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A Study of Machine Learning and Deep Learning Approaches for Breast Cancer Detection

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Abstract
The hallmark of cancer and related disorders is the uncontrolled growth of abnormal cells throughout the body, invading nearby tissues and eventually spreading to other organs. Unlike normal cells, cancer cells have an unchecked growth cycle and can form tumors or metastasize (spread through the blood and lymph). The tumor's claw-like grip on tissues may have inspired the ancient Greek term for "crab," which could explain the origin of the word "cancer." In breast cancer, a tumor develops when cells in the milk ducts or lobules of the breast multiply uncontrollably. A lump or tumor in the breast, along with other symptoms like skin or nipple changes, may result from this uncontrolled growth. Breast cancer can stay confined within the breast or progress to an invasive stage by spreading to other organs or tissues through the circulation. Although it primarily affects women, men can also develop breast cancer. This study focuses on diagnosing breast cancer using ultrasound, mammography, and histopathological imaging, exploring current machine learning and deep learning methods. We review the literature on various datasets (such as CBIS-DDSM, Breast Ultrasound Images dataset, and BreakHis), compare convolutional neural networks with traditional machine learning classifiers, discuss some challenges in deployment and evaluation, and outline specific goals for future research aimed at enhancing dataset diversity, robustness, interpretability, and clinical validation.
Keywords: Breast Cancer, ML, Deep Learning, disease, bloodstream.

1. Introduction
Cancer arises when atypical cells proliferate and engage with healthy cells, converting them into malignant cells. Breast cancer is unparalleled in both prevalence and severity. Breast cancer is classified into two categories: invasive and non-invasive.
An aggressive, invasive neoplasm has metastasized to other regions of the body. It persists in its native organ and is precancerous yet non-invasive. It ultimately advances to aggressive breast carcinoma. The malignant tissue in the breast is situated inside the lactiferous glands and their ducts. Malignant metastases from breast cancer often disseminate to other organs and may also traverse to other regions via the circulatory system. The proliferation rate differs across various types of breast cancer. Healthcare practitioners determine the kinds and subtypes of cancer to tailor therapy for optimal efficacy and minimum adverse effects.
Common forms encompass: Invasive ductal carcinoma (IDC), a type of breast cancer, originates in the milk ducts and disseminates to other regions of the breast. It is the most common type of invasive breast cancer, accounting for about 80% of cases. Symptoms can include a painless lump, swelling, redness, or changes to the nipple, but early-stage IDC may not have symptoms and can be found during a routine mammogram. The prognosis is good if caught early, and treatment typically involves surgery, radiation, chemotherapy, hormone therapy, or targeted therapy, depending on the cancer's stage and other factors.
Lobular breast cancer (Invasive Lobular Carcinoma or ILC) is the second most common type of invasive breast cancer, originating in the milk-producing lobules of the breast and representing

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about 5–15% of invasive breast cancers. Unlike other breast cancers that form a distinct lump, ILC cells tend to grow in single-file lines or strands, making them harder to detect on mammograms and leading to symptoms like breast pain, changes in skin texture, or nipple discharge. Because ILC cells often lose a protein called E-cadherin, they don't clump together. Treatment for ILC typically includes surgery, radiation, chemotherapy, and hormone therapy, as most ILCs are hormone-receptor positive.

Similar to IDC, ductal carcinoma in situ (DCIS) originates in the milk ducts but remains confined inside them. It is sometimes called stage 0 breast cancer and is often detected through screening mammograms. While not invasive, DCIS can progress to invasive breast cancer, so it requires treatment, which may include surgery and radiation therapy, with treatment tailored to the specific characteristics of the lesion.

Myelodysplastic breast cancer (DBC) manifests as a rash on the breast and is an uncommon, rapidly advancing tumor. Paget's disease, a rare form of breast cancer, may manifest as a rash on the skin around the nipple, constituting fewer than 4% of all occurrences. Breast cancer is categorized into many kinds according to receptor status. Receptors are proteins located on cell surfaces or inside cells that may attach to specific blood molecules, including hormones such as progesterone and estrogen. Estrogen and progesterone promote the proliferation of cancer cells. To enhance therapy, physicians must ascertain the presence of estrogen or progesterone receptors in the cancer cells.

Subtypes include:

ER-positive (ER+) breast cancers have estrogen receptors.

PR-positive (PR+) breast cancers have progesterone receptors.

HR-positive (HR+) breast cancers have estrogen and progesterone receptors.

HR-negative (HR-) breast cancers don't have estrogen or progesterone receptors.

HER2-positive (HER2+) breast cancers, which have higher than normal levels of the HER2 protein. This protein helps cancer cells to grow. About 15% to 20% of all breast cancers are HER2-positive.

2. Breast cancer symptoms

The condition can affect to breasts in different ways. Some breast cancer symptoms are very distinctive. Others may simply seem like areas of the breast that look very different from any other area. Breast cancer may not cause noticeable symptoms either. But when it does, symptoms may include:

- A change in the size, shape, or contour of the breast.
- A mass or lump, which may feel as small as a pea.
- A lump or thickening in or near the breast, or in the underarm, that persists throughout the menstrual cycle.
- A change in the look or feel of the skin on the breast or nipple. The skin may appear dimpled, puckered, scaly, or inflamed, and may look red, purple, or darker than other parts of the breast.
- A marble-like hardened area under the skin.
- A blood-stained or clear fluid discharge from the nipple.

3. Stages of breast cancer

Healthcare providers use cancer staging systems to plan treatment. Staging cancer also helps providers set a prognosis, or what you can expect after treatment. Breast cancer staging depends on factors like breast cancer type, tumor size and location, and whether cancer has spread to other areas of your body. Breast cancer stages are:

Stage 0: The disease is noninvasive, meaning it hasn't spread from your breast ducts to other parts of your breast.

Stage I: There are cancerous cells in nearby breast tissue.

Stage II: The cancerous cells have formed a tumor or tumors. The tumor is either smaller than 2 centimeters across and has spread to underarm lymph nodes or larger than 5 centimeters across but

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hasn't spread to underarm lymph nodes. Tumors at this stage can measure anywhere between 2 and 5 centimeters across, and may or may not affect the nearby lymph nodes.

Stage III: There's breast cancer in nearby tissue and lymph nodes. Stage III is usually referred to as locally advanced breast cancer.

Stage IV: Cancer has spread from your breast to areas like your bones, liver, lungs or brain.

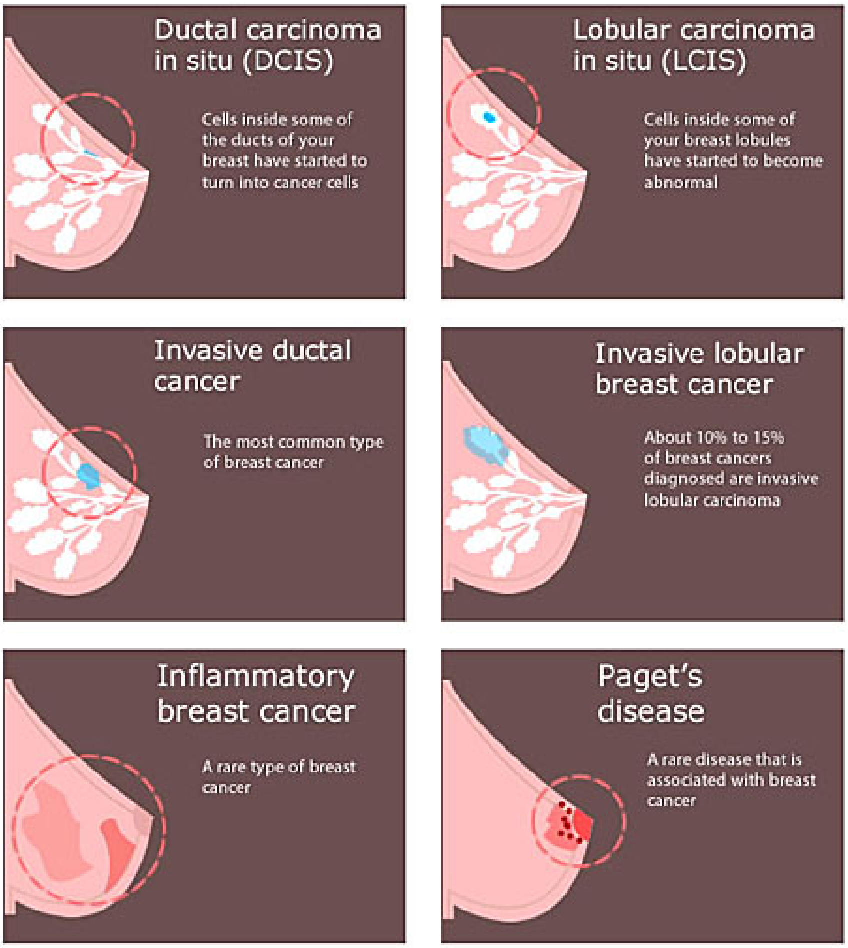

Figure 1: Breast Cancer Types: Ducual carcinoma in situ(DCIS), Lobular carcinoma in situ(LCIS)

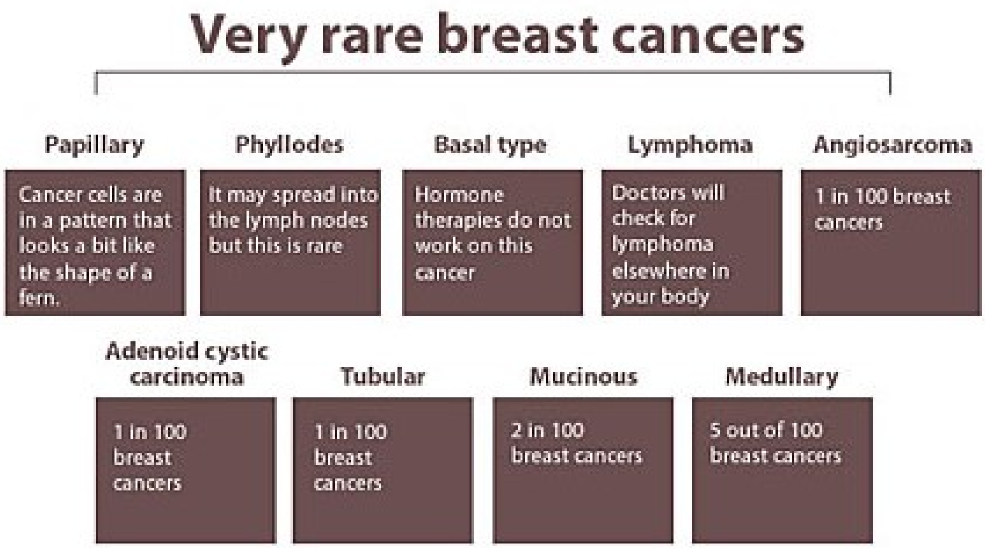

Figure 2: Other types of breast cancers

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4.Machine Learning and Deep Learning Approaches

Machine learning is the major method for breast cancer categorization. It is used to evaluate diagnostic pictures, which are an essential element of artificial intelligence. A multitude of programmers depend on machine learning to refine their models for enhanced performance. It processes linear data, and often, machine learning has superior performance with smaller datasets, whereas it encounters difficulties with bigger ones. Three primary categories of machine learning are used during model training. Supervised learning utilizes pre-existing knowledge and expert direction to analyze data. Unsupervised learning, as the term implies, functions without human supervision. Reinforcement learning is declining in prevalence. These algorithms derive the most relevant information from existing knowledge to facilitate precise decision-making.

Deep learning, a subset of machine learning, acquires knowledge from data—frequently using unlabeled or inadequately structured data—via an unsupervised methodology. A deep neural network has over two hidden layers, with an input layer preceding and an output layer succeeding them. In contrast to a basic neural network, a deep neural network has a greater number of hidden layers, each including nodes referred to as neurons. Deep learning surpasses regular machine learning mostly because of its unique attributes. The breast cancer dataset is categorized with a Convolutional Neural Network (CNN). Convolutional Neural Networks (CNNs) are used for image categorization by processing photographs from the dataset. They use the photos and their corresponding weights as input, modifying the weights to reduce mistakes and improve performance. Convolutional Neural Networks (CNNs) include many layers, including pooling, ReLU, fully connected, and convolutional layers. In the convolutional layer, a feature map captures characteristics and diminishes the picture dimensions, while pooling further lowers them. The ReLU layer verifies whether the value of the activation function is within a designated range. The last layer is completely linked, using the softmax function to aggregate data from all layers and allocate probabilities to each class.

5. Review of Written Works

With the expanding support for machine learning and artificial intelligence methods in traditional diagnostics, recent progress in breast cancer detection has accelerated. Research shows notable improvements in quickly providing accurate diagnoses by combining data from various sources, including ultrasound images, histology slides, mammograms, and clinical or blood test records. Initially, efforts depended heavily on statistical classifiers and basic models such as Naïve Bayes, Logistic Regression, Decision Trees, and Support Vector Machines (SVMs). These methods had limited generalizability and were often tested on small datasets; however, they could somewhat differentiate between benign and malignant tumors. Classifiers like KNN and Random Forest demonstrated strong performance on structured datasets, including the Wisconsin Breast Cancer Dataset (WBCD), with accuracy rates from 90% to 95%. Separate studies used ensemble approaches to boost predictive accuracy and robustness. Random Forest ensembles, boosting algorithms, and genetic algorithm-based weighted ensembles outperformed individual classifiers by reducing variance and preventing overfitting. These ensemble methods effectively handled different medical datasets and improved diagnostic consistency. Recent advances emphasize the importance of deep learning and hybrid systems. Models that combine traditional machine learning classifiers with deep neural networks (such as CNNs, RNNs, and GRU-SVM hybrids) achieve much higher accuracy in breast cancer prediction, often surpassing 96%. Improvements in the efficiency of ultrasonography and mammography have also come from transfer learning applied to large image datasets. Key domain-specific data preparation techniques identified in the literature include image enhancement, feature extraction, and dimensionality reduction. Carefully prepared input data improves classification accuracy and reduces false positives, especially when using preprocessing methods like color normalization, filtering, and feature selection.

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Mana Saleh Al Reshan, Samina Amin, etl..[1] The research aims to improve the accuracy and reliability of breast cancer detection and classification by combining multiple machine learning models and feature extraction methods. The focus is on enhancing predictive performance using ensemble learning and multi-model feature fusion.

Ferlay, J. et al. [2]:

Provided global cancer incidence and mortality data, highlighting the significant burden of breast cancer. This work serves as an epidemiological foundation for breast cancer research.

Boyd, N.F. et al. [3] investigated mammographic density and identified it as a significant risk factor for breast cancer. The study emphasized challenges in detecting cancer in dense breast tissues.

American Cancer Society [4] Outlined the role of ultrasound in breast cancer screening. It emphasized the benefits of ultrasound, such as safety and effectiveness in dense breast tissue.

Youn HJ, Han W.[5] The authors aimed to synthesize existing evidence on the epidemiology and risk factors of breast cancer (BC) in Asia, highlighting both modifiable (lifestyle, diet, reproductive behavior) and non-modifiable (age, genetics, family history) determinants. Given that Asia is highly diverse in culture, genetics, and healthcare infrastructure, the review attempts to contextualize BC risk factors within this region rather than extrapolating from Western studies.

Cheng-Har Yip [6] The article aims to examine the barriers and challenges that low- and middle-income countries (LMICs) face in detecting breast cancer early. Early detection is critical for reducing mortality, but many settings lack the infrastructure, awareness, and resources to make it feasible. The author seeks to identify what stops early detection, including socio-economic, cultural, health-system, and resource constraints, and to suggest possible strategies or priorities for improvement.

Unger-Saldana K, Miranda A, Zarco-Espinosa G, Mainero-Ratchelous F, Bargallo-Rocha E, Miguel Lazaro-Leon J.[7] The study examines how health system delays (the time from first medical consultation to the start of treatment) influence the clinical stage at diagnosis of breast cancer in Mexican women. The aim was to quantify delays across multiple hospitals and evaluate whether longer delays were associated with more advanced disease at presentation.

Romanoff A, Constant TH, Johnson KM[8] The study aimed to evaluate whether women in Peru who had undergone a previous clinical breast examination (CBE) experienced shorter diagnostic delays and earlier-stage breast cancer diagnoses compared with those who had not. This was important for low-resource settings where mammography is not widely available, and CBE may provide a feasible early detection strategy.

Ibekwe AM, Obeagu EI, Ibekwe CE[9] The paper investigated what prevents working-class mothers at Nnamdi Azikiwe University Teaching Hospital, Nnewi in Anambra State, Nigeria, from practising exclusive breastfeeding (EBF) for the first six months as recommended by WHO. It used a descriptive survey of 120 working mothers, and explored attitudes, socio-economic determinants, and knowledge/awareness.

Al-Dhabyani, W.; Gomaa, M.; Khaled, H.; Fahmy, A. [10] released a benchmark dataset of 780 ultrasound images annotated as benign, malignant, and normal. This dataset has become a standard for AI-based ultrasound research.

Rashmi, R.; Prasad, K.; Udupa, C.B.K. [11] developed BCHisto-Net, a CNN model that combines local and global features for histopathological images. Reported high accuracies on KMC and Break His datasets, showing strong classification performance.

Buist et al. [12] examined breast biopsy patterns following screening in women with and without a prior history of breast cancer using data from the Breast Cancer Surveillance Consortium. They found that women with a personal history underwent biopsies at roughly twice the rate of those without, but a smaller proportion of these biopsies detected malignancy. The study highlights the potential for over-biopsy and associated patient anxiety among breast cancer survivors. Strengths include the large, population-based cohort and comprehensive linkage of imaging, pathology, and registry data. Limitations involve its observational design and limited information on tumor biology

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or treatment history. Overall, the findings suggest a need to optimize surveillance strategies to balance early detection with minimizing unnecessary procedures.

Szegedy, C. et al. [13] proposed GoogLeNet with inception modules, a breakthrough CNN architecture later adapted for medical image classification.

Singh, S.; Gupta, P.R.; Sharma, M.K. [14] used a feed-forward neural network on H&E-stained biopsy images, achieving over 95% accuracy. Neural networks are recognized as valuable diagnostic tools.

Nawaz, M.A.A.; Hassan, T. [15] utilized DenseNet CNN for multi-class classification of breast cancer histopathology images. Achieved 96% accuracy, surpassing some human experts.

He, K.; Zhang, X.; Ren, S.; Sun, J. [16] introduced ResNet with skip connections, addressing vanishing gradients and enabling the development of deeper CNNs. Widely used in breast cancer imaging.

Mahdavi M, Nassiri M, Kooshyar MM, et al.[18]. It provides an overview of hereditary breast cancer, with emphasis on genes like BRCA1 and BRCA2, their penetrance, and how they compare to other susceptibility genes. It discusses how germline mutations in breast cancer susceptibility genes contribute to hereditary breast cancer, what is known about the spectrum of penetrance (high vs low), the pathological features of cancers associated with BRCA mutations vs nonhereditary ones, and implications for screening and treatment.

Table 1 Existing Related Work

Author & Ref.	Method	Findings	Dataset
Mana Saleh Al Reshan, Samina Amin, etl..[1]	Naive Bayes Classifier: A probabilistic classifier based on Bayes' theorem, assuming independence among predictors. Stochastic Gradient Descent (SGD): An optimization algorithm for minimizing a loss function, particularly useful for large-scale machine learning tasks. Bagging (Bootstrap Aggregating): An ensemble method that improves the stability and accuracy of machine learning algorithms by reducing variance and helping to prevent overfitting. ZeroR Classifier: A baseline classifier that predicts the majority class, serving as a reference point for evaluating other models. Bayesian Network Learning: A probabilistic graphical model representing a set of variables and their conditional dependencies via a directed acyclic graph.	NN Algorithms achieved the best accuracy, proving ML effectiveness for breast cancer detection	Wisconsin Diagnostic Breast Cancer (WDBC) dataset from the UCI Machine Learning Repository. 569 patient samples 30 numerical diagnostic features (texture, smoothness, concavity, symmetry, etc.) Output: Malignant or Benign
Ferlay, J. et al. [2]	Cancer statistics & epidemiology	Global cancer incidence and mortality data	Global Cancer Observatory (IARC, 2020)

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Boyd, N.F. et al. [3]	Mammographic density analysis	Higher breast density increases risk and challenges detection	Mammography datasets
American Cancer Society [4]	Ultrasound in breast cancer screening	Highlights ultrasound advantages (dense tissue, no radiation)	Clinical guideline (not dataset)
Youn HJ, Han W[5]	Systematic literature review following PRISMA guidelines. PubMed search (2011–2016), English-language, human studies from Asia. Review articles & meta-analyses excluded.	- Breast cancer incidence rising in Asia (esp. China, India, Thailand). - Non-modifiable risk factors: age, sex, family history, genetics (BRCA mutations), early menarche, late menopause. - Modifiable risk factors: obesity, high BMI, physical inactivity, smoking (active & passive), alcohol, high fat/sugar/meat intake. - Protective factors: fruits, vegetables, soy/isoflavones, fiber, regular physical activity. - Asian women show lower BC risk compared to US women, but survival varies widely across countries.	covering breast cancer incidence, prevalence, modifiable and non-modifiable risk factors across South-East Asia, Far East Asia, and Western Asia (excluding Middle East).
Yip, C.H. [6]	Narrative review and expert commentary; synthesis of published literature and global cancer control reports on breast cancer detection in LMICs.	- Breast cancer incidence rising in LMICs, but mortality remains high due to late presentation. - Mammographic screening is limited by high costs, infrastructure gaps, lack of trained personnel, and poor follow-up capacity. - Clinical Breast Examination (CBE) and Breast Self-Examination (BSE) are more feasible, but evidence for mortality reduction is limited. - Major barriers: lack of awareness, cultural beliefs, stigma, fear, and	based on synthesis of secondary sources (published studies, WHO/IARC reports, and LMIC breast cancer program experiences).

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		weak health systems. - Early detection via down-staging of symptomatic cases is more achievable than population screening in resource-poor settings.	
Unger-Saldaña K, Miranda A, Zarco-Espinosa G, Mainero-Ratchelous F, Bargalló-Rocha E, Miguel Lázaro-León J.[7]	Multicenter observational study across six Mexican hospitals; patient interviews and medical record review. Time intervals from first medical consultation → diagnosis → treatment were measured; regression analysis used to assess association between delay and clinical stage.	- Median health system delay: ~5 months. - Longer delays (>3 months) significantly associated with advanced stage (III–IV) at diagnosis. - System barriers: slow diagnostic process, referral inefficiencies, limited access to specialists. - Health system delay is a key factor driving late-stage presentation.	Women with newly diagnosed, untreated breast cancer (sample drawn from 6 hospitals in Mexico). Exact number: several hundred patients across public health institutions (study cohort from 2007–2011 period).
Romanoff A, Constant TH, Johnson KM[8]	Multicenter, cross-sectional study using structured patient interviews and chart reviews. Logistic regression models assessed associations between history of clinical breast examination (CBE), diagnostic delay, and stage at diagnosis.	- Only ~20% of women reported ever having a prior CBE. - Women with prior CBE were significantly less likely to present with advanced-stage disease (stage III–IV). - Prior CBE was associated with shorter diagnostic delays (fewer months from symptom recognition to diagnosis). - Despite this, most patients still presented at late stage, indicating systemic barriers.	441 women with newly diagnosed breast cancer (2010–2012), treated at three major cancer hospitals in Peru.
Ibekwe AM, Obeagu EI, Ibekwe CE[9]	- Design: Descriptive cross-sectional survey - Population: Working class mothers in Nnamdi Azikiwe University Teaching Hospital, Nnewi (Anambra State, Nigeria) - Sample Size: 120 mothers - Sampling: Convenience/availability sampling based on inclusion criteria - Data Collection: Structured	- High awareness of exclusive breastfeeding, but practice was lower - Many mothers had positive attitudes, but faced barriers to implementation - Challenges/barriers identified: short maternity leave, lack of workplace	- Size: 120 participants - Variables: Socio-demographics (age, education, type of work), knowledge & awareness of exclusive breastfeeding (EBF), attitudes, socio-economic

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	questionnaire - Analysis: SPSS v12.0; descriptive statistics & cross-tabulations	support/facilities, demanding work schedules, socio-cultural influences, and economic constraints - Socio-demographic factors (education, type of work) showed associations with EBF practice	determinants (maternity leave, workplace support, cultural beliefs), and practice of EBF - Setting: Nnamdi Azikiwe University Teaching Hospital, Nnewi, Nigeria - Year: 2022
Al-Dhabyani, W.; Gomaa, M.; Khaled, H.; Fahmy, A. [10]	Dataset creation of breast ultrasound images	Benchmark dataset with benign, malignant, and normal classes	Breast Ultrasound Images Dataset (780 images, 2018)
Rashmi, R.; Prasad, K.; Udupa, C.B.K. [11]	BCHisto-Net (CNN with global + local features), color normalization, Otsu, Gaussian smoothing	- Women with a prior breast cancer history underwent biopsies roughly twice as often as those without - Lower proportion of biopsies detected malignancy among women with prior history - Indicates potential over-biopsy and need for tailored surveillance strategies for breast cancer survivors.	- **Population:** Women undergoing breast cancer screening in the Breast Cancer Surveillance Consortium (BCSC) registries - **Size:** Over 170,000 women and ~900,000 mammograms - **Variables:** Biopsy occurrence, biopsy type, pathology results, personal history of breast cancer, demographic characteristics.
Buist DSM, Abraham L, Lee CI, et al.[12]	Observational, population-based cohort study analyzing breast biopsy intensity and outcomes following screening mammography. Compared women with and without a personal history of breast cancer. Data were linked from imaging, pathology, and cancer registries.	Standardizes color distribution in histopathology images	General use (not dataset specific)
Szegedy, C. et al. [13]	Inception architecture (GoogLeNet)	Introduced inception modules for deep CNN	ImageNet
Singh, S.; Gupta, P.R.; Sharma, M.K. [14]	Feed-forward neural network (FNN) on H&E-stained images	95.80% overall classification, 96.07% tumor-type precision	2600+ H&E-stained breast biopsy images

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Nawaz, M.A.A.; Hassan, T. [15]	DenseNet-based CNN	96% accuracy (multi-class), surpassing human experts	Breast histopathology dataset
Szegedy, C. et al. [16]	GoogLeNet (deep CNN)	State-of-the-art in 2015	ImageNet
He, K.; Zhang, X.; Ren, S.; Sun, J. [17]	ResNet (Residual Networks)	Solved vanishing gradient, very deep CNN	ImageNet

6. Conclusion and Future Work

As the most common and deadly cancer in women, breast cancer screening is a crucial yet complex issue. The survival rate for breast cancer is decreasing, and the disease is becoming more prevalent each year. Machine learning and deep learning algorithms are used to detect breast cancer. Previous research has shown that machine learning algorithms perform better in their specific applications. A variety of machine learning algorithms, along with dataset enhancements and augmentations, have been used in the studies mentioned above to achieve better results. However, it was found that the dataset size was too small. Future work might include using domain adaptation to manage heterogeneity between sources and collecting ultrasound, mammography, and histopathology data from multiple institutions while maintaining class balance. Existing research has applied SVM, KNN, and CNN algorithms with accuracy levels over 95%, but for physicians to trust AI predictions, they need outcomes that are explainable. Future approaches could involve building hybrid models that use CNN for feature extraction and SVM/KNN for classification, combined with explainable AI methods like GradCAM and LIME for visualization. So far, research has only focused on ultrasonography, mammography, or breast histology as diagnostic tools. Combining multiple imaging modalities—such as ultrasound, mammography, and histology—may enhance the diagnostic process in the future. The current literature emphasizes the importance of early detection, while also recognizing challenges in detecting small tumors, especially in dense breast tissue. Using high-resolution ultrasound datasets, we can train segmentation-enhanced CNNs like U-Net and ResNet, and validate these models with early-stage clinical cases. This could improve sensitivity to tiny cancers that are often missed. Previous studies relied solely on imaging data. However, factors such as heredity (e.g., BRCA mutations), lifestyle, and medical history also influence breast cancer risk. Incorporating non-imaging data, including biomarkers, patient history, and genetic information, could improve future predictions.

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