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A SYSTEMATIC REVIEW OF CAD SYSTEM BASED APPROACH IN DIAGNOSING BREAST CANCER AND ANALYZE EFFECTIVENESS OF MACHINE LEARNING AND DEEP LEARNING ALGORITHMS IN EARLY DETECTION

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ABSTRACT

This study intends to throw some light on the different treatment gateways of breast cancer. As we know that women are worst affected by this life threatening disease around the globe, everyone should be aware of the fact that this disease can be tackled if it is detected at the initial stage. In India, the most number of women are affected by this fatal carcinoma and that results in a huge death rate. MRI, Biopsy, USG, Mammography, Histopathological images and many other diagnostic tests can confirm the presence of breast cancer in women. This paper will focus on the prediction of the test samples to be malignant or not by studying the ways of performing machine learning based computer aided systems. By reviewing many important and promising papers in this area, it has been found that there is an established system of detection of carcinoma that is known as Computer Aided Detection. This system consists of the different stages as in image pre-processing, segmentation of images, extraction of relevant features and image classification. We also found from the review that the efficiency of CAD systems increases when the methodologies like CART, Decision Tree Classifier (DT), Logistic Regression (LR), Naïve Bayes (NB), Ensemble, Random Forest Classifier (RF), and K-nearest neighbor classifiers (KNN) used to extracted features. We reviewed several research papers and found a plethora of methodologies available for early detection of breast cancer by using CAD. When the WBCD dataset was evaluated by using Ensemble technique, it recorded about 98% of accuracy. Previously, radiologists could not diagnose breast cancer with so much efficacy as there was a scarcity of so many efficient techniques which are available nowadays. Although the ultimate result of the tests depends on the diagnostic ability of the radiologists, they get a significant amount of assistance by the latest methodologies.

Keywords: MRI, Biopsy, CAD, Histopathology, Invasive Ductal Carcinoma, Machine Learning, Deep Learning

1. INTRODUCTION

One of the commonest explanations for death after lung cancer is Breast cancer. Early identification and effective carcinoma therapy may enhance the therapy options and decrease the mortality rate. As reported in **[1]**, there were 20 million new cases of breast cancer worldwide resulting in the death of more than 62 million people in 2018. Incidence of breast cancer is more common in the western countries such as the USA compared to Africa and Asian countries. This fatal disease has increased worldwide at the rate of 0.5% annually and this increment is more in Asian countries which is around 3-4% **[2]**. In underdeveloped nations, mortality and breast cancer morbidity are prevalent **[3, 4]**. It is observed that in case of Indian women, breast cancer is detected at a very young age and thankfully they are diagnosed early in most of the cases and that helps the oncologists to treat them better and save their lives. It is also seen that, in rural areas, cervical cancer is more prevalent whereas in urban women evidence of breast cancer is more common **[5]**. There are many life style related reasons for this kind of discrimination. The rate of incidence of breast cancer in states like Delhi, Mumbai, Bangalore, Chennai and Kolkata are 41.0, 33.6, 34.4, 37.9 and 25.5 cases per one million women population respectively. A huge number of cases of breast cancer is reported per year in India as shown in Table 1. Every year there is a significant percentage (0.68%) of change observed in case of cancer, during the time span 2011 to 2014, by National Cancer Registry Program (NCRP), out of which about 2% of change in every year in case of breast cancer is found. From 1998 to 2012, the number of reported cases of breast cancer has increased manifold. In **[6]**, it is reported that the Annual Percentage Change (APC) rose up to 5.31% from 0.91% in Delhi during this period of time. They also predicted that among all cancers, about 10% would be breast cancer and this is a threat to the women's health of our country. The nature of breast cancer in India is no way similar to that of in western countries. Many researchers **[7]** reported that Indian women are caught with this disease at a very young age compared to other developed countries. Their tumor size is higher, they suffer from more negative hormone receptor conditions, lower ratings, more positive lymph nodes and aggressive illness. In **[8]**, it has been observed that tumors in stages 1, 2, 3 have an independent risk factor for premature mortality for the control matched patients.

1.1 Breast Cancer Susceptibility

In the US, it is reported that the median age of breast cancer patients is 62 years whereas the range of age is 60 to 69 years **[9]**. India is a country with diversity in all aspects such as economic conditions, education, climatic conditions and cultural heritages. The range of ages for urban population in India is found to be 40 to 49 years whereas in rural areas the range is between 65 and 69 years **[10, 11, and 12]**. Indian women are affected in their early life and mostly present in advanced stages. Some researchers found that Indian women are diagnosed with breast cancer with symptoms and mammographic detection doesn't work in case of them. It is also seen that almost 60% of the patients are detected in stage 3 or 4 leading to a higher death rate **[1], [13]**. In **[14, 15]**, authors reported that in 62% of the cases, the disease was diagnosed with TNM stage III in the women from Northern India. It is very unfortunate that only 1.4% are diagnosed in stage 1. They also studied that TATA Memorial Hospital, Mumbai reported that 54% patients with advanced stage and women from urban areas came to report in an early stage of the disease (OR = 0.64). Authors of **[16]** found that the stage of diagnosis depends on the level of education, socioeconomic background, area of residence and marital status of the patients. A few studies found that the mortality depends on the presentation of the disease in the later stage; it is better if the diagnosis is done within three months.

1.2. Breast Cancer Assessment and Motivation-In Context of Asian demographics and Indian Subcontinent

Mammography can be a specific imaging method for the assessment of the breast using low dose X-rays **[18]**. Mammography is the best known method for preliminary screening, but has certain limitations **[19, 20]**. Breast density might be some misleading element which makes it difficult for women with thick breasts to diagnose cancer **[19, 21-23]**. **Figure 1** demonstrates the different densities of breast in women obtained through breast ultrasound **[24-29]**. To gauge breast issues, ultrasound is proved to be one of the efficient tools. It is usually recommended by the profession, especially lactation period and pregnancy, to scan breasts. For biopsy guidance and mass locating, it can also be recommended. **Figure 2** shows how mammograms can detect the presence of lesions in the human breast **[23]**. However, ultrasound is very prone to detecting invasive ductal carcinoma in dense breasts as shown by Costantini *et al.* **[25], [30]**. MRI is usually recommended for screening women who have a high risk of MRI is usually recommended for screening women who have a high risk of developing breast cancer and is often used to investigate suspicious mammogram to assist detecting the dimensions of the mass. Patients who carry the BRCA1 and BRCA2 gene mutations have an underlying genetic predisposition for breast and ovarian cancers to detect the dimensions of the mass. The interpretation/ prediction procedure of MRI imaging, as shown in **Figure 3** is extremely time-taking and requires a considerable level of radiologist expertise to classify the differences between benign and malignant lesions shown by **[31] [32]**. Recent studies have shown that computer systems developed to facilitate MRI image analysis enhance the treatment and diagnosis many fold as demonstrated in **[31], [33] and [34]**.

1.3. Motivation behind CAD system based diagnosis and performance evaluation.

The contrast of the tumor between the background of the image and cancer is particularly poor in dense images of breast might alter the results of the diagnosis. Non-cancerous lesions (fake-positive value) were commonly misread in the mammographic examination, whereas malignancies were frequently overlooked (false-negative value). Therefore, radiologists often fail to detect breast cancers **[20]**. Several strategies are presented to strengthen the sensitivity and specificity of mammography to avoid needless biopsies. Double reading is one among the strategies which will contribute significantly towards achieving high sensitivity and specificity. CAD systems might be regarded as a supplementary mechanism to improve the doctor's interpretation as a powerful second reader. An autonomously cancer cells detection CAD system based on computer vision can assist radiologists distinguish cancer from non-cancer cells. Br0 1H are also analyzed using histopathology images in few studies **[35]**.

Bhardwaj *et al*. used deep neural networks to classify breast cancer while Niwas *et al*. extracted wavelet features from histopathological images **[36], [37]**. **Figure 4** presents a sample of histopathological images **[35]**.

Table 1: State wise statistics

States/UT	2016	2017	2018
Jammu & Kashmir	1421	1516	1618
Himachal Pradesh	613	647	681
Punjab	3321	3503	3694
Chandigarh	196	207	219
Uttaranchal	1217	1298	1384
Haryana	3103	3308	3526
Delhi	3181	3351	3530
Rajasthan	7536	7996	8483
Uttar Pradesh	21376	22737	24181
Bihar	9958	10644	11378
Sikkim	30	30	31
Arunachal Pradesh	82	84	85
Nagaland	67	67	68
Manipur	273	281	289
Mizoram	97	99	101
Tripura	129	130	132
Meghalaya	104	106	108
Assam	2406	2437	2467
West Bengal	10902	11550	12234
Jharkhand	3716	3962	4225
Orissa	4205	4448	4705
Chhattisgarh	2944	3145	3359
Madhya Pradesh	8334	8858	9414
Gujarat	8001	8504	9039
Daman & Diu	42	47	52
Dadra & Nagar Haveli	54	61	68
Maharashtra	14726	15522	16358
Telangana	4633	4918	5220
Andhra Pradesh	5901	6251	6620
Karnataka	8029	8527	9055
Goa	233	247	262
Lakshadweep	14	15	17
Kerala	5682	6189	6748
Tamil Nadu	9486	9870	10269
Pondicherry	227	242	257
Andaman & Nicobar Islands	44	45	47
Total	142283	150842	159924

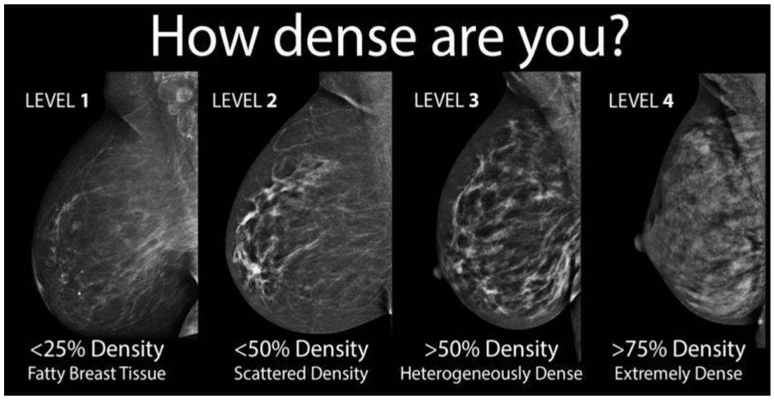

Figure 1: densities of breast in women obtained through breast ultrasound

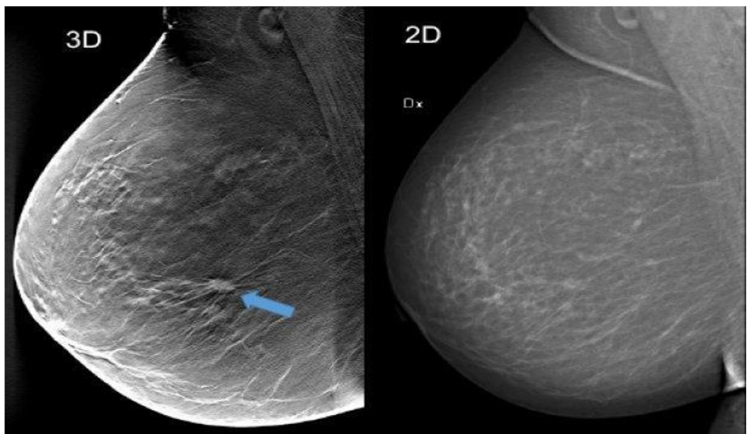

Figure 2: Detection of presence of lesions in human breast through mammograms

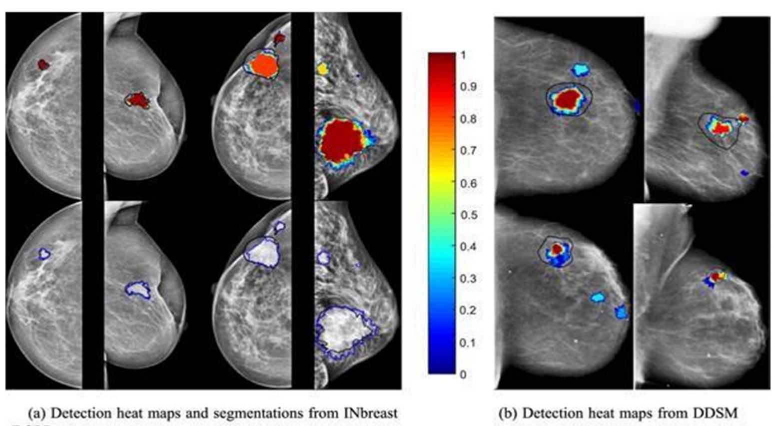

Figure 3: The interpretation/prediction procedure of MRI imaging

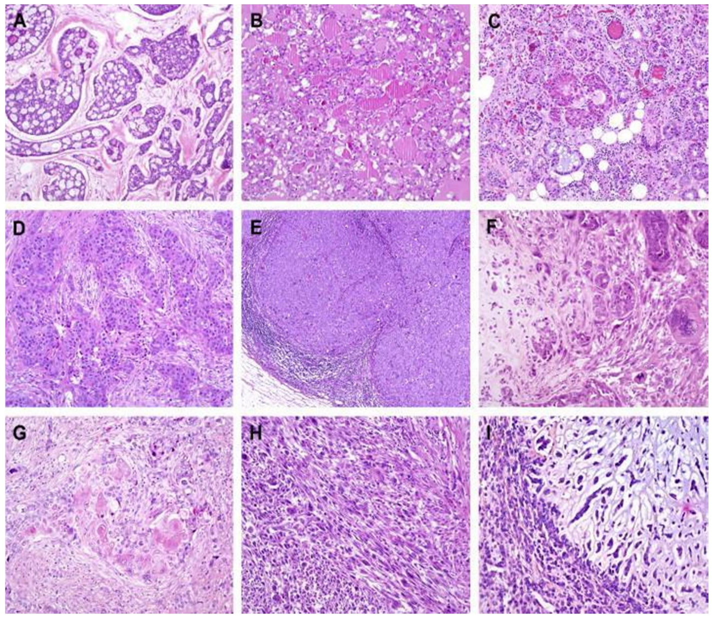

Figure 4: Sample histopathological images

Any CAD system is primarily based on the following 5 stages.

1) Image Preprocessing: Any kind of Biomedical Image preprocessing technique involves noise removal from the images being acquired. It also involves image resizing, enhancing the image intensity as shown by **[38]**, adjusting brightness and contrast or converting them into grayscale.

2) Image Segmentation: Image segmentation is again a key element in the recognition of computer vision and patterns. Segmentation techniques allow us to identify important areas and to remove various features for further analysis, such as the tumor or lesion. Based on the properties of images, segmentation approach can be classified as follows

- Similarity-based
- Discontinuity-based

Edge-based segmentation is an example of discontinuity-based approach. Lee *et al*., further divided the similarity approach into threshold, region-based and clustering methods **[39]**. Each procedure has its own benefits and limitations and is chosen according to the individual applications and imaging methods.

3) Feature Extraction: The characteristics of the lesions in the images are taken for the distinct attributes. These features are utilized for categorization of benign and malignant tumors in the next stage. One of the real challenges of the feature extraction process is the size of the feature set. Computing feature descriptors from a picture to scale back the quantity of knowledge ordinarily signifies feature extraction. Features are characteristics of the whole image or ROI. Often an image descriptor can be classified into three

dimensions; shape, pattern and spectra and density as claimed in **[40]**. Feature matching techniques can also be employed too by comparing the key points within the feature descriptor using algorithms like SIFT, SURF, BRIEF and ORB.

4) Classification: It is essential that a trustworthy classifier is applied to differentiate between cancer and non-cancer cells. Various such machine learning models like Linear Regression, Logistic Regression, DT, RF, Ensemble techniques, SVM, KNN, NB, CART have been used traditionally for the purpose of classification. We have discussed different such approaches in this paper and the accuracy being achieved in the most prominent works in the last decade on the topic.

5) Performance-Review or Evaluation: As in most systems, a CAD of detection of breast cancer demands high accuracy and precision. We have considered key features to measure accuracy like Sensitivity, F1 score, True Positive and True Negative and Overall Accuracy to justify our claim that a significant amount of research has been done for cancer classification using CAD system. A performance review of crucial works in the last decade has been thoroughly explored in this paper.

The flow of all five stages of the CAD system is illustrated in **Figure 5**.

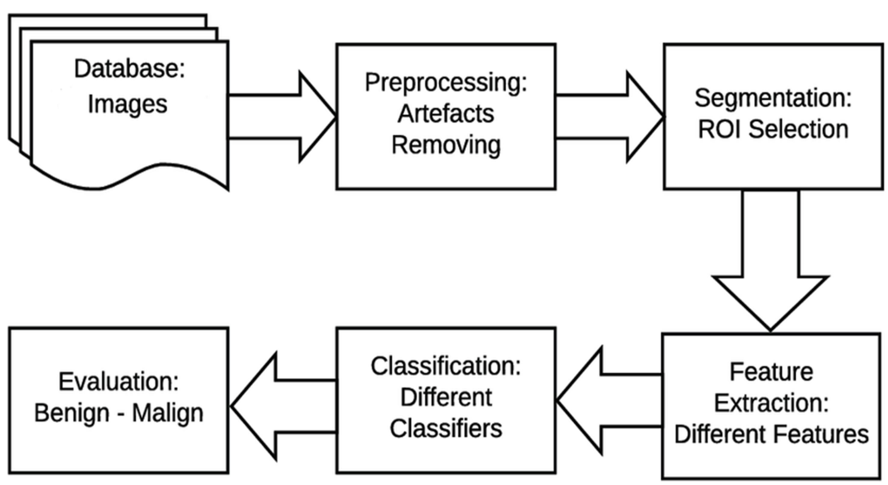

Figure 5: Stages of a CAD system

The rest of this paper is organized as follows in sequence. Literature review section discusses previous studies along with their area, different techniques used in this field along with a comparison among them. The research gap section discusses some of the unexplored areas. Finally, the conclusion section describes the applicability of results.

2. Literature Review-Evaluation of Existing Literature:

For breast cancer detection using different techniques relevant literature from multiple sources are being referred to. Various authors have worked on different datasets over a period of time and based on that conclusion are derived. Machine learning algorithms can be classified as following three types **[41]**.

- The Supervised learning algorithms;
- Unsupervised learning and
- Reinforcement learning

Supervised learning is the most common for every machine learning method that is used to predict cancer and supervised learning algorithms are on the basis of some criteria and conditions. Genetic algorithms, artificial neural networks and decision trees are some of the algorithms used in supervised learning. Physical examination, imaging and biopsy are some of the ways to diagnose breast cancer **[42]**. They also said that X-ray is used just to understand the shape of the breast but mammography is used for imaging the internal parts of the breasts. Some studies **[43]** reported that when different kinds of machine learning models are used for predicting breast cancer or cancer in general, machine learning models outperform the classical statistical models or expert based systems. In **[44]**, they tried to distinguish between the mammograms of healthy tissues and cancer tissues and to do that they applied DT, SVM and Bayes' approach. They used a 10-fold cross validation process by employing statistical parameters such as positive predictive value, negative predictive value, sensitivity and specificity. There are some studies that suggest a methodology which helps in computing contourlet coefficient, decomposed image for the purpose of classifying mammogram images **[45]**. The analysts in **[46]** showed that for predicting breast cancer, a combination of Mixed Gravitational Search Algorithm (MGSA) and Support Vector Machine (SVM) improved the performance of these models individually up to 93.1%. They used 70% of the data for training the dataset and the rest for the test. A study reported that for classification of mammogram images, CAD system gives 96% accuracy **[47]**. Classification of mammogram images has been studied by many researchers. In **[48]**, the authors studied the same by employing KNN and GLCM. In a study, it is found that the performance of machine learning models vary due to the parameter selection and dataset. They reported that SVM combined with Gaussian kennel gave the best result in the case of prediction of breast cancer both for recurrence and nonrecurrence one **[49]**. Authors in **[50]** have trained SVM, DT, NB and k-NN on the WBC dataset **[51]** and noticed that among all classifiers, SVN outperforms. A similar study done by researchers **[52]**. In **[53]** they used data mining techniques to explore the risk factors for predicting breast cancer while in **[54]** they compared two machine learning methods (ANN and SVM) for breast cancer detection. The nested ensemble approach based detection of the benign breast tumors from malignant cancers was proposed by **[55]**. They used Stacking and Voting as a combination of classifying techniques. In **[56]**, they worked on the WDBC dataset. In their study, the first dimension is reduced using PCA and then machine learning models are trained for classification of tumors. A similar study is made by **[57]**. Authors performed experiments on two standard databases i.e., Wisconsin Prognostic Breast Cancer (WPBC) and WBC using various machine learning approaches including decision tree, NN and SVM to classify tumors. Another comparative analysis is done by the researchers of **[58]**. When WBPC dataset is used, it was observed that use of PCA improved the results significantly. In **[59]**, the authors employed classification model ANN and extracted the parameters by using PCA. Based on the WBPC dataset, some studies used machine learning algorithms for predicting the recurrent cases of breast cancer **[60]**. Some studies compared different ML algorithms for predicting recurrent or non-recurrent breast cancers **[61], [62]**. A combination of neural network and weighted Naïve Bayes' classifier was used by many studies and they proved the improved performance of these models **[63], [64]**. The authors of **[65]** developed the models for prediction of breast cancer based on Radial Basis Function Network, Naïve Bayes' (NB) and Decision Tree (DT). They found NB to be the most efficient model with 97.36% of accuracy. A paper combined a GA with feed forward neural network and they used this combination of models for classification **[66]**. In **[67]**, the researchers studied the survival probabilities of breast cancer patients by using different survival analysis models. They used two different breast cancer datasets and proved their hypothesis. Some researchers showed that ML algorithms have improved the accuracy of classification models and prediction models by manifold. They reviewed many articles on the application of different ML algorithms for classification and prediction of breast cancer and then concluded **[68]**. In **[69]**, they proved that machine learning algorithms are capable of yielding almost 100% prediction accuracy when tested on the Wisconsin Diagnostic Breast Cancer dataset. Researchers in **[70]** studied the performance of breast cancer classification using KNN and NB classifiers. Model is trained using 683 samples of Breast Cancer Dataset. In the result, the reported a maximum accuracy of 97.51% which was achieved by KNN classifier. A two-stage architecture based deep model is trained in **[71]**. ResNet is used as a building block of the proposed architecture. Results suggest that the deep model successfully predicts the presence of cancer in the breast with AUC of 89.50%. A similar study based on deep learning and inspired from U-Net is done by authors of **[72]**. Extending the study of deep learning for breast cancer classification, in **[73]**, automatic and robust features are extracted using deep neural networks and trained using deep ensemble transfer learning. Authors have reported 88% classification accuracy with area under curve as 0.88. In the most recent work, a new CAD system is proposed which uses multi-DCNN to classify breast cancer **[74]**. The CBIS-DDSM and MIAS dataset is used for evaluation of the performance of deep models. Experimental results improvement of accuracy using deep feature fusion compared to state-of-the-art methods. In **[75]**, a deep neural network architecture is proposed to study breast cancer classification using histopathological images. Results suggest that among different numbers of layered architectures, 19-layer CNN performed well. A hybrid approach based on a combination of Graph convolutional network and convolutional neural network is proposed in **[76]**. Few more recent studies of breast cancer classification based on deep learning are available in **[77-80]**. **Table 2** depicts the few popular studies made in the last decade on breast cancer detection using deep learning and ML techniques. **Table 3** compares this study to other review papers being published in the last decade. **Table 4** describes the different modalities being taken as benchmark for researchers to study and implement ML/DL techniques on the appropriate data set. In **Table 5** we present how different ML/DL techniques have been used in analysis and classification of benign and malignant tumors of the breast.

In the past few decades, breast cancer classification gained the attention of many researchers. Many novel methods and techniques are proposed. Few researchers summarized the methodologies and published it as a survey. **Table 3** presents a few important surveys available in the literature (index value 2 to 7) and compares it with our study. From the **Table 3**, it can be noticed that our survey presents an extensive study and includes almost all machine learning techniques which are being used for classification of breast cancer. Our study can be uniquely distinguished from the indexed survey based on the study of Indian and Asian Demographics.

Table 2: Comparison of different BCD techniques in literature using different ML and DL Algorithms

Reference	Techniques/Methods used	Area	Result
[83]	Applied different classification techniques on BCW dataset for detection of breast cancer.	MLP, using back propagation , NN (MLP BPN) and SVM to diagnose and analyze breast cancer and performance is evaluated by calculating statistical parameters.	SVM is found to produce the lowest average error compared to MLPBPN.
[42]	ANN, GA, DT, LDA, and KNN have been applied.	Diagnosis and detection of breast cancer using different modalities include physical examination, biopsy and imaging	Texture analysis is a tested methodology that may be efficiently employed for classification of noncancerous and cancerous lesions with Sensitivity-94.28%, Specificity-100%, Accuracy-97.80%, AU-ROC-0.9714.
[57]	Comparative study is done for different ML/DL techniques like DT, NB, NN and SVM	Objective is to classify the labels in WPBC and WBC datasets	NN - 98.09% in WBC dataset, and SVM-RBF - 98.32% in WPBC dataset using 10 fold cross validation.(cv=10)
[46]	MGSA and SVM	Goal is to classify breast cancer as per given labels using machine learning techniques.	Outcome: SVM with 24 features - 86% MGSA – SVM with 12 features- 93.1%.
[47]	CAD	Normal and abnormal breast tissues differentiation for visual diagnostic aid of the radiologists.	Maximum accuracy of 96% if found using 3NN.
[62]	Breast cancer is detected using the "Relevance vector machine "(RVM).	LDA was used as a dimensional reduction method and feed the reduced features into the classifier	The "Relevance vector machine" outperforms other 'ML classifiers' in classifying the labels appropriately.
[60]	Use Cases of Invasive ductal carcinoma in the subjects on the basis of vital features as predicted by ML techniques	WPBC	SVM and DT (C 5.0) - 81% (highest) FCM 37% (lowest)
[44]	SVM, Bayes approach and DT	Distinguish cancer mammograms from normal samples.. Dataset is broken down into a train, test and validation sets and the model is subjected to training, taking cv=10.	NPR, FPR and AUC were measured. From the results it is observed that different feature extracting strategies and classifiers yield different and effective results to detect breast cancer in the given dataset.
[51]	Naïve Bayes, SVC classifier, RF, C4.5, k-NN and NN	Aim is to classify breast cancer where different ML /DL techniques are compared for the Wisconsin dataset and reported.	SVM and RF produced highest classification accuracy
[52]	SVM, GRU-SVM, LR, MLP, NN search and Softmax Regression	WDBC dataset is being used for experimentation	From the result it is noticed that MLP reports significantly higher accuracy when compared to other models.
[70]	NB and KNN are used as classification technique for breast carcinoma detection,	Identification using ML techniques. A set of Breast Cancer Image Dataset is used which consists of a total of 683 samples. Dataset is broken down into training and test	Highest accuracy is achieved by K-NN - 97.51% while Naive Bayes classifier produced 96.19% accuracy

		sets in a 60:40 ratio.	
[72]	As in, U-Net, a DL framework is proposed for initial detection of breast carcinoma and performance is compared with architectures like AlexNet, VGGNet and GoogleNet	CBIS-DDSM is used to train the deep model which contains 'Curated Breast Imaging Subsets'.	Classification accuracy: Micro calcification – 94.31% Masses- 95.01%
[55]	Two-layered nested ensemble technique is used along with SV-NaiveBayes-3-MetaClassifier and SV-BayesNet-3- Meta Classifier and compared with Bayesian Network, NB, SGD and Logistic model tree	Invasive Ductal Carcinoma was detected using ensemble techniques. Dataset being used is WBCD.	Among all other classifiers, the proposed SV-Naïve Bayes-3-MetaClassifiers generated highest accuracy – 98.07%
[71]	A DNN based on a two stage framework is proposed where ResNet is used as a building block of the model.	Diagnostic aid for breast cancer detection:Performance of the model is examined over two million exams having 10 million image samples ,thereby a large validation set.	The result shows that the model is capable to predict the presence of breast carcinoma with an AUC of 89.50%
[73]	Deep ensemble transfer learning approach is used to distinguish cancerous and noncancerous lesions using features extracted by DNN.	Classification of cancerous and non-cancerous lesions. The CBIS-DDSM dataset is used for experiments.	The classification accuracy achieved is 88% with AUC value as 0.88
[74]	A new CAD system is proposed which uses multi-DCNN to classify breast carcinoma. Deep feature fusion is also performed and SVM is used as a classifier.	Uses deep convolutional neural networks' for classification. The CBIS-DDSM and MIAS dataset is used for evaluation of the performance of deep models.	Result suggests an improvement of accuracy using deep feature fusion compared to traditional methods.
[75]	A DNN architecture is proposed to study breast cancer classification using histopathological images.	'Histopathological biopsy images' are used for breast cancer detection. AMIDA13 and MITOS-ATYPIA dataset is used to train deep models.	Results suggest that among different numbers of layered architectures, 19-layer CNN performed better.
[76]	A hybrid approach based on amalgamation of Graph based CNN(GCN) and conventional CNN is proposed.	The malignancy is classified using DL. The model is experimented on breast dataset mini-MIAS.	Statistical parameters are reported as follows: Sensitivity – 96.20% Specificity – 96% Accuracy – 96.10%

Table 3: Comparison of our survey along with other popular surveys

Models / Sl. No		1	2	3	4	5	6	7
Machine learning models	SVM	✓		✓	✓	✓	✓	✓
	Decision Trees	✓				✓	✓	✓
	K-NN	✓	✓	✓				
	Logistics Regression	✓	✓	✓				
	NB	✓	✓					
	Artificial				✓		✓	✓

	Neural Network (ANN)	✓						
Methods / data set	**Gaussian kernel**		✓					
	Wisconsin dataset	✓		✓	✓	✓	✓	
Indian and Asian demographics		✓						

Table 4: A table with reference of different testing modalities and their performance studied in different papers

Modalities	References
Mammography	**[18], [19], [20], [21], [22], [23]**
Ultrasonography	**[24], [25], [26], [27], [28], [29], [30]**
MRI	**[31], [32], [33], [34]**
Biopsy histopathological images	**[35], [36], [37]**

Table 5: Popular Machine learning techniques used for Breast cancer diagnosis in various researches

Machine Learning Models	References
Support vector machine (SVM)	**[44], [46], [50], [51], [52], [53], [54], [60], [61], [68]**
Decision Trees	**[50], [53], [57], [60], [65], [68]**
K Nearest Neighbors (KNN)	**[48], [49], [50], [58]**
Logistics Regression	**[49]**
Naïve Bayes	**[49], [51], [58], [63], [65]**
Artificial Neural Network (ANN)	**[53], [54], [59], [67], [68]**

3. Research Gap

Compared to traditional image processing methods, application of machine learning and deep learning in the field of breast cancer classification has drastically improved classification accuracy. In the last few decades, a number of researches have been done **[81, 82]**. Few authors well summarized the recent trends in this particular domain which are available in the literature **[4], [40]**. However, there are few points which still need to be investigated. In this study, we tried to bridge this gap by including most popular and recent work done on breast cancer classification using machine learning and deep learning techniques. We also discussed different stages of CAD systems in detail. In addition to that, we highlighted different testing modalities viz. Mammography **[19,**

20], Ultrasonography **[24-28]**, Biopsy histopathological images **[35-37]** and MRI **[31-34]** and their performances along with limitations. Finally, we focused on Breast cancer trends in Indian and Asian demographics. This study discusses different types of machine learning techniques and also reports which algorithm works well with different databases. We believe that this study will help beginners to understand the past researches and recent trends in the field of breast cancer classification and will help them to decide use of appropriate algorithms for their research work. We also present a list of dataset in **Table 6** along with sources and the modality being used in the dataset and what research can be undertaken on those set of data. Some of the areas of research which can be explored in this area are as under:

1. Using Transfer learning techniques on histopathological images.
2. Use of Knowledge distillation and semi-supervised techniques on available histopathological biopsy images and they can be validated against images checked by medical experts.
3. Use of Active Learning to train the available datasets obtained through different modalities like Mammogram, MRI, and Biopsy etc.

Table 6: A comprehensive overview of some publicly available datasets in the area of Breast Cancer Research and open areas of research

Available Data Set	Modality	Source	Scope of Research
WBCD	**Numerical values of cell nuclei extracted from FNAB histopathological images of the breast.**	**UCL Machine Learning repository, Kaggle**	**Exploratory analysis, Application of new ML/DL techniques, Feature Extraction techniques like PCA, LDA and Factor Analysis**
Breast Histopathological Images	**Histopathological biopsy to detect invasive ductal carcinoma**	**https://www.kaggle.com/paultimothymooney/breast-histopathology-images**	**Feature Extraction, Feature matching Classification, Knowledge distillation, Transfer Learning, CNN, Big Data Analysis of image**
MIAS Mammography	**Mammogram**	**https://www.kaggle.com/kmader/mias-mammography**	**Segmentation, Finding ROI, Implement object detection using mask R CNN, Yolo V4, Feature Extraction, Classification**
CBIS DDSM	**Mammograms**	**http://www.eng.usf.edu/cvprg/Mammography/Database.html**	**Segmentation, Finding ROI, Implement object detection using mask R CNN, Yolo V4, Feature Extraction, Classification,**

			RNN, GAN, Big data Analysis
BACH 2018	**Histopathology biopsy**	**https://iciar2018-challenge.grand-challenge.org/Dataset/**	**semi supervised KD,GAN, Big Data Analysis, Auto encoders, GAN, Multi label classification**
SEER Breast Cancer Dataset	**Numerical attributes being extracted from patient EMR**	**IEEE data port**	**Exploratory data analysis, Implementing Statistical methods to BCD for meaningful insights.**
Breast Ultrasound Images	**USG of the breast**	**https://www.kaggle.com/aryashah2k/breast-ultrasound-images-dataset**	**Segmentation, Detection and Classification**

CONCLUSION

Going by the statistics, the emerging trends and increased breast cancer rate in India as well as other parts of the world, the study of breast cancer has become the need of the hour though getting appropriate data for research remains a challenge. The socio-economic conditions vary across the world and radiologists are often not 100 percent accurate in diagnosing breast cancer. As such the use of CAD systems can be a great tool to assist radiologists and ascertain their predictions. The major aim of this study is to highlight all research conducted on ML and DL techniques for prediction of breast cancer. This article will help the beginner who wishes to explore the machine learning algorithms for classification problems and their performance on different breast cancer testing modalities. In this thorough review, the performance of different ML/DL techniques are assessed and compared. From the result it has been found that the efficiency of the CAD system can be improved significantly with the application of proper algorithms which can in turn enhance radiologists' performance. We have talked about the different options available as far as dataset is concerned and what kind of dataset can yield what results. We observed that the machine learning methods have demonstrated its exceptional capacity to classify and predict cancer cells with significant improvement in accuracy using computer- vision techniques.

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