International Journal of Scientific Research and Engineering Development-– Volume 5 Issue 3, May-June 2022
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Application of User Interactive Segmentation Algorithms in Low Resolution Images of Colourimetric Cholesterol Samples

Samuel Awuhe*, Patience E. Orukpe**, Inalegwu Bawa***
*(Department of Electrical and Electronics Engineering, Joseph Sarwuan Tarka University, Makurdi
Email: samzfrter@gmail.com)
** (Department of Electrical/Electronic Engineering, University of Benin, Benin City, Edo State
Email: patience.orukpe@uniben.edu)
*** (Department of Biochemistry, Joseph Sarwuan Tarka University, Makurdi
Email: inalegwubawa@yahoo.com)

--************************----------------------------------

Abstract:
The application of image processing and deep learning for medical diagnosis is on the rise. But the presence of background noise and some distortions in medical images often affect the accuracy of diagnosis.Segmentation isoften employed to create a region of interest as foreground and eliminate background noise in an image for further processing. However, interactive segmentation-based methods are usually used where natural images with complex content are involved. As segmentation is regarded as a complex problem in image processing and computer vision applications, it is often better to assess the performance of a segmentation algorithm before adopting it for a particular application. In this work, the performance of lazy snapping and grabcut algorithms were determined based on how fast an algorithm produces segmentation result on low image resolutions of cholesterol samples. The performances of the two algorithms were also examined using quality metrics such as sensitivity, specificity and pixel accuracy of segmentations. Findings from the research showed that the grabcut method was faster than the lazy snapping technique with an average time difference of 1.0136 seconds in producing segmentation results. The grabcut method also outperformed the lazy snapping technique under sensitivity, specificity and accuracy quality metrics in more than two-third of the images used in the research.

Keywords **—Segmentation, Superpixels, Cholesterol, Sensitivity, Specificity.**

--************************----------------------------------

I. INTRODUCTION

With the application of image processing and artificial intelligence in medical diagnosis, efforts have been made to automate computer aided diagnostic tools, which have the ability to classify and detect a variety of medical conditions from medical images [1-3].

Recently, convolutional neural networks (CNNs) have proven to be one of the most successful networks in image classification problems [4]. Convolutional neural networks are made up of a combination of several layers. Usually a CNN image classifier can take an image as an input, learn the spatial information from the image and create feature maps which serve as input to the next layers [5]. Generally, CNN architectures take low resolution images even though achieving a reasonable model performance might be seen improbable, a reduction in the number of features learned from input images is desirable as a means of reducing the number of parameters to be optimized which plays an important role in lowering the risk of model overfitting [6]. The input images to the CNN architectures are down-sampled to a fraction of the original image acquired by an image acquisition system because higher image resolutions increase resource requirement and processing time. In addition to image resolution, image quality factors such as noise, compression, blur just to mention a few also affect the visual information contained in an image [7]. Thus, the presence of background noise in some medical images can lead to wrong image classification and diagnosis. Therefore, to overcome the challenge of background noise in image processing applications, segmentation is often employed.

Image segmentation is a pixel labelling method that categorises image pixels into foreground and background regions. The foreground is usually the region which contains objects of interest while the background is often regarded as noise.To obtain high quality results of segmentation for image classification and diagnosis, user interaction is always used in practical applications [8].

In segmentation, regions of interest are extracted from an image background for tracking, object detection, and image recognition. Segmentation is a complex problem in image processing and has been widely applied in image classification and computer vision applications [9-11]. Depending on whether prior knowledge is needed for accurate segmentation, image segmentation can be classified into automatic and interactive segmentation. An interactive segmentation-based approach is usually used for natural images of different types with complex content, because its segmentation is more consistent with the subjective intentions of users [12-15].

Generally, there are several interactive segmentation algorithms including grabcut and lazy snapping algorithms. These algorithms segment an image into foreground and background using graph based segmentation. One of the advantages of a good user interactive segmentation is that it must perform accurate segmentation of an image with minimal user interaction and provides fast feedback time [16]. Graphcut is a semiautomatic segmentation algorithm that can be used to segment an image into foreground and background pixels without good initialization requirement. Graphcut algorithm uses scribbles to identify the region of interest in the foreground which separates it from the background. The region of interest in the foreground can be refined by applying more scribbles to the input image. Graph Cut uses interactive segmentation algorithms due to its robustness, global optimization and high execution efficiency [17]. It applies graph theory to image processing to attain fast segmentation results. Graph cut technique creates a graph of the image where each pixel is a node connected by weighted edges. The higher the weighting, the higher the probability that the segmented pixels are related. The algorithm cuts along weak edges for the purpose of accomplishing the segmentation of objects in the image. However, graph cut algorithm is applied only on grey scale images and the segmentation results are relatively inaccurate when the content of the input image is complicated. This segmentation technique also requires users to provide more interactive information for accurate segmentation of an image when the values of pixels in the foreground and background have close grey levels.

To overcome some of the challenges of the user interaction in graph cut, local graph cut algorithm known as grabcut algorithm was proposed [18]. The grabcut algorithm is a semiautomatic segmentation technique that is used to segment an image into foreground and background elements. Similar to graph cut technique, the grabcut segmentation technique applies graph theory to accomplish fast segmentation results in image processing.The grabcut technique only segments elements within the boundaries of the region of interest in the foreground of the segmented image.It treats all sub regions that are fully or spatially outside the region of interest mask as background and the object to be segmented must be fully contained within the region of interest surrounded by a small number of background pixels for optimal segmentation results to be achieved. The grabcut algorithm produces an output label matrix which contains pixels that should not belong to both the foreground and the background because the algorithm treats such a region as unmasked in such a scenario. The algorithm assumes that all clusters outside the region of interest belong to the background and by marking one of the clusters or sub regions as belonging to foreground or background; mask has no effect on the resulting segmentation.

In contrast, the lazy snapping algorithm clusters foreground and background pixel values using the K-means technique. The implementation of the lazy snapping algorithm however does not cluster similar pixels in the foreground or background. Therefore, to improve the performance of the algorithm, the number of pixels identified with similar values as foreground or background in the image must be reduced. The lazy snapping algorithm uses the colour information in an image instead of the grey information to improve the segmentation accuracy. The lazy snapping algorithm computes the mean colour of each region to represent the node and applies the K-means algorithm to cluster the marked sets of pixels as foreground and background [19].

As a pre-segmentation solution applied to most interactive segmentation algorithms, superpixel algorithms are applied in grabcut and lazy snapping algorithms. Superpixels group pixels into regions with similar values to reduce the complexity of further image processing. The Simple Linear Iterative Clustering (SLIC) superpixels algorithm is commonly used in grabcut and lazy snapping algorithms. The SLIC superpixels technique uses K-means clustering method to segment an image and it has several advantages over other gradient-decent-based algorithms. The algorithm allows the user to define the number of and the compactness of the resulting superpixels, which allows for a uniform time required to calculate the graph cut solution regardless of the image dimensions. The SLIC superpixels method also adheres to image boundaries in image segmentation [20].

In applying image processing in colourimetric enzymatic method for the detection of cholesterol levels, images of cholesterol samples must be taken for feature extraction. The colourimetric method is quite old but the principle is modernised and it is being used in strips on point-of-care devices for efficient and fast turnaround time of results in whole blood test for cholesterol level detection [21]. The colour intensity of the end product is directly proportional to the concentration of cholesterol and this is significant in the field of image processing because colour, texture and shape features are being used in content based image retrieval applications. The laboratory preparation of samples is as shown in Fig. 1.

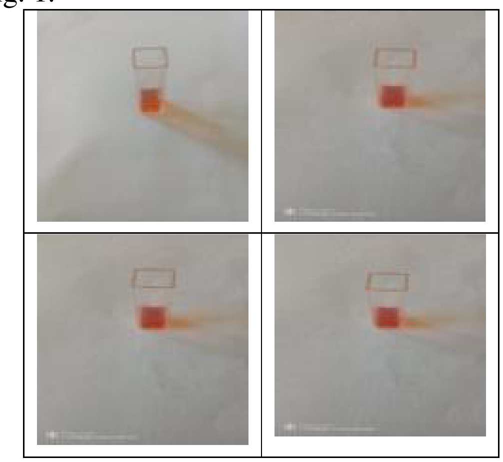


Fig. 1: Images of cholesterol samples.

To use such images in image processing, it will be useful to segment pixels of the region with the visible colour change of the sample as the foreground for appropriate feature extraction. Image segmentation can be used in applications where the background of the acquired image can limit the accuracy of classification or diagnosis. One of the challenges of using image segmentation is the task of identifying the right algorithm that will be used in a particular application. In segmenting pixels of the content with clear colour change for the detection of serum cholesterol levels, the choice of user interactive segmentation methods would be better since these algorithms are flexible. However, obtaining segmentations for accurate results in most cases cannot be achieved without generating ground truth results for comparison. User interactive segmentation algorithms produce different results when their performance is compared using segmentation metrics such as accuracy, true positive rate, true negative rate, false positive rate and so on. Therefore, a careful study of some algorithms is required before the correct choice of an algorithm can be applied.

In this paper, two graph based segmentation algorithms are applied to low image resolutions of cholesterol samples prepared by colourimetric enzymatic technique for serum cholesterol levels detection. Lazy snapping and grabcut algorithms are used to segment the pixels containing the colour intensity of the end product in the captured image as the foreground and pixels outside the region of interest are regarded as the background. The true positive rate, true negative rate and the accuracy of generating pixels in segmentation results in the two algorithms are compared.

II. QUALITY METRICS

The performance evaluation of segmentation algorithms is based on the number of pixels correctly and incorrectly predicted in the segmented image by an algorithm [22]. The following terms are used for verifying quality of a segmented image.

- True Positive (TP): pixels in the image that are correctly segmented as foreground
- False Positive (FP): pixels that are incorrectly segmented as foreground
- True Negative (TN): pixels in the image that are correctly segmented as background
- False Negative (FN): pixels that are incorrectly segmented as background

These metrics can be used for calculating sensitivity or True Positive rate (TPR), specificity or True Negative Rate (TNR) and accuracy of algorithms as shown in the following equations:

$$Sensitivity\ or\ TPR = \frac{TP}{TP + FN}$$

$$Specificity\ or\ TNR = \frac{TN}{TN + FP}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

III. MATERIALS AND METHOD

This work was implemented on a HP Elite Book laptop model running on 64-bit Windows 10 Home Edition, 500 GB ROM, 8 GB RAM, Intel ® Core™ i5 Central Processing Unit (CPU) at a frequency of 2.50 GHz and MATLAB software version 2020a. The study examined the performance of lazy snapping and grabcut graph based segmentation of cholesterol sample images. Thirty (30) different samples of cholesterol were prepared by the colourimetric method, which produces colour change in the end productof the biochemical reaction and the snapshot of each sample was captured by a techno smartphone. The images were resized to image resolutions ranging from 96 x 96 to 299 x 299 pixels.

IV. DATA PRE-PROCESSING

The input RGB images were converted to the CIELAB colour space so that the colours in the input image could be preserved in the chromaticity layers of the L*A*B* colour model prior to the application of some filtering operations. This method was implemented by using a CIE standardilluminant D65, which simulates midday light with correlated temperature of 6504 K. The input images were filtered channel by channel using median filtering method to remove impulse noise from the cholesterol sample images. Median filter was used because it reduces noise, preserves edges in an image and it is more effective than convolution. The median filtering operation applied a 3×3 neighbourhood size specified as a two-element vector of real integers and the input images were padded with zeros.

The lazy snapping and grabcut segmentation algorithms were implemented to compute superpixels of the input image using the scale factor for edge weights as 500. The superpixel method applies the SLICA algorithm, which groups pixels into regions with similar values for possible reduction in the complexity of processing operations. To balance between regularly shaped superpixels and adherence of superpixels to boundaries, the compactness parameter of the algorithm was chosen as 10. The background mask was created by using all pixels outside the ROI automaticallyand a morphological operation was implemented to perform a flood-fill on background pixels of input masked image to fill the holes in the background image. To improve the segmentation accuracy, regions of the label matrix or foreground were separated from regions of the background to prevent the lazy snapping algorithm from classifying them as background. The output image was a masked image with dark background.

V. RESULTS

Lazy snapping and grabcut segmentation algorithms were applied to the cholesterol sample images to determine the time taken by each algorithm to produce segmentation results, sensitivity, specificity or true negative rate of pixels in an image and pixel accuracy. The images of cholesterol samples were grouped into six (6) categories and down-sampled into 96 x 96, 112 x 112, 224 x 224, 227 x 227, 256 x 256 and 299 x 299 pixel resolutions. Some of the generated ground truth results are as shown in Fig. 2.

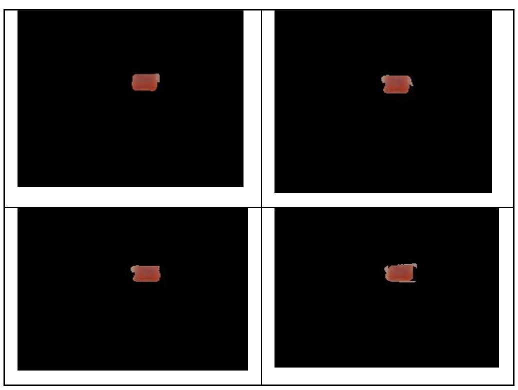


Fig. 2: Samples of ground truth images.

A MATLAB Graphical User Interface (GUI) was created and all the parameters for evaluating the performance of lazy snapping and grabcut algorithms were estimated. The GUI contains SELECT TEST IMAGE, SEGMENT IMAGE and RESET push buttons. In run time mode, the radio button corresponding to an algorithm on the GUI is selected and the SELECT TEST IMAGE button is clicked by the user to select a cholesterol sample image from the computer directory to be displayed in the first User Interface (UI) axes component of the GUI on the left hand side. When the user clicks on the SEGMENT IMAGE button, the selected image is displayed in the second UI axes component for the user to select pixels of the region with visible colour change. In each algorithm, the interactive draw rectangle tool is used to select the region with colour change as the foreground and all other pixels are set as dark background. The segmented region of interest or foreground is compared with the ground truth result displayed in the third UI axes on the GUI. The GUI was run for evaluating the performance of lazy snapping algorithm and grabcut algorithm as shown in Fig. 3 and Fig. 4 respectively.

Fig.3: GUI with results for lazy snapping method.

Fig.4: GUI with results for grabcut technique.

The average time in seconds required to produce segmentation results by the lazy snapping and grabcut algorithms are shown in Fig. 5.The bar chart in Fig. 5 was plotted using the data in Table1.

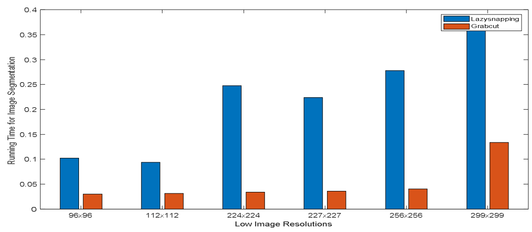
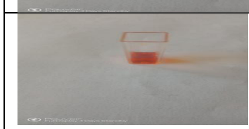


Fig.5: Average run-time for generating segmented images.

Table1: Time for generating segmentation results.

Original Image	Resolution	Lazysnapping	Grabcut
	96 X 96	0.1021	0.0299
	112 X 112	0.0941	0.0312
	224 X 224	0.2476	0.0340
	227 X 227	0.2238	0.0358
	256 X 256	0.2780	0.0405
	299 X 299	0.3730	0.1336

To compare the two segmentation techniques employed in this work, ground truth results in the various image resolutions were created in MATLAB. Then the sensitivity, specificity and pixel accuracy of lazy snapping and grabcut segmentation algorithms based on the proportion of pixels in the cholesterol images that corresponded to the ground truth pixels were calculated. The comparison was based on the average results obtained from each of the five images with image resolutions of 224 x224, 227 x 227 and 299 x 299 pixels as shown in Table 2, Table 3 and Table 4 respectively. The choice of these image resolutions was based on the input layer requirement of most pre-trained convolutional neural networks such as resnet18, squeezenet and inceptionv3 just to mention a few.

Table 2: Quality assessment on image resolutions with 224x224 pixels.

Lazysnapping Algorithm			Grabcut Algorithm		
TPR (100%)	TNR (100%)	Accuracy (100%)	TPR (100%)	TNR (100%)	Accuracy (100%)
78.29	99.44	98.91	84.84	99.30	98.94
91.70	98.58	98.41	90.56	98.74	98.53
82.44	98.85	98.44	94.68	98.95	98.84
90.18	98.63	98.42	88.57	99.38	99.11
90.90	99.43	99.21	91.75	99.44	99.24

Table 3: Quality assessment on image resolutions with 227x227 pixels.

Lazysnapping Algorithm			Grabcut Algorithm		
TPR (100%)	TNR (100%)	Accuracy (100%)	TPR (100%)	TNR (100%)	Accuracy (100%)
81.16	99.51	99.09	83.50	99.92	99.56
91.53	98.06	97.91	86.85	99.12	98.86
93.43	99.65	99.51	90.38	99.57	99.36
93.34	98.54	98.43	94.26	99.25	99.14
88.68	98.94	98.71	94.17	99.29	99.18

Table 4: Quality assessment on image resolutions with 299x299 pixels.

Lazysnapping Algorithm			Grabcut Algorithm		
TPR (100%)	TNR (100%)	Accuracy (100%)	TPR (100%)	TNR (100%)	Accuracy (100%)
82.68	99.39	98.99	74.94	99.21	98.62
87.88	99.78	99.50	89.76	99.75	99.51
94.38	99.87	99.74	93.63	99.85	99.70
71.06	99.17	98.50	71.07	99.31	98.63
84.49	99.21	98.86	82.10	99.51	99.09

The bar chart plots for the quality metrics used for evaluating the performance of lazy snapping and grabcut algorithms are presented in Fig. 6 to Fig. 8.

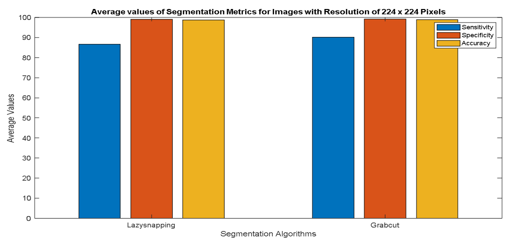


Fig. 6: Performance comparison of lazy snapping and grabcut algorithms on images with 224x224 pixels.

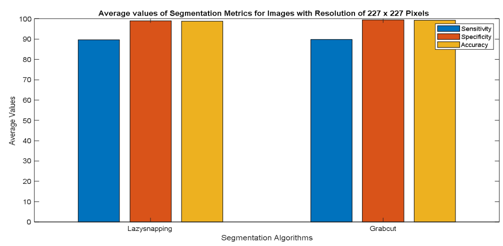


Fig. 7:Performance comparison of lazy snapping and grabcut algorithms on images with 227x227 pixels.

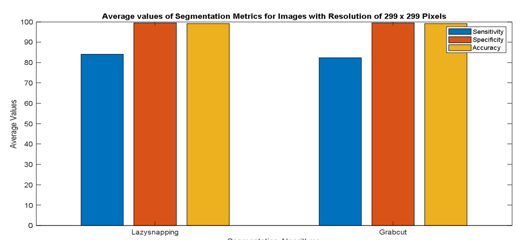


Fig. 8:Performance comparison of lazy snapping and grabcut algorithms on images with 299x299 pixels.

VI. DISCUSSION OF RESULTS

As shown in Table 1 and Fig. 5, the average time taken by the lazy snapping algorithm to produce foreground from segmentation results in any given image resolution was longer than the average time taken by the grabcut algorithm. In all the image resolutions considered, the lazy snapping algorithm achieved an average segmentation time of 1.3186 seconds, while the grabcut technique recorded segmentation time of 0.305 second with average time difference of 1.0136 second between the two algorithms. The quality metrics presented in Table 2, Table 3 and Table 4 were used to determine the performance of the two algorithms in segmenting cholesterol images. The grabcut technique outperformed the lazy snapping technique based on the average values of sensitivity, specificity and accuracy. As seen in Fig. 6, the performance of grabcut algorithm outperformed the lazy snapping algorithm by 3.38%, 0.90% and 0.25% under sensitivity, specificity and accuracy respectively. The grabcut technique was more efficient than the lazy snapping method by 0.20%, 0.49% and 0.49% in segmenting foregrounds under sensitivity, specificity and accuracy as illustrated in Fig. 7. However, the lazy snapping algorithm performed slightly better than grabcut by 1.80% under sensitivity and 0.01 % under accuracy with the grabcut having a marginal lead of 0.05% against the lazy snapping algorithm under specificity as shown in Fig. 8.

VII. CONCLUSION

Findings from this research show that the grabcut algorithm is faster and provides more accurate foreground segmentation results than the lazy snapping technique on the tested low-resolution images of serum cholesterol samples prepared by the colourimetric method. The reason for the underperformance of the lazy snapping algorithm could be that the region of the label matrix in most segmentation results contains pixels belonging to both the foreground mask and background mask, which prevents the lazy snapping algorithm from clustering similar foreground or background pixels accurately. However, there is need to undertake more studies using large cholesterol sample images and more low image resolutions to confirm that the grabcut algorithm is actually better than the lazy snapping algorithm under the quality metrics considered in this research.

REFERENCES

[1] A. Maqsood, M.S. Farid and M. H. Khan. Deep Malaria Parasite Detection in Thin Blood Smear Microscopic Images. *Applied Sciences.*11(5), 2021

[2] S. Awuhe and P. Orukpe**.** An automated system for the classification of fasting lipid profile parameters using image processing with deep learning. *International Journal of Advances in Engineering and Management*. 4(3): 960-966, 2022.

[3] S. Awuhe, I. Bawa and P. Orukpe. Image based method for the classification of serum cholesterol concentrations using deep learning with support vector machine. *International Research Journal of Engineering Technology*. 8(5): 3255-3265, 2021.

[4] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu and M.S. Lew. Deep Learning for Visual Understanding: A Review. *Neurocomputing.* 187: 27-48, 2016.

[5] H.C. Shin, H.R. Roth, M. Gao, I. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura and R.M. Summers. Deep Convolutional Neural Networks for Computer-Aided Detection. CNN Architectures, Dataset Characteristics and Transfer Learning. *IEEE Transactions on Medical Imaging.* 35: 1285-1298, 2016.

[6] V. Thambawita, I. Strumke, S.A. Hicks, P. Halvorsen, S. Parasa and M.A. Riegler. Impact of Image Resolution on Deep Learning Performance in Endoscopy Image Classification: An Experimental Study Using a Large Dataset of Endoscopic Images. *Diagnostics*. 11, 2021.

[7] H.R. Sheikh and A.C. Bovik. Image Information and Visual Quality. *IEEE Transactions on Image Processing*. 15: 430-444, 2006.

[8] V. Kwatra, A. Sch¨odl, I. Essa, G. Turk, and A. Bobick. Graphcut Textures: Image and Video Synthesis using Graph Cuts. In *ACM SIGGRAPH 2003 Papers, SIGGRAPH* 03: 277–286, New York, NY, USA, 2003.

[9] D. Popescu and L. Ichim. Intelligent Image Processing System for Detection and Segmentation of Regions of Interest in Retinal Images. Symmetry. 10: 73, 2018.

[10] S.R. Vantaram and E. Saber. Survey of contemporary Trends in Colour Image Segmentation. Journal of Electronic Imaging. 21, 2012.

[11] D. Stutz, A. Hermans and B. Leibe. Superpixels: An Evaluation of the State-of-the-Art. *Computer Vision and Pattern Recognition*. 166: 1–27, 2018.

[12] Y. Boykov, O. Veksler and R. Zabih. Fast Approximate Energy Minimization via Graph Cuts. *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 23: 1222–1239, 2001.

[13] Y. Boykov and V. Kolmogorov. An Experimental Comparison of Min-Cut and Max-Flow Algorithms for Energy Minimization in Vision. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 26: 1124–1137, 2004.

[14] Y. Boykov and G. Funka-Lea. Graph Cuts and Efficient and Image Segmentation. *International Journal of Computer Vision*. 70: 109–131, 2006.

[15] D. Chen, G. Li, Y. Sun, J. Kong, G. Jiang, H. Tang, Z. Ju, H. Yu and H. Liu. An Interactive Image Segmentation Method in Hand Gesture Recognition. ***Sensors***. 17: 253, 2017.

[16] D. Liu, Y. Xiong, L. Shapiro and K. Pulli. Robust Interactive Image Segmentation with Automatic Boundary Refinement. 225–228, 2010.

[17] Y. Boykov, O. Veksler and R. Zabih. Fast Approximate Energy Minimization via Graph Cuts. IEEE Transactions on Pattern Analysis and Machine Intelligence. 23: 1222–1239, 2001.

[18] C. Rother, V. Kolmogorov and A. Blake. Grabcut- Interactive Foreground Extraction using Iterated Graph Cuts. ACM Transactions on Graphics. 23: 309–314, 2004.

[19] Y. Li, S. Jian, C. Tang and H. Shum. Lazy Snapping In Proceedings from the 31st International Conference on Computer Graphics and Interactive Techniques, 2004.

[20] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua and S. Susstrunk. SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. IEEE Transactions on Pattern Analysis and Machine Intelligence. 34 (11): 2274-2282, 2012.

[21] L. J. Donato, G.R. Deobald, A. M. Wockenfus, J. M. Hornseth, A.K. Saenger and B.S. Karon. Comparison of Two Point of Care Devices Capillary Lipid Screening in Fasting and Postprandial Adults. Journal of Clinical Biochemistry. 48 (3): 2015.

[22] H. A. Aliyu, M .A. A. Razak and S. Sudirman. Segmentation and Detection of Sickle Cell Red Blood Image. AIP Conference Proceedings 2173. 2019.