Thermography-based Breast Abnormality Detection using Siamese Network

Ankita Dey[1] and Sreeraman Rajan[1]

[1] Systems and Computer Engineering, Carleton University, Ottawa, Canada

Abstract— **Thermography is a potential imaging modality for early breast abnormality detection. Both breasts of a healthy individual have a similar temperature distribution. Thermal asymmetry between the left and the right breasts may indicate the presence of an abnormality. This work introduces a novel Siamese network for learning the similarity between the left and the right breast thermogram images to identify breast abnormalities. This work also proposes a novel algorithm to identify breast abnormalities using the similarity scores obtained from the introduced Siamese network. A comparison of the proposed breast abnormality detection methodology at different margin values is presented. The proposed methodology using the Siamese network achieves an accuracy of 81% with a standard error of 0.3% when the margin was set to 1. All evaluations are done using a publicly available dataset.**

Keywords— **Breast cancer, thermography, Siamese network, bilateral analysis, detection.**

I. Introduction

Breast cancer is the most commonly diagnosed cancer globally and accounts for 1 in 8 diagnosed cancer cases worldwide [1]. Early detection of breast cancer can lead to a 5-year survival rate of 99% [1]. Thermography is a U.S. Food and Drug Administration-approved non-ionizing, painless, safe, and contactless breast imaging screening modality that can detect breast abnormalities at an earlier stage as compared to the gold standard diagnostic modality, mammography [2].

A healthy individual has thermal symmetrical breasts, that is, the temperature distributions of both breasts are similar. However, an abnormal growth or a tumor formation increases the temperature of the surrounding tissue and the skin surface, disrupting the thermal symmetry between both breasts. Thermography uses thermal cameras to record the regions of elevated temperature and examines thermal symmetry between the left and the right breasts to identify breast abnormalities. Since synchronous bilateral breast cancer (SBBC) or both breast cancerous is a clinical rarity [3], the majority of the existing literature exploits this concept of asymmetry analysis to identify breast abnormalities using thermography.

The majority of the current state-of-the-art thermography-based breast abnormality detection methodologies using asymmetrical analysis employ hand-crafted features [4] for machine-learning algorithms such as Support Vector Machine (SVM) and Artificial Neural Network (ANN) [5]. With the introduction of deep learning architectures, the use of abstract features has become more prevalent [6]. Several deep-learning architectures have also been introduced for breast abnormality detection using thermography [6]; however, these architectures require a large amount of data to produce reliable results. Moreover, the existing deep learning architectures do not exploit the concept of asymmetry analysis for breast abnormality detection.

This work introduces a novel Siamese network for thermography-based breast abnormality detection. The Siamese network is a few-shot deep learning approach that can reliably train on a small dataset such as the one at hand [7]. This work proposes a novel algorithm for asymmetry analysis using the similarity scores obtained from the Siamese network to detect thermography-based breast abnormalities. The abstract features generated using the proposed Siamese network are used for asymmetry analysis for breast abnormality detection. Though Siamese networks have been used for breast cancer detection using mammography [8], this work pioneers the application of Siamese networks in the field of thermography-based breast abnormality detection.

II. Proposed Methodology

A healthy subject exhibits symmetry in the temperature distributions between the left and the right breasts. An abnormal growth disrupts this thermal symmetry and causes dissimilarity between the left and right breasts of a breast thermogram. Siamese networks (also called twin networks) are a class of few-shot learning networks that compare a pair of input images and measure similarity or dissimilarity between them [9]. These networks consist of two identical subnetworks that share similar weights and produce lower dimension feature embeddings for the input pairs. The two subnetworks are jointly trained to identify similarity (or dissimilarity) between the feature embedding of the input pairs using a similarity metric such as a distance measure and can differentiate a similar pair of images from a dissimilar pair of images. This work proposes a novel Siamese network to identify an abnormal breast thermogram by estimating the similarity (or dissimilarity) between the left and the right breasts of a breast thermogram as shown in Fig. 1.

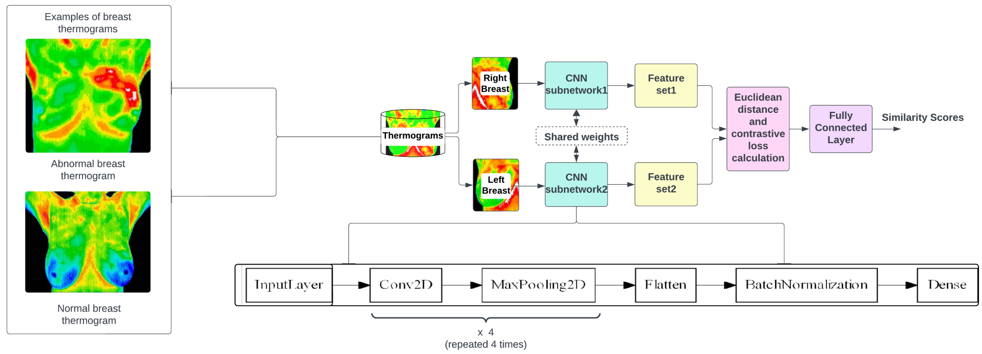

Fig. 1: Breast abnormality detection using Siamese Network with examples of an abnormal and a normal breast thermogram.

A. Asymmetry Analysis using Siamese Network

The thermal matrices obtained from the infrared cameras are first converted into grayscale breast thermograms that are used for further processing. These breast thermograms are divided vertically along the center to extract the left and right breasts [10]. The size of the input grayscale breast thermogram images is 640 × 480 pixels while the size of the left and right breast images is 320 × 240 pixels individually.

A Siamese network is a supervised similarity learning network that is trained using similar and dissimilar pairs of images. The left and the right breasts of a healthy subject are considered as a similar pair of images (Class 0) while the left and the right breasts of an unhealthy subject are considered as a dissimilar pair of images (Class 1). These similar and dissimilar pairs of breast images are used to train the proposed Siamese Network such that the Euclidean distance between the feature embeddings of the similar pair of breast images (healthy subjects) is minimized and the Euclidean distance between the feature embeddings of the dissimilar pair of breast images (unhealthy subjects) is maximized. For a given pair of input images, X_1 and X_1', the Euclidean distance (ED) between the feature embeddings of the pair of images is given as:

$$ED(X_1, X_1') = \sqrt{\left\{S_{n1}\left(X_1\right) - S_{n2}\left(X_1'\right)\right\}^2} \quad (1)$$

where $S_{n1}\left(X_1\right)$ and $S_{n2}\left(X_1'\right)$ are the feature embeddings of X_1 from sub-network 1 and the feature embeddings of X_1' from sub-network 2 respectively. It should be noted that sub-network 1 and sub-network 2 are identical and share the same weights. A contrastive loss function (CL) [11] using Euclidean distances is used to train the Siamese network through backpropagation. The CL function for a given pair of input images, X_1 and X_1', can be given as:

$$\mathrm{CL} = (1-Y)\frac{1}{2}(ED)^2 + (Y)\frac{1}{2}\left\{\max\left(0, m - ED\right)\right\}^2 \quad (2)$$

where Y is the class label for the pair of input images, that is, $Y = 0$ if X_1 and X_1' are similar pairs of images while $Y = 1$ if X_1 and X_1' are dissimilar pairs of images and m is the fixed margin of the distance function ED for dissimilar pair of images. The margin m ensures that only the dissimilar pairs with a ED less than m will contribute to the CL function and ensure that the dissimilar pairs are well-separated. The margin m plays a vital role in optimizing the loss function (Eq. 2) and in the proper training of a Siamese network. Therefore, in this work, the influence of the margin m for the performance of breast abnormality detection is analyzed.

As shown in Fig. 1, the proposed Siamese network consists of two convolutional neural network (CNN) subnetworks. Each CNN subnetwork consists of five convolutional layers with decreasing filter sizes of 32, 16, 8, 8, and 4 respectively. Each convolutional layer has a kernel size of 2×2 and uses a non-linear rectified linear unit (ReLU) activation function. Each convolutional layer is also followed by a MaxPooling layer to reduce the dimension of the extracted features. This helps in reducing the size of the proposed Siamese Network. The last convolutional layer is followed by a batch normalization layer and a fully connected with 10 units. The two CNN subnetworks are trained to minimize the CL function and the outputs of the two CNN subnetworks are passed into the final fully connected layer after batch normalization. This last fully connected layer uses a sigmoid activation function for predicting similarity scores SS for the pairs of the input images.

B. Abnormality Detection

The proposed Siamese network was trained using both abnormal (dissimilar pairs) and normal (similar pairs) breast thermogram images. The number of dissimilar pairs in the training dataset is N while the number of similar pairs in the training dataset is P. After training the proposed Siamese network, the similarity scores of the dissimilar pairs in the training dataset ($SS_{D1},\ldots,SS_{DN}$) and the similarity scores of the similar pairs in the training dataset ($SS_{S1},\ldots,SS_{SP}$) are obtained. The median of the similarity scores of the dissimilar pairs (abnormal breast thermograms) and the median of the similarity scores of the similar pairs (normal breast thermograms) are calculated for breast abnormality during the testing phase.

During the testing phase, the similarity score for a pair of input breast images (a breast thermogram) is predicted. If the predicted similarity score SS_t of the testing pair of breast images is closer to the median of the similarity scores of the dissimilar pairs, then the pair of breast images is considered an abnormal pair, and the subject is declared as abnormal. If the predicted similarity score of the testing pair of breast images is closer to the median of the similarity scores of the similar pairs, then the pair of breast images is considered a normal pair, and the subject is declared normal. This is summarized as Algorithm 1.

Algorithm 1 Proposed breast abnormality detection.

Input: ($SS_{D1},\ldots,SS_{DN}$) and ($SS_{S1},\ldots,SS_{SP}$)
Output: *Class Labels (Y) ← 0- Similar pair (Normal subject), 1- Dissimilar pair (Abnormal subject)*

1: $SS_{MD} = median(SS_{D1},\ldots,SS_{DN})$.
2: $SS_{MS} = median(SS_{S1},\ldots,SS_{SP})$.
3: Obtain $SS_t \leftarrow SS_t$: Similarity score for testing pair t
  if $|SS_t - SS_{MD}| < |SS_t - SS_{MS}|$ **then**
    $Y \leftarrow 1$ (Abnormal subject)
  else if $|SS_t - SS_{MD}| > |SS_t - SS_{MS}|$ **then**
    $Y \leftarrow 0$ (Normal subject)
  end if

III. Experimentation

A. Dataset Used

A publicly available dataset called Database for Mastology Research (DMR), Visual Labs [12] was used. A total of 258 grayscale breast thermogram images of size 640×480 pixels, collected from 167 normal subjects and 91 abnormal subjects using a FLIR SC-620 thermal camera are considered in this work. These grayscale images are standardized front-view breast thermograms that have been mapped from thermal matrices. All thermograms were collected following the Academy of Thermology (AAT) [13] pre-examination protocols for breast thermography. Diagnosis is available for all cases.

B. Classification Approach

The entire dataset is randomly split into 80%-20% training and testing datasets. The proposed Siamese network is trained using the training dataset for 30 epochs with an early stopping function of patience 5. A batch size of 64 and a root mean squared propagation optimizer are used for training the proposed Siamese network for breast abnormality detection. A repeated hold-out cross-validation testing strategy is employed in this work. This testing strategy involves a random training and testing (80%-20%) dataset split is repeated over 10 trials, and the performance of breast abnormality detection using the proposed Siamese network is evaluated over each trial. Four performance metrics, namely, accuracy (Accu.), sensitivity (Sens.), Precision (Prec.), and F1-score (F1-scr.) are used to evaluate the performance of breast abnormality detection. The average performance metrics and their standard errors over 10 trials are reported in Table. 1. The standard error (SE) helps in estimating the confidence interval [14] of the abnormality detection methodology and is given as:

$$\mathrm{SE} = \frac{\sigma}{\sqrt{n}} \tag{3}$$

where σ is the standard deviation over the average performances and n is the total number of trials.

IV. Results and Discussion

As mentioned in the previous section, the value of margin m of the contrastive loss plays an important role in the training of the Siamese network and eventually affects the performance of breast abnormality detection. Therefore, in this work, the influence of the margin value m on the performance of the proposed Siamese network for breast abnormality detection is analyzed. The performance of the breast abnormality using the proposed Siamese network with $m = 0.5, 1$, and 1.5 is presented in Table. 1. The average performance metrics along with standard error are shown in Table. 1. It can be observed that the highest average performance with the lowest standard deviation for breast abnormality detection is obtained at $m = 1$ (shown in boldface).

Table 1: Performance of the proposed Siamese network for breast abnormality detection.

Margin	Acc.	Prec.	Sens.	F1-Scr.
m= 0.5	71.73 ± 1.04	73.32 ± 0.86	70.23 ± 1.08	72.06 ± 1.00
m= 1	**81.00 ± 0.31**	**79.84 ± 0.42**	**80.00 ± 0.34**	**79.63 ± 0.50**
m= 1.5	76.15 ± 0.87	76.55 ± 0.78	76.04 ± 0.83	75.88 ± 1.11

Fig. 2 and Fig. 3 show the spread of the dissimilarity scores of the abnormal and the normal subjects of the training and testing dataset over trial 5. It can be observed that the median of the dissimilarity scores of the normal subjects and the abnormal subjects are distinct which in turn favors distinguishing abnormal subjects from normal subjects. A similar observation was made for other trials.

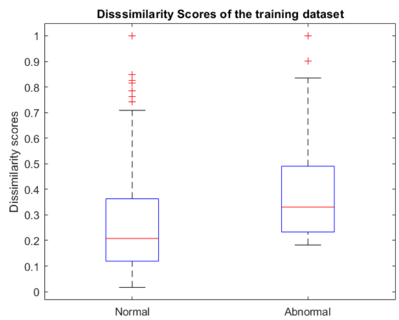

Fig. 2: Dissimilarity scores for the training dataset over trial 5.

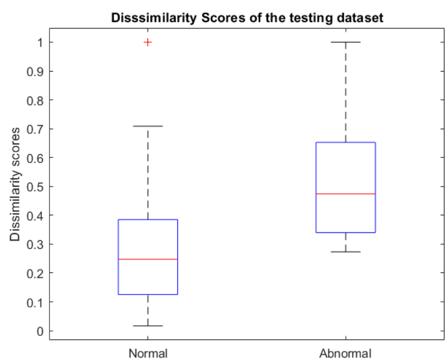

Fig. 3: Dissimilarity scores for the testing dataset over trial 5.

V. Conclusion

This work pioneers the application of Siamese networks for thermography-based breast abnormality detection. A novel algorithm for breast abnormality detection using the similarity scores obtained from the Siamese network is also proposed. The proposed breast abnormality methodology achieves a high accuracy of 81% with a low standard error of 0.3%. The effects of noise on the performance of breast abnormality detection will be studied as part of future work. This work lays a cornerstone in the field of thermography-based breast abnormality using meta-learning approaches.

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgements

This work is supported by the Natural Sciences and Engineering Research Council of Canada.

References

1. M. Arnold, E. Morgan, H. Rumgay, F. Cardoso, S. Siesling, and I. Soerjomataram, "Current and future burden of breast cancer: Global statistics for 2020 and 2040," *The Breast*, vol. 66, pp. 15–23, 2022.
2. S. H. Heywang-Kobrunner, A. Hacker, and S. Sedlacek, "Advantages and disadvantages of mammography screening," *Breast Care*, vol. 6, pp. 199–207, 2011.
3. M. Mejdahl, J. Wohlfahrt, M. Holm, E. Balslev, A. Knoop, A. Tjønneland, M. Melbye, and N. Kroman, "Breast cancer mortality in synchronous bilateral breast cancer patients," *British Journal of Cancer*, vol. 120, pp. 761–767, 2019.
4. A. Dey, E. Ali, and S. Rajan, "Bilateral symmetry-based abnormality detection in breast thermograms using textural features of hot regions," *IEEE Open Journal of Instrumentation and Measurement*, vol. 2, pp. 1–14, 2023.
5. H. Zerouaoui and A. Idri, "Reviewing machine learning and image processing based decision-making systems for breast cancer imaging," *Journal of Medical Systems*, vol. 45, no. 8, 2021.
6. M. A. S. A. Husaini, M. H. Habaebi, S. A. Hameed, M. R. Islam, and T. S. Gunawan, "A systematic review of breast cancer detection using thermography and neural networks," *IEEE Access*, vol. 8, pp. 208 922–208 937, 2020.
7. M. Byra, K. Dobruch-Sobczak, Z. Klimonda, H. Piotrzkowska-Wroblewska, and J. Litniewski, "Early prediction of response to neoadjuvant chemotherapy in breast cancer sonography using siamese convolutional neural networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 3, pp. 797–805, 2021.
8. A. Mohamed, S. Fakhry, and T. Basha, "Bilateral analysis boosts the performance of mammography-based deep learning models in breast cancer risk prediction," in *Annual International Conference of the IEEE Engineering in Medicine & Biology Society*, 2022, pp. 1440–1443.
9. D. Chicco, *Siamese Neural Networks: An Overview*. New York, NY: Springer US, 2021, pp. 73–94.
10. A. Dey and S. Rajan, "Red-plane asymmetry analysis of breast thermograms for cancer detection," in *IEEE International Symposium on Medical Measurements and Applications*, 2022, pp. 1–6.
11. J. Bai, A. Jin, T. Wang, C. Yang, and S. Nabavi, "Feature fusion siamese network for breast cancer detection comparing current and prior mammograms," *Medical Physics*, vol. 49, no. 6, pp. 3654–3669, 2022.
12. L. F. Silva, D. C. M. Saade, G. O. Sequeiros, A. C. Silva, A. C. Paiva, R. S. Bravo, and A. Conci, "A new database for breast research with infrared image," *Journal of Medical Imaging and Health Informatics*, vol. 4, no. 1, pp. 92–100, 2014.
13. "Guidelines: Breast thermography." aathermology.org. https://aathermology.org/organization-2/guidelines/ (accessed Aug. 21, 2023).
14. X. Wan, W. Wang, J. Liu, and T. Tong, "Estimating the sample mean and standard deviation from the sample size, median, range and/or interquartile range," *BMC Medical Research Methodology*, vol. 14, p. 135, 2014.

Author: Ankita Dey
Institute: Carleton University
Street: 1125 Colonel By Drive
City: Ottawa
Country: Canada
Email: ankitadey@cmail.carleton.ca