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Breast Cancer Detection Techniques: A Review

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Abstract

Breast cancer is an important global health issue affecting women, leading to death. Early detection is the best way to improve detection and survival rates. Deep learning (DL) and machine learning (ML) approaches have shown good results in detecting breast cancer. This study reviews ML and DL techniques, discussing their applications in medical image data like mammograms and histopathological images. This paper clarifies the challenges and limitations of detection techniques and clinical validation for successful implementation in real-world healthcare. The findings of this review are valuable for researchers and clinicians in terms of the usefulness of these technologies for detecting breast cancer.

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1. Introduction

Breast cancer is one of the biggest health challenges affecting women globally, presenting a big issue in terms of death rates [1],[2]. The early detection of breast cancer is important as it plays a key part in developing the prediction and survival rates for breast cancer patients [3], [4]. With quick improvements in technology, especially in the domain of DL and ML, there has been avert shift in how breast cancer is detected [5]. These techniques contain additional accuracy, efficiency, and detection methods, especially when evaluating medical image data like mammograms and histopathological images [6],[7],[8]. Recent methods have the potential to develop breast cancer diagnosis, but these techniques have challenges and limitations. This review aims to present a comprehensive review of the different DL and ML methods that have been utilized in breast cancer detection. It shows the specific applications of these methods in analyzing and interpreting medical images while also addressing the problems faced in implementing these methods effectively in real-world healthcare scenarios.

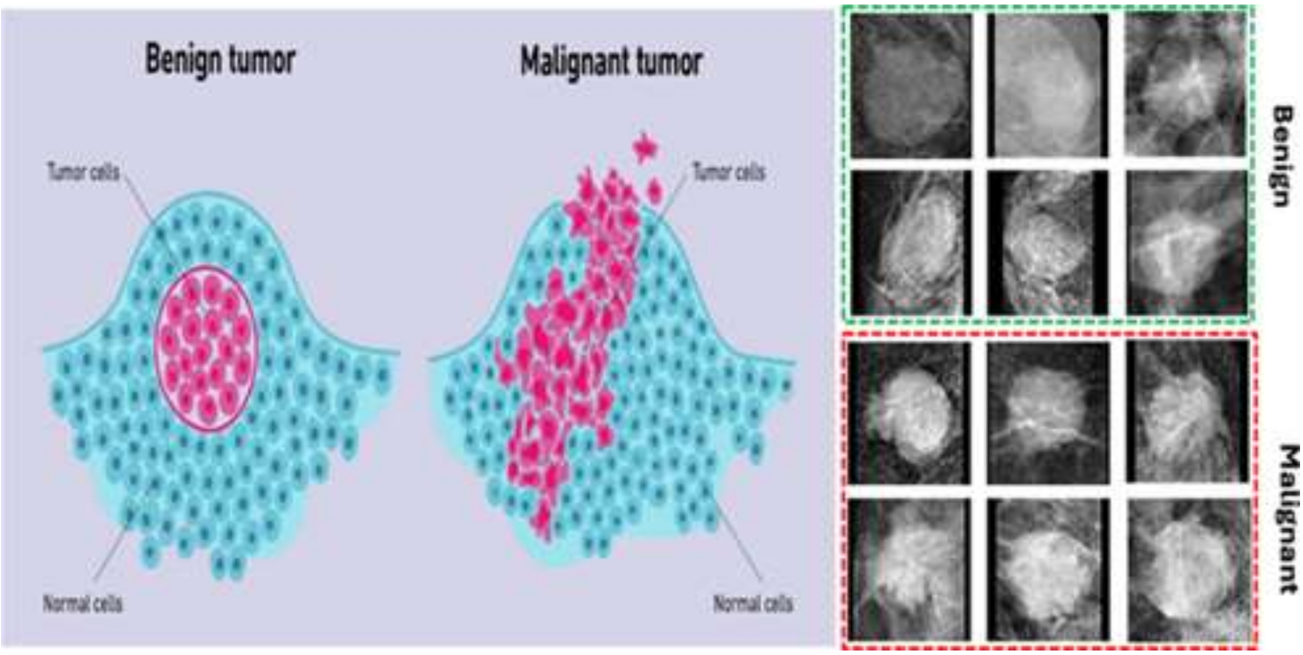
From the scaling highlight on the current breast cancer detection techniques utilizing DL and ML, this review shows an important source. It is proposed for a wide audience, including researchers, clinicians, and policymakers keen on harnessing the power of these advanced approaches to enhance breast cancer detection and diagnosis, aiming for improved patient outcomes. As shown in Figure 1, types of breast cancer. The paper is organized in Section 2, Breast Cancer Background, while in Section Physics Overview and Section 4, Breast Cancer Detection Techniques.

2. Breast Cancer background

Breast cancer is a real health risk to a considerable population, predominantly women, worldwide [10],[11]. This kind of cancer is characterized by the growth of a cancerous tumor within the breast tissue, typically originating from the cells lining the milk ducts or the lobules that produce milk [12],[13]. Although breast cancer can also affect men, it is significantly less prevalent in comparison [14].

The precise origin of breast cancer remains uncertain, but it is thought to result from a multifaceted interaction among genetic, hormonal, and environmental elements. Various risk factors have been identified, such as advancing age, a family history of breast cancer, inherited gene mutations (such as BRCA1 and BRCA2), early onset of menstruation, late onset of menopause, hormone replacement therapy, obesity, alcohol consumption, and lack of physical activity. Nevertheless, it is important to note that the presence of one or more risk factors does not guarantee the development of breast cancer, and many individuals diagnosed with breast cancer do not exhibit any identifiable risk factors [15].

The timely identification of breast cancer is vital for enhancing treatment outcomes. Typical indications and manifestations encompass the discovery of a new lump or mass in the breast or underarm region, alterations in breast size or shape, abnormal nipple characteristics like inversion or discharge, breast pain or sensitivity, and skin changes on the breast such as dimpling or redness. These symptoms can also appear from non-cancerous conditions, underscoring the significance of seeking medical knowledge for an accurate diagnosis. Breast cancer detection usually shows a combination of image techniques such as mammography, ultrasound mag,netic resonance imaging (MRI), and biopsy to examine suspicious tissue. The treatment strategies after detection are determined according to various factors of individual overall health. Possible treatment options include surgical treatment (e.g., lumpectomy or mastectomy), radiation therapy, chemotherapy, hormone therapy, and targeted therapy. The treatment plan is customized to meet the individual needs of each patient [16].



Figer 1: Types of breast cancer [9].

Breast cancer remains a significant health challenge; advancements in early detection, improved treatment options, and increased perception have contributed to higher survival rates and improved quality of life for individuals diagnosed with breast cancer. Continued efforts in research, education, and support are essential in the fight against breast cancer, with the ultimate goal of reducing its incidence, improving outcomes, and providing better care for those affected by this disease. Breast cancer is a significant contributor to female mortality. Most breast malignancies arise from invasive ductal carcinomas (IDCs), originating from the epithelial cells that line the ducts. Before becoming invasive, there exists a pre-invasive stage known as ductal carcinoma in situ (DCIS), where cancer cells are confined within the basement membrane. Research indicates that many DCIS lesions may never progress into IDC. Autopsy studies have revealed that occult DCIS affects approximately 9% of women, with a range spanning from 0% to 15%. Several small-scale studies have been conducted on patients who were misdiagnosed with DCIS, leading to a lack of surgery. Remarkably, after thirty years, IDC was detected in 14% to 53% of these patients. A meta-analysis of numerous investigations involving patients with DCIS found a 15-year invasive local recurrence rate of 28% after a diagnosis of DCIS through excisional biopsy.

Consequently, many DCIS lesions may not progress to IDC [17][18]. Different medical procedures are used in the traditional cancer treatment for distinct cancer stages. The treatment is carried out by the evaluation made by the pathologist and other medical professionals. Surgery is done to remove the tumor-containing area for level 1 malignancy. Radiation is used in addition to surgery. In radiation, the tumor cell is directly exposed to high-intensity rays. These rays effectively damage the DNA while destroying the malignant cell. At the terminal stage of cancer, chemotherapy treatments are administered. These medications target cells that are expanding quickly. The specific medications prevent cells from replicating during the early mitotic cycle. Before initiating treatment, it is essential to determine the stage of cancer, followed by grading the cancer based on that stage. Treatment is administered accordingly once the stage is determined through pathology and confirmed by medical experts. However, there is a noticeable disparity between pathology results and those of human experts, possibly due to fatigue or other factors. Consequently, researchers and medical professionals are rapidly adopting computer-assisted diagnostic methods. The availability of high-resolution whole slide images (WSI) of tissues and the ability to load these scanned images onto machines have facilitated the development of automated systems for image assessment, making it easier for researchers to create such systems [18].

2.1 Determine the Stage of Breast Cancer

Determining the stage of breast cancer is a crucial step in the diagnostic process[19]. The stage describes the extent and spread of cancer in the body, helping healthcare professionals plan the most appropriate treatment approach and predict the prognosis for the patient. Several factors are taken into consideration when determining the stage of breast cancer [20]:

Tumor Size (T): The size is measured and classified into different categories. This is achieved through image tests, such as mammography, ultrasound, or MRI, and during surgery if a tumor is removed.
Lymph Node Involvement (N): evaluating the lack of cancer cells in nearby lymph nodes. Breast cancer spreads through the lymphatic system, so lymph nodes (axillary lymph nodes) in the lower arm area are usually examined.
Metastasis (M): the presence of distant metastases, that is, whether cancer has spread to other parts of the body such as bones, lungs, liver, and the brain. This is usually determined through image tests such as bone scans, CT scans, PET scans, and MRIs.

2.2 Types of breast cancer

Cancer is characterized by the atypical proliferation and infiltration of cells in the body, disrupting the normal functioning of healthy cells. Breast cancer originates in the breast cells, where a cluster of cancerous cells forms and can invade neighboring tissues or spread to other parts of the body [21],[22]. Cancerous growth commences within the cells, which serve as the fundamental units that compose the body's tissues. The process of cell division occasionally malfunctions, leading to the generation of new cells. This accumulation of abnormal cells often culminates in developing a mass or tissue cluster, commonly called a tumor [23].

On the contrary, invasive cancers are distinguished by the proliferation of cancer cells that extend beyond the basement membrane of the ducts and lobules, infiltrating the adjacent normal tissue [24]. The most prevalent form of breast cancer is invasive ductal carcinoma (IDC), which comprises approximately 70% to 80% of cases and originates in the cells lining the breast ducts [25]. Invasive lobular carcinoma (ILC) represents about 10% of breast cancer cases and develops within the cells lining the breast lobules [26]. Furthermore, there exists a less common type of invasive breast cancer known as inflammatory breast cancer, accounting for approximately 1% to 5% of all breast cancer cases [27].

2.3. Types of tumours

Tumors are classified into two main types: benign and malignant.

2.3.1. Benign tumours

Benign tumors are characterized by cells that do not spread to other body areas and are not life-threatening[28]. When a tumor is diagnosed as benign, medical professionals often choose to monitor it rather than remove it. Although benign tumors generally do not aggressively affect surrounding tissues, they can continue to grow, exerting pressure on organs and causing pain or complications. The tumor may be surgically removed in such states to alleviate discomfort or resolve complications[29].

2.3.2. Malignant tumours

Malignant tumors display aggressive characteristics by infiltrating and causing harm to adjacent tissues and organs. They possess the ability to metastasize to distant regions of the body. When a tumor is suspected to be malignant, a biopsy is commonly conducted to ascertain its severity or level of aggression [30].

3. Physics overview

Breast cancer is a complicated disease defined via the uncontrollable production of irregular cells in the breast tissue, but understanding and combating breast cancer requires a deep understanding of biology and medicine; the area of physics also carries large importance in different sides of breast cancer research and diagnosis. This part briefly summarizes necessary physics theories that are relevant to breast cancer.

3.1. Biophysics and cancer growth

Biophysics is the study of biological techniques utilizing physical theories in the domain of breast cancer. It plays an important role in understanding the development and characteristics of cancer cells. Biophysical models help to discover the mechanical characteristics of cancer cells, their interaction with the closest tissues, and the forces involved in tumor development [31].

3.2. Imaging techniques

Images and physical technology are necessary for detecting, checking, and evaluating breast cancer efficacy. Mammography is the most common method of screening, using X-rays to create detailed images of breast cancer. Other imaging techniques, such as ultrasound and magnetic resonance imaging (MRI), use ultrasound waves and magnetic fields to visualize breast anomalies. The physics theories of these imaging techniques enable cancer detection, their detection characteristics, and operations to be guided [32].

3.3. Radiation therapy

Radiation therapy is a major treatment method for breast cancer. High-energy radiation, such as X-rays and gamma rays, targets and destroys cancer cells. In radiation therapy, physics is essential to providing a precise dose of radiation to the tumor and minimizing the exposure of healthy tissues. Dosimetry, measuring the dose of radiation, is an important physics concept for calculating optimal radiation treatment plans. Simulation and image technology based on physics support treatment planning by ensuring an accurate target of the tumor and minimizing side effects [33].

3.4. Biomechanics and tissue engineering

Biomechanics studies the mechanical properties of biological tissues and their reaction to external weights. In breast cancer research, biomechanical technology plays a role in understanding tissue deformation, tumor mechanical properties, and the impact of mechanical forces on cancer cell behavior. Tissue engineering techniques, including physics principles, have also been used to create artificial tissues for research purposes and develop innovative treatment strategies [34].

3.5. Nanotechnology and nanomedicine

Nanotechnology means the control of nanomaterials. In breast cancer, nanotechnology has become a promising field for drug approaches, image contrast agents, and early detection of cancer. Physics concepts such as quantum mechanics and surface physics are applied to the design and development of specific properties of nanoparticles suitable for breast cancer diagnosis and treatment. The researchers of breast cancer and health professionals can increase valuable perception into the basic mechanisms of disease utilizing physics principles, improve diagnostic accuracy, optimize treatment strategies, and study innovative ways to combat breast cancer. The research on breast cancer, including physics, biology, medicine, and other disciplines highlights the importance of merging to advance the understanding and management of this complex disease [35].

4. Breast Cancer Detection Techniques

4.1. Artificial intelligent:

AI can be utilized to develop breast cancer detection approaches [36],[37]. AI algorithms can analyze various sources of data, such as genetic information and medical records, and determine the risk of breast cancer among individuals [38]. AI models have identified high-risk individuals, improved the detection of breast cancer, and reduced death rates. The models analyze patient data to develop treatment plans for breast cancer patients to optimize outcomes and minimize side effects [39].

4.2. Machine learning (ml)

ML is a sub of AI section that learns and enhances performance via knowledge without programming. ML algorithms can evaluate big detect samples and make predictions based on the dataset. ML is utilized to create models to predict disease, recognize people at higher risk of severe symptoms, and contribute to developing potential treatments [40], [41]. ML algorithm's ability to analyze big data, identify patterns, and make predictions based on this information [42], [43], [44]. The applications of machine learning in breast cancer are to predict disease and metastaticity [45]. The ML algorithm analyzes tumor character, genomic profiles, and patient populations to detect the probability of tumor growth, the risk of tumor pathogens, and treatment responses. This information helps oncologists make informed decisions around personalized treatment plans and treatments for breast cancer patients [46], [47], [48]. As shown in Figure 2, there are different types of ML techniques.

4.3. Deep learning (dl)

DL is a subsection of ML that utilizes artificial neural networks to show complex patterns and connections in data [49]. The term "deep" refers to the reality of multiple layers of connected neurons forming the neural network. DL algorithms find applications in various fields, such as image recognition, language recognition, natural language processing, and anomalous detection. Deep learning has proved effective in breast cancer diagnosis, especially in medical image data analysis. Medical image techniques like mammography and ultrasound play a critical role in diagnosing breast cancer by revealing distinctive patterns and features associated with the disease. Deep learning-based approaches for breast cancer detection can be broadly categorized into supervised and unsupervised learning methods. In supervised learning, a DL algorithm is trained using labeled data, consisting of breast images annotated with corresponding cancer status. Conversely, unsupervised learning techniques learn patterns and features directly from the input data without relying on labeled information [50].

4.3.1. Supervised Learning

In breast cancer detection supervised DL methods usually show training the brain network (CNN) of breast cancer in a mammogram or ultrasound image labeled positive or negative. CNN is a special neural network that analyzes images and extracts detailed features from input images using several coevolutionary layers. Many studies have shown CNN's effectiveness in breast cancer detection. Supervising DL methods has many advantages, such as learning complex patterns and functions from large amounts of label data. They may also have some limitations. The performance of the supervised DL model depends heavily on the quality and quantity of training-based labeling data. Furthermore, if training data do not accurately represent a wider population, this method can cause bias and generalization problems [51].

4.3.2. Unsupervised Learning

Unsupervised methods for detecting breast cancer are usually used in training a deep (AE) or variable (VAE) encoder on X-ray or CT images. AEs and VAEs are neural networks that learn to encode input images into low-dimensional images and then decode them back into original images. Unsupervised methods have various advantages, including direct learning patterns and characteristics from input data without labeling.[52].

4.4. Related work

Farhadi et al. [53] proposed a deep transfer learning approach that effectively addresses the issue of imbalanced data commonly encountered in breast cancer datasets. They emphasized that many machine learning classification algorithms assume balanced class distributions, often not different in real-world applications, leading to performance challenges. The study specifically focused on utilizing publicly available structured breast cancer datasets to create a pre-trained model. The main hypothesis was that employing deep transfer learning with structured breast cancer datasets could improve the early detection and classification of malignant breast cancer.

Kim et al. [54] proposed a deep-learning model for diagnosing breast cancer, focusing on stained histological images. This study utilized image-processing techniques and data augmentation methods to extract high-level features from preprocessed images. The model utilized many DCNN architectures, including Inception v3, ResNetv2, Xception, and two VGGNet models. The experiment used 400 Breast Cancer Histology images from the ICIAR 2018 Grand Challenge dataset, achieving an impressive accuracy rate of 92.5%.
Huang al. [55] study tackled the rising breast cancer incidence and the limitations of traditional X-ray imaging screening. They used preprocessing techniques on a dataset of 9000 mammograms and a convolutional neural network as a classifier. The results showed that using preprocessed images significantly improved the model's accuracy compared to a model without preprocessing.

Soman al. [56] focused on identifying breast cancer types using histology images from the BACH 2018 grand challenge dataset. They trained and tested their capsule network model, suggesting that data preprocessing and transfer learning, specifically parameter tuning, could improve the performance of convolutional architectures. In this research [57], we proposed a hybrid diagnostic model for breast cancer classification, combining the Bat algorithm, Gravitational Search Algorithm, and Feed-Forward Neural Network. The model has two parts: a feed-forward neural network module for effective data training and an error minimization module utilizing Bat and GSA metaheuristic algorithms for optimizing and minimizing errors in the classification process. This approach combines the strengths of FNN and nature-inspired algorithms for effective data classification. This research [58] proposed a novel approach for the detection of breast cancer via merging individual losses and integrating them into an Artificial Neural Network (ANN) utilizing backpropagation. This method optimizes the loss function coefficients and weight parameters, making it particularly useful in high noise levels in patient data. This study [59] utilized a novel method for breast cancer classification in the medical field. It used a CNN architecture to determine pixel count within lesions, assigning quality scores to regions with higher pixel concentrations. The image kernel is then constructed using a multi-SVM method, incorporating the quality scores, enabling successful classification of breast cancer cases.

This paper [60] focuses on two main challenges in the application of deep belief networks (DBNs): fine-tuning network weights and biases and identifying the optimal number of hidden layers and neurons. This study proposed two novel evolutionary methods: E (T)- DBN-BP-ELM and E (T)- DBN-ELM-BP. These approaches integrate DBN with an ELM classifier to overcome the first difficulty. A genetic algorithm (GA) is applied for architecture optimization, facilitating global exploration in the solution space. A third method, E(TW)-DBN, also addresses both challenges. This work [61] proposed a three-stage approach for classifying epithelial and stromal regions from whole slide images. The first stage utilized an SVM feature learning classifier based on superpixels. The second stage applied a CNN segmentation method to segment membrane regions within the classified epithelial regions.

Table 1 shows the findings from the research studies on breast cancer detection, classification, and diagnosis. The models utilized in these studies range from CNN to hybrid approaches merging DL with ML techniques. These methodologies represent the forefront of computational research aimed at improving the accuracy and efficiency of breast cancer detection, a critical aspect of early diagnosis.
Various studies show good performance in binary classification tasks, classifying malignant and benign tumors. The eLFA-CRNN model achieved a high accuracy of 0.99 to show the potential of relating edge extraction systems with convolutional recurrent neural networks. The hybrid DL with ML approach, which mixes DL with DL methods, also achieves a high accuracy of 0.99. These results highlight the effectiveness of useful advanced techniques in correctly identifying breast cancer. Transfer learning enhances classification accuracy [54], [56]. These methods improve the generality and performance of CNNs in binary breast cancer detection. This highlights the importance of useful existing knowledge and expertise to enhance models' abilities in medical image analysis. Multiple algorithms and loss functions proposed contribute to improved detection accuracy [57] and [58]. Hybrid models combining various algorithms, such as BAT, GSA, and FNN, achieve high accuracy levels, underscoring the significance of algorithmic optimization in breast cancer detection. The combination of multiple loss functions in ANN models enhances the strength and accuracy of tumor detection, further highlighting the importance of algorithmic optimization in medical image analysis.

Knowing that the challenges and limitations depend on these studies is important. This study [59] achieves an accuracy of 0.70 and utilizes multiple CNN architectures, showing the complexity and variability of breast cancer image data. The availability of high-quality and varied datasets remains important for training robust models, as highlighted by studies [53] and [61]. Addressing these challenges via continued research and collaboration is imperative to improve further the accuracy and reliability of breast cancer detection techniques. Researchers can improve breast cancer detection and diagnosis by using DL, ML, and hybrid approaches. The review paper provides an overview of current challenges and advancements and highlights key points for further advancements in this field. DL and ML techniques have shown promise in early breast cancer detection, improving survival rates. However, challenges include large datasets, interpretability, biases, and technical challenges in real-world healthcare settings, highlighting the need for larger datasets and improved accuracy. Breast cancer research is interdisciplinary, including biology, medicine, physics, and computer science. Advancements in DL and ML techniques improve detection accuracy, efficiency, and accessibility, covering the way for future research.

Table 1: provides a summary of the relevant works.

Studies Paper	Models/ Algorithm	Binary or Multiclass	Classes	Accuracy	Task
[53]	CNN	Binary	Malignant/ benign	0.81	BC image classification
[62]	DCNN	Multiclass	4 tissue categories	0.92	BC diagnosis
[54]	eLFA-CRNN	Binary	Malignant/ benign	0.99	BC detection
[55]	CNN + transfer learning	Binary	Malignant/ benign	F1-score 0.88	BC detection
[56]	CNN + transfer learning	Binary	Malignant/ benign	0.87	BC image classification
[57]	BAT, GSA, FNN	Binary	Malignant/ benign	0.94	BC tumor detection
[58]	ANN + (Correntropy + Hinge + CrossEntropy)	Binary	Malignant/ benign	0.97	BC tumor detection
[59]	2CNN, 3CNN	Binary	Negative and positive	0.70	BC detection
[60]	DL + ML (Hybrid) Model 1: DBNELM- BP Model 2: DBNBP-ELM Model 3: DBN + GA	Binary	Negative and positive	0.99	BC detection
[61]	SVM, CNN, SLIC	Binary	Epithelial and non-epithelial	0.94	BC image classification

5. Conclusion

This review paper shows breast cancer detection techniques, focusing on the developments in DL and ML approaches. The review shows that these techniques have the potential to update early detection and diagnosis of breast cancer. The integration of these techniques has led to significant progress in correctly analyzing medical image data, like mammograms and histopathological images, to detect breast cancer. The review highlights the importance of algorithmic diversity, utilizing models like CNN, transfer learning, and hybrid approaches combining multiple algorithms. These approaches enhance the accuracy of breast cancer detection and improve the interpretability and robustness of computational models in medical image analysis. However, there are many challenges, such as the availability of high-quality datasets, algorithmic optimization, and the need to address variability in breast cancer image data. The review provides a valuable resource for researchers, clinicians, and policymakers interested in leveraging DL and ML methods to improve breast cancer detection and patient outcomes.

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