Comparative Analysis of Snake and Ellipse Segmentation Methods for Breast Cancer Detection using Breast Thermograms

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Abstract.

Breast cancer is a leading cause of mortality among women, and early detection is crucial in improving survival rates. Computer-aided tools assist radiologists in identifying abnormalities, with breast thermography emerging as a non-invasive and radiation-free technique for early diagnosis. However, robust segmentation is essential to enhance the accuracy of AI-based detection models. This study compares Snake and Elliptical segmentation methods for breast thermogram analysis. The Snake Algorithm achieved higher accuracy with Jaccard Index of 0.78 but required more processing time, while the Ellipse Method was faster with a Jaccard Index of 0.72. Texture features extracted using GLCM revealed contrast, eating habits, and age as significant indicators in distinguishing normal and abnormal breast. A Support Vector Machine classifier trained on 100 samples with these features achieved 78% accuracy. The results highlight a trade-off between segmentation accuracy and computational efficiency, suggesting that hybrid models could optimize both performance and speed in thermographic breast cancer detection.

Keywords. breast thermogram, ellipse, masking, segmentation, features, significance level, confusion matrix

1. INTRODUCTION

Breast cancer is the most commonly diagnosed cancer in women, with 2.3 million new cases and 685,000 deaths reported worldwide in 2020, according to GLOBOCAN [1]. Nowadays, it is observed that more and more young women are affected by the breast cancer due to the change in life style, environmental issues, obesity, genetical factors etc. Breast cancer originates from uncontrolled cell growth in the milk ducts, lobules, or connective tissue and can spread via the lymphatic system or bloodstream if not detected early [2]. Early and accurate detection significantly improves survival rates and treatment outcomes. Various imaging modalities, including mammography, ultrasound, MRI, CT, PET scans, and thermography are used for breast cancer diagnosis. Among these, mammography is the most widely adopted method, offering high-resolution imaging but with reduced sensitivity in dense breast tissue and the risk of radiation exposure with repeated use [3]. While ultrasound and MRI enhance detection in specific cases, they are often costly and time-intensive, limiting their accessibility for large-scale screening.

Thermography has emerged as a non-invasive, radiation-free imaging technique, detecting temperature variations associated with metabolic activity in breast tissue [14]. It provides a promising adjunct tool to traditional screening methods, particularly for frequent monitoring and early physiological detection [4]. However, its diagnostic accuracy heavily depends on precise segmentation to isolate the Region of Interest (ROI), which plays a crucial role in feature extraction and classification in computer-aided detection (CAD) systems. Effective segmentation enhances sensitivity and specificity while reducing computational complexity, yet challenges such as low contrast, noise, and anatomical variations remain [5]. This study compares two segmentation techniques such as Snake Algorithm and Ellipse method to evaluate their efficiency in breast thermogram processing. The Snake Algorithm iteratively refines contours for precise ROI detection but is computationally intensive, while the Ellipse Method provides a faster approach by fitting ellipses to breast regions, reducing processing time while maintaining accuracy. The rest of the paper is structured as follows: Section 2 presents a literature review of segmentation techniques in thermography, Section 3 describes the methodology, Section 4 discusses the results and findings, and Section 5 concludes with key observations.

2. LITERATURE REVIEW

Segmentation is essential in breast thermography to accurately detect abnormalities linked to breast cancer. It helps to extract the ROI in thermal images, improving diagnostic precision. Traditional methods like thresholding, edge detection, and region growing have been widely used but often struggle with noise, contrast issues, and thermal intensity variations. Recently, deep learning-based approaches, especially CNNs, have shown better accuracy and reliability. However, standardizing the segmentation remains a challenge due to differences in thermal contrast and anatomical variations [6]. Jayagayathri et al. [7] experimented with CNN architectures like DenseNet201 and ResNet101 for segmenting breast thermograms, achieving high classification accuracy. However, they mentioned that limited annotated datasets hinder real-time clinical applications. Kamila Fernanda et al. [8] proposed an elliptical segmentation model and evaluated its accuracy using the Dice Similarity Index and Pearson correlation. While their approach showed moderate success, improvements are needed for better ROI extraction and alignment. Dharani et al. [9] developed an enhanced CNN model combined with Fuzzy C-means clustering for ROI segmentation. Thanh Nguyen Chi et al. [10] introduced a lightweight CNN model optimized with a Chi-square filter and an SVM classifier. Despite of good performance, CNN models are computationally complex, requiring more efficient alternatives. Mohammed Abdulla Salim Al Husaini et al. [11] explored real-time segmentation using deep learning models like Inception v3 and v4, achieving a good accuracy but facing issues such as motion artifacts and image quality.

Among segmentation techniques, active contour models like the Snake algorithm are notable for refining boundaries iteratively. Eddie et al. [4] modified the Snake algorithm by incorporating pre-processing, gradient vector flow, and high-pass filtering, improving boundary detection. However, their method is sensitive to the initial contour placement and has slow convergence, affecting performance. Elliptical segmentation [14] has also gained attention due to the natural elliptical shape of the breast. Pu et al. [12] applied an ellipse-fitting method for mammogram registration, enhancing accuracy in mass localization across different views. Marcus C. Araújo et al. [3] explored elliptical segmentation for thermographic analysis, showing its effectiveness in anatomical conformity and ROI extraction. However, this method struggles when breast boundaries do not follow a perfect elliptical shape. This article compares the Snake algorithm and elliptical segmentation for breast thermography. By analysing their strengths and limitations, we aim to determine the most effective approach for improving breast cancer detection accuracy.

3. METHODOLOGY

3.1 Dataset Used

Breast thermogram images used in this study were obtained from the Database for Mastology Research (DMR) at Visual Lab, Fluminense Federal University, Brazil [13]. The images were acquired using a FLIR SC620 infrared camera with a resolution of 640 × 480 pixels. The dataset includes thermograms from patients with confirmed breast tumors based on clinical examination, ultrasound, mammography, and biopsy results.

3.2 Snake Algorithm based Segmentation

The Snake Algorithm, or Active Contour Model, is employed to detect and refine breast boundaries in thermal images through energy minimization [4] [14]. It iteratively adjusts the contour to align with object edges using internal and external forces. The segmentation steps include:

a. Gaussian filtering to reduce noise and enhance edge clarity.
b. Place an initial contour around the ROI.
c. The Snake model iteratively refines the boundary by balancing internal and external energy functions.

The Snake algorithm is governed by parameters α (smoothness control), β (stiffness), and γ (external force impact). Convergence occurs when contour movement stabilizes, effectively delineating the breast region.

3.3 Ellipse based Segmentation

An alternative segmentation method is the Elliptical Curve Approach, which simplifies the ROI definition by fitting elliptical curves to breast tissue boundaries based on thermal data [3] [13]. Figure 1 outlines the CAD model consists of filtering, segmentation into right and left breasts, followed by feature extraction and training/testing an SVM model.

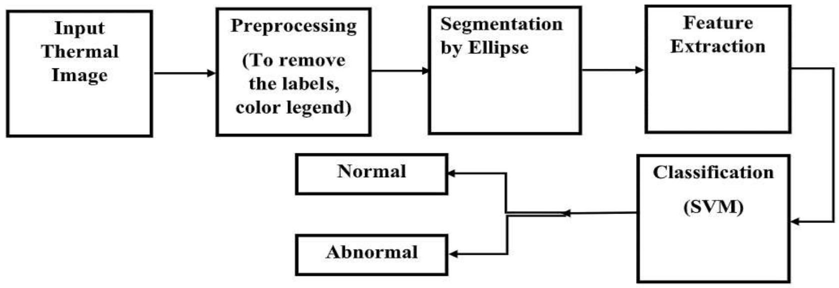

Figure 1. Classification using Ellipse method

Given the elliptical anatomical structure of the breast, an ellipse-fitting method is employed for segmentation [13]. The segmentation process consists of:

a. Define centres and radii based on breast size & shape to generate elliptical masks for the left and right breast regions.
b. Superimpose the elliptical masks onto the original thermogram to segment the breast regions.
c. Apply Gaussian filter to reduce noise while preserving key details.
d. Sharpen the image to refine boundaries, ensuring temperature variations remain visible.

3.4 Feature Extraction and Classification

After segmenting the breast regions into left and right from the thermal images using elliptical masks, texture features were extracted using the Gray-Level Co-occurrence Matrix (GLCM) as shown in Table 1, Also, patient history features such as age (F6) and dietary habits (F7) are considered to improve classification accuracy. The dataset consists of 100 images (50 normal, 50 abnormal).

Table 1 List of features extracted

Features Extracted						
GLCM Features					**History of Patient**	
Contrast (F1)	Correlation (F2)	Homogeneity (F3)	Energy (F4)	Entropy (F5)	Age (F6)	Eating habits (F7)

Asymmetry analysis is performed by computing feature values separately for the right and left breast regions, with absolute differences used to quantify texture variations. A statistical t test is then conducted to assess the significance of these differences in distinguishing normal and abnormal breast thermograms. The segmentation performance is evaluated using Jaccard Coefficient (JC), which measures the similarity between segmented regions and ground truths and computation speed to assesses the efficiency of Snake and Elliptical segmentation methods in processing breast thermograms.

4. Results and Discussions

4.1 Segmentation Results

The Snake method, requires precise tuning of parameters to balance flexibility and accuracy. Alpha (α) controls elasticity, preventing excessive stretching; Beta (β) ensures smoothness by reducing sharp bends; Gamma (γ) adjusts the speed of convergence; and Kappa (κ) determines sensitivity to image edges. Also, weights (wEline, wEedge, wEterm) influence how the algorithm detects intensity and boundaries. With 200 iterations, the algorithm processed each image in 13,560 milliseconds. Increasing to 5000 iterations improved boundary accuracy but significantly increased computation time. While the method effectively captured complex breast contours, it struggled with weak edges in certain cases, requiring further refinement.

The Ellipse segmentation method was applied to 100 breast thermograms, successfully isolating the region of interest in each case. This method efficiently separated left and right breast regions while maintaining segmentation accuracy. Compared to the Snake Algorithm, the Ellipse method required only 2256 milliseconds per image, demonstrating its computational efficiency. The JC is computed for segmented breast images and ground truth images, as shown in Table 2

Table 2 JC and Computation Time for Snake and Ellipse Method

Method	JC	Computation Time
Snake	0.78	13560 msec
Ellipse	0.72	2256 msec

The comparison of segmentation algorithms based on JC and computation time highlights the trade-off between accuracy and efficiency. The Snake Algorithm achieved a JC of 0.78, indicating a higher segmentation accuracy compared to the Ellipse Method (JC = 0.72). However, this improved accuracy comes at a cost, as the Snake Algorithm requires significantly more processing time of 13560 msec per image due to its iterative contour refinement process. In contrast, the Ellipse Method completed segmentation in just 2256 msec, demonstrating its computational efficiency.

The Ellipse segmentation method effectively handled various breast morphologies, including small, medium, large, and asymmetric breasts, as shown in Figure 2.

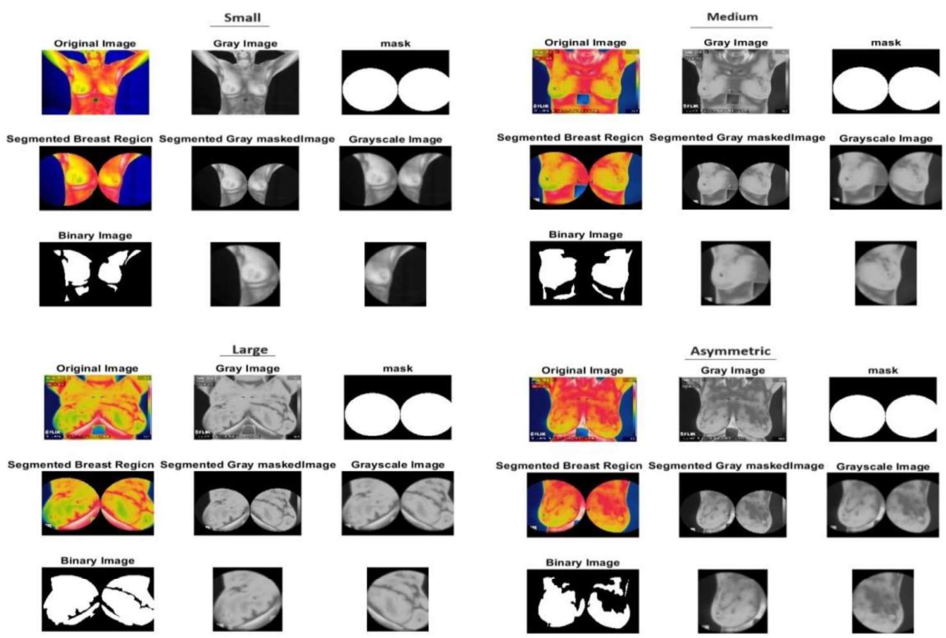

Figure 2: Segmentation outputs for different types of breasts

4.2 Feature Extraction and Classification

In this study, GLCM based texture features were computed from the segmented left and right breast regions to analyze asymmetry. A statistical t-test was performed to evaluate the effectiveness of each feature in distinguishing normal and abnormal breasts. The results indicate that correlation, energy, homogeneity, and entropy did not show a statistically significant difference between the two classes. However, contrast (F1), eating habits (F7), and age (F6) were found to be significant, with age being the most influential feature ($p = 0.0065$). The statistical significance of extracted features is summarized in Table 3.

Table 3 Significance level of extracted features using t test

Features	F1	F2	F3	F4	F5	F6	F7
Significance Level	0.0502	0.1652	0.07686	0.0614	0.0583	0.0065	0.0412

For classification, a SVM cubic classifier was trained using the three significant features from the dataset consisting of 100 thermograms (50 normal, 50 abnormal cases). The trained model achieved an accuracy of 78%, indicating its effectiveness in distinguishing normal and abnormal thermograms.

5. CONCLUSION

This study compared Snake and Ellipse segmentation methods for breast thermogram analysis, highlighting a trade-off between accuracy and computational efficiency. The Snake Algorithm achieved higher segmentation accuracy (Jaccard Index = 0.78) but required more processing time, whereas the Ellipse Method provided faster segmentation (2.2 sec) with slightly lower accuracy. Feature extraction using GLCM revealed that contrast, eating habits, and age were the most significant factors in distinguishing normal and abnormal breast thermograms, with age ($p = 0.0065$) being the strongest indicator. A cubic SVM classifier, trained using these key features, achieved an accuracy of 78%, demonstrating the feasibility of combining efficient segmentation with clinically relevant features for automated breast cancer detection. Future work can explore hybrid segmentation models to improve accuracy while maintaining computational efficiency for real-time applications

6. REFERENCES

[1] I. A. f. R. o. C. (. (. G. C. O. C. Today., 2020. [Online]. Available: https://gco.iarc.fr.

[2] D. Sathish, S. Kamath, R. KV and K. Prasad, “Medical imaging techniques and computer aided diagnostic approaches for the detection of breast cancer with an emphasis on thermography - A review,” International Journal of Medical Engineering and Informatics, Inderscience, vol. 8, no. 3, pp. 275- 299, 2016.

[3] M. C. Araújo, R. C. Lima and R. M. d. Souza, “Interval symbolic feature extraction for thermography breast cancer detection,” Expert Systems with Applications, vol. 41, no. 1, p. 6728–6737, 2014.

[4] E. Y.-K. NG and Y. CHEN, “SEGMENTATION OF BREAST THERMOGRAM: IMPROVED BOUNDARY DETECTION WITH MODIFIED SNAKE ALGORITHM,” Journal of Mechanics in Medicine and Biology, vol. 6, no. 2, pp. 123-136, 2006.

[5] D. Sathish, S. Kamath, K. Prasad and R. K. a. R. J. Martis, “Asymmetry Analysis of Breast Thermograms using Automated Segmentation and Texture Features,” Signal, Image and Video Processing, Springer, vol. 11, no. 4, pp. 745-752, 2017.

[6] J. S. a. A. S. Arora, “Automated approaches for ROIs extraction in medical thermography: a review and future directions,” Multimedia Tools and Applications, vol. 79, no. 1, p. 15273–15296, 2020.

[7] J. Iyadurai, M. Chandrasekharan and S. Muthusamy, “An Extensive Review on Emerging Advancements in Thermography and Convolutional Neural Networks for Breast Cancer Detection,” Wireless Personal Communications , vol. 137, no. 1, p. 1797–1821, 2024.

[8] K. F. F. C. d. Queiroz, J. R. A. d. Q. Júnior and H. D. a. R. d. C. F. d. Lima, “Automatic segmentation of region of interest for breast thermographic image classification,” Research on Biomedical Engineering , vol. 39, no. 1, pp. 199-208, 2023.

[9] N. P. Dharani, I. G. Immadi and M. V. Narayana, “Enhanced deep learning model for diagnosing breast cancer using thermal images,” Soft Computing, vol. 28, no. 1, p. 8423–8434, 2024.

[10] T. N. Chi, H. L. T. Thu and T. D. Q. a. D. Taniar, “A Lightweight Method for Breast Cancer Detection Using Thermography Images with Optimized CNN Feature and Efficient Classification,” Journal of Imaging Informatics in Medicine.

[11] M. A. S. A. Husaini and M. H. H. a. M. R. Islam, “Real time thermography for breast cancer detection with deep learning,” Discover Artificial Intelligence, vol. 4, no. 57, 2024.

[12] J. Pu, B. Zheng, J. K. Leader and D. Gur, “An ellipse-fitting based method for efficient registration of breast masses on two mammographic Views,” Medical Physics, vol. 35, no. 2, pp. 487-494, 2008.

[13] P. D. f. M. R. (DMR). [Online]. Available: Available at http://visual.ic.uff.br/en/proeng. [Accessed October 2022].

[14] S. Tello-Mijares and F. W. a. F. Flores, "Breast Cancer Identification via Thermography Image Segmentation with a Gradient Vector Flow and a Convolutional Neural Network," Journal of Healthcare Engineering Volume 2019, Article ID 9807619, 13 pageshttps://doi.org/10.1155/2019/9807619, vol. 2019, pp. 1-13.