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Research article

Automated tumor segmentation in thermographic breast images

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Abstract: Identifying and delineating suspicious regions in thermal breast images poses significant challenges for radiologists during the examination and interpretation of thermogram images. This paper aims to tackle concerns related to enhancing the differentiation between cancerous regions and the background to achieve uniformity in the intensity of breast cancer's (BC) existence. Furthermore, it aims to effectively segment tumors that exhibit limited contrast with the background and extract relevant features that can distinguish tumors from the surrounding tissue. A new cancer segmentation scheme comprised of two primary stages is proposed to tackle these challenges. In the first stage, an innovative image enhancement technique based on local image enhancement with a hyperbolization function is employed to significantly improve the quality and contrast of breast imagery. This technique enhances the local details and edges of the images while preserving global brightness and contrast. In the second stage, a dedicated algorithm based on an image-dependent weighting strategy is employed to accurately segment tumor regions within the given images. This algorithm assigns different weights to different pixels based on their similarity to the tumor region and uses a thresholding method to separate the tumor from the background. The proposed enhancement and segmentation methods were evaluated using the Database for Mastology Research (DMR-IR). The experimental results demonstrate remarkable performance, with an average segmentation accuracy, sensitivity, and specificity coefficient values of 97%, 80%, and 99%, respectively. These findings convincingly establish the superiority of the proposed method over state-of-the-art techniques. The obtained results demonstrate the potential of the proposed method to aid in the early detection of breast cancer through improved diagnosis and interpretation of thermogram images.

Keywords: breast cancer; cancer detection; image enhancement; image segmentation; thermography

1. Introduction

Medical imaging is pivotal in various clinical applications, including early detection, monitoring, diagnosis, and treatment evaluation of medical conditions [1]. Among these, breast cancer is one of the most frequently diagnosed cancers in women. Imaging examinations provide valuable information regarding breast lesions' size, location, and characteristics, aiding in formulating appropriate treatment strategies [2]. Breast cancer continues to pose a significant global health challenge. It is the most generally diagnosed cancer in women, affecting millions worldwide. According to the Global Cancer Observatory (GLOBOCAN) report, in 2020, the number of new breast cancer cases in both sexes and all age groups was significant, as shown in Figure 1. Breast cancer's impact extends beyond an individual's physical healing, influencing their emotional well-being, social dynamics, and overall quality of life. Early detection is crucial to improving patient outcomes, as it facilitates timely intervention and appropriate treatment strategies [3].

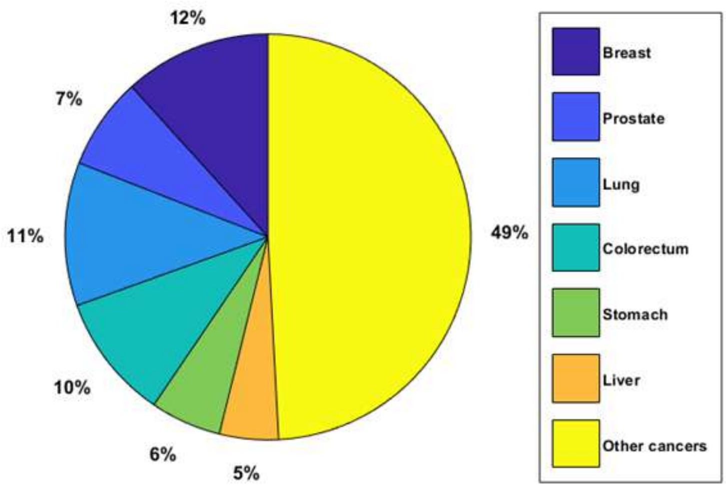


Figure 1. The total number of newly reported cases in 2020 across all age groups and genders.

Mammography (MG), a specialized low-dose X-ray imaging technique, is commonly used for routine breast cancer screening to facilitate early detection. Advancements in medical imaging technology have significantly contributed to the early detection and diagnosis of breast cancer [4]. However, MG has its limitations. Dense breast tissue, with a higher proportion of breast and connective tissues than fat, can make mammogram interpretation challenging, potentially obscuring lesions. This is especially true for younger individuals with denser breast tissue, rendering screening mammograms less effective for this group. Certain cancers may go undetected due to their location or breast tissue density. MG may not accurately identify tumors in specific populations, like many Chinese women with dense or mixed-type breast density.

To address the challenges and offer viable alternatives regarding dense breast tissue, thermal infrared imaging (TI) has emerged as a promising and safe diagnostic option. Dynamic thermography, a non-invasive procedure, has shown potential in detecting lesions in dense breasts, presenting advantages over mammography and magnetic resonance imaging (MRI) in terms of cost-effectiveness [5].

Thermal infrared imaging takes advantage of the fact that breast cancer regions often exhibit higher temperatures than surrounding tissues. Tumors increase metabolic heat and blood perfusion rates, leading to noticeable temperature differences. This non-ionizing imaging technique captures heat patterns emitted from the skin surface and can identify abnormal temperature variations between breasts or within a single breast. Furthermore, it provides valuable information about the size, shape, location, and depth of the lesion [6–8].

Moreover, other imaging tools such as MG, breast ultrasound, MRI, and breast computed tomography (CT) cannot provide skin vascular or metabolic information offered by medical thermology [9]. By utilizing thermal infrared imaging and dynamic thermography, healthcare professionals can offer an effective and safe alternative for women with dense breasts, providing valuable insights into breast health without exposing patients to ionizing radiation. Additionally, the clinical application of thermology can aid physicians in understanding breast pathophysiology and, ultimately, enhance patient outcomes. This advancement holds great promise in improving the early detection and diagnosis of breast abnormalities, contributing to better patient care and overall outcomes. Finally, breast infrared imaging (thermology) is a physiologic study that can assess changes in breast tissue by providing accurate and reproducible high-resolution images of skin temperature. This image can be analyzed both qualitatively and quantitatively for thermovascular mapping and for minute changes in skin heat emission, respectively. Then, these thermal findings can then be utilized as an assessment tool for breast health.

Despite its advantages, thermography is not a standalone method for breast cancer detection and diagnosis. It faces challenges such as low specificity, high false-positive rates, and the influence of environmental factors on temperature measurements. For reliable and accurate results, standardized protocols and guidelines must be followed. Therefore, thermography should be viewed as a complementary tool alongside imaging techniques like MG or MRI. Thermal image processing faces several challenges due to the unique characteristics and properties of thermal images [10]. The common challenges are as follows:

1) Thermal cameras often have a lower spatial resolution than visible light cameras, which makes extracting detailed information and accurately detecting small objects or features challenging.

2) TI is prone to various types of noise and artifacts, such as sensor noise, atmospheric interference, and non-uniformity, which can degrade the image quality and affect the accuracy of subsequent processing tasks.

3) TI captures temperature variations and different scenes may have varying temperature ranges. Handling a wide dynamic range of temperatures and accurately mapping them to an appropriate display scale is also challenging.

4) TI often contains complex scenes with multiple objects at different temperatures. Segmenting and extracting specific objects of interest from the background can be difficult due to the lack of clear boundaries and varying thermal signatures.

5) Various environmental conditions, including weather, humidity, and emissivity variations, can introduce distortions and affect the reliability of temperature measurements.

6) More TI formats, metadata, and processing techniques must be standardized. Different thermal camera manufacturers may use proprietary formats and processing algorithms, hindering the interoperability and compatibility across different systems.

Addressing these challenges requires advanced TI techniques, including noise reduction, segmentation methods, image fusion approaches, and robust thermal image object detection and tracking algorithms. This article aims to overcome these challenges and improve the accuracy and reliability of thermal image processing.

Table 1 provides a summary of the literature review of existing algorithms employed for segmenting regions of interest in breast thermograms and images. Each row in the table represents a different method used, and the columns describe the study's name, the segmentation techniques utilized, and the regions that were segmented.

Table 1. Summary of existing BC segmentation techniques and their characteristics.

Work	Method used	Description	Dataset	Advantages/limitations
[11] 1997	Unsupervised method for a semi-automatic segmentation	The objective is to generate objective measures for assessing the patient's cancer risk	No details about the dataset used	Focuses on asymmetry in heat patterns and "hot spots." However, perspective distortions and body asymmetry lead to inaccurate comparisons.
[12] 2004	Canny edge detectors used for exploring (modified Hough transform, longest connected edges, and edge density in the breast region).	aims to locate ROI in thermal images for breast cancer detection to identify the bottom breast boundary	21 different grayscale images	It is adaptable to various breast sizes and shapes due to the inclusion of adaptive processes. However, the method struggles with edge detection in images lacking strong edge lines for breast regions, and the HT limited success and manual parameter tuning are time-consuming.
[13] 2010	color K-means, and fuzzy c-means	The hotter regions in abnormal breasts, which indicate potential tumors	6 thermal cases were investigated	A good determination of the degree of malignancy. However, no analysis is shown for the likelihood of breast cancer based on these features and incorporating bio-data from questionnaires.
[14] 2010	Edge detection and Hough transform, and asymmetry analysis	The paper suggests an automatic approach through image segmentation and asymmetry analysis	images taken using IRI4040	Offers a feasible and practical method for breast cancer diagnosis.
[15] 2012	Hough transform + Canny edge detector and pattern classification (unsupervised clustering + supervised learning with feature extraction)	Two main steps are employed: automatic segmentation and pattern classification	i) Elliott Mastology Center (Inframetrics) and ii) Bioyear, Inc. (Microbolometer uncooled camera)	Advantages include objective diagnosis and early detection potential. Limitations involve dependence on dataset quality and the need for a substantial training set.

Table 1. Summary of existing BC segmentation techniques and their characteristics. (Continued)

Work	Method used	Description	Dataset	Advantages/limitations
[16] 2014	An improved level set. It involves anisotropic diffusion-based smoothing	The goal is to enhance and preserve edge information for accurate segmentation of breast tissues	-	The proposed segmentation method shows good agreement with ground truth images, achieving an average accuracy of 98% of regional similarity.
[17] 2014	3 image segmentation methods: k-means, fuzzy c-means, and level set	The level set algorithm is improved for efficient and accurate segmentation	30 images from various sources. Cases include fibrocystic and malignant cases	The level set algorithm proves to be more accurate, efficient, and robust for segmentation compared to k-means and fuzzy c-means.
[18] 2017	Fully automatic segmentation approach using shape features and Polynomial curve fitting and SVM for detection	The study aims to develop a CAD system for breast thermogram analysis	80 frontal view/ 40 normal and 40 abnormal cases	High accuracy 90%, and specificity 92.5% demonstrate the effectiveness of the method. However, performance may be impacted by image quality.
[19] 2019	A Gaussian filter for noise reduction, and ROI is segmented based on inframammary fold curves and bifurcation points. Classifiers based on support vector machine (SVM) with RBF, linear, and polynomial kernels	The proposed algorithm successfully segments the ROI and distinguishes between left and right breasts using shape concavity and convexity	35 normal and 25 abnormal frontal breast thermograms	The proposed methodology demonstrates high accuracy (95%), sensitivity (97.05%), and specificity (92.3%) in detecting. However, as with any CAD system, there is a possibility of FP and FN.
[20] 2019	The method combines the breast blood perfusion (BBP) model, an adaptive triangular histogram-based thresholding (ATHT) method, and a new energy functional-based level set method (LSM)	MSPSF is incorporated into a variational level set formulation thus challenges such as low contrast, intensity nonuniformity, noise, and complex background are addressed	DMR-IR database	The combination of BBP model, ATHT, and LSM provides an effective solution to challenging segmentation tasks in breast thermograms. However, the performance of the proposed may still be influenced by factors such as image quality, and dataset characteristics.
[21] 2019	The method includes identifying the upper boundary (UB) of the breast using an arc approximation algorithm and the lower boundary curve (LBC) to segment the inframammary fold region (IFR) of the breast and an IFR isolation method	Multiple steps, including boundary identification, tracing, and extrapolation, are employed to accurately segment the breast region	DMR-IR database	The proposed method achieves a high average segmentation accuracy of 95.75%. However, the study does not mention the potential challenges of the proposed, which might require further investigation.
[22] 2019	The paper proposes a cascaded convolutional neural network (CNN) architecture	Automated analysis of thermal images	DMR-IR database	The approach reduces errors and manual work required for segmentation, speeding up automated diagnosis.

Table 1. Summary of existing BC segmentation techniques and their characteristics. (Continued)

Work	Method used	Description	Dataset	Advantages/limitations
[23] 2020	The proposed method is called the Extending Contour Level Set (ECLS) model, which is a modification of the region-based level set method	A two-step approach is proposed to segment breast thermography images using the ECLS model in the first step and a new Controlled Chan-Vese (CCV) model in the second step.	DMR-IR database	The ECLS model is computationally efficient and less noise-sensitive compared to related segmentation methods. However, the limitations of the proposed ECLS and CCV model are not explicitly discussed.
[24] 2020	The paper proposes a segmentation based on the Chaotic Salp Swarm Algorithm (CSSA)	The proposed CSSA algorithm enhances the convergence rate and accuracy by controlling exploration and exploitation	DMR-IR dataset	The proposed CSSA algorithm optimizes the quick-shift method parameters, leading to improved accuracy in the segmentation process.
[4] 2020	Features are extracted using first and second-order statistics, and an artificial neural network (ANN) is trained with these features as input for classification	The proposed focuses on automatic segmentation using color intensities, thresholding operators, and local contrast enhancement	DMR-IR dataset	The proposed achieves competitive accuracy results ranging from 90.17% to 98.33%.
[2] 2020	automatic segmentation based on region growing	The proposed framework includes 3 main stages: image enhancement, tumor region segmentation, followed by coloring the segmented region	DMR-IR dataset	The proposed method achieves high segmentation accuracy 98.8%, outperforming state of the art methods.

Machine learning algorithms can be used for breast cancer detection, where they learn from labeled training data that experts annotate with cancerous or non-cancerous regions [2]. These supervised imaging methods can leverage the computational power of artificial intelligence and medical professionals' expertise to advance breast cancer detection. However, these methods also have some limitations and drawbacks that need to be addressed. One of the main drawbacks of supervised imaging for breast cancer detection is the reliance on labeled data. Collecting data accurately is costly and time-consuming, requiring expert knowledge and careful annotation of many medical images.

In recent machine learning-based segmentation methods, Acharya et al. [25] employed higher-order spectral features derived from thermograms in a feed-forward artificial neural network (ANN) classifier and a support vector machine (SVM). This novel approach exhibits a considerable potential for automating the classification of normal and abnormal breast thermograms, thereby eliminating the requirement for subjective interpretation. In a related investigation, Nicandro et al. [26] utilized Bayesian network classifiers to identify patients suspected of harboring cancer. Krawczyk et al. [27] devised a comprehensive methodology integrating three computational intelligence techniques. The ensemble comprised support vector machines as base classifiers, a neural fuser for amalgamating the individual classifiers, and a fuzzy measure for evaluating the diversity of the ensemble and eliminating specific classifiers.

Moreover, biases in the training data can affect supervised imaging techniques. These biases can stem from various factors, such as demographic and geographical differences in the data sources. Supervised imaging techniques also have limited adaptability to changing clinical situations and disease variations. The models learn from specific image features and patterns, which may not cover the range of variations in real-world cases. This lack of adaptability can lead to either false negatives or false positives, reducing the accuracy and reliability of the detection system.

The breast cancer detection system typically involves two key steps: image enhancement and segmentation. Image enhancement aims to improve the quality and clarity of the acquired images, thereby enhancing the visibility of potential cancerous abnormalities. Subsequently, segmentation techniques are applied to extract and isolate these regions of interest, enabling further analysis and diagnosis. This combined approach offers the potential to detect breast cancer at early stages, facilitating a prompt intervention and personalized treatment strategies [28]. On the other hand, segmentation plays a critical role in detecting breast cancer using thermal images. Its accuracy directly impacts the success of the classification system. Additionally, prior to feeding inputs into CNNs, image preprocessing of breast thermograms should be performed to facilitate a feature extraction process. Image preprocessing at this point could include image enhancement, denoising, and segmentation taking regions of interest (ROIs) of the breast thermograms. Feeding only the ROI portion into further supervised imaging techniques may accelerate the feature mapping operations in the convolutional layer because only the important parts of the breast thermograms are learned. Previous studies have shown that accuracy can be increased when the input images are segmented. Therefore, ROI segmentation needs to be targeted. The segmentation of the breast thermogram must cover all breast tissue and the area nearby the ganglion. Segmentation methods can be broadly categorized as manual, semi-automatic, and automatic.

Manual segmentation involves human experts manually outlining the regions of interest in the thermal images. This method is time-consuming and subjective, as it heavily relies on the expertise and experience of the annotator. Semi-automatic segmentation techniques combine manual inputs with automated algorithms. The algorithm performs the initial segmentation, and then the results are fine-tuned by human experts. This approach reduces the annotation time while still benefiting from human expertise. Automatic segmentation methods rely solely on computational algorithms to segment the breast tissue in thermal images. These algorithms analyze the image data and identify the regions of interest without human intervention. They are often based on advanced techniques such as machine learning and computer vision algorithms [29].

Subsequently, Araújo et al. [30] introduced a novel interval symbolic feature extraction method by employing morphological processing techniques on thermographic images. The efficacy of this approach was assessed by employing various parametric and non-parametric statistical classification rules. Ali et al. [31] investigated the necessity of predefining parameters in the data acquisition protocol, specifically the distance between the camera and the patient. The resulting segmented images are presented in a rectangular format, highlighting various breast regions; however, they fail to effectively identify specific regions associated with breast cancer. Etehadtavakol et al. [32] explored the utilization of higher-order spectral invariant features in classifying normal and benign classes by applying fuzzy c-means and Radon projections. The accuracy of this methodology is dependent upon the selection of appropriate Radon projection angles and slopes. Milosevic et al. [33] employed gray-level co-occurrence matrices to extract textural information from thermograms and subsequently segmented the ROIs using the minimum variance quantization technique. It is important to note that this approach is contingent upon the initial selection of cluster centroids and necessitates prior knowledge of the number of clusters. Lastly, Sathish et al. [34] proposed a technique that utilizes local energy features derived from wavelet sub-bands.

We will use the pre-segmentation step to reduce noise and enhance the image quality, making it more homogeneous and uniform. Various image processing techniques, such as noise filtering, contrast enhancement, and normalization, can be applied during this stage. Different methods can be employed post-segmentation to redefine the initial segmentation results. For instance, neutrosophic sets, which handle uncertainty in image segmentation, can be used to improve the accuracy of the segmentation. Moreover, optimized Fast Fuzzy c-mean algorithms, which leverage fuzzy logic principles, can be used to achieve better segmentation results.

However, despite advancements in segmentation techniques, there are still several challenges in thermal image segmentation for breast cancer detection. One challenge is noise/artifacts in the thermal images, which can affect the accuracy of segmentation algorithms. Additionally, individual breast shape, size, and texture variations can challenge achieving consistent and reliable segmentation results. Moreover, the need for annotated data for training and evaluating segmentation algorithms in thermal images limits the development and comparison of different methods.

To address these challenges, ongoing research focuses on developing robust segmentation algorithms that are less sensitive to noise and can handle variations in breast appearance. This research aims to enhance the prediction of a tumor prognosis using thermal imaging for breast cancer detection. The main contribution of the paper is listed as follows:

- Novel contrast enhancement algorithms combining local and so-called hyperbolization histogram equalization algorithms;
- Novel tumor segmentation algorithms using an image-dependent weighting strategy;
- The experimental results on the DMR-IR database have demonstrated that the proposed algorithm significantly enhances the performance of the state-of-art segmentation algorithms.

The subsequent sections of this paper are structured as follows. Section 2 provides comprehensive information on the materials and methods. The computer segmentation results are showcased in Section 3, including objective and subjective evaluations. In Section 4, the discussion of the experimental results is presented. Finally, Section 5 presents the paper by summarizing the key discoveries and proposing future directions.

2. Materials and methods

This section describes the proposed approach, starting with the data collection process. This subsection presents information about acquiring and selecting breast images from a suitable database. Next, we explain the methodology of breast cancer detection, describing the proposed technique or algorithm used in this study. It covers the step-by-step image enhancement procedure, tumor region segmentation, and breast cancer detection. This subsection aims to understand the methodology used to address the challenges associated with accurate cancer detection. Finally, we discuss the evaluation metrics used to assess the performance and effectiveness of the proposed method. Various quantitative metrics such as accuracy, sensitivity, specificity, and dice coefficient are considered to evaluate the segmentation and detection results. These metrics play a crucial role in objectively measuring performance and determining the strengths and limitations of the proposed approach. Figure 2 briefly summarizes the proposed method for the automated detection of breast cancer using thermography images.

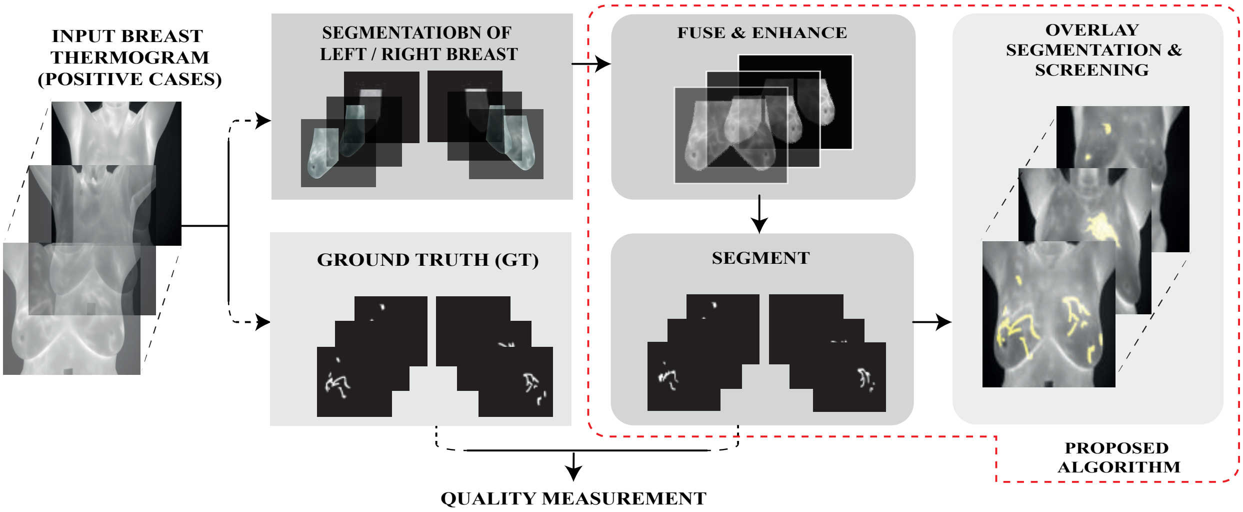
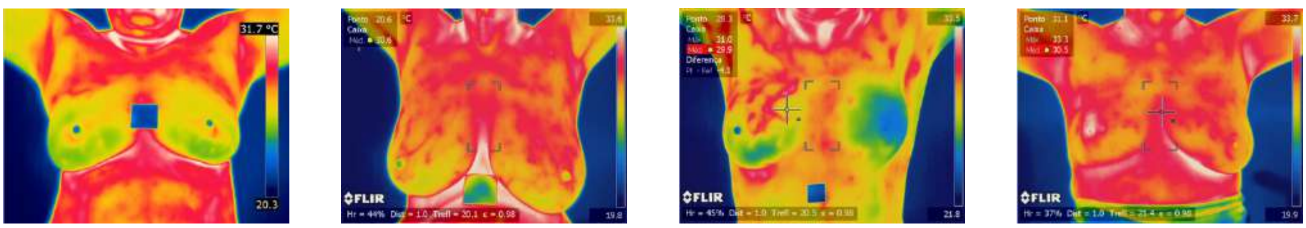


Figure 2. Flowchart of the proposed automated detection of breast cancer using thermogram.

2.1. Data used

In recent years, numerous databases have been established to investigate the diagnostic capabilities of breast thermography, including Perez [35] and Silva et al. [36], Ann Arbor Thermography [37], the American College of Clinical Thermology [38], the Thermal imaging lab in the San Francisco Bay Area [39], Thermography of Iowa [40], and Sunstate Thermal Imaging Center in Australia. Most of the breast thermograms are from private databases. Our study utilized the publicly available Database for Mastology Research (DMR-IR) database, which is comprised of personal and clinical data from 287 patients [36]. This database contains $(640 * 480)$ resolution thermal images with a thermal sensitivity of (40 mK), taken from five different views of the breast: front, right oblique 45° (R45), left oblique 45° (L45), right lateral 90° (R90), and left lateral 90° (L90). Additionally, the database includes corresponding thermal matrices that provide temperature information for each pixel. The thermal images were acquired using a FLIR SC620 thermal camera, employing both static and dynamic protocols. The static protocol involved capturing a single image after allowing the patient to rest for 10 to 15 minutes to achieve thermal stabilization.



(a) (b) (c) (d)

Figure 3. Sample images depict the breasts of several patients. Tumors exhibiting higher temperatures are visualized in shades of red or orange, whereas cooler tissues are represented in shades of green. Breast thermal images downloaded from the DMR-IR database [1,36].

Figure 3 compares thermograms depicting normal and abnormal breasts obtained from the DMR database [36]. These thermal images showcase three patients with distinct medical histories. Figure 3(a) shows a thermogram of a healthy patient without prior screening tests. Figure 3(b) presents a thermogram of another healthy patient, who had previously undergone MG, with no complaints or symptoms but with warts on the left breast. Figure 3(c) displays a thermogram of a patient diagnosed with breast cancer who had undergone a left breast biopsy. Similar to Figure 3(c), Figure 3(d) illustrates a thermogram acquired from a patient diagnosed with breast cancer, who had undergone a left breast biopsy. These images exhibit varying temperature distributions, which serve as crucial indicators in breast thermography for breast cancer detection. The observed temperature variations among these cases play a pivotal role in detecting and differentiating breast abnormalities, making thermography a valuable tool in the early identification and monitoring of breast cancer.

2.2. *Methodology of breast cancer detection*

This paper presents a comprehensive methodology for breast cancer detection using thermal images, employing an image enhancement-based fusion strategy with an image-dependent weighting approach. The proposed method is designed to improve the accuracy and reliability of the breast cancer detection system by refining the thermal images and identifying potential cancerous regions.

2.2.1. Image enhancement

The first stage of the proposed methodology involves image enhancement as a pre-processing step. When captured, thermal images may suffer from various artifacts, noise, and low contrast, which can impede accurate cancer detection. To overcome these challenges, we apply specific enhancement techniques to improve the quality and clarity of the thermal images. The enhancement process includes local linear and hyperbolization functions to enhance contrast and preserve over-brightness in the images. The enhanced images based on the linear and hyperbolization functions can be respectively expressed as follows:

$$[X_a]_{i,j}^{m,n} = \min\{[I_a]_{i,j}^{m,n}\} + (\max\{[I_a]_{i,j}^{m,n}\} - \min\{[I_a]_{i,j}^{m,n}\}) \cdot [c_a]_{i,j}^{m,n} \quad (X.1) \tag{2.1}$$

$$[Y_a]_{i,j}^{m,n} = \beta \max\{[I_a]_{i,j}^{m,n}\} \cdot e^{\ln(1+\frac{1}{\beta})\cdot[c_a]_{i,j}^{m,n}} \tag{2.2}$$

where β represents a constant, and $[c_a]_{i,j}^{m,n}$ denotes a local cumulative density function of a local image, $[I_a]_{i,j}^{m,n}$. Here, m and n are the size of a local block, and i and j are a pixel location of an input image, $I_{i,j}$. In this paper, β and m, n are set as 0.0001 and 9×9, respectively.

2.2.2. Image fusion

The core of the proposed methodology lies in the image fusion technique, which combines the enhanced thermal image with complementary information to augment the detection process. The fusion strategy is based on an image-dependent weighting approach, where different parts of the thermal image are given a varying importance depending on their characteristics and relevance to breast cancer detection. By assigning appropriate weights to different image components, the fusion process aims to highlight potential abnormalities indicative of breast cancer. The fused image can be calculated as follows:

$$E_{i,j} = \frac{I_{i,j}}{I_{L-1}} E_H + \left(1 - \frac{I_{i,j}}{I_{L-1}}\right) E_L \tag{2.3}$$

where E_H refers to an image enhanced by a local hyperbolization function, E_L denotes an image enhanced by a local linear function, $I_{i,j}$ represents an input thermal image, and I_{L-1} is the total number of luminance levels of an input image, $I_{i,j}$.

2.2.3. Segmentation

The enhanced and fused thermal image is analyzed using segmentation algorithms to identify regions that are suspected to be affected by breast cancer. Segmentation is a critical step that isolates potentially cancerous areas, allowing for further evaluation and analysis. The segmentation algorithm used in this methodology is designed to distinguish between healthy breast tissue and potentially cancerous abnormalities based on the local image luminance of enhanced regions. The regions identified through segmentation are further analyzed in subsequent stages to determine their malignancy. The segmentation process can be described as follows:

$$S_{i,j,\alpha} \Leftarrow R(E_{i,j}, T^{'}_{i,j}, \varepsilon) \tag{2.4}$$

where ε is an acceptable error of segmented regions, and R is a region growing algorithm. $E_{i,j}$ denotes a fused thermal image, $T^{'}_{i,j}$ refers to initializing regions, and α is the total number of initializing regions. The segmentation algorithm requires the initialization of regions to segment potentially cancerous regions based on local luminance intensities. They can be defined as follows:

$$T^{'}_{i,j} = T_{i,j} \otimes M_{a,b} \tag{2.5}$$

$$T_{i,j}(E_{i,j} \geq \mu) = 1 \quad (X.5) \tag{2.6}$$

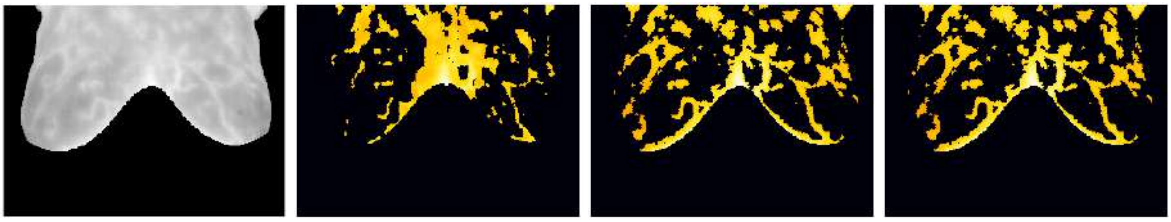
where $M_{a,b}$ represents a median filter, a and b are the size of an image filter, and μ refers to a global threshold. In this paper, μ and a, b are set as: 0.8627 and 3×3, respectively. This segmentation process enables the identification and isolation of potentially cancerous areas for further analysis and diagnosis. By employing these aforementioned key steps, the breast cancer detection system aims to enhance the accuracy and effectiveness of early detection, ultimately facilitating a timely intervention and improved patient outcomes. The breast cancer detection algorithm is technically illustrated in Algorithm 1.

The analysis of Figure 4 reveals significant observations about the breast cancer detection system. First, when solely employing an image enhanced by a local hyperbolization algorithm, the resultant segmented regions appear to be continuous but notably larger. Conversely, solely employing an image enhanced by a local linear algorithm yields segmented regions; however, certain areas are observed to be either absent or missing. Consequently, combining enhanced images and incorporating both local hyperbolization and local linear algorithms demonstrates a more precise depiction of cancer regions. This enhanced image amalgamation presents a more accurate representation, mitigating the limitations observed in the individual algorithms.

Algorithm 1 Breast Cancer Detection

Require: Thermal image, $I_{i,j}$
Ensure: Segmented Regions, $M_{i,j}$

Normalize the input image:
$I'_{i,j} \leftarrow \frac{I_{i,j}-\min\{I_{i,j}\}}{\max\{I_{i,j}\}-\min\{I_{i,j}\}}$
Apply Image Enhancement algorithms to the normalized image using Eqs (2.1) and (2.2).
Fuse the enhanced images using Eq (2.3).
Define the initializing regions:
$T'_{i,j}(E_{i,j} \geq \mu) = 1$, where μ is a global threshold.
for $\alpha \leftarrow 1$ to card($T'_{i,j}$), where card($\cdot$) is a cardinality operator **do**
    $T'_{i,j} = 1$
    Apply image segmentation using Eq (2.4).
end for
Combine the segmented regions:
$M_{i,j} \leftarrow \max_{\alpha}\{S_{i,j,\alpha}\}$, where $S_{i,j,\alpha}$ represents the segmented regions for each α.



(a) (b) (c) (d)

Figure 4. Comparison with different preprocessing enhancement algorithms; (a) input thermal image, (b) segmented regions on the image enhanced by a hyperbolization function, (c) segmented regions on the image enhanced by a linear function, and (d) segmented regions on the image enhanced by linear and hyperbolization functions.

3. Results

In this section, we comprehensively evaluate the breast cancer segmentation methods using visual and statistical assessments. The aim is to assess the performance of the proposed automatic method against the Tunable Weka trained method (automatic method), the Graph Cut manual method, and Segment Anything by Meta AI [41]. The assessments are carried out to determine each method's robustness, accuracy, and efficiency in segmenting breast cancer regions. On the other hand, the developed segmentation model was subjectively compared with existing methods in the literature. The performance of the proposed method on the DMR-IR dataset of thermal images using Accuracy, Sensitivity, and Specificity metrics was compared against the aforementioned segmentation methods.

3.1. Evaluation metrics

The fundamental tool in image processing involves segmenting an image into either distinct regions or objects. It plays a crucial role in various applications, such as medical imaging. Evaluating the performance of image segmentation algorithms is essential to assess their accuracy and effectiveness. Several evaluation metrics are commonly used to measure the quality of image segmentation results.

Specific terminologies are employed to assess the performance of cancer detection algorithms through image segmentation. The number of pixels correctly identified as cancerous is called True Positives (TP). In contrast, the number of pixels predicted as malignant but healthy is categorized as False Positives (FP). True Negatives (TN) represent the accurate identification of healthy pixels, and False Negatives (FN) indicate the misclassification of cancerous pixels as healthy. In this paper, we used three key metrics: Accuracy, Sensitivity, and Specificity.

Table 2 presents the corresponding equations and a brief description of each metric used in this study.

Table 2. Metrics used for segmentation evaluation.

Metric	Equation	Description
Accuracy	$\frac{TP+TN}{TP+FP+TN+FN}$	Accuracy is a primary evaluation metric that measures the overall correctness of the segmentation results. It represents the ratio of correctly classified pixels to the total number of pixels in an image.
Sensitivity	$\frac{TP}{TP+FN}$	Sensitivity measures the proportion of actual positive pixels correctly identified as tumor-positive by the given segmentation algorithm. It indicates the ability of the given algorithm to detect the TP regions in the image accurately.
Specificity	$\frac{TN}{TN+FP}$	Specificity measures the proportion of actual negative pixels correctly identified as negative by the segmentation algorithm. It indicates the algorithm's ability to accurately exclude or reject regions that do not belong to the objects of interest.

3.2. *Visual assessments*

In this subsection, we present a visual comparison of the breast cancer segmentation results obtained from three methods: the proposed one is automatic, alongside the Tunable Weka train model [42], Graph Cut manual methods [43], and Segment Anything model by Meta AI [41,44]. This comparison aims to evaluate the robustness and accuracy of the proposed automatic method compared to the other two approaches.

As can be seen from Figure 5 (third row), the segmentation results obtained from the proposed automatic method are visually assessed and compared to the Ground Truth (GT) (second row). The GT represents a medical professional's expert-labeled GT segmentation, serving as the evaluation reference. Through visual inspection, it can be observed that the proposed method achieves a high level of accuracy in delineating the boundaries of the breast cancer regions. The segmented areas closely align with the GT, indicating that the proposed method successfully captures the essential features and patterns of the cancerous regions.

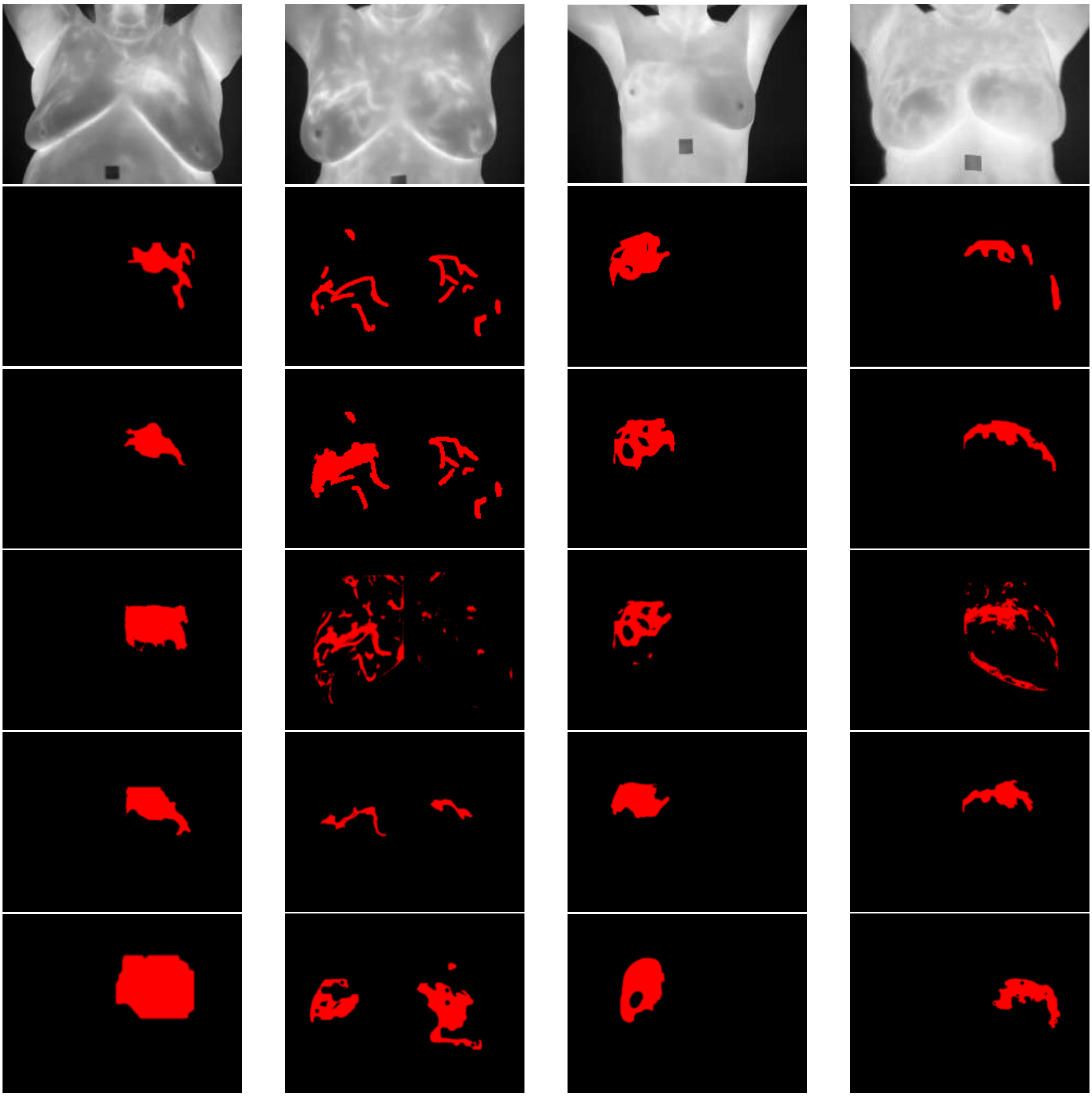


Figure 5. Visual BC segmentation comparison using various methods: rows 1:6 respectively show the original BC imagery, ground truth (GT), proposed, Tunable Weka, Graph Cut, and Meta segmentation results.

In terms of the results obtained from the Tunable Weka, this later demonstrates reasonably accurate segmentation, and there are certain regions where the boundaries do not precisely match those of the Ground Truth. Sometimes, the Tunable Weka method fails to capture fine details or may over-segment certain areas. Furthermore, the Graph Cut, which is a manual method, achieves high accuracy in segmentation, closely matching the GT. However, due to its manual nature, this method is time-consuming and labor-intensive, requiring significant expertise. Additionally, the manual method may be prone to inter-observer variability. Moreover, The META method demonstrates quite a good performance in segmentation, exhibiting a close alignment with the GT. However, it is important to note that the method falls short in terms of accuracy and tends to result in dilatation during the segmentation process. Overall, the visual assessments reveal that the proposed method outperforms both the Tunable Weka, Graph Cut, and META methods regarding robustness and accuracy. The proposed method achieves results comparable to GT, while eliminating the need for labor-intensive and time-consuming manual segmentation. These results highlight the potential of the proposed method for efficient and reliable breast cancer segmentation.

3.3. Statistical assessments

In this section, we conduct a comparative analysis of the proposed segmentation method against various studies, focusing on metrics such as accuracy, sensitivity, and specificity.

As shown in Table 3 the proposed method achieves the highest accuracy among the compared studies, at 97.8%. Moreover, it shows high specificity (True Negative Rate), at 99%, matching the performance of the study [45]. These values indicate that the proposed method can correctly identify most of the true positives and true negatives in the dataset, which are crucial metrics for evaluating the study quality. However, the proposed method has a lower sensitivity (True Positive Rate) than the study [46], at 100% compared to 60%. This suggests that the proposed method may miss some of the true positives and classify them as false negatives, affecting its reliability.

Table 3. Comparison of the proposed BC segmentation against the state-of-the-art methods. The best results with a green bar color.

	Quality metrics			
Study	Year	Accuracy	Sensitivity	Specificity
ETEHADTAVAKOL et al. [13]	2010	0.800	NG	NG
NICANDRO et al. [26]	2013	0.718	0.820	0.330
ARAÚJO et al. [30]	2014	NG	0.857	0.865
ACHARYA et al. [25]	2014	0.900	0.920	0.880
MILOSEVIC et al. [33]	2014	0.850	NG	NG
KRAWCZYK et al. [27]	2014	0.887	0.798	0.910
ALI et al. [31]	2015	0.881	0.850	0.800
PRAMANIK et al. [47]	2016	0.900	0.950	0.850
LESSA et al. [48]	2016	0.850	0.870	0.830
SATHISH et al. [18]	2017	0.910	0.872	0.943
GOGOI et al. [49]	2017	0.875	0.950	0.800
CACCIABUE et al. [42]	2019	0.940	0.670	0.940
TAYEL et al. [45]	2020	0.960	0.970	0.970
SANCHEZ et al. [46]	2021	0.970	1.000	0.830
BAFFRA et al. [50]	2021	0.943	NG	NG
Proposed	2023	0.978	0.600	0.990

4. Discussion

Thermal imaging has emerged as a widely adopted and cost-effective tool in detecting and classifying breast cancer. This paper introduces an automated segmentation tool designed for breast cancer analysis using thermal images. Through computer simulations conducted on the DMR-IR dataset, our proposed approach demonstrates a superior segmentation efficiency and flexibility compared to end-to-end learning approaches and supervised and unsupervised methods. The performance of our algorithms was evaluated using commonly employed assessment metrics such as accuracy, sensitivity, and specificity. Furthermore, the strengths of our work lie in its ability to extract cancer regions with reduced computational complexity, thereby enhancing its practical applicability.

The visual assessments involved comparing the segmentation results obtained from the proposed automatic method to the GT segmentation, which represents expert-labeled annotations. Through visual inspection (Figure 5), it was observed that the proposed method achieved a high level of accuracy in delineating the boundaries of breast cancer regions. The segmented areas closely aligned with the GT, indicating that the proposed method successfully captured the essential features and patterns of the cancerous areas.

Overall, the proposed method achieved results comparable to the GT, while eliminating the need for labor-intensive and time-consuming manual segmentation. These results indicate the potential of the proposed method for efficient and reliable breast cancer segmentation. In the statistical assessments, we conducted a comparative analysis of the proposed segmentation method against various state-of-the-art studies. The proposed method achieved the highest accuracy of 97.8%, indicating its ability to correctly identify most true positives and true negatives in the dataset. However, the proposed method had a lower sensitivity (True Positive Rate) than one of the studies, suggesting that it may miss some true positives and classify them as false negatives, thereby affecting its reliability. Sensitivity is crucial, as it indicates the ability to correctly identify true positives, thereby reducing false negatives. It is important to note that the comparison was made against a variety of studies with different segmentation approaches and datasets, which may have different complexities and characteristics. Therefore, the proposed method's performance, needs to be interpreted with respect to the specific dataset and conditions used in this study.

While the proposed method showed promising results, there are some limitations to consider. The relatively lower sensitivity indicates the need for further refinement to improve the detection of true positives. Additionally, the proposed method's performance may vary depending on the dataset and imaging conditions, highlighting the need for further validation on diverse datasets.

5. Conclusions

This paper introduces an innovative approach to enhance and segment thermal breast images, aiming to support radiologists in detecting breast cancer more effectively. The method focuses on increasing the contrast between cancerous regions and the background while ensuring uniform intensity levels within tumor areas. It is comprised of two stages: a local image enhancement technique based on a hyperbolization function that adapts to image characteristics and a dedicated segmentation algorithm employing an image-dependent weighting strategy for precise delineation of tumor boundaries. Evaluation of the proposed method on the DMR-IR database demonstrates outstanding segmentation accuracy, sensitivity, and specificity performance, surpassing existing techniques in image quality and tumor detection. The potential impact of the proposed method is substantial. Improving the interpretation of thermogram images can facilitate early breast cancer diagnosis. Furthermore, it can empower physicians to make more accurate and validated breast cancer diagnoses, benefitting patients with better-informed decisions. Integrating thermal infrared imaging and dynamic thermography into clinical practice represents an invaluable opportunity to advance breast healthcare. By complementing traditional imaging techniques with thermology, healthcare professionals can enhance their ability to evaluate and diagnose breast-related conditions, ultimately offering patients proactive and personalized care. Moreover, the method's versatility allows its application in various biomedical imaging domains. Looking ahead, the future direction of this research involves combining the developed segmentation method with accurate classification techniques. This integration promises to improve further sensitivity, specificity, and overall patient outcomes in breast cancer detection and management.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors have no conflicts of interest to declare. The co-author has seen and agreed with the manuscript's contents, and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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