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A systematic review of breast cancer detection on thermal images

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Abstract

Breast cancer poses a substantial global health concern, primarily regarding its impact on women. Thermal imaging has emerged as a promising tool for early detection with notable technological advancements between 2013 and 2023 in enhancing diagnostic capabilities. However, existing literature reviews often lack adherence to specific scholarly standards and may provide incomplete insights into research trends. This systematic literature review (SLR) addresses these issues by comprehensively analyzing research trends, publication types, contributions, datasets, methodologies, and effective approaches for breast cancer detection using thermal imaging. The review encompasses an examination of 40 articles from reputable digital libraries, revealing a predominant emphasis on deep learning algorithms among 25 applied methods. These algorithms consistently achieve commendable performance, frequently surpassing 90% accuracy rates. Consequently, current research in breast cancer detection via thermal imaging is marked by a strong focus on artificial intelligence, particularly machine and deep learning, recognized as the most promising and effective avenues for investigation.

Keywords: Artificial intelligence; breast cancer; deep learning; systematic literature review; thermal breast images

1. Introduction

Breast cancer globally represents the most diagnosed malignancy among women and carries a substantial mortality burden. In 2020 the World Health Organization, Indonesia recorded 68,858 new cancer cases out of 396,914 new cancer cases worldwide with the death rate of 22,000 [1]. It is proven that developing countries have a risk of getting cancer almost twice as much as some existing studies where the ratio of the incidence of death in developed countries is around 0.2; while in developing countries, it is 0.37 [2]. Early detection is crucial in reducing breast cancer incidence as it can increase a recovery chance for the patients [3].

Various methods have been utilized to aid in the early detection of breast cancer, such as mammography, ultrasound, and magnetic resonance imaging (MRI). Thermographic techniques are currently being studied to show promising results [3–6]. It can capture the temperature difference generated by the heat of the tumor area in the body, where the area is hotter than the healthy area [3]. Several previous researchers conducted early examinations of breast cancer detection using computer-assisted thermographic images, using a range of methods from conventional to artificial intelligence-based approaches such as the CNN method. Currently, research in the field of breast cancer detection has rapidly developed with many researchers focusing on image processing, machine learning, and deep learning. The main topics in this area are classification and segmentation.

Several recent studies have tested and suggested detecting breast cancer using infrared images, such as a study by Lakshman [7] who detected breast cancer using random forest and the support vector machine (SVM) methodology. The experiment results indicated that the support vector machine (SVM) and random forest (RF) methods achieved 94.5% and 98.40% accuracy, respectively through cross-validation. In addition, Khan [8] utilized a combination of texture features, feature selection methods, and ensemble classifiers to detect cancer with an accuracy of 92.55%. Further, Matheus [5] used artificial intelligence to conduct a similar research for automated breast cancer detection with infrared images. The researcher proposed to analyze the infrared image to classify the patient's image as healthy or unhealthy. The main contribution was to provide accurate classification using convolutional neural networks (CNN). The results showed 98% accuracy for static images and 95% for dynamic images. The advancement of breast cancer detection research poses a significant challenge in identifying novel research gaps for researchers in infrared image-based detection. The swift evolution of this research topic will influence future research, resulting in difficulties in identifying the most current research contributions. Therefore, collecting and identifying existing research to capture critical aspects, including the resulting performance, methods, weaknesses, research merits, data sets, and contribution to the research is necessary.

This study aims to locate and recognize recent research on

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breast cancer detection using infrared images and thoroughly investigates numerous factors such as the approach taken to address the problem, annual trend, performance results, and methodology utilized. The results of this study are expected to provide an overview of what trends are developing in research in breast cancer. This document structure has five main sections: introduction, related works, methodology, results and discussion, and conclusion. Section 2 discusses about research papers about the reviews of breast cancer with medical images. Section 3 of this paper outlines the methodology used for the research and Section 4 discusses about the outcomes and answers to the research. Lastly, Section 5 concludes this paper.

2. Materials and Method

2.1. Systematic literature review (SLR)

These studies [9–11] conducted systematic reviews on various aspects of breast cancer detection, including the use of thermography with artificial intelligence, advances in CNN models, and segmentation techniques. These reviews highlighted the need for more accurate and efficient detection methods using advanced technologies such as Deep Learning. Previous literature reviews lacked a clear framework and adherence to certain standards, necessitating the use of a systematic literature review method in this study.

The systematic literature review (SLR) method has become the standard for reviews. It is a framework that identifies, evaluates and interprets existing research findings and answers predetermined research questions. The method has been used in several studies in various fields. Sumi [12], for instance, conducted a review to identify recent research developments in the field of Plasmodium parasite detection, while Pachouly [13] reviewed software defect prediction using artificial intelligence. These studies followed the SLR approach, which consists of planning, implementation and reporting stages.

A systematic literature review (SLR) involves three stages as illustrated in Figure 1 consisting of planning, conducting, and reporting. During the planning stage, it is acknowledged that conducting a systematic literature review (SLR) is crucial for breast cancer detection using thermal images. Review rules are carefully developed to ensure a clear focus and minimize bias. This stage also involves defining research questions, designing search strategies, selecting relevant literature, extracting data, assessing the quality of each study, and synthesizing the results. The SLR outlined in this paper encompasses six review protocols, which were developed, evaluated, and refined iteratively during the implementation and reporting stages of the review.

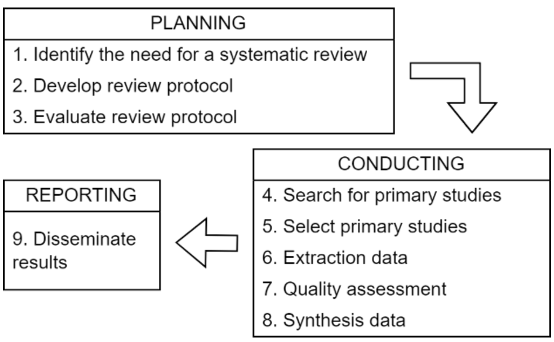

Fig. 1. Systematic literature review steps

2.2. Research question

The first step in defining the SLR protocol is the research question (RQ), which has a vital role in maintaining the focus of research implementation [14]. This paper formulates a research question with five elements: population, intervention, comparison, results, and context (PICOC). The PICOC criteria used in this SLR are presented in Table 1. The research questions in this SLR are designed based upon the PICOC criteria and the specific needs of the topic. Table 2 presents a list of research questions (RQ) that aim to investigate research trends related to breast cancer detection using infrared images (RQ1-RQ2) and to identify various aspects such as dataset, method, performance, most used method, and contribution of each study (RQ3-RQ7).

Table 1. PICOC summary

Population	Object detection and automatic detection
Intervention	Segmentation, Classification, and Dataset
Comparison	Methods
Outcome	The performance of methods that have been used, The accuracy of breast cancer detection
Context	Medical and Research studies in academia

Table 2. Research questions

ID	Research Question
RQ1	How many articles on thermal breast cancer detection are published each year?
RQ2	Which category of publications has the highest number of studies on breast cancer detection using thermal imaging?
RQ3	What contribution does the author make from research on breast cancer detection by thermal imagery?
RQ4	What dataset is employed for detecting breast cancer using thermal imaging?
RQ5	What are the methods utilized for breast cancer detection with thermal imaging?
RQ6	Which method is the most frequently utilized for detecting breast cancer with thermal imaging?
RQ7	Which method exhibits the highest performance in detecting breast cancer using thermal imaging?

2.3. Search strategy

The objective of the search strategy is to sift through the essential information. This involves data collection from relevant sources and search by means of appropriate keywords. The most used literature databases were searched to obtain a broad range of studies. The search strategy was developed through the following steps:

1. Identifying search terms related to the population and intervention from the PICOC criteria.
2. Extracting appropriate search terms from the research questions provided.
3. Including additional items in the list.
4. Identifying search terms from titles, abstracts, and relevant keywords.
5. Finding the correct and suitable spelling of the search terms.
6. Constructing search word combinations using Boolean operations (AND and OR).

(Classification OR detection OR segmentation) AND (breast) AND (cancer) AND (thermal) AND (image).

The keywords used in each database varied based upon the database specific requirements and relevance. It is essential to adjust the search terms to meet each database needs to ensure that the data obtained were relevant. This study focused on open-access papers and was limited to the publication year in the range of 2013 to 2022 and included conference proceedings and journals. The databases used in the search are listed below:

- ScienceDirect (sciencedirect.com)
- IEEE Explore (ieeexplore.ieee.org)
- Nature (nature.com)
- SpringerLink (link.springer.com)

Table 3. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
The journal article should be part of the journal papers or conference proceedings publication category	Research that does not use thermal images as the primary modality for breast cancer detection
The journal article should detail the data collection process, the methods employed, and the additions to the existing literature	Studies lack clear identification of the problem being investigated.
The journal articles should have been published within the last decade from 2013 to 2023	Journal articles are written in a language other than English.

2.4. Data selection

In this stage, the objective was to select journal articles and assess their suitability for use in a Systematic Literature Review (SLR). The inclusion and exclusion criteria, as displayed in Table 3, were established to ensure a focused and relevant selection of literature. The search results were stored in the Mendeley application, serving as a manager and repository for the search outcomes. Each database was searched using the appropriate terms to collect the desired data, as illustrated in Figure 2.

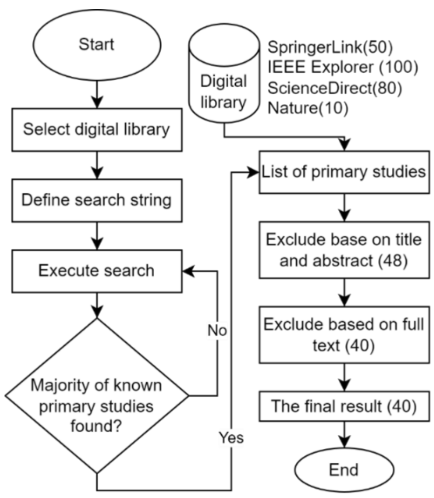

Fig. 2. Primary studies selection steps

An important aspect to note in our methodology is the deliberate focus on open-access articles. This decision was made to ensure the accessibility of the reviewed content for a broader audience, including researchers and practitioners who may not have access to subscription-based journals. While this limitation restricted our review to a subset of available literature, we believed that it would not reduce the quality of our review. The open-access articles included in this review are from reputable sources and peer-reviewed journals, ensuring the credibility and relevance of the findings discussed.

The initial search phase yielded 48 literature pieces. After applying our inclusion and exclusion criteria, we narrowed down the selection to 40 articles. Articles that did not align with the research objectives or failed to meet the criteria were excluded. This refined selection of open-access literature was used to gather preliminary information and delineate the sub-topics discussed.

It is important to acknowledge that by limiting our review to open-access sources, we may have excluded some relevant studies published in non-open-access journals. However, the extensive database search and systematic selection process employed ensured that the review comprehensively covered the key trends and developments in the field of breast cancer detection using thermal imaging. Future research could aim to include a broader range of sources, encompassing both open-access and non-open-access articles, to provide a more exhaustive overview of the research in this domain.

2.5. Data extraction

This paper performs a data extraction process from the selected information to create primary data that can address the research questions. This aims to simplify the process of extracting data. The form needs to include specific properties. These properties were determined by examining the research questions and conducting analysis and were then arranged in Microsoft Excel for mapping. Table 4 displays the characteristics of the data extraction process concerning the research questions.

Table 4. Data extraction

Properties	Research Question
Journal Publication	RQ1, RQ2
Original Research Contribution	RQ3
Method	RQ5, RQ6, RQ7
Dataset	RQ4

3. Results

3.1. [RQ1] Research trends

This study reviews 40 articles studying thermal image research for breast cancer detection. Literature was selected based on specific criteria according to the research questions and then sorted by year of publication to analyze trends in breast cancer detection research. The findings revealed a consistent upward trend over the years although a decrease was observed in 2023 due to the inclusion of only January's articles. These findings, as presented in Figure3, answered the research question (RQ1).

3.2. [RQ2] Publication type category

In addressing Research Question 2 (RQ2), this study identified two primary types of publications: journal articles and conference proceedings. Our analysis indicated a balanced distribution between these two categories with a slight majority of conference proceedings. Specifically, of 40 articles analyzed, 21 of them (53%) were conference proceedings, while the remaining 19 (47%) were journal articles.

This distribution can be attributed to several factors. Conference proceedings often serve as a platform for presenting the latest research developments and innovations, which is particularly relevant in rapidly evolving fields like breast cancer detection using thermal imaging. They provide an avenue for researchers to share preliminary findings and novel ideas in a more timely fashion compared to journal publications, which typically have longer review and publication cycles.

On the other hand, journal articles, especially those published in prestigious journals like IEEE Transactions on Medical Imaging, Applied Sciences, Traitement du Signal, and Computers in Biology and Medicine, offer a more rigorous peer review process. This contributes to a higher level of validation and scrutiny, ensuring that the research methodologies and results are thoroughly vetted. The presence of articles from these top-tier journals in our review underscores the significance and maturity of the research in this area.

It is also noteworthy that most of the conference articles came from similar conferences with the CBMS conference as the most prominent contributor, featuring two articles. This suggests a focused interest and a collaborative effort within the academic community attending these conferences, dedicated to the advancement of thermal imaging techniques in breast cancer detection.

The balance between conference proceedings and journal articles in this review reflects the dynamic nature of the research field. While conference proceedings provide a glimpse into cutting-edge and ongoing research, journal articles contribute depth and rigor, ensuring a comprehensive understanding of the field's progress and challenges.

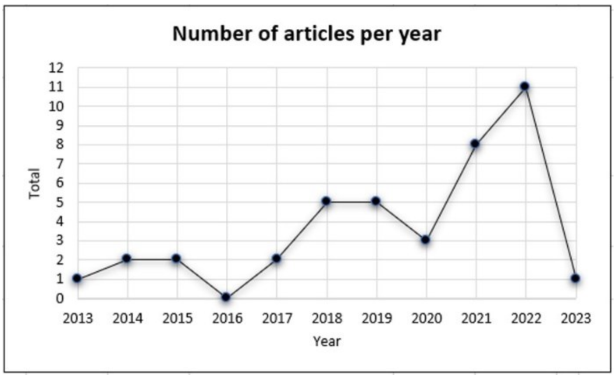

Fig. 3. Research trend of the breast cancer detection

3.3. [RQ3] Research contributions

This section aims to determine how the objectives of each study are met and answer the research questions (RQ3) by identifying research contributions. In generating this, several categories were used to elicit contribution information in each literature, including pre-processing, segmentation, optimization, and classification. The authors of each literature claimed that their proposed method's results are effective, but this study must accurately identify the literature to validate the results. Hence, it is necessary to note that this paper's main goal is to evaluate the proposed approach and methods used to address the research problem. Most proposed methods used modifications and additions to existing methods, and no stand-alone method exists.

In summary, this study narrowed the evaluation of contributions into four categories using reference methods from the respective literature. Table 6 shows that 67% of the research is related to the classification method, 20% to the segmentation method, 8% to optimization, 5% to pre-processing and 3% to extraction feature methods. The complete results of the contribution assessment are presented in Table 5.

3.4. [RQ4] Dataset used for detection of breast cancer

This section discusses about the datasets utilized in 40 studies reviewed. These datasets were broadly categorized into public and private datasets. Public datasets are those, which are publicly available or open access, while private ones are typically sourced from specific laboratories, institutions, or hospitals and are not openly accessible.

In our analysis, as detailed in Table 5, a significant majority of the studies, approximately 36 or 90%, employed public datasets. It is noteworthy that the DMR-IR dataset [52] emerged as the most frequently used public dataset among the reviewed literature. This dataset, comprising IR images from UFF University Hospitals, is publicly accessible and has become a benchmark in the field.

The predominant use of the DMR-IR dataset as the primary public dataset can be attributed to several factors. Firstly, the scarcity of comprehensive and publicly available datasets in this domain limits the options for researchers. The DMR-IR dataset, as one of the few publicly accessible datasets, offers a valuable resource for the research community. Additionally, its usage across multiple studies aids in establishing a consistent benchmark for the comparison and validation of various methodologies.

However, this reliance on a single, predominantly used public dataset like DMR-IR also points to a gap in the availability of diverse and extensive public datasets in thermal imaging for breast cancer detection. It underscores a need for more open datasets to foster varied and robust research in this area.

Furthermore, few studies that utilized both public and private datasets aimed to compare and validate results across different data sources, thereby enhancing the robustness of their findings. This approach also helps in understanding the applicability and generalizability of the proposed methods across different datasets.

3.5. [RQ5] Breast cancer detection using a thermal imaging method

The 40 selected types of literature were analyzed to identify the method used, which became the subject of the Research Questions (RQ5). The compendium of techniques for breast cancer detection through thermal imaging was organized into four major categories encompassing 25 models: Neural Networks and Deep Learning models like CNN and its variations lead the pack, followed by Evolutionary and Optimization Algorithms such as GA and PSO. Feature

Extraction and Texture Analysis methods, including edge detectors and texture classifiers, provide detailed image assessments. Hybrid and Combined Method integrate multiple computational techniques, and Statistical and Clustering Methods, like K-means, offer pattern recognition and data classification. Additionally, a range of Other Methods were employed for various specialized tasks within the field as shown in Figure 4.

Table 5. List of selected papers on breast cancer detection

Study	Topics	Pre-processing	Methods	Results
[15]	Pre-processing	-	Sobel edge detection	NA
[16]	Pre-processing	-	3D Filtering Technique (BM3D)	NA
[17]	Extraction Feature	Image Cropping	GLCM	Accuracy = 73% and Precision = 79%.
[18]	Optimization	Converting 2D images into 3 channels and im- age resizing	GA and PSO	F1-score of 0.92 for VGG-16 and 0.90 for ResNet-50
[19]	Optimization	Data Augmentation	GA and PSO	The improved F1-score from 0.92 to 1 for the DenseNet with GA and F1-score from 0.85 to 0.92 for the ResNet with PSO
[20]	Segmentation	Color Analysis	K-Means Clustering	NA
[21]	Segmentation	Removing Color Scale, Converting to Grayscale Image, and Removing Background Region and Gray-Level Reconstruction	CNN and SVM	Average accuracy:72.18% (public databases), 71.26% (private databases)
[22]	Segmentation	Averaging Filter, Thresholding and Image Cropping	MultiResUnet	The average accuracy of 91,47%
[23]	Segmentation	Anisotropic Diffusion Filter and Black Top- Hat Method	Texture analysis methods	AUC = 0.989
[24]	Segmentation	Image Cropping	Arc-approximation algorithm and IAT	The average accuracy of 95.75%
[25]	Segmentation	Resizing image	U-Net network and CNN	Accuracy= 99.33%, sensitivity= 100% and specificity= 98.67%
[26]	Segmentation	Color space conversion	K-Means FCM and GMM-EM	FCM segmentation gives good accuracy
[27]	Segmentation	Image denoising, Image enhancement, and Segmentation of chest and upper limb areas	Acupoint selection method for autonomous massage	Accuracy greater than 90.12%
[28]	Classification	Manual removal of background and Grayscale conversion	First-order statistical features	NA
[29]	Classification	Image Cropping	VGG16 + GLDA	100% diagnostic accuracy
[30]	Classification	Image cropping, Color space conversion, Im- age enhancement using anisotropic diffusion	Least Square Sup- port Vector Machine (LSSVM)	Accuracy = 89%
[5]	Classification	Summing all image Colors	CNN and SVM	98% accuracy on static data, 95% on dynamic data.
[31]	Classification	Removing background and converting to grayscale images	GLCM features	NA
[32]	Classification	Converting to grayscale images	Backpropagation neural network	Accuracy= 96.51%, sensitivity= 79.7%, and specificity= 98.25%
[33]	Classification	Removing background and converting to grayscale images	DLPE-LSM	Accuracy= 84.5%
[34]	Classification	Removing background and converting to grayscale images	Inception V3 (CNN) and SVM	Confidence of 0.94 for Healthy and 0.78 for Sick
[35]	Classification	-	VGG16, ResNet50 VGG19, and InceptionV3 (CNN)	ResNet50: 88.89% Highest test performance at
[36]	Classification	Resizing image	ResNet101, DenseNet, MobileNetV2, and ShuffleNetV2 (CNN)	Accuracy ResNet101 and MobileNetV2= 0.996, ShuffleNetV2=0.98
[37]	Classification	Image refinement, Image sharpening filter, and CLAHE	Inception-v3 (CNN)	Accuracy of 80% and a recall rate of 83.33%
[3]	Classification	ROI Segmentation, Database Cleaning, and Data Augmentation	Benchmark and Fine- Tuned Filter (CNN)	Accuracy= 92%, Precision= 94%, Sensitivity= 91%, and F1score= 92%
[38]	Classification	Image cropping	LINPE-BL: A Local Descriptor and Broad Learning	The average accuracy of 96.90% for public and 94% for private

Table 5. List of selected papers on breast cancer detection (Continued)

Study	Topics	Pre-processing	Methods	Results
[39]	Classification	Resizing image, Con- version to 3-channel images, and Data augmentation	VGG-16, Densenet201, and Resnet50 (CNN)	F1-score= 0.92, accuracy= 91.67%, sensitivity= 100%, and specificity= 83.3% obtained with the Densenet
[40]	Classification	Contrast enhancement, Resizing image, Crop- ping image, and Data Augmentation	inception v3 (CNN)	The achieved the highest accuracy is 99.928%
[41]	Classification	Resizing image	AlexNet, VGGNet, ResNet50,and GoogleNet (CNN)	Accuracy of 100%
[42]	Classification	Conversion to 3-channel images	SPAER: Sparse Deep Convolutional Autoencoder Model	The best accuracy of 78.2% (74.3–82.5%)
[43]	Classification	-	ResNet-18 (CNN)	Accuracy rate of 92.52%
[2]	Classification	Feature selection, Min-max scaling and Normalization	CNN	The best model achieves 97% accuracy, a specificity of 100% and a sensitivity of 83%
[44]	Classification	Global Pixel Similarity and Image Transformation	Hybrid computational method	The accuracy results reach 99% in the K-star classification
[45]	Classification	Contrast enhancement, Resizing image, Crop- ping image and Data Augmentation	VGG-16, VGG-19, ResNet50V2, inceptionV3 (CNN)	Accuracy VGG-16= 99%, VGG-19= 95%, ResNet50V2= 94%, InceptionV3= 89%
[46]	Classification	Resizing image	Two edge detectors and DenseNet121	Accuracy= 98.80%
[47]	Classification	Contrast enhancement, Resizing image, im- age cropping, Data Augmentation and Concatenation	Breast Cancer-Caps	Accuracies of 99.5% and 98%
[48]	Classification	Resizing image, denoising, normalization, data augmentation and data splitting	VGG16, GoogleNet, Resnet50, and VGG19 (CNN)	Outperformed other models with 100% accu- racy
[49]	Classification	Cropping image	VGG-19, DenseNet201, ResNet50, and EfficieNetB0 (CNN)	Accuracy= 0.93, precision= 0.94, sensitivity= 0.93 and specificity= 0.95
[50]	Classification	Resizing image, cropping image, normalization	CNN with attention mechanisms (AM)	Accuracy= 99.46%, sensitivity= 99.37% and specificity= 99.30%
[51]	Classification	Gaussian filter	Contiguous Convolutional Neural Network (CCNN) classifier	97.56% success and the lowest error rate of 0.8%

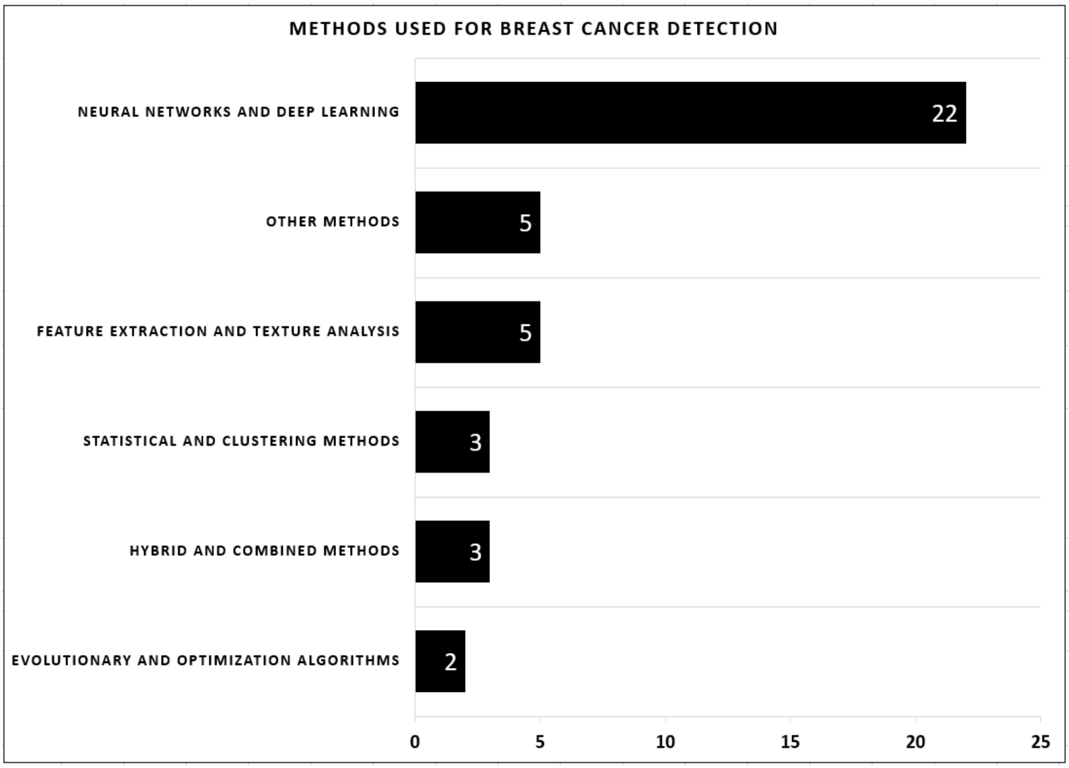

Fig. 4. The methods used in the detection of breast cancer

Table 6. The proportion of contribution by research methods

Dataset Type	Total	Percentage (%)
Classification	27	67
Segmentation	8	20
Optimization	2	5
Pre-Processing	2	5
Extraction Feature	1	3

Researchers use the method shown in Table 5 to perform various tasks in thermal image-based breast cancer detection studies, including preprocessing, optimization, Segmentation, and classification. The first step is preprocessing, which involves identifying the region of interest (ROI) or performing data augmentation. Subsequently, segmentation aims to isolate the breast object from the image background, allowing for the focused processing of segmented objects. Additionally, an optimization technique is used to update the weights based on the training data iteratively. Finally, classification is performed to determine the relevant class for the research. These processes are interdependent.

Numerous techniques have been implemented to enhance breast cancer detection using thermal images. For instance, Prabha [16] introduced an imaging method with an aim to separate right and left breast tissues in denoised images for asymmetry analysis, concentrating on image pre-processing. Their proposed technique successfully increased the signal-to-noise ratio and maintained precise edges and was found to eliminate thermal network noise according to experimental results.

Research conducted by Lou [22] aimed to develop a breast cancer segmentation method using the MultiResUnet model. This model was used to classify breast regions based on IR image series. To read the image for segmentation, the threshold method removed noise; then, it was cut and separated manually. This study used cross-validation and showed that MultiResUnet achieved an average accuracy of 91.47%. The research conducted by Goncalves [19] is like the learning optimization method, proposing two optimization techniques, GA and PSO. The goal was to find the best hyperparameters and architecture for the three connected CNNs: VGG-16, ResNet-50, and DenseNet-201. This study obtained an F1 score above 0.90 for the third network using optimization techniques.

Several researchers have researched the classification of breast cancer. Alshehri [50] is one such researcher using CNNs with attentional mechanisms (AMs) that evaluated model performance in terms of accuracy, sensitivity, and specificity in thermal images. The experimental results demonstrated that the promised model achieved the high testability of 99.46%, 99.37%, and 99.30% for the thermal breast dataset, representing an accuracy increase of 7% compared to CNN without AM. As shown in Figure 4 and discussed earlier, the techniques utilized in thermal breast cancer research are diverse. Nonetheless, deep learning, machine learning algorithms, and image processing methods remain prevalent in most studies.

3.6. *[RQ6] The most widely used method for detecting breast cancer with thermal detection*

Figure 4 displays 25 techniques used to identify breast cancer using thermal imaging. The four most frequently used methods are GLCM, CNN, CNN-SVM incorporation, and optimization with the GAPSO method, as shown in Table 7.

This section presents the findings for research questions (RQ6). As depicted in Figure 4, CNN methods remain the most popular choice for researchers in addressing breast cancer detection issues using thermal imaging. It is the most used for classification purposes among deep learning methods. Out of the 25 methods depicted in Table 7, 12 use the CNN method, either individually or in combination with other methods. The results indicated that deep learning and machine learning methods are reliable for accurately identifying breast cancer in thermal images for segmentation and classification tasks with accuracy rates above 90%.

This impacts traditional techniques, which are being replaced by deep learning and machine learning algorithms. However, these approaches have their limitations. They, for instance, require a lot of computing power and time, and deep learning algorithms require enormous amounts of training data to achieve the prominent levels of accuracy.

For this reason, some research works concentrate on enhancing computing optimization and resources. Another issue with deep learning methods is that there is no universally accepted formula for each scenario, so the only way to compare the outcomes of each CNN method used is to evaluate them. Existing resources, such as the number of datasets, still limit this strategy.

3.7. *[RQ7] The best method for detecting breast cancer with thermal imagery*

This section answers the research question (RQ7) and discusses 25 different methods that have been suggested for detecting breast cancer. Of the 25 methods proposed for breast cancer detection, CNN was the most used method with 12 reviewed papers utilizing this deep learning algorithm. The GLCM method has been used in three papers, and two papers use the combined methods of CNN-SVM and GA-PSO. CNN algorithm has shown excellent performance.

Determining the best-performing method requires the consideration of numerous factors, presenting a challenge for future research. Deep learning algorithms have their respective strengths and weaknesses as the most used algorithms. To use these algorithms effectively, researchers must first understand the nature of the problem they are trying to solve. One of the features of this approach is the lack of a specific formula for each problem, requiring an experimental approach. Therefore, researchers must analyze and understand the research object to choose the appropriate algorithm to solve the problem.

Looking at the most recent research and the best performance, the CNN method is prevalent in breast cancer research using thermal images because it has high value and reliable performance. Zuluaga's [3] diagnostic system utilizing thermal images is an instance of this where a convolutional neural network is employed for computer-aided diagnosis. The study examined the effects of data pre-processing, data augmentation, and database size on several

CAD models. The CNN model in this study achieved an accuracy of 92% and an F1 score of 92% in a dataset of 57 patients, outperforming some other advanced architectures.

Table 7. Most used methods

Methods	Total
GLCM	3
CNN-SVM	2
CNN	12
GA-PSO	2

Despite the CNN method having certain drawbacks, such as its high training data requirement, time-consuming training process, and overfitting, many related studies have previously conducted research using several types of CNN methods. As a result, in the future, researchers can continue using the CNN method with different modifications to obtain the desired level of accuracy. Judging from the dataset's characteristics, public data stands out in this study, meaning that the problems faced by researchers are the same, so many of the same methods are used. Some researchers also suggested to looking for additional or creating new datasets on breast thermal images because it is directly proportional to the early diagnosis made by experts in determining standards for breast cancer patients.

4. Discussion and Future Works

4.1. Distinction between conference papers and journal articles

In addressing the nuances of our source material, it was crucial to delineate the distinct characteristics and contributions of conference papers and journal articles in the field of breast cancer detection using thermal imaging.

Conference papers are often the first point of dissemination for new research ideas. They are characterized by their immediacy and potential for presenting preliminary findings and innovative approaches. The rapid publication cycle of conference proceedings allows for a quicker exchange of ideas, which is vital in a fast-paced research field such as thermal imaging in breast cancer detection. However, the brevity and time constraints associated with conferences might result in less comprehensive research compared to journal articles. The peer-review process, while rigorous, is typically less extensive than that of journals, potentially affecting the depth of analysis and validation.

In contrast, journal articles usually undergo a more thorough peer-review process, contributing to their reliability and validity. They are often more comprehensive, including detailed methodologies, extensive data analysis, and in-depth discussions. Journal articles in our review, such as those published in IEEE Transactions on Medical Imaging and Computers in Biology and Medicine, represent mature research with validated findings. They provide a deeper understanding of the subject matter, often building upon the preliminary findings first reported in conference papers.

Our review acknowledges the strengths and limitations of both types of publications. While conference papers offer a glimpse into the cutting-edge and evolving nature of research, journal articles provide the depth and rigor necessary for a holistic understanding of the field. By including both in our review, we aimed to present a balanced view, capturing the dynamic nature of ongoing research as well as the established, deeply-analyzed findings in the domain of thermal imaging for breast cancer detection.

This approach ensures that our review not only reflected the latest developments in the field but also encompassed the comprehensive research necessary for a nuanced understanding of the subject. In future studies, a longitudinal analysis of how conference findings evolve into journal publications could provide further insights into the maturation process of research in this domain.

4.2. The need for diverse datasets in thermal imaging research for breast cancer detection

The current research landscape in breast cancer detection using thermal imaging is heavily reliant on the DMR-IR dataset. While this dataset, sourced from UFF University Hospitals, pro- vided a rich collection of IR images, the over-reliance on a single dataset posed significant limitations to the generalizability and innovation in the field.

1. Generalizability issues: Sole reliance on DMR-IR raises concerns about the generalizability of research findings. Datasets with diverse patient demographics and cancer types are crucial for developing universally applicable detection methods in medical imaging [53].

2. Innovation and bias risks: The repeated use of the same dataset can lead to stagnation in methodological innovation and increased risks of bias and overfitting in machine learning models. Emphasizing the need for diverse datasets to prevent overfitting, especially in deep learning applications [54].

To address these issues, it is essential to explore additional datasets. Potential sources include collaborations with medical institutions for access to diverse patient data, utilization of international datasets to understand regional differences in breast cancer, and synthetic data generation where data privacy and availability are constraints.

Future research directions should include dataset comparison studies to evaluate the adaptability of detection methods across different datasets [55]. Moreover, methodological innovations are needed for algorithms that are robust against diverse data characteristics [56]. Cross-dataset validation can also help in assessing the generalizability and reliability of existing models [57].

In conclusion, diversifying the datasets used in thermal imaging research for breast cancer detection is crucial for the advancement of the field. Collaborative efforts and innovative approaches are key to overcoming the limitations posed by the current dataset-centric research paradigm.

5. Conclusion

Breast cancer is a significant health concern globally, particularly in developing countries, where mortality rates are higher due to the late detection. Early detection is crucial in improving patient outcomes and survival rates. Various imaging methods, including mammography, ultrasound, and MRI, have been employed for early breast cancer detection. However, thermal imaging techniques have emerged as a promising alternative due to their ability to capture temperature differences between healthy and tumor areas. In this study, we conducted a systematic literature review to explore recent research on breast cancer detection using thermal images. Our analysis revealed a rising trend in breast cancer detection research, focused on image processing, machine learning, and deep learning methods. The primary research topics were classification and segmentation. Several recent studies demonstrated successful breast cancer detection using infrared images. Various methods, including support vector machine (SVM), random forest (RF), convolutional neural networks (CNN), and hybrid techniques, have been proposed. Among these, CNN emerged as the most widely used and best- performing method, achieving the high accuracy rates for segmentation and classification tasks. The systematic review identified the critical aspects of the research, including dataset types, methodologies, and contributions made by researchers. We found that public datasets were predominantly used, highlighting a need for more diverse and standardized datasets for future studies. The most used method was CNN, which outperformed other algorithms in terms of accuracy and efficiency. Researchers emphasized the importance of deep learning and machine learning techniques in achieving accurate breast cancer detection results. However, some challenges remain, such as the high computational power and data requirements of CNN methods. Future research should focus on refining deep learning algorithms and exploring new datasets to improve breast cancer detection using thermal imaging.

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