

The Benefits and Challenges of e-Health Applications: A Content Analysis of the South African context

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ABSTRACT

Image binarization is the process of separation of pixel values into two groups, black as background and white as foreground. Thresholding can be categorized into global thresholding and local thresholding. This paper describes a locally adaptive thresholding technique that removes background by using local mean and standard deviation. Most common and simplest approach to segment an image is using thresholding. In this work we present an efficient implementation for thresholding and give a detailed comparison of Niblack and sauvola local thresholding algorithm. Niblack and sauvola thresholding algorithm is implemented on medical images. The quality of segmented image is measured by statistical parameters: Jaccard Similarity Coefficient, Peak Signal to Noise Ratio .

KEYWORDS

Thresholding, Niblack, Sauvola, PSNR, Jaccard

INTRODUCTION

Image segmentation is a fundamental process in many image, video, and computer vision applications. It is often used to partition an image into separate regions, which ideally correspond to different real-world objects. It is a critical step towards content analysis and image understanding [1]. The gray levels of pixels belonging to the object are entirely different from the gray levels of the pixels belonging to the background, in many applications of image processing. Thresholding becomes then a simple but effective tool to separate those foreground objects from the background. We can divide the pixels in the image into two major groups, according to their gray-level. These gray-levels may serve as “detectors” to distinguish between background and objects is considering as foreground in the image [2]. Select a gray-level between those two major gray-level groups, which will serve as a threshold to distinguish the two groups (objects and background). Image segmentation is performed by such as boundary detection or region dependent techniques. But the thresholding techniques are more perfect, simple and widely used [3]. Different binarization methods have been performed to evaluate for different types of data. The locally adaptive binarization method is used in gray scale images with low contrast, Variety of background intensity and presence of noise. Niblack’s method was found for better thresholding in gray scale image, but still it has been modified for fine and better result [4].

A number of thresholding techniques have been previously proposed using global and local techniques. Global methods apply one threshold to the entire image while local thresholding

methods apply different threshold values to different regions of the image. The value is determined by the neighborhood of the pixel to which the thresholding is being applied [5].

The binarization techniques for grayscale documents can be grouped into two broad categories: global thresholding binarization and local thresholding binarization [6]. Global methods find a single threshold value for the whole document. Then each pixel is assigned to page foreground or background based on its gray value comparing with the threshold value. Global methods are very fast and they give good results for typical scanned documents. For many years, the binarization of a grayscale document was based on the global thresholding statistical algorithms. These statistical methods, which can be considered as clustering approaches, are inappropriate for complex documents, and for degraded documents. If the illumination over the document is not uniform global binarization methods tend to produce marginal noise along the page borders. To overcome these complexities, local thresholding techniques have been proposed for document binarization. These techniques estimate a different threshold for each pixel according to the grayscale information of the neighboring pixels. The techniques of Bernsen, Chow and Kaneko, Eikvil, Mardia and Hainsworth, Niblack [7], Yanowitz and Bruckstein [8], and TR Singh belong to this category. The hybrid techniques: L.O’Gorman and Liu, which combine information of global and local thresholds belong to another category. In this paper we focus on the binarization of grayscale documents using local thresholding technique, because in most cases color documents can be converted to grayscale without losing much information as far as distinction between page foreground and background is concerned.

THRESHOLDING TECHNIQUES

Threshold technique is one of the important techniques in image segmentation. This technique can be expressed as:

$$T=T[x, y, p(x, y), f(x, y)]$$

Where T is the threshold value. x, y are the coordinates of the threshold value point. p(x,y), f(x,y) are points the gray level image pixels [9]. Threshold image g(x,y) can be define:

$$g(x,y)= \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T \end{cases}$$

Thresholding techniques are classified as bellow

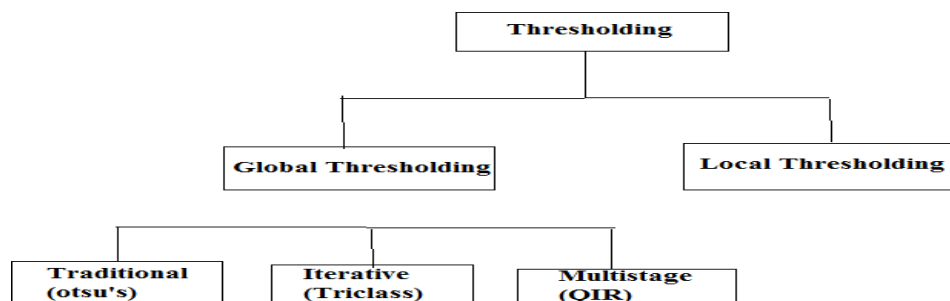


Figure 1. Thresholding Techniques

Thresholding is classified into two Global Thresholding and Local Thresholding, Global thresholding is divided into Traditional, Iterative, Multistage which is defined as a Figure 1.

Global Thresholding

Global (single) thresholding method is used when there the intensity distribution between the objects of foreground and background are very distinct. When the differences between foreground and background objects are very distinct, a single value of threshold can simply be used to differentiate both objects apart. Thus, in this type of thresholding, the value of threshold T depends solely on the property of the pixel and the grey level value of the image. Some most common used global thresholding methods are Otsu method, entropy based thresholding, etc. Otsu's algorithm is a popular global thresholding technique. Moreover, there are many popular thresholding techniques such as Kittler and Illingworth, Kapur, Tsai, Huang, Yen and et al [9].

Traditional Thresholding (Otsu's Method)

In image processing, segmentation is often the first step to pre-process images to extract objects of interest for further analysis. Segmentation techniques can be generally categorized into two frameworks, edge-based and region based approaches. As a segmentation technique, Otsu's method is widely used in pattern recognition, document binarization, and computer vision. In many cases Otsu's method is used as a pre-processing technique to segment an image for further processing such as feature analysis and quantification. Otsu's method searches for a threshold that minimizes the intra-class variances of the segmented image and can achieve good results when the histogram of the original image has two distinct peaks, one belongs to the background, and the other belongs to the foreground or the signal. The Otsu's threshold is found by searching across the whole range of the pixel values of the image until the intra-class variances reach their minimum. As it is defined, the threshold determined by Otsu's method is more profoundly determined by the class that has the larger variance, be it the background or the foreground. As such, Otsu's method may create suboptimal results when the histogram of the image has more than two peaks or if one of the classes has a large variance

Iterative Thresholding (A New Iterative Triclass Thresholding Technique)

A new iterative method that is based on Otsu's method but differs from the standard application of the method in an important way. At the first iteration, we apply Otsu's method on an image to obtain the Otsu's threshold and the means of two classes separated by the threshold as the standard application does. Then, instead of classifying the image into two classes separated by the Otsu's threshold, our method separates the image into three classes based on the two class means derived. The three classes are defined as the foreground with pixel values are greater than the larger mean, the background with pixel values are less than the smaller mean, and more importantly, a third class we call the "to-be-determined" (TBD) region with pixel values fall between the two class means. Then at the next iteration, the method keeps the previous foreground and background regions unchanged and re-applies Otsu's method on the TBD region only to, again, separate it into three classes in the similar manner. When the iteration stops after meeting a preset criterion, the last TBD region is then separated into two classes, foreground and background, instead of three regions. The final foreground is the logical union of all the previously determined foreground regions and the final background is determined similarly. The new method is almost parameter free except for the stopping rule for the iterative process and has minimal added computational load.

Multistage Thresholding(Quadratic Ratio Technique For Handwritten Character)

The QIR technique was found superior in thresholding handwriting images where the following tight requirements need to be met:

1. All the details of the handwriting are to be retained
 2. The papers used may contain strong coloured or patterned background
 3. The handwriting may be written by a wide variety of writing media such as a fountain pen, ballpoint pen, or pencil.
- QIR is a global two stage thresholding technique. The first stage of the algorithm divides an image into three sub images: foreground, background, and a fuzzy sub image where it is hard to determine whether a pixel actually belongs to the foreground or the background (Figure 2). Two important parameters that separate the sub images are A, which separates the foreground and the fuzzy sub image, and C, which separate the fuzzy and the background sub image. If a pixel's intensity is less than or equal to A, the pixel belongs to the foreground. If a pixel's intensity is greater than or equal to C, the pixel belongs to the background. If a pixel has an intensity value between A and C, it belongs to the fuzzy sub image and more information is needed from the image to decide whether it actually belongs to the foreground or the background.

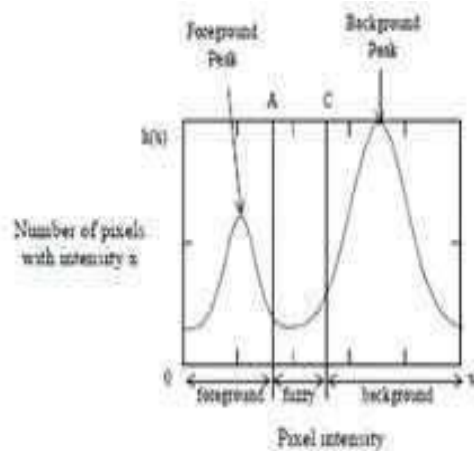


Figure 2. Three Subimages of QIR

Local Thresholding

A threshold $T(x,y)$ is a value such that

$$b(x, y) = \begin{cases} 0 & \text{if } I(x, y) \leq T(x, y) \\ 1 & \text{otherwise} \end{cases}$$

Where $b(x,y)$ is the binarized image and $I(x,y) \in [0,1]$ be the intensity of a pixel at location (x,y) of the image I . In local adaptive technique, a threshold is calculated for each pixel, based on some local statistics such as range, variance, or surface-fitting parameters of the neighborhood pixels. It can be approached in different ways such as background subtraction, water flow model, means and standard derivation of pixel values, and local image contrast. Some drawbacks of the local thresholding techniques are region size dependant, individual image characteristics, and time consuming. Therefore, some researchers use a hybrid approach that applies both global and local thresholding methods and some use morphological operators. Niblack, and Sauvola and Pietaksinen use the local variance technique while Bernsen uses midrange value within the local block.[10]

Niblack's Techniques

In this method local threshold value $T(x, y)$ at (x, y) is calculated within a window of size $w \times w$ was:

$$T(x, y) = m(x, y) + k * \delta(x, y)$$

Where $m(x, y)$ and $\delta(x, y)$ are the local mean and standard deviation of the pixels inside the local window and k is a bias. Set as $k = 0.5$. The local mean $m(x, y)$ and standard deviation $\delta(x, y)$ adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. The bias k controls the level of adaptation varying the threshold value.[11]

Sauvola's Technique

In Sauvola's technique, the threshold $T(x, y)$ is computed using the mean $m(x, y)$ and standard deviation $\delta(x, y)$ of the pixel intensities in a $w \times w$ window centered around the pixel at (x, y) and express as

$$T_{Sauvola} = m * (1 - k * (1 - \frac{s}{R}))$$

Where R is the maximum value of the standard deviation ($R=128$ for a grayscale document), and k is a parameter which takes positive values in the range $[0.5]$ [12].

Bernsen's Technique

This technique, proposed by Bernsen, is a local binarization technique, which uses local contrast value to determine local threshold value. The local threshold value for each pixel (x, y) is calculated by the relation.

$$T(x,y) = \frac{I_{max} + I_{min}}{2}$$

Where I_{max} and I_{min} are the maximum and minimum gray level value in a $w \times w$ window centered at (x, y) respectively [13]. But the threshold assignment is based on local contrast value and hence it can be expressed as

if $I_{max} - I_{min} > L$ //if the gray scale image is not uniform

Then

$$T(x,y) = \frac{I_{max} + I_{min}}{2}$$

Else $T(x, y) = GT$ // (else threshold value is calculated by global thresholding technique.)

Where L is a contrast threshold and GT is a global threshold value.

Yanowitz and Bruckstein's Method

Yanowitz and Bruckstein suggested using the grey-level values at high gradient regions as known data to interpolate the threshold surface of image document texture features [14]. The key steps of this method are:

1. Smooth the image by average filtering.
2. Derive the gradient magnitude.
3. Apply a thinning algorithm to find the object boundary points.
4. Sample the grey-level in the smoothed image at the boundary points. These are the support points for interpolation in step 5.
5. Find the threshold surface $T(x, y)$ that is equal to the image values at the support points and satisfies the Laplace equation using South well's successive over relaxation method.
6. Using the obtained $T(x, y)$, segment the image.
7. Apply a post-processing method to validate the segmented image

PROPOSED TECHNIQUES

Niblack's Algorithm

In local thresholding, the threshold values are spatially varied and determined based on the local content of the target image. In comparison with global techniques, local thresholding techniques have better performance against noise and error especially when dealing with information near texts or objects. According to Trier's survey, Yanowitz Bruckstein's method and Niblack's method are two of the best performing local thresholding methods. Yanowitz-Bruckstein's method is extraordinarily complicated and thus requires very large computational power. This makes it infeasible and too expensive for real system implementations. On the other hand, Niblack's method is simple and effective. As a result, we decided to focus on Niblack's method. Niblack's algorithm [15] is a local thresholding method based on the calculation of the local mean and of local standard deviation. The threshold is decided by the formula:

$$T(x, y) = m(x, y) + k \cdot s(x, y)$$

where $m(x, y)$ and $s(x, y)$ are the average of a local area and standard deviation values, respectively. The size of the neighborhood should be small enough to preserve local details, but at the same time large enough to suppress noise. The value of k is used to adjust how much of the total print object boundary is taken as a part of the given object.

Sauvola's Technique

In Sauvola's technique [16], the threshold $T_{Sauvola}$ is computed using the mean m and standard deviation of the pixel intensities in a window centered around the pixel and express

$$T_{Sauvola} = m * (1 - k * (1 - \frac{s}{R}))$$

where s is the maximum value of the standard deviation (for a grayscale document), and k is a parameter which takes positive values in the range [0.5].

The local mean m and standard deviation s adapt the value of the threshold according to the contrast in the local neighborhood of the pixel. When there is high contrast in some region of the image, $s \sim R$ which results in $T_{Sauvola} \sim m$. This is the same result as in Niblack’s method. However, the difference comes in when the contrast in the local neighborhood is quite low. In that case the threshold $T_{Sauvola}$ goes below the mean value thereby successfully removing the relatively dark regions of the background.

The parameter k controls the value of the threshold in the local window such that the higher the value of k , the lower the threshold from the local mean m . A value of $k = 0.5$ was used by Sauvola and Sezgin. Badekas et al. experimented with different values and found that $k = 0.34$ gives the best result. In general, the algorithm is not very sensitive to the value of k used. The statistical constraint gives very good result even for severely degraded document. In order to compute the threshold $T_{Sauvola}$, local mean and standard deviation have to be computed for each pixel its computational complexity is $O(n^2 \times w^2)$ in a naive way for an image of size $n \times n$. It means that its computational complexity is window size dependent. T.R Singh proposed window size independent technique of thresholding using integral sum image as prior process.

RESULT AND DISCUSSION





Images	Using Niblack Technique	Using Sauvola Technique
Image 1		
Image 2		


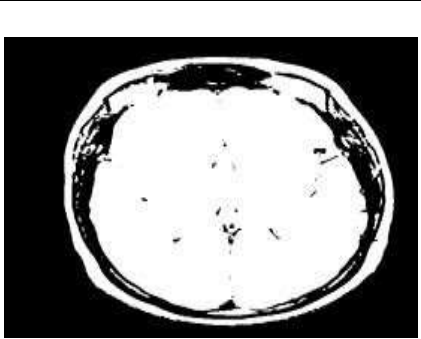
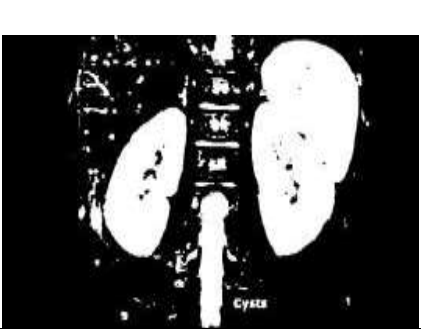
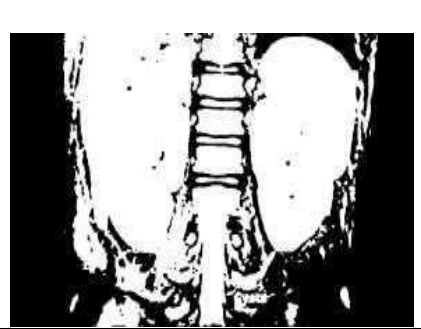
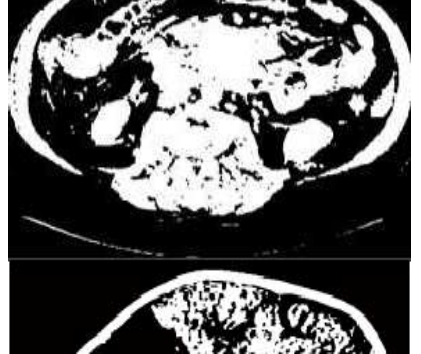
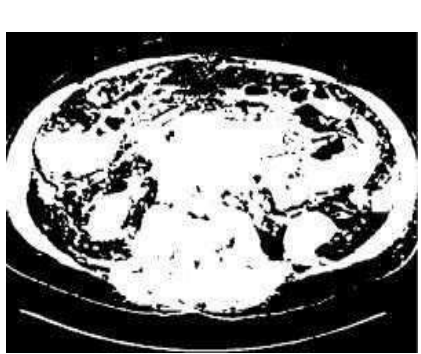

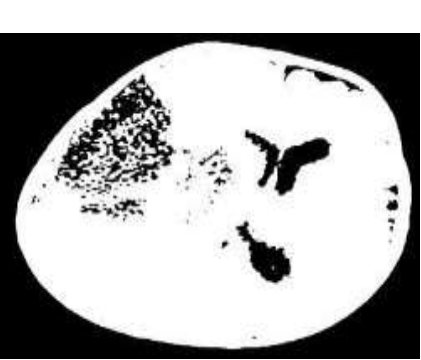
Image 3		
Image 4		
Image 5		
Image 6		

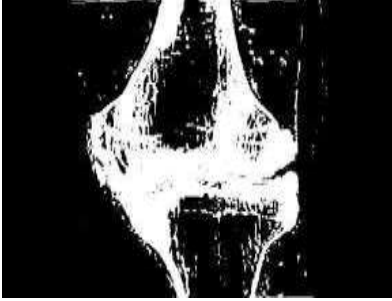
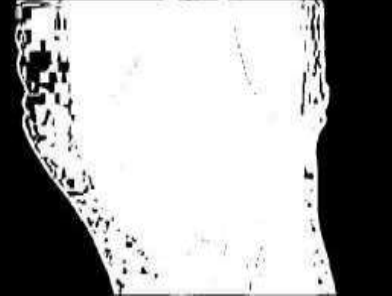


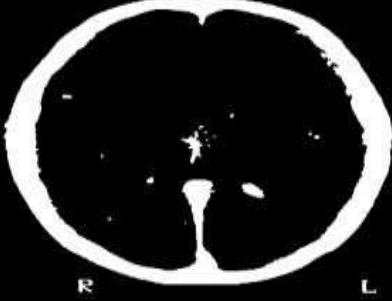
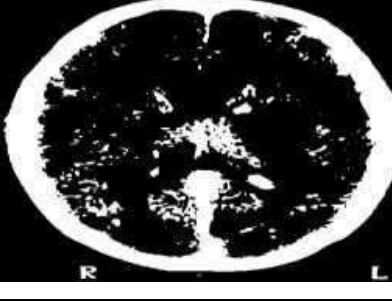

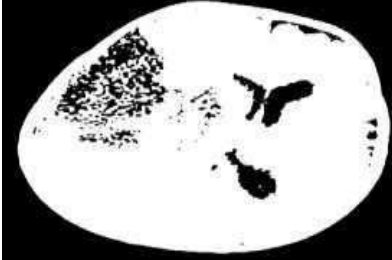
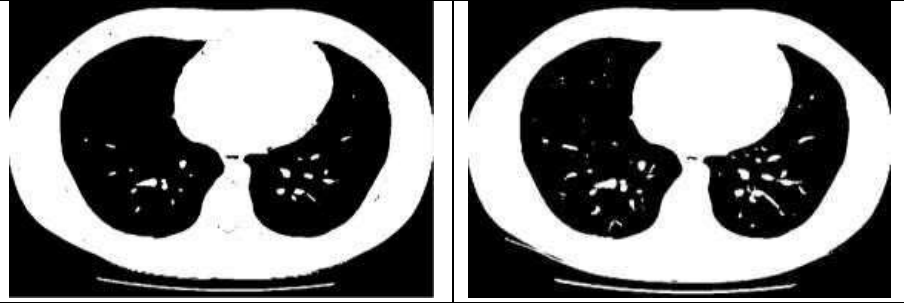
Image 7		
Image 8		
Image 9		
Image 10		

Image
11



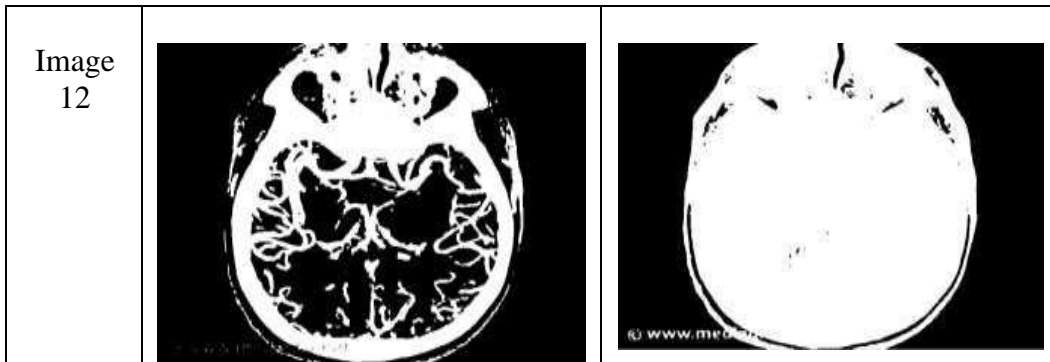


Table 1. Performance Evaluation

Images	Methods	PSNR	Jaccard
Image 1	Niblack	58.9606	0.5218
	Sauvola	52.0983	0.2771
Image 2	Niblack	54.0756	0.3493
	Sauvola	52.5357	0.2764
Image 3	Niblack	52.9222	0.4002
	Sauvola	52.2229	0.3636
Image 4	Niblack	68.6696	0.4074
	Sauvola	54.0028	0.2050
Image 5	Niblack	54.2790	0.3324
	Sauvola	52.3042	0.2117
Image 6	Niblack	54.7581	0.3969
	Sauvola	51.1339	0.2364
Image 7	Niblack	56.5496	0.3907
	Sauvola	50.6168	0.0459
Image 8	Niblack	55.0773	0.4460
	Sauvola	51.5917	0.2689
Image 9	Niblack	69.7794	0.5592
	Sauvola	59.2688	0.4824
Image 10	Niblack	54.5925	0.2953
	Sauvola	54.1678	0.2737
Image 11	Niblack	62.0404	0.4328
	Sauvola	54.5521	0.2767
Image 12	Niblack	56.1006	0.1131
	Sauvola	54.7955	0.0783

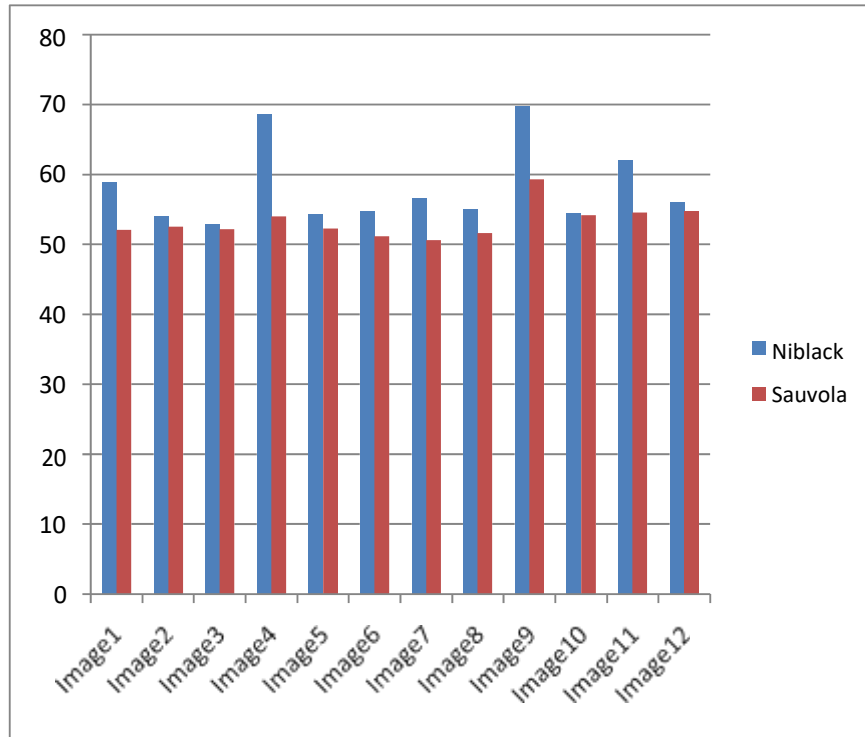


Figure 3. Comparison of Medical images using PSNR

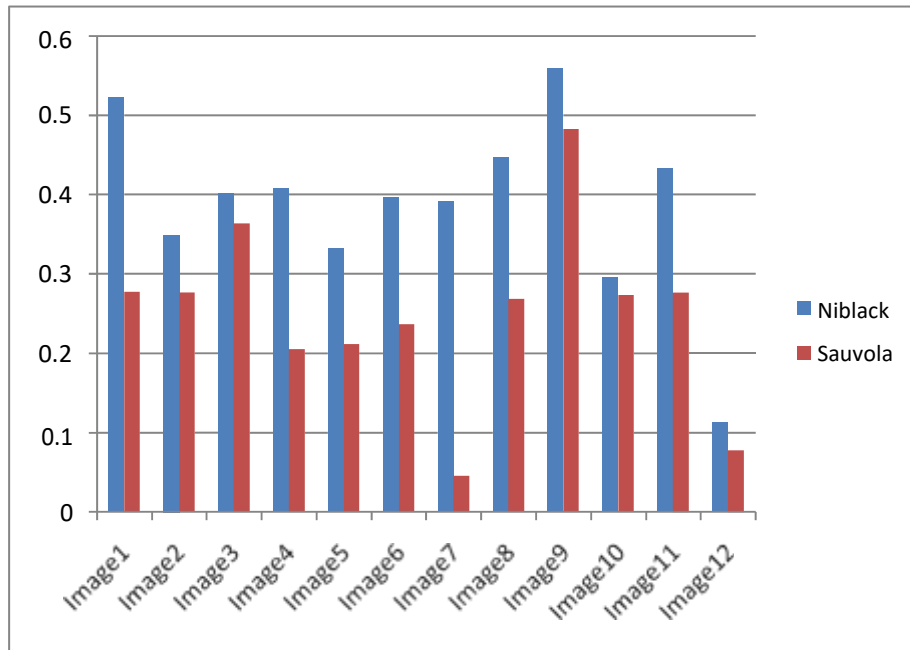


Figure 4 . Comparison of Medical images using Jaccard

CONCLUSION

In This paper describes a locally adaptive thresholding technique that removes background by using local mean and standard deviation. Niblack and sauvola thresholding algorithm is implemented on medical images. In this paper we compare Niblack and Sauvola thresholding algorithm .These approaches aiming at removal of background noise. Niblack algorithm reduce the background noise compare to Sauvola algorithm. The performance of proposed algorithms is measured using segmentation parameters PSNR, Jaccard Similarity Coefficient.The result of the Niblack algorithm is better than the Sauvola algorithm.

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