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# Breast Cancer Detection System from Thermal Images using SWIN Transformer

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## ABSTRACT

Breast cancer constitutes a significant public health challenge, demanding effective diagnostic approaches. While ultrasound, mammography, and MRI remain pivotal, their practicality for regular, short-interval mass screenings is limited. Thermography, as a non-invasive and cost effective option, holds potential for routine self-screening. Leveraging the self-attention based Vision Transformer designs in lieu of traditional CNNs, this study explores various SWIN transformer variations and augmentation strategies for breast cancer detection. DMR-IR benchmark dataset was used, which was partitioned into training, testing, and validation subsets with the ratio of 70:15:15%, the obtained results exhibit significant promise. The SWIN-L architecture exhibited exceptional performance, achieving 96.55% accuracy, 95.50% precision, 95.76% recall, 95.43% F1 score, 97.34% specificity, and 96.21% AUC, thus demonstrating its remarkable capability in breast cancer detection. Based on the observed results, it is evident that the proposed system holds promise and can be considered for breast cancer detection.

**Keywords:** Breast Cancer; Thermography Image, Vision Transformer; Self Attention; SWIN.

## 1.0 Introduction

Breast cancer emerges as a critical health challenge with potentially devastating consequences for women today, stemming from factors like genomic changes, hormonal imbalances, and lifestyle choices [1]. This complex ailment's progression is tied to DNA alterations induced by both environmental triggers and hormones, contributing to its grim status as a leading cause of female mortality [2]. Swift diagnosis remains paramount, as recovery rates fluctuate based on disease stage. Annual breast cancer screening, pivotal for early detection and mortality reduction, has seen a promising ally in ultrasound imaging due to its accessibility, real-time functionality, and cost-effectiveness [1], [3]. The integration of automated analysis in medical imagery aids radiologists in identifying masses and curtailing false negatives, thereby enhancing diagnostic accuracy. Genetic mutations in BRCA1 and BRCA2 genes are implicated in 5% to 10% of cases, and their correlation with early breast cancer underscores the significance of genetic influences [4]. While adult exposures like toxins and radiation can damage these genes, radiologists wield their expertise in image-based differential diagnoses, an essential aspect spanning disease identification to malignancy classification. Breast cancer's global impact is particularly evident in regions like India, where it ranks high among causes of death, necessitating efficient screening strategies. Thermography, offering non-invasive and radiation-free imaging, presents an intriguing avenue for research, especially given its potential in detecting temperature discrepancies indicative of cancerous tissues [5].

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The collaboration of expert radiologists and innovative technologies like dynamic thermography shows promise in expedited diagnosis and understanding the diverse visual cues associated with breast cancer. As the fight against breast cancer progresses, a multifaceted approach involving various imaging modalities, including mammography and thermal imaging, is advocated for their combined benefits in enhancing early detection [6]–[8].

In recent years, deep learning has emerged as a dominant force in various research domains, including the realm of medical image analysis [9]. Convolutional Neural Networks (CNNs), the cornerstone of deep learning, have been extensively employed for automatic medical image analysis, particularly in tasks like image classification. However, their inherent limitation in capturing long-range information due to localized receptive fields has led to challenges in more complex vision tasks [4]. This is particularly evident in medical applications like breast cancer identification, where precise detection remains a significant challenge despite ongoing efforts. The fusion of neural network layers in deep learning algorithms holds promise in enhancing the accuracy of imaging-based classifiers for medical applications [10]. A key hurdle is the scarcity of comprehensive and balanced training data in the medical field, compounded by class imbalance issues. Notably, architectures like VGG-16, rooted in CNNs, have demonstrated remarkable results in general image analysis on datasets like ImageNet.

Adapting CNNs for medical images has yielded promising outcomes, especially in conjunction with attention mechanisms that focus on salient regions, effectively boosting algorithm performance [9], [11]. While previous research in breast cancer diagnosis encompassed aspects such as thermography, tumor characterization, and image acquisition protocols, the recent integration of deep learning techniques, particularly CNNs, has demonstrated considerable potential. This shift towards utilizing CNNs, even for thermal images, signifies the growing recognition of their efficacy compared to traditional texture or statistical features, albeit considering the computational complexity [2].

In the dynamic field of deep learning, the Transformer architecture, initially tailored for natural language processing (NLP)[12], has now inspired the Vision Transformer (ViT) approach for image classification, as introduced[13]. This innovative methodology, involving the segmentation of images into patches treated akin to NLP words, and harnessed by self-attention modules, has shown significant promise in reshaping image analysis [14], [15]. Our pioneering research extends the transformer approach to thermal image analysis, particularly focusing on the classification of breast thermal images (thermograms) using Self Window (SWIN) transformer [16] models of varying patch sizes.

Through meticulous fine-tuning and leveraging a dedicated thermogram dataset, our study unveils the substantial capability of SWIN architectures in this domain, representing a pioneering effort and opening doors for more accurate and automated breast cancer diagnosis. The paper is structured into several primary sections. Section 2 provides a thorough examination of the current state of the field, while Section 3 delineates the dataset and presents the research methodology. Experimental results are detailed in Section 4 followed by an extensive discussion in Section 5. Finally, in section 6 we concluded the paper by summarizing findings and potential future directions.

## 2.0 Related Work

Conducting a comprehensive review of the current landscape in breast cancer detection via thermogram images, a literature survey was conducted, yielding a total of 42 pertinent papers. Through meticulous scrutiny of abstracts and titles, 32 irrelevant papers were excluded, leading to the inclusion of 10 articles in this study. These selected papers showcased the implementation of machine learning and deep learning methodologies with thermogram images, primarily focusing on breast cancer detection. In the subsequent section, the discussion revolves around the identified articles that leverage AI techniques for the detection of breast cancer in the context of thermography. Infrared thermal imaging has the capacity to surpass the constraints associated with mammography technique by enabling selective enhancement of contrast within regions containing dense tissues, a particularly advantageous attribute for addressing the imaging challenges posed by young women [17]. [18] presented a novel algorithm for extracting features from a combination of bio-data, image analysis, and image statistics. By employing a Convolutional Neural Network (CNN) that was fine-tuned using the Bayesian algorithm, the researchers successfully categorized thermograms into two groups: those indicating normal conditions and suspected. The results yielded by their devised approach demonstrated an impressive accuracy rate of 98.95%, showcasing the effectiveness of their proposed algorithm in accurately classifying thermographic data. [19], novel classifiers were developed using Inception V3, Inception V4, and a customized Inception MV4 model to categorize thermograms from the DMR database into healthy and sick groups. Employing transformations such as Blur, Shaken, Tilted, and Flipping on the images for enhanced accuracy, the research revealed that Inception V3 outperformed V4 and MV4 in grayscale images, demonstrating heightened accuracy, with a slight accuracy improvement of 0.0002% for blurred and shaken images and a decrease of nearly 11% for tilted images.

In their research as cited [20]**,** various CNN architectures were investigated for the purpose of semantic segmentation, focusing on the detection of hotspots within thermal images. Employing naive patch-based classifiers in conjunction with multiple adaptations of the encoder-decoder architecture, the study involved 180 subjects from a private database. The findings demonstrated that despite the constraint of limited thermal image datasets, the encoder-decoder architectures exhibited superior performance in terms of accuracy compared to the patch-based classifiers, effectively identifying hotspots in the thermal imagery. In the study [21], a technique was introduced to handle imbalanced datasets through the utilization of a multiple classifier system, which centered on a collection of asymmetry characteristics. The method was applied to 150 thermograms, and the ensemble of distinct base classifiers was trained on diverse object subspaces. Notably, the optimal outcome achieved an accuracy of 90.03%, accompanied by a sensitivity of 80.35% and a specificity of 90.15%, highlighting the effectiveness of this approach in addressing imbalanced dataset challenges. [22] proposed different variants of ViT and showed that ViT models exhibit better performance than the state-of-the-art CNNs for breast cancer detection. [23] in their study explores the potential of CNNs with attention mechanisms in detecting thermal breast cancer images, using DMR-IR dataset. A novel model is introduced and evaluated for accuracy, sensitivity, and specificity, outperforming existing methods. CNNs with AMs achieved test accuracy rates of 99.46%, 99.37%, and 99.30%, showcasing a 7% accuracy improvement compared to CNNs without AMs and surpassing previous models.

In [24]**,** a novel CNN architecture, drawing inspiration from the U-net structure, was introduced for the classification of mammography datasets containing mass and macro-calcification instances. Following training on a combined dataset of 692 mass images and 603 macro-calcification images, the model achieved an impressive accuracy rate of 94.31%. Subsequent testing on a separate dataset comprising 202 mass images and 152 macro-calcification images reaffirmed its robust performance.

In [25], CNNs performance was enhanced by adding a Self-Attention mechanism for classifying 18,157 collected mammograms images and introducing a novel benchmarking dataset. The model demonstrated superior performance compared to previous studies, achieving an accuracy of 92.17%.

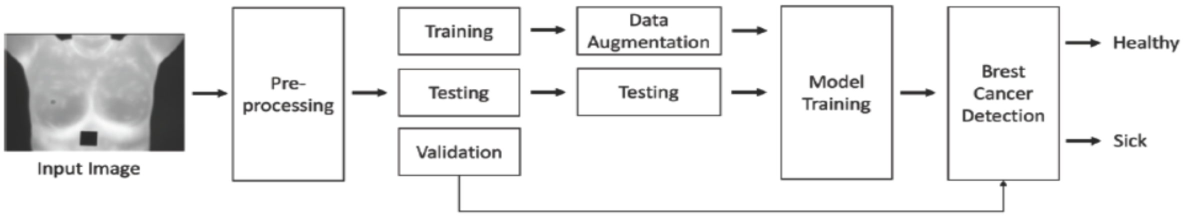
In an alternate study [26]**,** a novel CNN-based approach was introduced, incorporating two distinct attention units to enhance feature learning for the classification of 7909 histopathology images from the BreakHis dataset. This method achieved an outstanding 98% accuracy at 100× magnification, notably outperforming recent approaches on the same dataset.

The existing literature highlights the prevalence of deep learning approaches for breast cancer detection, with limited utilization of thermographic images and often constrained by small datasets. This research aims to explore the potential benefits of leveraging the SWIN transformer, known for its computational efficiency compared to the ViT [16], in the context of breast cancer detection using thermographic images.

## 3.0 Materials and Methods

In this study, we introduce a transformer-based framework for the detection of breast cancer using thermographic images. To enhance the model's performance, we employed data augmentation techniques. Figure 1 provides an overview of the key steps of our proposed system.

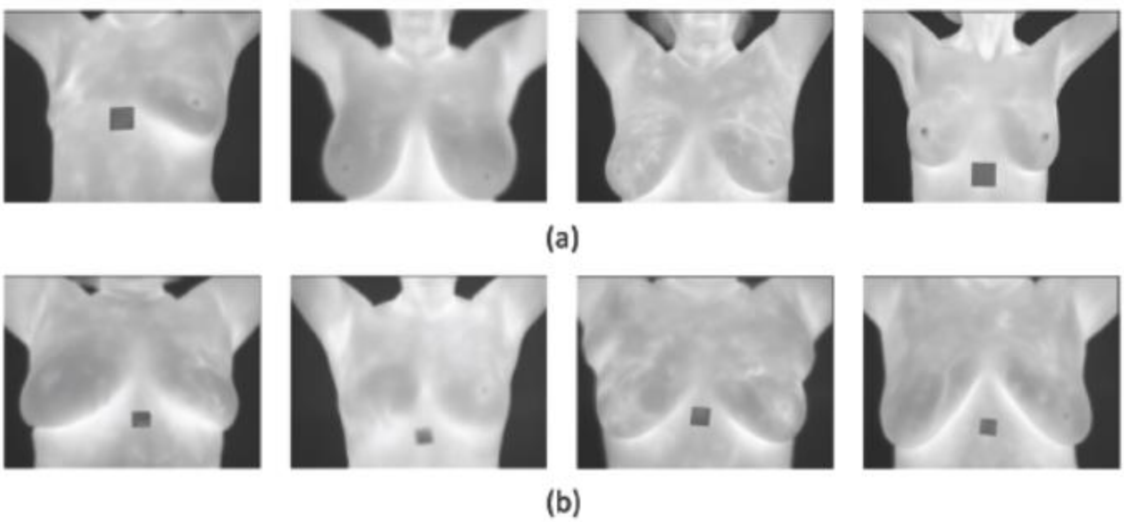
**Figure 1: Proposed Architecture for Breast Cancer Detection**




### 3.1 Dataset

In this investigation, we harnessed thermographic images sourced from a recognized benchmark dataset known as DMR-IR [27].

**Figure 2: Sample Thermal Images of Breasts from the DMR-IR Dataset (a) Healthy, and (b) Sick**




*Source: http://visual.ic.uff.br/dmi*

This particular database was meticulously curated by aggregating infrared (IR) images obtained from the Hospital of UFF University, ensuring ethical compliance through the requisite patient consent process. Our study specifically incorporated frontal thermogram images extracted from this dataset, encompassing data from a total of 290 patients. These thermal images were captured utilizing a FLIR SC-620 IR camera, boasting a resolution of 640 × 480 pixels. The dataset comprises a diverse range of breast shapes and sizes, as visually depicted in Figure 2, and encompasses a total of 185 healthy and 105 sick images for analysis.

### 3.2 Data pre-processing

The dataset was subdivided into three separate sets: training, testing, and validation. This partitioning distribution of 70% of the data for training, 15% for testing, and an additional 15% for validation purposes. To enhance the overall generalization capability of the proposed algorithm, this research consciously steers clear of extensive pre-processing procedures. All the images are resized into 224 × 224 pixel size.

### 3.3 Data augmentation

The challenge of generalization in deep learning approaches was effectively addressed through data augmentation. This technique empowers the neural network to grasp various image variations and extend its insights to previously unencountered images while mitigating the risk of over-fitting on small datasets. To achieve this, the following operations were applied to each image:
**1) Scaling:** Scaling with random sampling of frame size scales ranging from 70% to 120%.
**2) Rotation:** Rotation, involving image rotation within a range of zero to 15 degrees in both clockwise and counterclockwise directions.
**3) Horizontal flip:** Horizontal flipping, implemented with a 50% probability of flipping the image horizontally.
**4) Vertical flip:** Vertical flipping, implemented with a 50% probability of flipping the image vertically.

### 3.4 SWIN transformer

The SWIN Transformer presents a versatile framework for various computer vision tasks. This hierarchical Transformer employs a unique approach by calculating representations using shifted windows. This innovation offers notable computational efficiency by confining self-attention computations to non-overlapping local windows while still facilitating inter-window connections. The SWIN Transformer's hierarchical structure empowers it to effectively model image features across various scales, making it well-suited for a range of tasks. Notably, its linear computational complexity during inference adds to its appeal, especially for classification tasks. Figure 3 shows the general architecture of SWIN-L transformer. The standout feature of the SWIN Transformer lies in its utilization of shifted windows for processing image patches, a technique that enhances the model's ability to recognize image patches with arbitrary translations. Here are two key aspects:

#### 3.4.1 Hierarchical feature map

The SWIN Transformer's hierarchical feature map construction is achieved via a sequence of patch merging operations. These operations involve the fusion of features from neighboring 2×2 patches, effectively reducing the number of tokens while doubling the dimension through linear transformations. With the network's depth, the feature map's resolution progressively increases.

Notably, self-attention computations are conducted locally within non-overlapping windows, ensuring that the computational complexity maintains a linear scaling pattern.

### 3.4.2 ShiPed windows

In contrast to conventional ViT models, which perform global self-attention computations, incurring quadratic computational complexity, the SWIN Transformer adopts a distinctive approach. It dynamically shifts the window partition between successive layers within the hierarchical feature map, thereby facilitating self-attention calculations within localized and non-overlapping windows, ensuring linear computational complexity. This approach significantly enhances computational efficiency while preserving strong performance. Figure 4 shows the two successive SWIN Transformer Blocks.

**Figure 3: General Architecture of SWIN-L transformer**

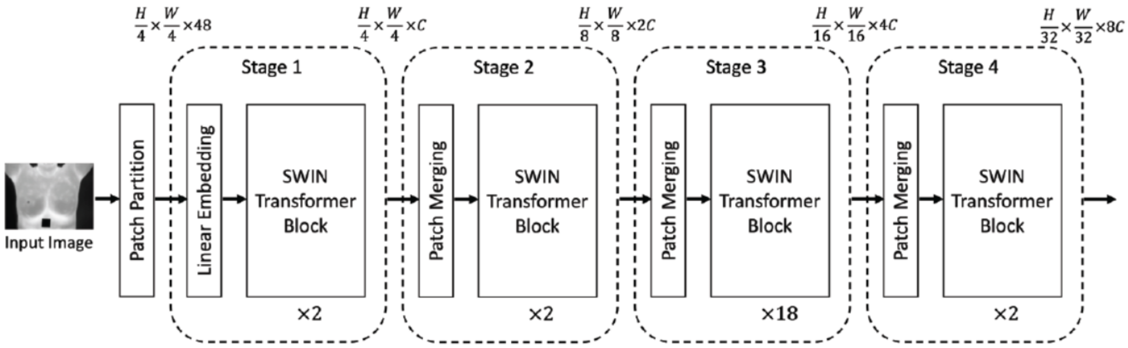
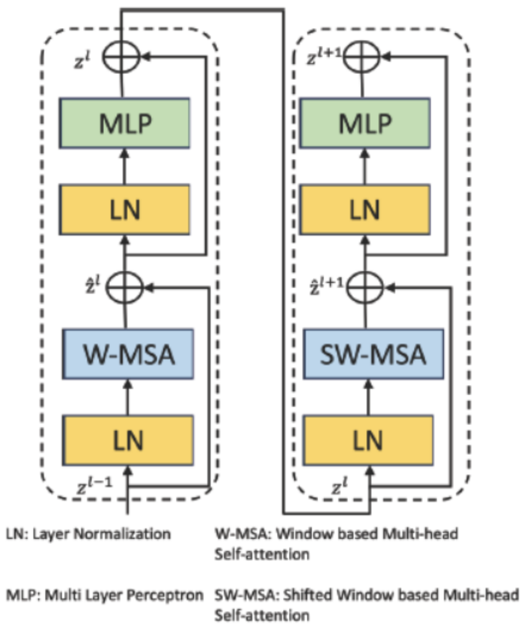



**Figure 4: Two Successive SWIN Transformer Blocks**




### 3.5 Evaluation Criteria

To assess the efficacy of the SWIN transformer, six key performance metrics are employed, namely accuracy, precision, recall, F1 score, specificity, and AUC (Area under the Curve). These metrics are computed utilizing the four fundamental parameters derived from the confusion matrix: True Positives (T.P.), False Positives (F.P.), True Negatives (T.N.), and False Negatives (F.N.). The mathematical formulations for accuracy, recall, precision, F1 score, specificity, and AUC score are provided below:

## 4.0 Results and Discussion

In this paper, to conduct a comprehensive comparative analysis of the SWIN transformer, all its variants including SWIN-T (SWIN-tiny), SWIN-S (SWIN-small), SWIN-B (SWIN-base), and SWIN-L (SWIN-Large) were implemented for the purpose of breast cancer detection. The specifics of each SWIN transformer variation, such as window size, the count of hidden layers, and the number of blocks in each stage, are presented in Table 1.

**Table 1: SWIN Transformer Variation**

| Model | Window Size, M | C, No. of hidden layers in Stage 1 | Blocks in Stage 1 | Blocks in Stage 2 | Blocks in Stage 3 | Blocks in Stage 4 |
|---|---|---|---|---|---|---|
| SWIN-T | 7 | 96 | 2 | 2 | 6 | 2 |
| SWIN-S | 7 | 96 | 2 | 2 | 18 | 2 |
| SWIN-B | 7 | 128 | 2 | 2 | 18 | 2 |
| SWIN-L | 7 | 192 | 2 | 2 | 18 | 2 |

**Figure 5: Aggregated Confusion Matrix for SWIN Transformer Variations (a) SWIN-T, (b) SWIN-S, (c) SWIN-B, and (d) SWIN-L**

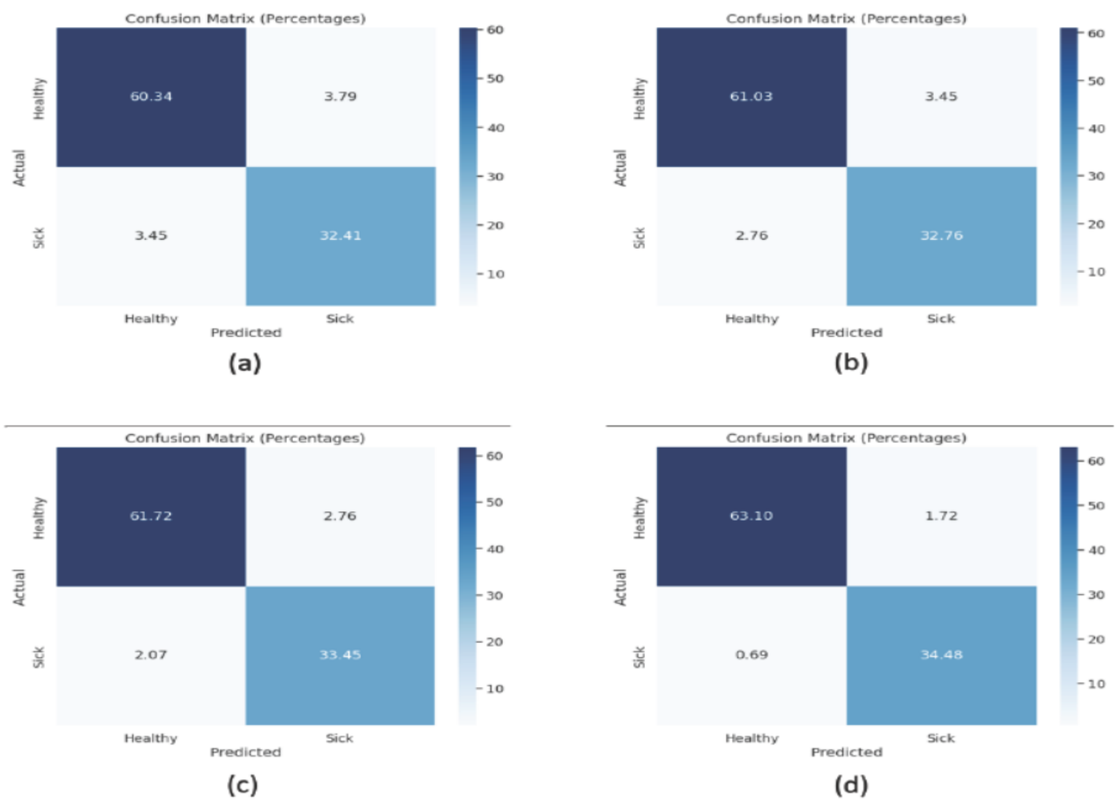


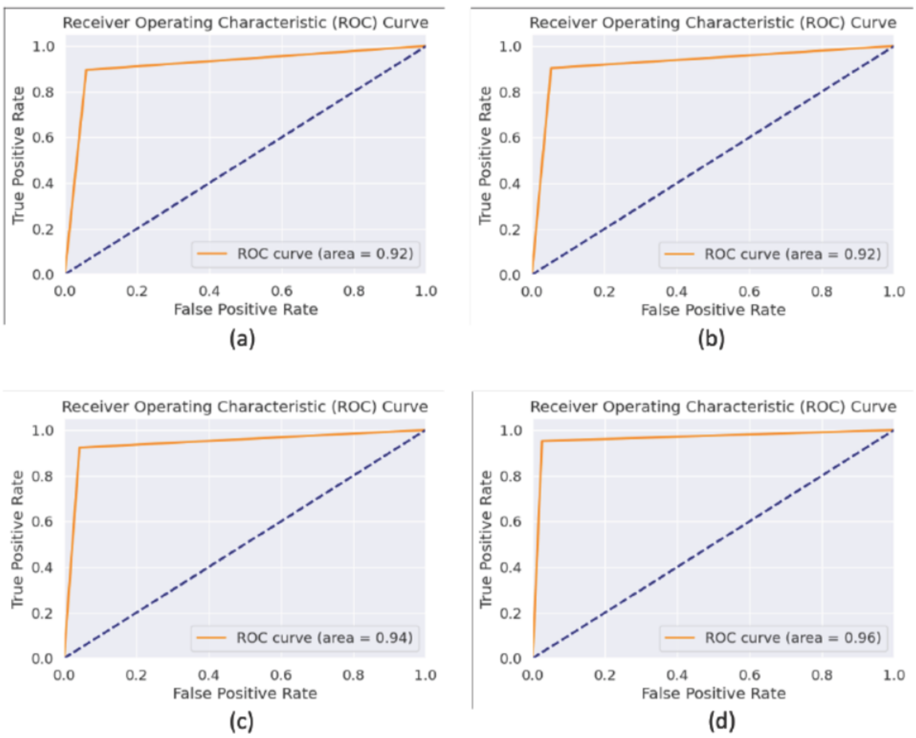
Figure 5 illustrates the combined confusion matrix for all variations of the SWIN transformer model, including SWIN-T, SWIN-S, SWIN-B, and SWIN-L, as applied to the DMR-IR dataset for breast cancer detection.

**Table 2: Performance Metrics of SWIN Transformer for Breast Cancer Detection**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1 score (%) | Specificity (%) | AUC (%) |
|---|---|---|---|---|---|---|
| SWIN-T | 92.41 | 89.94 | 90.21 | 89.98 | 94.08 | 91.75 |
| SWIN-S | 93.10 | 90.29 | 90.30 | 90.32 | 94.65 | 92.47 |
| SWIN-B | 94.48 | 92.22 | 92.26 | 92.29 | 95.72 | 93.97 |
| SWIN-L | 96.55 | 95.50 | 95.76 | 95.43 | 97.34 | 96.21 |

In this study, four distinct variations of the SWIN transformer exhibited notably high performance results. Specifically, SWIN-T, SWIN-S, SWIN-B, and SWIN-L achieved impressive accuracies of 92.41%, 93.10%, 94.48%, and 96.55%, respectively. The comprehensive details of the performance results for each model, including accuracy, precision, recall, F1 score, specificity, and AUC score, are concisely summarized in Table 2.

**Figure 6: ROC Curve for SWIN Transformer Variations**
**(a) SWIN-T, (b) SWIN-S, (c) SWIN-B, and (d) SWIN-L**




Based on the information provided in the confusion matrix and the performance table, it is evident that the SWIN-L transformer variant surpasses all other variants in terms of performance. This superiority is further depicted in Figure 6, which illustrates the Receiver Operating Characteristic (ROC) curve for all the SWIN transformer variants.

The predictive capabilities of the SWIN-L transformer have demonstrated commendable performance in detecting breast cancer patients within the DMR-IR dataset.

**Figure 7: Classification Results of SWIN-L Transformer (a) Healthy, and (b) Sick**

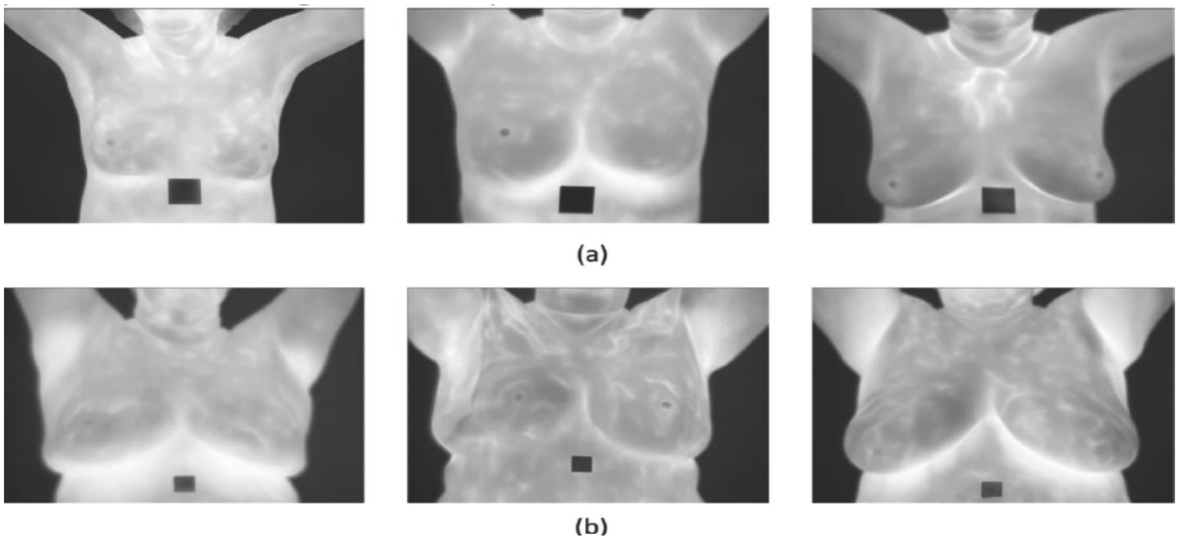



Figure 7 shows the classification results of the SWIN-L transformer. Upon a thorough review of these results, it becomes apparent that transformer-based approaches hold promise for the task of breast cancer detection and warrant further consideration. This robust outcome highlights the efficacy of leveraging self-attention mechanisms, offering enhanced feature extraction and discrimination in medical image analysis tasks.

## 5.0 Conclusions and Future Work

Breast cancer remains a global health concern, particularly among women, prompting extensive research efforts into segmentation and classification methodologies. Among these, thermography imaging stands out as an effective diagnostic tool, utilizing infrared technology. In this paper, we propose an entirely automated breast cancer detection system, comprising two main stages. Initially, thermal images are resized for computational efficiency, followed by the deployment of the SWIN transformer for classification. Our experimental results showcase the SWIN-L transformer's remarkable performance, with nearly 96% accuracy, 95% precision, 96% recall, 95% F1 score, 97% specificity, and 96% AUC.  While these results are promising, further validation with diverse datasets and potential expansion into multi-view breast image analysis could enhance the robustness of this approach in future research.

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