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Artificial Neural Network Based Breast Cancer Screening: A Comprehensive Review

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***Abstract*: Breast cancer is a common fatal disease for women. Early diagnosis and detection is necessary in order to improve the prognosis of breast cancer affected people. For predicting breast cancer, several automated systems are already developed using different medical imaging modalities. This paper provides a systematic review of the literature on artificial neural network (ANN) based models for the diagnosis of breast cancer via mammography. The advantages and limitations of different ANN models including spiking neural network (SNN), deep belief network (DBN), convolutional neural network (CNN), multilayer neural network (MLNN), stacked autoencoders (SAE), and stacked de-noising autoencoders (SDAE) are described in this review. The review also shows that the studies related to breast cancer detection applied different deep learning models to a number of publicly available datasets. For comparing the performance of the models, different metrics such as accuracy, precision, recall, etc. were used in the existing studies. It is found that the best performance was achieved by residual neural network (ResNet)-50 and ResNet-101 models of CNN algorithm.**

***Keywords*:** CAD, ANN, DBN, accuracy, AUC.

I. Introduction

Breast cancer is a very fatal and common disease for women worldwide. There are several cancer types such as liver cancer, breast cancer, lung cancer, brain cancer, and so on where the third common cancer is breast cancer among the several types of cancers. According to the world health organization (WHO), 11.3% (1.7 million) of patients affected in 2015 has been connected to breast cancer (WHO 2018). Moreover, the several quantity of new breast cancer affected patients is estimated to grow by 75% in the next 20 years. As a result, precise and early diagnosis shows a crucial role to develop the diagnosis and rise the patients' survival rate with breast cancer from 20% to 60% according to the WHO in 2019. Generally, there are 2 types of breast tumors such as malignant and benign. Malignant is the cancerous tumor (invasive) and benign is the non-cancerous tumor (noninvasive) [1-2]. Those tumors have more subtypes that require to be detected separately as each can lead to treatment plans and various prognosis. Breast cancer with its subcategories need accurate diagnosis, which is known as multi-classification. Medical imaging systems are more simply effective and adopted for breast and lung cancer recognition than new testing methods [3, 4]. Some of the well-known medical imaging systems for the diagnosis of breast cancer are breast X-ray mammography, sonograms or ultrasound imaging, computed tomography, MRI, and histopathology images [5-7]. Figure 1 shows an example of breast mammography, while Figure 2 shows an example of screening of mammograms. Medical imaging is generally done by manually through one or other skilled doctors (such as sinologists, radiologists, or pathologists). The complete decision is prepared after consent if several pathologists are present for breast cancer histopathology image analysis; otherwise findings are described by a pathologist. However, manual histopathology image investigation have several issues [8, 9]. Firstly, expert pathologists are rare in some low income and developing countries. Secondly, the technique of multi-class classification with image analysis is time consuming and cumbersome for pathologists. Thirdly, pathologists may have deteriorated attention and may experience fatigue at the time of image analysis. Finally, a consistent of subtype identification of breast cancer depends on the domain knowledge and professional experience of a skilled pathologist. Especially, these issues are for the breast cancer early stage and caused misdiagnosis. Conversely, computer-aided diagnosis (CAD) schemes can help as a second outlook to resolve multi-classification problems for breast cancer. A CAD scheme is an inexpensive, fast, reliable source, and readily available of cancer early diagnosis [10, 11]. About 30% to 70% reduction in the morality rate can be achieved in this process [12]. The introduction of digital medical images has given an edge to artificial intelligence (AI) for pattern recognition conducting a CAD scheme. CAD schemes are considered to assist physicians by interpreting automatic images. Therefore, such a system diminishes human dependency, rises diagnosis rate, and decreases the total treatment expenses by decreasing false negative (FN) and false positive (FP) predictions [13]. Furthermore, higher FN rate may cause breast cancer carriers with no treatment, and misdiagnoses occur in the breast cancer early stages. It is described in [11] that a CAD scheme uses for the classification which rises sensitivity to 10%. Despite of classifications [14, 15], CAD systems may be established to implement new diagnosis-related tasks, for example, lesion

detection [16, 17], registration, segmentation [18, 19], and grading [20, 21].
Recently, numerous research papers have been proposed to explain breast cancer classification [1], registration, detection, segmentation, and grading problems by conducting machine learning schemes such as, naïve Bayes, random forest, support vector machine (SVM), decision tree, or by conducting artificial neural networks (ANN)-based approaches, deep neural networks (DNN) and spiking neural network (SNN).

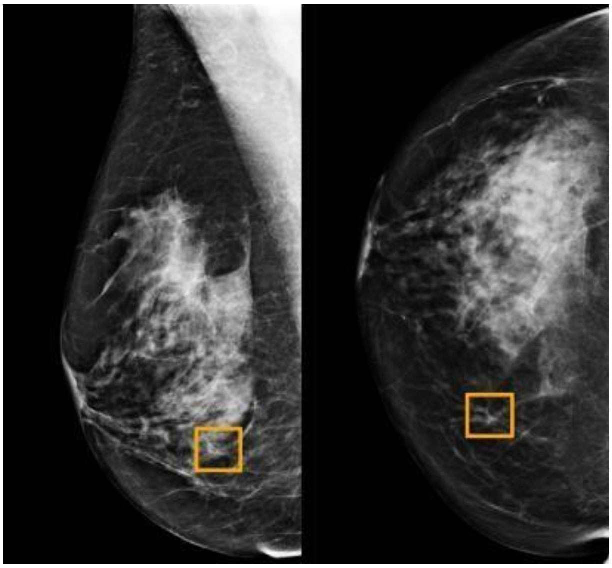

Figure 1. Breast Mammography (Adapted from [98])

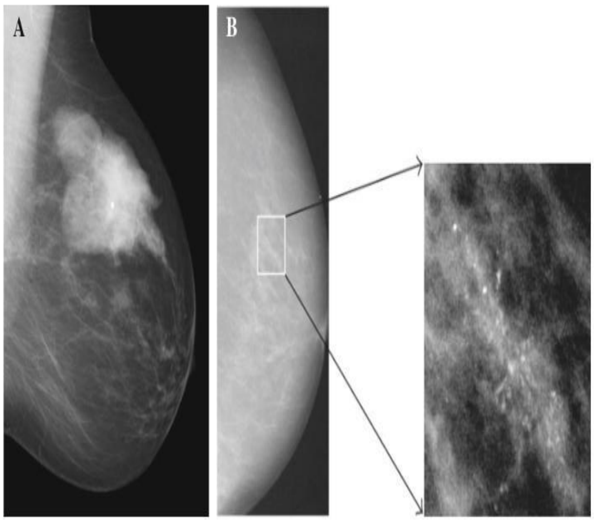

Figure 2. Screening of mammograms (a) normal view (b) magnified view with micro-calcifications (Adapted from [86, 97])

This paper provides a comprehensive review of the application of ANN models for mammographic detection of breast cancer. The rest of the paper can be structured as follows. Section II illustrates ANN approaches used for breast cancer classification. Section III describes different computer-aided diagnosis (CAD) systems using deep learning. Section IV illustrates the result analysis of different deep learning models for breast cancer classification. Limitations of the existing research are described in Section V, while the direction for future research is presented in Section VI. Finally, a conclusion is provided in Section VII.

II. Breast Cancer Classification using ANN

Figure 3 shows a sample of ANN consisting of input, hidden and output layers. An ANN is a machine learning algorithm suitable for different tasks including classification, prediction and visualization. Furthermore, an ANN is suitable or multi-disciplinary tasks with the use of multiple types of data which may be unstructured, semi-structured and structured data. For breast cancer medical images which are a form of unstructured data, shallow ANN and DNN are considered. Table 1 summarizes ANN models for breast cancer diagnosis. Figure 4 and Figure 5 show some categories under DNN and Deep CNN.

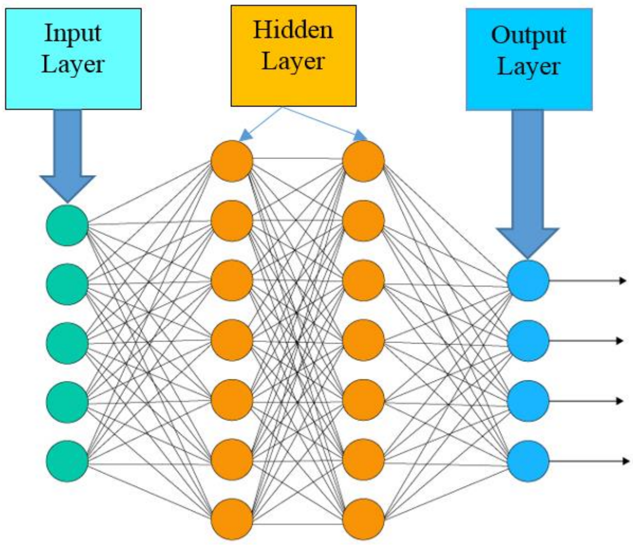

Figure 3. Sample of ANN

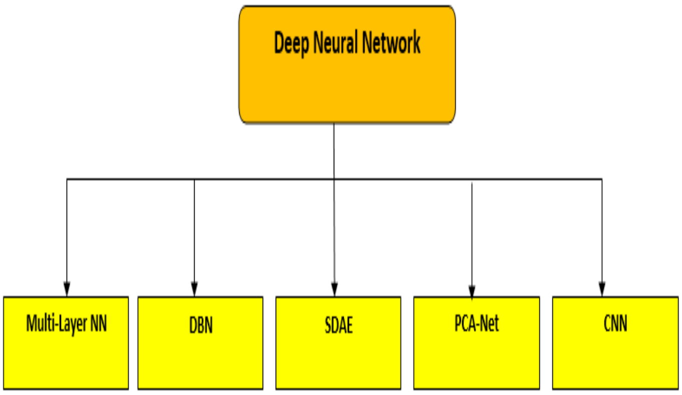

Figure 4. DNN Models in breast Cancer

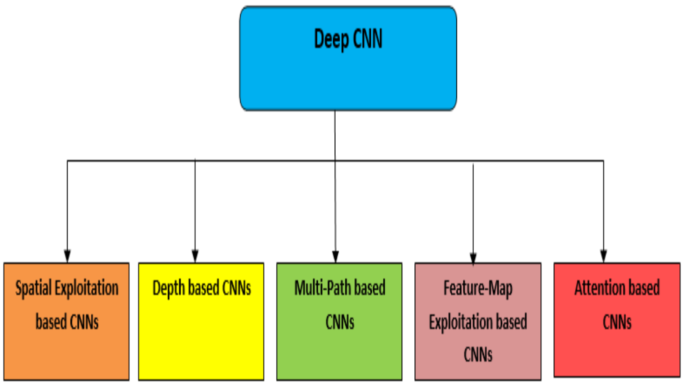

Figure 5. Categories of Deep CNN architecture

Types of ANN	Strengths	Weaknesses
Machine Learning driven NN	(i) Network size is small. (ii) Less training time is required. (iii) Requires less memory. (iv) Better generalization performance can be achieved using the additional hidden layers.	(i) Cannot provide good results when data is high dimensional. (ii) More data is needed to obtain good performance for the additional hidden layer.
SNN	(i) Network size is small. (ii) Less training time is required. (iii) Easy to train (iv) Not complex to optimize the training parameters for achieving better accuracy (v) Small scale data can also achieve good performance.	(i) Cannot provide good results when data is high dimensional. (ii) Performance depends on the structure of ANN and also on the features that are designed. (iii) Not easy to generalize the predictive results.
DBN	(i) Automatic de-noising system for high dimensional data improves the breast cancer classification with its performance in real medical images. (ii) It is the models learning like backpropagation that may minimize cross entropy.	(i) The log likelihood is to unable the track the loss.
SDAE	(i) This greedy learning with efficiency can be monitored. Combined with other learning techniques that the all weights fine-tune to develop the discriminative or generative performance of the entire network. (ii) It can be used for HD data that keep correlated features.	(i) Breast cancer images can be affected by noise. De-noising process in order to eliminate the undesired noise performs better on image data having high dimension.
PCA-Net	(i) Owing to big receptive field, PCANet can extract whole explanations of the objects' images and seizures more information according to semantic level. (ii) Owing to block histogram and binary hashing PCA-Net is very flexible for justification and mathematical analysis of its usefulness.	(i) The procedure of simple hashing scheme has not provided rich sufficient information to draw the features. Therefore, it effects the performance of representation desired when possess of data has numerous irrelevant information.
CNN	(i) Performs well to extract the relevant information from the image having fewer weights in its layers. (ii) Automatically detects the desired features without the human supervision. (iii) Computational cost is low. (iv) CNN performs better in disease detection fast compared to others.	(i) Provides poor result for small target datasets such as 80 images. (ii) CNN fine-tuned model (FTM-ARL) needs more training time compared to the other CNN types. Since in this model new layers need to be trained from the scratch. ARL means append or remove layer.

Table 1. ANN Model For Breast Cancer With Its Summary

III. CAD Models and its Basic Concept

A CAD model has been conducted to offer extra information and maintain the decision creation on cancer staging and disease diagnosis. It is dissimilar from a CAD model which targets to detect, segment, or localize suspicious regions.

Conversely, it has been detected that a CAD model could be located ahead of an identification model for complete investigation from the localization and detection to the suspicious regions diagnosis.

A. ML-Based CAD

A ML-based CAD system refers to ML-based classification and feature extraction as visualized in Figure 6 where feature selection scheme is elective in this system. Generally conducted features derive from image descriptors which quantify the shape, intensity, and suspicious region textures [22]. Desired ML classifiers have not been limited to SVM [91], ANN, KNN, Random Forest, Naïve Bayesian [23]. Owing to the radiomics emergency, it has been well-known that feature selection can be very significant and it targets to suspicious lesions feature with retrieve intrinsic.
Figure 6 shows the flow diagram of the ML based CAD architecture.

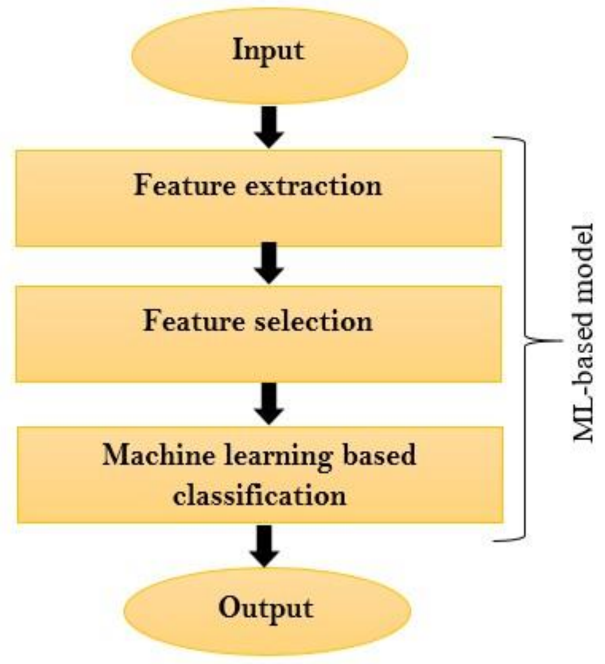

Figure 6. ML-based CAD architecture

B. CNN-Based CAD

CNN is a kind of computational model composed of multiple layers to recover features as raw data. It represents hierarchical abstraction [24]. CNN model is visualized in Figure 7.

A DNN consists of a number of layers including convolution layers, fully connected (FC) layers, pooling layers, and an output layer. Among these layers, a convolution layer are useful for learning high-level features for example the edges of an image. FC layers are for learning features at the pixel level. A pooling layer can reduce the size of convolved features resulting in the reduction in required computational power. This layer can perform two types of operations, max pooling and average pooling [87, 88].

The CNN used for breast image or breast data classification can be categorized into two sections, de novo trained model and transfer learning based model. The CNN based models generated and trained from the scratch are denoted as “de novo model” [89]. On the contrary, CNN models utilizing previously trained neural network models such as AlexNet, visual geometry group (VGG), residual neural network (ResNet), etc. are called “transfer learning (TL)-based models” [92].
Figure 8 displays the VGG16 architecture which refers to thirteen convolutional layers, five pooling layers, three full-connection layers, and one softmax layer [25].
For more development in the classification of object, several methods have been embedded, containing nonlinear filtering, normalization of local response, data augmentation, multiscale representation, and hyperparameter optimization [26, 27]. There are several deep learning systems such as AlexNet [28], VGG [29], ResNet [30], LeNet [31], you only look once (YOLO) [32], GoogLeNet [33, 34], LSTM [35], and faster R-CNN [36].
Note that CNN may be trained end on and can be data-driven. It enables the feature extraction with integration, feature selection, as well as malignancy prediction according to an optimization technique. Consequently, human engineers cannot design these retrieved features from the input. Generally, CNN-based CAD provides a remarkable performance which comes from hardware resource in advanced computing (i.e., distributed computing and GPU), open-source software, i.e., TensorFlow, and HQ labeled images with open challenges, i.e., ImageNet. It also gets advantages from the new architectures design of deep learning, i.e., identity and inception mapping.

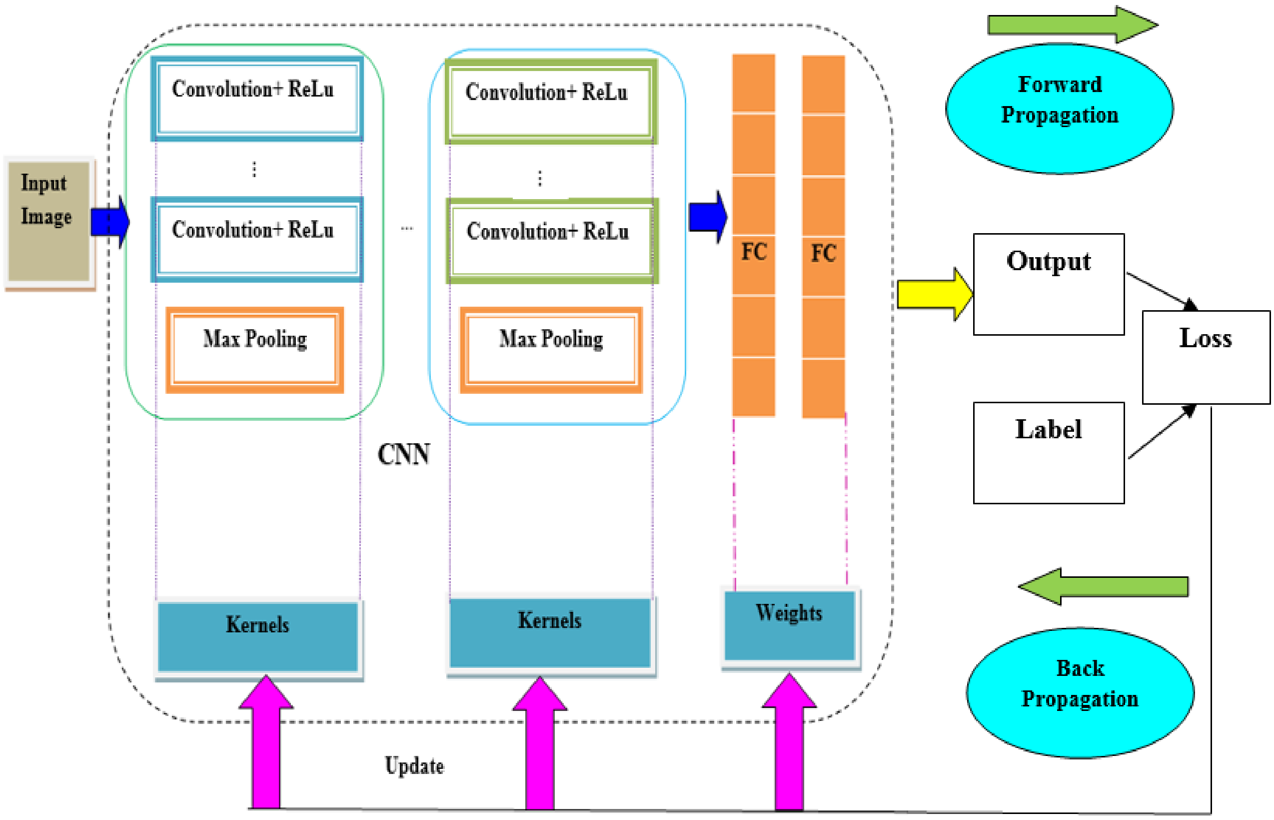

Figure 7. Basic CNN-based CAD

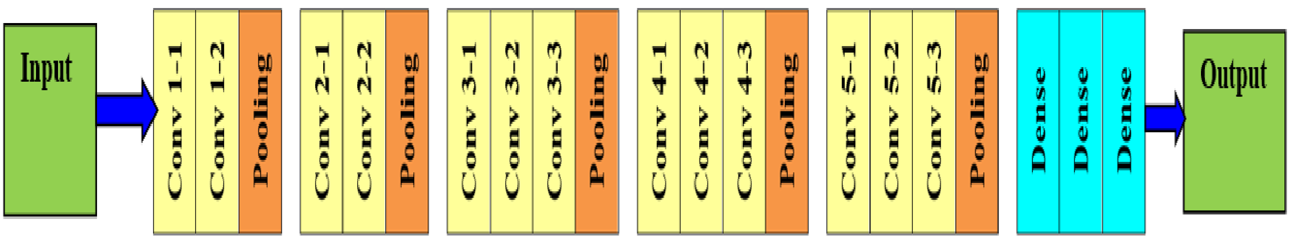

Figure 8. Basic VGG-16 model

IV. Result Analysis of different ANN models

Many studies use single CNN without a fusion. A number of research works [67, 82] embeds some residual blocks in the convolutional layer on the basis of pre trained models. The combination of convolution layer and residual block showed good performance with an accuracy of 92.19% [82]. However, the work in [82] showed that CNN showed much better performance than fusion models such as long short-term memory (LSTM), and a fusion of CNN and LSTM. This result was for a sample of small number of images which might have influenced the finding.

Table 2 presents different DNN models applied to several datasets of breast cancer classification. In this case, most studies perform classification tasks using CNN instead of SNN or multi-layer NN. The datasets used for classification are DDSM, INBreast, BCDR-FO3, and min-MIAS.

The performance of the models are evaluated using confusion matrix where actual classes and predicted classes can be placed in rows and columns, respectively. Thus, breast cancer can be classified as true positive when correctly classified, or classified as false negative when incorrectly classified. Other metrics for evaluation of breast cancer classification are testing accuracy, sensitivity, specificity, precision, area under the receiver operation characteristics curve (AUC), F1-measure, etc.

The performance results of various models adopted by researchers on different types of breast cancer datasets are summarized in Table 2 where the value of achieved accuracy, AUC, sensitivity and specificity are described.

Publication year	Quantity of images	Database	Model	Accuracy	AUC	Sensitivity	Specificity	Ref.
2018	736	BCDR-F03	GoogLeNet	81%	88%	-	-	[37]
2018	736	BCDR-F03	AlexNet	83%	79%	-	-	[37]
2018	736	BCDR-F03	Shallow CNN	73%	82%	-	-	[37]
2018	115	INbreast	Faster R-CNN	-	95%	-	-	[38]
2018	82,000	DREAM	Faster R-CNN	-	85%	-	-	[38]
2018	600	DDSM	ROI based CNN	97%	-	-	-	[39]
2018	5316	DDSM	Inception V3	97.35% (±0.80)	98%	-	-	[40]
2018	200	INbreast	Inception V3	95.50% (±2.00)	97%	-	-	[40]
2018	600	BCDR-F03	Inception V3	96.67% (±0.85)	96%	-	-	[40]
2018	5316	DDSM	VGG16	97.12% (±0.30)	-	-	-	[40]
2018	5316	DDSM	ResNet50	97.27% (±0.34)	-	-	-	[40]
2018	120	MIAS	Deep CNN	96.7%	-	-	-	[41]
2018	20,000	Private dataset (University of Pittsburgh)	AlexNet, Transfer Learning	-	98.82%	-	-	[54]
2018	2620,115, 847	DDSM INbreast and private dataset by Semmelweis University Budapest	Faster R-CNN	-	95%	-	-	[42]
2018	78	FFDM	CNN	-	81%	-	-	[43]
2018	736	BCDR-F03	MV-DNN	85.2%	89.1%	-	-	[44]
2018	322	MIAS	Deep CNN	65%	-	-	-	[92]
2017	3158	FFDM	Deep CNN	82%	88%	81%	72%	[45]
2017	115	INbreast	CNN (COM)	95%	91%	-	-	[46]
2017	2242 (1057 malignant, 1397 benign)	SFM, DM	Deep CNN	-	82%	-	-	[47]
2017	2796	IRMA	CNN-CT	83.74%	83.9%	79.7%	85.4%	[48]
2017	2796	IRMA	CNN-WT	81.83%	83.9%	78.2%	83.3%	[48]
2017	245	FFDM	VGG19	-	86%	-	-	[49]
2017	560	FFDM	Custom CNN	-	79%	-	-	[50]
2017	2795	IRMA	VGG16	100%	100%			[64]
2016	600	DDSM	Deep CNN	96.7%	-	-	-	[51]
2016	607 (219 lesions)	FFDM	AlexNet	-	86%	-	-	[52]
2016	736 (426 benign, 310 malignant	BCDR- F03	CNN	-	82%	-	-	[53]

	lesions)							
2017	480	DDSM	SNN	79.5%	-	-	-	[76]
2017	-	MIAS, CBIS-INBreast	CNN (COM)	57%	77%	-	-	[76]
2018	58	ED (HP)	SDAE	98.27% (Benign), 90.54% (Malignant)	-	97.92% (Benign), 90.17% (Malignant)		[77]
2016	-	UCI, DDSM	SNN	89.175%, 86%	-	-	-	[78]
2018	-	BreakHis	CNN (UDM)	96.15%, 98.33% (2 Classes), 83.31-88.23 % (8 Classes),	-	-	-	[79]
2016	-	ED(US)	ML-NN	98.98%	98%	-	-	[80]
2017	1057 malignant, 1397 benign	ED(Mg),DDSM	Multitask DNN	82%	-	-	-	[81]
2017	-	ED (HP)	CNN (COM)	95.9% (2 classes), 96.4% (15 classes),	-	-	-	[82]
2016	-	ED(US-SWE)	DBN	93.4%	94.7%	88.6%	97.1%	[83]
2017	-	BreakHis	ImageNet	93.2%	-	-	-	[84]
2018	400×(× represents magnification factor)	BreakHis	CNN-CH	96%	-	97.79%	90.16%	[85]
2018	400×(× represents magnification factor)	BreakHis	CNN-CH	97.19%	-	98.20%	94.94%	[85]
2020	2620	DDSM [90]	InceptionV3	79.6%	-	89.1%	-	[89]
2020	2620	DDSM [90]	ResNet 50	85.7%	-	87.3%	-	[89]
2020	10713	DDSM patch	ResNet50	75.1%	-	-	-	[95]
2020	10713	DDSM patch	Mobile Net	77.2%	-	-	-	[95]
2020	10713	DDSM patch	MVGG16	80.8%	-	-	-	[95]
2020	10713	DDSM patch	MVGG16 + ImageNet	88.3%	93.3%	-	-	[95]
2019	190	DDSM	CNN	93.24%	-	92.91%	91.92%	[93]
2019	190	DDSM	CNN based LBP	96.32%	97%	96.81%	95.83%	[93]
2020	292	DDSM	GAN and CNN	80%	80%	-	-	[94]

Table 2. Comparison Of Results

CNN Model	Scratch Training Scenario				Initialization on pre-trained weights			
	DDSM-400		CBIS-DDSM		DDSM-400		CBIS-DDSM	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
AlexNet	61%	65.7%	65.6%	71.6%	73.3%	80.5%	75.3%	80.2%
ResNet-50	54.8%	59.5%	62.7%	63.7%	74.3%	85.6%	74.9%	80.4%
ResNet-101	58.8%	63.7%	66.2%	64.1%	78.5%	85.9%	75.3%	79.1%
ResNet-152	54.3%	59.6%	64.7%	60.9%	63%	78.6%	75.5%	79.3%
VGG16	59%	62.1%	58%	70.2%	74.8%	84.4%	71.6%	78.1%
VGG19	58.8%	64.4%	58.1%	70.7%	73.8%	83.5%	73.6%	78.3%
GoogleNet	56.9%	58%	59.8%	59%	75.8%	83%	72%	76.7%
Inception-v2	59%	65.2%	65.4%	57.7%	78%	85%	74.7%	77.4%

Table 3. Performance of deep neural networks using the from-scratch training scenario

The performance of multiple networks performed in [96] is summarized in Table 3 from scratch training scenarios and fine tuning scenarios, respectively.

Pre-processing technique	Approach	Ref.
Augmentation	Geometric Transform	[54-60]
	Patch creation Approaches	
	Distortion/Add noise	
Scaling	Methods like Bi-cubic interpolation, Gaussian Pyramid, Bilinear interpolation	[61-65]
ROI Extraction	Methods conducted like Nuclei Segmentation, region growing, Markov Random, Otsu Method	[55, 66-67]
Remove Artifacts	Using the pixel intensity thresholding, and binary images, Extracting Bigger areas, cropping border	[20, 58, 61, 68]
Enhancement and Normalization	Adaptive Mean, Histogram equalization, Log transforms, Median filters, Wiener Filter, CLAHE technique	[62,69-72]
Stain Normalization or Removal	Color Deconvolution, Stain Normalization	[62,73-75]

Table 4. Studies Of Pre-Processing Techniques

AUC and classification accuracy values were used as performance metrics in [96]. They achieved maximum performance using fine-tuning in ResNet-50 and ResNet-101 models in both datasets.

Table 4 illustrates some pre-processing techniques that researchers used in their papers.

V. Limitations

In the literature, most of the models used publicly available free datasets for BrC classification. This is because the deep learning methods used for BrC classification actually requires a large number of annotated images which is difficult to obtain. A large dataset of breast cancer images require many images and require expert doctors to label the images perfectly. The creation of datasets is thus time consuming and difficult. Hence, researchers prefer to use existing publicly available datasets. However, these models applied to public datasets may not be the optimum solution. These models may be less effective when applied to real-life cancer images.

According to the literature review, SNN and DNN are used for classification of BrC. Some studies preferred SNN as SNN performs better than DNN for small datasets. However, SNN does not work well for high dimensional data and BrC datasets can be high dimensional. On the other hand, DNN based on ML-NN or CNN work well for high dimensional multicast BrC image datasets. Furthermore, the previous studies used two types of CNN which are de novo model (trained from scratch) and pre-trained TL-based model.

VI. Direction for Future Research

This section represents novel research direction in order to exploit the classification of breast cancer. One direction for classification of breast cancer is the reinforcement learning method supporting ANN. The system architecture and parameter tuning of its environment are the major challenges in recent time. The novel prospects of ML is hybrid ML or ANN technique. Case-based reasoning in breast cancer classification is a method to solve novel problems by the solution of previous problem. It updates and retains the present solution prepared through humans and solves future problems.

VII. Conclusion

This study represents a review for breast cancer mammographic screening where we describe CAD systems and ANN. We have focused the strengths and weaknesses of some ANN models such as ML-NN, SNN, SADE, DBN, and PCA-Net. Moreover, after the basic concept of CNN-based CAD, we have also provided CNN-based system evaluation where we have included ACC, AUC, SEN, and SPE scores. Furthermore, we have described data pre-processing systems with these approaches. For in-depth evaluation, ANN types (such as SNN, DBN, CNN etc.) are described for different databases. Finally, we have outlined some future scope, challenges, and limitations of this research field.

References

[1] Subrato Bharati, Mohammad Atikur Rahman, Prajoy Podder, "Breast cancer prediction applying different classification algorithm with comparative analysis using WEKA". In *Proceedings of the 2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT), IEEE*, pp. 581-584, 2018.

[2] Subrato Bharati, Md. Robiul Alam Robel, Mohammad Atikur Rahman, Prajoy Podder, and Niketa Gandhi, "Comparative Performance Exploration and prediction of Fibrosis, Malign Lymph, Metastases, Normal Lymphogram using Machine Learning Method", in: *Innovations in Bio-Inspired Computing and Applications*, Abraham, A., Panda, M., Pradhan, S., Garcia-Hernandez, L., Ma, K. (eds.). Advances in Intelligent Systems and Computing, Vol. 1180, Springer, Cham, 2020.

[3] Subrato Bharati, Prajoy Podder, Rajib Mondal, Atiq Mahmood, Md Raihan-Al-Masud, "Comparative performance analysis of different classification algorithm for the purpose of prediction of lung cancer", in: *Intelligent Systems Design and Applications. ISDA 2018*, Abraham A., Cherukuri A., Melin P., Gandhi N. (eds), Advances in Intelligent Systems and Computing, vol 941. Springer, Cham, pp. 447-457, 2018.

[4] Subrato Bharati, Prajoy Podder, Pinto Kumar Paul, "Lung cancer recognition and prediction according to random forest ensemble and RUSBoost algorithm using LIDC data", *International Journal of Hybrid Intelligent Systems*, 15(2), pp.91-100, 2019.

[5] Beutel J, Kundel HL, Van Metter RL, "*Handbook of medical imaging*", vol 1. SPIE Press, Bellingham (2000).

[6] Goceri, E. "Advances in Digital Pathology", *International Journal of Emerging Trends in Health Sciences*, 1(2), pp. 33-39, Jan. 2018. doi:10.18844/ijeths.v1i2.3107.

[7] H. Kasban, M. A. M. El-Bendary and D. H. Salama, "A comparative study of medical imaging techniques", *International Journal of Information Science and Intelligent System*, 4(2), pp. 37-58, 2015.

[8] Gurcan M. N. Gurcan, L. E. Boucheron, A. Can, A. Madabhushi, N. M. Rajpoot and B. Yener, "Histopathological Image Analysis: A Review," in *IEEE Reviews in Biomedical Engineering*, vol. 2, pp. 147-171, 2009, doi: 10.1109/RBME.2009.2034865.

[9] M. G. Ertosun and D. L. Rubin, "Probabilistic visual search for masses within mammography images using deep learning", *Bioinformatics and Biomedicine (BIBM) 2015*, pp. 1310-1315, November 2015.

[10] Doi, Kunio. "Computer-aided diagnosis in medical imaging: Historical review, current status and future potential", *Computerized medical imaging and graphics: the official journal of the Computerized Medical Imaging Society*, 31(4-5), pp. 198-211, 2007.

[11] Sadaf A, Crystal P, Scaranelo A, Helbich T, "Performance of computer-aided detection applied to full-field digital mammography in detection of breast cancers, *European Journal of Radiology*, 77(3), pp.457–461, 2011.

[12] Dezső Ribli, Anna Horváth, Zsuzsa Unger, Péter Pollner & István Csabai, "Detecting and classifying lesions in mammograms with Deep Learning", *Scientific Reports*, Vol. 8, Article Number: 4165, 2018.

[13] Goceri E, Songul C, "Biomedical information technology: image based computer aided diagnosis systems". In *Proceedings of the 7th International Conference on Advanced Technologies (ICAT'18)*, Antalya, Turkey, 2018.

[14] Rahimeh Rouhi, Mehdi Jafari, Shohreh Kasaei, Peiman Keshavarzian, "Benign and malignant breast tumors classification based on region growing and CNN segmentation", *Expert Systems with Applications*, 42 (3), pp.990-1002, 2015, doi: 10.1016/j.eswa.2014.09.020.

[15] Xu J, Zhou C, Lang B, Liu Q, "Deep learning for histopathological image analysis: towards computerized diagnosis on cancers", in: Lu L, Zheng Y, Carneiro G, Yang L (eds) *Deep learning and convolutional neural networks for medical image computing: precision medicine, high performance and large-scale datasets*, Springer, Cham, pp 73–95, 2017.

[16] Wang J, Yang Y, "A context-sensitive deep learning approach for micro calcification detection in mammograms", *Pattern Recognition*, Vol. 78, pp. 12–22, 2018. doi: 10.1016/j.patcog.2018.01.009

[17] Yousefi M, Krzy˙ zak A, Suen CY, "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. doi: 10.1016/j.compbiomed.2018.04.004

[18] Chiao Lo, Yi-Wei Shen, Chiun-Sheng Huang, Ruey-Feng Chang, "Computer-Aided Multiview Tumor Detection for Automated Whole Breast Ultrasound", *Ultrasonic Imaging*, 6(1), pp. 3–17, 2014. https://doi.org/10.1177/0161734613507240

[19] Shan J, Alam SK, Garra B, Zhang YT, Ahmed T, "Computer-aided diagnosis for breast ultrasound using computerized Bi-rads features and machine learning methods", *Ultrasound in Medicine & Biology*, 42(4), pp. 980-988, April 2016. doi: 10.1016/j.ultrasmedbio.2015.11.016.

[20] Jinjin Hai, Hongna Tan, Jian Chen, Minghui Wu, Kai Qiao, Jingbo Xu, Lei Zeng, Fei Gao, Dapeng Shi, Bin Yan, "Multi-level features combined end-to-end learning for automated pathological grading of breast cancer on digital mammograms", *Computerized Medical Imaging and Graphics*, Vol. 71, pp-58-66, 2019.

[21] Wan T, Cao J, Chen J, Qin Z, "Automated grading of breast cancer histopathology using cascaded ensemble with combination of multi-level image features", *Neurocomputing*, Vol. 229, pp.34–44, 2017. doi: 10.1016/j.neucom.2016.05.084

[22] D. C. Moura and M. A. Guevara Lopez, "An evaluation of image descriptors combined with clinical data for breast cancer diagnosis", *International Journal of Computer Assisted Radiology and Surgery*, 8(4), pp. 561–574, 2013.

[23] G. An, K. Omodaka, S. Tsuda et al., "Comparison of machine-learning classification models for glaucoma management", *Journal of Healthcare Engineering*, Vol. 2018, Article ID 6874765, 8 pages, 2018.

[24] Y. Liu, S. Stojadinovic, B. Hrycushko et al., "A deep convolutional neural network-based automatic delineation strategy for multiple brain metastases stereotactic radiosurgery", *PloS One*, 12(10), Article ID e0185844, 2017.

[25] K. Simonyan and A. Zisserman, "Very deep convolutional networks for largescale image recognition," 2014, https://arxiv.org/abs/1409.1556

[26] J. R. Burt, N. Torosdagli, N. Khosravan et al., "Deep learning beyond cats and dogs: recent advances in diagnosing breast cancer with deep neural networks", *British Journal of Radiology*, vol. 91, article 20170545, 2018.

[27] A. Hamidinekoo, E. Denton, A. Rampun, K. Honnor, and R. Zwiggelaar, "Deep learning in mammography and breast histology, an overview and future trends", *Medical Image Analysis*, Vol. 47, pp. 45–67, 2018.

[28] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks". In *Proceedings of the Advances in Neural Information Processing Systems*, Lake Tahoe, NV, USA, pp. 1097–1105, December 2012.

[29] Y. Li, J. Huang, N. Ahuja and M. Yang, "Joint Image Filtering with Deep Convolutional Networks", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 41(8), pp. 1909-1923, 1 Aug. 2019. doi: 10.1109/TPAMI.2018.2890623. ,

[30] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition". In *Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, Las Vegas Valley, NV, USA, June 2016.

[31] Y. LeCun, B. Boser, J. S. Denker et al., "Backpropagation applied to handwritten zip code recognition", *Neural Computation*, 1(4), pp. 541–551, 1989.

[32] Y. J. Tan, K. S. Sim and F. F. Ting, "Breast cancer detection using convolutional neural networks for mammogram imaging system". In *Proceedings of the 2017 International Conference on Robotics, Automation and Sciences (ICORAS)*, pp. 1-5, Melaka, 2017. doi: 10.1109/ICORAS.2017.8308076. June 2016.

[33] C. Szegedy, W. Liu, Y. Jia et al., "Going deeper with convolutions". In *Proceedings of the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1–9, Boston, MA, USA, June 2015.

[34] C. Szegedy, V. Vanhoucke, S. Ioffe et al., "Rethinking the inception architecture for computer vision". In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2818–2826, Las Vegas, NV, USA, June 2016.

[35] I. Sutskever, O. Vinyals, and Q. V. Le, "Sequence to sequence learning with neural networks". In *Proceedings of the Advances in Neural Information Processing Systems*, pp. 3104–3112, Montreal, Canada, December 2014

[36] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks". In *Proceedings of the Advances in Neural Information Processing Systems*, pp. 91–99, Montreal, Canada, December 2015.

[37] S. Yu, L. L. Liu, Z. Y. Wang, G. Z. Dai, and Y. Q. Xie, "Transferring deep neural networks for the differentiation of mammographic breast lesions", *Science China Technological Sciences*, 62 (3), pp. 441–447, 2018.

[38] D. Ribli, A. Horv ́ath, Z. Unger, P. Pollner, and I. Csabai, "Detecting and classifying lesions in mammograms with deep learning", *Scientific Reports*, 8(1), pp. 85–94, 2018.

[39] M. A. Al-masni, M. A. Al-antari, J.-M. Park et al., "Simultaneous detection and classification of breast masses in digital mammograms via a deep learning YOLO-based CAD system," *Computer Methods and Programs in Biomedicine*, Vol. 157, pp. 85–94, 2018.

[40] H. Chougrad, H. Zouaki, and O. Alheyane, "Deep convolutional neural networks for breast cancer screening", *Computer Methods and Programs in Biomedicine*, Vol. 157, pp. 19–30, 2018.

[41] Z. Jiao, X. Gao, Y. Wang, and J. Li, "A parasitic metric learning net for breast mass classification based on mammography," *Pattern Recognition*, Vol. 75, pp. 292–301, 2018.

[42] Ribli D, Horváth A, Unger Z, Pollner P, Csabai I., "Detecting and classifying lesions in mammograms with deep learning", Scientific Reports, 8(1):4165, 2018. doi: 10.1038/s41598-018-22437-z.

[43] K. Mendel, H. Li, D. Sheth, and M. Giger, "Transfer learning from convolutional neural networks for computer-aided diagnosis: a comparison of digital breast tomosynthesis and full-field digital mammography", *Academic Radiology*, 2018.

[44] H. Wang, J. Feng, Z. Zhang et al., "Breast mass classification via deeply integrating the contextual information from multi-view data", *Pattern Recognition*, Vol. 80, pp. 42–52, 2018.

[45] W. Sun, T.-L. Tseng, J. Zhang, and W. Qian, "Enhancing deep convolutional neural network scheme for breast cancer diagnosis with unlabeled data", *Computerized Medical Imaging and Graphics*, Vol. 57, pp. 4–9, 2017.

[46] N. Dhungel, G. Carneiro, and A. P. Bradley, "A deep learning approach for the analysis of masses in mammograms with minimal user intervention," *Medical Image Analysis*, Vol. 37, pp. 114–128, 2017.

[47] R. K. Samala, H.-P. Chan, L. M. Hadjiiski, M. A. Helvie, K. Cha, and C. Richter, “Multi-task transfer learning deep convolutional neural network: application to computer aided diagnosis of breast cancer on mammograms”, *Physics in Medicine & Biology*, Vol. 62, no. 23, p. 8894, 2017.
[48] M. M. Jadoon, Q. Zhang, I. Ul Haq, S. Butt, and A. Jadoon, “Three-class mammogram classification based on descriptive CNN features”, *BioMed Research International*, Vol. 2017, Article ID 3640901, 11 pages, 2017.
[49] N. Antropova, B. Q. Huynh, and M. L. Giger, “A deep feature fusion methodology for breast cancer diagnosis demonstrated on three imaging modality datasets”, *Medical Physics*, 44 (10), pp. 5162–5171, 2017.
[50] Y. Qiu, S. Yan, R. R. Gundreddy et al., “A new approach to develop computer aided diagnosis scheme of breast mass classification using deep learning technology”, *Journal of X-Ray Science and Technology*, 25 (5), pp. 751–763, 2017.
[51] Z. Jiao, X. Gao, Y. Wang, and J. Li, “A deep feature based framework for breast masses classification”, *Neurocomputing*, Vol. 197, pp. 221–231, 2016.
[52] B. Q. Huynh, H. Li, and M. L. Giger, “Digital mammographic tumor classification using transfer learning from deep convolutional neural networks,” *Journal of Medical Imaging*, 3 (3), article 034501, 2016.
[53] J. Arevalo, F. A. Gonzalez, R. Ramos-Pollan, J. L. Oliveira, and M. A. Guevara Lopez, “Representation learning for mammography mass lesion classification with convolutional neural networks”, *Computer Methods and Programs in Biomedicine,* Vol. 127, pp. 248–257, 2016.
[54] Mohamed AA, Berg WA, Peng H, Luo Y, Jankowitz RC, Wu S, “A deep learning method for classifying mammographic breast density categories”, *Medical Physics*, 45(1), pp.314-321, January 2018.
[55] Araujo T, Aresta G, Castro E, Rouco J, Aguiar P, Eloy C et al, “Classification of breast cancer histology images using convolutional neural networks”, *PLoS ONE* 12(6):14, 2017. doi: 10.1371/journal.pone.0177544
[56] J. Cao, Z. Qin, J. Jing, J. Chen and T. Wan, "An automatic breast cancer grading method in histopathological images based on pixel-, object-, and semantic-level features". In *Proceedings of the 2016 IEEE 13th International Symposium on Biomedical Imaging (ISBI)*, Prague, pp. 1151-1154, 2016. doi: 10.1109/ISBI.2016.7493470.
[57] Feng Y, Zhang L, Yi Z, “Breast cancer cell nuclei classification in histopathology images using deep neural networks”, *International Journal of Computer Assisted Radiology and Surgery*, 13(2), pp. 179– 191, 2018. doi: 10.1007/s11548-017-1663-9.
[58] Gandomkar Z, Brennan PC, Mello-Thoms C, “MuDeRN: Multi-category classification of breast histopathological image using deep residual networks”, *Artificial Intelligence in Medicine*, Vol. 88, pp.14-24, June 2018. https://doi.org/10.1016/j.artmed.2018.04.005
[59] Samala RK, Chan HP, Hadjiiski LM, Helvie MA, Richter C, Cha K, “Evolutionary pruning of transfer learned deep convolutional neural network for breast cancer diagnosis in digital breast tomosynthesis”, *Physics in Medicine & Biology*, 63(9), 2018. https://doi.org/10.1088/1361-6560/aabb5b
[60] Zhang X, Zhang Y, Han EY, Jacobs N, Han Q, Wang X, Liu J: Whole mammogram image classification with convolutional neural networks”. In *Proceedings of the 2017 IEEE international conference on bioinformatics and biomedicine (BIBM)*, 2017.
[61] Abdullah-Al N, Bin Ali F, Kong YN, “Histopathological breast-image classification with image enhancement by convolutional neural network”. In *Proceedings of the 2017 20th International conference of computer and information technology, New York. IEEE*, 2017.
[62] Arefan D, Talebpour A, Ahmadinejhad N, Asl AK, “Automatic breast density classification using neural network”, *Journal of Instrumentation*, Vol. 10, 2015. https://doi.org/10.1088/1748-0221/10/12/t12002
[63] Chang J, Yu J, Han T, Chang H, Park E, “A method for classifying medical images using transfer learning: a pilot study on histopathology of breast cancer”, In *Proceedings of the 2017 IEEE 19th international conference on e-health networking, applications and services (Healthcom)*,2017.
[64] S. J. S. Gardezi, M. Awais, I. Faye and F. Meriaudeau, "Mammogram classification using deep learning features". In *Proceedings of the 2017 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, Kuching, pp. 485-488, 2017.
[65] Zhongyi Han, Benzheng Wei, Yuanjie Zheng, Yilong Yin, Kejian Li & Shuo Li, “Breast Cancer Multi-classification from Histopathological Images with Structured Deep Learning Model”, *Scientific Reports*, Vol. 7, Article number: 4172, 2017.
[66] Rasti R, Teshnehlab M, Phung SL, “Breast cancer diagnosis in DCE-MRI using mixture ensemble of convolutional neural networks”, *Pattern Recognition*, Vol. 72, pp. 381–390, 2017.
[67] Rouhi R, Jafari M, Kasaei S, Keshavarzian P, “Benign and malignant breast tumors classification based on region growing and CNN segmentation”, *Expert System Applications*, 42(3), pp. 990–1002, 2015. https://doi.org/10.1016/j.eswa.2014.09.020
[68] Wan T, Cao J, Chen J, Qin Z, “Automated grading of breast cancer histopathology using cascaded ensemble with combination of multi-level image features”, *Neurocomputing*, Vol. 229, pp. 34–44, 2017. https://doi.org/10.1016/j.neucom.2016.05.084
[69] Arevalo J, González FA, Ramos-Pollán R, Oliveira JL, Lopez MAG, “Convolutional neural networks for mammography mass lesion classification”. In *Proceedings of the 2015 37th annual international conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015.
[70] Bejnordi BE, Zuidhof G, Balkenhol M, Hermsen M, Bult P, van Ginneken B et al., “Context-aware stacked convolutional neural networks for classification of breast carcinomas in whole-slide histopathology images”, *Journal of Medical Imaging*, 4(4):8, 2017. https://doi.org/10.1117/1.jmi.4.4.044504.
[71] Duraisamy S, Emperumal S, “Computer-aided mammogram diagnosis system using deep learning convolutional fully complex-valued relaxation neural

network classifier", *IET Computer Vision*, 11(8), pp.656–662, 2017. doi:10.1049/ietcvi.2016.0425

[72] Han S, Kang HK, Jeong JY, Park MH, Kim W, Bang WC, Seong YK, "A deep learning framework for supporting the classification of breast lesions in ultrasound images", *Physics in Medicine and Biology*, 62(19), pp. 7714–7728, 2017. doi: 10.1088/1361-6560/aa82ec.

[73] N. Bayramoglu, J. Kannala and J. Heikkilä, "Deep learning for magnification independent breast cancer histopathology image classification", In *Proceedings of the 2016 23rd International Conference on Pattern Recognition (ICPR)*, Cancun, pp. 2440-2445, 2016. doi: 10.1109/ICPR.2016.7900002. 2017.

[74] Bevilacqua V, Brunetti A, Triggiani M, Magaletti D, Telegrafo M, Moschetta M, "An optimized feedforward artificial neural network topology to support radiologists in breast lesions classification". *In Proceedings of the 2016 on Genetic and Evolutionary Computation Conference Companion*, pp. 1385–1392, July 2016.

[75] Sert E, Ertekin S, Halici U, "Ensemble of convolutional neural networks for classification of breast microcalcification from mammograms". In *Proceedings of the annual international conference of the IEEE engineering in medicine and biology society, EMBS*, 2017.

[76] Kumar I, Bhadauria HS, Virmani J, Thakur S, "A classification framework for prediction of breast density using an ensemble of neural network classifiers", *Biocybernetics and Biomedical Engineering*, 37(1), pp. 217–228, 2017. doi:10.1016/j.bbe.2017.01.001

[77] Feng Y, Zhang L, Yi Z, "Breast cancer cell nuclei classification in histopathology images using deep neural networks", *International Journal of Computer Assisted Radiology and Surgery*, 13(2), pp. 179–191, 2018. https://doi.org/10.1007/s11548-017-1663-9

[78] Leod PM, Verma B, "Polynomial prediction of neurons in neural network classifier for breast cancer diagnosis". In *Proceedings of the International conference on natural computation*, 2016.

[79] Bardou D, Zhang K, Ahmad SM, "Classification of breast cancer based on histology images using convolutional neural networks", *IEEE Access*, 2018. https://doi.org/10.1109/access.2018.2831280

[80] Nascimento CDL, Silva SDS, da Silva TA, Pereira WCA, Costa MGF, Costa Filho CFF, "Breast tumor classification in ultrasound images using support vector machines and neural networks", *Revista Brasileira de Engenharia Biomedica*, 32(3), pp. 283–292, 2016. https://doi.org/10.1590/2446-4740.04915

[81] Samala RK, Chan HP, Hadjiiski LM, Helvie MA, Cha KH, Richter CD, "Multitask transfer learning deep convolutional neural network: application to computer-aided diagnosis of breast cancer on mammograms", *Physics in Medicine and Biology*, 62(23), pp. 8894–8908, 2017. https://doi.org/10.1088/1361-6560/aa93d4.

[82] Zheng Y, Jiang Z, Xie F, Zhang H, Ma Y, Shi H, Zhao Y, "Feature extraction from histopathological images based on nucleus-guided convolutional neural network for breast lesion classification", *Pattern Recognition*, Vol. 71, pp. 14–25, 2017. doi:10.1016/j.patcog.2017.05.010.

[83] Zhang Q, Xiao Y, Dai W, Suo JF, Wang CZ, Shi J, Zheng HR, "Deep learning based classification of breast tumors with shear-wave elastography", *Ultrasonics*, Vol. 72, pp. 150–157, 2016. doi:10.1016/j.ultras.2016.08.004

[84] Han S, Kang HK, Jeong JY, Park MH, Kim W, Bang WC, Seong YK, "A deep learning framework for supporting the classification of breast lesions in ultrasound images", *Physics in Medicine and Biology*, 62(19), pp. 7714–7728, 2017. doi:10.1088/1361-6560/aa82ec.

[85] Nahid AA, Kong Y, "Histopathological breast-image classification using local and frequency domains by convolutional neural network", *Information (Switzerland)*, 9(1), 19, 2018. doi:10.3390/info9010019.

[86] Jonathan J. James, A. Robin M. Wilson, Andrew J. Evans, "The breast", Retrieved from https://radiologykey.com/the-breast-2/.(last accessed on May 16, 2020)

[87] Yamashita, R., Nishio, M., Do, R.K.G. et al., "Convolutional neural networks: an overview and application in radiology", *Insights Imaging*, Vol. 9, pp. 611–629, 2018. doi: 10.1007/s13244-018-0639-9.

[88] O. Hadad, R. Bakalo, R. Ben-Ari, S. Hashoul and G. Amit, "Classification of breast lesions using cross-modal deep learning". In *Proceedings of the 2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*, Melbourne, VIC, pp. 109-112, 2017. doi: 10.1109/ISBI.2017.7950480.

[89] A. S. Abdel Rahman, S. B. Belhaouari, A. Bouzerdoum, H. Baali, T. Alam and A. M. Eldaraa, "Breast Mass Tumor Classification using Deep Learning". In *Proceedings of the 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT)*, Doha, Qatar, pp. 271-276, 2020. doi: 10.1109/ICIoT48696.2020.9089535.

[90] Michael Heath, Kevin Bowyer, Daniel Kopans, Richard Moore and W. Philip Kegelmeyer, "The Digital Database for Screening Mammography". In *Proceedings of the Fifth International Workshop on Digital Mammography*, M.J. Yaffe, ed., pp. 212-218, Medical Physics Publishing, 2001. ISBN 1-930524-00-5.

[91] Raihan-Al-Masud M., Mondal MRH, "Data-driven diagnosis of spinal abnormalities using feature selection and machine learning algorithms", *PLoS ONE*, 15(2): e0228422, 2020.

[92] S. Charan, M. J. Khan and K. Khurshid, "Breast cancer detection in mammograms using convolutional neural network". In *Proceedings of the 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)*, Sukkur, pp. 1-5, 2018. doi: 10.1109/ICOMET.2018.8346384.

[93] R. Touahri, N. AzizI, N. E. Hammami, M. Aldwairi and F. Benaida, "Automated Breast Tumor Diagnosis Using Local Binary Patterns (LBP) Based on Deep Learning Classification". In *Proceedings of the 2019 International Conference on Computer and Information Sciences (ICCIS)*, Sakaka, Saudi Arabia, pp. 1-5, 2019. doi: 10.1109/ICCISci.2019.8716428.

[94] Vivek Kumar Singh, Hatem A. Rashwan, Santiago Romani, Farhan Akram, Nidhi Pandey, Md. Mostafa Kamal Sarker et. al., "Breast tumor segmentation and

shape classification in mammograms using generative adversarial and convolutional neural network", *Expert Systems with Applications*, Vol. 139, 2020. https://doi.org/10.1016/j.eswa.2019.112855.

[95] Subrato Bharati, Prajoy Podder, "Diagnosis of Breast Cancer using Hybrid Transfer Learning", *arXiv preprint*, arXiv:2003.13503.

[96] Tsochatzidis, L.; Costaridou, L.; Pratikakis, I., "Deep Learning for Breast Cancer Diagnosis from Mammograms—A Comparative Study", *Journal of Imaging*, 5 (3), 37, 2019.

[97] Hao Jing, Yongyi Yang, Robert M Nishikawa, "Regularization in retrieval-driven classification of clustered microcalcifications for breast cancer", *International Journal of Biomedical Imaging*, 2012:463408, 2012.

[98] A.I. Is Learning to Read Mammograms, Available at: https://www.nytimes.com/2020/01/01/health/breast-cancer-mammogram-artificial-intelligence.html (Last accessed: 21 May 2020)

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