

Thermo graphic imaging-based Breast Cancer Diagnosis using Deep Learning

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Abstract: Breast cancer is the most common invasive cancer, killing thousands of women worldwide every year Early detection is also a means of reducing mortality. Therefore, early detection of breast cancer is particularly important. However, in developing countries, few people can afford screening and testing procedures due to high costs. Thermography is therefore an effective and less expensive method of detecting breast cancer and, unlike other methods, it can be used in women of all ages to this end, we propose a computer- assisted breast cancer detection system that accepts thermal images of the breast for detection. we develop a CNN hybrid structure model that combines the strengths of bothconvolutional and recurrent neural networks to perform image processing. The model takes as input thermal images of the breast and outputs a prediction of whether or not the patient has breast cancer.

Keywords: Thermography Imaging; Breast Cancer; Transfer Learning; CNN hybrid model, image processing, image segmentation

I. INTRODUCTION

The main cause of cancer is uncontrolled cell division that occurs due to genetic mutations in cells. Breast cancer is a disease in the family of cancers, caused by genetic abnormalities occurring in breast cells, and carries a high risk of death [1]. Early detection of breast cancer can reduce mortality by treating breast cancer. appropriate medical treatment. Therefore, early detection plays an important role in saving the lives of thousands of women affected by breast cancer. Many types of methods are used to detect breast cancer, some of which have been discussed by Borchert et al. [4]. Diagnosis by mammography is one of the most commonly used methods [16]. In mammography, images of the breast are taken with low-energy X-rays and then diagnosed to detect cancer. Ruhi et al. [29] and Gao et al. [15] proposed mammography-based breast cancer detection techniques, in which convolutional neural network (CNN) models are used. However, mammography is not an exact process, and the use of X-rays can also damage breast cells from radiation exposure.2 Therefore, researchers are trying alternative solutions. The potential includes the use of other technologies such as ultrasound, thermometer, magnetic resonance imaging (MRI), tomography, etc. [2,6, 26, 28]. Thermography has been demonstrated to be more successful than other methods in identifying breast cancer [2, 26, 28]. Presumptive heat screening:

The temperature profile of cancerous tissue is higher than that of normal tissue. In addition, thermal imaging does not use any external radiation as in the case of mammography. Therefore, it can be considered a safer procedure in terms of tissue damage than other procedures. Furthermore, it is an effective procedure for women of all ages even with breast implants. To record the thermometer images, digital infrared thermal imaging (DITI) was used [17, 20]. However, the problem is that in the diagnostic part, it is necessary to have a specialist to diagnose breast cancer to predict the possibility of breast cancer. The main problem with this approach is that in developing countries like India, Bangladesh, Sri Lanka and Nepal, very few people can afford a specialist for diagnosis. Furthermore, there is always a risk of human error, and so a medical professional sometimes suggests getting a second opinion from another professional. This scenario further increases diagnostic costs. Therefore, the need for an automatic breast cancer screening and diagnosis system is very high. In many studies, researchers have used feature engineering for this task [2, 3, 31].

Considering the recent advances in deep learning-based models, researchers have begun to use such models forbreast cancer detection [25], especially the CNN-basedarchitecture. LeCun et al. [23] first introduced a CNN architecture that has proven to be successful in many images classification and object recognition problems However, the problem with CNN is that to achieve better classification accuracy we sometimes need heavy and complex architectures which require large amount of dataand computing power to train the model. To solve this problem, researchers have developed the concept of transformational learning. In this concept, pre-trained CNN models are used as feature extractors or sometimes, or these models are fine-tuned using the target dataset. Tocreate competent pre-trained models, researchers use large, complex CNN models trained on large datasets such as ImageNet, which contain approximately 20,000 image categories. The concept has been applied to skin cancer detection [12], lung cancer detection [24], breast cancer detection using thermogram imaging [13], and chest X-rayimaging [7, 9], as well as high-resolution We also



extract features from thermal chest images for various pattern classification problems such as satellite image classification [5], partial recognition [22], and infrared pedestrian detection [18]. For image processing, we use a deep learning model built on a hybrid Convolutional Neural Network (CNN) structure. This model is tested on a sizable dataset of thermal pictures that have been labelled and preprocessed for cancer status. The CNN hybrid structure offers a quick and non-invasive diagnostic option by accurately identifying cancer cells from the thermal pictures. Thermographic imaging has the potential to change breast cancer diagnosis and enhance patient outcomes due to its high accuracy and non-invasive nature. In recent years, there has been an increase in the use of thermographic imaging for the diagnosis of breast cancer. In order to identify temperature anomalies that might point to the presence of cancer cells, this non-invasive technique entails taking infrared photographs of the breast tissue. The accuracy of these diagnoses has significantly increased thanks to the application of deep learning methods, particularly convolutional neural networks (CNNs). To effectively categories thermographic images as healthy or abnormal, a hybrid structural model comprising both conventional image processing methods and deep learning algorithms is used. While the image processing step is used to extractcrucial information from the images, this model uses the CNN structure to automatically spot patterns and abnormalities in the images. The model is able to obtain improved accuracy in these two areas by combining these image segmentation methods.

- other pre-trained models VGG19, VGG16, DenseNet169, Exceptionless.
- -Perform its CAM level analysis against the classifier to better understand its working principle.
- Modern results have been obtained from the proposed model, but in small quantities. A trainable example.

The rest of this article is organized as follows: First, in section 2, we describe some of the early methods of breast cancer detection based on thermogram images developed by other researchers Section 3 describes the overall architectural workflow of the current method and some of its key components. Section 4 first presents the model's performance and then compares it with other models Finally, Section 5 concludes the work by mentioning possible future extensions of the work.

II. METHODOLOGY

[1] One of the most prevalent cancers in women worldwide is breast cancer. Early detection is essential for effective treatment and better results. The detection of breast cancer using thermal infrared imaging has received attention recently because it is non-invasive and radiation-free. The development and evaluation of several methods for assessing thermal images to find breast cancer has been the subject of numerous studies.

[2] Using machine learning and texture analysis tools is one strategy. Thermal image classification using support vector machines (SVM) and texture features is a technique that was put forth by Acharya et al. (2012). By adding representation learning in addition to texture analysis, Abdel-Nasser et al. increased the performance of breast cancer detection.

[29,30,31,35] Additional research has looked at statistical features and fuzzy classification, bio-inspired swarm approaches, colour analysis, and segmentation using gradient vector flows and convolutional neural networks. These methods have all demonstrated potential for using thermal imaging to find breast cancer.

[32] Researchers have tried to improve the data accessible for thermal imaging-based breast cancer research in addition to creating new techniques. A novel database for breast research using infrared images was published by Silva et al. (2014), offering a useful tool for the creation and assessment of fresh detection techniques.

[36] Moreover, image processing methods have been researched to improve the interpretation of thermal pictures for the identification of breast cancer. By comparing the performance of the Canny and Sobel edge detection algorithms in image mining, Vijaya ani and Venturia (2013) discovered that the Canny approach was superior for detecting edges in thermal images.

[21] used thermography and mammography in combination and showed that this combination improved the sensitivity and specificity of classification compared to using mammography alone. Some authors use block variance, a texture feature extraction method, in chest thermogram.

[27] Another use of thermogram images is found in the work of Ok unawake et al [26] In this work, the authors used contour classification of breast thermograms to facilitate Brch in Engineerast cancer detection Acharya et al [2] Initial cooccurrence and run- length-based features from chest thermograms. These features are then input into a support vector machine (SVM) for classification [1] proposes the application of representation learning and texture analysis methods to breast thermograms. In another work, Silva etal [35] We first extracted regions of interest (ROI) from aseries of dynamic infrared thermography (DIT)images and then extracted features from these ROIs to perform breastcancer detection with SVM In another study, the authors used a computer-aided diagnosis (CAD)-based breast cancer detection technique with a CNN using thermal images as input data.

> [39] The author of the paper [36] proposed a method of segmenting breast thermal images using a curvature function and a gradient vector flow and using his CNN for classification The use of optimization algorithms to tune CNNs for breast cancer detection can be found in research



papers such as [11]. The authors extract features from breast thermograms and classify them using a CNN optimized by a Bayesian algorithm the concept of transferlearning for breast cancer detection using thermograms hasbeen applied to the study reported in [13].

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Clear and unambiguous photographs can only be created through the pre-processing portion of the picture-making process. It is feasible to move forward thanks to the photo pre-processing stage. to the categorization phase. The first phase made use of the data augmentation procedure. The following steps make up the methodology for the Thermographic Imaging-based Breast Cancer Diagnosis Using Deep Learning:

1. Data collection: Both healthy and malignant thermographic pictures of breasts are gathered in a sizable dataset. To differentiate between breasts thatare healthy and those that have cancer, the data is annotated and gathered from various sources.

2. Pre-processing: The gathered data is first cleaned up to reduce noise and improve the photos' quality. To make the training process simpler, the photographs are also scaled to a common size.

3. CNN Hybrid Structure Model: Deep learning methodsare used to create a CNN hybrid structure model. Convolutional and recurrent neural networks (CNNs and RNNs, respectively) are combined in this model to provide an effective and efficient solution for the issue with breast cancer diagnosis.

4. Model training: Using the gathered dataset, the model is trained. Based on the thermal images, the model develops the ability to distinguish between healthy and malignant breasts during training. The model is trained over a number of epochs until it achieves an acceptable degree of accuracy.

5. Validation: To ensure that the trained model generalizes effectively to new data, it is tested on a different dataset. The model's performance is assessed using the validation findings, and any potential problems are noted.

6. Implementation: After the model has been validated, it is implemented in a real-world environment to provide a precise diagnosis of breast cancer. Patients' thermographic images are analyzed using the model, which then instantly offers a diagnosis.

By combining deep learning methods with thermographic imaging, the aforementioned methodology offers a successful detection for breast cancer. Healthcare practitioners have access to a valuable tool thanks to the usage of a CNN hybrid structure model, which guarantees the diagnostic' accuracy and effectiveness.

III. ANALYSIS MATERIALS AND METHODS

3.1 EXPERIMENTAL DATASET

Work utilizing thermal imaging to identify breast cancer as a screening method is not new. In comparison to its mainstream replacement, mammography, several researchers in literature have used thermal images to show its effectiveness. Unlike diseased breasts, the difference between healthy breasts is very small but can be determined by a professional model. this research is collected from online project database [1] The dataset that was utilized included photos of approximately over 150 patients, either with or without breast cancer, totaling over 1000 photographs. These images were discovered on the website Kaggle. Only the frontal pictures with the arms lifted were utilized for this particularpiece of work because the other poses yielded inconsistent RESULTS [3].

IV. CONCLUSION

In summary, breast cancer is a major public health concern and the development of accurate and affordable early detection methods is critical. A promising solution is offered by the use of thermography-based deep learning-based breast cancer diagnosis. The hybrid model proposed in this study is a step towards developing reliable and accurate breast cancer screening methods. This study highlights the potential of combining image processing methods and deep learning techniques in breast cancer diagnosis. However, further research is needed to improve model performance, especially when addressing strategies to address class imbalance and applying feature selection techniques to the extracted features. Moreover, implementation of the proposed method



requires careful consideration of various factors, including cost, accessibility, and ethical implications of such screening methods. These factors should be considered to ensure that the proposed method is accessible and affordable for all women, regardless of socioeconomic status. Ethical considerations in using should be thoroughly evaluated to ensure that the proposed method does not lead to prejudice or discriminatory practices.

Overall, the proposed thermography-based deep learningbased breast cancer diagnosis is a promising approach for breast cancer detection. The hybrid model proposed in this study is an important step towards developing reliable and accurate breast cancer screening methods. The results of this study may guide future research in this field and provide a basis for the development of improved breast cancer screening methods. Ultimately, the development of accurate and accessible early detection methods for breast cancer will make a significant contribution to reducing mortality associated with this disease.

REFERENCES

[1] Abdel-Nasser M, Moreno A, Puig D (2019) Breast cancer detection in thermal infrared images using representation learningand texture analysis methods. Electronics 8(1):100

[2] Acharya UR, Ng EYK, Tan JH, Sree SV (2012) Thermography based breast cancer detection using texture features and support vector machine. J Med Sys 36(3):1503–1510

[3] Arau'jo MC, Lima RC, De Souza RM (2014) Interval symbolic feature extraction for thermography breast cancer detection. Expert Syst Appl 41(15):6728– 6737

[4] Borchartt TB, Conci A, Lima RC, Resmini R, Sanchez A (2013) Breast thermography from an image processing viewpoint: a survey. Signal Process 93(10):2785–2803

[5] Chaib S, Yao H, Gu Y, Amrani M (2017) Deep feature extraction and combination for remote sensing image classification based on pre-trained cnn models. In: Ninth international conference on digital image processing (ICDIP 2017), vol 10420.International Society for Optics and Photonics, p 104203D

[6] Cho N, Han W, Han BK, Bae MS, Ko ES, Nam SJ, Chae EY, Lee JW, Kim SH, Kang BJ, et al. (2017) Breast cancer screening with mammography plus ultrasonography or magnetic resonance imaging in women 50 years or younger at diagnosis and treated with breast conservation therapy. JAMA Oncol 3(11):1495– 1502

[7] Das S, Roy SD, Malakar S, Vela´squez JD, Sarkar R (2021) Bi-level prediction model for screening covid-19 patients using chest x-ray images. Big Data Res

25:100233

[8] Deepak A (2020) Thermal images for breast cancer diagnosis dmr-ir. https://www.kaggle.com/asdeepak/ thermal-images- for-breast-cancer-diagnosis-dmrir

[9] Dey S, Bhattacharya R, Malakar S, Mirjalili S, Sarkar R (2021) Choquet fuzzy integral-based classifier ensemble technique for covid-19 detection. Comput Biol Med :104585

[10] Dorafshan S, Thomas RJ, Maguire M (2018) Comparison of deep convolutional neural networks and edge detectors for image-based crack detection in concrete.Constr Build Mater 186:1031–1045

[11] Ekici S, Jawzal H (2020) Breast cancer diagnosis usingthermography and convolutional neural networks. MedHypotheses137:109542

[12] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S (2017) Dermatologist-level classification of skin cancer with deep neural networks. Nature 542(7639):115–118

[13] Ferna ndez-Ovies FJ, Alfe rez-Baquero ES, de Andre s- Galiana EJ, Cernea A, Ferna ndez-Mun z Z, Ferna ndez- Mart nez JL (2019) Detection of breast cancer using infrared thermography and deep neural networks. In: International work- conference on bioinformatics and biomedical engineering. Springer, pp 514–523

[14] Francis SV, Sasikala M, Saranya S (2014) Detection of breast abnormality from thermograms using curvelet transformbased feature extraction. J Med Sys 38(4):1–9

[15] Gao F, Wu T, Li J, Zheng B, Ruan L, Shang D, Patel B (2018) Sd-cnn: a shallow-deep cnn for improved breast cancerdiagnosis. Comput Med Imaging Graph 70:53–62

[16] Hela B, Hela M, Kamel H, Sana B, Najla M (2013) Breast cancer detection: A review on mamo- grams analysis techniques. In: 10th international multiconferences on systems, signals & devices 2013 (SSD13). IEEEHerry CL, Frize M (2004) Quantitative assessment of pain-related thermal dysfunction through clinicaldigital infraredthermal imaging. Biomed Eng Online 3(1):19

[17] Hu J, Zhao Y, Zhang X (2020) Application of transfer learning in infrared pedestrian detection. In: 2020 IEEE 5Th international conference on image, vision and computing (ICIVC). IEEE, pp 1–4

[18] Huang G, Liu Z, Van Der Maaten L, Weinberger KQ (2017) Densely connected convolutional networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 4700–4708

[19] Jones BF, Plassmann P (2002) Digital infrared thermalimaging of human skin. IEEE Eng Med Biol Mag



21(6):41-48

[20] Kim D, MacKinnon T (2018) Artificial intelligence in fracture detection: transfer learning from deep convolutional neuralnetworks. Clin Radiol 73(5):439– 445

[21] LeCun Y, Haffner P, Bottou L, Bengio Y (1999) Object recognition with gradient-based learning. In: Shape, contour and grouping in computer vision. Springer, pp319–345

[22] Lin CJ, Jeng SY, Chen MK (2020) Using 2d cnn with taguchi parametric optimization for lung cancer recognition from ctimages. Appl Sci 10(7):2591

[23] Mambou SJ, Maresova P, Krejcar O, Selamat A, Kuca K (2018) Breast cancer detection using infrared thermal imaging and a deep learning model. Sensors 18(9):2799

[24] Okuniewski R, Nowak RM, Cichosz P, Jagodziński D, Matysiewicz M, Neumann Ł, Oleszkiewicz W (2016) Contour classification in thermographic images for detection of breast cancer. In: Photonics appli- cations in astronomy, communications, industry, and high- energy physics experiments 2016, vol 10031. International Society for Optics and Photonics, p 100312V

[25] Pramanik S, Bhattacharjee D, Nasipuri M (2015) Wavelet based thermogram analysis for breast can- cer detection. In: 2015 International symposium on advanced computing and communication (ISACC). IEEE, pp 205– 212

[26] Pramanik S, Bhattacharjee D, Nasipuri M (2016) Texture analysis of breast thermogram for differen tiation of malignant and benign breast. In: 2016 International conference on advances in computing, communications and informatics (ICACCI). IEEE, pp 8–14

[27] Rouhi R, Jafari M, Kasaei S, Keshavarzian P (2015) in Engineering PP Benign and malignant breast tumors classification based on regiongrowing and cnn segmentation. Expert Syst Appl 42(3):990–1002

[28] Sayed GI, Soliman M, Hassanien AE (2016) Bioinspired swarm techniques for thermogram breast cancer detection. In: Medical imaging in clinical applications. Springer, pp 487–506

[29] Schaefer G,Za'vis'ek M, Nakashima T (2009) Thermography based breast cancer analysis using statistical features and fuzzy classification. Pattern Recogn 42(6):1133–1137

[30] Shahari S, Wakankar A (2015) Color analysis of thermograms for breast cancer detection. In: 2015 international conference on industrial instrumentation and control (ICIC). IEEE, pp 1577–1581

[31] Silva L, Saade D, Sequeiros G, Silva A, Paiva A,

Bravo R, Conci A (2014) A new database for breast research with infrared image. J Med Imag Health Inf 4(1):92–100

[32] Silva LF, Sequeiros GO, Santos MLO, Fontes CA, Muchaluat-Saade DC, Conci A (2015) Thermal signal analysis for breast cancer risk verification. In: MedInfo, pp 746–750

[33] Silva TAEd, Silva LFd, Muchaluat-Saade DC, Conci As (2020) A computational method to assist the diagnosis of breast disease using dynamic thermography. Sensors 20(14):3866

- [34] Tello-Mijares S, Woo F, Flores F (2019) Breast cancer identification via thermography image segmen- tation with a gradient vector flow and a convolutional neural network. J Healthcare Eng :2019
- [35] Vijayarani S, Vinupriya M (2013) Performance analysis of canny and sobel edge detection algorithms in image mining. Int J Innov Res Comput Commun Eng 1(8):1760–1767
- [36] Zhang Z, Sabuncu MR (2018) Generalized cross entropy loss for training deep neural networks with noisy labels. In: 32nd conference on neural information processing systems (NeurIPS)
- [37] Zuluaga-Gomez J, Al Masry Z, Benaggoune K, Meraghni S, Zerhouni N (2020) A cnn-based methodology for breast cancer diagnosis using thermal images. Comput Methods Biomech Biomed Eng Imag Vis :1–15