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A Novel Thermography Based Artificial Intelligence Powered Solution for Screening Breast Cancer

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ABSTRACT

Background and objectives: Breast cancer is one of the most common cancers in women and 7% of breast cancer cases in the United States occur in women under the age of 40. Early diagnosis and intervention are essential not only for better patient prognosis, but also to reduce the ever increasing burden on the healthcare system across the globe. The current gold standard for breast cancer diagnosis, mammography, is limited in its capacity to detect breast cancer in early stages especially with younger women with dense breast tissue. Additionally, there is limited accessibility and affordability of mammography in low and middle income countries. Thermography, on the other hand, can detect cancer in very early stages and in this paper; we discuss an AI-powered thermography based breast cancer prediction tool.

Methods: The proposed method involves data pre-processing, data augmentation, a detailed training strategy, and a post-processing risk calculation step. The proposed algorithm was trained using 1600 images from breast thermography databases to detect abnormalities in the breast tissue.

Results: On our dataset, we obtained an accuracy of 93%, 95% precision with >90% specificity and sensitivity, which is a significant breakthrough in using thermography as a potential screening for breast cancer. Additionally, with the risk calculator, the model can predict the risk of developing breast cancer in the future

Conclusion: The high accuracy of our proposed model and the risk prediction capabilities enable the AI-powered screening tool by AI Talos to become the computer aided diagnostic system that supports screening and early detection of breast cancer especially in younger population.

Keywords: Transfection breast cancer screening; Thermography; CNN; Deep learning; Artificial intelligence

INTRODUCTION

The Breast cancer is one of the world's most prevalent cancers. According to the World Health Organization, in 2020, there were 2.3 million women diagnosed with breast cancer and 685,000 deaths globally [1]. The average risk of a woman, in the US, developing breast cancer in her lifetime is ~13% [2]. Though breast cancer is more common in women, 1% of all diagnosed cases occur in men [3]. The breast cancer mortality rates are higher in low and middle income countries than the developed countries because of two main reasons late diagnosis at advanced stages of the disease and limited access to affordable medical care [4,5]. Additionally, 7% of breast cancer cases occur in women under 40 years of age in the United States, and the disease tends to be more aggressive in younger women [6]. However, breast cancer screening by mammography is recommended to the general population at/after 40 years of age [7,8]. Detection of breast cancer at early stages is important for a better prognosis. Research studies have suggested that early diagnosis and medical intervention significantly reduces the long term breast cancer mortality rate [9].

Early detection of breast cancer is hugely dependent on clinical examination and imaging modalities, such as mammography, ultrasound, thermography, breast magnetic resonance imag-

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ing (MRI) and histopathology imaging. Mammography is the gold standard screening tool for breast cancer, and patients with equivocal screening results usually require further confirmation by diagnostic imaging, such as breast MRI or biopsy or combination [10]. However, one of the limitations of the gold standard technique (s) is the inaccessibility in low and middle income countries. Additionally, these techniques fail to detect breast cancer is young women (<40 years) who have dense breast tissue [11]. Contrary to the gold standard diagnostic modalities, thermography can detect physiological changes even in dense breast tissue and is currently used as an adjunctive tool in breast cancer screening [12,13].

Thermography

Infrared imaging or thermography is a fast, non-invasive, non-contact, radiation free method to measure temperature distribution on the surface of the body using an infrared camera. A visual map, called a thermo gram, of the temperature distribution on the surface of the body is created. The infrared cameras have a sensitivity of detecting temperature differences up to 0.025°C, which equips the cameras to detect minor variations in temperature [14]. The reliability of IR cameras to measure actual body temperatures and the fundamentals of thermography have been described in previous studies [15-20]. Thermography was first used in 1956 for the diagnosis of breast cancer [21]. The principle of thermography in cancer detection is that the tumor cells have an increased blood supply due to angiogenesis and an increased metabolic rate [22,23], which creates a temperature spike on the surface of the breast. This temperature spike is easily detectable by an infrared camera [24-26].

Related Work

Earlier studies have shown that abnormal breast thermogram is associated with an increased risk of breast cancer, and, in fact, is the earliest sign of breast cancer [27-29]. In comparison to mammograms, thermography can detect abnormal activity in the breast tissue at an early stage or in dense tissue [30,31]. Visual inspection and interpretation of thermograms by clinicians to identify suspicious areas is a time consuming task and the effective interpretation of the thermograms is dependent on the expertise of the clinician. There is also a degree of intra and inter observer variability among clinicians leading to an observational bias and/or interpretational failures resulting in false positives and false negatives. Recent research studies on breast cancer detection using thermography have focused on developing computer aided methods for faster and more accurate detection of the tumor even in early stages of the disease [32-36]. Computer aided detection and computer aided diagnosis systems have been adopted as second opinion tools for interpretation of imaging techniques by clinicians. These tools rely on image analysis, machine learning, deep learning, or a combination approach [37,38]. In the past decade, researchers have focused on developing breast cancer diagnostic tools using various machine learning techniques. In this paper, we discuss an AI-powered thermography based prediction tool.

AI-Powered Breast Cancer Prediction Tool by AI Talos

AI Talos is inspired by the gigantic bronze warrior from Greek mythology, Talos, who was programmed to guard the island of Crete. AI Talos has developed a novel computer aided diagnostic system to detect early signs of breast cancer in thermograms with deep learning guided algorithms at its core. Deep learning focuses on knowledge inference mechanisms from data and one of the most influential deep learning networks is the Convolutional Neural Network (CNN) [39].

Earlier research studies have shown promising results using CNN in imaging applications for breast cancer diagnosis [40-45]. Zuluaga-Gomez et al. have discussed a CNN based methodology for diagnosis of breast cancer using thermograms that highlights the benefits of data augmentation and CNNs in breast thermograms [46]. We have developed a novel CNN based methodology that predicts the risk of cancer in breast thermograms with a higher accuracy and specificity.

METHODS

Dataset Description

The thermal images have been obtained from two public databases-Databases for Mastology Research (DMR) Database [47-49] from Brazil, and Digital Infrared Analysis (DIA) from Hospital General de México in Mexico [50]. The DMR-IR database contains infrared images along with the clinical data from patients of the Hospital Universitário Antônio Pedro (HUAP) of the Fluminense Federal University in Brazil. The infrared images are captured using a FLIR thermal camera model SC-620. The DMR-IR database followed the previously described [24,51]. Thermal image acquisition protocol to ensure that quality of database is maintained. The details for the DIA database are not available. Online search using the PubMed database was followed in this study. The snowball method was also used to extract other publications. The keywords used included terms 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. Due to the exponential growth of papers published in the field and space limitations, only articles between 2015 and March 2022 were retrieved. Titles in non-English language were excluded. After vigorous screening and detailed evaluation, only 136 articles were selected for data extraction.

CNN Methodology

Our database is composed of 3200 images from 95 patients, where 2100 images were normal and 1100 images had anomalies in the breast tissue. 1600 images were used to train the dataset, 640 for validation, and the remaining 960 were used as a test set. **Table 1** shows the distribution of splitting of the 3200 image database across normal breast images and breast images with anomalies. We trained different models from the same architecture with different depth and parameters together and used different steps for data pre-processing. Finally, we chose the best model. Using a novel formula, we also estimat-

ed the risk of breast cancer using five images for each input. We have created a cloud based panel, called Talos Cloud, to store patients' records in the EHR system which is password protected to ensure data safety and compliance with HIPAA.

The technology behind the model has 4 phases. The pictorial representative is shown in **Figure 1**.

Table 1: Distribution of splitting of the 3200-image database across normal breast images and breast images with anomalies

	Total Images	Splitting		
		Training	Validation	Testing
	3200	1600	640	960
Normal Breast Tissue	2100	1050	420	630
Breast Tissue with Anomalies	1100	550	220	330

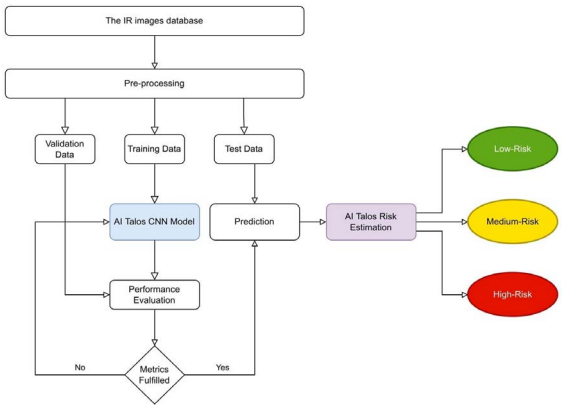

Figure 1: The detailed approach of the four phases of technology behind the AI- powered model using breast thermograms

Phase 1 Data Pre-Processing and Data Augmentation

This phase is essential to extract the region of interest for our proposed CNN. During pre-processing, we removed any unwanted area of the thermogram by different methods, such as eliminating watermarks, cropping, resizing, and normalizing thermal breast images. In the data augmentation step, we generated new images by methods, including horizontal and/or vertical flipping, rotation, zoom, and normalization for noise.

Phase 2 the Training Strategy

The CNN presented is based on the structure of the previously described VGG16 neural network [52]. Several depths of the neural network were tested, ranging from 1 to 5 convolutional sections, and each depth was followed by a fully connected section with two layers (**Figure 2**). For the depth-1 configuration, the CNNs had an input of dimension 224 × 224 pixels. The thermal images were resized to this size. They were convolved by 3 × 3 filters to produce 64 channels of dimension 224 × 224 pixels. The outputs were then passed through a set of ReLU (Rectified Linear Activation Unit) activations. The process was repeated with an identical convolution, ReLU activation, and then pooled to produce 64 channels of dimension 112 × 112 pixels. The output was next passed through a 1 × 1 convolution to produce two channels of 112 × 112 pixels. The result was processed through a fully connected layer with 4096 outputs, ReLU activation, and dropout, a second identical fully connected layer, and finally a layer with two outputs and sigmoid activation that computes the classification probability for two different classes.

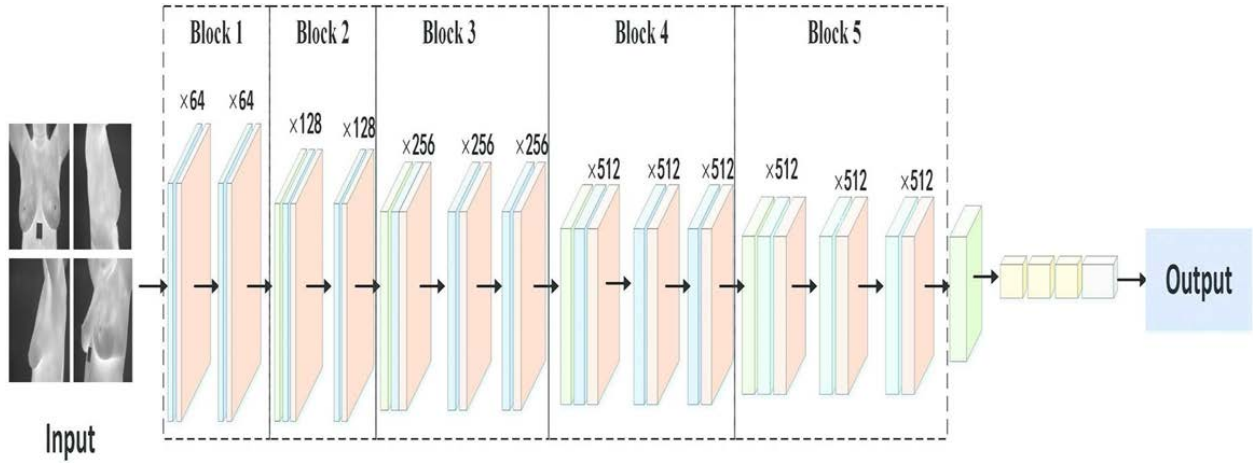

Figure 2: The detailed workflow of the proposed model

For depth-2 configuration, the first convolution layer was similar to depth-1. After the first pool, two more convolutions were added that produced 128 channels of size 112 × 112 pixels, reduced to 128 × 56 × 56 pixels. The next layers had similar structures as in the 1-layer configuration, where the input to the first fully connected layer was 8 × 56 × 56 pixels. We built the configurations with 3, 4, and 5 layers using the same methodology.

Phase 3 Performance Metrics

We evaluated our model using defined performance metrics calculated from the confusion matrix shown in **Table 2**. The results are shown in **Tables 3 and 4**.

Table 2: Confusion Matrix

Total Test Samples	Predicted Positives	Predicted Negatives
Actual Positives	True Positives	False Negatives
Actual Negatives	False Positives	True Negatives

Table 3: Confusion Matrix data for depth-2 model during training, validation, and testing steps

Label		Training		Validation		Testing	
True Positive	False Negative	1019	31	378	42	586	44
False Positive	True Negative	5	545	28	192	30	300

Table 4: Performance Metrics for the depth-2 model during training, validation, and testing steps

	Training	Validation	Testing
Accuracy	97.8	89.1	92.3
Sensitivity	97	90	93
Specificity	99.1	87.3	90.9
Precision	99.5	93.1	95.1
F1 Score	98.2	91.5	94

- **Accuracy:** Shows how often the result is correct, and is calculated

$$\frac{(True\ Positive+True\ Negative)}{(True\ Positive+True\ Negative+False\ Positive+False\ Negative)}$$

- **Sensitivity:** It is the proportion of positive data points that are predicted positive correctly, and is calculated

$$\frac{True\ Positive}{(False\ Negative+True\ Positive)}$$

- **Specificity:** It is the proportion of negative data points that are predicted negative correctly, and is calculated

$$\frac{True\ Negative}{(False\ Positive+True\ Negative)}$$

- **Precision:** Reflects how reliable the model is in classifying samples as positive, and is calculated

$$\frac{True\ Positive}{False\ Positive+True\ Positive}$$

- **F1 Score:** It is calculated

$$2\times\frac{Precision\times Sensitivity}{Presicion+Sensitivity}$$

Phase 4 Post-Processing

During the post-processing step, we used a novel formula to estimate the risk of having breast cancer as low , medium, or high risk. The outputs were probabilistic and needed calibration to obtain a more realistic risk prediction score. We used five images and calculated the risk using the calibrated number for each image, and then calculated the overall risk.

Code Availability

The CNN model, training and validation data, and post-processing data are proprietary to AI Talos, and thus they are not made available

RESULTS AND DISCUSSION

The ROC curves for all depths are shown in **Figure 3**. The model in depth-2 yielded the best results when evaluated using the performance metrics. Depth-2 had 93% accuracy, 93% sensitivity, 91% specificity, and 95% precision.

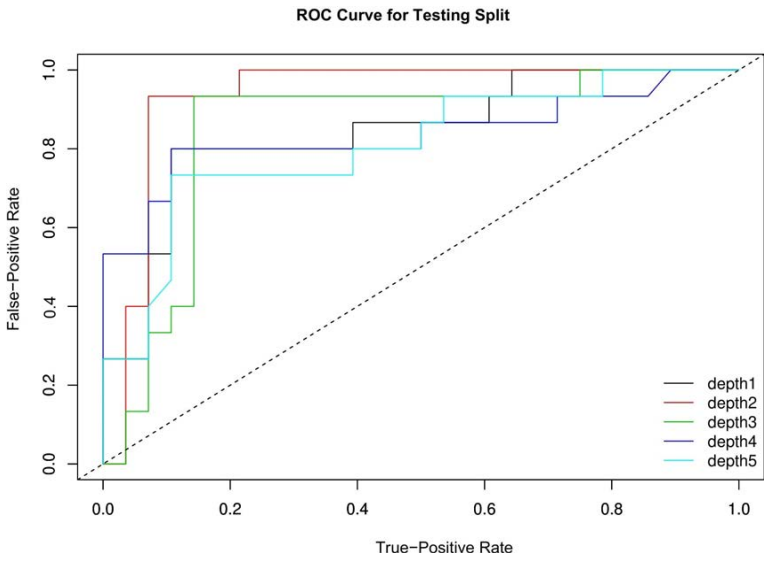

Figure 3: Receiver Operating Characteristics (ROC) Curves for all depths. The depth-2 showed the most promising results

The post-processing step calculated the risk of having breast cancer and categorized the risk as low (1-5), medium (5-7), or high (7-11). The representative images for low and high risk are shown in **Figures 4 and 5**, respectively. The model yielded a high score of 10.36, which is a high risk for having breast cancer (**Figure 5**). This was corroborated with clinical evidence for the particular case, where the diagnosis of breast cancer was confirmed by biopsy and histopathology

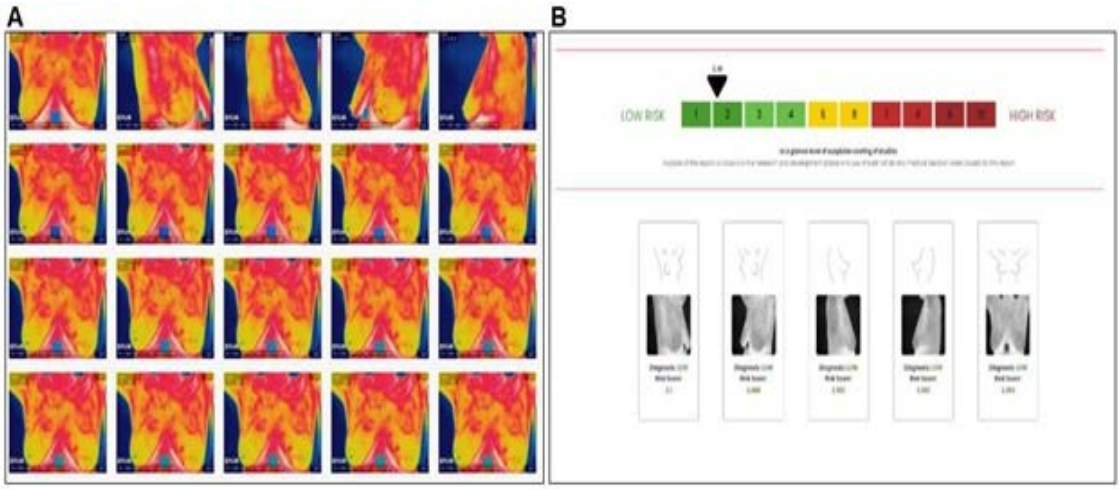

Figure 4: Representative image of the (A) input breast thermograms of a healthy individual, and the (B) output result from the AI Talos model showing low-risk score of 2.30

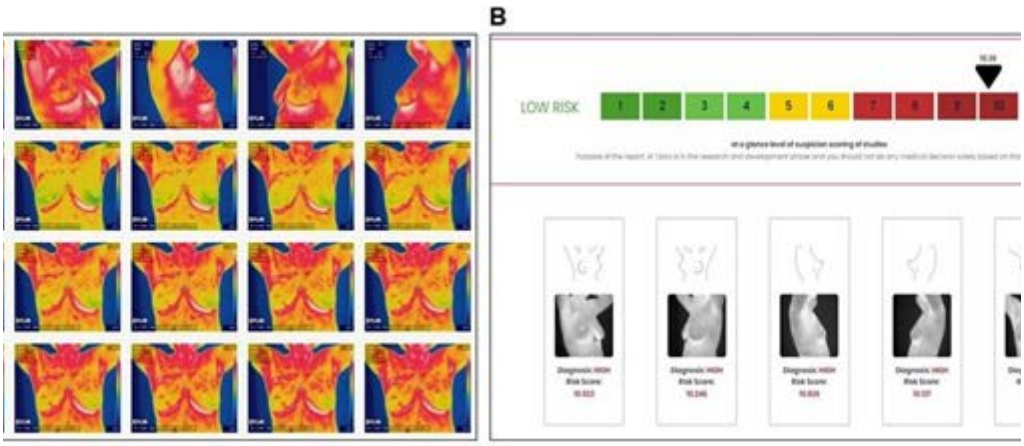

Figure 5: Representative image of the (A) input breast thermograms of an individual confirmed to have breast cancer, and the (B) output result from the AI Talos model showing high-risk score of 10.36

CONCLUSION

Early detection of breast cancer is essential for a better prognosis. Since the current gold standard diagnostic modality, mammography, doesn't detect breast cancer at the early stages, it is important to develop better diagnostic modalities. Thermography, with its ability to detect early anomalies in the breast tissue, can be supplemented with computer aided detection and diagnosis systems to become one such modality. In this paper, we proposed a CNN based model to aid detection of anomalies in thermal images of breast tissue. Our model also estimates a risk of having breast cancer, which is critical for follow up screenings for breast cancer. Physicians prefer systems that can not only detect malignant tumors with high accuracy, but also predict the risk of developing such tumors in the future. Additionally, thermography has the advantages of being an affordable, non-invasive, portable and painless diagnostic modality, thus making it a potential viable alternative to currently used mammography. This will have a significant impact in low and middle income countries with limited access to affordable healthcare. A low cost thermography based AI-powered diagnostic system will enable early detection of breast cancer, which will in turn lower the load on the already limited medical infrastructure in these communities. To summarize, with a high accuracy of 93% and risk prediction capabilities, the screening tool developed by AI Talos has the potential to become the computer aided diagnostic system that physicians can depend on for early diagnosis of breast cancer.

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