Performance Improvement of Breast Cancer Diagnosis Using Artificial Intelligence and Image Processing Techniques

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Abstract. One of the most deadly and terrible diseases in the world that kills women is breast cancer. The timely detection of breast cancer can significantly impact and potentially save the lives of numerous women. Radiologists and clinicians have turned to computer-aided diagnosis as the burden of diagnosing breast cancer has grown. Based on thermal imaging, machine learning, and deep learning are employed in this study to diagnose breast cancer. Three stages—preprocessing, features extraction, and artificial neural network classifier—are used to investigate the proposed technique. Additionally, four Deep Learning models—AlexNet, GoogleNet, SqueezNet, and ResNet18—are suggested to attain high performance and accurate breast cancer diagnosis. The Machine Learning algorithm achieves accuracy of 89,74%, sensitivity of 82,35%, and specificity of 95,45% in simulation results. Additionally, Deep Learning models, like AlexNet, achieve accuracy levels of 100%.

Keywords: Breast cancer, computer-aided diagnosis, Thermogram image, Artificial Neural Network, convolutional neural network.

1. Introduction

One of the most frequently diagnosed cancers in women worldwide is breast cancer [1]. Globally, 2.3 million women (11.7%) received a breast cancer diagnosis in 2020, and 685 000 people died from the disease. By the conclusion of 2020, breast cancer is projected to become the most prevalent form of cancer worldwide, with approximately 7.8 million women living who were diagnosed within the past five years [2].

Breast cancer can be found using a variety of breast image modalities, including ultrasound, magnetic resonance imaging (MRI), mammography, thermography, and others. In contrast to thermal imaging, which is suitable for all patients, non-invasive, inclusive, painless, and safe, mammography is expensive, ineffectual, and not ideal for women with dense breasts. Mammography is considered the definitive method for early detection of breast cancer [3].

Thermal imaging of the breast shows that breast cancer tissue has a higher temperature than normal tissue, resulting in hotspots on the thermogram. In healthy breasts, the temperature distribution is symmetric [4]. Due to errors in interpreting and differentiating between healthy and diseased breast thermal images using the naked eye, doctors have turned to computer-aided diagnosis (CAD), smart systems, and computer vision techniques, leading to consistent and effective diagnostic performance [5].

2. Literature Survey of Research

CAD heavily relies on Artificial Intelligence (AI), specifically Machine Learning and Deep Learning techniques, to analyze the breast. These techniques analyze the breast through different methods. The three fundamental steps in any computer-assisted breast cancer detection system are pre-processing, feature extraction, and classification.

2.1 Step I: Pre-processing process and Segmentation.

The pre-processing stage of an image is used to improve the thermographic images' quality. Following the conversion of the RGB colour input image into intensity grayscale, the steps of the image pre-processing include image segmentation and image de-noising by a filter. Due to its significance, some study separates the image segmentation step from the pre-processing stage of the image. Image segmentation is the process of breaking an image up into distinct pieces to make analysis easier. Many image segmentation techniques, such as edge detection, thresholding, clustering, compression-based techniques, histogram-based techniques, etc., are presented in [6–12] either entirely manually or fully automatically [6].

The technique of segmenting the breast region involves dividing it from the rest of the body. The Region of Interest is the name of this area (ROI). The diagnosis will be accurate depending on how thoroughly this area is segmented. The ROI must be included Breast structure and all its tissues.

In [7], manual breast segmentation was performed using techniques that divide each breast into four quadrants and others that use an ellipse on a patient to isolate the ROI. Due to the lack of a distinct shape and visible breast boundaries in thermal images in [8], others were manually split.

The area of the tumor search can be narrowed down, and the time and effort needed for manual segmentation can be reduced with automatic segmentation and separation of the breast area from thermal pictures. Using the subtle edge detection operator and the gradient operator, [9] created a novel method for automatically segmenting the ROI of a breast thermogram. In [10], the ROI of the right and left breasts were extracted using a segmentation method that used four terminal lines to divide the breast region (upper, lower, left, and right). In [11], it was demonstrated that a suggested algorithm could successfully divide all different breast types (small, medium, large, asymmetric, and flat). In [12], it was suggested to use trained Convolutional and Deconvolutional Neural Networks (C-DCNN) to automatically segregate breast areas in thermal images.

2.2 Step II: Features Extraction

Feature extraction, one of the key procedures in CAD systems, is used to lessen the complexity of the classification process. The texture of thermogram photographs reflects changes in temperature. There are numerous ways to extract texture features, including statistical and structural information transformation. Tumors and certain tissue activities are some common characteristics of cancer that experts utilize to make an early diagnosis [13].

In [14], a Non-parametric t-test analysis, which gave the statistical and textural features differences between sick and healthy breasts, was used to choose the features. Texture and entropy features were used in [15] to extract 112 features. From 40 thermal images, 20 features were extracted by GLC matrices in a study [16].

The feature extraction process can be carried out either manually or mechanically. Deep learning (DL) is frequently employed in the context of autonomous extraction by training a dataset with multi-layer convolutional neural networks, a well-liked machine learning (ML) method [17].

2.3 Step III: Classification

After pre-processing and features extraction, classification is the last step. For categorization, ML and DL are employed. Multi-Layer Perceptron (MLP), K Means Clustering Algorithm, Support Vector Machine (SVM), Decision Trees (DT), Random Forests, K-Nearest Neighbors (KNN), Extreme Learning Machines (ELM), and Artificial Neural Network (ANN) are the most used ML algorithms.

Different approaches to classifying breast tumors were put forth in [18] by extracting properties using the Haralick and Zernike descriptors. DT, MLP, ELM, and Bayesian classifiers were applied. The accuracy of the MLP classifier achieved 76.01%. [19] employed the Backpropagation Neural Network Model (BPNN) classifier, which has good accuracy. In [20], an SVM classifier was used to classify 80 frontal breast pictures, 50 of which were normal and 30 of which were pathological. This approach's accuracy, sensitivity, and specificity were 91.25%, 93.3%, and 90%, respectively. In [21], significant machine learning classification models—KNN, DT, SVM, and RF—were employed to classify the photos and identify potential malignant images. In this investigation, the KNN classifier provides the best classification.

ELM classifier with a more significant activation function was utilized in [22]. One of the best methods for detecting breast cancer is the ELM classifier with "Tribas" activation function, which achieved an accuracy of 95.94%. In [23], two techniques: ELM and MLP, were evaluated for the thermal imaging-based early diagnosis of breast cancer. The outcomes demonstrated that the ELM classifier had the best accuracy. In [24], the K-Star classifier was used for dynamic thermography images (20 DIT images), obtaining high accuracy using a 10-fold cross-validation method. In [25], images captured using dynamic thermography were classified using the ANN. The system demonstrated high accuracy with negative predictive values of 99.1% and positive predictive values of 83.67%. Deep learning was used in [26] to categorize breast thermograms. Less than 190 photos from the dataset were used. Although the results were not satisfactory and not all aspects were accurately graded, it was nevertheless a significant step forward for deep learning.

The difference between ML and DL is that the DL doesn’t need to extract features because it contains this process in its architecture. In DL, CNN is regarded as the most popular computer vision-based AI approach for identifying breast cancer. Due to their resilience and ease of use, CNN methods are more practical than those relying on texture and statistical data. In [27], a CNN model named "AlexCNNbreast.m" was used to classify images using the Gradient Vector Flow technique (GVF), which provided great accuracy. [28] suggested the CNN app as a classifier for dynamic and static images. This study's accuracy rates for the dynamic and static protocols were 95% and 98%, respectively. In [29], static and dynamic images were classified using four CNN models: ShuffleNetV2, DenseNet, ResNet101, and MobileNetV2 for breast cancer detection. The results showed that MobileNetV2 achieved high accuracy.

The performance of seven pre-trained CNN models, including ResNet-101, ResNet-50, Inception-v3, GoogLeNet, VGG-19, AlexNet, and VGG-16, was compared to that of the dataset in [30]. The VGG-16 had the highest specificity and balanced accuracy, both of which was 82.35%. Another comparison of the CNN designs resnet18, resnet34, resnet50, resnet152, vgg16, and vgg19 can be found in [31]. The outcomes were highly accurate. Conversely, ShuffleNet was used and altered in [32] by adding a convolutional layer and extra filters to enhance its performance and achieve higher accuracy.

[33] compares various CNN models, including Inception V4, Inception V3, and Inception MV4, based on various optimization techniques, including Root Mean Square Prop (RMSPROP), Adaptive Moment Estimation (ADAM), and Stochastic Gradient Descent (SGD). This DCNN Modified Inception MV4 is more accurate and faster than Inception V4. The study in [34] introduced the CNN DenseNet121 model that was used to extract the features for constructing a classifier. The performance of DenseNet121 was compared with six other pre-trained models (VGG16, VGG19, DenseNet169, Xception, and Inception) in terms of extracting features from 3-channel edge-prominent breast images. The results showed that the DenseNet121 model achieved impressive accuracy.

3. Proposed Method

Two totally autonomous systems for the early identification of breast cancer are suggested in this research. The three stages of a proposed system are, in order, pre-processing the images, feature extraction, and machine learning classifier. Second, to quickly and accurately diagnose the other automatic system, four CNN models are pre-trained to be used: AlexNet, SqueezNet, ResNet18, and GoogleNet.

This section demonstrates the dataset, the proposed methods, the pre-processing and segmentation step, the features extraction step, and various classification methods.

3.1. Dataset

In this paper, the two automatic systems are implemented based on a database of 190 thermal images (112 healthy and 78 sick) obtained from [35]. Figure (1) presents procedures for taking a thermal image of the breast in real work. The patient must be in an upright position with their hands raised. Images are taken with a camera made of Forward-looking infrared (FLIR). These images usually included the abdomen and breasts axilla, and neck areas.

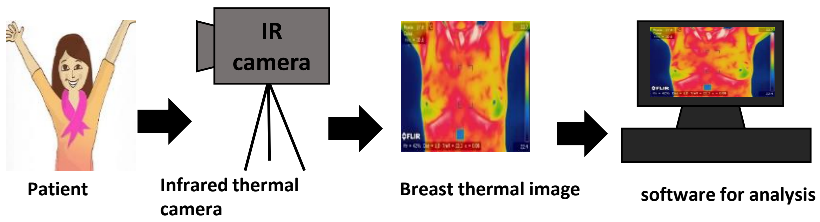

Fig. 1. The procedure for capturing thermal images.

3.2. The First Proposed Method:

The pre-processing stages for thermal photos must be completed first. The proposed method then divides the breast into its left and right halves for analysis. Different features are taken from the image after it has been segmented. The ANN classifier receives the retrieved features as input to evaluate this new model as shown in Figure (2).

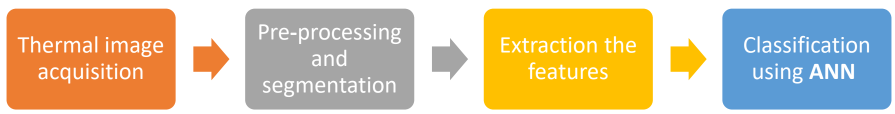

Fig. 2. The procedural framework for carrying out the core operations in the first proposed approach.

3.2.1 Image Pre-Processing and Segmentation Stage:

The image pre-processing method is used to enhance the thermographic image quality and increase the effectiveness of the features extraction phase from the Region of Interest (ROI) and classification phase. Image noise reduction is a crucial stage in the pre-processing process which comes after transforming the RGB input image into grayscale image where black pixels indicate the lowest temperatures and white pixels the highest.

To eliminate the impulsive noise brought on by the flaws in the thermal camera, the median filter is used for the original grey image. The Region of Interest (ROI) section is separated from other body parts in the proposed Algorithm (1) by dividing the image horizontally into two halves (the top part of the body and the ROI part), as illustrated in Figure 3(a).

Algorithm 1: Proposed Image Pre-processing Approach
1: Read original thermal image X.
2: Convert X to grey scale image G.
3: Apply median filter to G.
4: Determine the height of G as T.
5: Define upper ratio U, initially set U=0.225, which may be changed.
according to the axilla position found in Algorithm 2.
6: Compute the upper part M = round (T*U).
7: Extract the ROI part G_L.

In ROI segmentation: The proposed segmentation algorithm is used to segment the left and right breasts from the ROI image based on the breast structure.

Step I: The ROI image is converted to a binary image using threshold value λ.

Step II: Breast points determination for the right breast (left part in the image) The axilla point is determined by the point at which the position (P) of the white pixels at the boundary increases and then decreases starting from the top left of the image as shown in Figure 3(b). After the axilla, the maximum curvature point is determined by the pixel at the position where the white pixels decrease and then increase. The position of the white pixels increases again after the curvature point till it reaches a constant value which means that the breast ends. And the opposite will be done for the left breast (breast in the right part), starting from the top right.

The breast area in the grey version is formed by a horizontal cut at the axilla and a vertical cut through the center of the image. This proposed algorithm does not cut through the inframammary incision, but the cut is determined by the axilla not to lose a part of the breast because some images have the nipple at that point.

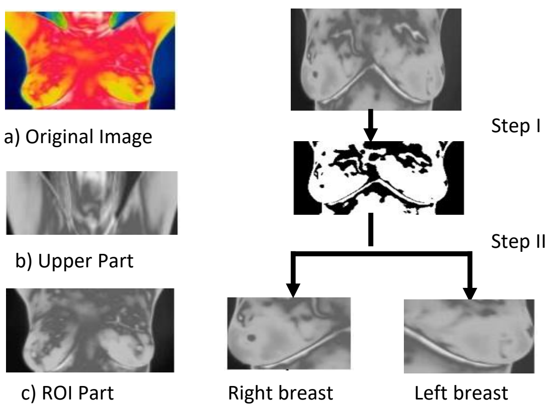

Fig 3. (a) The results of pre-processing step, (b) The results of the segmentation step.

3,2.2 In the Feature Extraction stage:

Extraction of efficient features is a step required for asymmetry analysis. The segmented image of breast thermograms is used in this study to extract two different sorts of characteristics. The mean, variance, skewness, and kurtosis are examples of first-order statistical features. By counting the occurrences of various combinations of grey levels in an image or by distributing the grey levels among the area's pixels, texture characteristics are formed. It was calculated for each pixel-distance interval. Twenty-two features were taken from these textures (GLCM) [36]. These features are called Energy, Cluster Prominence Contrast, Cluster Shade, Correlation,.. etc. [16]. So, the total extracted features are 26 features. Finally, the features will be passed to the ANN classifier.

3.2.3 In the Classification stage:

A typical Artificial neural network (ANN) is one of the ML methods containing millions of units that form an interconnected network that processes enormous amounts of information. In this study, ANN was used with one hidden layer. After data pre-processing and segmentation, 22 features were extracted using GLCM from each image. Four additional features were appended, variance, mean, skewness, and kurtosis, to obtain 26 features for each image. These features feed ANN (26 inputs) one hidden layer with 52 neurons and one output (healthy or sick), as shown in Figure 4. 80% of the dataset (152 images) was trained along 1000 epochs to find optimal performance. After that, we tested 20% of the dataset we tested 38 images.

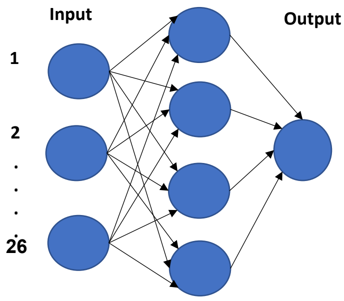

Fig 4. Artificial Neural Network (ANN)

3.3. The Second Proposed Method:

Because of the poor results for ML, we turned to DL to improve accuracy. To automate and enhance the accuracy of the proposed technique, four pre-trained CNN models were used after the pre-processing stage, as shown in Figure 5.

3.3.1 In Image Pre-Processing and Resizing:

In this phase, the image is resized and converted from RGB to grayscale. Additionally, the thermal images are resized to a smaller dimension of 227 × 227 pixels to enhance computational efficiency.

Fig 5. The primary steps undertaken in the second proposed approach.

3.3.2 In Deep Learning Model for Classification

In this method, the CNN app was used as a classifier for thermal images. CNNs comprise layers that receive an input image, conduct mathematical operations, and generate predictions for the class or label probabilities at the output, as shown in Figure 6. The types of layers are:

- Convolutional Layers (CONV): The Convolutional Layers extract local features from input data and improve spatial awareness for tasks like image recognition.
- Pooling Layers (POOL): The pooling layers reduce the spatial dimensions of the input data, helping to extract and retain important features while reducing computational complexity.
- Fully Connected Layers (FC): Fully Connected Layers make the final classification decision based on the extracted features. They enable the model to learn complex relationships and make accurate predictions.

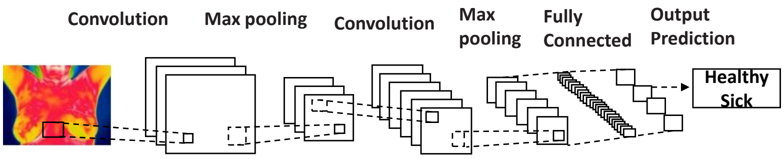

Fig 6. The Convolutional Neural Network (CNN) architecture

In this study, we created a set of options for training CNN. Then, we loaded the dataset after pre-processing and split them randomly into 80% for training and 20% for testing. In this paper, we created a set of options for training CNN. Then, the pre-processed dataset was loaded and randomly divided into 80% for training and 20% for testing, following the approach used in prior studies to achieve optimal system performance. The accuracy of the network was then calculated.

4. Simulation Results and Discussion

This section presents the results of two classification methods used and several tests performed based on the DMR-IR database to evaluate the performance of the proposed approaches.

4.1 Evaluation of The Machine Learning

In the breast cancer detection method, the last step is classification, which entails both training and testing phases. Hence, in the first proposed method, we use the extracted features to analyze the thermal breast images as inputs into the classification algorithms. This paper utilizes ANN and Deep Learning Models classifiers, and their outcomes have been assessed and analyzed. A series of equations are employed to assess the experiments conducted for breast cancer detection, encompassing metrics such as accuracy, specificity, and sensitivity.

Accuracy: measures the proportion of cases that are correctly classified. It is computed by dividing the total number of correct predictions by the total number of predictions made. Eq. (1) is used for computation.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \qquad (1)$$

Specificity: is computed by considering the count of patients whose condition was incorrectly identified. Eq. (2) is used for computation.

$$\text{Specificity} = \frac{TN}{FP+TN} \qquad (2)$$

Sensitivity: is determined by accurately estimating the number of patients with the condition. Eq. (3) is used for computation.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad (3)$$

First, 190 frontal thermogram images are used, and extract 26 features for each thermal image. Next, the ANN classifier is utilized to differentiate between normal and abnormal breast tissue and give us TP=10, TN=23, FP=3, FN=3 that achieved accuracy 89,74%, sensitivity 82,35%, and specificity 95,45%.

4.2 Assessment of the Deep Learning Models' Performance

In the second method proposed, the performance of a deep convolutional neural network is assessed by employing four pre-trained CNN models. Table 1 presents a comparison of the evaluation outcomes of the pre-trained CNN models. Based on the findings presented in Table 1, it can be observed that the AlexNet model outperforms other CNN models in terms of performance on this particular dataset. AlexNet was used with different values of epochs, learning rates, and optimization methods. The proposed model, AlexNet, demonstrated exceptional performance with 100% accuracy, sensitivity, and specificity. It achieved these results within a training period of 6.49 minutes, utilizing 8 epochs, a learning rate of 1×10-4, and employing the Stochastic Gradient Descent with Momentum (SGDM) solver. The training progress of the model can be visualized in Figure 7.

Table 1. Comparing the Performance Metrics of Various CNN Models

CNN model	*Accuracy*	*sensitivity*	*specificity*
AlexNet	100	100	100
GoogleNet	94,7	87.5	100
SqueezNet	84.2	62.5	100
ResNet18	97,4	100	95,5

Fig 7. Progress in Training the Proposed Deep Learning Model.

5. Conclusion:

Breast cancer ranks among the top causes of death for women worldwide. Numerous research has used various techniques for breast segmentation and classification. Utilizing infrared technology, thermal imaging is an efficient diagnostic method for identifying breast cancer. In this study, we introduce two fully automated systems for breast cancer detection. The first system involves image processing to partition the breast, followed by feature extraction and classification using an ANN. The ANN achieved an accuracy of 89.74%, sensitivity of 82.35%, and specificity of 95.45%. In recent years, CNNs have emerged as a prominent and effective approach for breast cancer diagnosis. CNN-based CAD systems are preferred over texture and statistical feature-based systems due to their robustness and ease of implementation. In the second approach, the thermal image undergoes processing and classification using four pre-trained convolutional neural network (CNN) models, namely AlexNet, SqueezeNet, GoogleNet, and ResNet18. Compared to other pre-trained models, the Alexnet model achieved a fast and accurate diagnosis of breast cancer with accuracy, sensitivity and specificity of 100 %. In order to improve efficiency, it will involve utilizing a significantly larger database. This expanded database will not only increase the diversity of the data but also provide a more comprehensive foundation for training and evaluation purposes. Additionally, cutting-edge machine learning and deep learning techniques will be employed to further refine the accuracy and performance of the breast cancer detection system. By leveraging advanced algorithms and models, it is anticipated that the system will exhibit enhanced precision, sensitivity, and specificity, leading to more reliable and efficient outcomes in the detection and diagnosis of breast cancer.

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