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REVIEW ARTICLE

A Systematic Review on Breast Cancer Detection Using Deep Learning Techniques

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Abstract

Breast cancer is a common health problem in women, with one out of eight women dying from breast cancer. Many women ignore the need for breast cancer diagnosis as the treatment is not secure due to the exposure of radioactive rays. The breast cancer screening techniques suffer from non-invasive, unsafe radiations, and specificity of diagnosis of tumor in the breast. The deep learning techniques are widely used in medical imaging. This paper aims to provide a detailed survey dealing with the screening techniques for breast cancer with pros and cons. The applicability of deep learning techniques in breast cancer detection is studied. The performance measures and datasets for breast cancer are also investigated. The future research directions associated with breast cancer are studied. The primary aim is to provide a comprehensive study in this field and to help motivate the innovative researchers.

1 Introduction

Breast cancer is categorized among the most frequently reported cancers in the World. It has been reported in both males and females. However, its frequency with females is far beyond the comparison. In 2018, it is estimated that 6,27,000 women died due to breast cancer, which is approximately 15% of all cancer deaths among women [1, 2]. The early detection of breast cancer may help the patient to be recovered in time. However, it is advisable not to go for frequent breast cancer screening due to lack of convenience and discomfort with traditional examinations such as mammograms. It is reported in literature that 2,68,600 females suffered from breast cancer out of 2,71,270 cases. Breast cancer alone accounts for 30% of all new cancer diagnoses in women. The estimated number of deaths in both cases is 42,260. However, the death rate (number of deaths) of women (i.e., 41,760) is much higher than men (i.e., 500). The early screening and treatment of this cancer can be helpful to decrease the mortality rate.

According to National Centre for Disease Informatics and Research (NCDIR), the estimated breast cancer cases and mortality in females in India are shown in Fig. 1. It is observed from Fig. 1 that the estimated number of breast cancer cases in 2016 was 1,56,423 and increased to 1,78,361 in 2020. The estimated number of deaths in 2016 was 80,973. 90,408 women died due to breast cancer in 2020. Figure 2 shows the number of new cancer cases in India in 2020. According to National Agency for Research on Cancer, the number of new breast cancer cases is 1,78,361, which is approximately 26% of all cancer-related cases registered in 2020.

Male breast cancer represents 1% only of all breast cancer cases [4]. The frequency of breast cancer in transgender individuals, as well as the impact of gender-affirming hormonal treatment (GAHT) on the risk of breast cancer, remains largely unexplored. It is less clear however, what risk breast cancer poses to the transgender individual and how, if at all, physicians should screen these patients. Reports of transgender men breast cancer have been mentioned in the medical literature [5]. Number on the incidences of breast cancer in trans women receiving GAHT remains vague. As of 2018, two population-based studies assessed the breast cancer risk attributable to GAHT. Both studies were limited by small number of breast cancer cases and a lack of genetic risk stratification [6, 7]. In the trans man case, ductal carcinoma in-situ (DCIS) was diagnosed in the course of chest reconstruction surgery. To maintain masculinization,

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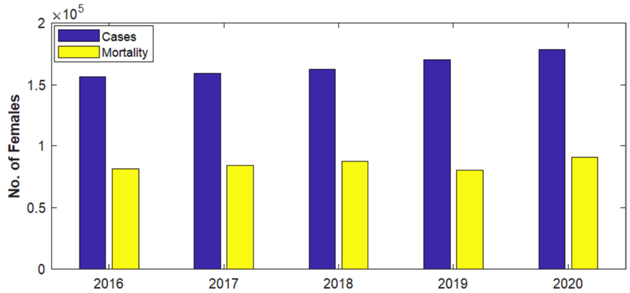


Fig. 1 Breast cancer cases and mortality in females in India [3]

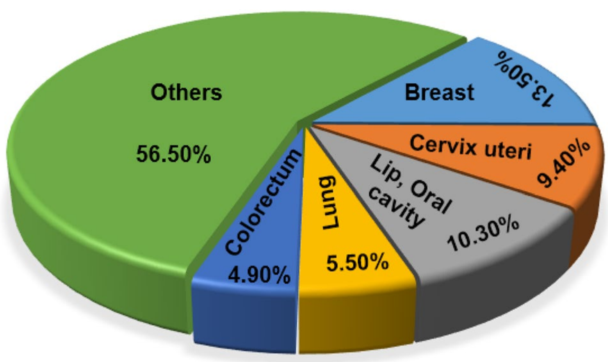


Fig. 2 Number of new cases of cancer found in India during 2020

low dose transdermal application of testosterone may be applied as these doses may minimize the amount of circulating testosterone and thus avoid unnecessary aromatization to estradiol [8]. In [7], authors suggested the risk of breast cancer in transgender people is lower than cisgender women, however, it is comparable to the risk in cisgender men. They also concluded that the overall risk of breast cancer in transgender people remains low. Therefore, it seems sufficient for transgender people using hormone treatment to follow screening guidelines as for cisgender people. Table 1 shows the cancer data statistics 2020 for India. This data is obtained from National Centre for Disease Informatics and Research (NCDIR). According to the data, Breast Cancer is amongst the top 5 most frequent cancers in India.

Normally, patients with breast tumors undergo multiple different examinations including B-ultrasonography, Mammography, Computed Tomography (CT), and Nuclear Magnetic Resonance Imaging (MRI) [9]. Mammography is the main method used for screening breast cancer. Mammography is the only imaging test that reduces breast cancer mortality [10–12]. Mammogram does not prevent cancer. However, the early detection of cancer can be possible through mammography [13]. The sensitivity of mammography is estimated between the range of 77% and 95%. The specificity estimated through the mammography lies in the range of 92% to 97% [14]. However, mammography is suboptimal in breasts with dense tissue [15]. Due to this, approximately 38% of tumors are missed or misdiagnosed [16]. Another drawback of mammography is subject discomfort and radiation exposure. The interpretation of mammograms is a time-consuming and error-prone task [17].

1.1 Motivation

From the literature, it is observed that while substantial strides have been made, the prevalence of cancer tends to increase. For women globally, breast cancer is the most prevalent disease. A woman's chance of breast cancer today is one in eight [18]. Altering is a co-morbidity of breast cancer that can promote the development of breast cancer due to aging-related transcriptome changes [19, 20]. However, the age of females diagnosed with cancer is shifting from +50 years of age to 40 years of age or less [21]. Early identification of breast cancer improves prognoses according to the World Health Organization (WHO) [22]. Mammography is the main method for breast cancer detection. The sensitivity of mammography decreases with increase in thickness of breast [23, 24]. Hence, it is important to understand breast cancer detection techniques so that the

Table 1 Statistics of Cancer Data in India during 2020

	Male	Female	Total
Population	717,100,976	662,903,415	1,380,004,378
Number of cancer cases	646,030	678,383	1,324,413
Number of cancer deaths	438,297	413,381	851,678
Age-standardized incidence rate (World)	95.7	99.3	97.1
Age-standardized mortality rate (World)	65.4	61	63.1
5-year prevalent cases	1,208,835	1,511,416	2,720,251
Top 5 most frequent cancers excluding non-melanoma skin cancer (ranked by cases)	Lip, oral cavity Lung Stomach, Colorectum, Oesophagus	Breast Cervix uteri Ovary, oral cavity Colorectum	Breast Lip, oral cavity Cervix uteri Lung Colorectum

quality of diagnosis can be improved for good in upcoming years. The following factors are motivated us to perform this research:

(1) The first factor is the analysis of different types of screening techniques. Various type of screening techniques has a different representation of the targeted area. They have their own pros and cons. This fact motivated us to study the properties of different types of breast cancer screening techniques so that appropriate screening techniques can be selected for breast cancer detection.
(2) The use of deep learning techniques in the identification of breast cancer is another factor. In medical research, deep learning techniques are commonly used. We are studying and analyzing these strategies for breast cancer detection because of the development of novel optimization functions and techniques.
(3) Different types of evaluation parameters are used to validate breast cancer detection techniques. The nature of evaluation measures varies from one to the next. The new technique may perform better on some parameters while performs poorly on others. This feature motivates us to investigate the effectiveness of breast cancer detection evaluation measures.

1.2 Contribution

This paper focuses on the study of breast cancer screening techniques with their pros and cons. This study discusses mainly:

(1) Theoretical aspects of breast cancer for females, males, transgenders including deep learning implementations for the detection of breast cancer.
(2) The different breast cancer screening approaches/techniques, risk factors, target connection, and common datasets.
(3) The mathematical representations of performance evaluation measures
(4) The comparative analysis of deep learning-based breast cancer prediction techniques in terms of performance measures.
(5) The possible future research directions for breast cancer detection

To the best of our knowledge, no review of breast cancer detection involving all of the above mentioned contributions has been reported so far. This study provides a thorough review of the published literature on breast cancer detection screening methods and techniques. Undoubtedly, this study is going to be beneficial for young researchers. Figure 3 depicts the layout of this paper.

The remaining structure of this paper is as follows. Section 2 presents the research methodology used in this study. The datasets for breast cancer detection are discussed in Sect. 3. Section 4 deliberates the performance evaluation measures. Section 5 presents the brest cancer screening techniques. The deep learning techniques for breast cancer detection are mentioned in Sect. 6. Section 7 covers the discussion followed by future research directions in Sect. 8. The concluding remarks are drawn in Sect. 9.

2 Research Methodology

This section presents the survey papers related to breat cancer detection techniques followed by the papere selection and exculsion methodology used in this study.

2.1 Existing Surveys

In the recent past, several research papers were published to summarize the breast cancer detection techniques. The relevant survey papers are discussed as below:

Yassin et al. [25] presented the findings of a systematic review (SR) aimed at determining the current state-of-the-art for computer aided diagnosis and detection (CAD) systems for breast cancer. They provided a broad assessment of CAD systems for image modalities and machine learning-based classifiers. Prospective research studies to develop more objective and efficient CAD systems have been discussed. A brief review of various reported methods and systems for early breast cancer detection was presented by Gupta et al. [26]. A variety of microwave imaging approaches such as microwave tomography and radar-based imaging were investigated. Lu et al. [27] presented some diagnostic imaging methods for breast cancer diagnosis. The breast cancer detection using computer vision and machine learning techniques were investigated. The performance of various methods was analyzed on mammographic images. Huppe et al. [28] presented a comprehensive review on molecular breast imaging. Their research covered the current literature, indications, clinical application, biopsy approach, and MBI integration into medical practice. Oyelade et al. [29] analyzed various deep learning methods for the detection of architectural distortion from digital mammography. The main focus of their study was the detection of abnormalities such as masses and micro-calcification, which are indicators of the disease's advanced stage. Their study indicated that about 70% of the existing literature used Gabor Filters, while only 10% used survey results in computer vision and deep learning to build outstanding computational models for the detection of architectural distortion. Husaini et al. [30] studied the use of thermography and artificial

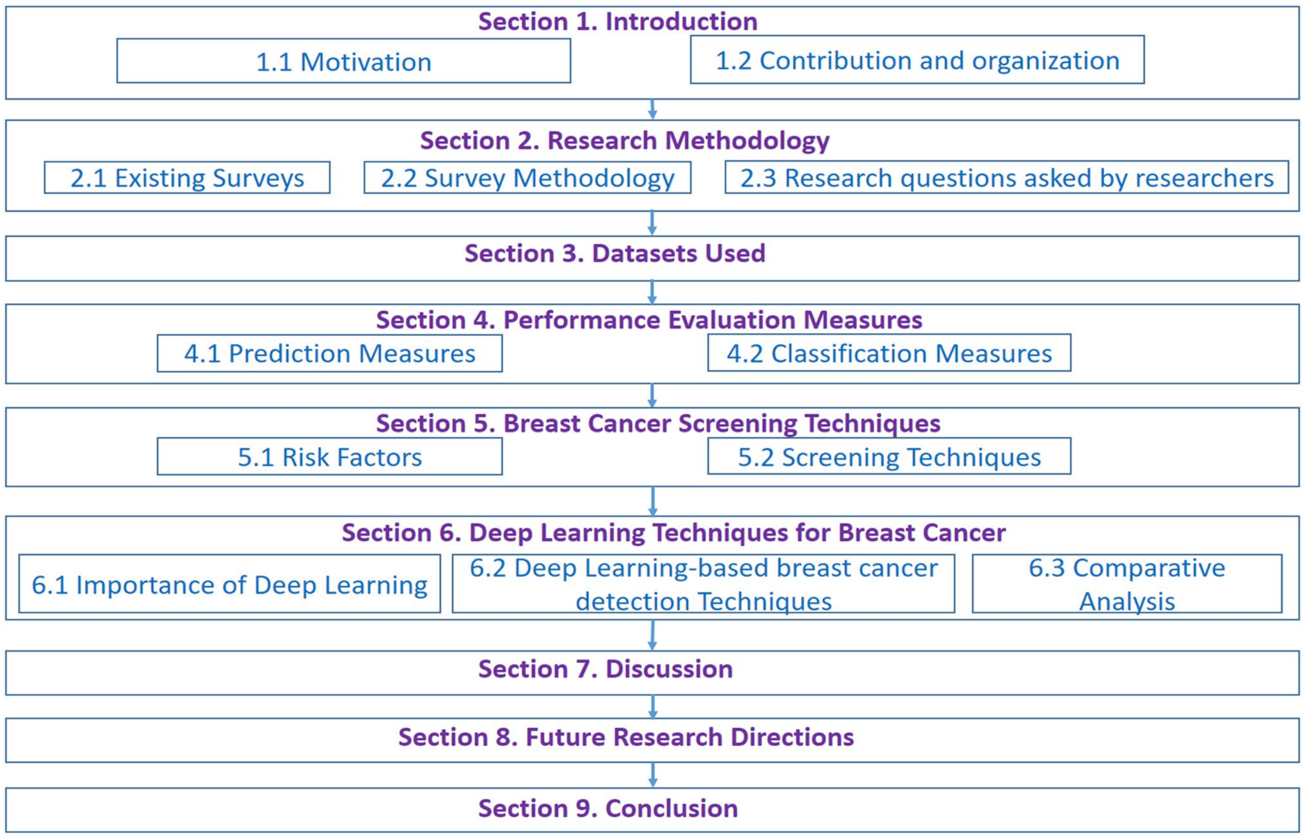


Fig. 3 Structure of paper

intelligence techniques for breast cancer detection. Various deep learning models such as Radial Basis Function Network (RBFN), K-Nearest Neighbors (KNN), Probability Neural Network (PNN), Support Vector Machine (SVM), ResNet50, SeResNet50, V Net, Bayes Net, Convolutional Neural Networks (CNN), Convolutional and De-Convolutional Neural Networks (C-DCNN), VGG-16, Hybrid (ResNet-50 and V-Net), ResNet101, DenseNet and InceptionV3 were analyzed to process thermographic images of breast cancer. Some research works discussed the breast cancer in transgender patients [5, 31]. The qualitative analysis was performed on patient demographics, breast cancer characteristics, breast cancer presentation and management. According to their study, breast cancer present in transgender men is mainly depends upon the top surger.

Due to advancement in deep learning techniques for medical imaging, a need was felt to prepare a survey of research articles summarizing the applications of deep learning techniques for breast cancer detection. Our survey presents the computational studies on breast cancer detection over the last decade, i.e., from 2000 to 2020. The main focus of this study is to investigate the existing breast cancer detection techniques using deep learning, risk factors associated with techniques, and open challenges associated with the existing techniques.

2.2 Survey Methodology

This study on breast cancer detection is conducted through PRISMA [32, 33]. The reason behind the use of PRISMA is that it helps enhance the delineation of CR. It provides the guidance to choose, recognize, and evaluate the studies.

Four different databases namely Google Scholar, Scopus, PubMed, and Preprint plateforms have been used for this study. Four preprint plateforms namely ArXiv, TechRxiv, MedRxiv, and ChemRxiv have been used to conduct the search for appropriate papers. The search string consists of “breast cancer” or “cancer” or “((deep learning) AND (breast cancer))” or “((machine learning) AND (breast cancer))” or “((Artificial Intelligence) AND (breast cancer) AND (detection techniques))” or “breast cancer detection techniques”. Figure 4 shows the search string used for

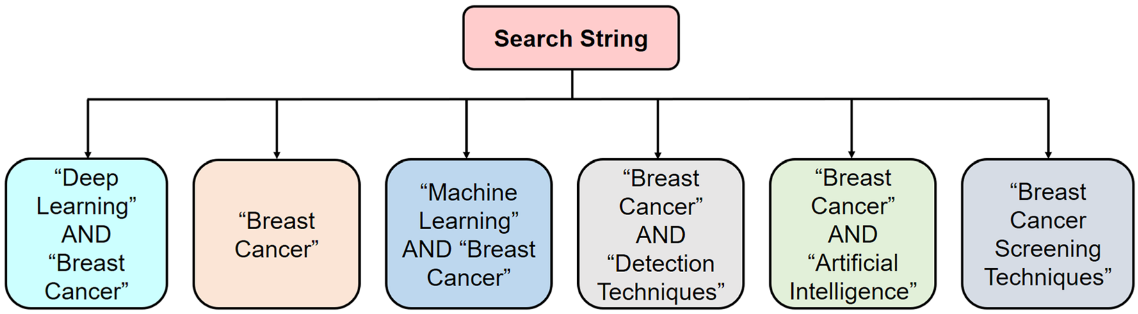


Fig. 4 Search string for searching the research articles

conducting the search. Manual search was also conducted to find out the relevant research papers. In the identification phase, a total of 1600 research publications were chosen.

In the screening phase, 900 research articles were selected after the removal of unsuitable, duplicate, and unrelevant research articles. 750 research articles were excluded after reading the title, abstract, and introduction. The remaining 150 research articles were analyzed through removal criteria and 90 research articles were excluded. Thereafter, 60 research articles were moved to the next phase. In eligibility phase, 30 research articles were eliminated after the evaluation of whole papers. Ultra wideband radar imaging [34], ensemble empirical mode decomposition by ultra-wide band [35], flexible 16 antenna array for microwave [1], Ion-Sensitive Field-Effect Transistor based CMOS integrated Lab-on-Chip system [36] are few related schemes other than deep learning, used for detection of breast cancer. The research articles on these techniques were also eliminated. 30 research articles were designated for review of breast cancer detection techniques. The selection and removal criteria for research articles are mentioned in Table 2. Figure 5 depicts the different phases of PRISMA for this review.

2.3 Research Questions Asked by Researchers

The primary goal of this review is to inspire the young researchers in this area. This paper addresses a number of breast cancer detection-related questionnaire, some of which are listed in Table 3. This will assist innovative researchers in grasping the fundamental concepts of breast cancer detection and determining the open challenges in this field.

Table 4 summarizes the comparsion between the existing surveys and the proposed one in terms of research questions. In this table, denotes that the survey has answered the respective research question, while indicates otherwise.

3 Datasets Used

A variety of datasets is required to develop the computational methods fro breast cancer detection. The datasets are varied in nature. Some datasets have small number of features and tuples. Wheras, some datasets have large number of features and tuples. Researchers use a variety of breast cancer databases for the development and evaluation of computational methods. Some datasets are open to the public and some are limited to specific categories. Table 5 shows the detail description of breast cancer datasets. Table 6 shows the dataset used by researchers in recent years.

Table 2 Selection and removal criteria for selection of research articles

S. no.	Parameter	Selection criteria	Removal criteria
1	Time duration	Research article published from 2010–2021	Research article published before 2010
2	Analysis	Research article including breast cancer detection	Research article including different cancer detection
3	Comparison	Research article focus on deep learning techniques used for breast cancer detection	Research article focus on other techniques used for breast cancer detection
4	Study	Research involving mathematical foundation and experimental results	Research involving case study and articles in different language other than English

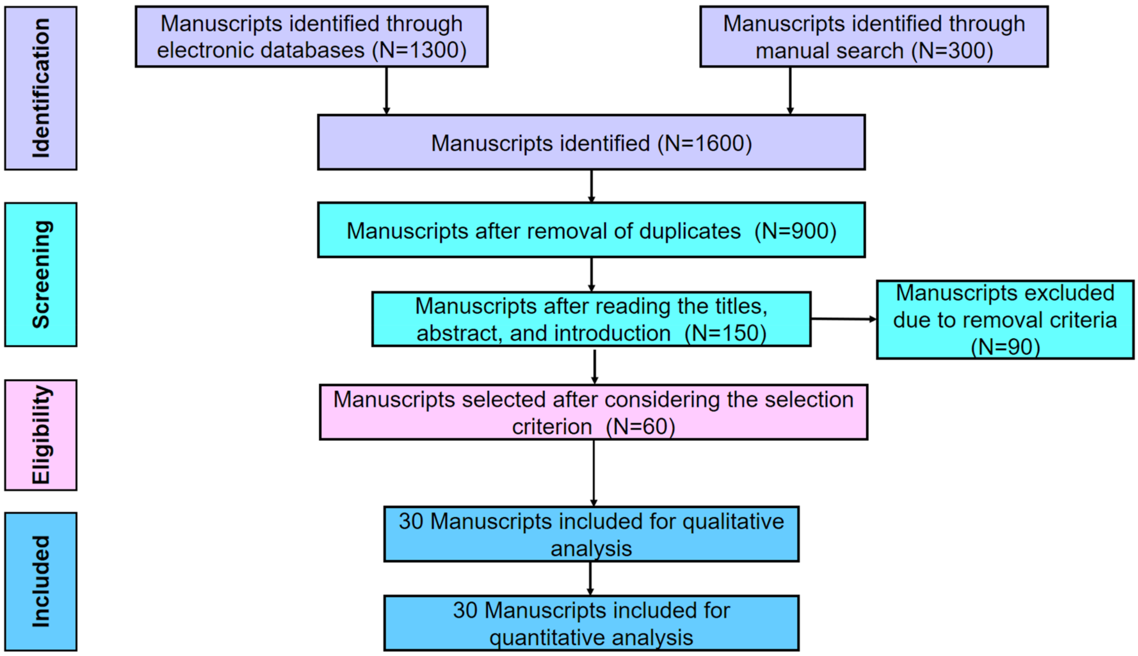


Fig. 5 PRISMA flow diagram on breast cancer review strategy

Table 3 Research questions related to breast cancer detection

Questions	Research questions
Q1	What is breast cancer?
Q2	Explain breast cancer in females, males, trans males, and trans females, along with detection techniques
Q3	What are the risk factors associated with breast cancer?
Q4	What are different types of screening methods involved in breast cancer detection?
Q5	What are different types of deep learning techniques in breast cancer detection?
Q6	What are the performance evaluation measures for validating deep learning based breast cancer detection techniques?
Q7	What are the challenges of breast cancer detection using deep learning?
Q8	What are the future research directions for breast cancer detection using deep learning?
Q9	What is the role of deep learning in breast cancer detection?
Q10	How breast cancer detection using deep learning is different from the other approaches?

Table 4 Comparative analysis of survey papers on breast cancer detection in terms of research questions

Survey	Review year	Research questions									
		Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
VYassin et al. [25]	2018	✓	✗	✗	✓	✓	✗	✗	✓	✗	✗
Gupta et al. [26]	2020	✓	✗	✗	✓	✗	✗	✗	✓	✗	✗
Lu et al. [27]	2018	✓	✗	✗	✓	✓	✓	✗	✗	✗	✗
Huppe et al. [28]	2017	✓	✗	✗	✓	✗	✗	✗	✗	✗	✗
Oyelade et al. [29]	2020	✓	✗	✗	✗	✓	✓	✓	✓	✗	✗
Husaini et al. [30]	2020	✓	✗	✗	✓	✓	✗	✓	✓		✓
Hartley et al. [31]	2018	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
Stone et al. [5]	2018	✓	✓	✗	✗	✗	✗	✗	✗	✗	✗
Proposed study	2021	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 5 Detail description of breast cancer datasets

Datasets	References	Description	Resource	Comment
Mammographic Image Analysis Society (MIAS)	[37]	The database is available on 2.3 GB 8 mm (Exabyte) tape and contains 322 digitized films. The database has been padded/clipped and reduced to a 200 micron pixel edge, resulting in images that are all 1024 × 1024	Available at the Pilot European Image Processing Archive (PEIPA) at the University of Essex	Improves logistical practice, allows for the use of computer-aided detection programs, and has a cancer detection rate comparable to that of the screen- lm mammography. It's unclear how this will affect recall rates
Digital Database for Screening Mammography (DDSM)	[38]	The database is now fully functional, with 2620 cases. This is a mix of benign without callback, benign, normal and cancer volumes that were specially selected and digitized for DDSM	The research com- munity has made extensive use of the DDSM. It is kept at the University of South Florida so that it can be accessed via the inter- net	
IN breast	[39]	The images were taken at the Breast Centre in CHSJ, Porto, between 2008 and 2010, with approval from both the Hospital's Ethics Committee and the National Committee for Data Protection	IN Breast dataset can be requested online at http://medicalresearch.inescporto.pt/breastresearch/index.php/GetINbreast Database	
US1	[40]	The data came from an expert didactic media le for breast screening specialists in 2001. The dataset contains 306 images with a mean image size of 377 × 396 pixels from various cases	To acquire this dataset, the user must purchase it from Prapavesis et al	Requires a skilled operator, the examination technique is not standardized, the interpretation criteria are variable, and micro calcifications are not detected
US2	[41]	This data was gathered in 2012 from the Parc Taul' Corporation's UDIAT Diagnostic Centre in Sabadell (Spain). The database contains 163 images from various women, with an average image size of 760 × 570 pixels	The breast lesions dataset is available on the internet (goo.gl/SJmoti) for research purposes	
Breast Ultrasound Dataset	[42]	Breast ultrasound images from women aged 25 to 75 years old were collected at the start of the study. This information was gathered at Baheya Hospital in 2018. The total number of female patients is 600. There are 780 images in the database, with an ordinary image size of 500 × 500 pixels	Publically Available at https://cholar.cu.edu.eg/?q=afahmy/page s/dataset [43]	

Table 5 (continued)

Datasets	References	Description	Resource	Comment
Reference Image Database to Evaluate Therapy Response (RIDER)	[44]	Data was gathered in order to reach an initial agreement on how to harmonize collection of data and analyze quantitative imaging techniques for assessing drug or radiation therapy response	Publically available at https://wiki.cancerimageingarchive.net/display/Public/RIDER+Breast + MRI	In women at increased risk, it is more sensitive and marginally less specific than mammography. No radiation necessitates intravenous contrast, which is time-consuming and inconvenient for some women, such as those who have a pacemaker, aneurysm clips, or claustrophobia
QIN Breast DCE-MRI	[45]	The breast DCE-MRI data set used for study was collected provisionally under a HIPAA (Health Insurance Portability and Accountability Act of 1996)-compliant, Approval From the institutional Board with the exemption of consent	Publically available at https://wiki.canceri magingarchive.net/display/Public/QIN + Breast + DCE-MRI	
DBT-TU-JU	[46]	There are 1100 Breast thermograms of 100 subjects in the DBT-TU-JU database. This research reflects the generation of ground truth images of the hotspot areas, whose presence in a breast thermograms indicates the presence of breast abnormality, due to the necessity of evaluating any breast abnormality detection system	Only patients and their physicians have access to private databases that are only accessible for internal purposes	Not harmful, non-invasive, time consuming, requires more work to be done, still in practice
DMR: Database For Mastology Research	[47]	Thermal and mammography images obtained by our research group are among the images available in this database. For a sample of 64 breasts, the accuracy was 100% (composed of 32 healthy and 32 unhealthy)	The images are stored in the Database for Research Mastology with Infrared Image-DMR-IR, accessible on the website http://visual.ic.u.br/dmi	

Table 6 Breast cancer datasets used by researchers in recent years

References	Year	Dataset									
		MIAS	DDSM	INbreast	US1	US2	BUSI	ABUS	DCE-MRI	DBT-TU-JU	DMR
[48]	2015	✘	✘	✘	✘	✘	✘	✘	✓	✘	✘
[49]	2016		✘	✘	✘	✘	✘	✘	✘	✘	✘
[47]	2017	✘	✘	✘	✘	✘	✓	✘	✘	✘	✘
[50]	2018	✘	✘	✘	✘	✘	✘	✘	✘	✘	✓
[41]	2018	✘	✘	✘	✓	✓	✘	✘	✘	✘	✘
[51]	2019	✘	✘	✘	✘	✘	✘	✘	✘	✘	✓
[52]	2019	✘	✘	✘	✘	✘	✘	✘	✘	✓	✘
[53]	2020	✘	✓	✓	✘	✘	✘	✘	✘	✘	✘
[54]	2020	✘	✘	✘	✘	✘	✘	✓	✘	✘	✘
[55]	2020	✘	✓	✓	✘	✘	✘	✘	✘	✘	✘

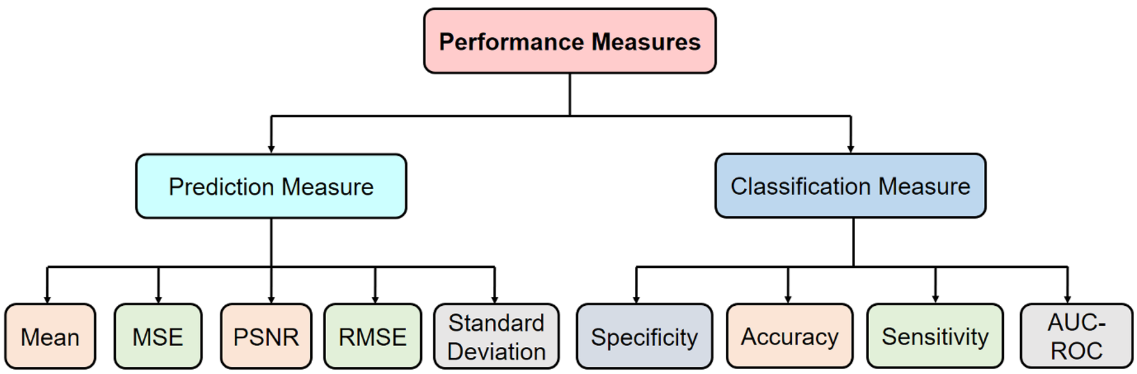


Fig. 6 Classification of performance measures

4 Performance Evaluation Measures

Different performance measures are used to evaluate the performance of breast cancer prediction models. The performance measures are generally claasified into two main categories namely, prediction and classification measures [56]. Figure 6 shows the classification of performance measures.

4.1 Prediction Measures

Mean, standard deviation, mean square error (MSE), root mean square error (RMSE), and peak signal to noise ratio (PSNR) are the well-known prediction measures. The mathematical formulation of these measures is given in succeeding subsections.

4.1.1 Mean (μ)

Mean represents the average brightness of an image. If the average intensity of a breast cancer image is much high, then the density of tissue is also high. The mathematical formulation of mean (μ) is defined as [57]:

$$\mu = \frac{1}{mn} \sum_{a=1}^{m} \sum_{b=1}^{n} pA(a,b), \tag{1}$$

where m and n signify the number of rows and columns in an image. pA is the coefficient of approximation. The value of mean should be high for better results [57].

4.1.2 Standard Deviation (σ)

Standard deviation (σ) can be described as a measure of how much the contrast intensity increases when the texture irregularity increases [58]. It is defined as:

$$\sigma = \sqrt{\frac{1}{mn}\sum_{a=1}^{m}\sum_{b=1}^{n}(pA(a,b) - \mu)^2} \tag{2}$$

4.1.3 Mean Square Error

The differential between observed and predicted values is measured using the mean square error (*MSE*) [59]. The mathematical formulation of *MSE* is given below:

$$MSE = \frac{1}{mn}\sum_{a=1}^{m}\sum_{b=1}^{n}(I_o - I_p)^2, \tag{3}$$

where I_o and I_p denote the observed and predicted values, respectively.

4.1.4 Root Mean Square Error

The square root of second moment of difference between the observed and predicted values is known as root mean square error (*RMSE*) [60]. It can be defined as the standard deviation of prediction errors.

$$RMSE = \sqrt{\frac{1}{mn}\sum_{a=1}^{m}\sum_{b=1}^{n}(I_o - I_p)^2} \tag{4}$$

RMSE is a reliable indicator of the accuracy obtained from the prediction model. *RMSE* has a non-negative value at all times. It is proportional to the scale. It is sensitive towards the outliers.

4.1.5 Peak Signal to Noise Ratio

Peak signal-to-noise ratio (PSNR) is the ratio of an image's maximum achievable power to the power of degrading noise that influences its representation quality [61].

$$PSNR = 10\log_{10}\frac{(l-1)^2}{MSE}, \tag{5}$$

where l is the number of highest allowable intensity levels in an image.

4.2 Classification Measures

The performance of breast cancer prediction model is evaluated by using classification measures. These measures are positive predictive value, sensitivity, accuracy, specificity, and area under receiver operating characteristics. The mathematical formulation of these measures is mentioned in the succeeding subsections.

4.2.1 Positive Predictive Value (PPV)

Positive predictive value (PPV) is the fraction of suitable instances among the recovered instances [62]. It is also known as Precision and is defined as [62]:

$$PPV = \frac{TP}{TP + FP}, \tag{6}$$

where TP is the number of true positives and FP is the number of false positives, respectively. The true positives are the positive tuples that the prediction model accurately predicts. The false positives are the negative tuples that the model predicts incorrectly. The value of PPV lies in the range of [0, 1].

4.2.2 Sensitivity

Sensitivity (S_n) is a metric for assessing the efficacy of breast cancer detection prediction models. S_n is also known as the rate of recognition [62]. It specifies the percentage of positive tuples that the prediction model successfully predicts.

$$S_n = \frac{TP}{TP + FN}, \tag{7}$$

where FN shows the number of false negatives. The false negatives are the positive tuples that the prediction model predicts incorrectly.

4.2.3 Accuracy

The percentage difference of projected synergy scores from observed results within the allowable error range is called accuracy [62]. It is defined as:

$$A_c = \frac{(TP + TN)}{(TP + TN + FN + FP)} \times 100, \tag{8}$$

where TN represents the number of true negatives. The term "true negative" refers to negative tuples that the prediction model accurately predicts.

4.2.4 Specificity

True negative rate is used to describe the specificity. It refers to the percentage of negative tuples properly predicted by the prediction model [63].

$$S_f = \frac{TN}{TN + FP} \tag{9}$$

4.2.5 Area Under Receiver Operating Characteristics Curve

Receiver Operating Characteristic (ROC) represents the trade-off between true positive rate (TP_r) and false positive rate (FP_r) [63]. The false positive rate and true positive rate are represented by the x-axis and y-axis of ROC curve, respectively. The area under ROC curve (AUC-ROC) is a metric for computing the model accuracy. The value of AUC-ROC lies in the ranges of [0.5, 1].

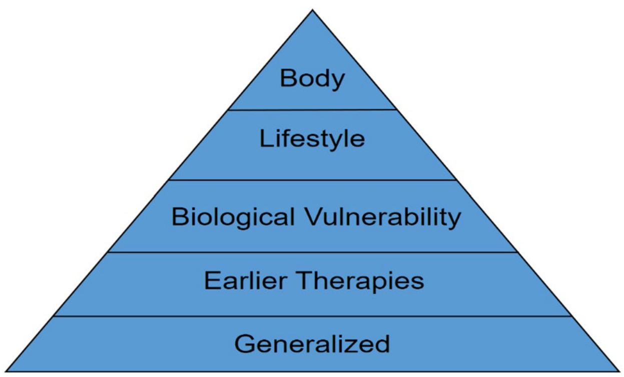


Fig. 7 Risk factors associated with breast cancer

$$TP_r = \frac{TP}{TP + FN} \tag{10}$$

$$FP_r = \frac{FP}{FP + TN} \tag{11}$$

5 Breast Cancer Screening Techniques

This section discusses the risk factor associated with breast cancer followed by the breast cancer screening techniques.

5.1 Risk Factor Associated with Breast Cancer

According to the American Cancer Society, many factors are responsible for enhancing the likelihood of breast cancer [7]. Figure 7 depicts the risk factor associated with breast cancer. The well-known risk factors are age, family history, reproductive factors, earlier therapies, and lifestyle. The detail description of these factors is mentioned in Table 7.

5.2 Screening Techniques

Breast cancer awareness provides help to the affected people so that they can take better decisions about their health.

Table 7 Description of risk factors related to breast cancer

Risk factor	Factor	Explanation
Generalized	Gender	Being a female is perhaps the most critical risk factors for breast cancer growth
	Age	The risk of breast cancer rises as the woman grows older
	Race	Pretty much across the globe, white women tend to get breast cancer marginally more often than African-American women
Body	Menstrual history	The risk of breast cancer is marginally higher among women who start menstruation early (before age 12) and/or menopause early (after the age 55). This rise in risk may have been caused by the progesterone and estrogen hormones being released longer in life
	High breast density	Dense breast tissue means more tissue and less tissue is contained in the gland. The risk of breast cancer is higher for women with denser breast tissue
	Not having offspring	Females who do not have babies or who were later pregnant might be more likely to develop breast cancer. Breastfeeding may contribute to reducing your risk of breast cancer
	Weight	Fat tissue can increase estrogen after menopause, and high estrogen levels can increase the risk of breast cancer. Adult weight gain and excess corporeal fat may also be significant around the waist
Lifestyle	Inactive Lifestyle	Breast cancer risk reduction is helped by physical activity
	Alcohol	Increased risk of breast cancer is associated with consumption of alcohol. With alcohol consumed, the risk increases
Earlier therapies	Therapy with DES	The risk of breast cancer is marginally higher for women who have been given DES (diethylstilbestrol) in the course of pregnancy
	Hormone treatment after menopause	The risk of breast cancer is raised by the use of estrogen and progesterone during menopause
Biological vulnerability	Family Background	A mother, sister or daughter who experiences breast cancer may increase the risk
	Ancestral Factor	Hereditary modifications (genetic changes) may increase risk in certain genes, such as BReast CAncer gene (BRCA) 1 and 2

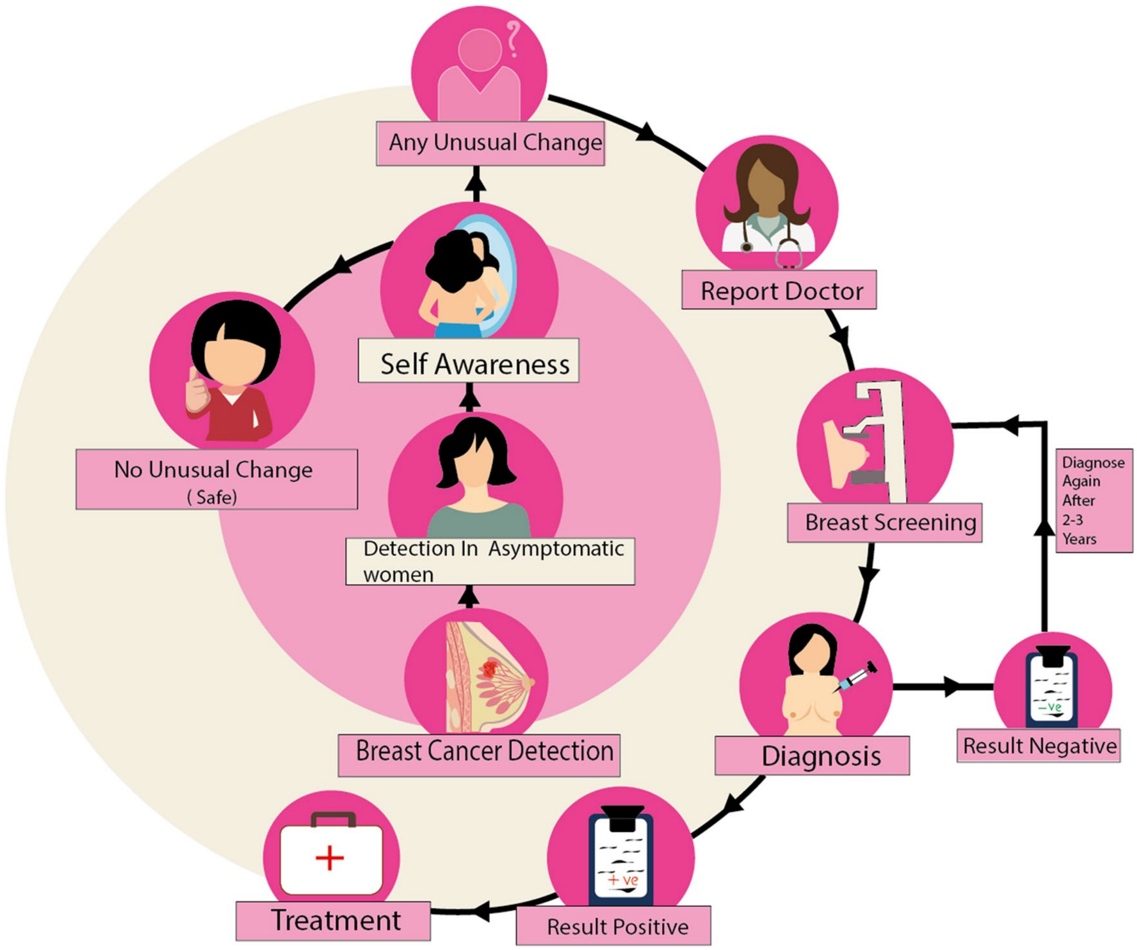


Fig. 8 Breast Cancer detection for asymptomatic women

Hormonal changes, genetics, breast density, and lifestyle are greatly affected the appearance of breasts. Understanding the morphology and physiology of usual breast tissue is an essential for predicting the any development of breast cancer and may aid in the early diagnosis of abnormal lesions. Figure 8 shows breast cancer detection in asymptomatic females.

Breast cancer diagnosis entails a variety of screening techniques to improve the accuracy of diagnosis. The well-known breast cancer screening techniques are X-ray mammography, breast ultrasound, Magnetic Resonance Imaging (MRI), and Positron Emission Mammography (PEM) [8]. X-ray mammography is the most effective technique. Breast Ultrasound uses sound waves to create a picture of tissues inside the breast. However, this technique suffers from low specificity, high cost, and a lack of availability [23]. The accuracy of breast ultrasound is approximately 67.8%. MRI is the another technique for breast cancer detection. It creates detailed images of organs by combining a large magnet, radio waves, and a computer. This technique has a higher sensitivity, however, high cost and low specificity that can lead to overdiagnosis [23, 64, 65]. The accuracy obtained from MRI may lie in the range of 70% to 72%. PEM is an alternate method for breast cancer screening [66]. It has high specificity as compared to the other techniques. However, it suffers from low sensitivity and high radiation expose. Breast cancer screening techniques are broadly categorized into three main groups such as physical, electrical, and mechanical (see Fig. 9).

5.2.1 Physcial Screening Techniques

The well-known physical screening techniques are mammography, ultrasound, and MRI. The detail description of these techniques are given in the succeeding subsections.

5.2.1.1 Mammography Breast self-examination (BSE), Clinical breast examination (CBE), and mammography are commonly used screening techniques for breast cancer detection [67, 68]. Nowadays, digital mammograms are widely used for breast cancer detection. In digital mammogram, X-rays are replaced with solid-state detectors that

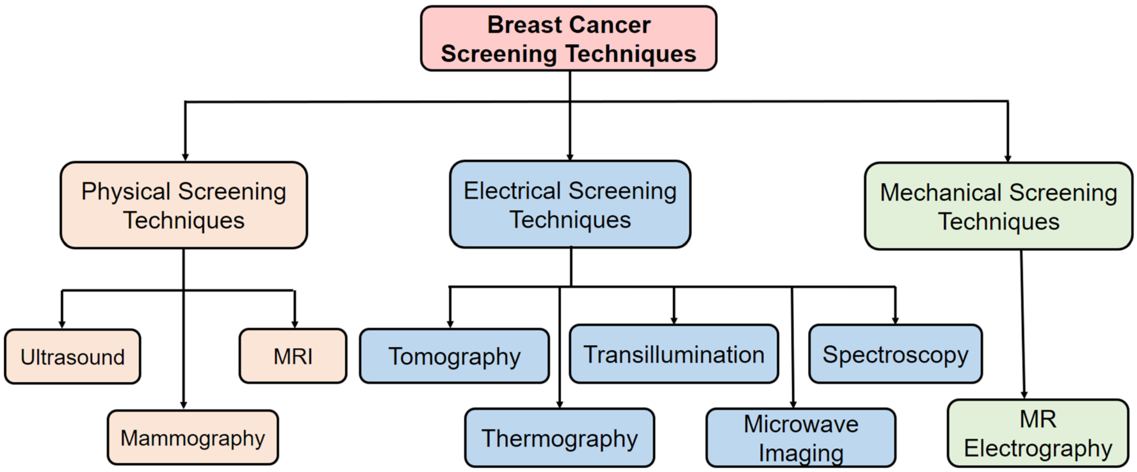


Fig. 9 Classification of breast screening techniques

translate X-rays into electrical signals. It is also known as full-field digital mammography (FFDM). The detectors in digital cameras are identical. Electrical impulses are used to create breast images and displayed on a computer screen [69]. Computer-aided detection (CAD) solutions are created to read mammographs. CAD systems usually interpret a mammogram and identify questionable places, which are investigated by the radiologist [70].

Ribli et al. [50] proposed a CAD program focused on Faster R-CNN. This program was able to classifiy malignant or benign tumors in a mammogram without user intervention. Wang et al. [53] proposed an end-to-end method for mammographic diagnosis. This approach eliminated the manual preprocessing. The treatment of mammograms was introduced in one situation with a different approach focused on Multiscale (MS) system and Multi-Instance (MI) system. MS module selects the basic features of mammograms and MI module took the general situation into account in one event. The output of these modules are combined to get the better results. Heidari et al. [71] introduced a new computer-aided diagnosis (CADx) scheme based on analysis of global mammographic image features. This research demonstrates the possibility to build a modern CADx mammogram high-performance global picture processing scheme. This technique is more effective and reliable than the previous techniques. Ekici et al. [51] utilized a convolution neural network (CNN) for thermographic breast cancer screening. They used five different processes namely, data acquisition, image processing, segmentation, extraction, and classification. CNN provides better results than the other techniques in terms of prediction results.

5.2.1.2 Ultrasound Breast ultrasound is a common way to test for breast cancer as it allows the screening sensitivity can be increased in thick breasts [72–74]. Wang et al. [54] developed an automatic breast cancer diagnosis of Automated Breast Ultrasound System (ABUS). They showed a lack of control for the existence of the adaptive barrier at voxel stages for cancer and non-cancer patients. The suggested network allows for an effective breast cancer screening scheme by utilizing ABUS with small false positives. Shen et al. [75] studied the comparative analysis of both mammography and breast ultrasound. It is observed that China's breasts appear to be tiny and compact. Ultrasound is a standard tool for screening the breast cancer in China. For clinical experiments, though, the efficacy and risks of mammograms were not measured. Nyayapathi et al. [76] introduced a new photoacoustic tomography device that displays angiographic features with mammogram-like images in the breast. The mechanism portrays a highly compact breast of two flat, 2.25 MHz transceiver clusters of 128 components, and line optical fiber bundles from top to bottom. The soft compression is done using silicone prints, which allows the woman more relaxed than hard metal plate used with conventional mammograms. Dual Scan Mammoscope (DSM) technology developed in this study acquired both ultrasound and photoacoustic breasts.

5.2.1.3 Magnetic Resonance Imaging Magnetic resonance imaging (MRI) plays a significant role in medical field. The scan in this method is used to produce detailed images of the inner body utilizing intense magnetic fields and radio waves [77]. MRI scans are being used to investigate nearly any area of the body including the brain, bones, breasts, heart, and even internal organs. MRI is widely used in breast cancer imaging. Sun et al. [78] identified glioma classification methods for the prediction of radiomics feature. MRI extracted quantitative features from tumor areas. The modality of extraction by radiomics was greater than the other combinations of tumor area.

Whereas, Li et al. [35] used ultra-wideband microwave imaging for early breast cancer detection. They also used an ensemble empirical mode decomposition (EEMD) for direct extraction of tumor. Only isolated signals from as-detected waveforms are required for the reconstruction of the picture for tumor detection. They used MRI to create more precise models for electromagnetic analysis. Here, a tumor of 4 mm in diameter within the glandular or at the interface between fat and the gland has been shown by the proposed procedure. In case the glandular tissue has a bigger dielectric constant of 35, tumor reaction may also be identified. Their research showed that the solution presented could serve as an important alternative to direct tumor response extraction. Mahrooghy et al. [48] suggested the spatiotemporal dynamic properties of wavelet from dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) to quantify breast cancer intra-tumor heterogeneity.

The receiver operating characteristic (ROC) and area under the curve (AUC) were computed to assess the performance of classifier using leave-one-out (LOO) cross-validation. The heatwave features outperformed the other features. The combination of heatwave and standard features can further enhance the performance of classifier [62]. Table 8 summarize the physical scrrening techniques for breast cancer.

5.2.2 Electrical Screening Techniques

Impedance spectroscopy, thermography, transillumination, microwave imaging, and tomography are the well-known electrical screening techniques. The detail description of these techniques are given in the succeeding subsections.

5.2.2.1 Impedance Spectroscopy Researchers are using this technique to improve breast cancer detection techniques. Haeri et al. [82] introduced two experimental breast cancer screening instruments namely, electrical impedance spectroscopy (EIS)-Probe and the EIS-Hand-Breast (EIS-HB). EIS-Probe and EISHB system were able to assess the electrical properties of breast tissue. Cancerous tissues were identified by determining the change in parameters of healthy tissues. Huerta-Nuñez et al. [83] utilized the bioimpedance spectroscopy to investigate the cancer cells in an aqueous media. Experimental results revealed that impedance spectroscopy has a sufficient sensitivity for identification of extraordinarily low cancer cell composition in an aqueous solution. Lederman et al. [84] designed a seven-probe resonance-frequency-based electrical impedance spectroscopy (REIS) system and used the data of 174 females. Artificial neural network (ANN), support vector machine (SVM), and Gaussian mixture model (GMM) were used. The results revealed that ANN attained the maximum values of ROC and AUC as compared to the other classifiers. REIS examinations provide the relevant information to build classifier for the stratification of breast cancer risk. Ward et al. [85] evaluated the inter-arm impedance ratio range for evaluating the value of threshold as a standard for detecting lymphedema associated with breast cancer. When an impedance of 1106 is surpassed by a danger to the neuronal limb and 1134 when the dominant limb is at danger, relative to those currently in use of 1066 and 1139, the existence of lymphedema is recorded. The variation in these values can be considered as the minor significance towards the clinical practice.

5.2.2.2 Thermography A special camera is used to measure skin temperature on the surface of the breast and is known as thermography. It is a non-invasive and radiation-free research [86]. Ekici et al. [51] developed an automatic breast cancer detection technique. They used image processing and analytics techniques to analyze the thermal images of breast. The feature extraction algorithm was proposed to extract the features for identification of breast images as regular or suspicious. Their technique attained the accuracy of 98.95% for the thermal images of 140 females. Jose-Luis et al. [87] proposed a technique to solve the inverse thermal transfer problem in the Levenberg Marquardt algorithm. This technique was used to identify and locate malignant tumors within the breast using a patient-specific digital breast model and clinical infrared imaging (IRI) images. Digital heat amplification systems were used to tackle the challenges occurred during the identification of size and position of malignant tumor within the breast. This technique can be combined with mammography to detect the breast cancer, especially in the case of dense breasts. In [52], the advancements in thermography-based techniques were investigated for breast cancer detection. It is observed from breast thermograms that breast cancer signs can be detected through the asymmetrical thermal spreads between breasts. Their study showed that the neural network systems enhanced the prediction accuracy of breast cancer thermograms. Mambou et al. [88] explored an infrared digital imaging techniques for breast cancer. The basic assumption in this technique is that the increase in thermal activity in the precancerous tissues and the areas surrounding developing breast cancer. They concluded that infrared image processing techniques require a CAD system for detection. Roslida et al. [76] studied the three convolutional neural network (CNN) models namely, ResNet101, DenseNet201, MobileNetV2, and ShuffleNetV2 for breast cancer detection. Database for Mastology Research (DMR) was used to evaluate the performance of above-mentioned models. DenseNet201 was capable to classify both static or dynamic images. Transillumination.

Transillumination is a procedure used in an organ or part of the body to detect anomalies. The examination is

Table 8 Classification of breast cancer detection using physical screening methods

References	Classification model	Performance measures	Challenges	Advantages
[50]	Pre-processing + Faster R-CNN + Regional proposal network	AUC = 0.85 lesion detection sensitivity = 90%	The detection performance could only be evaluated on the small INbreast dataset	Model reaches high sensitivity with very few false positive marks
[53]	Pre-processing and image cropping + CNN for feature selection + Multi-instance module + final diagnosis of the whole case	AUC = 0.865	In future author could assist other advanced applications, such as size measurement, lesion characterization	Their method learned the unique features of lesions via the multiscale module
[49]	Pre-processing + CS-LBP features from each 2 × 2 blocks in Wavelet Domain + SVM-RFE based feature selection + Random Forest classification	Accuracy: 97.25%, Precision: 97.3%, Recall: 97.2%, F-measure: 97.2% MCC: 94.1% ROC Area: 97.61%	The author can further classify the type of tumor	Fast feature extraction, small feature dimension, fast modelling and prediction
[55]	Image enhancement and segmentation + DenseNet169 for feature extraction + Region based Group-max Pooling + Prediction	(INbreast)RGP: AUC = 0.934 and GGP: AUC = 0.924 (CBIS-DDSM) RGP: AUC = 0.838 and GGP:AUC = 0.823	The results of visualization show that the proposed model can roughly locate suspicious regions	Ability of learning lesion location information
[79]	Pre-processing + feature extraction + deep multi-view classifier	AUC = 0.895	AUC could be increased	Their model could improve radiologist sensitivity for breast cancer detection
[54]	Pre-processing + pre-trained UNet + DDS feature extraction + TM	Sensitivity = 95% with 0.84 false positives per volume	In future author could assist other advanced applications, such as size measurement, lesion characterization	High sensitivity and low false positives
[71]	Image segmentation + SSIM feature extraction + DCT feature extraction + FFT feature extraction + SVM classifier	AUC = 0.85–0.91(from one of the three sub categories) AUC = 0.96 ± 0.01(in three sub categories)	Its clinical utility or impact on radiologists' performance in diagnosis of breast cancer using mammograms has not been tested	significantly higher performance with AUC
[9]	HA-BiRNNs	AUC: 0.8854 REC: 0.8771 F1 score of prediction:0.9070	The author wish to develop methods to interpret the representation learned by Knowledge-powered Deep Breast Tumor Classification model to classify malignant and benign tumor pattern	Method achieves higher performance
[35]	Pre-processing + canny edge detection technique for boundary selection + antenna arrangement and simulation process + extraction of tumor response signals + result	N/A	Their method offers the efficient detection even for a tumor of 4 mm diameter located within the glandular or at the interface between the gland and fat	They state that their approach can be an effective alternative to direct extraction of the tumor response
[48]	Pre-processing + DCE-MRI (wavelet transform) + heatwave feature extraction + classification	(AUC = 0.88 HetWave vs. 0.70 standard features). The combination of HetWave and standard features further increase classifier performance (AUCs 0.94)	HetWave could assist other advanced applications such as feature extraction approach for characterizing tumor heterogeneity, providing valuable prognostic information	Superior ROC AUC
[80]	Data acquisition + image preprocessing + co-occurrence analysis computing framework + neural network classifier + hypothesis testing	TPF = 0.90 FPF = 0.09	Author could help with more advanced applications in the future, such as size measurement and lesion characterization	It investigate heterogeneous tumors by separately distinguishing the benign and necrotic tissues within a lesion having malignancy

Table 8 (continued)

References	Classification model	Performance measures	Challenges	Advantages
[81]	Pre-processing + fuzzy c-means thresholding based image segmentation + hybrid feature extraction + feature selection + classification	SVM-MLP classifier: 87% accuracy, 95% sensitivity, and 75% specificity SFS-KNN: 87.50% accuracy, 95.83% sensitivity, and 62.50% specificity	Some SVM classifier's are not capable of classifying the negative sample	GA-MI based feature selection the SVM classifiers for MLP, linear, and quadratic classifier are performing better
[23]	Pre-processing + construction of bio-mechanical model + image registration + image fusion + analysis of USCT images + result	–	The current limitations of their method is that overall accuracy is not improved with heterogeneous stiffness distribution models	Smaller training and test errors rates

conducted in a dark room with a light-reflecting on a particular body segment to look under the skin [89]. It is an invasive method and is not being used much nowadays.

5.2.2.3 Microwave Imaging Microwave imaging is a promising method for detecting the early-stage breast cancer [90]. Li et al. [35] proposed a direct tumor response extraction technique based on the ensemble empirical mode decomposition for early breast cancer detection. The extracted signals were used to reconstruct the image for tumor detection. diFlorio [91] designed some enhancements in both hardware and software for microwave breast imaging. The hardware monitors the signals down to sub-centimeter screen resolution compatible with a test time of fewer than 2 min. The software resolves the huge time workload and produces accurate images in less than 20 min. They were able to produce the first microwave tomographic images. Klemm et al. [90] studied the imaging of inhomogeneous breast phantoms for microwave breast cancer. They introduced an image enhancement algorithm, which utilizes the concepts of the delay and sum algorithm (DAS) and coherence factor. Their proposed approach was able to reduce clutter and provide better images as compared to the previous techniques. Tuncay et al. [92] presented an effective way to design 3D microwave models. Yin et al. [34] suggested ultrawideband radar imaging for the breast cancer detection. Robust and Artifact Resistant (RAR) algorithm was developed to overcome the negative effects of both artifact and glandular tissues. RAR enhanced the identification capacity, robust artefact resistance, and high detection range.

5.2.2.4 Tomography Tomography is a technique that creates images of single planes of tissue. Kao et al. [94] studied Electrical Impedance Spectroscopy (EIS) to locate and differentiate cancer from normal tissues and benign tumors. The tumors are different from the normal tissue in terms of their conductivity and permittivity. The high contrast tissue, occurs between several kHz and several MHz, can be able to distinguish the malignant from benign. In a silicone phantom breast, the system can detect a 10 mm tumor in a silicone phantom breast. Baran et al. [95] investigated the potential clinical usability phase-contrast micro-computed tomography (micro-CT) with high spatial Resolutions. SYRMEP beamline of the Elettra Synchrotron was scanned with 10 breast tissue specimens of 2 mm in diameter using the phase-contrast micro-tomography propagation method. The high-resolution images was able to provide the detail tissue design assessment at a close-to-histological level. Table 9 summarizes the electrical screening techniques in terms of performance measures and datasets.

Table 9 Classification of breast cancer detection using electrical screening techniques

References	Classification model	Performance measures	Challenges	Advantages
[93]	Image-Based 3-D Surface Reconstruction + Model-Based Segmentation of Breast + Data Collection and accuracy evaluation + Result	The system can detect a 10 mm tumor in a silicone phantom breast	A limitation of these dense optical flow techniques is their sensitivity to lighting variation	Their system can reconstruct the breast surface with average errors of less than 1 mm
[82]	Two innovative instruments' setups for early detection of breast cancer were used	Method expose promising validity in comparison to other breast cancer detection tools	The LSM error function has not been used due to its higher sensitivity	Promising validity
[51]	Data acquisition + preprocessing + segmentation + feature extraction + CNN classifier	98.95% Testing accuracy	The author can further classify the type and size of tumor	Obtained good accuracy rate was obtained for the thermal images
[87]	Breast imaging + Patient specific digital breast model + extract temperature of region of interest + levenverg-marquardt algorithm	The screening technique is found to be more accurate and harmful radiation free	Requires more computation time	The technique has potential to be an accurate adjunct to mammography
[91]	combination of hardware and software to create 3-D microwave tomographic images of the breast	The hardware used in this work has the capability of gathering data up to 3 GHz	The results can be improved by operating at higher frequencies and/or using a multi-frequency approach over an ultra-wide band	Its advantage is its specificity driven by the wide range of dielectric properties
[92]	Preprocessing of MRI data + Bias Field Correction + Segmentation of Two Main Tissues + Electromagnetic Properties Mapping + Building the 3-D Structure	The test conducted was successful	Work could be done to improve correlation between mammographic density and the MRI density	More consistent to classify ARN-MBPs with BTI score rather than ACR classification
[84]	Breast REIS + mirror matched feature extraction + ANN/SVM/GMM + fusion	ANN classifier was found to be the best single classifier among the three tested classifiers, with an AUC of 0.81 and sensitivity of 75% at 80% specificity	The main limitation of their work is smaller sample size	The REIS-based classification decisions are consistent with biopsy recommendations

Table 10 Classification of breast cancer detection using MS Elastography

References	Classification model	Performance measures	Challenges	Advantages
[96]	Acoustic shear waves generating device + elasticity imaging + an algorithm for processing the wave images to generate quantitative images depicting tissue stiffness + prototypic breast MR elastography technique + results	The results confirm the hypothesis that the prototypic breast MR elastographic technique can quantitatively depict the elastic properties of breast tissues in vivo and reveal high shear elasticity in known breast tumors	Considerable scope exists for technical improvement to determine the possible performance of an optimized MR elastographic technique in terms of resolution and quantitative accuracy	Their work shows that it is feasible to use a technique combining MR imaging and acoustic technologies

5.2.3 Mechanical Screening Techniques

MR elastrography is a well-known mechanical screening technique. The detail description of this technique is mentioned in the succeeding subsection.

5.2.3.1 MR Elastrography In [96], electromechanical operators vibrate the breast in MR electrography and produce the acoustic sound waves. An algorithm was used to produce the quantative images from these waves. This technique was evaluated on six healthy persons and six patients. then described by MRI [96]. Goddi et al. [97] presented a review on breast elastography. They discussed future techniques, which are not yet in clinical practice. Table 10 depicts the classification of breast cancer detection using MS Elastography.

6 Deep Learning Techniques for Breast Cancer

This section presents the importance of deep learning in the field of breast cancer followed by the classification of deep learning-based breast cancer detection techniques.

6.1 Importance of Deep Learning in Breast Cancer

The literature reports that machine learning is widely used technique for breast cancer research. K-Nearest Neighbor (KNN), support vector machines (SVM), and naive bayes classifier perform better in their respective fields. However, the tracking and detection processes in machine learning are done manually. For efficient cancer detection, the system needs to process 200 to 300 cells per frame, which is not possible through manual tracking. Hence, there is a need to develop the efficient methods for breast cancer detection. Whereas, deep learning can identify the complex patterns in raw data. Nowadays, deep learning is widely used to identify the breast cancer. According to a study published in Nature Medicine, deep learning models are capable of detecting breast cancer 1 to 2 years earlier than those with the standard clinical methods [98] would have. Deep learning models can learn the most relevant features to solve the problem optimally. Due to this, deep learning models can serve as the best hierarchical feature extractors [99]. The above-mentioned facts motivate the researchers to use learn and hence apply the deep learning techniques for breast cancer detection.

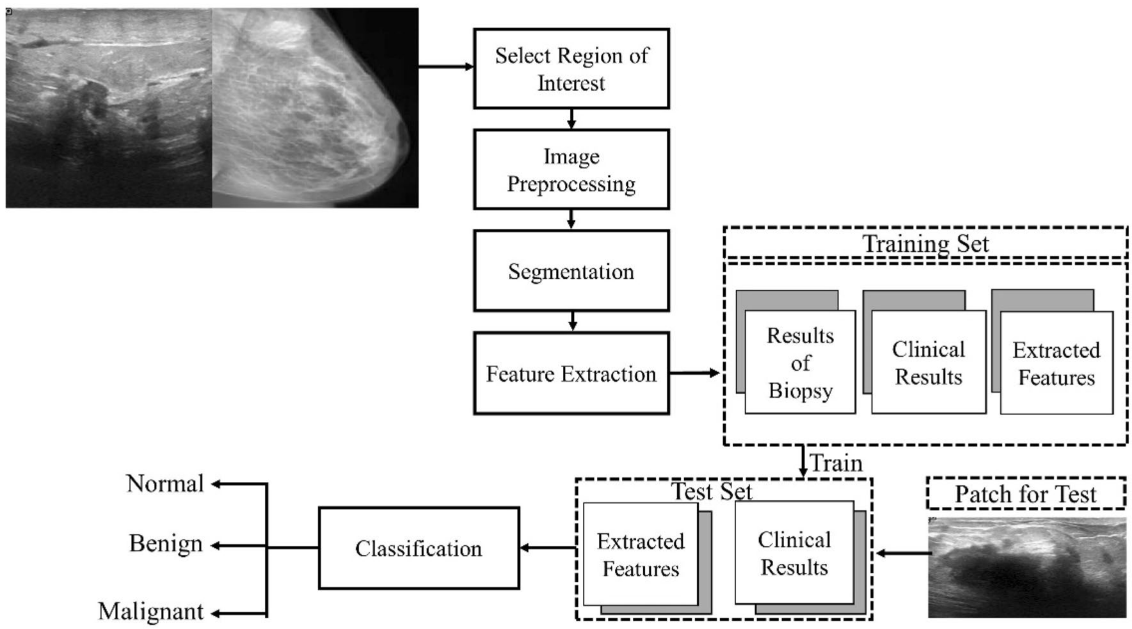
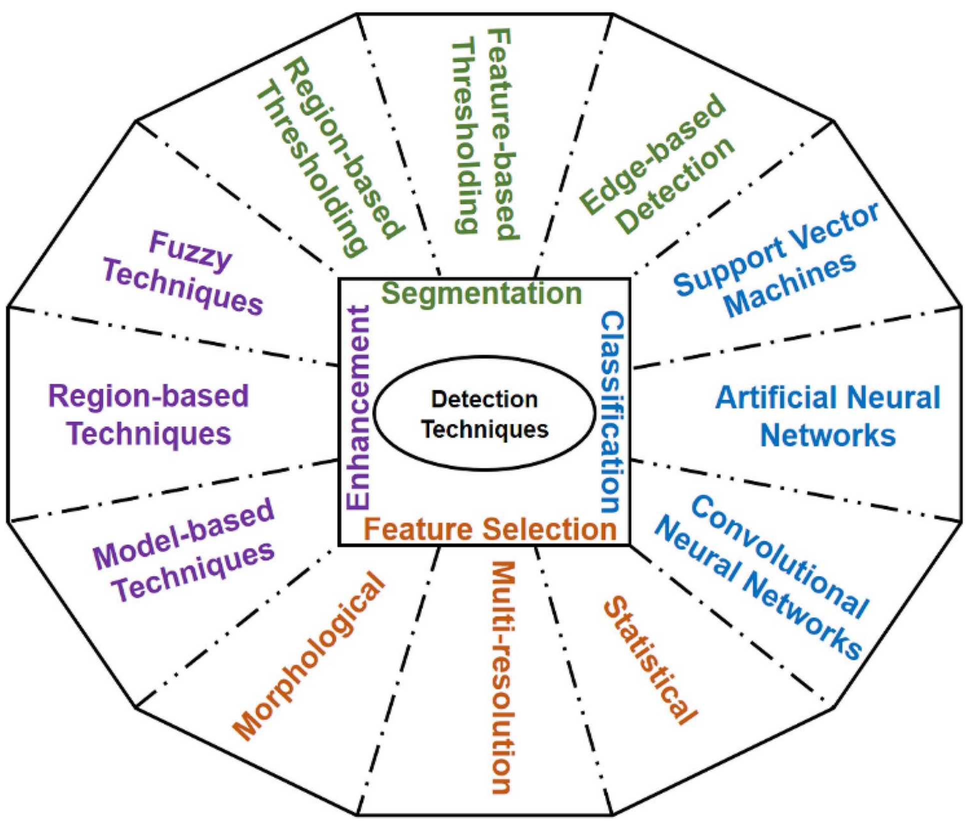


Fig. 10 General framework for breast cancer detection using deep learning

Fig. 11 Classification of Breast Cancer Detection Techniques



6.2 Deep Learning-Based Breast Cancer Detection Techniques

Deep learning architectures are successfully used in the detection of breast cancer. Figure 10 shows the general framework for breast cancer detection using deep learning technique.

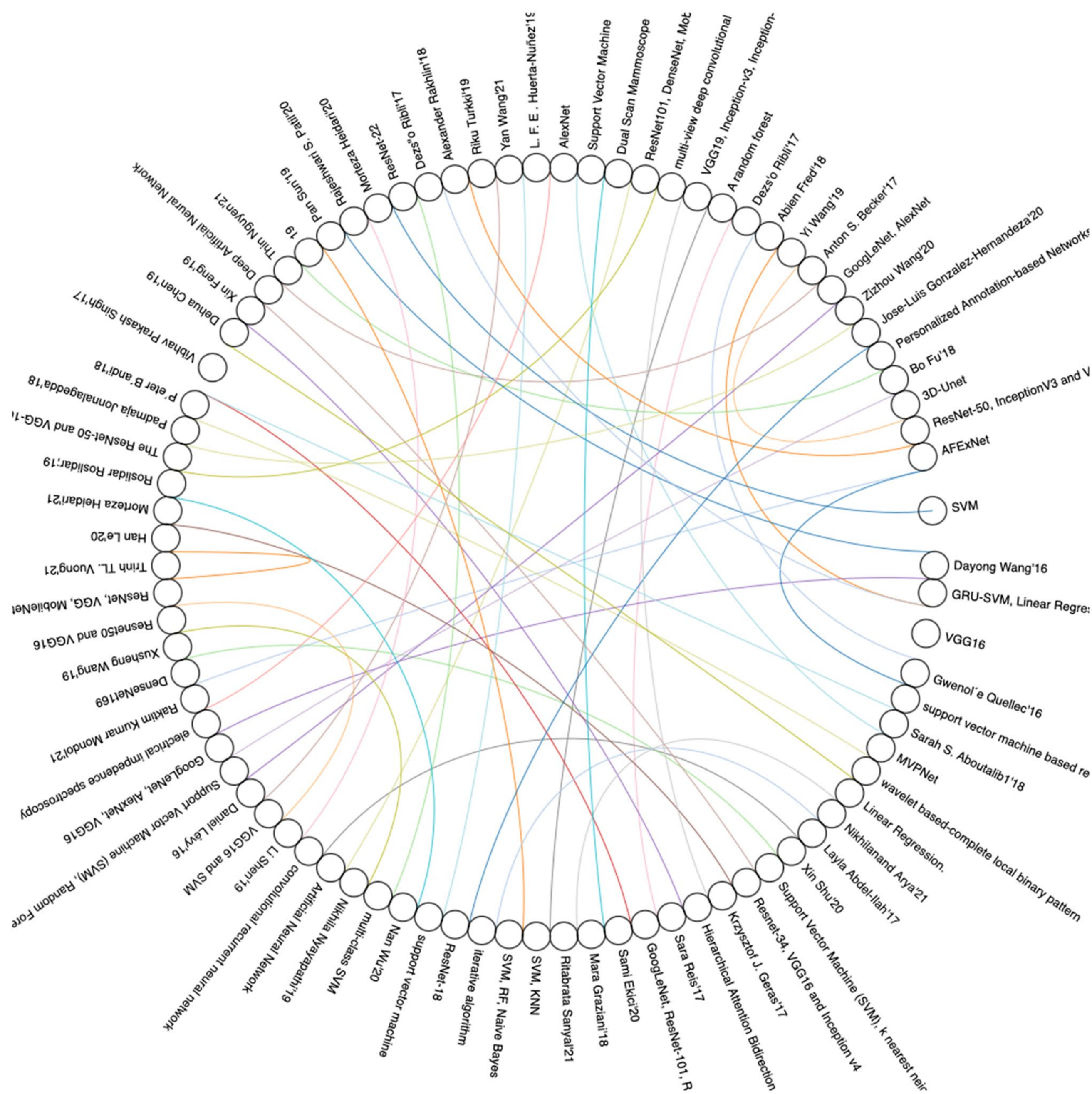


Fig. 12 Chord chart showing the connection of author with deep learning and machine learning techniques from last 5 years

The breast cancer detection techniques are broadly categorized into four classes such as image enhancement, lesion segmentation, feature extraction, and classification techniques (see Fig. 11). Deep learning techniques are used in fourth category, i.e., classification. Figure 12 shows the connection of authors with the deep learning techniques that are used for breast cancer detection from last 5 years.

Wang et al. [53] used ResNet-50 to detect breast lesion regions. They used self-created dataset with the help of West China Hospital. Wang et al. [54] created a dataset using the Invenia ABUS system in Sun Yat-Sen University Cancer Center. They used Unet and DDS pooling to enhance the detection sensitivity for breast cancer. The sensitivity obtained from their model was 0.95. Shu et al. [55] used INbreast dataset and CBIS dataset for breast cancer detection. Pre-trained CNNs and deep machine learning models were used for classification of breast lesion region. Heidari et al. [4] used SVM classifier for breast image. Fu et al. [100] proposed a model to predict Invasive Disease-Free Survival (iDFS) for the early-stage breast cancer patients. They used

XGBoosting and attained the AUC of 0.845. The dataset was self-created with the help of CRCB in West China Hospital of Sichuan University. Nyayapathi et al. [76] shown the fusion of ultrasound images with photoacoustic images for the early detection of breast cancer. Experimental results revealed the improvement in probability, speed, and also the patient's comfort zone. Ekici et al. [51] used CNN classifier on DMR dataset and obtained the accuracy of 98.95%.

Yin et al. [34] proposed a new scheme for the early detection using UWCEM database. They created 3-D anatomically accurate FDTD-based breast models, which resulted in improved identification capability, robust artifact resistance, and high detectability of tumors. Srivastava et al. [81] used different SVM classifiers (i.e., MLP, Quadratic, linear, and RBF) to achieve good accuracy. SVM-RBF performed better than the others. SVM-RBF attained the accuracy of 87.5%. Dheeba et al. [101] worked on the detection of tumors from breast tissue structure using a mammogram. MIAS dataset and ANN classifier were used. The recognition score obtained from this method was 97.8%. Wang et al. [53] used SoftMax classifier on DDSM dataset to detect the size of breast lesions. The value of AUC obtained from this method was 0.865. However, there is a need to develop more advance automatic breast cancer detection techniques to improve the diagnosis of breast cancer. Table 11 shows the advancement in breast cancer detection techniques.

6.3 Comparative analysis

The effectiveness of deep learning-based breast cancer detection techniques is assessed using the performance measures mentioned in Sect. 4. Table 12 shows the comparative analysis of deep learning and machine learning techniques in terms of performance measures. In this table, denotes that the approach has used the associated performance meaures, while indicates otherwise. The quantative analysis of different deep learning and machine learning techniques is illustrated in Table 13.

7 Discussion

In order to assist in cancer treatment, diagnostic imaging modalities are important for tumor classification. Over the last few years, imaging is considered an important tool for the diagnosis of tumors. Various screening techniques are used to detect and characterize the tumors. Screening techniques do not prevent cancer, however, they make early detection possible to make the patient alert for their treatment. Every screening technique has its own advantages and disadvantages. The most common screening method for breast cancer detection is an X-ray mammogram. Breast Ultrasound creates an image of tissues inside the breast using sound waves. The advantages involve non-invasive, quick visualization of breast tissue, the area closest to the chest wall, which is difficult to study with a mammogram, can be seen with ultrasound. Breast ultrasound has a low specificity and is more expensive. MRIs use a large magnet and radio waves to produce excellent tissue differentiation and sensitivity for breast cancer detection. CT scan images are made up of X-rays taken from various angles. Patients look for non-invasive and non-contact screening techniques as all the above-mentioned techniques involve contact. Thermography is one such technique. It uses infrared sensors to detect heat and increased vascularity as the result of biochemical reactions. Table 14 depicts the comparison of different breast tumor screening techniques in terms of pros and cons.

The performance of system can be judged by its accuracy, sensitivity, and specificity. The value of these measures should be high to achieve good results. When the likelihood of malignancy is established using a system, lively observation or biopsy can be recommended to evade inadequate and further invasive treatment. The main focus of this study is multi-scale module to improve the performance.

7.1 Relevance of Clinical Validation

Cancer severity can be measured through cancer research by describing a normal or abnormal state of cancer in the individual [113–115]. For this, the performance measures of cancer detection techniques are analyzed. In terms of clinical relevance, a cancer detection study may assess the risk of developing cancer in a specific tissue, or it may assess the risk of cancer progression or response to therapy. The conceptual framework of cancer research is mentioned in Fig. 13. The framework involves multiple processes, linking initial discovery in basic studies, validation, and clinical implementation.

A technique is discovered at the start of any cancer research technique development, and it is typically validated within the same initial report. When independent patient sets are not available, cross-validation-based methods are frequently used to replace validation based on a predefined prediction rule in an independent patient series. Prior to the analysis, the research question and plan, as well as the fundamental use of the technique, research design is clearly defined. Analytical validation is carried out after the new cancer research development phase [116]. This demonstrates how accurately and consistently the test measures the patient's analyte(s). Next is clinical validation, it tests to confirm its ability to predict or diagnose the clinical phenotype or outcome of interest, as demonstrated during the discovery and initial validation phases. A cancer detection

Table 11 Advancement in breast cancer detection techniques

References	Proposed approach	Targeted problem	Models	Classifier	Measures	Challenges	Advantages
[53]	Create dataset + Multiscale module (screening of unique features) + Multi-instance module	Detection of the breast lesion regions	CNN (ResNet-50)	–	AUC: ResNet-50 MSMI = 0.901	In future author could assist other advanced applications, such as size measurement, lesion characterization	Their method learned the unique features of lesions via the multi-scale module
[54]	Pre-processing + pre-trained UNet + DDS feature extraction + TM	Enhance the detection sensitivity for breast cancer	3D CNN (U-net + DDS Pool)	–	Sensitivity = 95% with 0.84 FP per/volume	Author could help with more advanced applications in the future, such as size measurement and lesion characterization	High sensitivity and low false positives
[55]	Edge detection and segmentation + feature extraction + RGP/GGP	Classification based on breast lesion region	CNN (DenseNet169 + max pooling)	Pretrained CNNs and deep MIL models	Acc: INbreast data-set = 0.934 ± 0.0003(RGP) 0.922 ± 0.0002(GGP) CBIS data-set = 0.838 ± 0.0001(RGP) 0.767 ± 0.0002(GGP)	The results of visualization show that the proposed model can roughly locate suspicious regions	Ability of learning lesion location information
[71]	Data Preprocessing + Image feature extraction + Classification	Classification based on image feature extraction	CNN (SVM)	SVM (FFDM image, DCT maps, FFT maps, fusion of features)	FFT: 66–77% DCT: 64–83% SSIM: 63–71% Fusion: 67–89%	Its clinical utility or impact on radiologists' performance in diagnosis of breast cancer using mammograms has not been tested	significantly higher performance with AUC
[100]	Statistical Feature Selection + Ensemble Feature Selection + XGBoost algorithm + PREDICT and Adjuvant Online	Predict the relapse or metastasis breast cancer	ANN (XGBoost)	PREDICT and Adjuvant Online	AUC: 0.8451	In future works, additional clinical data can be collected for improving accuracy of the 5-year iDFS prediction algorithm	XGBoost algorithm performance improved by 3%
[76]	System Design + Breast Coupling + Imaging Procedure + Reconstruction and Alignment	Early detection of tumor	–	Fusion of ultrasound images with photoacoustic images	benefits of portability, speedy scanning, and patient comfort	Patients with different tumor characteristics and breast sizes should be imaged to identify the photoacoustic features of different tumor grades and types	Their system possesses the benefits of portability, speedy scanning, and patient comfort

Table 11 (continued)

References	Proposed approach	Targeted problem	Models	Classifier	Measures	Challenges	Advantages
[51]	Data acquisition + Pre-processing + Segmentation + Feature Extraction + Classification	Classification based on image feature extraction	CNN	CNN (Bayes algorithm)	Accuracy: 98.95%	The author can further classify the type and size of tumor	Obtained good accuracy rate was obtained for the thermal images
[87]	Digital breast model + Parameter estimation for thermal images	Detect and localize tumor		iCAD	–	Requires more computation time	The technique has potential to be an accurate adjunct to mammography
[75]	Data acquisition + designed deep model + cross domain SVM	learning deep features from large-scale X-ray images	CNN	CNN (multi-class SVM)		Author could help with other advanced applications in the future, such as size measurement and lesion characterization	Good effectiveness and efficiency of proposed recognition system
[93]	Create data-set + Model-Based Segmentation + Compute optical flow	Accurately measuring 3-D surface motion	–	DIET machine	The system can detect a 10 mm tumor in a silicone phantom breast	A limitation of these dense optical flow techniques is their sensitivity to lighting variation	Their system can reconstruct the breast surface with average errors of less than 1 mm
[48]	Heterogeneity Wavelet Kinetic Features + Classification	Quantify intra-tumor heterogeneity in breast cancer	–	Dynamic contrast-enhanced magnetic resonance imaging	AUCs: 0.94	HetWave could assist other advanced applications such as feature extraction approach for characterizing tumor heterogeneity, providing valuable prognostic information	Superior ROC AUC
[34]	3-D anatomically accurate FDTD-based breast models + Pre-processing for Artifact Removal + RAR algorithm	Early stage detection	Robust and Artifact Resistant	DAS, DMAS, MWDAS, and FDAS	Improved identification capability, robust artifact resistance, and high detectability	The investigation of RAR's performance for further enhancement of tumor detection in severely dense breasts is missing	Their results show the high potential of RAR for the early stage cancer detection in low to medium density breasts
[102]	Breast-Body Segmentation	Automatically compute breast density in breast MRI	–			Complex analysis	Their proposed method is good at investigating the correlation between breast density measurements obtained from MRI and mammograms

Table 11 (continued)

References	Proposed approach	Targeted problem	Models	Classifier	Measures	Challenges	Advantages
[2]	Input raw pixels of training patches + Feature representation (SSAE) + Softmax classifier	Appearance of breast cancer nuclei in histopathological images	SSAE	Softmax Classifier	SSAE + SMC: Precision = 88.84% F-measure = 84.49% AveP = 78.83%	Stacked Sparse Autoencoder could be integrated with feature extraction methods to characterize cancer better	Their framework can provide accurate seed points or vertices for developing cell-by-cell graph features that can enable characterization of cellular topology features on tumor histology
[81]	Data Acquisition + Segmentation + Feature extraction and selection + Classifier	Feature extraction	ANN (GA-MI)	SVM (MLP, Quadratic, linear, RBF)	SVM-MLP: accuracy 84.3750% SVM-linear: accuracy 81.25% SVM-quadratic: accuracy 84.3750% SVM-RBF: accuracy 87.5%	Some SVM classifier's are not capable of classifying the negative sample	GA-MI based feature selection the SVM classifiers for MLP, linear, and quadratic classifier are performing better
[101]	Data acquisition + ROI Selection + Feature extraction + classification	Detection of tumor from breast tissue structure using mammogram	ANN	ANN (Modified Genetic Algorithm)	Recognition score of 97.8%	The results are not comparatively good on other mammogram datasets	Classifier is good at recognition
[103]	Data acquisition + slide level preprocessing + ResNet Classifier	cancer metastases in lymph nodes	CNN	ResNet	The best results were obtained with pre-trained architectures such as ResNet	At the slide level, the best ranked team misclassified 67 of the 500 slides in the test set	The submitted algorithms were not only able to detect the presence of metastases but also measure their extent to derive the metastasis category, including ITC, and to determine the pN-stage that is used in clinical practice

Table 12 Comparative analysis of braest cancer detection techniques in terms of performance measures

References	Technique	Prediction measure					Classification measure				
		μ	σ	*MSE*	*RMSE*	*PSNR*	*PPV*	S_n	A_c	S_f	*AUC-ROC*
[104]	Resnet-34, VGG16	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓
[105]	Resnet50, VGG16	✗	✗	✗	✗	✗	✗	✓	✗	✓	✓
[50]	VGG16	✗	✗	✗	✗	✗	✗	✓	✗	✓	✓
[106]	Linear regression	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗
[54]	3D-Unet	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗
[55]	DenseNet169	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓
[107]	MVPNet	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
[108]	EfficientNet	✗	✗	✗	✗	✗	✗	✓	✓	✓	✓
[109]	AFExNet	✓	✓	✗	✓	✗	✓	✓	✓	✓	✓
[110]	GoogLeNet, AlexNet	✓	✗	✗	✗	✗	✗	✓	✓	✗	✓
[111]	Random forest	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓
[112]	DTree, RF, XGBoost	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗

Table 13 Quantitative assessment of breast cancer prediction technique on classification measures

References	Technique	Classification measures				
		PPV	S_n	A_c	S_f	AUC-ROC
[104]	Resnet-34, VGG16	–	–	89.0%	–	0.950
[105]	Resnet50, VGG16	–	86.7%	–	96.1%	0.98
[50]	VGG16	–	0.9	–	–	085
[106]	Linear Regression	–	–	92.43 ± 0.657	–	–
[54]	3D–Unet	0.84	95%	–	–	–
[55]	DenseNet169	–		0.923 ± 0.0003 0.762 ± 0.0002		0.762 ± 0.0002 0.838 ± 0.0001
[107]	MVPNet	–	94.2 ± 2.2%	92.2%	92.3 ± 2.4%	0.91 =/–0.05
[108]	EfficientNet	0.819	0.74	90.2%	95%	0.93
[109]	AFExNet	98.57	98.58	98.57	98.57	–
[110]	GoogLeNet, AlexNet	0.7051	–	–	–	0.925
[111]	Random forest	–	–	84%	–	0.84–0.86
[112]	DTree, RF, XGBoost	–	0.8429	86.96%	0.8964	–

technique that has been analytically and clinically validated is now ready for use in clinical care.

8 Future Research Directions

Many females overlook the need of breast cancer diagnosis because they find it discomforting. Most of the breast cancer screening techniques are invasive. An alternative technique is required for breast cancer screening in which the skin is not pierced. The possible future research directions are as follows:

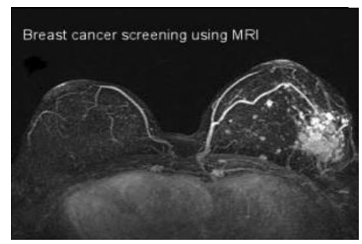
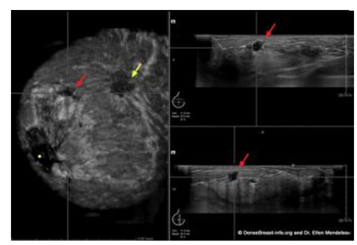
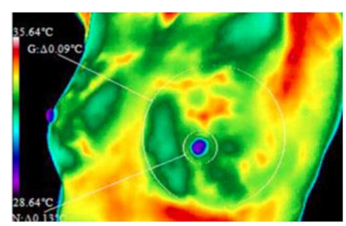
8.1 Ensure Safe Engagement

Safety is a major issue when radioactive rays or ionizing radiation are directly exposed to one's body. Many screening techniques use harmful waves that may cause the allergic reaction or contraindicate in some patients [117–119]. A system should be designed in such a way that it uses non-ionizing radiations and also provides accurate results.

8.2 Multimodal Approaches

Multimodality-based approach should be considered for the detection of breast cancer at an early stage. Screening tools for breast cancer need to expand their expertise by providing the multimodal method to enhance the precision by improving the outcome of screening techniques.

Table 14 Comparison of different breast tumor screening techniques for diagnosis of tumor

Screening Technique	Spatial Resolution	Advantages	Disadvantages	Image
Mammogram	Lower Spatial resolution	Time efficient, requires lower average radiation dosage	Lower spatial resolution, uses X-rays, costly	
CT Scan	High spatial resolution	Precise, High spatial resolution,	Uses X-rays, can cause allergic reaction	
MRI	High spatial resolution	No-ionizing radiation, high sensitivity, good tissue differentiation	Costly, invasive procedure, low specificity	
Ultrasound	Moderate spatial resolution	Less expensive, uses sound-waves	Low specificity, not able to detect all types of tumors	
Thermography	Low spatial resolution	Non-invasive, does not involve exposure to radiation	It can only alert a person to changes that may need further investigation	

8.3 Model Generalization

A variety of deep learning models are used in breast cancer research. Deep learning models provide different results for different application site [120, 121]. Hence, there is a necessity to develop the generalized model for breast cancer detection.

8.4 Clinical Implementation

Deep learning-based breast cancer detection models proved their significance in the medical research. However, the practical implementation of these models in clinics is still not done [122]. The implementation of these model in clincis will be beneficial for doctors.

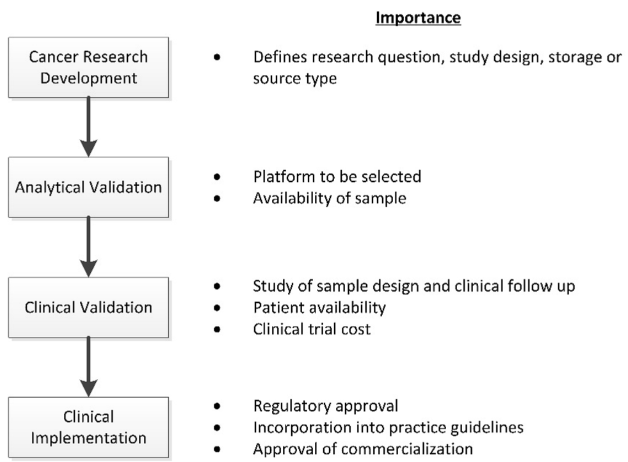


Fig. 13 Conceptual framework of cancer research

9 Conclusions

There are several methods for diagnosis and planning of initial breast cancer screening such as mammography, CT, breast ultrasound, MRI, and thermography. The outcome of these screening procedures help the doctors to aid in the selection of treatment or track the status of recovery. The aim of this paper is to provide the useful information to recognize and classify the breast tumor to make the early detection so that life can be saved. An attempt has been made to investigate the breast cancer detection using different intelligent systems along with their datasets. In addition to recent developments in various imaging techniques, the problems associated with the existing techniques have also been discussed. The possible future research directions for the ideal imaging modality are also suggested. In the wake of the limitations of existing techniques, it is imperative to improve the existing techniques for breast cancer detection as the core of personalized medicine and healthcare remains to determine the most suitable screening modality for the proper diagnosis of breast cancer.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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