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Article *in* Archives of Computational Methods in Engineering · July 2023

DOI: 10.1007/s11831-023-09968-z

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REVIEW ARTICLE

A Comprehensive Review on Breast Cancer Detection, Classification and Segmentation Using Deep Learning

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Received: 16 February 2023 / Accepted: 26 June 2023

Abstract

The incidence and mortality rate of Breast Cancer (BC) are global problems for women, with over 2.1 million new diagnoses each year worldwide. There is no age range, race, or ethnicity threshold, as all women are susceptible; however, no permanent remedy has been developed for it. Therefore, the survival of patients with BC can be improved significantly with an early and accurate diagnosis. There are a number of studies that have created automated approaches employing various types of medical imaging to detect the emergence of BC, but the accuracy of each method varies depending on the resources available, nature of the problem and dataset being employed. However, there is a dearth of review articles that summarize the current research on BC diagnosis. This manuscript addresses the current state of the art in artificial Deep Neural Network (DNN) techniques for BC detection, classification and segmentation using medical imaging. In addition, it emphasizes the working principles, benefits and limitations of imaging modalities used to detect BC, along with a comprehensive analysis of those modalities. The primary purpose of this paper is to identify the most effective imaging modalities and DL approaches that can handle the huge dataset with reliable predictions. The results of this review indicate that mammography and histopathologic images are primarily employed for BC classification. Furthermore, approximately 55% of the research used public datasets while the rest used private data sources. To reduce variability and overfitting in BC images, several studies have used pre-processing methods such as data augmentation, scaling, and normalization. Moreover, distinct neural network architectures, both shallow and deep, are used to analyze BC images. The CNN is widely employed to develop an efficient BC classification model and several studies either used a pre-trained model or created a new DNN. Lastly, this review addressed 13 significant challenges that are encountered throughout the course of the review for future researchers that aim to improve BC diagnosis models using a wide range of imaging techniques. This paper has the potential to be a helpful resource for both beginners and experts in the field of medical image analysis, particularly those who focus on DL based BC detection, classification and segmentation employing a variety of imaging modalities.

Keywords Breast cancer (BC) · Deep learning (DL) · Convolution neural networks(CNN) · Mammography · MRI · Ultrasonography · Histopathological

1 Introduction

BC is a genetic disease that occurs when cells in the breast tissue proliferate uncontrollably. In 85% of cases, BC originates in the lining cells (epithelium) of the ducts and 15% in the lobules of breast glandular tissue [1]. Initially, the malignant lesion is localized to the duct or lobule, where it normally causes no symptoms and has a low risk of spreading (metastasis). These malignancies, if left untreated, can spread to neighboring lymph nodes (regional metastasis) and eventually to other organs in the body (distant metastasis). Figure 1 illustrates a morphological change that occurs in cancer cells. Metastasis of BC is a primary cause of death

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Published online: 07 July 2023

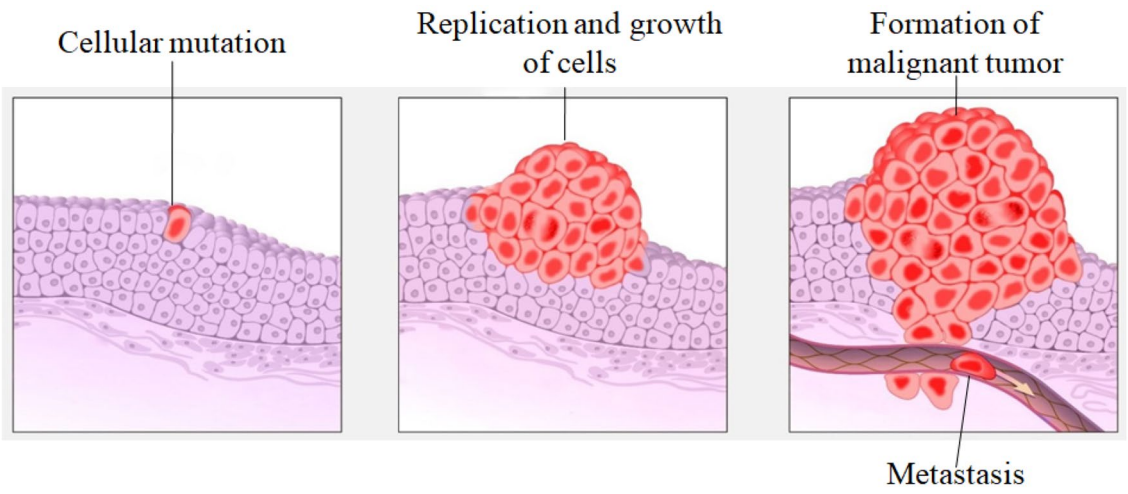

Fig. 1 Morphological transition of cancer cells

among women. There are four distinct phases of BC that are determined by the Tumor Nodes Metastases (TNM) system, which was created by the American Joint Committee on Cancer (AJCC) [2]. BC is not a contagious or infectious condition. It is estimated that almost 50% of all breast cancers occur in women who have no recognised breast cancer risk factors other than their gender and age ($age > 40 years$). In addition, obesity, consumption of alcohol, having a family history of breast cancer, radiation exposure, smoking, and undergoing postmenopausal hormone therapy are all variables that enhance the risk of developing BCBC [3]. Therefore, it has the highest incidence and mortality rate among women and is one of the primary causes of cancer related fatalities around the world [4, 5]. However, the frequency of this disease in females is significantly higher than that of males [6, 7].

When compared to developed nations, death rates are significantly higher in middle and low income countries. The World Health Organization (WHO) reports that in the year 2020, 2.3 million women had BC and 68,500 died through this globally [8]. In 2022, approximately 287,850 new cases of invasive BC and 51,400 cases of Ductal Carcinoma In Situ (DCIS) have been diagnosed among US women, and 43,250 women died of BC [9]. Moreover, according to the National Institute of Cancer Prevention and Research (NICPR) in India, for every two new instances of BC, one woman dies [10]. As per the GLOBOCAN data 2020, in India, BC accounted for 13.5% (1,78,361) of all cancer cases and 10.6% (90,408) of all deaths [11]. Additionally, in developing nations like Egypt and Africa, higher mortality is caused by a combination of factors, including a large population, lack of awareness about disease symptoms, and delay in seeking medical help until it is a critical condition. Furthermore, inadequate access to specialists and experts in rural areas makes it harder to identify and detect BC early and accurately, which contributes to a higher mortality rate. Early detection of BC aids in providing better quality treatment to patients, hence reducing the mortality rate. Figure 2 shows the incidence and mortality rates for the ten most common female malignancies in the year 2020.

Medical specialists believe that the best way to improve patients' chances of being cured and reduce the risk of morbidity and mortality caused by this disease is to treat it in the early phase. Thus, experts have suggested screening approaches to aid in early diagnosis [12, 13]. The most accurate way TO diagnosiS BC is through the evaluation of medical images. Different types of Medical Imaging Modalities (MIM) are used to perform BC diagnosis. However, the area of interest is depicted differently on the basis of the screening method. This fact encouraged us to study several screening approaches in order to choose the most effective screening for detecting and classifying BC. Images generated through screening techniques aid radiologists and doctors in detecting diseases, thereby lowering mortality risk by 30–70% [14]. The screening techniques that are most often used to detect BC are Digital Mammogram (DM), Breast Ultrasound (BUS), Breast Magnetic Resonance Imaging (BMRI), Computed Tomography (CT) scan, Positron Emission Tomography (PET) scan, Histopathological (HP) images and Thermography. However, these imaging techniques are much more operator-dependent, and interpreting the images requires skilled medical experts with a high inter-observer variation rate. Moreover, a meta-analysis conducted in 2021 indicates that nearly 2/3 of the country's population lives in rural areas and has access to 33% of the country's total health workers and 27% of its total doctors [15]. In addition, the World Health Organization (WHO) states that India's doctor-to-patient ratio is 1:1000

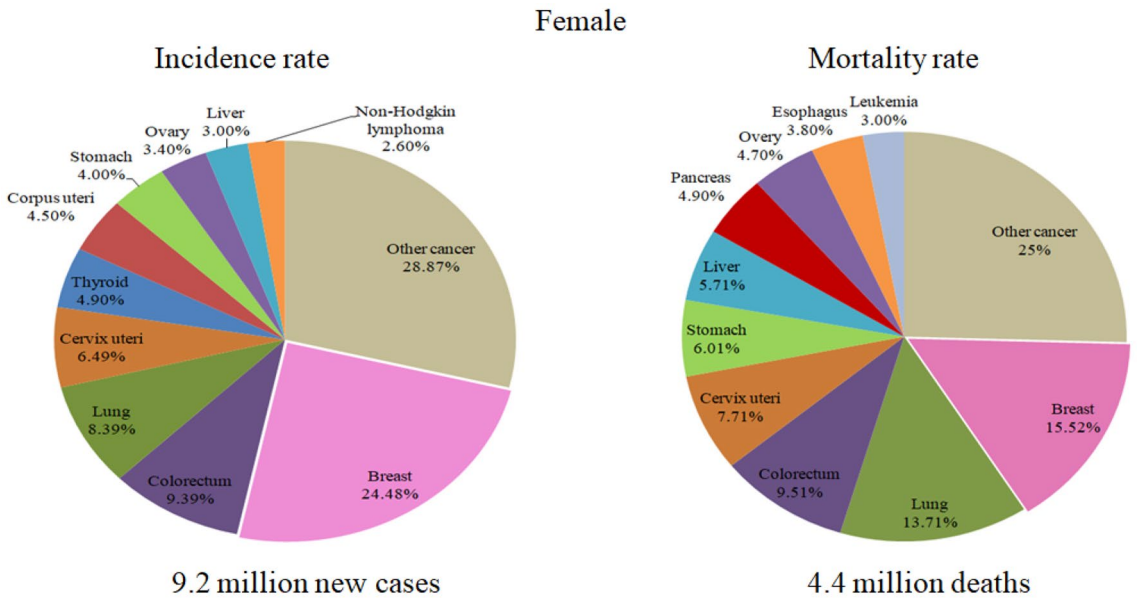

Fig. 2 Distribution of cases and deaths for the top ten most prevalent cancers among women in 2020

[16]. Furthermore, due to limited resources and a shortage of expert opinions the process of detecting a vast number of targeted people has become laborious. Thus, because of the constraints of traditional methods such as rigorous detection methods, treatment delays, unreliable detection processes, high error rates, etc. have reduced the reliance on conventional approaches. Hence, traditional imaging methods are feasible but time-consuming.

Additionally, for patients with metastatic BC, it is routine to conduct recurrent diagnostic imaging, often with intervals as short as 6 weeks [17]. Therefore, this practice is associated with high costs and the potential for toxicity from iodine-based or gadolinium contrast agents. As an alternative approach, the evaluation of biomarkers provides a means for medical experts to assess the stage and prognosis of BC. The use of biomarkers [18] has the potential to improve prognosis and treatment outcomes. Proteins, nucleic acids, ribonucleic acids, and metabolites are examples of biomolecules that can serve as cancer indicators [19]. By analyzing biomarkers, clinicians can gain a deeper understanding of a patient's disease status and make better decisions regarding treatment therapies. Various biomarkers are employed in BC management, particularly the expression of estrogen receptor (ER), progesterone receptor (PR), and human epidermal growth factor receptor 2 (HER2) [20–22]. These biomarkers can be identified in fluid samples like blood, urine or tissue samples obtained from a tumor.

However, there are a few downsides of utilizing biomarkers in the diagnosis of BC that require careful consideration [23]. One of the issues is limited specificity, where biomarkers may show elevated levels in other non-BC conditions, leading to false positive results. For instance, CA 15-3 biomarker levels may increase in conditions like liver disease and lung disease, which can result in misdiagnosis. Another challenge is the variability of biomarker expression, which can differ between different subtypes of BC, and even within the same subtype. This inconsistency makes it difficult to identify biomarkers that are reliable for all types of BC. As a result, there is a need for an improved version of the clinical diagnosis system that can assist and ease the work of medical professionals to conduct routine checkups, and help them produce better results for faster detection of BC.

Therefore, computer-aided diagnosis (CAD) is needed to assist the radiologist in the different analysis stages and to offer them a second opinion on the final decisions. CAD is a hybrid system that combines multiple elements, for instance, Artificial Intelligence (AI), Computer Vision and Medical Image Processing (MIP). CAD approaches help to minimize the effect of the operator-dependent nature and increase the diagnostic sensitivity and specificity. Identifying and classifying subtypes of BC correctly is a significant clinical task. However, it has been observed that 65–90% of the biopsies turned out to be benign, therefore, a crucial goal of CAD systems is to distinguish benign and malignant lesions to reduce unnecessary biopsy. Hence, these automated approaches can be employed to save time and reduce error. Different imaging modalities with CAD systems have proven to be highly effective in reducing BC mortality, especially in the early stages. AI and ML have been utilized to automate the process of mass detection, classification, estimate their risks accurately and quickly, take timely preventive measures, and assist medical professionals in making

effective conclusions using Deep Learning (DL) to carry out a variety of clinical tasks. Figure 3 illustrates the workflow of the CAD system.

ML has become widely used in several fields, from recommendation systems [24] to health care [25], sentiment analysis [26], and transportation [27]. Amongst all, DL is the frequently used ML algorithm in these applications [28–31]. Traditional ML approaches are limited to carry out tasks such as feature extraction, pre-processing, segmentation, classification, etc. in terms of accuracy and efficiency. Because feature extraction and selection procedures are performed manually ("edge irregularity", "color", "pattern", "shape" etc.). After manual segmentation, traditional ML models (such as k-nearest neighbors, k-mean, Naive Bayes etc.) are employed to make final conclusions. However, these manual techniques are laborious and require more time to process. In addition, the manual feature selection approach sometimes fails to adequately extract the desired feature.

To address these challenges, the idea of an advanced ML approach such as DL has been introduced, which is robust in extracting the appropriate data from the raw images and effectively differentiating classes. DL models are capable of learning new features on their own through identifying and learning hidden patterns in ROI (Region of Interest) due to their hierarchical design of Deep neural networks (DNN). Throughout the training and learning procedure, crucial image attributes are recognised and enhanced for the specific application, such as classification, detection, and segmentation while extraneous elements are screened out. Because of its immense benefits, DL technologies are the primary standard in the CAD field. Various DL models have been proposed, such as the Gamma function based ensemble model [32], deep fuzzy model [33], DCNN [34–39],hybrid rule-based [40], CADNet157 [41] etc. for the early diagnosis of BC.

Thus, this manuscript highlights the significant drawbacks and constraints of traditional approaches for BC diagnosis, which proves the significance of a CAD system. Furthermore, it identifies and studies the fundamental concepts, strengths and limitations of different imaging modalities employed for BC detection, classification and segmentation. Besides, it reports the recent advancements in the design of CAD using DL analyses and their limitations.

The rest of the paper is organized as follows: Sect. 1 explains the procedures for identifying and evaluating relevant prior studies, research questions, and criteria for selecting relevant articles. Sections 3, 4, and 5 discuss the history of BC evolution, screening techniques and their related observations. Sections 6, 7, and 8 provide information on dataset availability and previous work in the field of CNN and hybrid DL. In Sects. 9 and 10, the comparison and quality matrices are explained, followed by the challenges encountered, future implications, and a conclusion in Sects. 11 and 12.

2 Research Methodology

To conduct the review for this paper, a systematic approach is used to search for relevant literature in multiple databases. Initial steps in the analysis involve defining the scope of the review, which included various aspects such as screening modalities, segmentation techniques, DL tools, datasets, quality metrics, and challenges. The sub section then discussed the article selection criteria used in the review.

2.1 Scope Identification

The aim of this study is to compile data from a wide range of research that explore the use of medical imaging techniques for the purposes of classifying, detecting, and segmenting BC. The primary purpose of the review is to provide answers to the following research questions, which are as follows:

Q1. What are the different screening techniques used for BC diagnosis and what are their strengths and limitations ?
Q2. What medical imaging datasets are utilized to develop DL based classification models?
Q3. What are the DL techniques employed for BC classification?
Q4. How do segmentation techniques improve the classification results in BC classification?
Q5. What performance evaluation metrics are implemented to assess the results of classification models?
Q6. What are the current challenges and opportunities in the field of BC?

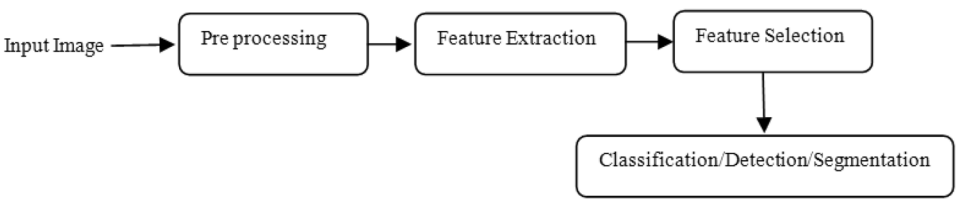

Fig. 3 Workflow of the CAD system

2.2 Article Selection Criteria

In this comprehensive review, we intend to identify and evaluate various studies associated with BC, screening techniques used, and its detection using DL methods. Figure 4 illustrates the keywords and search criteria that are used to retrieve the papers incorporated in this review. The search began with terms such as "BC classification", "BC detection" and "BC segmentation". The use of these keywords leads to the formation of a variety of strings, which are displayed as follows:

- "BC"+ "DM/BUS/CT/BMRI/HP/TI/PET"
- "BC"+ "history" + "first time applied CNN model"
- "BC"+ "screening techniques"
- "BC"+ "publicly available datasets" + DL
- "BC"+ "DL" + "hybrid DL"
- "BC"+ "segmentation technique"

The papers are searched and collected from credible online database sources like Springer, Wiley, Elsevier, IEEE and PubMed etc.

The objective of selecting studies is to determine the appropriate time frame for the review process. For the BC review, research papers published between 2014 and 2023, within the last decade, are included. A thorough search of prominent and reputable electronic databases, such as Springer, Wiley, Elsevier, IEEE, and PubMed, is conducted utilizing specific keywords outlined in Fig. 4. The final collection consists only of journals, articles, conferences and book chapters that directly relate to the topics. We excluded certain articles from our final collection for several reasons: many articles were eliminated as redundant because the same articles appeared in multiple databases and publications. In addition, some papers were found irrelevant since they dealt with pure medical science, rather than computer science so those articles were also rejected for inclusion in the final collection. Some were published in languages other than English, others only had abstracts available, and some concentrated on medical disorders rather than BC. Hence, such research papers were rejected.

The number of research papers published each year on BC detection, classification, and segmentation using DL is also mentioned in this review paper. Between the years of 2014 and 2018, there was not a significant shift in the total number of articles on BC classification using DL but a significant increase can be observed from 2019 onwards. Figure 5 presents the count of research papers retrieved based on their year of publication.

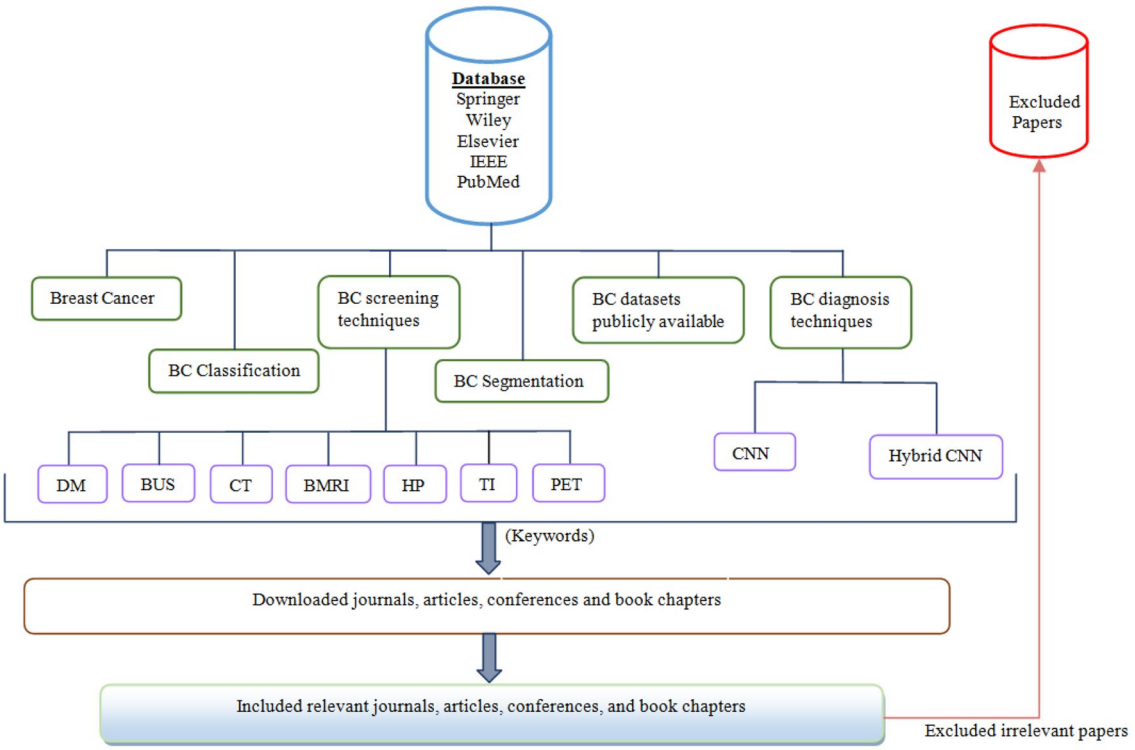

Fig. 4 Describing the search terms used for inclusion and exclusion of research papers included in this BC review

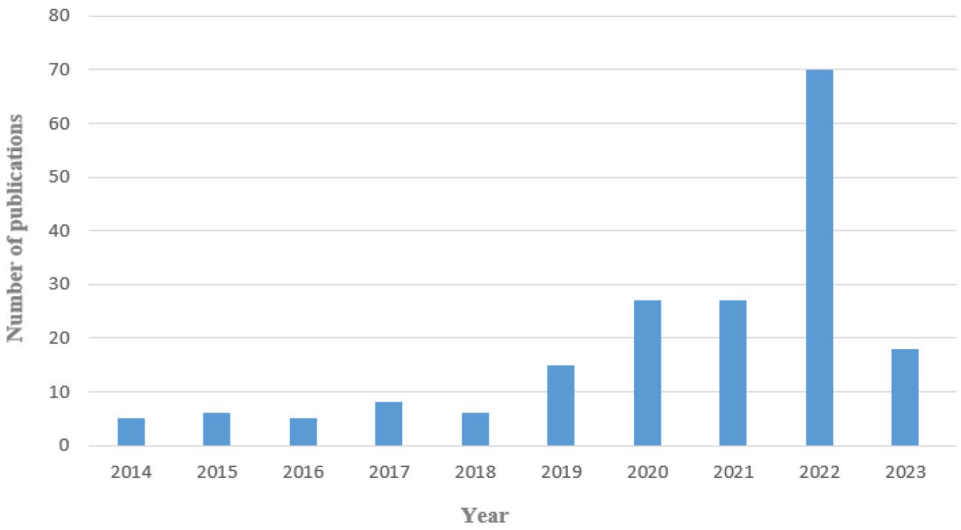

Fig. 5 Number of papers published in a decade on BC using DL

3 BC Research Evolution

BC research has evolved significantly over the years. Here is a brief overview of the key developments in BC research:

3.1 History of BC Using CNN

In the past, early detection of BC relied heavily on manual examination and mammography imaging. A manual examination involved physicians and patients physically feeling for lumps or changes in the breast tissue. Mammography, which was introduced in the 1970s [42], uses X-rays to produce images of the breast tissue and has been the primary method for early detection of BC for several decades. In recent years, there have been significant advancements in the early detection of BC, particularly with the use of DM, which produces clearer and more detailed images. In addition, other imaging techniques, such as BMRI and BUS, have been developed and are used in conjunction with mammography to improve the accuracy of early detection.

ML and DL algorithms have also been developed to aid in the early detection of BC. Wu et al. [43] have contributed to the classification of microcalcifications for the diagnosis of BC through introducing the first CNN model. Afterwards, many papers presented various CNN models for accurate BC classification, such as AlexNet, GoogleNet, VGG-16 [44], ResNet 50 [45], Xception [46], EfficientNet [47] etc. Figure 6 illustrates the timeline of CNN models employed for BC classification. These models analyze large amounts of data and identify patterns that may indicate the presence of BC. This has led to increased efficiency and accuracy in early detection, facilitating early diagnosis and improving patient outcomes. Overall, BC research and detection have undergone a significant evolution, from manual approaches to machine learning techniques and finally to DL algorithms, which have significantly improved the accuracy and efficiency of BC detection.

3.2 Evolution of Segmentation Methods

BC segmentation methods have evolved significantly over time, with advances in imaging technologies and DL models. Here are some key developments in BC segmentation methods: In late 1987, the first BC, segmentation was performed using gray level thresholding [48], which involved manually outlining the tumor regions on mammography images. This approach is time-consuming and prone to inter-observer

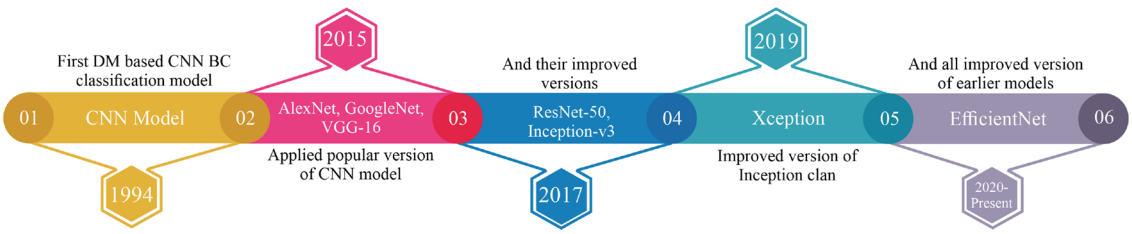

Fig. 6 Timeline of CNN models used for BC detection

variability. Therefore, in the late 1993s semi-automated segmentation methods were developed that combined manual segmentation with CAD tools [49, 50]. These tools helped radiologists segment tumor regions more accurately and efficiently. Furthermore, in the early 2000s, clustering and threshold-based segmentation [51, 52] methods were introduced, which used intensity thresholding to identify tumor regions. These methods were more objective than manual segmentation, but suffered from sensitivity to noise and variations in image quality. Besides, region-growing segmentation [53] methods were introduced, which relied on identifying seed points in tumor regions and growing them into contiguous regions using predefined criteria. These methods were more robust than threshold-based methods, but required careful parameter tuning.

In recent years, segmentation techniques based on ML and DL have gained immense popularity. DL methods, particularly CNNs, have been used to automatically segment tumor areas. Among the various DL-based segmentation models, U-net, Mask R-CNN, and Pyramid Scene Parsing Network (PSP Net) are frequently utilized in breast tissue segmentation. Figure 7 illustrates the timeline of segmentation techniques used for BC detection.

These methods have shown superior performance compared to earlier methods, especially for complex or heterogeneous tumors. Therefore, BC segmentation methods have evolved from manual to semi-automated to fully automated approaches, with increasing reliance on DL based techniques. These evolutions have contributed to more accurate and efficient BC diagnosis and treatment planning, ultimately improving patient outcomes.

4 Breast Cancer Screening Techniques

In order to detect and classify BC in its early stages, several imaging modalities are being used. BC diagnosis and detection rely primarily on the analysis of medical images. The application of these modalities entirely depends on the patient's condition and circumstances. This section describes the imaging techniques used for the identification and categorization of BC.

4.1 Digital Mammogram (DM)

Clinically, DMs are the most common and primary method of imaging for BC diagnosis. The American Cancer Society (ACS) considers mammograms a standard for the early identification of BC [54]. This screening is conducted on asymptomatic women to locate early and clinically undetected BC. In this technique, X-ray imaging is used to produce images of both breasts. For each breast, dual views of a mammogram, the cranio-caudal (top-down view) and the mediolateral oblique (side view at a specific aspect) are obtained by compressing the breast at a nearly vertical plane. After comparing both views of the same breast, it is helpful to comprehend the 3D pattern of masses. However, contrast views of bilateral images help to identify mass lesions, since bilateral breast views are generally identical. Using this modality, several methodologies have been proposed, such as CADNet157 [41], BCDTVC [55], BI-RADS [56], TSDLF [57], 2-PD [58], CNNI-BCC [59], AGAN [60], cGAN [61], and many more. The sensitivity of this imaging method for detecting BCs during screening is 84% [62]. The remaining 16% that are not recognised, due to the fact that radiologists are limited to visual acuity [62]. Moreover, DM is limited in a few instances, such as it may miss numerous malignant cases especially, women with dense breasts are more susceptible to false-negative outcomes. As reported

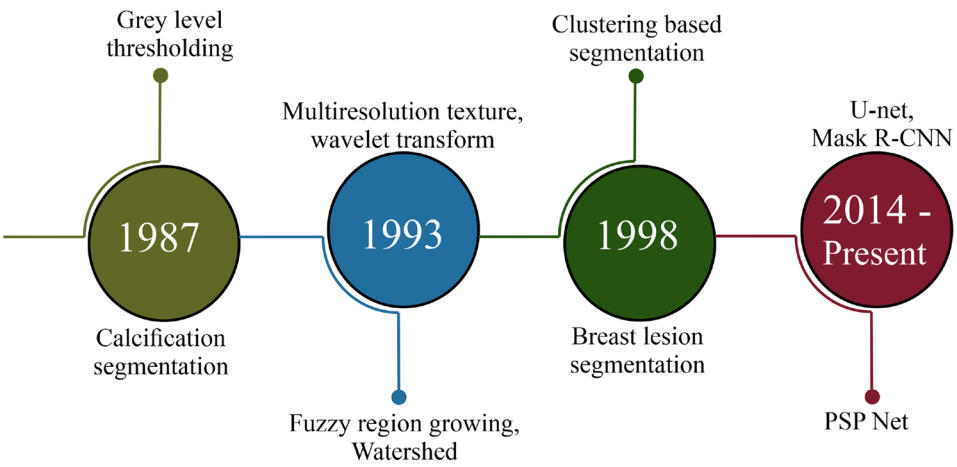

Fig. 7 Timeline of segmentation techniques used for BC detection

by the ACS, this procedure overlooks about 1 in 8 breast cancers [63, 64]. Thus, integrating BUS with mammography substantially enhances the accuracy of BC detection.

4.2 Breast Ultrasound(BUS)

As a screening tool, BUS is the second most common way to get a medical diagnosis, after mammography. It is being applied as a supportive screening technique to mammography. When both modalities are used together, the results are more sensitive and specific. This technique is potentially effective, noninvasive, safe, economical, and widely accessible for detecting BC. Moreover it is more sensitive than mammography for detecting abnormalities in dense breasts, hence, it is valuable for women younger than 35 years of age. Using BUS imaging, detection accuracy of simple cysts can reach 96–100% [65]. The process of ultrasonography involves the transmission of high-frequency sound waves through the breast and transforming the signals that return into images that can be seen on a screen. A transducer is employed to determine the edges of the tissue and interpret the reflected signals. Furthermore, the inside organs' shape and motions can be visualized in real time. It has a number of benefits over other methods for diagnosing BC, still rarely used as a primary modality to detect BC due to its operator reliant and low resolution quality. Since a portable transducer is used to do the scan, the quality of an image appears primarily depends on the knowledge and expertise of the clinician performing the scan. Therefore, BC diagnosis is concerned about the aberrant size or shape of lesions; such procedure is significantly influenced by the clinician's placement of the transducer, like the pressure exerted to the breast. BUS is used in the methods SDAEs and GANs [66], ResNet-GAP [67], NURBS [68], IRDx[69], SUAS [70], DLR [71], HMB-DLGAHA [72], ABUS [73] and many more. However, BUS has significant benefits, but it is not yet capable of replacing mammography. In addition, researchers are working on calibrating transducers with micro scale pressure sensors, to obtain consistent images through this method in the future [74]. BUS normal, benign, and malignant tissue samples are shown in Fig. 8.

4.3 Breast Magnetic Resonance Imaging (BMRI)

BMRI is a technique that employs a powerful magnetic strength of 1.5T and radio waves to generate detailed images of the breasts [75]. In 1986, BMRI first reported complementary imaging with mammography and BUS [76]. MRI has been incorporated as a preliminary screening of the affected breast in women with recently diagnosed BC, since it discovers new cancer cells that conventional imaging may have missed. Additionally, it is particularly used for screening the abnormalities in women at high risk for having BC,

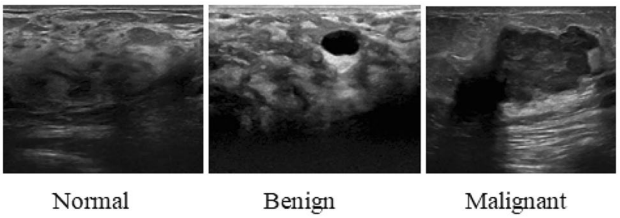

Fig. 8 BUS image samples

evaluating the staging period, genetic mutation, assisting surgical planning and following up after neoadjuvant chemotherapy (NAC) [77]. The statistical study revealed that the MRI is liable for 16% of all new diagnosis [78]. Moreover, it supports multi-planar scanning and 3D reconstruction techniques to accurately depict the magnitude, structure, and position of breast lesions [79, 80]. Several approaches have been proposed using this modality for instance ESBC [81], Ab-MRI [82], mpMRI [83], EUSOBI [84], DCE-MRI[85], T1-W MRI [86], DWI [87] and so on. However, the process has several significant advantages but it may also have some drawbacks, for instance it is time-consuming, expensive and Positive Predictive Value (PPV) is diminished by the high rate of false-positive reports, which may lead to needless breast biopsies. Furthermore, microcalcifications are beyond the scope of its detection abilities. Due to the use of a powerful magnet and a contrast substance, pregnant women are not advised to undergo this examination [88, 89].

4.4 Computed Tomography (CT) Scan

In 1972, Godfrey Huundsfield invented the CT scan that uses X-ray technology to capture images of the body parts that are being examined [90]. CT provides excellent 3-D visualization of the anatomy including the location and magnitude of soft tissue lesions [91]. It is not employed as an early BC detection modality but it does help in staging BC that has already been diagnosed, to assist doctors in course of treatment. The precise assessment of BC staging is crucial because it may affect the decision to proceed with axillary dissection or not [92, 93]. Patients with symptoms that could be caused by metastasis to the lung or liver, cancer cells in the lymph nodes under the axilla, or tumor that is larger than 5 cm are tend to undergo this procedure. Typically, CT has low contrast, thus contrast dye such as iodine based compounds, barium-sulfate, gadolinium, and air mixture are used to inject intravenously to enhance the visibility for differentiating malignant from benign lesions [94–96]. In CT scans patients may be prone to radiation exposure if they get multiple scans for screening purposes because CT has a higher radiation level than DMs, hence, this should be recommended for those who are contradicted for MRI. In

addition, it has a lower detection threshold for microcalcification compared to DM. However, the development of spiral CT [97–99] has shown significant results for addressing challenges in breast lesion diagnosis and providing better information about the spread of BC. In the preoperative evaluation of BC, it has the possibility of being used as an alternative to 3D MRI. Several strategies have been proposed utilizing this technique including [100, 101] and so on.

4.5 Positron Emission Tomography (PET) Scan

PET scan is a radionuclide-based imaging technique that uses a radioactive substance (tracer) in order to diagnose and monitor the progression of BC [102, 103]. This tracer can assist in identifying cancerous tissue that might not be visible on a CT or MRI scan. It produces precise images that can be used to analyze the structure and physiologic information of tissues. In order to do a PET scan a little amount of radiotracer substance is injected into a patient's vein, typically on the inside of the elbow or in a small vein in the hand [104, 105]. Fluorodeoxyglucose (FDG), a form of sugar, is frequently used as a substance for this procedure, because it is significant for anticipating neoadjuvant treatment [106, 107]. The drug is inserted intravenously to a patient, circulates throughout the blood and accumulates in organs and tissues, where it emits a signal that aids the radiologist to better visualize the affected area or condition. The FDG PET has the potential to identify malignant lesions in general, but BC detection requires the ability to demonstrate non-palpable, small (1.0 cm) invasive and in situ malignancies [108, 109]. Besides, the current state of whole-body FDG PET cannot meet these criteria, therefore, FDG PET is not applied for early BC diagnosis. The primary use of PET is in the assessment of metastatic progression. In addition, PET is not typically employed independently in the detection of BC, therefore, fusing PET and CT together leading to more reliable results, thus increasing accuracy [110, 111]. using this modality several methods have been proposed such as [112, 113].

4.6 Histopathological (HP) Images

The term histopathology is used to describe the process of removing a specimen of tissue from a suspicious area of a human body for further testing and evaluation by medical experts [114]. In medical terms, this procedure is referred to as a biopsy. It provides a comprehensive view of diseases and is the benchmark for identifying all types of cancer. In order to generate HP images, biopsy samples are placed on glass slides, labeled with Hematoxylin and Eosin (H & E) before being examined under microscope [115]. The objective of H & E is to generate coloured HP images for clear vision and depth examination of the tissues [116, 117]. Moreover, the ability to recognise color transitions in stained images is crucial for making a correct diagnosis of BC. Hence, it provides a high level of authenticity in BC classification; particularly in subtype classification. However, it suffers from some drawbacks as well, for instance, biopsies are invasive procedures that require considerable time to translate into digital images. Due to their inconsistent staining, color variation, and overlap, HP images are difficult to analyze. Moreover, the ability to correctly identify BC relies on proper understanding of color variations in stained images. Hence, specialists are required for their precise analysis. Different approaches have been proposed using HP images [118–122].

4.7 Thermal Imaging (TI)

Breast thermography is a cost effective, painless, and radiation-free technique used to detect and classify BC [123, 124]. The clinical interpretation of TI depends primarily on color i.e., lower thermal levels are represented by the blue color (healthy), whereas red, orange, or yellow (depending on the operator settings) patches signify a deformity [125]. In thermography, infrared cameras are used to capture temperature maps of the breast. The fundamental idea behind thermography is that cells that proliferate uncontrollably have a higher metabolic rate and need more blood flow than the tissue around them. Thus, the location of a tumor can be identified by the temperature variations in breast surface. Thermography alone possesses 83% sensitivity. and 95% of sensitivity while fused with mammograms [126]. In addition, it is recommended for women at the age of 23 [127]. However, this modality is limited in its ability to detect merely surface temperature changes; hence deep information cannot be obtained. Figure 9 provides a comprehensive overview of the seven BC screening methods, highlighting their strengths and limitations for a better understanding of each method's effectiveness.

5 Observations on Different Imaging Modalities

Based on breast composition: Currently, a wide range of digital image processing modalities are available for the detection of BC. A female breast structure is divided into 4 distinct categories based on its composition [128]: (i) almost exclusively fatty (ii) discrete areas of fibroglandular tissue; (iii) heterogeneously dense (iv) extremely dense. A mammogram is a golden and early stage detection tool for BC diagnosis, yet not an ideal solution due to repeated radiation exposure is required [129, 130]. Besides, false-positive BC detection rates are significantly higher in women

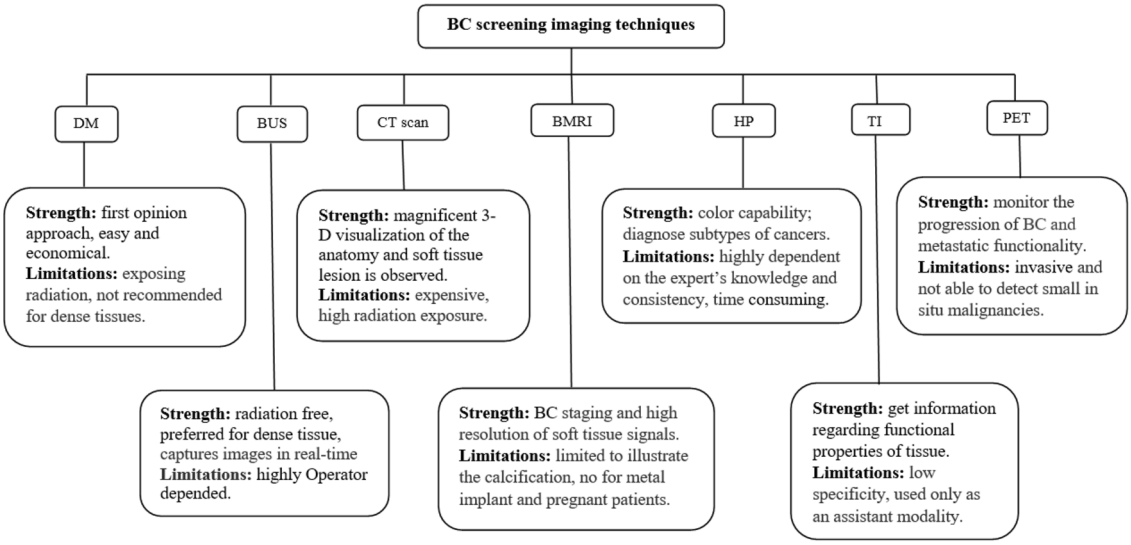

Fig. 9 Types of BC screening approaches with their strength and limitations

with dense tissue [83]. Thus, the USGs are recommended clinically [131], it can identify tumors through transmitting sound waves at the tissue surface that can lead to the better detection of BC with dense breasts, thus increasing accuracy. However, the effectiveness of this technique is highly reliant on the experience and expertise of the treating physician. These two imaging modalities are initial and adequate to detect BC at an early phase [132].

Based on cost/affordability: In BC diagnostic procedure, multiple imaging modalities are employed and the cost of each modality can be influenced by a variety of factors such as quality, the hardware it uses, clarity, resolution, availability, demand by patients and physicians [133, 134]. The cost of detecting BC has increased over the past decade as new technology has been incorporated into imaging modalities to improve detection rates. Radiotherapy is a minimally intrusive and effective method of BC treatment. Moreover, the costs associated with radiation therapy can be expensive, particularly when modern equipment is required including intensity modulated radiation therapy (IMRT) and proton therapy [135, 136]. In addition to the psychological and physical difficulties, this expense can be a substantial financial hardship for a BC diagnosis. Besides, using hybrid imaging modalities for screening BC contribute to more accurate detection. Therefore, the cost of a hybrid device will be high; nevertheless, it is possible to design a system that can detect the key patterns from hybrid modalities, in order to extract significant information. Comparatively, MRI, HP, TI, and PET scans are more expensive than DM and USG, whereas CT has moderate cost [137]. Thus, cost-effective analysis is necessary in order to maintain the cost and make it accessible to all individuals [138]. Hence, CAD systems are required to make BC diagnosis faster, affordable and easier to overcome the challenges of traditional detection systems and processes [139].

Based on stages of BC: Staging is a term in which medical experts determine whether or not the disease has spread, and if so, how far it has spread from the original tumor. Moreover, in newly diagnosed BC, it is crucial to precisely determine the level of localized and metastatic malignancy to improve treatment strategies and outcomes. It is observed that MRI, CT and PET are recognised to be among the advanced imaging modalities used in the staging of BC [140, 141]. Among all, MRI is often regarded as the gold standard because it has an excellent capability for soft tissue imaging, preoperative planning, and interpreting lesioned regions, thus used for initial staging of BC. However, it requires time and a skilled radiologist [85]. Moreover, based on the guidelines provided by the National Comprehensive Cancer Network (NCCN) and the European Society for Medical Oncology (ESMO), PET/CT is approved for the staging of metastatic BC. A comprehensive analysis of the existing literature has shown that, in case of bone metastases detection, PET/MRI are significantly better than CT in the patients with newly diagnosed BC [142, 143].

Based on facilities/expertise available: In order to achieve the best possible results from BC treatment, an early diagnosis and a well-coordinated, interdisciplinary strategy are essential. However, efficient healthcare management approaches can be challenging to implement in rural areas due to resource constraints, poorly skilled staff, and inadequate infrastructure [144]. The majority of patients who seek medical care are already in advanced stages of their disease which leads to the negative outcomes. Moreover, in countries with low to middle (LTM) income, mammography screening is the only method that has been shown to

minimize BC deaths. Yet, the research on mammography's effectiveness in developing nations is limited despite LTM income countries having lower BC incidence rates, younger populations, and less reliable access to good-quality care [145]. The incidence of advanced BC rates are common in rural areas due to a lack of access to BC facilities; however, the overall mortality rate is lower in urban areas because of the higher percentage of BC facilities serving the population there [146, 147]. To promote the resource-sensitive guidelines for BC screening, early diagnosis, and treatment in LTM income area, the Breast Health Global Initiative (BHGI) was organized in 2002. As recommended by the BHGI, health care facilities for the treatment of BC should be built on a regional basis, demographics and the resources available. The literature analysis highlights that there is a gap in women's awareness and perspective towards BC and their screening alternatives [148]. Therefore, emphasizing the significance of annual Clinical Mammography (CM), enlightening on the signs and symptoms of BC, organizing BC awareness programs, modifying health care systems might be cost-effective and feasible BC control measures for treatable cancers, thus, improve BC survival rates.

Modalities either for diagnosis or treatment: There are two imaging techniques used to diagnose BC: radiography and histology. The field of radiology is concerned with the capturing of images of internal structures of the body in order to diagnose or treat patients through evaluating the presence or absence of disease, injury and abnormalities. In addition to radiography imaging techniques for BC include: DM, BUS, MRI, CT and PET scan. However, histopathology entails analyzing cancer cells and tissues at ultrahigh magnification under a microscope. Moreover, a breast biopsy, in which a small piece of breast tissue is taken out for analysis, serves as a confirmatory test for a BC diagnosis, is a histopathological imaging. Though there are several types of biopsies available depending on the patient's state at the time of the procedure. Each of the imaging modalities mentioned above is employed as a part of the BC diagnosis tool. Once a tumor and its nature have been accurately detected using imaging techniques, the next step is to select the most appropriate treatment option. BC effective treatments include surgery, radiation therapy and chemotherapy. In addition, depending on the nature and size of the tumor, surgical removal is the primary course of treatment, followed by a biopsy to determine the lesion's grade and malignancy potential. Radiotherapy is preferable post surgery, if the tumor has high malignancy potential because it allows for regional control of tumors, including the lymph nodes of the chest wall and armpits, whereas surgery is limited to the breast. The literature study shows that, MRI is the most effective imaging technique for detecting cancer recurrence following tumor excision, since it can detect the presence of new cancer cells in its original locations [149, 150]. Therefore, treatments for BC are painful and expensive, thus, early detection is required to avoid all invasive operations, which is feasible through employing a reliable CAD system.

6 Dataset Availability

This section provides an overview of both public and private datasets used in various studies on the classification of BC. The majority of BC datasets are not openly accessible. The Digital Database for Screening Mammography (DDSM) [151], INBreast [152], Mammographic Image Analysis Society (MIAS)/mini-MIAS [153], and Image Retrieval in Medical Applications (IRMA) [154] are commonly used and easily accessible DM datasets. The Breast Ultrasound Images (BUSI) is an extensively utilized ultrasound imaging dataset and has been cited in numerous BC classification papers. The BreaKHis dataset comprises several breast biopsy samples, with a total of 7909 HP images. The samples are sourced from the "Pathological Anatomy and Cytopathology" Lab located in Brazil, and are obtained from 82 anonymous patients. It is the most exhaustive collection of such samples currently available. For BMRI and TI, the Duke-Breast-Cancer-MRI and DMI-IR datasets are publicly available. PET/CT scans are not included as they are more effective in detecting distant metastasis, making them less suitable for early diagnosis of BC compared to the other imaging modalities mentioned. Table 1 provides an overview of available datasets used in BC classification research, including public and restricted datasets. In addition, a major obstacle encountered by almost all BC researchers is the scarcity of a standardized dataset. Due to the limited availability of benchmark imaging datasets for BC, many researchers have gathered their own datasets, as reported in various articles [155–163]. In these articles, private datasets are addressed while keeping to the constraint of being unable to disclose their data due to confidentiality restrictions.

Moreover, a significant observation that emerged from this analysis is that researchers experienced a higher probability to achieve better outcomes when employing datasets that are publicly accessible, whereas their own datasets that are not public generate less favorable results. This can be attributed to the fact that public datasets are carefully processed, refined, and close to balanced, thereby yielding more favorable results. To ensure the authenticity authors validate their results with other similar approaches. However, the accuracy of the private datasets cannot be confirmed until tested by other researchers utilizing diverse classification techniques.

Table 1 List of datasets used in this review and their corresponding URL

Paper ref	Imaging modality	Availability	Dataset	URL
[154]	DM	Public	IRMA	https://www.researchgate.net/publication/228351601_Toward_a_standard_reference_database_for_computer-aided_mammography
[153]	DM	Public	MIAS	https://www.mammoimage.org/databases/
[164]	DM	Public	DDSM	http://www.eng.usf.edu/cvprg/mammography/database.html
[152]	DM	Public	INbreast	https://pubmed.ncbi.nlm.nih.gov/22078258/
[165]	DM	Restricted	Hologic digital mammography systems	https://link.springer.com/chapter/10.1007/978-3-319-41546-8_5
[166]	DM	Restricted	Department of Radiology at the University of Chicago	https://www.sciencedirect.com/science/article/pii/S0031320318300086
[167]	BUS	Public	BUSI	https://www.sciencedirect.com/science/article/pii/S2352340919312181
[168]	BMRI	Public	RIDER Breast MRI	https://wiki.cancerimagingarchive.net/display/Public/RIDER+Breast+MRI
[169]	BMRI	Public	DBC-MRI	https://wiki.cancerimagingarchive.net/pages/viewpage.action?pageId=70226903
[170]	HP	Public	BICBH	https://rdm.inesctec.pt/dataset/nis-2017-003
[171]	HP	Public	BreakHis	https://web.inf.ufpr.br/vri/databases/breast-cancer-histopathological-database-breakhis/
[172]	TI	Public	DMI-IR	https://sci-hub.hkvisa.net/10.1166/jmihi.2014.1226
[173]	BUS	Public	OASBUD	https://pubmed.ncbi.nlm.nih.gov/28859252/
[174]	BUS	Public	UDIAT	https://sci-hub.hkvisa.net/10.1109/JBHI.2017.2731873
[175]	BMRI	Public	DCE-MRI	https://ieeexplore.ieee.org/stamp/stamp.jsp?tp= &arnumber=8713352

7 Breast Cancer Detection Using CNN

DL has become the standard method for diagnosing BC, because it can automatically acquire basic features. Some recent models on diagnosis of BC through CNN technique are highlighted in this section. This section provides an overview of currently existing CNN-based CAD models for BC detection, classification and segmentation.

Ding et al. [66] have used a ResNEtGAP network to classify and localize the tumor simultaneously. The network uses B-mode ultrasound (BUS) images and elastography ultrasound (EUS) images across different channels for training. 264 patients were used for the study. The network achieved an accuracy of 88.6%, and a sensitivity of 95.3% in the classification task. The major limitation of the work is the lack of EUS images for testing.

Aljuaid et al. [176] have presented a novel CAD method that uses fine tuned ResNet 18, ShuffleNet, and Inception-V3Net for feature extraction from histopathological publicly available dataset. Furthermore, transfer learning is employed to enhance the classification procedure and decrease the duration required to complete the complex task. In addition, data augmentation and preprocessing are applied to enhance the results and preserve the originality of the input image. Therefore, it is observed that among the three DCNN classifiers, ResNet is the most precise and effective classifier, yielding the highest average accuracy ranging from 97.81 to 99.70% for both binary and multiclass classification.

To reduce the problems of dataset constraints, misclassification and wrong predictions, Jabeen et al. [131] have proposed a completely automated system utilizing a modified version of the pre-trained deep model named DarkNet53. The model has trained on augmented BUS images through transfer learning. Therefore, the optimal features are identified through the use of Reformed Differential Evolution (RDE) and Reformed Gray Wolf (RGW) optimization algorithms. In addition, a probabilistic method is utilized to integrate the selected features before applying machine learning algorithms to classify the data. The proposed framework has attained an accuracy of 99.1%, which is outperforms compared to recent DL techniques.

Maqsood et al. [177] have introduced a transferable texture convolutional neural network (TTCNN) to accurately detect and classify BC in less computation time using DM images. Histogram Equalization is utilized to enhance the sharpness of the contours in DM images.Then, the preprocessed images are given to TTCNN for classification. Moreover, an energy layer is being used, which allows to maintain texture information, restrict the output vector size, and boost the model's capability of learning. Additionally, the entropy

controlled firefly technique and feature fusion are applied in order to enhance the effectiveness of the feature selection. Across three different DM datasets (DDSM, INbreast, and MIAS), this method is able to achieve an average accuracy of 97.49 %.

In Joseph et al. [178], have presented an approach where handcrafted feature extraction techniques and DNN are employed for BC multi-classification using HP images. In addition, data augmentation, denoising, and segmentation are performed in the preprocessing step to optimize classification performance and counteract the issue of overfitting. Moreover, it is observed that augmenting the data significantly contributes to enhancing the classification accuracy. According to the results, using handcrafted techniques as feature extractors and DNN classifiers yielded the best results in multi-class classification of BC compared to other methods reported in the literature. The model has achieved an accuracy of 97.87%, 97.60%, 96.10% and 96.84% respectively.

BC has been diagnosed using two different approaches by Taheri et al. [179] one for single-magnification HP images and the other with multiple magnifications. The first system makes use of a pre-trained DenseNet201 CNN architecture, while the second is split into four distinct modules. Then, the information from those four modules is combined to produce a final decision. An experiment is carried out to assess the merits and drawbacks of various approaches using both Magnification-specific binary classification (MSB) and Magnification-independent binary classification (MIB). The findings indicated that the DenseNet201 architecture outperformed the other methods in the MSB scenario. The outcomes are evaluated in comparison with current techniques, and in every instance, the proposed systems exhibited better performance.

Luo et al. [180] have proposed a framework named Segmentation-Based Attention Network (SBANet), which is a segmentation-to-classification model designed to operate on BUS images. Initially, a segmentation network is trained to produce images that enhance the segmentation of tumors. In order to classify images, features are retrieved from both the segmentation-improved and the reference image. The outcomes of the experiments show that the segmentation-to-classification architecture has the ability to enhance diagnostic accuracy by 90.78%.

Another crucial technique for enhancing the performance of a single classifier is the application of an ensemble classifier. Podda et al. [181] have presented a multi-layer and fully automated pipeline for identifying and categorizing breast lesions that are linked to an increased risk of cancer, using BUS images. Ensemble-based classifiers utilize various techniques to combine the predictions of a single classifier, resulting in improved overall predictions that are more accurate than those made by a single classifier. In the segmentation task, the proposed method obtained a dice coefficient of ~82%, while in the classification task, it achieved an accuracy of ~ 91%.

Ting et al. [59] have developed a novel algorithm called Convolutional Neural Network Improvement for BC Classification (CNNI-BCC) through DM images. An approach used CNN for the classification of DM using patch features into normal, benign and malignant. The patch-based method enables the handling of non-rectangular areas in the image, through removing patches from the collection, which can be masked to exclude particular regions during processing. The sensitivity, accuracy, AUC and specificity of the suggested model are 89.47%, 90.50%, 0.901 $\pm$ 0.0314 and 90.71% respectively. respectively.

Hossain et al. [182] have proposed an automated method that segments micro-calcification regions from mammogram images. The proposed method applies preprocessing techniques to enhance the image quality and segment the breast region from the pectoral region. Fuzzy C-means clustering algorithm is utilized to detect suspicious regions. The positive patches containing micro-calcification pixels are used to train a modified U-net segmentation network. Finally, the trained network is employed to segment the micro-calcification region automatically from the mammogram images. The proposed method achieved an average accuracy of 98.2%, with an F-measure of 98.5%, a Dice score of 97.8%, and a Jaccard index of 97.4%, which outperforms state-of-the-art methods.

Huang et al. [183] have presented a novel CAD system for accurately and timely classifying BC as benign and malignant through BUS images. This study employed a combination of bicluster-based ensemble learning and the AdaBoost algorithm to identify consistent patterns within columns of training data. In addition, the patterns that frequently occurred in tumors with the same label were considered as potential diagnostic rules. Since BUS imaging relies entirely on the operator, thus, a new approach has been introduced to score features based on the operator's assessment rather than relying on traditional CAD systems that involve image denoising, segmentation, and feature extraction processes. The results of the experiment indicate that the suggested technique has excellent predictive capability and has promising clinical applications. The model has attained an accuracy, Sensitivity and Specificity are 95.75%, 96.26% and 95.12% respectively.

Hepsağ et al. [184] have discussed the need for a more reliable technique to diagnose BC and the use of CAD methods to reduce the number of unnecessary biopsies. The authors applied DL using CNN to classify abnormalities as benign or malignant in mammogram images, using two different databases: mini-MIAS and BCDR. The initial results showed accuracy, precision, recall, and f-score values between around 60% and 72%. The authors then used

preprocessing methods, including cropping, augmentation, and balancing image data, to improve the results. They created a mask to find the region of interest in the BCDR dataset, and after applying the preprocessing methods, the classification accuracy improved from 65% to around 85%. Finally, the authors compared the classification performance between the two datasets and found that MIAS images are producing better results than BCDR datasets.

Sahu et al. [132] have presented a novel approach that uses five hybrid CNN models to diagnose BC through BUS and DM images. The suggested hybrid model retains the advantages of both networks and demonstrates superior performance compared to the individual base classifiers. Moreover, the efficient and precise operation of the system depends significantly on the use of thresholding and probability-based elements. The proposed system is tested using datasets from two distinct BC modalities: BUS and DM. The proposed model produces superior outcomes compared to the current leading methods by incorporating the ShuffleNet and ResNet techniques. In addition, this approach achieves 99.17% and 98.00% accuracy in detecting abnormalities and malignancies, respectively, in the DM dataset, and 96.52% and 93.18% accuracy in detecting abnormalities and malignancies, respectively, in the BUS dataset using fivefold cross-validation.

In order to improve classification accuracy with DM datasets, Altameem et al. [185] have proposed a fuzzy ensemble method that employs multiple deep CNN models as basis classifiers. In this model, the decision scores of the underlying classification methods are adaptively integrated to produce final predictions, and the Gompertz function is employed to generate fuzzy rankings of these methods. Additionally, pre-trained DCNN models are used to extract features and classify mammography images using dense and softmax layers. Initially, a number of pre-trained DCNN models, such as VGG-11, ResNet164, DenseNet121, and Inception V4, are used to diagnose cancer in mammography images. Nonetheless, the ensemble model of Inception V4 with a Gompertz function based on fuzzy ranking achieved a 99.32% level of accuracy.

Hu et al. [186] have proposed a method that uses deep transfer learning and four dimensional information to enhance the contrast of MRI images. In this procedure, it is observed that to distinguish between benign and malignant breast lesions accurately, the maximum intensity projection (MIP) of features is used through CNN, whereas in the classification process Support Vector Machine (SVM) is implemented. MIP based architecture is evaluated and compared with state of arts based on Area Under Curve (AUC) and DeLong test, it achieved high performance of 91% and 93% respectively, for the independent test set.

Mohammed et al. [187] have used several types of DL models that are evaluated on HP dataset, in order to reduce the risk of misdiagnosis. Among all, Densenet169, Resnet50, and Resnet101 are performing best. In this work data are treated in two different manner, firstly, examined accuracy without preprocessing procedure and found the accuracies of 62%, 68%, and 85% respectively. Moreover, after incorporating preprocessing steps such as data augmentation and segmentation, achieving 20%, 17% and 6% increments in accuracies. Further, ensemble learning techniques also enhanced the accuracy of the model and it has attained a highest accuracy of 92.5%.

Shen et al. [188] developed an end-to-end DL algorithm that can accurately detect BC on screening mammograms, while eliminating the reliance on rarely available lesion annotations. In addition, DL models can accurately classify screening mammograms with only clinical ROI annotations used in the initial stage, and can be fine-tuned using additional datasets without ROI annotations. The study found that the quality of the patch classifiers is critical to the accuracy of the whole image classifiers, and that using larger or more patches can improve accuracy but also increase computational burden. The study also found that VGG-based and Resnet-based classifiers can complement each other, and that retaining full resolution of digital mammography images can improve performance.

Pérez-Benito et al. [189]have discussed the development of a fully automated framework based on DL to estimate breast density from mammograms. The framework includes breast detection, pectoral muscle exclusion, and fibroglandular tissue segmentation. The study addresses important challenges in breast density measurement, such as differences in images from different devices and the lack of an objective gold standard. Specifically, the study reports that the automated framework achieved a DICE score of 0.77, which is the same as the DICE score achieved by the two radiologists when their segmentations were compared.

Wang et al. [72] have demonstrated the effectiveness of novel DL models with the addition of Automatic Segmentation Network (ASN) for morphological analysis and determined the performance for diagnosis BC in BUS images. Furthermore, the comparison of various DL models is performed and the comparison is based on True positive rate (TPR), True negative rate (TNR), specificity, sensitivity accuracy, false negative rate (FNR), Average Precision (AP), Area Under Curve (AUC) and false positive rate (FPR). It is observed that the ResNet34 v2 model has higher specificity (76.81%) and TPR (82.22%), the ResNet50 v2 has higher accuracy (78.11%) and FPR (72.86%), and the ResNet101 v2 model has higher sensitivity (85.00%). Moreover, based on the AUCs and APs, the proposed ResNet101 v2 model produced the best result 85% and 90% respectively, compared with the remaining five D L models.

Nagalakshmi [190] has employed DCNN with K-means clustering and a multiclass SVM model to establish a CAD

system that boosts the quality of DM images for BC. To differentiate and improve the lesion from the background, the model is trained using the ensemble-net model, which combines the transfer learning model with multiple CNN structures. Furthermore, an entity's pixel range is masked out in the segmentation step by generating multiple regions of interest (ROI) that encompass it from the input images. In addition, it utilizes global average pooling, followed by softmax classification, to categorize the type of BC. The proposed model outperforms the other classical classifiers with an accuracy of 96.72%.

Raaj et al. [191] have designed a CAD system for the classification of tumors of DM based on the descriptors of the texture in the early stage. In addition, the proposed system incorporates a radon transform, an enhanced data module, and a hybrid CNN structure. To boost the detection rate of the proposed approach, the spatial image of the source DM is transformed using the radon transform into a time-frequency format image. Meanwhile, a morphological segmentation technique is employed to separate the cancerous area in the mammogram, and a hybrid CNN architecture is performed to categorize the tumor as normal, benign, or malignant with an accuracy of 98.44%.

To improve the accuracy of detecting and classifying microcalcification in DMs with higher level of accuracy, Yurdusev et al. [192] have proposed the use of a difference filter as a novel and efficient preprocessing step to be employed in DL algorithms. Furthermore, the classification process is carried out using Yolov4 and R-CNN DL models, in order to detect the appropriate regions by differentiating between the noises and microcalcification-containing regions, thus increasing the ratio of accuracy. It is noted that the combination of difference filter and DL models is the first method to effectively classify microcalcification. Table 2. shows the brief summary of recent DL models using CNN for BC classification, detection and segmentation. Tables 2 and 3 employs the abbreviations B, M, and N to respectively denote benign, malignant, and normal images. Additionally, the abbreviation Acc is utilized to represent Accuracy of the DL models.

8 Breast Cancer Detection Using hybrid DL approach

Qi et al. [65] have developed a novel framework to detect BC in the early stage through a reliable CAD system using BUS images. Due to differences in the level of clinical skills among medical experts, BUS image analysis is highly inconsistent and insensitive. To address this problem and improve the quality of diagnoses, an automated BC diagnosis system is developed. The novelty of this work is deploying images on mobile phones and performing diagnosis on each image. The developed system consists of three subsystems: (i) to remove noise from BUS images stacked denoising autoencoders are used, (ii) CNN is being implemented to classify images into benign and malignant (iii) to reduce false negative rate, Generative Adversarial Networks (GAN) is implemented.

Aslan [193] has proposed a method in which, for each task training and classification two distinct kinds of end-to-end DL networks are developed. Both networks use CNNs, but the second network is a hybrid structure that combines a CNN with Bidirectional Long Short Term Memories (BiLSTMs), which extract features based on temporal correlations. Furthermore, the preprocessing is performed on each image, and then the preprocessed images are fed to the proposed networks. In terms of classifying accuracy, it is observed that the first one achieves a 97.50% accuracy in classification, while the second one achieves a 98.56%. However, the imaging approach requires high computational capacity to preprocess the images.

Demir [194] has proposed a novel and robust approach, based on the convolutional-LSTM (CLSTM) learning model using HP images. The combination of CNN and LSTM has boosted the performance of the model, since CNN is better at extracting useful information from references and LSTM is not only effective in processing sequential data but also in recognizing the relationship among similar samples. Furthermore, the softmax classifier is replaced with the SVM classifier with hyperparameter optimization because the softmax classifier performs poorly for the malignant class despite showing consistently high results across all the benign class. Hence, the optimized SVM exceeded the softmax classifier with a 100% accuracy across all magnification factors.

Patil1 et al. [195] have presented a framework that uses two different DL architectures termed as CNN and recurrent neural network (RNN) to process DM images. This framework comprises four stages, including Pre-processing, segmenting the tumor, extracting features, and classifying the data. Furthermore, in order to improve the accuracy of the segmentation, an optimized region-growing algorithm is implemented. Thus, the outcome indicates that the diagnostic accuracy is superior compared to baseline models.

Yao et al. [196] have proposed a method for extracting features from HP images using a CNN and RNN in a parallel structure, unlike the conventional serial approach, where image features are extracted by CNN and then fed into RNN. Moreover, to integrate the data generated by the two distinct neural networks are united through a natural language processing (NLP)-inspired perceptron attention method. Therefore, a novel, normalizing approach is introduced to improve classification accuracy.

Accurate segmentation of breast masses on medical images is a tremendous assistance in diagnosing and treating

Table 2 Some latest BC classification, detection and segmentation models using CNN are listed below

Paper	Authors, Publisher	No. of images	Technique used	Type of image sequence	Performance(%)	Challenges and limitations
[66]	Ding et al., IEEE Journal of Biomedical and Health Informatics (2022)	129 B and 135 M	ResNET-GAP	BUS	Acc 88.6	Random augmentation is used,therefore, the outcomes might be biased towards a particular class
[176]	Aljuaid et al., Computer Methods and Programs in Biomedicine (2022)	2480 B and 5429 M	DNN and transfer learning	HP	Acc 99.7,97.66, and 96.94	Model complexity is high and used the breakHis dataset, which includes four distinct types of images but only benign and malignant ones were put to use in this study
[131]	Jabeen et al., MDPI sensors (2022)	133 N, 210 M and 487 B	Transfer learning	BUS	Acc 99.1	Lack of explainability and interpretability of the model in terms of disease detection
[177]	Maqsood et al., MDPI applied sciences (2022)	373 N and 223 M	TTCNN	DM	Acc 97.49	Clip Limit for CLAHE has been arbitrarily decided, no metricused to assess the improvement or degradation of image quality post CLAHE
[178]	Joseph et al., Intelligent Systems with Applications (2022)	82 patients, 2480 B and 5429 M	Handcrafted and DCC	HP	Acc 97.87, 97.60, 96.10 and 96.84	No other datasets tested on the proposed approach, model is not generalizable
[179]	Taheri et al., Signal, Image and Video Processing(2022)	2480 B and 5429 M	MSB and MIB	HP	93.32±2.47	Not explored different CNN models and hyperparameter optimization is not considered
[180]	Luo et al., Pattern Recognition (2022)	Dataset A: 160 benign and 132 malignant Dataset B: 786 benign and 916 malignant	SBANet and channel attention	BUS	Acc 90.78, Sensitivity 91.18, Specificity 90.44, F1-score 91.46, and AUC 95.49	Classification method has two stages, increases complexity and training time and it lacks end-to-end functionality
[181]	Podda et al., Journal of Computational Science (2022)	437 B, 210 M and 133 N	Ensemble learning	BUS	Accuracy 91	Lack of attention given to the unclear tissue structures or noise that may be present in the image
[59]	Ting et al., Expert Systems with Applications (2019)	21 B, 17 M and 183 N	CNNI-BCC	DM	Sensitivity, Acc, AUC and Specificity 89.47, 90.50, 0.901 ± 0.0314 and 90.71	CNNI-BCC method has not been tested on different datasets
[182]	Li et al., Biomedical Signal Processing and Control (2019)	Total images 2620	FCM clustering-U-net segmentation	DM	Acc 98.2, F-measure 98.5 and 97.8 Dice score	Skilled radiologist is needed to carry out a qualitative analysis due to the substandard performance on the MIAS

Table 2 (continued)

Paper	Authors, Publisher	No. of images	Technique used	Type of image sequence	Performance(%)	Challenges and limitations
[183]	Huang et al., IEEE TRANSACTIONS ON KNOWLEDGE AND DATA ENGINEERING(2020)	418 B and 644 M	Ensemble learning, Biclustering mining and AdaBoost learning	BUS	Acc, Sensitivity and Specificity 95.75, 96.26 and 95.12	Proposed model uses an operator-based feature scoring scheme, but it does not explain how this approach improves the system's performance or why it is more easily acceptable to doctors
[184]	Hepsağ et al., 2nd International Conference on Computer Science and Engineering (2017)	MIAS: 240 M, 392 B and BCDR: 840 M, 864 B	CNN	DM	Acc on MIAS 87 and on BCDR 88	The effectiveness of calcification for BCDR has decreased
[132]	Sahu et al.,Biomedical Signal Processing and Control(2023)	BUS:B 487, M 210, N 133 DM: N 2728, M 3596, B 3360	Hybrid CNN	BUS and DM	Acc 99.17 and 98.00 with DDSM dataset. 96.52, 93.18 with BUSI dataset	The combined outcomes of parse learning and transfer learning are not reported
[185]	Altameem et al., MDPI Diagnostics (2022)	11145 N 1145 B 1145 M	Gompertz function and fuzzy ensemble method	DM	Acc 99.32	Lack of discussion regarding breast tissue localisation and segmentation
[186]	Hu et al., Radiology: Artificial Intelligence(2021)	1979 Total 1494 M 496 B	CNN	BMRI	AUC of 91 and 93	Reported sensitivity and specificity operating points are not based on inadequate knowledge about the clinical use case
[187]	Mohammed et al., Journal of Computing and Communication(2022)	100 N 100 invasive carcinomas 100 B 100 in situ carcinomas	Ensemble learning	HP	Acc 92.5	The effectiveness of the model is reduced when BACH is used instead of BreakHis
[188]	Shen et al. Nature Publishing Group UK London (2019)	2478 images from 1249 patients	Resnet-50 and VGG16	DM	AUC of 0.88,sensitivity: 86.1%, specificity: 80.1%	Mammograms are downsized to fit available GPU memory, and the datasets used are not nationally representative samples
[189]	Pérez-Benito et al., Computer Methods and Programs in Biomedicine (2020)	4992 images and 1785 number of patients	Entirely convolution neural network (ECNN)	DM	DICE score per acquisition device reached 84	More supervised, unsupervised, and mask-based methods need to be examined
[72]	Wang et al.,European Radiology(2022)	315 B 454 M	ASN	BUS	Acc 78.11, Specificity 76.81 and Sensitivity 85	A retrospective analysis is conducted with data from a single center; however, there are no external tests conducted
[190]	Nagalakshmi.T., Neural Processing Letters (2022)	208 N, 62 B and 52 M	Ensemble-Net	DM	Acc 96.72	Neglected clinical features in favour of feature extraction for tumor detection

Table 2 (continued)

Paper	Authors, Publisher	No. of images	Technique used	Type of image sequence	Performance(%)	Challenges and limitations
[191]	Raaj et al.,Biomedical Signal Processing and Control (2023)	For DDSM=N:1600 M: 1024 MIAS= N: 175 M: 147	Hybride CNN	DM	98.44 Acc on DDSM dataset 99.17 Acc on MIAS dataset	The morphological segmentation approach used for detecting and segmenting the interior cancer pixels, which reduces the accuracy of cancer pixel detection in abnormal mammogram images
[192]	Yurdusev et al., Biomedical Signal Processing and Control (2023)	404 M 596 N	Yolov4 DL	DM	Sensitivity, Specificity and Acc 98.36, 97.19, and 97.67	Lacking in use of different dataset, CNN models and image processing methods

BC. Pan et al. [197] have developed a tumor segmentation model titled Spatial-Channel Fully Convolutional Network (SC-FCN), which uses BUS images. In addition, to improve classification process, fully convolutional networks are incorporated with bi-directional long short-term memory (BLSTM) and spatial-channel attention modules. The proposed method is evaluated on a private BUS dataset; the obtained results for the Dice similarity coefficient (DSC), Precision (PR) Recall, and Hausdorff distance (HD) are 81.78%, 82.92%, 80.67% and 11.1367% respectively.

To assist in the early detection of BC using MRI images, Dewangan et al. [198] hhave proposed a novel Back Propagation Boosting Recurrent Wienmed (BPBRW) model with Hybrid Krill Herd African Buffalo Optimization (HKH-ABO) mechanism. In addition, the wienmed filter and the HKH-ABO function are used for preprocessing and classifying types of BC, which led to a more precise classification of BC. The obtained results show that the proposed method outperforms the existing DL methods by providing a higher accuracy and lower error rate of 99.6% and 0.12% respectively.

Saleh et al. [199] have proposed a hybrid model using RNN and the Keras-Tuner optimization technique for BC diagnosis. The optimized deep RNN has an input layer, five hidden layers, five dropout layers, and the output layer. The proposed model has trained on both regular ML models and the optimized deep RNN. In comparison to the other models, the results revealed that the optimized deep RNN is able to obtain the maximum performance and has achieved accuracy (AC), precision (PR), recall (RE), and F-measure (FM) are 95.18%, 95.44%, 95.18% and 95.2% respectively. Table 3 shows the brief summary of hybrid DL models for BC classification, detection and segmentation.

9 Comparison with Existing Works

From previous published papers, it has been observed that a very limited amount of work has been done on the survey of BC classification. Hassan et al. [129] have focused on the current state of DL and machine learning CAD systems for detecting and classifying masses using mammography imaging modality only. They have not covered all screening modalities currently available. Roslidar et al. [200] have presented a survey of the potential use of thermography imaging using DL, specifically CNNs, for BC detection. The authors focused primarily on thermal imaging of the breast, which is not particularly efficient for detecting BC at an early stage.

Li et al. [201] have presented a systematic review that has been conducted to outline the changes observed in clinical and health services outcomes for breast screening and

Table 3 Some latest BC classification, detection and segmentation models using hybrid DL are listed below

Paper	Authors, Publisher	No. of images	Technique used	Type of image sequence	Performance(%)	Challenges and limitations
[65]	Qi et al., Neurocomputing(2022)	8146 M 9979 Non M	CNN, GAN and denoising autoencoders	BUS	Acc, Sensitivity and Specificity 89.34, 87.71 and 90.68	The model is limited to detecting potentially harmful changes in the breast lump, but the identification of solid nodules is also medically significant
[193]	Aslan M. F., Computers and Electrical Engineering (2023)	220 B, 67 N and 49 M	CNN and BiLSTM	DM	Acc 97.60 and 98.56	Prioritized determining the type of cancer over identifying the location of the tumor
[194]	Demir.F., Biocybernetics and biomedical engineering (2021)	5429 M, 2480 B	CLSTM	HP	Acc 100	The CLSTM has a complicated design, it requires powerful hardware to handle large datasets
[195]	Patil1 et al., Evolutionary Intelligence(2021)	Not mentioned	CNN and RNN	DM	Acc 93.59	Employed a median filter to eliminate noise, but it has a demerit of eliminating fine details and thin lines in the image,even at low noise level
[196]	Yao. et al., Cancers (2019)	400 training,100 test image	CNN and RNN	HP	Acc 97.5	Computationally expensive
[197]	Pan. et al., Ultrasonics (2021)	124 patients	SC-FCN-BLST	BUS	DSC, recall, PR and HD are 81.78, 80.67, 82.92 and 11.13	A problem is present in sensitivity, resulting in the failure to detect certain lesions
[198]	Dewangan et al., Multimedia Tools and Applications (2022)	735 M 265 B	BPBRW and HKH-ABO	MRI	Acc 99.6	The BPBRW has a complicated design
[199]	Saleh et al., Computational Intelligence and Neuroscience (2022)	Not mentioned	RNN and Keras-Tuner optimization	HP	AC, PR, RE, FM are 95.18, 95.44, 95.18 and 95.2 respectively	Lack of clear explanations and interpretations regarding disease detection

diagnosis as a result of the pandemic. The techniques currently employed in DL to detect BC are not addressed in this paper.

Nasser et al. [202] have discussed a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to investigate different DL-based methods for BC detection. The paper lacks a discussion on the ideal imaging modality to be used for each stage and an in-depth analysis of the screening modality for detecting BC.

To a certain extent, the performed surveys are restricted in terms of imaging approaches, analyzed components, segmentation, classification methods and challenges. No surveys have been reported that explicitly focus on systematic literature review in the context of all problems mentioned above. Therefore, we are encouraged to conduct a systematic literature review on this topic. This survey covers various aspects of BC research, including detection, classification, segmentation, screening techniques, datasets, challenges and highlights the most recent advances and innovations in each area. By providing a detailed analysis of the current state of the art BC research, this survey can serve as a valuable resource for upcoming researchers. Overall, this survey is intended to contribute to the ongoing efforts to improve the understanding of BC and develop more effective strategies for its prevention and treatment. Table 4 highlights the comparison between our proposed survey and the existing survey.

10 Quality Metrics for Evaluating Performance

DL algorithms are assessed based on several metrics such as accuracy, F1 score, and AUC. Below is a description of these evaluation parameters.

The outcomes achieved by each DL approach in terms of accuracy, F1 score, and AUC are compared in Table 5 and Fig. 10 shows the graphical representation of the best-performing DL models for predicting BC based on these metrics.

Table 5 shows a comparison of DL approaches in terms of the obtained Accuracy, AUC and F1 score

Ref	Accuracy (%)	F1 Score (%)	AUC (%)
[180]	90.78	91.46	95.49
[214]	98.87	97.99	98.88
[215]	91.27	84.17	93
[216]	95.58	89	85
[217]	98.60	93.50	99.40
[218]	97.98	95.97	98.46
[219]	99.41	98.08	97.61
[206]	96.70	96	98.30
[207]	98.96	97.66	99.50
[208]	89	85	85
[209]	91.92	91.92	99.29
[210]	93.83	93.8	95.61
[212]	83	76.94	80.35
[211]	94.62	91.14	97.11
[213]	97	98	96

Moreover, it is observed that the BreakHis, DDSM and MIAS datasets are commonly used in research papers for implementation. Based on that observation, it can be concluded that the aforementioned datasets are the gold standard in terms of quality and performance.

These studies [206–213]have proposed methods for DL models that rely on metrics such as accuracy, F1 score, and AUC.

To compute the accuracy and F1 score equ-1 and equ-2 are employed. In the equations, the terms TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives. In the process of evaluation, analyzing and interpreting data is an indispensable component,

Table 4 Comparison of proposed survey with existing surveys

Author	Prospects								
	1	2	3	4	5	6	7	8	9
Nassif et al. [203]	✓	✓	✗	✗	✗	✓	✓	✓	✗
Elouassif et al. [204]	✓	✓	✗	✓	✗	✓	✗	✗	✗
Nasser et al. [202]	✓	✓	✓	✗	✗	✓	✓	✓	✓
Li et al. [201]	✓	✓	✗	✓	✓	✗	✗	✓	✓
Yassin et al. [205]	✓	✓	✓	✓	✓	✗	✗	✓	✗
Hassan et al. [129]	✓	✓	✓	✗	✗	✓	✓	✗	✗
Roslidar et al.[200]	✓	✓	✓	✗	✗	✓	✓	✗	✗
Proposed survey	✓	✓	✓	✓	✓	✓	✓	✓	✓

*1-Detection, 2-Classification, 3-Segmentation, 4-Screening Techniques, 5-Critical analysis on Imaging modalities, 6-DL, 7-Hybrid DL, 8-Dataset, 9-Challenges

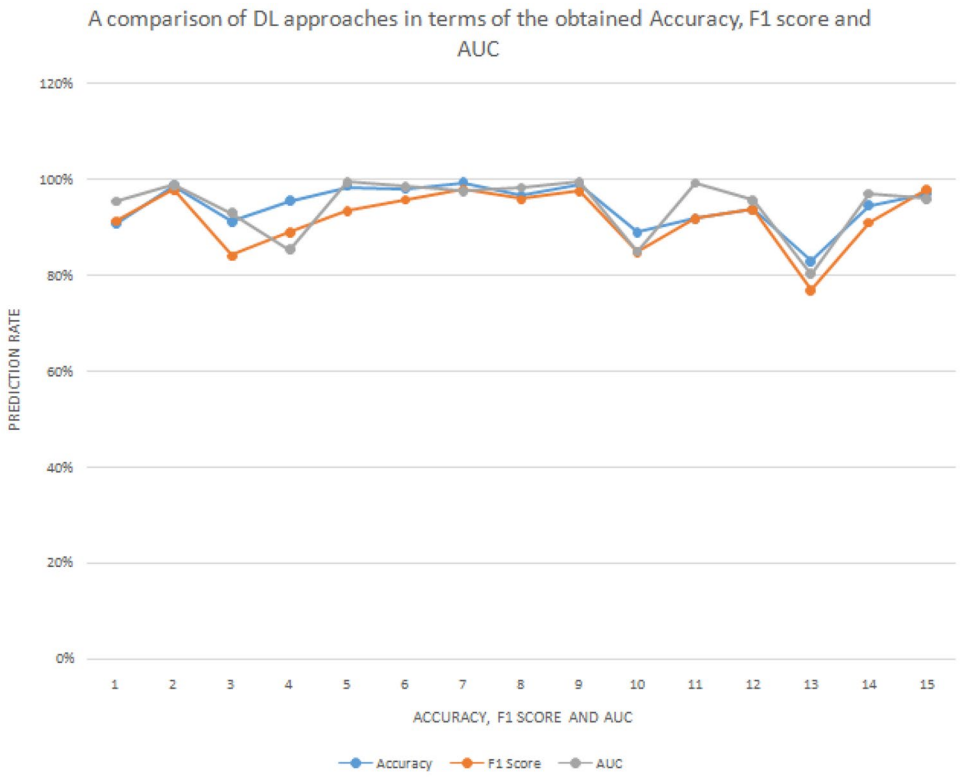

Fig. 10 Comparative Analysis of DL based models on the basis of quality parameters (Accuracy, F1 Score and AUC)

as it yields clear and comprehensible results that can be utilized and enhanced.

- Accuracy refers to the ability of the model to correctly classify images or other types of data and is calculated using Eq. 1.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- AUC curve is a graphical representation of the performance of a binary classification model. It measures the performance of the model over all possible classification thresholds.
- F1 score is a weighted harmonic mean of the precision and recall, where the F1 score reaches its best value at 1 and worst at 0. The F1 score is calculated using Eq. 2.

$$F1Score = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{2}$$

11 Challenges and Future Implications

BC is the leading cause of mortality among women worldwide; hence, early detection is a crucial step in order to minimize mortality rates. Nowadays, several imaging modalities have been employed to provide a more comprehensive understanding of BC. Nevertheless, manually analyzing various imaging modalities with a large number of images is an inefficient and challenging task that might lead to misdiagnosis and an elevated false-detection rate. Therefore, an automated strategy is required to address these issues. In order to early detection of BC, medical image analysis employing CAD has been shown to be the most efficient method. The purpose of CAD systems is to aid medical staff in making accurate decisions based on medical imaging. While using a CAD system, radiologists can easily spot abnormalities, which helps minimize the number of false negatives. However, CAD systems typically detect a greater number of false features than actual markings, hence, it is the duty of the clinician to analyze the outcomes. Because of this feature of CAD systems, the reading time is prolonged and the number of instances that radiologists can analyze is constrained. However, the recent developments in AI, particularly DL-based approaches, have the potential to significantly accelerate the image analysis process, assisting radiologists in making earlier diagnoses of BC.

The research revealed that DL-based CAD systems can produce satisfactory outcomes in the field of medical image analysis. But there are still several obstacles that prevent these approaches from being used in a clinical context. In spite of the success that has been achieved by DL models, there are a few issues and constraints associated with them that need to be solved for BC detection, classification and

segmentation. The following are the few significant issues that are encountered throughout the course of the review are addressed here:

- The primary challenge is the scarcity of a comprehensive dataset to train DL algorithms for medical imaging, due to their reliance on large and high-quality training datasets, an adequate dataset is needed to operate effectively. In addition, the creation of an adequate dataset is difficult, since the annotation of medical images is tedious, time-consuming, and entails considerable effort to eliminate human error. Since there are less anomalous instances relative to normal ones, collecting adequate data would be expensive. The collection of data is also affected through the number of patients who undergo a certain test based on the accessibility of tools and regulations in various healthcare centers. For instance, the DM datasets are typically large, containing information of thousands of patients. Contrarily, there are fewer patients included in MRI and PET/CT datasets. Thus, due to its availability, more DL algorithms have been developed and validated on DM datasets than any other modalitiy. Therefore, one approach to generating a large dataset for several imaging modalities is a multi-institutional alliance. The dataset gathered through these collaborations comprises a diverse population of patients in terms of demographics, clinical history, imaging modality, and treatment procedure. The use of these datasets improves the robustness, accuracy and reliability of DL algorithms.
- In most cases, the existing imaging datasets have a limited range of data. However, it is hard to use DL and get the best possible results with limited training data, because DL algorithms require extensive training data to achieve desirable results. These problems caused by insufficient data can be addressed with the aid of a few potential alternatives. For instance, it is possible to generate a larger dataset by combining data from multiple healthcare centers. Nonetheless, patient confidentiality guidelines must be considered. Federation learning [220, 221] seems to be another approach to this issue; in this approach, the algorithm is trained on datasets regionally, but it must also move across hubs so that it can be updated on datasets in each location. However, the federated learning algorithms have not yet gained widespread adoption.
- The majority of studies relied on private datasets, which are considered confidential, for their analyses. Therefore, it is difficult to compare the efficacy of such models across studies. Several analyses employed transfer learning to deal with insufficient data. And some studies have attempted pretrained models to extract features from images, then fed those features into DL models to train it to accomplish the desired task. In contrast, several works have used pre-trained model parameters as a reference point for their models, afterward, fine-tuned their models using medical image datasets. For smaller datasets, transfer learning has been shown to be effective, however, the effectiveness of the target model is heavily dependent on the differences between the features of the source dataset and the target dataset. To boost prediction results, some studies have used data augmentation to artificially enlarge the dataset. However, it has to be noted that, unlike new independent images, data augmentation fails to contribute a significant amount of additional information to the DL model.
- DL-based CAD systems also struggle with a lack of completely labeled datasets. The majority of DL approaches are based on supervised algorithms, which means they require labeled data. Therefore, generating a wide variety of data that has been completely labeled is a difficult task because the process of annotation takes a lot of time and is prone to error. In order to avoid the necessity of labeled dataset, unsupervised techniques are utilized in several publications; however, the results have been less reliable than those from supervised techniques.
- The issue of class imbalance poses a significant obstacle for DL models. Therefore, there is a possibility that the results may be skewed in favour of the majority class. Even in the multiclass classification, there is an uneven distribution at both the patient and image level. Thus, the absence of diverse and ethnic datasets is another issue that must be tackled.
- A further significant difficulty for DL algorithms is the need to protect the confidentiality of sensitive medical information. Because of privacy regulation, sharing data in a central database becomes challenging. Hence, DCNN can be trained collaboratively and autonomously without the need to disclose patient information. Currently, few DL models exist that incorporate both imaging and non-imaging (cancer history, biochemical and genetic data) features. There is a need for several models, which integrate radiomic features with the imaging data.
- One such problem that DL models have to deal with is label noise. During the growth of BC, it spreads from one part of the breast to other breast tissues. Therefore, a single image may be annotated with various stages of BC, since specific regions of the same breast may be affected differently. These images may cause confusion for the DL model when it comes to the multi-classification scenario.
- In terms of DL techniques, there has not been extensive research on the potential of Auto-Encoder, GAN, LSTM, RNN, deep belief network and deep reinforcement learning, hence, it is still a wider field for further research.
- In many cases, the process of decision-making is not open and transparent because of DL algorithms black box nature. Since, medical experts have to know the

actual meaning of the decision being made by the algorithms and what aspects of an image are extremely discriminatory, thus, they do not favour these opaque DL algorithms. Therefore, to boost the level of trust and reliability on the actions taken by DL tools, adoption of interpretable methodologies with appropriate explanations of DL algorithms is essential, hence, ensure the safe and effective use of DL.

- Moreover, few studies indicate that employing omics [222] data rather than imaging data can potentially lead to better classification accuracy. When compared to imaging data, the omics data has less features, but those are more powerful. Therefore, DL approaches may extract features that turn out to be irrelevant towards the end label, which may negatively impact the performance of the model. However, the cost of computing omics data is higher than that of processing images. Besides, a number of different techniques and imaging data are widely available, whereas it is not in the case of omics data.
- During the study of the relevant literature, it is observed that the DL-based CAD approaches overlook the correlation that exists between the two vision tasks of tumor region segmentation and classification. The network is fed only breast tumor images based on the defined ROI without any prior information about the tumor's outlines. The clinical parameters associated with tumor segmentation may be retrieved using these methods but it is difficult to improve beyond, which limits their effectiveness in terms of improving classification accuracy. Tumor segmentation is closely correlated with features such as tumor morphology, orientation, edge integrality, margin ambiguity, angularity, microlobulated margins, spiculatedness, posterior feature, calcification in mass, and structural deformity. Furthermore, the tumor segmentation can direct feature extraction for tumor classification, hence enhancing performance. If the DL model is trained to focus more on these parameters then the classification of breast tumors will improve tremendously. Therefore, it is crucial to design the system that improves the features including the segmentation information based on clinical diagnosis criteria.
- In some papers [196, 223] it is observed that the authors train models on a slice by slice basis at time, which provides higher accuracy, but there is considerable data leakage. This can be reduced by seeing that the same patient's data is not present in the training and testing sets that do patient wise split rather than splits based on total number of available slides basis.
- It is observed that hybrid DL approaches can produce better results than CNN alone in certain scenarios [193, 194, 198], however, the structures are challenging to understand, which slows down the process of fine-tuning parameters. Besides, the computing time grows proportionally with the size of the images used, thus, necessitates the use of high-performance hardware.

12 Conclusions

BC survival rates can be increased with early diagnosis. Since, technology has reached the point where early detection of BC is feasible. Moreover, AI based techniques in medical image analysis have allowed for the automatic extraction of crucial features from large datasets, enabling a better BC diagnosis. This study aims to analyze the state-of-the-art literature on DL across a range of MIM for BC diagnosis. Besides, it critically analyzes medical images to compare and contrast the strengths and limitations with DL approaches. This study includes everything from detection to segmentation of BC, in addition, generation and processing of images. Despite the remarkable results achieved by DL techniques, several challenges must be addressed before DL technologies may indeed be integrated into clinical practice. Also, ethical concerns regarding the explainability and interpretability of these systems need to be taken into consideration. Therefore, this work highlights potential future research directions and challenges in adopting AI-based approaches for BC diagnosis based on a variety of MIM. This analysis indicates that there is a significant need for an integrated, fully-automated framework that can reliably identify BC with minimum intervention.

Data Availibility Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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