which are unrepresentative of their environments. Mean filtering is generally thought of as a convolution filter.

Like other convolutions it is based around a kernel, which signifies the shape and size of the neighborhood to be sampled when computing the mean. Often a 3×3 square kernel is used, as shown in Figure 1, although larger kernels (e.g. 5×5 squares) can be used for more simple smoothing. (Note that a small kernel can be applied more than once in order to create a comparable - but not identical - effect as a single pass with a large kernel.) The simplest of these algorithms is the Mean Filter is given by the equation 1. The Mean Filter is a linear filter which practices a mask over each pixel in the signal. Each of the components of the pixels which comes under the mask are averaged together to form a single pixel. This new pixel is then used to replace the pixel in the signal calculated. The Mean Filter is poor at sustaining edges within the image.

$$Mean\ Filter(x_1, \dots\dots, x_N) = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{1}$$

3.3.2. Median Filter

The median filter is usually used to decrease noise in an image, rather like the mean filter. Though, it often does a better job than the mean filter of conserving useful detail in the image. Like the mean filter, the median filter deliberates each pixel in the image in turn and looks at its nearby neighbours to decide whether or not it is demonstrative of its surroundings. Instead of simply substituting the pixel value with the mean of neighboring pixel values, it substitutes it with the median of those values. The median is computed by first sorting all the pixel values from the surrounding neighbourhood into numerical order and then substituting the pixel being considered with the middle pixel value. (If the neighbourhood under consideration comprises an even number of pixels, the average of the two middle pixel values is used.). The use of the median in signal processing was first introduced by J. W. Tukey. The Median Filter is performed by taking the magnitude of all of the vectors within a mask and sorting the magnitudes as in equation 2. The pixel with the median magnitude is then used to substitute the pixel studied. The Simple Median Filter has anbenefit over the Mean filter in that it relies on median of the data instead of the mean. A single noisy pixel present in the image can considerably skew the mean of a set. The median of a set is more robust with respect to the presence of noise.

$$Median\ Filter(x_1, \dots\dots, x_N) = median(\|x_1\|^2, \dots., \|x_N\|^2) \tag{2}$$

When filtering using the Simple Median Filter, an original pixel and the resultant filtered pixel of the sample considered are sometimes the same pixel. A pixel that does not change due to filtering is well-known as the root of the mask. It can be displayed that after sufficient iterations of median filtering every signal converges to a root signal.

3.3.3. Wiener Filter

The inverse filtering is a restoration method for deconvolution, i.e., when the image is blurred by a known lowpass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering. Though, inverse filtering is very sensitive to additive noise. The approach of decreasing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering performs an optimal tradeoff between inverse filtering and noise smoothing. It eliminates the additive noise and inverts the blurring consecutively.

The Wiener filtering is best in terms of the mean square error. In other words, it reduces the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear approximation of the original image. The method is based on a stochastic outline. The orthogonality principle suggests that the Wiener filter in Fourier domain can be expressed as follows:

$$W(f_1, f_2) = \frac{H^*(f_1,f_2)S_{xx}(f_1,f_2)}{|H(f_1,f_2)|^2 S_{xx}(f_1,f_2)+S_{\eta\eta}(f_1,f_2)} \quad (3)$$

where$S_{xx}(f_1, f_2)$, $S_{\eta\eta}(f_1, f_2)$ are correspondingly power spectra of the original image and the additive noise, and is the $H(f_1, f_2)$ blurring filter. It is easy to see that the Wiener filter has two distinct part, an inverse filtering part and a noise smoothing part. It not only do the deconvolution by inverse filtering (high pass filtering) but also eliminates the noise with a compression operation (low pass filtering).

3.4. Edge Detection

EDGE detectors of some kind, mostly step edge detectors, have been an essential part of many computer vision systems. The edge detection process helps to simplify the analysis of images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries. There is certainly aexcessive deal of diversity in the applications of edge detection, but it is felt that many applications share a mutual set of requirements. These desires yield an abstract edge detection problem, the solution of which can be applied in any of the original issue domains.

3.4.1. Sobel

The Sobel operator performs a 2-D spatial gradient measurement on an image and so highlights regions of high spatial frequency that relate to edges. Naturally it is used to find the estimated absolute gradient magnitude at each point in an input grayscale image. Standard Sobel operators, for a 3×3 neighborhood, each modest central gradient estimate is vector sum of a pair of orthogonal vectors. Each orthogonal vector is a directional derived estimate multiplied by a unit vector specifying the derivative's direction. The vector sum of these simple gradient estimations amounts to a vector sum of the 8 directional derivative vectors. Therefore a point on Cartesian grid and its eight neighboring density values as shown:

a	b	c
d	e	f
g	h	i

A convolution mask is used is frequently much lesser than the actual image. As a result, the mask is slid over an area of the input image, changes that pixel's value and then moves one pixel to the right and remains to the right until it reaches the end of a row. It then starts at the beginning of the next row. The example below displays the mask being slid over the top left portion of the input image denoted by the green outline. The formula shows how a specific pixel in the output image would be calculated. The center of the mask is placed over the pixel you are manipulating in the image and the i&j values are utilized to change the file pointer so it can multiply, for example, pixel (A22) by the corresponding mask value (M22). It is significant to notice that pixels in the first and last rows, as well as the first and last columns cannot be manipulated by a 3x3 mask. This is because when placing the center of the mask over a pixel in the first row (for example), the mask will be outside the image boundaries.

The masks can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be joined together to find the complete magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by equation 4.

$$|G| = \sqrt{Gx^2 + Gy^2} \quad (4)$$

Although typically, an approximate magnitude is computed using equation 5.

$$|G| = Gx + Gy \tag{5}$$

Often, this absolute magnitude is the only output the user sees the two components of the gradient are appropriately computed and added in a single pass over the input image.

3.4.2. Canny

Canny edge detection is a multi-step algorithm that can identify edges with noise suppressed at the same time. Smooth the image with a Gaussian filter to decrease noise and undesirable details and textures. The Canny edge detector is a surround suppression stage that improves object contours by inhibiting texture edges. First of all the image is smoothed by Gaussian convolution. Then a simple 2-D first derivative operator (somewhat like the Roberts Cross) is applied to the smoothed image to focus regions of the image with high first spatial derivatives. Edges give increase to ridges in the gradient magnitude image. The algorithm then tracks along the top of these ridges and sets to zero all pixels that are not fundamentally on the ridge top so as to give a thin line in the output, a process well-known as non-maximal suppression. The tracking process displays hysteresis controlled by two thresholds: T1 and T2, with T1 > T2. Tracking can only begin at a point on a ridge higher than T1. Tracking then remains in both directions out from that point until the height of the ridge falls below T2. This hysteresis helps to assurance that noisy edges are not broken up into multiple edge fragments.

Them it can also visualize the gradient and the derivatives of a Gaussian function that are used to compute the gradient. Select an input image or upload your own input image as in equation 6.

$$g(m,n) = G_{\sigma}(m,n) * f(m,n) \tag{6}$$

Compute gradient of $g(m,n)$ using any of the gradient operators (Roberts, Sobel, Prewitt, etc) to get M(n, n) as in equation 7.

$$M(n,n) = \sqrt{g_m^2(m,n) + g_n^2(m,n)} \tag{7}$$

Then threshold M is computed using equation 8.

$$M_T(m,n) = \begin{cases} M(m,n) & if\ M(m,n) > T \\ 0 & otherwise \end{cases} \tag{8}$$

where T is chosen that all edge elements are kept while most of the noise is suppressed.

Suppress non-maxima pixels in the edges in MT attained above to thin the edge ridges (as the edges might have been broadened in step 1). To do so, check to see whether each non-zero MT(m,n) is greater than its two neighbors along the gradient direction ɵ(m,n). If so, have MT (m,n) unchanged, otherwise, set it to 0.Compute the Threshold value for the previous result by two different thresholds t1 and t2 (where t1 < t2) to obtain two binary images T1 and T2. Note that T2 with greater t2 has less noise and fewer false edges but greater gaps between edge segments, when compared to T1 with smaller t1. Then Link edge segments in T2 to form continuous edges. To do so, trace each segment in T2 to its end and then search its neighbors in T1 to find any edge segment in T1 to bridge the gap until reaching another edge segment in T2.

3.4.3. Perwitt

The Prewitt edge detector is one of the classical operators used in image processing tools. The function of sobel operator is nearly same as of prewitt operator but prewitt operator have dissimilar kernels, where constant c=1. It is a way to guess the magnitude and orientation of an edge. The prewitt operator is limited to 8 possible orientations, though most direct orientation estimates are not much more correct. This gradient based edge detector is assessed in the 3x3 neighborhood for 8 directions. Then it calculated all the eight convolution masks. The convolution mask with the largest module is then chosen. The convolution masks of the Prewitt detector are given in Figure.

1	1	1
0	0	0
-1	-1	-1

-1	0	1
-1	0	1
-1	0	1

G_x G_y

In simple terms, the operator computes the gradient of the image intensity at each point, giving the direction of the biggest possible increase from light to dark and the rate of change in that direction. The result thendisplays how "abruptly" or "smoothly" the image changes at that point, and hence how likely it is that part of the image signifies an edge, as well as how that edge is probable to be oriented. In practice, the magnitude (likelihood of an edge) calculation is more consistent and easier to interpret than the direction calculation.

Scientifically, the operator uses two 3×3 kernels which are convolved with the original image to compute approximations of the derivatives - one for horizontal changes, and one for vertical. If we state A as the source image, and G_x and G_y are two images which at each point comprise the horizontal and vertical derivative approximations, the latter are computed as:

$$\mathbf{G_x} = \begin{bmatrix} -1 & 0 & +1 \\ -1 & 0 & +1 \\ -1 & 0 & +1 \end{bmatrix} * \mathbf{A} \quad \text{and} \quad \mathbf{G_y} = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} * \mathbf{A}$$

Where * here signifies the 2-dimensional convolution operation. Meanwhile the Prewitt kernels can be decayed as the products of an averaging and a differentiation kernel, they calculate the gradient with smoothing.

The x-coordinate is definite here as increasing in the "right"-direction, and the y-coordinate is definite as increasing in the "down"-direction. At each point in the image, the resulting gradient approximations can be joined to give the gradient magnitude, using: $\mathbf{G} = \sqrt{\mathbf{G}_x{}^2 + \mathbf{G}_y{}^2}$

3.5. Segmentation

Image segmentation is one of the most essential and problematic issue in image analysis. Image segmentation is ansignificant part in image processing. In computer vision, image segmentation is the process of separating an image into meaningful regions or objects. There are numerous applications of image segmentation like locate tumors or other pathologies, measure tissue volume, computer-guided surgery, treatment planning, study of anatomical structure, locate objects in satellite images and fingerprint recognition etc.

Segmentation subdivides an image into its constituent region or object. Image segmentation methods are categorized on the basis of two properties discontinuity and similarity (Rafael C. Gonzalez, Richard E. Woods 2007). Based on this property image segmentation is categorized as Edged based segmentation and region based segmentation. The segmentation techniques that are based on discontinuity property of pixels are considered as boundary or edges based techniques.

3.5.1. Otsu

Otsu technique is type of global thresholding in which it depend only gray value of the image. Otsu technique was proposed by Scholar Otsu in 1979. Otsu method is global thresholding selection technique, which is extensively used because it is modest and effective (Zhong Quand Li Hang, 2010). The Otsu techniqueinvolvescalculating a gray level histogram before running. Though, because of the one-dimensional which only consider the gray-level information, it does not give better segmentation result. So, for that two dimensional Otsu algorithms was proposed which works on both gray-level threshold of each pixel as well as its Spatial correlation data within the neighborhood.

Otsu's technique was one of the better threshold selection approaches for common real world images with respect to uniformity and shape measures. However, Otsu's technique uses an exhaustive search to estimate the criterion for exploiting the between-class variance. As the number in classes of an image rises, Otsu's technique takes too much time to be practical for multilevel threshold selection.

After preprocessing, the optic disc has some visual characteristics quite similar to those of hard exudate: bright intensity and sharp boundaries with the background. To thwart the optic disc from interfering with exudate detection, we first detect the optic disc and eliminate it from consideration as exudate during training and testing. We find that the optic disc is easily distinguished from the rest of the retina by its smooth texture. To define which regions of the image are smooth or textured, for each point x we obtain a probability mass function. The local pixel intensity entropy measure is large when the region around a pixel is complex and low when it is smooth. After filtering with the entropy operator we apply Otsu's binarization algorithm to isolated the complex regions from the smooth regions.

3.5.2. MCSA

It is also a meta-heuristic optimization algorithm evolved due to the captivating reproduction policy of certain Cuckoo species developed by Yang and Deb (2009). They lay eggs other bird's nest and even eliminate host eggs to rise the probability of their eggs getting hatched. Some species of host birds simply throw out cuckoo's eggs or even leave their nest and put up a new one when alien eggs are discovered. Certain Cuckoo species are clever enough to mimic the color and texture of the egg of the host birds which reduces the chances of being caught. For simplifying the whole process we consider these three conditions

- One egg will be laid at a time by each cuckoo in any nest chosen randomly.
- Nest which have the best quality eggs are carried over to the forthcoming generation.
- The probability of host species discovering cuckoo's egg lies within the probability range pa $\in [0, 1]$ and the total number of nests is fixed.

Once the host species discovers the cuckoo's egg in its nest, it will abandon the nest or throw away that egg which is implemented in the algorithm by replacing pa of the total number of nests by new. Each egg corresponds to a feasible solution and its fitness value is calculated.

3.5.3. Locality based Active Region Detection (LERD)

The main chore of the segmentation routine is to localize the inner/outer boundary from the iris. Apart from the proper localization of the iris structure, the segmentation scheme should also identify the eyelid and eyelash occlusions and detect the other noisy regions such as reflections. The localization error may result in lower recognition performance due to improper encoding of the textural content of the iris. For iris segmentation, most of the researchers assume that the iris is circular or elliptical. Though, in the case of un-ideal iris images, which are captured in an uncontrolled environment, iris may appear as noncircular or non-elliptical.

The segmentation of the iris image is a difficult task because of the noncircular shape of the pupil and the iris, and the shape differs depending on the image acquisition techniques. The method divides the iris segmentation process into two steps. In the first step, we use an elliptical model to approximate the inner (pupil) and outer (iris) boundaries of the iris, and then, the method apply the region-based active contour model to find the exact inner and outer boundaries of the iris based on the approximated boundaries obtained in the previous step.

This work proposes a natural framework that allows any region-based segmentation energy to be re-formulated in a local way. The method considers local rather than global image statistics and evolves a contour based on local information. Localized contours are proficient of segmenting objects with heterogeneous feature profiles that would be difficult to capture correctly using a standard global method. In this section, that describes the proposed local region-based framework for guiding active contours. Within this outline, segmentations are not based on global region models. Instead, we allow the foreground and background to be described in terms of smaller local regions, removing the assumption that the foreground and background regions can be represented with global statistics.

The method will see that the analysis of local regions leads to the construction of a family of local energies at each point along the curve. In order to enhance these local energies, each point is considered separately, and moves to minimize (or maximize) the energy computed in its own local region. To compute these local energies, local neighborhoods are split into local interior and local exterior by the evolving curve. The energy optimization is then finished by fitting a model to each local region.

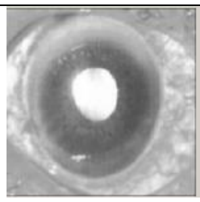
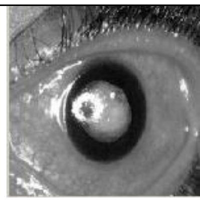
The proposed local region-based method begins by initializing every pixel in the narrow band with the confined interior and exterior statistics. The nature of this operation varies depending on the energy implemented. Computation of local means, for instance, is simpler than computation of local histograms. An additional cost occurs whenever the narrow band moves to include an uninitialized pixel. In this case, the local statistics of this new pixel must be primed as well. The number of initialization operations performed is, therefore, dependent on how far from its final position the contour is initialized. The initialization operation is only performed once for each pixel and, therefore, adds a constant complexity increase. However, depending on the size of the local radius, these computations can be significant.

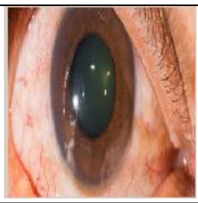
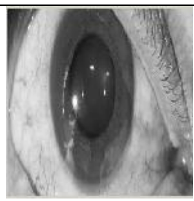
The update stage happens when any initialized pixel is crossed by the contour moving it from the interior to the exterior or vice versa. In our application we keep local statistical models in memory for every initialized pixel. When the interface crosses a pixel, the statistical models of all pixels within the neighborhood are modernized. When local means are used, each pixel must sustain the number of pixels in the local regions both inside and outside of the curve as well as the sums of pixel intensities in those two regions. Updating this model comprises of transferring values from the “inside” groups the “outside” groups or vice versa. For the histogram separation energy, we have a full histogram of the local interior and exterior regions for each initialized pixel. Although this involves considerably more memory to maintain than the means model, updates are just as simple: pixel intensities are subtracted from bins of the interior histogram and added to the same bin of the related exterior histogram or vice versa.

4. RESULT AND ANALYSIS

In this section, the results and analysis for the iris image for glaucoma identification is illustrated. Then the performance evaluation for the glaucoma identification using image processing techniques is evaluated. The illustrations and descriptions are as follows with the performance metrics evaluation.

Table 1. Original Iris Image and its Gray Scale Conversion Image

No	Original Image	Gray Scale
Image 1		
Image 2		

No	Original Image	Gray Scale
Image 3		

The original image with the grayscale converted image is depicted in Table 1. Then the denoising filters are employed to enhance the image is shown in Table 2

Table 2: Removal of Noises using Denoising Filters

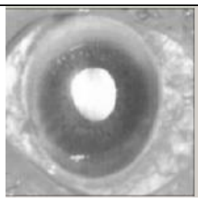
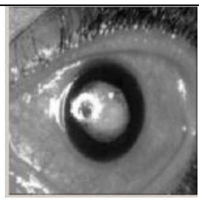
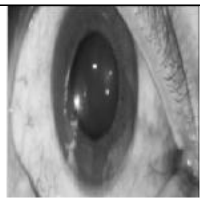
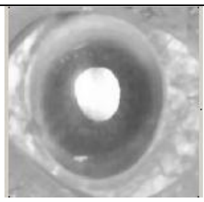
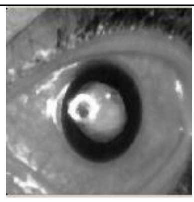
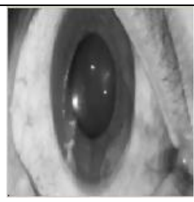
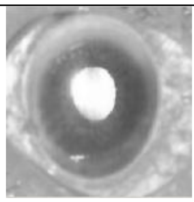
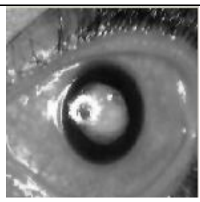
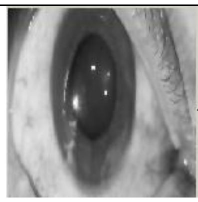
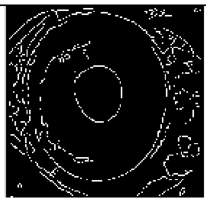
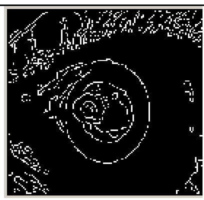
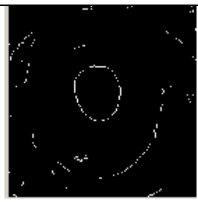
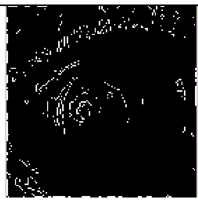
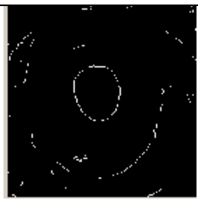
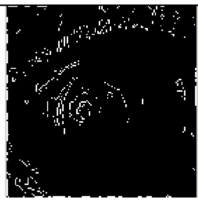
Filters	Image 1	Image 2	Image 3
Mean			
Median			
Wiener			

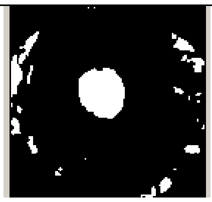
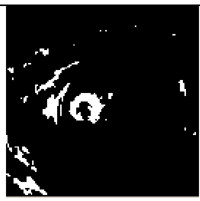
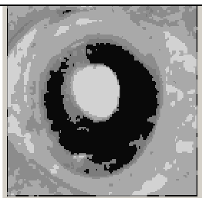
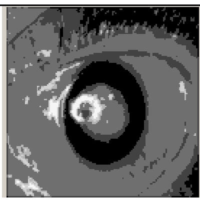
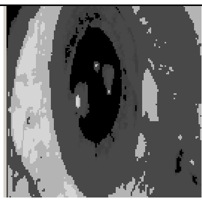
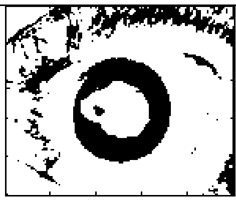
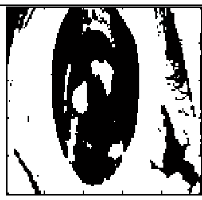
Table 3: Edge Detected Images using Various Techniques

Edge Detection Technique	Image 1	Image 2	Image 3
Canny			
Sobel			

Edge Detection Technique	Image 1	Image 2	Image 3
Perwit			

The various edge detection techniques are employed to detect the iris image outer boundary detection for the identification of the glaucoma.

Table 4: Segmented Region of Glaucoma Affected Region using Various Techniques

Segmentation Technique	Image 1	Image 2	Image 3
Otsu			
MCSA			
LERD			

Then the inner region detection for the identification of the glaucoma disease is performed using various segmentation techniques and the outcome of the segmentation result is shown in Table 4.

Table 5: Performance Metrics Evaluation for Denoising Filters

Images	**Filter**	**MSE**	**PSNR**	**SNR**
Image 1	Mean Filter	65.7859	29.9835	26.5673
Image 2	Mean Filter	74.7520	29.4286	23.1236
Image 3	Mean Filter	76.9899	29.3005	24.3631
Image 1	Median Filter	17.1922	35.8115	32.3954
Image 2	Median Filter	117.4905	27.4648	21.1598
Image 3	Median Filter	66.0652	29.9651	25.0277
Image 1	Wiener Filter	10.2942	38.0389	34.6227
Image 2	Wiener Filter	39.7656	32.1697	25.8647
Image 3	Wiener Filter	31.6870	33.1560	28.2187

The above table 5 represents the performance metrics computation for various denoising filters for different input images. The performance metrics such as PSNR, SNR and MSE is evaluated.

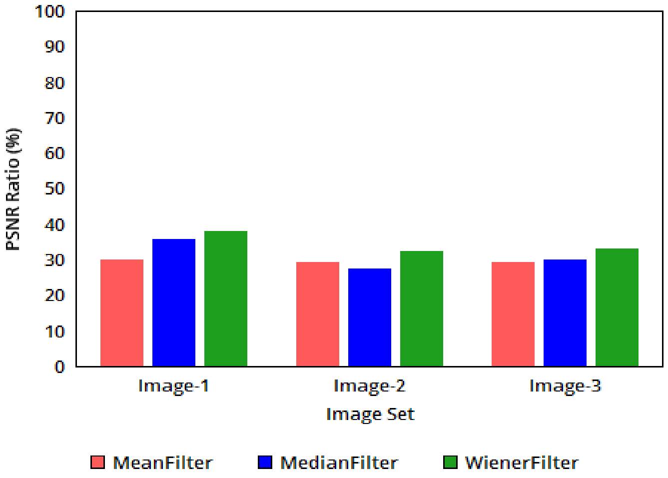


Figure 3. PSNR Evaluation for Denoising Filters

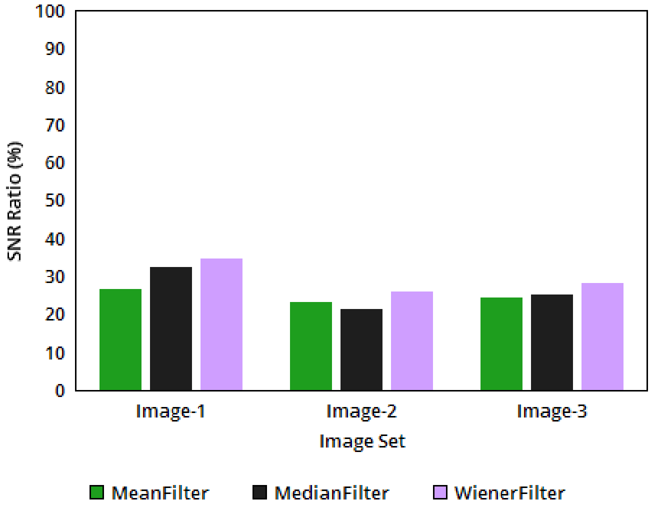


Figure 4. SNR Evaluation for Denoising Filters

Figure 3 and 4 represents the PSNR and SNR performance evaluation for denoising filters for input Iris image. Then the figure 5 depicts the MSE rate for the evaluation of Mean Square Error for the denoising filters.

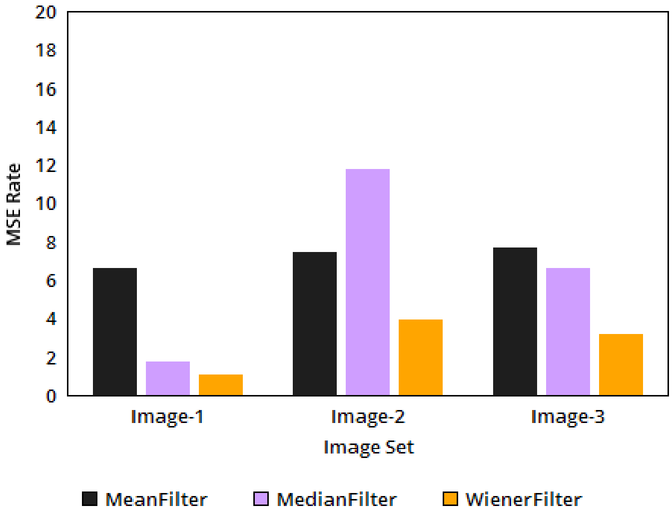


Figure 5. MSE Evaluation for Denoising Filters

Table 6: Performance Metrics Evaluation for Edge Detection Methodologies

Images	Filter	ED	Bias	CC
Image 1	Canny	0.1822	0.9998	0.4598
Image 1	Sobel	0.0511	0.9999	0.7451
Image 1	Perwitt	0.0513	0.9999	0.7462
Image 2	Canny	0.2770	0.9992	0.4069
Image 2	Sobel	0.1208	0.9997	0.5949
Image 2	Perwitt	0.1205	0.9997	0.5932
Image 3	Canny	0.2729	0.9994	0.2568
Image 3	Sobel	0.0931	0.9998	0.5928
Image 3	Perwitt	0.0924	0.9998	0.5939

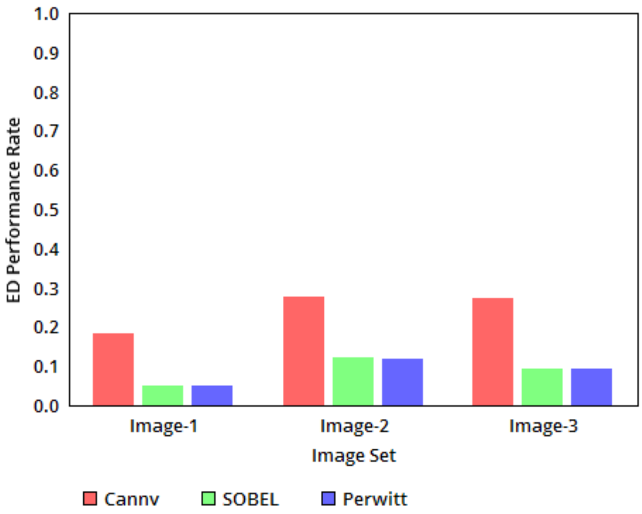


Figure 6. ED Performance Rate for various Edge Detection Methods

The above figure 6 illustrates the performance rate for Entropy Difference (ED) for various edge detection methodologies for various image set.

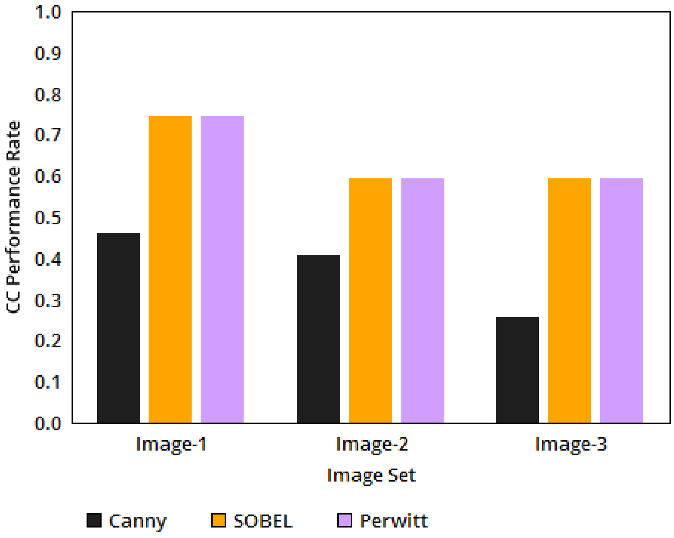


Figure 7. CC Performance Rate for various Edge Detection Methods

Figure 7 illustrates the performance rate for Correlation Coefficient (CC) for various edge detection methodologies for various image set.

Table 7: Performance Metrics Evaluation for Segmentation Methodologies

Images	Filter	Jaccard	Dice	RFP	RFN
Image 1	Otsu	0.0921	0.0872	1.0211	0.9079
Image 1	MCSA	0.0897	0.1878	1.0023	1.0298
Image 1	LERD	1	1	0	0
Image 2	Otsu	0.0490	0.0547	0.7396	0.9510
Image 2	MCSA	0.8180	0.8312	0.1504	0.1820
Image 2	LERD	0.9864	0.8945	0.0038	0.0022
Image 3	Otsu	0.2042	0.2350	0.5339	0.7958
Image 3	MCSA	0.8850	0.9275	0.0234	0.1150
Image 3	LERD	1	0.9987	0.0011	0.0021

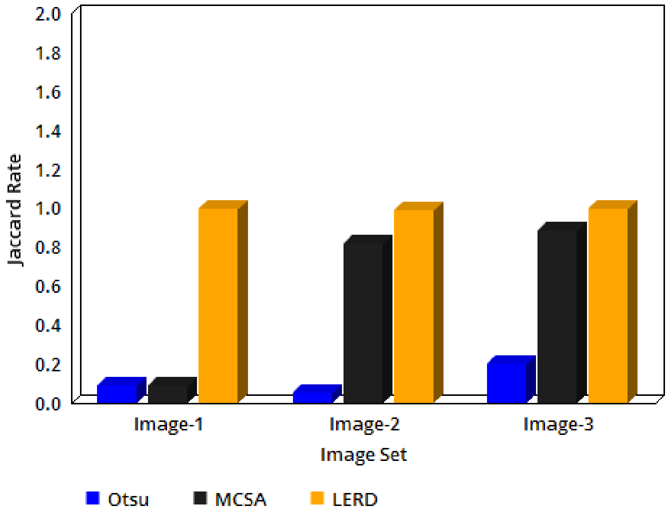


Figure 8. Jaccard Analysis for Segmentation

Figure 8 and 9 represents the Jaccard and Dice performance analysis for segmentation methodologies.

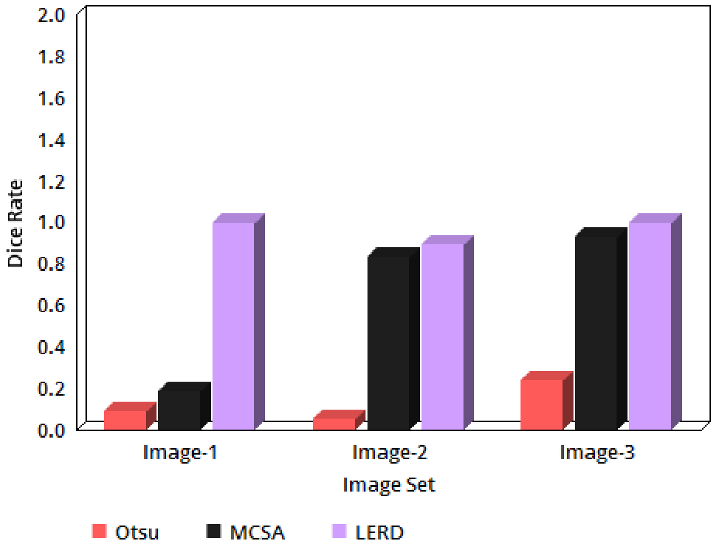


Figure 9. Dice Analysis for Segmentation

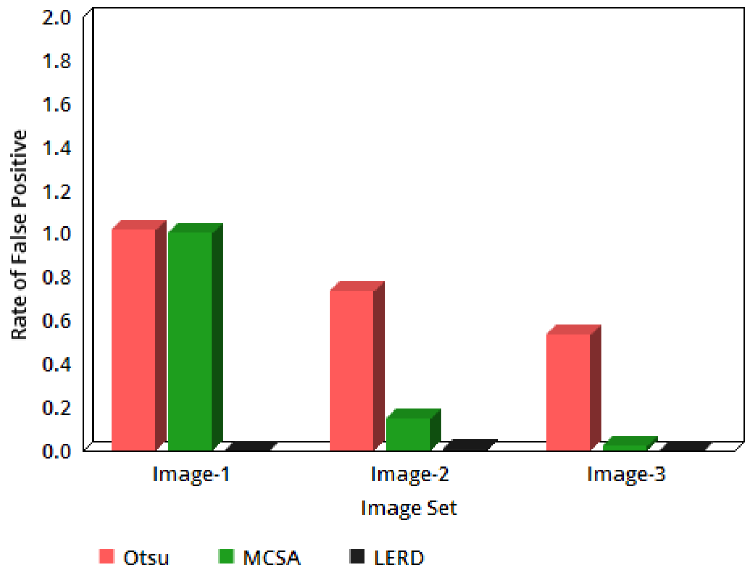


Figure 10. RFP Analysis for Segmentation

Figure 10 and 11 represents the RFP and RFN performance evaluation for segmentation for input Iris image.

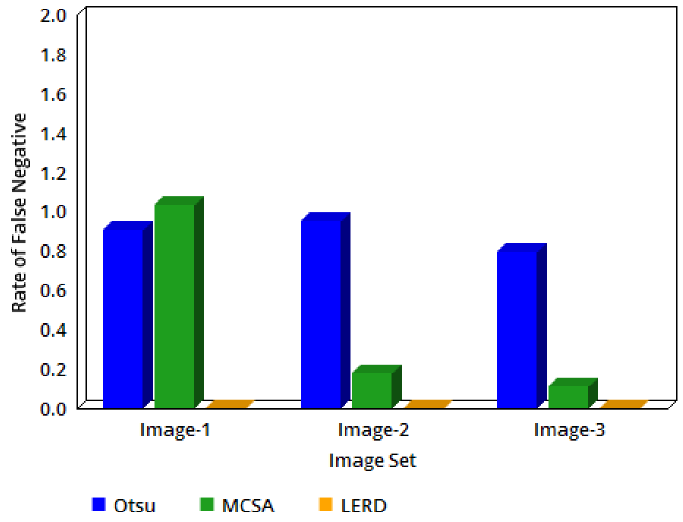


Figure 11. RFN Analysis for Segmentation

5. CONCLUSION AND FUTURE ENHANCEMENT

Glaucoma detection is the most significant research topic of medical field nowadays. Different medical devices have come into existence for the detection and diagnosis of glaucoma but their use is very much expensive. A huge number of people across the world are infected of this serious eye disease. Segmentation of the optic disc and optic cup has caught the interest of many researchers. Though there are many promising approaches, there is still room for improvement in segmentation techniques. Only few of the existing methodologies for optic disc or for optic cup segmentation can be applied for glaucomatous retinal images. In this work, various image processing techniques as well as different computer based systems involved mostly in the detection and diagnosis of glaucoma are discussed in detail. The main purpose of this work is to highlight the severity of glaucoma across the globe as well as cover the research work done so far on this disease. This work also expresses minor effort regarding detection of glaucoma disease.

The future directions relating to detection of eye disease is analysis of varied algorithms mentioned during this work by implementing and testing them on large amount of information.

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