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Review

Breast Cancer Detection Through Deep Learning and Breast Thermography: A Study of Review

Ali Hamad Ali [1], Naaman Omar Yaseen [2*]

[1] Information Technology Department, Technical College of Duhok, Duhok Polytechnic University, Duhok, Iraq; ali.ali@dpu.edu.krd
[2] Information Technology Department, Technical Institute of Amedi, Duhok Polytechnic University, Duhok, Iraq
* Correspondence: naaman.omar@dpu.edu.krd

Abstract

Breast cancer is an alarming worldwide health concern, and early detection is crucial for improving patient outcomes. This study explores the application of deep learning algorithms in breast thermography, a non-invasive and radiation-free imaging technique, to enhance diagnostic accuracy. This research synthesizes peer-reviewed literature from 2020 to 2025, focusing on various deep learning architectures, including CNNs, GANs, RNNs, U-Net, and transfer learning, in relation to thermographic datasets like DMR-IR and Visual DMR. The methodology employs a structured approach encompassing literature searches, criteria for inclusion and exclusion, data extraction, and synthesis. The findings indicate that deep learning significantly enhances segmentation, classification, and anomaly detection in thermal breast images, frequently surpassing traditional diagnostic techniques. While accuracy rates are promising, challenges persist, such as limitations in datasets, variability in images, and a lack of standardization. This study highlights the potential of AI-enhanced thermography as a cost-effective and scalable method for breast cancer screening, while also identifying key areas for further research to enhance generalizability and clinical application.

Keywords: Deep Learning, Breast Thermography, Thermal Imaging, Breast Cancer Detection, Medical Imaging.

1. Introduction

The global rate of cancer continues to be high worldwide in recent years. Tens of millions of individuals receive a new cancer diagnosis every year. Suffering from cancer also claims the lives of millions, if not tens of millions, of individuals every year across the entire world. [1]. "According to the WHO, female breast cancer accounts for 11.6% of all new cases, with 2.3 million instances, placing it as the world's second most prevalent cancer after lung cancer" [2]. Most patients with breast cancer are already at an advanced stage, which contributes to the high death rate from the disease. If breast cancer is detected at stage I without the cancer cells invading the lymph nodes, the cure rate is 80–90%[3].

Overall, tumors larger than 30 mm are seen in 70% of instances of breast cancer. Because breast cancer can manifest in a variety of ways, a comprehensive medical checkup is necessary. Consequently, reducing disease-related mortality relies on early detection and periodic exams [4]. Standard testing should be conducted on women who demonstrate persistent anomalies lasting one month or longer. The two most popular techniques for breast screening are mammography and clinical breast examination [5]. However, thermography is currently another screening method that can be employed. Thermal imaging assists in recognizing cancer by using an infrared camera to capture heat map

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images of the target surface of breast. Recent developments in technology have made it possible to use thermography for screening processes with the aid of machine learning[6] [7].

The focus of intense research in computer vision and artificial intelligence is the employ of deep learning technology to diagnose cancer from medical image. In addition to the intrinsic particularity and complexity of medical imaging, cancer detection demands extremely high accuracy and timeliness due to the rapid development of deep learning techniques [8]. A comprehensive review of relevant works is essential to assist readers in understanding the current status of research and ideas more clearly. This review aims to study the techniques of deep learning to detect breast cancer through breast thermography. Compared with other methods such as radiography and ultrasound, breast thermography is low-cost, less harmful, and shows high accuracy compared to previously existing methods. Through the review conducted, breast cancer detection methods show high accuracy by applying deep learning techniques to breast thermography. The organized rest of this review paper is presented as follows: The methodology is outlined in Section 2. Section 3 is basic information about breast cancer detection. While, Section 4 discusses breast thermography in cancer detection. Section 5 reviews the most important literature reviews and comparative summary of the reviewed literature during the five years related to the topic of this research paper. Sections 6 discussion of what was summarized. Finally, there is a conclusion in Section 7.

2. Methodology

This review followed a structured and transparent methodology to identify, screen, and synthesize recent works on the use of thermography and deep learning techniques for breast cancer detection between 2020 and 2025. Several academic databases, including Scopus, Google Scholar, IEEE Xplore, PubMed, and ScienceDirect, were extensively searched using keywords and Boolean combinations such as "breast thermography," "deep learning," "thermal imaging," "convolutional neural network," "DMR-IR dataset," and "breast cancer detection," while references from major papers were also reviewed to locate additional sources.

Studies were included if they employed breast thermography as the imaging modality, utilized state-of-the-art machine learning and deep learning methods such as autoencoders, CNNs, or transfer learning, and reported quantitative performance metrics such as accuracy, precision, specificity, sensitivity, or balanced accuracy. Only peer-reviewed journal and conference papers published between 2020 and 2025 were considered, while studies based on other imaging modalities (e.g., mammography, ultrasonography), works focusing purely on hardware development without algorithmic evaluation, and grey literature such as theses or preprints were excluded.

From each eligible study, the year of publication, dataset used (e.g., DMR-IR, Visual DMR, multicenter thermograms), deep learning technique (e.g., CNN, U-Net, ResNet, VGG, DenseNet, autoencoder, attention mechanism), evaluation metrics, and key findings and limitations were extracted. The synthesis of findings indicated that deep learning considerably enhances the performance of breast thermography for cancer diagnosis, with CNNs, GANs, U-Nets, and transfer learning models applied to DMR-IR and Visual DMR datasets consistently achieving strong results in classification and segmentation tasks. Hybrid models and data augmentation strategies further improved robustness, while transfer learning proved especially effective with limited datasets. Despite these promising outcomes, challenges such as small dataset sizes, inconsistent imaging methodologies, and low generalizability remain, highlighting the need for standardized datasets, transparent models, and stronger validation protocols to advance AI-enhanced thermography toward clinical adoption.

According to the reviewed studies, deep learning considerably improves breast thermography for cancer diagnosis. Using the DMR-IR and Visual DMR datasets, CNNs, GANs, U-Nets, and transfer learning models consistently achieved good results in classification and segmentation tasks. While hybrid models and augmentation strategies enhanced robustness, transfer learning was especially effective with less data.

Challenges continue even though there were positive results. Clinical adoption is hindered by small datasets, inconsistent imaging methodologies, and low generalizability. Results highlight the need for more consistent datasets, more transparent models, and stronger validation to pave the way for AI-enhanced thermography to be used in the real world.

3. Breast Cancer Detection Background

Among women worldwide, breast cancer continues to be the most prevalent cancer. and it poses a serious threat to modern society. Timely identification of breast cancer has the ability to significantly improve the lives of innumerable people who are at risk globally. Age, history of family, and reproductive variables are the most significant risk factors for breast cancer. Furthermore, although there is currently little evidence to draw firm conclusions, hormonal factors and contemporary lifestyle choices are related to a higher risk of breast cancer in women. The variables that affect the risk of breast cancer are listed in Table 1 by [9] P. Wang, J. Chen, and W. Zhao. The possibility of a successful course of therapy and survival is significantly increased when breast cancer is detected early. Here are a few methods for identifying breast cancer.

Table 1: Categories of breast cancer risk factors and their roles

Category	Protective Role	Risk-Increasing Role	Uncertain / Debated
Demographic	–	**Female gender, Advanced age**	–
Reproductive	**Full-term pregnancy, Early first childbirth**	**Late menopause, Nulliparity, Abortion**	**Age at menarche, Menstrual cycle regularity**
Hormonal	–	**Postmenopausal hormone therapy, Ovulation-inducing drugs**	**Contraceptive methods, Pregnancy-related hormones**
Hereditary	–	**Family history of breast cancer, Inherited genetic mutations**	–
Breast-related	–	**High breast density, Benign breast disorders**	**Shorter lactation duration**
Lifestyle	**Regular physical activity, Healthy diet, Adequate vitamin D**	**Alcohol intake, Smoking, Obesity/overweight**	**Coffee consumption, Sleep duration**
Environmental / Other	–	**Radiation exposure, Diabetes, Air pollution**	**Night-shift work, Low socioeconomic status**

4. Breast Thermography in Cancer Detection

As a complement for the early detection of abnormalities in the female breast, thermography measures the temperature of the breast area as the heat radiated to the environment by the skin surface. [9]. Through the transformation of radiation intensity, "a thermographic camera generates a thermogram, which is shaped by the temperatures arranged in a two-dimensional array" [10]. Figure 1 shows the entire workflow of the above method.

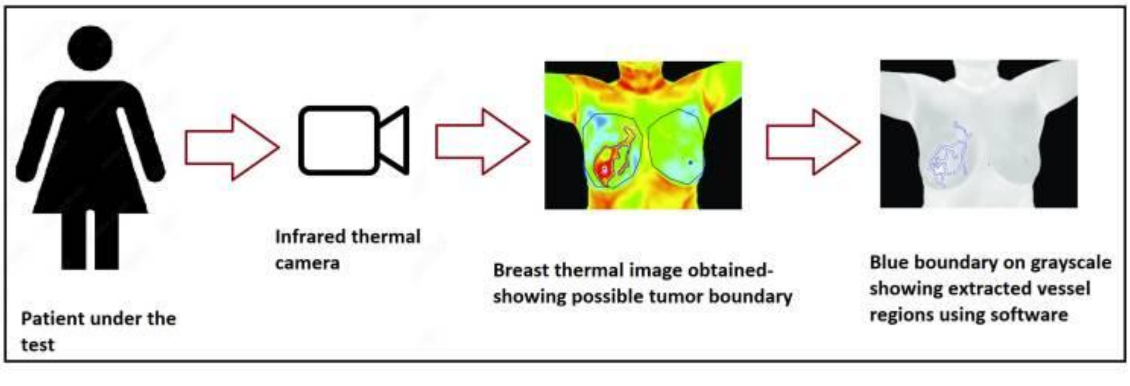

Figure 1 : process of breast thermography for the screening of malignancy cancer

Because each area is influenced by both endogenous and exogenous factors, the temperatures that each breast projects are not consistent. Tumors distort vascularization, which causes localized temperature changes that are transferred to the skin's surface. Breast thermography depends on evaluating these thermographic images to detect tissue abnormalities early in order to lessen the suffering and death rate from breast cancer [11]. Additionally, thermograms have been used as datasets to perform image processing tasks, such as segmentation, feature extraction, and classification [12]. In 2014, Da Silva et al. “published accessible via Federal Fluminense University the first public database of breast thermography images, marking a significant milestone” [13].

5. Literature Review

Deep learning has revolutionized medical image analysis by providing highly accurate, flexible, and generalizable models compared to traditional mathematical and signal-processing approaches[14] [15] . Convolutional Neural Networks (CNNs) are the most widely applied, as they can automatically extract hierarchical features from input data and have proven effective in classification, segmentation, and anomaly detection, particularly in breast cancer detection where they often outperform conventional methods [16]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks extend this capability to sequential and temporal data, making them useful for dynamic imaging tasks and image denoising, where they help suppress artifacts such as white noise and salt-and-pepper noise[17] [18]. Autoencoders contribute by compressing and reconstructing data, enabling anomaly detection, noise reduction, and synthetic data generation, which is especially valuable when labeled datasets are limited [19]. Generative Adversarial Networks (GANs) further enhance data augmentation and segmentation by generating realistic synthetic images, although challenges such as instability and mode collapse persist; refined designs, including U-Net–based generators with adversarial and reconstruction loss, have achieved remarkable accuracy in breast thermography segmentation [20] [21].

U-Net and Fully Convolutional Networks (FCNs) remain crucial for pixel-level predictions, with U-Net’s encoder–decoder architecture and skip connections making it highly effective for medical image localization tasks, while FCNs are more suited for broader semantic segmentation[22] [23]. Transfer learning has become indispensable in adapting pre-trained models to specialized medical applications with limited annotated data, reducing training time while improving diagnostic accuracy, and when combined with few-shot learning, it yields even greater performance gains[24] [25]. Meanwhile, 3D Convolutional Neural Networks (3D-CNNs) expand the analysis to volumetric imaging such as CT, MRI, and dynamic thermography, capturing both spatial and temporal dependencies with high precision[26] [27]. Finally, attention mechanisms mimic human cognitive focus by directing the model toward the most relevant regions of input data, thereby improving feature extraction, enhancing interpretability, and increasing diagnostic reliability [28] [29]. Together, these deep learning approaches demonstrate a transformative role in medical imaging and hold particular promise for breast thermography-based cancer detection. Breast thermography as a method for early cancer detection has recently been explored and improved by researchers in various countries. A number of researchers' studies, published in prestigious international journals, are reviewed here.

Tang et al., 2025 [30] presents a “multi-input lightweight CNN” called “Multi-light Nett” for more accurate early detection of breast cancer. It combines thermal image from various angles with a lightweight CNN based on model performance and scale. In addition, a novel weighted label smoothing regularisation (WLSR) is proposed for the Multi-light Nett to improve the network's generalisation and classification accuracy. The experimental results show that the proposed strategy, which combines front and side views, outperforms the typical approach that just uses the front view. In addition, the Multi-light Nett outperforms the currently popular lightweight CNNs.

Attallah, 2025 [31] presented an innovative “computer-aided diagnosis” (CAD) system, “Thermo-CAD”, that uses thermal imaging to detect early breast cancer.To improve accuracy, the system uses multiple convolutional neural networks (CNNs).Non-negative matrix factorisation and Relief-F are two approaches for integrating and reducing the dimensionality of deep data.The Thermo-CAD system was evaluated using two datasets: the DMR-IR, which distinguishes normal from diseased breast tissues, and a unique thermography dataset that distinguishes benign from malignant instances.The system achieved 100% accuracy on the DMR-IR dataset using the CSVM and MGSVM classifiers.However, it demonstrated a reduced capacity to discriminate between benign and malignant patients, with a CSVM accuracy of 79.3%.

Bani Ahmad et al., 2025 [32] produced A new way to use deep learning to diagnose breast cancer was based on thermography images. This method fixes some of the problems with mammograms, such as their cost and the radiation they give off. The “Rock Hyraxes Dandelion Algorithm Optimization” (RHDAO) optimizes a thresholding value to segment images after they have been preprocessed with CLAHE. StackVRDNet is a new deep learning architecture that uses VGG16, ResNet, and DenseNet to do the classification. The RHDAO is used to improve the weights and parameters of these models, which makes them better at diagnosing. The model that came out of it was 97.05% accurate and 86.86% precise in simulations.

Veerlapalli and Dutta , 2025 [33] suggested combining a framework between a “Generative Adversarial Network” and a “Hybrid Deep Learning” model as novel deep learning. to use thermogram images to detect breast cancer. The proposed framework exceeds traditional deep-learning models by attaining a 98.56% accuracy rate, as validated through experiments on the DMR-IR benchmark dataset. The goal is to raise the bar for diagnostic accuracy by combining important ROIs and using deep feature extraction to make classification better.

Alzahrani et al., 2025 [34] suggests an automated classification method that employs "convolutional neural networks" (CNNs) to distinguish between cancerous and normal thermographic breast images. An Enhanced Particle Swarm Optimization (EPSO) method is employed to automatically optimize CNN hyperparameters, minimizing manual effort and enhancing computational efficiency. To improve classification performance, the system uses advanced image preprocessing methods like Mamdani fuzzy logic-based edge detection, “Contrast-Limited Adaptive Histogram Equalization” (CLAHE) for improving contrast, and median filtering for reducing noise. The suggested framework has a classification accuracy of 98.8%, which is better than traditional CNN implementations in terms of speed and accuracy.

Munguía-Siu et al., 2024 [35] Introduced hybrid “convolutional neural network-recurrent neural network” (CNN-RNN) models for identifying tumor anomalies in dynamic breast thermography images. Five advanced pre-trained CNN architectures were combined with three RNNs. The optimal hybrid architecture was VGG16-LSTM, exhibiting a specificity of 98.68%, an accuracy of 95.72%, and a sensitivity of 92.76%, with a CPU runtime of 3.9 seconds. AlexNet-RNN was the fastest model, with a CPU runtime of 0.61 s and performance of 92.76% specificity, 68.52% sensitivity, and 80.59% accuracy, still outperforming stand-alone AlexNet. The findings show that “CNN-RNN” hybrid models perform better than standalone CNN models, which means that dynamic breast thermographs can have their temporal data recovered without a major impact on classifier runtime.

Hanieh et al., 2024 [36] examines the process of extracting features from a dataset of thermographic photographs using a CNN technique. The initial stage was to use the CNN network to get a feature vector from the pictures. The following stage is to use machine learning to sort the pictures. The study utilized four distinct classification methods to identify breast cancer from thermographic images: KNN (94.1% accuracy), “fully connected neural network” (FCnet) (94.2% accuracy), “support vector machine” (SVM) (95% accuracy), and “classification linear model” (CLINEAR) (95% accuracy). Additionally, the sensitivity of these classifiers were determined to be 95.5% for FCnet , 94.1% for SVM , 90.4% for CLINEAR , and 93.2% for KNN, while the reliability parameters were determined to be 92.1% for FCnet, 97.5% for SVM, 96.5% for CLINEAR, and 91.2% for KNN. These results can help experts create an expert approach for diagnosing breast cancer.

Shojaedini and Bahramzadeh, 2024[37] presents an innovative method that uses deep autoencoder ideas to remove unnecessary or damaging information from synthetic thermograms while maintaining important and independent properties. As a result, the suggested method improves the representation of artificial pictures for deep network training, which improves thermogram diagnosis of breast cancer. When compared to benchmark approaches, the suggested method's performance on the DMR-IR dataset demonstrates a notable enhancement in thermogram detection of malignant breasts. The basic model of the innovative integration, the average accuracy, sensitivity, and specificity increased to 92.3%, 93%, and 91.4%, respectively, exceeding the basic model's 89.1%, 86%, and 92.5%. reduced difference between the training and validation curves showed that the suggested approach performed better at preventing over-fitting, leading to a 7% gain in accuracy and a 3.2% increase in sensitivity. Even though the specificity decreased by 1.1%, other parameter improvements exceeded.

Ahmed et al., 2024 [38] uses a pre-trained VGG16 convolutional neural network and transfer learning to suggest deep learning (DL) model utilizing the most advanced technique. Thermal image from the (DMR-IR) Database for Research are used by authors to train and assess the model. To enhance model performance, they also employ normalization and augmentation techniques. The DL-based model predicted BC lesions with a promising 99.4% (accuracy) detection rate. In comparison to earlier models, it has AUC-ROC of 99.8%, specificity of 97.5%, precision of 98.9%, F1-Score of 99.8%, recall of 99%, and a sensitivity of 100%.

Al Husaini et al., 2024 [39] developed a system that improves breast cancer classification accuracy by using in situ cooling support and preserving spatial features. The framework uses Deep Learning models and real-time thermography video streaming to find breast cancer early. Inception v3, Inception v4, and a changed version of Inception Mv4 were all made with MATLAB 2019. However, a mobile phone was connected to a thermal camera to take pictures of the breast area so that normal and diseased breast tissue could be told apart. The study's training dataset consisted of 1000 thermal photos, of which 300 were suitable for the abnormal class and 700 were deemed appropriate for the normal breast thermography class. The Deep Convolutional Neural Network models that are tested include Inception version 3 (v3), Inception version 4 (v4), and a modified version called modified Inception version 4 (Mv4). The results show that Inception Mv4 can accurately identify even the smallest temperature differences in breast tissue sequences in real time, with an accuracy of 99.748%. Inception version 3 and Inception version 4, on the other hand, had accuracies of 96.8% and 99.712%, respectively. The in situ cooling gel used for thermal imaging made breast imaging more effective. A 0.1% rise in tumor surface temperature led to a 7% rise in accuracy for detection and classification.

Mohammed Jawad Khudhur, 2024[40] suggests employing an improved "Deep Convolutional Neural Network" (DCNN) to detect and diagnose breast cancer early and accurately. Researcher employs a DCNN with 12 stacked processing layers, enhancing diagnostic and detection accuracy compared to prior methodologies. The Mini Mammographic Database (MIAS) serves as the dataset for assessing the efficacy of the proposed system. The findings indicate that the Deep CNN achieves an impressive accuracy of 99.1%. The advantages of the proposed DCNN-based approach are demonstrated through a comparison with analogous studies.

Dihmani et al., 2024 [41] proposed a "computer-aided diagnostic" (CAD) scheme utilizing thermal imaging for breast cancer diagnosis and Explainable Artificial Intelligence. To enhance classification accuracy and interpretability, the authors employed a distinctive approach utilizing metaheuristic algorithms, specifically the "Hybrid Particle Swarm Optimization" (HPSO) and "Hybrid Spider Monkey Optimization" (HSMO). These strategies improved both feature selection and hyperparameter tweaking in the CAD system. Techniques employed for feature extraction included Gabor filters, "Histogram of Oriented Gradients" (HOG), "Local Binary Patterns" (LBP), and Canny edge detection. To enhance diagnostic accuracy, "dynamic infrared thermography" (DIT) images under controlled cooling conditions were incorporated into the "DMR-IR dataset". The model achieved high performance metrics utilizing a 70-30 train-test split of patient images. Utilizing the HSMO, the system effectively identified cancerous tissues by thermographic analysis, attaining an F1-score of 98.15% and an accuracy of 98.27%, while selecting just 25.78% of HOG characteristics.

Da Silva et al., 2024 [42] uses thermographic images and "convolutional neural networks" to tell the difference between breast cancer and other types of cancer. To do this, two methods are compared: one uses CNNs to get the original feature vectors, and the other uses Particle Swarm Optimization to make the vectors smaller for feature selection. The results show that both strategies work very well. The highest accuracy of 79.92% was achieved using full feature vectors with the Inception V3 convolutional neural networks (CNN) and a support vector machine with a third-degree polynomial kernel. The Inception V3 CNN combined with a support vector machine using $\gamma = 0.25$ for the RBF kernel achieved the highest sensitivity and specificity scores, recording 100% sensitivity and 99.49% specificity. The same combination produced the highest AUC, which was 0.83. Using the Inception V3 CNN with a 4th-degree polynomial kernel and PSO-selected features, the highest accuracy was 78.55%.

Nigam and Swarnkar, 2024 [43] suggested approach advocates for a deep learning methodology, specifically Convolutional Neural Networks (CNNs), for the detection of breast cancer. The goal was to create a CNN-based model for diagnosing breast cancer that could tell the difference between benign (non-cancerous) and malignant (cancerous) tumors. The study aimed to enhance the accuracy of early diagnosis, which is essential for effective treatment. authors used the "Discrete Wavelet Transform" (DWT) to analyze the images, and we made the images clearer and less noisy to make feature extraction more accurate. The images were classified as either benign or malignant using a CNN model, and the effectiveness of different classifiers—Support Vector Machine, Logistic Regression, and Random Forest—was compared. The proposed model identified both benign and malignant cases with an accuracy of up to 85%.

Ahmad et al., 2024 [44] suggested a "computer-aided diagnostic" (CAD) system based on deep learning that would make it easier to find breast cancer by finding and classifying tumors. authors used advanced technologies like BreastNet-SVM for classification, Associat-ed-ResUNets for hashing, and YOLO networks for detection. Researchers showed that the system could do better than other technologies by getting 98.5% of tumors detected correctly and 99.16% of tumors classified correctly.

Wang et al., 2024 [45] proposed a novel model termed "DeepClinMed-PGM", which stands for "Deep Learning Clinical Medicine Based Pathological Gene Multi-modal", designed to predict DFS by integrating "clinicopathological data with molecular insights". The external testing group had 95 people, the internal validation group had 184 people, and the training group had 741 people. The AUC values for 1-, 2-, and 3-year DFS predictions were 0.851, 0.878, and 0.938 in the external cohort and 0.979, 0.957, and 0.871 in the training cohort. Strong dis-criminative skills were shown by the external cohort (HR 0.061, 95% CI 0.017–0.218, P < 0.0001), internal validation cohort (HR 0.117, 95% CI 0.041–0.334, P < 0.0001), and training cohort (HR 0.027, 95% CI 0.0016–0.046, P < 0.0001). The C-index scores were 0.864, 0.823, and 0.925.

Tsietso et al., 2023 [46] demonstrate a tool called thermal infrared-based "computer-aided diagnosis" (CADx) that is cheaper, safer, and better for kids. Most "CADx" systems use frontal breast thermograms, so they probably won't find lesions that grow on the sides. These systems also often miss important clinical data, like risk factors. The author introduces an innovative CADx system for breast cancer detection utilizing deep learning methodologies. The system has a lot of different views of the breast thermogram and the clinical information that goes with it to make the diagnosis more accurate. The author explains how the system works, such as how transfer learning is used to train three different models and how regions of interest are found in photos. The results show that multi-input models are better than single-input models. They have an AUROC curve of 0.94, a sensitivity of 93.33%, and an overall accuracy of 90.48%.

Husaini et al., 2023 [47] suggests a method for the early diagnosis of breast cancer that makes use of "deep learning models and real-time thermography video streaming". The framework uses "Inception v3", "v4", and a "modified Inception Mv4" of deep convolutional neural network models to classify normal and abnormal breasts. It is implemented in MATLAB 2019 with infrared camera and records high-quality real-time video streams. The findings show that the Inception Mv4 model can efficiently identify even the smallest temperature differences in tissue of the breast by producing a series of infrared image taken from various perspectives when paired with real-time video streaming. Adding cooling gel to the breast area makes the contrast even better, which helps with accurate detection and an effective picture acquisition process. In addition, the study shows that a small rise in the temperature of the tumor surface area of 0.1% can lead to an average gain of 7% in detection and classification accuracy.

Ali et al., 2023 [48] introduces the "Enhanced Channel-Wise Attention Mechanism" (ECAM), a deep learning analysis tool for "breast invasive ductal carcinoma" (BIDC) histopathology images. The study's primary objectives are to augment computational efficiency by employing a separable Convolutional Neural Networks architecture, to improve data representation via hierarchical feature aggregation, and to enhance accuracy and interpretability through channel-wise attention mechanisms. The developed ECAM model was compared to DenseNet121, VGG16, and AlexNet using two publically available datasets, BreakHis and DataBioX IDC. On the IDC dataset, the proposed ECAM model obtained an F1-score of 96.65% and an exceptional accuracy rate of 96.70%. Once again, the proposed ECAM model performed exceptionally well on the BreakHis dataset, with an accuracy rate of 96.33% and an F1-score of 96.37%.

Khan et al., 2023 [49] suggest a thermal imaging-based model to identify breast cancer. Create a personalized CNN-based machine learning model that has been trained on different thermal image datasets showing breast problems. Use thermal image processing algorithms to predict breast cancer based on outside signs. To find images that cause cancer, segmentation, texture-based feature extraction, and image classification are used. Use 2D CNNs and activation algorithms to mix ResNet with parts of GoogleNet to make a custom classifier. Add layers for maxpooling and batch normalization. Use DMR-IR images to teach the model. The proposed 2D CNN classifiers surpassed CNN (71%) and SVM (91%), attaining a 95% classification rate.

Alshehri and AlSaeed, 2023 [50] proposed a novel approach for breast cancer diagnosis that integrates deep attention mechanisms (AMs) in thermal imaging with pre-trained VGG16 convolutional neural networks. Three different kinds of AMs were used to make the classification more accurate and the feature extraction process better: hard attention, self-attention, and soft attention. The authors used the DMR-IR dataset, which had "1542 thermal images" of 56 patients' breasts. Of these, 762 showed malignant cases and 780 showed healthy cases. To get around the limits of the dataset, data augmentation techniques were used to make a bigger dataset with 4146 photos. The VGG16 model with hard attention had the highest accuracy at 99.80%, followed by self-attention at 99.49% and soft attention at 99.32%. This method performed better than previous research, demonstrating how AMs can greatly improve thermal imaging for breast cancer diagnosis.

Torres-Galván et al., 2022 [51] proposed "automatically classify thermograms as normal and abnormal using a deep convolutional neural network with transfer learning" model . A sample of "311 females" subjects was used to test the CNN's performance in two ways: one in a typical screening co-hort with a low number of unusual thermograms, and the other with a balanced class distribution. The transfer-learned ResNet-101 model exhibited a sensitivity of 92.3% and a specificity of 53.8%. In contrast, the corresponding values were a sensitivity of 84.6% and a specificity of

65.3%, characterized by an imbalanced distribution. archived accuracy of balanced class is 73.1% and unbalanced class is 74.9%.

Mammoottil et al., 2022 [52] demonstrates a “convolutional neural network”-based model that uses the Visual DMR dataset to identify breast cancer by utilising several thermal images of the breast. The clinical data is then used to confirm these models' performances. Results show that the model's performance improved when clinical data judgements were added. The model that had the same architecture for all three views fared the best after two models with different architectures were constructed and tested. With the addition of the clinical data decision, its accuracy rose from 85.4% to 93.8%. When selecting sick patients as the positive class, the model was able to classify more patients properly with a sensitivity of 88.9 % and specificity of 96.7% after adding clinical data decisions.

Mohamed et al., 2022 [53] suggest a method that detects breast cancer entirely automatically. Initially, the breast region is automatically separated and isolated from the rest of the body that acts as noise in the detection model of breast cancer, using the U-Net network. Second, author provides a two-class deep learning model for the categorisation of normal and pathological breast tissues using thermal pictures. This model is trained from scratch. Additionally, it is employed to extract additional features from the dataset that aid in network training and enhance classification process efficiency. When tested on database (DMR-IR), the suggested system obtained 99.33% accuracy, 100% sensitivity, and 98.67% specificity.

Ensafi et al., 2022 [54] propose a novel method for combining many thermography imaging views to enhance the diagnosis of breast cancer. The technique uses pre-trained deep learning architectures with transfer learning to merge frontal-45, lateral-45, and lateral views of thermal images. Improving these algorithms' ability to identify breast cancer was the aim. In comparison to existing deep learning or handcrafted methods, the suggested method produced a specificity increase of 2-30%and a sensitivity increase of 2-15%. In particular, compared to using only the frontal view, the sensitivity increased to 2 and the specificity reached 1 when lateral views were included. The suggested approach performed at least 2% better in terms of sensitivity and specificity than alternatives when it came to differentiating between healthy and malignant tissues.

Dey et al., 2022 [55] suggest system to detect breast cancer that can identify the disease by using thermal breast imaging. Here, the author builds a classifier for the stated objective by using the DenseNet121 pre-trained model to extract the feature. The author work with the original thermal image of breast to obtain outputs utilising two edge detectors, Prewitt and Roberts, prior to feature extraction. The original image and these two edge-maps combine to form the DenseNet121 model's 3-channel input. the model's performance is assessed using the “Database for Mastology Research (DMR-IR)”, a collection of thermal breast images. On the aforementioned database, the author achieved 98.80% as highest classification accuracy.

Aidossov et al., 2022 [56] Develop CNN methods to diagnose breast tumours with intelligence and precision. Breast thermograms obtained from a multicenter database were used for binary classification without any preprocessing is the work's primary innovation. The findings in this research demonstrate the effectiveness and use of deep learning for thermogram standardisation. It is discovered that the constructed model can achieve 80.77% accuracy, 44.44% sensitivity, and 100% specificity.

Alshehri and AlSaeed, 2022 [57] Assess the degree to which attention mechanisms (AMs) combined with convolutional neural networks (CNNs) can produce adequate detection outcomes for thermal breast cancer photos. The authors use thermal pictures from the Database (DMR-IR) to demonstrate a deep neural network-based breast cancer detection model with AMs. The model's accuracy, sensitivity, and specificity will be assessed, and it will be contrasted with the most advanced techniques for detecting breast cancer. On the breast thermal dataset, the AMs using the CNN model had positive test accuracy rates of 99.46%, 99.37%, and 99.30%. CNNs without AMs had a test accuracy of 92.32%, but CNNs with AMs improved their accuracy by 7%.

Houssein et al., 2021 [58] suggested a novel and effective version of the well-known chimp optimization technique (ChOA): the opposition-based Lévy Flight chimp optimizer (IChOA). Opposition-based learning (OBL) is used to expand the population variety of ChOA, while the Lévy Flight is used to improve its exploitation. The IChOA is used to solve the picture segmentation problem using multilevel thresholding. The Otsu and Kapur techniques were used to test the method on the DMR-IR database. It was then compared to seven other meta-heuristic algorithms: ChOA, SSA, SCA, WOA, MFO, GWO, and EO. When it came to separating different positive and negative examples, IChOA did better than its competitors in terms of accuracy, consistency, quality, and evaluation matrices like FSIM, SSIM, and PSNR.

Zadeh et al., 2021[59] proposed a novel approach to breast cancer diagnosis that extracts features from thermal imaging using a dynamic segmentation model and classifies data using a deep autoencoder neural network. The method employs a semi-automated procedure to identify breast areas according to their morphological characteristics by extracting eight statistical factors from thermography images. An unsupervised deep-learning autoencoder processes these traits to tell the difference between cancerous and healthy tissues. The authors achieved an impressive accuracy rate of 94.87% and a specificity of 96.77% by validating their method on a dataset of 196 individuals. This demonstrated the model's capability to accommodate various breast morphologies and accurately identify anomalies.

Ucuzal et al., 2021 [60] designed a system using pre-trained networks to classify breast cancer from thermographic images. The dataset, which was converted from.txt to.jpeg format, contained 179 healthy images and 101 patients (source: http://visual.ic.uff.br/dmi/). After testing a number of pre-trained models, ResNet50V2 produced the best accuracy, 99.6%. Medical professionals can now more effectively detect breast cancer thanks to an interface designed as a computer-aided diagnosis tool.

Sánchez-Ruiz et al., 2020 [61] suggested approach divides the area of interest using statistical operators, local operations, and overlap. First- and second-order statistics are then used to extract features. These characteristics are then used to train an artificial neural network (ANN). The approach produced competitive accuracy values ranging from 90.17% to 98.33% when tested on a popular image database. The study addresses the drawbacks of conventional mammography and emphasizes the benefits of breast thermography as a low-cost, non-invasive screening method. The outcomes demonstrate how well the suggested approach works to increase the precision of thermograph-based breast cancer detection.

Silva et al., 2020 [62] suggest a computational approach that uses supervised and unsupervised machine learning approaches to analyses breast dynamic image of thermography infrared in order to identify patients for breast abnormalities. A benign tumor or a malignant tumor (cancer) might be an anomaly. The author uses accuracy, sensitivity, specificity, and the area under the ROC curve as performance metrics. With an accuracy of 98.57%, the K-Star classifier produces the best results. The findings support the suggested method's potential for screening patients for breast abnormalities.

Ekici and Jawzal, 2020 [63] Develop system for automatic breast cancer detection that analyses thermal breast photos using image processing methods and algorithms to find illness indicators, enabling early breast cancer identification. A novel approach based on bio-data, image statistics, and image analysis is put forth for the extraction of breast distinctive features. CNNs optimised by the Bayes algorithm will be used for breast image classify as suspicious or normal based on these attributes that were retrieved from the thermal images. The accuracy rate of the suggested approach was 98.95% for the thermal pictures in the dataset that included 140 people.

Khomsi et al., 2020 [64] presents a new way to use superficial thermography to find breast cancer early. The authors conceptualized the breast as a multi-layered structure exhibiting varying thermal properties and utilized COMSOL Multiphysics software to simulate temperature gradients induced by tumors within breast tissue. To test these models in a lab, they made a breast imaging phantom out of organic materials that simulate the thermal and physical properties of real tissue. They put heat sources in different places and depths to make tumors. A heating control system kept the temperature of these model tumors at a certain level. Thermography is a potential non-invasive and affordable method for early breast cancer detection, as evidenced by the results showing that thermographic devices could accurately detect minute temperature changes on the surface.

6. Comparative Summary of Reviewed Studies

This section gathers all of the studied studies into a structured comparison to provide a better understanding of the various studies. Table 2 compiles datasets, methods, advantages, disadvantages, and evaluated performance.

Note: The "Results" column shows a summary of other performance measures like sensitivity, specificity, precision, and F1-scores. Accuracy values are shown in a separate column.

Table 2: Comparative Summary

Cite	Dataset	Algorithm / Technique	Advantage	Disadvantage	Results	Accuracy
Tang et al., 2025 [30]	**Thermography dataset**	**Multi-light Net (multi-input lightweight CNN)**	**Lightweight, efficient, suitable for limited resources**	**Slightly lower than heavier models; requires careful tuning**	**Balanced sensitivity and specificity with strong overall performance**	**~96%**
Attallah, 2025 [31]	**DMR-IR and novel dataset**	**Multi-CNN CAD + feature transformation (NMF + Relief-F)**	**Multi-dataset testing; interpretable CAD system**	**Lower performance on benign vs malignant cases**	**100% accuracy (normal vs abnormal, DMR-IR); 79.3% (benign vs malignant, new dataset)**	**100% / 79.3%**
Bani Ahmad et al., 2025 [32]	**Thermography dataset**	**StackVRDNet (VGG16 + ResNet + DenseNet + RHDAO heuristic optimizer)**	**High accuracy, hybrid ensemble improves robustness**	**Complex architecture; higher training time**	**Precision 86.86%, strong feature weighting**	**97.05%**
Veerlapalli and Dutta , 2025 [33]	**Breast thermography dataset**	**Hybrid GAN + DL classifier**	**Tackles dataset scarcity with synthetic data; boosts classification**	**GAN training instability; requires more computation**	**Enhanced classification performance; improved sensitivity and specificity**	**~96–98%**
Alzahrani et al., 2025 [34]	**Thermographic images (public)**	**CNN + Enhanced Particle Swarm Optimization (EPSO) + preprocessing (CLAHE, fuzzy edge detection, median filter)**	**Automated CAD, improved hyperparameter tuning, better preprocessing**	**Requires high computational resources, complex pipeline**	**Improved CNN performance compared to baseline; strong sensitivity & specificity**	**~97–99%**
Munguía-Siu et al., 2024 [35]	**Dynamic thermography sequences (DMR-IR DIT protocol)**	**VGG16 + LSTM (Hybrid CNN–RNN)**	**Captures both spatial and temporal features from dynamic sequences**	**Requires sequential inputs and more complex modeling**	**Outperformed single CNNs; hybrid models improved classification performance**	**95.72%**
Hanieh et al., 2024 [36]	**Thermograms**	**CNN + Machine learning (FCnet, SVM,**	**High accuracy and reliability**	**Requires large datasets for training**	**Reliability: 91.2%–97.5%; Sensitivity: 90.4%–95.5%**	**94.1-95.0%**

		CLINEAR, KNN)				
Shojaedini and Bahramzadeh, 2024[37]	Synthetic thermograms	Deep autoencoders	Improved feature representation and detection accuracy	Requires synthetic data generation	Significant improvement in detection accuracy	92.3%
Ahmed et al., 2024 [38]	DMR-IR	VGG16 with transfer learning	High accuracy, sensitivity, specificity, and other metrics	Requires large datasets and computational resources	F1: 99.8%; Precision: 98.9%; Recall: 99%; Specificity: 97.5%; Sensitivity: 100%;	99.4%
Al Husaini et al., 2024 [39]	Real-time thermography videos	Inception v3, v4, modified Inception Mv4	Real-time detection, high accuracy, enhanced with in-situ cooling	Requires specialized hardware and software	High accuracy (96.8-99.748%)	99.7%
Mohammed Jawad Khudhur, 2024 [40]	MIAS	DCNN	High accuracy, early detection	Requires large datasets and computational resources	High accuracy (99.1%)	99.1%
Dihmani et al., 2024 [41]	DMR-IR	Hybrid PSO and SMO, XAI	Interpretable, high accuracy, feature selection	Complex optimization process	High accuracy (98.27%), high F1-score (98.15%)	98.27%
da Silva et al., 2024[42]	Thermograms	CNNs with PSO for feature selection	High accuracy, sensitivity, and specificity	Requires careful feature selection	High accuracy (78.55-79.92%), high sensitivity and specificity	78.55-79.92%
Nigam and Swarnkar, 2024 [43]	Thermograms	CNNs with DWT	Improved image quality and feature extraction, high accuracy	Requires careful data preprocessing and model training	High accuracy (up to 85%)	Up to 85%
Ahmad et al., 2024 [44]	Medical images	YOLO, ResUNet, BreastNet-SVM	High accuracy in detection and classification	Requires large datasets and computational resources	98.5% detection accuracy, 99.16% classification accuracy	98.5%, 99.16%
Wang et al., 2024 [45]	Multi-modal data (pathology imaging, molecular, clinical)	DeepClinMed-PGM	Improved DFS prediction, robust performance across cohorts	Requires large and diverse datasets	High AUC values, low hazard ratios	Not explicitly stated
Tsietso et al., 2023 [46]	clinical data, Thermal infrared images	Deep learning	Incorporates multiple views and clinical data	May miss lesions on the sides, disregards some clinical data	accuracy 90.48%AUROC 0.94, sensitivity 93.33%,	90.48%

Husaini et al., 2023 [47]	**Real-time thermography videos**	**Inception v3, v4, modified Mv4**	**Real-time detection, high accuracy, enhanced with in-situ cooling**	**Requires specialized hardware and software**	**High accuracy (96.8-99.748%)**	**99.748%**
Ali et al., 2023 [48]	**Histopathological images (IDC and BreakHis)**	**ECAM (Enhanced Channel-Wise Attention Mechanism)**	**High accuracy, improved feature representation, computational efficiency**	**Requires large and diverse datasets**	**High accuracy and F1-scores on both datasets**	**96.65% (IDC), 96.33% (BreakHis)**
Khan et al., 2023 [49]	**Thermal images**	**Customized 2D CNN**	**High accuracy, improved classification**	**Requires careful data preprocessing and model training**	**High accuracy (95%)**	**95%**
Alshehri and AlSaeed, 2023 [50]	**Thermal images**	**VGG16 with AMs**	**High accuracy, improved performance over baseline VGG16**	**Requires careful tuning of AMs**	**High accuracy (99.32-99.80%)**	**99.80%**
Torres-Galván et al., 2022 [51]	**Thermograms**	**Deep convolutional neural network , transfer learning**	**High sensitivity for abnormal thermograms**	**Lower specificity, especially with unbalanced distribution**	**Sensitivity of 92.3%, specificity of 53.8% (balanced), sensitivity of 84.6%, specificity of 65.3% (unbalanced)**	**balanced class: 73.1% unbalanced: 74.9%**
Mammoottil et al., 2022 [52]	**Visual DMR dataset**	**Convolutional neural networks**	**Improved performance with clinical data**	**Limited public datasets for thermography**	**Accuracy 85.4% before clinical data, 93.8% after clinical data**	**93.8%**
Mohamed et al., 2022 [53]	**Real data (DMR-IR)**	**U-Net for breast area extraction, two-class deep learning model**	**Fully automatic, high accuracy**	**Not explicitly stated**	**Accuracy of 99.33%, sensitivity of 100%, specificity of 98.67%**	**99.33%**
Ensafi et al., 2022 [54]	**DMR-IR (Database for Mastology Research)**	**Multiple views of thermograms with transfer learning**	**Improved sensitivity and specificity through multi-view fusion**	**Requires combining different thermogram views**	**increase Sensitivity 2-15% , increase specificity 2-30% over single-view models**	**up to 93%**
Dey et al., 2022 [55]	**DMR-IR**	**DenseNet121 with edge detection**	**High accuracy; edge detection enhances**	**Preprocessing adds complexity**	**Highest 98.80% classification**	**98.80%**

			feature extraction		accuracy on dataset DMR-IR	
Aidossov et al., 2022 [56]	Multicenter database (unnamed)	CNNs without preprocessing	Simple implementation ; non-invasive method	Low sensitivity	Useful for standardized analysis; accuracy of 80.77%	80.77%
Alshehri and AlSaeed, 2022 [57]	DMR-IR	CNNs with Attention Mechanisms (AMs)	Improved accuracy with attention mechanisms	Requires high computational resources	test Achieved accuracy 99.46%, 99.37%, and 99.30%	99.46%
Houssein et al., 2021 [58]	DMR-IR	Opposition-based Lévy Flight Chimp Optimization	Efficient segmentation; improved convergence	Algorithm complexity and potential stagnation	Outperformed seven meta-heuristic algorithms in segmentation quality	Not directly applicable
Zadeh et al., 2021[59]	Database for Mastology Research (Brazil): 196 subjects, 41 with cancer and 155 healthy, 1,960 thermography images total	Deep autoencoder neural network	High specificity (96.77%) and robustness across various breast morphologies; non-invasive	Imaging sequence sensitive to positional changes, requires a stable patient position	Successfully classified abnormal vs. normal thermograms	94%
Ucuzal et al., 2021 [60]	Public dataset	Pre-trained networks (ResNet50V2)	High accuracy; pre-trained networks reduce training time	Dataset limitations	Best classification performance with ResNet50V2	99.6%
Sánchez-Ruiz et al., 2020 [61]	Widely used image database	ANN with local and statistical operations for ROI segmentation	Non-invasive, low-cost screening; high accuracy with ANN	Limited generalization for new datasets	Achieved competitive accuracy results ranging from 90.17% to 98.33%	90.17%-98.33%
Silva et al., 2020[62]	Dynamic Infrared Thermography images	K-Star classifier	Effective screening tool; high specificity	Limited sensitivity for certain cases	Best results with an accuracy of 98.57%	98.57%
Ekici and Jawzal, 2020 [63]	Thermal images dataset (140 individuals)	CNNs optimized by Bayes algorithm	High accuracy in classification; early detection capabilities	Bio-data requirements for feature extraction	High classification accuracy achieved at 98.95%	98.95%
Khomsi et al., 2020 [64]	Simulated breast	Surface thermography simulation	Physical mimicry of breast tissue;	Limited to simulated environment	Demonstrated potential for early detection using	N

	imaging phantom	**using COMSOL**	**early detection potential**	**surface thermography**

7. Discussion

The reviewed research demonstrate that deep learning has considerably improved the use of "thermal imaging" for breast cancer detection. The reported findings are consistently high, with most investigations obtaining accuracy above 90% and some nearing 100%. Transfer learning architectures, such as "VGG", "ResNet", and "Inception", are still the most popular methods, but more recent advancements involve attention mechanisms, hybrid CNN-RNN models, and optimization-assisted frameworks. These approaches often outperform classic CNNs, highlighting the significance of model architectures and preprocessing methodologies in enhancing diagnostic outcomes.

Figure 2 shows the reported accuracies for each reviewed study from 2020 to 2025, ranked from highest to lowest. Almost all of trials obtained performance levels above 90%, with a few exceeding 99%. However, some research that used simpler CNNs or smaller datasets found more modest results, ranging from 75 to 85%. This distribution demonstrates the significant impact of dataset quality, class balance, and methodology design on reported findings.

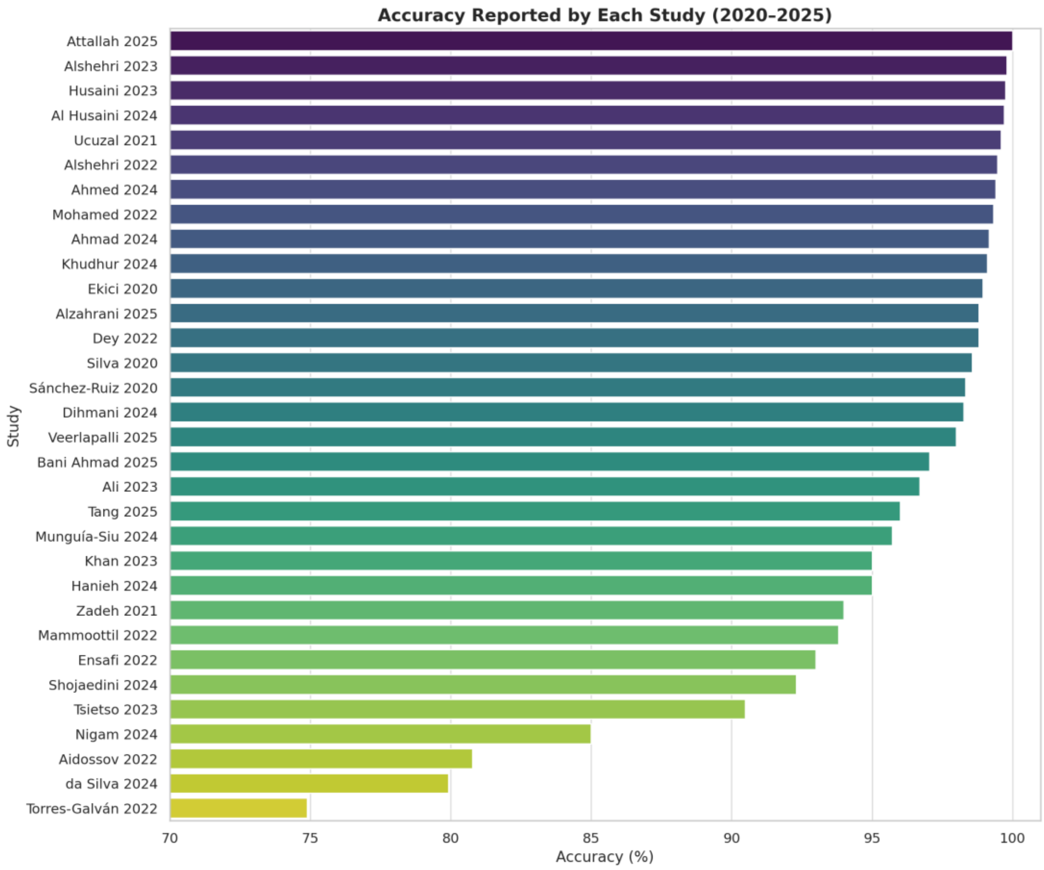

Figure 2: Accuracy reported by each reviewed study (2020–2025), sorted from highest to lowest

Figure 3 categories results by technique and displays the average accuracy achieved across categories. Transfer learning techniques, attention-based CNNs, and hybrid models clearly outperform traditional CNNs and handmade approaches, with mean accuracies that are consistently higher. This illustrates how innovation in architecture design, particularly by the use of pre-trained models, the addition of attention mechanisms, or the combination of spatial and temporal modelling, immediately translates into improved classification reliability.

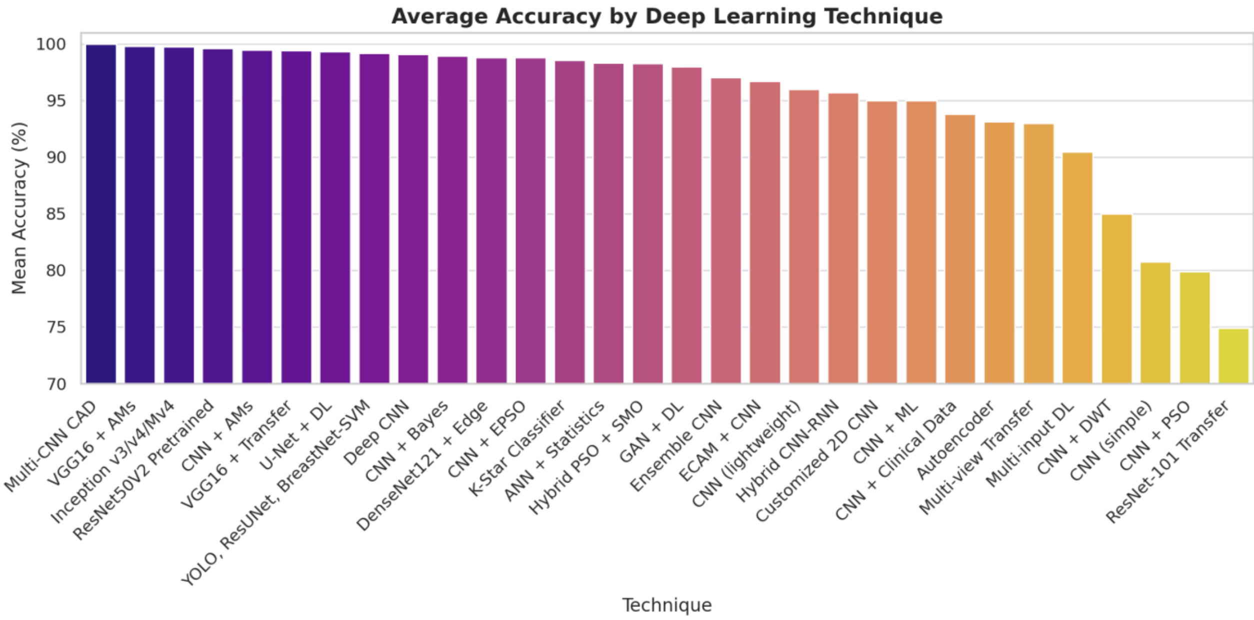

Figure 3: Average accuracy categories by deep learning technique across reviewed studies.

Even though these results are very good, there are some limits that need to be acknowledged. First, the heavy reliance on the DMR-IR dataset in many studies makes it hard to apply the results to other situations. When models are tested on photos from other schools or devices, high claimed accuracies may not be a good indicator of how well they work in the real world. Several studies have shown high accuracies (≥99%), which should be viewed with caution. These kinds of results are often made with small or unbalanced datasets and without outside validation. These factors can artificially enhance performance while constraining clinical utility. Third, while generative models like GANs can solve data scarcity by creating synthetic thermograms, their use is limited due to training instability and computational cost. Similarly, real-time or multi-view thermography systems show promise, but they require larger and more diversified datasets for reliable validation.

Overall, the literature shows that AI-driven thermography has a lot of potential as a non-invasive and cheap way to find breast cancer early, but more research is needed before it can be used in real life. Future endeavors must prioritize the development of larger, standardized, and multi-institutional datasets, the implementation of external validation processes, and the publication of clinically relevant metrics such as sensitivity, specificity, and AUC, alongside accuracy. Also, looking into underused methods like GANs for data augmentation, hybrid "CNN-RNNs" for dynamic thermography, and attention mechanisms that make it easier to extract features could be helpful. Addressing these limitations will bring the field closer to developing a reliable, explainable, and clinically trusted framework for breast cancer screening.

8. Conclusion

The study emphasizes the growing potential for enhancing early breast cancer detection by fusing deep learning methods with breast thermography. Models which include CNNs, GANs, U-Net, and transfer learning continuously demonstrated high accuracy, sensitivity, and specificity in interpreting thermal images in the research that was examined. These technologies offer a strong substitute for traditional imaging techniques, especially when non-invasiveness, affordability, and accessibility are crucial considerations. The path to clinical adoption presents several challenges. Numerous studies utilize small or imbalanced datasets, and variations in imaging techniques may hinder model generalizability. Furthermore, while AI models demonstrate promise, their interpretability and incorporation into real-world diagnostic procedures require additional refinement.

Future research should emphasize the creation of standardized, diverse thermographic datasets, explore multimodal imaging methodologies, and enhance AI models for transparency and clinical reliability. Ongoing research and collaboration between the medical and technical sectors may render AI-enhanced thermography a feasible and scalable instrument for global breast cancer screening.

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