Review and Survey of Deep Learning Approaches for Enhanced Breast Cancer Detection in Mammograms

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Breast cancer is one of the prevalent malignancies affecting women and the foremost cause of deaths among them globally. Breast cancer is characterized by its heterogeneous nature in both of its molecular and clinical presentations. Mammography is the predominantly used and recognized image modeling for the screening and diagnosis of Breast Cancer. In this review paper, we examine the latest advancements in Deep Learning (DL) architectures such as CNNs, ensemble models, hybrid frameworks(CNN+ViT) for enhancing the early detection of breast cancer in mammograms and concludes by highlighting the performance of the respective frameworks.

Keywords: Mammogram Screening Analysis, Tumor Detection, Deep Learning, Medical Imaging Modalities, Ensemble Learning, Convolutional Neural Network

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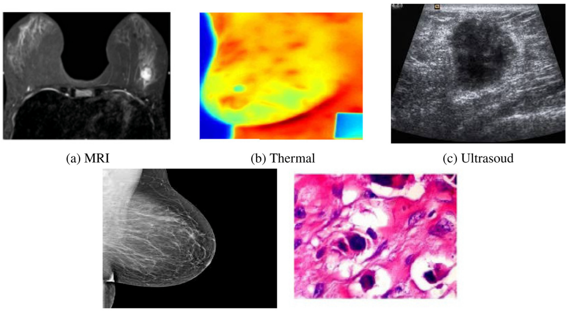
1 Introduction

Breast cancer is a tumor which continues to pose a great threat to women around the globe. It consistently tops as one of the most common cancer types and is a leading cause of mortality among women worldwide.For improving the survival rates of patients through effective treatment, it is essential to timely and accurately detect the breast cancer [1, 2]. Since 2020, the estimates showed over 2.3 million new cases and over 685,000 deaths around the globe [3, 4]. Breast Cancer, Alzheimer's, Dementia are among those diseases which are detected based on image modalities such a mammogram, MRI respectively [5, 6] The age-adjusted/standardized incidence rate is about 22 to 25 and age-adjusted/standardized mortality rate is roughly 11 to 13 over a census of 1 million people [7]. In India, as of 2018, out of total cancer incidences in females, 27.70% of cases are of breast cancer out of which 12.11% resulted in cancer mortality [8]. Mammography is the foundational technique for early detection of breast cancer, considered as the benchmark and is used widely for breast cancer screening [9]. Mammography has a number of significant drawbacks. The interpretation of mammograms can be time-consuming and subjective, which leads to differences and potential oversight in the manual interpretation of radiologists [10].The key challenges include to the appearance of the tumor, cancer hiding dense breast tissue and most significantly the risk of false alarm (false positives) and missed detection (false negatives) [11]. The rapid advancements of machine learning, notably deep learning (DL), have stimulated significant interest in its utilization to medical imaging problems. Deep learning is a sub-branch of machine learning, which has exhibited exceptional outcomes in numerous domains, especially in the biomedical sector, due to its capacity to effectively process and handle large volumes of high-dimensional image data.

Unlike conventional machine learning, Deep Learning algorithms improve overall performance by automatically extracting intricate features from raw images without intervention by a human being [12]. Specifically for mammography, deep learning algorithms have the capacity to develop a next generation of CAD-like tools [8] that can detect intricate patterns that may not may not be visually perceptible to the naked eyes, hence improving the accuracy of the diagnosis process and reducing the false positive rates [13].In the world of mammography, deep learning is evolving and two recent trends are emerging: a prevalent use of transfer learning to overcome the drawbacks of variable dataset sizes [2], and the rise of hybrid CNN-ViT models that combine CNNs' local feature extraction capabilities with ViTs' ability to capture global context [14].

2 Imaging techniques for Breast Cancer Detection

As discussed earlier, an early and precise detection of breast cancer is essential to enhance the chances of accurate diagnosis. Continuous advancements are being made to develop numerous medical imaging techniques are constantly being developed to enhance early detection methodologies for breast cancer. Medical images are a great source for the identification of cancerous tumor and its diagnosis. At present several image modeling techniques are implemented depicted in Figure 1 which are further described as follows:



(a) MRI (b) Thermal (c) Ultrasoud

(d) Mammogram (e) Histopathology

Figure 1: Medical images of various breast tissues: (a) MRI (b) Thermal image (c) Ultrasound (d) Mammogram (e) Histopathology.

2.1 Mammography

Mammography is a highly specialized imaging technique in the medical field that serves as a critical component in breast cancer diagnosis [1, 14]. For capturing the images of the breast, it uses a low-dose X-ray system [4, 15]. Regular mammography screening has proven to substantially reduce both incidence and mortality rates in breast cancer [15,16].

Types of mammography There are various types of mammography techniques available as follows:

Screen-Film Mammography (SFM) It is a conventional imaging method which uses low-dose X-rays to imprint images onto radio graphic films directly, generating high-resolution images .

Full-Field Digital Mammography (FFDM) This imaging modality invoIes capturing of digital images for displaying on a computer screen. FFDM comes with certain advancements wallowing users for instant image viewing, storage, retrieval and transmission much more easily.

Digital Breast Tomosynthesis (DBT) DBT, commonly known as three-dimensional(3D) mammography. It takes several X-ray images from multiple angles and creates a three-dimensional reconstruction of breast by combining those images. DBT improves the ability to identify and describe abnormalities by reducing tissue overlap in dense breast [3, 12].

Contrast-Enhanced Digital Mammography (CEDM) CEDM is a significant advancement in the breast imaging techniques that uses intravenous iodinated contrast and digital mammography to improve the visualization of lesions of a breast [11].

2.2 Ultrasound

It is a non-radioactive and minimally invasive procedure which takes images of breast from different angles. The non-invasive, non-contact, and non-radioactive behavior of ultrasound makes it safe for repeated use and for individuals who are sensitive to radiation [1, 2].

2.3 MRI

Magnetic Resonance Imaging (MRI) is a non-invasive medical imaging modality. It uses a strong magnetic fields and radio frequency pulses to produce detailed cross-sectional images of internal organs and tissues of a body. Among all the screening tests for breast cancer, it is known as a method which offers highest sensitivity [19].

2.4 Histopathology

Histopathology, also known as Histopathological Imaging (HI), is a medical imaging modality in which microscopic examination of an organ's tissue is performed. It is widely regarded as a gold standard for the assessment of breast cancer providing phenotype information which plays a crucial role in the diagnosis and treatment of breast cancer [12].

2.5 Thermography

Breast Thermography, or Thermal Imaging, is a medical imaging modality that uses heat patterns generated by malignant cells to identify breast abnormalities . It records the natural infrared energy that the breast surface releases in relation to the body temperature. The concept is based on the observation that when a tumor occurs, then due to increased blood perfusion and metabolic activity, the skin over that tumor has higher local temperature [19, 20].

3 Mammography Data-Sets

Datasets are the fundamental for the development of image classification models and plays a crucial role for training, validating, and evaluating them. Mammography datasets are widely used since they encompass thousands of patients that makes them generally extensive. The BI-RADS (Breast Imaging Reporting and Data System) evaluation system is a benchmark procedure used to categorize mammograms and describe various levels of findings related to breast cancer [20]. Some major datasets used for breast cancer detection are compared in Table 2 and described as follows:

3.1 Mammographic Image Analysis Society (MIAS) Dataset

Description This dataset is comprised of 322 digitized mammogram images where each image has a resolution of 1024x1024 pixels in portable gray scale map (PGM) format. It is categorized into three distinct classes: 61 benign cases, 52 malignant cases, and 209 normal cases. It was designed by research group in the UK [11, 14].

Used by It has a wider application for feature extraction with pre-trained Convolutional Neural Networks (CNNs) such as ResNet50, VGG-19, VGG-16, Inception-V2 & Inception V3 and ResNet [14].

Table 1: Mammogram datasets for detection of BC

S.No.	Name of dataset	Image Count	Issue Year	Public/Private
1	MIAS	322 images	1994	Public
2	DDSM	10,239 images	1997	Public
3	INbreast	410 mammograms	2012	Public
4	CBIS-DDSM	10,239 images	2017	Public
5	VinDr-Mammo	20,000 images	2022	Public
6	Mammogram CLAHE dataset from Kaggle	10,000 labeled images	N/A	Public

3.2 CBIS-DDSM (Curated Breast Imaging Subset of DDSM

Description This is the largest mammogram image data set was issued in the year 2017 for image analysis . This dataset encompasses thousands of screening and diagnostic images from full-field digital and digitized film mammography . The images are stored in DICOM format. Due to its analyzed and revised version of data, it is considered to be the most suitable database for research.

Used by Widely used for transfer learning, feature extraction, training machine leaning models and crucial for the development of artificial applications [11].

3.3 Kaggle Mammogram CLAHE Dataset

Description This dataset includes of 10,000 labeled mammogram images, evenly divided into samples of 5,000 benign and 5,000 malignant. The images are high-resolution (512x512 pixels) and features both type of views a Craniocaudal (CC) view and a Mediolateral Oblique (MLO) View [2].

Used by This dataset was used for training and applying its CNN+ViT hybrid model [2].

3.4 INbreast Database

Description For digital mammography research, a publicly accessible dataset was issued in 2012 . It consists of over 410 mammogram images acquired in excess of 115 patients [10]. This dataset has features as binary mask annotations for regions of interest (ROIs), becoming appropriate for segmentation, classification, and detection. It also certain drawbacks as it requires reliable pathological confirmation for all diagnoses, leading to the involvement of assessments by radiologists for labels [10].

Used by Some researchers chose not to use it due to its reliance on radiologists and lack of essential metadata, outdated format, and as compared to newer dataset it also miss out the standardization.

3.5 VinDr-Mammo Dataset

Description This dataset was collected from hospitals in Hanoi, Vietnam and was released in the year 2022.It comprises of 5,000 screenings and 20,000 images which are stored in DICOM format. Each sample image was examined by three radiologists and the metadata gives the details on breast density, lesion characterization. One of the major limitation of this dataset is the absence of pathology-confirmed outcomes making findings to rely on interpretations of radiology experts [17].

Used by Training ML models.

4 Deep Learning Architectures and Techniques for Breast Cancer

Deep Learning, a powerful technique which has been lately emerged and has overcome certain limitations of machine learning. Deep learning is a broader form and is a subset of artificial neural networks [17].

4.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a highly effective class of deep learning algorithms, especially suited for image-centric applications such as image classification. They have gained remarkable popularity in recent times and have shown great potential in various fields, including medical diagnosis, particularly for breast cancer detection [18].

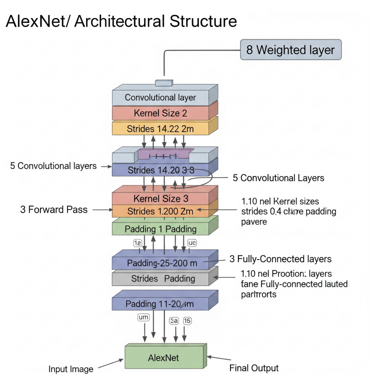
4.1.1 AlexNet

It was introduced by Krizhevsky et al. in 2012, is a pioneer architecture which uses deep convolutional neural network (CNN) and is widely applicable in computer vision. Its architecture is designed to process images of size 227x227x3 and it consists of eight

Table 2: Comparative table highlighting size, resolution, annotations, and typical applications of datasets

Dataset Name	Primary Modality	Size	Resolution	Key Annotations	Typical Applications
MIAS	Mammography	**322 grayscale** images are included in the dataset. The class distribution shows slight variations across different studies, with approximately 207 categorized as	**1024 × 1024 pixels.**	The ground-truth data encompasses background tissue characteristics, abnormality classifications (such as calcification, mass, and asymmetry), tumor	Breast cancer detection and classification, especially for developing and validating Computer-Aided Diagnosis (CAD) systems. Frequently used as a benchmark dataset.
CBIS-DDSM	Mammography	An improved variant of DDSM which consists of 2478 medical images derived from 1249 female patients	Transformed to DICOM format(1152 X 896)	Pixel-level annotations for Regions of Interest (ROIs) are provided with benign or malignant status pathological confirmation.	This dataset is utilized in classification, detection, and segmentation tasks.
Kaggle	Mammography	10,000 labelled images (5,000 Benign, 5,000 Malignant)	512 × 512 pixels	Benign or Malignant class are labeled and Craniocaudal (CC) and Mediolateral Oblique (MLO) views are available	It uses binary characterization procedure therefore used in early breast cancer identification and for development of diagnostic tools
INbreast	Mammography	The dataset consists of 410 medical images from 115 patients	High FFDM images	The dataset incorporates binary mask delineations for ROIs with comprehensive mass annotations	Applicable for designing of deep learning frameworks for mass identification.
VinDr-Mammo	Mammography	An extensive compilation of 20,000 images from over 5,000 multi-view mammograms	DICOM format	Bounding box annotations for findings such as mass, calcification, asymmetry, and distortion	Mammographic assessment, BC Detection and classification

weighted layers: five convolutional and three fully-connected layers [11]. An AlexNet architecture is depicted in Figure 2.



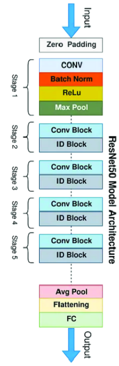


Figure 3: ResNet Architecture

4.1.2 ResNet

ResNet stands for Residual Network. It was proposed by Microsoft Research Team and is one of a powerful CNN architecture. It has taken deep learning to another level by addressing the vanishing gradient problem [14]. It does this through ”residual learning” using ”skip connections”. Through these skip connections information gets skipped in between layers and go straight to later layers shown in Figure 3. Due to this approach, optimization becomes easier which allow for building much deeper networks [20].

4.1.3 VGGNet

VGG network was introduced by Visual Geometry Group at Oxford University. It is a widely adopted Convolutional Neural Network architecture which is specifically engineered to perform image analysis tasks such as image recognition. The architecture of VGG network is straightforward and possesses a deep structure. It has a stack of multiple convolutional layers, followed by pooling layers and then fully connected layers [10, 11].

4.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks, or RNNs, are a special and unique type of deep learning model since they possess a kind of ”memory”. Due to the presence of hidden internal states, RNNs can remember the information from previous sequential steps which influences their current output. They are particularly effective for processing the sequential data because of their ability to memorize previous sequences. In the context of breast cancer detection, they can process 3D volumetric images like MRI scans and by series of sequential images the change in features can be analyzed. The key characteristic of an RNN is that it works like a pipelined procedure , where the output of a previous state is fed as an input to the next state, and the same parameters are applied across each layer in the sequence. Compared to other neural networks, this design of RNN helps it to reduce the complexity of parameters [23] .

4.3 Vision Transformers (ViTs)

Vision Transformers (ViTs) have taken inspiration from models that are initially designed for understanding language. These are a recent and exciting deep learning models which has changed the way how computers identify and interpret the images. They excel at capturing certain patterns and relationships among them across different parts of a mammogram, which is essential for the detection of tiny or widespread abnormalities. They are highly useful in the fields such as medical imaging for breast cancer detection for the following reasons:

Thinking in ”Patches” Traditional Convolutional Neural Networks (CNNs) process images by looking at small and overlapping windows whereas, ViTs break down an image into tiny and non-overlapping ”patches”. It is like dividing an image into several small squares [2].

Giving Patches ”Context” Now, each of these patches is then treated individually just like a ”word” in a sentence, and then the model identifies how all of these ”words” (patches) related to each other. This is done through a procedure called as ”self-attention mechanisms”. With the help of this mechanism, ViTs gain an to understand the big picture – the ”global context” and long-range relationships across the entire image [19].

5 Image Preprocessing and Data Augmentation Techniques

Preprocessing and data augmentation are fundamentally important techniques used for the development of robust and accurate deep learning (DL) models.These methods are essential for addressing the inherent limitations of the medical imaging datasets [12].

5.1 Preprocessing Methods

There are several methods for data preprocessing described as follows:

Noise Removal The unwanted sounds and blurring effects in medical images is known as noise. A noise in the dataset can cause erroneous detection during diagnosis and to prevent this and to maximize image quality, noise from the dataset has to be removed. Techniques such as Laplacian of Gaussian (LoG) filter with a 2-D Gaussian filter and 2D median filters are used.

Morphological Analysis In this process, removal of non-breast regions from images before segmentation takes place, ensuring that the analysis is focused only on the affected areas and is not influenced by irrelevant structures [14].

Segmentation of Regions of Interest (ROI) As the name suggests, this technique automatically identifies tumor regions or other areas of interest from medical images, which reduces the computational time and allows analysis to concentrate on critical areas for breast cancer detection [14].

Image Resizing and Normalization In this technique, resizing images to a uniform pixel resolution (e.g., 224x224 or 512x512) is performed [19, 20] .

5.2 Data Augmentation Strategies

There are several data augmentation techniques described as follows:

Geometric Transformations (Rotation, Flipping, Resizing) These methods modify the images by altering the spatial orientation or scale of images to artificially increase dataset size by changing the spatial orientation or scale of images. These alterations can be done by rotating images by various angles, flipping them horizontally or vertically, and resizing or zooming to different scales [10, 12] .

Pixel-Level Modifications (Brightness, Contrast) These are image enhancing techniques often performed by adjusting pixel intensity values. Examples: Updating the brightness and contrast of an image to highlight subtle tissue variations.

Synthetic Data Generation using GANs This techniques involves an advanced method that creates new, realistic images that closely resemble original medical images. It trains two neural networks simultaneously: a generator and a discriminator [19].

6 Key Model Architectures and Their Performance Comparison

This research summarizes and compares several models for early breast detection and the comparison is shown in Table 3:

6.1 Convolutional Neural Networks (CNNs)

CNN serves as the backbone for almost all models, whether they are transfer learning models or custom-designed architectures. CNN have the ability to automatically fetche the hierarchical features from the image, hence they are highly effective for image analysis [2, 3] .

6.2 Transfer Learning Models

Here, CNN models are pre-trained on larger, dataset such as ImageNet, and then fine-tuned for breast cancer detection. Some commonly used architectures in this research include:

- • VGG-16/VGG-19: It is often used because of its simple but deep architecture(referring to VGG-16/VGG-19 as a class) and strong performance [14].

Table 3: Comparative review of deep learning models for detection of breast cancer

S.No.	Paper Title or Author/Year	Model Architecture	Dataset(s) Used	Performance Metrics Achieved
1	Adyasha Sahu et al. (2024)	Proposed: Deep learning-based ensemble classifier (AlexNet, ResNet, MobileNetV2). Also evaluated individual Vgg19, AlexNet, Xception, ResNet18, MobileNetV2, InceptionV3, NasNetMobile	mini-DDSM	mini-DDSM: Abnormality detection Accuracy: 99.17%; Malignancy detection Accuracy: 97.75%
2	Abeer Saber et al. (2021)	Transfer learning using pre-trained CNN architectures: VGG16 (highlighted as powerful), VGG19, Inception V3, ResNet50, Inception-V2 ResNet	MIAS dataset	Accuracy: 98.96%, Sensitivity: 97.83%, Specificity: 99.13%, Precision: 97.35%, F-score: 97.66%, AUC: 0.995
3	Vasudha Rani Patheda et al. (2025)	Hybrid CNN+ViT model	Mammogram CLAHE dataset from Kaggle	Accuracy: 90.1%, Precision: 0.91 (benign), 0.89 (malignant), Recall: 0.89 (benign), 0.92 (malignant)
4	Nan Wu et al. (2020)	Novel two-stage architecture with a custom ResNet-based network	study with 229,426 digital screening mammography (1,001,093 images) from 141,473 patients	AUC: 0.895 for predicting cancer presence
5	Doaa Youssef et al. (2025)	Hybrid feature extraction combining traditional methods with ResNet-50 and MobileNet, Classifiers: SVM	DMR-IR database	Accuracy: 95.51%, Sensitivity: 96.62%, Specificity: 94.76%
6	Farag H. Alhsnony et al. (2024)	Simplified custom Convolutional Neural Network (CNN) model	MIAS dataset (322 grayscale mammographic images)	Accuracy: 94.23%
7	Dilawar Shah et al. (2025)	EfcientViewNet model	RSNA Breast Cancer Detection Screening Mammography dataset	High F1 score and Recall of 0.99
8	Junjie Liu et al. (2022	Convolutional Neural Network (CNN)	DDSM, MIAS, INbreast	Sensitivity: 0.961, Specificity: 0.950, AUC: 0.974
9	Li Shen et al. (2019)	Convolutional Neural Network (CNN), Uses VGG16 as patch classifiers	CBIS-DDSM (2478 mammography images)	Best single model per-image AUC: 0.88
10	R. Sathesh Raaj (2023)	Proposed hybrid CNN architecture using convolutional and pooling layers in parallel	MIAS dataset (322 mammograms)	ensitivity: 98%, Specificity: 98.66%, Accuracy: 99.17%, JI: 98.07%
11	Ojonugwa Oluwafemi Ejiga Peter et al. (2025)	MammoFormer framework (Transformer-based Explainable Deep Learning)	mammography images	high accuracy and efficiency

- • ResNet (e.g., ResNet18, ResNet50): ResNet has residual connections because of which it is widely adopted. It can mitigate vanishing gradient problems in very deep networks, which leading to robust performance [19].
- • AlexNet: Although released early, but still an effective CNN model for image analysis, either used as a baseline or as part of ensembles [1].
- • Inception (e.g., InceptionV3, Inception-V2 ResNet, InceptionV4): It employs multiple filter sizes in parallel thus utilizing the computational resources efficiently [14].
- • MobileNetV2: It is well suited when the datasets are small or in resource-constrained environments due to its high efficiency [19].

6.3 Ensemble and Hybrid Models:

Many studies have integrated various models or feature extraction techniques to boost the performance and robustness. Examples include the following:

- • Ensemble of Transfer Learning Models: Predictions from multiple pre-trained CNNs (e.g., AlexNet, ResNet, MobileNetV2) are combined.
- • CNN+ViT Hybrids: It is a hybrid model obtained by integrating Convolutional Neural Networks (for local feature extraction) with Vision Transformers (for global context) which is an emerging approach.
- • Hybrid Feature Extraction: The deep features extracted by CNNs (e.g., ResNet-50, MobileNet) are combined with traditional image processing features (e.g., HOG, Gabor filters) before classification [20, 21].

7 Conclusion

The advent of artificial intelligence (AI) and machine learning (ML) techniques has significantly enhanced the automatic detection and classification of breast cancer (BC). These techniques provide a vital support for early diagnosis, thereby improving it. This review paper highlights the remarkable capabilities and enduring challenges in this field. For the diagnosis of breast cancer using mammography,Deep Learning-Based Ensemble Classifiers(combining AlexNet, ResNet, and MobileNetV2) has recorded the accuracy of 99.17%. Convolutional Neural Networks (CNNs) have shown excellent performance and are most effective for classification of imaging modalities. Hybrid CNN Architectures have also yielded the accuracy of 99.17%. In addition to CNNs, Support Vector Machines(SVMs) have also shown promising results, often yielding high accuracy rates. Pre-trained models such as AlexNet, ResNet, MobileNetV2, InceptionV3, VGG16, and EfficientNet are optimized for BC detection, resulting in an accuracy of 98.96% . A hybrid architecture obtained by the combination of multiple transfer learning models (e.g., AlexNet, ResNet, MobileNetV2) into an ensemble classifier which yields more accurate and reliable results. Hybrid models, such as CNN+ViT, utilize the strengths of both architectures. CNN architecture excels at local feature extraction and ViT architecture excels at global context capture, which enhances the classification and generalization without overfitting. For addressing the dataset limitations such as small size and class imbalance, Data augmentation, including synthetic image generation using GANs are implemented, which significantly improves the classification performance and generalization capabilities. In this review paper certain dataset limitations have been pointed out, such as Scarcity and Diversity, Class Imbalance, Computational Intensity, Integration of Non-Imaging Data. A future research can be directed in having Dataset Enhancement, Advanced Data Augmentation,Model Optimization and Hybrid Architectures, Multi modal Data Fusion, Explainable AI (XAI) Development.

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