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Detection of Breast Cancer using Deep Learning Techniques

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Abstract

Breast cancer poses a global health challenge due to the high false-positive rates associated with traditional mammographic diagnostics. This study introduces a novel model using infrared digital imaging to exploit the thermal difference between healthy and tumorous breasts for early cancer detection. This study employed a Support Vector Machine model and a fine-tuned Deep Neural Network (DNN) to classify thermal images as cancerous or healthy, using a dataset of 67 diverse subjects. Images with confidence levels between 0.5 and 0.6 were directed to the SVM for further prediction, improving diagnostic accuracy. The model's utility was validated on a new set of 12 breasts. In this study, the results showcase the potential of infrared imaging in breast cancer detection and suggests improvements in thermal conduction levels and advocating for further model refinement research.

Keyword : Breast cancer, Deep learning, Computer-Aided Diagnostic, Segmentation

1. Introduction

The human body typically manages cell proliferation, development, and apoptosis seamlessly. However, when this balance is disrupted, leading to an excessive rate of cell proliferation relative to cell death, it can give rise to neoplastic conditions. Breast cancer, which occurs when breast cells proliferate uncontrollably, is a global health issue. In the US alone, one in eight women will be diagnosed with breast cancer in their lifetime, with over 40,000 fatalities annually. The global health burden could be reduced by improving early detection methods, awareness campaigns, diagnostic tools, and treatment strategies.

Historically, mammography has been one of the most common diagnostic techniques for breast cancer. Kosus et al., 2010 started a testimonial that highlights the constraints of screen-film mammography [1]. For instance, it comes with a high false-positive rate, ranging from 4% to 34%, signifying a need for more precise diagnostic methods. Consequently, much research have turned their focus to image processing using neural networks, which have shown promising results in the detection and classification of cancerous cells [2-4].

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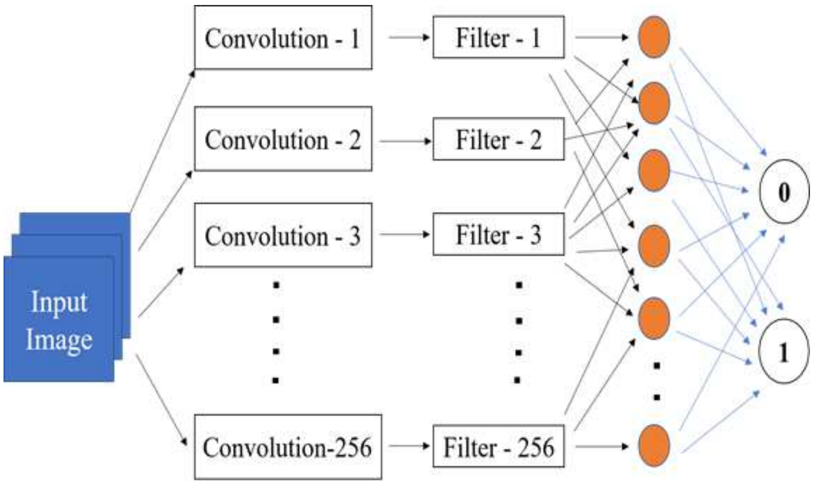
Despite the historical preference for mammography, the demand for innovative methods to overcome its limitations has grown considerably. Image processing, particularly utilizing Near-Infrared Fluorescence (NIRF) light signals, has become an essential element in cancer evaluation procedures and ongoing health condition monitoring [5]. Early detection and treatment initiation significantly enhance the chances of successful outcomes. Several researchers have also addressed the challenge of estimating cancer parameters such as metabolic temperature, tumor depth, and the size of the thermogram [6][7]. However, limitations persist in techniques such as CT and MRI scans, which display low sensitivity to sub-centimeter lesions due to their limited spatial resolution. Moreover, studies have indicated the drawbacks of annual mammography screenings, with Kandlikar et al. reporting a 49.1% false-positive diagnosis rate for women undergoing mammograms annually for ten years [8].

In this study, we aim to elucidate the utility of infrared imaging for breast cancer detection and propose a novel model to aid in the early identification of breast anomalies, thereby augmenting conventional methods. For this, this paper aims to introduce the concept of infrared digital imaging, an emerging diagnostic technique. This method is premised on the notion that a significant thermal difference can be discerned between a healthy breast and a tumorous one. This difference can be attributed to the increased metabolic activity and vascular circulation within and around the tumorous cells.

2. Related Work

Kontos et al. highlighted the limitations of thermographic imaging in clinical decision-making due to its propensity for false positives [9]. Their study concluded that thermal diagnosis was unsuitable for initial examinations. Then, Full-Field Digital Mammography (FFDM) and Digital Infrared Thermal Imaging have been identified as promising tools that could address mammography's shortcomings. The efficacy of these techniques lies in their ability to enhance contrast in areas of dense parenchyma and detect increased metabolic activity and vascular circulation in precancerous cells because a ConvNet model successfully categorizes cancer as invasive as shwon in [Fig. 1] Despite these advantages, the high false negative rate of Computer Thermographic Imaging (CTI) reduces its clinical utility.

Mehdy et al. emphasized the annual importance of thermal prognosis [10]. They suggested that a proper procedure should be followed during examination and post-treatment analysis of thermograms. The Artificial Neural Network (ANN) could further enhance thermal diagnosis by providing images with and without breast cancer cells. Furthermore, integration of ANNs, genetic algorithms, and computer simulations could enhance prognosis by correlating skin surface temperature with tumor depth, size, and thermal generation. Geometric models, including the hemispheric computational domain, have been proposed to better understand breast cancer [11]. Although this model does not represent the actual breast shape, it provides insights into the relationship between tumor depth and surface temperature. Further studies are needed to investigate the asymmetric temperature distribution and the relation between tumor depth and surface temperature. Understanding the breast's natural heat transfer equation could help resolve the uncertainty surrounding tumor depth, size, and location.



[Fig. 1] Convolution architecture

Thermal physical functionalities in breast cancer detection require methodologies such as the slope descent procedure, Levenberg Marquardt algorithm, or genetic algorithms. Boquete et al. noted that IR radiation from the body is critical for successful diagnosis and improving image processing algorithms [12]. Additionally, Independent Component Analysis (ICA), a subspace estimation technique, helps in extracting information related to malignant carcinomas from the initial image. An agent-like structure that could encapsulate the tumor and generate a Near-Infrared Fluorescent (NIRF) signal was discussed for accurate tumor localization and for the important role of Fluorescence Imaging (FI) in detecting small superficial liver tumors and providing real-time assessment and revealing otherwise undetectable tumors [13]. Namikawa and Yamazaki focused on the Sentinel Lymph Node (SLN), identifying it as the first lymph node at high risk of primary tumor metastasis [14]. Indocyanine Green (ICG) used for SLN detection binds to plasma proteins and fluoresces under specific NIR light wavelengths, providing high detection rates and minimal false negatives.

The correlation between tumor size and depth is challenging due to the complex structure of the breast. However, the tumor's reaction time increases with depth, and smaller tumors have longer reaction times. Finally, twelve areas of investigation to improve breast cancer detection and treatment was suggested [15]. It highlighted the importance of genetic testing in people with a familial history of breast cancer, asserting that confirmation of genetic predisposition supports risk reduction strategies. The genetic testing tools should be coupled with accurate interpretation of results and uncertainties for informed clinical decision-making.

3. Proposed Model

Breast cancer, constituting 23% of all newly diagnosed oncology cases, significantly affects families and national budgets. It is estimated a potential saving of 247 million USD in medical expenses and income losses related to breast cancer in a cohort of Mexican women [16]. For this economical concerns and nursing burdens, modern approaches to understanding the etiology of breast cancer enhance precision in cancer detection. Technologies including the Sentinel Breast Scan and the No Touch Breast Scan have shown potential in reducing false positives, primarily through neural network applications. In this regard, this paper employed reliable computer system vision procedures since a Computer-Aided Diagnostic (CAD) accomplished by infrared visuals handling cannot be accomplished without a design such as the widely known hemispheric variation.

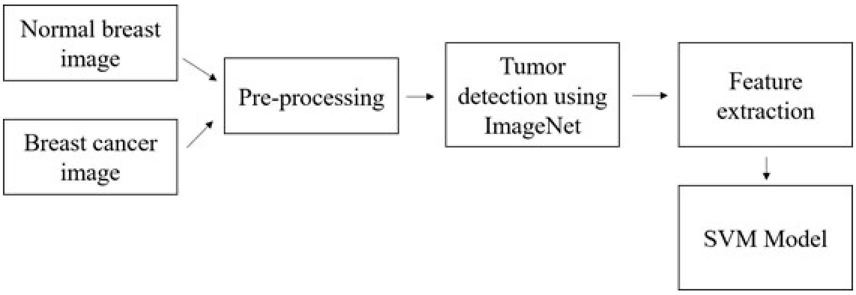
The fundamental images extracted for this study rely on Diagnostic DMR and minimal thermogram illustrations, captured using the FLIR SC-621 IR model equipment with a resolution of 640 × 480 pixels. These images encompass individuals aged between 28 and 86 years, featuring breasts of various sizes and shapes, including medium, wide, and irregular.

The demographic data of the subjects are as follows : a) Total number of subjects N = 67, b) Total number of healthy/normal subjects NH = 43, c) Total number under indifferent subjects NS = 26.

Considering the prior analysis of the data, the significance of image processing, currently well-executed by humans but not as efficiently by artificial intelligence methods, is highlighted. The focus is mainly on CAD, which aids in understanding consistent images acquired through various camera system models. A CAD-based Support Vector Machine (SVM) model serves as a separator, classifying the thermal images as either cancerous or not. The deep learning component provides the probability that a breast's conduction image is categorized as unhealthy (with cancer) or healthy. The confidence outcome by the Deep Neural Network (DNN) ranges between 0.4 and 0.7. Consequently, it relies on the

SVM classification to discern the condition of an individual's breast based on the thermal image's feature matrix.

As shown in [Fig. 2], the proposed system in this paper aligns with a systematic workflow where each block represents a distinct function. Both existing and novel techniques used for breast cancer detection and prevention are described.



[Fig. 2] Proposed SVM Model

3.1 Pre-Processing

The preprocessing involves the treatment of breast thermal images. These images were captured following a dynamic process involving breast cooling via an air current. During the individual's body acclimatization to the environment, 22 consecutive images were acquired at 17-second intervals. The images, initially large for DNN, were cropped to eliminate unnecessary regions. The Region of Interest (ROI) is extracted from each grayscale image. These separate ROI images are converted into a feature array for processing, and areas likely containing cancer cells are transferred to the initial phase of the next point. Thus, pre-evaluation involves grayscale RGB transformations and image cropping to remove undesirable areas, such as the trachea region, hands, and intermediate sections of the area. In the context of extracting a Region of Interest from medical images, RGB transformations are often applied to images in the preprocessing stage for dimensional reduction, highlighting features and uniformity. The aim is to highlight relevant features such as the contours of a tumor while reducing unnecessary information and computational load. By transforming to grayscale, the algorithm can focus on the structural and intensity information, which is often of primary interest in medical imaging.

3.2 Classification of Image Framework

Given the principle of transfer learning, this study utilized a pre-trained Inception V2 model, proficient for feature extraction. This Deep Neural Network (DNN) is structured such that there's an initial layer consisting of 11 neurons, each connected to 22 neurons in the subsequent layer, and each of these linked to 10 neurons in the third layer. In this study, we further fine-tuned the final classification layer to discern cancerous from non-cancerous cells with substantial confidence. If the confidence level of the final layer's output was between 0.5 and 0.6, we directed the feature matrix to the Support Vector Machine (SVM) for prediction. The specific confidence interval of <0.6 and ≥ 0.5 for routing the output to the SVM is likely based on empirical data or heuristic reasoning. In many machine learning models, the final layer's output is a probability or confidence value that a given input belongs to a particular class, in this case, the presence or absence of cancer. Generally, a threshold of 0.5 is used. If the output is greater than 0.5, the input is classified as positive for cancer, and if it's less than 0.5, it's classified as negative. However, if the confidence value is near the 0.5 threshold, it indicates that the model is relatively unsure about the classification. To improve the accuracy of the model's predictions in these uncertain cases, these borderline outputs can be processed further with another machine learning model, such as the SVM.

The model was trained with a learning rate of 0.0001, epoch count of 15, and step count of 4000. The training sample consisted of 64 breasts, evenly divided between healthy and those exhibiting abnormalities, with each breast represented by 20 sequential images. To validate our model, we used a completely new set of 12 breasts. In this study, we employed a standard linear SVM architecture. The primary layer functions as an initial segment containing features derived from Inception V2. The hidden layer, composed of several neurons, executes an inner-product operation. This logical framework facilitates an efficient and accurate process for diagnosing breast cancer.

4. Results

From an academic and logical perspective, the procedure described entails a validation test using breast images from a set of 14 ideal breast models. Given that each breast provides 20 sequential images, the model was ultimately tested on a total of 480 images, presented in a sequential arrangement. This substantial volume of data helps to ensure the model's robustness and reliability.

[Fig. 3] and [Fig. 4] illustrate the final model's predictions, further demonstrating the performance of the model in real-time prediction scenarios. This comprehensive assessment methodology supports the rigorous examination of the proposed model's accuracy, robustness, and generalizability in detecting breast anomalies. Therefore, such a logical approach underpins the validity of the study, ensuring its scientific rigor and applicability.

[Fig. 3] Input as sick image

[Fig. 4] Input as healthy image

5. Conclusions

In the scholarly assessment of existing literature, it was discerned that contributing to the field of breast cancer detection from a technoscientific perspective could be highly valuable. For this purpose, this paper presented an evaluation of the most prevalent methodologies for breast cancer detection and scrutinized their respective strengths and limitations. One particular method, notably characterized by its non-invasive nature and the substantial data volumes it demands, appears to have a promising future. This strategy involves the use of infrared techniques, combined with an agent administered to the patient, thereby potentially leading to precise cancer detection. In addition, this study addresses this exigency by proposing a novel model for early detection of breast cancer utilizing infrared digital imaging. Capitalizing on the significant thermal difference discernible between healthy and tumorous breasts, this method provides a potential alternative to conventional techniques.

Future research should consider utilizing a consistent thermal conduction level of 0.6 and propose a breast model that might facilitate more accurate diagnostic conclusions. Such advancements will significantly enhance the capabilities of our understanding and approaches towards breast cancer detection and treatment.

References

[1] N. Kosus, A. Kosus, M. Durna, S. Simavli and N. Turhan, "Comparison of standard mammography with digital mammography and digital infrared thermal imaging for breast cacner screening", Turkish-German Gynecological Association, vol. 11, no. 3, pp. 152-157, doi: 10.5152/jtgga.2010.24.

[2] R. Nithya and B. Santhi, "Mammogram density classification using deep convolutional neural network", Journal of Instrumentation, vol. 16, no. 1, January 2021, P01019. doi: 10.1088/1748-0221/16/01/P01019.

[3] L. Ahmed, M. M. Iqbal, H. Aldabbas, S. Khalid, Y. Saleem and S. Saeed, "Images data practices for semantic segmentation of breast cancer using deep neural network", Journal of Ambient Intelligence and Humanized Computing, January 2020, pp. 1-17, doi: 10.1007/s12652-020-01680-1

[4] D. A. Ragab, M. Sharkas, S. Marshall and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines", PeerJ, vol. 7:e6201, January 28, 2019, doi: 10.7717/peerj.6201.

[5] D. Rajasekaran Subramanian, R. Devika Rubi and S. R. K. Priyal Jain, "Breast Cancer Lesion Detection and Classification in Radiology Images using Deep Learning", European Journal of Molecular & Clinical Medicine, vol. 7, no. 3, 2020, pp. 677-684.

[6] M. H. Motlagh, M. Jannesari, H. Aboulkheyr, P. Khosravi, O. Elemento, M. Totonchi, and I. Hajirasouliha,, "Breast cancer histopathological image classification: A deep learning approach", BioRxiv, January 2018, doi: 10.1101/242818.

[7] N. Khuriwal and N. Mishra, "Breast Cancer Detection From Histopathological Images Using Deep Learning", 2018 3rd International Conference and Workshops on Recent Advances and Innovations in Engineering (ICRAIE), November 1, 2018, Jaipur, India, pp. 1-4, doi: 10.1109/ICRAIE.2018.8710426.

[8] S. G. Kandlikar, I. Perez-Raya, P. A. Raghupathi, J. G. Hernandez, D. Dabydeen, L. Medeiors and P. Phatak, "Infrared iamging technology for breat cancer detection - current status, protocols and new directions," International Journal of Heat and Mass Transfer, Vol. 108, May 2017, pp. 2203-2320, 10.1016/j.ijheatmasstransfer.2017.01.086.

[9] M. Kontos, R. Wilson and I. Fentiman, "Digital infrared thermal imageing (DITI) of breat lesions: sensitivity and specificity of detection of primary breats cancers," Cilinical Readiology, vol. 66, No. 6, June 2011, pp. 536-539, doi.org/10.1016/j.crad.2011.01.009.

[10] M. M. Mehdy, P. Y. Ng, E. F. Shair, N. I. Md Saleh and C. Gomes, "Artificial Neural Networks in Image Processing for Early Dectection of Breast Cancer", Computational and Mathematical Methods in Medicine, Vol 2017, doi.org/10.1155/2017/2610628.

[11] G. Chugh, S. Kumar and N. Singh, "Survey on Machine Learning and Deep Learning Applications in Breast Cancer Diagnosis", Cogn Comput 13, January 2021, pp. 1451-1470, doi: 10.1007/s12559-020-09813-6.

[12] L. Boquete, S. Oretega, J. M. Miguel-Jimenez, J. M. Rodriguez and R. Blanco, "Automated Dectection of Breast Cancer in Thermal Infrared Images, Based on Independent Component Analysis", Journal of Medical

Systems, vol. 36, March 2010, pp. 103-111.

[13] K. S. Priyanka, "A Review Paper on Breast Cancer Detection Using Deep Learning", In IOP Conference Series: Materials Science and Engineering, vol. 1022, no. 1, January 2021, pp. 012071, doi: 10.1088/1757-899X/1022/1/012071.

[14] K. Namikawa and N. Yamazaki, "Sentimal Lymph node biopsy guided by indocyanine green fluorescence for cutaneous melanoma", Europena Journal of Dermotology, vol. 21, March-April 2011.

[15] B. Haibe-Kains, C. Desmedit, F. Piette, M. Buyse, F. Cardoso, L. Veer, M. Piccart, G. Bontempi and C. Sotirious, "Comparison of prognostic gene expression sigatures for breast cancer", BMC Genomics, vol. 9, no. 394, August 2008.

[16] S. R. Nayak, D. R. Nayak, U. Sinha, V. Arora and R. B. Pachori, "Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study", Biomedical Signal Processing and Control, vol. 64:102365, Feburary 2021, doi: 10.1016/j.bspc.2020.102365.