ICCK Journal of Image Analysis and Processing
http://dx.doi.org/10.62762/JIAP.2025.780624

REVIEW ARTICLE

# Recent Advances in Breast Cancer Detection: A Review on Segmentation and Classification Techniques

**Muhammad Moosa Raza Khan**[1], **Mehwish Zafar**[1,*], **Abdul Majid**[1] and **Fadia Ali Khan**[1]

[1] Department of Computer Science, HITEC University Taxila, 47080 Taxila, Pakistan

## Abstract

**Breast Cancer (BC) is still one of the most significant, life-threatening, and prevalent diseases that affects women all around the globe. The early recognition and strategies of effective treatment measures improve the rate of survival among patients significantly, contributing to a critical research area in medical science. This review presents a comprehensive review of recent trends and advancements in the recognition of BC recognition, diagnosis, and treatment. It covers multiple imaging modalities, including Magnetic Resonance Imaging (MRI), ultrasound, mammography, and histopathology, along with various approaches of Machine Learning (ML) and Deep Learning (DL) that enhance the efficiency of diagnosis and improve accuracy. In particular, in some recent decades, the Computer-Aided Diagnosis (CAD) system gained noteworthy attention for the recognition of affected regions, for the minimization of diagnostic rates, and for assisting radiologists. ML algorithms have robust capabilities for feature extraction and classification, while the DL models, specifically Convolutional Neural Networks (CNNs), have shown remarkable performance in image-based diagnostic tasks. Moreover, the presented review also discusses some challenges, such as dense breast tissue, noise, and tumor heterogeneity, along with the limitations of the current studies. The review concludes with a compact summary of current trends, research problems, and future directions for the improvement of BC detection.**

**Keywords**: breast cancer, tumor detection, early diagnosis, computer-aided diagnosis, machine learning, deep learning.

## 1 Introduction

Breast Cancer (BC) is a major health concern worldwide and the most common cancer in women. It develops due to a mix of genetic and environmental factors that cause mutations in important genes. People inherit a high risk from genes like BRCA1 and BRCA2, while others may be affected by multiple smaller genetic changes over time [1]. BC also refers to the erratic growth and proliferation of cells that originate in the breast tissue [2]. In 2024, the U.S. expects around 310,720 new invasive BC cases and over 42,000 deaths. Since 1989, mortality has dropped by 44%, preventing 517,900 deaths. However, incidence rates have risen by 1% annually since 2012, with

**Submitted:** 31 August 2025
**Accepted:** 18 September 2025
**Published:** 07 November 2025

**Vol.** 1, **No.** 4, 2025.
10.62762/JIAP.2025.780624

***Corresponding author:**
Mehwish Zafar
mehwish.zafar@hitecuni.edu.pk

**Citation**
Khan, M. M. R., Zafar, M., Majid, A., & Khan, F. A. (2025). Recent Advances in Breast Cancer Detection: A Review on Segmentation and Classification Techniques. *ICCK Journal of Image Analysis and Processing*, 1(4), 147–161.

a 1.4% increase among women under 50. Asian, American, and Pacific Islander women saw annual increases of 2.5% and 2.7%. Black women have the lowest survival rates across most subtypes and stages. BC accounts for 30% of new cancer cases in U.S. women, with a 12% lifetime risk and a 3% chance of death. Globally, 2.3 million women were diagnosed in 2022, leading to 670,000 deaths. Early detection and screening remain crucial [3]. Several types of tumors may develop within different areas of the breast. Most tumors are the result of benign (non-cancerous) changes within the breast. Some most frequently occurring BC are Lobular carcinoma in situ, Ductal carcinoma in situ, Infiltrating lobular carcinoma (ILC), Infiltrating ductal carcinoma, and less frequently occurring types are Medullary carcinoma, Mutinous carcinoma, Tubular carcinoma [2]. Modalities in BC include Mammography is X-ray imaging of the breast that is designed to find any abnormalities or tumors. Ultrasonography is used to differentiate between cysts and solid masses as well as to differentiate in benign and cancerous tumors [4]. Different modalities are shown in Figure 1, including Ultrasound, MRI, and Mammography. MRI is a technique used to produce high-resolution images. MRI is not commonly used for BC but is considered a useful addition to mammography in some specific situations [5]. Computed Tomography (CT) scanners quickly capture and reconstruct images without extra radiation, helping diagnose lung clots, heart artery calcifications, and aortic disease, while also imaging breast tissue on chest CT safely [6]. BC can be caused by a previous history of the disease, a strong family history, or genetic mutations. Hormonal factors, including early menstruation, late menopause, pregnancy, hormone therapy, or birth control, may also contribute.

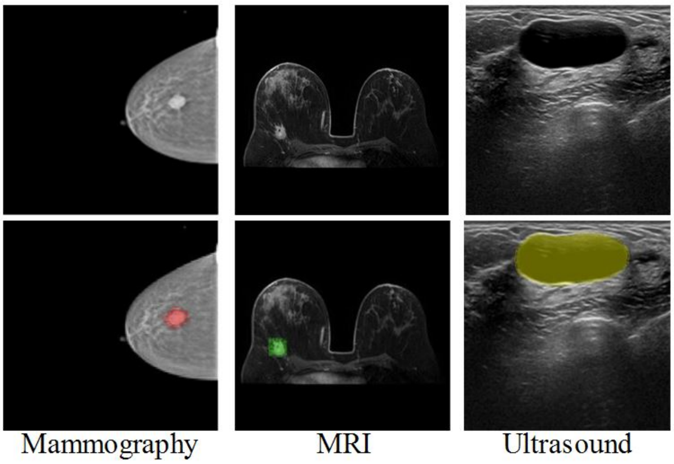


**Figure 1.** Modalities of breast cancer.

Lifestyle choices like inactivity, a high-fat diet, obesity, and alcohol consumption increase the risk. Long-term exposure to low-dose radiation can also be a factor also likely due to later diagnoses, more aggressive tumors, and unequal access to treatment [2]. BRCA1 and BRCA2 are tumor-suppressing genes that are important for genetic stability and DNA repair. When these two genes are mutated and changed, that leads to damage to the DNA, which further causes genetic mutation, resulting in an increased risk of cancer. Both these genes are linked to causing BC [7]. Artificial Intelligence (AI) has transformed BC detection through Deep Learning (DL), which enhances computer-aided diagnosis (CAD) systems and sidesteps the need for traditional Machine Learning (ML) to manually learn features from the data. The classical CAD systems relied on handcrafted image features, whereas DL models, like convolutional neural networks (CNNs), can take imaging data into account and provide highly accurate output for large volumes of data. Though successful, the impediments to the adoption of AI in clinical practice are data quality, transparency, and trust issues. AI models require training in well-annotated and ideally bias-free data, and techniques like federated learning help to secure one's privacy. To win acceptance, explainable AI (XAI) methods such as heat maps can shed light on the model's decision. AI is now being interfaced into BC screening to assist and reduce the workload of radiologists in making decisions in breast cancer detection, improving detection while minimizing false positives [8].

### 1.1 Motivation

BC poses a massive and prominent health burden as millions of new cases are diagnosed annually, which causes a high mortality rate among women. The early and timely recognition of BC and accurate diagnosis are very important to enhance the survival rate and treatment outcomes. Despite the advancements in technology, traditional detection techniques still face many challenges, limitations in the recognition of abnormalities, and variability in interpretation. The integration of AI, ML, and DL techniques offers a significant solution to overcome the limitations. The presented survey was conducted having the primary goal of not only summarizing existing AI and CAD methods for BC recognition but also emphasizing and highlighting their limitations and existing challenges, thereby highlighting clear directions for future research to overcome these limitations. Although much research has been conducted on the BC detection systems but the presented review tries to cover the maximum aspects. The brief comparison is provided below:

- The researchers [9] present a review that focuses on the deep learning methods for BC recognition in histopathology images. Their work provides a deep and very detailed content, but the scope of their survey is restricted to a single modality.
- The researchers [10] performed a broad review of BC recognition, which emphasizes the future aspects and emerging technologies. Although the review summarizes the advancement but it does not systematically analyze DL and AI techniques across various imaging modalities.
- The researchers [11] conduct a structured survey on CNN in mammography, which discusses tasks including mass detection, calcification, asymmetry detection, and breast density classification. The scope of the survey is single modality.

The gaps motivate us to perform a survey that consists of a detailed, multimodal perspective while systematically analyzing the task of segmentation and classification, and exploring the recent research trends and contributions that enhance BC diagnosis with the help of advanced computational approaches by highlighting their limitations and proposing a future roadmap.

### 1.2 Scope

The presented survey focuses on the modern computational techniques in the detection and classification of BC. It covers many datasets having various imaging modalities such as mammography, ultrasound, MRI, and histopathology. The article examines the part and role of CAD systems, ML, and DL architectures for the betterment of diagnostic accuracy. Further, it focuses on the recent developments and highlights the performance and limitations of the existing models and emerging directions of research in this domain. The scope of this review is to deliver image-based approaches for BC recognition, especially Ultrasound, Mammography, MRI, and histopathology. Having these modalities, the focus is to present proposed methods between 2018 to 2025 that provide effective techniques based on AI, ML, and DL for BC segmentation as well as for classification. The presented survey also delivers details about widely used datasets and performance measures for this domain. By setting the above boundaries, the aim is to provide both clarity and depth, also ensure that the discussion remains close and relevant to researchers working on the BC domain.

### 1.3 Objectives

The research objective of the presented article includes:

- Analyze and review the current trends in BC recognition with the help of CAD, DL, and ML methodologies.
- To evaluate the efficiency of various imaging modalities utilized in BC detection.
- To figure out the limitations and challenges and limitations associated with the existing techniques.
- To highlight the research gaps, limitations, and challenges.
- Provide a comprehensive future roadmap for advanced approaches to tackle these challenges.

### 1.4 Proposed Research Questions

To ensure the systematic layout of the presented review, it has been organized according to the following research questions:

- RQ1: What are the motivations that figure out the need to performing the survey on BC segmentation and classification using AI, ML, and DL models, and what are the defined objectives and scope of the presented work?
- RQ2: What AI, ML, and DL methods have been proposed by the researchers on BC segmentation and Classification across various modalities in recent years?
- RQ3: What are the key challenges and limitations that are faced by the researchers during implementation, including data, methodology, and computational cost etc.?
- RQ4: What are the findings of existing studies, and what are their insights from their results?
- RQ5: What are the research gaps and an extensive roadmap that can guide the researchers in the future?

The rest of the article consists of various sections and sub-sections. Section 2 presents the literature about BC detection along with datasets and performance measures. Section 3 describes the limitations of the existing methods. Section 4 is about the discussion,

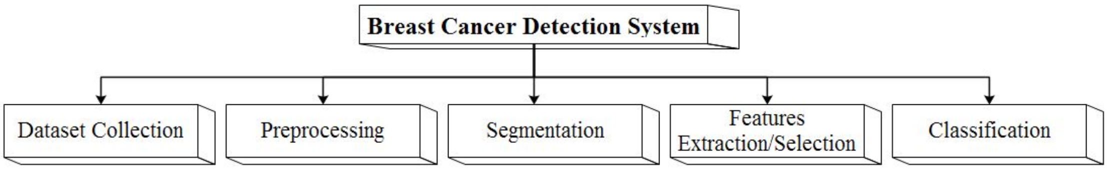


**Figure 2.** Steps of a generalized breast cancer detection system [12].

and Section 5 concludes the article with a future roadmap.

## 2 Breast Cancer Detection and Classification System

In recent decades, various studies have been carried out for the betterment and improvement of the efficiency and accuracy of BC recognition with the help of the latest and modern techniques. Literature provides a wide range of techniques that involve several steps, including preprocessing, segmentation, feature extraction, and classification, as shown in Figure 2. Every stage performs a vital role in the overall accomplishment of CAD systems.

Preprocessing refines and enhances the quality of the image and also removes the noise artifacts, while the segmentation is utilized to separate the region of interest. The techniques of feature extraction help in the identification of the informative patterns, and after that, the algorithms of the classification assist in distinguishing between classes. This part of the presented article provides a detailed review of the existing techniques.

### 2.1 Preprocessing Techniques for Breast Cancer Detection

Preprocessing is an important step that mainly involves getting the data ready to be processed. In preprocessing, we remove any kind of noise or unnecessary information that is in the data. Preprocessing is also done to enhance the features that are related to the tumor using various filters, as shown in Figure 3.

Researchers have explained preprocessing as the technique to enhance image features relating to cancer detection [13]. Here are several preprocessing techniques: Morphological techniques are used for noise suppression, texture analysis, shape analysis, edge detection, skeletonization, and multiscale filtering on images [14]. The binary images are limited to certain filtering operations as they are bounded by the pixel encoding. A median filter is one of those operations that binds non-linear filters with the grayscale images and is used to remove noise while preserving the edges [15]. A Gaussian filter is also one of the linear filtering techniques that is used to smooth and remove noise from an image. This also blurs the image to remove Gaussian noise. In the Gaussian convolution process is carried out on an input image using Gaussian kernels that give a noise-free and smooth image [16]. Mean filtering is also a linear filtering technique that uses the mean or the average value of the pixels and replaces them with the current pixels. It is used to process the noises when the value of noise is zero, but it can also blur edges [17]. Histogram Equalization is a technique of image adjustment in which a histogram is used to adjust the contrast of the image. It uses the most frequent values and then spreads them. It works best on images with high color depth, and then the palette size, which makes the image easier to analyze and improves image quality [18]. Min-Max Normalization is a technique that provides a linear transformation on the original range of data and keeps the data in that range. In other words, we can say that this is a technique that can fix data in a predefined boundary [19]. Z-score Normalization is a technique that normalizes the gradient tensor across all the layers. It is applied layer-wise. This technique adjusts the gradient without modifying the architecture, increasing the training speed and performance of the model [20]. Image Augmentation involves techniques like rotating, flipping, cropping, zooming, histogram-based methods, and finishing at Style Transfer and Generative Adversarial Networks. Image Augmentation can be put into two categories: traditional, white box method, or black box method based on neural networks [21]. In stain normalization, an ACD (Adaptive Colour Deconvolution) based color normalization algorithm was utilized, through which stain variability is handled. In this independent stain, components are separated, which is done on each pixel of the image. After applying certain calculations separated stains have now became weighted stains and are again combined [22]. ReliefArrributeEval is a technique used in coexistence with the Ranker search method. This technique uses to numerical

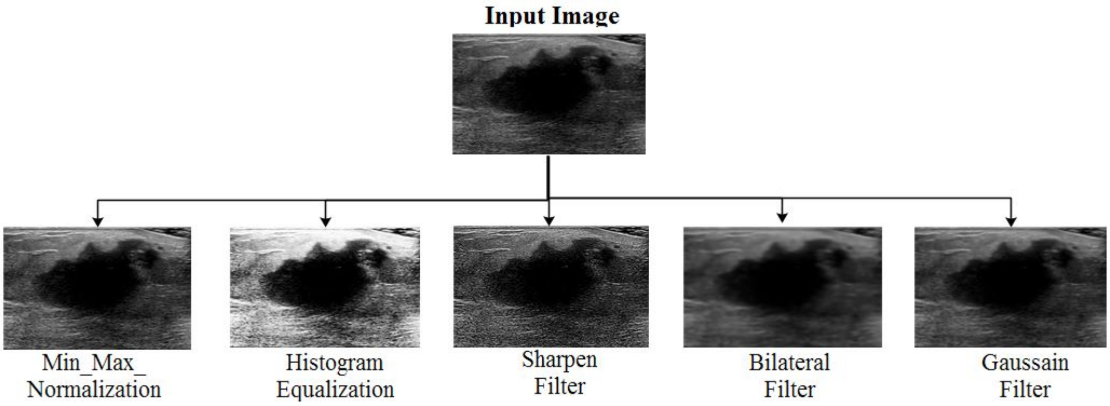


**Figure 3.** Outcomes of various pre-processing techniques.

value of each feature that indicates its importance and based on that unimportant features are dropped or ignored [23]. Overall, all the pre-processing methods ensures the reliable input by minimizing or eliminating the variability and noise, thereby it enable more efficient analysis of lesions in BC imaging.

### 2.2 Breast Cancer Segmentation

In the diagnosis of BC, segmentation is one of the most important techniques is segmentation which outlines the cancerous regions for precise diagnosis and treatment [24]. Segmentation is crucial for detection, image analysis, feature extraction, and classification [25]. The RDAU-Net model has been proposed by researchers to segment tumors in BUS images. This model is based on a conventional U-Net, but the residual unit is added to enhance the edge information [26]. Researchers have divided segmentation into five different categories, which involve which are thresholding technique, morphology-based, active contour, region growing, and texture-based techniques [27]. Researchers have used the cGAN segmentation technique to achieve high segmentation accuracy and dice coefficient with a score of 94%, 87% for Dice coefficient and IOU, and overall accuracy of 80% [28]. Researchers have used Dual CNN in this article [29] on DDSM and INbreast datasets to do mass segmentation and have outperformed all recent state-of-the-art models. Researchers have also used the R-CNN technique on the 3D ABUS dataset to perform segmentation in 3D ultrasounds [30]. Researchers have used the segmentation technique U-net on the WSI dataset to do vigorous segmentation and achieved an IOU and accuracy of 68% and 91% respectively [31]. With a Dice score of 96.8%, and 87.7% for FGT, a Correlation coefficient of up to 99.5% researchers have used the nnU-Net segmentation technique [32]. Researchers have used the ESTAN technique on ultrasound images to boost small tumor segmentation and achieved dice scores of 89%, 80%, and 81% [33]. Another researcher has worked on the RCA-IUnet segmentation technique on the BUSI dataset to do spatial attention-guided inception [34]. Researchers have proposed a joint phase attention network that can mine both pre- and post-contrast representations for the segmentation [35]. The BreastSAM Segmentation technique is used by this researcher to improve accuracy and achieved a score of 96.61% pixel accuracy, 83.92% Dice score, and 73.61% IoU [36]. Researchers have used the DAU-Net segmentation technique on Ultrasound images using BUSI and UDIAT datasets and achieved high accuracy with a dual attention mechanism [37]. Researchers have used the SC-Unet segmentation technique to do lightweight segmentation and, on the BUSI dataset, achieved a Dice Score of 75.29% and accuracy of 97.09% and on the Private dataset, achieved a Dice score of 90.62% and accuracy of 98.37% [38]. Researchers have used ACL-DUNet segmentation technique to Enhances feature extraction capability and dense layer for robust segmentation with Dice Similarity Coefficient (DSC) of 87% and 83% [39]. DL based automatic Segmentation technique is used by researcher to enhance accuracy and reduce computational cost [40]. nnUNet segmentation technique is used for Enables assessment of cancer progression with Dice similarity of 89% , Hausdorff distance of 3.52 mm and after doing fine tuning it the score are Dice is 78% and HD 4.95mm [41]. Researchers have used a combination of AIPT and CASDN methods in segmentation on DMR-IR and CBIS-DDSM datasets to overcome issues like noise, variation in contrast, and low resolutions [42]. AMFFR-Net models have been used on CBIS-DDSM, INbreast, UCHCDM, and BCDR-01 DB datasets to achieve precise segmentation utilizing multi-modal feature fusion and refinement methods [43]. The summary of the reviewed segmentation techniques is presented in Table 1.

The performance comparison considering the Dice Score is conducted, and a graphical comparison is shown in Figure 4.

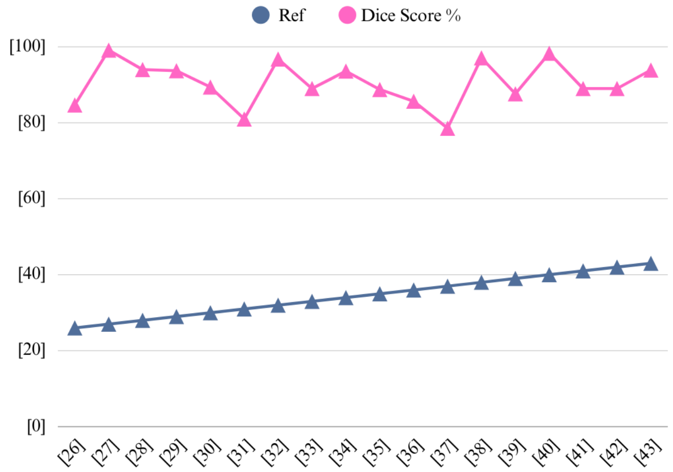


**Figure 4.** Performance comparison of reviewed segmentation techniques.

### 2.3 Breast Cancer Classification

BC is one of the leading causes of death from cancer in women worldwide [44]. Diagnosing BC is a challenging medical task that involves many steps, and classification is one among them [45]. In classification, firstly, the classifier is trained on labeled data after training, unlabeled data is given to test the classifier's performance [46]. In ML classification methods like logistic regression, random forest, SVC, AdaBoost, bagging, voting classifiers, and the Xception model are used [47], and Deep learning classification using transfer learning with pre-trained models like VGG16, VGG19, and ResNet50 [48]. Researchers have used a Custom CNN with a small SE-ResNet classification module and demonstrated improved accuracy over traditional methods [49]. Classification techniques using A-MIL models have been used to improve interpretability without compromising accuracy [50]. Researchers have made a model named ResHist for an automated approach for diagnosing bc using histopathological images. This model learns and discriminates features and also classifies images into benign and malignant [51]. Another researcher has used VGG-16, VGG-19, and ResNet-50 classification models to compare ML and DL approaches and has concluded that deep learning approaches perform better at higher magnification [52]. Researchers have used ResNet-34 and MobileNet-v2 to do multi-class classification, mainly focusing on the classification of IDC [53]. ResNet50 and InceptionV3 models have been used by researchers to propose the MCU (Multi-level Context and Uncertainty) model [54]. Researchers have purposed BCCNN model that can detect and classify breast cancer into 8 classes and also fine-tuned Xception, InceptionV3, VGG16, MobileNet and ResNet50 and achieved the result BCCNN outperformed all models (Acc: 98.30%, F1: 98.28%), then Xception (Acc: 97.66%, F1: 97.65%), ResNet50 (Acc: 98.14%, F1: 97.98%), VGG16 (Acc: 97.67%, F1: 97.74%), InceptionV3 (Acc: 95.33%, F1: 95.28%) and MobileNet (Acc: 93.98%, F1: 94.04%) [55]. Researchers have used classification techniques to achieve higher accuracy by combining AlexNet and ResNet features and making the AlexResNet+ model [56]. Researchers have used multimodal fusion networks for the segmentation and classification of ultrasound images, and this method outperforms the existing single- and multimodal methods [57]. Researchers have used CNN-based DL models that can differentiate between benign and malignant using histopathological images [58]. Researchers have used VGG16, Xception, ResNet50, and DenseNet201models in order to improve classification [59]. Classification techniques using models ResNet50, ResNet101, VGG16, and VGG19 have been used to detect invasive ductal carcinoma [60]. Using ViT and DeiT models of classification, researchers have categorized data into 8 classes, 4 benign and 4 malignant, with 98.17% accuracy [61]. Classification models VGG16, ResNet50, and InceptionV3 have been used by researchers to improve accuracy [62]. Classification models like ResNet50, MobileNet, VGG16, and a custom CNN have been used by researchers have evaluate models and concluded that ResNet50 achieved the highest accuracy [63]. Hybrid binary optimization methods have been used in the classification process, utilizing optimization algorithms to efficiently identify an optimal feature subset [64]. An enhanced shallow convolutional neural network (ES-CNN) has been used in multi-class classification to achieve better performance and reduced training time across 4 magnifications and 8 bc types [65]. Table 2 summarizes the BC classification techniques which are reviewed in this study.

A comparison of the classification accuracies of reviewed techniques is conducted and presented in Figure 5.

**Table 1.** Summary of breast cancer segmentation techniques.

| Ref | Year | Techniques | Modalities | Dataset/Source | Results |
|---|---|---|---|---|---|
| [26] | 2019 | RDAU-NET | Ultrasound | Private | For input size **64×64**: Acc: 0.9758, DC: 0.7966, Sen: 0.7921, Sp: 0.9914, F1: 0.7968, Pc: 0.8471, M-IOU: 0.7863, AUC: 0.9094For input size **96×96**: Acc: 0.9775, DC: 0.8286, Sen: 0.8232, Sp: 0.9920, F1: 0.8291, Pc: 0.8669, M-IOU: 0.8019, AUC: 0.9186For input size **128×128**: Acc: 0.9791, DC: 0.8469, Sen: 0.8319, Sp: 0.9934, F1: 0.8478, Pc: 0.8858, M-IOU: 0.8067, AUC: 0.9227For input size **256×256**: Acc: 0.9668, DC: 0.8335, Sen: 0.8208, Sp: 0.9935, F1: 0.8403, Pc: 0.8807, M-IOU: 0.7992, AUC: 0.9147 |
| [27] | 2020 | Hybrid segmentation approach | Mammogram | mini-MIAS, INbreast, BCDR | INbreast: ACC: 100%, SEN: 100%, SP: 100%, Jaccard: 98.61%, DSC: 98.7% BCDR: ACC: 99.8%, SEN: 99.71%, AP: 100%, Jaccard: 99.31%, DSC: 99.1% mini-MIAS: ACC: 98.13%, SEN: 98.9%, SP: 98.8%, Jaccard: 98.01%, DSV: 99.01% Average: ACC: 99.31%, SEN: 99.54%, SP: 99.41%, Jaccard: 98.67%, DSC: 99.14% |
| [28] | 2020 | cGAN | Mammography | INbreast, Private Dataset | 94% DCS, 87% IoU, 80% ACC |
| [29] | 2021 | Dual Core Net | Mammography | DDSM, and INbreast | INbreast AUC 0.93, DDSM AUC 0.85, DI score 93.69% in INbreast and 92.17% in DDSM |
| [30] | 2021 | R-CNN | 3D ABUS | Private | DSC (Cross-validation): 85.0% $\pm$ 10.4% (Median: 89.4%) DSC (Hold-out test): 82.1% $\pm$ 14.5% (Median: 85.6%) HD95 (mm): 1.646 $\pm$ 1.191 (CV), 1.665 $\pm$ 1.129 (Test) MSD (mm): 0.489 $\pm$ 0.406 (CV), 0.475 $\pm$ 0.371 (Test) RMSD (mm): 0.755 $\pm$ 0.755 (CV), 0.751 $\pm$ 0.508 (Test) CMD (mm): 0.672 $\pm$ 0.612 (CV), 0.665 $\pm$ 0.729 (Test) |
| [31] | 2021 | U-net | Ultrasound | Whole Slide Images | 68% IoU, 91% ACC, DCS 81% |
| [32] | 2021 | nnU-Net | MRI | Private dataset collected from the clinical PACS system in Shanghai Cancer Hospital | 96.8% DCS 87.7% FGT, 99.5% Correlation coefficient |
| [33] | 2022 | ESTAN | Ultrasound | BUSIS, Dataset B, and BUSI | 89%, 80%, 81% DCS |
| [34] | 2022 | RCA-IUnet | Ultrasound | BUSI and BUSIS | Trained on BUSIS, tested on BUSI:Accuracy: 0.957, Precision: 0.913, Recall: 0.885, Dice Coefficient: 0.901, mIoU: 0.855, AHD: 4.879, MAE: 0.023 Trained on BUSI, tested on BUSIS:Accuracy: 0.990, Precision: 0.959, Recall: 0.921, Dice Coefficient: 0.936, mIoU: 0.926, AHD: 4.897, MAE: 0.019 |
| [35] | 2023 | Joint phase attention network | DCE-MRI | 3 datasets privately collected | Average Dice of 88.77%, 82.77%, 83.03%, Jaccard of 81.27%, 71.89%, 73.23%, and ASSD of 2.21, 3.63, 2.69 |
| [36] | 2023 | BreastSAM | Ultrasound | Private from Baheya Hospital | Benign cases ACC is 0.9795, DCS 0.8567, IOU 0.7628 Malignant cases ACC is 0.9382 , DCS 0.8029, IOU 0.6805 |
| [37] | 2024 | DAU-Net | Ultrasound | BUSI and UDIAT | dice score of 74.23% and 78.58% |
| [38] | 2024 | SC-Unext | Ultrasound | BUSI and Private | 75.29%, 90.62% DCS 97.09%, 98.37% ACC |
| [39] | 2024 | ACL-DUNet | Ultrasound | Mendeley and BUSI | 0.8764, 0.8313 DCS |
| [40] | 2025 | UNet, UNet++, DenseNet, FCNResNet50, FCNResNet101, DeepLabv3ResNet50, DeepLabv3ResNet101 | DCE-MRI | Private from Stavanger University Hospital | Net DSC 0.9831 $\pm$ 0.0142, IoU of 0.9671 $\pm$ 0.0264, and Recall of 0.9963 $\pm$ 0.0069. UNet++ DSC 0.9771 $\pm$ 0.0133, Recall 0.9867 $\pm$ 0.0412. DenseNet IoU at 0.9314 $\pm$ 0.0330 FCNResNet50 DSC 0.9672 $\pm$ 0.0182, FCNResNet101DSC 0.9672 $\pm$ 0. DeepLabv3ResNet50 PRE 0.9743 $\pm$ 0.0236, Recall 0.7597 $\pm$ 0.2084, DeepLabv3ResNet101 PRE (0.9692 $\pm$ 0.0258), Recall (0.9735 $\pm$ 0.0286), DSC of 0.9709 $\pm$ 0.0190. |
| [41] | 2025 | nnUNet | 18F-FDG PET image | Private | 78 %, 89% DCS |
| [42] | 2025 | Combination of AIPT and CASDN | Mammography | DMR-IR,CBIS-DDSM | 0.89 DCS, 0.85 IoU HD 5.2, ACC 85.3 %, AUC-ROC of 0.9 |
| [43] | 2025 | AMFFR-Net model | Mammography | CBIS-DDSM, INbreast, UCHCDM, and BCDR-01 DB | DSC 93.9, IOU 94.7 , 98.94% AUC, 94.8% F1-S, 97.0% ACC |

### 2.4 Breast Cancer Datasets

Datasets consist of data in the form of either numerical data or images; these are the measurements associated with matrices and entities [66]. In this section, BC cancer datasets are described, which are widely used in evaluating the BC segmentation and classification techniques. A summary of the discussed datasets is provided in Table 3.

**BreakHis:** BreakHis is a histopathological image classification dataset consisting of 9109 microscopic images. This data is taken from 82 people using different magnifying factors. A total of 7909 samples are in this data, of which 2,480 are benign and 5,429 are malignant [67].

**BCDR:** BCDR stands for Breast Cancer Digital Repository, consisting of mammography images.

**Table 2.** Summary of breast cancer classification techniques.

| Ref | Year | Methods | Modalities | Dataset/Source | Results |
|---|---|---|---|---|---|
| [49] | 2018 | Custom CNN with a small SE-ResNet module | Histopathological | BreaKhis, TMA | 99.8%, 98.7% ACC 0.996 AUC |
| [50] | 2019 | CustomNet, A-MIL, VGG16_pretrained, ResNet18_pretrained | Histopathological | BreakHis, BACH | Accuracy of different magnifications (40×, 100×, 200×, 400×). customNet 80.56, 82.13, 79.11, and 83.89; VGG16_pretrained 78.64, 78.88, 78.57, and 72.16; ResNet18_pretrained 83.6, 82.58, 85.11, and 84.23; and A-MIL 82.95, 86.45, 86.56, and 84.43 |
| [51] | 2020 | ResHist | Histopathological | BreakHis | Accuracy 84.34%, F1-score 90.49% and when data augmentation is employed, accuracy 92.52%, F1-score 93.45% is achieved. |
| [52] | 2021 | VGG-16, VGG-19, and ResNet-50. | Histopathological | BreaKHis, KIMIA Path960 | 94.05%, 98.13% , 76.77%, 88.95% ACC |
| [53] | 2021 | ResNet-34 and MobileNet-v2 | Ultrasound | UDIAT Diagnostic Centre Breast Ultrasound | MobileNet-v2 2-class (Acc: 0.84, Prec: 1.0, Rec: 0.25, F1: 0.4) and 4-class (Acc: 0.90, Prec: 0.8, Rec: 0.50, F1: 0.62), while ResNet-34 achieved 2-class (Acc: 0.71, Prec: 0.38, Rec: 0.62, F1: 0.48) and 4-class (Acc: 0.84, Prec: 0.67, Rec: 0.50, F1: 0.57). |
| [54] | 2021 | ResNet50 and InceptionV3. | Mammography | CBIS-DDSM | 98.11% ACC |
| [55] | 2021 | BCCNN(Proposed), Xception, InceptionV3, VGG16, MobileNet and ResNet50 (Fine Tuned) | Histopathological | Kaggle | BCCNN outperformed all models (Acc: 98.30%, F1: 98.28%), then Xception (Acc: 97.66%, F1: 97.65%), ResNet50 (Acc: 98.14%, F1: 97.98%), VGG16 (Acc: 97.67%, F1: 97.74%), InceptionV3 (Acc: 95.33%, F1: 95.28%), and MobileNet (Acc: 93.98%, F1: 94.04%). |
| [56] | 2021 | AlexResNet+ | Mammogram | DDSM | 95.87% ACC, 97% PRE, 1.0 SEN, 96% SPE, 98% F1-Score, 96% AUC |
| [57] | 2023 | MFF comprising IFN , VGG-16(Fine-tuned), EmbraceNet , DN and W-MM-U-Net | B-mode and strain elastography Ultrasound Image | Private | Sensitivity: 100% $\pm$ 0.00% Specificity: 94.28% $\pm$ 7.00% Accuracy: 98.46% |
| [58] | 2023 | AlexNet, VGG 19, Inception V3, ResNet-50, ResNet50+ random forest, ResNet50+KNN | Histopathological | BreakHis | Acc of all models are AlexNet 0.81, VGG-19 0.90, Inception V3 0.96, ResNet-50 0.97, ResNet50+ random forest 0.89 , ResNet50+KNN 0.74 |
| [59] | 2023 | VGG16, Xception, ResNet50, DenseNet201. | Histopathological | Breakhis | 98.9% ACC |
| [60] | 2023 | ResNet50, ResNet101, VGG16, and VGG19. | Histopathological | Kaggle | 90.2% ACC, 94.7% REC |
| [61] | 2023 | ViT, DeiT | Histopathological | Breakhis | 98.17% ACC, 98.18% PRE, 98.08% REC, 98.12% F1-Score. |
| [62] | 2024 | VGG16, ResNet50, and InceptionV3. | Histopathological | Private | ACC 84.0% |
| [63] | 2025 | ResNet50, MobileNet, VGG16, and a custom CNN | Ultrasound | Kaggle | 98.41%, 97.91%, 98.19%, 92.94% ACC |
| [64] | 2025 | hybrid binary optimization methods | Mammography | DDSM and CBIS | 96%, 82.86 ACC, 0.97 PRE, 0.83 REC, and 0.99 F1-Score, 0.8291 AUC |
| [65] | 2025 | ES-CNN | Histopathological | BreakHis | 96%, 95%, 98%, and 96% ACC |

There are a total of 7,315 (3,703 Film Mammography + 3,612 Digital Mammography) taken from 1,734 patients and a total of 3 sample classes [68].

**INbreast:** INbreast consists of digital mammographic images. This database has a total of 115 cases and 410 images; several types of lesions were also included in this dataset [69].

**DDSM:** DDSM stands for Digital Database for Screening Mammography. The total number of cases in this database is 2620, consisting of 10480 images. There are primarily two classes in this database: malignant and benign [70].

**BACH:** Breast Cancer Histology dataset was designed to advance the development of automated methods

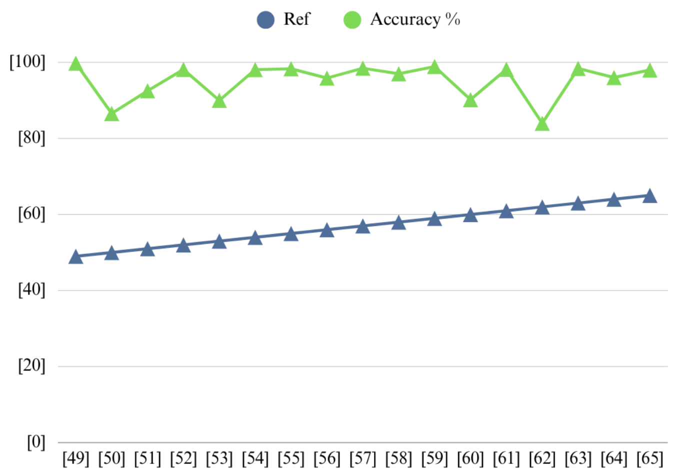


**Figure 5.** Comparison of classification accuracies of reviewed BC classification techniques.

for BC classification. It consists of Histopathological microscopy images with a total of 400 images and four classes: Normal, Benign, In situ carcinoma, and Invasive carcinoma [71].

**MIAS:** MIAS stands for Mammographic Image Analysis Society database and consists of 3 classes: Normal, Benign, Malignant. It has 332 images, and the type in this database is mammography [72].

**CAMELYON17:** The CAMELYON17 dataset is a combination of sentinel lymph nodes consisting of 1399 whole-sided images. There are four classes: No metastases, Isolated tumor cells, Micro-metastases, and Macro-metastases. The image type in this dataset is Histopathological microscopy images [73].

**BreCaHAD:** BreCaHAD stands for Breast Cancer Histopathological Annotation and Diagnosis. This dataset consists of 6 classes: Mitosis, Apoptosis, Tumor nuclei, Non-tumor nuclei, Tubule, and Non Tubule. There are a total of 162 histopathology images [74]. The summary of datasets is presented in Table 3.

### 2.5 Performance Measures

The performance measures are a set of statistics that have been developed to evaluate and describe the predictive performance under different conditions [75]. Here are a few performance measures presented in Table 4.

## 3 Limitations of Breast Cancer Detection Models

Limitations are referred to as the restrictions that occurred in the research. Researchers face certain limitations while working on a problem that binds their research to those limitations. Researchers have used ESTAN to boost small segmentation, although it achieved impressive results, but failed to detect cancer in cases where cases had high speckle noise, extremely low contrast, and no clear tumor boundaries [33]. Another research using the DAU-Net technique identified that this model performs excellently across various segmentation tasks, but gives relatively less precision and accuracy due to the misclassification of tumorous regions. This limitation enabled the researcher to further work on this problem, which is due to dataset complexity and image quality variation [37]. While researching SC-Unext: A Lightweight Image Segmentation Model, the researchers faced a limitation, which was that due to reduced computation resource consumption and model parameters resulted in less accuracy in more complex cases [38]. In ACL-DUNet: A tumor segmentation method researcher faced a limitation relating to hyperparameters and training details. The performance of the model depends on the hyperparameter, and the value of these is obtained from doing experiments again, which makes this method less optimal. During training, this model faced issues with instability and difficulty in convergence, especially in cases of large parameter spaces and multiple layers [39]. While using Generative Adversarial Networks (GANs) and CNNs for breast tumor segmentation and shape classification, the researchers faced limitations in that prior knowledge of cancer must be provided, and another limitation is that the model only segments tumors contained in the ROIs; otherwise model fails to segment [28]. Researchers conducted a comparative analysis of the DL models and saw that training dice loss is higher in ResNet101 shows that it can learn in more detail only if the dataset is insufficiently large, but still, because of the loss, it is not significantly superior to those of ResNet-50. Also, ResNet101 has additional layers that are not fully utilized. DenseNet has a dense connectivity pattern, but it lacks skip connections, and the poorest results can be attributed to this absence of skip connections [40]. Researchers have worked on 18F-FDG PET image segmentation and have said that they have faced these two limitations: first is that the proposed pipeline needs to be validated with a large and diverse dataset, and second that they worked on 18F-FDG PET imaging, but integrating multimodal imaging could enhance the depth of examination [41]. Researchers have worked on 2D images, and the limitation they faced is that there is

**Table 3.** Summary of breast cancer datasets.

| Dataset | Location | No of classes | No of Images | Image Dimensions | Modality |
|---|---|---|---|---|---|
| **Breakhis** | Federal University of Paraná (UFPR), Brazil | 2 | 7909 | 700 × 460 pixels | Histopathological |
| **BCDR** | University of Porto, Portugal | 3 | 7,315 | **BCDR-FM:** 720 × 1,168 pixels **BCDR-DM:** 3,328 × 4,084 pixels or 2,560 × 3,328 pixels | Mammography |
| **INbreast** | Centro Hospitalar de S. João, Porto, Portugal | 6 | 410 | 3328 × 4084 pixels | Full-Field Digital Mammography (FFDM) |
| **DDSM** | University of South Florida | 2 | 10480 | 4,800 × 6,000 pixels | Film Mammography |
| **BACH** | ICIAR 2018 | 4 | 400 | 2048 × 1536 pixels | Histopathological microscopy |
| **MIAS** | UK | 3 | 332 | 1,024 × 1,024 pixels. | Mammography |
| **CAMELYON17** | Five medical centers in the Netherlands | 4 | 1339 | Depends on the tissue sample size. | Histopathological microscopy |
| **BreCaHAD** | Private | 6 | 162 | 512 × 512 pixels. | Histopathological |

**Table 4.** Performance measures used for breast cancer segmentation and classification.

| Performance Measures | Mathematical Representation |
|---|---|
| Accuracy | $\frac{TP+TN}{TP+FP+TN+FN}$ |
| Precision | $\frac{TP}{TP+FP}$ |
| Recall | $\frac{TP}{TP+FN}$ |
| F1-Score | $\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$ |
| Dice Coefficient | $\frac{2TP}{2TP+FP+FN}$ |
| Jaccard Index or Intersection-Over-Union (IoU) | $\frac{TP}{TP+FP+FN}$ |

a possibility of using same method for segmentation for 3D images but during slicing data can be lost and accuracy can be reduced due to lack of context between slices [36]. Researcher have used AIPT and CASDN for image segmentation and during this process the limitation they have faced are the preprocessing which is computationally intensive and is less ideal. Another limitation is the replicating and confirming methods are very comprehensive [42]. Researchers used ensemble learning and transfer techniques for classification and have concluded that even though they achieved the goal, there is room for improvement, like classifiers with better performance can be selected. Along with the weighted voting method used in that paper, other ensemble strategies and weights can be used. Another limitation is that this research paper focuses on two class classifications; in the future, multi-class classification can also be done [59]. Researchers have done deep analysis on transfer learning and have discussed the things that could be done to improve accuracy, which were to employ more sophisticated pre-trained transfer learning models to detect breast cancer [60]. Researchers have worked on BC Histopathological Image Classification and have faced limitations, which are variations in image quality that cause difficulty in distinguishing cancer types. The dataset used in this research has images from different devices, which also affects how the model performs [49]. Researchers have used AlexResNet+ for classification, and during that, they have faced certain limitations, which are that combining features of two deep learning models needs extra attention and processing that can be exhausting, and also the selection of the right classifier is important that Suggests that achieving reliable performance requires sophisticated model configurations [56]. Researchers have worked on BC Image Classification Method Based on Deep Transfer Learning and limitations they face are firstly their model does only binary classification without distinguishing the subtypes. Another limitation is models parameters and size are higher without optimization [62]. While the proposed hybrid binary optimization method performs well but the influence of nested transfer function is yet to be analyzed because this function play an important role in optimization process [64].

## 4 Discussion

The BC detection mechanism evolved through the integration of various techniques, including DL and ML. From the reviewed literature, it is evident that DL architecture, especially CNNs, is most commonly used by researchers for better efficiency and improvements across various imaging modalities. The efficiency of DL is attributed to its potential to autonomously learn hierarchical features, which are critical in the recognition of tumors. The DL models are widely adopted for classification and segmentation and demonstrate high performance in terms of robustness. Although DL models are more often and widely used, on the other hand, ML techniques also hold relevance in some scenarios, including limited datasets and when there are constrained on computational resources. The choice of the modality creates a significant influence on the design and performance of the model. Ultrasound, being cost-effective and non-invasive, suffers from speckle noise and inter-operator variability, which affect the performance of both DL and ML models. Mammography is also a standard one but exhibits a decrease the sensitivity in dense breast tissues. MRI gains high sensitivity, but is not often utilized for primary screening. Histopathology samples provide cellular-level resolution and are used for confirmatory disorder, but require fine and detailed annotations. Another observation from the literature is the reliance on the imbalance and limited datasets, which raises major concerns about the generalization and overfitting of the models. This limitation underscores the need for large and more inclusive datasets. Further, the computational limitations are very significant challenges, as the DL model requires high-performance GPUs. Hyperparameter tuning is very important for the optimization of the model. Various models are trained in controlled settings, which lack real-world validation in clinical data. Lastly, various research gaps are identified, and addressing these gaps is essential for the better recognition of BC from experimental to real-world applications.

## 5 Conclusion and Future Directions

BC detection is still a critical area of research due to its significant global impact on health outcomes. The presented survey has reviewed the variety of DL and ML-based approaches across multiple modalities, including histopathology, ultrasound, and MRI. The literature demonstrates that the DL methods have shown promising outcomes in both segmentation and classification tasks; however, many challenges persist. The efficiency of the model is bound by limitations such as an imbalance of datasets, small datasets, and computational demands. The current state of the research reflects and highlights the gaps that must be addressed.

### 5.1 Future Roadmap

For this emerging domain, to guide the researchers in the future, a roadmap is proposed below:

- Integration of multimodal architecture: the research in the future should demonstrate the integration of complementary details from multiple modalities for the enhancement of the diagnostic accuracy.
- Trust and explainability: the development of explainable AI architectures is crucial in trust-making in decisions for real-world applications and clinicians.
- Standardization and data quality: the creation of large, standard, and balanced annotated datasets is very important for overcoming bias, and it also ensures reproducibility across various studies.
- Effective and lightweight models: the development of resource-effective DL frameworks will enable the making of low-resource settings and make new AI solutions that will be accessible worldwide.
- Personalized and longitudinal analysis: the system in the future should be more patient-specific to support prognosis and personalized treatment planning.

## Data Availability Statement

Not applicable.

## Funding

This work was supported without any funding.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Ethical Approval and Consent to Participate

Not applicable.

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**Muhammad Moosa Raza Khan** is a BS Computer Science student at HITEC University Taxila. (Email: 22-cs-044@student.hitecuni.edu.pk)

**Mehwish Zafar** received a Master's degree from COMSATS University Islamabad, Wah Campus in 2022 and is presently pursuing her PhD. Her research focuses on medical imaging, machine learning, and deep learning, with a particular interest in developing AI-driven solutions for healthcare. (Email: mehwish.zafar@hitecuni.edu.pk)

**Abdul Majid** received a Master's degree from COMSATS University Islamabad, Wah Campus in 2020, and he is currently pursuing a Ph.D. at the same institution. His research focuses on medical imaging, machine learning, and deep learning, with a particular interest in developing AI-driven solutions for healthcare. (Email: abdul.majid@hitecuni.edu.pk)

**Fadia Ali Khan** received a Ph.D degree in Electrical Engineering. She is currently working as Assistant Professor in HITEC University. (Email: fadia.ali@hitecuni.edu.pk)