

ANALYSIS OF BENIGN AND MALIGNANT BREAST TUMOR USING IMAGE PROCESSING TECHNIQUES

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Abstract: Breast cancer is the most common cause of death in women. Early detection of this disease and diagnosis can cut the passing of women. Segmentation is an imperative technique in digital image analysis science. The aim of this work is focused on image analysis of breast tumors using image processing. The infected area of breast tumor identified by applying edge detection, filling gaps, dilating gaps, removing the border, smoothing objects have been used. This method appears more familiar to radiologists to check the abnormality of benign and malignant breast tumors. The analysis shows that both benign and malignant tumors have well-detected to find the tumors at the first stages.

Key words: Breast tumor, segmentation, detection, MIAS, benign, malignant.

INTRODUCTION

Breast cancer is a type of vulnerable disease. The cell in the breast can easily damage and invade other parts of the body. There are different types of breast tumors. Infiltrating ductal carcinoma cancer is found in the milk ducts of the breast. The second type is ductal carcinoma *in situ* in its early stage. The third type is infiltrating lobular carcinoma, found in the region where breast milk is produced, but it can distribute to other parts of the breast. The other type is lobular carcinoma is found only on lobules of the breast [10].

According to Siegel *et al.* [21, 22], breast abrasion is one of the significant problems in the world. Detecting the breast tumors helps to improve the prognosis of cancer and other health problem related to the breast shown in [13, 21, 22]. Treatment and prognosis are essential in clinical practice in the era of precision medicine [14, 26].

The tumor size, shape, and intensity give an inclusive tumor characterization, defining what has been called the radiomics signature of the tumor [8]. Different scholar reports [5, 14, 17, 20, 25, 28] show the most common challenges in patient sides are lack of awareness of the signs and symptoms of cancer, travel, diagnosis, and treatment costs.

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Recent studies [16] show that breast lumps appear in the breast region with different shapes and sizes. Breast cancer is a malignant tumor found in the cells of the tissue [13, 16]. A malignant tumor is a bunch of cancer cells that can invade and spread to nearby tissues [18].

Benign breast masses are non-cancerous and not violent, but they can nurture and invade the nearby tissues that force other problems [18]. The benign tumor is not cancer but can rise upsurge the risk of developing breast cancer. The study done by Rosenberg *et al.* [18] shows that benign tumors have three clusters, according to whether they have no menace, a slight upsurge, and a moderate increase in risk.

Moreover, the shortage of well-trained oncologists, specialized cancer nurses, and medical physicists have added tailbacks of fighting cancer in developing countries like Ethiopia [6, 15, 20]. Therefore, this study aims to analyze the image of cancer from the mini MAIS database [23] using MATLAB software to detect and segment the tumor.

MATERIALS AND METHODS

The mini-MIAS (mini-mammographic) is a reduced version of the Mammography Image Analysis Society (MIAS) database with a resolution of 200 microns by a pixel and clipped/padded so that every image size is equal to 1024×1024 pixels [23]. We randomly selected a representative dataset that included diverse classes of abnormalities: calcifications, well-defined/circumscribed masses, spiculated masses, ill-defined masses, architectural distortions, and asymmetries [23].

The database has a character of background tissues represent by F stands for fatty, G stands for fatty glandular, D stands for dense glandular. The class of abnormality of the breast tumor is shown in Table 1.

Table 1

Class of abnormality of breast tumors [23]

Class	Abnormality
CALC	Calcification
CIRC	Well-defined or circumscribed densities
SPIC	Speculated densities
ARCH	Architectural distortion
ASYM	Asymmetry
NORM	Normal

This work aims at CIRC, MISC, and ARCH abnormality breast tumors shown in Table 2 and selected only three malignant and three benign mammographic images [23]. Therefore, we apply MATLAB codes to the analysis of these images [24].

Image enhancement is the process of upsurge its view to be more suitable for an analysis of the image [24]. The method is vital to produce quality output. The techniques can enhance a digital image without change the nature of the input image. There are two types of image enhancement methods; spatial and frequency domain-based methods [27]. The media filter techniques help to call the function in MATLAB to improve the quality of the image. This technique helps to explain the enhancements of input images at each point and local operations. The operations depend on the region of interest input pixel values [3, 4, 13].

Image segmentation is another technique used for extracting the image. The aim is to make the input images easy to analyze and interpret [3, 4]. The borders assessment is within the input images, and the pixels are according to their intensity and characteristics.

Edge detection is a segmentation technique to assess the border of the image strictly associated with the pixels of the regions [29]. It helps to find the discontinuity of the border images. Identification of the input image is to analyze the border where a massive variation in intensity arises [19, 29].

Morphology is an operation in image processing to analyze the shape in the image [3, 4, 16, 29]. The basic processes are dilation and erosion [3, 4, 16]. Dilation enhances pixels to the boundaries in the image, while erosion removes pixels from the image boundaries [2, 3, 4, 16]. The pixels added or removed from the images depend on the size and shape of the input image. Dilation and erosion processes are given pixel to the output image by applying the rule to the input image. The operation is applicable to evaluate the pixels and by defining the operation as dilation or erosion.

A histogram of an image describes the image. It represents the occurrence of various gray levels on frequencies.

RESULTS AND DISCUSSION

RESULTS

The research and technology in medical science change because of the fast-shifting field with technology. Nowadays, treatment for detection and cure of cancer at the infant stage. Nowadays, breast cancer detection technologies have the potential to enhance the detection processes.

Input images were taken from the mini MIAS mammogram database [23]. The first three images are from the benign group, and the other three are from the malignant ones. The nature and the characteristics of the input images are shown in Table 2 and have a different class of abnormality. The background issues of the breast contain fatty (F), fatty-glandular (G), and dense-glandular (D) are shown in Table 2. The size of the input images of the breasts is 1024×1024 gray levels, in 10 bits [23].

Table 2

Characteristics of benign (B) and malignant (M) mammographic image [23]

Database reference	Background issue	Class of abnormality	Severity of abnormality
Mdb001	G	CIRC	B
Mdb030	G	MISC	B
Mdb080	F	CIRC	B
Mdb072	G	ASYM	M
Mdb075	F	ASYM	M
Mdb105	D	ASYM	M

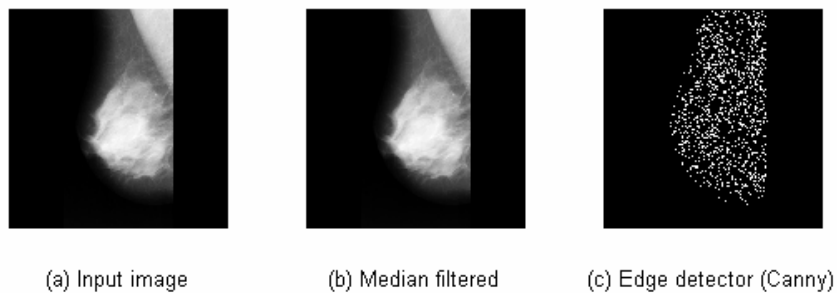


Fig. 1. a) Input image of benign and a class of abnormality CIRC breast cancer (mdb001) [23], b) median filtered, and c) edge detection of the tumor.

The right breast image shown in Figure 1 was benign, fatty-glandular, and the class of abnormality is well-defined or circumscribed masses. The median filtered technique is applied in this work and is shown in Figure 1(b). The median filter process is applied to carry out by sliding a window over the image by removing the unwanted part from the original image. The edge of the image is applied using the Canny gradient [3, 4, 29] shown in Figure 1(c).

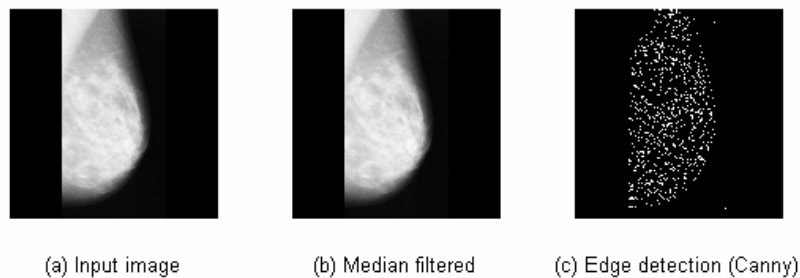


Fig. 2. Left image of breast cancer a class of abnormality MISC pre-processing a) input image (mdb030) [23], b) median filtered, and c) edge detection of benign tumor.

Figure 2 shows the second left breast benign image in Figure 2(a); Figure 2(b) is the median filtered image of the input, and the last Figure 2(c) is the edge detection using the Canny method. The principle of the median filter is applied to obtain the gray level of each level pixel. The output image is shown in Figure 2(b) by median filters and replaces each value with the median value of neighbored pixels. Figure 2(c) is the detected image obtained by applying the Canny edge method using a morphological operation.

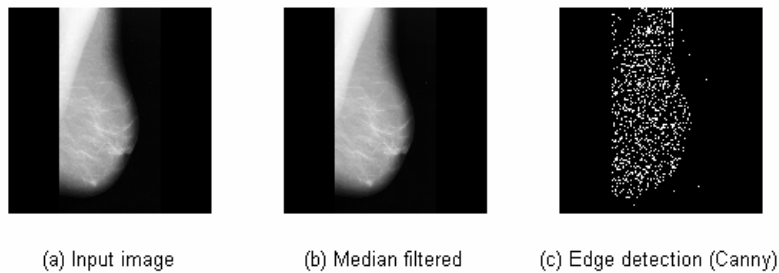


Fig. 3. a) Input image (mdb080) and a class of abnormality CIRC [23], median filtered (b), and c) edge detection of benign tumor.

Figure 3 shows left benign input image, median filter, and edge detection. The median filtering is shown in Figure 3(b), and edge detection in Figure 3(c). Edge finds the structural information of the image. The nature of all input images shown in Figures 1(a), 2(a), and 3(a) have the same characteristics, but they have different natures of abnormality, as shown in Figure 4. The contrast limited adaptive equalization of input images shown in Figure 4(b) is more exposed than the other two input images shown in Figure 4(a) and 4(c). The contrast enhancement is an extensive technique for the image which uses for improving the image quality for human perception and recognition [11]. It can enhance the detail part of regions of interest of the images.

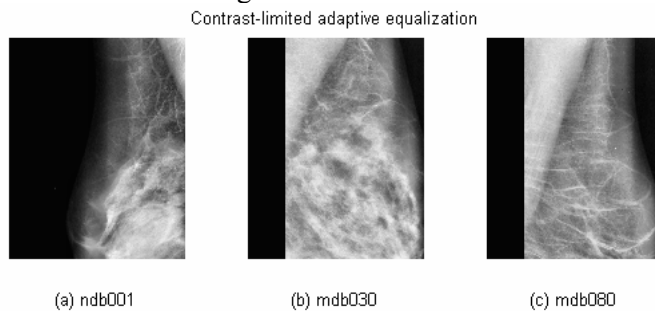


Fig. 4. Contrast-limited adaptive equalization of benign breast tumors of mdb001, mdb030, and mdb080 [23].



Fig. 5. Breast tumor detection for benign breast whose class of abnormality CIRC; a) input image (mdb001) [23], b) segmented image, and c) detected breast tumor.



Fig. 6. Breast tumor detection from benign tumor whose class of abnormality MISC; a) input image (mdb030) [23], b) segmented image, and c) detected breast tumor.

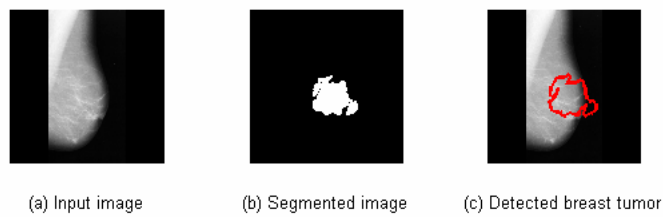


Fig. 7. Breast tumor detection from benign tumor whose class of abnormality CIRC; a) input image (mdb080) [23], b) segmented image, and c) detected breast tumor.

The efficiency of breast cancer diagnosis depends on the accuracy of the segmentation and its classification. The segmentation techniques help to split the image into different regions of the breast tumors. The differentiation was conducted on the segmented image by a hole-filling operation. Figures 5– show the input image and detection after median filter applied, shown in red-circled. Figures 5–7(a) are input images, denoted by mdb001, mdb030, and mdb080 [23]. Figures 5–7(b) shows the output images where the borders are removed by extracting the region of interest. Figures 5–7(c) represent the tumor-detected part of the breast.

The breast tumor segmented image shown in Figure 6(b) has a large area portion compare to the above two Figures 5(b) and 7(c). White spots shown in

figures 5–7(b) are the results of the threshold segmentation. The results are shown in Figures 5–7(c), encircled by red color the regions of the tumor.

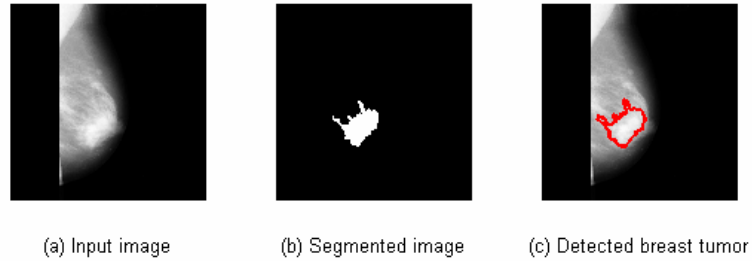


Fig. 8. Malignant breast tumor whose class of abnormality ASYM; (a) input image (mdb072) [23], b) segmented image, and c) detected image as breast tumor.



Fig. 9. Malignant breast tumor whose class of abnormality ASYM; (a) input image (mdb075) [23], b) segmented image, and c) detected breast tumor.

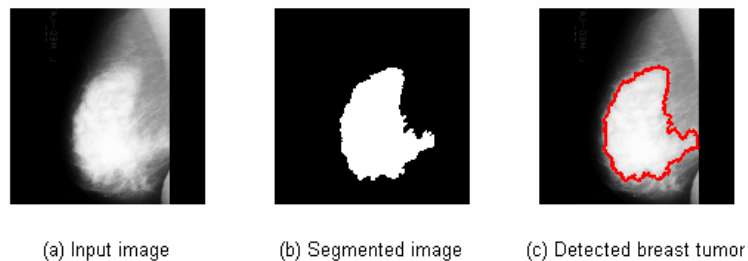


Fig. 10. Malignant breast tumor whose class of abnormality ASYM; (a) input image (mdb105) [23], b) segmented image, and c) detected breast tumor.

The possible outcomes of malignant tumors are shown in Figures 8–10. They illustrate three breast tumor images from the MIAS database for the malignant severity of the abnormality [23]. The left part of Figures 8(a), 9(a), and 10(a) show the input images. The images after reducing the noise using filter techniques and

segmentation are shown in Figures 8–10(b). Enhancing the image is applied to increase image contrast, as shown in Figures 8–10(c). The red marked points show the region where the tumor was detected. In general, the results shown in Figures 8–10(b) that segmented breast cancer for malignant tumors was the area of interest for this study.

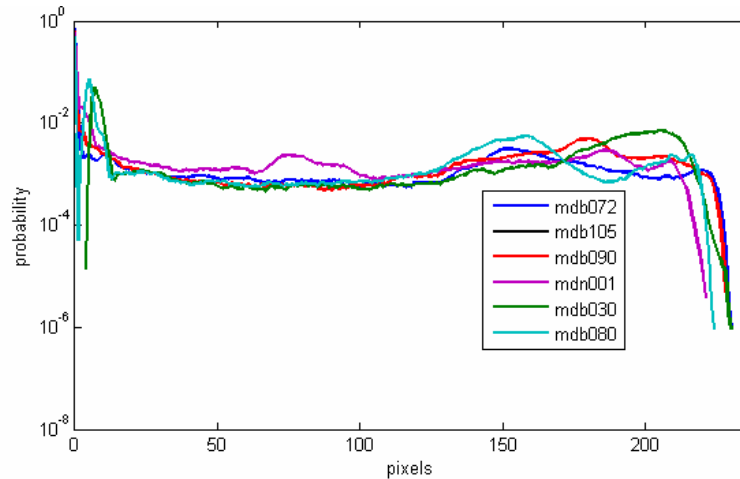


Fig. 11. Probabilistic distribution of malignant and benign breast tumors [23].

Probability distribution of selected breast abnormality from mini IMAS database as depicted in Figure 11. The maximum probability of irregularity is found near 15 pixels in mdb080 mammography. Furthermore, mdb080 and mdb105 mammography show a peak probability of around 210 pixels. Approximately at the lower grayscale values between 50 and 100 pixels, they all have an equal chance, except mbd001 mammography [23].

DISCUSSION

In this study, segmentation techniques and the Canny edge detection are applied to extract breast cancer from tumor cells images. Furthermore, Figures 8–10(b) show the size of cells exposed to cancer with the clear border of the masses, as found using edge detection.

The results show in Figures 8–10(b) of malignant tumors, compared to [16, 21], are highly dependent on the grayscale. Extraction of any clot from the input image, the regions in segmented output images shown in Figures 5–10(b) have homogenous properties with textures and gray level or color. The segmentation techniques improve the quality of the output image shown in Figures 5–10(b), as it was suggested by [3, 4].

Tumor size is one of the most influential predictors of tumor behavior in breast cancer [7, 12]. The detected tumor masses which appear in Figures 5(c), 6(c), and 7(c) are as a lump in the breast region with different shapes and sizes. The size of output images shown in Figure 6(c) is larger than the other two figures shown in 5(c) and 7(c). The benign tumor is non-cancerous and not aggressive, but it can grow and invade the surrounding tissues for complications [11]. Increasing tumor size has been reported by [9, 17] to be related as influential prognostic factors in breast cancer. Therefore, the result is shown in Figure 6(c) might be at the stage of cancer symptoms [12].

CONCLUSIONS

Breast cancer is one of the leading killers of women in the world. In the diagnosis processes, due to the nature of abnormalities, there are misinterpretations of the results. In this work, we found benign and malignant tumors using image processing algorithm codes by MATLAB. Computer-aided detection diagnoses are very useful nowadays. Image enhancement techniques have been applied to improve the visual quality of the image form suited for the analysis. The system automatically segments the image and distinguishes the tumor regions from other regions. Here, an extended method of edge detection was applied based on the Canny edge method for the final segmentation of the images. Radiologists can effortlessly detect the diseases which cause by the growth of cells or design a strategy for early detection of breast cancer in a shorter time at the earlier stage of development. Segmentation techniques help the extraction of cancer in malignant tumors compared with [1, 29] works.

REFERENCES

1. ABDALLAH, Y.M.Y., *Application of Analysis Approach in Noise Estimation, Using Image Processing Program*, Lambert Publishing Press GmbH & Co. KG, Germany, 2011, pp. 123–125.
2. ABDALLAH, Y.M.Y., R.M. BEN YOUSEF, Augmentation of X-rays images using pixel intensity values adjustments, *Int. J. Sci. Res.*, 2015, **4**, 2425–2430
3. ABDALLAH, Y.M.Y., T. ALQAHTANI, *Research in Medical Imaging Using Image Processing Techniques*, Lambert Publishing Press GmbH & Co. KG; 2011, pp. 123–125.
4. ABDALLAH, Y.M.Y., S. EIGAK, H. ZAIN, M. RAFIQ, E.A. EBAID, A.A. ELNAEMA, Breast cancer detection using image enhancement and segmentation algorithms, *Biomedical Research*, 2018, **29**(20), 3732–3736
5. ARSLAN, A.A., S.C. FORMENTI, Mammography in developing countries: the risks associated with globalizing the experiences of the Western world, *Nat. Clin. Pract. Oncol.*, 2009, **6**, 136–137.
6. BEAULIEU, N., D. BLOOM, R. BLOOM, R. STEIN, Breakaway the global burden of cancer—challenges and opportunities: a report from the Economist Intelligence Unit,

- http://graphics.eiu.com/up-load/eb/EIU_LIVESTRONG_Global_Cancer_Burden, Accessed July 27, 2010.
7. FITZGIBBONS, P.L., D.L. PAGE, D. WEAVER, A.D. THOR, D.C. ALLRED, G.M. CLARK, S.G. RUBY, F. O'MALLEY, J.F. SIMPSON, J.L. CONNOLLY, D.F. HAYES, S.B. EDGE, A. LICHTER, *et al.*, Prognostic factors in breast cancer. College of American Pathologists Consensus Statement 1999[J], *Arch. Pathol. Lab. Med.*, 2000, **124**, 966–978.
 8. GILLIES, R.J., P.E. KINAHAN, H. HRICAK, Radiomics: Images are more than pictures, they are data, *Radiology*, 2016, **278**(2), 563–577.
 9. GOLDHIRSCH, A., J.H. GLICK, R.D. GELBER, A.S. COATES, B. THÜRLIMANN, H.-J. SENN, PANEL MEMBERS, Meeting highlights: international expert consensus on the primary therapy of early breast cancer, *Ann. Oncol.*, 2005, **16**, 1569–1583.
 10. JOHNSON, M.C., Anatomy, and physiology of the breast, In: I. Jatoi, M. Kaufmann, eds, *Management of Breast Diseases*, Springer, Berlin, Heidelberg, 2010, <https://doi.org/10.1007/978-3-540-69743-5-1>.
 11. LIDONG, H., Z. WEI, W. JUN, S. ZEBIN, Combination of contrast limited adaptive histogram equalization and discrete wavelet transform for image enhancement, *IET Image processing*, 2015, **9**(10), 908–991 Doi: 10.1049/iet-ipr.2015.0150, www.ietdl.org.
 12. LODISH, H., A. BERK, S.L. ZIPURSKY, P. MATSUDAIRA, D. BALTIMORE, J. DARNELL, Tumor cells and the onset of cancer, in *Molecular Cell Biology*, 4th edition, W.H. Freeman, New York, 2000, Section 24.1, Available from: <https://www.ncbi.nlm.nih.gov/books/NBK21590/>.
 13. LIU, J., X. ZHUANG, L. WU, D. AN, J. XU, T. PETERS, L. GU, Myocardium segmentation from de MRI using multicomponent Gaussian mixture model and coupled level set, *IEEE Trans. Biomed. Eng.*, 2017, **64**, 2650–2661.
 14. MIRZA, A.N., N.Q. MIRZA, G. VLASTOS, S.E. SINGLETARY, Prognostic factors in node-negative breast cancer: a review of studies with sample size more than 200 and follow-up more than five years, *Ann. Surg.*, 2002, **235**, 10–26.
 15. NGOMA T., World Health Organization cancer priorities in developing countries, *Ann. Oncol.*, 2006, **17**(8), 9–14.
 16. PUNITHA, S., A. AMUTHAN, S.K. JOSEPH, Benign and malignant breast cancer segmentation using optimized region growing technique, *Future Computing, and Informatics Journal*, 2018, **3**, 348–353.
 17. RIZWAN, M.M., M. SAADULLAH, Lack of awareness about breast cancer and its screening in developing countries, *Indian J. Cancer*, 2009, **46**, 252–253.
 18. ROSENBERG, J., Y.L. CHIA, S. PLEVITIS, The effect of age, race, tumor size, tumor grade, and disease stage on invasive ductal breast cancer survival in the US SEER database[J], *Breast Cancer Res. Treat.*, 2005, **89**, 47–54.
 19. SHESHADRI, H.S, A. KANDASWAMY, Detection of breast cancer by mammogram image segmentation, *J. Cancer Res. Ther.*, 2005, **1**(4), 232–234.
 20. SHYYAN, R., S. MASOOD, R.A. BADWE, K.M. ERRICO, L. LIBERMAN, V. OZMEN, H. STALSBERG, H. VARGAS, Breast cancer in limited-resource countries: diagnosis and pathology, *Breast J.*, 2006, **12**(1), 27–37.
 21. SIEGEL, R.L., K.D. MILLER, A. JEMAL, Cancer statistics, *Cancer J. Clin.*, 2015, **65**(1), 5–29.
 22. SIEGEL, R.K., K.D. MILLER, A. JEMAL, Cancer Statistics, *Cancer J. Clin.*, 2017, **67**(1), 7–30.
 23. SUCKLING, J., S. ASTLEY, D. BETAL, N. CERNEAZ, D.R. DANCE, S.L. KOK, J. PARKER, I. RICKETTS, J. SAVAGE, E. STAMATAKIS, P. TAYLOR, The Mammographic Image Analysis Society Digital Mammogram Database Excerpta Medica, 1964, *International Congress Series* **1069**, 375–378
 24. TAMILIKA, C., *Medical Image Processing: Advanced Fuzzy Set-Theoretic Techniques*, first edition, CRC Press, Boca Raton, London, New York, 2015, pp. 1–236.
 25. URASA, M., E. DARJ, Knowledge of cervical cancer and screening practices of nurses at a regional hospital in Tanzania, *Afr. Health Sci*, 2011, **11**, 48–57.

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26. VALDORA, F., N. HOSSAMI, F. ROSSI, A.S. CALABRESE, A.S. TAGLIAFCO, Rapid review: radiomics and breast cancer, *Breast Cancer Research and Treatment*, 2018, **169**(2), 217–229.
 27. VISHNUKUMAR, K.P., U. SYED, A.C. SUTHAR, Mammogram of breast cancer detection based using image enhancement algorithm, *International Journal of Emerging Technology and Advanced Engineering*, 2012, **2**(8), 143–147.
 28. WONG, L.P, Y.L. WONG, W.Y. LOW, E.M. KHOO, R. SHUIB, Cervical cancer screening attitudes and beliefs of Malaysian women who have never had a pap smear: A qualitative study, *Int. J. Behav. Med*, 2008, **15**, 289–292.
 29. YONGXIA, Z., *Medical Image Principles and Application*, Books on Demand, 2019, pp. 1–108.

