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Review Article

A Deep Learning Based Methodological Analysis for Breast Cancer Classification

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Abstract - *Breast cancer (BC) is the world's most common and rapidly spreading disease. BC can be controlled, reducing the death rate if detected early. As a result, some researchers have recently developed deep-learning-based efficient algorithms for predicting cancer cell growth using different modalities of medical imaging, for example, mammograms, tomosynthesis, MRI ultrasound, etc., for their efficiency and accuracy. Only a few review articles on BC diagnosis synthesize some existing studies. These investigations, unfortunately, are unable to identify new structures and modalities in the diagnosis of BC. The changing frameworks of DL for BC detection are the subject of this review. This assessment explores the strengths and limitations of earlier deep-learning (DL) based methods, investigates the datasets employed, and examines image preprocessing approaches based on different medical imaging modalities. The performance results with evaluation, obstacles, and further enhancement are also provided.*

Keywords - *Breast cancer, Dataset, Deep learning, Image classification, Medical imaging modalities.*

1. Introduction

Recently BC has been the most common deadly disease for women, uncommon in men. Therefore, death rates are rising due to the absence of technology and poor understanding among the general public. According to World Health Organization (WHO) estimates, India's total population in 2019 was 1,366,417,756 people, of which 784,821 died from cancer among the 1,157,294 people diagnosed with 9,555,027 cancer deaths. By the year 2040, it is anticipated that 2,778,850 persons worldwide will be suffering from BC. In India, it is expected that 261,850 persons will be affected by 2040 [1]. A complete overview of cancer data for 2018 is shown in Figure 1.

As can be seen, BC is a common disease, accounting for 14% of all malignancies. According to the Globocan 2018 survey [2, 3], there were 162,468 new BC cases and 87,090 fatalities. BC cases are rising at an alarming rate in India, as seen in Figure 2, notably among women in their 30s and 40s. Because breast cancer can be completely cured if detected in time, accessing appropriate diagnostic techniques is critical for recognizing the first signs of the disease with different modalities utilized in the screening process to identify this condition [4]. Mammography was among the unusual diagnosis procedures for breast cancer because it is ineffective for stable breasts, so ultrasound procedures are commonly employed. From radiography, the Micro masses could be skipped through radiations, and thus thermography may be more successful than ultrasonography in identifying tiny malignant tumours, given these limitations.

Researchers have used approaches have been used by researchers to anticipate diseases once they manifest symptoms. As a result, proper breast cancer diagnosis and prognosis are seen as interesting and challenging undertakings for physicians in the medical and healthcare sectors. In line with the inherent challenges accompanying an image, such as low contrast and various noises, as well as a deficiency of awareness by the eye, image processing devices have been developed.

AI, ML, and DL are among the fastest-growing in the medical field today [5], using the latest technologies to perform complex chores without human intelligence [6]. It aids in the prediction and aids in the distinction of malignant and benign lesions by providing more information; diagnostic efficiency can be enhanced in terms of both specificity and sensitivity while being cost-effective. When suspicious lesions have been identified, a CAD can predict whether they will lead to malignancy. Figure 3 shows ML (Machine Learning)-based computer-aided-aided design (CAD) and DL-enhanced CAD models. The grey indicates that the blocks can be changed, although it only has a minor impact on the image.

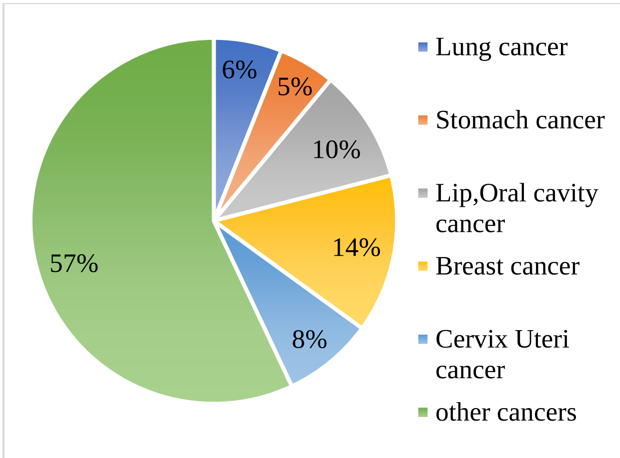

Fig. 1 Cancer statistics in India 2018 [2]

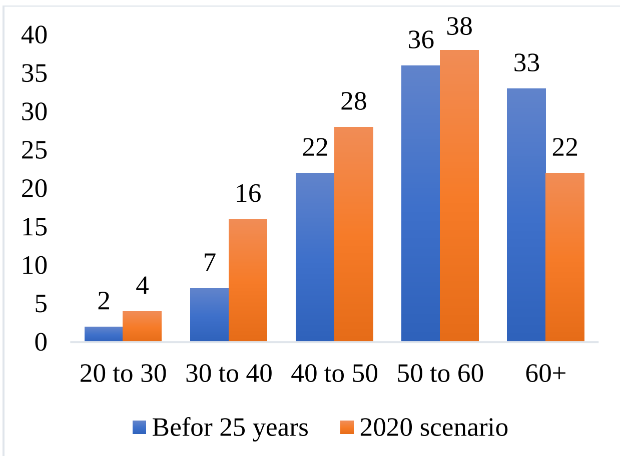

Fig. 2 Incidence rate of BC in India [2]

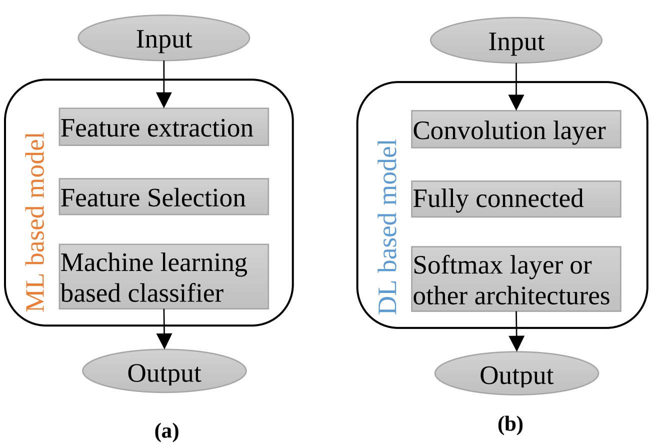

Fig. 3 CAD-based flow diagram (a) ML-based (b) DL-based

A stable architecture will have a red outline box showing that each step in machine learning is interpretable and a red box indicating that the CNN-based model is statistics. Recent studies have shown that various DL methods, widely DNNs (deep neural network), Deep Convolutional-NN (DCNN), GoogleNet, DBN (deep belief network), VGGNet, RNNs (Recurrent-NN) etc., among them CNNs are frequently used in areas such as computer-based applications, recognizing audio, video and speech, natural language processing for text retrieval (NLP), game development, filtering of social networks, developing translation machines, designing methods for drug discovery, bioinformatics, analyzing medical images, and histopathological diagnosis [7-9]. These novel technologies can increase cancer detection diagnostic accuracy and efficiency [10]. In addition, DL-based CAD has been proven accurate in detecting breast cancer early [11, 12]. This study aims to explore the literature related to DL architectures used for detecting breast cancer by utilizing models for BC diagnosis with performance metrics. The article is organized: In Section 2, there is a review of breast cancer diagnosis methods employing DL, which includes datasets details for several imaging modalities. Section 3 gives performance metrics for research methodology result analysis[13, 14]. Section 4 finishes the article by presenting problems and potential research directions.

2. Literature Review

Various ways of breast imaging have been introduced in this part. For each imaging approach, articles from the previous ten years were identified using electronic search engines, and then the most relevant papers were chosen. Finally, the results of approximately 40 papers were grouped and presented as a report. Mammography, digital tomosynthesis, ultrasounds, magnetic resonance imaging (MRI), magnetic sonographic, magnetic spectrometry, nuclear medicine, diffusion-weighted imaging, optical coherence tomography, and electromagnetic imaging were among the techniques extracted. The standard imaging modalities for diagnosing breast cancer in clinics are ultrasound, X-ray, tomosynthesis, mammography, and MRI; thus, the survey focused on those methods.

2.1. Breast Cancer Detection in X-ray Mammography

Wu et al. [15] showed a DCNN for cancer prevention, showing categorization learned and evaluated from more than 200000 images. A customized ResNet-based network is employed as such model building block and seems to have a depth and width balance tuned for significant healthcare images. When tested on the diagnosing sample, the model is used to predict the presence of BC with an attained AUC of 0.895. Because of the remarkable accuracy attained with the benefits of the recommended strategy, it can use the network with an increased patch level while learning from pixel and breast-level labels. Wang et al. [16] suggested a feature-sensitive deep CNN technique for detecting BC using a pre-trained framework with unique layers to gather features from images. Then these features are accompanied by a feature fusion module that improves to determine the weights within each feature vector. It makes the classifier react to specific other occurrences of the same instance. Ultimately, the fused features are claimed to be classified by a classifier module, which is more effective.

Wang et al. [17] focused on feature fusion for the automatic detection of BC using in-depth features from CNNs, which are used for extracting deep features for clustering unsupervised ELM. A feature set was created by combining feature representations, morphological attributes, feature descriptors, and thickness interactive elements. Lastly, an ELM classifier takes input from a merged feature set and is classified as two labels benign and malignant breast lesions. The recommended methodologies outperform conventional bulk identification and diagnosis systems on 400 cases of female mammograms in northeast China. The DLA-EABA (Deep Learning Assisted Efficient Adaboost Algorithm) developed by Zheng et al. [18] for BC diagnosis was already methodologically proposed using new computing teaching methods. The method relies on the dynamic development of transfers via deep CNNs. Compared to other existing schemes, the studies show a high degree of accuracy of 97.2 percent, a sensitivity of 98.3 percent, and a specificity of 96.5 percent. According to the inquiry's findings, the proposed model significantly decreases processing time and enhances the ideal solution[19, 20].

Siddiqui et al. [21] proposed a cloud-based Internet of Medical Things (IoMT) architecture for adaptive BC stage prediction. The system has been proposed for the prediction of BC stages aided by the DL (IPBCS-DL) model outperforms existing framework methods, meaning that it has the potential to reduce BC death rates significantly. The studies revealed 97.81 percent and 98.86 percent accuracy for the validation and training stages. Croock et al. [22] devised an all-encompassing technique for mammographic BC detection, in which a median filter-based denoising from medical images during the preprocessing phase. The grasshopper optimization algorithm (GOA) was utilized to optimize medical image characteristics and segmentation, and CNN was employed to determine the malignant zone. For the outcome modelling, two databases, MIAS and DDMS, were employed that show the suggested system is effective with an accuracy of up to 90% and reduces the attempts of medical staff while assisting patients. Finally, the suggested technique can assist patients with malignant lesions earlier than usual and refer them to the appropriate expert centre in areas far from hospitals. Saber et al. [23] used Inception V3, Inception-V2, VGG-19 (Visual Geometry Group networks-19), VGG-16, ResNet, and ResNet50, as well as a pre-trained CNN architecture. The test results indicate that the VGG16 model's Transfer Learning (TL) is appropriate for BC detection, categorizing mammography breast imaging with an overall accuracy of 98.96%, a sensitivity of 97.83%, specificity of 99.13%, precision of 97.53%, F-score of 97.66%, and attained AUC of 0.995 for the 80-20 technique. Automated mass identification continues to be a challenge when training a large dataset. Instead of just the conventional pooling approaches, Shu et al. [24] proposed alternative pooling structures for CNNs whereby they partition the image into regions and select further parts using a strong probability of image. The suggested pooling architectures could enhance various CNN-based algorithms that greatly enhance the classifiers' effectiveness on mammographic image data to the same data. The system works considerably better on mass mammography than calcification mammography, especially indicated again by the attained AUC of 0.87 in the massive data. This seems to be since the image volume of the quantity is usually more significant than that of the calcification. Chen et al. [25] used HA-BiRNNs to preserve the preprocessor interpretation of clinical reports. This method has a hierarchical learning algorithm with two degrees of concentration: word-level and sentence-level attention. Moreover, the model encrypts the semantic representations of clinical reports utilizing a Tree-Structured RNN with gated recursive units where the syntactic and semantic interpretations of medical features-based classification are made but unsuitable for complicated medical scenarios.

Li et al. [26] introduced the DualCoreNet, which accomplishes entirely automatic BC diagnosis by integrating an automatic detection setup. Experiments reveal that this model overcomes comparable studies from classification and segmentation functions, with a DI coefficient of 92.27 percent and an attained AUC score of 0.85. Using a separate INbreast dataset gets the highest mammography segmentation with 93.69 percent DI coefficient and classification performance with 0.93 attained AUC score. Shen et al. [27] proposed a fuzzy learning-based hierarchical integrated model to enhance segmentation functionality with pixel-wise and segmentation and mammogram image grading using ResU-segNet with a hierarchical fuzzy classifier (HFC). Zhang et al. [28] determined that combining data augmentation and TL approaches with CNN for categorizing 2D and 3D tomosynthesis images greatly improved classification performance. Malebary and Hashmi [29] introduced a novel BC detection and classification based on a mix of k-mean clustering, RNN, Long Short-Term Memory network (LSTM), CNN, random forest (RF), and boosting algorithms for classifying BC since mass regions as usual, malignancy, and benign. This method is compared to previous classification methods with two readily accessible datasets. The recommended model achieves using the DDSM dataset and MIAS dataset. Chen et al. [30] presented multi-adversarial learning to acquire highly accurate and reliable multi-scale images with effective segmentation. Here effectively improve values in segmentation results using adversarial networks and thus a discriminating structure.

An upgraded U-Net creates suspicious region masks that operate at various scales to discriminate the decisive influence. Kavitha et al. [31] used the median filter based on an adaptive fuzzy approach for the preprocessing method to construct a BC diagnosis model for a novel DL-enabled Capsule Network with an effective Optimal Multilevel Thresholding-based Segmentation (OMLTS-DLCN). The Shell Game Optimization (SGO) was implemented with the Optimal Kapur-based Multilevel Thresholding approach (OKMT-SGO) for segmenting BC. This methodology additionally utilized a CapsNet-based feature extraction and a BPNN classifier approach to determine the existence of BC. The optimized hybrid classifier was used by Patil and Biradar [32] to frame mammography-based breast classification models. The tumour is segmented from the image using a median filter and optimum region growth segmentation based on firefly restructured chicken-based swam optimization (FC-CSO). One last step in the tumour segmentation process is feature extraction which includes extracting characteristics, namely the GLCM (grey-level co-occurrence matrix) and grey-level run-length matrix (GRLM). CNN and RNN are two DL architectures used for final BC detection.

Ittannavar and Havaldar [33] offered an improved infinite feature selection utilizing an automated genetic process DNN (IFSGA-DNN) model for BC segmentation and categorization. A multi-objective EML optimization approach with a higher precision value for BC identification is provided for segmenting the benign and non-cancerous regions. Oyetade et al. [34] developed deep CNN and fuzzy support vector machines (FSVM) and produced two or three class labels to recognize the severity of BC. The results show that this DCNN and FSVM hybrid technique attains adequate accuracy than the earlier methods. Melekoodappattu et al. [35] used an implementation strategy that included CNN with image texture attribute extraction to create a system for autonomous identifying cancer. After the texture features are determined and its dimensionality is reduced using UMAP (Uniform Manifold Approximation and Projection) to improve categorization quality. An ensemble method was used to aggregate the findings from each phase to conclude. El Houby and Yassin [36] used two approaches: one utilizing patches of the region of interest (ROI) and the other using the entire image. The preprocessing and the CNN building phases are the two steps of the developed framework for producing malignant or nonmalignant image results. The INbreast dataset's sensitivity, specificity, accuracy, and attained AUC were 96.55 percent, 96.49 percent, 96.52 percent, and 0.98, respectively, whereas the MIAS datasets were 98 percent, 92.6 percent, 95.3 percent, and 0.974.

Table 1. Details of algorithms for BC detection using the DL method in mammography images with the dataset and performance metrics

Reference Numbers	Dataset	Method	Performance metrics
[15]	229,426 digital screening mammography exams	Deep convolutional neural network (ResNet)	Attained AUC is 0.895
[16]	INbreast and CBIS-DDSM	DCNN	Attained AUC 0.86 ± 0.05
[17]	400 mammograms	CNN and US-ELM	Accuracy of 76.25, Sen of 76.38, spe of 76.12 and attained AUC of 0.828
[18]	The Cancer Imaging Archive (TCIA) Public Access	DLA-EABA	MCC of 98.5%, dice coefficient of 96.4%, accuracy of 97.2%, Sen of 98.3%, and Spe of 96.5%
[19]	BC Histopathological Database (BreakHis)	IPBCS-DL	Reached accuracy of 99.82%
[21]	Mammographic image analysis- society (MIAS) and DDMS	CNN	Reached accuracy of 90%
[23]	MIAS	CNN	Reached Accuracy of 98.96%, sen of 97.83%, spe of 99.13%, precision of 97.35%, F-score of 97.66%, and attained AUC of 0.995
[22]	INbreast and CBIS	CNN	Reached accuracy of 0.701, attained AUC of 0.805, False positive rate (FPR) of 0.089 and false negative rate (FNR) of 0.115
[24]	real medical dataset with reports of 3960 patient	HA-BiRNNs	Reached accuracy of 0.8854, recall of 0.8771 and f1-score of 0.9070
[26]	DDSM and INbreast	DualCoreNet0	DDSM dataset: DI coefficient of 92.27% and 0.85 of AUC INbreast: 93.69% of DI coefficient and 0.93 of attained AUC score
[27]	INbreast and Private dataset	HFC with IT2PFCM	Average attained AUC of 93.26% for the INbreast dataset and 90.67% for the Private dataset.
[28]	institutional review board approval (IRB 17-0011-P3K)	CNN	AUROC of 0.7237
[29]	DDSM and MIAS	Ensemble DL	DDSM dataset: Sen of 0.97%, spe of 0.98%, F-measure, 0.97%, Reached accuracy of 0.96% MIAS dataset: Sen of 0.97%, spe of 0.97%, F-measure of 0.98%, and Reached accuracy of 0.95%, respectively.
[30]	INbreast and CBIS-DDSM	An improved U-Net	Dice of 82.16%,, sen of 85.23%,, spe of 99.86% and Reached Accuracy of 99.81%
[31]	Mini-MIAS and DDSM	OMLTS-DLCN	Mini-MIAS dataset: Reached accuracy of 98.50 and DDSM dataset: 97.55%
[32]	Mammogram dataset	FC-CSO-CRNN	Reached accuracy of 0.9359, Sen of 0.97015, Spe of 0.92216, the precision of 0.83333, FPR of 0.077844, FNR of 0.029851, NPV of 0.92216, FDR of 0.16667, F1 score of 0.16667, MCC of 0.85566
[33]	MIAS and DDSM	IFSGA-DNN	MIAS: Reached accuracy of 95.83% DDSM: Reached accuracy of 97.43%
[34]	DDSM and curated breast imaging subset (CBISDDSM)	DCNN with fuzzy SVM	Reached accuracy of 99.61%

[35]	MIAS and DDSM	Modified CNN	MIAS: spe of 97.8% and Reached Accuracy are 98% DDSM: spe 98.3% of and Reached Accuracy are and 97.9%
[36]	MIAS, INbreast and DDSM	CNN	INbreast: Sen of 96.55%, spe of 96.49%, Reached accuracy of 96.52% and attained AUC reached 0.98, respectively. MIAS dataset: Sen of 98%, spe of 92.6%, Reached accuracy of 95.3% and attained AUC reached 0.974, respectively.
[37]	INbreast and CBIS-DDSM and one ultrasonic database UDIAT	ARF-Net	Dice index of 86.1%,85.75%, and 88.12% INbreast and CBIS-D.DSM) UDIAT, respectively.

Table 2. Details of algorithms for BC detection using the DL method in ultrasound images with the dataset and performance metrics

Reference Numbers	Dataset	Method	Performance metrics
[38]	Ultrasound breast image database	CRNN	Reached accuracy of 99.75% and lowest loss of 0.0257
[39]	219 patients with 614 ABUS volumes	Deeply-Supervised Networks	Sensitivity of 95% and 0.84 of False Positive per volume
[40]	85 patients	Bi-Modal Transfer Learning	Reached accuracy of 90%
[41]	Dataset A 306 images (60 malignant and 246 benign), and Dataset B comprises 163 images (53 malignant and 110 benign)	FCN-AlexNet	Dataset A: 0.98 TPF, 0.16 FPs and 0.91 F1-score Dataset B: 0.92 TPF, 0.17 FPs and 0.89 F1-score
[42]	8145 breast ultrasonography images	Deep convolutional neural networks (Sn-Net and Mt-Net)	Sn-Net: F-β of 0.941, Reached Accuracy of 89.39%, Sen of 95.29% and Spe of 77.30% Mt-Net: F-β of 0.942, Reached Accuracy of 94.48%, Sen of 95.65% and Spe of 93.88%.
[43]	250 ultrasound images	CNN	Reached accuracy of 100%
[69]	510 images	U-Net architecture	Dice similarity coefficient of 90.5%
[44]	641 images	CNN	Reached an Accuracy of 92.01%, and the attained AUC increased to 0.9716%.
[45]	10,464 images	Attention-augmented network	F1 of 0.9580, Reached Accuracy of 0.9641, Sen of 0.9517 and Spe of 0.9734.
[46]	697 BUS images	Deep convolutional neural network (CNN)	92.8% of Reached Accuracy
[47]	5000 breast ultrasound images	CNN	Attained AUC for VGG19, ResNet50, VGG16, and Inception-V3 models were 0.847, 0.851, 0.866, and 0.905.
[48]	316 breast lesions	CNN	Attained AUC value of 0.9468 sen and spe were 0.886 and 0.876, respectively.

Adaptive Receptive Field Network (ARF-Net) was created by Xu et al. [37] for the exact segmentation of lesion regions in full mammographic and ultrasound images, a pixel-wise classifier. Here on two mammography databases, such as INbreast, CBIS-DDSM, and UDIAT, the suggested ARF-Net achieves dice indexes of 86.1 percent, 85.75 percent, and 88.12 percent, correspondingly. Table 1 describes the details of algorithms for BC detection using the DL method in Mammography images with the dataset and performance metrics.

2.2. BC Detection using DL Methods in Ultrasound Images

Kim et al. [38] proposed an edge extractor strategy dubbed a modified convolutional RNN (CRNN) model to diagnose BC that retrieves line-segment data reliably are then separated into sixteen groups, including one labelled and squeezed separately. The modified CRNN model was utilized to evaluate the suggested computing performance, and this operation was employed as an input. With 99.75 percent Reached Accuracy and 0.0257 percent loss, the proposed model was the most accurate and had a minor loss. Wang et al. [39] suggested a novel 3D CNN for computerized breast cancer with good recognition and minimal false positives (FPs). One intense supervision methodology considerably increases detection capability by effectively leveraging multi-layer features. Therefore, provide a voxel-level thresholding technique for discriminating cancer from non-cancer with high sensitivity and minimal false positives. With 0.84 FP per volume, this method has a sensitivity of 95%, according to extensive testing.

Misra et al. [40] used two DNNs, AlexNet and ResNet, to find benign and malignant lesions. The two models were again integrated and tested, using layer or image-wise settings on a data set of fifty-six medical samples from the final eighteen patients. The model incorporates the multiple features accessible in SE images B-mode and merges contextual features from ResNet and AlexNet models to extricate benign from malignancy tumours. Yap et al. [41] offered DL algorithms for BC lesion diagnosing in ultrasonography, including Patch-based LeNet, U-Net, and then TL strategy employing a pre-trained FCN-AlexNet. Their results are evaluated to appropriate regulatory lesion recognition strategies using quality metrics such as Node density Filtering, Radial Contour Index, Commandment Region Ranking, and Adaptive Part Models.

Qi et al. [42] recommended employing DCNN with multi-scale kernels with skip correlations to evaluate breast ultrasound images. This process involves detecting whether the image contains malignant tumours and recognizing solid lumps. Another region upgrade approach based on class connection weights is created to enable the connections to operate cooperatively[43]. Masud et al. [44] employed CNN-based techniques that were perfect for retrieving defining features from ultrasound images and reached the accuracy of seven standard current pre-trained networks using different optimizers, and hyper-parameters were assessed through fivefold cross-validation. The Adam optimizer may also accurately distinguish between healthy and BC patients. Zeimarani et al. [45] proposed a novel technique for identifying BC based on CNN, in which the collection comprises 641 images. The suggested technique provides a more accurate assessment of the model's classification performance.

Pi et al. [46] developed an effective attention-augmented multi-instance (MI) network, especially in rural and low-resource areas, that help sonographers spot illegible lesions, enhance diagnostic performance, and condense the cost. Saba et al. [47] employed deep CNN approaches like AlexNet and DenseNet201. This model was utilized to accomplish classification tasks on 697 images and find the result as benign and malignant tumours. The DensNet201 model was utilized to accomplish the benign and malignant assignment classification and Reached an Accuracy of 92.8 percent. Using a standard data set, the findings studied compared with the previous technique, and it was concluded that the proposed model outperformed in terms of the accuracy of a breast cancer diagnosis at the earlier stage.

Finally, the suggested technique might benefit radiologists in efficiently detecting benign and severe cancers by screening suspected patients. Zhang et al. [48] evaluated BC's diagnostic effectiveness-based CNN approach. Prospective research was conducted on 5000 images for the training group of 2500 benign and 2500 malignant images. With CNN, several classification methods relying on ResNet50, InceptionV3, VGG16, and VGG19 were developed, and the results indicated that BC had excellent prediction performance.

Wang et al. [49] proposed CNN and formed two class labels such as malignant or benign, where the modified Inception-v3 structure was designed for successful feature extraction. This method attained an AUC of 0.9468 with specificity and sensitivity of 0.876 and 0.886. The suggested CNN, which employed a Multiview approach to detect BC, showed promise and might have served as repeats to increase diagnosis Reached Accuracy. Table 2 shows the specifics of the algorithms for BC identification in Ultrasound medical images using the DL approach and the dataset and performance metrics.

2.3. BC Detection using DL Methods in MRI Images

Feng et al. [50] proposed using the KFLI (Knowledge-driven Feature Learning and Integration) framework, a deep network ensemble with domain knowledge that could retrieve adequate features in each sub-sequence to identify BC. The KFLI outperforms other current algorithms regarding sensitivity, specificity, and reached accuracy, with

84.6 percent, 85.7 percent, and 85.0 percent, respectively, in 100 MRI investigations. The SRVFL-AE (The stacked random vector functional link-based autoencoder) was presented by Nayak et al. [51] to identify multiclass brain illnesses and enhance generalization potential and learning speed over typical autoencoder-based DL systems. Furthermore, the deep network described employs the rectified linear unit (ReLU) activation function to provide a quicker, more accurate, hidden representation of input data. The approach exhibited a 96.67 percent accuracy and 95.00 percent on the MD-1 and 2 data sets, respectively. Dalmş et al. [52] developed an integrated automated CADe system with the DL method. Instead of using the temporal information collected in the postoperative-operative, the objective was to do as much of the spatial intelligence gathered at the start of the contrast enhancement (CE). While DL provides benefits over traditional machine vision approaches, such as the capacity to analyze spatial data using periodically learned features instead of constructed attributes, DL is becoming more popular.

Rasti et al. [53] created ME-CNN (mixed ensemble of CNN) that can probabilistically split a high-dimensional sensory experience by learning its components concurrently and finding breast tumours. In collecting 112 images, the proposed technique was assessed on DCE-MRI data using a range of classification metrics and attained a precision of 96.39 percent, a sensitivity of 97.73 percent, and a specificity of 94.87 percent. The suggested ME-CNN model might be a valuable tool for radiologists analyzing BC.

Zhang et al. [54] used DL approaches such as CNN and RCNN. The bounding box enclosing cancer ROI was utilized as an input for DL for generating the system in the training data set utilizing CNN and CLSTM (convolutional LSTM). During training, the CLSTM-based RCNN could follow changes in contrast enhancement with more Reached Accuracy than a regular CNN. TL is used to fine-tune the model and improve Reached Accuracy for datasets collected with different parameters.

Anderson et al. [55] developed and compared two deep TL techniques based on extracting features and fine-tuning them in diagnosing BC. The extraction of features is done using five max-pooling layers, average-pooling of the features is done subsequently, performing merging the CNN features with an SVM and feature reduction were the first TL techniques used in the classification of breast cancer. The present TL technique employed 64 percent training, 16 percent validation, and 20 percent testing data set split to fine-tune the final FC layers of the pre-trained VGG-19 to categorize the medical images as cancerous or benign. Zhang et al. [56] employed Mask R-CNN (Mask Regional CNN) to detect hazardous lesions, employing a fuzzy c-means clustering technique to segment the tumour. The proposed model generated bounding boxes and a segmented tumour for the assessment using the Dice Similarity Coefficient (DSC). The proposed model was discovered to be a promising technique for finding, detecting, and segmenting lesions in MRI. Fujioka et al. [57] developed DenseNet121, InceptionV3, DenseNet169, InceptionResNetV2, InceptionV3, and NasNetMobile to evaluate the likelihood of malignancy. Two studies evaluated the test findings and assessed each patient's malignancy risk via the Breast Imaging Reporting and Data System. The CNNs fared similarly to human users when categorizing MRI. The top CNN had a specificity of 96.0 percent and attained 0.895 AUC for detecting breast MRI. Table 3 shows the specifics of the algorithms for BC identification in MRI images using the DL approach and the dataset and performance metrics.

2.4. BC Detection using DL Methods in Tomosynthesis Images

Samala et al. [58] created a layered route evolution approach for compressing a DCNN for BC classification. The objective is to keep the recognition Reached Accuracy while reducing the number of customizable factors. During the second step of TL, the DCNN was utilized for extracting features with feature selection, and classification was analyzed using Random Forest (RF). Yousefi et al. [59] created a DCNN architecture that extracts features from relevant 2D slices and a MIL with randomized trees that classifies DBT samples using the retrieved information from 2D slices. Testing results show that this model was highly influential on the DBT dataset.

Bevilacqua et al. [60] assessed the effectiveness of various supervised classifier topologies-based frameworks. The first approach is founded on features, but it feeds hand-crafted structural and textural properties acquired from each ROI into improved ANN classifiers. Next uses non-neural classifiers based on dynamic features and tests the classifier's effectiveness by extracting different sets of features using various CNN models. To create a deep CNN for classifying malignant and benign tumours in DBT, Samala et al. [61] employed a multi-stage TL technique with data from comparable supplementary fields for approximate fine-tuning. In addition, the degree to which fine-tuning utilizing auxiliary data improves CNN performance depends on the relative sizes of the presented training samples in the objective and auxiliary domains.

To design for masses in DBT, Fan et al. [62] employed faster-RCNN (faster region-based CNN) for such analysis. Data from 89 individuals with 105 masses were collected. The CNN with RPN (region proposal network) constructed regional bounding boxes with a mass probability score for each slice. The findings suggest that a faster R-CNN can improve the ability to strengthen the CAD system's mass pre-screening and FP reduction.

Table 3. Details of algorithms for BC detection using the DL method in MRI images with the dataset and performance metrics

Reference Numbers	Dataset	Method	Performance metrics
[50]	100 MRI studies	KFLI	Sensitivity and specificity reached an accuracy of 84.6%, 85.7% and 85.0%, respectively.
[51]	MR brain datasets	SRVFL-AE	MD-1: Accuracy 96.67% MD-2: Accuracy 95.00%
[52]	385 MRI scans	CNN	Average sensitivity (0.6429±0.0537)
[53]	112 DCE-MRI images	CNN	Reached an Accuracy of 96.39%, a Sen of 97.73% and a Spe of 94.87%
[54]	244 patients	Recurrent network using CLSTM	Mean accuracy 0.91 by CNN and 0.83 by CLSTM
[55]	2006 breast lesions	VGG19-CNN	Attained AUC = 0.90
[56]	Two DCE-MRI datasets were used with 241 patients	Deep learning using Mask R-CNN	Accuracy 99.5%
[58]	286 contrast-enhanced breast MRI	CNN architectures (DenseNet-121 and 169, Xception, InceptionV3, Inception ResNet-V2, and NasNetMobile)	96.0% specificity and attained 0.895 AUC

Table 4. Details of algorithms for BC detection using the DL method in tomosynthesis images with the dataset and performance metrics

Reference Numbers	Dataset	Method	Performance metrics
[60]	1,655 screen-film mammography (SFM) views and 310 digital mammographies (DM)	DCNN	Attained AUC of 0.8
[57] and [61]	DBT dataset	Deep CNN	Attained AUC of 0.87, Reached Accuracy of 86.81%, Spe of 87.5%, Sen of 86.6%
[60]	39 breast exams	CNN	Reached accuracy of 93.26%
[67] and [66]	441 patients	DCNN	Attained AUC of 0.984± 0.004 ACC of (%)93.6 ± 0.9 SEN of (%)95.3 ± 3.2 SPE of (%)91.7 ± 2.2
[59]	4,039 unique ROIs	CNN	Attained AUC of 0.91±0.03
[62]	89 patients with 105 masses	faster-RCNN	Attained AUC of 0.92, Sen of 90%
[63]	FFDM and DBT imaging	CNN	Attained AUC of 0.89, Sen of 0.04
[64]	100 DBT exams	GGGAN-VGG	Cohen kappa coefficient of 0.73, percent agreement of 91.9%
[69]	100 DBT exams	deep convolutional neural network	Accuracy is 90%, Sen is 96%, and the AUROC curve is 0.89.

Table 5. DL methods for BC detection with advantages and disadvantages

Reference Numbers	Methods	Advantages	Disadvantages
[15], [16], [34], [42], [47], [61], [57], [26], [69], [32]	DCNN	It could provide a big contextual window and a lot of modelling power. It could be used for representation learning to learn features instead of the explicitly constructed features used within standard machine learning and decrease dimensionality with no prior data knowledge.	The DCNN algorithm takes a long time to run. Though DCNN could train to represent the training data's features, if the testing data does not reflect the training data, the DCNN may confound the learning process rather than reflect the dataset's qualities.
[39], [22], [23], [24], [28], [35], [36], [44], [45], [48], [49], [53], [54], [55], [58], [60], [63]	CNN based methods	Manually operate on a region of images centred on the aberrant tissue. CNN could learn features from image data on its own.	The computing cost of CNNs is high.
[38], [32], [25], [56]	RNN based methods	Minimal formal dataset training and flexibility in dealing with partial, missing, and noisy data are required.	Furthermore, it cannot execute feature learning.
[20]	DLA-EABA	DLA's Reached Accuracy has improved It is more user-friendly and thus requires less parameter tinkering.	The RNN structure is susceptible to translation and shift variation, which impacts classification Reached Accuracy.
[21]	IPBCS-DL	High Spe and Sen	It is, nevertheless, vulnerable to homogenous noise.
[26]	DualCoreNet	Address the heterogeneity of complicated diseases effectively.	To examine each sample without showing the actual lesions, use different levels of depiction.
[27]	HFC with IT2PFCM	Sort the samples into more specific groups.	For BC, ample memory space is required for training and testing the image dataset.
[29]	Ensemble DL	By detecting distinct metastases in breast cancers, the model considerably reduces processing time and enhances the quality of the solutions.	The computing cost of CNNs is high.
[30] and [43]	U-net	Improves the level of technology and automation in the detection of BC diseases.	Furthermore, it cannot execute feature learning.
[31]	OMLTS-DLCN	It has the potential to discover more right samples, particularly negative samples.	The RNN structure is susceptible to translation and shift variation, which impacts classification Reached Accuracy.
[37] and [40]	ARF-Net	BC detection requires the least network parameters and delivers the highest average precision.	It is, nevertheless, vulnerable to homogenous noise.
[19]	Deeply-Supervised Networks	Model diversity, model performance, and model generalization can all be enhanced by integrating supervised network classifiers.	To examine each sample without showing the actual lesions, use different levels of depiction.
[40]	Bi-Modal Transfer Learning	Reduce the time spent on training and the number of times it is done.	For BC, ample memory space is required for training and testing the image dataset.
[46]	Attention-augmented network	More right samples, particularly negative samples, should be identified.	The computing cost of CNNs is high.

Mendel et al. [63] examined the prospect of employing CNNs and feature extraction to determine lesions and generate two class labels as malignant and benign breast tumours, and with the increased use of DBT in BC screening, understanding the distinctions between how these modalities are employed and obtaining high-accuracy results in detecting BC.

The DCNN was proposed by Jiang et al. [64], where the Gradient-guided conditional generative adversarial networks (GGGAN) were used as an objective function to sustain delicate BCs and perceptual loss was applied to improve the suggested DCNN's perceptual quality performance. A range of image quality characteristics was used to assess the results, including maintaining masses and MCs. The trials revealed that using a variety of objective functions increased the network's performance over time regarding the quality criteria of medical images. Table 4 shows the specifics of the methods for BC identification in Tomosynthesis medical images using the DL approach, as well as the dataset and performance metrics.

2.5. Inference from Literature Review

From the literature review, it is confirmed that using DL to classify medical images produces higher Reached Accuracy than using alternative neural network (NN) methods. A DL algorithm requires big datasets to accomplish 100 percent Reached Accuracy validation. As a result, the availability of a comprehensive dataset is critical for the efficiency of DL in classifying BC. The CNN designs ZFNet, AlexNet, Inception-V1/GoogleNet, ResNet, and VGGNet were the competition winners from 2012 to 2015, demonstrating the performance of CNN. One of the primary obstacles in using DL for BC diagnosis is the scarcity of datasets.

Furthermore, because most open-access datasets contain raw medical images, researchers must collect the ground truth. A data augmentation strategy was presented to address the problem of a limited dataset. To make feature extraction easier, image preprocessing of BC should be done before feeding inputs into CNNs. Denoising input medical images and obtaining ROIs of the breast images are examples of image preprocessing at this stage. Previous research has shown that segmenting the input images improves accuracy. Therefore, ROI segmentation should be addressed, and CNN allows for automatic feature extraction. As a result, defining which traits distinguish the healthy and malignant image is theoretically unnecessary.

Nevertheless, the feature learning process can be sped up because we consider BC's knowledge of relevant features while creating a DL model. However, if the data contains more negative than positive examples, the system will be biased and produce primarily negative results. Therefore, training data equality is critical, which has been overlooked by a few studies, and developing a lightweight CNN model with appropriate layers and kernels can speed up convolution calculation. Each algorithm discussed above has different advantages and disadvantages, as shown in Table 5.

3. Performance Analysis Comparison and Discussion

This research looks at how DL may be used to define breast masses for predictive, diagnostic, or segmentation using MRI, ultrasound, Digital Breast Tomosynthesis (DBT), and mammography. Images are delivered in three phases[69]. This review aims to offer clinical imaging data for developing and evaluating quantitative imaging techniques in the early stages of BC therapy. DL needs a massive set of data for training to reach high precision. Since the vast dataset has limited data, training and research have been undertaken using the data accessible from the following link: https://wiki.cancerimagingarchive.net/

Approaches like HA-BiRNN, CNN, DLA-EABA, and CRNN are tested for heart recognition using performance criteria including Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), Precision (Prec), and F-Score (F1). The numerical results are tabulated in Table 6. The formulas for five performance metrics are given below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$F1\ score = \frac{2*Precision*Recall}{Precision+Recall} \quad (5)$$

Where TP is the number of correctly detected BC, TN denotes the number of correctly undetected BC, FP denotes BC from other categories classified as this category, and FN denotes BC classified as other categories.

Table 6. Experimental results of DL methods for BC detection

Methods	Acc	Sen	Spe	Prec	F1
HA-BiRNN [19]	88.54	89.2	90.1	90.5	90.70
DLA-EABA [14]	97.2	98.3	96.5	98.35	94.70
CNN [17]	98.96	97.83	99.13	98.35	97.66
CRNN [32]	99.75	97.21	96.76	98.37	98.41

3.1. Comparison of Results

Figure 4 depicts the Reached Accuracy of reviewed models for the number of available datasets in each directory. The CRNN enhances Reached Accuracy while cutting down on computation time and memory usage because of its lightweight network structure. Compared to all other algorithms, the CRNN obtains a 99.75 percent Reached Accuracy since it does not require many derived components during reduction. As a result, this method beats current strategies for confirming BC detection findings. Fig.5 and Fig.6 exhibit the sensitivity and specificity of reviewed models for the number of accessible datasets in a specific case. When the number of datasets accessible increases, both values rise. The CRNN has a sensitivity of 97.21 percent and a specificity of 96.76 percent. High-dimensional datasets could be used with the current CNN-based techniques. As a result, the CRNN-based system surpasses earlier systems in terms of enhanced BC lesion prediction testing findings.

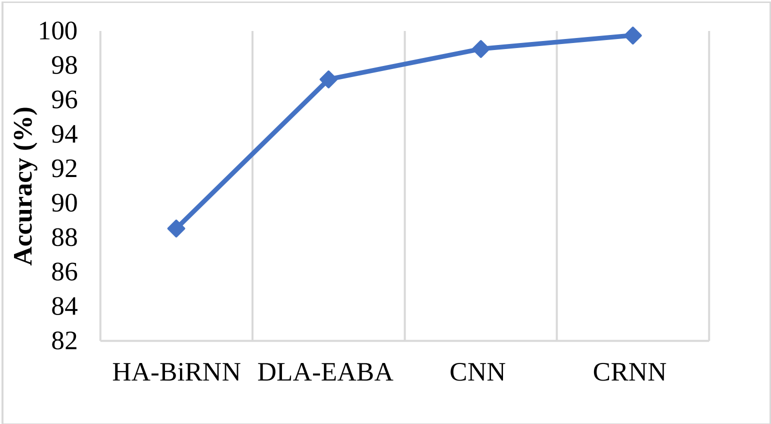

Fig. 4 Accuracy performance comparison

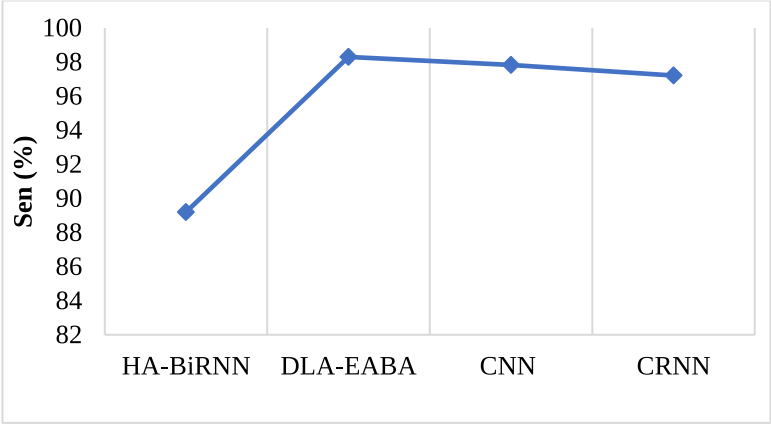

Fig. 5 Sensitivity performance comparison

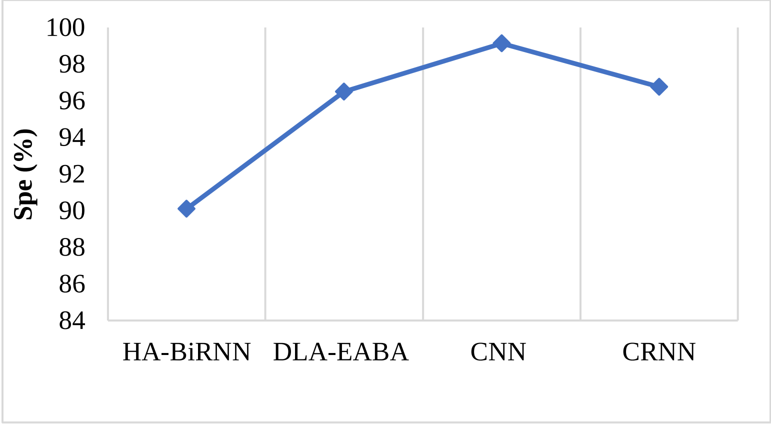

Fig. 6 Specificity performance comparison

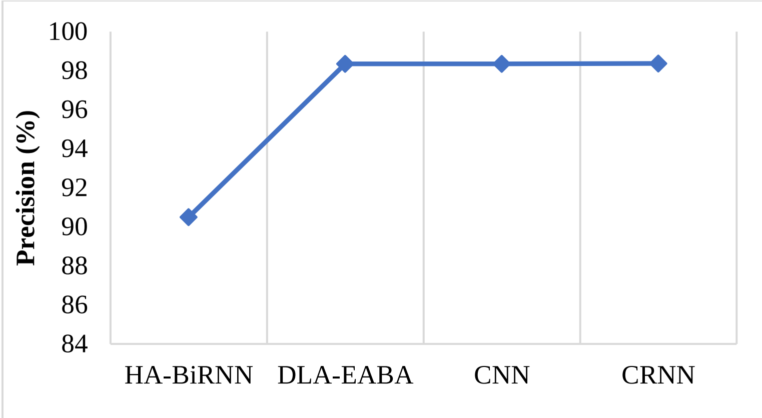

Fig. 7 Precision performance comparison

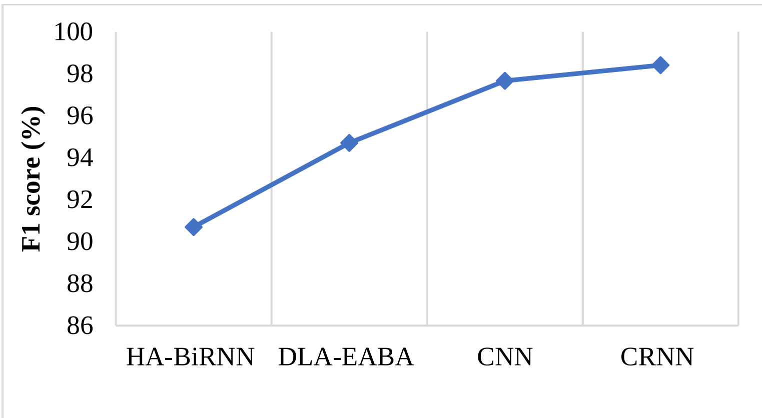

Fig. 8 F1-Score performance comparison

For detecting BC mass, the CRNN technique offers excellent sensitivity and specificity. As a result, because the approach detects automatic BC in the early stages, it can improve patient survival rates. Fig .7 depicts the precision of reviewed models for the number of available datasets in each directory. CRNN has a 98.37 % recall, CNN has a 98.35 % memory, DLA-EABA has a 98.35 % recall, and HA-BiRNN has a 90.5 % recall. This is because CRNNs and their variations have excelled at BC identification with limited data and have been repeatedly trained with unlabeled data for crucial feature representation. Fig.8 shows the F1-sore of planned and present models for the number of datasets accessible in given sources. The CRNN has an f-measure of 98.41 %, compared to 97.66 % for CNN, 94.7 % for DLA-EABA, and 90.7 % for HA-BiRNN.

4. Conclusion

A DL algorithm could assist the diagnostician in detecting BC. The DL algorithm may diagnose BC in various ways, including identifying lesions, metastasis, mitotic, and gene expression. The DL algorithm significantly impacts the diagnosis process by lowering the amount of human error, which can lead to erroneous diagnoses. Compared to manual diagnosis, the invention of this algorithm improves diagnostic Reached Accuracy in the medical profession. As a result, various DL algorithms have been created to achieve specific goals in BC diagnoses using diverse modalities. The evolution of DL algorithms in medical diagnostics, particularly in BC, was documented in this review study. In the diagnosing process, they all showed a high level of accuracy. This demonstrated that erroneous diagnostics might be avoided by using the DL method. Nevertheless, the researcher must consider various DL system restrictions; otherwise, the diagnosis will be inaccurate.

Further novel DL algorithms may be employed in the future to identify the stage of the BC. Nevertheless, several tuning parameters will be required to successfully train the model for this task. The dropout rate, kernel functions, and learning rate are among the hyperparameters. A small change in these factors can result in a drastic model with confirming results. These parameters have relied on human specialists in previous years. Finally, an efficient swarm technique is needed to determine the best hyperparameters for the DL algorithm.

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References

[1] Krishan K. Thakur, Devivasha Bordoloi, and Ajaikumar B. Kunnumakkara, “Alarming Burden of Triple-Negative Breast Cancer in India,” *Clinical Breast Cancer*, vol. 18, no. 3, pp. E393-E399, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[2] Cancer Statistics-Indian Against Cancer, Statistics - India Against Cancer, 2018. [Online]. Available: http://cancerindia.org.in/cancer-statistics/

[3] Globocan IAC, Globocan 2018_ India Factsheet - India Against Cancer, 2018. [Online]. Available: http://cancerindia.org.in/globocan-2018-india-factsheet/

[4] Xiaoli Yao et al., “A Comparison of Mammography, Ultrasonography, and Far-Infrared Thermography with Pathological Results in Screening and Early Diagnosis of Breast Cancer,” *Asian Biomedicine*, vol. 8, no. 1, pp. 11-19, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[5] PBCR, Trends of Breast Cancer in India, 2020. [Online]. Available: https://www.breastcancerindia.net/statistics/trends.html

[6] Iqbal H. Sarker, “Machine Learning: Algorithms, Real-World Applications and Research Directions,” *SN Computer Science*, vol. 2, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Gunjan Chugh, Shailender Kumar, and Nanhay Singh, “Survey on Machine Learning and Deep Learning Applications in Breast Cancer Diagnosis,” *Cognitive Computation*, vol. 13, no. 6, pp. 1451-1470, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Mariam Shadan et al., “Histological Categorization of Stromal Desmoplasia in Breast Cancer and Its Diagnostic and Prognostic Utility,” *SSRG International Journal of Medical Science*, vol. 4, no. 6, pp. 8-11, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[9] Nidhi Mongoriya, and Vinod Patel, “Review the Breast Cancer Detection Technique using Hybrid Machine Learning,” *SSRG International Journal of Computer Science and Engineering*, vol. 8, no. 6, pp. 5-8, 2021. [CrossRef] [Publisher Link]

[10] Seung Ja Kim et al., “Comparison of Two Software Versions of A Commercially Available Computer-Aided Detection (CAD) System for Detecting Breast Cancer,” *Acta Radiologica*, vol. 51, no. 5, pp. 482-490, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[11] Kaizhu Huang et al., *Deep Learning: Fundamentals, Theory and Applications*, Cognitive Computation Trends (COCT), Springer, vol. 2, pp. 1-163, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[12] S. Kevin Zhou et al., “A Review of Deep Learning in Medical Imaging: Imaging Traits, Technology Trends, Case Studies with Progress Highlights, and Future Promises,” *Proceedings of the IEEE*, vol. 109, no. 5, pp. 820-838, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] Zulaiha Parveen A, and T. Senthil Kumar, “The Deep Learning Methodology for Improved Breast Cancer Diagnosis in MRI,” *International Journal of Computer and Organization Trends*, vol. 11, no. 3, pp. 11-14, 2021. [CrossRef] [Publisher Link]

[14] Brotobor Deliverance, Edeawe Isaac Osahogie, and Brotobor Onoriode, “Awareness and Practice of Student Nurses on Breast Self Examination: A Risk Assessment Tool for Breast Cancer,” *SSRG International Journal of Nursing and Health Science*, vol. 6, no. 1, pp. 66-69, 2020. [CrossRef] [Publisher Link]

[15] Nan Wu et al., “Deep Neural Networks Improve Radiologists’ Performance in Breast Cancer Screening,” *IEEE Transactions on Medical Imaging*, vol. 39, no. 4, pp. 1184-1194, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[16] Yan Wang et al., “Feature-Sensitive Deep Convolutional Neural Network for Multi-instance Breast Cancer Detection,” *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 19, no. 4, pp. 2241-2251, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Zhiqiong Wang et al., “Breast Cancer Detection using Extreme Learning Machine Based on Feature Fusion with CNN Deep Available Datasets,” *IEEE Access*, vol. 7, pp. 105146-105158, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[18] Jing Zheng et al., “Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis,” *IEEE Access*, vol. 8, pp. 96946-96954, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[19] H. S. Laxmisagar, and M. C. Hanumantharaju, “Evaluating the Statistical Stability of POSIT Arithmetic and IEEE 754 Float to Accelerate Data for Detection of Breast Cancer,” *SSRG International Journal of Electrical and Electronics Engineering*, vol. 9, no. 9, pp. 47-53, 2022. [CrossRef] [Publisher Link]

[20] Md. Nawaj Sharif et al., “Design and Simulation of a Circular Microstrip Patch Antenna for Breast Cancer Diagnosis,” *International Journal of Recent Engineering Science*, vol. 7, no. 3, pp. 57-60, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[21] Shahan Yamin Siddiqui et al., “IoMT Cloud-Based Intelligent Prediction of Breast Cancer Stages Empowered with Deep Learning,” *IEEE Access*, vol. 9, pp. 146478-146491, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] Muayad Sadik Croock et al., “Early Detection of Breast Cancer using Mammography Images and Software Engineering Process,” *Telkomnika*, vol. 18, no. 4, pp. 1784-1794, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[23] Abeer Saber et al., “A Novel Deep-Learning Model for Automatic Detection and Classification of Breast Cancer using the Transfer-Learning Technique,” *IEEE Access*, vol. 9, pp. 71194-71209, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] Xin Shu et al., “Deep Neural Networks with Region-Based Pooling Structures for Mammographic Image Classification,” *IEEE Transactions on Medical Imaging*, vol. 39, no. 6, pp. 2246-2255, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[25] Dehua Chen, Meihua Huang, and Weimin Li, "Knowledge-Powered Deep Breast Tumour Classification with Multiple Medical Reports," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 18, no. 3, pp. 891-901, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[26] Heyi Li et al., "Dual Convolutional Neural Networks for Breast Mass Segmentation and Diagnosis in Mammography," *IEEE Transactions on Medical Imaging*, vol. 41, no. 1, pp. 3-13, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[27] Tianyu Shen et al., "Hierarchical Fused Model with Deep Learning and Type-2 Fuzzy Learning for Breast Cancer Diagnosis," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 12, pp. 3204-3218, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[28] Xiaofei Zhang et al., "Classification of Whole Mammogram and Tomosynthesis Images using Deep Convolutional Neural Networks," *IEEE Transactions on NanoBioscience*, vol. 17, no. 3, pp. 237-242, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[29] Sharaf J. Malebary, and Arshad Hashmi, "Automated Breast Mass Classification System using Deep Learning and Ensemble Learning in Digital Mammogram," *IEEE Access*, vol. 9, pp. 55312-55328, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[30] Juan Chen et al., "A Novel Multi-Scale Adversarial Networks for Precise Segmentation of X-Ray Breast Mass," *IEEE Access*, vol. 8, pp. 103772-103781, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[31] T. Kavitha et al., "Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis using Mammogram Images," *Interdisciplinary Sciences: Computational Life Sciences*, vol. 14, pp. 113-129, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[32] Rajeshwari S. Patil, and Nagashettappa Biradar, "Automated Mammogram Breast Cancer Detection using the Optimized Combination of Convolutional and Recurrent Neural Network," *Evolutionary Intelligence*, vol. 14, no. 4, pp. 1459-1474, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[33] S. S. Ittannavar, and R. H. Havaldar, "Detection of Breast Cancer using the Infinite Feature Selection with Genetic Algorithm and Deep Neural Network," *Distributed and Parallel Databases*, vol. 40, no. 4, pp. 675-697, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[34] Idowu Sunday Oyetade et al., "Hybridized Deep Convolutional Neural Network and Fuzzy Support Vector Machines for Breast Cancer Detection," *SN Computer Sci*ence, vol. 3, no. 1, pp. 1-14, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[35] Jayesh George Melekoodappattu et al., "Breast Cancer Detection in Mammogram: Combining Modified CNN and Texture Feature-Based Approach," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[36] Enas M. F. El Houby, and Nisreen I. R. Yassin, "Malignant and Nonmalignant Classification of Breast Lesions in Mammograms using Convolutional Neural Networks," *Biomedical Signal Processing and Control*, vol. 70, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[37] Chunbo Xu et al., "ARF-Net: An Adaptive Receptive Field Network for Breast Mass Segmentation in Whole Mammograms and Ultrasound Images," *Biomedical Signal Processing and Control*, vol. 71, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[38] Chang-Min Kim, Roy C. Park, and Ellen J. Hong, "Breast Mass Classification using eLFA Algorithm Based on CRNN Deep Learning Model," *IEEE Access*, vol. 8, pp. 197312-197323, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[39] Yi Wang et al., "Deeply-Supervised Networks with Threshold Loss for Cancer Detection in Automated Breast Ultrasound," *IEEE Transactions on Medical Imaging*, vol. 39, no. 4, pp. 866-876, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[40] Sampa Misra et al., "Bi-Modal Transfer Learning for Classifying Breast Cancers via Combined B-mode and Ultrasound Strain Imaging," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 69, no. 1, pp. 222-232, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[41] Moi Hoon Yap et al., "Automated Breast Ultrasound Lesions Detection using Convolutional Neural Networks," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 4, pp. 1218-1226, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[42] Xiaofeng Qi et al., "Automated Diagnosis of Breast Ultrasonography Images using Deep Neural Networks," *Medical Image Analysis*, vol. 52, pp. 185-198, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[43] Aleksandar Vakanski, Min Xian, and Phoebe E. Freer, "Attention-Enriched Deep Learning Model for Breast Tumour Segmentation in Ultrasound Images," *Ultrasound in Medicine & Biology*, vol. 46, no. 10, pp. 2819-283, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[44] Mehedi Masud et al., "Pre-Trained Convolutional Neural Networks for Breast Cancer Detection using Ultrasound Images," *ACM Transactions on Internet Technology*, vol. 21, no. 4, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[45] Bashir Zeimarani et al., "A Novel Breast Tumour Classification in Ultrasound Images, using Deep Convolutional Neural Network," *XXVI Brazilian Congress on Biomedical Engineering*, pp. 89-94, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[46] Yong Pi et al., "Automated Diagnosis of Multi-Plane Breast Ultrasonography Images using Deep Neural Networks," *Neurocomputing*, vol. 403, pp. 371-382, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[47] Tanzila Saba et al., "Optimizing the Transfer-Learning with Pre-Trained Deep Convolutional Neural Networks for First Stage Breast Tumour Diagnosis using Breast Ultrasound Visual Images," *Microscopy Research and Technique*, vol. 85, no. 4, pp. 1444-1453, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[48] Heqing Zhang et al., "Diagnostic Efficiency of the Breast Ultrasound Computer-Aided Prediction Model Based on Convolutional Neural Network in Breast Cancer," *Journal of Digital Imaging*, vol. 33, no. 5, pp. 1218-1223, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[49] Yi Wang et al., "Breast Cancer Classification in Automated Breast Ultrasound using A Multiview Convolutional Neural Network with Transfer Learning," *Ultrasound in Medicine & Biology*, vol. 46, no. 5, pp. 1119-1132, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[50] Hongwei Feng, "A Knowledge-Driven Feature Learning and Integration Method for Breast Cancer Diagnosis on Multi-Sequence MRI," *Magnetic Resonance Imaging*, vol. 69, pp. 40-48, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[51] Deepak Ranjan Nayak et al., "A Deep Stacked Random Vector Functional Link Network Autoencoder for Diagnosis of Brain Abnormalities and Breast Cancer," *Biomedical Signal Processing and Control*, vol. 58, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[52] Mehmet Ufuk Dalmış et al., "Fully Automated Detection of Breast Cancer in Screening MRI using Convolutional Neural Networks," *Journal of Medical Imaging*, vol. 5, no. 1, p. 014502, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[53] Reza Rasti, Mohammad Teshnehlab, and Son Lam Phung, "Breast Cancer Diagnosis in DCE-MRI using Mixture Ensemble of Convolutional Neural Networks," *Pattern Recognition*, vol. 72, pp. 381-390, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[54] Yang Zhang et al., "Prediction of Breast Cancer Molecular Subtypes on DCE-MRI using A Convolutional Neural Network with Transfer Learning Between Two Centers," *European Radiology*, vol. 31, no. 4, pp. 2559-2567, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[55] Rachel Anderson et al., "Evaluating Deep Learning Techniques for Dynamic Contrast-Enhanced MRI in the Diagnosis of Breast Cancer," *Proceedings Medical Imaging 2019: Computer-Aided Diagnosis*, vol. 10950, pp. 26-32, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[56] Yang Zhang et al., "Automatic Detection and Segmentation of Breast Cancer on MRI using Mask R-CNN Trained on Non–Fat-Sat Images and Tested on Fat-Sat Images," *Academic Radiology*, vol. 29, no. 1, pp. S135-S144, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[57] Mina Yousefi, Adam Krzyżak, and Ching Y. Suen, "Mass Detection in Digital Breast Tomosynthesis Data using Convolutional Neural Networks and Multiple Instance Learning," *Computers in Biology and Medicine*, vol. 96, pp. 283-293, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[58] Tomoyuki Fujioka et al., "Deep-Learning Approach with Convolutional Neural Network for Classification of Maximum Intensity Projections of Dynamic Contrast-Enhanced Breast Magnetic Resonance Imaging," *Magnetic Resonance Imaging*, vol. 75, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[59] Ravi K. Samala et al., "Evolutionary Pruning of Transfer Learned Deep Convolutional Neural Network for Breast Cancer Diagnosis in Digital Breast Tomosynthesis," *Physics in Medicine and Biology*, vol. 63, no. 9, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[60] Vitoantonio Bevilacqua et al., "A Performance Comparison between Shallow and Deeper Neural Networks Supervised Classification of Tomosynthesis Breast Lesions Images," *Cognitive Systems Research*, vol. 53, pp. 3-19, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[61] Ravi K. Samala et al., "Breast Cancer Diagnosis in Digital Breast Tomosynthesis: Effects of Training Sample Size on Multi-Stage Transfer Learning using Deep Neural Nets," *IEEE Transactions on Medical Imaging*, vol. 38, no. 3, pp. 686-696, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[62] Ming Fan et al., "Computer-Aided Detection of Mass in Digital Breast Tomosynthesis using A Faster Region-Based Convolutional Neural Network," *Methods*, vol. 166, pp. 103-111, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[63] Kayla Mendel et al., "Transfer Learning from Convolutional Neural Networks for Computer-Aided Diagnosis: A Comparison of Digital Breast Tomosynthesis and Full-Field Digital Mammography," *Academic Radiology*, vol. 26, no. 6, pp. 735-743, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[64] Gongfa Jiang et al., "Synthesis of Mammogram from Digital Breast Tomosynthesis using Deep Convolutional Neural Network with Gradient Guided cGANs," *IEEE Transactions on Medical Imaging*, vol. 40, no. 8, pp. 2080-2091, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[65] Hu Zilong et al., "Deep Learning for Image-Based Cancer Detection and Diagnosis-A Survey," *Pattern Recognition*, vol. 83, pp. 134-149, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[66] Ravi Aggarwal et al., "Diagnostic Accuracy of Deep Learning in Medical Imaging: A Systematic Review and Meta-Analysis," *NPJ Digital Medicine*, vol. 4, no. 1, pp.1-23, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[67] Naveed Chouhan et al., "Deep Convolutional Neural Network and Emotional Learning Based Breast Cancer Detection using Digital Mammography," *Computers in Biology and Medicine*, vol. 132, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[68] Xin Li et al., "Digital Breast Tomosynthesis versus Digital Mammography: Integration of Image Modalities Enhances Deep Learning-Based Breast Mass Classification," *European Radiology*, vol. 30, no. 2, pp. 778-788, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[69] R. Ricciardi et al., "A Deep Learning Classifier for Digital Breast Tomosynthesis," *Physica Medica*, vol. 83, pp. 184-193, 2021. [CrossRef] [Google Scholar] [Publisher Link]