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Breast Cancer Classification Utilizing Deep Learning Techniques on Medical Images: A Comprehensive Review

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Abstract: **-** Breast cancer is a major public health concern, affecting millions of women worldwide. Good patient outcomes and a successful course of therapy depend on a prompt and accurate diagnosis. The application of deep learning algorithms to the breast cancer classification problem has yielded some encouraging results; this might open the way for more rapid and accurate diagnostics. This article examines the many deep learning (DL) approaches taken to date for BC classification tasks, outlining each one's strengths, weaknesses, and current challenges. This study discusses several DL algorithms like convolutional neural networks, multi-layer neural networks, and autoencoders that analyze histopathological pictures, mammograms, and other forms of medical imaging. Furthermore, we investigate the interpretability & explainability features of DL models as they pertain to BC diagnoses, drawing attention to the need for reliable decision-making tools for medical practitioners. Throughout the review, we identify challenges and potential biases in current research. Finally, we provide an outlook on the future directions of DL in BC classification, focusing on promising research areas. By highlighting the achievements and gaps in the existing literature, this review aims to inspire further advancements in DL-based BC diagnosis, eventually resulting in better healthcare and reliable diagnosis.

Keywords: Autoencoder (AE), Breast Cancer Classification (BCC), Convolutional Neural Networks (CNN), Deep Learning (DL), Multi-layer Neural Networks (MLNN), Medical Images (MI).

I. INTRODUCTION

As a significant global public health risk, breast cancer ranks second among female cancers in terms of fatality rates [1]. Breast cancer death rates can be drastically reduced with early identification and precise categorization. Numerous research has shown encouraging results for breast cancer categorization using deep learning techniques, which have recently emerged as effective tools [2-9]. Worldwide, breast cancer ranks high among cancer-related fatalities among women, making it a significant public health problem [10,11]. Regarding to early identification of BC, the gold standard is often a biopsy with subsequent histological assessment. This dramatically improves survival rates [11]. Nevertheless, this procedure is not easy, requires a lot of work, and might cause pathologists to dispute a lot [12]. Technological developments in digital imaging in the last several years have opened the door to the prospect of pathological picture evaluation by computer vision and machine learning. Faster and more accurate quantification, less observer variability, and greater objectivity might result from these technologies automating parts of the diagnostic pathology procedure [13].

Deep learning, a portion of ML, has been demonstrated to be very successful on numerous tasks, including image processing, natural language processing, and, most importantly, medical picture analysis [2-4]. Classification of breast cancer has made use of deep learning models, with an emphasis on Convolutional Neural Networks, to examine ultrasonography and histological pictures, yielding important information for prognosis and therapy [1,3-6].

Breast cancer categorization frameworks based on deep learning have been suggested in many publications. For instance, a framework for classifying ultrasound images using deep learning and feature fusion has been put forth, exhibiting better performance than traditional techniques [1]. Utilizing deep learning-based BC segmentation and classification approaches, an automated detection mechanism was introduced in a different study for separating benign from malignant mass tumours [2]. Histopathological image-based breast cancer classification utilizing deep learning models optimized for certain tasks and pre-trained on massive datasets has been the subject of other studies [5-9].

Despite initial encouraging outcomes, the implementation of deep learning in breast cancer categorization continues to face obstacles. Some of these challenges include using small-scale datasets, potentially leading to overfitting, and a lack of labelled training data. Deep features that are extracted also have a high degree of dimensionality Researchers have used techniques including feature selection, data augmentation, and transfer

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learning to solve these issues [4-6]. In order to provide a thorough explanation of how DL is being used to classify breast cancer, the intention of this review study is to analyze the advantages and disadvantages of the neural networks that were utilized in each reference. The issues that are currently being faced in this subject as well as prospective solutions will be discussed in the paper, which will provide significant insights for future study. Over the last several years, considerable progress has been achieved in the utilization of DL in categorizing BC. In the multi-classification of BC using histological photos, the structured deep learning model proposed by Han et al. achieved 93.2% accuracy on average using a large-scale dataset [10]. This study demonstrates how DL might be a useful technique for clinical breast cancer multi-classification. DL was developed by Bayramoglu et al. to eliminate the requirement for magnification Regarding the categorization of breast cancer histopathology images [13]. Their method enhanced the efficiency of models tailored to different magnification levels, and the results indicated that more training data could be beneficial, according to the study. To classify breast cancer histopathology photos, Hameed et al. suggested a combination of deep learning algorithms. [11]. The researchers published a demonstration of the effectiveness of DL in the automated classification of histological pictures of complicated breast cancer. The system attained an overall accuracy of 95.29% and a sensitivity of 97.33% for the carcinoma class. An approach to breast cancer histology picture categorization utilizing multi-size discriminative patches grounded in deep learning was put forth by Li *et al*. [12]. Their strategy outperformed other cutting-edge approaches, achieving a 95% success rate on the first test set and an overall success rate of 88%. figure.1 shows the breast cancer classification methods.

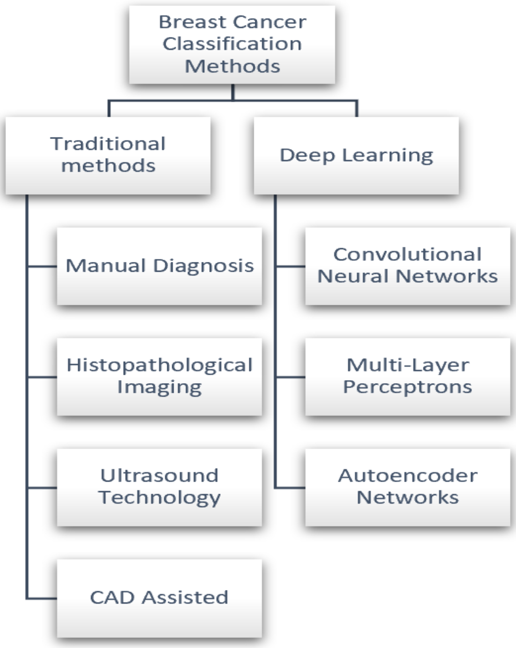

Figure 1 Breast Cancer Classification Methods.

1.1 Scope of the Review

In this review, we will look at deep learning as it pertains to breast cancer classification. The process of assigning a specific breast cancer sample to one of numerous established categories, usually using histological pictures, is known as classification in this context. This is a critical task within the detection and treatment of BC, as different types of BC require different treatment strategies. The review does not cover applying DL to tasks other than the prediction and segmentation of breast cancer. Prediction refers to the task of predicting the future progression of the disease based on current data, while segmentation refers to the task of identifying specific regions of interest, such as tumors, within an image. While these tasks are undoubtedly important, our focus here is on classification, given its vital part in the initial detection of BC. Some of the DL models that have been used for the problem of breast cancer classification include autoencoders, Multi-Layer Deep Learning Networks (MLNNs), and convolutional neural networks. We'll talk about the benefits and drawbacks of these models, as reported in the literature, and provide a comparative analysis of their performance. This article greatly increases medical imaging and breast cancer detection by offering a comprehensive overview of the latest techniques and advancements in deep learning-based approaches to BC categorization. Giving academics, medical professionals, and practitioners a comprehensive understanding of the latest advancements in this ever-evolving subject is our aim.

- Extensive Literature Review: In order to find the most up-to-date and pertinent research on BC categorization using DL algorithms, we performed a thorough literature study. By scrutinizing a vast array of research papers, conference proceedings, and other scholarly resources, we ensure the inclusion of the most up-to-date and relevant information in this review.
- Categorization of DL Models: To facilitate a clearer understanding of it, we carefully categorize the different DL models and architectures that have been applied to breast cancer classification. Our analysis covers a wide range of models, including CNNs, Multi-Layer Deep Learning Networks and Autoencoder. We thoroughly examine the advantages and disadvantages of each model, as well as their potential applications.
- Analysis of Datasets: Understanding the importance of data in deep learning, we critically evaluate the datasets used in different studies for breast cancer classification. By assessing the diversity, size, and quality of these datasets, we illuminate the difficulties and opportunities in this domain, encouraging future researchers to consider appropriate datasets to foster more reliable and robust models.
- Present Challenges and Future Directions: In addition to highlighting the state of the art at this time, we also emphasize the barriers and limitations that deep learning models face in terms of breast cancer classification. By acknowledging these obstacles, we aim to guide future research efforts toward addressing key issues and facilitating the practical implementation of AI-driven tools in clinical settings.

1.2 The Paper's Structure Brief Overview

This review paper appears as this structure:
Section 2: Breast Cancer and Its Classification - This section offers a concise introduction to breast cancer and highlights how important classification is when diagnosing the disease. It also reviews the traditional methods of BC categorizing.
Section 3: Deep Learning for BC Diagnosis - An introduction to deep learning and its application to breast cancer classification are covered in this part. It offers a thorough synopsis of the applications of DL approaches in this subject.
Section 4: Review of Neural Networks in Breast Cancer Classification - This section delves into the specific kinds of NNs used in the literature for breast cancer classification. Each Neural Network type is discussed in a separate subsection, which includes A synopsis of the Neural Network, a review of papers that utilized this Neural Network for BC classification, and a discourse on the advantages and disadvantages of this Neural Network as reported in the literature.
Section 5: Discussion - This section presents a comparative analysis of the different NNs based on the reviewed literature. It goes on to talk about where the field of BC deep learning categorization is going, what needs fixing, and what patterns are emerging.
Section 6: Conclusion - This final section summarizes the main findings of the review and provides a conclusion based on the analysis.
Our goal in organizing the paper in this way is to present a thorough yet easy-to-understand overview of DL's role in BC classification.

II. Breast Cancer and Its Classification

Breast Cancer, which is a severe and multifaceted illness, is one of the primary causes of death for women worldwide and is connected to cancer. The unrestrained multiplication of cells that occurs in this situation can result in the growth of a breast tumor or lump. Both of these outcomes are possible. There are a few different varieties of illnesses that may be distinguished from one another according to the tumor location, the degree to which the disease has progressed, and the molecular features of the tumor cells. Invasive lobular carcinoma (ILC), ductal carcinoma in situ (DCIS), and invasive ductal carcinoma (IDC) are the primary forms (ILC). Each of these types has distinct clinical and pathological features that influence treatment decisions and patient prognosis [14].

2.1 Brief Overview of Breast Cancer

It is the epithelial cells which line the lactiferous ducts and lobules of the breast that are responsible for the development of breast cancer. The disease progression is typically gradual, starting with hyperplasia, advancing to atypical hyperplasia, then to carcinoma in situ (non-invasive cancer), and finally to invasive cancer. Several factors work in conjunction to elevate the possibility of getting breast cancer [15]. These include age, a personal or familial history of ovarian or BC, specific genetic abnormalities (including BRCA1 and BRCA2), the time at which menstruation begins and menopause, the age of the first child, and estrogen exposure. Biopsies, ultrasonography, mammograms, and physical exams all have a part in confirming a BC diagnosis. The next step in developing a treatment strategy is confirming the diagnosis, which in turn dictates the type of tests to be administered. The vast majority of women who are diagnosed early-stage BC patients can undergo radiation therapy or a mastectomy while still preserving their breasts [16]. Surgical excision, radiation, chemotherapy, hormone replacement, targeted therapy, immunotherapy, and targeted therapy are all components of a comprehensive breast cancer treatment plan. The type and stage of the cancer, the patient's general health, and the patient's preferences all affect the course of treatment [17]. Recent decades have witnessed a significant improvement in breast cancer prognoses due to developments in early identification and treatment. However, the disease remains a major health concern due to its high prevalence and the potential for recurrence and metastasis [18].

2.2 Importance of Classification in Breast Cancer Diagnosis

The importance of classification in BC detection is underscored by the fact that it can significantly influence the course of treatment and prognosis. Classification allows for a more personalized approach to patient care, enabling clinicians to tailor treatments based on the specific type and stage of cancer. Cancer cells produce tiny vesicles called exosomes in the bloodstream. These exosomes carry different molecular components from the cell that released them. A microfluidic chip showed promise in one study for immunocapture and measurement of these exosomes. This technology was applied in a clinical investigation, where EpCAM-positive exosomes in circulation were quantified in both healthy controls and breast cancer patients. In this regard, three varieties of breast cancer cells in humans' lines as well as negative control samples are investigated in this study as four classes of the classification problem. The researchers discovered that patients had a considerable rise in the level of EpCAM-positive exosomes, which might be a useful instrument for molecular categorization and detection of breast cancer [19]. Another study highlighted the variety of breast cancer types and the significance of advanced molecular diagnostic tools for early detection. The authors pointed out that breast cancer cells' cytology, growth pattern, and expression of important biomarkers can be used to create better diagnostic and treatment tools. They also emphasized the potential of portable biosensors for quick and non-invasive point-of-care analysis [20]. Another area that has made use of ML algorithms is breast cancer classification. For instance, one research looked at breast cancer diagnosis using SVM, ANNs, and Naive Bayes. The researchers proposed a hybrid method that combined dimensionality reduction and machine learning, achieving high accuracy, sensitivity, and specificity for classifying benign and malignant cancers [21]. Another study used the WDBC datasets to train an artificial neural network to categorize BC cases as benign or malignant with the express intention of identifying malignancy. To cut down on training time and increase accuracy, the scientists suggested an island-based training approach [22]. These studies underscore the importance of classification in breast cancer diagnosis, as it can facilitate early detection, inform treatment decisions, and ultimately improve patient outcomes.

2.3 Traditional Methods of Breast Cancer Classification

Methods for classifying breast cancer have depended previously on the tumor's histological characteristics, such as its size, grade, and status of lymph nodes, as well as the presence or lack of particular biomarkers, such as the progesterone receptor, estrogen receptor, and human epidermal growth factor 2 (HER2). These features are utilized to categorize various forms of breast cancer and subtypes, which can help guide treatment decisions and predict prognosis [23]. While working to integrate ultrasound technology into clinical practice, in 1951, Wild and Neal made the initial findings about the A-mode echographic diagnosis of live intact breast carcinoma [24]. Ultrasound can detect and diagnose breast lesions that are both benign and cancerous, as demonstrated by Wild and Reid (1952) [25] using the pulse-echo method in conjunction with the A-mode display. These authors brought up the possibility of using the A-scan area echographic ratio between tumor tissue and normal breast tissue to distinguish between malignant and benign tissue in a real human breast. Researchers, including physicists and doctors, began looking at computerized image analysis in the 1960s and 1970s to automate the detection or classification of anomalies, for a binary classification problem using breast pictures [26]. In the middle of the 1980s, a team of radiologists and medical physicists started studying computer-aided detection (CAD). CAD refers to the practice of using computer output to assist radiologists, rather than completely automating interpreted by a computer. At first, they focused on methods for identifying lesions on mammograms and chest radiographs. [27,28]. According to this definition, CAD refers to a diagnosis provided by a radiologist who bases their choice on the results of a computer analysis of the image data. The radiologist makes the final medical judgment; the computer does not. The original plan, as shown in Figure 2, was for radiologists to use the results of computerized analysis of medical images as a "second opinion," like a spellchecker, to help them describe and identify lesions and make diagnostic decisions [29].

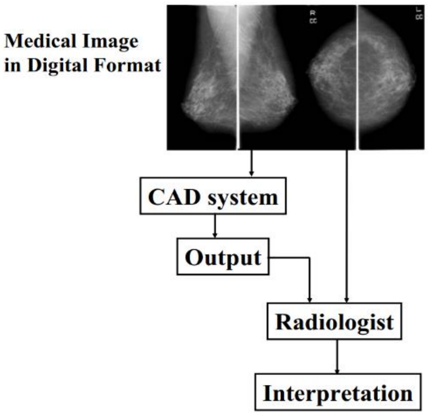

Figure 2 A CAD System's Schematic Diagram for Interpreting Medical Images [29].

However, these traditional methods have several limitations. First, they rely heavily on the subjective interpretation of the pathologist, which can lead to variability in diagnosis. Second, they might not adequately convey the intricacy of the molecules in the tumor, which can result in inaccurate classification and prediction of prognosis. A history of traditional breast cancer classification methods appears in Table 1.

Table 1 Traditional Breast Cancer Classification Techniques.

Reference	Traditional Classification Methods	Brief Description	Advantages	Disadvantages
[1]	Manual Diagnosis	This traditional method involves an expert manually diagnosing cancer using mammogram images.	-Easy to implement (no need for advanced technology)	-Low accuracy -Hard to interpret -Need an expert
[23]	Histopathological Imaging	Using histopathological imaging, this approach can diagnose breast cancer. Because there are a lot of complicated images, processing them takes a long time.	-More accurate and interpretable than radiological images	-Need large space for storage of data -Time-consuming
[25]	Ultrasound Technology	The ratio of tumor to normal breast tissue in an A-scan region echography can be applied to differentiate between benign and cancerous breast tissue in a living human being.	-Low computational complexity	-The threshold adjustment needs a wide study and the fixed threshold might not be accurate

[26]	CAD Assisted	Physicists and doctors began looking at computerized image analysis in the '60s and '70s to automate the process of abnormality detection and classification.	-More accurate than manual methods	-Not able to classify the lesions -Less accurate than machine learning and deep learning-based methods

One newer method is the one described in the following study: Gene expression profiling has become an effective technique for breast cancer categorization [30]. This approach uses microarray or next-generation sequencing technologies to measure the expression levels of thousands of genes in a tumor sample, providing a more comprehensive view of the tumor’s molecular makeup. Luminal A, Luminal B, HER2-enriched, and Basal-like are the four intrinsic subtypes of breast cancer that the PAM50 classifier divides the expression of fifty genes into. This is one of several gene expression-based classifiers that have been developed. Moreover, advances in genomic technologies have led to the discovery of numerous genetic and epigenetic alterations associated with breast cancer, further enhancing our understanding of the disease's molecular heterogeneity. As an example, a thorough genomic characterization of breast cancer has been provided by the Cancer Genome Atlas (TCGA) project, which has identified numerous important driver genes and pathways [31]. Despite these advances, the integration of these molecular data into clinical practice remains challenging. Prospective research must to concentrate on creating greater accurate and clinically applicable classification methods that can guide personalized treatment strategies for breast cancer patients.

III. Deep Learning for Breast cancer Classification

There is some evidence that deep learning can successfully classify breast cancer photos, albeit the level of success varies from case to case. Thanks to developments in technology, deep learning's use in breast cancer categorization has skyrocketed in the past few years [32]. In this part, we'll look at how convolutional neural networks and their hybrids, two of the most recent and innovative methods, employ DL to classify BC. Moreover, DL algorithms has been instrumental in achieving high accuracy rates in breast cancer classification. For instance, the BC2NetRF framework proposed by Jabeen et al. achieved an accuracy of 95.4% for the CBIS-DDSM dataset and 99.7% for the INbreast cancer dataset. This framework utilized a contrast enhancement technique to improve the quality of mammogram images and trained the EfficientNet-b0 deep learning model on these enhanced images. The deep features extracted from these images were then optimized using an Equilibrium-Jaya controlled Regula Falsi-based feature selection technique, significantly reducing the computational time [33].

3.1 Introduction to Deep Learning

Known as artificial neural networks, deep learning is a branch of machine learning that attempts to model algorithmic behavior after that of the human brain [34]. By simulating the way the human brain learns from experience, these algorithms enable computers to autonomously process data, draw valid conclusions, and make sound decisions [35]. Deep learning models are composed of multiple layers of artificial neurons, or "nodes", each of which performs a small, simple computation on the data. The outputs of these computations are passed on to other nodes in subsequent layers, creating a complex network of interconnected nodes. Deep learning models can learn hierarchical data representations because of this layered structure, wherein each layer acquires the ability to detect even more complicated features [36]. Feature learning, sometimes called representation learning, is a crucial capability of deep learning that allows it to autonomously learn and extract features from raw data. This is in contrast to more conventional machine learning approaches, which sometimes necessitate human intervention in the form of feature engineering to prepare raw data for learning [37]. Image and speech identification, medical diagnosis, natural language processing, and many more fields have all found useful uses for deep learning [38]. Many diseases have profited substantially from deep learning methods, particularly convolutional neural networks [39], including breast cancer detection and classification. Nevertheless, there are several obstacles to overcome when using deep learning for medical imaging. These include the need for large amounts of annotated training data, the difficulty of interpreting the "black box" models, and the risk of overfitting due to the high complexity of the models [40]. Notwithstanding these challenges, deep learning holds significant potential to improve the accuracy and efficacy of breast cancer classification and diagnosis. New deep learning architectures and methodologies have been the focus of recent research in an effort to overcome these obstacles and enhance breast cancer classification performance. [41]. As aforementioned, deep learning, has shown remarkable success in the field of medical imaging, particularly in the diagnosis of breast cancer [42]. To enhance the contrast of mammography images, train deep learning models more effectively, and train them on original and upgraded pictures, researchers have developed automated computerized frameworks for breast cancer classification, employing deep transfer learning ideas (e.g., EfficientNet-b0) [33]. Moreover, deep learning has been used to investigate breast cancer invasive disease events (IDEs), such as recurrence, contralateral, and second cancers. Explainable Artificial Intelligence (XAI) frameworks have been designed to determine the IDE driving features, making deep learning approaches more interpretable [43]. Below, we will explore the particular deep learning methods employed for breast cancer categorization and talk about their advantages and disadvantages.

3.2 Importance and Relevance Deep Learning in Breast Cancer Classification

The use of DL has revolutionized breast cancer categorization, outperforming more conventional approaches in terms of both accuracy and efficiency. Patients and their prognoses are greatly impacted by the automated diagnosis of breast cancer by the analysis of histological images (HIs). The ability to automatically extract features is what makes deep learning systems so useful, and this is especially true in medical imaging [44]. Thanks to deep learning, gene expression data may now be used to classify breast cancer into subgroups. Molecular subtyping is closely related to devising clinical strategy and prognosis, and deep learning-based models have been shown to accurately classify these subtypes [45]. In contrast to cutting-edge outcomes, deep learning in conjunction with other techniques like HOG and LBP outperforms them when it comes to mammogram-based breast cancer classification [46]. Deep learning has also been used to study the connection between breast cancer subtypes and genes. Explainable deep learning models have made it possible for researchers to explore the meaning of feature variables and provide insight into the underlying mechanisms of intrinsic subtypes of breast cancer [47]. Lastly, techniques such as contrast-limited Adaptive Histogram Equalization (CLAHE) have been shown to increase picture contrast and decrease the vanishing gradient problem, hence improving the accuracy of deep learning models in the classification of breast cancer [48].

IV. Review of Neural Networks in Breast Cancer Classification

There has been encouraging progress in the use of NNs for BC categorization, regarding both accuracy and efficiency. Different kinds of neural networks have different pros and cons and are used in different ways in the literature. This section will review the types of neural networks used in breast cancer classification, focusing on their descriptions, the papers that utilized them, and their reported advantages and disadvantages.

4.1 Convolutional Neural Networks

Among the many deep learning models, Convolutional Neural Networks stand out for their remarkable ability to analyze images. Images are mostly classified, objects are detected, and semantic segmentation is performed using them. In essence, Kunihiko Fukushima invented the "Neocognitron" in 1980 [49], which was the first CNN-based model ever. The research on cats by Hubel and Wiesel [50] that resulted in the identification of two different types of visual cells in the brain served as inspiration for it. The two fundamental CNN layer types convolutional layers and down-sampling layers were introduced by the Neocognitron. CNNs are built to learn feature hierarchies from input data automatically and adaptively. A convolutional, pooling and a fully connected layer are fundamentally three layers that makeup CNN. Layering these layers allows for the construction of a deep architecture capable of automatically extracting features [51]. Nevertheless, CNNs typically consist of a minimum of one convolutional layer, with additional layers like pooling, fully connected, and normalization serving to reduce the network's parameter and computation burden by progressively shrinking the representation's spatial dimension (so that the network is more stable). By doing a dot product on its weights and a tiny area it is linked to in the input volume, the convolutional layer makes the network translation invariant [35]. Figure 3 shows how the CNN approach is organized.

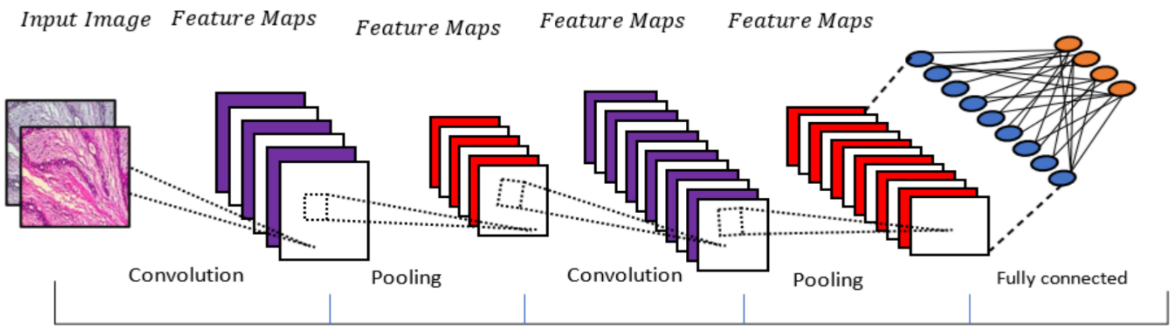

Figure 3 An illustration of the CNN model [52].

4.1.1 *Review of Papers that utilized CNNs for Breast Cancer Classification*

Taking a look at the training states of CNNs that are utilized for BC classification is one method for classifying these networks. First, there are the Transfer Learning-based models which are the CNN models utilizing previously trained networks (such as GoogleNet, ResNet and AlexNet), and then the de Novo Trained models that are composed and trained from scratch.

A. *Convolutional Neural Networks on DMR-IR dataset:*
- Raquel, et.al (2021) [53]: The authors propose a multi-input CNN model that processes thermal images from three views (front, R90, and L90) to classify patients as healthy or sick. A sensitivity level of 83%, specificity of 100%, area under the ROC curve of 0.99, and accuracy of 97% are all achieved by the model.

B. *Convolutional Neural Networks on MIAS dataset:*
- According to Saira et al. (2018), as stated in reference [54]: The MIAS dataset is analyzed using morphological operations to identify ROIs, which are further classified using a CNN. An overall accuracy of 65% is achieved by the procedure.
- Abeer, et.al (2021) [55]: The authors propose a novel deep-learning model for improving the classification results on the MIAS dataset. The model Applies transfer learning and data augmentation to CNNs. The model achieves an accuracy of 98.87%.
- "Hossein, et.al. (2020) [56]:" A two-stage segmentation method utilizing deep learning and graph-based image processing is presented by the writers. The method's performance on the MIAS dataset is 97.59 percent according to Dice.

C. *Highway-Network-based CNN on IRMA dataset:*
- Naveed, et.al (2021) [57]: Using a deep highway network to extract dynamic characteristics, the authors introduce an automated approach for detecting breast cancer based on diverse features (DFeBCD). The CNN achieves an accuracy of 81.07%, the SVM classifier achieves an accuracy of 80.5%, and the ELiEC classifier achieves an accuracy of 80.3%.

D. *Convolutional Neural Networks on DDSM (CBIS) datasets:*
- Xin Shu, et.al (2020) [58]: A DCNN end-to-end design, together with two pooling structures, is suggested by the writers. An accuracy rate of 92.2% is achieved by the design of the DDSM (CBIS) dataset.
- Hossein, et.al (2020) [56]: The authors also did their survey on this dataset. The method achieves a Dice score of 97.69% on the CBIS-DDSM.
- Mugahed et al. (2020) [59] suggested a CAD system that uses deep learning to identify and categorize breast lesions. The system employs a YOLO detector and three deep-learning classifiers for detection and classification. The system was tested on two digital X-ray mammogram databases, DDSM and INbreast, and achieved high detection accuracies and F1-scores (accuracy of 99.17% and an F1-score of 99.28% for the DDSM and dataset).
- Y. Nguyen Tan et al. (2023) [60] created an FL system to diagnose BC using transfer learning and SMOTE. The system used the FeAvg-CNN + MobileNet model to ensure privacy and

security and outperformed many other methods in classification performance (97.91% Accuracy). The system has potential for use in AI healthcare applications.

- A novel Model using a mammogram is presented in paper [61]. The goal of the suggested method is to use a mammography picture to create an understandable classification. For classification, a Case-Based Reasoning (CBR) system is used, and the quality of the retrieved features has a significant impact on the system's accuracy. A pipeline comprising data augmentation and picture improvement is proposed to increase feature quality and provide a final diagnostic in order to improve classification relevance. A U-Net architecture-based effective segmentation technique is applied to extract Regions of Interest (RoI) from mammograms. To improve classification accuracy, deep learning and CBR are intended to be combined. While CBR offers a clear and accurate classification, DL offers exact mammography segmentation. Using the CBIS-DDSM dataset, the suggested method is evaluated and performs well, with an accuracy of 86.71% and a recall of 91.34%.

E. *Convolutional Neural Networks on INbreast datasets:*

- Hossein, et.al (2020) [56]: also did a Dice score of 96.39% on the INbreast dataset.
- Xin Shu, et.al (2020) [58]: Two pooling structures and a deep convolutional neural network end-to-end architecture are proposed by the authors. Applying the architecture to the INbreast dataset yields an accuracy rate of 92.2%.
- Mugahed et al. (2020) [59] as previously mentioned, used three DL classifiers, namely feedforward CNN, ResNet-50 and InceptionResNet-V2 in their study and using the INbreast, they achieved an accuracy of 97.27% and F1-score of 98.02%.

F. *Convolutional Neural Networks on BreakHis dataset:*

- In the paper by Bardou et al. (2018) [62], two machine-learning approaches for breast cancer histology image classification are compared. Using the BreakHis dataset for both approaches, the first Methodology uses handcrafted features and support vector machines while the second uses convolutional neural networks. Techniques such as dataset augmentation were experimentally tested to improve accuracy. Results showed that CNNs were more effective than handcrafted feature-based classifiers, achieving high accuracy rates for both binary and multi-class classification (Accuracy of 83.31–88.23% (8 Classes), and 96.15%-98.33% (2 Classes)).
- In the study by Bayramoglu et al. (2017) [13], Regardless of the magnification level of the images, CNNs were suggested as a way to classify the histology of breast cancer. A malignancy prediction architecture and a combination of malignancy/image magnification level prediction architecture were both showcased. Utilizing the BreaKHis dataset, an average accuracy of 80.10% was achieved.
- The author of another paper (Nahid et al. (2018) [63]) utilizes innovative DNN techniques to classify a group of biomedical breast cancer images from the BreakHis dataset. Statistics and structural data extracted from the pictures serve as a basis for the methods. An LSTM, a CNN, or a hybrid of the two might be applied to categorize photos of breast cancer, the study found. The experiment produced accuracy and precision values of 91.0 percent and 96.0 percent, respectively.
- In order to classify four benign and four malignant breast cancer subtypes, a hybrid model utilizing a convolutional neural network and long short-term memory recurrent neural network (LSTM RNN) is created in [64]. The suggested CNN-LSTM model uses ImageNet transfer learning for subtype classification and prediction. The BreakHis dataset—which includes 5429 cancer and 2480 benign pictures at different magnifications—is evaluated. The hybrid CNN-LSTM model is compared with existing CNN models like VGG-16, ResNet50, and Inception models for breast histopathological image classification. All models are trained using three different optimizers (Adam, RMSProp, and SGD) with varying numbers of epochs. Results indicate that the Adam optimizer performs best, yielding for both training and validation sets, the highest accuracy and the lowest model loss. On the BreakHis dataset, the hybrid CNN-LSTM model that has been suggested performs best overall, with 99% accuracy for binary

classification of benign and malignant cancer and 92.5% accuracy for multi-class classification of benign and malignant cancer subtypes, respectively.

- A pretrained ReNet18 model for feature extraction from X-ray images and a support vector machine (SVM) for cancer diagnosis are used in the paper [65] to propose a computer-aided ensemble technique for breast cancer diagnosis. After applying haze reduction to improve image quality, the tumor is segmented from the image using a K-means algorithm based on histograms. Investigations are carried out using the BreakHis dataset, which includes classifications for benign and malignant conditions, at four different magnification levels (40x, 100x, 200x, and 400x). After evaluation, the suggested model had the best accuracy, coming in at 92.6% at 200x magnification. At the 100x magnification factor, the maximum specificity and precision were attained, with respective values of 93.1% and 86.5%.

G. *Convolutional Neural Networks on Breast Ultrasound Images (BUS) Dataset:*

- In paper [66], the classic CNN architecture LeNet is applied successfully to the breast cancer data. Its capacity to identify and extract discriminating characteristics between malignant and benign tumours with high accuracy is demonstrated, supporting early detection and diagnosis of breast cancer. The use of a corrected Rectified Linear Unit (ReLU), a modification of the traditional ReLU activation function, is found to enhance the performance of LeNet in breast cancer data analysis tasks by addressing the "dying ReLU" problem and improving the discriminative power of extracted features. This improvement leads to more accurate and reliable breast cancer detection and diagnosis, ultimately improving patient outcomes. Batch normalization is shown to enhance the performance and training stability of small and shallow CNN architectures like LeNet by mitigating the effects of internal covariate shifts, thereby reducing overfitting and runtime. The designed classifier is evaluated against benchmarking deep learning models, demonstrating a higher recognition rate. The accuracy of the breast image recognition rate is reported as 89.91% on the Breast Ultrasound Images Dataset.

H. *Convolutional Neural Networks on multiple datasets:*

- In study [67], a contemporary deep learning (DL) framework for computer-aided diagnosis (CAD) is examined to help radiologists diagnose breast cancer. Four separate experiments are carried out to ascertain the optimal classification technique: first, pre-trained Deep CNNs such as AlexNet, GoogleNet, ResNet50, and Dense-Net121 are utilized; second, Deep CNNs are used to extract features that are subsequently applied to a Support Vector Machine (SVM) algorithm with three different kernels; third, different deep features are fused to improve classification; and finally, Principal Component Analysis (PCA) is utilized to lower computational costs and diminish large feature vectors resulting from fusion. The experiments are carried out on two mammogram datasets, MIAS and INbreast (97.93% for MIAS and 96.646% for INbreast), surpassing state-of-the-art frameworks.
- A study [68] uses an integration strategy integrating CNN and picture texture attribute extraction to develop a system for autonomously identifying cancer. The CNN stage uses a nine-layer tailored convolutional neural network for data classification. In order to increase the efficacy of categorization, texture characteristics are defined and their dimension is lowered during the extraction-based phase utilizing Uniform Manifold Approximation and Projection (UMAP). To get the final conclusion, an ensemble algorithm combines the results of each phase. If any output from the phases is malignant, then malignancy is assumed in the final classification. The testing specificity and accuracy of the ensemble approach are stated as 97.8% and 98% on the MIAS repository, respectively, and as 98.3% and 97.9% on the DDSM repository.
- Rather than depending on a single CNN model, a unique rank-based ensemble method is proposed in paper [69] that incorporates the results of three transfer learning CNN models: GoogleNet, VGG11, and MobileNetV3_Small. The ensemble model tackles a 2-class classification problem of breast histopathology pictures by leveraging the Gamma function in its formulation. Better classification results are obtained when compared to state-of-the-art methods, with accuracies of 96.95% on another well-known dataset, ICIAR-2018, and 99.16%,

98.24%, 98.67%, and 96.16%, respectively, for magnification levels of 40X, 100X, 200X, and 400X on the publicly accessible standard dataset BreakHis.

- Five new deep hybrid convolutional neural network-based frameworks for the detection of breast cancer are developed in study [70]. By utilizing the combined strengths of both networks, the suggested hybrid systems outperform their respective base classifiers. In order to achieve efficient hybridization, a probability-based weight factor and threshold value are essential. Accuracy and speed of the system are improved by an optimal threshold value chosen through experimentation. Significantly, in contrast to conventional deep learning techniques, the suggested framework performs exceptionally well even with little datasets. The datasets from two distinct breast cancer modalities—the mini-DDSM (mammogram), BUSI, and BUS2 (ultrasound)—are used to validate the suggested approach. The experimental findings demonstrate the superior performance of the suggested ShuffleNet-ResNet scheme compared to the state-of-the-art techniques on all datasets presented. Additionally, the suggested approach obtains accuracy of 96.52% and 93.18% for abnormality and malignancy identification in BUSI datasets, and 99.17% and 98.00% for those same tasks in mini-DDSM. BUS2 provides a 98.13% malignancy detection accuracy.
- In order to evaluate the performance efficiency of the created deep learning architecture, Article [71] uses the Mammographic Image processing Society (MIAS) and Digital Database for Screening Mammography (DDSM) datasets for mammography image processing. Using mammography images from the DDSM dataset, the CNN architecture obtains a sensitivity of 97.91%, specificity of 97.83%, accuracy of 98.44%, and Jaccard index of 98.57%. It achieves 98% sensitivity, 98.66% specificity, 99.17% accuracy, and 98.07% Jaccard index on mammography pictures from the MIAS dataset. For both datasets, the experimental results are contrasted with similar recent efforts. The thorough study of experimental findings demonstrates how well the approaches described in the article define the border of the cancer location in abnormal mammography images.images, as evidenced by the extensive analysis of experimental results.

I. *Convolutional Neural Networks on <u>Private</u> Datasets:*

- Ahmed, et.al (2019) [72], explored three convolutional neural networks models for ultrasound breast lesion classification: a baseline model that uses a freshly trained CNN architecture, a transfer-learning model that uses a pre-trained VGG16, and a fine-tuned learning model. where the parameters of the deep learning system are adjusted to prevent overfitting. The experiments' results showed that the optimized model worked the best (0.97 accuracy, 0.98 AUC).
- Zhiqiong, et.al (2019) [73]: The authors use a CNN in combination with an Unsupervised Extreme Learning Machine (US-ELM) for mass detection in breast images. The ELM classifier achieves an accuracy of 76.25%, and the SVM classifier achieves an accuracy of 74.50%.
- Guoming, et.al (2020) [74]: The authors suggest a convolutional neural network classifier that uses the bit-plane slicing characteristic of images to improve the detection accuracy of breast cancer images. The classifier achieves an accuracy of 0.78% on the seventh bit-plane.
- Two datasets were utilized in [75], with the first containing 176 cases, including 103 cancer and 73 benign cases, while the second comprised 84 cases, with 53 cancer and 31 benign cases. The inputs for detection to take symmetry into account were pre-contrast and subtraction pictures of the left and right breasts. Three DCE parametric maps were used as inputs by ResNet50 to characterize the identified suspicious area. A lesion-based diagnosis was obtained by combining the results of slice-based analysis. A sensitivity of 96% was obtained in the first dataset using Mask R-CNN to identify 101 out of 103 tumors as suspicious. Of those, 99 were accurately classified using ResNet50. Furthermore, 131 normal areas and 48 benign lesions were marked as suspicious. Only 16 benign and 16 normal areas were still identified as malignant after ResNet50 classification. After independent testing with the second dataset, the sensitivity was 81%. Of the 121 non-cancerous lesions that were found, only 6 were categorized as benign, while 22 normal tissues were diagnosed as malignant

4.1.2 Advantages and Disadvantages of CNN as Reported in Literature

Convolutional Neural Networks have several benefits and drawbacks when it comes to breast cancer classification, according to the study's literature review:

A. Advantages

- *High Accuracy:* Results from breast cancer classification challenges demonstrate that CNNs perform admirably. For instance, a study by Nazir et al. (2022) [76] reported an accuracy of 99.2% using CNN-Inception-V4-based hybrid model for breast cancer classification. Another study by Mewada et al. (2020) [77] reported an accuracy of 97.58% using a CNN for classifying cancer images.
- *Effective Feature Extraction:* Medical imaging benefits from CNNs because of their ability to automatically train and extract high-level features from images, which is a huge time saver compared to manual feature extraction [78].
- *Versatility:* Combining CNNs with other models can boost their performance. For instance, to achieve better results than conventional CNN models, Wei Wang et al. (2022) [79] suggested a Vision Transformer (ViT)-based semi-supervised learning framework that employed adaptive token sampling for efficient performance gain, supervised and consistency training for model robustness. Similarly, A. E. Minarno et al. (2022) [80] improved CNN performance by combining EfficientNet-B0 with data augmentation and dropout layers, leading to increased accuracy and reduced overfitting. Zaharaddeen Sani et al. (2023) [81] introduced a novel architecture that combined a group convolutional neural network (G-CNN) with a special Euclidean (SE2) motion group and discrete cosine transform (DCT), aiming to enhance breast cancer classification and data efficiency. Finally, a study conducted by A. Elkorany and Z. Elsharkawy (2023) [82] showcased the potential of combining CNNs with other models to achieve better results. The researchers used three Deep Learning (DL) CNN models, namely Inception-V3, ResNet50, and AlexNet, as feature extractors. The features that were selected based on Term Variance (TV) were then fed into a multiclass support vector machine (MSVM) classifier.

B. Disadvantages

- *Computational Complexity:* CNNs, especially deep models, require significant computational resources and time for training, which might be a limitation in resource-constrained settings [83, 84].
- *Risk of Overfitting:* CNNs, due to their complexity, are prone to overfitting, especially when the amount of training data is limited. Techniques such as dropout and batch normalization are often used to mitigate this issue [85,86].
- *Need for Large Datasets:* CNNs typically require large amounts of labelled data for training to achieve high performance [87]. In medical imaging, obtaining such large datasets can be challenging due to privacy concerns and the effort required to manually label images [88].

4.2 Multi-Layer Deep Learning Networks (MLNNs)

An artificial neural network that is composed of multiple layers of nodes in a directed graph is referred to as a Multi-Layer Neural Network. This type of neural network is also referred to as a Multi-Layer Perceptron (MLP) and is considered to be the less complicated of the deep learning methods [36]. The ability to understand intricate patterns is made feasible by the layers' complete connectivity. They are a vital part of deep learning, a subfield of machine learning, and have found wide applicability in various applications, such as the categorization of breast cancer. An MLNN is composed of an input layer, a hidden layer (or layers), and an output layer. This indicates that each node (or neuron) in a layer is linked to each node in the layer below it, each of which has a particular weight attached to it. The neurons carry out an activation function, which is a non-linear alteration, before transferring their inputs to the next layer, on the information that they receive. This structure allows although not the best tool, an acceptable one-to-model complex, non-linear relationships [89]. To get the required outcomes, MLNN training must be set. In order to execute the best training, an MLNN must be configured. Parameters must be initialized and modified in this process. For example, weights can be initialized by producing or by applying previously acquired domain knowledge [90]. A diagram of the MLP's structure is shown in Figure 4.

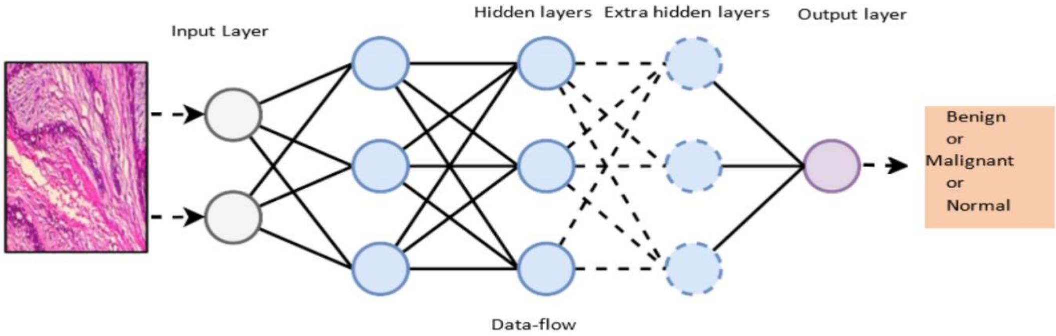

Figure 4 An illustration of the MLP [52].

4.2.1 *Review of papers that utilized Multi-Layer Neural Networks for breast cancer classification*

Several recent studies have utilized MLP Networks for breast cancer classification:

- Amin Rezaeipanah and Gholamreza Ahmadi (2020) [91] MWAMLP, a hybrid classification technique, was developed using a neural network that includes Multi-Stage Weights Adjustment. Averaging across all datasets in the Wisconsin Breast Cancer Database, the study reached a 99.35% accuracy rate.
- In continuation of the previous article, The authors provide a genetic approach for simultaneous feature selection and MLP neural network parameter tuning as part of an automated breast cancer diagnosis method. The objective is to improve breast cancer diagnosis by introducing a hybrid classification algorithm based on Multi-stage Weights Adjustment in the MLP (MWAMLP) neural network in two sections. Three classifiers are simultaneously trained on the learning dataset in the first section. The result of these classifiers, along with the learning dataset, is utilized to create a new dataset. This dataset employs a hybrid classifier method to establish the mapping between the outputs of each ordinary classifier from the first part and real output labels. The proposed algorithm is implemented with three different variations of the backpropagation (BP) technique, including Levenberg–Marquardt, resilient BP, and gradient descent with momentum, for fine-tuning the weight of the MLP neural network. Their performances are compared, and one of the proposed algorithms, titled MWAMLP-RP, achieves the best results, with an average correct classification of 99.35% and 98.74% on the Wisconsin Breast Cancer Database dataset [92].
- M. Oliveira et al. (2020) [93] examined the MLP ANN in comparison to the Nearest Neighbors approach for diagnosis of breast cancer and classification. The study used data from the UCI Machine Learning Repository (Wisconsin Breast Cancer Database), and the results (Accuracy of 0.9717 for MLP, and 0.9596 for KNN) showed that the MLP network outperformed the KNN in several aspects.
- Another study by Al-Tam et al. (2022) [94] presents a new CAD system for breast lesions that combines deep learning with a hybrid approach, employing the Transformer Encoder and MLP for classification. The system is tested on two datasets, CBIS-DDSM and DDSM, and compared against different deep learning models. With total accuracies of 100% for binary prediction problems and 95.60% for multiclass prediction challenges, the suggested CAD system shows encouraging results.
- The paper [95] develops a model using Normalized MLP Neural Network on the Breast Cancer Wisconsin dataset to classify breast cancer with high accuracy (99.27%).
- In this study, Raad et al. examined the effectiveness of MLP and RBF network-based neural networks for classification using (WBCD) [96].
- Study [97] aims to predict the probability of breast cancer in patients using machine learning (ML) models, including MLP. The breast cancer diagnostic medical dataset from the Wisconsin repository, containing 569 observations and 32 features, is utilized. Following the data analysis methodology, tasks such as data cleaning, exploratory analysis, training, testing, and validation are performed. The models' performance is evaluated based on classification accuracy, specificity, sensitivity, F1 count, and precision. Training and results indicate that the six trained models can provide optimal classification and prediction results. MLP model achieved a performance of 96.92%.
- In research [98], the Wisconsin Breast Cancer Dataset (WBCD) from the UCI machine learning repository serves as a training set to evaluate the performance of different machine learning techniques.

Various classifiers including MLP are utilized to classify breast cancer into benign and malignant tumours. Various performance metrics such as error rate, accuracy, precision, F1-score, and recall are employed to assess the models' performance. The accuracy of the MLP Algorithm is reported as 94.41%, which icreases to 97.54% after feature optimization.

- Paper [99] introduces IEC-MLP for breast cancer diagnosis. The method comprises two stages: parameter optimization and ensemble classification. In the first stage, the Evolutionary Algorithm (EA) is utilized to optimize parameters of the MLP Neural Network (MLP-NN), such as optimal features, hidden layers, hidden nodes, and weights, to maximize classification accuracy. In the second stage, an ensemble classification algorithm is applied to classify patients using MLP-NN with optimized parameters. The proposed IEC-MLP method reduces the complexity of MLP-NN, selects the optimal subset of features effectively, and minimizes misclassification costs. Classification results are evaluated using IEC-MLP across different breast cancer datasets, yielding promising prediction results with 98.74% accuracy on the WBCD dataset. The objective of paper [100] is to tune the parameters of the MLP neural network for breast cancer detection. An MLP-based homogeneous ensemble approach is presented for classifying breast cancer samples, utilizing ensemble learning to enhance the classification process by combining different basic classifiers to derive a new classifier. Optimization algorithms including GA, PSO, and ODMA are employed to determine the most suitable parameters for MLP, such as effective features, number of hidden layers, number of nodes in layers, and weight values. The proposed algorithm is applied to three datasets from the Wisconsin Breast Cancer Database (WBCD, WDBC, and WPBC), and a comparison is conducted between different algorithms to achieve the highest accuracy. Experimental results demonstrate that the proposed classifier yields promising results in breast cancer detection compared to other state-of-the-art classifiers, achieving 98.79% accuracy in the WBCD dataset.
- Study [101] proposes a data mining-based method for breast cancer diagnosis, combining a Multi-Layer Perceptron neural network with an evolutionary approach. The aim is to tune MLP parameters using Teaching-Learning-Based Optimization (TLBO), a new evolutionary approach. The capabilities of TLBO are compared to Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Open-Source Development Model Algorithm (ODMA). The proposed method, named MLP-TLBO, adjusts all MLP parameters simultaneously, including effective features and their number, the number of hidden layers, the number of neurons in each hidden layer, and the weights of links. To enhance the classification process, MLP-TLBO employs an ensemble classification mechanism where multiple MLPs simultaneously model the training data. The evaluation of the proposed method is conducted on the Wisconsin Breast Cancer Database, using for simulations three common Wisconsin datasets: WBCD, WDBC, and WPBC.
- In the publication [102], different machine-learning algorithms were analyzed to assess a patient's risk of breast cancer. Owing to the intrinsic qualities of early-stage features, a multilayer perception model incorporating PCA was put into practice, and it was discovered to be more successful than alternative detection techniques. On the BCCD dataset, the 4-layer MLP-PCA network had the highest accuracy of 100%, with a mean accuracy of 90.48%.
- In order to detect breast cancer from patient data, a new machine learning-based framework called Multilayer Perception, Random Forest, Gradient Boosting, Support Vector Machine, and Artificial Neural Network is introduced in Paper [103]. A hybrid Multilayer Perceptron Model and a 5-fold cross-validation framework are utilized to use and classify the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. For better categorization, a connection-based feature selection method that removes recursive features is used. The Wisconsin Prognostic dataset (WPBC) and Wisconsin Original Breast Cancer (WOBC) datasets are the two distinct datasets used to validate the system. With an 80-20 train-test split for MLP, the results show improved accuracy of 99.12% ascribed to effective data preprocessing and feature selection strategies applied to the input data.

4.2.2 Advantages and Disadvantages of MLPs as Reported in the Literature

The following are the benefits and drawbacks of Multi-Layer Perceptron Neural Networks when categorizing breast cancer, according to the literature review:

A. Advantages

- *Ability to Handle Complex Datasets:* MLP networks can manage complex and large datasets. They can learn and model non-linear and complex relationships, which is crucial in many real-world applications. A study by Deuk-Hwan Lee et al. (2020) [104] used an MLP structure in an artificial neural network to handle complex landslide susceptibility mapping, indicating MLP's ability to manage complex datasets. Another Study [105] presents a hybrid method that uses MLP networks to handle complex hyperspectral image data, demonstrating MLP's capacity to handle complex and large datasets.
- *Flexibility in Design:* Any amount of layers and neurons within these layers can be used to create MLP networks [106]. This flexibility allows the network to be tailored to the specific needs of the problem. A paper by Amin Rezaeipanah et al. [91] mentions the optimization of MLP Neural Network (MLP-NN) parameters with an Evolutionary Algorithm (EA) to maximize the classification accuracy. This suggests that MLP networks can be designed with any number of layers and neurons, and these parameters can be optimized for the specific needs of the problem.
- *Good Performance:* With sufficient training data, MLP networks can yield robust and high-performing models. They have been shown to achieve high accuracy in tasks like breast cancer classification. In a study by Yosra Mohammed and E. Saleh (2021) [107], they used MLP in conjunction with other methods to predict the type of breast tumour, achieving high accuracy rates (94.2%). Authors in another study [108] trained MLPs using the Sine Cosine Algorithm, a metaheuristic optimization method and achieved high accuracy rates of up to 97% on several disease-related datasets, including breast cancer. With a sensitivity of 98.06%, specificity of 99.99 percent, accuracy of 98.50%, and precision of 99.99 percent, a new system for selecting features for breast cancer classification using deep learning cascades was developed and tested in another study [4].

B. Disadvantages

- *Risk of Overfitting:* Too many parameters in a multi-layer perceptron network can cause it to overfit its training data and underperform on new data. This is a common problem when the network has more neurons and layers than necessary. These papers [109, 110] discuss the issue of overfitting in MLP networks and propose some solutions, such as using 1/f noise injection, batch normalization, etc. to overcome this issue
- *Need for Manual Tuning:* The performance of MLP networks is highly dependent on the choice of parameters, such as the number of hidden layers and neurons in these layers. These parameters need to be manually tuned, which can be time-consuming. According to the paper by Luka Gajic et al. [111], the problem of hyperparameter tuning for MLP, which includes the number of hidden layers and neurons, is an NP-hard space search problem, which implies that the performance of MLP networks can indeed be dependent on the choice of parameters. Moreover, another paper [112] also mentions the use of a grid search-based hyperparameter tuning for an MLP neural network, indicating that manual tuning of parameters can be necessary for optimal performance.
- *Local Minima:* The training process of MLP networks involves optimizing a loss function. This optimization process can get stuck in local minima, leading to sub-optimal solutions. This is particularly a problem when the network has many layers and parameters. These papers [113-116] discuss the problem of local minima in the context of training MLP networks and propose several Optimization or Hybrid methods to address this issue.
- *Black Box Nature:* MLP networks, like many other neural networks, suffer from being "black boxes" [117, 118]. While they can model complex relationships and make accurate predictions, their internal workings are not easily interpretable. This lack of interpretability can be a problem in applications where understanding the model's decision-making process is important. There are some attempts here and there to make the structure of MLP as a neural network more understandable [119, 120].

4.3 The Autoencoder Neural Networks

Autoencoders are a subset of artificial neural networks that can learn to code input data efficiently. With these unsupervised learning models, which employ the backpropagation principle, the inputs are used to set the target values [121]. Autoencoders are used for feature extraction, classification, learning generative models of data, dimensionality reduction, and can be used for compression. By reducing the size of the data, autoencoder algorithms extract the most discriminating features from unlabeled data [122]. In order to reduce the likelihood of errors, the encoder converts the input data into hidden features that are then reconstructed using the decoder [123]. In figure 5, we can see a common autoencoder model in action.

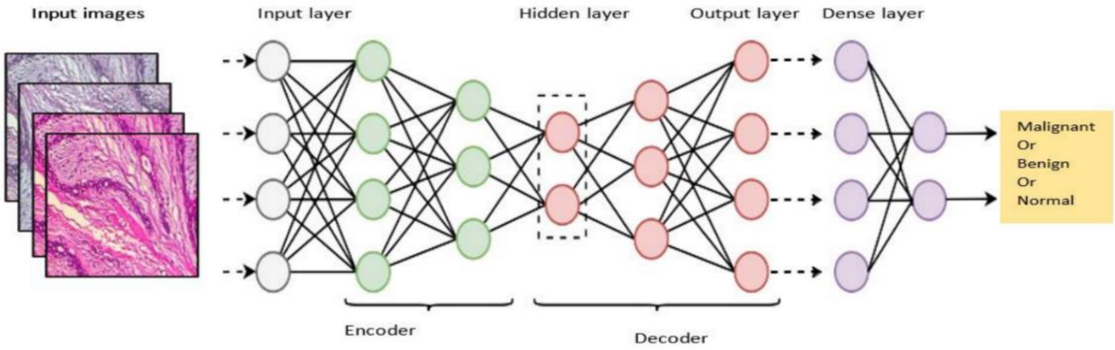

Figure 5 An illustration of the Deep Autoencoder [52].

4.3.1 Review of papers that utilized Autoencoder Neural Network for breast cancer classification

There are many breast cancer classification types of research done with the direct or indirect aid of Autoencoder neural networks. Study by Nazeri et al. (2018) [124] proposed a patch-based technique consisting of two consecutive CNNs for breast tissue classification of microscopy images. With a remarkable 95% accuracy, the first "patch-wise" network serves as an Autoencoder, removing irrelevant details from picture patches, and the second network classifies the entire image. In a study by Zhang et al. (2018) [125], To forecast clinical outcomes in breast cancer, an ensemble classifier (PCA-AE-Ada) based on the AdaBoost algorithm was created. In the study by Toğaçar et al. (2020) [126] the researchers combined CNNs and an Autoencoder network to classify invasive ductal carcinoma, a common type of BC. This combined method achieved a high classification success rate of 98.59%, demonstrating the effectiveness of using Autoencoders in conjunction with other deep-learning models for complex classification tasks. An improved autoencoder (AE) network was designed in [127] learning useful characteristics for CAD breast cancer classification tasks from histopathology pictures using a Siamese framework. To obtain multi-scale features, the input image is first processed using a Gaussian pyramid at several scales. The pre-trained AE is then constrained in the feature extraction stage using a Siamese framework, guaranteeing that the retrieved features show greater inter-class variance and less intra-class variance. On the BreakHis dataset, experimental findings show that the suggested technique obtains a classification accuracy of 97.8%. This technique performs better and faster than commonly used algorithms in the histological categorization of breast cancer. In paper [128] initially, machine learning algorithms, such as Random Forest and Support Vector Machine (SVM), were employed for classifying histopathological images as cancerous or non-cancerous, yielding promising outcomes. Subsequently, ANNs were introduced for the same purpose. An approach involving image reconstruction using a Variational AE (VAE) and Denoising VAE (DVAE) was proposed, followed by classification using a Convolutional Neural Network model. The prediction of whether the input image depicted cancerous or non-cancerous tissue was then made. The implementation yielded predictions with 73% accuracy, surpassing the performance of a custom-built CNN on the dataset. A publication [129] presents a comparative analysis of different machine-learning methods for breast cancer screening. In order to find a condensed representation of features significantly related with breast cancer, an autoencoder model is also presented for unsupervised breast cancer diagnosis. The publicly accessible Breast Cancer Wisconsin (Diagnostic) Dataset from Kaggle is used to assess the methods. The autoencoder performs better than its rivals, with a 98.4% recall and precision rate. A novel method for classifying breast cancer is presented in paper [130] and makes use of beta wavelet autoencoders (BWAE) and fully convolutional networks (FCNs). Known for its powerful image segmentation skills, FCN is used to identify key zones for modeling and extract meaningful information from mammography pictures. After that, WAE is used to model the acquired data, demonstrating its superiority over a number of feature extraction techniques. Combining these two methods preserves and models just the pertinent and helpful aspects for recognizing and characterizing breast masses, which improves the feature extraction stage. When compared to cutting-edge techniques on the same dataset of mammography images, experimental results show how successful the suggested strategy is. With a recall rate of 92% for benign cases and 95% for malignant cases, a precision rate of 94% for benign cases and 93% for malignant cases is achieved. Furthermore, a 100% success rate is attained for typical scenarios. A unique method for categorizing pictures as malignant or non-malignant is put forth in paper [131]. The strategy makes use of the latent space embeddings that convolutional autoencoders acquire. Reconstruction learning is used to compress the input histopathological picture into a latent space representation, which yields these embeddings. The best features for differentiating between benign and malignant photos are then extracted using a feature selection module that is based on reinforcement learning. To verify the robustness of the outcomes, the suggested method is assessed using the K-Fold Cross Validation technique on the BreakHis dataset. Strong performance is shown by the proposed model's achieved accuracy of 96.8%. In [132], a brand-new deep learning method called Moanna is put forth to integrate multi-omics data and predict breast cancer subtypes. Moanna's architecture integrates a multi-task learning network with a semi-supervised Autoencoder to generalize a combination of somatic mutation, copy number, and gene expression data. Moanna is assessed using an independent cohort of TCGA samples and the remaining hold-out METABRIC samples after being trained on a portion of the METABRIC breast cancer dataset. When Autoencoder is used in conjunction with other dimensionality reduction approaches, it is shown to be superior in terms of learning patterns related to different subtypes of breast cancer. The Moanna model as a whole demonstrates great accuracy in ER status prediction (96%), basal-like sample differentiation (98%), and PAM50 subtype classification (85%). Additionally, Moanna's predicted subtypes exhibit a stronger correlation with patient survival compared to the original PAM50 subtypes. Using an encoder-decoder architecture, a 3D Connected-UNet model for tumor segmentation from 3D magnetic resonance imaging is described in [133]. Owing to the training dataset size constraints, the input picture itself is improved via a variational autoencoder outlet, making it easier for the shared decoder and other controls on its layers to identify it. via examining 2D neighbor areas and 3D volume statistics, a completely connected 3D temporary unsystematic domain is used to enhance segmentation results after the first segmentation via Connected-UNets. Furthermore, the 3D-connected module assessment is carried out to guarantee robustness around large modules and minimize segmentation noise. Two publicly accessible datasets—INbreast and the curated breast imaging subset of the digital database for screening mammography—are used to assess the suggested methodology. Additionally, a private dataset is used to assess the suggested model. The results of the experiments show that the suggested model outperforms the most advanced techniques for segmenting breast tumors. An automated method for segmenting breast regions according to different morphological structures inside the breast tissue is presented in paper [134]. The categorization of these morphologies using live patient photos is essential to the segmentation stages. The suggested model is then used for feature extraction, obtaining eight statistical features from a set of single breast photos. An unsupervised deep-learning algorithm called an autoencoder neural network is used to categorize thermography images as either healthy or unhealthy. The Database for Mastology Research, which contains information from 196 people—41 cancer cases and 155 healthy cases—is used to assess the suggested model. A total of 1,960 thermography photos were evaluated, with each participant contributing 10 images. The technique produced a 94.87% accuracy rate and a specificity of 96.77%. Article [135] introduces the use of Deep Stacked Sparse Autoencoders (SSAE) for breast cancer diagnosis and classification. Algorithms and methods are evaluated and tested on the Breast Cancer Wisconsin (Diagnostic) Data Set (WDBC) using MATLAB R2017b platform. The achieved classification accuracy ranges from 97.2% to 100%. An advantageous type of Autoencoder network is the Stacked Sparse Autoencoder. An SSAE is a type of deep learning model that is particularly effective for unsupervised feature learning. This neural network is a variation of the classic autoencoder, which can learn to efficiently code input data.

- The "stacked" part of SSAE means that multiple layers of these autoencoders are placed one on top of another. The following layer takes its input from the previous one. This paves the way for the network to understand the input data in a more nuanced way.
- The "sparse" component is a regularization method that prevents the model from using an excessive amount of hidden layer neurons. As a result, the model is motivated to learn a more balanced and resilient data representation, which can lead to better performance and less overfitting.

In a study by Parekh et al. (2018) [136], a multiparametric deep learning (MPDL) network for segmentation and classification was developed using Stacked Sparse Autoencoders. They demonstrated an AUC of 0.9 for the differentiation of malignant from benign lesions. Xu et al. (2014) [137] used a Stacked Sparse Autoencoder (SSAE) for the categorization of nuclei in the histology of breast cancer. High-level characteristics that more accurately matched the input data were learned by the SSAE with good results. The SSAE combined with Softmax outperformed the other methods, achieving an accuracy of 83.7%, an F1 score of 82%, and an AUC of 0.8992 in the classification process. Xu et al. (2015) [138] conducted research that used (SSAE) to efficiently recognize nuclei in high-resolution breast cancer histopathology pictures. These features were then fed to the SoftMax classifier, which categorized each image patch as nuclear or non-nuclear. Outperforming nine other state-of-the-art nuclear detection algorithms, the SSAE displayed increased performance in nuclei detection with an estimated area under the Precision-Recall curve (AveP) of 78.83%. Stacked denoising autoencoders are another kind of autoencoders that work to remove noisy features (SDAE). Because lumps can vary so much in size, shape, and appearance, the SDAE network may be able to help with these problems. Improving the reliability of feature extraction might be possible by reducing the impact of image processing errors through the use of SDAE-based models' autonomous feature extraction capabilities and inherent noise tolerance. Cheng et al. (2016) [139] utilized an SDAE to differentiate nodules or lesions in breast ultrasound and lung CT scan pictures, to maximize the utility of the SDAE model. Then using SoftMax for the benign and malignant classification process, they achieved an accuracy of 94.4% and an AUC of 98.4%. In the same way, Feng et al. (2018) [140] developed a novel deep neural network that uses a Stacked Denoising Autoencoder (SDAE) for the categorization of cell nuclei in histopathology photos of breast cancer. Layer-by-layer feature extraction is performed using the SDAE, and once more, SoftMax is used to identify benign and malignant conditions. The authors state that they achieved 98.28% accuracy on the malignant subset and 90.54% accuracy on the benign subset with this technique. In study [141], an approach is introduced where a Subspace KNN algorithm is combined with SAE for diagnosing breast cancer using a microarray dataset, marking the first such application. Hybrid approaches like this offer the potential for improved results in classifying datasets with high dimensionality and uncertainty. The dataset utilized is sourced from the Kent Ridge-2, comprising 97 samples (51 benign, 46 malignant) and 24,482 attributes. The performance of the proposed method is evaluated and compared with other established techniques in dimension reduction and machine learning. Through the use of SAE and Subspace KNN, the dataset is reduced to 100 attributes, resulting in an accuracy of 91.24%. This outcome underscores the significance of achieving accurate classification, particularly in datasets with high dimensionality. Additionally, this study introduces the application of stacked autoencoder-SoftMax classifier model for breast cancer microarray data using a variety of classifiers to increase its success rate, marking a novel contribution to the field.

4.3.2 Advantages and Disadvantages of Autoencoder Networks as Reported in the Literature

Based on the studies done around the globe, here are some advantages and disadvantages of Autoencoder Deep Learning Networks:

A. Advantages

- *Efficient Data Compression:* Autoencoders are effective in compressing high-dimensional data into smaller latent representations, which is beneficial for efficiently learning policies, especially in embedded systems [142]. Also, the authors in another study [143] used an autoencoder for dimensionality reduction and feature extraction from multi-omics data for cancer subtype analysis.
- *Unsupervised Learning:* Unsupervised learning models include autoencoders. In situations when obtaining labelled data is difficult or costly, they can be utilized because they do not necessitate labelled data. Many studies mention the utilization of autoencoder neural networks handling unlabeled datasets or multi-temporal images [144-146].
- *Feature Learning:* Automatic feature learning from data is within the capabilities of autoencoders. When manually engineering features becomes a challenge, this may be quite helpful. To categorize nuclei and non-nuclei patches retrieved from BC histology, for instance, Jun Xu et al. (2014) [147] used SSAE to get knowledge of important high-level traits for better input raw data representation.
- *Noise Reduction:* Autoencoders can be used to remove noise from data. This can be particularly useful when the data is corrupted with noise. Apart from the previously mentioned papers [139, 140] that used SDAE networks, there are other ways to denoise the input data. Aleisa et al. (2022) [147], used a Beta Wavelet Autoencoder was used for feature extraction from mammography images, which inherently

involves noise reduction. Also, a study by Manar Ahmed Hamza (2023) [148], mentioned that a Hybrid Denoising Autoencoder was specifically used for noise reduction in digital mammograms.

- *Anomaly Detection:* Autoencoders have been successfully used in anomaly detection tasks, such as detecting fraud in large-scale accounting data [149] and anomaly detection in distribution systems [150]. Although it's not directly related to breast cancer classification, it shows the capability of autoencoders in anomaly detection.

B. Disadvantages

- *Black Box Problem:* Like many other deep learning models, autoencoders can suffer from the "black box" problem, where their internal workings are not easily interpretable [151]. In return, some autoencoder models, like XOmiVAE, can provide insights into each gene's and latent dimension's contribution to each classification prediction, which can aid in comprehending the "black box" issue of deep learning applications in the field of omics [151].
- *Training Complexity:* The training process of autoencoders involves optimizing a loss function, which can get stuck in local minima, leading to sub-optimal solutions [152]. Moreover, training deep autoencoder networks can be energy-consuming, especially when the network has many layers and parameters [142].
- *Overfitting:* Autoencoders can easily overfit the training data, especially if they have too many parameters (i.e., they are too complex) relative to the amount of training data, and not enough regularization is applied [153]. It's also important to note that while autoencoders can overfit, techniques such as regularization, early stopping, and dropout can be used to mitigate this issue.
- *Local Minima:* The training process of autoencoders involves optimizing a loss function, typically a reconstruction loss that measures the difference between the input and the output of the autoencoder. This optimization process can indeed get stuck in local minima, especially when the network has many layers and parameters. However, various techniques, such as different types of regularization and initialization, can be used to mitigate this issue.
- *Choice of Architecture:* How well autoencoders work is highly sensitive to settings like hidden layer density and the number of neurons per layer [154]. It can take some time to manually adjust these parameters [155, 156].

V. DISCUSSION

Doing a comparative analysis of the evaluated sources is the main objective of this part. Given that breast cancer is one of the main causes of death worldwide, integrating cutting-edge computer methods—particularly deep learning networks—has shown significant promise in improving detection accuracy and facilitating early diagnosis. In this regard, evaluation criteria can be used to compare different models. To evaluate how well predictive models work, evaluation measures are essential. Accuracy, precision, sensitivity, and F1 score are four important metrics that are frequently used in breast cancer detection models. By showing the proportion of properly categorized cases to all cases, accuracy measures how effectively the model predicts results. The ratio of actual positive predictions to total positive predictions is used by precision to gauge the accuracy of the model. It demonstrates how well the model can identify favorable circumstances. The ratio of the number of accurate predictions to the total number of true positives in the dataset is known as the sensitivity of the model. To give a fair evaluation that takes into account both false negatives (misdiagnosed cancer cases) and false positives (misdiagnosed healthy patients), the F1 score combines sensitivity and precision. As these measures quantify the model's capacity to decrease false negatives and false positives, medical practitioners may make better-informed judgments regarding patient care and treatment options. This is particularly important in breast cancer diagnosis. Table 2 shows a comparison of the referenced works according to the accuracy measure.

Table 2 Comparing DL-Based Methods for BC Classification.

Corresponding Reference	**Method**	**Dataset**	**Accuracy**
[52]	Convolutional Neural Networks	DMR-IR	97%
[53]	Convolutional Neural Networks	MIAS	65%
[54]	Convolutional Neural Networks	MIAS	98.87%
[55]	Convolutional Neural Networks	MIAS	97.59%
[56]	Highway-Network-based CNN	IRMA	81.07%
[57]	Convolutional Neural Networks	DDSM (CBIS)	92.2%
[58]	YOLO detector and three deep learning classifiers	INbreast and DDSM (CBIS)	99.17% for the DDSM dataset
[59]	FeAvg-CNN + MobileNet	DDSM (CBIS)	97.91%
[60]	Convolutional Neural Networks	BreakHis	83.31% (8 classes) 96.15% (2 classes)
[62]	CNN, an LSTM, and a combination of both	BreakHis	91%
[63]	Convolutional Neural Networks	Private datasets	97%
[72]	Convolutional Neural Networks	Private datasets	76.25%
[73]	Convolutional Neural Networks	Private datasets	78%
[90]	MWAMLP MLP ANN and KNN	Wisconsin Breast Cancer	99.35%
[91]	Transformer encoder with MLP	Wisconsin Breast Cancer	97.17% for MLP ANN and 95.96% for KNN
[93]	Normalized MLP Neural Network	CBIS-DDSM and DDSM	100% for binary and 95.80% for multiclasses.
[94]	MLP	Wisconsin Breast Cancer	99.27%
[95]	Autoencoder Neural Network	Wisconsin Breast Cancer	-
[123]	An Ensemble classifier (PCA-AE-Ada)	-	95%
[124]	Combined CNNs and an Autoencoder network	-	-
*-: Not mentioned			

Table 3 Comparison of the Deep **Learning Techniques Based on Advantages and Disadvantages.**

Techniques	Advantages	Disadvantages
CNN	High Accuracy, Effective Feature Extraction, Versatility.	Computational Complexity, Risk of Overfitting and Need for Large Datasets.
MLPs	Ability to Handle Complex Datasets, Flexibility in Design and Good Performance.	Risk of Overfitting, Need for Manual Tuning, Local Minima and Black Box Nature.
Autoencoder	Efficient Data Compression, Unsupervised Learning, Feature Learning, Noise Reduction and Anomaly Detection.	Black Box Problem, Training Complexity, Overfitting and Choice of Architecture.

VI. DATASETS

Here, we give a quick rundown of some of the more extensively employed imaging approaches for identifying and researching breast cancer. Numerous Research has indicated that breast cancer may be detected using a wide range of imaging techniques. These modalities include digital breast tomosynthesis, positron emission tomography, ultrasound, magnetic resonance imaging, histopathology, and mammography (multimodalities). Numerous public and private datasets are available for these modalities. Screening for breast cancer using mammography is widespread; in fact, the two modalities are linked to about 70% of public datasets. However, histopathology and magnetic resonance imaging (MRI) were also extensively used by researchers to confirm cancer and address issues with mammography and ultrasound imaging modalities, such as the fact that there are huge variations in the shape, morphology, and density of breast tissues, among other things. In this section, we detail the breast cancer detection datasets and imaging modalities that have already been mentioned [157]. Table 4 provides more information regarding the benefits and drawbacks of datasets. Table 5 also includes a summary of the most frequent features of the public datasets that were reviewed.

Table 4: The benefits and limitations of using public datasets for analyzing various imaging modalities in breast cancer.

Image Modality	Advantages	Limitations
MM	• Research on breast cancer using computational and experimental methods accounts for almost 70% of the total. • Compared to other modalities, this method of image capture and processing is shorter and cheaper. • When compared to other approaches, there is no requirement for highly trained radiologists to diagnose and detect cancer.	• Since MMs are produced by low-dose X-ray, it is not possible to record micro-calcification. • Cancer detection in thick breasts is hindered. • For a precise diagnosis, more testing is necessary. • Classification requires extensive pre-processing to account for numerous potentially confusing features and anatomical features like hypertrophied lobules, fibrous strands, the breast border, etc. Issues with cancer detection in dense breast tissue.
	• Because it can take pictures from all sorts of different perspectives, it's a great tool for cutting down on diagnostic false negatives. • The most effective and least invasive way to perform regular	• Taking low-resolution pictures to study the bigger sample of tissues. • Unintelligible SWE pictures. • Cancerous tissues cannot be detected by a single Nakagami parametric picture. Due to the shadowing effect, which makes

US	checkups, the US is also the safest. • Possibility of identifying regions of invasive cancer Particularly useful for locating breast lesion ROIs because to extra features like color-coded SWE pictures.	the tumour's outline harder to discern, accurate ROI calculation is extremely challenging.
MRI	• No exposure to dangerous ionizing radiation means this procedure is safe. • Takes pictures with greater clarity. • Compared to other modalities, it captures a greater number of suspicious spots for additional examination. • Addition of contrast agents to depict more detailed images has the potential to improve it.	• Taking low-resolution pictures to study the bigger sample of tissues. • Unintelligible SWE pictures. • Cancerous tissues cannot be detected by a single Nakagami parametric picture. Due to the shadowing effect, which makes the tumour's outline harder to discern, accurate ROI calculation is extremely challenging. • Not all tumors are caught by it, although it can be used in conjunction with MMs. • Raspberries raise core temperature. • The potential for triggering allergic reactions Method that is both invasive and harmful.
HP	• Results in pictures with different colors for different cancer subtypes and early diagnosis. • As MMs, they are often utilized for cancer diagnosis. • The two kinds of tissues shown are WSI and ROI taken from WSI. • Compared to other imaging modalities, it produces the most accurate diagnostic results. • ROI enhances the precision of cancer analysis and diagnosis. • Apt for archiving for use at a later date.	• A costly and laborious approach to analysis is required. • Exceptional pathologist. • The analysis and ROI extraction processes are tiresome, which could reduce their accuracy. • Fixation, laboratory techniques, sample orientations, human competence in tissue preparation, color variance, and other factors greatly impact HP analysis. • It requires a lot of computing power to analyze and is the most challenging imaging modality to use a DL technique to cancer classification.
DBT	• Helps find cancer earlier. • Could detect tumors that were completely overlooked by MMs. • Gives artificial intelligence systems a once-in-a-lifetime chance to build techniques based on DBT, starting from the bottom. • A more in-depth look of the tissues can be obtained by	• Producing 3D photographs is a time-consuming and costly process. • Poor data classification and organization. • Using 2D slices as opposed to 3D images reduces the accuracy of the study. • The question of whether AI models perform better with

	rotating the X-ray emitter to take multiple pictures. • Exhibits excellent capability to differentiate minute lesions that could obstruct MM-derived projections.	identified abnormalities remains unanswered when examining only 2D slices. • By making use of bounding boxes or carefully drawing the lesion borders. • Storage requirements for DBT investigations are easily an order of magnitude more than those for MMs.

Table 5 Different Public Databases and Their Features.

Dataset	**Modality**	**No. of Images**	**Resolution**	**Image Type**
MIAS	MM	322	8 bit / pixel	PGM
INbreast	MM	410	14 bit / pixel	DICOM
BCDR	MM	3703	14 bit / pixel	TIFF
DDSM	MM	10,480	8 or 16 bit / pixel	LJPEG
CBIS-DDSM	MM	3468	16 bit / pixel	DICOM
Magic-5	MM	3369	16 bit / pixel	DICOM
BancoWeb	MM	1473	12bit/pixel	TIFF
OPTIMAM	MM	2,889,312	-------------	DICOM
BUS	US	250	-------------	BMP
Breast Ultrasound Dataset	US	780	-------------	PNG
Duke-Breast-Cancer-MRI	MRI	922	-------------	DICOM
RIDER Breast MRI	MRI	1500	-------------	DICOM
BreakHis	HP	7909	8 bit / pixel	PNG
TUPAC	HP	73	-------------	DICOM
BACH	HP	75	12 bit/pixel	TIFF
Wisconsin	HP	569	-------------	DICOM
TCGA	HP	1097 Malignant	-------------	DICOM
BCS-DBT	DBT	22,032	-------------	DICOM

VII. Conclusion

As possible methods for breast cancer classification, we have looked at and assessed three types of deep learning networks in this thorough review: autoencoders, multi-layer neural networks and CNNs. Each category of networks has its unique strengths and limitations, shedding light on their applicability and challenges in this critical domain. With its impressive feature extraction capabilities and high accuracy, Convolutional Neural Networks have become a vital weapon in the fight against breast cancer. The versatility of CNNs in combination with other models allows for the creation of robust and comprehensive classification systems. However, the computational complexity of CNNs remains a concern, and the risk of overfitting poses a significant challenge, particularly when data is scarce. Addressing the need for large datasets is vital for unleashing the full potential of CNNs in BC detection. The use of MLNNs to classify breast cancer has demonstrated encouraging outcomes, particularly when dealing with complicated datasets. Their flexibility in design allows for customization and adaptation to specific clinical scenarios. Nevertheless, MLNNs are not without their drawbacks, as they are susceptible to overfitting, necessitating careful manual tuning of hyperparameters. Additionally, the black-box nature of MLNNs, where their internal workings are not easily interpretable, may hinder their acceptance and trustworthiness in clinical applications. Autoencoders have proven to be efficient data compression and unsupervised learning techniques, offering valuable feature learning capabilities for breast cancer classification tasks. Their noise reduction and anomaly detection capabilities make them promising candidates for addressing specific challenges in medical imaging analysis. However, the black-box problem of autoencoders remains a concern, as their complex internal representations may not be readily interpretable, limiting their utility in certain clinical settings. Training complexity, overfitting, and the choice of architecture are additional challenges that need to be carefully considered when employing autoencoders in BC classification.

In conclusion, this review highlights the potential of deep learning Models, including CNNs, MLNNs, and autoencoders, for breast cancer classification. Each category brings distinct advantages and disadvantages, which should be carefully weighed based on specific clinical requirements and data availability. Future research should concentrate on overcoming the noted challenges in order to fully realize the potential of deep learning for breast cancer diagnosis. Better patient care and results in the fight against breast cancer will result from this.

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