

Enhancement and Segmentation of Mammograms for Further Analysis

¹Kayode, A. A.

Dept. of Computer Science
Osun State College of Technology,
Esa-Oke, Nigeria
kayodeaa2@gmail.com

²Odeniyi, O. A.

Dept. of Computer Science
Osun State College of Technology,
Esa-Oke, Nigeria
olufemiodeniyi@gmail.com

³Efunboade, A. O.

Dept. of Computer Science
Osun state College of Technology,
Esa-Oke, Nigeria
ayo_efun@yahoo.com

¹Corresponding Author

Abstract— Breast cancer is the most prevalent cancer and the leading terminal disease among women worldwide. At the present time, there are no effective ways to prevent breast cancer, because its cause is not yet fully known, therefore, early detection, which can be achieved by mammography, has become the only effective way to diagnose and manage breast cancer. To diagnose breast cancer, Radiologists need to examine mammograms to locate abnormalities like masses and calcifications that indicate breast cancer. These abnormalities are very tiny in size and are obscured by the fibroglandular tissue of the breast region. The fibroglandular region of the breast is being evaluated by the Radiologist in the interpretation of mammographic images. Nevertheless the interpretation is subjective and varies from one Radiologist to another.

In this paper, mammograms acquired from the Department of Radiology, Obafemi Awolowo University Teaching Hospital Complex (OAUTHC), Ile-Ife, Nigeria were enhanced and segmented to improve and make better further analysis of the images by Radiologists.

Keywords – enhancement; segmentation; region of interest; mammograms; breast cancer.

I. INTRODUCTION

Breast cancer continues to be a public health problem in the world as it is the leading cause of death resulting from cancer in women, however, early detection of breast cancer increases the treatment options and also increases the likelihood of cure. Several imaging techniques such as: magnetic resonance imaging (MRI), Mammography and Breast ultrasound scans, are being used to obtain images of the breast used in the diagnosis and treatment of breast cancer, yet Mammography is considered the "gold standard" for early detection of breast cancer [1].

Classification of mammographic images constitutes a difficult and complex cognitive task which requires advanced levels of expertise and knowledge by trained Radiologists.

Several studies ([2]; [3]; [4]; [5]) have reported that significant variability exists in the interpretation of the same mammogram when done independently by different Radiologists which leads to diagnostic errors known as false positive (FP) and false negative (FN). Going by these diagnostic errors, it is expedient to use computer algorithms in facilitating mammograms enhancement and segmentation in order to assist Radiologists in further analysis of the mammograms.

Digital mammography processing allows the separation of image acquisition, processing, analysis and classification and may therefore represent a solution to many of the inherent limitations of screen-film mammography. Through image processing, small differences in attenuation between normal and abnormal breast tissue can be amplified and region of interest can be isolated [6].

Digital mammography includes the use of computer algorithms to convert an image into digital form and perform some operations on it in order to get an enhanced image, which in turn, makes isolation of the suspicious region easier and assist Radiologists in the further analysis of the images. With the increasing number of mammographic images, implementation of computer algorithms for the enhancement of the whole image and segmentation of suspicious regions, otherwise known as regions of interest, are a key component in assisting and automating specific radiological tasks.

Image processing allows a wider range of algorithms to be applied to input data, these algorithms can correct inherent problems such as the building up of noise and signal distortion which occur during image acquisition. Image enhancement and segmentation are among rapidly growing technologies today

and both of them form a core research area within biomedical engineering and computer science disciplines [7].

II. LITERATURE REVIEW

The birth of image processing has aroused interest in their applications in various areas of medicine, one of them is the mammography. Digital image processing has become a vital tool in the health care delivery system, including mammography.

Several authors have worked on pre-processing of mammograms, only the most recent and most relevant ones are mentioned: Ref [8] presented a survey of several enhancement techniques used in mammography and the authors concluded that CLAHE works very well for biomedical images such as mammograms. Ref. [9] proposed an efficient ROI segmentation of digital mammogram images using Otsu's N thresholding method. In this work, it was argued that finding an accurate, robust and efficient ROIs help in making the classification task reliable. In the like manner, Ref [10] gave a survey on the preprocessing techniques of mammogram for the detection of breast cancer; in this paper the existing approaches used in preprocessing mammographic images were discussed. An automatic Mammographic Mass Segmentation based on Region Growing Technique, a fully automatic mass segmentation scheme which includes automatic seed region growing technique is proposed by [11]. The difference in the mean of the manual markup by an expert and the proposed segmentation obtained is 0.356, the result showed that automatic segmentation is better than manual one. Also, Ref [12] proposed segmentation of breast regions into pectoral muscle, fatty and fibroglandular regions, using a Bayesian technique with the adaptation of Markov random field for detecting regions of different tissues on mammograms.

Ref [13] in their paper classified breast density into one of four BIRADS categories according to the characteristic features of the gray level histogram. They found that the correlation between computer-estimated percent dense area and the Radiologist manual segmentation was 0.94 and 0.91 with root-mean-square (RMS) errors at 6.1% and 7.2%, respectively, for CC and MLO views. Also, breast mammogram images were divided into three regions using variance histogram analysis and discriminant analysis in [14]. Then, they classify each of the three regions into four categories, which are fatty, mammary gland diffuseness, non-uniform high density and high density, by using the ratios of each of the three regions. Ref [15] segmented the fibroglandular disc with a statistical method based on a Gaussian mixture modeling. Mixtures of up to four weighted Gaussians represent a particular density class in the breast. Gray-level statistics of the pectoral muscles were used to determine the tissue region that represents the fibro-glandular disc.

III. MAMMOGRAPHIC PATTERN OF FEMALE BREAST

The radiographic appearance, or mammographic pattern of the normal female breast differs from one individual to the other because of differences in the relative amounts of fat, connective and epithelial tissue, and different x-ray attenuation

characteristics of these tissues. Figure 1 shows the sample mammogram displaying the breast anatomy, while Figure 2 illustrates the four categories of mammographic pattern as provided by the Breast Imaging Reporting and Data Systems (BIRADS) lexicon of the American College of Radiology (ACR).

The Breast Imaging Reporting and Data System (BIRADS), which was developed by the American College of Radiology (ACR) is the recent standard in radiology for categorizing the breast density [17]. The BIRADS classified breast density into four major categories, namely: fatty; fibro-glandular; heterogeneously dense; and extremely dense respectively.

As illustrated in Figure 2, Different types of breast tissue density according to the ACR were presented by [16], ACR type 1 is fatty; ACR type 2 is fibro-glandular; ACR type 3 is heterogeneously dense; and ACR type 4 is extremely dense. Table 1 presents the interpretation of the breast density types illustrated in Figure 2, as density is increasing sensitivity is decreasing, a fatty breast is more penetrable by x- ray and other electromagnetic radiation than other type of breasts.

IV. THE NEED FOR MAMMOGRAM ENHANCEMENT AND SEGMENTATION

A. Image Enhancement: An Overview

There are lots of inherent problems with image acquisition such as scanner induced artifacts, excessive background noise, scratches and dust artifacts which can influence the reliability of images. Image enhancement is the process of adjusting digital images so that the results are more suitable for display or further image analysis. For example, you can remove noise, sharpen and brighten an image, or magnify an image, thereby making it easier to identify key features.

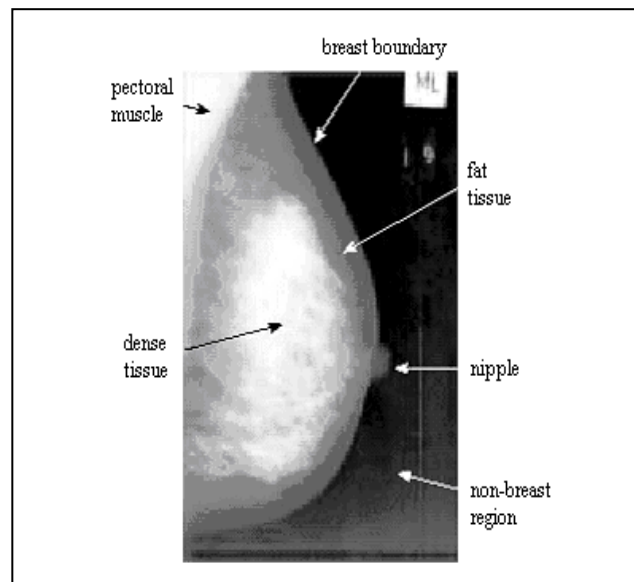


Figure 1. Female Mammographic Breast Anatomy [16].

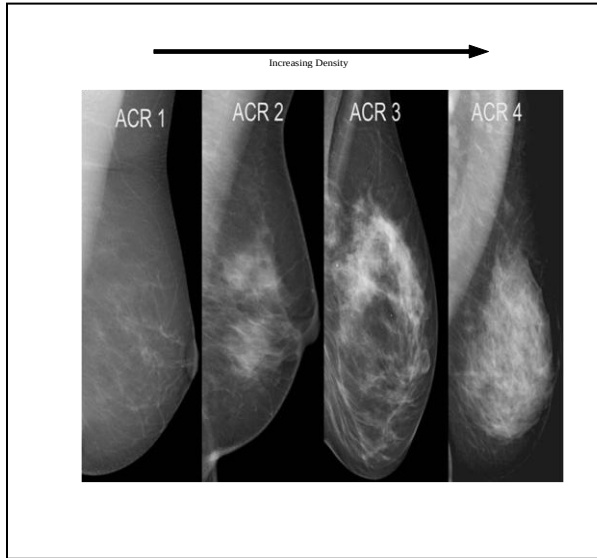


Figure 2. Different types of breast tissue density

The aim of image enhancement is to process a given image so that the result is more suitable than the original image for a specific application. It emphasizes or sharpens image features such as edges, boundaries, or contrast to make an image more suitable for display and analysis.

Mammogram enhancement is the process of manipulating mammogram to increase their contrast, decrease the noise present and magnify them in order to aid Radiologists in the detection of abnormalities. Mammogram enhancement can improve Radiologists' perception of subtle abnormalities and thus helps to make a more accurate diagnosis [18].

Mammograms are medical images whose interpretation require a high level of expertise, thus an enhancement phase is needed in order to improve the image quality and make the segmentation results more accurate. According to [19], the main objective of this process is to improve the quality of the image to make it ready for further processing. When enhancing mammograms, the inherent information content of the images is not amplified, but the obscured features present is clearer and the abnormalities are detected easily. Another purpose of mammogram enhancement is to improve the reliability and robustness of the mammogram segmentation.

TABLE I. BI-RADS INTERPRETATION FOR BREAST DENSITY TYPE

Density type	BI-RADS interpretation
1.	The breast is almost entirely fatty
2.	There are scattered fibroglandular densities that could obscure a lesion on mammography.
3.	The breast is heterogeneously dense. This may lower the sensitivity of mammography.
4.	The breast tissue is extremely dense, which lowers the sensitivity of mammography.

Source: ACR, 2003

Image enhancement is an important issue in low-level image processing. The underlying principle of mammogram enhancement is to enlarge the intensity difference between objects and background and to produce reliable representations of breast tissue structures.

B. Segmentation of Mammogram

Segmentation of mammogram comes after enhancement, while enhancement makes the suspicious regions present in mammograms to be magnified, become clearer and easily detected, segmentation allows the isolation of those regions. It was claimed in [20] that there is no exact border in biomedical images; so, it is expedient to segment the whole image into regions of interest (ROIs) by implementing a segmentation algorithm which uses discontinuity and similarity properties of the regions.

Image segmentation divides the input image into multiple segments or regions, which show objects (that is the meaningful parts) of the image. It segments the image into homogeneous regions, thereby making it easier to analyze the regions separately. Segmentation algorithms are usually based on one of the two properties of intensity value which are: discontinuity (the abrupt change in images, such as edges) and similarity (the partition of images into regions according to some similarity criteria).

Some kinds of segmentation technique will be found in any application involving analysis, the detection, recognition, and classification of objects in images. The role of segmentation is crucial in most tasks requiring image analysis. The success or failure of further analysis tasks depends on the success or failure of segmentation.

C. Mathematical Definition of Mammogram Segmentation

Let M be the entire mammogram

Then $\{M_i\}$ is the entire segmentation of mammogram M if:

- $M = \bigcup_{i=1}^n M_i$, this means that the union of all

regions covers entire mammogram M , that is,

All pixels in the mammogram must be assigned to regions.

- $M_i \cap M_j = \emptyset$, for all i and j , $i \neq j$, this means,

no region in the mammogram must overlap with others, that is, every pixel must belong to a single region only.

- $P(M_i) = \text{true}$ for $i = 1, 2, \dots, n$, P is the logical uniformity predicate defined over the points in set M_i , that is, every region of the mammogram must be uniform.
- $P(M_i \cup M_j) = \text{false}$, for, $i \neq j$ and M_i and M_j are neighbouring regions in the mammogram, that is, any combined pair of adjacent regions must be non-uniform
- M_i is a connected region for $i = 1, 2, \dots, n$, that is, every region of the mammogram must be a connected set of pixels.

V. MATERIALS AND METHODS

The mammographic images obtained from the Department of Radiology, OAUTH, Ile-Ife, Nigeria, used in this study were acquired from patients treated at the Hospital in collaboration with Faculty of Health Sciences, Obafemi Awolowo University, Ile-Ife. Most mammograms in OAUTH, Ile-Ife are obtained using screen-film technique which must be digitized for processing and analysis purposes. Digital mammography allows the separation of image acquisition, processing, and display and may therefore represent a solution to many of the inherent limitations of screen-film mammography.

The screen-film mammograms were converted into digital format using an HP 200 flatbed digital scanner with its resolution held at 1600 dpi and stored on an HP laptop of Intel Core 2 Duo Processing power of 2.4 GHz CPU with 4 GB RAM. All images were held at 8-bit gray level scale images with 256 different gray levels (0-255) and physically in portable gray map (pgm) format. The patients' information (names, x-ray identification, etc.) is cropped out to ensure confidentiality.

The mammograms were enhanced by implementing both edge detection and contrast limited adjustment histogram equalization (CLAHE) algorithms while segmentation was done by implementing Otsu threshold algorithm. The image loading, enhancement and segmentation models were implemented using MATLAB 2013a which has the ability to read in a wide variety of both common and domain-specific image formats and a very large (and growing) database of built-in algorithms for image processing and computer vision applications. MATLAB R2013a has numerous image processing and statistics toolboxes. It is a technical computing language used mostly for high performance numerical calculations and visualization [21].

MATLAB incorporates computing, programming, signal and image processing in an easy to use environment in which problems and solutions can be expressed using mathematical notation [22]

VI. EXPERIMENTAL RESULT

The image acquisition interface, where digitized mammograms are loaded for display is as represented by Figure 3. The user is prompted to choose the mammogram that will be enhanced and segmented. Figure 4 shows the selected image where the user is prompted to enhance the image. Figure 5 is a snapshot of the result of the enhancement algorithms used on the chosen mammogram while Figure 6 is a snapshot of the segmented region. In addition, during the testing of the system, the Expert Radiologist suggested that it will be worthwhile if the user can carve out the segmented region for further manipulation like magnification, printing, saving and so on, this was modeled and included and the result is represented in Figure 7.

VII. DISCUSSION AND CONCLUSION

The system has been evaluated positively by a Radiologist who is an expert in reading x-ray of the breast. Same expert, along with his apprentice Radiologists, evaluated the system's functionality. The system was tested by an expert Radiologist who ascertained that the algorithm implemented for the enhancement of mammograms sharpens the image and magnified the key features on mammograms; it was established that the algorithm implemented for the enhancement of these mammograms has really modeled the task of magnifying glass being used by Radiologist when trying to isolate key features.

It is concluded that the system is worthwhile in assisting Radiologists to locate and isolate suspicious regions on digital mammograms.

VIII. SUGGESTION FOR FURTHER STUDY

The system enhanced and segmented local (internal dataset) mammographic images obtained from OAUTH, Ile-Ife, Nigeria as the input to the model developed in this work, further research can be geared towards the use of external database of mammograms available on the Internet. These mammograms can be downloaded, enhanced and segmented and the result obtained can be compared with the one obtained in this study. Also further Radiological tasks like classification of mammograms can be automated by future research.

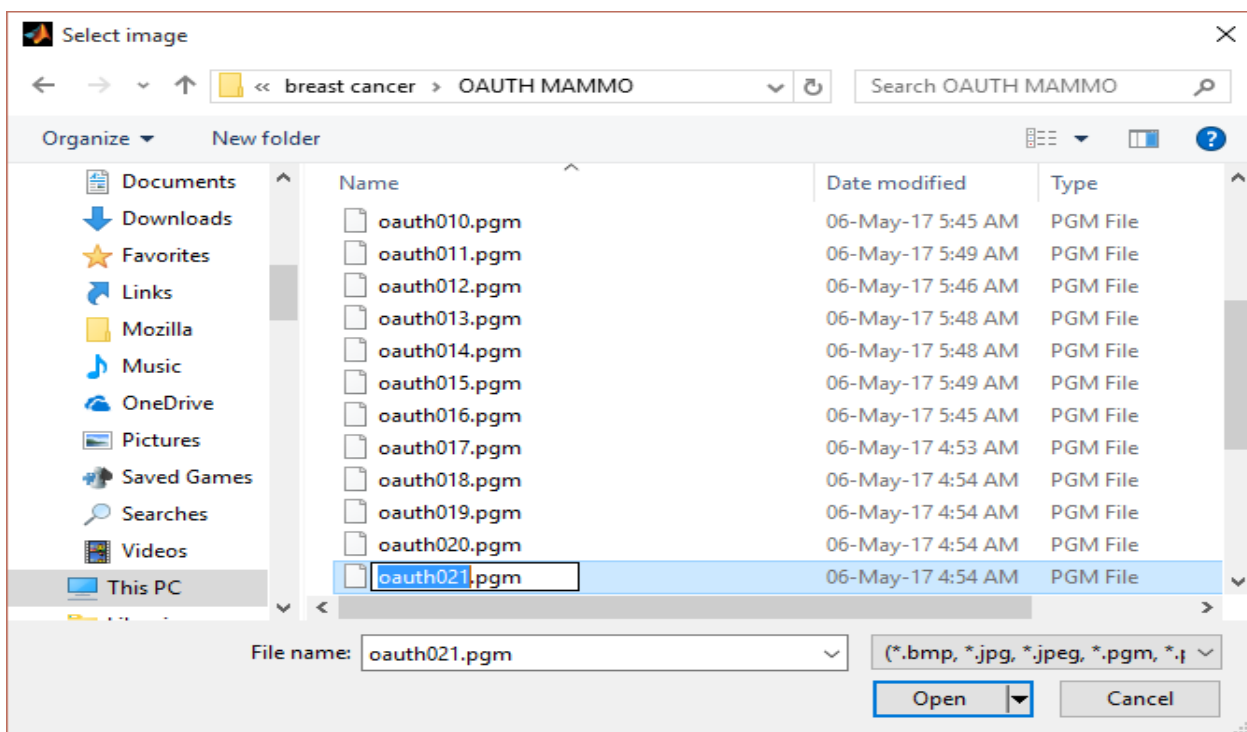


Figure 3. Mammogram Acquisition Interface

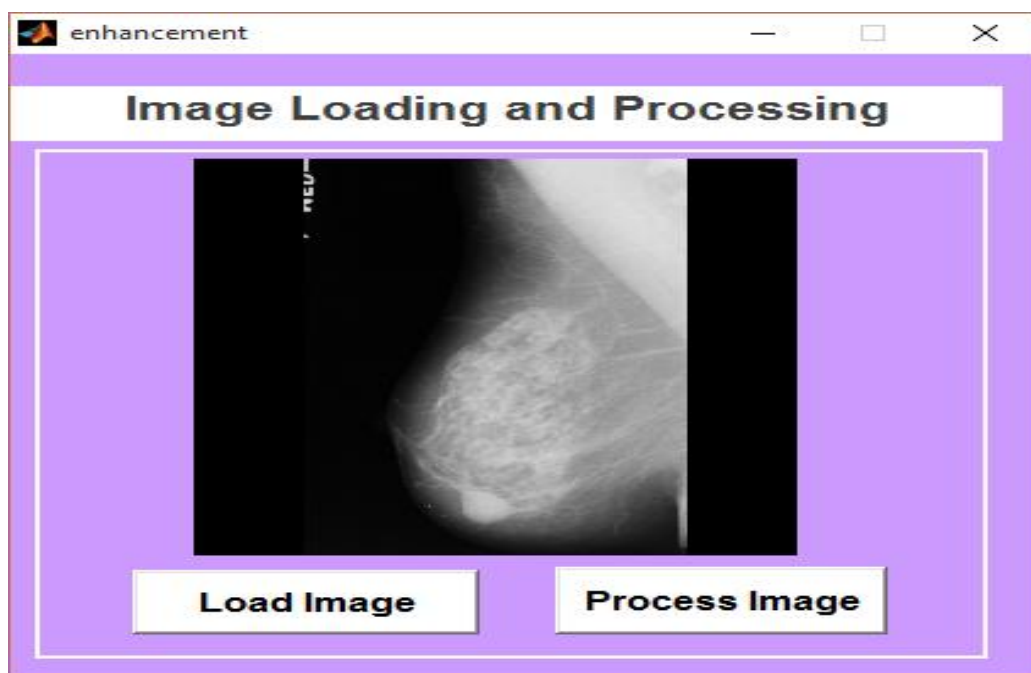


Figure 4. Image Loaded for enhancement

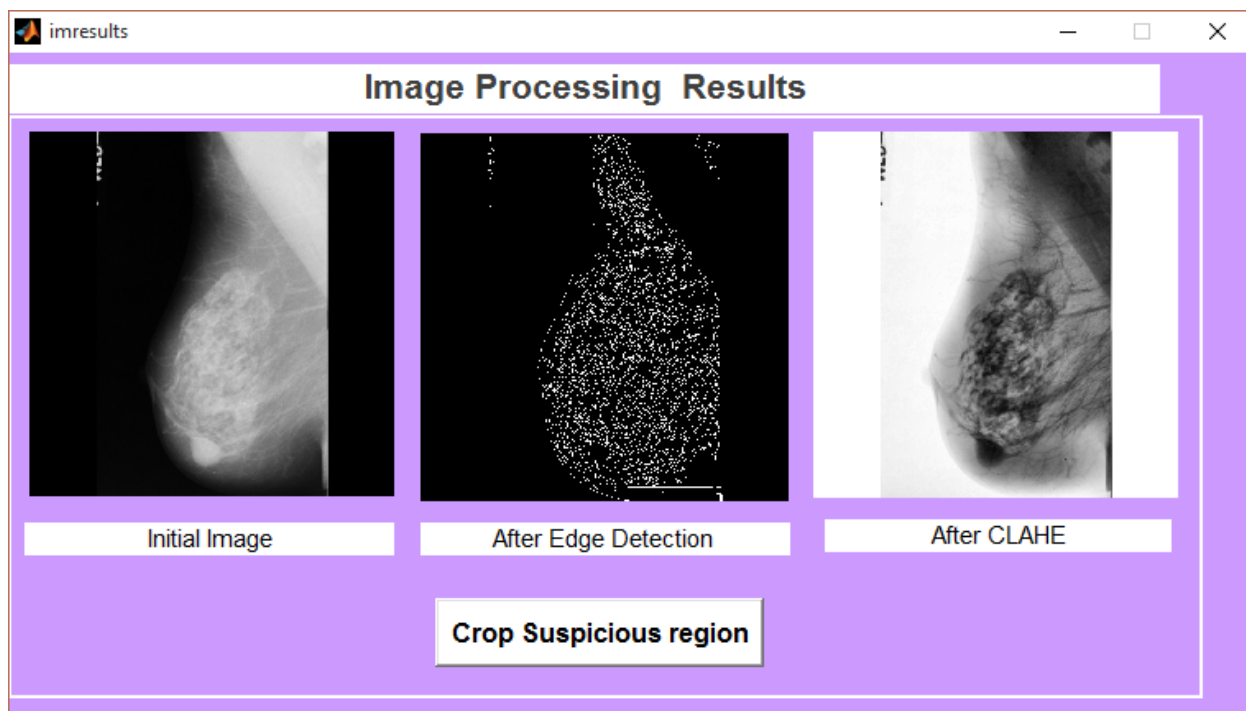


Figure 5. Result of Enhancement algorithms on Mammogram

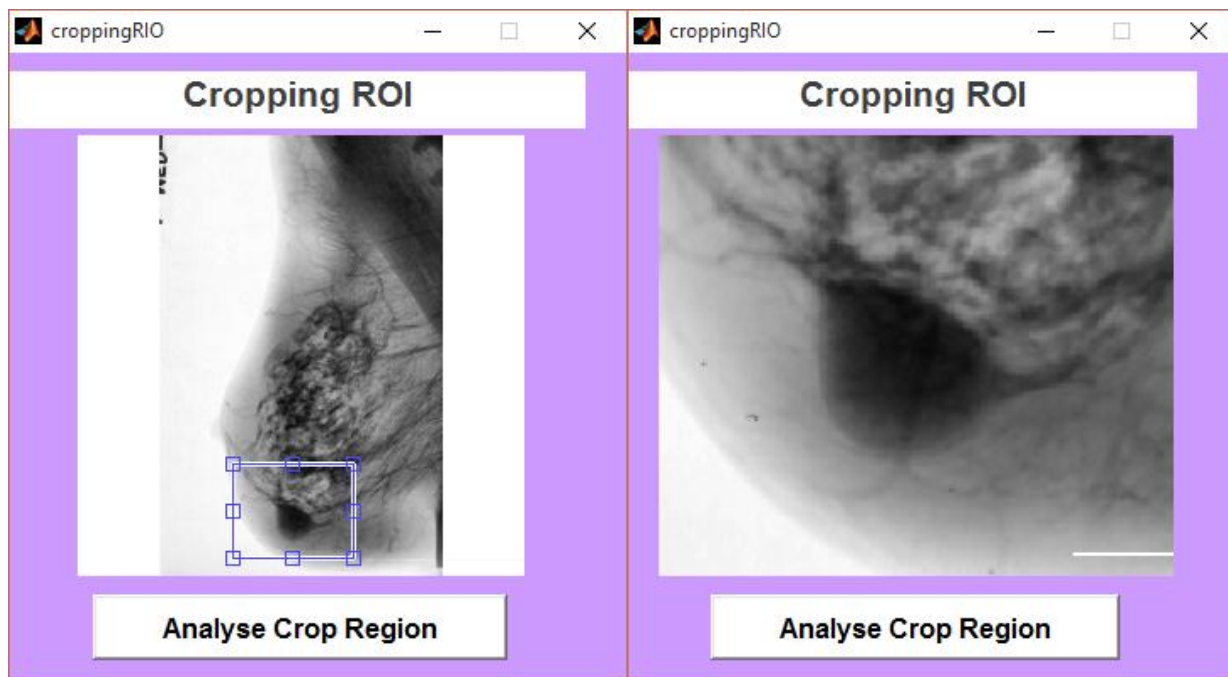


Figure 6. Segmentation of the ROI

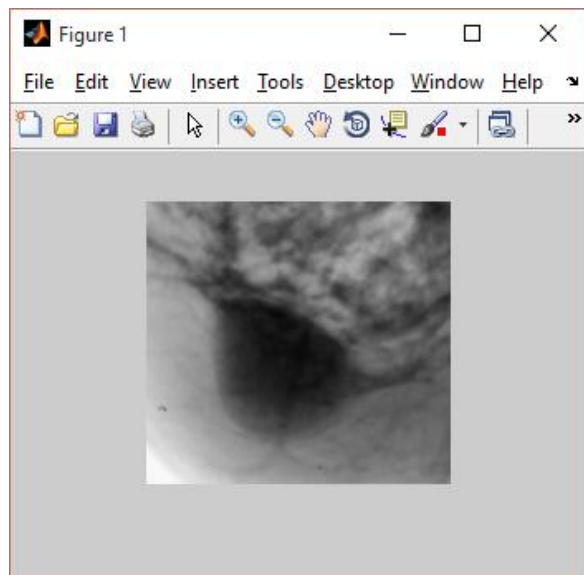


Figure 7. Segmented ROI

IX. ACKNOWLEDGEMENT

The authors wish to thank the Ethics and Research Committee of Obafemi Awolowo University Teaching Hospital, Ile-Ife, Nigeria, for allowing us to make use of her patients' mammograms. We thank all the members of staff of the Department of Radiology of the same teaching Hospital, especially, Dr. Bolanle O. Ibitoye, a Consultant Radiologist in the Department for giving us the necessary support during the acquisition of the mammograms used in this study and during the testing of the system.

REFERENCES

- [1] Andreea, G. I., Pegza, R., Lascu, L., Bondari, S., Zoia Stoica, Z. And Bondari, A. (2011). The Role of Imaging Techniques in Diagnosis of Breast Cancer. *Journal of Current Health Sciences*, 37(2):241-248.
- [2] Azar, A. T. (2014). Statistical Analysis for Radiologists' Interpretations Variability in Mammograms. *International Journal of Systems Biology and Biomedical Technologies*, 1(4):28-46.
- [3] Duijm, L. E., Louwman, M. W., Groenewoud, J. H., Poll-Franse, L. V., Fracheboud, J., and Coebergh, J. W. (2009) Inter-observer variability in mammography screening and effect of type and number of readers on screening outcome. *British Journal of Cancer* **100**(6): 901-907.
- [4] Ooms, E. A., Zonderland, H. M., Eijkemans, M. J., Kriege, M., Delavary, B. M., Burger, C. W. and Ansink, A. C. (2007). Mammography: Interobserver variability in breast density assessment. *The Breast*, 16(6):568-576
- [5] Elmore, J. G., Miglioretti, D. L., Reisch, L. M., Barton, M. B., Kreuter, W., Christiansen, C. L., and Fletcher, S. W. (2002). Screening Mammograms by Community Radiologists: Variability in False-Positive Rates. *Journal of the National Cancer Institute*, 94(18):1373-1380.
- [6] Cherie M. Kuzmiak (2012). Digital Mammography, Imaging of the Breast - Technical Aspects and Clinical Implication. In Tabar, L. (Ed.), ISBN: 978-953-51-0284-7, InTech, Available at: <http://www.intechopen.com/books/imaging-of-the-breast-technical-aspects-and-clinical-implication/digitalmammography-chapter>. Visited: March 14, 2017.
- [7] Maitra, I. K., Nag, S. and Bandyopadhyay, S. B. (2012). A Novel Edge Detection Algorithm for Digital Mammogram. *International Journal of Information and Communication Technology Research*, 2(2): 207-215.
- [8] Kayode, A. A., Babajide, B. S. and Ibitoye, B. O. (2015). An Explorative Survey of Image Enhancement Techniques Used in Mammography. *International Journal of Computer Science Issues*, 12(1):72-79
- [9] Deepa, S. and Bharathi, V. S. (2013). Efficient ROI segmentation of Digital Mammogram images using Otsu's N thresholding method. *Indian Journal of Automation and Artificial Intelligence*, 1(2): 51-56.
- [10] Ponraj, D. N., Jenifer, M. E., Poongodi, P. and Manoharan, J. S. (2011). A Survey on the Preprocessing Techniques of Mammogram for the Detection of Breast Cancer. *Journal of Emerging Trends in Computing and Information Sciences* 2(12): 656-664
- [11] Yuvaraj, K. and Ragupathy, U.S. (2013). Automatic Mammographic Mass Segmentation based on Region Growing Technique. 3rd International Conference on Electronics, Biomedical Engineering and its Applications (ICEBEA'2013) Singapore, pp 169-173.
- [12] Adel, M., Rasigni, M., Bourennane, S. and Juhan, V. (2007). Statistical segmentation of regions of interest on a mammographic image. *EURASIP Journal on Advances in Signal Processing*, Article ID 49482, 2007, pp. 1-8. [11] Yuvaraj and Ragupathy (2013).
- [13] Zhou, C., Chan, H. P., Petrick, N., Helvie, M. A., Goodsitt, M. M., Sahiner, B. and Hadjiiski, L. M. (2001). Computerized image analysis: estimation of breast density on mammograms. *Medical Physics*, 28(6): 1056-1069.
- [14] Matsubara, T., Yamazaki, D., Kato, M., Hara, T., Fujita, H., Iwase, T. and Endo, T. (2001). An automated classification scheme for mammograms based on amount and distribution of fibroglandular breast tissue density. *International Congress, series* 1230.
- [15] Ferrari, R. J., Rangayyan, R. M., Borges, R. A. and Frere, A. F. (2004) Segmentation of the fibro-glandular disc in mammograms via Gaussian mixture modeling. *Med. Biol. Eng. Comput.*, 42:378-387.
- [16] Obenauer, S., Hermann, K. P. and Grabbe E. (2005). Applications and literature review of the BI-RADS classification. *Eur Radiol*; 15:1027-1036.
- [17] American College of Radiology (2003). *ACR BI-RADS: Mammography, Ultrasound and Magnetic Resonance Imaging*, 4th ed. ACR, Reston, VA.
- [18] Rangayyan, R., Ayres, F., and Desautels, J. (2007). A review of computer aided diagnosis of breast cancer: Towards the detection of subtle signs. *Journal of Franklin Institute*.344: 312-348.
- [19] Bandyopadhyay, S. K. (2010). Pre-processing of Mammogram Images. *International Journal of Engineering Science and Technology*, 2(11): 6753-6758.
- [20] Dougherty, G. (2010). Image analysis in medical imaging: recent advances in selected examples. *Biomedical Imaging and Intervention Journal*. 6(3):e32.
- [21] Nasiruzzaman, A. B. M. (2010). Using MATLAB to Develop Standalone Graphical User Interface (GUI) Software Packages for Educational Purposes, *Matlab - Modelling, Programming and Simulations*, Emilson Pereira Leite, E. P. (Ed.), ISBN: 978-953-307-125-1, InTech.
- [22] MathWorks, Inc. (2013a). *MATLAB® Creating Graphical User Interfaces*, The MathWorks, Inc, Natick, MA 01760-2098, USA.

AUTHORS PROFILE

Aderonke A. Kayode has Ph. D. degree in Computer Science. She is presently the Head, Department of Computer Science, Osun State College of Technology, Esa-Oke, Nigeria. Dr. Kayode is a member of Computer Professional Registration Council of Nigeria (MCPN), Member, Nigeria Computer Society (MNCS) and Member, Association for Computing Machinery (MACM). Her research areas include Information storage and retrieval, Health Informatics and Artificial Intelligence.

Olufemi A. Odeniyi received both B. Tech. and M. Tech. in Computer Science from Ladoko Akintola University of Technology (LAUTECH), Ogbomoso, Nigeria, he is currently a Ph. D. student in the same

University. He is presently a Senior Lecturer in the Department of Computer Science, Osun State College of Technology, Esa-Oke, Nigeria. Mr. Odeniyi is a member of the following professional bodies: Computer Professional Registration Council of Nigeria (CPN), Nigeria Computer Society (MNCS), IEEE/CS and Association for Computing Machinery (ACM). His research areas include Artificial Intelligence, Database Systems, ICT among others.

Ayodeji O. Efunboade, is an Assistant Lecturer in the Department of Computer Science, Osun State College of Technology, Esa-Oke, Osun State. He holds a B.Sc degree in Computer Science from Joseph Ayo Babalola University, Ikeji-Arakeji, Nigeria. He is an Oracle Certified Database Expert, Microsoft Certified Professional and Comptia A+ certified professional. He is a member of Association of Computing Machinery. His research interest includes soft computing, biometrics among others.