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ORIGINAL RESEARCH ARTICLE

Enhancing breast cancer detection in thermographic images using deep hybrid networks

Rezazadeh Hanieh, Saniei Elham*, Salehi Barough Mehdi

Department of Nuclear Engineering, Central Tehran Branch, Islamic Azad University, Tehran 14174, Iran

*** Corresponding author:** Elham Saniei, el.saniei@iau.ac.ir, elhsaniei@gmail.com

ABSTRACT

Breast cancer was a prevalent form of cancer worldwide. Thermography, a method for diagnosing breast cancer, involves recording the thermal patterns of the breast. This article explores the use of a convolutional neural network (CNN) algorithm to extract features from a dataset of thermographic images. Initially, the CNN network was used to extract a feature vector from the images. Subsequently, machine learning techniques can be used for image classification. This study utilizes four classification methods, namely Fully connected neural network (FCnet), support vector machine (SVM), classification linear model (CLINEAR), and KNN, to classify breast cancer from thermographic images. The accuracy rates achieved by the FCnet, SVM, CLINEAR, and k-nearest neighbors (KNN) algorithms were 94.2%, 95.0%, 95.0%, and 94.1%, respectively. Furthermore, the reliability parameters for these classifiers were computed as 92.1%, 97.5%, 96.5%, and 91.2%, while their respective sensitivities were calculated as 95.5%, 94.1%, 90.4%, and 93.2%. These findings can assist experts in developing an expert system for breast cancer diagnosis.

Keywords: breast cancer detection; deep learning; hybrid network; thermography images; convolutional neural network

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1. Introduction

Breast cancer was one of the most prevalent forms of cancer worldwide. Early detection plays a crucial role in successful treatment. Thermography was a method for imaging breast cancer. It employs an infrared camera to capture temperature patterns in the target area. This technique was both safe and cost-effective compared to other imaging methods. However, it had limitations such as a relatively high rate of false positives and false negatives (around 10%), making accurate determination of affected areas challenging[1]. Recent advancements in this field include the detection of areas with high temperature gradients, automated identification of desired areas within each breast, and analysis of asymmetry[2].

Several deep learning techniques had been proposed for accurate breast cancer diagnosis, including multi-layer perceptron neural networks, convolutional neural networks, and fuzzy neural network expert systems[3]. These techniques had been evaluated using diverse datasets and features, such as histopathological images, mammography images, and thermograms. Moreover, researchers had explored the integration of artificial intelligence-based tools in clinical practice to enhance the accuracy and efficiency of breast cancer screening and grading. Desai and Shah introduced a novel approach for breast cancer diagnosis that employs deep learning techniques[4]. Their study used the efficacy of multi-layer perceptron

(MLP) and convolutional neural network (CNN) models in classifying mammography into benign and malignant classes. The findings revealed that CNN outperformed MLP in terms of accuracy for cancer detection. Algehine and colleagues introduced a fuzzy neural network expert system for early detection of breast cancer in mammography[5]. Their approach combined fuzzy logic, neural networks, and machine learning algorithms to achieve high accuracy in diagnosing early-stage breast cancer. In summary, these studies highlight the potential of deep learning techniques, such as MLP, CNN, and fuzzy neural network expert systems, for accurate breast cancer diagnosis. The integration of artificial intelligence-based tools in clinical practice had showed promise, but further investigation was required to ensure safe and effective implementation.

Convolutional neural networks (CNNs) had played a crucial role in establishing non-linear mappings between input and output, autonomously learning local and high-level features through multilayer network architectures, as well as predefined feature sets. In a study[6], a deep learning-based approach utilizing CNNs was proposed for early breast cancer detection, achieving a remarkable classification accuracy in distinguishing between benign and malignant classes. Riggio et al. explored the current understanding of metastatic breast cancer and addressed unresolved challenges that need to be tackled to improve patient outcomes. Despite the complexity and computational slowness caused by simultaneous use of different algorithms, their study achieved an accuracy of 98% in accurately differentiating cancerous parts from healthy breast tissue[7].

Gonçalves and others used pretrained convolutional neural networks such as VGG16, Densenet201, and ResNet50 to classify thermography images. The DenseNet model did the best, with an accuracy of 91.67%, sensitivity of 100%, and specificity of 83.3%. This study showed that using deep learning models was effective for detecting breast cancer. They used 38 pictures for each category[8]. Shahnaz et al. reviewed naive bayes, SVM, logistic regression, KNN, random forest neural networks, MLP and CNN classifiers for the detection of breast cancer[9]. The CNN had the highest accuracy at 98.06%, while the accuracy of MPL was 97.891 at five layers. This showed that CNN was better than other methods. Desai et al. used MLP and CNN for mammography image classification, achieving an accuracy of 93.6%, with CNN outperforming MLP[4]. In order to increase diagnostic accuracy, research incorporated machine learning and deep learning algorithms. They used the effectiveness of their approach in diagnosing metastasis using various features extracted from histopathological images, including color, texture, and morphology. The results exhibited high diagnostic accuracy (96.8%), highlighting the potential benefits of hybrid approaches.

Dey et al. made a model called DenseNet121 and added two detectors (Prewitt and Roberts) to convert input from thermal images. It does really well with 98.8% accuracy on the DMR-IR dataset, doing better than other ways people had tried[10]. In a study introduced a new computer Aided System that used deep learning to find breast cancer[10]. It used all breast thermogram views and patient information. In this research, they used AlexNet to analyze thermograms, and a classic neural network for clinical data. The findings showed that using more than one input did better than using just one input, and the overall accuracy was 90.48%, with a sensitivity of 93.33%. The approach to doing something had changed compared to past references. While recent models[10] show better accuracy, it may not be suitable for devices with limited memory due to its numerous parameters. Also, these models were time consuming on a high-dimensional data set that includes many predictor variables. Our recommendation for resolving these issues was to employ the deep hybrid network. To identify important features, we designed a CNN and then used some machine learning (ML) techniques to categorize the patterns into separate groups. The use of the CNN allows for the extraction of significant features by producing detailed features that can be used in combination with ML classifiers and undergo thorough testing. The essential aspect of ML classifiers was that they were fast. This paper had made important contributions.

- A simple CNN model was made with limited parameters, instead of pre-trained network that can be used on a mobile device.
- Four deep learning-based identification method of breast cancer from thermal images was proposed by combining CNN and different ML classifiers: Fully connected neural network (FCnet), support vector machine (SVM), classification linear model (CLINEAR), k-nearest neighbor (KNN)
- A comparison was made between the proposed models and other related works.

2. Methodology

This research proposed a hybrid strategy to recognize breast cancer from thermographic Images. The recommended procedure was illustrated in **Figure 1**. Deep learning was a type of machine learning that takes inspiration from the way the brain works. Convolutional neural networks (CNN) were the most essential types of deep neural networks designed to process and predict various features simultaneously. They had used remarkable capabilities in extracting meaningful features from images. we proposed the utilization of CNNs for feature extraction from thermographic images. Then the features were classified using four different ML classifiers for choosing the best hybrid method. The suggested methodology was divided into five steps were talked about further down.

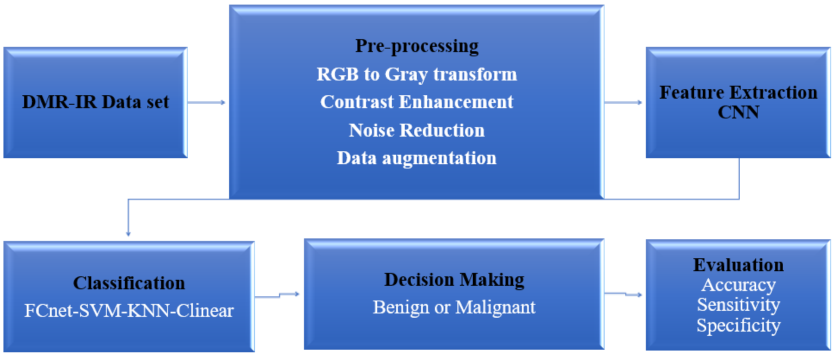


Figure 1. The illustration of the proposed method.

2.1. Pre-processing

Preparing the images before using it in machine learning was important, and preprocessing was the first step in this process. Several preprocessing methods were used in this study, which were mentioned below.

- Grayscaling:

Images data can be simplified and computational requirements reduced by converting color images to grayscale. The images from the dataset were colored. Therefore, they were converted to gray images at first in **Figure 2b**.

- Contrast enhancement:

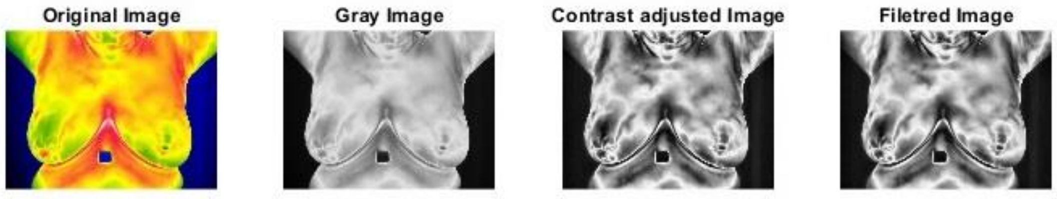
After grayscaling, the contrast of the images was adjusted using histogram equalization as shown in **Figure 2c**.

- Noise reduction:

Median filter was applied to remove unwanted noise from the images. It analyzes the image pixel by pixel, and replaces each pixel with the median of neighboring entries. The smoothed image was shown in **Figure 2d**.

- Data augmentation:

In machine learning, “imbalanced classes” was a familiar problem particularly occurring in classification. Ideally, all classes would had an equal number of observations. However, the classes in data set were imbalanced (2800 cancer images, 4500 normal images) and if not handled correctly, this imbalance can be detrimental to the learning process because the learning was biased in favor of the dominant classes. To handle this issue, data augmentation technique was employed. Data augmentation was a way to increase the number of training images by manipulating the original image. In this study, this involved scaling up the original image size by 50%, applying random rotations of up to 20 degrees in any direction, and introducing random translations of up to a maximum of 3 pixels. This was applied on the images from the cancer classes.



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

Figure 2. A example of pre-processing steps: **(a)** original image; **(b)** gray image; **(c)** contrast adjusted image; **(d)** median filtered image.

2.2. CNN proposed architecture for feature extraction

CNNs had used remarkable capabilities in extracting meaningful features from images. They were one of the most essential types of deep neural networks designed to process and predict various features simultaneously. In this research, a CNN architecture with four convolutional layers was employed. It consists of the normalization, pooling and two fully connected layers. **Figure 3** provides an overview of the network layout. It will be described as follows:

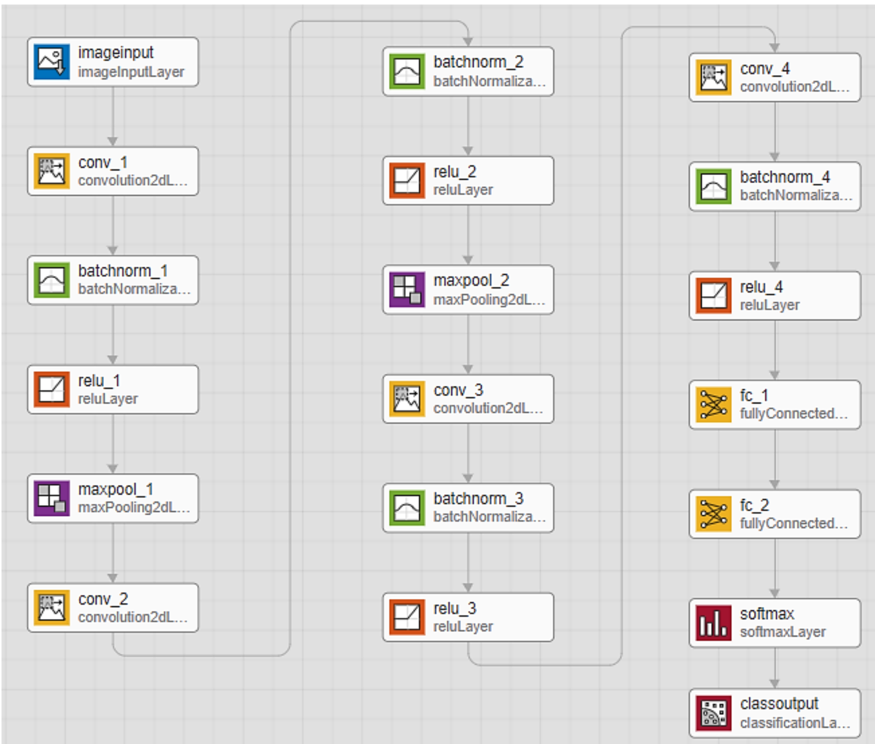


Figure 3. The diagram of the proposed convolutional neural network.

1) The first convolutional layer incorporates 8 filters with a kernel size of 77 pixels. Additionally, we used the padding option, which expands the border pixels before the convolution operation.
2) Stacked convolutional layers were accompanied by a batch normalization operation. After each convolutional layer, a modified linear unit operation was applied. The network also includes a max-

pooling layer with a kernel size of 22 pixels and a stride of 2.

3) The subsequent stacked convolutional layers and the batch normalization layer follow the same pattern as the first layer. However, the convolution kernel sizes were set to 55, 33, and 33, respectively. The filter size and number for each convolutional layer was given in **Table 1**.

Table 1. The layers of the proposed CNN and their parameters.

Name	Type	Activation shape	Learnable parameters
Image input	Image Input	480 × 640 × 3	-
conv1	Convolution	480 × 640 × 8	Weights 7 × 7 × 3 × 8 Bias 1 × 1 × 8
batchnorm_1	Batch Normalization	480 × 640 × 8	Offset 1 × 1 × 8 Scale 1 × 1 × 8
relu_1	ReLU	480 × 640 × 8	-
maxpool_1	Max Pooling	240 × 320 × 8	-
conv2	Convolution	240 × 320 × 8	Weights 7 × 7 × 8 × 8 Bias 1 × 1 × 8
batchnorm_2	Batch Normalization	240 × 320 × 8	Offset 1 × 1 × 8 Scale 1 × 1 × 8
relu_2	ReLU	240 × 320 × 8	-
maxpool_2	Max Pooling	120 × 160 × 8	-
conv3	Convolution	120 × 160 × 8	Weights 7 × 7 × 8 × 8 Bias 1 × 1 × 8
batchnorm_3	Batch Normalization	120 × 160 × 8	Offset 1 × 1 × 8 Scale 1 × 1 × 8
relu_3	ReLU	120 × 160 × 8	-
conv4	Convolution	120 × 160 × 8	Weights 7 × 7 × 8 × 8 Bias 1 × 1 × 8
batchnorm_4	Batch Normalization	120 × 160 × 8	Offset 1 × 1 × 8 Scale 1 × 1 × 8
relu_4	ReLU	120 × 160 × 8	-
fc_1	Fully Connected	1 × 1 × 16	Weights 16 × 1153600 Bias 1 × 1 × 16
fc_2	Fully Connected	1 × 1 × 2	Weights 2 × 16 Bias 1 × 1 × 2
SoftMax	SoftMax	1 × 1 × 2	-
Class output	Classification Output	-	-

Training hyperparameters:

The CNN network was trained for 100 epochs. In order to stabilize the network during the initial training phase, a low learning rate (0.01) was used initially, gradually increasing over time. The ‘adam’ optimizer was selected over the ‘sgdm’ optimizer because it’s a combination of two different optimizers, rmsprop and adagrad. To train and test the CNN network, an 80:20 split was employed, with 80% of the dataset allocated for training and 20% for testing. This ratio was commonly used in machine learning programs. Additionally, to mitigate the risk of overfitting, a cross-fold validation method with a ratio of 5 was employed. There was a list of hyperparameters in **Table 2**.

Table 2. Training hyper parameters.

Hyper parameters	Specifications
Epoch	100
Initial learning rate	0.01
MiniBatchSize	64
Optimizer	Adaptive moment estimation (Adam)
Validation frequency	10

2.3. Classifiers

After applying the CNN on each image, the corresponding feature vector was obtained. In this research, to compare the accuracy and speed of different classifiers, four machine learning methods were employed: fully connected neural network (FCnet), support vector machine (SVM), classification linear model (CLINEAR), k-nearest neighbor (KNN). Typically, at the end of the CNN, a fully connected neural network (FCnet) was used to classify the images. This approach balances speed and accuracy, aligning with the characteristics of the convolutional network. The first fully connected layer consists of 16 neurons and the second fully connected layer contains 2 neurons. The output layer employs a SoftMax activation function, with output values representing the probabilities of belonging to each group (0 or 1) which effectively segregate the images into normal and cancer groups.

Support vector machine (SVM) was a supervised learning method commonly used for classification. It had used superior performance compared to older classification methods in recent years. The SVM classifier operates based on linear classification of data. Various kernel functions, such as exponential, polynomial, and sigmoid kernels, can be used to generate these boundaries, thereby increasing the complexity and accuracy of the SVM method.

The k-nearest neighbor (KNN) algorithm was a non-parametric statistical method commonly used for statistical classification and regression. This algorithm selects k closest training examples in the data space, and its output varies depending on the type used for classification or regression. In the classification mode, given a specified value for k, it calculates the distance between the point we want to label and its closest neighbors. Based on the maximum number of votes from these neighboring points, the algorithm makes a decision regarding the label of the point. Euclidean distance was typically used to calculate this distance.

A classification linear classifier (CLINEAR) was a model that categorizes a set of data points into discrete classes based on a linear combination of their variables. This method minimizes the objective function using techniques that reduce computation time, such as stochastic gradient descent. **Table 3** provides information on the number of features associated with each classifier.

Table 3. Classifier parameters in the proposed method.

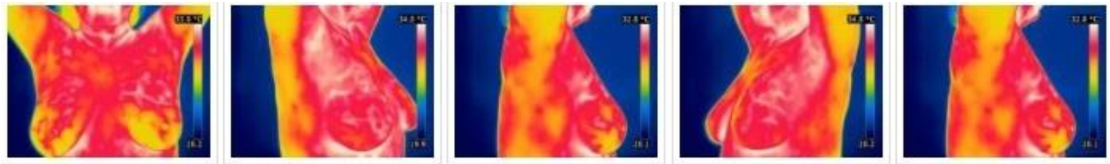
Classifier	Function	Features dimension
FCnet	SoftMax Layer	2 × 4344
SVM	fitcSVM	2 × 4344
CLINEAR	fitclinear	2 × 4344
KNN	fitcknn	2 × 4344

Overall, these different classifiers provide varying approaches to image classification, each with its advantages and considerations. By comparing their performance, we can gain insights into their accuracy and speed for the given task.

3. Results analysis

- Dataset

The study was based on the DMR-IR database[11], which was obtained from volunteers in Brazil by the Federal University of Fluminense. For research purposes, the dataset was publicly available and its collection was ethically approved. These images originated from diverse sources, such as hospitals, clinics, and research institutes, and encompassed a wide range of age and gender groups. Patient-related information, including age and gender, was available for most images, which provides valuable data for the development of breast cancer detection algorithms. The dataset provided by this group was widely recognized for its accuracy and reliability, making it a valuable resource for academic and professional research. The thermographic images in the database were captured using a FLIR SC-620 camera with a resolution of 480 × 640 and a thermal sensitivity of 40 mK. During the image processing stage, all images were converted to grayscale. For each individual, images were taken from angles of 45°, 90° to the right, and 90° to the left, resulting in a total of five thermographic images per person (**Figure 4**). The dataset used in this study comprised thermography images of 4500 healthy individuals and 2800 individuals diagnosed with cancer.



(a) **(b)** **(c)** **(d)** **(e)**

Figure 4. Example of thermographic images utilized: **(a)** front view; **(b)** right 45-degree angle; **(c)** right 90-degree angle; **(d)** left 45-degree angle; **(e)** left 90-degree angle.

- Performance evaluation

The research algorithms were implemented using MATLAB 2021 programming language. **Figure 5** illustrates the accuracy and error graphs at each stage of training. It was evident that increasing the training steps leads to a reduction in losses and higher accuracy. Additionally, **Table 4** presents a comparison of the speed and accuracy of the results for each classifier. The results indicate that the KNN classifier was approximately twice as fast as the concrete CNN. The experimental setup used a Windows system with 8 GB RAM, an Intel(R) Core i5-4430 CPU@3.00GHz x64-based processor. Despite the CNN network demonstrating good accuracy, it exhibits slower speed compared to other methods.

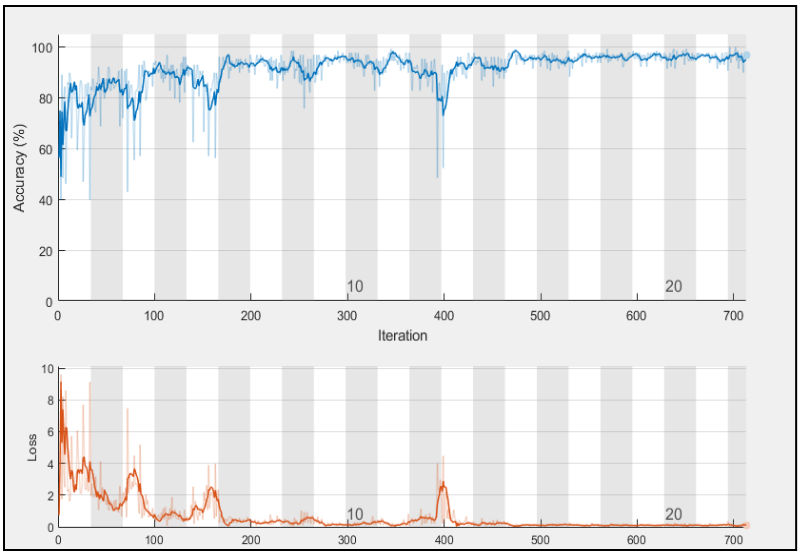


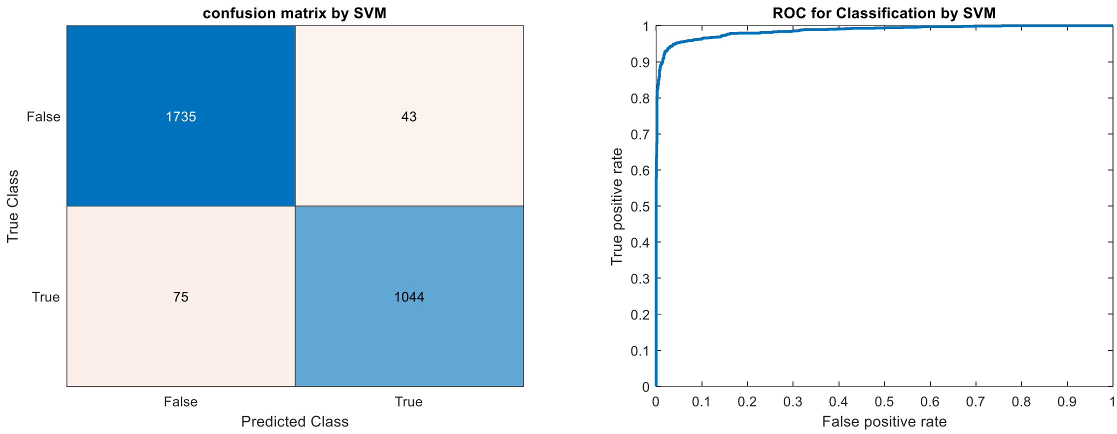
Figure 5. Training progress graph of the proposed CNN.

Table 4. Comparison of learning speed in cancer diagnosis using different classification methods.

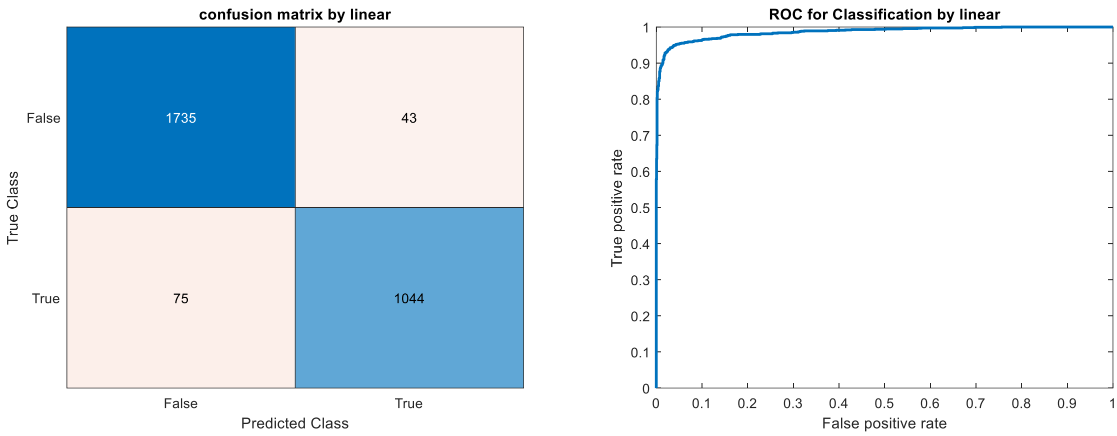
Classifier	Speed (second)
FCnet	336.1
SVM	205.7
CLINEAR	165.5
KNN	162.7

The performance of all classifiers was evaluated using ROC curves and confusion matrices (**Figure 6**).

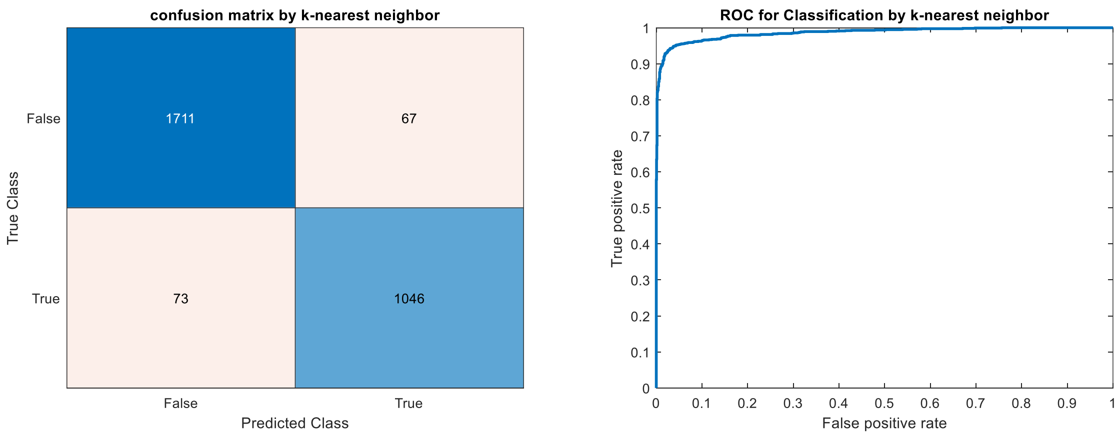
The SVM and CLINEAR methods yielded nearly identical results, with a total of 118 misclassified individuals. However, the KNN classifier resulted in a higher misclassification rate, with 140 misclassified individuals. **Table 5** provides further insights into the accuracy of the testing process. It shows that the SVM and CLINEAR classifiers exhibited higher training accuracy compared to other classifiers.



(a)

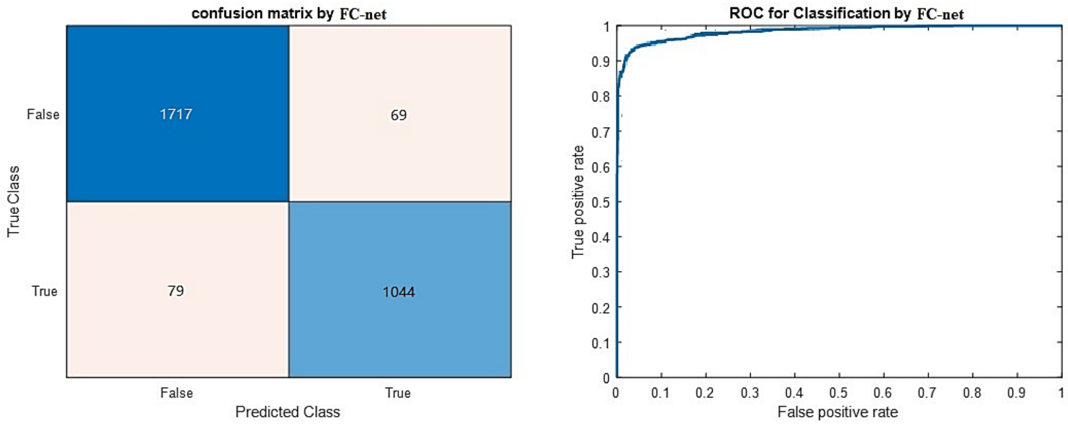


(b)



(c)

Figure 6. (*Continued*).



(d)

Figure 6. ROC curve and confusion matrix for image classification using **(a)** SVM; **(b)** CLINEAR; **(c)** KNN; and **(d)** FC-Net.

Table 5. Performance comparison of different hybrid methods.

Hybrid method	Accuracy	Sensitivity	Specificity
CNN-FCnet	94.2%	93.2%	91.2%
CNN-SVM	95.0%	90.4%	96.5%
CNN-CLINEAR	95.0%	94.1%	97.5%
CNN-KNN	94.1%	95.5%	92.1%

4. Conclusion

Table 6. Comparison of the proposed hybrid methods with existing methods.

Study	Year	Methodology	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)
Abdel-Nasser M[13]	2019	CAD (Computer-Aided Diagnostic), ML	DMR-IR Dataset	95.8		94.6
Algehyne EA et al.[5]	2022	Fuzzy NN Expert System	Wisconsin breast cancer database	95.5	93.8	94.9
Dey S et al.[10]	2022	DenseNet121+, VGG16, VGG19	DMR-IR	98.8	98	
Tsietso D et al.[12]	2023	CADx, DNN, AlexNet	DMR-IR Dataset	90.48	93.33	
Desai M and Shah M[4]	2023	MLP, CNN	Kaggle data set (BC)	93.6	92.1	95.4
Awotunde JB et al.[14]	2023	Hybrid ML & DL	Histopathological images	96.8	94.5	96.0
Gonçalves CB et al.[15]	2022	VGG-16, Densenet 201, and Resnet 502	Thermography	91.67	100	83.3
Our propose method	2024	CNN + (SVM, CLINEAR, KNN)	DMR-IR Dataset	94.2–95.0	90.4–95.5	91.2–97.5

Several papers[4,5,10,12,13] experimented on the thermal images to detect breast cancer. **Table 6** compares the current methods of deep learning for breast cancer detection. Tsietso et al.[12] use a variety of deep learning techniques for cancer detection from thermographic images. Transfer learning was used by Dey et al.[10] and feature extraction was done by pretrained VGG16, VGG19. Pre-trained models in transfer learning were complicated and had lots of parameters. The suggested method in some studies[1–6] been shown to be more accurate but cannot be used with memory constrained devices due to its high number of parameters. In contrast to a previously trained network, the proposed method is uncomplicated. Creating a smaller network is good because it can help to use algorithms on mobile devices. It is possible to use an automated algorithm such as

CNN for the extraction of features, since it is capable of producing deep learning features that can be used for the evaluation of ML classifiers and a comprehensive evaluation. The essential aspect of ML classifiers is that they are fast.

The proposed algorithms employed a CNN with 4th layers to detect relevant features from input images. The extracted features were then fed into the four ML classifier for the purpose of breast cancer detection. The results indicate that both SVM and CLINEAR classifiers yield similar outcomes, with a total of 118 misdiagnosed individuals. On the other hand, the KNN method results in 140 misdiagnosed cases. It is worth noting that the training accuracy of SVM and CLINEAR algorithms surpasses that of other networks. Nevertheless, the FCnet classifier also exhibits high accuracy, outperforming the KNN method by a margin of 0.1%. This improved accuracy can be attributed to the object detection kernel used in the convolutional algorithm, which proves particularly effective for high-resolution images. Additionally, it is important to highlight that the network executed the image only once, contributing to the speed of the CNN, especially when running on parallel processing cards, enabling real-time processing. Furthermore, the findings reveal that the KNN method demonstrates higher sensitivity compared to the other methods, whereas the SVM method exhibits the lowest sensitivity. In terms of false positive rates, the FCnet method performs better than all other methods, while the CLINEAR method yields higher rates than the remaining approaches.

The differences in the effects of the various classification methods used in this study can be attributed to their unique algorithmic structures and operational mechanisms. FCnet demonstrates superior accuracy in classifying thermographic images due to their ability to extract hierarchical and meaningful features from raw data through multiple convolutional layers. This capability allows CNNs to capture intricate patterns and variations within the images, making them particularly effective for complex data sets. In contrast, SVM and CLINEAR classifiers operate by identifying optimal hyperplanes that maximize the margin between different classes. This approach was robust for high-dimensional feature spaces and provides reliable performance, although it may not be as adept as FCnet in handling non-linear and highly complex data patterns. KNN, a non-parametric method, classifies data points based on the majority vote of their nearest neighbors, making it simple and effective for smaller datasets. However, KNN’s performance can degrade with larger datasets due to the increased computational cost during the prediction phase. Comparatively, traditional methods like SVM and KNN exhibit strengths in specific scenarios but may fall short in versatility and accuracy when compared to complicated approaches like FCnet. This comparative analysis underscores the importance of selecting the appropriate classifier based on the dataset characteristics and the specific requirements of the diagnostic application.

This comparative summary highlights the competitive performance of our proposed method and the potential of integrating newer deep learning architectures and hybrid models to further enhance breast cancer detection using thermographic images. Future research should focus on leveraging these advancements and validating the approach on larger, more diverse datasets to ensure robust and reliable performance in clinical settings. Additionally, incorporating other classification methods such as genetic algorithms in conjunction with convolutional networks was suggested as a potential avenue for investigation.

Author contributions

Conceptualization, RH and SE; methodology, RH; software, RH; validation, RH, SE and SBM; formal analysis, RH; investigation, RH; resources, SE; data curation, SE; writing—original draft preparation, RH; writing—review and editing, RH; visualization, RH; supervision, SE; project administration, SE; funding acquisition, RH. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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