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State-Of-The-Art Techniques for Classification of Breast Cancer Using Machine Learning and Deep Learning Methods: A Review

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Abstract: Breast cancer is among the most challenging illnesses for medical workers to diagnose. Breast cancer is none other than the formation of cancer cells in the area of breasts, and it can occur mostly in women rather than in men. So, diagnosing this disease at the earliest stage possible is the main aim of healthcare workers. Machine Learning (ML) and Deep Learning (DL) methodologies made significant advancements in Computer Vision and adapted to the healthcare domain. When DL methodologies adapted for diagnosing breast cancer, two main challenges affect the performance. One is with the non-availability of the large dataset for training the models; other is with the datasets having an imbalanced distribution of the classes. As a result, this study provides a review of several DL and ML-based classifiers presented by various academics over the last decade to tackle these problems, while also emphasizing the significance of the classification process of breast mammographic images. The key accomplishments expressed in the diagnostic measures and their success indicators of qualitative and quantitative measurements are reviewed.

Keywords: *Artificial Intelligence (AI), Breast Cancer, Classification, Deep Learning (DL), Machine Learning (ML), Mammogram.*

1. Introduction

The fast progress of machine learning, notably deep learning approaches, has got the attention of the healthcare imaging community in using those same technologies to improve cancer screening accuracy. Breast cancer (Figure 1) seems to be the second biggest reason for cancer-related fatalities of many women in the U.S (American Cancer Society, 2018). On the other hand, the improved prediction accuracy of mammogram screenings is found to have lowered the death rate (Oeffinger et al. (2015)). Despite its advantages, mammography screening has interconnected to a significant chance for the prediction of false positives and negatives. The average sensitivity and specificity of mammography screening in US are 86.9% and 88.9% respectively (Lehman et al.2016). Since the 1990s, Computer-Assisted Detection and Diagnosis software in clinical usage enables radiologists to enhance the prediction accuracy of screening mammography. Unfortunately, proposed data in pre-commercial CAD systems did not result in substantial performance improvements (Fenton et al. (2007); Etler et al. (2014); Lehamn et al. (2015); Lecun et al. (2015)), and development has been stagnant for more than a decade after they were adopted. Incredible success in visual object recognition and detection, as well as several other knowledge areas, there would be substantial desire in establishing deep learning tools to facilitate radiologists as well as enhance screening mammography accuracy (Wu. et al. (2018);Nagy et al. (2018); Rampun et al. (2018);Jie.et al. (2018); Bram et al. (2017); Diaz et al. (2019)). According to the latest researches (Rodriguez et al. (2019) Rodriguez et al. (2018), Dhungel et al. (2015)) while a deep learning-based CAD system worked, radiologists were in independent mode and enhanced radiologists' performances in support mode.

Preclinical breast cancer detection upon mammography screening seems to be difficult like an image classification work because cancer occupies just a tiny fraction of a picture upon the whole breast. "Full-Field Digital Mammography (FFDM) picture was generally 4000x3000 pixels, although a possibly malignant Region of Interest (ROI) is as tiny as 100x100 pixels". As a result, some studies (Jamieson et al. (2012), Oliviera et al. (2015), Arevalo et al. (2016), Levy et al. (2016), (2015); Dhungel et al. (2016)) have focused more on annotated lesions categorization. Existing entity recognition and classification algorithms, including the R-CNN as well as its variations (He et al. (2014), (2015); Sun et al. (2015);

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Li et al. (2016), might be quickly employed if ROI annotations are broadly accessible in mammography databases. Indeed, only a few publicly available mammography datasets were entirely documented (Moreira et al., 2012). Another research (Aboutalib et al., 2018) is tried to train neural networks utilizing entire mammograms even without annotations. Unfortunately, it's really unclear whether such networks are capable of identifying medically vital abnormalities as well as predicting outcomes depending on the relevant portions of mammograms. Deep learning has broadly acknowledged requiring massive training datasets to function efficiently (Kumar et al. (2020); Golatkar et al. (2018);Diao et al. (2014)). It's indeed critical to employ both constrained entirely annotated datasets and also broader datasets clearly labeled with the status of cancer of every picture to boost the accuracy of breast cancer classification methods (Ertosun et al. (2015); Akselrod-Ballin et al. (2016); Ribli et al. (2017)).

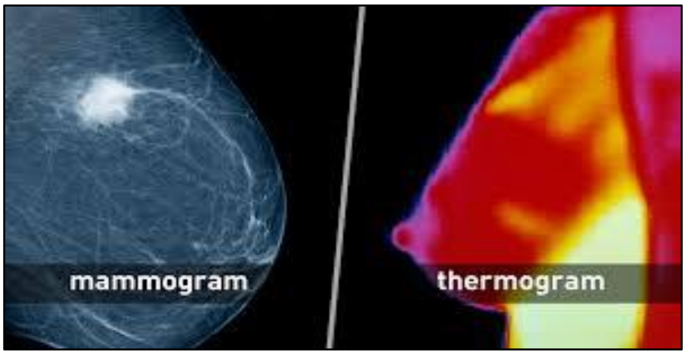


Fig. 1. Breast Cancer mammogram and thermogram image (Yamini Ranchod, (2020))

Pre-training seems to be a possible solution to the challenge of training a classifier once massive as well as whole training datasets were also unavailable. Hinton et al. (2006) generated the weight values of a Deep Belief Network (DBN) with 3 layers which are hidden using layer-wise pre-training, which they subsequently fine-tuned for classification. Pre-training enhanced both times of training and the accuracy of handwritten digit identification, according to the researchers. A typical training method was used to train a deep learning approach using large dataset, that includes ImageNet, and thereafter fine-tune the system for intended purpose (Russakovsky et al. (2015)). Even though the particular work could be unrelated to an initial dataset for training, a method's weight parameters for realizing basic attributes like edges, corners, even textures have already been defined as well as could be readily added to some other work. It typically shortens training time while boosting the performance of the model (Oquab et al. (2014); Shen et al. (2019); Totoriya et al. (2019)).

In accordance with WHO, approximately 2.3 million women will be identified with breast cancer in 2020, with 685000 mortalities globally. There are 7.8 million females whose lives are brought back by the end of 2020 who would be identified with breast cancer within the past five years, ranking it one of the most prevalent illnesses worldwide. Breast cancer can attack any woman from any country at the age after puberty, with rates growing with age. Among nations having earlier diagnostic strategies joined to various forms of therapy to eliminate invasive disease, life expectancies started rising in the 1980s. Figure 2a depicts the graphical representation of 2020 statistics on breast cancer in which the figure shows a clear view with 30.1% of cancer has occurred with breast when compared to lung, stomach and the most published year related to breast cancer is over the year 2020 as well as it will increase in future as well which illustrated in Figure 2b.

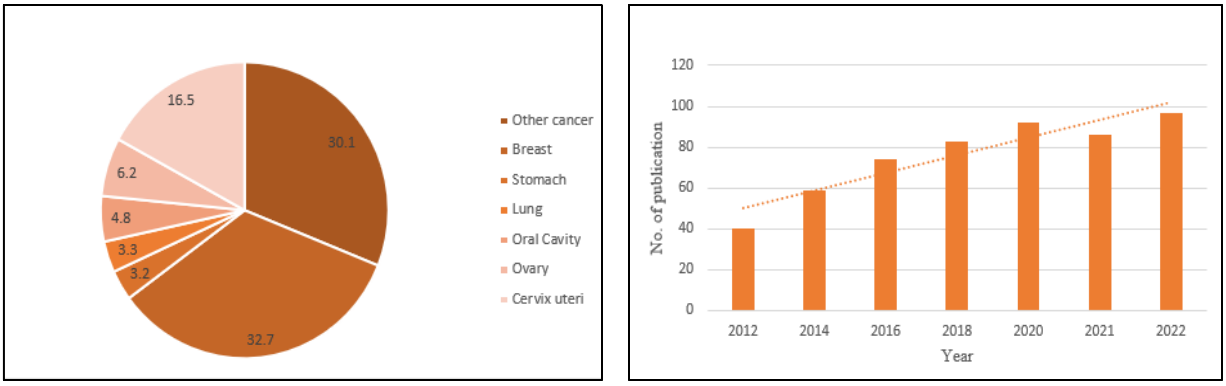
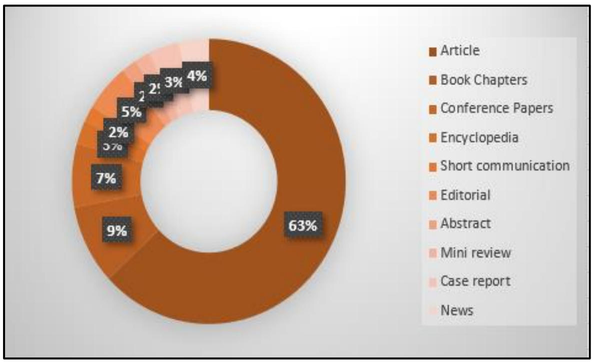


Fig. 2.a) Statistics of Breast Cancer, b) No. of publication per year on Breast Cancer

The main challenges in the medical image diagnosis, while applying DL methods is indeed the non-availability of a reasonably bigger dataset and the imbalance in class distribution for the dataset. These issues significantly deteriorate the classification performance of DL approaches. Therefore, this paper brings an effective review of classification over the problems that include class imbalance and insufficient data issues in breast mammographic images.

Bibliometric Analysis

Review of different articles were discussed in this paper which are bibliometrically analyzed from a database as; "IEEE Xplore, Science Direct, MDPI, ASCE library, Copernicus, AAS, Springer, Science press, Oxford Academic Press, Scopus as followed by state-of-art models". In this database, the Keywords used for data extraction are "Breast Cancer classification" and "Review: Breast Cancer using deep learning". 8000 documents were taken from these 10 databases to cluster into certain categories. The clusters obtained are "Article (70%), Book Chapters (10%), Conference Papers (8%), Encyclopedia (3%), Short communication (2%), Editorial (6%), Abstract (2%), Mini review (2%), Case report (4%), News (4%)". Figure 3a shows percentage of groups formed in 10 databases over the Keyword- "Breast Cancer classification" in which 63% published in the form of an article. Figure 3b shows a percentage of groups formed in 10 databases over Keyword – "Review: Breast Cancer using deep learning" in which 50% published in the form of an article.



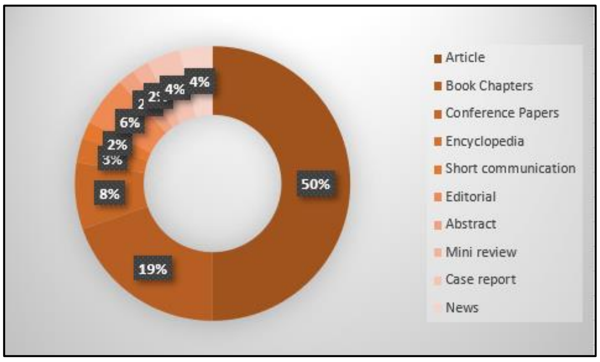


Fig. 3.a) Represents a percentage-wise cluster in 10 databases over Keyword- "Breast Cancer classification". b) shows percentage-wise cluster in 10 databases over Keyword – "Review: Breast Cancer using deep learning"

1.1 Key Objectives

This paper depicts a review of breast cancer which has been proposed for a decade in which following are the highlights:

a. Papers proposed on breast cancer for the past 10 years.

b. Concentrating on breast cancer categorization to resolve class imbalances and inadequate data samples.

c. Quantitative study of different measurements through ongoing plans.

d. Useful for breast surgeons for diagnosing breast cancer at the earlier stages.

Organization of this paper:

Section 1 gave the introductory part; the following is the rest of the article. 2nd section provides an overview of the AI –ML – DL technique, image modalities, and challenges. Section 3 depicts the ML and DL classifiers for breast cancer diagnosis. Experimental findings and observations are discussed in 4th Section . And at the end, I.e 5th section depicts Conclusion.

2. Introduction to Artificial Intelligence and its classes

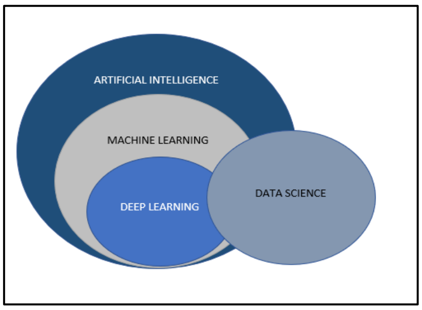


Fig. 4. AI and its subclasses (ML, DL)

Artificial intelligence (AI) enables machinery to imitate human behaviour . Experiences helps machines to study by detecting patterns and analyzing data, according to AI (Harshita (2020)).

Machine Learning (ML) is yet another subcategory of Artificial Intelligence (AI) that integrates statistical approaches for allowing a computer to behave as well as produce data-driven judgments to complete a work. When subjected to fresh data, such methods were built in such a way that they can learn and grow with time (Jordan et al., 2015).

● Machine learning algorithms do better even with fewer datasets.

● Machine learning techniques operate well on low-end computers as well.

● Necessary characteristics must be manually retrieved or discovered and then coded according to the discipline and type of data.

Deep Learning (DL) is a significant field of ML which is influenced by the functioning of cells in the human brain named neurons, which give rise to the idea of Artificial Neural Network (ANN) (Good fellow et al., 2016).

- DL method requires massive quantities of data. As the amount of data rises, DL networks frequently enhance.
- Deep learning techniques rely significantly on high-performance computer equipment. GPUs are required because they execute a higher number of matrix multiplication calculations.
- They automatically retrieve essential features from data.

2.1 Application of AI in medical diagnosis

Artificial Intelligence (AI) is becoming associated with support and effectiveness in the medical domain. AI advanced out of a system considered with scepticism and claims promoted as a substitute for healthcare personnel to the second pair of eyes that refuses to nap. In healthcare diagnosis and treatment, artificial intelligence provides trustworthy assistance to exhausted healthcare specialists, lowering workload pressure while boosting the effectiveness of clinicians (Marley (2020)).

Artificial intelligence contributes to clinical diagnostics by assisting in treatment planning, management, automation, administration, and procedures. It is utilized to identify cancer, triage significant medical imaging findings, flag acute anomalies, helps radiologists to prioritize life-threatening patients, find cardiac arrhythmias, anticipate stroke results, to help in chronic disease management. Greenspan et al. (2016); Norman (2018); Recht and Bryan (2017) defined AI as a massive ocean of information, algorithms, analytics, deep learning, neural networks, as well as findings that are always advancing to suit the necessities of the medical field and its patients. Artificial intelligence in healthcare diagnostics clearly shows massive potential for improving the standards of medical treatment while decreasing the immense requirements encountered by the healthcare field in recent years.

In a policy article named "The Coming of Age of Artificial Intelligence in Medicine," Stefanalli et al. (2009) discussed the outcomes of a forum debate conducted in 2007 during a conference on AI in Medicine (AIM) held at Netherlands. The researchers investigated the growth of AI research as well as its effects on the medical field, intending to characterize AI's impact in medicine thus far. One indicator of AI's efficacy in healthcare, according to the authors, is that AIM methods are rapidly being embedded into applications and are not clearly evident as such. King Jr. (2018) analyzed the potential effects of artificial intelligence on the discipline of radiology. “The researcher feels that another milestone can be achieved by AI employing imaging data currently accessible via imaging modalities like ultrasound, CT, MRI, and PET rather than new scanner technology (Kruskal et al. (2017); Ahuja (2019)).

2.2 Image Modalities for Breast Cancer diagnosis

“Mammography, breast ultrasound, breast thermography, Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Scintimammography, Optical imaging, Electrical impedance imaging, as well as Computed Tomography (CT) are the image modalities used to diagnose breast cancer”. Table 1 provides an overview of imaging modalities for breast cancer**.**

2.2.1 Mammography

One of the important breast imaging forms is mammography. This utilized minimal amplitude-X-rays to observe the human breast. Malignant tumors, as well as calcium deposits, appear brighter on mammography. To identify calcifications and Ductal Carcinoma in Situ (DCIS), we use this technique. Mammography is currently the golden level approach in recognizing cancer at an earlier phase before tumours become clinically palpable. After 5 to 7 years, screening by mammography decreased mortality to 25% -30% in monitored women contrasted to a control cohort (Kerlikowske et al., 1995). As per randomized studies of mammographic screening, it is capable of reducing mortality by earlier identification and treatment of breast cancer (Nystrom et al., 2002).

Breast cancer is hard to detect in its early stages employing mammographic screening. Additional breast cancer screening tests, on the other hand, may lower the mortality risks. Mammography screening has been significantly lowered the mortality rate in randomized controlled studies of entire populations (Kopans (2002); Kopans (2004); Tabar et al. (2003)). Mammographic imagery is scientifically utilized for screening, and as a result, can be utilized for universal screening. Malur et al. (2001) screened individuals with aberrant breast observations employing mammography, sonography, as well as magnetic resonance (MR) mammography. Carcinoma in situ has been detected among 78.9% of mammography patients and 68.4% of MR mammography patients, correspondingly. A mixture of all three diagnostic techniques detects cancer tumors as well as multifocal illnesses well. The combined sensitivity of mammography and sonography, on the other hand, was similar to the MR mammography (i.e., 94.6 %). Figure 5 depicts the mammography images of breast cancer (medical news today, 2020).

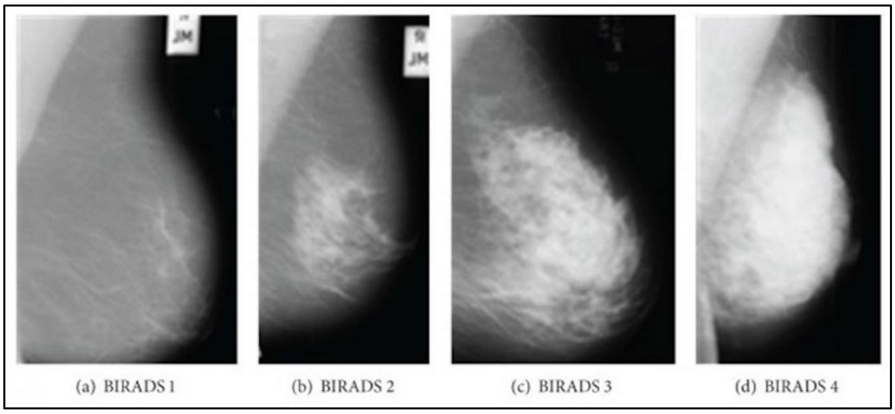


Fig. 5. Samples of mammography images of breast cancer

2.2.2 Breast Ultrasound

Ultrasound imaging can be employed to diagnose breast tumors and opted as a secondary technique to pinpoint the site of a suspicious lesion. An ultrasonic transducer sends high-frequency sound waves to breast tissue and afterward measures the reflected waves. As a result, the determined waves are employed to generate two-dimensional pictures. Continuous real-time images may be recorded, when the sensor moves over the breast. During a clinical examination, ultrasound can be used in combination with mammography to detect tangible and intangible breast abnormalities.

Mammography alone uncovers many malignancies among dense-breasted women. Mammography that used "an Automated Whole Breast Ultrasound (AWBU) has a high detection rate in women with heavy breasts or who are at greater risk of breast cancer". According to Kelly et al. (2010), 87 percent of cancer detections added by AWBU were discovered in 68% of investigations in women with thick or very dense breasts. As a consequence, comparing mammography alone, AWBU led to a substantial enhancement in cancer diagnosis. 3D ultrasound, which transforms data obtained as sound wave to 3D images (Carsten et al. (2005)), automated ultrasound for a better overall view of the breast (Carsten (2006)), Doppler Ultrasound (Kook et al. (1999)), and sonography (Scaperrotta et al. (2008) are examples of advances in ultrasound technology. Figure 6 depicts a breast cancer ultrasound picture sample (Al-Dhabyani et al. (2020)).

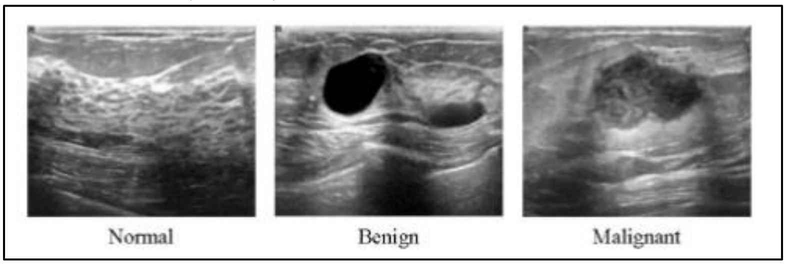


Fig. 6. Samples of ultrasound breast images

2.2.3 Breast Thermography

Cancerous and pre-cancerous tissues have faster metabolic rate, which leads to the formation of new blood vessels, which feed nutrients to cancer cells. As a result, the temperatures of the region around pre-cancerous and malignant breast tissues are greater than that of normal breast tissue. The breast has a circadian rhythm that corresponds to its physiology. These rhythms, which appear to be non-circadian and associated with malignant cell development (Keith et al. (2001); Salhab et al.

(2005)), appear to be non-circadian. Breast skin temperature has been connected to breast cancer (Gautherine and Gros (1976)); Gros et al. (1975)). Skin temperatures differ substantially in clinically benign and cancerous breasts. In limited settings, the cyclic temperature variation and vascularization of nonmalignant thermograms were examined (Ng EYK et al. (2001)). The findings of this study will aid in differentiating between normal as well as pathologic breast thermography.

Nowadays breast thermograms are extensively utilised for reliable breast cancer assessment (Ng EYK (2009); Ng EYK and Susharsan (2004); Ammer and Ring (2006); Amalu et al. (2006); Wiecek et al. (2010); Qi et al. (2006); Ring and Ammer (2000)). Thermography seems to be a potential screening technique because it can detect breast cancer before 10 years. Figure 7 depicts breast cancer thermographic picture samples (Tello Mijaris et al. (2019)).

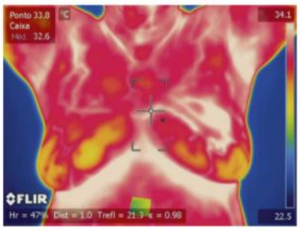


Fig. 7. Samples of thermographic images of breast cancer

2.2.4 Magnetic Resonance Imaging

Because the hydrogen nucleus (a single proton) is plentiful in water and fat, thus it is used for imaging in MRI. The hydrogen nucleus magnetic properties are utilized to generate a detailed picture out of any area of the body. A magnetic field is applied to the patient, and then a radio frequency wave is used for generating large contrast pictures of the breast. Before the pictures in Dynamic Contrast Enhanced-MRI (DCE-MRI) have been recorded, a contrast agent is administered (Heywang et al., 1997). This method was discovered to be highly delicate than mammography (Liu et al., 1998).

For accurate detection of human breast cancers and tracking, chemotherapy responses have been explored by the use of cutting-edge imaging modalities, such as “MRI, Magnetic Resonance Spectroscopy (MRS), nuclear imaging, and optical imaging” (Basilion (2001)). MRI aids in the investigation of vascular alterations related to neoangiogenesis (Leach (2001)). It is widely used in the diagnosis and is currently being used to evaluate tumour response to therapy. New contrast agents that advance in measurements and analytical methodologies are expected to support the usages of MRI in examining the vascular dependency of tumour development as well as the efficiency of vascular-directed treatments.

Breast MRI can detect breast cancer in its early stage (Schnall (2001)). According to the most recent study on breast MRI with three Tesla magnets, it has improved in spatial and temporal resolution, as well as a higher signal-to-noise ratio (Lehman 2005). MRI is beneficial for women who may be in a greater hazard of breast cancer (Stephan et al., 2010). Demerits of this technique include its ineffectiveness in identifying Ductal Carcinoma In Situ (DCIS), the possibility of numerous false positives, sluggishness (30 minutes to one hour), higher expense, and the possibility of not detecting all calcifications. Recent research looked at the relationship between the film mammography as well as MRI (Lee et al. 2009). The researchers discovered no statistically significant association as well as discovered that integrating two screening modalities increases the likelihood of finding early-stage malignancies. Figure 8 depicts breast cancer MRI samples (Mayoclinic, 2018)

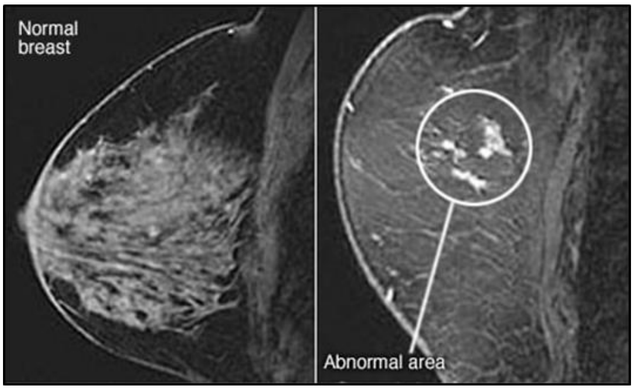


Fig. 8. Sample MRI images of normal and abnormal breast cancer

Table 1. Overall summary of image modalities

Image Modality	Sensitivity	Specificity	PPV (Positive Predictive Value)	Indicators
Mammography	63-95% > 95% palpable, 50% impalpable, 50-year-old: 83-92%, 35% decrement for dense breasts	14-90% palpable	10-50% (94% palpable)	Initial analysis for symptomatic breast cancer in women over the age of 35.
Ultrasound	68-97% palpable	74-94% palpable	92% palpable	Initial screening for palpable lesions in women under the age of 35.
MRI	86-100%	21-97% (<40% primary cancer)	52%	Scarred breast: implants, multifocal lesions, and borderline lesions for breast conservation, helpful for screening at-risk women
Scintigraphy (*Scintimammography)*	76-95% palpable, 52-91% impalpable	62-94% impalpable	70-83% (83% palpable, 79% impalpable)	Lesions > 1 cm and axilla assessment
PET	96% (90% axillary metastases)	100%		Axilla assessment of scarred breast and multifocal lesions

2.2.5 Positron Emission Tomography(PET)

PET is a "nuclear medicine imaging approach that generates 3D pictures. It recognizes the set of rays released by a radionuclide injected into body of a man". When compared to normal cells, malignant tumours have enhanced glucose consumption. It results in a clear distinction between malignant as well as typical issues in PET scans. These describe basic chemical processes that occur within organs and tissues. PET is costly and produces pictures with low resolution. Moreover, individuals are subjected to radiation. PET is widely employed to forecast treatment response in a variety of malignancies. (Fass 2008). Figure 9 depicts breast cancer PET imaging samples (The American Society of Breast Surgeons Foundation, 2018).

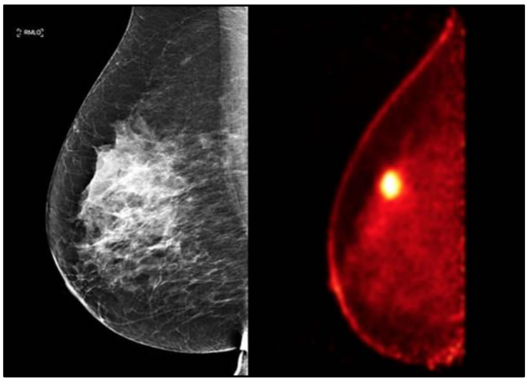


Fig. 9. PET images of breast cancer

2.2.6 *Scintimammography*

Mammography has a tough time detecting breast tumours in thick breast cells. Subsequently, mammogram-based breast tumour screening approaches produce a substantial number of false positives. For women with thick breasts, scintimammography employing technetium tetrofosmin (Tc-99 tetrofosmin) improves diagnostic accuracy. Having thick breasts, can image implants, and also can capture huge and palpable anomalies. It can be utilized when numerous tumours have been discovered (Munshi 2008). Brem et al. (2005) examined occult breast cancer in patients having greater chance of breast tumour utilizing a high-resolution breast-specific gamma camera. Researchers discovered that large-resolution breast-specific scintimammography identifies tiny (1 cm), mammographically occult, non-palpable lesions that cannot recognize via a mammogram or physical assessment in women at increased risk for breast cancer. A combination of mammography in conjunction with "99mTc-methoxy isobutyl isonitrile (MIBI) Scintimammography" has been explored to minimize the no. of biopsies needed in people with suspected breast cancer (Prats et al. (1999)). Figure 10 depicts scintimammography pictures of breast cancer (Das et al., 2006).

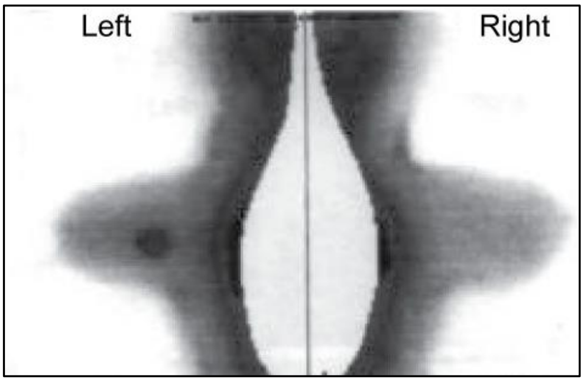


Fig. 10. Scintimammography images of left and right breast cancer

2.2.7 *Optical Imaging*

In optical imaging, Near Infrared (NIR) wavelength light is utilized to identify the lesions." Diffuse optical imaging(DOI) (which utilizes NIR light to penetrate the breast), diffuse optical tomography (which employs NIR light with wavelengths ranging from seven hundred to thousand nm), as well as optical mammography (which uses laser beam)", are the various forms of optical imaging that utilize distinct wavelengths of light to identify malignant lesions. DOI is a noninvasive optical method that takes Near-Infrared (NIR) light to quantify basic characteristics of dense tissues. DOI performance is influenced by intrinsic and extrinsic contrast procedures, quantification of biological substances, and image formation/visualization (Tromber et al. (2008); Murillo-Ortiz et al. (2020)). Figure 11 depicts breast cancer optical image samples (Scolaro et al., 2014).

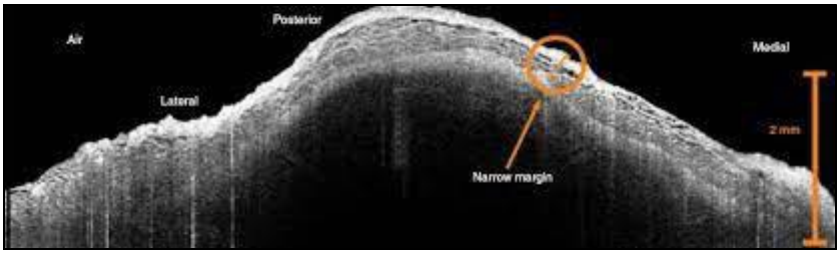


Fig. 11. Optical tomography of breast cancer

2.2.8 Electrical Impedance Imaging

Our bodily tissues serve as an impediment to the flow of electric current. According to the analysis ,the malignant breast cells exhibit lesser impedance than usual ones. "Electrical Impedance Tomography (EIT) and Electrical Impedance Scanning (EIS)" are the two categories of electrical impedance imaging strategies that are at hand. EIT reconstructs 2-Dimensional or 3-Dimensional pictures out of a massive number of impedance values collected by inserting electrodes in a circular pattern around the breast surface. However, with electrical impedance scanning or electrical impedance mapping (EIM), an array of a flat electrode is utilized, therefore no complex reconstruction methods are required, just like in EIT.

Zou et al. (2003) reviewed non-invasive impedance imaging approaches in the diagnosis of breast cancer, including EIT as well as EIM. Researchers hypothesized that combining an invasive impedance method with additional cancer markers may improve its success rate. They recommended utilizing a set of electrode arrays; one is utilized to stimulate the breast area and another for monitoring impedance, to improve EIM. Figure 12 depicts breast cancer EIS pictures (Murillo-Ortis et al. (2020)).

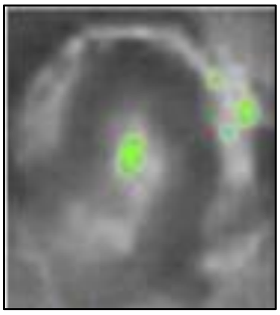


Fig. 12. EIS of breast cancer image

2.2.9 Computed Tomography

Computed Tomography (CT) captures 2D pictures or slices of the investigated bodily sections using X-rays. After that, several algorithms have been performed to create matching 3D pictures that provide anatomical details that include lesion location. Due to the low contrast of CT scans, an iodinated contrast medium were given intravenously to improve contrast. An iodine contrast injection significantly improves tumour visibility.Investigated (Liu et al., 2007) that CT perfusion imaging might be beneficial for examining expanded axillary lymph nodes in breast cancer patients.

Lifetime Attributable Risk (LAR) of cancer occurrence linked with sixty four-slice Computed Tomography Coronary Angiography (CTCA) radiation intake were investigated, as well as the influence of age, gender, and scanning protocols of cancer danger(Einstein et al. (2007); Sree et al. (2011)). Depending on simulation models, our estimates show that utilizing 64-slice CTCA has been related to a non-negligible LAR of cancer. The danger differs widely and therefore is significantly higher among females, younger patients, among people who have combined cardiac and aortic imaging. Breast cancer CT images are seen in Figure 13 (Radiopedia, 2020).

Fig. 13. CT image of breast cancer

2.3 Data Collection for Breast Cancer

A reliable dataset of a large number of patients with pathologically tested labels is an essential requirement of any machine learning model to train classifiers (Moura et al. (2013; Shin et al. (2016); Zhang et al. (2019)). An ideal mammographic dataset should contain clear images with proper resolution in two main perspectives, viz. the Mediolateral Oblique (MLO) and the CranioCaudal (CC) in any popular image format. The following are ideal features of a mammography dataset:

- Include samples from all demographic, ethnic, and age categories that are relevant.
- Sufficiently large in number for the proper generalization of features to train and test the model
- Malignant and benign cases must be almost equal in number
- Include both MLO and CC views of each sample as different images with the same patient Id
- Avoid any repetition of patient
- Only biopsy tested (pathologically proven) cases shall be included
- Include images from multiple mammography machines, and all required clinical information

Classifiers trained with non-standard datasets with high classification accuracies will not make any clinical impacts (Zhang et al. (2019)). The success of any medical classification model relies on the quality of well-characterized datasets (Sun et al. (2017)). The importance of a systematic method to develop reliable datasets to build classifiers for medical diagnosis is discussed in (Oakden et al. (2020)). The clinical impact of the accuracy, meaning, and relevance of the labels are considered by the dataset developers. And there shall be a well-explained document on the expansion process, strengths of the dataset. Many studies of mammogram classifications are based on the datasets viz. “CBIS-DDSM (Miyake et al. (2017)), breast FFDM (Moereira et al. (2012)), BCDR FMR (Posada et al. (2012)), MIAS Digital Mammogram Database (Suckling (1994)), and the BancoWeb LAPIMO Database (Matheus and Sciabel (2010)), Wisconsin Breast Cancer (original) Wisconsin Diagnosis Breast Cancer (WDBC), Wisconsin Prognosis Breast Cancer (WPBC) (Salama et al. (2012))”. Table 2 shows the overall popular datasets used for breast cancer prediction. Figure 14(a, b, c) depicts the mammographic images of breast cancer.

Table 2. Overall datasets for breast cancer

Datasets	Format	No. of instances
CBIS-DDSM	DICOM	2620
INbreast FFDM	DICOM	410
BCDR FMR	DICOM	1010
MIAS	DICOM	320
BancoWeb LPIMO	DICOM	1473
Wisconsin Breast Cancer	Feature values	699
WDBC	Feature values	569
WPBC	Feature values	198

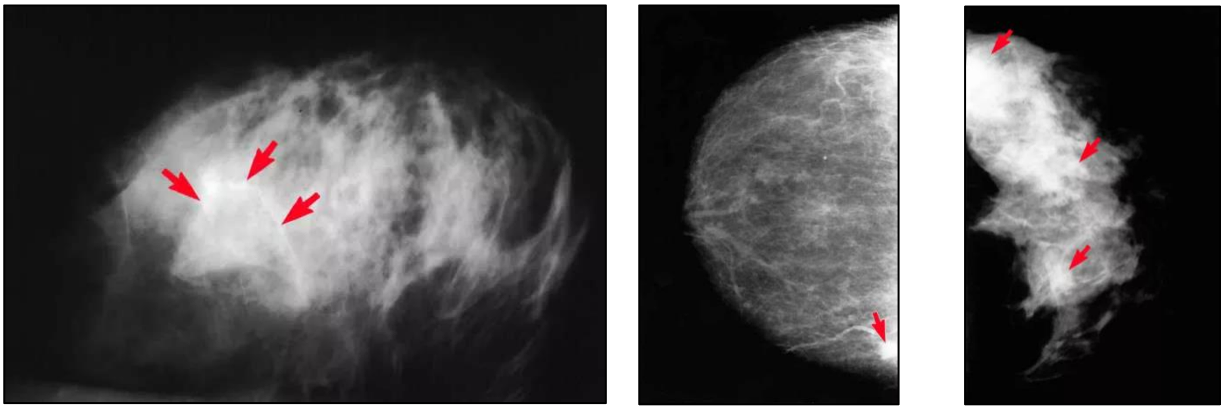


Fig. 14. a) breast calcification, b) breast tumour, c) fibrocystic breast tissue (Pam Stephan (2021))

2.4 Challenges of classification

Perfect classification is possible using machine learning techniques when there are sufficiently large numbers of balanced training samples. As far as medical imaging is considered, it is difficult to get a dataset that contains pathologically tested large numbers of training instances with a balanced class nature. It is an actual problem that often arises in the classification of medical images. Hence two issues need to be addressed: one is lack of data or data rarity (Raudys et al. (1991); Weiss (2004)) and the other is data with class imbalance (Krawczyk (2016); Alberto et al. (2018)) in which the sum of the majority class occurrences significantly out statistics that of the marginal class instances.

Small dataset size is the main challenge while performing the classification of healthcare pictures. Machine learning model needs large set of data for classification. Practically it is very difficult (Raudys et al. (1991); Mary et al. (2020)).

Class imbalance is among the most difficult issues in the classification. In the healthcare dataset, there are not equal numbers of cases of non-illness and disease. If there is an inappropriate class allocation, a dataset is termed unbalanced. When there is a high disparity across classes one or even more classes might be misrepresented within the dataset (Krawzcyk, 2016).

3. Machine Learning & Deep Learning classification methods

Even though ML and DL methods, in general, are very successful in the computer vision domain, there are two main challenges when it comes to the medical domain as detailed in Section 2.4. Several authors have proposed various approaches to addressing these issues. Table 3 depicts a comparative study of existing techniques' performance measures. Some of the popular approaches in classifying the breast cancer categories are given below:

3.1 SVM

Wu and Hicks (2021) used RNA-Sequence data from The Cancer Genome Atlas from hundred and ten triple-negative as well as nine hundred and ninety two non-triple negative breast cancer tumour specimens to identify its characteristics (genes) utilized in the creation and validation of several classifiers. "Support Vector Machines(SVM), K-nearest neighbour(KNN), Naive Bayes, and Decision tree classification models" are examined, with features taken at distinct threshold levels for training the methods in identifying between the 2 types of breast cancer. Their suggested approach SVM was used to independent gene expression datasets for performance evaluation and validation.

Yang et al. (2013) presented an efficient approach to breast cancer classification that relies on isometric feature mapping (Isomap) that employs SVM with various kernels. They began collecting data via the Wisconsin Diagnostic Breast Cancer (WDBC). With the help of an Isomap for projecting high-dimensional breast cancer information onto a considerably lesser-dimensional environment in the first step. Secondly, they categorized the lower dimensional breast cancer information utilizing SVM with different kernels. Lastly, the test results reveal that this suggested approach beats standard SVM within breast cancer classification.

3.2 Naïve Bayes

Amrane et al. (2018) explained two alternative classifiers for breast cancer classification: "the Naive Bayes (NB) classifier and K-nearest neighbor (KNN) classifier". They present a comparison of these two solutions and evaluate their correctness. Compared to the NB classifier, the results reveal that KNN gives the best accuracy (98 %) with lower error rate (96.19 %). Rane et al. (2020) compare six ML algorithms on a WDBC dataset, which contains retrieved features out of a fine needle aspirate of breast mass: Naive Bayes (NB), Random Forest (RT), Artificial Neural Networks (ANN), KNN, SVM, as well as Decision Tree (DT). This dataset is then splits into two phases for the execution of the ML algorithms: training and testing. The diagnosis tool is chosen by best algorithm, and thus categorize cancer as either malignant or benign (Mary et al., 2019; Ara et al., 2021).

3.3 Random Forest

Kabiraj et al. (2020) described the research that employs a dataset to forecast breast cancer utilizing the two prominent ML algorithms. Random Forest, as well as Extreme Gradient Boosting (XGBoost) was employed to forecast breast cancer. 275 cases with 12 characteristics have been used in this study. The Random Forest algorithm achieved 74.73% of accuracy in this investigation, whereas XGBoost attained 73.63%.

The objective of the research (Kumar and Nair (2021)) is to evaluate the datasets used, and compare the effectiveness of different algorithms of ML and their combinations for forecasting breast cancer. To distinguish benign and malignant tumors, classifiers (Support Vector Machine, Logistic Regression, K-Nearest Neighbors, Decision Tree, Naive Bayes, Random Forest and their combinations)were employed. According to the findings, “accuracy of Random Decision Forest Classifier with Bayesian Optimization for Breast Cancer (RDF-BOA) is 5.376% higher than that of Hybridized neural network-decision tree-based classifier (HNN-DTC)”. These classifiers have been utilised to create an automated diagnostic mechanism for the early breast cancer detection.

3.4 CNN

Kamruzzaman et al. (2021) explored that several convolutional neural networks (CNN) designed to recognize breast cancer automatically. A large collection of about 275000, 50x50-pixel RGB picture patches led all designs. For quantitative findings, validation tests were performed using the performance metrics for each technique. The suggested method is proven to be successful, obtaining findings with an accuracy of 87 %, which might decrease human errors in the diagnosing process. Furthermore, our suggested method outperforms 78 % of machine learning techniques.

Aslam et al. (2020) introduced a Deep Convolutional Neural Network accompanied by a SoftMax classifier CAD approach for breast cancer diagnosis. Utilizing the WBCD, the presented approach has been verified. The suggested classifier obtained 100% and 99.1% accuracy for two separate datasets, WBCD, and local datasets, indicating good diagnostic skills and promising outcomes.

3.5 DCNN

Kassani et al. (2019) sought to create a completely automated, deep learning-based procedure for the categorization of histological breast cancer pictures stained with hematoxylin and eosin (H&E). Pictures utilizing descriptive features retrieved using Deep Convolutional Neural Network as well as pooling procedure. Improved the performance of the DCNN, several data augmentation approaches were used. They also looked at the effectiveness of several stain normalizing techniques as a pre-processing stage. This network design gives an average accuracy of 92.50 %.

3.6 **Transfer** ***Learning***

Albabshish et al. (2021) developed a transfer learning method with a 16-layer deep model architecture (VGG16) relying on the Visual Geometry Group, which was employed to retrieve high-level characteristics from the BreaKHis benchmark histopathology picture dataset. Following that, three machine learning models (SVM, NB, and KNN) have been employed to tackle a variety of Breast Cancer (BC) histopathological image classification problems..Inferences of the experimental studies on publicly accessible BreakHis benchmark dataset clearly demonstrated that the suggested frameworks beat previous studies on the same dataset. Furthermore, the outcomes illustrate that the presented models outperform traditional machine learning techniques.

Mehra (2018) proved the capacity of transfer learning on the histopathological imaging modality in contrast to fully-trained network by analyzing behavior of the three previously trained networks(“VGG16, VGG19, as well as ResNet50”) for magnification independent breast cancer categorization. At the same time, they investigated the impacts of training–testing data quantity on the effectiveness of a network under consideration. With 92.60 percent accuracy, 95.65 percent AUC, and 96 percent Accuracy, Precision Score (APS) for 90 percent —10 percent splitting of training–testing data, a fine-tuned previously trained VGG16 with logistic regression classifier showed better outcomes.

Rodrigues et al. (2021) seek to identify breast cancer in histological pictures utilizing VGG-7, a simpler convolutional neural network. The findings reveal that VGG-7 outperforms VGG-16 as well as VGG-19, having 98 % accuracy, 99 % precision, 98 % recall, and a 98 % F1 score.

Salama et al. (2020) employed ResNet50 and VGG-16 to retrain two approaches to identify two classes instead of 1000 classes having the maximum accuracy and low computational requirements. Furthermore, transfer learning and data augmentation have been employed for fixing the issues due to the lack of labeled data. To achieve high accuracy, the support vector machine classifier was adopted rather than the final completely connected layer. The efficiency of their approach is verified using k-fold cross-validation. . Three mammographic datasets were used to train and assess our suggested methods. The suggested approach of utilizing ResNet50 hybridized with SVM delivers excellent outcomes, especially with the DDSM dataset, generating accuracy, area under the curve, sensitivity, precision, F1 score, as well as computational time with 97.98% , 98.46% , 97.63% , 96.51% ,95.97% and 1.8934 s respectively.

Al-haija et al. (2020) developed a precise and all-inclusive computational breast cancer diagnostic framework based on histopathology microscope images classified by the ResNet-50 convolutional neural network.BreakHis dataset is trained and categorized as noncancerous or cancerous, this model utilizes a transfer learning approach using the powerful ResNet-50 CNN that has been previously trained on ImageNet. According to the simulation results, their suggested model outperforms other comparison methods trained on a similar dataset, with an impressive accuracy of ninety nine percent.

Alkhaleefa et al. (2020) developed "a novel approach known as Double-Shot Transfer Learning (DSTL) that related to the concept of transfer learning. It is utilized for enhancing the entire accuracy as well as efficiency of previously trained breast cancer classification networks. DSTL fine-tunes the learnable parameters of the previously trained network utilizing a larger dataset identical to the target dataset. This redesigned network was then fine-tuned with the target dataset. Additionally, the number of X-ray pictures were enhanced by a range of augmentation approaches".This technique improved previously trained networks' classification accuracy and performance, rendering it highly appropriate for medical imaging.

Nawaz et al. (2018) suggested fine-tuning a deep convolutional neural network (ALEXNET) mostly by altering as well as introducing input layer convolutional layers and also completely connected layers. Our approach obtains patches and image accuracy of 76 percent and 81percent accordingly, on the validation set and image-wise accuracy of 57 percent on the ICIAR-2018 breast cancer challenges hidden test set.

Zejmo et al. (2016) presented a method that uses microscopic pictures to discriminate between benign and malignant instances. The study has been carried out using cytological samples that were taken out of 50 patients (25 benign as well as 25 malignant instances) at Zielona Gora Regional Hospital. GoogLeNet and AlexNet, which are the two types of Convolutional Neural Networks (CNN) were used for categorize microscopic pictures. Because the pictures of cytological specimens were so big (on average 200000 x 100000 pixels), they were split into smaller 256 x 256-pixel patches. Breast cancer has been classified depending on the morphometric characteristics of the nucleus. Because of the results, a svm is used to choose training and validation patches that show an appropriate quantity of cell content.

Jiang et al. (2019) introduced a unique convolutional neural network comprised of convolution layer, tiny SE-ResNet module, as well as a completely coupled layer. Furthermore, they provided a new learning rate scheduler that could achieve great effectiveness by not requiring extensive learning rate fine-tuning. They utilized their system to classify breast cancer histologic pictures as benign, malignant, and eight subcategories. Their approach yielded accuracy that between 98.87% and 99.34% throughout binary classification as well as an accuracy somewhere ranges from 90.66 - 93.81 percent for multi-class classification, as per the findings.

Murtaza et al. (2019) employed a convolutional neural network model focused on transfer learning that can produce mostly dependable, precise approach which uses limited resources. The proposed approach utilizes the trained model after fine-tuning, using fewer pictures, and producing better outcomes with fewer resources. The BreakHis dataset, which is freely available to the public, was utilized in this study's overall experiments. For experimentation, BreakHis dataset is partitioned into three main sections: training, testing, as well as validation. Furthermore, the training dataset was extended, followed by stain normalization. AlexNet was maintained until the last layer for binary classification, such as malignant as well as benign, was fine-tuned utilizing the Transfer Learning approach (TL). The preprocessed pictures are then given to the TL-based technique for training.

4. Findings

From the above various sections, the importance of different classifiers developed with both machine learning and deep learning techniques to effective detection of breast cancer over mammographic images in much accurate way, also usage of these advanced classifiers for avoiding two main challenges brings much effective in the performance of the overall model, as well as the final result with less memory utilization.

Table 3. Summary of existing systems

Classification Methodology	Authors	Dataset	F1-score	Accuracy (%)
VGG16	Albabshish et al. (2021)	BreakHis	0.88	86.23
VGG16, Resnet50, VGG19	Mehra (2018)	BreakHis	0.93	92.60
VGG7	Rodrigues et al. (2021)	WDBC	0.98	98
SVM, Resnet50	Salama et al. (2020)	DDSM	0.96	97.98
DCNN	Kassani et al. (2019)	ICIAR, BACH	-	92.5
Resent50, CNN	Al-haija et al. (2020)	BreakHis	0.99	
DSTL	Alkhaleefa et al. (2020)	CBIS-DDSM, MIAS, and BCDR	-	89.11
Alexnet	Nawaz et al. (2018)	ICIAR	-	81.25
Google Net, Alexnet, SVM	Zejmo et al. (2016)	Local	-	83
Resnet50	Jiang et al. (2019)	BreakHis	0.95	98.87
Transfer Learning	Murtaza et al. (2019)	BreakHis	0.87	81.25
CNN	Alanazi et al. (2021)	WDBC	0.91	87
DCNN	Aslam et al. (2020)	WDBC	0.98	99.1
SVM, NB, KNN	Wu and Hicks (2021)	Local	0.65	90
KNN, NB	Amrane et al. (2018)	WDBC	0.96	97.51
FW-KNCM + BOA-RDF	Kumar et. Al (2021)	Wisconsin Prognosis dataset		97.9

Table 3 represents the summary of existing systems; it contains sixteen studies' findings of detecting breast cancer using different methodologies and datasets. It shows the F1-Score and Accuracy of each method

Note that the performance measure accuracy of classification may not indicate the success of classification in all cases, especially in the case of imbalanced datasets. Hence other measures like sensitivity, specificity, recall, F1-score as well as precision are utilized for obtaining a clear picture of classification efficiency in various studies. Also, it can be noticed from the table that there is a consistent improvement in the classification performance year after year due to the methodology upgradation.

5. Conclusion

This study analyses latest approaches for breast cancer categorization developed by several breast cancer researchers over the last decade. Here the goal is to treat breast cancer as soon as possible using ML and DL approaches for exact estimation of breast cancer. Even though there are elementary stages for processing breast cancer, within the classification stage is the essential part where a relatively accurate framework can be generated by classifying the incoming images. So, those two main challenges are class imbalance and small dataset size, which will eventually affect the classification success rate. This problem was solved by depicting various researchers who are involved in breast cancer research. An analysis of research in which the most publications occurred in

Science Direct out of 10 databases has also been displayed. Based on statistical parameters, various hybrid classifiers may be employed to maximize the effectiveness of the present system, leading to better promising results.

References

[1] American Cancer Society. How Common Is Breast Cancer? https://www.cancer.org/cancer/breast-cancer/about/howcommon-is-breast-cancer.html (2018).

[2] Oeffinger, K. C. et al. Breast Cancer Screening for Women at Average Risk: 2015 Guideline Update From the American Cancer Society. JAMA 314, 1599–1614 (2015).

[3] Lehman, C. D. et al. National Performance Benchmarks for Modern Screening Digital Mammography: Update from the Breast Cancer Surveillance Consortium. Radiol. 283, 49–58 (2016).

[4] Murillo-Ortiz, B., Hernández-Ramírez, A., Rivera-Villanueva, T., Suárez-García, D., Murguía-Pérez, M., Martínez-Garza, S., ... & López-Partida, X. M. (2020). Monofrequency electrical impedance mammography (EIM) diagnostic system in breast cancer screening. BMC cancer, 20(1), 1-10.

[5] Fenton, J. J. et al. Influence of Computer-Aided Detection on Performance of Screening Mammography. New Engl. J. Medicine 356, 1399–1409 (2007).

[6] Das, B. K., Biswal, B. M., & Bhavaraju, M. (2006). Role of scintimammography in the diagnosis of breast cancer. The Malaysian journal of medical sciences: MJMS, 13(1), 52.

[7] Lehman, C. D. et al. Diagnostic Accuracy of Digital Screening Mammography With and Without Computer-Aided Detection. JAMA Intern. Medicine 175, 1828–1837 (2015).

[8] LeCun, Y., Bengio, Y. & Hinton, G. Deep learning. Nat. 521, 436–444 (2015).

[9] Aboutalib, S. S. et al. Deep Learning to Distinguish Recalled but Benign Mammography Images in Breast Cancer Screening. Clin. Cancer Res. (2018).

[10] Kim, E.-K. et al. Applying Data-driven Imaging Biomarker in Mammography for Breast Cancer Screening: Preliminary Study. Sci. Reports 8, 2762 (2018).

[11] Hamidinekoo, A., Denton, E., Rampun, A., Honnor, K. & Zwiggelaar, R. Deep learning in mammography and breast histology, an overview and future trends. Med. Image Analysis 47, 45–67 (2018).

[12] Burt, J. R. et al. Deep learning beyond cats and dogs: Recent advances in diagnosing breast cancer with deep neural networks. The Br. J. Radiol. 20170545 (2018).

[13] Kooi, T. et al. Large scale deep learning for computer aided detection of mammographic lesions. Med. Image Analysis 35, 303–312 (2017).

[14] Agarwal, R., Diaz, O., Lladó, X., Yap, M. H. & Martí, R. Automatic mass detection in mammograms using deep convolutional neural networks. J. Med. Imaging 6, 031409 (2019).

[15] Rodriguez-Ruiz, A. et al. Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists. JNCI: J. Natl. Cancer Inst (2019).

[16] Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L. & Guevara Lopez, M. A. Representation learning for mammography mass lesion classification with convolutional neural networks. Comput. Methods Programs Biomed. 127, 248–257 (2016).

[17] Rodríguez-Ruiz, A. et al. Detection of Breast Cancer with Mammography: Effect of an Artificial Intelligence Support System. Radiol. 290, 305–314 (2018).

[18] Dhungel, N., Carneiro, G. & Bradley, A. P. The Automated Learning of Deep Features for Breast Mass Classification from Mammograms. In 19th International Conference, Athens, Greece, October 17–21, 2016, Proceedings, Part II, 106–114 (Springer International Publishing, Cham, 2016).

[19] Jamieson, A. R., Drukker, K. & Giger, M. L. Breast image feature learning with adaptive deconvolutional networks. Proc. SPIE 8315, (6–13 (2012).

[20] Ourselin, S., Joskowicz, L., Sabuncu, M. R., Unal, G. & Wells, W. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016:

[21] Girshick, R., Donahue, J., Darrell, T. & Malik, J. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. In Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition, CVPR' 14, 580–587 (IEEE Computer Society, Washington, DC, USA, 2014).

[22] Girshick, R. Fast r-cnn. In Proceedings of the IEEE International Conference on Computer Vision, 1440–1448 (2015).

[23] Ren, S., He, K., Girshick, R. & Sun, J. Faster R-CNN: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems, 91–99 (2015).

[24] Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L. & Lopez, M. A. G. Convolutional neural networks for mammography mass lesion

classification. In 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 797–800,

[25] Dai, J., Li, Y., He, K. & Sun, J. R-FCN: Object Detection via Region-based Fully Convolutional Networks. arXiv:1605.06409 [cs], 1605.06409 (2016).

[26] Dhungel, N., Carneiro, G. & Bradley, A. P. Automated Mass Detection in Mammograms Using Cascaded Deep Learning and Random Forests. In 2015 International Conference on Digital Image Computing: Techniques and Applications (DICTA), 1–8, https://doi.org/10.1109/DICTA.2015.7371234 (2015).

[27] Ertosun, M. G. & Rubin, D. L. Probabilistic visual search for masses within mammography images using deep learning. In 2015 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 1310–1315, https://doi.org/10.1109/BIBM.2015.7359868 (2015).

[28] Akselrod-Ballin, A. et al. A Region-Based Convolutional Network for Tumor Detection and Classification in Breast Mammography. In Carneiro, G. et al. (eds) Deep Learning and Data Labeling for Medical Applications: First International Workshop, LABELS 2016, and Second International Workshop, DLMIA 2016, Held in Conjunction with MICCAI 2016, Athens, Greece, October 21, 2016, Proceedings, 197–205 (Springer International Publishing, Cham, 2016).

[29] Ribli, D., Horváth, A., Unger, Z., Pollner, P. & Csabai, I. Detecting and classifying lesions in mammograms with Deep Learning. arXiv:1707.08401 [cs], 1707.08401 (2017).

[30] Moreira, I. C. et al. INbreast: Toward a Full-field Digital Mammographic Database. Acad. Radiol. 19, 236–248 (2012).

[31] Yamini Ranchod (2020) https://www.mayoclinic.org/diseases-conditions/breast-cancer/symptoms-causes/syc-20352470)

[32] Hinton, G. E., Osindero, S. & Teh, Y.-W. A fast learning algorithm for deep belief nets. Neural Comput. 18, 1527–1554 (2006).

[33] Russakovsky, O. et al. ImageNet Large Scale Visual Recognition Challenge. Int. J. Comput. Vis. 115, 211–252 (2015).

[34] Oquab, M., Bottou, L., Laptev, I. & Sivic, J. Learning and Transferring Mid-Level Image Representations using Convolutional Neural Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 1717–1724 (2014).

[35] WHO, 2020, https://www.who.int/news-room/fact-sheets/detail/breast-cancer)

[36] Harshita Pandey (2020) https://medium.com/analytics-vidhya/introduction-to-artificial-intelligence-machine-learning-deep-learning-and-data-science-5aa5051e9792

[37] Shen, L., Margolies, L. R., Rothstein, J. H., Fluder, E., McBride, R., & Sieh, W. (2019). Deep learning to improve breast cancer detection on screening mammography. Scientific reports, 9(1), 1-12.

[38] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255-260.

[39] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT press.

[40] Marley (2020) https://www.aidoc.com/blog/artificial-intelligence-medical-dia

[41] Norman (2018) Norman A. Your future doctor may not be human. this is the rise of AI in medicine. 2018. https://futurism.com/ai-medicine-doctor. [January 2018]. https://futurism.com/ai-medicine-doctor

[42] Patel et al. (2009) Patel VL, Shortliffe EH, Stefanelli M, Szolovits P, Berthold MR, Bellazzi R, Abu-Hanna A. The coming of age of artificial intelligence in medicine. Artificial Intelligence in Medicine. 2009;46(1):5–17. doi: 10.1016/j.artmed.2008.07.017.

[43] King Jr (2018) King Jr B. Artificial intelligence and radiology: what will the future hold? Journal of the American College of Radiology. 2018;15(3 Part B):501–503.

[44] Recht & Bryan (2017) Recht M, Bryan RN. Artificial intelligence: threat or boon to radiologists? Journal of American College of Radiologists. 2017;14(11):1476–1480.

[45] Kruskal et al. (2017) Kruskal JB, Berkowitz S, Geis JR, Kim W, Nagy P, Dreyer K. Big data and machine learning-strategies for driving this bus: a summary of the 2016 intersociety summer conference. Journal of American College of Radiologists. 2017;14(6):811–817. doi: 10.1016/j.jacr.2017.02.019.

[46] Greenspan, Van Ginneken & Summers (2016) Greenspan H, Van Ginneken B, Summers RM. Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique. IEEE Transactions on Medical

Imaging. 2016;35(5):1153–1159. doi: 10.1109/TMI.2016.2553401.
[47] Ahuja, A. S. (2019). The impact of artificial intelligence in medicine on the future role of the physician. PeerJ, 7, e7702.
[48] Kerlikowske K, Grady D, Rubin SM, Sandrock C, Ernster VL. Efficacy of screening mammography. A meta-analysis. JAMA. 1995;273:149–154.
[49] Nyström L, Andersson I, Bjurstam N, Frisell J, Nordenskjöld B, Rutqvist LE. Long-term effects of mammography screening: updated overview of the Swedish randomised trials. Lancet. 2002;359:909–919.
[50] Kopans DB. Beyond randomized controlled trials: organized mammographic screening substantially reduces breast carcinoma mortality. Cancer. 2002;94:580–581; author reply 581-583
[51] Kopans DB. Sonography should not be used for breast cancer screening until its efficacy has been proven scientifically. AJR Am J Roentgenol. 2004;182:489–491
[52] Tabar L, Yen MF, Vitak B, Chen HH, Smith RA, Duffy SW. Mammography service screening and mortality in breast cancer patients: 20-year follow-up before and after introduction of screening. Lancet. 2003;361:1405–1410.
[53] Malur S, Wurdinger S, Moritz A, Michels W, Schneider A. Comparison of written reports of mammography, sonography and magnetic resonance mammography for preoperative evaluation of breast lesions, with special emphasis on magnetic resonance mammography. Breast Cancer Res. 2001;3:55–60
[54] Kelly KM, Dean J, Comulada WS, Lee SJ. Breast cancer detection using automated whole breast ultrasound and mammography in radiographically dense breasts. Eur Radiol. 2010;20:734–742.
[55] Carsten Riis C, Lernevall A, Sorensen FB, Nygaard H. 3D Ultrasound-based evaluation of lesions in the uncompressed breast. In: Ueno E, Shiina T, Kubota M, Sawai K, editors. Research and Development in Breast Ultrasound. Tokyo: Springer; 2005. pp. 151–155
[56] Carsten Riis C. TechniScan. Svara™ Warm Bath Ultrasound (WBU™) Imaging System. Available from: http://www.techniscanmedicalsystems.com/index.php?p=Home
[57] Kook SH, Park HW, Lee YR, Lee YU, Pae WK, Park YL. Evaluation of solid breast lesions with power Doppler sonography. J Clin Ultrasound. 1999;27:231–237.
[58] Scaperrotta G, Ferranti C, Costa C, Mariani L, Marchesini M, Suman L, Folini C, Bergonzi S. Role of sonoelastography in non-palpable breast lesions. Eur Radiol. 2008;18:2381–2389
[59] Keith LG, Oleszczuk JJ, Laguens M. Circadian rhythm chaos: a new breast cancer marker. Int J Fertil Womens Med. 2001;46:238–247
[60] Salhab M, Sarakbi WAI, Mokbel K. Vol. 2. Tokyo: Springer; 2005. The evolving role of the dynamic thermal analysis in the early detection of breast cancer. Int Semin Surg Oncol; p. 8. Available from: http://www.issoonline.com/content/2/1/8.
[61] Gautherine M, Gros C. Contribution of infrared thermography to early diagnosis, pretheraputic prognosis and post-irradiation follow-up of breast carcinomas. Med Mundi. 1976;21:135–149.
[62] Gros C, Gautherie M, Bourjat P. Prognosis and post-therapeutic follow-up of breast cancers by thermography. Bibl Radiol. 1975:77–90.
[63] Ng EYK, Chen Y, Ung LN. Computerized breast thermography: study of image segmentation and temperature cyclic variations. Int J Med Eng Technol. 2001;25:12–16.
[64] Ng EYK. A review of thermography as promising non-invasive detection modality for breast tumour. Int J Therm Sci. 2009;48:849–859
[65] Ng EYK, Sudharsan NM. Numerical modeling in conjunction with thermography as an adjunct tool for breast tumour detection. BMC Cancer. 2004;4:1–26.
[66] Ammer K, Ring EFJ. Standard procedures for infrared imaging in medicine. In: Biomedical Engineering Handbook. CRC Press; 2006. pp. chapter 36: 1–14.
[67] Amalu WC, Hobbins WB, Head JF, Elliott RL. Infrared imaging of the breast - an overview. In: Biomedical Engineering Handbook. CRC Press; 2006. pp. chapter 25: 1–36.
[68] Wiecek B, Wiecek M, Strakowski R, Jakubowska T, Ng EYK. Wavelet-based thermal image classification for breast screening and other medical applications. In: Ng EYK, Acharya RU, Suri JS. Performance Evaluation Techniques in Multi-modality Breast Cancer Screening, Diagnosis and Treatment. American Scientific Publishers; 2010.
[69] Ring EFJ, Ammer K. The technique of infra red imaging in medicine. Thermology Int. 2000;10:7–14
[70] Heywang-Köbrunner SH, Viehweg P, Heinig A, Küchler C. Contrast-enhanced MRI of the breast: accuracy, value, controversies, solutions. Eur J Radiol. 1997;24:94–108
[71] Liu PF, Debatin JF, Caduff RF, Kacl G, Garzoli E, Krestin GP. Improved diagnostic accuracy in dynamic contrast enhanced MRI of the breast by

combined quantitative and qualitative analysis. Br J Radiol. 1998;71:501–509.
[72] Basilion JP. Current and future technologies for breast cancer imaging. Breast Cancer Res. 2001;3:14–16.
[73] Radipedia, 2020, https://radiopaedia.org/cases/breast-cancer-ct-appearances
[74] Medical News Today, 2020, https://www.medicalnewstoday.com/articles/322068
[75] Leach MO. Application of magnetic resonance imaging to angiogenesis in breast cancer. Breast Cancer Res. 2001;3:22–27.
[76] Schnall MD. Application of magnetic resonance imaging to early detection of breast cancer. Breast Cancer Res. 2001;3:17–21
[77] Lehman CD, Schnall MD. Imaging in breast cancer: Magnetic resonance imaging. Breast Cancer Res. 2005;7:215–219.
[78] Fass L. Imaging and cancer: a review. Mol Oncol. 2008;2:115–152.
[79] Stephan P. In: Hayat MA, editor. Lung and breast carcinomas. Elsevier; 2010. Mammography and Breast MRIs. Available from: http://breastcancer.about.com/od/mammograms/a/mammo_vs_mri_2.htm.
[80] Munshi S. In: Hayat MA, editor. Lung and breast carcinomas. Elsevier; 2008. Scintimammography - an emerging technique for Breast Imaging. Available from: http://www.frost.com/prod/servlet/market-insight-top.pag?docid=137248277.
[81] Brem RF, Rapelyea JA, Zisman G, Mohtashemi K, Raub J, Teal CB, Majewski S, Welch BL. Occult breast cancer: scintimammography with high-resolution breast-specific gamma camera in women at high risk for breast cancer. Radiology. 2005;237:274–280.
[82] Prats E, Aisa F, Abós MD, Villavieja L, García-López F, Asenjo MJ, Razola P, Banzo J. Mammography and 99mTc-MIBI scintimammography in suspected breast cancer. J Nucl Med. 1999;40:296–301.
[83] Zou Y, Guo Z. A review of electrical impedance techniques for breast cancer detection. Med Eng Phys. 2003;25:79–90
[84] Liu Y, Bellomi M, Gatti G, Ping X. Accuracy of computed tomography perfusion in assessing metastatic involvement of enlarged axillary lymph nodes in patients with breast cancer. Breast Cancer Res. 2007;9:R40
[85] Einstein AJ, Henzlova MJ, Rajagopalan S. Estimating risk of cancer associated with radiation exposure from 64-slice computed tomography coronary angiography. JAMA. 2007;298:317–323.
[86] Sree, S. V., Ng, E. Y. K., Acharya, R. U., & Faust, O. (2011). Breast imaging: a survey. World journal of clinical oncology, 2(4), 171.
[87] Salama, G. I., Abdelhalim, M. B., & Zeid, M. A. E. (2012, November). Experimental comparison of classifiers for breast cancer diagnosis. In 2012 Seventh International Conference on Computer Engineering & Systems (ICCES) (pp. 180-185). IEEE.
[88] Moura, D. C., & López, M. A. G. (2013). An evaluation of image descriptors combined with clinical data for breast cancer diagnosis. International journal of computer assisted radiology and surgery, 8(4), 561-574.
[89] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M. (2016). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging, 35(5), 1285-1298.
[90] Zhang, S., Han, F., Liang, Z., Tan, J., Cao, W., Gao, Y., ... & Hou, W. (2019). An investigation of CNN models for differentiating malignant from benign lesions using small pathologically proven datasets. Computerized Medical Imaging and Graphics, 77, 101645.
[91] C. Sun, A. Shrivastava, S. Singh and A. Gupta, "Revisiting Unreasonable Effectiveness of Data in Deep Learning Era," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, 2017, pp. 843-852, doi: 10.1109/ICCV.2017.97.
[92] Oakden-Rayner, L. (2020). Exploring Large- scale Public Medical Image Datasets. Academic radiology, 27(1), 106- 112.
[93] Lee, R. S., Gimenez, F., Hoogi, A., Miyake, K. K., Gorovoy, M., & Rubin, D. L. (2017). A curated mammography data set for use in computer-aided detection and diagnosis research. Scientific data, 4, 170177.
[94] Moreira, I. C., Amaral, I., Domingues, I., Cardoso, A., Cardoso, M. J., & Cardoso, J. S.(2012). Inbreast: toward a full-field digital mammographic database. Academic radiology, 19(2), 236-248.
[95] Lopez, M. G., Posada, N., Moura, D. C., Pollán, R. R., Valiente, J. M. F., Ortega, C. S., ... & Fernandes, T. C. (2012, July). BCDR: a breast cancer digital repository. In 15th International conference on experimental mechanics.
[96] SUCKLING J, P. (1994). The mammographic image analysis society digital mammogram database. Digital Mammo, 375- 386.

[97] Matheus BR, Schiabel H. Online mammographic images database for development and comparison of CAD schemes. J Digital Imaging 2010; 24:500–506
[98] Pam Stephan, 2021 https://www.verywellhealth.com/mammogram-images-descriptions-and-details-4020351
[99] Raudys, S.J., Jain, A.K., et al.: Small sample size effects in statistical pattern recognition: recommendations for practitioners. IEEE Trans. Pattern Anal. Mach. Intell. 13(3), 252–264 (1991)
[100] Weiss, G.M.: Mining with rarity: a unifying framework. ACM SigkddExplor. Newslett. 6(1), 7–19 (2004)
[101] Krawczyk, B. Learning from imbalanced data: open challenges and future directions. Prog ArtifIntell 5, 221–232 (2016). https://doi.org/10.1007/s13748-016-0094-0
[102] Alberto Fernández, Salvador García, Mikel Galar, Ronaldo C. Prati, Bartosz Krawczyk, Francisco Herrera, "Learning from Imbalanced Data Sets", Springer International Publishing, 2018
[103] Albashish, D., Al-Sayyed, R., Abdullah, A., Ryalat, M. H., & Almansour, N. A. (2021, July). Deep CNN Model based on VGG16 for Breast Cancer Classification. In 2021 International Conference on Information Technology (ICIT) (pp. 805-810). IEEE.
[104] Mehra, R. (2018). Breast cancer histology images classification: Training from scratch or transfer learning?. ICT Express, 4(4), 247-254.
[105] Rodrigues Filho, M. L., & Cortes, O. A. C. (2021, July). Efficient Breast Cancer Classification Using Histopathological Images and a Simpler VGG. In Anais do XV Brazilian e-Science Workshop (pp. 9-16). SBC.
[106] Salama, W. M., Elbagoury, A. M., & Aly, M. H. (2020). Novel breast cancer classification framework based on deep learning. IET Image Processing, 14(13), 3254-3259.
[107] Kassani, S. H., Kassani, P. H., Wesolowski, M. J., Schneider, K. A., & Deters, R. (2019, October). Breast cancer diagnosis with transfer learning and global pooling. In 2019 International Conference on Information and Communication Technology Convergence (ICTC) (pp. 519-524). IEEE.
[108] Alkhaleefah, M., Ma, S. C., Chang, Y. L., Huang, B., Chittem, P. K., & Achhannagari, V. P. (2020). Double-shot transfer learning for breast cancer classification from X-ray images. Applied Sciences, 10(11), 3999.
[109] Nawaz, W., Ahmed, S., Tahir, A., & Khan, H. A. (2018, June). Classification of breast cancer histology images using alexnet. In International conference image analysis and recognition (pp. 869-876). Springer, Cham.
[110] Żejmo, M., Kowal, M., Korbicz, J., & Monczak, R. (2017). Classification of breast cancer cytological specimen using convolutional neural network. In Journal of Physics: Conference Series (Vol. 783, No. 1, p. 012060). IOP Publishing.
[111] Jiang, Y., Chen, L., Zhang, H., & Xiao, X. (2019). Breast cancer histopathological image classification using convolutional neural networks with small SE-ResNet module. PloS one, 14(3), e0214587.
[112] Murtaza, G., Shuib, L., Wahab, A. W. A., Mujtaba, G., Raza, G., & Azmi, N. A. (2019, December). Breast cancer classification using digital biopsy histopathology images through transfer learning. In Journal of Physics: Conference Series (Vol. 1339, No. 1, p. 012035). IOP Publishing.
[113] Alanazi, S. A., Kamruzzaman, M. M., Islam Sarker, M. N., Alruwaili, M., Alhwaiti, Y., Alshammari, N., & Siddiqi, M. H. (2021). Boosting breast cancer detection using convolutional neural network. Journal of Healthcare Engineering, 2021.
[114] Aslam, M. A., & Cui, D. (2020, July). Breast Cancer Classification using Deep Convolutional Neural Network. In Journal of Physics: Conference Series (Vol. 1584, No. 1, p. 012005). IOP Publishing.
[115] Wu, J., & Hicks, C. (2021). Breast Cancer Type Classification Using Machine Learning. Journal of personalized medicine, 11(2), 61.
[116] Amrane, M., Oukid, S., Gagaoua, I., & Ensari, T. (2018, April). Breast cancer classification using machine learning. In 2018 Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT) (pp. 1-4). IEEE.
[117] Rane, N., Sunny, J., Kanade, R., & Sulochana, D. (2020). Breast cancer classification and prediction using machine learning. International Journal of Engineering Research & Technology, 9(02), 576-580.
[118] Kumar, V., Mishra, B. K., Mazzara, M., Thanh, D. N., & Verma, A. (2020). Prediction of malignant and benign breast cancer: A data mining approach in healthcare applications. In Advances in data science and management (pp. 435-442). Springer, Singapore.
[119] Golatkar, A., Anand, D., & Sethi, A. (2018, June). Classification of breast cancer histology using deep learning. In International Conference Image Analysis and Recognition (pp. 837-844). Springer, Cham.

[120] Petersen, K., Nielsen, M., Diao, P., Karssemeijer, N., & Lillholm, M. (2014, June). Breast tissue segmentation and mammographic risk scoring using deep learning. In International workshop on digital mammography (pp. 88-94). Springer, Cham.

[121] Raudys, S.J., Jain, A.K., et al.: Small sample size effects in statistical pattern recognition: recommendations for practitioners. IEEE Trans. Pattern Anal. Mach. Intell. 13(3), 252–264 (1991)

[122] Krawczyk, B. Learning from imbalanced data: open challenges and future directions. Prog ArtifIntell 5, 221–232 (2016). https://doi.org/10.1007/s13748-016-0094-0

[123] Mary Amala Bai, Geetha G Nair, Challenges and Solutions in CNN based Diagnostic Techniques on Breast Mammographic images: A Survey, ISSN 0975-2366, 2020

[124] Mary Amala Bai, Geetha G Nair, A Survey on Machine Learning Algorithms Used for the Diagnosis of Breast Cancer, Proceedings of International Conference on Networks, Images and Security ICNIS‘19-April 10th& 11th, 2019.

[125] Kumar, P. and Nair, G.G., 2021. An efficient classification framework for breast cancer using hyper parameter tuned Random Decision Forest Classifier and Bayesian Optimization. Biomedical Signal Processing and Control, 68, p.102682. - discussing the following ML Techniques

[126] Yang, X., Peng, H., & Shi, M. (2013, August). SVM with multiple kernels based on manifold learning for Breast Cancer diagnosis. In 2013 IEEE International Conference on Information and Automation (ICIA) (pp. 396-399). IEEE.

[127] Kabiraj, S., Raihan, M., Alvi, N., Afrin, M., Akter, L., Sohagi, S. A., & Podder, E. (2020, July). Breast cancer risk prediction using XGBoost and random forest algorithm. In 2020 11th international conference on computing, communication and networking technologies (ICCCNT) (pp. 1-4). IEEE.

[128] Scolaro, L., McLaughlin, R. A., Kennedy, B. F., Saunders, C. M., & Sampson, D. D. (2014). A review of optical coherence tomography in breast cancer. Photonics & Lasers in Medicine, 3(3), 225-240.

[129] Al-Dhabyani, W., Gomaa, M., Khaled, H., & Fahmy, A. (2020). Dataset of breast ultrasound images. Data in brief, 28, 104863.

[130] Tello-Mijares, S., Woo, F., & Flores, F. (2019). Breast cancer identification via thermography image segmentation with a gradient vector flow and a convolutional neural network. Journal of healthcare engineering, 2019.

[131] Mayoclinic, 2018, https://www.mayoclinic.org/tests-procedures/breast-mri/about/pac-20384809

[132] The American Society of Breast Surgeons Foundation, 2018, https://breast360.org/topic/2017/01/01/breast-pet-scan/

[133] Al-Haija, Q. A., & Adebanjo, A. (2020, September). Breast cancer diagnosis in histopathological images using ResNet-50 convolutional neural network. In 2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS) (pp. 1-7). IEE