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A New Artificial Intelligence-Powered Thermography-Based Method for Breast Cancer Screening

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1. Abstract

1.1. Background and objectives: One of the most prevalent malignancies in women is breast cancer, which affects 7% of American women under the age of 40. Prompt diagnosis and action are crucial for improving patient outcomes and mitigating the mounting strain on global healthcare systems. Mammography, the current gold standard for diagnosing breast cancer, has limitations when it comes to early detection, particularly in younger women with dense breast tissue. Furthermore, mammography is not as widely available or as reasonably priced in low- and middle-income nations. However, thermography can identify cancer in very little can detect cancer in very early stages and in this paper; we discuss an AI-powered thermography based breast cancer prediction tool

1.2. Methods: The suggested approach involves pre-processing and augmentation of the data, a thorough training plan, and a post-processing risk calculation step. The suggested algorithm was trained to identify anomalies in the breast tissue using 1600 pictures from databases of breast thermography.

1.3. Results: We achieved 93% accuracy, 95% precision, and >90% specificity and sensitivity on our dataset. This represents a major advancement in the use of thermography as a possible breast cancer screening method. Furthermore, the model can forecast the chance of acquiring breast cancer in the future using the risk calculator.

1.4. Conclusion: Our suggested model's high accuracy combined with its ability to forecast risk makes AI Talos' AI-powered screening tool a computer-aided diagnostic system that can help with early identification and screening for breast cancer, particularly in younger populations.

Keywords:
CNN; deep learning; artificial intelligence; thermography; transfection breast cancer screening

2. Introduction

One of the most common malignancies in the world is breast cancer.
The World Health Organization estimates that 2.3 million women worldwide received a breast cancer diagnosis in 2020, and 685,000 of those cases resulted in death [1]. In the United States, a woman's lifetime risk of having breast cancer is approximately 13% [2]. 1% of all instances are diagnosed in men, despite the fact that women are more likely to get breast cancer [3]. Two primary factors contribute to the higher breast cancer death rates in low- and middle-income nations compared to industrialized nations: delayed detection at an advanced stage of the illness and restricted access to reasonably priced healthcare [4,5]. Furthermore, women under 40 account for 7% of all instances of breast cancer in the United States, and the disease tends to be more aggressive in younger women [6].

3. Thermography

As thermography, or infrared imaging, it's a quick, non-invasive, an infrared camera and a non-contact, radiation-free technique to measure the body's surface temperature distribution. A thermogram is a visual representation of the temperature dispersion is produced on the body's surface. The infrared cameras are equipped to detect small temperature variations because of their sensitivity, which can detect variances as small as 0.025°C [14]. Previous research [15–20] have detailed the basics of thermography and the accuracy with which infrared cameras assess body temperature. Breast cancer was initially diagnosed using thermography in 1956 [21]. The idea behind thermography in the detection of cancer is that angiogenesis causes the tumor cells to have an enhanced blood supply.

4. Related Work

Previous research has demonstrated that an abnormal breast thermogram is the first indication of breast cancer and is linked to a higher risk of the disease [27–29]. Thermography is more sensitive than mammography at identifying aberrant activity in dense or early-stage breast tissue [30, 31]. It takes time for doctors to visually analyze and interpret thermograms to find suspicious areas, and their level of skill in doing so determines how well the thermograms are interpreted. Clinicians also differ to some extent from one another as observers, which can cause bias in their observations and/or errors in interpretation that result in false positives and false negatives. Current studies on thermography-based breast cancer diagnosis have concentrated on creating computer assisted methods for faster and more accurate detection of the tumor even in early stages of the disease [32-36]. Clinicians are using computer-aided diagnostic and detection systems as instruments for second opinions when interpreting imaging techniques. These technologies use a combination of machine learning, deep learning, image analysis, and/or combination approaches [37, 38]. Over the last ten years, scientists have concentrated on creating machine learning-based breast cancer detection systems. This research presents a thermography-based prediction tool driven by artificial intelligence.

AI-Powered Breast Cancer Prediction Tool by AI Talos

AI Talos draws inspiration from the massive bronze warrior known as Talos from Greek mythology, who was designed to protect the island of Crete. With deep learning driven algorithms at its heart, AI Talos has created a revolutionary computer aided diagnostic system to identify early indicators of breast cancer in thermograms. Convolutional neural networks (CNNs) are among the most prominent deep learning networks. Deep learning is concerned with knowledge inference methods from data [39].

5. Methods

5.1. Dataset Description

The thermal images came from two public databases: Digital Infrared Analysis (DIA) from Hospital General de México in Mexico [50] and Databases for Mastology Research (DMR) Database [47–49] from Brazil. Infrared pictures and clinical information from patients at the Hospital Universitário Antônio Pedro (HUAP) of the Fluminense Federal University in Brazil are both included in the DMR-IR database. The FLIR thermal camera type SC-620 is used to take the infrared pictures. The DMR-IR database adhered to the previously mentioned guidelines [24,51]. A thermal image acquisition procedure is used to guarantee database quality. There are no details available for the DIA database. In this investigation, an online search utilising the PubMed database was conducted. Other papers were also extracted using the snowball method. Among the terms utilized were describing various delivery methodologies and the factors that influence transfection efficiency. Thanks to the efforts of a large number of researchers and new ideas for improving equipment and strategies.

5.2. CNN Methodology

There are 3200 photos in our database from 95 patients. where 1100 pictures showed abnormalities in the breast tissue and 2100 images showed normalcy. The dataset was trained using 1600 photos, validated using 640 images, and used the remaining 960 images. as an experimental group. The distribution of the 3200 image database's splitting between normal and abnormal breast photos is displayed. We employed several data pre-processing techniques and trained various models with varying depth and parameters using the same architecture. In the end, we selected the ideal model.

6. Results and Discussion

ROC curves for all depths. The model in depth-2 produced the best outcomes when the performance metrics were applied. 93% accuracy, 93% sensitivity, 91% specificity, and 95% precision were recorded by Depth-2.

7. Conclusion

A better prognosis for breast cancer requires early detection. Better diagnostic modalities must be developed because mammography, the gold standard diagnostic tool now in use, is unable to identify breast cancer in its early stages. One such modality is thermography, which can be enhanced with computer-aided detection and diagnosis tools to further enhance its capacity to identify early irregularities in the breast tissue. In order to facilitate the identification of anomalies in thermal imaging of breast tissue, we presented a CNN-based model in this study. A crucial component of our methodology for follow-up breast cancer screenings is the estimation of the risk of developing breast cancer. Medical professionals favor systems that can accurately identify malignant tumors and forecast the likelihood that such tumors will form in the future.

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