aurum

AURUM MÜHENDİSLİK SİSTEMLERİ VE MİMARLIK DERGİSİ
AURUM JOURNAL OF ENGINEERING SYSTEMS AND ARCHITECTURE

Cilt 5, Sayı 2 | Kış 2021
Volume 5, No 2 | Winter 2021, 225-236

ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

COMBINATION OF FUZZY C-MEANS AND THRESHOLDING FOR SEGMENTATION USING MEDICAL IMAGES

Barish Mohammed Izaddin IZADDIN[1]
[1]Electrical and Computer Engineering, Altınbaş University, Istanbul Turkey
barish.izaddin@ogr.altinbas.edu.tr, ORCID No: 0000-0002-3821-0287

Ayça Kurnaz TÜRKBEN[2]
[2]Software Engineering, Faculty of Engineering and Natural Sciences,
Altınbaş University, Istanbul Turkey,
ayca.turkben@altinbas.edu.tr, ORCID No: 0000-0002-8541-9964

GELİŞ TARİHİ/RECEIVED DATE: 12.09.2021 KABUL TARİHİ/ACCEPTED DATE: 01.12.2021

Abstract

Breast tumor segmentation is a crucial stage in breast cancer therapy and follow-up. Radiologists can minimize the high workload of breast cancer analysis by automating this difficult process. After pre-processing source pictures, this article established a system for accurately segmenting breast tumors and non-infected areas (breast) on medical imaging using combination of Fuzzy c-Means and Thresholding (FCMT). This is a computer-aided diagnostic method that works on each individual breast slice without any training for segmentation. On a database of 79 images of Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). To increase the image quality, we used pre-processing techniques such as contrast augmentation before applying the FCMT for segmentation. To assess the effectiveness of the devised approach, the Mean Square Error, dice coefficient, Structured Similarity Index, Peak Signal-to-Noise Ratio, accuracy, and sensitivity were computed. On the same dataset, we compared our technique to different segmentation methods. With a dice coefficient of 0.9568 and an accuracy of 0.9731, our approach surpassed the other substantially. The suggested approach is more resilient and accurate in segmenting tumor progression on medical pictures, according to the findings of the experiments.

Keywords: Brest Tumor, Image processing neural Network , Fuzzy c-Means and Thresholding (FCMT)

TIBBİ GÖRÜNTÜLERİ KULLANARAK MEME TÜMÖRÜ SEGMENTASYONU İÇİN BULANIK C-ORTALAMALAR VE EŞİK DEĞERİNİN KOMBİNASYONU

Özet

Meme tümörü segmentasyonu, meme kanseri tedavisi ve takibinde çok önemli bir aşamadır. Radyologlar, bu a indirebilirler. Kaynak resimleri zorlu süreci otomatikleştirerek meme kanseri analizinin yüksek iş yükünü en az ön işleme tabi tuttuktan sonra, bu makale, Fuzzy c-Means ve Thresholding (FCMT) kombinasyonunu kullanarak tıbbi görüntülemede meme tümörlerini ve enfekte olmayan alanları (meme) doğru bir şekilde segmentlere ayırmak için bir sistem kurdu. Bu, segmentasyon için herhangi bir eğitim almadan her bir göğüs dilimi üzerinde çalışan bilgisayar destekli bir teşhis yöntemidir. 79 Bilgisayarlı Tomografi (BT) ve Manyetik Rezonans Görüntüleme (MRI) görüntüsünün bulunduğu bir veritabanında. Görüntü kalitesini artırmak için, FCMT'yi segmentasyon için uygulamadan önce kontrast artırma gibi ön işleme teknikleri kullandık. Tasarlanan yaklaşımın etkinliğini değerlendirmek için Ortalama Kare Hatası, zar katsayısı, Yapılandırılmış Benzerlik İndeksi, Tepe Sinyal-Gürültü Oranı, doğruluk ve hassasiyet hesaplandı. Aynı veri setinde, tekniğimizi farklı segmentasyon yöntemleriyle karşılaştırdık. 0.9568 zar katsayısı ve 0.9731 doğruluk ile yaklaşımımız diğerini önemli ölçüde aştı. Deneylerin bulgularına göre, önerilen yaklaşım, tıbbi resimlerde tümör ilerlemesini segmentlere ayırmada daha esnek ve .doğrudur

Anahtar kelimeler: Meme Tümörleri Görünrtü işletme Sinir Ağı, Bulanık c-Ortalamalar ve Eşik (FCMT)

1. INTRODUCTION

Cancer is a disease caused by alterations in cells that spread uncontrolled. Most cancerous breast cells form a lump or mass known as a tumor, which is named for the part of the body where it originates. Breast cancer is the most common cancer in women and the second greatest cause of death. Breast cancer generally causes little discomfort in its early stages when it is treatable, which is why screening is critical for early diagnosis. Early cancer identification, followed by appropriate treatment, can lower the chance of mortality.

Recognizing the presence of a tumor and the kind of malignant tumor would be crucial in doctors' choice to apply appropriate treatment approaches and, as a result, reclaim people's lives (not less than 40%). Cancers are collections of aberrant cells that manifest themselves as lumps or growths. They can originate in any of our body's billions of cells. Depending on whether a tumor is malignant (cancerous), benign (non-cancerous), or precancerous, it develops and behaves differently. Tumors that are cancerous can start anywhere on the body. A malignant tumor is formed when malignant cells clump together to create a mass or growth. When a cell develops into surrounding tissues, contains cells that may break out and move through the circulatory and lymph drainage systems, it then spreads to the surrounding tissue and other vital organs., it is termed malignant.

The term "metastasis" refers to cancer that has spread from the initial tumor location to another part of the body. The process through which cancer cells grow and form new tumors is referred to as "metastasis." Non-cancerous tumors are those that are not malignant. (Alias and Paulchamy, 2014) They do not spread to other regions of the body; (Cheng et al. 2010) they do not return after removal; (Wu et al. 2014). they have a normal and sleek form with a covering called a capsule; and (Redcay et al. 2007) they may be readily handled through tissue.

Several papers were discovered by the authors, including one that used a conditional random field (CRF) to detect tumor activation, one that used data collected from children during normal sleep to predict the early development of a functional breast tumor, and one that calculated and visualized tumor characteristics. Volumetric white ratios of diffusion tensor (DT) in magnetic resonance imaging (MRI) (Schultz et al. 2007). Topological imaging of human brain development with magnetic resonance imaging, as well as the isolation of histological areas in the tumor's white matter and the identification of single cells

MRI is used to identify breast tumors in different stages. In medical imaging classification and analysis, segmentation is recognized to be an important yet challenging phase. The Fuzzy C-Means (FCM) clustering approach developed by Sharma and Sivakumar is often utilized for image segmentation. Furthermore, the author presented an isolation of breast tumor technique on the basis of a combination strategy that used FCM in. Classical methods which proposed in, as well as the shear let transform, can be used to the arrangement of linearity and non-linear characteristics in mathematical computer vision (edges, boundaries).

In, determining the kind of cancer is considerably more challenging. Malignant tumors have a clumped appearance, isolated ducts, a loosely defined mass, and other characteristics. Because of the weak contrast and indistinct boundaries of the tumors in breast ultrasound images, automatically segmenting breast malignancies from ultrasound images remains a tough task. In, they reported a novel computer method for identifying and segmenting breast lesions in ultrasound images. Breast cancer is defined as the development of a malignant tumor in a female's breasts. Except when detected early, there is no known treatment for breast cancer.

The work is in provides a method for identifying breast tumors by segmenting mammography pictures with basic image processing algorithms that give satisfactory results only in real-time, while employed wavelet transformation and K-means clustering for cancer tumor mass segmentation on mammogram images. The authors of utilized a method based on double binarization that has been improved for mammogram image isolation, at the end, applied the image boundaries detection has been applied as a contour of the objects in source image, allowing doctors to more easily diagnose with cancer in diverse scans. In this work we have used combination of FCM clustering and thresholding methods for breast and tumor segmentation and size measurement after preprocessing phase.

2. MATERIALS AND METHODS

The outcome of processing is determined by the quality of MRI or CT images obtained by medical equipment. Most of the time, noise can be seen in acquired images (or image sets) due to technical characteristics of device operation. There are many techniques for identifying and segmenting brain tumors and breast malignancies in diverse systems. The authors of this work recommend adopting the technique described through the findings of used MRI and CT scans may be influenced by the presence of noise in the medical images in Figure 1 on pre-step to evaluate breast cancers in medical data. Five main steps have been performed:

a. Source image
b. Data pre - processing

c. Isolations
d. In medical scans of the breast, the contour depiction of a tumor and normal areas
e. Conducting data analysis

The improvement noise removing filter is used to increase the quality and contrast during the scan improvement stage of source image. To enhance and highlight the region of foreign bodies (tumor or nodules), we recommended utilizing the modified Balance of the Contrast using the Enhancement Technique. The separation and measurement of the medical image are advised after image enhancement to more accurately identify the limits of the region of interest (breast tumor). FCM clustering and thresholding methods were used for segmentation. The edge map is produced in the final stage using the Canny edge detector.

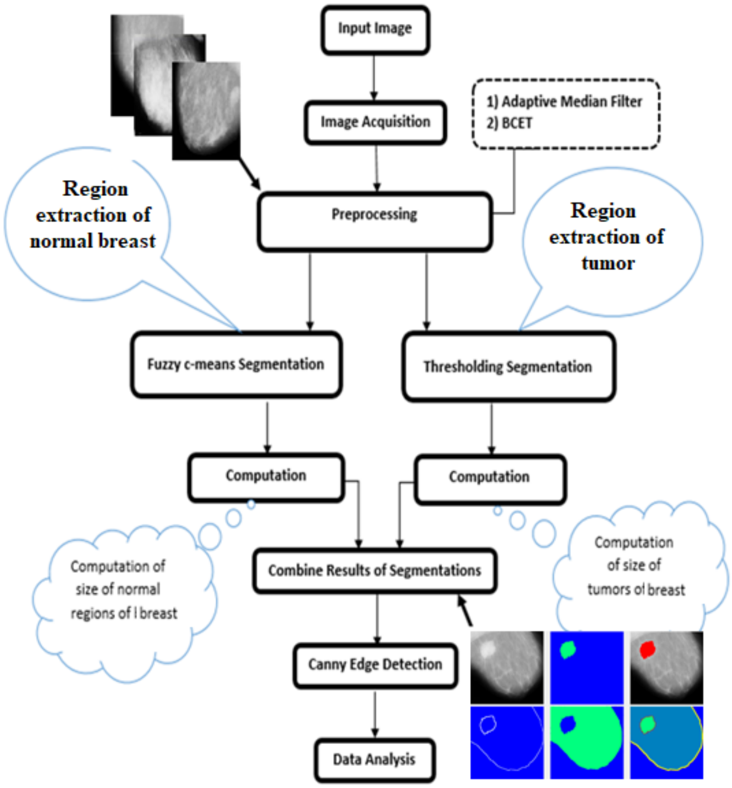

Figure 1. The computational methodology of diagnostic analysis for interactive visualization

2.1 Image Enhancement

Pre-processing has the primary goal of enhance the features of brain and breast medical images (MRI and CT) which can be further processed by a human or machine vision system. Furthermore, pre-processing reduces the false segmentation, the visual look of medical pictures, eliminating superfluous noise and undesirable sections in the background, smoothing the inner part of the region, and keeping its borders in breast or brain MRI images. Adaptive data augmentation, which is based on a customized nonlinear function, was used to improve the accuracy, and decrease false detection, as well as the brightness of the MR image features.

Extraction of features, evaluation of segmentation, identification, and measurements become more challenging when the MRI quality is poor. Medical scans (MRI and CT) are commonly additive-contaminated, spontaneous, or additive noise cause of variety of faults in the image capturing process using medical devices. The experts advised you to utilize to increase the contrast in order to highlight the region of interest (BCET). Contrast augmentation is typically necessary for the region of interest during medical image processing. Kumbha's work has been utilized to increase features and get enhanced the texture of medical scans for a sensitive enhancement using method of Contrast Limited Adaptive Histogram Equalization (CLAHE). Previously, the author shown that the proposed method improved the characters of MRI scans. The results of utilizing different males of BCET instead of varied thresholding are shown in Figure 2 since the MRI image has varying contrast and tumor segmentation is not reliable in such a circumstance.

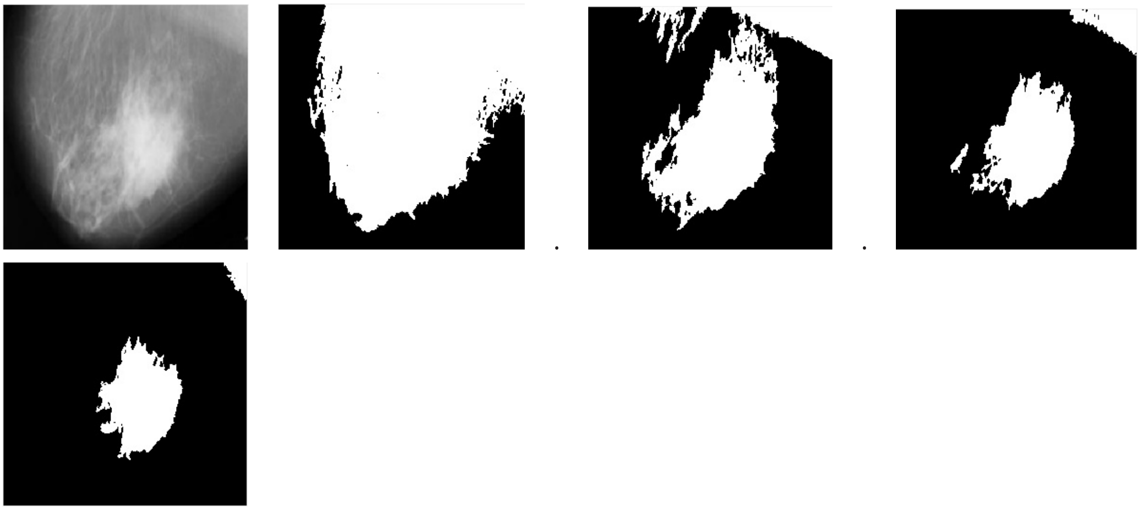

Figure 2. Breast tumor segmentation example for different BCET means a) original CT images, b) BCET 120, c) BCET 100, d) BCET 80, e) BCET 60.

2.2 Segmentation

The technique of identifying objects and boundaries (lines, form, size, and location) in medical images is known as object segmentation. Using medical scans, medical image segmentation is a crucial step in finding the optimal treatment for brain and breast malignancies. Image segmentation generates either a collection of contours based on the slide or a group of regions that comprise the whole image. Each pixel in a certain region has the same property or trait, such as intensity, color, or texture and each feature of the image. The thresholding approach, which uses binary image partitioning, is utilized to segment the

MR images. The thresholding approach uses a binary division of image intensity to segment MR images. The CT image is split into distinct sections during the segmentation process. Following improvement of the image quality, early tumor extraction and measurement of the medical scans generates the most precise area of interest borders. The Fuzzy clustering and binarization techniques were used for segmentation with improvement by morphological information. To apply the segmentation (normal area extraction) of the non-infected area on the breast, the improved Fuzzy C-Means approach was employed, and the thresholding segmentation was used to convert the improved MRI to convert the image to black and white in order to extract the infected area of the breast tumor (size, location, and form).

3. RESULTS AND DISCUSSION

The authors employed two breast tumor datasets in their study. The DICOM (Digital Imaging and Communications in Medicine) dataset is a collection of digital images and communications in medicine is the first. The researchers looked at 50 medical images from the DICOM collection for this study, all of which had tumor-infected breast tissues. However, there were no ground truth pictures in this collection. Figure 3 depicts several examples. The datasets comprise tumors with various locations and types of diseases, as well as form, volume, and texture, as well as the measurement size of the afflicted tissue region surrounding the tumor space. Surface features and highlighted objects can be observed on images before and after processing form image to another.

In the analysis, the authors used two breast tumor databases. The first dataset is the DICOM (Digital Scanning and Comms in Medicines) collection of digital images and information systems in medicine. For this investigation, the researchers examined 50 medical CT scans from the DICOM collection has infected breast tissues. However, there were no photographs of actual events in this collection. Figure 3 illustrates a number of instances. The datasets include tumors with a variety of illness sites and kinds, as well as form, size, and density, as well as the extent of the tissue that has been impacted region surrounding the breast tumor location. It can also be noticed that the picture's brightness and contrast change from image to image.

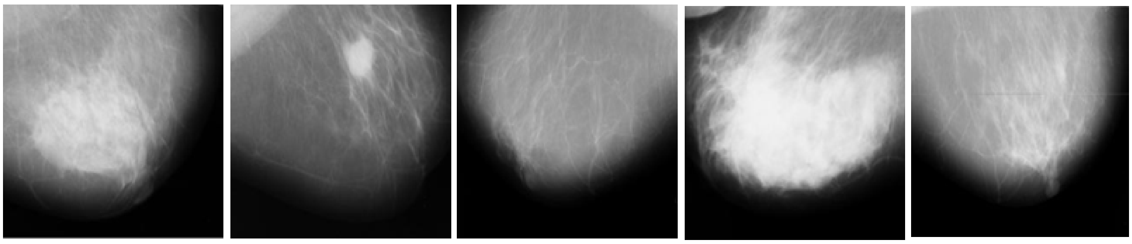

Figure 3. CT Images of the breast from an experimental data collection (DICOM).

As an example of segmentation, we tested with a range of scans of breast tumors, all of which were 256 by 256 in size. In the instance of a novel segmentation approach, present the findings of several examples of breast tumor segmentation and detection in Figure 4, sorted from left to right. The first column contains the original images of the breast, the second column contains the findings of the preprocessing step and is displayed as a color map, the third column contains the extracted tumor (segmented tumor), and the last column contains outlines of the breast tumor (extracted tumor) and the normal regions of the breast.

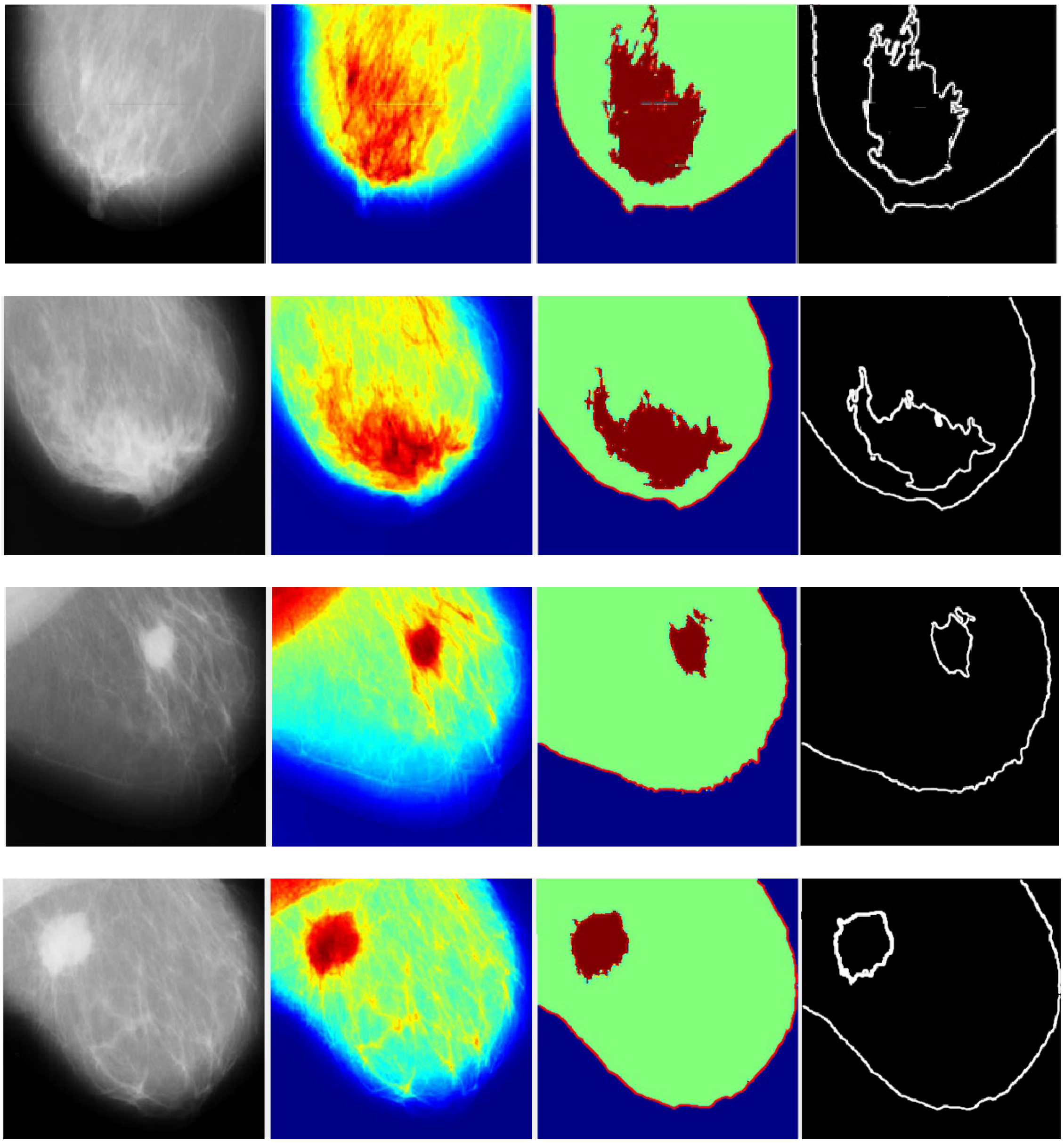

Figure 4. Some results of the proposed methodology of breast tumor segmentation

Differentiating between normal and malignant cells, which also aids in calculating the area of tumor affected parts. It displays the calculated area in pixel units. For breast tumor identification and segmentation, we compare our technique to methods in. Visual analysis shows that our technique outperforms the other way in segmenting cancers and normal brain and breast areas. Whereas the methods in provide some area of the normal region of breast in the experimental that is difficult to diagnose and lacks the boundary lines of cancers and normal regions of the breast to realize the location of tumors, our method able to detect only tumor region and successfully locates tumor region and normal region of breast on the original input image with color results. Table 1 compares the accuracy and reliability of the tumor and normal regions of the breast edge map produced using the suggested approach.

Table 1. Characteristics for tumor and breast delineation and edge detection.

Matrix	Name	Matrix	Name
SSIM	Structured Similarity Index	Sen.	sensitivity
MSE	Mean Square Error	Acc.	accuracy
PSNR	Peak Signal-to-Noise Ratio in dB	*TP*	True positive
P_{CD}	percentage of detected pixels	*TN*	True negative
P_{ND}	percentage of false detection	*FP*	False-positive
P_{FA}	percentage of false alarm	FN	False-negative
FOM	figure of merit		

The range of measurements is 0 to 1, with the highest value being the best. The following equation can be used to describe sensitivity:

$$Sen. = \frac{True\ of\ positivity}{true\ of\ positive + false\ of\ positive} \tag{1}$$

The percentage of correct findings is known as accuracy. The accuracy % indicates how many objects and background pixels were correctly identified. The result is the same as the input if the accuracy value equals 1. The term "accuracy" is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FB + FB} \; . \tag{2}$$

The combined method provides for the precise identification of a tumor's location and normal components in medical imaging, as well as the true and quick segmentation of tumor in breast images. Table 2 shows the results of the performance analysis of edge detected pictures, as well as the calculation of the tumor and normal areas in the breast.

Table 2. The performance analysis parameters for the identified tissues as well as the region of the excised malignancies (tumor) and non-effected region of breast.

Data	Region of an extracted tumor (pixel)	Region of the extracted normal breast in (pixel)	Damage areas (tumor) %	PSNR	MSE	SSIM	Dice	Execution Time in second
image 1	8940	41272	22%	68.990	1.920	0.9565	0.9562	21.1247
image 2	7025	39541	18%	64.004	1.35	0.9675	0.9639	22.5821
image 3	2029	43394	5%	65.066	1.215	0.9700	0.9698	20.2568
image 4	4311	45380	9%	64.03	2.172	0.9663	0.9750	21.0215

The following tests were carried out to show that the proposed technique has a good degree of performance and can withstand average levels of noise. The suggested methodology is compared against edge detection methods based on simple slope operations like Roberts, Prewitt, and Sobel, as well as more sophisticated approaches, such as Canny in the first study. The medical image as MRI or CT with the least obvious noise impact were chosen for comparison. All of the study's assessment parameters were computed using reference pictures created by a medical professional.

The data for the target region is obtained. Figure 5 shows samples of boundary finding of this study showed for breast cancer and normal regions.

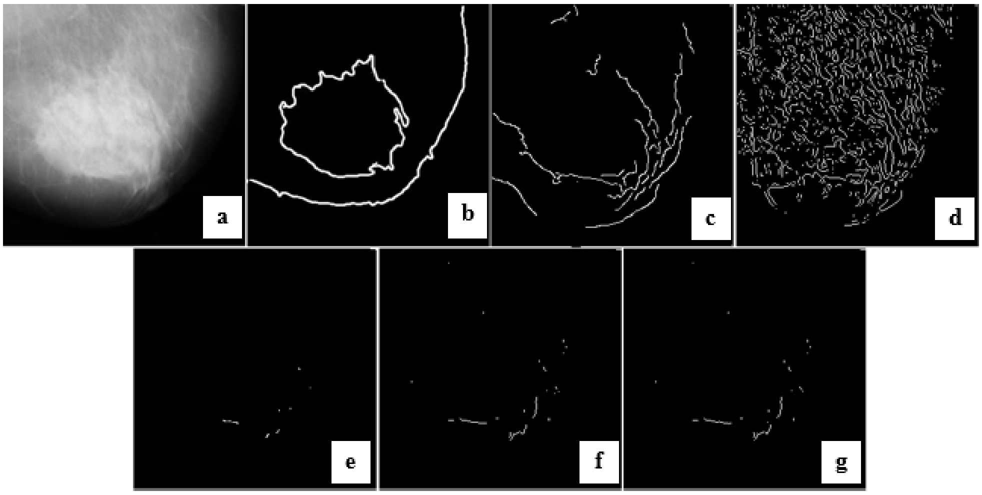

Figure 5. An example of how to make an edge map: a) the source image; b) the improved technique; c) Canny; d) LoG; e) Roberts; f) Prewitt; g) Sobel

In Table 3 shown a comparative of different approaches for creating a contour identification of breast cancers using the model photographs shown in Figure 5.

Table 3. Compares the contour detection created by several detector algorithms of tumor (infected area) and normal breast cells.

Data	Approach	P_{CD}	P_{ND}	P_{FA}	FOM	Sens.	Acc.
Image (a)	Proposed method	0.7398	0.3643	0.2601	0.9158	0.9489	0.9731
	Classic Canny	0.0934	0.5063	0.9065	0.5532	0.1557	0.8476
	Prewitt	0.0115	0.1469	0.9884	0.4523	0.0727	0.7579
	Roberts	0.0045	0.1189	0.9954	0.4236	0.0366	0.7586
	Sobel	0.0119	0.1473	0.9881	0.3582	0.0749	0.5579
	LoG	0.1292	1.7912	0.8707	0.2564	0.0673	0.6013

The developed technique improves the accuracy of contour detection of the item of interest (area of tumor and normal breast) by 37% on average. Furthermore, the suggested approach shows a decreased percentage of pixels incorrectly identified as the margins of brain and breast cancers.

4. CONCLUSION

In medical images, BT edge detection and segmentation aid clinicians in diagnosis. The zone (edge map) of infected areas of breast tumors and non- infected parts of the breast may be defined with a more accuracy of precision using segmentation. There are various techniques accessible, and the developed approach producing the best performance with high accuracy results were picked. The created methodology is a mix of different approaches utilized, and it can be observed that the findings gained are much more accurate and clearer.

An adaptive median filter is used to de-noise the input picture before it is improved by BCET. The CT scans is then segmented using two methods: the FCM clustering technique to segment the normal region and the thresholding method to segment the tumor region. The Canny detector lung detector is then used to create an edge map of a tumor and normal breast areas. The suggested approach outperforms others because it employs the Canny detector method on ideal input pictures that have been enhanced in quality and segmented into homogenous areas using the BCET, thresholding, and FCM. As the obtained experimental result, the approach proposed in this study yields strong estimators with great image quality for medical professional analysis. Medical professionals evaluated the edge maps and discovered that in situations of breast tumor pathology, the obtained accuracy of developed method of segmentation and measurement is 10-15% higher than the equivalent expert estimations. The experimental investigation proved the stability of the edge detection created under the suggested approach under the impact of noise.

In addition, with minor adjustments, the suggested method may be used to identify the pathology of lung as COVID-19 infections. The developed methodology can be used to a CT scan pathology and lung segmentation, and other areas where malignant cells can be recognized. The findings demonstrate that the proposed method can recognize more features, which is very useful in determining the kind of infected area.

5. REFERENCES

Alias, A., and B. Paulchamy. 2014. Detection of Breast Cancer Using Artificial Neural Networks. International Journal of Innovative Research in Science, 3(3).

Canny, J. 1986. A computational approach to edge detection. IEEE Transactions on pattern analysis and machine intelligence, (6), 679-698.

Cheng, H.D., J. Shan, W. Ju, Y. Guo, and L. Zhang. 2010. "Automated breast cancer detection and classification using ultrasound images", Pattern Recognition No 43, pp. 299-317, 2010.

Kang, X., T.J. Herron, U. Turken, and D.L. Woods. 2012. Diffusion properties of cortical and pericortical tissue: regional variations, reliability and methodological issues. Magnetic Resonance Imaging, 30(8), 1111-1122.

Kanojia, M.G., and S. Abraham. 2016. "Breast Cancer Detection Using RBF Neural Network", 2nd International Conference on Contemporary Computing and Informatics (IC3I), IEEE, 363978-1-5090-5256-1/16, 2016.

Redcay, E., D.P. Kennedy, and E. Courchesne. 2007. fMRI during natural sleep as a method to study brain function during early childhood. Neuroimage, 38(4), 696-707.

Schultz, T., H. Theisel, and H.P. Seidel. 2007. Topological visualization of brain diffusion MRI data. IEEE Transactions on Visualization & Computer Graphics, (6), 1496-1503.

Selvakumar, J., A. Lakshmi, and T. Arivoli. 2012. Brain tumor segmentation and its area calculation in brain MR images using K-mean clustering and Fuzzy C-mean algorithm. In Advances in Engineering, Science and Management (ICAESM), 2012 International Conference on (pp. 186-190). IEEE.

Sharma, P., M. Diwakar, and S. Choudhary. 2012. Application of edge detection for brain tumor detection. International Journal of Computer Applications, 58(16).

Stosic, Z., and P. Rutesic. 2018. An Improved Canny Edge Detection Algorithm for Detecting Brain Tumors in MRI Images. International Journal of Signal Processing, 3.

Wu, W., A.Y. Chen, L. Zhao, and J.J. Corso. 2014. Brain tumor detection and segmentation in a CRF (conditional random fields) framework with pixel-pairwise affinity and superpixel-level features. International journal of computer assisted radiology and surgery, 9(2), 241-253.

Zanaty, E.A. 2012. Determination of gray matter (GM) and white matter (WM) volume in brain magnetic resonance images (MRI). International Journal of Computer Applications, 45(3), 16-22.