

Early 2024 Research on Recent Advances in the Diagnosis of Breast Cancer Leveraging Deep Learning Techniques

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Article History:

Received: 23-10-2024

Revised: 09-11-2024

Accepted: 17-12-2024

Abstract:

Breast Cancer (BrC) is still a serious worldwide health issue, requiring innovative methods of early detection to enhance patient outcomes. If BrC is detected and treated early, there is a strong chance that the patient will recover. In order to predict the growing of cancer cells using medical imaging modalities, a number of researchers have developed automated DL-based approaches that are effective and accurate. There are currently very few review studies that provide an overview of some of the existing research on BrC diagnosis. Emerging architectures and modalities in the diagnosis of BrC, however, were not covered by this research. This review canters on the developing deep learning (DL) architectures for the detection of BrC. However, were unable to address new modalities and architectures in the diagnosis of BrC. The developing DL architectures for BrC detection are the main topic of this review. The survey that follows outlines current DL based architectures, evaluates the advantages and disadvantages of previous research, looks at the datasets that have been used, and goes over image pre-processing methods. This study supports ongoing efforts by the global healthcare community to improve BrC outcomes by utilizing state-of-the-art technology to enable timely and effective detection. It also presents research directions for future researchers, challenges, and performance metrics and results.

Keywords: Deep Learning methodologies, Image data processing methods, Breast Cancer Diagnosis, Classification algorithms.

Introduction

Globally, BrC is the most frequently diagnosed cancer. More than 2.26 million new cases of BrC were predicted for 2020 by the World Health Organization's (WHO) study on the disease's present and future problem. According to a more recent study, 31% of female cancers in 2023 will be BrC, making it the most common cancer diagnosed in women. Since mid-2000s, female BrC incidence rates have risen by about 0.5% annually, a tendency that has been at least partially ascribed to increases in excess body weight [2] and also in 2022, BrC was the most prevalent cancer among women in 157 out of 185 countries [1]. In developed nations, ML and DL algorithms are commonly used for BrC screening. These algorithms are used to predict whether digitalized images [3-6] from magnetic resonance imaging will have anomalies associated with BrC. This study demonstrates that DL algorithms can be applied to the prognosis of BrC by applying DL to heterogeneous data from medical records (demographic and anthropometric information), biological indicators from routine blood samples, and relative risks from meta-analyses and publicly available databases.

simple summary: BrC is the most common cancer, with 2.3 million women receiving a diagnosis and approximately 685,000 deaths from the disease reported worldwide in 2020. Improving the prediction and raising the percentage of patients who survive to 50% depends on early and precise detection of BrC. In the early detection of BrC, DL based computer aided diagnosis (CAD) has demonstrated impressive results. The literature examining DL architecture for BrC diagnosis is the main focus of this review. The comprehensive, analytical review of this study is based on model architecture of BrC diagnosis, datasets and image data preprocessing, BrC imaging approach and performance measures. When certain cells in the breast begin to grow out of control and form a mass known as a tumor, BrC starts. Usually, a BrC diagnosis is classified as either malignant or benign. Malignant tumors are dangerous because they have the ability to metastasize or spread to other body parts through the bloodstream or circulatory systems.

Here figure 1 illustrates the distinction between benign and malignant tumors by comparing the normal and tumor cells, and both benign and malignant tumors are shown in Figure 1(b). Generally speaking, benign tumors stay localized and do not spread. A newly inverted nipple, changes in skin covering the breast, such as puckering or dimpling, a noticeable lump or mass in the breast, breast pain, and release from the nipples other than breast milk are some of the symptoms that indicate breast cancer. BrC is the second most common cause of death for women, after heart disease. Additionally, about 8% of women will encounter it. According to the WHO annual report, over 500,000 women receive a BrC diagnosis each year. In impoverished countries, women often arrive at early stage with limited treatment possibilities due to a lack of screening facilities and knowledge. Genetic mutations, hormones, obesity, early-life radiation exposure, and family history are all recognized risk factors for BrC.

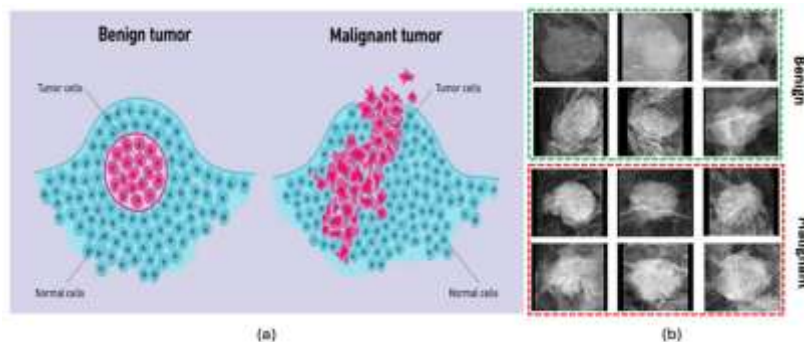


Figure 1. Shown in the BrC visualization. (a) benign and malignant tumour cells, (b) benign and malignant masses.

In the battle against maternal cancer-related mortality, early detection and timely treatment have become crucial components. The use of routine mammography exams has helped achieve these objectives. On the other hand, because mammography screenings depend on the knowledge of human specialists, they are highly costly and resource-intensive. Several nations are on the verge of putting radiologists to death, which would make matters worse. The high rate of incorrect results from mammography tests is a minor but important adverse effect. This situation leads to a number of problems, such as the patient's unwarranted mental distress, the requirement for unwanted help with

follow-up care, further imaging tests, and occasionally the utilization of invasive tissue collection methods like needle biopsies.

The medical imagination sector is willing to use these methods to increase the precision of BrC detection because of the continuous development of DL in particular. Among cancers that affect women in the US, BrC ranks as the second important origin of death. Screening mammography is an important strategy for reducing mortality rates. However, screening mammography has a high rate of false positives and false negatives in spite of these advantages. Figure 2 depicts the system architecture intended for early cancer diagnosis. It uses state-of-the-art technologies like DL and medical imaging to increase the accuracy of the diagnosis.

The architecture emphasizes smooth data flow from medical image collecting to automated analysis with state-of-the-art algorithms. By detecting any abnormalities as soon as possible, this abbreviated process aims to improve early diagnosis. By facilitating quick intervention and treatment options through the combination of innovative approaches, the proposed system aims to enhance the results for patients.

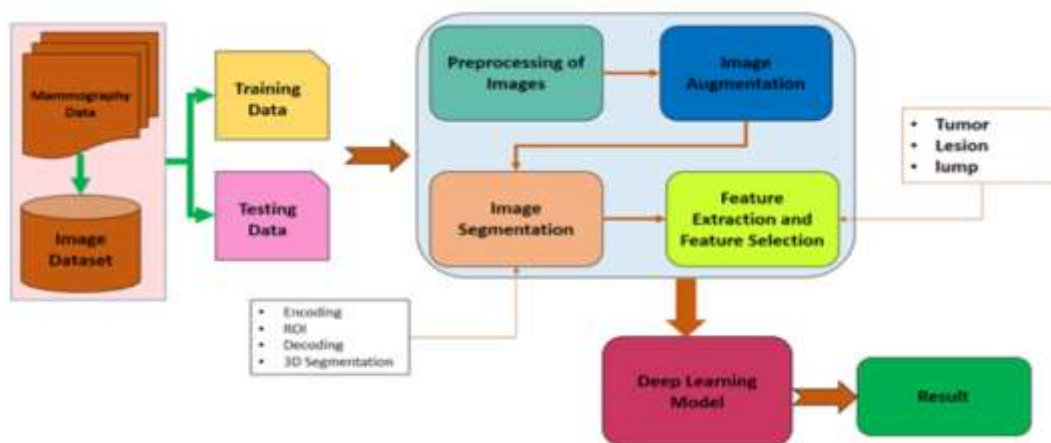


Figure 2: Early-stage Cancer Detection basic procedural architecture

The typical digital screening mammography sensitivity and specificity [7] in US are 86.9% and 88.9%, respectively. Radiologists have been using CAD software to increase the prediction accuracy of screening mammograms since the 1990s. Unfortunately, performance was not greatly improved by the first generation of commercial CAD systems, which caused research to stall for ten years. However, because of its remarkable performance in object identification and other domains, DL has rekindled interest in developing DL tools for radiologists. According to recent studies, DL-based CAD systems can even perform better than radiologists when used in support mode than when used independently.

Literature Survey

Background & Objective:

One of the main causes of death for women, particularly in poorer nations, is BrC. In order to lower death rates, timely diagnosis, detection, prediction, and effective treatment are now essential. Models for predicting and diagnosing BrC become more reliable and accurate as artificial intelligence (AI),

machine learning (ML), and DL approaches are used more frequently. Examining the efficacy of various ML and contemporary DL models for BrC diagnosis and prediction is the goal of this study.

Breast-Cancer-Diagnosis Methods Based on DL: Recent advances in DL algorithms and their exceptional performance have encouraged several researchers to use DL to the diagnosis of BrC. The ability to categorize breast masses as benign or malignant without the requirement for a selection procedure, lesion segmentation, or image feature calculation is one of the benefits of the DL-based CAD technique [11-19]. This section discusses the main categories of DL-based BrC diagnosis methods currently in use. These include generative adversarial networks (GAN), autoencoders, DL networks, CNN, ELM, and ANN. The number of research on BrC diagnosis that are published annually employing various architectures is shown in Figure 3.

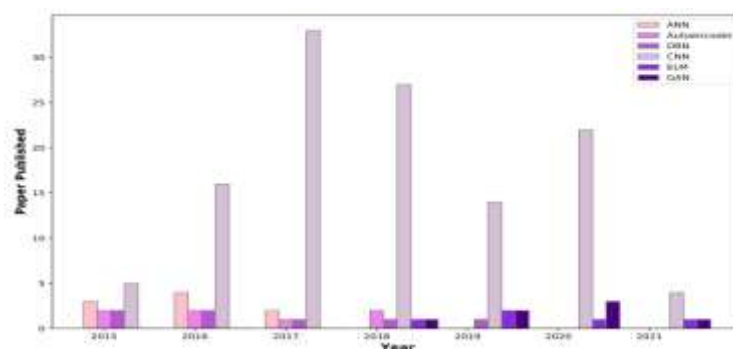


Figure 3. The number of DL-based BrC studies that have been published during the last six years is displayed in this image.

Artificial Neural Network (ANN)

ANN is a scientific model that is in line with the capabilities and structure of a biological neural network. From a computer science perspective, it receives, processes, and transmits information in a manner akin to that of a real human brain. The diagnosis of BrC relies heavily on ANNs. It is crucial to make clear that ANNs are meant to assist radiologists in maintaining their accuracy and dependability, not to take their position. ANN-using radiologists will eventually displace their non-ANN-using counterparts. Radiologists are receiving training on how to identify the weaknesses of ANNs and take use of their benefits. Radiologists shield patients from false-positive results from artificial neural networks [21]. Although it requires more time to train for complex tasks, ANNs with several hidden layers perform well.

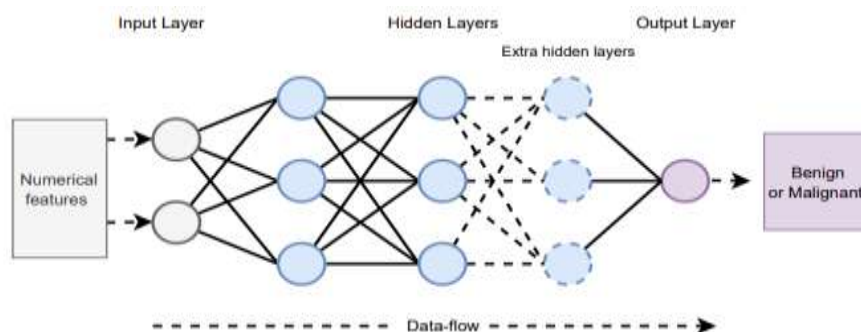


Figure 4. An example of a multi-layered ANN used to diagnose BrC

Figure 4 shows the fundamental design of an ANN [22-23] with several hidden layers. A few-layer ANN, on the other hand, is easy to design and train, optimize the training parameters. Moreover, greater generalization efficiency is achieved with a smaller amount of data. However, function well with high-dimensional statistics.

Table 1. Cutting-edge research using ANN architecture

Author	Datasets	Design Study	Strong point	Limitation
Jafari Marandi et al. [21]	WDBC	LS-SOED	Motivated to make better choices	Including the missing values from the dataset
Becker et al. [22]	BCDR	ANN	accurately detect a tiny mass lesion	Not enough pictures
Rouhi et al. [23]	DDSM, MIAS	ANN	Recognize tiny masses correctly	Not enough pictures

Convolutional Neural Network (ConvNet)

A CNN often known as ConvNet or CNN is a DL framework that design ideas form the foundation of CNN architecture: sub-sampling, weight sharing. The original purpose of the ConvNet was to recognize patterns in two-dimensional images. Three layers comprise a ConvNet an output layer, max-pooling layers, and convolution layers. Since the ConvNet is a key tool in BrC classification.

In earlier research, ConvNets are more frequently used to create a trustworthy BrC classification model [18-19], ConvNet s are utilized with a range of imaging modalities due to their strong picture performance. However, training a ConvNet requires a lot of images. Achieving decent performance with a small number of photos is challenging. Furthermore, the cost of acquiring labelled datasets in medical imaging makes it challenging to acquire sufficient training data. ConvNet has a lot of benefits. A ConvNet requires far less pre-processing than other classification techniques. A single ConvNet design completely combines feature extraction and classification. Finally, it can withstand local geometric aberrations and image noise. As a result, research has employed ConvNet s to perform BrC classification and extract valuable features from medical images [21]. BrC classification mostly uses TL-based ConvNets (pre-trained CNNs) and de-novo ConvNet s (ConvNets trained from the beginning).

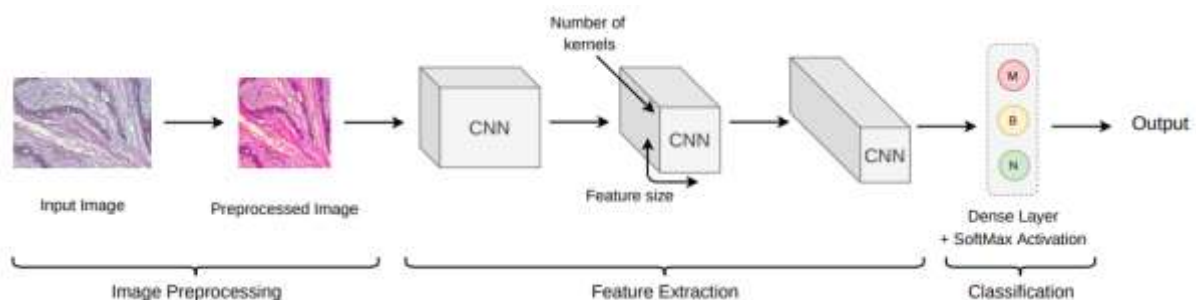


Figure 5. An example of a CNN-based model for diagnosing BrC.

Autoencoder

An approach to unsupervised learning by using back-propagation, the autoencoder modifies the desired values to correspond with the inputs. Input layer, hidden layer and decoding layer are the three layers that make up this neural network. An input is transformed into a hidden layer by an autoencoder and input from the hidden layer is then reconstructed by the decoder. Autoencoders come in four varieties: contractive autoencoders (CAE), variational autoencoders (VAE), sparse autoencoders (SAE), and denoising autoencoders (DAE). A denoising variant of the stacked autoencoder is the stacked denoising autoencoder (SDAE). We benefit from auto-encoders since they lower the data's dimensionality. Training an autoencoder requires a lot of data, processing time, model validation, and hyperparameter tweaking. Despite their similarities, autoencoders are more adaptable than principal component analysis (PCA). An autoencoder is capable of both linear and non-linear transformation, whereas PCA is limited to linear transformation. Figure 6 depicts an autoencoder's construction.

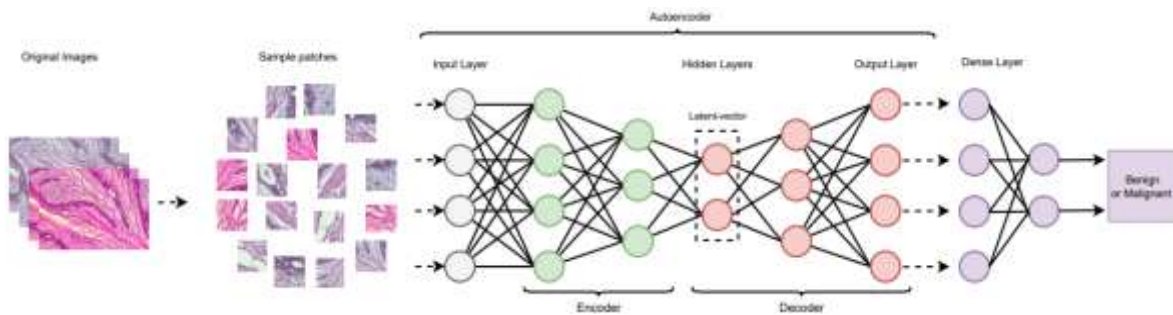


Figure 6: A sample of the autoencoder model used to diagnose BrC.

In order to classify nucleus patches on breast cancer histopathology pictures, Xu et al. [24] proposed a stacked sparse autoencoder (SSAE) framework made up of two SAE. The SSAE framework learns high-level features for better raw input data representation in an unsupervised way. In comparison to PCA+Softmax, SAE+Softmax, and the traditional softmax classifier, the assessment result using SSAE+Softmax for classifying nuclei patches was superior. However, only 17 patients were included in the cohort from which the breast histopathology pictures were gathered. Follow-up research comprising 537 H&E-stained histopathology pictures was then reported by Cheng et al. [27]. They suggested using the SSAE framework to detect BrC nuclei. They did not, however, take into account any pre-processing methods. Kadam et al. [25] shown that feature ensemble learning with SSAE outperforms the SSAE+softmax architecture in another investigation.

Table 2: Cutting-edge research using autoencoder architecture

Author	Dataset	Design Study	Strong Point	Limitation
Xu et al. [24]	PD	SSAE + Softmax	Advanced feature learning	Not enough pictures
Kadam et al. [25]	WDBC	FE-SSAE-SM	Sufficient assessment	Lack of methods for data preprocessing

Feng et al. [26]	BCC	SSAE + Softmax	Making use of strong breast cancer nuclei characteristics	Not enough pictures
Cheng et al. [27]	PD	SDAE	Sufficient model assessment	Lack of a model comparison

De-Novo ConvNet

A ConvNet with a limited layers or several layers that was trained from the beginning was used in a number of research. We call these De-novo CNN. Deep CNNs with multiple layers and a lot of data can produce superior picture classification results. Compared to standard ImageNet-transferred models (pre-trained models), the lightweight CNNs that were built from scratch perform better. According to research by Arevalo et al. [30], the pre-trained model was outperformed by the smaller CNN that was constructed from scratch. Figure 6 shows a basic CNN method for diagnosing BrC.

Table 2. Cutting edge research created on De-novo CNN.

Author	Dataset	Design Study	Strong Point	Limitation
Albarqouni et al. [28]	BreakHis	AggNet	Evaluated using a standard dataset	untrustworthy annotations
Kooi et al. [29]	PD	CNN	Centered on identifying solid, cancerous lesions, such as architectural abnormalities	No benign tumours were seen in the training set
Arevalo et al. [30]	BICBH	CNN(UDM)	Classification into multiple classes	Not enough pictures
Ting al. [31]	MIAS	CNN-BCC (UDM)	Feature-based data enhancement	Not enough pictures
Yan et al. [32]	PD	CNN+RNN	published a more extensive and varied dataset	Insufficient pre-processing of data
Wang et al. [33]	BreakHis	CNN (UDM)	There is classification for various magnification factors	Insufficient preprocessing of images

Previous studies employed benchmark datasets with ConvNets for image classification; however, some studies used their own dataset, which prevented other researchers from conducting comparisons [28, 29]. Image segmentation and feature extraction are further applications for CNNs [31–33]. Using ConvNet’s extracted features to train an SVM classifier, Arevalo et al. [30] demonstrated how well a ConvNet can extract important features.

Transfer Learning (TL)-Based ConvNet

TL works well with small datasets because it allows pre-trained networks to be adjusted and changed to handle problems from a particular domain or imaging modality. Using a pre-trained version pre-initializes the model weights rather than initializing them randomly during training from scratch. But because of its tendency to overfit, TL could be troublesome. Most commonly used are AlexNet, VGG-Net, GoogLeNet, and ResNet as TL-based models.

Natural images are used to train the pre-trained models, which frequently have deep architectures to learn a lot of class labels. For instance, AlexNet had three fully connected layers and five convolution layers after being trained for 1000 class labels. For the classification of breast masses, a multi-task TL DCNN was proposed by Samala et al. [35]. This work shown that when the number of images is restricted, multi-task DCNN may still be useful. A pre-trained ConvNet was used in a reviewed by Chougrad et al. [36] to extract valuable characteristics from a small amount of data (78 photos). [37,38] evaluated de-novo and tuning models on four medical imaging applications. In addition to being more resilient to the training set scale, the authors demonstrated that ConvNets that were tuned (TL-based) outperformed ConvNets that were learnt from beginning (de-novo).

Table 3. Cutting-edge research using a TL-oriented ConvNet.

Author	Dataset	Design Study	Strong Point	limitation
Huynh et al. [34]	PD	AlexNet	Segmenting lesions automatically	Insufficient assessment of the model
Samala et al. [35]	DDSM	CNN (FTM-ML)	Transfer learning across many tasks	There is no model comparison
Chougrad et al. [36]	DDSM, BCDR	VGG16, ResNet50, Inception v3 (FTM-ML)	Merged three datasets	Insufficient assessment of the model
Xie et al. [37]	BreakHis	CNN (FTM-LL)	resolved the imbalance in the sample distribution	Absence of pre-processing for pictures
Kumar et al. [38]	BreakHis	VGGNet-16 (FTM-ML)	Examination of the impacts of image preprocessing	Magnification affects the accuracy
Yu et al. [39]	PD	CNN (FTM-ML)	Pictures are gathered online	The images may not be of sufficient quality.
Hu et al. [40]	PD	CNN (FTM-ML)	Large datasets, lengthy training periods, and pre-processing are not necessary	Class inequality is a problem

Extreme-Learning-Machine (ELM)

ELM is an ANN variant that has a lot of promise for managing BrC classification. Classification, pattern recognition, grouping, and regression are common applications for ELM [42], a feed-forward neural network having one or more hidden layers. The analytic calculation of the final weights and the random initialization of the input weights and biases form the basis of this methodology. As a result, the ELM is not affected by manually setting parameters. ELM’s advantages of rapid learning and low computational costs have made them famous for solving a different range of challenging problems [43-46]. ELMs can be useful in situations requiring real-time network retraining, despite their lower accuracy compared to normal neural networks. Additionally, the ELM training process takes a long period. Figure 6 displays the ELM's architecture.

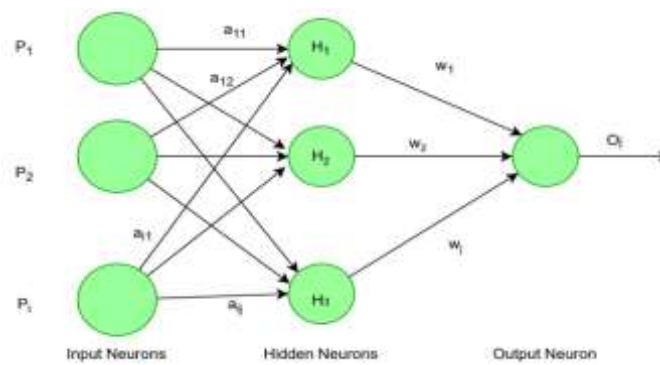


Figure 6. A simple machine architecture for extreme learning.

Table 4. cutting-edge research using the ELM design.

Author	Dataset	Design Study	Strong Point	Limitation
Lahoura et al. [42]	WBCD	ELM	Taking feature engineering into consideration	Lack of an image preprocessing method
Wang et al. [43]	PD(Mammograms)	ELM	Fusing features	Too small data
NEMISSI et al. [44]	WBCD	ELM	Better success in generalization	Poor assessment
Wang et al. [45]	BreakHis, ImageNet	ELM(ICELM)	A New Approach	An end-to-end design is not used
Muduli et al. [46]	WBCD	ELM	In terms of speed and performance, ELM outperforms alternative techniques	Unbalanced classes

Latest and Novel Techniques Summarization

Table 5: Recently proposed techniques are summarization

Author	Methodology	Challenges	Challenges and Limitations
Ghughe and Saravanan (2024)	Swin ResUnet3+	It effectively segments the abnormal regions. It performs better in image restoration and edge detection tasks.	Training the model consumes more time.
Chakravarthy et al. (2023)	ELM	It learns the data very faster. The generalization performance and the robustness of the model are high.	Due to the presence of hidden layer, the complexity of the model is high.
Kavitha et al. (2022)	Capsule Neural Network	It has the ability to remove noise in the images. The infected breast region is segmented effectively.	The complexity of the model is high. It is not suitable for large datasets.
Sarrawe et al. (2023)	CNN	The features from mammogram images are retrieved automatically. Overfitting is eliminated by employing global pooling method.	Need of labelled data is high. Time taken for training the model is high.
Kumari and Jagadesh (2022)	XGBoost	The intensity, shape and texturebased features are retrieved for effective classification process	Overfitting issues occur while training small datasets. Tuning hyperparameters is difficult
Kaur et al. (2019)	multi-class SVM	It is suitable for resizing and noise handling operations. Even in high dimensional spaces, it performs effectively.	It does not rectify the overlapping issues. It does not provide stable results if the training samples are large.
Altameem et al. (2022)	CNN and Fuzzy	It provides correct decision scores from the input images	It is not useful for localization of brain tissues.
Omonigho et al. (2020)	DCNN	It helps to learn and retrieve features automatically. It attains high classification accuracy.	It needs a greater number of parameters. Time consumption is high

Datasets and Utilizations in Recent Trends

The Wisconsin BrC Dataset is established by the University of Wisconsin Hospitals' Wisconsin BrC Database (WBCD) [42,44,46] and it is extensively utilized clinical data set. There are 699 cases in this collection, and each case has 11 attributes. The independent features include mitoses, naked nuclei, bland chromatin, normal nucleoli, single epithelial cell size, cell size and shape uniformity, lump thickness, and marginal adhesion. For training, DL algorithms require a large dataset. One of the biggest challenges in using DL algorithms for medical diagnostics is the absence of data. Many researchers classified BrC using data they individually acquired; these are known as private datasets (PD) [43].

Our study's most significant criticism is that academics train and validate the proposed approaches using such a limited dataset. In order to tackle this issue, most researchers used TL. Nonetheless, a number of studies made use of publicly available databases. To ascertain the patient's current state, professionals carefully examine histopathological pictures, which offer important information. The BreakHis and TUPAC16 databases provide histopathological pictures. CBIS-DDSM, mini-MIAS, and MIAS are common mammography datasets.

Table 6. Comprehensive details of datasets that are accessible to the public

Dataset	Category	No. of Images	Classes	Image Format
DDSM [48]	Mammograms	10,480	Benign, cancer, normal, benign without callback (bwc)	JPEG
MIAS [49]	Mammograms	322	Benign, malignant, normal	PGM
CBIS-DDSM [50]	Mammograms	1644	Normal, benign, and malignant	DICOM
BreakHis[51]	Histology images	7909	Benign and malignant	PNG
WBCD or WBCO [52]	Multivariate	699	Malignant, Benign	..
WDBC [53]	Multivariate	569	Benign, malignant	..

Problem Identification Study

The current techniques for detecting BrC are ineffective when lumps and abnormalities are visually examined. To identify structural deformation and bi-lateral asymmetry, better imaging methods should be employed. The methods used to detect BrC should be reliable in order to identify if malignant tissues are present or not. Table 5 lists some of the characteristics and difficulties of the current BrC detection technique. In addition to performing better in image restoration and edge detection tasks, Swin ResUnet3+ efficiently segments the aberrant regions. However, it takes more time to train the model. ELM picks up information far more quickly. Additionally, the model's resilience and generalization performance are excellent. However, the model's complexity is large because of the hidden layer. The Capsule Neural Network [53] can eliminate noise from pictures. The area of the diseased breast is successfully segmented. The model is not appropriate for huge datasets due to its high level of

complexity. CNN [54] mechanically extracted features from mammography pictures. The global pooling method eliminates overfitting.

On the other hand, training the model takes a lot of time and requires a lot of labeled data. For an efficient classification method, XGBoost [55] recovers features based on texture, shape, and intensity. However, it is challenging to adjust the hyperparameters and overfitting problems arise while training tiny datasets. Multi-class SVM [56] is appropriate for noise handling and resizing tasks. It works well even in high dimensional spaces. However, if the training samples are extensive, it does not produce steady findings and does not address the overlapping difficulties. Based on the input photos, CNN and Fuzzy [58] produce accurate decision scores. However, it is useless for locating brain tissues. DCNN [59] achieves high classification accuracy and aids in automatically learning and retrieving information. However, it requires more settings and takes a lot of time. Therefore, a sophisticated method for segmenting and classifying BrC is suggested.

Technical Discussion

The aforementioned research compares recent advancements in segmentation, feature extraction, and classification techniques based on ML and DL to detect BrC from mammograms. Table 5 summarizes a few newly suggested methods. Fair performance analysis is a highly difficult undertaking because multiple researchers utilize different datasets and validation standards. The database-wise quantitative performance analysis of a few widely used mammography-based BrC screening methods is another main emphasis of this part.

Key Challenges and Issues

Even if ML and DL approaches yield positive outcomes, there are still some problems and obstacles that must be resolved. Here, we've highlighted some of the main issues raised in this section.

- There aren't many standard mammography databases that are openly accessible. As a result, established methods are struggling to produce high-quality results. Combining different methods, such as data augmentation, TL, active learning, and cooperation, can produce a comprehensive plan to get over the limitations of tiny, publicly available mammography databases. These approaches should improve the performance of traditional BrC detection techniques while also boosting the system's overall accuracy and dependability.
- Rather than three classes (normal, benign, and malignant), some datasets only offer two classes (benign and malignant). These class databases use a three-class classification approach to give a more complete view of BrC cases. This makes it possible for researchers and medical professionals to evaluate and develop classification models that accurately distinguish between benign abnormalities, healthy breast tissue, and cancerous tumors. The additional "normal" category makes it easier to distinguish between benign and malignant breast tissue abnormalities. The three-class categorization simultaneously detects cancer, benign, and normal, despite the fact that it is quite difficult. Thus, this could be a worthwhile line of inquiry.
- The noise, outliers, weak edges, and intensity variation make it harder to detect and classify BrC. The solution includes picture enhancement preprocessing, robust feature extraction and selection, robust classification algorithm implementation, ensemble methods, data enhancement, local characteristic adjustment, quality control, and error analysis. These methods aim to improve image

quality, manage variations, enhance feature representation, strengthen resilience, and optimize algorithms for precise BrC diagnosis and classification.

Further Implementation Scopes

From the above analysis adequate scope for more research to be done. This section presents some of the future scopes.

➤ A standard public database that includes multiple image modalities of the same individual can be created. Adding images from various light conditions, resolutions, and mammography views can create a new, larger database that offers a platform for reliable BrC detection and classification. Therefore, by combining the capabilities of each of these modalities, a reliable and precise system can be created.

➤ The development of more reliable and accurate ML, TL, and DL-based methods may improve the segmentation and classification performance. By using an ensemble or hybrid classifier, the performance can be further improvised. An ensemble classifier typically has a higher overall accuracy than any single classifier because it combines the predictions of many different classifiers. They use the combined knowledge of multiple base models to offset the shortcomings and biases of individual classifiers. In a similar vein, a hybrid classifier combines multiple classifier types to capitalize on their complementary advantages and get around their distinct drawbacks, thus enhancing the system's overall performance.

Conclusion

Outlines of this study to improve the BrC categorization outcomes. The possible future research directions are indicated below based on a thorough investigation of this subject. Currently, BrC is diagnosed using CNNs and ANNs. Other types of DL networks, including clustering, RNNs, and GANs, should be investigated in this area. CNN's capacity to extract valuable information from images makes it a popular choice for BrC classification. We recommend that different CNN architecture-based methodologies and hyperparameter tuning be studied. The choice of features and classifiers has a significant impact on model efficiency. Performance could potentially be improved by taking into account the features and classifiers chosen. According to a study, more clinical data could improve the classifier's effectiveness. In contrast to managing data scarcity, expanding data would enhance model performance and facilitate experimentation with core model performance. The training technique known as "same-domain TL" makes use of pictures that are similar to the target dataset. For instance, the model is trained on X-ray images of different breast disorders before being refined and trained on X-ray images of BrC to diagnose BrC. Since same domain TL has lately shown encouraging results, it should be investigated. Studies that use these imaging modularity's also examine unpublished datasets. For the sake of future knowledge discovery and application, the study datasets ought to be disclosed.

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