



# A Novel Visual saliency Thresholding Method for Accurate ROI Segmentation in Optic Disc from FEIs for Glaucoma detection

V. Subha<sup>1</sup> and S. Niraja Rayen<sup>2</sup>

<sup>1</sup>Department of Computer Science and Engineering, MS University, Tirunelveli, India

<sup>2</sup>Department of Computer Science and Engineering, MS University, Tirunelveli, India

**Abstract:** In medical image processing, segmentation is the one of the significant area of clinical diagnosis and image processing phases. In 'retinal fundus' images, optic disc segmentation plays an important role in analyzing several pathologies, including the abnormalities associated to 'eye retina'. Emerging the perfect automated segmentation of glaucoma region is an extremely hard because of many anomalies present in the input image. In this research paper, presents a method for segmentation/extraction of 'Optic Disc (OD) region' from retinal images along with ROI (Region of Interest) is generated automatically by Visual Saliency Thresholding(VST) method. The mathematical morphology is fully utilized in the proposed segmentation technique. The ROI of OD is recognized by optic cup region with threshold value by means of markers, whereas optic disc is extracted from visual regions through saliency parameters. The achieved experimental results are positive. For assessing the proposed segmentation method that has been verified with many images also compared with the other segmentation algorithms such as Otsu thresholding and region growing. The implementation results direct that proposed technique can be achieved the maximum accuracy than other algorithms. DRISHTI-GS1 dataset is utilized to approve the performance of our proposed segmentation system.

**Keywords:** Visual saliency, Threshold, Otsu, region growing, Glaucoma, segmentation

## 1. INTRODUCTION

Glaucoma is a one kind of 'eye diseases', which portrayed by the procedure 'optic nerveneuropathy' with OD, that prompts the expanding shrinking in visualization meadow, finishing with visual deficiency. The right side of 'Optic Disc (OD)' perhaps with exodus of the 'Optic Nerve' of the eye is known as 'blind spot'. It encircles neuro-retinal edge with pink tone and central positioned yellowish cup. The state of the 'optic disc' is about circle, hindered through the active vessels that fluctuate for every patient in size. Its width lies somewhere in the range of 40 and 60 pixels on 640x480 shading photos. Glaucomatous in retina has different variations of neuro-retinal edge as well as cup with the consequence of nerve filaments harms [1]. 'Optic Disc' structures assessment is one kind of important valuations in glaucoma conclusion. These structures are shown in the following Figure 1.(a).

Glaucoma region of a fundus image is identified by an isolation of Optic disc from other bright cells, such as solid and artifact in a fundus image, using higher level measurement of blood vessel. The main objective is to obtain an improved optic disc location by combining several predictive algorithms based on detection instructions algorithms in fundus image. In the normal (healthy) optic disc, the neuro-retinal edge has its ordinary shape by its

greatest portion in the substandard area, trailed via the prevalent area known as 'Inferior', 'Superior', 'Nasal', 'Temporal' (ISNT). As shown in Figure 1.(b) the 'neuro-retinal' edge is more slender than in the normal optic circle as well as the optic cup is consequently bigger and the cup is more profound in the glaucomatous optic disc. The accurate recognition of glaucoma disease is not a simple chore as it doesn't provide exact outcomes even with the knowledgeable 'ophthalmologist'. Therefore, there is an essential for best techniques, which permit automatic recognition as well as categorization of digital 'Fundus Eye Images' (FEIs) into well (healthy) glaucomatous affected images. The most significant stage in entire approaches is 'automatic segmentation' of optic disc structures from FEIs [2]. The below diagram represents system architecture that followed in this research paper is given in Figure 2.

The segmentation is process of grouping homogeneous fragments of a preprocessed (without noise) image into entities. This can also be observed as a method of pixel organization in the sense that all pixels in the image that fit to the similar region are allocated by identical label. In automatic object recognition, many processing applications are followed with a fundamental step is known as 'image segmentation'. Consequently, it moderates the processing effort to splitting regions that are allowed in region of

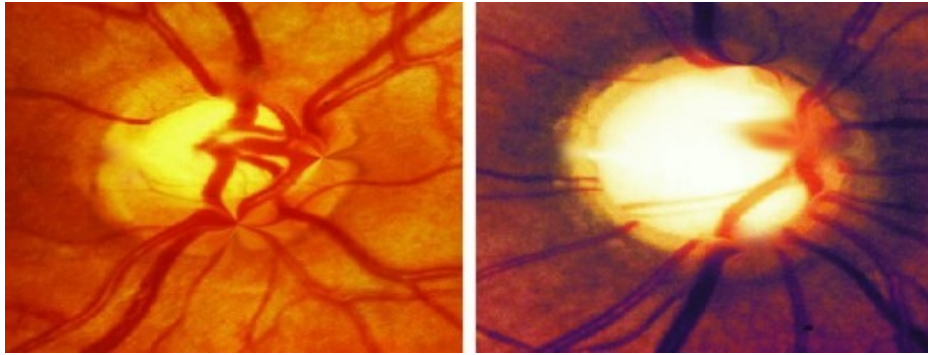


Figure 1. (a) Healthy Optic Disc (b) Glaucomatous Optic Disc

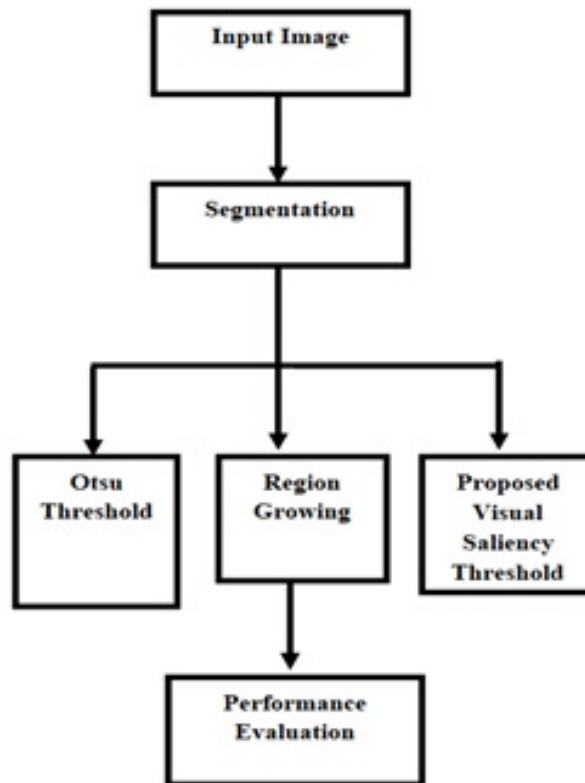


Figure 2. System Architecture

interest of an input image.

In the existing approaches, most of the researchers concentrated on the detection of the optic disc segmentation of FEIs for supporting glaucoma inspections. Existing methodologies has automated detection method with parameter values like ISNT quadrant and Cup-to-Disc Ratio (CDR). So, computation time of automated system requires quite longer corresponding to incompatible noisy data. Subsequently, threshold mechanism also considered to detect an 'OD' using segmentation. It endures with

less possibility to analyzing abnormalities of artifact when a fundus input images with unequal class of threshold value. This paper proposes a novel visual saliency threshold automated segmentation method for ROI detection of 'optic disc region' in FEIs. The proposed method utilized to extract the proceeding zone which is required for optic disc segmentation, enhances the performance and also reducing the computational cost for every retinal image in a prominent way as follows,

- 1) Segmentation is obtained by isolation of the 'OD' re-

gion with specific threshold based probability structure called 'saliency map'.

- 2) Saliency map combines each pixel into one set at maximum level, whose having similar characteristics in a segmented region.
- 3) Visual projection is to identify the 'OD' region by histogram of gray level intensity with high accuracy.
- 4) The time complexity is reduced in the proposed algorithm when compared with the other existing algorithms for FEIs segmentation process.

The remaining portion of the research paper is systematized as follows. Section 2 surveys existing works on segmentation methods. Section 3 defines Preliminary View. Section 4 focuses on the proposed method that evolves image segmentation algorithms. In Section 5 & 6 results, conclusions are drawn

## 2. RELATED WORKS

Phenomenon ways to detect boundaries in medical images are carried out by the active contours segment isolation. The following genre emphasizes segmentation types that describes optic disc detection belonging with region of interest to originate the organ boundaries.

Lu et al. (2011) presented an idea to identify the OD using circular bordering with specific color disparity along with 'circular transform' rather than Hough method. Conversely, the technique utilizes exact outcomes to consume clear boundary of OD part with color difference throughout the input images. This method finalizes irregular OD boundary corresponding to OD's origin.

Hsiao et al. (2012) proposed a new type of phases with a combination, namely localization with segmentation. Localization is followed by bright alteration and to extract dissemination features of input image with specific intensity of green band value. In segmentation, OD boundary categorization is done by 'Gradient Vector Flow (GVF)' in a supervised manner and preceded by classifier called 'Bayesian classifier' [3].

Roychowdhury et al. (2015) stated the method to identify the OD region in three process. Firstly, thresholding method is used to detect a bright region that exists in an OD. After the detection, regions are classified into the groups based on the type of regions. Then segmentation is generated by well-known shape structures like ellipse and convex hull [4].

Bharkad (2017) utilized a filtering mechanism to stimulate the process of OD segmentation with 'low-pass filter' and 'median filter'. Belonging to that, OD identification is carried out by blood vessel blurring and morphological dilation. So, the proposed technique disappeared to locate an OD center [5]. Mary et al. (2015) referred two approaches, named as OD localization using Circular Hough Transform (CHT) and OD segmentation using active contours formulated by GVF. In this approach, OD segmentation system

reaches the accuracy at 94%. Though the OD is located, it overcomes the interference caused from segmentation by removing the atrophy level [6].

Hu et al. (2017) followed color variance feature to differentiate each vessel bend in 'Optic Cup (OC) region' for the segmentation purpose. This technique associated with trivial colors to represent a particular vessel at constant level for the fundus image that used for segmentation. It assesses the presence of reliable boundary that exists in 'OC'. Likely, many features are considered to combine for the screening process of glaucoma [7].

Joshi et al. (2010) formulated the way to identify the 'OC' boundary with 'spline interpolation' as well as blood vessel's bends. In this segmentation, depth of data is perceived with error due to the data absence [8].

From the literature survey, it is noticed that there are many phase to retrieve the region of interest in OD segmentation. It consumes more time. The segmentation accuracy can be further improved and to overcoming the interface causes around the isolation of OD due to the entropy. This research addresses this problem very efficiently.

## 3. PRELIMINARY VIEW

### A. Region Growing(RG) Segmentation

RG is a method to digital image segmentation depends on choosing 'seed points'. In addition to that adjacent pixels that are corresponding to the given region of an image are selected, based on definite attribute like color similarity, intensity range and so on. In this algorithm, the input image can be separated into '2' regions such as foreground and background [9]. It requires an easy mode to do so is to select a seed ' $X \in I$ ' and then enlarges it. Here, ' $X \in I$ ' be an arbitrarily chosen pixel in an input '**2D image I**'. Let ' $R_f$ ' is a ROI of the input image **I** called foreground and ' $\delta_1$ ' is the acceptance of the variance intensity. An easy method to enlarge ' $R_f$ ' is to relate every adjacent pixels with primary seed.

The region growing algorithm is clearly given below

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### Algorithm: Region Growing

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- Input: Input Image  
Output: Region Of Interest (ROI)  
Steps:
- Step 1: Read an input image 'I' as FE image.
  - Step 2: Choose the seed pixel 'x' from input image 'I'.
  - Step 3: Examine the adjacent pixels 'N(p)' insert them to the ' $R_f$ ' is a ROI if they are related to the seed point.
  - Step 4: Repeat 'Step 2' for all of the recently inserted pixels and end if no more pixels can be inserted [10].
-

Allocate every pixel to  $R_f$  using the Equation

$$|x - N(p)| \leq \delta_1 \quad (1)$$

where  $x$  is a neighborhood pixel of  $N(p) \in I$ ,  $\delta_1$  is the absolute variance of intensity. When a pixel is allocated to ' $R_f$ ', the fresh adjacent pixel can be assessed in the similar manner. In appropriately, once a noise pixel is selected accidentally, the result will lead to an undesirable result. To overcome this problem, alternative method is to relate the pixel at the external regions with the neighboring pixel. This is related to Equation 1 but the evaluation is between ' $N(p)$ ' and outermost pixel of ' $R_f$ ' called as ' $S(x)$ '. The occurrence of noise pixels are evaluated using the equation

$$|S(x) - N(p)| \leq \delta_1 \quad (2)$$

where  $\delta_1$  is absolute variance of intensity,  $N(p)$  is a neighborhood pixel of  $I$ ,  $S(x)$  is outermost pixel of ' $R_f$ '. The Equation 1 proceeds to constant segmented regions however it is very subtle to noise whereas the subsequent Equation 2 could result with erroneous segmentations. Particularly in that cases the pixel attributes change progressively. So it encounters difficulty to fix a noise. The identification of the noisy pixel in an input image can be appeared as shown in Figure. 3 [11]. To rectify the above problem, the multiple seeds can be utilized for segment process. The initialization process with a set of pixels is used to find the better region by statistical tools like mean/variance and expansion also. To implicate a statistic operation, there is a need of cost effective operation because each adjacent pixel is assessed in the region area.

### Drawbacks

- Seed point must be specified initially so it has sensitive initialization process. Images may be under-segmented or over-segmented while selecting unsuitable initial seed point [13].
- Sometimes FEIs are normally endure with 'low-resolution', 'condensed contrast' as well as 'speckle noise' that result in disjointedness of uncertainty in segmented confines.
- The computation time is quite long and it is not compatible with noisy data [14].

### B. Threshold Based Segmentation

In image processing, thresholding is widely used segmentation method that is considered as a pixel categorization process. There are many threshold techniques. Manual thresholding and automatic thresholding is available. Manual thresholding takes more time. So it is considered to use automatic thresholding.

Thresholding frameworks can be categorized into three fundamental types such as 'local', 'bi-level', 'multi-level'

thresholding. In bi-level thresholding, two different classes i.e. 'foreground' and 'background' can be considered to distinct given input image as a binary image. A binary image is gray scale value is generated with thresholding by setting pixel values to '0' or '1' depends on whether they are larger than the threshold value or lower than the threshold value. This technique is commonly utilized to isolate a region or object with the input image depends on its pixel values. But, the main limitations of these methods are corresponding with the 'computational time'. If the number of threshold values rises, it also becomes a 'computationally difficult' system. Instead, 'local thresholding' based techniques assign various threshold values for every area of the input image [15]. In general, threshold value depends with apprehensive pixel's adjacent data. Moreover, local handling execution process is used to measure the total time consuming while 'local thresholding' takes part.

**Otsu Method:** Basically, it depends on global thresholding with gray level intensity of an image. The image is processed as a binary value by separation of two classes into background and object with global threshold value ' $T$ ' using the Equation 4. Otsu method defines the threshold value, which reduces the interclass difference of the threshold 'black as well as white' pixels. This segmentation method is called as one of the most general methods of best thresholding also it gives an 'automatic threshold' value calculation to distinct an object from its 'background'. Belonging with this technique, picked an initial assessment for threshold value as ' $T_0$ ' by computing the 'average gray level' of an input image ' $I$ '. After that, yield a member of two pixel groups as ' $S1 < TVAL$  &  $S2 \geq TVAL$ '. Calculate average intensity value ' $\alpha_1$  &  $\alpha_2$ ' for the pixels of ' $S1$  &  $S2$ ' respectively by using below Equation,

$$T = \frac{1}{2}(\alpha_1 + \alpha_2) \quad (3)$$

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### Algorithm: Threshold Segmentation

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- Step 1: Choose primary threshold value ' $T_0$ '.
- Step 2: Segment the input image using threshold value ' $T_0$ '. It will yield groups of pixels which is ' $S1$ ' residing of whole pixels with intensity values ' $> T_0$ ' and ' $S2$ ' comprising of pixels with values ' $< T_0$ '.
- Step 3: For the every pixel in the regions  $S1$ ,  $S2$ , generate the average intensity values ' $\alpha_1$ ' and ' $\alpha_2$ '.
- Step 4: Find a expected threshold value  $TVAL = \frac{1}{2}(\alpha_1 + \alpha_2)$
- Step 5: If the variance in ' $TVAL$ ' in consecutive repetitions is greater than a predefined parameter ' $T_0$ ', then exit from repetitions. Otherwise continue to repeat the steps 2 through 4 till the less variance in ' $TVAL$ '.

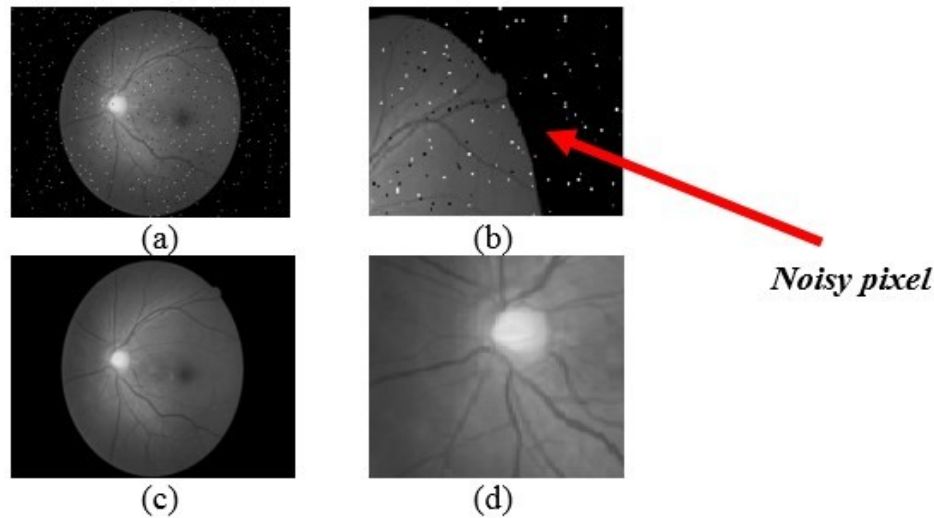


Figure 3. (a) Noisy input image (b) Noise pixel (Zoom view), (c) Preprocessed image (without noise), (d) Object area (Zoom view) [12]

Otsu method defines the threshold value of a pixel by specifying a gray level histogram. The below Figure 4 demonstrates the 'histogram' of an input image replicates the extraction of region of the background's histogram from the given input image's histogram by separation of pixel group.

Repeat the separation until, new threshold  $T$  is less than pre-specified ' $T_0$ '. It distinguishes the background and object by converting gray scale image into a binary image with following relation.

$$S(x,y) \begin{cases} 1 & \text{if } I(x,y) > T \\ 0 & \text{if } I(x,y) \leq T \end{cases} \quad (4)$$

Using Equation 4, pixels are grouped into set ' $S(x,y)$ '. The input image  $I(x,y)$  has pixel values between 0 and 255. The resultant facts, which have the 2 states (0 and 1), as histogram slice points. In the above equation, '1' is object and '0' is background, if the pixel value is below  $T$  that has been added into background otherwise that is considered to be an object [16].

**Drawbacks**

- Maximum false value may happen in threshold value selection.
- The technique inclines to preciously increase the size of minor classes for improved segmentation. In this method, combination of minor classes can be neglected.
- The main drawback of the Otsu is, when the number of segments increases, then the selected thresholds has less accuracy [17].

**4. PROPOSED SYSTEM**

The final goal of the constructed model is to exactly segment the 'Region of Interest (ROI)' of optic disc in Digital Fundus Eye image sets. Several models were available for segment of ROI in optic disc however the suggested system is considered to being effectual by incorporates the threshold system. The working mechanism of the proposed algorithm is shown in below Figure 5.

**Stage I: Removal of noise by Adaptive Median (AM) filtering** The AM filtering system works in 2 levels. This can be indicated by level I and level II as follows

Stage 1 deal with image noise filtering/removal. In this case, the Adaptive Median (AM) filtering is utilized for eliminating the noises in the 'FEIs' followed by usual noise filtering technique to acquire the noise free images.

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**Algorithm:3 AM Filtering System**

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**Level I:**

1. if ( $Z_{min} < Z_{mid} < Z_{max}$ ) then  $Z_{mid}$  is not a noise go to level II to test if  $Z_{xy}$  is a noise
2. else  $Z_{mid}$  is a noise
- 2.1 Increase the window size
- 2.2 Repeat Level I until  $Z_{mid}$  is not a noise
3. End

**Level II:**

4. if ( $Z_{min} < Z_{xy} < Z_{max}$ ) then  $Z_{xy}$  is not a noise output is  $Z_{xy}$
5. else  $Z_{xy}$  is a noise output is  $Z_{mid}$
6. End



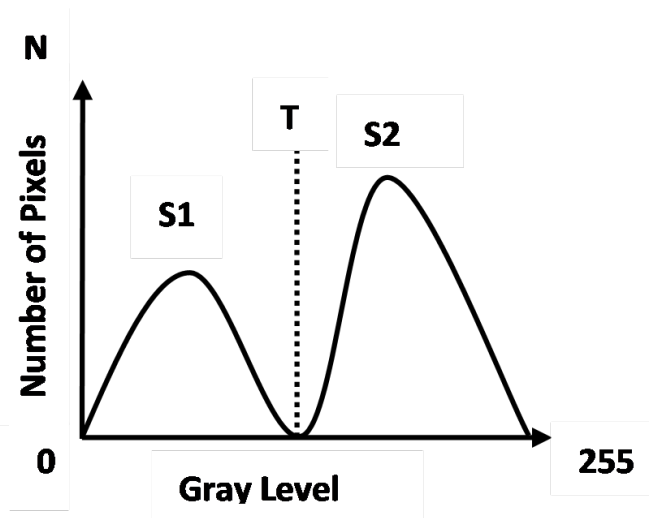


Figure 4. Separation two groups of pixels S1 & S2 of the input image

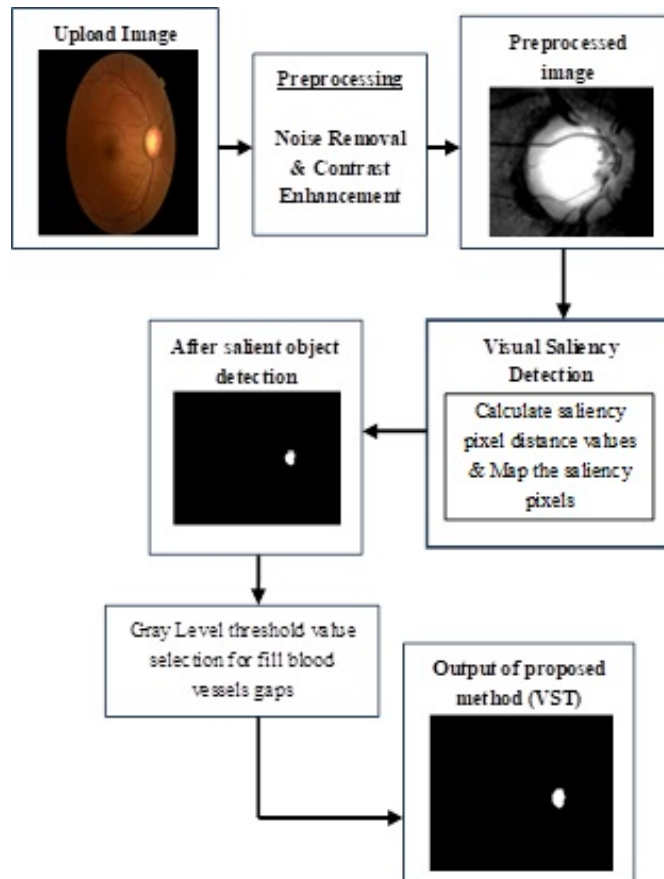


Figure 5. Proposed architecture



The 'Adaptive Median (AM) filter' carries out spatial progressing to determine that noisy pixels in a original image. This categorizes pixels as noise through matching every pixel value in the given input image to its adjacent pixels value. When a pixel is unrelated to its contiguous pixels or when a pixel is un-structurally ranged with those pixels and then it is considered as 'noise pixel'. Lastly, to replace these noise pixels, the average of the pixel value is generated by this filter as median value.

The AM filter works on a 'rectangular' region 'R<sub>xy</sub>'. This filter changes the size of R<sub>xy</sub> during the filtering process depending on some conditions [18]. The methodology of AM filter is as follows,

- Z<sub>min</sub> = minimum pixel value in R<sub>xy</sub>
- Z<sub>max</sub> = maximum pixel value in R<sub>xy</sub>
- Z<sub>mid</sub> = median pixel value in R<sub>xy</sub>
- Z<sub>xy</sub> = pixel value at coordinates (x,y)

**II: Segmentation of ROI by Visual Saliency Threshold (VST)** It is the procedure of splitting the images with various values of textures as well as pixels. Numerous techniques have been created for segmenting the digital images. In this work, novel approach has been presented that is called as 'Visual Saliency Threshold (VST)'. It totally decomposes the particular input images into condensed and varied elements. There will be a deduction of needless constituents in the input images [19].

The first phase of VST is preprocessing of an image is accepted with contrast improvement by brightening the object from the background [9], hence that the 'ROI' can simply be distinguished from the fundus eye image. In proposed scheme, contrast improvement with 'Histogram Equalization'(HE) handling is working on the frequency of input FE image after noise removal. In a gray level/binary image, the probabilities allocated to every gray level can be provided by the relation equation:

$$p_r(i_k) = \frac{p_k}{N} 0 \leq r_k \leq 1, k = 0, 1, 2, \dots, L - 1 \quad (5)$$

where  $i_k$  is the normalized intensity value, L is the number of gray levels (0 – 255) in the image,  $p_k$  is the number of pixels with gray level  $i_k$  and N is the total number of pixels in input image. The plot of  $p_r(i_k)$  with respect to  $i_k$  is called histogram of the image. The result of the probability is shown in the Figure 6 [11].

After improving the contrast of the pixels by histogram equalization, there is a need to calculate the parameter is known as distance. The distance among the pixels is considered to be the most important parameter in 'visual saliency descriptors' [20].The descriptor detects the distance among the pixels. It is defined as,

$$VSAL(D_x) = \sum_{j=0}^N (D_x - D_j) \quad (6)$$

where  $D_x$  – 'value of pixel x, ( $x \in [0, 255]$ )'. The above defined equation is extended as below,

$$VSAL(D_x) = |D_x - D_1| + |D_x - D_2| + \dots + |D_x - D_N| \quad (7)$$

The above equation can be again simplified to compose similar value of pixel set  $F_n$  by using,

$$VSAL(D_x) = \sum F_n \times |D_y - D_n| \quad (8)$$

The above described equation is utilized for computing similar pixel characteristics like as the intensity, orientation and color texture mechanism that are exposed in the below Figure 7 [11].

The next phase is to define the 'threshold value' by 'Saliency method' to obtain a segmented region area. 'Saliency method' holds the color specification to isolate region with unique color in the input image. So the 'salient image' is facilitating the areas which has high spot as maximum pixel value [22]. The step targets to obtain the 'saliency map'  $Smap$  of input image that is acquired from the saliency descriptors,

$$Smap(x, y) = \| I_\mu - I_{S(x,y)} \| \quad (9)$$

Where ' $I_\mu$ ' the mean of preprocessed image feature vector, ' $I_S$ ' is the vector that matches the given input image pixel vector value to same input image with its Gaussian blurred version, and  $\|$  is the distance from saliency descriptors. The causing 'saliency maps' are superior suitable to 'salient object' segmentation [21]. This can consistently highlight the 'salient regions' with refined confines. A 'saliency map' gives the below result, as shown in Figure 8 [12].

From visual examination of the image in Figure 8.a, the 'vessels' still have a little gaps. The identified object is filled by a GrayLevel threshold value selection to reduce this problem.

GrayLevel threshold value selection is based on intensity value which signifies the numerical distribution of intensities in the adjacent of a specific pixel. Figure 8.a shows the Contrast Improved 'FEI' of blood vessel and it look to be darker when compare to their environs. Therefore, it statistically describes the 'intensity variations' can be utilized to enumerate the occurrence of blood vessels.

Intensity modification is executed with the help of intensity values gained from threshold. The threshold is computed on the input channels and the maximum intensity is chosen. After intensity adjustment, final regions of interest are detected. In the final output, optic disc of the input image is completely removed. 'Optic Disc (OD)' elimination is proposed to avoid wrong recognition in the segmentation stages due to the OD's color and contrast, which nearly the similar to the regions [22]. The absolute image next to this processing is displayed in Figure 8.b.

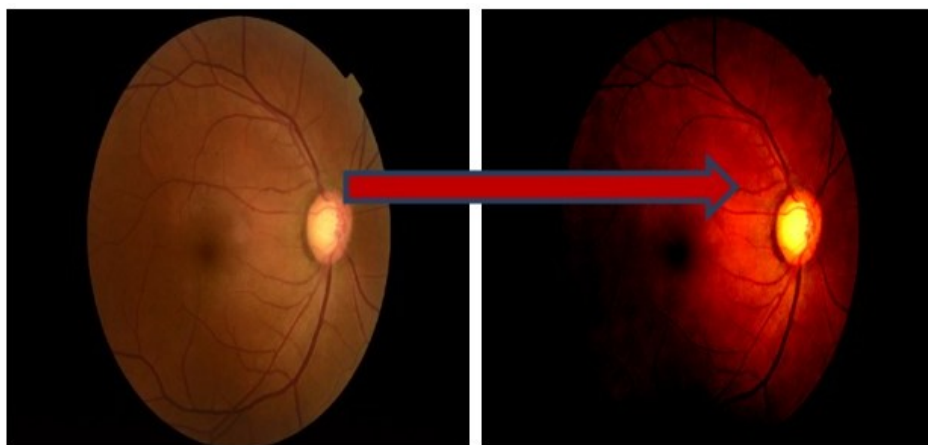


Figure 6. (a) Before HE (b) After HE [11]

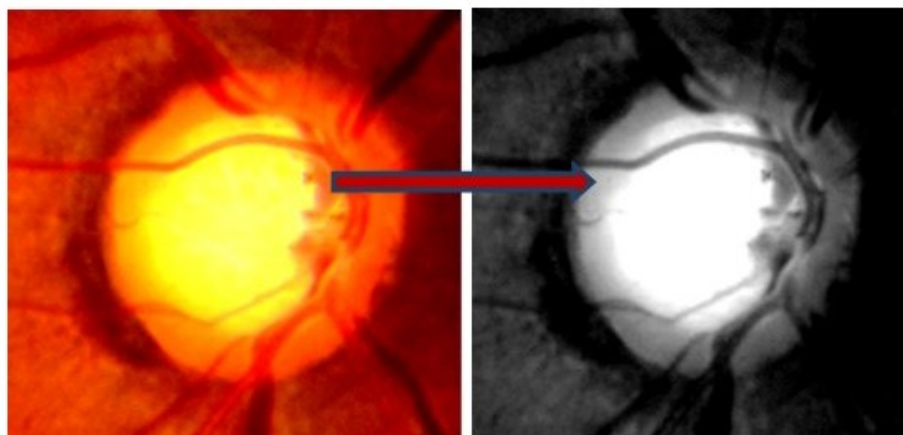


Figure 7. Image Textures [11]



Figure 8. (a) Segment with gap (b) Gray Level selection [12]



## 5. RESULTS

### A. Dataset Descriptions

The 'FEI' datasets were employed for testing and assessing the proposed VST algorithm that is downloaded from the two different resources are: (1) 'DRISHTI-GS1' public dataset of retinal images. It completely comprised with '50' images with the dimension of 2896X1944 pixels [12].

(2) The Proposed model has been experimented with [github.com/yiweichen04/retina\\_dataset](https://github.com/yiweichen04/retina_dataset), which contains 101' images in addition to that which has '31' normal and '70' abnormal (disease) retinal images. For all input image, the location of 'OD' is properly identified by four experts belong with glaucoma detection.

### B. Metrics for Performance Evaluation of Segmentation Algorithms

To assess the performance of segmentation algorithms, four performance metrics, namely SNR (Signal to Noise Ratio), MSE (Mean Squared Error), Peak Signal-to-noise ratio (PSNR) and Mean absolute error (MAE) are utilized in this work [23]. The proposed metrics evaluate the performance of given segmentation algorithm by comparing the qualities of input and output images.

1) *SNR*: The SNR is an illustrative of the average signal power to the predictable constituent present for a pair of original and segmented image. The (SNR) is defined by the equation,

$$SNR = 10 \log_{10} \left( \frac{\sum_{i=1}^M \sum_{j=1}^N (g_{i,j}^2 + f_{i,j}^2)}{\sum_{i=1}^M \sum_{j=1}^N (g_{i,j}^2 - f_{i,j}^2)} \right) \quad (10)$$

Let  $g_{i,j}$  is the original input image plus  $f_{i,j}$  is the output segmented image.  $i = 1, 2, \dots, M$  (range index) and  $j = 1, 2, \dots, N$  (cross-range index)

2) *PSNR*: PSNR measured is measured in decibels. It signifies the quantity of highest error. It defines the reassembled/ segmented image with the superior excellence by,

$$PSNR = 10 \log_{10}(R_2)/MSE \quad (11)$$

'R' is the data type of 'input image' with extreme variation. 'R' can be either 1 for data type with double precision or '255' for data with 8 bit unsigned type.

3) *MSE*: MSE is calculated to compute the alteration in excellence between the input image and segmented image. It signifies the 'cumulative squared error' among the segmented and the input image.

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (g_{i,j} - f_{i,j})^2 \quad (12)$$

The MSE value is the square of the 'Euclidean

distance' among the input image plus its assessment. In above equation,  $g_{i,j}$  is the original input image and  $f_{i,j}$  is the estimated image.  $i = 1, 2, \dots, M$  (range index) and  $j = 1, 2, \dots, N$  (cross-range index).

4) *MAE*: MAE is a quantity applied to identify how close estimates are to the final results. The MAE is described by below equation.

$$MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (f_{i,j} - y_{i,j}) \quad (13)$$

In above equation,  $f_{i,j}$  is the input/original image and  $y_{i,j}$  is the evaluated image.  $i = 1, 2, \dots, M$  (range index) and  $j = 1, 2, \dots, N$  (cross-range index).

### C. Results and Discussion

The Proposed model has been tested on MATLAB 2018, Intel i7 CPU with the 2TB hard disk, 8GB RAM with Windows 10 Operating Systems. The proposed model segments the ROI from DRISHTI-GS as shown in Figure 9.

The performance of the proposed system has been assessed by the various algorithms and the corresponding results are displayed in the table.

Table I clearly shows that proposed algorithm has a maximum SNR in the segmentation of FEIs. The highest SNR obtained from proposed algorithm has been assessed with other segmentation algorithms that evaluate performance at the various FE images.

Table II clearly shows that proposed algorithm has a maximum PSNR in the segmentation of FEIs. The highest PSNR obtained from proposed algorithm has been compared with other segmentation algorithms that evaluate the performance at different FE images.

Table III clearly shows that proposed algorithm has a minimum MSE in the segmentation of FEIs. The lowest MSE obtained from proposed method has been compared with other segmentation algorithms that evaluate the performance at different FE images.

Table IV clearly shows that proposed algorithm has a minimum MAE in the segmentation of FEIs. The lowest MAE obtained from proposed method has been compared with other segmentation algorithms that evaluate the performance at different FE images.

### D. Time Analysis

The time has been considered as an important metric for the 'proposed VST' as well as compared with the other existing segmentation techniques. The table illustrates the comparative analysis of time for various techniques.

The above table illustrated that the time complexity is reduced in the proposed algorithm when compared with the

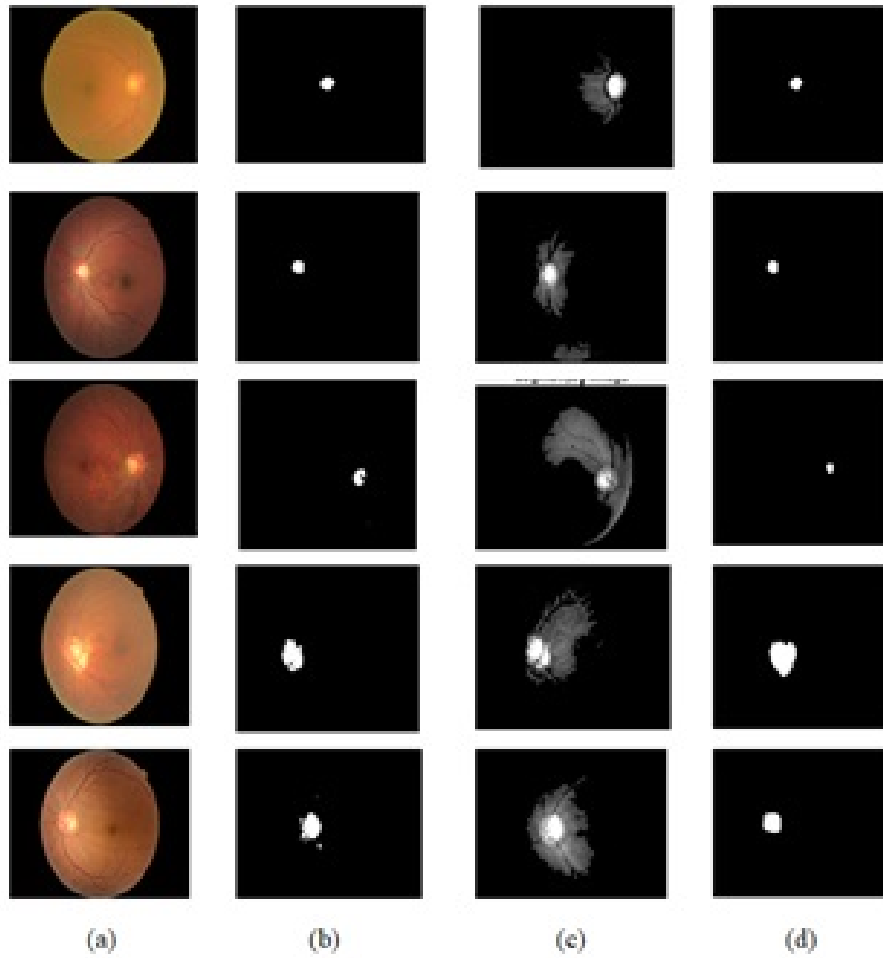


Figure 9. (a) Input FEI [12] (b) Otsu Threshold (c) Region Growing (d) Proposed Method

TABLE I. SNR Comparison for Different Segmentation Algorithms

Images	Segmentation Methods		
	Otsu Threshold	Region Growing	Proposed Method
IM1	0.29	3.06	28.75
IM2	0.02	2.69	35.86
IM3	1.05	3.59	37.35
IM4	0.23	3.26	36.00
IM5	0.13	2.61	14.00
IM6	1.70	3.79	15.52
IM7	1.03	4.21	17.52
IM8	1.68	3.76	18.03
IM9	1.04	2.80	16.28
IM10	1.16	3.07	17.09



TABLE II. PSNR Comparison for Different Segmentation Algorithms

Images	Segmentation Methods		
	Otsu Threshold	Region Growing	Proposed Method
IM1	2.45	0.22	7.60
IM2	1.02	1.31	7.23
IM3	2.19	2.80	7.27
IM4	0.75	1.09	6.38
IM5	0.19	1.72	7.17
IM6	0.10	2.78	6.77
IM7	2.12	2.79	6.77
IM8	2.40	2.79	6.52
IM9	0.39	1.47	6.79
IM10	0.23	1.56	7.06

TABLE III. MSE Comparison for Different Segmentation Algorithms

Images	Segmentation Methods		
	Otsu Threshold	Region Growing	Proposed Method
IM1	1.04	0.95	0.17
IM2	1.05	0.93	0.19
IM3	1.10	0.52	0.19
IM4	1.07	0.78	0.23
IM5	1.06	0.85	0.19
IM6	1.98	0.53	0.21
IM7	1.10	0.53	0.21
IM8	1.11	0.53	0.22
IM9	1.06	0.90	0.21
IM10	1.06	0.88	0.20

TABLE IV. MAE Comparison for Different Segmentation Algorithms

Images	Segmentation Methods		
	Otsu Threshold	Region Growing	Proposed Method
IM1	1.13	0.95	0.41
IM2	1.15	0.93	0.38
IM3	1.22	0.52	0.42
IM4	1.19	0.78	0.46
IM5	1.17	0.85	0.39
IM6	1.22	0.53	0.40
IM7	1.22	0.53	0.41
IM8	1.23	0.53	0.42
IM9	1.16	0.90	0.41
IM10	1.17	0.88	0.41

TABLE V. Comparing Time of Proposed VST Model with the Other Existing Algorithms

S. No.	Algorithms	Time (secs)
1	Otsu Threshold	12.945
2	Region Growing	9.213
3	Proposed (VST)	8.707



other existing algorithms for FEIs segmentation process.

## 6. CONCLUSION

This approach implemented with a new as well as computationally talented technique for the image segmentation of the 'ROI' in 'OD' from 'FE' image is established. The highest impact of this research is the development of an effective technique to segment the ROI in OD by a method based on 'visual saliency threshold' algorithm. The proposed method is simple to implement also yields the finest result with a minimum computation time. Furthermore, this can attain hopeful results as well as it has an ability of spontaneously zooming into an object region anywhere these outcomes. 'Saliency' exploits factor control that can regulate the values of input parameters in the segmentation process. The proposed method improved the extraction of ROI in optic disc from retinal images to improve classification accuracy. The outcome was significantly improved than existing segmentation methods. Hence this development of proposed segmentation technique utilized 'OD' segmentation policy. The proposed 'VST' algorithm has proved to be more effective when compared to the other segmentation algorithms.

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**Dr. V. Subha** Dr. V. Subha received B.E. (Electronics and Communication Engineering) from Bharathiyar University Coimbatore in 2000. She received her M.E. (Computer Science and Engineering) and Ph.D degrees from Manonmaniam Sundaranar University, Tirunelveli in 2002 and 2016. She has 15 years of teaching experience. She is presently working as Assistant Professor in Manonmaniam Sundaranar University. She

has published 15 articles in international journals. Her areas of interest are Data Mining and Pattern recognition.



**S. Niraja P Rayen** S. Niraja P Rayen completed her M.C.A degree from Madurai Kamaraj University, Madurai, India, in 2006, and the M.Phil in Computer Science from Manonmaniam Sundaranar University, Tirunelveli, India, in 2014. She is doing Ph.D. degree under Manonmaniam Sundaranar University Tirunelveli, India. Her Area of Specialization is Image Processing and Data Analytics.