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# Artificial Intelligence-Driven Breast Cancer Detection: Current Progress, Challenges, and Future Directions

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## Abstract

Breast cancer remains one of the leading cancer-related causes of fatalities among women globally. Consequently, the improvement of survival rates relies heavily on the advancement of early and precise detection. Studies suggest that breast cancer detection rates will rise sharply in the coming decades (1990-2026). For instance, it is anticipated that by 2050 there will be 3.2-3.5 million new cases per annum, up from 2.3 million reported in 2022. As part of induced cancer research, new deep learning and machine learning algorithms enabled Artificial Intelligence (AI) to enhance breast cancer diagnosis. AI can improve detection in imaging techniques such as mammography, ultrasound, and MRI. The authors of the review provide a comprehensive insight into the AI-based detection systems of today. Advances in convolutional neural networks, computer-aided diagnosis, and predictions are discussed. The authors also consider the problems that have been said to have previously restricted the adoption of such technologies in the clinic. These include algorithmic inequity, data heterogeneity, the interpretability challenge, and regulatory issues. The authors explore explainable AI, the fusion of multimodal data, and trustworthy and fair validation for future breast cancer detection tools that will augment radiologists' practice as an additional tool.

***Keywords:*** Breast cancer; artificial intelligence; mammography; deep learning, medical imaging, biopsy, machine learning.

## 1. Introduction

Breast cancer is the cancer that is most commonly diagnosed in women and is one of the leading cancers causing death in women. The 2024 GLOBOCAN estimates of the International Agency for Research on Cancer and the American Cancer Society project that, in 2024, female breast cancer will account for about 11.8% of the total number of cancer cases diagnosed, making it the second most diagnosed cancer after lung cancer, and will contribute significantly to cancer deaths [1]. The World Health Organization reports that breast cancer will account for approximately 694,000 deaths in 2024. Breast cancer will also be the most commonly diagnosed cancer in 164 out of 186 surveyed countries. In countries where most of the surveyed countries are located, there is limited access to early detection methods. These results show that there is a great need for accessible and accurate diagnostics. The only way to significantly impact breast cancer mortality is

through early detection. Diagnosis options are contingent on treatment. The foundation of breast cancer screening is mammography, which is supplemented by the use of ultrasound, MRI, and digital breast tomosynthesis. Standard screen-reading is labor-intensive and has a high degree of inter- and intra-observer variability. There is a global shortage of radiologists, which also contributes to the problem. This all leads to delayed diagnoses, unnecessary recalls, and missed tumors. The limitations have sustained interest in computer-aided detection and the use of imaging data to develop artificial intelligence, which have been active for decades.

In the last decade, deep learning, particularly convolutional neural networks, and more recently hybrid CNN-transformers and vision transformers, have dominated the study of computer-aided detection for breast cancer imaging, replacing previous paradigms of hand-crafted feature-based machine learning [3, 4]. These architectures have been implemented in nearly all imaging modalities utilized in breast care, including, but not limited to, full-field digital mammograms, tomosynthesis, breast ultrasound, MRI, thermography, and breast histopathology. In several studies, the performance of these computer-aided diagnosis systems has approached that of expert radiologists and pathologists [3, 5]. We are expanding the application of AI beyond lesion detection and classification and incorporating deep learning radiomics for risk stratification and prognosis and for molecular subtyping [6, 7]. This is a significant shift towards tailoring breast cancer care. The prospective and randomized clinical validations of AI in breast imaging have now outstripped retrospective benchmarks in the evidence collection for the clinical value of AI. A large randomized, population-based, screening-accuracy study in Sweden, the Mammography Screening with Artificial Intelligence (MASAI) Trial, has tested the large-scale implementation of AI in mammography. The MASAI Trial reported that AI-assisted double reading achieved a cancer detection rate that was at least comparable to conventional double reading by two radiologists and eliminated 44% of the screen-reading workload [8]. A further analysis of the MASAI Trial reported that AI-assisted double reading resulted in a 29% increase in the cancer detection rate and no increase in the rate of false positive diagnoses [9]. There is continuing positive evidence that AI-supported mammography screening has the potential to reduce interval cancers and improve the effectiveness of screening programs beyond what can currently be achieved with human performance on retrospective test cases in mammography screening [10]. AI integrated into the current screening workflow, along with complementary prospective research (e.g., a multi-site implementation study of AI-assisted screen reading), has substantially improved the early detection of clinically significant cancers [11]. When viewed holistically, these studies have transitioned AI in breast imaging from a promising research tool to one with increasing real clinical utility.

Despite these improvements, many challenges remain before achieving widespread, secure, and equitable deployment of AI for breast cancer screening. Model performance can degrade when trained data from one population, scanner manufacturer, or acquisition protocol is used clinically for a different population [11]. Questions remain about the representativeness and generalizability of publicly available training datasets, many of which contain limited racial and demographic diversity [12]. Interest in explainable and interpretable AI models has also increased in light of the “black-box” nature of many deep learning algorithms, which continues to limit clinician trust and uptake. Availability of large-scale multi-institutional datasets with extensive annotations, challenges in prospectively validating AI methodologies before clinical implementation (necessary for regulatory approval), issues with workflow/accountability/liability when AI results disagree with human readers, and logistical difficulty of incorporating AI models into clinical radiology/puretology workflows without affecting clinical throughput are additional barriers [3, 5, 12, 13]. Additional caveats need to be considered when examining studies in this area given how quickly AI methods, datasets, and clinical outcome data are evolving.

## 2. Anatomy of the breast

Figure 1 below represents the anatomical structure of the female breast. The breast or mammary gland is a modified sweat gland found over the pectoralis major muscle in the superficial fascia of the anterior thoracic wall. The breast consists of 15-20 lobes, which are arranged radially, with the nipples at the center. Each lobe is divided into sublobules by connective tissue, with numerous alveoli in each division. The alveoli are small sacs that open into the lactiferous ducts, which carry milk from the alveoli to the nipples. Each duct is widened into a sinus to form the ducts that open independently from the ends of the nipples. The breast has 15-20 openings for the milk ducts in the center. The colored region around the nipples is known as the areola. Sebaceous glands or Montgomery's glands are present on the areola, secreting oil to lubricate the nipples during breastfeeding. The breast consists of fibrous tissue or Cooper's ligaments that extend from the skin to the pectoralis major muscle, with fatty tissues surrounding the lobules and ligaments. These tissues hang and sag when the breast develops cancer. The ribs provide bony support below the pectoralis major muscle that forms the breast. The axillary lymph nodes are the primary drainage site for the breast, except the internal mammary nodes. Breast cancer spreads predominantly through the lymphatic route, making it the most critical region for therapeutic intervention. The intercostal nerves from the 2nd to the 6th thoracic vertebrae provide sensory innervation to the nipples and breasts.

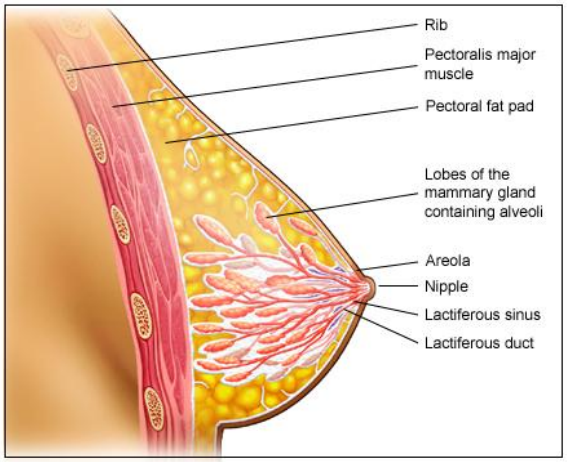



Figure 1: Anatomy of a breast

## 3. Types of breast cancer

Breast cancer is a group of diseases that differ qualitatively in cell biology and natural history and, therefore, require fundamentally different treatments. The determination of prognosis and therapeutic strategy are complicated by the wide spectrum of histological and molecular subtypes. The present work discusses the main histological and molecular subtypes of breast cancer, as well as the risk factors and pathogenic mechanisms associated with them. According to the classification of breast cancer, two main axes are used for classifying cancer types: (1) the histological axis implies the localization of tumor cells and their infiltration capability, and (2) the molecular or receptor axis, implying the expression of hormone receptors and HER2, which is increasingly important in selecting treatment options [14].

### *A. Histological Classification*

**(i) Non-Invasive (In Situ) Carcinomas:** The most common category of non-invasive breast cancer comprises ductal carcinoma that is also referred to as DCIS (ductal carcinoma in situ) (see Figure 2(a)). This disease occurs when the cells lining the milk ducts turn cancerous and proliferate uncontrollably, but the cancerous cells do not extend beyond the walls of the ducts into the surrounding breast tissue. However, if DCIS is not treated, it has the potential to transform into invasive cancer [15]. Similarly, lobules in the breast can also become affected by cancer. The condition is referred to as LCIS (lobular carcinoma in situ) or lobular neoplasia (see Figure 2(b)). Unlike DCIS, LCIS is regarded as a risk factor for developing additional breast cancer instead of a precursor for invasive cancer.

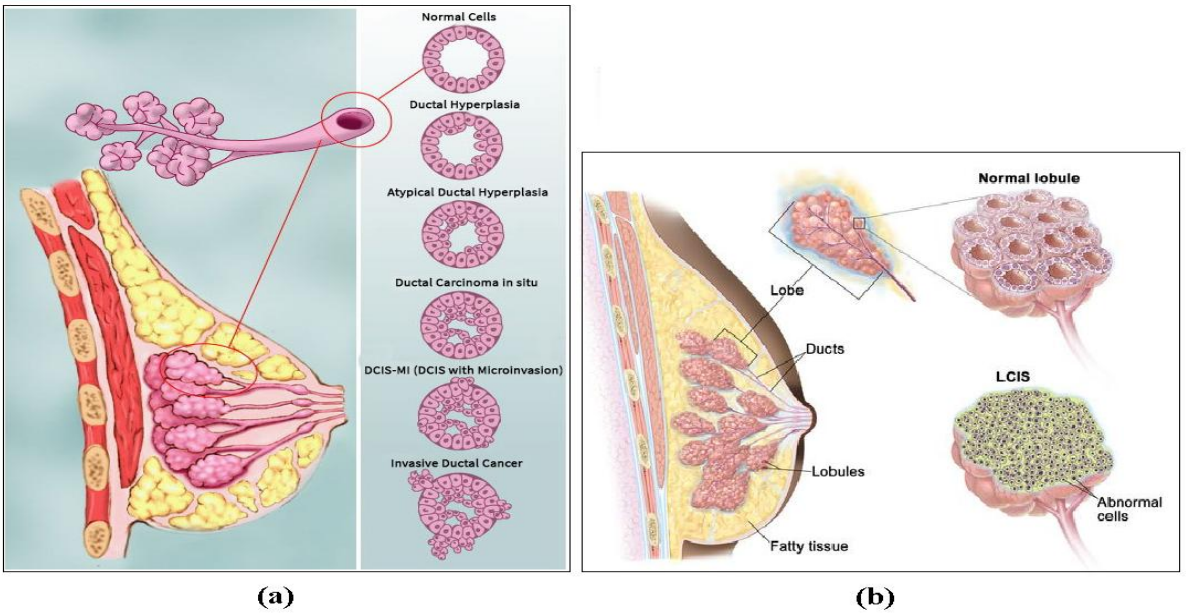



Figure 2: (a) Ductal carcinoma in situ (DCIS), (b) Lobular carcinoma in situ (LCIS)

**(ii) Invasive (Infiltrating) Carcinomas:** Invasive ductal carcinoma (IDC), also called invasive carcinoma of no special type, is the most common type of breast cancer. It accounts for 70-80% of all breast cancer cases. Ductal carcinoma is cancer that has begun in the milk ducts and spread to other parts of the breast tissue, and then it may spread to the lymph nodes and other parts of the body [15] (see Fig. 3(a)). However, 10-15% of invasive breast cancers are of the second most common type of invasive lobular carcinoma (ILC) (see Fig. 3(b)). ILC is a cancer that has begun in the lobules and often grows in a scattered fashion, and unlike most breast cancers, it does not form a lump, making it harder to see on a standard mammogram or on a physical exam; in such cases, a special breast MRI is sometimes used to diagnose it [16].

**(iii) Less Common Special Histological Subtypes:** Several less common invasive subtypes have unique microscopic characteristics and, in some situations, better prognoses than standard IDC such as:

- **Mucinous (colloid) carcinoma** - tumor cells often develops slowly and is encircled by mucus pools.
- **Tubular carcinoma** - tiny, tube-shaped structures that are often low-grade and have a favorable prognosis.
- **Medullary carcinoma** - soft, meaty tumor with well-defined margins; more usually triple-negative but often has a pretty positive result.

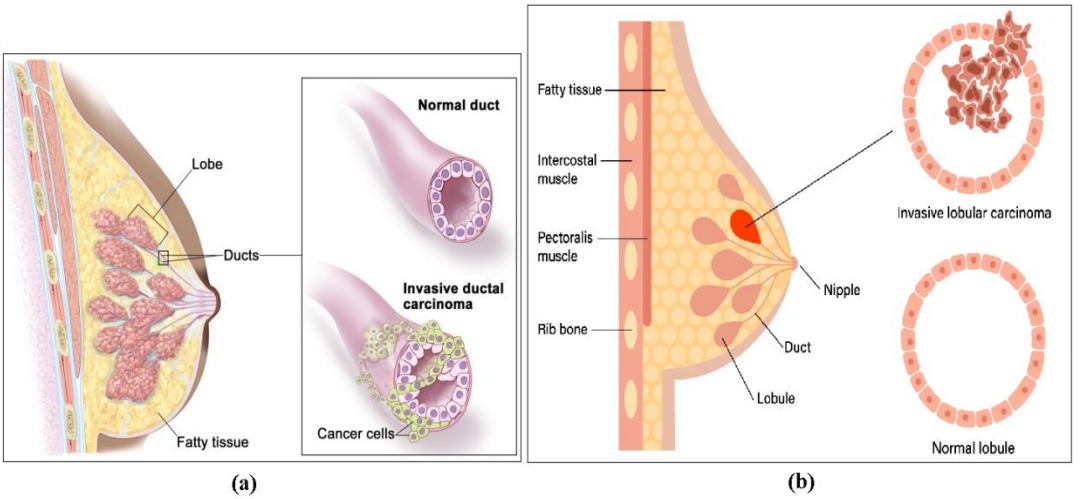



Figure 3: (a) Invasive ductal carcinoma (IDC), (b) Invasive lobular carcinoma (ILC)

- **Papillary carcinoma** - projections inside the tumor that resemble fingers; more prevalent in older women.
- **Metaplastic carcinoma** - ductal cells can change into other cell types (such as squamous or spindle cells) in this uncommon and diverse category, which is often triple-negative and more aggressive.
- **Adenoid cystic carcinoma** – less than 0.1% of breast cancers have this extremely uncommon, typically triple-negative subtype, which is typically linked to a favorable prognosis despite the triple-negative characteristics [17].
- **Inflammatory breast cancer (IBC):** Instead of forming a distinct lump, inflammatory breast cancer (IBC) is an uncommon but aggressive form of invasive ductal carcinoma characterized by cancer cells blocking dermal lymphatic capillaries leading to the breast appearing red, swollen, and warm ("inflamed"). It is fast spreading and occurs more frequently among black women, overweight and obese women, and women under 40 years old.
- **Paget disease of the breast:** It is a rare disorder affecting the skin of the nipple and areola, often linked to an underlying DCIS or invasive cancer.
- **Phyllodes tumors and breast sarcomas:** In contrast to epithelial breast cancers, phyllodes tumors and breast sarcomas (including angiosarcoma and leiomyosarcoma) are rare tumors that arise from the connective tissue of the breast rather than the epithelium of the ducts or lobules.

### *B. Molecular (Receptor-Based) Classification*

Beyond histology, human epidermal growth factor receptor 2 (HER2), progesterone receptor (PR), and estrogen receptor (ER) expression are commonly used to categorize invasive breast tumors. Treatment planning now heavily relies on this classification, which was first suggested in gene-expression research in 1999–2000 [18]:

- **Luminal A** – The most prevalent and typically slowest-growing subtype, making up around two-thirds of cases, is ER-positive and/or PR-positive, HER2-negative, and low proliferation (low Ki-67).
- **Luminal B** – ER-positive and/or PR-positive, with strong proliferation (high Ki-67) or HER2 positivity; more aggressive than luminal A.
- **HER2-enriched (HER2-positive)** – 15–25% of invasive breast tumors have overexpression of the HER2 protein; these malignancies have historically been aggressive but are very sensitive to HER2-targeted

therapy [18] ((refer to Figure 4(a)).

- **Triple-negative breast cancer (TNBC)** – It accounts for 15-20% of all breast tumors and does not express ER, PR, and HER2 receptors. Since there are no therapies targeting these receptors, the treatment of choice for TNBC is chemotherapy. This type of breast cancer is more diverse in terms of biology, often occurs in younger women and women of African-American and Hispanic descent, is frequently linked to BRCA1 mutations, and usually has a poorer prognosis [19] (see Figure 4 (b)).
- **Triple-positive** – About 10% of cases are HER2-positive, ER- and PR-positive, and respond to both hormonal and HER2-targeted treatment.

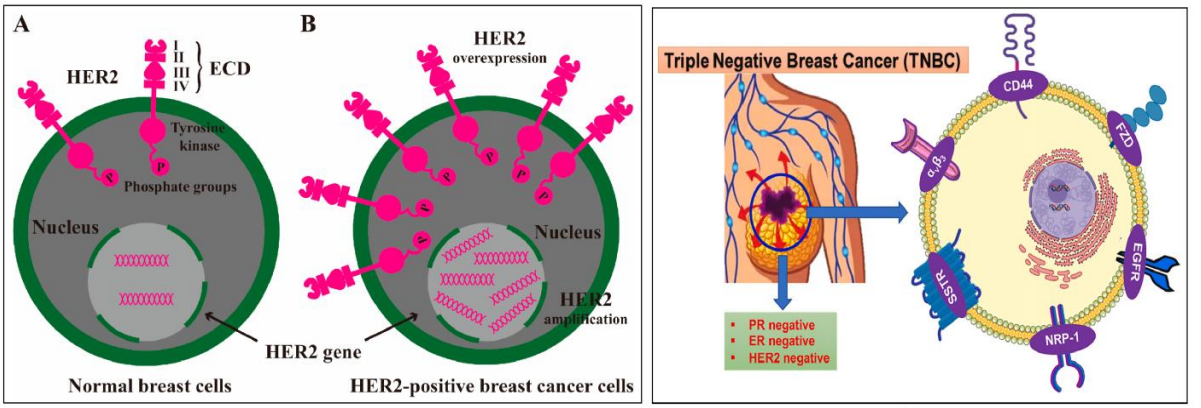



Figure 4: (a) HER2-positive, (b) Triple-negative breast cancer (TNBC)

## 4. Causes of breast cancer and risk factors

Inherited genetic susceptibility, exposure to hormones, and environmental and lifestyle factors contributing to DNA damage and normal cell transformation in breast tissue are risk factors for breast cancer; however, breast cancer rarely occurs from one particular cause. The two most common risk factors for developing breast cancer are being female and advancing age. The risk increases significantly after menopause, typically at 40–50 years old due to the accumulation of exposures to female sex hormones and genetic predisposition [20]. In addition to the general risk factors for breast cancer, hereditary predisposition accounts for 5-10% of cases. Genes that play an essential role in this process are tumor suppressor genes involved in DNA repair, BRCA1 and BRCA2, located on 17q and 13q chromosomes, respectively. It is estimated that these genes are responsible for about 50–80% of the risk of developing breast cancer, with pathogenic variants responsible for 3-8% of all breast cancer and 15-20% of hereditary breast cancer [21]. Other genes that account for a lesser extent of polygenic hereditary breast cancer are TP53, PTEN, PALB2, CHEK2, ATM, CDH1, and STK11. In addition, having affected relatives increases the risk of developing the disease even without a known genetic predisposition. According to the results of the combined analysis of multiple epidemiological studies, the cumulative incidence of breast cancer by age 80 was 7.8% among women with no affected first-degree relatives, as compared to 13.3% with one breast cancer survivor and 21.1% with two affected relatives on average [22]. The increased risk was explained by both genetic and environmental factors, including potential susceptibility genes beyond BRCA1/2. Apart from the genetic and hormonal contributions to breast cancer development, other reproductive and physiological factors are implicated. It is established that exposure to estrogen and progesterone throughout a woman's life is a risk factor for breast cancer. In particular, early menarche, late menopause, nulliparity, older age at first birth, lack of breastfeeding, use of combined oral contraceptives, and post-menopausal hormone replacement therapy, especially combined

estrogen-progesterone, are among the most important breast cancer risk factors [21].

In addition, increased mammographic breast density is an important independent risk factor for breast cancer and may also be associated with reduced sensitivity of mammographic screening; moreover, certain benign breast diseases (e.g., atypical hyperplasia) carry an additional risk beyond that of other known factors. Furthermore, current alcohol consumption is associated with a significant increase in breast cancer risk that is dose-dependent; approximately a 10% increase in risk per 10 g/day of alcohol consumption (about one drink) [23]. Obesity is associated with decreased breast cancer risk in premenopausal women but increased risk in postmenopausal women, presumably because of conversion of androgens to estrogens in adipose tissue. Physical activity is associated with decreased breast cancer risk, whereas lack of exercise is a risk factor. Findings from large epidemiologic studies also suggest that tobacco use is a risk factor. Another significant clinical risk factor is a history of therapeutic radiation to the chest, for example, for the treatment of another cancer (e.g., Hodgkin lymphoma), especially during adolescence, when the breast is developing. Understanding this broad spectrum of possible risk factors is important in risk assessment, screening, and selection of appropriate therapy based on tumor subtypes.

## 5. Traditional Detection Techniques for Breast Cancer

Breast cancer can be detected using numerous methods established by years of research and clinical trials. Each of them has its own advantages and disadvantages and areas of application. The list below represents the most common ways of breast cancer detection that are used today.

### *A. Clinical methods*

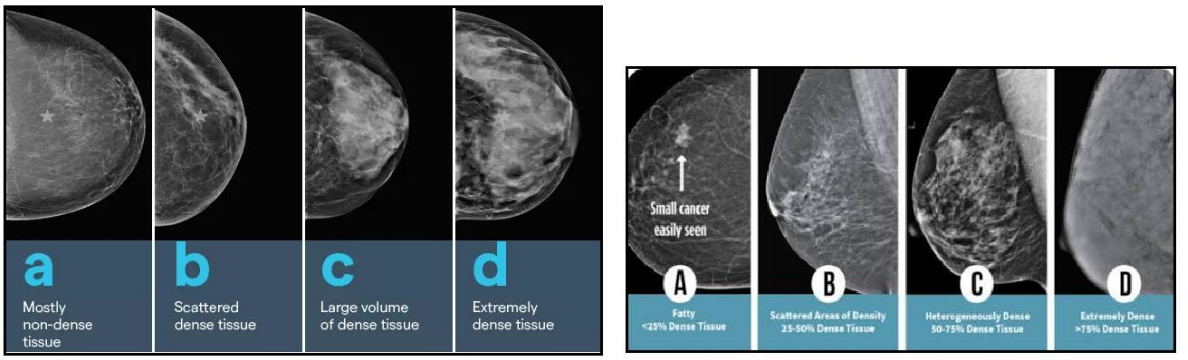
- **Clinical Breast Examination (CBE):** To check for lumps, skin changes, or other abnormal conditions of the nipples, a qualified professional visually examines and manually palpates the breasts and underarm region. While it is a simple procedure that involves no risk or side effects, it is not very sensitive for small tumors and can miss abnormalities, especially those deep in the breast, and should be used with diagnostic imaging procedures as an additional test.
- **Breast Self-Examination (BSE):** Individuals frequently perform Breast Self-Exams (BSE) to detect any lumps or changes in the size or shape of their breasts. However, research conducted by major health sectors reveals that although BSE raises body awareness, it has proved ineffective in reducing mortality rates and is therefore only a complementary activity.

### *B. Imaging Techniques*

- **Mammography:** Mammography, a standard procedure for population screening, is based on taking X-ray images of the breast tissue using low doses of ionizing radiation (see Figure 5a). Mammography can detect microcalcifications associated with malignancy and identify tumors at an early stage before they can be manually palpated. One of the primary shortcomings of mammography is the reduced sensitivity associated with dense breasts, while another limitation is related to the possibility of false positive results leading to unnecessary biopsies.
- **Digital Breast Tomosynthesis (3D Mammography):** Tomosynthesis is a method of obtaining a three-dimensional image of the breast that allows to reduce the overlapping of tissues, thus increasing the accuracy of cancer diagnosis compared to standard X-ray mammography.The new technology is advantageous in cases of dense breasts, as most tumors are located in such tissues and it is challenging to detect them with X-rays. Moreover, Tomosynthesis reduces the number of false-positive results,

leading to fewer unnecessary biopsies.

- **Breast Ultrasound:** It creates images of the breast tissue by using high-frequency sound waves (see Figure 5 (b)). It is often used as a primary imaging method in patients with dense breast tissue or as a secondary test if mammography is abnormal. It is particularly useful in differentiating between solid tumors and fluid-filled cysts. The ultrasound technique is safe for young patients and can be used multiple times since it does not expose them to ionizing radiation.
- **Breast Magnetic Resonance Imaging (MRI):** MRI produces highly precise images of the breast tissue by using magnetic fields and contrast medium (see Figure 6(a)). It is typically used for additional screening in high-risk groups, as MRI is more sensitive but more expensive than mammography and has a higher false-positive rate.




(a) (b)

Figure 5: Photographs of (a) mammography, (b) breast ultrasound

- **Positron Emission Tomography (PET)/PET-CT:** A radioactive tracer is used to identify metabolically active tissue, which may indicate malignant change in PET scans (see Figure 6(b)) . The study could be used for determining the extent of the disease during treatment, as well as assessing treatment response and detecting metastasis; however, it is not used as a screening test.
- **Ductography (Galactography):** This approach, which primarily aims to investigate abnormal nipple discharge, involves injecting a contrast dye into the milk duct followed by x-ray imaging to visualize any masses within the ducts (see Figure 6(c)).
- **Elastography:** As malignant tumors are usually harder than the healthy ones, it is possible to use elastography as a supplementary test to ultrasound for evaluating tissue rigidity (see Figure 6(d)). It allows reducing unnecessary biopsies and differentiating benign and malignant tumors.
- **Thermography:** The technology utilises infrared imaging to depict blood circulation and heat patterns within the breasts, based on the hypothesis that cancerous tissue exhibits higher temperatures. Regulatory agencies responsible for health matters have discouraged the use of thermography as a standalone screening technique, citing its inadequacy compared to mammography as a reliable diagnostic tool (see figure 6(e)).

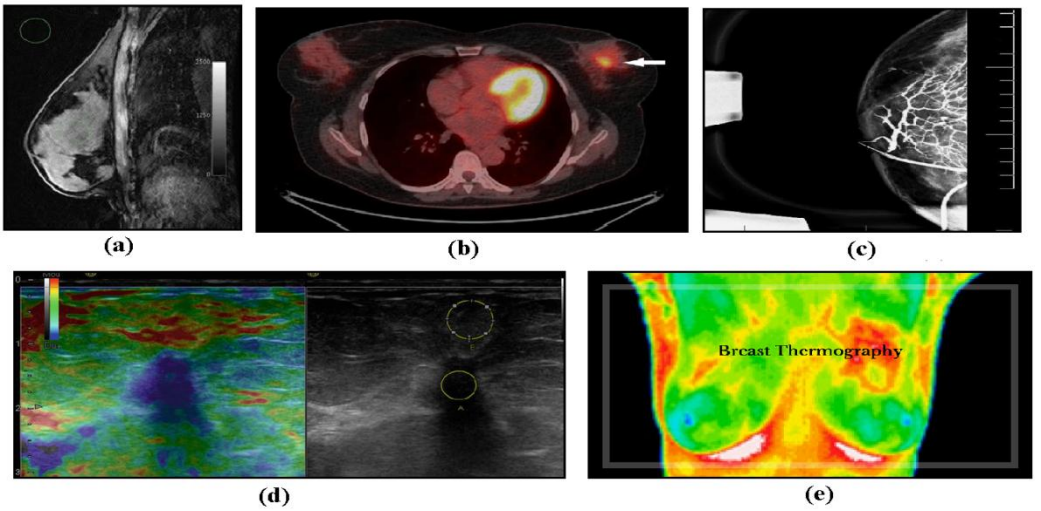



Figure 6: Photographs of (a) Breast Magnetic Resonance Imaging (MRI), (b) Positron Emission Tomography (PET), (c) ductography, (d) elastography, and (e) thermography

### *C. Tissue-Based and Pathological Methods*

- **Biopsy:** A biopsy, which is the gold standard for diagnosing breast cancer, entails taking a sample of tissue for examination in a lab (refer Figure 7). Typical kinds include of:

1. **Fine-needle aspiration (FNA):** Cells or fluid are extracted using a thin needle.
2. **Core needle biopsy:** To enable a more thorough examination, a little tissue cylinder is removed using a bigger needle.
3. **Vacuum-assisted biopsy:** With a single needle insertion, many tissue samples are collected using suction.
4. **Surgical (excisional) biopsy:** When other biopsy techniques yield no definitive results, a suspicious lump may be removed entirely or in part.

Pathologists assess biopsy samples for the presence of cancer cells, tumor grade, and biomarkers that influence treatment choices, such as HER2 expression and hormone receptor status (ER/PR).

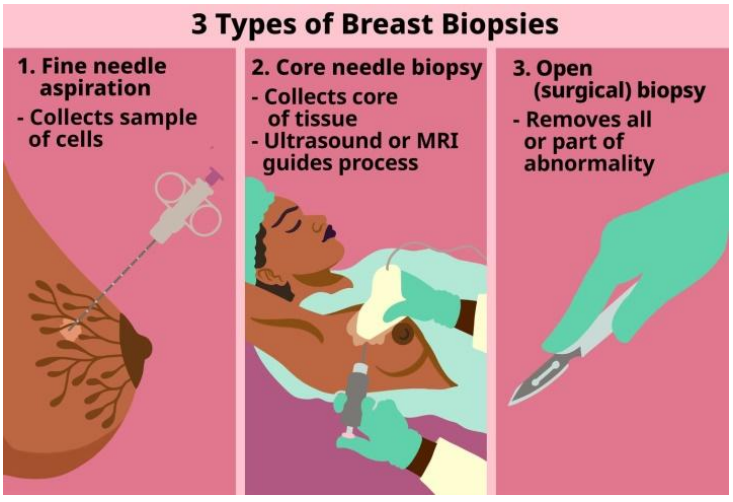



Figure 7: Three types of breast biopsies

### *D. Molecular and Genetic Techniques*

- **Genetic Testing:** Mutations in BRCA1, BRCA2, PALB2 genes can be detected by genetic testing. This test result will prevent cancer or help detect it at an early stage. If the mutation is present in the genes, doctors can prescribe regular screenings, such as an MRI every year instead of a mammogram.
- **Liquid Biopsy and Circulating Biomarkers:** · Detection of circulating tumor DNA (ctDNA), circulating tumor cells (CTCs), and protein biomarker in the blood (i., e., CA15-3, CA27.29) – currently understudied and insufficiently validated tumor markers; though not indicated for cancer screening, their assessment has demonstrated promising results to ensure the absence of cancer metastases or recurrence.
- **Genomic Assays:** Tests like Oncotype DX and MammaPrint look at genetic markers in tumors to see if there is an increased risk of cancer coming back after treatment and help decide if more treatment is needed. It is performed post diagnosis not as a way to identify the cancer.

### *E. Comparison of Breast Cancer Detection Techniques*

Table 1 summarizes the performances of different techniques of breast cancer detection discussed so far. It has been revealed from the Table that each technique is unique with respect to its application, advantages and disadvantages. The selection of a particular technique is obviously a concern of the doctors, and pathologists based on the condition of the patient.

**Table 1:** Comparative analysis of different breast cancer techniques

| Technique | Primary Use | Radiation | Advantages | Disadvantages |
|---|---|---|---|---|
| Clinical Breast Exam | Initial assessment | Yes | Low cost; no equipment needed; quick to perform | Low sensitivity for small/deep lumps; misses non-palpable cancers |
| Mammography | Standard screening | No | Widely available; proven mortality reduction; detects microcalcifications | Reduced accuracy in dense breasts; false positives/ negatives; some discomfort |
| Tomosynthesis | Screening, dense breasts | No | Better performance in dense tissue; fewer false positives than 2D mammography | Higher cost; slightly higher radiation dose than standard mammography; not universally available |
| Ultrasound | Cyst vs. solid mass, dense tissue | No | No radiation; distinguishes cysts from solid masses; safe for repeated use | Operator-dependent; higher false-positive rate; less effective at detecting microcalcifications |
| MRI | High-risk screening | No | Highest sensitivity; excellent for high-risk patients and dense breasts | Expensive; higher false-positive rate; requires contrast agent; longer scan time |
| PET/PET-CT | Staging, metastasis | No | Useful for detecting metastatic spread and treatment response | Not suited for early/ primary screening; costly; involves radioactive tracer |
| Elastography | Characterizing masses | Yes | No radiation; helps differentiate benign vs. malignant lesions; add-on to ultrasound | Limited standalone use; results can vary by operator and equipment |

| | | | | |
|---|---|---|---|---|
| Biopsy (various) | Definitive diagnosis | No | Only method providing definitive diagnosis; enables biomarker testing | Invasive; minor procedural risks (bleeding, infection); sampling error possible |
| Genetic Testing | Hereditary risk assessment | No | Identifies high-risk individuals early; informs personalized screening plans | Does not detect existing cancer; psychological impact of results; not relevant for all patients |
| Liquid Biopsy | Recurrence monitoring (emerging) | No | Minimally invasive; potential for early recurrence detection | Still largely investigational; not yet standard for primary diagnosis; variable sensitivity |
| Genomic Assays | Post-diagnosis treatment planning | No | Guides treatment decisions (e.g., chemotherapy benefit); personalized risk of recurrence | Used only after diagnosis; costly; not a detection tool itself |

## 6. Breast Cancer Detection by Artificial Intelligence, Machine Learning and Deep Learning

Artificial intelligence (AI), and, specifically, deep learning (DL) and classical machine learning (ML) methods, have found application in almost all data types related to breast cancer diagnosis and treatment in the last decade. Clinical/cytological, mammography, ultrasound, MRI, and histology data have all been used to train DL/ML algorithms. This section aims to present an overview of the main approaches and their variations, the data types they are applied to, significant results reported in the literature, and outstanding challenges.

### *A. Classical Machine Learning on Clinical and Cytological Data*

Before the advent of deep learning, supervised machine learning classifiers were often benchmarked based on well-established feature-encoded datasets, such as the UCI Wisconsin Diagnostic Breast Cancer (WDBC), which encodes information about nuclear morphology extracted from fine-needle aspirate (FNA) images. The WDBC has been used to train SVM, Random Forests, k-Nearest Neighbors, Naïve Bayes, Decision Trees, and Logistic Regression classifiers. On the Wisconsin dataset, the highest accuracy was reported by the Random Forest algorithm at 99.26%, followed by SVM and kNN at 97.78% and 97.04%, respectively, in one comparison study [24]. In another analysis comparing the performance of ANN, SVM, Random Forest, kNN, Decision Tree, and Logistic Regression classifiers on the WDBC, ANN showed overall superiority over other algorithms in terms of accuracy, precision, and F1 score, with particularly remarkable results of 98.57%, 97.82%, and 0.989, respectively [25]. Following hyperparameter optimization, the Random Forest pipeline achieved holdout accuracy as high as 100% and 99.30% on this diagnostic task, significantly surpassing SVM, kNN, and other approaches [26]. GRU-SVM, linear regression, multilayer perceptron, nearest-neighbor search, softmax regression, and SVM were also evaluated on the WDBC in early neural-network benchmarking studies. On this diagnostic task, all algorithms under consideration showed test accuracy of over 90%, with the multilayer perceptron reaching 99.04% [27]. Finally, a Seagull optimization algorithm combined with a Random Forest classifier achieved a mean accuracy of 99.01% on the gene-expression-based breast cancer dataset using only 22 selected features, significantly outperforming linear regression, SVM, and kNN baselines [28]. Notably, recent studies have focused on combining conventional machine learning algorithms with metaheuristic optimization to select informative features.

### *B. Deep Learning for Mammography*

The primary method for screening breast cancer is mammography, where the deep learning area has been at the forefront for automated detection and classification. An in-depth analysis of the deep learning algorithms applied to mammography identified that, despite issues with interpretability and clinical applicability, DL overall addresses the sensitivity and specificity deficiencies of traditional X-ray mammography to improve individual risk assessment, prognosis, and management [29]. The research reviewed the progression of CAD systems from the early image-processing approaches, through the classical machine learning methods, to the latest deep learning techniques applied to microcalcifications segmentation and classification tasks over more than 50 years in a PRISMA-guided systematic survey [30]. To assess the generalizability of findings, as limited by the availability of smaller datasets for prior studies, one study compared the performance of ConvNeXt-Small and EfficientNetV2-S architectures using the large-scale RSNA screening mammography dataset to classify normal and abnormal mammograms [31].

In addition, CNNs based on ResNet50 were trained on annotated data consisting of mammograms to automatically detect masses, microcalcifications, and architectural distortions associated with malignancy with increased sensitivity and specificity rates than traditional analysis [32]. Second, a patch-based and curriculum-learning CNN model with explainable AI (Grad-CAM) was proposed in 2025 to reduce the annotation workload of experts. The model was trained on both weakly labeled and strongly labeled data with bounding boxes from three centers while achieving good performance on an external test set of 4,276 mammograms [33]. In addition, computer-aided diagnosis (CAD) pipelines involved in lesion detection and segmentation, as well as classification, have been implemented. For example, a deep learning and computer-vision system, which achieved the best-reported performance on the CBIS-DDSM benchmark with a 99 percent success rate, independently detects and classifies breast abnormalities while also segmenting the mass and classifying it according to pathology [34]. Moreover, the most well-known large-scale clinical study was conducted by Google Health and published in Nature. The experiment revealed that an AI system reduced false positives by 5.7 percent in the United States and 1.2 percent in the United Kingdom, and false negatives by 9.4 percent in the U.S. and 2.7 percent in the UK while outperforming six radiologists in an independent reader study on AUC-ROC [36]. Finally, it is noteworthy that this study provoked a significant academic debate about replicability and resulted in a subsequent addendum with additional methods published later [35].

### *C. Deep Learning for Histopathology Images*

The gold standard for diagnosis is histopathological examination of biopsy material, and CNNs have been trained on the BreakHis database, which includes benign and malignant tissue at different magnifications. Transfer learning has proven to be a valuable tool for this kind of task. One study found that CNN-based classification outperformed earlier methods that utilized manually engineered texture features by a significant margin when CNNs pretrained on ImageNet were used on BreakHis patches, without requiring complex alterations to the original architecture [36]. Another work that used transfer learning achieved 99% accuracy for the binary classification task (benign vs malignant) and 92.5% accuracy for the multi-class classification task (differentiating between four subcategories of benign and four subcategories of malignant tissue) using a CNN-LSTM hybrid, compared to standard Vision models like VGG-16, ResNet50, and Inception [37].

CNN-based full-slide classifiers utilizing multi-view posterior estimation and patient-level cross-validation achieve approximately 94.7% accuracy, 96% sensitivity, and 92% specificity, as stated in the general overview. Moreover, a 152-layer residual “ResHist” architecture was suggested for the problem [38]. A “Dual-Activated Lightweight Attention ResNet50” classifier was engineered to address the issue of class imbalance since conventional CNN-based approaches demonstrated insufficient performance on imbalanced

histopathological data sets [39]. Attention-based augmentation of CNNs is a relatively new direction. The first study on breast histopathology utilizing deep learning employed a lightweight CNN with handcrafted features and SMOTE oversampling to classify mitotic-nuclei images with an exceptionally small sample size reported in a bibliometric survey [40]. Apart from binary benign/malignant classification, multi-class histological subtyping was also explored. For instance, one CNN-based approach was trained to differentiate between normal tissue, benign lesions, carcinoma in situ, and invasive carcinoma in the HE-stained biopsy images [41].

### *D.* ***Deep Learning for Breast Ultrasound***

DL has been applied to both lesion segmentation tasks and benign/malignant classification; in particular, the value of ultrasound is high, especially in women with dense breasts, since mammography's sensitivity is reduced. An improved deep learning model recently compared the backbones of ResNeXt and Vision Transformer (ViT) to classify breast ultrasound images. The study revealed that the self-attention mechanism of ViT enables the capture of global context, but its performance was compromised on small sample sizes; by contrast, ResNeXt's grouped convolutions with residual connections allow for a flexible combination of local information, being particularly effective for the fine-grained classification of benign/malignant tumors [42]. To aid clinicians in distinguishing malignant from benign tumors with fewer manual steps, fusion algorithms have been proposed that combine handcrafted radiomic features with deep learning-derived features for ultrasound and mammography images; these methods have been evaluated on public BUSI and mini-DDSM databases [43]. Most of the research in the field makes use of a two-stage "detect-then-classify" pipeline. For instance, one study's 2025 dual-stage architecture was trained on BUSI and the Breast-Lesions-USG database from the Cancer Imaging Archive. It utilized a "detect-then-classify" approach, first segmenting suspicious regions in ultrasound images and then determining whether they were benign or malignant [44]. A systematic review of ultrasound-based DL literature published in 2023 found that, despite the limitations, DL-enabled automated diagnosis could reduce the burden on radiologists; most publications focused on benign/malignant classification, with fewer studies analyzing BI-RADS categories, benign tumor subtyping, and cyst classification [45]. A diagnostic test accuracy study assessed the performance of diagnostic tests in 16 studies with more than 9,000 participants, comparing the performance of DL and human experts; it analyzed the role of diagnostic tests in the context of ultrasonography [46].

### *E.* ***Ensemble, Hybrid, and Feature-Fusion Approaches***

Ensemble and hybrid approaches are typically superior solutions for improving the robustness of the results achieved by individual models. In particular, when working with small data sets, applying multiple classifiers after CNN-based feature extraction (e.g., CNN + SVM, CNN + Random Forest) is one of the common practices for obtaining accurate results. Using ensemble learning along with big-data fusion, the creation of big-data ensemble pipelines, which implement such machine learning techniques as AdaBoost, XGBoost, and Random Forest, has allowed researchers to significantly improve the accuracy of the analysis of a sample from the Wisconsin database for the early detection of breast cancer, and thereby enhance the quality of diagnosis [47]. The application of feature selection in combination with ensemble classifiers leads to particularly impressive results in genomics. Thus, using hybrid machine learning approaches, such as the combination of Seagull Optimization Algorithm and Random Forest, to find the optimal feature subset can significantly improve results compared to standard individual classifiers and even the initial combination of an optimization algorithm and a classifier.

### *F.* ***Ensemble, Hybrid, and Feature-Fusion Approaches***

The literature typically calls for clinical models to be simultaneously both interpretable and highly predictive for downstream adoption. As introduced in subsection B on curriculum-learning for mammography [33], explainable AI methods such as gradient-weighted class activation mapping are embedded into the diagnostic cascade, allowing visual inspection by clinicians of the image regions used by an algorithm to form its diagnostic conclusions. State-of-the-art benchmarks and regular adoption practices have failed to account for the necessity of interpretability, validity, and generalizability across different populations, according to reviews on deep learning for mammography and computer-aided detection [29-30].

## 7. Challenges

Although artificial intelligence (AI), machine learning, and, especially, deep learning algorithms have achieved outstanding results in the field of breast cancer detection, there are still some challenges that need to be addressed for their practical implementation in the clinical setting. The generalizability and robustness of the models are frequently limited by factors such as small sample sizes, imbalances, and institutional biases in available data, low data variability, and the high cost of annotated data. Moreover, lack of interpretability, overfitting, low repeatability, and domain shifts between different scanners and populations challenge the application of deep learning (DL) in clinical practice. Strict regulatory supervision, the integration of AI into the current radiology workflow, and clinicians' reluctance due to a lack of transparency and legal accountability issues are also significant barriers to implementation. Finally, ethical concerns regarding algorithm bias, responsibility, fairness, and privacy issues should not be overlooked. Addressing these technical challenges, including the considerable computational complexity of DL algorithms, attaining real-time performance, and combining multimodal medical data with clinical outcomes, will enable the creation of reliable and trustworthy AI-powered systems for breast cancer detection and treatment.

## 8. Future Directions

To make future AI applications in breast cancer screening more reliable and private, the researchers should focus on improving the data quality via large multi-center datasets, federated learning, and synthetic data. To make them more transparent and clinically interpretable, the computer science field should develop explainable AI (XAI). The joint use of pathology reports, clinical data, genomics, and imaging by multimodal approaches could help create more accurate diagnoses and better individualized treatment. To increase generalizability and flexibility, future studies should include domain adaptation, transfer learning, and self- and semi-supervised learning approaches. To accomplish effective clinical integration and regulation, it is critical to pay more attention to clinical validation, standardization, and regulatory science, where AI would function as an assisting technology to radiologists. By estimating the risks of cancer occurrence, recurrence, and treatment response, artificial intelligence is also expected to contribute to developing individualized and predictive medicine. To ensure equal chances for all populations, it is essential to invest in ethical AI, fairness, bias, and trust. And finally, to provide better breast cancer screening in low-resource settings, there is a chance to benefit from edge-AI lightweight models.

## 9. Conclusion

The article under review presents a survey on the application of artificial intelligence (AI) to breast cancer screening. Advanced deep learning algorithms have demonstrated diagnostic accuracy comparable to that of radiologists and pathologists in mammography, ultrasonography, magnetic resonance imaging, and

histopathological analysis. Nevertheless, the current capabilities of AI in this field are hampered by several limitations, including the technology's insufficient generalizability to different populations and equipment, the absence of standardized data sets, its "black box" nature, unresolved ethical and regulatory issues, and the risk of exacerbating healthcare inequalities. It will take extensive research and clinical trials to surmount these challenges and fully integrate AI as an efficient and reliable instrument in breast cancer screening and diagnosis. The ultimate goal is to promote multidisciplinary collaboration and ensure the technology's compliance with regulatory standards while making it accessible to diverse populations. This will enable physicians to offer more patients timely and high-quality breast cancer screening and diagnosis while expanding access to care.

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